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Investigating cross-market interdependence in frontier markets

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Thesis Certification

I, Hameedah Sayani, declare that this thesis, submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy, in the Faculty of Business, University of Wollongong in Dubai, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Hameedah Sayani

15 June 2015

To my loving husband Minhas, and my children Madiha and Daanish

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Abbreviations and Acronyms

ADC	Asymmetric Dynamic Covariance
ADCC	Asymmetric Dynamic Conditional Correlation
ADF	Augmented Dickey Fuller
ADSM	Abu Dhabi Securities Market
AIC	Akaike Information Criterion
APARCH	Asymmetric Power ARCH
ARCH	Autoregressive Conditional Heteroscedasticity
ASEAN	Association of Southeast Asian Nations (Members: Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam)
BEKK	Baba-Engle-Kraft-Kroner Model
CAPM	Capital Asset Pricing Model
CCC	Constant Conditional Correlations
CEEC	Central and Eastern European Countries (Countries included: Albania, Bulgaria, Croatia, the Czech Republic, Hungary, Poland, Romania, the Slovak Republic, Slovenia, Estonia, Latvia and Lithuania)
CIVETS	Colombia, Indonesia, Vietnam, Egypt, Turkey and South Africa
DCC	Dynamic Conditional Correlation
DED	Double Exponential Distribution
DF Test	Dickey Fuller Test
DJ	Dow Jones
DW	Durbin Watson Statistic
EC	European Community
ECM	Error Correction Model
EDB Index	Ease of Doing Business Index
EEC	European Economic Community
EGARCH	Exponential GARCH
EMU	European Monetary Union
ES	Exponential smoothing
ETF	Exchange Traded Funds

EU	European Union
F-ARCH	Factor ARCH
F-GARCH	Factor GARCH
FDI	Foreign Direct Investment
FPE	Final Prediction Error
FTA	Free Trade Agreements
G3	Free Trade Agreement between Colombia, Mexico and Venezuela
G7	Group of Seven Industrialized Countries (France, Germany, Italy, Japan, USA, UK and Canada)
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GARCH-M	GARCH in Mean
GC Index	Global Competitiveness Index
GCC	Gulf Cooperation Council
GDP	Gross Domestic Product
GED	Generalized Error Distribution
GJR GARCH	Glosten-Jagannathan-Runkle GARCH
GMM	Generalized Method of Moments
GNI	Gross National Income
GO-GARCH	Generalized Orthogonal GARCH
GQARCH	Generalized Quadratic GARCH
ICSS	Integrated Cumulative Sum of Squares Algorithm
iid	Independent and Identical Distribution
KSE	Karachi Stock Exchange
KSE100	Karachi Stock Exchange 100 Index
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ME	Mean Error
MENA	Middle East and North Africa
MA	Moving Average
MVGARCH	Multivariate GARCH

NAFTA	North American Free Trade Agreement
OECD	Organization for Economic Co-operation and Development (Members: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israël, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States)
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PGARCH	Periodic GARCH
PNP-ARCH	Partially Non-Parametric ARCH
PP	Phillips and Peron
RMSE	Root Mean Squared Error
S&P	Standard and Poor's
SECP	Securities and Exchange Commission of Pakistan
SIC	Schwartz Information Criterion
SPARCH	Semi-Parametric GARCH
SWARCH	Switching ARCH
TARCH	Threshold GARCH
UAE	United Arab Emirates
UK	United Kingdom
USA	United States of America
VAR	Vector Autoregression
VECM	Vector Error Correction Model
WDA	Wavelength Decomposition Analysis

Abstract

The primary aim of this thesis is to quantify the magnitude, direction and duration of conditional returns and volatility spillovers between the financial markets of Pakistan and those of its key trade partners. Accordingly, this thesis 1) examines the impact of the financial crisis of 2008 on all markets under consideration, 2) measures cross-market returns and volatility spillovers across groups of countries categorized according to country classification and geographical proximity to Pakistan, 3) quantifies interaction of returns and volatility between pairs of countries, and 4) evaluates whether the magnitude of spillovers differs in pre-crisis, crisis, and post-crisis periods.

The finance literature emphasizes the importance of bilateral trade and geographical proximity in determining the interdependence between financial markets. The literature also presents evidence of segmentation of smaller financial markets from world markets despite globalized trade relationships. Moreover, the literature suggests that domestic events influence volatility in frontier markets, and these markets may provide diversification opportunities and superior returns to investors.

This study attempts to understand whether the trade and proximity hypotheses can be generalized to global markets. It also investigates whether frontier markets defy the norms observed and presented in the relevant literature.

The study focuses on a lesser-known frontier market, Pakistan. The Pakistani financial market appears to be a peculiar market, as it has been documented to exhibit attributes normally associated with frontier markets, yet also to behave differently from them. The study includes Pakistan and eleven of its key trade partners. The markets are classified into developed, emerging and frontier markets according to MSCI classification. Besides trade, the other relevant factors determining the interdependence between markets, such as geographical proximity, foreign investments and political relationships, are also investigated.

The data comprise daily log returns and range volatility with 7-day frequency for the twelve markets in the sample for the period January 2006 to December 2012, yielding 2,544

observations for each time series. After addressing the non-synchronity of the data, the time series are examined using graphs, descriptive statistics, autocorrelations and stationarity. The impact of the financial crisis of 2008 on the selected markets is examined with the help of GARCH (p, q) with Gaussian distribution and inclusion of dummy variable “CRISIS”. The results suggested that all the relevant markets were affected by the crisis except Singapore and China, and to a lesser extent, Malaysia.

Preliminary analysis with correlations coefficients, Granger causality, and OLS estimation indicate the existence of association between Pakistan and other financial markets in the study. Employment of the Spillovers Index enables the quantification of interaction between conditional returns and volatility of the relevant financial markets. The index decomposes the variance errors and attributes them to the markets included in the sample. The Spillovers Index is applied in multiple ways to examine the static and dynamic spillovers between Pakistan and pairs and groups dependent on the MSCI country classification and geographical proximity of financial markets in the study.

Results relating to the influence of developed markets on each other and on other markets show: a growing influence of Asian developed markets in the group of developed markets; high self-contribution to returns and volatility in frontier markets and their relative segmentation from world markets; exaggerated cross-market spillovers during crisis; increased importance of global markets as compared to regional markets during crisis; and an upward trend in returns spillovers. These findings are consistent with the existing finance literature.

However, the volatility spillovers, especially for developed markets, demonstrated an upward trend, which contrasts with earlier findings. This trend can potentially be attributed to heightened spillovers due to the prolonged financial crisis of 2008 and Eurozone crisis, and then to difference in periods of analysis between this study and the earlier studies. Higher spillovers are witnessed during the Eurozone crisis for some groups and pairs, indicating the need for further examination in future studies.

With respect to Pakistan, high self-contribution to both returns and volatility are witnessed, reaffirming the importance of domestic events in determining the returns and volatility of

Pakistan, during tranquil and turbulent times. Extremely high self-contributions to returns and volatility are also apparent in China and Saudi Arabia, which are independent of the magnitude of cross-border bilateral trade and geographical proximity. Interaction of spillovers between Pakistan and India, and China and India indicate some relevance of deteriorating political relations in determining the magnitude of spillovers. Moreover, it seems that the extent of deregulation of markets and limited foreign investments, limits the exchange of returns and volatility between markets. The findings indicate that the trade and proximity hypotheses cannot be generalized to all markets around the world as some market-specific factors may determine the exchange of returns and volatility between markets.

This thesis contributes empirically to the finance literature in several ways. First, it provides insight into the interaction of conditional returns and volatility across developed, emerging and frontier markets. Second, it enhances our understanding of peculiar behavior of returns and volatility spillovers in frontier markets in general and of Pakistan in particular. Third, it facilitates greater understanding of interaction between Pakistan's financial market and those of its key trade partners and markets within close geographical proximity. Lastly, the extended application of the Spillovers Index on countries classified under developed, emerging, and frontier markets, and based on geographical proximity makes a valuable contribution as it facilitates understanding of asymmetric responses of various markets to foreign events and shocks.

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1 Introduction

The prime objective of this thesis is to examine the association and interaction between frontier financial markets and their key trade partners, specifically Pakistan. This thesis measures the magnitude, duration, and direction of cross-market conditional returns and volatility with the help of various statistical and econometric tools.

The finance literature provides contrasting evidence regarding interdependence between financial markets. An overwhelming number of studies cite trade and geographical proximity as prime reasons for increased interdependence between international financial markets and cross-country transmission of shocks. Intra-regional interdependencies between markets are documented to supersede inter-regional interdependencies, indicating the importance of regional trade links and geographical proximity. Since bilateral trade between countries is virtually inevitable in today's globalized world, researchers intuitively hypothesize heightened interdependence between markets due to trade, with close geographical proximity being a contributory factor. In contrast, some finance literature provides evidence that several financial markets, particularly small frontier markets, are relatively segmented from global markets regardless of the magnitude of their economic ties with other countries. This indicates that while the phenomenon of interdependence between markets is complex to understand and model, it also suggests that the trade hypothesis may not be generalized to all international markets. Indeed, some market-specific factors may play a compelling role in determining the association and interaction between financial markets. Besides these findings, the finance literature asserts that the onset of a significant financial crisis alters the nature of interaction between different sets of financial markets, either temporarily or permanently. Given the evidence on relative segmentation of smaller frontier markets, it is worthwhile evaluating the impact of crisis on these markets and to examine whether the crisis alters the dynamics of returns and volatility exchange in these markets.

Given the divergent findings in the finance literature on trade and interdependence between markets, this study focuses on frontier markets that are documented to be relatively

segmented from the world markets. The MSCI (2012)[1] classifies approximately 35 markets as frontier markets. It is difficult to include all 35 markets in the study due to unavailability of reliable data for some financial markets as well as a lack of clearly established trade links. Pakistan is chosen as the focus of this study as a representative frontier market due to well established bilateral trade links and availability of financial time series data. The relevant literature on the Pakistan financial market is not only sparse; it presents contrasting findings on this market. On the one hand, it is argued that the Pakistani financial market exhibits characteristics typically associated with frontier markets (for example, Samarakoon, 2011; Kohlert, 2011). On the other hand, studies like Akdogan (1996), Bekeart and Harvey (1997), Uppal (1998), Amin and Orlowski (2014) present some findings that set it apart even from its frontier counterparts.

Other considerations include the fact that the attractiveness of any financial market can be examined based on risk (primarily associated with volatility), returns, degree of correlations with other markets and resilience to foreign shocks. Berger *et al.* (2011) provide evidence that the portfolios including frontier markets resulted in a 2% reduction in risk while maintaining the same level of return as for the developed and emerging market portfolios. In fact, during the 1990-2007 bull period, the portfolios with frontier markets provided better returns than the portfolios excluding frontier markets with reduced risk. With respect to risk and volatility in frontier markets, the finance literature implies the importance of local events in determining volatility in frontier markets, including Pakistan. However, in terms of returns, the Pakistani market returns are impressive (SECP, 2013) and appear to be uncorrelated with developed markets[2]. Lastly, Pakistan appeared to have been relatively resilient to the global financial crisis and exhibited signs of recovery much earlier than the other international financial markets. Collectively these factors make Pakistan an interesting case to examine in terms of its association and interaction with its most important trade partners and evaluate the cross-country transmission of returns and volatility, during the crisis and otherwise.

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[1] MSCI is a publicly traded investment research firm based in the USA. The firm was previously owned by Morgan Stanley. It provides indices, portfolio risk and performance analytics and governance tools to institutional investors and hedge funds.

[2] Lower interdependence and integration between frontier and developed markets is documented by Miles (2005), Berger *et al.* (2011), Samarkoon (2011), Baumöhl and Lyócsa (2014), Chen *et al.* (2014).

Although the focus of this thesis is Pakistan, it contributes in general to the understanding of frontier markets. With many emerging markets gradually inching towards becoming developed markets and getting increasingly integrated with developed markets[3], subsequently the potential for diversification in these markets is eroding. Consequently, investors look for alternative avenues for investment and frontier markets can provide them the desired diversification opportunities.

Moreover, high GDP growth, increasing market capitalization, low PE ratios and improving regulatory environment make frontier markets attractive avenues for investment. Accordingly, frontier markets in general have been identified as avenues for lucrative investment returns and diversification (For example, Speidell and Krohne, 2007; Jayasuriya and Shambora, 2009; Samarakoon, 2011). This highlights the need for further research into the phenomenon of interdependence of frontier markets with markets of different statures, in order to understand their attributes and progressive behavior, especially during crises.

Given the evidence in the relevant finance literature regarding the importance of trade, the selection of other financial markets in the study is based on their trade volume with Pakistan. To further our understanding of frontier markets, Pakistan's key trade partners are grouped into developed, emerging and frontier markets according to MSCI (2012) classification. Furthermore, considering the importance of geographical proximity in determining association and interaction between financial markets, Pakistan's key trade partners in the study are further classified into groups depending on their geographical propinquity with Pakistan. These classifications based on volume of trade and distance enable the identification of peculiar patterns of interaction across different groups of countries. Besides trade and geographical proximity, cross-border foreign investments and political relationships are also considered.

The primary research question for this thesis is presented below and this is further supported by sub-questions to guide detailed analysis. The econometric tools employed for

[3] The Catch-up hypothesis or the Theory of Convergence suggests that the developing economies grow at a faster rate than the developed economies as they have access to technological know-how of the developed economies and that the per capita growth in developing countries will converge to the growth in developed economies in the long run. This economic growth convergence may lead to greater interdependence and eventual integration of financial markets. For a review, refer to Islam (2003).

analysis are also introduced. The chosen tools provide comprehensive insight into the phenomenon studied.

The remainder of this chapter discusses the significance and implications of the study and concludes with a brief outline of the structure of the thesis.

1.1 Background

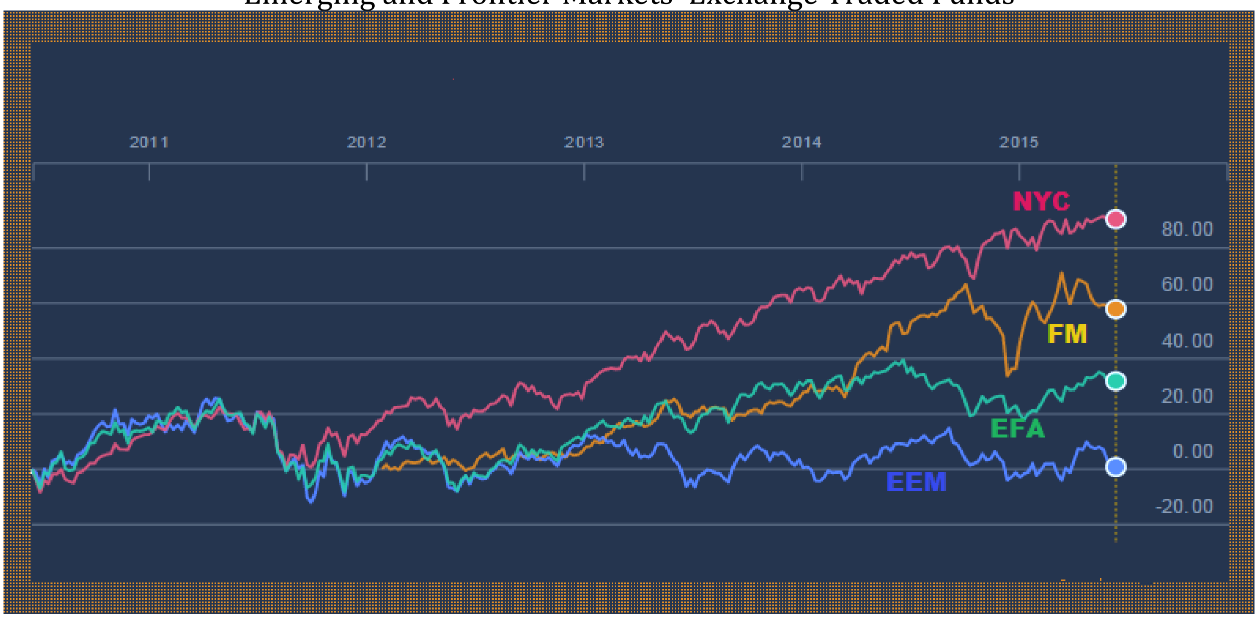
Globalization has played an important role in the economic and financial integration of the international financial markets (Refer to Appendix 1.1). Bilateral trade and liberalization of financial markets has been on the rise since the 1980s (IMF Staff Paper, 2011) and formation of trade and economic blocs such as the European Union has contributed greatly to the boost in trade, leading to a world with great economic and financial connectivity (Moshirian, 1999). Moreover, due to technology, geographical boundaries have virtually diminished, transaction costs have significantly decreased, information has become more readily available, and capital has become mobile. Liberalization of financial markets has also played its role in increased financial interdependence between markets. While developed markets started liberalizing in the 1970s (Taylor and Tonks, 1989), most emerging economies liberalized their financial markets only in the early 1990s (Bekaert, 1995; Bekaert *et al.,* 2002). Since then, emerging economies have experienced a high influx of foreign investment (Appendices 1.2 and 1.3). Among global emerging markets, Asian emerging economies received approximately 50% of the total capital inflows to global emerging markets, led by China and India (Eurobank, 2012).

Liberalization of financial markets enables individual and institutional foreign investors to diversify their risks and maximize their returns. Bekaert and Harvey (2003) suggest that despite investors' irrational behavior towards emerging markets, portfolios comprising of emerging markets have performed better than the widely quoted benchmarks. Gottesman and Morey (2007) provide evidence that between 2003 and 2005, the annualized return of an average diversified emerging market fund was 36.05% as compared to 14.38% return provided by the S&P500. Emerging economies generally performed better than the developed economies during the period 2003 to 2010 in a cross sectional comparison, and only 11% of emerging markets rendered a negative trend in performance as compared to 45% developed markets over the same period (Galagedera, 2012). Kearney (2012) suggests

that the emerging markets have offered higher risk-return ratios from 2000 to 2010 as compared to developed markets and that this is true in both pre- and post-crisis periods. More recently the performance of Exchange Traded Funds (ETFs)[4] of frontier markets have superseded the performance of both non US developed and emerging markets, as depicted in Figure 1.1.

All the factors discussed above have contributed to the integration of financial markets (Herring, 1994). Many researchers find evidence that correlations between financial markets around the world have increased significantly during the last few decades (for example Longin and Solnik, 1995; King and Wadhwani, 1990; Lee and Kim, 1993; Cheung *et al.*, 2008).

Figure 1.1 - Comparison of Performance of Developed, Emerging and Frontier Markets' Exchange Traded Funds



Source: Bloomberg, 2015

Notes: FM measure the performance of frontier markets
EEM measures the performance of Emerging Markets
EFA measure the performance of Non-USA developed markets, excluding Canada
NYC measures the performance of the USA market

The literature on interdependence and integration between markets published within the last decade provides evidence of greater integration of emerging markets into developed markets (for example Friedman and Shachmurove, 1997; Ratanapakorn and

[4] Exchange Traded Funds are marketable securities that track the performance of benchmark indices

Sharma, 2002; Diebold and Yilmaz, 2009; Yilmaz, 2010; Diebold and Yilmaz, 2012; Graham *et al.*, 2012). Although there are contrasting theories like the "Decoupling Hypothesis" which claim that emerging economies have decoupled from developed economies due to strengthening macroeconomic variables and increased local demand (for example, Kose *et al.*, 2008; Levy Yeyati and Williams, 2012), a large body of literature provides evidence of progressive increased integration of markets.

Increased integration of markets erodes diversification opportunities, as similar events may impact on most markets around the world (Paas and Kuusk, 2012), prompting investors to look for alternative avenues for diversification and risk management. This quest has led to the popularity of smaller markets, classified as frontier markets by MSCI, Standard & Poor's (S&P) and Dow Jones (DJ). S&P describes frontier markets as smaller and less liquid markets in comparison with their emerging counterparts. Accordingly, they are also referred to as "pre-emerging" markets. The attractiveness of frontier markets can be evaluated based on the relative market capitalization, GDP growth, level of corruption, and foreign capital inflows.

In 2005, the market capitalization of the 35 MSCI frontier markets was just US$ 500 billion in 2005 (Speidell and Krohne, 2007), but by 2012 it had more than doubled and stood at US$ 1.08 trillion (The World Bank, 2014)[5]. These markets are increasingly becoming investors' havens as they offer attractive returns and exhibit isolation from global markets during normal times (For example Akdogan, 1996; Kohlert, 2011; Samarkoon, 2011; Baumöhl and Lyócsa, 2014; Amin and Orlowski, 2014).

In recent years the frontier markets have further exhibited their growth potential. According to the World Bank (2014) the frontier markets collectively grew at an average rate of 4.2%, the developing countries in the MENA region grew at 4.1%, and the South Asia economies, comprised mainly of frontier markets, grew at 7.1%. In contrast, the world economy grew at an average of 2.4%, while the USA economy grew at a bare 1.21% over the

[5] A detailed background on MSCI (2012) classification and market capitalization of frontier markets is presented in Appendices 1.4 and 1.5.

same period (World Bank, 2014)[6]. Speidell and Krohne (2007) assert that due to the positive relationship between GDP per capita and the size of the market, the growth potential of the frontier markets is apparent. The authors suggest that a five-fold increase in GDP per capita of these countries will increase market capitalization to GDP ratio from 28% to 66%. Furthermore, Kohlert (2011) argues that the frontier markets have considerable growth potential, as their Price-to-Earnings (PE) ratios are significantly lower than the PE ratios of their developed and emerging counterparts.

Since international investors prefer to invest in relatively liquid markets with low information asymmetry and minimum transaction costs (Thapa and Poshakwale, 2012), governments of the emerging and frontier economies have made efforts to develop their capital markets in such a manner that they provide suitable ground for foreign investments. The enhanced trading activity and liquidity in these markets is a product of the governments' efforts to promote foreign investments and employ appropriate measures to increase the competitiveness of these countries. Speidell and Krohne (2007) suggest that the frontier markets have gradually improved their ranking on the corruption perception index, which may lead to greater investor confidence and, in turn, may cause an increase in foreign capital inflows[7].

The Foreign Direct Investment (FDI) index developed by Groh and Wich (2012) ranked 127 countries in terms of their attractiveness for foreign investments using four key factors: economic activity, legal and political system, business environment, and infrastructure. While developed countries were ranked high on the FDI index, many emerging and frontier countries were not far behind. For example, the United Arab Emirates (UAE) was among the top five most attractive destinations for FDI. Many other frontier economies also were ranked high on the FDI index, suggesting that these emerging economies may provide a flourishing environment for foreign investment. With respect to economic activity, emerging and developing countries did not lag far behind the developed

[6] A more comprehensive comparison between the annual growths of these markets is presented in Appendices 1.6 and 1.7.

[7] The Corruption Perception Indices (2013) for frontier markets, provided by Transparency International, are presented in Appendix 1.8.

economies, scoring even better than the developed markets on variables like real GDP year-on-year growth, economic stability, and taxation (Groh and Wich, 2012).

As illustrated earlier in Figure 1.1, the frontier markets have presented impressive returns during 2012 and 2014, which have surpassed the returns provided by the United States of America (USA), Non-USA developed markets, and emerging markets. Literature on frontier markets, although sparse, provides evidence on viable and rewarding investment and diversification opportunities offered by frontier markets. Berger *et al.* (2011) examined the integration between 25 frontier markets and the developed markets using the MSCI World Index as a proxy and found lack of integration between frontier and world markets. Similarly, Speidell and Krohne (2007) and Samarakoon (2011) documented low correlations between frontier and developed market equities. Jayasuriya and Shambora (2009) found that the inclusion of frontier markets to a portfolio of emerging and developed markets improves the portfolio's risk-reward ratio[8]. De Groot *et al.* (2012) found that momentum-trading strategies lead to abnormal returns within the frontier markets that remain economically and statistically significant even after considering transaction costs. Clearly, higher returns and a combination of the above-mentioned factors make frontier economies an attractive avenue for international investors.

The recent financial crisis that emerged in the USA quickly turned into a global crisis, resulting in sharp declines in indices and enhanced volatility across markets (Dooley and Hutchison, 2009; Bartram and Bodnar, 2009; Huyghebaert and Wang, 2010; Baur, 2012; Hwang, 2012; Gupta and Guidi, 2012). The crisis started in 2007 and its gravity increased after the fall of Lehman Brothers in September 2008[9]. Most countries, irrespective of their location, were affected asymmetrically by the crisis (Dooley and Hutchison, 2009). While the impact of the crisis on developed markets was intense, Asian emerging markets also suffered a decline in asset prices (Bartram and Bodnar, 2009). However, it is argued that this decline was a product of foreign shocks and was not associated with domestic factors (IIF Research Note, 2012). Frontier markets were not isolated from the crisis either, as Samarakoon

[8] Berger *et al.* (2011), Speidell and Krohne (2007), and Jayasuriya and Shambora (2009) include Pakistan as a component in a larger sample of frontier markets.
[9] See Bartram and Bodnar (2009) for a detailed timeline of events surrounding the global financial crisis.

(2011), Baumöhl and Lyócsa (2014), and Amin and Orlowski (2014) document enhanced volatility of selected frontier markets during the crisis indicating that while these markets remain relatively segmented from developed markets during normal times, foreign shocks may induce exaggerated volatilities in them. This suggests that a grave crisis affects global markets indiscriminately irrespective of their location, size and other attributes.

1.2 Purpose Statement, Research Questions and Methods

Frontier markets in general are the primary focus of this study. Due to practical, academic and applicative reasons elaborated in Section 1.3, Pakistan is chosen as a representative frontier market. Accordingly, the purpose of this thesis is to quantify the interactions between conditional returns and volatility between financial markets of Pakistan and those of its most active trade partners (USA, UK, Germany, Japan, Singapore, China, India, Malaysia, Saudi Arabia, Kuwait and UAE) classified under developed, emerging and frontier markets using various econometric tools, especially a relatively new method, the Spillovers Index. The period of analysis extends from January 2006 to December 2012. While unconditional returns and volatility are determined by historical values, conditional returns and volatility are a reflection of current economic, political and financial events. Conditional returns and volatility facilitate forecasting of possible outcomes of investments in various markets and are more relevant to investors. Moreover, conditional estimates may have limitations due to heteroscedasticity, endogeneity, and omitted variables bias (Rigobon, 2004). Hence, the thesis focuses on conditional returns and volatility.

The inclusion of selected countries in the sample is based on extensive evidence widely provided in the finance literature related to bilateral trade and geographical proximity (for example Calvo and Reinhart, 1996; Glick and Rose, 1999; Morana, 2008). Paas and Kuusk (2012) term fundamental economic relationships between countries due to trade as "real links". Morana (2008) argues that financial integration is a product of economic integration and regional economic factors play a major role in co-movement of financial markets. Masih and Masih (2001) suggest that trade has a positive relationship with market interdependencies, and hence, the higher the bilateral trade volume, the greater the cross-market dependencies. Subsequently, Pakistan's eleven key trade partners have been selected for inclusion in the study. Additionally, geographical proximity is also a consideration in the

sample as eight out of the eleven countries in the sample are located in Asia and have close proximity to Pakistan, with India and China being the closest neighbors to Pakistan.

Besides trade and geographical proximity, the finance literature also provides evidence that foreign investment and capital inflows are important determinants of cross-market interdependencies (Sachs *et al.,* 1996; Dornbusch *et al.*, 2000). While foreign investments are generally seen as a positive indicator for recipient countries, there are also potential negative impacts. Dornbusch *et al.* (2000) and Cheung *et al.* (2008) assert that foreign markets provide investors with an opportunity for portfolio diversification, but during turbulent times investors treat markets indiscriminately and pull out investments even from markets which are not affected by the crisis, hence creating a spillover effect from one market to the other. Dornbusch *et al.* (2000) also highlight that investors' reasons for pulling out investments from foreign markets may be related to lack of liquidity at home, whereby investors are forced to liquidate their assets in foreign markets to generate cash flows. Thus, the sell-off may lead to transmission of shocks from one market to the other.

Political relationships and political events also determine financial integration between countries. For example, Akdogan (1992, 1996) and Aggarwal *et al.* (2010) find that some political events in the European Union (EU) led to a greater financial integration of European markets. On the other hand, political crises in one country may affect some macroeconomic variables and capital markets in other countries. For example, Amihud and Wohl (2004) and Rigobon and Sack (2005) find that events associated with the Iraq War impacted on equity prices in the USA. In line with the evidence provided in literature, political relationships and political events are also considered in selection of countries in the study. China, Malaysia, and the GCC countries share close political relationships with Pakistan and have bilateral agreements that are mutually beneficial for the countries involved. The strained political relationships between Pakistan and India have resulted in some peacekeeping agreements, which are also of consideration in examining the interdependence between financial markets.

Besides having good political relationships with most Asian countries, Pakistan is a strategic ally of the USA in its war on terror described by Kronstadt (2012 p. 1) as "A stable, democratic, prosperous Pakistan actively combating religious militancy is considered vital

to U.S. interests". Although the political relationship between the two countries has seen many ups and downs in recent times, both countries are indispensable for each other. This suggests that not only political economy events but also crises in Pakistan (including acts of terrorism) may impact on USA capital markets and vice versa. Beyond the USA, countries like the UK and Germany are also a part of this alliance, especially the UK, which has contributed significantly to the operations in Afghanistan (Wallace and Phillips, 2009). Therefore, it is likely that the markets included in the sample are interdependent due to their political association.

Considering all of the above determinants of evolving interdependence between markets, the study hypothesizes that there is significant cross-market interaction between Pakistan and the chosen countries. Hence, this thesis aims to answer the following research question: *What are the direction, duration, and magnitude of conditional returns and volatility spillovers between financial markets of Pakistan and those of its most active trade partners?*

Given that the research question is clearly broad and entails multiple dimensions of potential interaction between the markets under consideration, several sub-questions are subsequently derived from the primary research question to garner greater understanding of the cross-market interactions. The sub-questions are listed below along with methods employed to shed more light on Pakistan's interaction with its major trade partners:

i. Was the impact of the 2008 financial crisis significant on all the markets included in the sample?

To answer this question, GARCH (p, q) with Gaussian distribution is employed. A dummy variable "CRISIS" is included in the model to incorporate the impact of crisis. This dummy variable assumes a value of one during the crisis period and zero otherwise. The statistical significance of the coefficient of the dummy variable for developed, emerging, and frontier markets, provides insight into the impact of the financial crisis and whether it had a lasting impact on the countries included in the sample. If the impact of the crisis is significant, the persistence of volatility (as denoted by the sum of α and β) decreases. The relevant literature also provides evidence on asymmetric volatility transmission across markets (Ng, 2000; Martens and Poon, 2001; Enders, 2010; Valls and Chuliá, 2012). Given the scale and

magnitude of the crisis, and the evidence documented in the finance literature, it is expected that all the markets in the sample would have been affected significantly.

ii. *What is the nature of causality between Pakistan's financial market and those of its most active trade partners?*

Bivariate Granger Causality is employed to examine lead-lag relationship between the returns of Pakistan and its trade partners at different lags. The results of Granger causality tests enable a primitive understanding of association between the markets under consideration. Unidirectional causality from developed markets to Pakistan is anticipated, as Pakistan is a very small market and may not have any impact on the returns of developed markets. On the other hand, bidirectional causality is expected between Pakistan and its emerging, frontier counterparts, as all these markets are located in the same region as Pakistan, and in some cases, the volume of trade is substantial. Moreover, in line with the evidence provided in relevant literature, it is lagged causality between these markets that is anticipated, as some of these markets are informationally inefficient and take time to process and reflect information (For example Kawakatsu and Morey, 1999; Buguka and Brorsen, 2003; Worthington and Higgs, 2006; Omran and Farrar, 2006; Griffin *et al.*, 2010).

iii. *Can the Pakistan market's returns at multiple lags explain returns of its trade partners and vice versa?*

The use of OLS estimation facilitates understanding of any association between Pakistan and its trade partners. Two kinds of models are used: one with Pakistan as regressand and the other with Pakistan as regressor. Returns at multiple lags in all the markets are used in the models to capture delays in transmission due to different time zones and non-synchronous trading in the markets under consideration. Given the small size and negligible influence of Pakistan, it is expected that the returns in developed markets may affect Pakistan but the opposite may not be true. On the other hand, some two-way influence between Pakistan and selected emerging and developed markets is anticipated. Furthermore, greater statistical significance of later lags is expected due to different time zones and weekends, and informational efficiency of some markets included in the sample.

iv. *What is the magnitude of static and time-varying, mean and volatility spillovers between the financial markets of Pakistan and those of a group of selected developed, emerging and frontier markets?*

To answer this question and the other question henceforth, this study uses the returns and volatility spillovers indices. The Spillovers Index enables the decomposition of conditional returns and volatility spillovers across markets with the help of the Vector Autoregressive model. It is identified in the economics and finance literature that despite trade relationships, smaller markets exhibit higher volatilities surrounding domestic events rather than global shocks (for example Aggarwal *et al.*, 1999; Kearney, 2012). Therefore, limited foreign influence on Pakistan's returns and volatility is anticipated with high self-contributions from Pakistan to its own returns and volatility. Moreover, greater contributions from the Asian developed markets than those from the European markets are expected due to geographical proximity.

All the emerging markets included in the sample are located in the same continent as Pakistan. Bilateral trade between China and Pakistan is high; however, the bilateral trade is low between the Pakistani and the other emerging markets in the sample. Higher spillovers between China and Pakistan are expected due to the significant trade volume between them. Frontier markets are expected to exhibit high self-contributions[10] to their own returns and volatility due to the greater importance of domestic events and the marginal exchange of returns and volatility with the other markets under consideration. It is also expected that the frontier markets in the sample may be affected by developed markets, but not so much by emerging markets or by each other.

v. *Is the magnitude of returns and volatility spillovers between Pakistan's financial market and its border-sharing neighbors different from those with its regional neighbors?*

Geographical proximity is also a major consideration in the financial integration of markets. The pertinent literature suggests that financial crises tend to be regional due to the close proximity of countries (For example Glick and Rose, 1999; Bracker *et al.*, 1999; Ahluwalia, 2000; Johnson and Soenen, 2003; Morana, 2008). Subsequently, to capture the

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[10] Self-contributions refer to internally generated returns and volatility, which are primarily associated with domestic events.

interplay of geographical proximity in determining the magnitude of spillovers exchange, the sample is divided into groups, depending on their distance from Pakistan. In line with the existing literature, relatively higher spillovers between Pakistan and its closest neighbors are expected in comparison to those between Pakistan and its more distant neighbors in Asia.

vi. *What is the magnitude of net pairwise returns and volatility spillovers between Pakistan market and the financial markets of its key trade partners in the sample?*

Investigating pairwise effects between Pakistan and those of its trade partners enables the capturing of country-specific net spillovers. If the trade hypothesis holds, then varying degrees of spillovers between Pakistan and its developed, emerging, and frontier counterparts is predicted. However, it is also anticipated that self-contributions to returns and volatility will be greater in magnitude as compared to foreign contributions.

vii. *What was the impact of the financial crisis of 2008 on the returns and volatility spillovers of the financial markets under consideration?*

Diebold and Yilmaz (2009, 2012) assert that the Spillovers Indices are capable of capturing amplified spillovers associated with both negative and positive shocks[11]. Since the period of analysis entails a period of extreme turbulence in the markets, it is appropriate to examine whether the returns and volatility spillovers increased across groups and pairs, during this period. In line with existing finance literature, which suggests that frontier markets are not insulated from crisis (Samarakoon, 2011; Baumöhl and Lyócsa, 2014; Amin and Orlowski, 2014), the cross-country spillovers are expected to be higher surrounding the crisis period.

1.3 Contribution to Literature and Significance

The study contributes empirically to the finance literature in several ways. First, this thesis adds to a relatively nascent body of literature on frontier markets and provides detailed insight into cross-market returns and volatility dynamics with respect to frontier markets.

[11] In their most recent book, Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring, and Diebold and Yilmaz (2015a) emphasize that the network relationships between markets are multi-dimensional and argue that the bivariate spillovers may not be able to capture the complex nature of "connectedness" between markets. Diebold and Yilmaz (2015b) provide further evidence on the complex nature of connectedness among markets and highlight the role of financial institutions in exaggerated volatility connections between markets.

Interdependencies between developed markets like the USA, the UK, and emerging markets such as China, India, Malaysia, Thailand, Indonesia, and other Pacific Basin economies (for example Worthington and Higgs, 2003; Wong *et al.*, 2004; Baele, 2005; Kuper and Lestano, 2007; Abd. Majid *et al.,* 2008) and Latin American countries (for example Calvo and Reinhart, 1996; Pahan and Soydemier, 2000; Barari, 2004; Meric *et al.*, 2012) have been widely studied. However, a review of the literature on cross-market interdependencies reveals that only a handful of studies have attempted to investigate frontier markets (Akdogan, 1996; Bekaert and Harvey, 1997; Miles, 2005; Logoarde-Segot and Lucey, 2007; Berger *et al.*, 2011; Samarakoon, 2011; Bley and Saad, 2012; De Groot *et al.*, 2012; Demirer, 2013; Chen *et al.*, 2014; Amin and Orlowski, 2014). The importance of frontier markets in both the regional and global arenas cannot be under-stated due to their relatively high growth in GDP and market capitalization, foreign capital flows, improved governance mechanisms, bilateral and multilateral trade, and political relationships with countries around the world. Moreover, frontier markets have provided extraordinary returns to investors in the recent past and have clearly exhibited their attractiveness as possible diversification avenues due to their relative segmentation from developed markets. This study contributes to the knowledge on frontier markets and provides greater insight into their interaction with their trade partners classified as developed and emerging markets as well as among themselves.

Second, the focus on a country like Pakistan makes this thesis relatively unique. The choice of Pakistan as a primary focus of the study is based on some practical, academic and applicative considerations, such as:

- Availability of reliable data: it is difficult to find reliable time series data with clearly developed trade linkages for frontier markets.
- Lack of available literature: very few studies consider Pakistan in the sample (For example Bekaert, 1995; Akdogan, 1996; Bekaert and Harvey, 1997; Uppal, 1998; Miles, 2005; Mukherjee and Mishra, 2010; Singh *et al.*, 2010; Chen *et al.*, 2014; Amin and Orlowski, 2014).
- Contradictory findings in the relevant finance literature: Akdogan (1996) found Pakistan to be one of the least segmented markets in their sample of 25 countries of

developed and smaller markets. On the contrary, Amin and Orlowski (2014) provide evidence that while other South Asian countries were clearly affected by the financial crisis of 2008, Pakistan's self-contributions to its volatility remained significantly high, suggesting that transmission of shocks is limited to Pakistan. With respect to Pakistan's relationship with other countries, Singh *et al.* (2010) identified a lack of association between India and Pakistan and report that Malaysia affects Pakistan. On the other hand, Choudhry (2004), Abbas *et al.* (2013) and Amin and Orlowski (2014) provide evidence of spillovers between Pakistan and India.

- Peculiar traits: for example, Bekaert and Harvey (1997) find that Pakistan is the only market in their sample of 19 countries that exhibited greater volatility post-liberalization, while volatility in other newly liberalized markets declined.
- Superior returns: regarding performance of the market, Pakistan has provided superior returns to investors in the past and was the world's best performing market in 2002 (Bloomberg Business Week, 2003). More recently, MSCI Index representing Pakistan rose by 60% in dollar terms since 2012, and its performance is reported to be ahead of most global indices (The Economist, 2014).
- Potential for diversification: segmentation of smaller markets is well documented in the finance literature; greater interdependence between markets leads to greater integration between them, resulting in erosion of risk premium differentials. Akdogan (1996) argues that in a globalized world, no markets can be 100% segmented and the degree of segmentation may vary. In this regard, smaller yet investable markets like Pakistan, which have potential as possible diversification avenues, are of great interest.

Third, the selection of countries in the study, classification and data frequency for employment of the Spillovers Index developed by Diebold and Yilmaz (2012), makes a distinctive contribution. The Spillovers Index enables quantification of static and dynamic conditional returns and volatility transmissions between markets, by using an *N-variable* VAR model with *H-steps* ahead forecast for variance decomposition. The index captures self-contribution as well as foreign contribution of each participant in the overall returns and

volatility of a financial time series. The Index comprises two components: the Spillovers Table and Spillover Plots. While the Spillover Table estimates average mean and volatility spillovers across markets over a certain period of analysis, the Spillover Plots present the evolution of returns and volatility in Rolling Windows during the same period. The Rolling Window Spillovers Plots facilitate identification of shocks in the time series and enable determination of associated events with these shocks, negating the need to incorporate a dummy variable (For example Aggarwal et al., 1999; Malik *et al.*, 2005; Kang *et al.*, 2009) or an event study (for example King and Wadhwani, 1990; Chan *et al.*, 2008; Huyghebaert and Wang, 2010; Abd Majid *et al.*, 2008) to capture the impact of a crisis.

Studies that use the Spillovers Index to measure cross-market spillovers across a variety of markets and asset classes in the financial sector are, for example developed and emerging markets (Diebold and Yilmaz, 2009; Zhou *et al*., 2012), East Asian equity markets (Yilmaz, 2010) various asset classes in the USA (Diebold and Yilmaz, 2012), spot exchange rates for developed markets (Antonakakis, 2012), G7 countries (Antonakakis and Badinger, 2012), G3 and ASEAN4 (Fujiwara and Takahashi, 2012), and real sector (Yilmaz, 2009) . However, none of the studies has chosen the markets based on theoretical grounds like bilateral trade and geographical proximity. Moreover, to our knowledge, no study so far has attempted the application of the Spillovers Index on a group of countries classified according to their stature of developed, emerging, and frontier markets. Finally, all the studies that employ the Spillovers Index use either weekly or 5-day frequency daily data; however, this study uses 7-day frequency data in order to resolve the problem of non-synchronous data.

Essentially, this study provides an in-depth understanding of interdependencies between Pakistan's financial market and those of its most active trade partners, and largely reconciles the contradictory findings in past studies. Additionally, analyses of cross-country spillovers, with Pakistan at the center of investigation, facilitates the understanding of how foreign returns and volatility spillovers affect the conditional returns and volatility in Pakistan. It also provides insight into the reaction of the Pakistan market to foreign shocks during the financial crisis.

An enhanced knowledge of interdependencies between markets is important for academics, investors and policy makers. The findings of the study provide researchers with

evidence regarding similarities and differences between developed, emerging, and frontier markets with respect to their returns and volatility dynamics. Knowledge gained through research flows from academia to industry and governments; hence, the measures developed by researchers to measure cross-market interdependencies, and the recommendations based on the findings can be adopted by policy makers to design policies and regulations to effectively govern financial markets. For example, Morana (2008) provides evidence that the Asian financial crisis was regionally bound due to bilateral trade and geographical proximity between the countries involved in the crisis. Therefore, the knowledge of volatility transmission across countries within the region and across regions is of utmost importance for the policy makers and regulators as they can corroborate to formulate appropriate policies to restrain foreign shocks from being transmitted to domestic markets.

Moreover, capital markets provide a platform for investors to allocate capital efficiently and diversify risk while maximizing returns. Better understanding of the relationships between markets enables investors to allocate resources more efficiently, and improve risk return ratios. Understanding and estimation of mean and volatility dynamics across markets allows investors to predict future outcomes with relative accuracy and employ better risk management strategies.

1.4 Outline of the Thesis

Chapters 2 and 3 provide a detailed literature review of the studies conducted on interdependencies between markets. Specifically, chapter 2 provides a detailed account of studies documenting interdependencies across developed and emerging markets, reasons for increased interdependencies, and consequences of increased financial integration; and chapter 3 provides a comprehensive account of the most widely used econometric methods in literature to model and estimate cross-market interdependencies, along with their strengths and weaknesses.

Chapter 4 justifies the selection of markets for the study and provides brief insight into the attributes of each market in the sample. The chapter also describes the data treatment and filtering process, and details various statistical and econometric tools that are

used to examine the characteristics of individual time series and to estimate the mean and volatility spillovers between Pakistan and its most active trade partners.

The analysis of individual time series is comprised of simple mechanisms like graphs of closing prices, returns and range-volatility, descriptive analysis of log returns and volatility, autocorrelations, and unit roots tests. Since the data period includes a period of extreme turbulence in most markets, a version of modified GARCH (p, q) with Gaussian distribution is used to examine the impact of the financial crisis on individual markets.

The association between Pakistan and the selected trade partners is examined with the help of correlations, pair-wise Granger causality, OLS estimation, and the Spillovers Index. The application of the Spillovers Index is extensive as the sample is not only analyzed collectively, but is classified into a variety of groups and pairs to gain detailed insight into cross-country interaction of returns and volatility, with Pakistan being at the center of analysis.

Chapter 5 presents the results of data analysis, with the help of numerous tables and figures allowing comparisons of results between groups and pairs of countries included in the sample. This chapter also incorporates the findings of some robustness checks that are performed to ensure consistency and reliability of results.

Lastly, Chapter 6 provides an interpretation of the results, and compares and contrasts the results with the existing finance literature. This chapter also discusses the contributions, significance, and the limitations of the study and the methods employed. The chapter also presents the details about the explicit and implicit measures taken to ensure consistent results, and the study in general. Lastly, the chapter presents suggestions on avenues for future research.

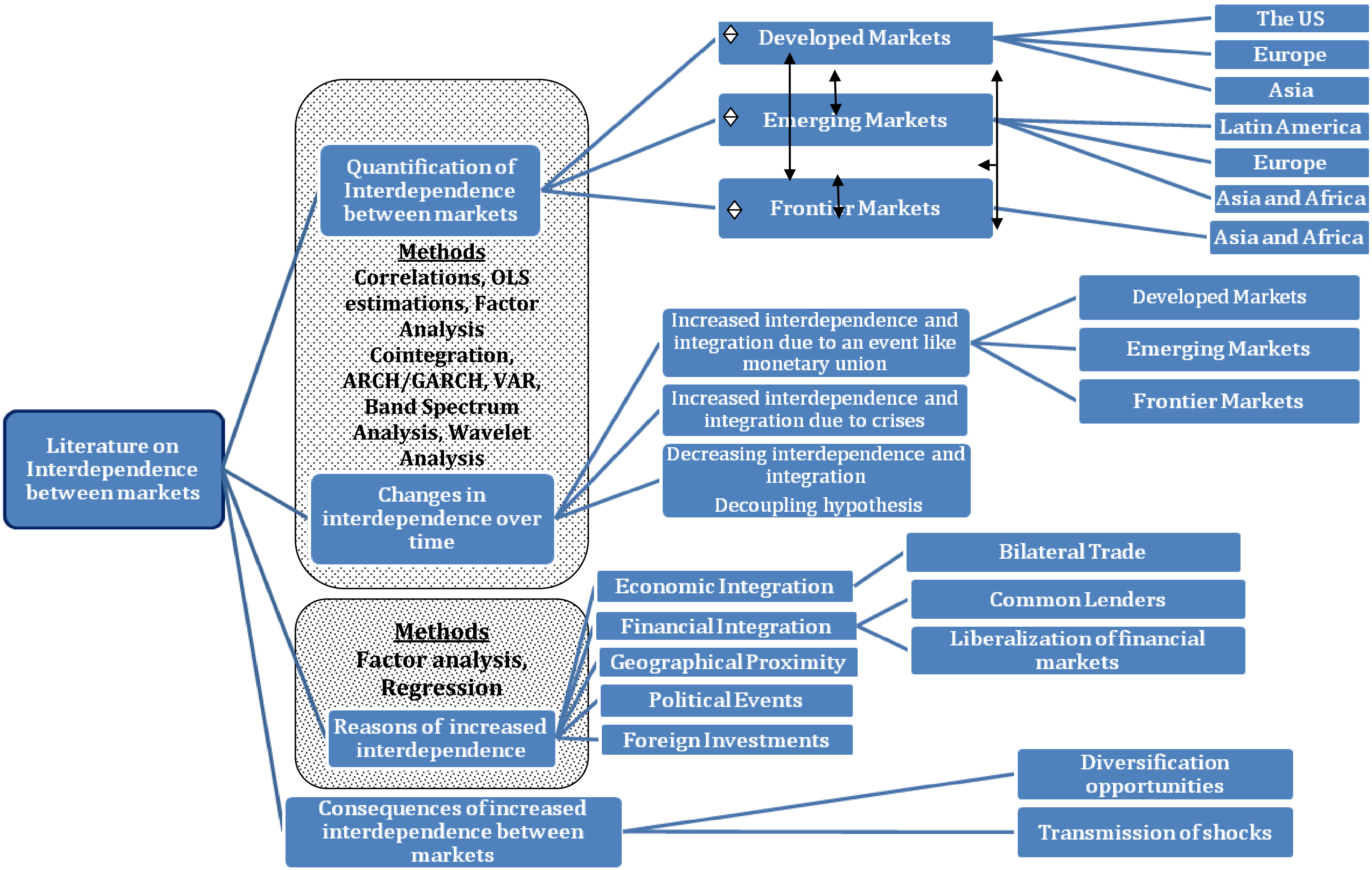
2 Literature Review on Interdependence Between Markets

The literature on interdependence between financial markets is plentiful. The relevant literature presents various aspects of interdependence, such as, evolution of interdependence between developed and emerging markets across different continents and reasons for evolution of interdependence and subsequent consequences. The finance and econometrics literature presents numerous methods to examine the phenomenon of cross-market interdependence, which have evolved greatly over the period resulting in improved ways of quantifying interaction and interdependence between financial markets.

Due to the extensiveness of the relevant literature it is deemed appropriate to present the literature review in two chapters. Chapter 2 presents a comprehensive survey of literature published primarily in the finance discipline in relation to interdependence between markets. Studies documenting progressive interdependencies between markets and their evolution, reasons for increased interdependence between markets, and consequences of amplified interdependence between markets are presented in this chapter. Chapter 3 presents a detailed review of the methods used in various studies to quantify interdependence between markets and discusses the strengths and weaknesses associated with each method. Figure 2.1 illustrates a detailed map of the literature review presented in chapters 2 and 3.

The knowledge of interdependence between financial markets has theoretical, empirical, economic, and policy consequences. Panton *et al.* (1976) suggest that for individual and institutional investors, this knowledge is important for diversification and related decisions; for economists this information is crucial as it affects capital flows, investment, and consumption decisions; and that researchers are curious to understand the dynamics of association between world markets and ways to measure it. Furthermore, understanding the association between markets allows governments and regulators to devise policies that may prevent international financial crises that create havoc in national markets.

Figure 2.1 – Map Presenting the Literature Review Structure



The notion of interdependence between financial markets has been of interest to researchers for many decades. In the 1960s and 1970s, the use of techniques such as correlations (Lessard, 1974), mean-variance portfolio frameworks (Grubel, 1968; Levy and Sarnat, 1970), variance-covariance matrices (Grubel and Fadner, 1971), spectral analysis (Hilliard, 1979), cluster analysis (Panton *et al.*, 1976), factor analysis (Ripley, 1973), and regression analysis (Agmon, 1972; Lessard, 1974, Minot, 1974; Maurent and Joy, 1976) was common. With the exception of Levy and Sarnat (1970), all the above-mentioned studies focused on developed countries only, with the USA being included in all of them, providing evidence of the increased integration of developed financial markets. For example, Panton *et al.* (1976) found that markets like the USA and Canada were highly similar, and formed primary clusters 90% of the time between 1963 and 1972. The authors also found that some European countries formed primary clusters 50% or more of the time during the period of analysis. Similarly, Hilliard (1979) also found greater association between common markets, especially during the times of crisis. Levy and Sarnat (1970) documented higher correlations between developed countries and lower correlations between developed and developing markets and suggested that the inclusion of developing markets in portfolios would improve the risk-return profile for investors.

While those studies were novel in that era, considering the limited analytical capabilities and relative availability of data, the methods used in those studies had limitations. For example, Agmon (1972) argued that the diversification benefits might not be available as world markets could be considered as one multi-country market. He used univariate regression on monthly data to access the relationships between four developed markets, namely the USA, the UK, Germany and Japan, under the one market hypothesis, and found that the USA acted as a world factor. The author found other countries in the sample comparatively unrelated to each other, and found that one central market, the USA, connected the otherwise unrelated foreign markets in the sample. Although Agmon's findings can be termed as novel in the earlier stages of research on the topic, the results can be challenged based on the assumptions of the hypothesis, modeling, sample selection, and data frequency. Assumptions associated with perfect markets such as no entry barriers, zero transaction costs, similar products, perfect price, and information discovery were

unrealistic. Besides these assumptions, there were some limitations associated with the employment of regression analysis, such as normal distribution of time series, homoscedasticity of errors, and lack of serial correlation in residuals. Furthermore, interdependence between developed markets was documented even in the earlier days of research on the topic (for example Grubel, 1968; Levy and Sarnat, 1970; Ripley, 1973; Maurent and Joy, 1976). Furthermore, the use of monthly data in the analysis may not have been useful as the time series of different markets converge in the long-run, and variations in the smaller windows were not captured by monthly data. Despite the limitations associated with Agmon (1972), the study contributed significantly to the literature on the association between markets, and remains widely cited. However, the need for more sophisticated methods for modeling the association between markets was apparent, and Lessard (1974) rightly pointed out the need to employ multifactor models for better estimations.

Beyond the 1970s, the theoretical and applied aspect of econometrics has evolved significantly. The progress is attributed to enhanced technical and analytical ability, and the desire for knowledge creation, as well as economic benefits. Diebold (2001) asserts that three factors have contributed greatly to this evolution. First, the technological advancements have increased the data storage and analysis capabilities. Second, researchers have identified that that empirical finance and time series analysis go hand in hand, and accordingly appropriate methods have been devised to analyze the time series data. Lastly, generations of knowledge surrounding the forecasting of returns and volatility contribute significantly to risk management and portfolio management practices and lead to greater economic benefits. The factors discussed above have collectively led to greater creativity and innovation in measuring interdependence across markets, which in turn has resulted in a phenomenal increase in the number of studies on the subject, using a variety of markets and methods.

The 1980s heralded one of the most exciting periods in the development of econometrics techniques for the measurement of volatility and interdependence between markets. Sims (1980) introduced Vector Autoregression to accommodate bivariate as well as multivariate analysis of macroeconomic data. Causality, impulse response functions, and

variance decomposition were developed as variations of Vector Autoregressive models. Engle (1982) formulated the Autoregressive Conditional Heteroscedasticity (ARCH) model, followed by the generalized version of ARCH, commonly known as GARCH by Bollerslev (1986). Since then many variations of ARCH/GARCH have been presented in the relevant literature. Bollerslev (2010) surveyed articles published between 1982 and 2007 and identified more than 100 variations of ARCH/GARCH models. Many of these variation models were appropriate to evaluate the first and second moments of the time series but were not applicable on time series with a trend. Cointegration by Engle and Granger (1987) addressed this limitation and subsequently devised cointegration techniques, which became extremely popular for modeling time series with trend. Boswijk *et al.* (2009) argue that the several factors contributed to the popularity of cointegration techniques, such as an inclination towards more precise estimates for economic reasons, discovery of stochastic trends in time series analysis, availability of large data sets, and technological advancements in data analysis.

Besides the reasons discussed above, the financial and economic liberalization in the majority of emerging economies in the 1990s[12] prompted increased interest in the subject. Globalization, financial liberalization, and economic integration across countries and regions impelled researchers to explore relationships between markets in depth. The knowledge about interdependencies between markets is not only consequential for researchers but also for investors, as a lack of knowledge on the subject may have dire consequences for portfolio and risk management.

Other than early evidence on integration of developed economies (for example Grubel, 1968; Levy and Sarnat, 1970; Ripley, 1973; Maurent and Joy, 1976), many studies published in the 1980s and beyond provide evidence on gradually evolving interdependence and integration between developed and developing markets, which is in line with the notion of globalization that has resulted in interdependent economies globally. Besides equity capital markets, enhanced interdependence between bond markets (Forbes and Chinn, 2004; Johansson, 2008; Claeys and Vasicek, 2012), currency markets (Andersen and

[12] For a timeline of financial liberalization of emerging countries see Bekaert (1995).

Bollerslev, 1998; Glick and Rose, 1999; Nekhili *et al.*, 2002), and derivatives markets (Booth *et al.*, 1997; Booth and So, 2003) are also well documented.

The literature on interdependence between markets can be broadly classified into the following four major streams, presented in the four sub-sections in this chapter:

1. Section 2.1 presents studies that quantify the interdependence between countries during a certain period of analysis using the MSCI (2012) typology of developed, emerging and frontier markets.
2. Section 2.2 presents selected literature that uses event studies or rolling window analysis to document the changes in interdependence due to specific events such as the formation of monetary unions (for example the European Union), deregulation of markets, or a crisis.
3. Section 2.3 focuses on the reasons for evolving interdependence between countries. The literature under this stream is rather limited, as many authors have examined evolving interdependencies with preconceived assumptions. For example, Taylor and Tonks (1989) used an event study to evaluate the changes in correlation between developed markets after the deregulation of capital flows in the UK. However, the study does not include deregulation as a variable in the model. Hence, it cannot be claimed that the changes in correlations were a product of the deregulation of markets.
4. Section 2.4 discusses the consequences of increased interdependence and integration of markets, suggesting diminishing diversification opportunities and amplified transmission of shocks during turbulent times.

2.1 Interdependence Between Markets

As suggested earlier, this section presents an overview of the studies that document interdependencies between developed, emerging (Asia, Europe and Latin America) and frontier markets.

Developed Markets

Studies documenting the interdependence between countries are abundant. Several studies have documented interdependencies and integration between developed markets in the 1960s and 1970s (For example Grubel, 1968; Levy and Sarnat, 1970; Grubel and Fadner, 1971; Agmon, 1972; Ripley, 1973; Lessard, 1974; Solnik, 1974; Panton *et al.,* 1976; Lessard,

1974; Minot, 1974; Maurent and Joy, 1976). Beyond this period, the studies listed in Table 2.1 summarize key studies reporting on the nature of interdependence and integration between various developed markets.

Table 2.1 – Studies Documenting Interdependence and Integration Between Developed Markets

Authors and Year	**Markets Included**	**Period of Analysis and Data Frequency**	**Techniques Used**
Taylor and Tonks (1989)	The USA, the UK, West Germany, Netherlands and Japan	1973-1986 Monthly data	Correlations and Cointegration
Findings: High correlations and long-run association between these markets			
Jeon and Chiang (1991)	New York, London, Tokyo and Frankfurt	1975-1990 Weekly and monthly data	Unit root and Multivariate Cointegration
Findings: Presence of a common stochastic trend and a long-run equilibrium relationship between the chosen markets was highlighted			
Corhay *et al.* (1993)	France, Germany, the Netherlands and the UK	1975-1991 Biweekly data	Cointegration
Findings: Common stochastic trends between markets studied were found			
Chowdhury (1994)	USA, Japan, Hong Kong, Korea, Singapore and Taiwan	1986-1990 Daily data	Vector Autoregressive Model
Lin *et al.* (1994)	USA and Japan	1985-1989 Daily data	Cross-market correlations, OLS Estimation, GARCH-in-mean
Findings: Asian developed markets were integrated with the USA market and were most responsive to changes in the USA stock market			
Masih and Masih (1997)	The USA, the UK, Japan, Canada, Germany, France	1979-1994 Monthly data	Cointegration, Vector Error Correction Model, Variance Decomposition
Findings: Evidence of long-run integration between markets found. Post-1987 crash, the USA has assumed the leading position			
Kasibhatla *et al.* (2006)	The UK, Germany and France	1990-2002 Daily data	Cointegration and Vector Error Correction
Findings: a long and short-run association between the markets with relatively strong causal association between the UK and Germany			
Fraser and Oyefeso (2005)	The USA, the UK, Germany, France, Belgium, Italy, Spain, Denmark and Sweden	1974-2001 Monthly data	
Findings: long-run equilibrium with significant short-run transitory deviations			

Predictability of returns in global markets with the help of returns in other markets is also indicative of interdependence between markets. For example, Becker *et al.*, (1990), Ferson and Harvey (1993), Harvey (1995a), Wu and Su (1998) and Rapach *et al.* (2013)

provide evidence on predictive power of the returns in the USA. Wu and Su (1998) confirmed that the returns in the USA market led the returns in other markets, hence adding to the predictive power of the USA market. Becker *et al.* (1990) found that during 1985 to 1988, returns in the USA possessed predictive capability for returns in the Japanese markets despite non-overlapping trading hours in the two markets. More recently, Rapach *et al.* (2013) found that returns shocks in the USA are transmitted to the industrialized countries around the world, and therefore, the returns in the USA have the capability to predict lagged returns in other industrialized markets. However, returns in other markets may have limited predictive capability for returns in the USA. This suggests a strong association and causality between developed markets globally. Friedman and Shachmurove (1997) documented higher correlations between the European Community Stock Markets and concluded that larger European markets such as the UK, France, Germany, and the Netherlands, are more integrated as compared to smaller markets. The authors found that shocks from one European market are transmitted to other markets; however, they do not persist for more than two days.

Developed and Asian Emerging Markets

In the 1990s, Asian emerging markets were of particular interest to researchers due to their peculiar traits, liberalization, diversification opportunities, and the Asian financial crisis (for example Masih and Masih, 1997; Goldstein, 1998; Masih and Masih, 1999; Mishkin, 1999; Ratner and Leal, 1999; Jang and Sul, 2002; Worthington and Higgs, 2003; Wong *et al.*, 2004; Arestis *et al.*, 2005; Click and Plummer, 2005; Khan and Park, 2009; Awokuse *et al.*, 2009; Huyghebaert and Wang, 2010; Yilmaz, 2010; Park and Lee, 2011; Bai *et al.*, 2012).

Most of these studies have documented interdependence between developed markets in North America, particularly the USA, as well as European and Asian markets in different periods of analysis and different circumstances. Studies like Akdogan (1992, 1996) documented different levels of integration between groups of countries, suggesting that none of the markets is completely segmented from other markets in the world. Ferson and Harvey (1993) suggest that the knowledge of country-specific betas and global risk premia can help in improving the predictability of returns in a particular market. Harvey (1995a) found that although the USA market has some predictive capability for emerging markets,

greater predictive power in emerging markets could be traced back to local information. Some widely cited studies documenting interdependence between developed and Asian emerging are summarized in Table 2.2 below.

Table 2.2 – Studies Documenting Interdependence and Integration Between Developed and Emerging Markets

Authors and Year	**Markets Included**	**Period of Analysis and Data Frequency**	**Techniques Used**
Masih and Masih (1999)	Taiwan, South Korea, Singapore, Hong Kong, the USA, the UK, Germany, and Japan.	1980 Daily data	Granger Causality Vector Error Correction Model
Findings: Presence of a long-run relationship between the selected emerging markets in Asia and developed markets.			
Wong *et al.* (2004)	United States, United Kingdom, Japan, Malaysia, Thailand, Korea, Taiwan, Singapore and Hong Kong	1981-2002 Weekly data	Cointegration
Findings: Presence of a long-run relationship between the selected emerging markets in Asia and developed markets. Increased interdependence after 1987 crash, which intensified surrounding the Asian financial crisis.			
Phylaktis and Ravazzolo (2005a)	USA, Japan, Hong Kong, South Korea, Malaysia, Singapore, Taiwan and Thailand	1980–1998 Monthly data	Multivariate Cointegration
Findings: Lack of inter-market linkages during the period of analysis. The Asian crisis had a marginal impact on the degree of linkages of these markets. Japan has a greater influence on the Pacific-Basin countries compared with the USA.			
Yu and Hassan (2008)	The USA, the UK, France, Bahrain, Oman, Saudi Arabia, Jordan, Egypt, Morocco, and Turkey.	1999-2005 Daily data	Impulse response function, EGARCH-M model, Multivariate ARGARCH
Findings: Relative segmentation of the GCC markets from developed markets and significant contribution of the GCC markets to their own returns and volatility.			
Awokuse *et al.* (2009)	Hong Kong, India, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Thailand, Taiwan, the UK and the USA.	1981-2002 Daily data	Rolling Cointegration methods and algorithms of inductive causation
Findings: Long-run dynamic association between Asian emerging markets and selected developed markets with a weak impact from Hong Kong market. Japan and the US have the greatest influence on the emerging markets. Increased influence of Singapore and Thailand since the Asian financial crisis.			
Menon *et al.* (2009)	India, China, Singapore, Hong Kong and the USA.	1997-2007 Daily data	Cointegration

Authors and Year	Markets Included	Period of Analysis and Data Frequency	Techniques Used
Masih and Masih (1999)	Taiwan, South Korea, Singapore, Hong Kong, the USA, the UK, Germany, and Japan.	1980 Daily data	Granger Causality Vector Error Correction Model
Findings: Presence of a long-run relationship between the selected emerging markets in Asia and developed markets.			
Wong *et al.* (2004)	United States, United Kingdom, Japan, Malaysia, Thailand, Korea, Taiwan, Singapore and Hong Kong	1981-2002 Weekly data	Cointegration
Findings: Presence of a long-run relationship between the selected emerging markets in Asia and developed markets. Increased interdependence after 1987 crash, which intensified surrounding the Asian financial crisis.			
Phylaktis and Ravazzolo (2005a)	USA, Japan, Hong Kong, South Korea, Malaysia, Singapore, Taiwan and Thailand	1980–1998 Monthly data	Multivariate Cointegration
Findings: Lack of inter-market linkages during the period of analysis. The Asian crisis had a marginal impact on the degree of linkages of these markets. Japan has a greater influence on the Pacific-Basin countries compared with the USA.			
Yu and Hassan (2008)	The USA, the UK, France, Bahrain, Oman, Saudi Arabia, Jordan, Egypt, Morocco, and Turkey.	1999-2005 Daily data	Impulse response function, EGARCH-M model, Multivariate ARGARCH
Findings: Relative segmentation of the GCC markets from developed markets and significant contribution of the GCC markets to their own returns and volatility.			
Awokuse *et al.* (2009)	Hong Kong, India, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Thailand, Taiwan, the UK and the USA.	1981-2002 Daily data	Rolling Cointegration methods and algorithms of inductive causation
Findings: Long-run dynamic association between Asian emerging markets and selected developed markets with a weak impact from Hong Kong market. Japan and the US have the greatest influence on the emerging markets. Increased influence of Singapore and Thailand since the Asian financial crisis.			
Findings: Lack of Cointegration between India and the USA, as well as India and Hong Kong. Weak Cointegration between the Indian and Chinese markets and a strong long-run association between India and Singapore.			
Gupta and Guidi (2012)	India and Hong Kong, Japan, and Singapore.	1999-2009 Daily data	Cointegration
Findings: A stable long-run relationship between these markets is non-existent; however, the presence of short-run relationships between these markets was documented.			
Graham *et al.* (2012)	22 emerging markets across different continents and the USA.	2001-2009 Weekly data	Wavelet analysis based on frequencies

<table>
<tr><th>Authors and Year</th><th>Markets Included</th><th>Period of Analysis and Data Frequency</th><th>Techniques Used</th></tr>
<tr><td>Masih and Masih (1999)</td><td>Taiwan, South Korea, Singapore, Hong Kong, the USA, the UK, Germany, and Japan.</td><td>1980
Daily data</td><td>Granger Causality Vector Error Correction Model</td></tr>
<tr><td colspan="4">Findings: Presence of a long-run relationship between the selected emerging markets in Asia and developed markets.</td></tr>
<tr><td>Wong et al. (2004)</td><td>United States, United Kingdom, Japan, Malaysia,
Thailand, Korea, Taiwan, Singapore and Hong Kong</td><td>1981-2002
Weekly data</td><td>Cointegration</td></tr>
<tr><td colspan="4">Findings: Presence of a long-run relationship between the selected emerging markets in Asia and developed markets. Increased interdependence after 1987 crash, which intensified surrounding the Asian financial crisis.</td></tr>
<tr><td>Phylaktis and Ravazzolo (2005a)</td><td>USA, Japan, Hong Kong, South Korea, Malaysia, Singapore, Taiwan and Thailand</td><td>1980–1998
Monthly data</td><td>Multivariate Cointegration</td></tr>
<tr><td colspan="4">Findings: Lack of inter-market linkages during the period of analysis. The Asian crisis had a marginal impact on the degree of linkages of these markets. Japan has a greater influence on the Pacific-Basin countries compared with the USA.</td></tr>
<tr><td>Yu and Hassan (2008)</td><td>The USA, the UK, France, Bahrain, Oman, Saudi Arabia, Jordan, Egypt, Morocco, and Turkey.</td><td>1999-2005
Daily data</td><td>Impulse response function, EGARCH-M model, Multivariate ARGARCH</td></tr>
<tr><td colspan="4">Findings: Relative segmentation of the GCC markets from developed markets and significant contribution of the GCC markets to their own returns and volatility.</td></tr>
<tr><td>Awokuse et al. (2009)</td><td>Hong Kong, India, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Thailand, Taiwan, the UK and the USA.</td><td>1981-2002
Daily data</td><td>Rolling Cointegration methods and algorithms of inductive causation</td></tr>
<tr><td colspan="4">Findings: Long-run dynamic association between Asian emerging markets and selected developed markets with a weak impact from Hong Kong market. Japan and the US have the greatest influence on the emerging markets. Increased influence of Singapore and Thailand since the Asian financial crisis.</td></tr>
<tr><td colspan="4">Findings: Degree of co-movements of all the markets evolved after 2006. Varying degrees of co-movements across markets, and also that the markets located in close proximity to the USA exhibit higher co-movements with the USA.</td></tr>
</table>

Developed and European Emerging Markets

The results regarding interdependence between developed and European markets are mixed. For example, studies like Voronkova (2004) and Syriopoulos (2007) documented long-run relationships between selected European emerging and developed markets, and the USA. Voronkova (2004) found the results to be robust even in the presence of structural

breaks. On the other hand, Syriopoulos (2007) provided evidence that the USA plays a prominent role in integration of the markets and that the emerging European markets exhibited stronger relationships with their mature counterparts as compared to those within themselves.

In contrast to the studies mentioned above, Serwa and Bohl (2005) and Égert and Kočenda (2007) found lack of long-run relationships in European emerging and developed markets. The authors investigated the relationships between three central European countries and three developed western European countries between 2003 and 2005, using intraday data at 5-minute intervals. The presence of short-run returns and volatility spillovers, and bi-directional causality between the selected markets was observed. Similarly, evaluation of daily returns of Czech, Hungarian, Polish, German, and UK stock markets, for the period July 1995 to February 2005 by Gilmore *et al.* (2008), revealed unstable short-run correlations and irregular long-run co-integration among these countries. The authors also found little evidence of progression towards long-run association and argued that short-run country-specific factors overpower long-run co-integration between these countries.

Developed and Latin American Emerging Markets

Fewer studies include Latin American markets in the analysis and the results can best be described as incoherent. Chen *et al.* (2002) investigated the dynamic interdependence between major Latin American markets (Argentina, Brazil, Chile, Colombia, Mexico and Venezuela) for the period 1995 to 2000. The results revealed the presence of long-run associations between these markets, which remained unaffected in the Russian and the Asian financial crises. A study by Diamandis (2009) consisted of four Latin American markets, namely Argentina, Brazil, Chile and Mexico, as well as the USA, for the period 1988 to 2006. The authors found evidence of partial integration but long-run association between returns of these markets with momentary deviations from common stochastic trends, especially during turbulent times due to the Mexican currency crisis.

On a different note, Pimenta and Famá (2002) attempted to document the association between the Latin American emerging markets (Argentina, Brazil, Chile, and Mexico) and some developed markets in Southeast Asia (Singapore, South Korea, Hong Kong,

and Taiwan). The period of analysis extended from 1991 to 1999 and is of importance in this study as most emerging countries started deregulating their markets at this time. The results of variance decomposition and impulse response suggest that all the markets included in the sample were more susceptible to country-specific factors. The study also found that while Southeast Asian markets had no influence on Latin American markets, Latin American markets explained marginal variance in Southeast Asian markets. The authors also highlighted the apparent regional interdependence in Latin American countries, with Argentina taking the lead.

An extensive study by Beirne *et al.* (2010) comprised of 41 emerging markets and spanning several regions, such as Latin America, Asia and Europe and a lengthy period of analysis (1993 to 2008)[13] found prominent mean spillovers from global to Asian and Latin American emerging markets, and pronounced volatility spillovers from global to emerging European markets.

An analysis of linkages between the CIVETS markets (Colombia, Indonesia, Vietnam, Egypt, Turkey and South Africa) by Korkmaz *et al.* (2012) revealed generally low contemporaneous returns and volatility spillovers with episodic high spillovers in selected markets. The authors found that out of thirty pairs, only ten pairs exhibited statistically significant causal links. Choudhry (2004) documented volatility spillovers between selected pairs of friends and foes, including India and Pakistan, and Abbas *et al.* (2013) documented volatility spillovers between selected Asian countries (China, India, Pakistan, and Sri Lanka). Both studies documented prominent spillovers from larger to smaller markets.

Developed and Frontier Markets

Frontier markets in general have received less attention in the literature, although these markets have provided investors with impressive returns in the recent past (Caldwell, 2013). Low interdependence among frontier markets and between developed and frontier markets are documented in several studies, which are discussed below.

[13] The sample also included Pakistan in the emerging Asian markets.

Miles (2005) provides evidence of a long-run association between frontier and developed markets, but asserts that short-run deviations between these countries are present. A study by Berger *et al.* (2011) comprised of 25 frontier markets in different regions and proxies for developed and emerging markets revealed periodically low and stagnant levels of integration between frontier and world markets. Baumöhl and Lyócsa (2014) examined the fluctuating correlations and conditional volatility in 32 emerging and frontier markets for the period January 2000 to 2012 using daily data. The authors documented a positive relationship between volatility and correlations across most markets; however, they also found symmetric reaction to positive and negative news in frontier markets. Logoarde-Segot and Lucey (2007) assessed the co-integration between the Middle East, North Africa, the EMU, the USA; and a regional benchmark index during the period between 1998 and 2004. The authors documented a lack of long-run association between these markets. Amin and Orlowski (2014) present evidence that the South Asian frontier markets (Pakistan, Sri Lanka and Bangladesh) are more integrated into the leading regional markets of India as compared to those of the USA.

Samarakoon (2011) examined the linkages between a total of 62 markets, comprising 22 emerging markets and 40 frontier markets, during the period April 2000 to September 2009. The sample was segregated into markets with and markets without hours overlapping those of the USA. Results indicated that returns of markets with partially overlapping hours with those of the USA were influenced by their returns. Moreover, some lagged effect from the US returns was also observed in such markets. Markets with hours overlapping longer with those of the US exhibited larger concurrent impact from the USA. On the other hand, markets with shorter overlapping hours exhibited significant lagged interdependence coefficients. In totality, the concurrent and lagged coefficients of interdependence were the highest for European markets, while this was not as pervasive for Asian, Middle Eastern and European markets with shorter overlapping hours. With respect to the markets with no overlapping hours, the impact of the USA returns was obviously lagged and significant during normal times. Shocks originating from the USA market during normal times, had no impact on partially overlapping frontier markets; however, the lagged

US influence on frontier markets with no overlapping hours was apparent, especially in European frontier markets.

The literature reviewed in this section provides evidence on interdependencies between markets; however, it is apparent that the extent of interdependence between markets varies depending on their stature, geographical location, size and market-specific attributes. Some findings highlighted in literature stand out clearly. First, the asymmetric effect of developed markets on various markets located across continents seems obvious. Second, intra-regional interdependencies appear to supersede inter-regional interdependencies. Lastly, smaller frontier markets are documented by some studies to be segmented from their developed and emerging counterparts. Incoherence in results is also apparent, which can be attributed to the choice of markets, data frequency, and the techniques used for analysis.

Studies highlighting evolving interdependencies between developed and frontier markets and their consequences are presented in sections 2.2 and 2.4.

2.2 Evolving Interdependence Between Markets

This section presents studies that provide evidence of the changing magnitude of interdependence between markets, citing various reasons for this evolution. Two contrasting views found in literature are presented here, and evidence on increasing as well as decreasing trends in cross-market interdependence is discussed in sections 2.2.1 and 2.2.2.

Several studies suggest an increasing trend in cross-market correlations, co-movements and integration since the 1960s. For example, Longin and Solnik (1995) documented amplified correlations between the seven OECD markets between 1960 and 1990. Barari (2004) argued that integration between Latin American emerging markets and global markets became prominent in the late 90s. Graham *et al.* (2013) found that co-movements between the USA and selected MENA markets, and within the MENA markets themselves, increased between 2002 and 2010. Similarly, Graham *et al.* (2012) found that the co-movements between the USA and emerging markets across four continents have evolved, and greater co-movements are observable after 2006.

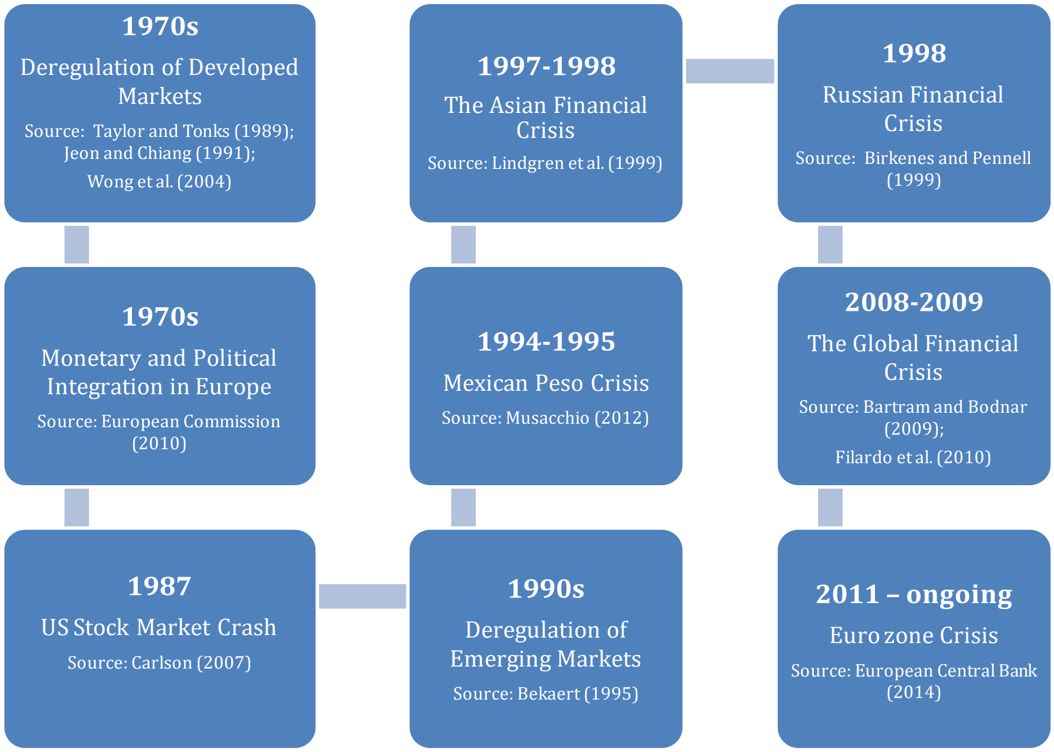
Besides previously mentioned studies, Akdogan (1992, 1996), Friedman and Shachmurove (1997), Ratanapakorn and Sharma (2002), Diebold and Yilmaz (2009, 2012), and Yilmaz (2010) decomposed cross-market variances to measure the contribution of exogenous shocks to the returns and volatility of a particular financial market. These studies also found progressive enhanced asymmetric interdependencies across markets and are summarized in section 2.2.1.

While the conventional literature provides sufficient evidence of increased interdependencies between markets, there are some studies that challenge a nearly established norm and argue that some emerging markets have in fact "decoupled" from developed markets due to their macroeconomic strengths (for example Kose *et al.*, 2008; Cutrini and Galeazzi, 2012). Arguments and evidence provided by these studies, and some counter arguments presented by other researchers, are discussed in section 2.2.2.

2.2.1 Evidence on Increased Interdependence Between Markets

The pertinent finance literature considers specific events such as the removal of capital controls (Taylor and Tonks, 1989), the creation of a monetary or economic union such as the formation of the EU (Kim *et al.*, 2005; Syriopoulos, 2007; Caporale and Spagnolo, 2011), or a major crisis (Goldstein, 1998; Wu and Su, 1998; Jang and Sul, 2002; Arestis *et al.*, 2005; Click and Plummer, 2005; Goh *et al.*, 2005; Fernandez, 2006; Bartram and Bodnar, 2009; Frank and Hesse, 2009; Khan and Park, 2009; Huyghebaert and Wang, 2010; Mun and Brooks, 2011; Samarakoon, 2011; Kim *et al.*, 2012; Neaime, 2012) as reasons for the changing magnitude of interdependence between markets. Figure 2.2 presents the timeline of the most significant events in the last few decades.

Figure 2.2 – Significant Financial Events Between 1970 and 2014[14]



The wide-spread deregulation of developed markets in the late 1970s and 1980s prompted a phenomenal increase in the number of studies on the subject. The USA markets were deregulated in 1975, followed by those of the UK and Germany in 1979 (Jeon & Chiang, 1991) and Japan in 1978-79 (Wong *et al.*, 2004). Taylor & Tonks (1989) suggest that post-deregulation, outward capital flow from deregulated markets increased by nearly 1,800% and the inward capital flow to deregulated markets marked an increase of 57% between 1980 and 1983. Taylor & Tonks (1989) and Jeon & Chiang (1991) argue that removal of capital controls resulted in greater integration of developed markets.

Kim *et al.* (2005) conducted a detailed study on several Eurozone countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain), three non-Eurozone countries (Denmark, Sweden and the UK), and Japan and the USA, for the period 1989 to 2003. The results of the study highlighted that the

[14] A detailed chronology of financial crises in the last 40 years is presented by Wiedenbrüg and Post (2012).

formation of the European Monetary Union (EMU) and the introduction of a common currency played a major role in the stock market integration, resulting in greater returns and volatility spillovers across member states. Caporale and Spagnolo (2011) investigated the linkages between selected stock markets of Central and Eastern European countries (CEEC) including the Czech Republic, Hungary and Poland, Russia and the UK, between 1996 and 2008, following the accession of the European Union (EU) and the introduction of the Euro. The authors reported greater co-movements among the markets under consideration, volatility spillovers from Russia and the UK to the other European countries, and greater integration of CEE markets with the UK post-EU accession. Wang and Moore (2008) also found that the correlations between the CEEC emerging markets and the aggregate Eurozone market increased after their entry into the EU.

A study by Dunis *et al.* (2013) explored the interdependence between relatively new members of the EU such as Cyprus, Estonia, Malta, Slovakia and Slovenia that have already adopted the Euro as common currency, and the EU in general, between 2003 and 2011. A proxy for the Eurozone was also included in the study. The findings of the study were mixed and the countries under consideration exhibited varied degrees of integration. Estonia seemed to be the most segmented market in the group and the Malta and Slovenia markets exhibited a heightened degree of integration. Increased integration between Cyprus and Slovakia was found post-EU accession, but the trend altered after adopting the Euro. In general, the authors documented increased integration between countries after the EU accession, but a reverse trend post-monetary union. Moreover, it was observed that while Malta and Slovenia are more prone to foreign shocks from mature European markets, the same does not hold true for the other three markets.

Syriopoulos (2007) conducted an event study to examine the relationships between four Central European emerging markets and selected developed European markets before and after their entry into the EMU. The overall period of analysis was split into two: Pre-EMU Period (January 1997 to December 1998) and Post-EMU Period (January 1999 to September 2003). Although the results provided evidence of a long-run association between these markets, the authors could not find evidence of heightened integration in the post-EMU era.

Beyond political and economic events, crises are considered to be a prime cause of evolving market interdependencies. The term "crisis" in the context of financial markets can be defined as a significant decline in prices of a large group of assets, unrelated to micro and macro fundamentals (Hong and Stein, 2003). The history of financial markets is punctuated with several crises[15]. The most commonly cited crises are the 1994/1995 Mexico Crisis, the Asian financial crisis in 1997, the Russian crisis in 1998, and the most recent financial crisis of 2008 that emerged in the USA but that engulfed most international markets. The finance literature in general has documented a negative heterogeneous impact of these crises across markets globally.

The earliest evidence of enhanced co-movements of financial markets during financial crises was documented by Hilliard (1979). The author used daily data (July 1973 to April 1974) of 10 major world indices to analyze the co-movements of markets in the presence of a crisis "the OPEC Embargo" in 1973. The author found pronounced intra-continental co-movements during the crisis, as compared to inter-continental co-movements. The study concluded that the chosen countries possessed greater unsystematic risk associated with national or regional factors, and lower systematic risk associated with the world factor.

Eun and Shim (1989), King and Wadhwani (1990), Arshanapalli and Doukas (1993), Lee and Kim (1993) and Wu and Su (1998) suggested that the interdependencies between markets increased after the 1987 market crash. Arshanapalli and Doukas (1993) examined the impact of the 1987 crash dynamic interdependence between several developed countries including the USA, the UK, France, Germany and Japan between 1980 and 1990. In the pre-crisis era, the markets appeared segmented from each other; however, enhanced international co-movements after the 1987 market crash were evidenced, with Japan being an exception. Similar results were reported by Wu and Su (1998) for the USA, the UK, Japan and Hong Kong.

Jang and Sul (2002), Click and Plummer (2005), Abd. Majid *et al.* (2008), Awokuse *et al.* (2009) and Lim (2009) found evidence of enhanced interdependence and integration

[15] For a detailed review and timeline of various crises in the last century see Reinhart and Rogoff, 2008.

between Asian markets post-Asian financial crisis. Goh *et al.* (2005) observed high positive correlations and enhanced co-movements in the returns of the ASEAN markets of Singapore, Malaysia, Indonesia, Thailand and the Philippines during the crisis. Moreover, the magnitude of co-movements enhanced during turmoil, with Indonesia taking the lead. While long-run association between these countries was observed in the pre-crisis period, a short-run relationship was evident during crisis.

Khan and Park (2009) evaluated cross-country dynamic correlation coefficients among pairs of East Asian countries that were primarily affected by the Asian financial crisis, including Thailand, Malaysia, Indonesia, Korea and the Philippines, during 1994 to 1999, incorporating both calm and turbulent times. The results indicated that after controlling for macro-fundamentals and global shocks, eight out of ten pairs exhibited exaggerated dynamic cross-country correlations during crisis. However, an increase in correlations between Korea and Thailand, and the Philippines and Thailand, were moderate during the crisis. Lim (2009) investigated the long-run associations between the five original members of ASEAN during 1990 and 2008. The study documented greater convergence of the ASEAN markets after the Asian financial crisis. The author also found that the USA market influenced all markets in the regions, with mature markets in ASEAN, such as Singapore, having greater association with the USA.

Huyghebaert and Wang (2010) examined the integration and causality between seven East Asian stock markets before, during, and after the Asian financial crisis. Their study also included the USA, in order to analyze the contribution of exogenous variables on the chosen markets. The results highlighted limited interdependencies across East Asian markets before the crisis, which increased significantly after the crisis. Furthermore, the importance of Singapore and Hong Kong in the transmission of shocks increased post-crisis. Conversely, China appeared to be relatively isolated from East Asian and the USA markets. These findings suggest that beyond trade and geographical proximities, there are other reasons that may promote or constrain interdependencies across markets.

Chan *et al.* (2008) documented significant changes in the causal relationships between Hong Kong and the USA after the Asian financial crisis. In the pre-crisis era, bi-directional causality between the two was prominent and was primarily driven by long

cycles with low frequency; however, in the post-crisis era, unidirectional causality from the USA to Hong Kong, driven by short cycles, was more evident. While most of the above studies on East Asian markets considered a longer period for analysis, including turbulent as well as tranquil periods, Click and Plummer (2005) specifically focused on the post crisis period, which extended from 1998 to 2002. Their analysis on daily and weekly data revealed that the selected East Asian markets were partially cointegrated.

With respect to the impact of the Asian financial crisis on other regions, Ratanapakorn and Sharma (2002) investigated the short- and long-run relationships between the USA, Asia, Europe, Latin America and the Middle East during the Asian financial crisis period, using MSCI regional indices. The authors documented an absence of any long-run association between the chosen indices in the pre-crisis period; however, during the crisis, short-run associations were evident. Moreover, during the crisis, the European index had an impact on the USA index directly, and other markets indirectly affected the USA market, with European markets being the channel of transmission. Chen *et al.* (2002) found that the long-run association between selected Latin American emerging markets remained immune to the Asian Financial crisis. On the contrary, Barari (2004) found prominent regional integration among the Latin American countries in the pre-crisis period and the pronounced global integration in the post-crisis period.

Serwa and Bohl (2005) explored linkages between 17 countries, both developed and emerging, between 1997 and 2002. Several crises occurred during that period, such as the Asian and Russian financial crises. The results revealed that the smaller and emerging European markets were less prone to crises, implying lower interdependence between European emerging and developed markets. Wang and Moore (2008) found similar results for Poland, Hungary, and the Czech Republic during a longer period of analysis extending from 1994 to 2006.

Recently, various authors have studied the impact of the 2008 financial crisis on financial markets' interdependence. Assidenou (2011) evaluated cointegration between a large set of countries classified as OECD (the USA, the UK, France, Germany, Japan and Sweden), Pacific (Japan, Hong Kong SAR, New Zealand, South Korea and Taiwan) and East-Asian (Japan, China Mainland, Hong Kong SAR, South Korea and Taiwan) countries from

September 2008 to August 2009. The null of no cointegration was rejected in all three groups of countries, suggesting the existence of a long-run association between countries specifically at the time of the recent financial crisis. Cheung *et al.* (2008) also concluded that the cross-market interdependencies between East Asian and Asia-Pacific markets have increased progressively since 2006 and amplified sharply after the fall of Lehman Brothers in 2008.

Dooley and Hutchison (2009) and Huyghebaert and Wang (2010) found that the interdependence between markets, especially between emerging and developed markets, increased during the 2008 financial crisis. Baur (2012) documented similar results and asserted that post-crisis, the co-movements of returns increased, especially in the financial sector stocks across countries. Hwang (2012) assessed the impact of the financial crisis on stock market linkages between Asia-Pacific countries (Australia, China, Hong Kong, Japan Korea, Malaysia, New Zealand, Singapore and Taiwan) and the USA. The results suggested high positive conditional and unconditional correlations between the selected markets during the crisis with an exception of China. Gupta and Guidi (2012) found that the conditional correlations between India and selected Asian developed markets rose dramatically following the 9/11 terrorists attacks as well as at the time of the recent financial crisis, albeit temporary.

Neaime (2012) examined the impact of the recent financial crisis on selected oil producing (Kuwait, Saudi Arabia and the UAE) and non-oil producing countries in the MENA region (Egypt, Jordan, Morocco and Tunisia), along with developed markets of the USA, the UK and France. The period of analysis stretched from 2007 until 2010. The author documented strong causal links between the non-oil producing countries and the developed markets, and observed a weak causal relationship between Saudi Arabia and developed markets. The impact of the financial crisis was less evident on Saudi Arabia and Egypt and it was more pronounced on the other MENA markets, included those in the sample.

Valls and Chuliá (2012) found that during the recent financial crisis, the pattern of volatility transmission from the USA to the ten emerging economies in their analysis was marginal, and that the interdependence between markets was associated with the economic openness and development of the market. For example, in their study, the authors found that

China was less integrated with the USA market due to its relatively closed financial sector; a finding which is consistent with Zhou *et al.* (2012) and Wang and Wang (2010). Allen *et al.* (2013) documented non-constant and occasional negative correlations between the USA and China during the crisis. Similarly, Wang and Wang (2010) found weak volatility spillovers between China, the USA and Japan, with a marginal impact of negative foreign shocks on the Chinese market. The authors attributed these traits of the Chinese market to its size, comparable to the selected developed markets and lower degree of open-ness.

In a recent study, Ranta (2013) analyzed 25 years of data (1984 to 2009) in order to evaluate the progression of interdependence between developed markets of the USA, the UK, Germany, and Japan in general, and at the time of various crises, in particular. The author drew the following conclusions (p. 140):

- The interdependence between the selected developed markets during the last 25 years has increased, especially between the USA and the European markets.
- Co-movements during the 1987 market crash, Gulf war, Asian and Russian financial crises, and the recent financial crisis increased significantly.
- The effects of the financial crisis of 2008 are most pronounced.

The literature on frontier markets remains sparse. A handful of studies include frontier markets in the sample (For example Akdogan, 1996; Miles, 2005; Logoarde-Segot and Lucey, 2007; Berger *et al.*, 2011; Kohlert, 2011; Samarakoon, 2011, Bley and Saad, 2012; De Groot *et al.*, 2012; Demirer, 2013; Chen *et al.*, 2014; Baumöhl and Lyócsa, 2014; Amin and Orlowski, 2014). All these studies documented low correlations and interdependence between frontier markets and their developed and emerging counterparts. Furthermore, low correlations were also documented among frontier markets themselves (Amin and Orlowski, 2014).

Although there is evidence of the segmentation of frontier markets from developed markets, Samarakoon (2011) argued that while these countries may remain decoupled from the developed markets during tranquil times, they tend to be affected by a financial crisis in an influential market like the USA.

However, there are exceptions to these standard results regarding the behavior of frontier markets during the crisis. For example, Amin and Orlowski (2014) demonstrated

that while the South Asian frontier markets experienced high volatility spillovers from the USA during the crisis, Pakistan's self-contributions to its volatility were more pronounced in the same period.

Some studies in the finance literature distinguish between interdependence and contagion across markets. Forbes and Rigobon (2002, p. 2,223) define contagion as "as a significant increase in cross-market linkages after a shock to one country (or group of countries)". The authors distinguish between interdependence and contagion and argue that interdependence leads to permanently high correlations between markets, while contagion is short-lived. Many studies have explored the presence or absence of contagion in turbulent times, especially during a financial crisis (for example, Calvo and Reinhart, 1996; Glick and Rose, 1999; Ahluwalia, 2000; Dornbusch *et al.*, 2000; Van Rijckeghem and Weder, 2001; Forbes and Rigobon, 2002; Billio and Pelizzon, 2003; Caramazza *et al.*, 2004; Hon *et al.*, 2004; Arestis *et al.*, 2005; Bekaert *et al.*, 2005; Corsetti *et al.*, 2005; Serwa and Bohl, 2005; Chiang *et al.*, 2007; Fazio, 2007; Cheung *et al.*, 2008; Baur and Fry, 2009; Bodart and Candelon, 2009; Markwat *et al.*, 2009; Khan and Park, 2009; Chiang and Wang, 2011; Castellanos *et al.*, 2011; Baur, 2012; Marcal *et al.*, 2011; Samarakoon, 2011; Ranta, 2013). Most of the studies published in the 1990s and prior to 2008 investigate the presence of contagion surrounding the Asian financial crisis, with an exception of Calvo and Reinhart (1996), which focuses on the Mexican currency crisis. Studies published after 2008 considered the recent financial crisis to be the main source of contagion.

Paas and Kuusk (2012) reviewed 75 studies published on the topic of financial contagion. The authors argue that while the contagion hypothesis is well established, there is lack of coherence among the results, possibly due to varied definition, methods, nature of crises and selection of countries in the sample. A brief review of literature on contagion due to highly integrated markets is discussed later in the chapter (Section 2.4.2).

2.2.2 Evidence on Decreasing Interdependence Between Markets

While most of the studies surveyed have documented increased interdependencies and spillovers across markets, some studies present a different viewpoint. Bekaert and Harvey (1995) suggested that some markets have become progressively less integrated. The

authors, however, did not investigate the possible reasons for the reversal trends in integration across some markets. More recently "Decoupling Hypothesis", a phenomenon that challenges the conventional wisdom of enhanced interdependencies between markets due to globalization and other factors has been recognized.

Kose *et al.* (2008) proposed the decoupling hypothesis, suggesting that the business cycles of emerging economies have decoupled from the developed economies like the USA due to their strong macroeconomic fundamentals and evolving economic maturity. Specifically, endogenous factors such as a strong economy, locally generated demand, and a strong financial sector have contributed greatly to decoupling of these markets from developed markets (Kose *et al.*, 2008; Cutrini and Galeazzi, 2012).

The literature on the decoupling hypothesis is focused on either "real" or "financial" sectors, whereby the former discusses synchronization of business cycles, and the latter mainly focuses on the integration of financial markets. The decoupling phenomenon in the real sector became popular when Kose *et al.* (2008) examined the global cyclical interdependence between 100 industrial, emerging, and developing markets between 1960 and 2005. The authors used a dynamic factor model and investigated the contribution of global, regional, and country-specific effects on various macroeconomic variables of each of these countries. In the study, the authors decomposed the GDP growth of emerging economies into "world" and "country" specific measures and found that the weightage of the world factor declined during the period of analysis. The results highlighted the declining importance of global factors in emerging economies, which in turn can be attributed to decoupling. Cutrini and Galeazzi (2012) found that while long-run synchronization between developed and emerging markets prevailed, internal factors like increased regional trade and strong economic factors contributed to the decoupling of emerging economies in the last decade. However, the authors also argued that the opposing forces of international trade and financial linkages hampered decoupling.

Researchers like Wälti (2012) contested the decoupling hypothesis and argued that the hypothesis challenges the notion of globalization and is therefore a myth. Wälti examined the interdependence between the business cycles of a large group of emerging economies in Asia, Europe, and Latin America, as well as several developed economies and groups of

developed countries, such as the G7 group. The author used pooled regression analysis to examine business cycle interdependence of the chosen economies between 1980 and 2008. The study concluded that there is no evidence of decoupling between emerging and developed economies. Wälti's research challenged the results presented by Kose *et al.* (2008) based on the measure used for analysis in their study as well as the interpretation of results. The author asserts that the emerging markets have experienced accelerated growth in the past few decades while the mature and developed economies have grown at a relatively slower but stable rate; hence, the results for emerging markets cannot be associated with decoupling[16].

Similarly, Levy, Yeyati and Williams (2012) evaluated the decoupling hypothesis with respect to both real and financial sectors. The authors document that while business cycles in emerging markets may have become less dependent on developed markets due to trade diversification and the emergence of China as a dominant new trade partner, there is clear evidence that emerging financial markets have not decoupled from developed markets. Fujiwara and Takahashi (2012) also documented the increased influence of China on the economic activities in the region; however, they also suggested that the complete decoupling of Asian emerging economies from developed economies does not hold true.

While the evidence on the decoupling and recoupling of economic sectors is mixed, there seems to be consistent evidence regarding the lack of decoupling of financial markets, especially during turbulent times. If the decoupling hypothesis holds, then the shocks from developed financial markets should not be transmitted to emerging economies, but this was nullified during the recent financial crisis when markets all around the world were affected.

Dooley and Hutchison (2009) and Bartram and Bodnar (2009) documented asymmetric impact of the financial crisis on seemingly decoupled emerging markets. Dooley and Hutchison (2009) evaluated the transmission of financial crisis to the emerging markets in order to identify whether the structural changes, post-Asian financial crisis, have resulted in a resilient banking system. The authors conducted an event study to investigate the

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[16] Wälti's assertion appears to be consistent with the Catch-up hypothesis or Theory of Convergence referred to in footnote 3.

transmission of shocks from the USA to CDS spread in emerging markets. The results suggested that news from the developed markets during the recent financial crisis affected the emerging markets heterogeneously. This indicates that a crisis triggered in a developed and influential market, especially in the USA, affects markets around the world, irrespective of their location and stature. Hence, the markets that may appear independent or decoupled otherwise, recouple during the crises.

Bartram and Bodnar (2009) analyzed whether the news associated with financial crisis caused havoc in emerging markets. The authors concluded that most markets around the world were affected in the period September to October 2008, whereby the financial sectors suffered more losses than did the non-financial sectors. Mun and Brooks (2011) affirmed the importance of news and volatility during the financial crisis in altering the correlations across developed and emerging markets. Turgutlu and Ucer (2010) and Amin and Orlowski (2014) also documented that turmoil in developed markets may permeate to emerging markets, but that the same might not be true during a boom.

Dufrénot *et al.* (2011) tested the decoupling hypothesis and assessed the impact of the financial crisis on five emerging markets of Latin America. The authors could not find enough evidence of the complete decoupling of Latin American economies and found varied extent and duration of volatility transmission from the USA to Latin American markets. According to the study, Mexico experienced the greatest impact during the crisis, most likely due to its trade links and geographical proximity to the USA. Regional factors appeared to be more prevalent in affecting the remaining Latin American markets, probably due to weaker economic ties with the USA. On the other hand, countries like Brazil were not impacted as greatly, due to restrictions on the levels of risk taken by the investors (Dufrénot *et al.*, 2011).

The debate regarding the decoupling-recoupling of developed and emerging markets remains unsettled. More sophisticated models like the one presented by Korinek *et al.* (2010) are required to draw meaningful conclusions to settle the debate. The authors suggested a stylized model to capture the decoupling and recoupling phenomenon, particularly observed during the recent financial crisis. The model comprises two parameters, presenting either two sectors in the economy or two countries, financed by the financial sector. The authors argue that the model can capture the effect of changes in one

variable on the other, and can also be extended to include other factors such as bank leverage, factor prices, and bankruptcy costs. The application and further development of the model suggested by Korinek *et al.* (2010) may better facilitate the decoupling-recoupling phenomenon.

Some questions also remain unanswered as to whether the emerging economies will be able to sustain the growth patterns accomplished in the recent past and whether they will be able to achieve economic autonomy, due to the endogenous drivers, to an extent that their cyclical dependency on developed markets is minimized (Cutrini and Galeazzi, 2012). The authors argue that if this transition occurs and the emerging economies are able to sustain their economic growth and self-reliance, then the world economy may progress towards a multi-polar[17] economic system, whereby the total costs of recession will be reduced. Subsequently, in a world with low interdependencies between financial markets, the opportunities for diversification will be plentiful.

Given these contrasting arguments on interdependencies between markets, Bekaert, *et al.* (2009, p. 2,591) appropriately state:

> "It is fair to say that there is no definitive evidence that cross-country correlations are significantly and permanently higher now than they were, say, ten years ago."

Therefore, even in the presence of a large body of literature, the need for further research cannot be disregarded.

2.3 Reasons for Increased Interdependencies Between Markets

The third stream of literature focuses on the reasons for increased interdependencies between markets. Bilateral trade, geographical proximity, and financial linkages are the most commonly cited reasons for enhanced market interdependence (for example, Ripley 1973; Calvo and Reinhart, 1996; Glick and Rose, 1999; Pretorious, 2002; Forbes, 2004; Forbes and Chinn, 2004; Barari, 2004; Campa and Fernandes, 2006, Morana, 2008; Karim and Abd.

[17] Polski (2009) argues that a polycentric financial system, like the one that the USA offers, may not be suitable in today's globalized world. The concept of a centralized systematic regulator is not feasible due to increased complexity of financial system, disintermediation, innovation in financial instruments and services, increased intervention from governments and diversity of asset holders. Subsequently, the need for multiple centers of specialized regulatory activity has increased over time.

Majid, 2010; Didier *et al.*, 2010; Meric *et al.*, 2012; Liu, 2013). Beyond these commonly cited reasons for greater integration of markets, some authors have cited other plausible reasons as well, such as:

- Liberalization and development of financial markets (Bekaert and Harvey, 1997; Ng, 2000; Bekaert and Harvey, 2003; Phylaktis and Ravazzolo, 2005a; Carrieri *et al.*, 2007; Bekaert *et al.*, 2011),
- Globalization (Jeon and Chiang, 1991; Baele, 2005; Phylaktis and Xia, 2006; Aggarwal et., 2010),
- Political economy events (Akdogan, 1992; Akdogan, 1996; Aggarwal *et al.*, 2010),
- Capital flows and increased mobility of capital (Wong *et al.*, 2004; Bekaert and Harvey, 2003),
- Common creditors (Caramazza *et al.*, 2004),
- Technological advancements (Calvo and Reinhart, 1996; Herring, 1994),
- Increased flow and access to information (Phylaktis and Ravazzolo, 2005a),
- Increased geographical reach of companies and reduction in home bias among investors (Brooks and Del Negro, 2002),
- Interest rate spreads, exchange rate risk, market capitalization, and business cycle synchronization (Büttner and Hayo, 2011),
- Macroeconomic and demographic variables, natural resources, energy, state of financial and private sector, technology exports (Chen *et al.*, 2014), and
- Similar income levels across countries, dominance of financial centers facilitating regional capital flows, reduced real interest rate differentials between countries, and the inclusion of multinational firms in multiple indices (Hilliard, 1979).

Levy and Sarnat (1970) exposited that constraints on international trade and/or capital flows effect the pattern of security returns significantly and lead to persistence of inefficient markets. Bekaert *et al.* (2011) argued that although globalization and financial openness (liberalization) have contributed to the integration of international markets, researchers are still facing challenges in quantifying the sources, the timing and magnitude

of market integration. The authors find that the liberalization and development of stock markets are the key variables that explain the degree of market segmentation across borders. On the other hand, Lee *et al.* (2012) found that adjacent markets with structural backgrounds similar to those of the capital markets may result in greater co-movements, as in the case of Hong Kong and Taiwan in their analysis. Liu (2013) argued that information capacity, industrial structure and financial integration determines interdependence between developed and developing markets; however, economic integration drives interdependence between developing countries and other markets.

While the literature presents many reasons for increased interdependence across markets, this survey now focuses on the most commonly cited reasons, namely trade and geographical proximity, foreign investment, and political events and political crises.

2.3.1 Bilateral Trade and Geographical Proximity

Bilateral trade and geographical proximity are widely cited as prime determinants of higher cross-market interdependence. The emergence of economic trading blocs like the European Union (EU), and regional bilateral trade agreements like the North American Free Trade Agreement (NAFTA) have resulted in the deregulation of national markets and have accelerated the integration of regional markets (Moshirian, 1999). Maurent and Joy (1976) provide evidence of increased cohesiveness among the members of the European Economic Community (EEC) between 1961 and 1970. The results of the study highlighted that there was a significant relationship between the USA and EEC countries in the first half of the 1960s; however, the association between EEC countries and the USA market declined in the latter half of and the increasing association among EEC countries became apparent during this period. The authors suggest that the increased interdependence may be a product of greater regional, economic, and financial integration, although the prime reasons were not examined.

Analysis of the five largest economies and 40 other markets for the period between 1986 and 2000 by Forbes and Chinn (2004) revealed that the returns in markets around the world are driven by cross-country and sectoral factors. Bilateral trade and financial association explained the transmission of returns from developed markets to other markets

included in the sample, and trade linkages were the most prominent factor in determining cross-market interdependence in stock and bond markets.

Glick and Rose (1999) used univariate regression and multivariate probit to examine the relationship between trade and spread of currency crisis. They found currency crises to be regionally concentrated due to strong regional trade links. Liu *et al.* (2006) explored the trade relationship hypothesis to test the interdependence between the USA and its trading partners. The authors found that shocks in the USA market led to asymmetric responses in the markets of its prominent trading partners. Morana (2008) and Cheung *et al.* (2008) also found stronger intra-regional interdependencies as compared to inter-regional interdependencies due to trade links. These studies not only highlight the importance of regional bilateral trade but also indicate that geographical proximity is crucial in market integration.

Ahluwalia (2000) provided evidence that besides regional trade links, the geographical location of countries is an important determinant in the transmission of crisis, as the investors penalize countries in the same region, especially if they exhibit weaknesses in key macroeconomic variables, which are similar to those in the epicenter of the crisis. Fazio (2007) suggested that following the initial crisis episode, investors tend to discriminate based on the location of the country, leading to regional dissemination of crisis. Barari (2004) documented distinct regional integration until the mid-1990s in selected Latin American countries and found prominent global integration between Latin American markets in the late 1990s.

Bracker *et al.* (1999) analyzed the drivers of market interdependence across nine developed countries, namely Japan, Australia, Hong Kong, Singapore, Switzerland, Germany, the UK, the USA and Canada, between 1972 and 1983. The sample was further divided into regions and macroeconomic variables such as bilateral trade, inflation differentials between countries, real interest rate differentials, change in exchange rates, volatility in the bilateral exchange rate, geographic distance between markets, and the size of the market. Bilateral trade and geographical distance emerged to be statistically significant in the study. Following a similar line of inquiry, Pretorius (2002) attempted to identify economic determinants of enhanced interdependencies between 1995 and 2000 across ten emerging countries

belonging to different regions, including Argentina, Brazil, China, Greece, India, Korea, Malaysia, Mexico, South Africa and Turkey. Most variables included in Bracker *et al.* (1999) were included in the model with some additional variables like a dummy variable for the Asian financial crisis. The results clearly highlighted the importance of trade and production output as the drivers of interdependence across pairs of countries. Moreover, the author also found that regional dummy variables were statistically significant in the models, indicating the importance of geographical proximity. A study by Johnson and Soenen (2003) considered North and South American countries for the period between 1988 and 1999, and also produced similar results.

Wälti (2011) attempted to identify the primary reasons for co-movements of 15 European developed countries between 1975 and 2006. The author included economic, financial, and monetary integration in the model besides using variables such as the product of GDP per capita, distance, creditor rights, corruption index, common language, and a dummy variable for EU. All the variables except distance had a positive sign and all of them were statically significant, explaining nearly 60% of the variability in stock market integration. The negative coefficient for distance indicated that shorter distance between countries leads to greater market integration.

With respect to regional interdependencies in other regions, Darrat *et al*. (2000) found that the markets in the MENA region are relatively segmented from the global markets; however, regional interdependencies among the MENA countries are prominent. Similarly, Alkulaib *et al.* (2009) found that the markets in the GCC exhibited greater interdependence among themselves as compared to their counterparts in North Africa between 1999 and 2004.

Hence, the finance literature provides ample evidence that bilateral trade as well as geographical proximity between countries leads to prevalent and increasing interdependencies between countries.

2.3.2 Foreign Investment and Capital flows

Foreign investment and capital flows across borders also determine cross-market interdependencies and the transmission of shocks. Dornbusch *et al.* (2000) discuss that the

cross-country returns and volatility spillovers can be due to the financial and economic integration of countries, or can be associated with the abrupt flight of foreign investments from a country during the time of crisis. The authors argued that foreign investors may induce volatility in capital markets with their irrational (Herding[18] and information asymmetries) or rational (lack of liquidity and incentives problem) decision-making.

The literature related to financial markets provides evidence that foreign portfolio investment leads to long-term growth in the capital markets as it is associated with regulatory and policy reforms (for example Bhattacharya and Daouk, 2009). Claessens (1995, p. 14) suggests:

> "[Increased] equity portfolio flows can benefit developing countries by diversifying the sources of external finance, increasing the risk-bearing by investors, reducing the cost of capital, improving incentives for managing the investment process, assisting in the development of domestic capital markets, and enhancing the mobilization of domestic resources".

Additionally, increased foreign participation in the financial markets increases company listings, market capitalization and turnover ratios, and improves the regulatory environment (Hargis, 2002). However, increased globalization of financial markets and foreign investment leads to increased uncertainties and a wider transmission of impulses (Cutrini and Galeazzi, 2012). A financial crisis in one country or region may prompt foreign investors to rebalance their portfolios to manage risk and liquidity (Caramazza *et al.*, 2004). The markets are exposed to the mercy of foreign investors who may treat markets indiscriminately in times of turmoil and pull out investments irrespective of the origin of crisis (Calvo and Reinhart, 1996; Nissanke, 2010), which may trigger exaggerated volatilities across markets. This behavior of investors is detrimental to the growth and development of the capital markets.

Didier *et al.* (2010) investigated the impact of the financial crisis of 2008 on 83 markets and investigated the transmission channels of crisis from the USA to other countries.

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[18] "Herding" is an irrational behavior of investors, whereby investors follow each other's actions without having detailed knowledge of the event/crisis. For a detailed literature review on herding behavior in financial markets, refer to Spyrou (2013).

Real linkages (trade), and direct (foreign investments) and indirect (common creditors[19]) linkages were investigated as probable transmission channels. The results of the study suggested that the financial linkages, both direct and indirect, contributed greatly to volatility transmission across markets while trade did not contribute significantly to volatility transmission. Similarly, Kim *et al.* (2012) documented spillovers from the USA to five Asian emerging economies around the collapse of Lehman Brothers in September 2008. The authors found that greater foreign investment by the USA in the Asian emerging markets contributed in creating spillovers effects. The study also acknowledged that markets become more susceptible to crises in the presence of large liabilities owing to foreign investors that result in sudden capital outflows during crises.

Caramazza *et al.* (2004) and Van Rijckeghem and Weder (2001) also provide evidence that the probability of the transmission of shocks beyond domestic boundaries increases if the countries are linked through a common creditor. The authors documented that the spillovers from common lenders were crucial during the Mexican, Thai, and Russian currency crises and that the competition of funds from the common lender appeared to be statistically significant in various regression estimates; however, the inclusion of trade linkages for Asian markets resulted in robust results.

Mukherjee and Bose (2008) studied the integration of Indian markets with several Asian markets and the USA. The results suggested that Japan played a major role in the integration of Asian Markets between 1999 and 2005. The authors attributed increased integration of India with its Asian counterparts and the USA to augmented foreign institutional investments in India from these countries.

Komulainen and Lukkarila (2003) analyzed the factors leading to crises in emerging markets, and expounded that while crises in emerging markets are a product of weaknesses in key macroeconomic variables like unemployment and inflation, several indicators of indebtedness, such as private sector liabilities and the foreign liabilities of banks, are also responsible for crises in emerging economies. Although the deregulation of markets coupled

[19] The term "Common Creditor" refers to common lenders across countries, which can be banks or governments.

with superior technology provides diversification opportunities for investors, they also pose a challenge to policy makers and regulators who are continuously facing problems, which arise from erratic returns and volatility in national markets, sometimes independent of local events.

2.3.3 Political Relationships, Events and Crises

Besides trade relationships, geographical proximity and foreign investment, some political relationships, events, and crises may also contribute towards increased market volatility and integration. Political events, such as an election or a military coup, contribute to the volatility in financial markets (Aggarwal *et al.*, 1999; Martínez and Santiso, 2003) and political risk is cited as one of the major causes of capital flight from any country (Le and Zak, 2006).

Political and economic integration of European countries has contributed positively to the enhanced interdependence between countries that are part of this union. Akdogan (1992) measured integration across eight European countries in the 1970s and 1980s. The results indicated that integration between European markets has gradually increased in the decades under consideration and that this is mostly associated with the political decisions of governments to promote economic cooperation and institutional integration in the European common market. In a unique and significant study, Aggarwal *et al.* (2010) found a positive relationship between political economy events and financial integration across Europe during 1988 and 2002. The authors used nominal daily returns of the European and USA markets in Euros and US dollars respectively. The results highlighted that the integration across markets increased from 40% in 1988 to 70% at the end of the period under consideration. The authors documented incremental short- and long-run integration among European markets and also with the USA markets.

Christiansen and Ranaldo (2009) found that the developed and emerging European stock markets have become more integrated in the post-EU enlargement era and that the frequency of co-movement of returns increased significantly between the new and old EU members. Büttner and Hayo (2011) determined the impact of the level of European integration status on stock market association by grouping the countries into Euro area members that have adopted the Euro, old EU member states that have not adopted the Euro,

and new EU member states. The results of the study highlighted that increased integration of the markets is associated with the adoption of a single currency and the enhanced depth of the capital markets. This indicates that regional integration in Europe has strengthened, due to the economic and political integration of countries in the EU.

Choudhry (2004) studied the returns and volatility spillovers between "friends and foes", and found evidence of volatility spillovers, especially from larger to smaller markets. This suggests that while the trade and foreign investments between traditional foes might be limited due to animosity, politically strained relationships might contribute to the co-movements between markets. More recently, Abbas *et al.* (2013) documented similar results between Asian markets comprised of China, India, Pakistan and Sri Lanka. While volatility spillovers between friendly countries were observed, volatility spillovers between India and Pakistan were also noticed; also, the spillovers from India to Pakistan were greater than the spillovers in the other direction.

Just as positive political events can lead to increased integration across markets, a political crisis in one region can also lead to volatility spillovers across markets. Fernandez (2007) evaluated the impact of the political crises in the Middle East on countries like Israel, Turkey, Morocco, Egypt, Jordan, Pakistan, Indonesia, the UK, Germany, Japan, the USA, Spain and several regional proxy indices between April 2000 and March 2005. The results affirmed that political conflicts in the Middle East induced structural breaks in the volatilities of Middle Eastern and certain Asian emerging markets and transitory volatility changes in other markets.

Rigobon and Sack (2005) documented the negative impact of the war in Iraq on Treasury yields, equity prices, value of the US Dollar, and lower-grade corporate spreads, alongside a rise in oil prices. On the other hand, Amihud and Wohl (2004) found that the expectation of the fall of Saddam Hussein had a positive impact on most of the above-mentioned variables. Frijns *et al.* (2012) evaluated the impact of 58 political crises between 2001 and 2006 on stock market integration using the data of more than 5,000 companies, spanning 19 emerging markets in three different regions. The results revealed that the integration declined before the political crisis but increased substantially during and after the crises. However, the authors also observed that the impact on stock market integration

is also dependent on the number of countries involved in the crisis as well as on the extent of involvement of the USA in the event.

Causal links between terrorism and stock market volatility have also been explored in the literature (For example Fernandez, 2008; Nikkinen, 2008; Drakos, 2010a; Kollias *et al.*, 2011; Chesney *et al.*, 2011). Increased volatility in financial markets due to political terrorism, for example, the war on terror post-9/11, the London bombings in July 2005, etc., are documented in the relevant literature. Nikkinen *et al.* (2008) assessed the effect of 9/11 on 53 different markets. The study found that although volatility across different markets increased around the event temporarily, relatively segmented markets, such as those in the MENA region, were less affected. On the other hand, developed markets exhibited greater volatility and took about three to six months to absorb the shocks.

Drakos (2010b) explored the determinants of the shock's transmission from the center of the act of terrorism to other markets. The author evaluated the reactions of 68 financial markets post-9/11. The author found that the overall integration of markets contributed the most towards non-uniform market reaction. Besides market integration, bilateral trade linkages played a major role in determining market reactions. The results of the study indicated that bilateral trade could explain approximately 24% of the cross-country variations in returns and liquidity in stock markets.

Another aspect of political relationships is foreign financial aid. Studies like Easterly (2003), Easterly *et al.*, (2004), Rajan and Subramanian (2008) could not find a positive impact of foreign aid on economic growth of a particular country. Burnside and Dollar (2000) argued that the effectiveness of foreign aid is conditional on the effectiveness of the regulatory environment. However, Easterly (2003) could not find a relationship between the impact of aid and a prudent regulatory environment. Wahab and Ahmed (2011) documented an inverse relationship between foreign aid and GDP growth in Pakistan, and a positive relationship between foreign aid and savings[20]. These results can best be described as inconclusive. With respect to foreign aid and the development of financial markets, Kaya *et*

[20] Wahab and Ahmed (2011) do not classify foreign aid into military, economic or humanitarian aid. This classification might be pertinent, as section 4.3.1 clearly highlights that Pakistan has been a recipient of large sums of military and economic aid during and after the Afghanistan war.

al. (2012) found a link between foreign aid and the possibility of liberalization of financial markets in developing countries. The authors argued that liberalization of financial markets can lead to economic development; however, they did not provide evidence in this regard. Ang (2010) found that financial liberalization allowed India to absorb foreign aid more effectively. The link between foreign aid and integration between financial markets of aid supplying and the aid receiving countries remains largely unexplored.

2.4 Consequences of Evolving Interdependence Between Markets

The previous three sections focused on providing a comprehensive overview of interdependence, integration, and spillovers across markets and their progressive evolution, as well as the reasons for enhanced synchronization and co-movements of markets. The focus now turns to the consequences of these interactions between markets.

Efficient allocation of resources, maximizing returns, and minimizing risk are the primary objectives of all investors. Financial markets provide a platform for the attainment of these objectives. However, with increased interdependence between, and integration of markets, viable and attractive diversification opportunities may diminish. Moreover, exaggerated volatilities surrounding global crises make investors vulnerable to unanticipated shocks. This section presents literature on the availability of diversification opportunities for investors, and the contagion and spillovers effects that stock markets face, especially during times of turmoil.

2.4.1 Diversification Opportunities

Portfolio Theory is based on the notion of market segmentation and suggests that investment in a basket of securities may enhance returns while reducing risk associated with investment in individual securities. On the other hand, the concept of market integration is associated with the “One Market Hypothesis” (Agmon, 1972, p. 839). Akdogan (1996, p. 34) provided a cohesive definition of market integration by stating:

> “Integration of capital markets implies the absence of risk premium differentials. If risk is priced equally across world markets, the markets are said to be integrated. If it is not, investors exploit the differential risk premiums via arbitrage.”

This suggests that if the return-differentials across markets are non-zero and the markets are segmented to an extent, opportunities to earn excess returns by diversifying the portfolio exist. There is a positive association between cross-market interdependence and market integration. Higher interdependence pushes markets towards greater integration. For a portfolio manager, it is important to understand the level of segmentation and integration of a particular country and security from the world benchmark and its evolving behavior (Akdogan, 1996) so that appropriate resource allocation and risk management decisions can be made.

In the last decade, the understanding and estimation of integration between markets, and the mean and volatility spillovers across markets has taken center stage in the literature on financial markets, not only for theoretical and empirical reasons but also for economic reasons (Dufrénot *et al.*, 2011). Liberalization of emerging markets in the 1990s provided alternative avenues for portfolio diversification to investors (Turgutlu and Ucer, 2010), which provided them with amplified returns (Gottesman and Morey, 2007). There is an inverse relationship between the returns on portfolio diversification and correlations across markets (Turgutlu and Ucer, 2010). Simply put, the lower the correlations between markets, the higher the gains from diversification.

International diversification opportunities exist as markets around the world are not perfectly integrated due to country-specific factors such as monetary and fiscal policies, legal and accounting regimes, economic openness, financial integration, trading activity, industrial concentration, and development (Phylaktis and Xia, 2006; Campa and Fernandes, 2006). These unique factors lead to superior returns on internationally diversified portfolios. This is particularly pertinent to emerging and developing markets whereby the country's effects are more visibly associated with the diversification benefits (Phylaktis and Xia, 2006; Turgutlu and Ucer, 2010; Christoffersen *et al.*, 2012). Brooks and Del Negro (2002) argue that although the correlations in returns of developed countries have increased significantly since 1980, the opportunities for cross-market diversification have not been completely eliminated. On the other hand, Christoffersen *et al.* (2012) argue that while diversification benefits may have diminished from developed markets, emerging markets still offer reasonable diversification opportunities.

Carrieri *et al.* (2007) developed an integration index to measure the magnitude and time-varying integration for eight emerging countries during during the period 1977 and 2000. The index estimated both global systemic and non-systemic risks. The results indicated that the emerging countries exhibit varying levels of integration with developed markets. For example, Mexico demonstrated the highest level of integration with developed markets while India exhibited the lowest. The evolution of integration across markets was evident; however, some reversal of integration was also documented. Similarly, Bai *et al.* (2012) conducted a study comprising only emerging markets from Africa, Asia and Latin America. The results of the study highlighted that diversification within emerging markets during crisis may not be fruitful due to systemic risks; however, portfolio managers may be able to extract better returns if they also diversify across industries within the emerging countries.

The finance literature provides some evidence on the segmentation of frontier markets. Miles (2005), Logoarde-Segot and Lucey (2007), Berger *et al.* (2011), Samarkoon (2011), Baumöhl and Lyócsa (2014), Chen *et al.* (2014) found the frontier markets to be less integrated into global markets and argued that they present viable options for diversification during normal times. Kohlert (2011) argued that not all frontier markets have similar traits; therefore, their diversity can be capitalized through portfolio investments. Kohlert (2011) investigated the benefits of international diversification with the help of the following indices: S&P500, MSCI Europe, MSCI Emerging markets, MSCI Asia Pacific, MSCI Frontier Markets, MSCI Frontier Markets excluding GCC, and World REITs[21]. The results indicated that although the frontier markets may have under-performed their emerging counterparts previously, they still offered return potential due to their low PE ratios in comparison to both emerging and the GCC markets. The MSCI frontier markets index with the heavyweight GCC markets may not perform well due to the inclusion of these markets, which are mostly oil-based economies. On the other hand, the frontier markets index *sans* the GCC markets may provide better returns as the underlying economies are much more diverse, and therefore, closely reflect the desired properties of a well-diversified portfolio.

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[21] Benchmark index for World Real Estate Investment Trust.

Similarly, Amin and Orlowski (2014) suggested that smaller markets with distinct market capitalization, financial regulations, and deregulation exhibit asymmetric reactions to domestic and international events, which not only vary in timing but also in depth. Subsequently, these markets may be feasible for diversification in different time horizons. Miles (2005) asserted that although the returns of frontier markets exhibited long-run cointegration with their developed counterparts, the possibilities of diversification in different time horizons cannot be overruled. The author suggested that small and at times negative coefficients present diversification opportunities as short-run deviations from long-run trends may take a long time to reach equilibrium. Amin and Orlowski (2014) studied the interdependence between the South Asian markets, which mainly comprise frontier markets. The authors found significant self-contributions to returns and volatility. During the normal market periods, shocks from India to the frontier markets are more pronounced. However, during the crisis period, shocks from the global markets become more conspicuous. This suggests that global interdependence may outweigh regional interdependence during the crisis. Samarakoon (2011) found amplified correlationshiops between the USA markets and frontier markets during the crisis. These countries may not have strong linkages with the US during tranquil times, but they are susceptible to greater shocks during turbulent times. On the other hand, Logoarde-Segot and Lucey (2007) found that frontier markets in the MENA markets reacted differently to different crises, hence, they can be considered as viable diversification avenues during various kinds of crises. The potential of the frontier markets with respect to diversification is apparent from the results of the studies discussed above. Moreover, the inconsistency in findings highlights the need for further research.

Besides evidence of integration and overall cross-market diversification opportunities, literature on international portfolio diversifications can be segregated in terms of returns and risk. Bekaert *et al.* (2011) developed a market-valuation-based measure to estimate the level of segmentation across markets. The extensive study included 69 markets (23 developed and 46 emerging) in the sample and the period of analysis was 20 years. The results of the study highlighted the segmentation of emerging markets from their developed counterparts, hence providing diversification benefits. Harvey (1995a) analyzed

monthly returns of twenty emerging and three developed markets across various continents and documented that emerging markets are characterized by high returns and exaggerated volatility; however, due to their low correlations with the developed markets, they offer superior diversification opportunities. The author also provided evidence on predictability of returns in emerging markets and highlighted the importance of domestic events rather than global events.

The aspect of risk associated with international portfolio diversification is also of prime consideration. Bai and Green (2010) argued that investors in emerging markets opt to maximize returns without paying much attention to total risk, which may lead to their bearing excess risk without being rewarded with excess returns. Harvey (1995b) suggested that diversification benefits associated with emerging markets are not limited to superior returns; rather, these markets are capable of minimizing risk also as they have low exposure to global risk factors like changing commodity prices, global business cycles and inflation. The author used the Capital Asset Pricing Model (CAPM) model to estimate the risk associated with twenty emerging and twenty-one industrial markets, as measured by the β coefficient. The results indicated that only a few emerging markets have significant exposures to the above-mentioned factors and only one market in their sample had a β of greater than one, when compared to the world market portfolio. The author asserted that since the emerging markets are not well integrated into world markets, the opportunity to diversify risk remains accessible. Bai and Green (2010) emphasized that the risk associated with a well-diversified international portfolio is essentially market risk as the unsystematic risk is diversified away. The authors decomposed the total stock risk of 1,500 firms across thirteen emerging markets into global, country, industry and idiosyncratic risk in order to assess their contribution to overall risk. The authors reiterated the findings of previous studies and found the country risks to be most prevalent in emerging markets, followed by industry risks.

Akdogan (1996) used the CAPM to develop a ranking mechanism for countries' segmentation with regional and global markets by decomposing international risk. The author ranked the countries based on their systemic risk contribution to the overall risk of the world portfolio. The results highlighted that smaller countries such as Peru and the

Philippines contribute less towards the overall risk of the world index. The results of the study also indicated that the smaller markets have segmented more in the 1980s as compared to the 1970s. The findings implied that segmented markets offer non-zero risk differentials and provide diversification opportunities. Interestingly, the authors found Pakistan to be least segmented from the world portfolio.

Besides stock markets, bond markets provide an alternative avenue for risk diversification. Johansson (2008) suggests that after the Asian financial crisis, the Asian governments opted to develop their local bond markets so that the firms could raise capital domestically. The authors explored the interdependencies among Asian bond markets and found that despite strong long-run interdependencies, the Asian bond markets still offered possibilities for short-term trading, therefore the possibility of international portfolio diversification could not be completely ruled out.

In an effort to assess the collective impact on risk and return in international portfolio diversification, Berger *et al.* (2011) analyzed multiple portfolios of developed and emerging markets as well as 25 frontier markets. The authors attempted to examine whether the inclusion of frontier markets in the portfolio affects the risk and return dimensions. The results revealed low levels of integration between frontier, developed, and emerging markets. The authors then formed portfolios with and without frontier markets. The portfolios with frontier markets resulted in a 2% reduction in risk while maintaining the same level of return as the developed and emerging market portfolio. This performance was apparent during the bull period (March 2009 to February 2010), whereby the returns provided by the portfolios with frontier markets were higher than the returns provided by the portfolio excluding frontier markets. To check the robustness of the results, the authors replaced the indices with the ETFs and acquired similar results.

Cheng *et al.* (2010) evaluated the markets in the MENA region using a traditional CAPM, a variation of CAPM, and a multivariate GARCH model. The authors concluded that Turkey and Israel were the most integrated with the global markets, while other MENA markets were quite segmented; hence Turkey and Israel offered diversification benefits. Additionally, the authors also documented an inverse relationship between market integration and oil prices. Moreover, the authors found that while the oil producing and

exporting countries within MENA may generate superior returns with incremental oil prices, other countries may exhibit a downward trend in asset prices.

Classifying the diversification opportunities according to time horizon, Aggarwal *et al.* (2010) argued that the majority of the studies focused on short-term conditional and unconditional correlations across markets, while the investment horizons of different investors may vary from short to long-term. While short-term investors are interested in co-movements of the market on high frequencies, long-term investors consider low frequencies to facilitate the investment decision-making (Dajčman *et al.* 2012). Rua and Nunes (2009) found pertinent long-run co-movements in developed markets and insignificant diversification benefits. Wong *et al.* (2004), Awokuse *et al.* (2009), and Yu and Hassan (2008) documented a long-run association between developed and some Asian emerging markets and implied that while long-run diversification opportunities in these markets may be non-existent, viable short-run diversification opportunities may be available.

Phylaktisa and Ravazzolo (2005a) found that the investors might not be able to reap the long-run benefits of diversification by investing in semi-open economies; however, short-run diversification benefits may be available due to transitory changes in these markets. On the other hand, though the linkages between open Pacific Basin economies and developed economies may have increased over time, the global effect appears to be limited in these economies; hence the long-term benefits of diversification remain available (Ibid).

Thupayagale and Molalapata (2012) analyzed the interdependence between the bond markets of three emerging markets (Mexico, South Africa and South Korea) and the USA market for the period between 2002 and 2011. The authors found that long-term benefits of diversification existed in emerging markets due to lack of long-term association with the developed markets. On the contrary, Lucey and Muckley (2011) found that while European developed markets provided superior long-term diversification benefits to USA investors, the developed Asian markets might be viable for investors with short-term diversification objectives. Since the study included developed markets of both Europe and Asia, the relationships between developed and emerging markets with respect to investment time horizons remain relatively unexplored.

With the onset of the financial crisis in 2008, there has been increased interest among researchers evaluating the impact of crisis in the USA and other developed countries on emerging markets, and attempting to understand how it affected the risk and return of internationally diversified portfolios. Dooley and Hutchison (2009), Huyghebaert and Wang (2010), and Baur (2012) found evidence that the financial crisis influenced both developed and emerging countries; however, the impact was asymmetric. On the other hand, Dajčman *et al.*, (2012) found that although the financial crisis influenced the European emerging markets, it resulted only in short-term synchronized stock market returns in the developed European markets. The authors also found that various financial crises had a short-term impact on the returns of European developing markets, which abated in a maximum 400 days.

Additionally, comparison across industries provided evidence that the financial sector was the most affected across countries while the impact on the health, technology, and telecommunications sectors was less severe (Baur, 2012). Although the shocks of the financial crisis were transmitted to emerging markets, they still offered better risk return ratios post-crisis than the developed markets (Kearney, 2012). This suggests that in times of crisis, the benefits of international diversification may diminish as most of the markets move in tandem (Baumöhl and Lyócsa, 2014; Chen *et al.*, 2014).

2.4.2 Volatility Transmission

As global markets move towards greater interdependence and integration, the transmission of shocks across borders becomes highly probable, as witnessed during the Asian financial crisis and most recently during the financial crisis of 2008. Contagion has a domino effect and local and regional crises generally precede global crises (Markwat *et al.*, 2009).

Due to deregulation of markets and availability of diversification avenues, global markets are essentially exposed to the same pool of investors with particular risk appetite and liquidity preferences (Levy, Yeyati, and Williams, 2012). These investors resort to risk aversion (Claeys and Vašíček, 2012) and may yield to irrational herd behavior during turmoil (Calvo and Reinhart, 1996; Turgutlu and Ucer, 2010), causing an asymmetric correlations shift across markets. If investors are capable of differentiating markets, volatility in a

particular market is a product of idiosyncratic variables (Claeys and Vašíček, 2012), which in reality is not true. Dornbusch *et al.* (2000) and Cheung *et al.* (2008) assert that the investors treat the markets indiscriminately during turbulent times and penalize even those markets that are not at the center of the crisis, hence creating a volatility spillover effect across markets. Preference for "flight from risk" (Fazio, 2007, p. 1264) during crises encourages investors to divest from markets based on visible similarities across markets (Ahluwalia, 2000).

Forbes and Rigobon (2002) distinguished between contagion and interdependence. They term contagion as amplified short-lived cross-market co-movements and interdependence as permanent high correlations. The finance literature classifies contagion as follows:

- Fundamentals based contagion due to the economic integration of countries (Calvo and Reinhart, 1996).
- Shift contagion due to shift in investors' expectations about a particular market due to change in fundamentals (Dornbusch *et al.*, 2000).

As discussed in Section 2.2.1 and 2.3, economic integration is widely cited as a prime reason for enhanced interdependence between markets.

With respect to shift contagion, investors' expectations may change due to financial cognitive dissonance, endogenous liquidity shock, discernment of political risks (Forbes and Rigobon, 2000), portfolio adjustments (Kodres and Pritsker, 2002), borrowing constraints or illiquidity (Boyer *et al.*, 2006), and informational spillovers (Calvo and Mendoza, 2000). The "wakeup call hypothesis" by Goldstein (1998, p. 18) suggests that financial crisis in a particular country acts as a wakeup call for the investors, prompting them to pull out investments even from those countries which are not the epicenter of crisis. Visible weaknesses in key macroeconomic indicators, especially in the ones similar to those in the country of origin of the crisis, prompt investors to liquidate their investments from multiple countries (Goldstein, 1998). This subsequently leads to ''discriminating contagion'' (Ahluwalia, 2000, p. 3), whereby investors distinguish between markets based on weak and strong fundamentals. Initiation of a financial crisis in one country prompts the investors to

reassess the credit worthiness of the countries in the same region and adjust their portfolios accordingly, as occurred in the case of the Asian financial crisis. These phenomena were also apparent in the recent financial crisis during which an increase in investors' risk aversion due to distress in developed markets was transmitted to emerging markets, and the investors pulled out from those markets and invested in the most liquid and safe assets such as fixed income securities and gold (Frank and Hesse, 2009).

Chiang *et al.* (2007) found evidence of contagion in eight Asian countries surrounding the Asian financial crisis. The authors classified the enhanced correlations across eight markets into two phases. In the first phase, the authors found evidence of contagion, which was dominated by the investors' herd behavior in the second phase, resulting in amplified co-movements across the sample. Bodart and Candelon (2009) found evidence of regionally constrained contagion amongst Latin American and Asian countries during the Mexican and Asian crises in 1994 and 1997 respectively. However, during the Asian financial crisis interdependence between selected markets was also evident.

Ranta (2013) provided evidence on contagion and enhanced co-movements of the USA, the UK, Germany and Japan markets, at the time of multiple regional and global crises such as Black Monday in 1987, the Asian and Russian financial crises, the Gulf War, and the recent financial crisis. While the contagion surrounding Black Monday and the recent financial crisis was pronounced, the contagion surrounding the Asian and Russian crises was weak.

In contrast to the above-mentioned studies, Forbes and Rigobon (2002) and Baur and Fry (2009) document the lack of contagion as well as the presence of interdependence during the Asian financial crisis. Forbes and Rigobon (2002) argued that controlling for fundamentals and heteroscedasticity in the model reveals lack of contagion during the Asian financial crisis and temporary shocks to regional markets. Similarly, Baur and Fry (2009) found that both positive and negative shocks across the Asian countries surrounding the Asian financial crisis were a product of regional interdependencies and therefore cannot be termed as contagion.

While these studies challenge the otherwise documented contagion in markets during crises, the temporary volatility induced in financial markets makes investors nervous, leading to a domino effect, and thereby creating disruption across world markets.

2.5 Chapter Summary

This chapter presented a comprehensive summary of the finance literature available on the topic of interdependence and integration of financial markets. Section 2.1 presented relevant literature that documents the varied degrees of interdependence between developed, emerging, and frontier markets. The findings regarding developed markets are largely consistent and indicate their greater integration; however, the findings related to emerging and frontier markets are rather mixed. Evidence on increased interdependence between markets during and after significant events, such as the deregulation of markets and the removal of capital controls, monetary union and political events, and financial crises was presented in section 2.2.1. An alternative view, the "Decoupling Hypothesis" by Kose *et al.* (2008) on declining interdependence and integration between emerging and developed markets due to strong macroeconomic variables and improved regulatory systems in emerging markets was discussed in Section 2.2.2. Findings of studies by authors like Wälti (2011) were also presented that challenge the decoupling hypothesis and term it a myth. Further studies on the topic suggested that while decoupling between emerging and developed markets may be pertinent during tranquil times, these markets tend to recouple during crisis, as emphasized by Dooley and Hutchison (2009) and Bartram and Bodnar (2009).

The most commonly cited reasons for increased interdependence across markets were discussed in Section 2.3. Researchers suggested that increased economic and financial integration, geographical proximity, foreign investments and enhanced cross-border capital flows, political relationships and events, technology, and liberalization and development of financial markets contributed significantly to the integration of financial markets. Although it is apparent that reasons for heightened cross-market interdependence cannot be generalized on all markets. The consequences of increased interdependence between markets were discussed in Section 2.4. The finance literature provides evidence that increased interdependence between markets results in the transmission of shocks from one

market to the other and erodes diversification opportunities for investors at the time when they are needed the most, as witnessed during the financial crisis of 2008. Although there may be no respite for investors during turbulent times, frontier markets may provide investors with short-term diversification opportunities as their reaction to various crises is documented to vary depending on the nature of crisis.

It is apparent from this review that the relevant literature available on various aspects of interdependence across markets is abundant. In chapter 3, the focus shifts to the methods employed in the finance literature to investigate and quantify cross-markets' interdependence.

3 Survey of Methods Used in the Literature on Market Interdependencies

Chapter 2 presented a comprehensive discussion on the topics of interdependence between markets, detailing how it has evolved, and considering reasons for and consequences of changing interdependencies between markets as presented in the finance literature.

The studies cited in chapter 2 have used an array of statistical and econometric methods to examine and estimate the cross-market interdependence and integration. The extensive variety of the methods employed for this purpose requires them to be discussed in detail. Subsequently, the most commonly used methods in the finance literature are presented in this chapter focusing on their relative strengths and weaknesses.

Forbes and Rigobon (2002) classify the approaches to evaluate the interdependencies between markets into four broad categories:

1. Cross-market correlation coefficients.
2. Univariate and multivariate statistical methods (Such as OLS estimations, factor analysis and logit/probit analysis).
3. ARCH and GARCH Models.
4. Cointegration, Vector Error Correction, Vector Autoregressive Models (such as causality, Impulse response, and variance decomposition including the Spillovers Index).

Each of these categories is discussed with respect to the relevant literature in sections 3.1 to 3.4 below. The Spillovers Index (Diebold and Yilmaz, 2009 and 2012), the primary method used in this study to estimate spillovers across the sample countries, is a variation of the Vector Autoregressive method and fits into variance decomposition analysis, is detailed in Section 3.4.5.

Besides these widely used methods mentioned above, some researchers have also used less conventional methods inspired by methods used in economics (like the band spectrum approach) and in natural sciences such as physics (like time scale analysis) to model volatilities across markets and assets. These innovative methods use either frequency domain, or a combination of time and frequency domain-based models instead of time

domain models to explore interdependencies between markets. Studies using these methods are discussed in section 3.5.

As discussed in Chapter 2, the research on the topic of market interdependencies using a variety of countries and methodologies is exhaustive, although the findings of the studies are inconsistent and at times contradictory. However, there does seem to be a consensus that the USA market is a major exporter of volatility across borders (for example Becker *et al.* 1990; Koutmos and Booth, 1995; Huyghebaert and Wang, 2010) and that this influence has progressively increased. A market segmentation scoring mechanism by Akdogan (1996) found that the USA is the largest contributor of systemic risk to the world portfolio.

Another aspect of interdependencies across markets that researchers agree on is the dynamic nature of interdependence between markets. Ignoring the time-varying aspect of cross-market interdependence leads to biased and inaccurate estimates, further leading to inaccurate risk management and portfolio diversification strategies (Lucey and Muckley, 2011). To incorporate the time-varying characteristic of volatility, researchers have used event studies and rolling window estimations, combined with various techniques such as correlations, cointegration, VAR, and GARCH variations (for example Forbes and Rigobon, 2002; Lucey and Muckley, 2011; Aggarwal *et al.*, 2010 among many others).

Billio and Pelizzon (2003) and Paas and Kuusk (2012) argue that the inconsistency in findings regarding interdependence between markets can be attributed to differences in data frequency (intraday, daily, weekly, monthly), geographical locations, and methods used for analysis. It is evident from Tables 2.1 and 2.2 that earlier researchers opted for monthly data, probably due to limited availability of a more comprehensive dataset. Use of weekly and daily data appears to be more common in the 1980s and later. Use of weekly data is preferred to avoid non-synchronicity in the data, short-term autocorrelations, and noise (for example Aggarwal *et al.*, 1999; Ng, 2000). While the use of weekly data addresses the problem of non-synchronous trading days and hours, aggregation in weekly and monthly data results in loss of information (Galagedera and Maharaj, 2008) as markets tend to absorb foreign shocks within three days (for example Nekhili *et al.*, 2002; Fernandez, 2004; Dajčman, 2013).

The subsequent availability and richness of daily data has popularized its use in research, as it enables capturing of finer details available in smaller windows. Researchers deal with non-synchronicity of data by making appropriate adjustments to the time series[22] (for example Kenett *et al.*, 2012). Besides weekly and daily frequencies, use of high frequency intra-day is also becoming popular (for example Nekhili *et al.*, 2002; Égert, and Kočenda, 2007; Hussain and Harju, 2008). Intraday data allows identification of transmission of shocks across markets within a single trading day and provides useful information on the nature of information that triggers cross-market spillovers. However, intraday data may prove to be a noisy measure of volatility due to exaggerated autocorrelations between consecutive observations.

Despite the phenomenal increase in research on the topic of cross-market interdependence and integration, challenges associated with identification and treatment of structural breaks, regime changes and outliers surrounding crises still remain to be addressed. Allen and Morzuch (2006) argue that challenges in estimation of cross-market interdependence are two-fold: first, how to detect unusual and unanticipated shocks and which remedies to use to model them; and second, how to test the specifications. Mierau and Mink (2013) contest that market synchronity during a crisis is mostly dependent on arbitrary selection of crisis windows and a particular country as the epicenter of the crisis, which is not only restrictive but it also induces bias in results. All the methods employed in the relevant literature possess some strengths and weaknesses; hence, no method developed to date has been able to produce broadly accurate and consistent results.

The following sub-sections provide a comprehensive review of the methods commonly used in the relevant literature to explore the cross-market interdependencies, highlight the results of some widely-cited studies, and discuss the strengths and weaknesses of these methods.

[22] In most cases, the missing values in a time series are replaced with the previous day's prices to ensure that values are available for all the markets of interest on a particular day. This study uses this treatment to convert 5-day data frequency to 7-day data frequency. A detailed discussion is presented in Section 4.4.

3.1 Cross-Market Correlation Coefficients

Most studies on interdependence between markets published since the 1970s employ correlations in one form or another. Theoretically, correlation coefficients measure the strength and direction of the relationship between two markets. High correlations present some indication of association between the variables; however, the association should not be mistaken as causation. The earliest use of correlations to estimate association between markets was observed in Levy and Sarnat (1970) and Lessard (1974). Since then there has been a gradual progression in considering correlations between markets from being constant to being time-varying. Consequently, event studies are widely used to study correlations between markets before and after important events. For example, Taylor and Tonks (1989) documented enhanced correlations between developed markets after deregulation of capital flows in the UK. Similarly, King and Wadhwani (1990) used an event study to analyze the correlations between the USA, the UK and Japan and concluded that correlations increased significantly after the 1987 market crash. Lee and Kim (1993) found that the correlations between 12 developed markets increased by approximately 70% after the 1987 crash. More recently, estimation of correlations in rolling windows has also become popular. For example, Forbes and Rigobon (2002) and Lucey and Muckley (2011) used rolling window analysis to estimate time-varying correlations between markets, especially at the time of the Asian financial crisis.

Despite the widespread use of correlation coefficients in exploring the potential association between markets, the method has its limitations. Correlation estimates provide limited information to an investor with a long-term investment horizon (Lucey and Muckley, 2011). Its inability to incorporate asymmetric responses of various markets to shocks (for example Dooley and Hutchison, 2009; Huyghebaert and Wang, 2010; Baur, 2012) also pose a challenge, as a single estimate generated by correlation coefficients may not be relevant for decision-making (Fazio, 2007). The correlation coefficients do not distinguish between normal and abnormal innovations, and assign equal weight to both, resulting in inaccurate estimates (Fernandez, 2004). In fact, this is the problem associated with any factor model, in which increased factor volatility leads to higher synchronization of returns (Bekaert *et al.*, 2005). Even if event and rolling windows analysis is used to measure asymmetric responses

of different markets during crises, the classification of sub-periods and choice of window sizes remains arbitrary, which may result in inconsistent results (Walti, 2012). Forbes and Rigobon (2002) and Doyle and Faust (2003) assert that a temporary increase in correlations should not be associated with a permanent increase in interdependence across markets, as during the times of exaggerated volatility, the correlation estimates tend to be higher, giving an impression of increased synchronization between markets, which may be statistically insignificant. Doyle and Faust (2003) analyzed a large dataset (from 1960 to 2002) for the G7 countries. The authors divided the period of analysis into four decade-long sub-periods. Their results suggested a statistically insignificant progressive increase in correlations between G7 countries despite increased trade volume.

Carrieri *et al.* (2007) argue that it is inappropriate to use correlations as a measure of integration, as correlations tend to underestimate integration. The authors compared the correlation estimates with the Integration Index developed for eight emerging markets and the world index. The results highlighted that both conditional and unconditional correlations were lower even when the country ranked high on the integration index, especially after 1992.

Conditional correlations have limitations as the high frequency data exhibits heteroscedasticity, endogeneity, and omitted variables bias (Rigobon, 2004). Forbes and Rigobon (2002) assert that although most of the studies provide evidence in favor of increased correlations between markets before and after the periods of turmoil, the changes to the correlations between markets are marginal if the models are controlled for unequal variances or heteroscedasticity, as the cross-market correlations are volatility dependent and are biased upwards in times of excessive volatility. Rolling window analysis of 29 markets across six continents surrounding major crises (the 1987 market crash, 1994 Mexican Peso and 1997 Asian Financial crises) provided no evidence of increased correlations when the model was adjusted for heteroscedasticity. This indicates that the conditional cross-market correlations might be over-stated in times of turmoil.

In line with Forbes and Rigobon (2002), Arestis *et al.* (2005) conducted an analysis of four Asian economies that were at the center of the Asian financial crisis (Thailand, Indonesia, Korea and Malaysia) and four developed markets (Japan, the UK, Germany and

France). The study found evidence of greater spillovers from Indonesia and Thailand to the UK and from most Asian countries to Japan. The authors concluded that the high spillovers from Asian economies to developed economies was a result of increased international lending by developed countries to Asian economies. With respect to the sensitivity of results to data frequency and choice of windows, Billio and Pelizzon (2003) reanalyzed the Asian Financial crises with Hong Kong, Eurostoxx50[23], Japan and USA markets using the Forbes and Rigobon (2002) method. The authors divided the period of turmoil into smaller windows, using both two-day moving averages and daily returns. The authors found the results to be sensitive to data frequency and the size of windows. This emphasizes the fact that the findings of studies are dependent on the nature of inputs as well as the method used.

3.2 Univariate and Multivariate Statistical Methods

Statistical methods such as univariate and multivariate regression, PCA, and conditional probabilities are widely used in the literature on interdependencies between markets. The simplicity of these methods has prompted many researchers to employ them for the purpose of measuring interdependence between financial markets. Each of these statistical methods is discussed below in sub-sections 3.2.1 to 3.2.3.

3.2.1 Univariate and Multivariate Regression Analysis

In the initial studies on cross-market interdependence and integration, the study by Agmon (1972) is worth a mention. He used univariate regression to find the association between the returns of the USA, the UK, Germany and Japan. The results of the study suggested that the returns in the three latter markets were dependent on the innovations in the USA market. Agmon theorized that the global markets were not segmented and therefore could be evaluated under "One Market Hypothesis", and that the USA market was a good proxy for the common factor in a multinational one-market setting. The CAPM results for the period 1961–1966 highlighted that approximately 37% returns of the German market were dependent on the USA market, followed by the UK and Japan. He argued that the German, Japanese and UK markets were the subsets of a four-country market and were related to the common market factor that is the USA. These results were true for both national indices and

[23] A stock index measuring the performance of 50 Euro-zone companies.

for company level data. The method used by Agmon had some inherent limitations that were associated with the assumptions for regression like homoscedastic and normally distributed returns. The literature provides sufficient evidence that these two assumptions were invalid for financial assets time series. The problem of multi-collinearity in regression also induces problems. First, the estimates generated can be biased if the independent variables included in the analysis are highly correlated with each other. Second, due to multi-collinearity amongst variables, one cannot isolate the impact of individual explanatory variables on the dependent variable.

Beyond the standard univariate regression, the most widely used statistical estimation method is univariate or multivariate regression analysis in the form of CAPM. The classic CAPM is a regression model that states a linear relationship between expected returns of an asset and market risk premium. The classic CAPM model is written as:

$$R_i = \alpha_i + \beta_i(R_w - R_f) + \varepsilon_i$$

$$\beta_i = \text{Covariance}\ (R_i, R_w)\ /\ \text{Variance}\ (R_w)$$

Where R_i is the return on market *i*, α_i is the constant of the regression equation, or in other words the risk free return, β_i denotes the systemic risk associated with the market *i*, R_w is the return on world portfolio index, and ε_i is the excess return generated by the market *i*. Although the classic CAPM is clearly a univariate regression model, extensions of CAPM are capable of including a variety of exogenous independent variables. For example, Cheng *et al.* (2010) used the growth rate in oil prices to evaluate the impact of macro factors on asset pricing in the MENA region.

Akdogan (1992) used CAPM to measure regional integration across eight European markets across the European Community (EC). The author formed market portfolios by calculating the weighted average returns of national markets according to their share in the market capitalization of the EC index. The data were classified in sub-periods according to the legislative steps taken by the governments to promote regional integration. The ratio between the systemic risks of each market versus the total systemic risk of the EC composite index was calculated, followed by a calculation of the difference between this contribution and the market's share in total EC capitalization. The resulting score indicated the level of

integration across EC markets. The results projected greater integration between European markets over the period, presumably due to certain political and legal advancements in the EC. Developing on this technique further, Akdogan (1996) attempted to decompose the risk factor of the portfolio and considered the variance of the portfolio *i* as:

$$Var(R_i) = \beta_i^2\, Var(R_w) + Var(\varepsilon_i)$$

The right hand side risk arguments can be expressed as a fraction of total risk as follows:

$$p_i + q_i = 1$$

where

$$p_i = \beta_i^2\, Var(R_w)\ /\ Var(R_i)$$

and

$$q_i = Var(\varepsilon_i)\ /\ Var(R_i)$$

In the equation above, p_i designates the risk contribution of market *i* to overall world market risk. The resulting estimate is an approximate estimate of integration market *i* with the world market, whereby the higher the p_i, the greater the integration with the world market. In line with Akdogan (1992) the data was divided into sub-periods based on some institutional developments across nations, an attempt to capture the evolution of integration across time and markets. The results highlighted that while markets like the UK, Canada, Japan and Australia are the most integrated with the world market, smaller markets like Austria, Finland, and Peru, among others are the most segmented from the world index. It was also observed that the level of segmentation has increased from the 1970s to the 1980s in these markets[24].

Thapa and Poshakwale (2012) applied the international CAPM to assess the attributes of markets that contribute significantly to the decision to invest in foreign markets. The results highlighted that international investors prefer to invest in sizeable,

[24] Surprisingly, Pakistan, the market of primary interest in this study, was reported to be the least segmented markets from the world portfolio.

liquid, and informationally efficient markets with low transaction costs; therefore, the portfolio weightage of such markets is higher than those markets that lack these attributes. The findings of the study were robust even when the recent financial crisis of 2008 was considered.

While the application of classic CAPM and its variations is simple and intuitive, its inherent weaknesses cannot be ignored. First, the assumptions associated with CAPM seem unrealistic and over-simplified. The CAPM assumes that the capital markets are perfect, the investors are risk averse, that they can borrow at risk-free rate, that they hold a diversified portfolio whereby all the unsystemic risk is diversified (Brealey *et al.*, 2004) and that the diversified world portfolio offers maximum return and minimum risk (Chan *et al.*, 2005). In reality, not all investors are risk averse and the risk appetite varies across individuals and institutions. In terms of portfolio diversification, the standard deviation of the portfolio is well below the standard deviation of individual securities, but it is not zero; hence, the complete diversification of risk through portfolio investment is not true[25].

Moreover, access to securities around the world to form a world portfolio is not barrier free (Claessens, 1995). These barriers can be direct, like the legal restrictions constraining investors to invest into foreign markets (Bekaert, 1995), or indirect like information asymmetry, investor protection (Bekaert and Harvey, 1995). Home bias whereby investors value securities within their home country more than the foreign securities (Chan *et al.*, 2005) can also act as a barrier in achieving maximum diversification benefits. Concerning borrowing, investors cannot borrow on risk-free rates. Even large banks that invest in capital markets are expected to borrow on interbank borrowing rates that are usually above the risk-free rate. Lastly, the capital markets cannot be classified as perfect competition[26] as they do not have all the characteristics of perfect competition.

Besides the shortcomings embedded in the CAPM assumptions, some estimation problems are also worth mentioning. The choice of proxy markets, risk free rates and data

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[25] This is evident from the standard deviation of any benchmark index - a basket of securities representing an economy, which is not equal to zero.

[26] Assumptions of perfectly competitive markets: many buyers and sellers each with no power to affect the price, free entry and exit for the firms, sellers are price takers, homogeneity of products, availability of costless perfect information.

frequency is arbitrary. Handa *et al.* (1989) and Gençay *et al.* (2003, 2005) provide evidence regarding varied estimates of β at different frequencies. With respect to proxy markets, using the local market returns as the benchmark incorporates the perspective of a domestic investor, using a global market index returns as a benchmark may integrate the preferences of an international investor (Garcia and Ghysels, 1998). Besides this, the choice of instrument to benchmark the risk free rate is subjective and may incite inaccurate estimates. Structural breaks and episodes of exaggerated volatility also induce problems in asset pricing. Garcia and Ghysels (1998) applied conditional CAPM on emerging markets with a world market factor. The resulting model for emerging markets was unstable due to presence of structural changes and exaggerated volatility associated with domestic events in these markets.

3.2.2 Principal Component Analysis

Another multivariate statistical method, Principal Component Analysis (PCA) is also used in the literature to estimate segmentation or integration across markets. Unlike regression analysis whereby the dependence structure between variables is extracted, PCA serves the purpose of data reduction by evaluating interdependencies between variables (Hair *et al.*, 2009). It is pertinent for analyzing the multifaceted relationships between variables. It transforms a large number of correlated variables into a smaller set of new non-directly-observable fused components or factors, enabling dimension reduction and parsimony of the models (Curto *et al.*, 2006). Application of PCA for the identification of integrated markets is apposite for decisions regarding portfolio diversification, as highly correlated markets that are merged into one factor or component may not offer any diversification benefits.

Curto *et al.* (2006) used PCA to segregate 25 national indices from developed and emerging markets across North America, Europe, Africa, the Middle East and Asia Pacific. The factor model segregated the chosen indices into five components explaining 58% of the variance. Although the results of Curto *et al.* (2006) provided evidence that PCA can be useful in determining groups of countries whose returns move in tandem, unexplained variance can be a major hurdle in decision-making for investors.

Pentecost and Holmes (1995) used PCA to analyze the changes in the extent of financial integration (monetary and capital markets) within the European countries

between the 1970s and 1990s. The Eigen values highlighted incremental market interdependence after the introduction of the Euro. Similarly, Cappiello *et al.* (2010) found that the altitude of co-movements among Eurozone equity markets increased significantly upon the introduction of the Euro and that this increase was primarily determined by the financial, industrial, and consumer services sectors.

Berger *et al.* (2011) used PCA to evaluate levels of integration between developed, emerging, and frontier markets. The results of the study highlighted high levels of integration between developed and emerging markets, but the same was not true for frontier markets. A related but slightly different application of PCA is exhibited in Bowers and Heaton (2011), whereby the authors measure the systematic risk across the Australian equity markets. The study documented weak association between factors like investor sentiment, exchange rates, crude oil returns, the world stock index, interest rates and the changes in interest rates, and the Australian market.

Forbes and Chinn (2004) used PCA to model the association between the five largest economies and 40 other markets between 1986 and 2000. The model considered the returns in a particular market as a product of cross-country factors, global factors, sectoral factors, and country-specific factors, such as trade linkages, competition in third country, bank lending, and foreign investment. The results indicated that the cross-country and sectoral factors determine returns in markets. Bilateral trade and financial association explained the transmission of returns from developed markets to other markets and trade linkages prominently explained cross-country association in stock and bond markets.

Although PCA is widely used in the literature to estimate the interdependence between variables, it is not devoid of limitations. For example, inclusion of uncorrelated variables in the model makes factor analysis redundant. Additionally, the loading of some variables on multiple factors, means the researcher has to decide whether to exclude the said variable from the analysis or to load the market on a particular factor with theoretical underpinning, which could be viewed as subjective. Furthermore, PCA only reveals information about interdependence between variables; the relationship between dependent and independent variables can only be examined further by using multiple regression or

other dependence examining techniques. Besides these, some common weaknesses of the statistical models are discussed later in this section.

3.2.3 Logit and Probit Analysis

Application of probit and logit models is also common in estimating the relationships between financial markets, especially in the context of financial crises. Logit and probit models allow appraisal of probabilities of crisis at a specific horizon (generally one or two years), considering the information available on the economic variables (Coudert and Gex, 2008). Primarily these models highlight linear binomial relationships between response variables and are closely related to regression that can be estimated through OLS or maximum likelihood. In its simplistic form, the probit model outlines binomial relationships and the results are limited to only two outcomes (for example yes or no), which in the case of time series analysis is too restrictive. Probit models are preferable when the time series is normally distributed, a condition that is generally imposed on the time series data and is not ideal, as most financial time series deviate from normality.

A slight variation on the Probit models is the Logit model, whereby the models are estimated by taking the log of the odds *logit(P) = log P/ (1-P)*. Logit models provide a better fit in the presence of extreme values and when the data exhibits non-normality; hence its application on time series data is more common than probit. Given the limitations of the binomial probit and logit models, multinomial versions have been formulated which are more appropriate for time series data analysis.

The following diverse applications of logit and probit models are observed in the finance literature:

- Analysis of determinants of crises in different markets (Komulainen and Lukkarila, 2003).
- Prediction of crisis in financial markets (Eichengreen *et al.*, 1995; Eichengreen *et al.*, 1996; Frankel and Rose, 1996; Berg and Pattillo, 1999; Glick and Rose, 1999; Bussiere and Fratzscher, 2006).
- Prediction of crisis in a particular sector such as banking (Demirgüc-Kunt and Detragiache, 1997 and 1999).

- Evaluation of relationships between local, regional and global crises and its impact on various asset classes (Markwat *et al.*, 2009).
- Assessing the role of investors (both shareholders and creditors) in inducing crises across markets (Caramazza *et al.*, 2004; Fazio, 2007).
- Estimating the changes in co-movements of stock market returns after a political and economic event (Christiansen and Ranaldo, 2009).
- Prediction of stock market returns with the help of macroeconomic fundamentals (Nyberg, 2008).

Komulainen and Lukkarila (2003) examined 31 emerging markets using 23 dependent variables representing their real and financial sectors. The results revealed that weaknesses in key macroeconomic variables, such as, unemployment and inflation, and several indicators of indebtedness, private sector liabilities and the foreign liabilities of banks determine the crises in emerging markets. The results affirmed that presence of large liabilities owing to foreign investors make countries more susceptible to crises as it leads to sudden capital outflows during crisis.

Eichengreen *et al.* (1996) analyzed a sample of 20 industrial economies from 1959 to 1993, and concluded that the probability of a domestic currency crisis increases with a speculative attack in other countries. Glick and Rose (1999) used the multivariate probit model in conjunction with univariate regression to analyze five different currency crises (in 1971, 1973, 1992, 1994, and 1997). The authors found that the crises are regionally concentrated due to intra-regional trade. Bussiere and Fratzscher (2006) used a multinomial logit model with three regimes (pre-crisis, during crisis, and post-crisis) to predict the possibility of crisis. They found that their model was capable of predicting financial crises in emerging economies beforehand.

Markwat *et al.* (2009) used the probit model and found that a local crisis provides signals for further deepening of turmoil and it precedes regional and sometimes global crisis, as witnessed in 1987 market crash and the 1997-1998 Asian financial crisis. A negligible impact of fluctuations in the currency was found; however, volatility in interest rates, stock and bond market returns significantly impacted the local, regional, and global turmoil

probabilities. The authors also documented a positive relationship between interest rates, stock market volatility, and probabilities of severe crashes, and an inverse relationship between bond returns in emerging markets and crash probabilities. The findings implied regional and global interdependence between markets.

Fazio (2007) decomposed the transmission of shocks across countries due to weakness in fundamentals and due to herding by investors with the help of a probit model. The results revealed that the crises in emerging markets can be a product of investors' impulsiveness, which can be attributed to information asymmetry between informed and uninformed, and global and local investors. Similarly, Caramazza *et al.* (2004) used the probit regressions for 41 emerging markets to evaluate the role of a common creditor in the transmission of shocks across countries while controlling for domestic and external macroeconomic factors as well as trade linkages. The results highlighted that the financial linkages induced through a "common creditor" substantially raises the prospects of a crisis within a region.

Christiansen and Ranaldo (2009) evaluated the level of integration across developed and emerging European countries in the post-EU enlargement era by estimating the joint occurrence of extreme returns in the candidate markets with the help of a logit model. The authors used the following dependent variables: volatility clustering, various asset classes, volatility in returns (stock market, interest rate and currency markets), asymmetry effects, and EU enlargement. The results affirmed positive relationships between the dependent and explanatory variables; moreover, old EU states seemed to be more integrated with the USA market.

Application of the probit model by Nyberg (2008) was different from the previous studies. The author attempted to predict the USA monthly excess stock returns with the help of various explanatory variables like short-term and long-term interest rates, and the recession indicators. Nyberg emphasized that the future expectations regarding key macroeconomic indicators are already incorporated in the current share prices. Hence, it is appropriate to use these indicators as explanatory variables in the model. The results of the study highlighted that the direction of excess returns is predictable in-sample; however, it is significantly weaker out-of-sample. Nyberg suggested an alternative use of probit models;

however, much work is required to improve their performance with regards to their predictive capabilities.

Although the application of statistical models in the finance literature is quite diverse, they exhibit the following weaknesses that make their application difficult with respect to time series data:

- Distribution of time series: Finance and economic literature provides evidence of non-normality of time series data. Normality of data series is integral in application of the statistical models discussed above.
- Heteroscedasticity or unequal variances: Regression analysis, PCA, and logit/probit analysis is incapable of capturing episodic high volatility in time series data.
- Structural changes and regime shifting: inability to integrate structural changes and regime shifts in the specifications restricts the application of these statistical models.
- Parsimony: Inclusion of the appropriate number of variables in the model is of concern as there is a trade-off between capturing maximum information and the parsimony of the model.
- Time-varying returns and volatility: The statistical models do not capture the dynamic nature of returns and volatility, although the use of event studies can address this problem.

Given these limitations, the estimates generated by the application of the statistical methods of logit and probit may be biased, inaccurate, and/or inconsistent.

3.3 ARCH and GARCH Models

ARCH and GARCH models are most commonly used in the finance literature to explore mean and volatility dynamics, and measure cross-market interdependencies. Prior to ARCH/GARCH models, standard deviation was frequently used to estimate historical volatility, but was of little relevance to investors (Engle, 2004). Interdependence between markets was modeled using OLS estimation (For example Agmon, 1972; Lessard, 1974, Maurent and Joy, 1976; Minot, 1974). It is widely recognized in literature that all financial time series exhibit serial correlations, heteroscedasticity, and leptokurtic distribution; modeling these attributes posed a challenge to researchers before the advent of ARCH/GARCH type models.

Engle (1982) developed Autoregressive Conditional Heteroscedasticity (ARCH), which was generalized by Bollerslev (1986). These models enabled a relatively accurate estimation of volatility in return series and facilitated forecasting of volatility based on historical data. Since then, researchers have developed many variations of ARCH and GARCH models. The popularity of GARCH models can be gauged by the fact that more than a hundred variants of ARCH and GARCH models have been used in published studies (Bollerslev, 2010)[27].

The progression in developing variants of ARCH/GARCH models and other econometrics techniques is fuelled by multiple factors, such as technological advancements in data storage and data analysis as well as economic motivations associated with risk management and portfolio diversification (Diebold, 2001). The factors discussed above led to greater creativity and innovation in measuring interdependence across markets, which in turn resulted in a phenomenal increase in the number of studies on the subject, using a variety of markets and methods.

The mostly commonly used variations of univariate GARCH are Exponential GARCH (EGARCH), Threshold GARCH (TARCH), GARCH in Mean (GARCH-M), and Glosten-Jagannathan-Runkle (GJR GARCH). The parametric Multivariate GARCH (MVGARCH) models include simplified models like VEC and the Baba-Engle-Kraft-Kroner Model (BEKK), and more complex models such as Constant Conditional Correlations (CCC), Dynamic Conditional Correlations (DCC), Asymmetric Dynamic Conditional Correlation (ADCC), amongst many others. Beside parametric GARCH variations, some MVGARCH specifications are semi and non-parametric, like SPARCH. Detailed discussion on all the GARCH models is beyond the scope of this thesis; however, an attempt is made to provide a concise yet comprehensive review of the most commonly used variations of univariate and multivariate GARCH models and to discuss their strengths and limitations.

Univariate GARCH Models

[27] As noted earlier, a detailed review on variations of ARCH and GARCH models can be found in Bollerslev (2010).

ARCH by Engle (1982) is a simplistic and parsimonious approach (Hansen and Lunde, 2005) to model volatility and suggests autoregressiveness in the squared returns. Simply put, the conditional volatility at time *t* depends on the information available at time *t-1*. ARCH was generalized by Bollerslev (1986) and the GARCH (1,1) model states that conditional variance of a return series at time *t* depends on squared error term in the previous time period but also on its conditional variance in the previous time period (Engle, 2001; Gujarati and Porter, 2009). Zivot (2009) suggests that the GARCH model facilitates understanding of stylized facts about the volatility of financial and economic time series, like volatility clustering, fat tails, mean reversion, and asymmetry. The phenomenon of volatility clustering suggests that volatility persists and shocks take longer to decay; however, the volatility eventually returns to its long-run level i.e. it reverts to its mean value (ibid). The asymmetry and non-normal distribution of error terms is partially captured by heteroscedasticity; however, it needs to be explicitly modeled by allowing the error term ε_t to have a non-Gaussian distribution or by incorporating the asymmetric behavior in the variance equation (Enders, 2010). Though in most cases GARCH (1,1) suffices (Zivot, 2009; Hansen and Lunde, 2005), it can be generalized in terms of lags to be used and can be written as GARCH *(p, q)*, where *p* designates the lagged term of the squared error term and *q* signifies the lagged conditional variance (Enders, 2010). Hansen and Lunde (2005) compared the performance of standard GARCH (1,1) with other sophisticated models. The results revealed superior performance by GARCH (1,1). This indicates that simplistic and parsimonious models may suffice in volatility forecast.

However, the standard GARCH has a restriction that the constant and all estimated coefficients must be positive i.e. $\omega_t > 0, \alpha, \beta \geq 0$ and that their sum must be close to unity. The model is therefore too restrictive. It considers a symmetric response to both positive and negative shocks and is therefore not able to incorporate the "leverage effect"[28] or the impact of crises that lead to large residuals and volatility persistence thereafter (Reider, 2009). Hansen and Lunde (2005) found that while GARCH (1,1) performed relatively better than its

[28] The "leverage effect" introduced by Black (1976) suggests an inverse relationship between returns and volatility; hence a positive shock relays a smaller impact and a negative shock has a steeper impact on volatility (Enders, 2010).

more sophisticated counterparts in the absence of leverage effects, it performed poorly when asymmetric response to positive and negative news was considered.

Alternative measures were adopted in the finance literature to incorporate sudden changes in volatility and improve the performance of the classic GARCH. Lamoureux and Lastrapes (1990) used a modified version of GARCH to incorporate the impact of structural breaks on conditional volatility. The authors used arbitrarily chosen sub-samples to signify breaks in the time series, and compared the estimates generated by standard GARCH and modified GARCH. The results highlighted that ignoring structural breaks results in imprecise volatility estimates and the conditional volatility persistence (denoted by the sum of α and β) is over-stated. The authors highlighted that a mechanism needs to be developed to identify breaks in the time series rather than using an arbitrary sub-sample. Building on this gap, Aggarwal *et al.* (1999) used a multi-step approach using data from several developed and emerging markets. In their study, the ICSS algorithm was used to first identify breaks in the time series. The information on shocks generated by the ICSS algorithm was then incorporated as dummy variables into a modified version of GARCH. The results of the study highlighted that persistence in volatility decreases when information of shocks is incorporated in the GARCH equation. The study also highlighted that the shocks in an emerging market do not overlap with those in the developed markets and the shocks in emerging markets are affected by local events rather than international events.

A similar technique was employed by Hammoudeh and Li (2008) and Kang *et al.* (2009) to identify points of sudden change in the return series of Gulf markets and selected Asian Markets respectively. This was followed by application of conventional and modified GARCH. Hammoudeh and Li (2008) found evidence that the Gulf markets are affected by global events, while Kang *et al.* (2009) found that the Asian markets in their sample are not affected by global events. Although the findings regarding the impact of global events on Gulf and Asian markets may vary, the results on volatility persistence were in line with Aggarwal *et al.* (1999). While the studies cited above divulge a limitation of GARCH model, none of them attempt to statistically separate significant shocks from insignificant shocks, resulting in non-parsimonious models and possibly biased estimates. This consideration of distinguishing significant shocks from insignificant shocks is important, as the tails

dependence decreases to a great extent when the conditional heteroscedasticity is excluded using univariate and bivariate GARCH models (Poon *et al.*, 2003).

While the above studies focused on the impact of structural changes on conditional volatility and the simultaneous effect on all parameters of GARCH modeling, Galeano and Tsay (2010) examined the impact of such changes on parameters of the GARCH model individually, and suggested an iterative procedure to detect structural changes. Galeano and Tsay (2010, p. 124) assert that:

> "a change in the constant term of the volatility equation permanently alters the level of the volatility, whereas a change in any other parameter also affects the dynamic structure of the volatility series".

Hence, quantification of changes in individual parameters may provide a better comprehension of the impact and implication of a detected structural change in a return series. The authors used the Langrage Multiplier (LM) tests by Andrews (1993) to test for single structural change in each of the parameters of the general nonlinear model, followed by the application of the binary segmentation process to detect multiple change points. The structural change points in the individual parameters associated with major events were successfully identified. Moreover, the results also highlighted that although all the examined changes have a long-term effect on the volatility; excess kurtosis is permanently affected solely by the changes in the parameters α and β.

Although the modified versions of classic GARCH (1,1) discussed above, addressed the inability of the GARCH model to incorporate asymmetric responses to positive and negative news to some extent, the "second generation" models, such as EGARCH and TARCH are documented to perform better (McMillan and Speight, 2004). Some widely cited variations of GARCH models are presented in chronological order in Table 3.1 below:

Table 3.1 - Selected ARCH/GARCH Models

No	Year	Model	Invented by	Specifications
1	1987	ARCH-M ARCH-in-Mean	Engle, Lilien and Robins (1987)	This model is an extension of ARCH. The model suggests that the conditional mean of a variable is dependent on its conditional variance, for example mean inflation might be dependent on inflation volatility.
2	1988	MVGARCH Multivariate GARCH	Bollerslev, Engle and Wooldridge (1988)	Facilitates the understanding of whether the volatility in a market is driven by volatility in other markets, the degree of association between markets, and the impact of positive and negative news on volatility. It also captures the time-varying nature of volatility.
3	1988	VECH	Bollerslev, Engle and Wooldridge (1988)	*A variation of MVGARCH* Suggests that present conditional variance and covariance is a product of past conditional variances and covariances, past squared returns, and cross-products of returns.
4	1989	F-ARCH Factor ARCH	Diebold and Nerlove (1989)	*Variations of MVGARCH* Assumes that the observations are generated by conditionally heteroscedastic factors having GARCH-type structure.
5	1990	F-GARCH Factor GARCH	Engle, Ng and Rothschild (1990)	
6	1990	AGARCH Asymmetric GARCH	Engle (1990)	Enables capturing of asymmetric effects of positive and negative news on volatility.
7	1990	CCC Constant Conditional Correlations	Bollerslev (1990)	*A variation of MVGARCH* Allows analysis of co-movement of markets through the changes in correlations of the observed variables. CCC forces the assumption of progressively constant conditional correlations.
8	1991	EGARCH Exponential GARCH	Nelson (1991)	Incorporates the asymmetric response to positive and negative news but also nullifies the need for non-negative coefficients that are required by standard GARCH model.
9	1991	GED-GARCH Generalized Error Distribution GARCH	Nelson (1991)	Assumes a generalized error distribution, or exponential power distribution of standardized errors.
10	1992	AARCH Augmented ARCH	Bera, Higgins and Lee (1993)	Conditional variance dependent on cross products of the lagged innovations.

No	Year	Model	Invented by	Specifications
11	1993	TARCH Threshold ARCH	Zakoian (1994)	Captures the leverage effect by incorporating a dummy variable assuming a value of one when $\varepsilon_{t-1} < 0$ and is equal to zero when $\varepsilon_{t-1} \geq 0$.
12	1993	GJR-GARCH Glosten, Jagannathan and Runkle GARCH	Glosten, Jagannathan, and Runkle (1993)	Allows asymmetric response of conditional variance to past negative and positive errors.
13	1995	BEKK Baba, Engle, Kraft and Kroner	Engle and Kroner (1995)	*A variation of MVGARCH* Positive definitiveness of the conditional covariance matrices is enforced by construction, hence relegating the need for super imposition.
14	1996	PGARCH Periodic GARCH	Bollerslev and Ghysels (1996)	Allows the parameters of the model to diverge over the cycle to account for episodic dependencies in the conditional variance.
15	1997	HARCH Heterogeneous ARCH	Müller, Dacorogna, Davé, Olsen, Puctet and Weizsäcker (1997)	Incorporates the time-varying nature of volatility and provides estimates to facilitate decision-making in different time horizons.
16	2002	DCC Dynamic Conditional Correlations	Engle (2002)	*A variation of MVGARCH* Takes the time-varying nature of volatility into account and addresses the probability of bi-directional spillovers. While DCC allowed the modeling of dynamic correlations, the predecessor.
17	2002	GO-GARCH Generalized Orthogonal GARCH	Van der Weide (2002)	Models temporal variation in the N×N conditional covariance matrix in terms of N conditionally uncorrelated components.
18	2006	ADCC Asymmetric Dynamic Conditional Correlations)	Cappiello, Engle and Sheppard (2006)	*A variation of MVGARCH* Allows asymmetry in both conditional variance and covariance and encompasses various widely-used time-varying covariance models, such as the BEKK, VECH, Factor ARCH, and CCC models. It considers both the constant and time-varying components of correlations, consequently producing relatively accurate estimates.

EGARCH by Nelson (1991) not only incorporates the asymmetric response to positive and negative news but also nullifies the need for non-negative coefficients that are required by standard GARCH model (Enders, 2010). The EGARCH specification can be written as:

$$\ln(h_t) = \alpha_0 + \alpha_1 \left(\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}\right) + \lambda_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}\right| + \beta_1 \ln(h_{t-1})$$

The above model implies a log-linear equation for conditional variance. The coefficients can be negative, as regardless of the magnitude of $\ln(h_t)$, the implied value of h_t can never be negative. The EGARCH model uses the standardized value of ε_{t-1}, which according to Nelson (1991) allows for better interpretation of the magnitude and clustering of shocks. The model incorporates leverage effects through the term $\left(\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}\right)$.

Another model worth mentioning is TARCH (Glosten *et al.*, 1993), which also considers asymmetric response to good and bad news. The model is written as:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \lambda_1 d_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

The model suggests that $\varepsilon_{t-1} = 0$ is the threshold and that $\varepsilon_{t-1} > 0$ has a different impact than $\varepsilon_{t-1} < 0$. The leverage effect is captured by d_{t-1}, which is a dummy variable assuming a value of one when $\varepsilon_{t-1} < 0$ and is equal to zero when $\varepsilon_{t-1} \geq 0$. If the coefficient λ_1 is statistically significant, then the time series contains a threshold effect.

McMillan and Speight (2004) compared the performance of various volatility forecasting models such as moving average (MV), exponential smoothing (ES), TARCH and Component GARCH in order to estimate and forecast volatility in 17 exchange rates, using in-sample and out-of-sample techniques. The results indicated the superior forecasting performance of GARCH models in most cases as compared to the MV and ES. In the GARCH models, the authors used the cumulative squared returns from intra-day data rather than using the standard squared returns as the measure. The authors argued that the former is the true measure of volatility and the latter includes a large "noisy component", leading to poor performance of GARCH models.

In other words, the poor performance of GARCH models cannot be attributed to the models themselves but is associated with the improper specification of the volatility measure

(Brailsford and Faff, 1996; McMillan and Speight, 2004). A study by Haniffa and Pok (2010) compared the performance of non-periodic GARCH variations (GARCH, EGARCH and TARCH) and Periodic GARCH (PGARCH) using intra-day returns of Kuala Lumpur Composite Index (KLCI). The results highlighted superior performance by EGARCH as measured by Log Likelihood, Akaike Information Criterion (AIC), and Schwartz Information Criterion (SIC).

Rodríguez and Ruiz (2012) compared various GARCH models with the leverage effects, namely EGARCH, TARCH, GQARCH, GJR, and APARCH. The study took an approach different from those of earlier studies, and evaluated the performance to the above models in the presence of restrictions such as the positivity of volatilities, the covariance stationarity and finite kurtosis of returns. The authors were able to present some interesting facts about each of the asymmetric models. According to the authors, in the TARCH model, the restriction on the asymmetry parameter to ensure stationarity and finite kurtosis does not inflict strong limitations on the leverage effect, given that the volatility persistence is not too significant. The authors found EGARCH and APARCH to be less rigid and comparable to the TARCH and documented marginal differences between conditional volatility estimates. Similarly, Brailsford and Faff (1996) applied random walk, historical mean, MV, exponential smoothing, exponentially weighted average moving average, univariate regression, standard GARCH, and GJR-GARCH on the data for Australian markets in an attempt to compare the out-of-sample performance of each of these models. The authors used various measures of forecast error statistics, such as mean error (ME), mean absolute error (MAE), the root mean squared error (RMSE), and mean absolute percentage error (MAPE), to evaluate whether the chosen models produce different forecasts with different error statistics. The results of the study were mixed and inconsistent. However, they suggested a relatively better performance by univariate regression models, followed by GARCH models indicating that parsimony of the model is important. Moreover, the results implied that the performance of the volatility models is sensitive to the choice of error statistic and is not a straightforward task.

Multivariate GARCH Models

While the standard GARCH is a univariate model, MVGARCH allows for the consideration of multiple variables and enables concurrent estimation of volatilities across markets without the need for estimating univariate models for different markets individually. Unlike the traditional OLS estimation, the bivariate MVGARCH directly stipulates the conditional variance-covariance matrix for current and future innovations, whose by-products can then be used for meaningful interpretations, for example, hedge ratios. Silvennoinen and Terasvirta (2008) argue that although univariate models are simple and parsimonious, they may prove to be insufficient in providing a detailed insight into volatility dynamics of various asset classes, a weakness that MVGARCH models attempt to overcome. However, there is a trade-off between parsimony and detailed insight.

The application of MVGARCH is very diverse and these models are used in literature as follows:

- To estimate volatility in the financial markets (for example Ng, 2000).
- To examine the interaction between volatility in stock markets and macroeconomic fundamentals (for example Flannery and Protopapadakis, 2002).
- To explore mean and volatility spillovers between Asian developed and emerging markets (Worthington and Higgs, 2003).
- To capture evolution of volatility over a period of time and cipher time varying hedge ratios (Bauwens *et al.*, 2006).

Table 3.1 presented a brief overview of selected variations of the MVGARCH models[29] and highlighted the extensive developments since Engle's original work. Bauwens *et al.* (2006) classify the MVGARCH variations into the following four categories driven by various motivations:

1. Need for simplicity: These models estimate the conditional covariance matrix H_t directly and include models like Vector-half (VECH) and Baba-Engle-Kraft-Kroner (BEKK) models.

[29] For a comprehensive survey of the variations of MVGARCH refer to Bauwens *et al.* (2006) and Silvennoinen and Terasvirta (2008).

2. Need for parsimony: These models include Factor GARCH (F-GARCH) models. These models allow simultaneous consideration of multiple factors while constraining the number of parameters.
3. Need for modeling the conditional variances and correlations separately: this category includes models, such as the CCC, DCC, and ADCC, which relegate the need for modeling the conditional covariance matrix by measuring the conditional correlations and variances separately.
4. Need for accommodating non-normal distribution of time series: The last category includes semi and non-parametric models, which do not enforce normality of distribution while estimating the conditional covariance matrices.

Under the first genre of MVGARCH models, the preliminary VECH (Bollerslev *et al.*, 1988) constitutes a rather simple generalization of the univariate GARCH. The VECH model can be written as:

$$vech\ (H_t) = \ c + \sum_{j=1}^{q} A_j\ vech\left(r_{t-j} r_{t-j}'\right) + \sum_{j=1}^{p} B_j\ vech\ (H_{t-j})$$

where *vech (.)* accumulates the columns of the lower triangular part of its argument square matrix, c is an N(N+1)/2 X 1 vector, and A_j and B_j are *N (N+1) /2 X N (N+1) /2* parameter matrices. While the model is flexible and simple, the imposition of H_t to be positive definitive for all t is restrictive (Silvennoinen and Terasvirta, 2008). Moreover, it is also evident from the equation that with a large N the number of parameters to be estimated increases subsequently, making the model computationally tedious.

A restricted variation of the VECH model is the BEKK model (Engle and Kroner, 1995). The model is distinctive from the standard VECH model, whereby the positive definitiveness of the conditional covariance matrices is enforced by construction. The model is written as:

$$H_t = C\acute{C} + \sum_{j=1}^{q} \ \sum_{k=1}^{K} \acute{A}_{kj} r_{t-j} \acute{r}_{t-j} A_{kj} + \sum_{j=1}^{p} \ \sum_{k=1}^{K} \acute{B}_{kj} H_{t-j} B_{kj}$$

where A_{kj} and B_{kj} and C are $N\ X\ N$ parameter matrices and C is lower triangle. The positive definitiveness of $H_t$is ensured by decomposing the constant term into a product of two triangular matrices. Application of BEKK encompasses four different variations of GARCH. The

BEKK model has a few advantages. The model ensures that the variance and covariance matrix is positive definite and that the standard errors are robust even if the assumption of normality is violated (Kuper and Lestano, 2007). However, there are some limitations identified with this model as well. Bauwens *et al.* (2006) argue that BEKK estimation requires a large number of unknown parameters, even in the presence of some restrictions, hence making the estimation burdensome. Therefore, the application of these MVGARCH models is either limited to studies using fewer markets and asset classes for analysis, or to an alternative treatment of using pairwise BEKK model that attempts to resolve the problem of numerous parameters.

Fedorova and Saleem (2010) used the BEKK model to estimate volatility spillovers across five stock and foreign exchange markets of Eastern Europe. Studies like Ng (2000) Valls, and Chuliá (2012) opted to use BEKK in combination with other models. However, rather than considering all the markets in one model, the studies mentioned above segregated the markets into bi-variate BEKK models for analysis. Valls, and Chuliá (2012) used the multivariate asymmetric GARCH model to evaluate the volatility transmission across the USA and eleven Asian markets (one mature and 10 emerging markets), especially during the financial crisis. To incorporate the impact of the financial crisis a dummy variable was introduced in the mean equation. The authors performed pair-wise analysis using bi-variate GARCH and regressed the log returns of the USA market against each of the Asian emerging markets. The conditional variance-covariance matrix was estimated using an asymmetric version of the BEKK model to assess the impact of both positive and negative shocks. Ng (2000) used a combination of bivariate BEKK and ADC to analyze interdependencies between local, regional, and world markets. The analysis included USA, Japan, Korea, Hong Kong, Malaysia, Singapore, Taiwan and Thailand. The study concluded that the markets are affected by both regional and global shocks, and bear shocks in global and regional markets have a deeper impact on the local markets as compared to bull shocks. Although using the bivariate BEKK in the above studies resolved the problem of large number of parameters, it may have resulted in the loss of important insight into the joint dynamics of volatility across markets.

While the first genre of MVGARCH models was motivated by the need for simplicity, the second genre of MVGARCH models, the F-GARCH models was driven by the need for parsimony and was inspired by PCA. The F-GARCH model assumes that conditional covariance

matrix H_t is produced by K factors that are not essentially uncorrelated, and that $K < N$. The model is written as:

$$H_t = \Omega + \sum_{k=1}^{K} w_k \acute{w}_k f_{k,t}$$

where Ω is an N X N positive semi definitive matrix, w_k, *k = 1, 2, ….., K,* are linearly independent N X 1 vectors of factor weights, and $f_{k,t}$ represents the factors having first order GARCH structure:

$$f_{k,t} = w_k + \alpha_k (\acute{\gamma}_k r_{t-1})^2 + \beta_k f_{k,t-1}$$

where w_k, α_k and β_k are scalars and $\gamma_k$is an *N X 1* vector of weights. The number of factors is expected to be smaller than the number of assets *N*, which makes the model viable.

The F-GARCH by Engle *et al.* (1990) chose the number of factors in the model as a priori to measure the volatility of excess returns of stocks and treasury bills in a portfolio. The weights of the assets included in the portfolio were arbitrarily considered as factors in the study. Engle *et al.* (1990) highlighted the need for developing an empirical process for choosing the appropriate number of factors in the model. Lanne and Saikkonen (2007) proposed a test procedure to identify the correct number of factors to be included in the model to address the limitation of F-ARCH and F-GARCH models. Besides proposing this test, the authors also put forward a generalized variation of the Orthogonal GARCH, and assert that the maximum likelihood estimations can be obtained easily not only for Gaussian distributions but also for other distributions. The authors applied the model on exchange rates of four European countries against the US Dollar. The results highlighted volatility transmissions across the currencies involved in the analysis. To prove the significance of the new model, the authors compared the results with the BEKK model, which suggested lack of volatility transmission across chosen currencies and also highlighted the deficiencies in the BEKK model.

Given the characteristics of the F-GARCH models, they may seem superior to the VECH and BEKK models as they allow simultaneous consideration of multiple factors while

constraining the number of parameters in the model[30]; however, the trade-off between parsimony and information extraction is pertinent. Another limitation of the standard F-GARCH model is associated with the inclusion of correlated factors whereby the interdependence of factors does not isolate the effect of each factor on the returns series. This inadequacy of the standard factor model prompted development of various factor models that assumed that the return series R_t is linked to uncorrelated factors $z_t$through a linear, invertible transformation *W,* a nonsingular *N X N* matrix*:*

$$r_t = Wz_t$$

Given the limitations of F-GARCH, Van Der Weide (2002) developed the Generalized Orthogonal GARCH (GO-GARCH), which standardized the uncorrelated factor z_t to have unit unconditional variances, that is, $Ez_t\acute{z}_t = I$.

In other words, the form of constant term enforces restriction $Ez_t\acute{z}_t = I$.

Zhang and Chan (2009) proposed the following variations of GO-GARCH:

- Independent-factor GARCH: entails factors that are largely uncorrelated.
- Best-factor GARCH: involves factors with the largest autocorrelation in their variance.
- Conditional-decorrelation: factors are considered to be conditionally uncorrelated to a great extent.

Zhang and Chan (2009) employed a two-step process to extract the models. The first step involved the use of independent component analysis to extract the factors with statistical significance, and the second step involved estimating univariate models for each factor to produce conditional covariance matrix of the time series. The authors argue that the models can resolve the problems associated with multi-dimensional data. They also contest that the results of all three models will be the same if the same conditions are met. First, all the factors in the model have zero correlation; second, no more than one factors is normally distributed; third, all factors exhibit serial correlations in their squared values, and are temporally uncorrelated; and last, for every pair of factors, the ratio of their local variances is not constant.

[30] For a comprehensive taxonomy of the various factor models refer to García-Ferrer *et al.* (2012).

The models were tested using return series of ten companies listed on the Hong Kong stock exchange. The results as measured by Value-at-Risk estimates revealed superior performance of the models using uncorrelated factors, i.e. independent-factor GARCH and conditional-decorrelation GARCH, implying that the factor models with correlated factors may conceal important non-mutual information regarding volatility in time series.

The third genus of MVGARCH attempts to model the conditional variances and correlations discretely and can be categorized as the non-linear synthesis of univariate GARCH models. Bauwens *et al.* (2006) argue the results on stationarity, ergodicity, and different moments of the time series acquired by the application of these models may not be easily comprehendible as compared to the other genres of MVGARCH; however, these models are advantageous in terms of parsimony. This class includes CCC (Bollerslev, 1990), Extended CCC (Jeantheau, 1998), and DCC (Engle, 2002) amongst others, and these models are widely used in literature (for example Ng, 2000; Kuper and Lestano, 2007). The popularity of these models can be attributed to their intuitive deduction and relatively easy estimation. The DCC model calculates the current correlation between variables as well as within variables as a function of historic volatility and relaxes the assumption of constant conditional correlations among the variables imposed in CCC. This model allows analysis of time-varying co-movement of markets through the changes in correlations of the observed variables, and addresses the probability of bi-directional spillovers (Frank and Hesse, 2009).

The ADC model allows asymmetry in both conditional variance and covariance and encompasses various widely-used time-varying covariance models, such as the BEKK, VECH, F-GARCH, and CCC models, hence increasing the utility of the model. Furthermore, the ADC model considers both the constant and time-varying components of correlations, consequently producing relatively accurate and meaningful estimates.

Martens and Poon (2001) used the ADC model to analyze variance, covariance, and correlations spillovers between markets with overlapping trading hours. The purpose of using markets with overlapping hours was not only to measure mean and volatility spillovers, but also to measure contemporaneous correlations between markets. The authors used daily synchronous and non-synchronous data from the USA, the UK, and French stock markets for the period between 1990 and 1998. The findings of the study revealed that there are no return

spillovers from the USA to European markets; however, there were significant bi-directional volatility spillovers between markets. In addition, the study documented that negative shocks in the previous time period, both locally and from abroad, had a magnified impact on the volatility as compared to positive shocks.

Besides parametric MVGARCH models, there are some semi-parametric and non-parametric variations too, such as Semi-parametric ARCH (SPARCH) and Partially Non-parametric ARCH (PNP-ARCH). While all parametric variations of MVGARCH assume that the time series is normally distributed, semi and non-parametric variations do not make such assumptions. The non-parametric models are parsimonious in terms of underlying assumptions and the only required assumption is the stationarity of returns over the period of analysis, making these models more flexible.

Giannopoulos *et al.* (2010) explored the mean and volatility spillovers across the USA, Japanese, German, and the UK markets using a combination of Filtered Historical Simulation and non-parametric regression. The study concluded that volatility transmits from the USA to other markets in the sample, and these markets take around three days to absorb the foreign shocks.

Silvennoinen and Terasvirta (2008) highlighted at least three deficiencies of the MVGARCH model. First, the MVGARCH model tends to be exhaustive, and therefore, maintaining a balance between parsimony and flexibility is challenging. Second, imposing the restriction of positive definitive conditional covariance matrix is numerically exigent, especially in large systems. Lastly, in the case of the parametric model, the increase in dimensions of returns leads to problems with the numerical optimization of likelihood function, leading to a time consuming and numerically unstable procedure.

In spite of the widespread use of GARCH models in the finance literature, all the variations have some shortcomings in common, which are briefly elaborated below:

- The need for large sample size: GARCH models are inherently capable of handling a large amount of time series data; this capability may at times become a limitation. In the absence of a minimum sample size, the GARCH model becomes unstable. Ng and Lam (2006) found that a sample size of less than 700 observations in conventional GARCH may produce two or more

optimal solutions as suggested by maximum likelihood, and therefore, the authors suggested using a sample of minimum 1,000 observations for conventional GARCH.

- Parametric specifications: GARCH models, in general, force the assumptions that the time series are normally distributed. Researchers have repeatedly provided evidence that the financial assets time series are leptokurtic, that is, the errors exhibit more extreme values as compared to normal distribution. Although modeling heteroscedasticity in GARCH partly addresses this problem, apt specification about the conditional distribution of the error term ε_t, is required. Appropriate specification of error distribution like the Student's *t*-distribution, Generalized Error Distribution (GED), and the Double Exponential Distribution (DED) (Zivot, 2009) may lead to better volatility estimates.
- Estimation of conditional variances: GARCH models are not capable of providing insight into unconditional variances; hence, they often fail to capture highly unanticipated asymmetrical trends.

It is apparent from the above discussion that the application of ARCH and GARCH models in the literature has progressed significantly. In the progression from the first generation GARCH model which assumed symmetric response to positive and negative news, to second generation models that incorporate the asymmetric impact to negative shocks, researchers have invested a lot of time and effort into producing models that can enhance the predictive capabilities and allow investors to employ better risk management strategies.

3.4 Cointegration, Vector Error Correction, Vector Autoregressive Models

The attention now turns to another strand of the literature, one that uses Cointegration, Vector Error Correction (VECM), and Vector Autoregressive (VAR) modeling to explore long- and short-term association between markets. These methods are discussed in sections 3.4.1 to 3.4.5.

3.4.1 Cointegration

Cointegration equations are a modified form of OLS estimation with some additional requirements. It is evident from Tables 2.1 and 2.2 in Chapter 2 that this technique is widely used in finance literature to estimate long-run association between selected time series.

For a cointegration model to be non-spurious, the stationarity of variables, that is, all the variables converging to zero in the long run, is a prerequisite (Durlauf and Blume, 2010). If the time series i_t and j_t are non-stationery, then the regression equation,

$$i_t = \beta_1 + \beta_2 j_t + u_t$$

divulges unsatisfactory estimates for constant β_1 and coefficient β_2. The problem can be resolved by using the first difference of the time series to generate a series *I(0)*. Hendry (1995, p. 43) states,

> "A finite (non-zero) variance stochastic process which does not accumulate past errors is said to be integrated of order zero..." .

The first differenced series can then be referred to as R_{it} and R_{jt} and the regression model can be rewritten as

$$R_{it} = \alpha_1 + \alpha_2 R_{jt} + \Delta u_t$$

and

$$\hat{u}_t = i_t - \hat{\beta}_1 - \hat{\beta}_2 i_t$$

Since both the time series R_{it} and R_{jt} are de-trended, they lack information about the long-run behavior of association between the two time series, a problem that needs attention. The term in the second equation provides a long run connection between the two time series. If the primary conditions of stationarity of time series are met, the model delineates a long-run relationship amongst the variables included in the model.

Various unit root tests to examine the stationarity of the time series are suggested in the literature. Dickey Fuller (DF), Augmented Dickey Fuller (ADF) and Phillips and Peron (PP) tests are widely used as prerequisites to test for the presence of unit root. Either one or a combination of the above-mentioned tests is used to examine the stationarity of the price or returns series. Chapter 4 provides the details for applying the ADF test and PP test for unit root.

After unit root tests, cointegration analysis can be conducted using various tests. The most commonly used test for cointegration are the Engle-Granger (1987), Johansen's Cointegration, (Johansen, 1988) and the Johansen and Juselius (1990) tests.

Menon *et al.* (2009) used the Engle and Granger (1987) test to evaluate if the Indian market is cointegrated with USA, Chinese, and Hong Kong markets. The results indicated a lack of cointegration between India, Hong Kong, and the USA. The authors witnessed weak cointegration between India and China, and strong cointegration between India and Singapore. The study, however, did not explore the reasons for cointegration or the lack of it between markets. Wong *et al.* (2004) used the cointegration test to find out whether the developed and Asian Emerging markets were cointegrated. Using a variation of the conventional cointegration test, Aggarwal *et al.* (2010) employed time-varying cointegration to identify if political events had resulted in a higher integration of equity markets in Europe. The study found that certain political events resulted in greater integration of European equity markets in the late 1980s and early 1990s.

There are several limitations associated with cointegration techniques. Lee and Tse (1996) and Gabriel *et al.* (2002) provide evidence that Johansen's Cointegration test tends to reject the null hypothesis of no cointegration more often than it accepts it. Moreover, eigenvalues under the test are highly sensitive to the presence of heteroscedasticity in the time series and may generate results that are of limited empirical significance (Hoglund and Ostermark, 2003). Cointegration primarily focuses on long-run associations between variables with which investors with a short-term investment horizon may not be able to use the results for decision-making (Fernandez, 2004; Rua and Nunes, 2009; Dajčman *et al.*, 2012; Dajčman, 2013). Inclusion of an error correction term is required to provide insight into the short-run association between variables of interest.

Though the cointegration tests in their original form divulge limited information about the linkages between markets, they are still useful and widely used as preliminary results regarding long-term cointegration between markets and provide a case for further investigation. These tests can be used in conjunction with other more sophisticated techniques to provide a better understanding of cross-market relationships. For example, Yilmaz (2009) used the Johansen (1988) Cointegration test preceding the estimation of the Spillovers Index for international business cycles. Abd. Majid *et al.* (2008) used unit root and cointegration tests before using Generalized Method of Moments (GMM), in order to analyze the interdependence between ASEAN 5, USA, and Japanese markets during 1988 and 2006. The application of GMM

enabled researchers to study all four moments of the time series, that is, mean returns, volatility, skewness and kurtosis respectively. The authors found evidence of greater integration of the ASEAN markets after the Asian financial crisis. Singapore was documented to be more integrated with the USA and Japan than the other ASEAN markets.

3.4.2 Vector Error Correction Model

VECM, an extension of the cointegration model, is also widely used to investigate the economic relationships between time series. Gaining popularity after Engle and Granger (1987), the objective of the VECM model is to find the short-run economic relationship and to capture short-run disequilibrium in the long-run relationship between dependent and independent variables.

In the case of short-term disturbance to the model, the VECM system of equations illustrates the short-run dynamics of the cointegrated variables towards their long-run equilibrium. If R_{it} and R_{jt} are cointegrated, then the relationship between the two variables with error correction specification can be written as:

$$R_{it} = \alpha + \beta R_{jt} - \pi \hat{u}_{t-1} + I_t$$

and

$$\hat{u}_{t-1} = j_{t-1} - \hat{\beta}_1 - \hat{\beta}_2 i_{t-1}$$

where β signifies the short run effect that a change in R_{jt} has on R_{it} and π denotes the adjustment effect and exhibits the degree of correction in disequilibrium, and $\hat{u}_{t-1}$ constitutes information regarding long-term relationship between the time series via β_2.

Boswijk and Franses (1995) applied the periodic VECM on the Swedish aggregate income and consumption data, whereby the authors allowed seasonal variation to both long and short-run components in the VECM model; Carlson *et al.* (1999) used the VECM to model money demand in the USA during 1990s; Gabriel *et al.* (2002) used the model to estimate money demand in Portugal; and Bonham *et al.* (2009) applied the VECM to the Hawaiian tourism industry to explore the demand and pricing behaviors. The VECM has also been used, though sparingly, to measure interdependencies across financial markets.

Masih and Masih (2001) used cointegration, VECM and VAR to identify and measure long and short-run linkages between the OECD and Asian markets. The authors conducted the generalized impulse response analysis to identify the impact of a foreign shock to the markets included in the study. An asymmetric response across markets due to foreign shocks was documented. Sarno and Valente (2005) used the linear and non-linear VECM to model the dynamic relationships between spot and futures stock markets incorporating the effects of international spillovers and structural changes. The results of the study highlighted a long-run relationship between the spot and futures markets and documented cross-market returns spillovers. The authors tested the viability of the model both in-sample and out-of-sample and found a marginal difference between the performance of linear and non-linear models. This implies that the VECM can be modified to explore non-linear relationships. Gabriel *et al.*, (2002) also used modified VECM to accommodate information on structural change and to improve forecasting capabilities of the model.

Asteriou and Hall (2007) list the following advantages of the VECM model:

- The model allows convenient measurement of correction of disequilibrium in a system of equations.
- It resolves the problem of spurious regression by de-trending of the variables used in the model.
- It provides the best fitting parsimonious model for a given data set.
- Most importantly, the inherent correction process prevents the errors in the long-run relationships from becoming larger by pulling them towards equilibrium.

The most prominent criticism of the VECM is its inability to identify structural breaks and regime changes. Durlauf and Blume (2010) assert that the VECM application is useful within regimes, but leads to forecast failure in the presence of regime shifts in the time series. Gabriel *et al.* (2002) argue that it is important to explore whether the coefficients in the model are temporally stable and if they can provide similar results even when the time series is divided into sub-periods. Therefore, ignoring structural break within the time series may lead to biased and amplified estimates, which in turn have implications for Value-at-Risk appraisals, and risk and portfolio management.

Boswijk and Franses (1995) introduced a variation of cointegration and VECM to reflect periodic cointegration and error correction, as some series in their sample exhibited gradually varying cyclic patterns. The authors highlighted that the periodic models are non-parsimonious models; therefore, it is crucial to check for periodicity before proceeding with the application of the periodic model. If the variations are statistically insignificant, models with constant parameters may suffice. The authors applied the model on the Swedish aggregate data on income and consumption between 1963 and 1988. The results revealed that the adjustments towards equilibrium occur in the second and fourth quarter, which can have forecasting and policy implications.

3.4.3 Vector Autoregressive Models

VAR is also widely used in the finance literature to measure the association between markets. The method gained popularity in the mid-1980s to early 1990s after seminal work by Sims (1980). Subsequently, three forms (reduced, recursive, and structural forms) emerged (Allen and Morzuch, 2006).

The bivariate or multivariate VAR system allows for the consideration of more than one variable, both endogenous and exogenous, treated symmetrically in one system. The model also highlights the importance of each variable to the overall returns or volatility (Lastrapes and Koray, 1990). VAR can be considered a self-sufficient system whereby the bias introduced by excluded variables is addressed by including several lags of variables included in the analysis (Allen and Morzuch, 2006). Most researchers opt for symmetric lag lengths for all the variables included in the VAR system; however, the literature does not provide any evidence against using asymmetric lag lengths across variables (Ozcicek and McMillin, 1999). Asteriou and Hall (2007) suggest that the VAR models are useful in determining simultaneity between variables, whereby not only can the explanatory variables explain changes in dependent variables, but changes in explanatory variables can also be determined by dependent variables. For a detailed description of *N-variable* VAR for *H*-step ahead forecast, refer to Chapter 4 under Data and Methodology.

Allen and Morzuch (2006) compared the VECM and VAR models and asserted that in the occurrence of disturbance to the equilibrium, the VECM tends to adjust to the old

equilibrium, while the VAR models adapt to the disturbance quickly. Hence, VAR models are robust to changes.

Lastrapes and Koray (1990) employed a VAR model and cointegration to examine whether the fixed or floating exchange regimes could cause or limit volatility transmissions across the USA and three European countries, namely France, Germany and the UK. The cointegration results revealed long-run association between variables during 1959 to 1985, and the VAR model suggested asymmetric short-run linkages between macroeconomic variables of the candidate countries with fixed and floating rate exchange regimes. The findings suggested that fixed rate regimes do not insulate countries from foreign shocks and the capability of VAR system in capturing the contribution of each explanatory variable to the overall variance of the dependent variable was highlighted.

Morana (2008) examined the interactions between the G7 stock markets and various macroeconomic variables during 1980 to 2005, using idiosyncratic and foreign, real, and financial factors in a VAR model. The highly correlated macroeconomic variables were segregated into factors with the help of PCA to avoid multi-collinearity and to isolate the pure effects of macroeconomic variables on the co-movements of stock markets. The model allowed for the decomposition of error variance into contributions from each factor in the system. The econometric model included 39 equations including both endogenous and global exogenous factors. Additionally, impulse response functions were used to determine the response of the stock market returns to the shocks induced by various economic and financial factors. The results highlighted significant integration between stock markets based on economic factors, whereby the regional factors were more prevalent in the overall variance of a country. The author also concluded that financial integration across G7 countries is dependent on economic integration.

Some authors (for example Mahmoud, 1984; McNees, 1986; Lastrapes and Koray, 1990) argue that VAR models provide superior estimates as compared to other simultaneous equation models. Specifically, the VAR models have several strengths, which are listed below:

- Simple and intuitive to estimate and interpret.

- Simultaneous treatment of endogenous and exogenous variables redeems the need for distinction between the two (Asteriou and Hall, 2007).

However, VAR models are criticized on various accounts: first, the consideration of simultaneity between variables leads to a plethora effect (Asteriou and Hall, 2007). This weakness is addressed by using statistical significance measures, and coefficients appearing to be insignificant are dropped from estimation. Second, in the case of unrestricted VAR, the parsimony of the model is compromised with over-parameterization. Asteriou and Hall (2007) argue that if the sample size is insufficient, then a large number of parameters consume many degrees of freedom, leading to an unstable VAR model. Third, Diebold and Yilmaz (2012) suggest that the variance decomposition models under VAR are sensitive to the order of variables, which is undesirable. This limitation requires additional measures for generalization, which the authors presented in their study discussed below. Fourth, omission of variables in the model may result in biased estimates. Allen and Morzuch (2006) suggest that this bias can be reduced by including sufficient lags of the variables included in estimating the VAR model; however, it can be argued that the inclusion of a large number of lags in the model may result in a loss of information associated with specific omitted variables. Lastly, the choice of lag length is one of the most important considerations under VAR, which is facilitated by Likelihood ratio, Akaike, or Schwartz Information Criterion (Ozcicek and McMillin, 1999; Enders, 2010). Inappropriate lag length may produce a mis-specified model. For example, a shorter than required lag length might fail to capture delayed responses to a domestic or foreign shock (Huyghebaert and Wang, 2010), while unnecessarily long lag lengths may result in wasted degrees of freedom and diluted estimates (Enders, 2010).

3.4.4 Causality Tests

VAR modeling can also be used to explore causality between variables. These tests reveal whether one variable causes the other without measuring the magnitude of causation. Granger (1969) developed a simple test, which states that if R_{it} causes R_{jt} then the value of R_{jt} can be predicted relatively accurately using the past values of R_{it}. Refer to chapter 4 for numerical representation of Granger causality test.

Sims (1980) proposed an alternative causality test, arguing that it is not possible to predict present values based on future values. Therefore Sims (1980) suggested an estimation of causality using the following VAR model:

$$R_{it} = \alpha_1 + \sum_{x=1}^{n} \beta_x R_{jt-x} + \sum_{y=1}^{m} \gamma_y R_{it-y} + \sum_{\rho=1}^{k} \zeta_\rho R_{jt+\rho} + e_{1t}$$

$$R_{jt} = \alpha_2 + \sum_{x=1}^{n} \theta_x R_{jt-x} + \sum_{y=1}^{m} \delta_y R_{it-y} + \sum_{\rho=1}^{k} \xi_\rho R_{1t+\rho} + e_{2t}$$

Here, R_{it} and R_{jt} denote the returns of markets *i* and *j* respectively. The difference between the Granger causality and Sims (1980) causality was the inclusion of a leading variable in both VAR equations.

Though both Granger causality and Sims causality are used in the literature, Granger causality has an advantage over Sims causality in terms of parsimony and lower loss of degrees of freedom (Asteriou and Hall, 2007). Malliaris and Urrutia (1992) evaluated the propagation of the stock market crash of 1987 using Granger causality and for this purpose the data was divided into three sub-periods: before, during, and after the market crash. A significant increase in causality between markets was reported during the crisis. The study also reported feedback between the USA, the UK and Hong Kong markets, and also that the USA market led the crisis in Japan. Lee and Rui (2002) explored causality between stock returns and volume. The authors attempted to distinguish contemporaneous relationships from dynamic causality between stock returns and volume across the USA, the UK and Japan. The results demonstrated unidirectional Granger causation from stock returns to trading volume. Additionally, trading volume in the USA was found to have predictive power for stock returns and volume in the UK and Japan.

Phylaktis and Ravazzolo (2005b) explored the short and long-run association between Pacific-Basin stock prices and exchange rates using cointegration and Granger causality. Besides this, a modified version of Granger causality formulated by Dolado and Lutkepohl (1996) was also employed to evaluate the mediums through which exogenous shocks impact the linkages between markets. The modified Granger causality allowed the

authors to identify the "causing" variables that feed into the linkages between Pacific-Basin markets and the moderating role of the USA market was highlighted. Surprisingly, the results indicated that the effect of the Asian financial crisis was marginal on the countries under analysis.

While this method is commonly used and is generally employed as a stepping-stone for further investigation (for example Ng, 2000; Rodríguez-Moreno and Peña, 2013), it has certain weaknesses. First, by definition, causality models are bi-variate and cannot be extended to accommodate multivariate relationships. However, the relationship between dependent and independent variables can be altered by including a moderator variable in the OLS estimation (for example Dolado and Lutkepohl, 1996; Phylaktis and Ravazzolo, 2005b). Second, the causality tests only divulge whether there is causality between two return series or not, and do not provide information on the degree of causation. Third, causality tests do not implicitly incorporate information on structural breaks, heteroscedasticity, and regime switching, which is of prime importance in time series analysis, as the presence of structural breaks or exaggerated variances may induce spuriousness in the results (Baek and Brock, 1992). This can be remedied by explicitly incorporating structural breaks in the data analysis by conducting event studies and dividing the time series into sub-periods, after which, before and after causation is evaluated (for example Malliaris and Urrutia, 1992; Lee and Rui, 2002; Phylaktis and Ravazzolo, 2005b; Bekiros and Marcellino, 2013). Otherwise, the return series are filtered using mechanisms like EGARCH, and the resulting series is then used for the causality analysis (Abhyankar, 1998).

The final and most important criticism of the causality tests is that they measure linear causality, that is, causality in returns, and not in higher moments. The limitations of linear causality are addressed by Baek and Brock (1992), Hiemstra and Jones (1994) and Abhyankar (1998); however, the techniques used by these researchers are seldom used in literature. Baek and Brock proposed the non-linear Granger causality tests and ran a Monte-Carlo analysis on money and income to investigate any causation between the two variables. The authors assumed that the time series are mutually independent and that each of the series is independent, and identically distributed Gaussian with zero mean and unit variance. Their

results revealed some non-linear predictability between money and income, with some limitations.

Hiemstra and Jones (1994) explored the stock price and volume relationship using linear and non-linear Granger causality. The causality tests used in Hiemstra and Jones were slightly modified where no assumption was made regarding the distributional property of the time series. The results highlighted that linear Granger causality tests insinuated unidirectional causation from returns to trading volume, which was confirmed by Lee and Rui (2002); however, the non-linear Granger causality test revealed bi-directional spillovers between returns and trading volume. Similarly, Abhyankar (1998) studied the relationship between the UK cash and stock index futures using both linear and non-linear Granger causality tests. By applying the standard Granger causality test on high frequency data, the authors found a lead-lag relationship between future and cash index returns, whereby the future index returns precede the cash index returns by five to fifteen minutes and a unidirectional causality was revealed from futures to cash index returns. However, the non-linear causality tests formulated by Baek and Brock (1992) exposited bi-directional causality between the two returns and the results held ground even after accounting for volatility persistence.

Bekiros and Marcellino (2013) used Granger causality and the Baek and Brock (1992) test to explore the linear and non-linear causalities between the US Dollar, Euro, British Pound and Japanese Yen. Both linear and non-linear bi-directional causalities were observed in most sub-periods, with a few exceptions. Some peculiar patterns of causality emerged in the analyses that were further explored by wavelength analysis. This indicates that the linear causality tests are insufficient to depict causation, and that further investigation is required to explore non-linear causality between time series.

3.4.5 Spillovers Index

The methods measuring interdependencies between markets have evolved from being simplistic to more sophisticated. Diebold and Yilmaz (2009) suggested an innovative approach to estimate return and volatility spillovers across markets using a combination of static and dynamic approaches, and called it the "Spillovers Index". Put broadly, the Spillovers Index is a

cointegration technique and facilitates variance decomposition with an N-variable VAR. The Spillovers Index comprises two components:

1. The Spillovers table decomposes the conditional returns and volatility into foreign and self-contributions and then provides an overall estimate of static conditional mean and volatility spillovers across groups of countries over the period of analysis. The spillovers not accounted for by the Spillovers table are unconditional spillovers, which require further investigation.
2. The Spillovers plots provides insight into the evolution of mean and volatility spillovers in rolling windows and enable the understanding of changes surrounding domestic and foreign shocks.

Collectively, the above components of the Spillovers Index provide a wealth of information on interaction between markets of interest.

The studies using the Spillovers Index (for example Dielbold and Yilmaz, 2009; Yilmaz, 2009; 2010) performed unit roots tests before its application and in some cases tested for cointegration also. For a detailed explanation of estimation of the Spillovers Index refer to chapter 4, section 4.5.2.

Though the studies employing the Spillovers Index are limited in number, they clearly demonstrate the diverse application of the method. The application of the Spillovers Index is plausible for returns and volatility time series (Diebold and Yilmaz, 2009; Yilmaz, 2010; Diebold and Yilmaz, 2012; Fujiwara and Takahashi, 2012; Tsai, 2014) and real sectors (Yilmaz, 2009; Fujiwara and Takahashi, 2012), as well as for different assets classes (Diebold and Yilmaz, 2012; Sumner *et al.*, 2010; Antonakakis, 2012; Antonakakis and Badinger, 2012; Zhang and Wang, 2014; Sugimoto *et al.,* 2014). Some common findings are reported in all the above-mentioned studies. First, an upward trend in mean spillovers is documented with a steep increase in recent times suggesting increased integration of markets. Second, a lack of trend in volatility spillovers with exaggerated volatility spillovers surrounding a particular crisis is highlighted. Yilmaz (2010) emphasized that the recent financial crisis has had the gravest impact on both mean and volatility spillovers, signifying the severity of the crisis.

Yilmaz (2009) used the Spillovers Index and plots to measure business cycle spillovers across G6 countries. The results of the study suggested that the USA and Japan are the major transmitters of business cycle shocks to the other G6 countries. On the other hand,

the USA received marginal spillovers from other countries. The author also documented a sharp increase in the Spillovers Index between May and December 2008, capturing the severity of the recent financial crisis.

While the above studies focused either on real sectors or financial sectors, Fujiwara and Takahashi (2012) analyzed volatility spillovers not only across Asian financial markets but also across real sectors. The authors developed Spillover Indices for all the countries included in their sample (the USA, Europe, Japan, Singapore, Philippines, Taiwan, Korea, China, Malaysia, Indonesia and Thailand) and then further classified their sample into various groups such as G3, Asia, newly industrialized nations and ASEAN. In line with existing literature, Fujiwara and Takahashi (2012) confirmed that volatility in the USA drives up the volatility in international stock and bond markets. With respect to the real sector, the authors observed a surge in volatility spillovers during the financial crisis. The authors found similar progression of Spillovers Index in financial markets across regions and various assets markets and concluded that the stock market interdependence has become a global phenomenon and that the regional interdependence between the ASEAN markets has increased progressively. The authors also found that the influence of China on the global financial market is marginal; however, China's contributions to the shocks in the real sector are significant for all groups in the sample. While the authors quantified significant contribution of the USA and China to the overall volatility of capital markets and real sectors respectively, they did not discuss the possible reasons for the increased influence of China on the economic activities in the region, and otherwise.

The Spillovers Index is not only effective in measuring spillovers across different sectors of economy; it is also capable of measuring spillovers across diverse asset classes. Sumner *et al.* (2010) used the Spillovers Index to measure return and volatility spillovers across gold, stocks, and bonds. The authors found that while returns spillovers appeared to be marginal, volatility spillovers hovered around the mean level but surged dramatically during the financial crisis, whereby the volatility Spillovers Index reached nearly 40%. The authors also documented a significant contribution of the stock markets to the overall Spillovers Index; however, no evident relationships between the gold and stocks, and gold and bonds was found. The authors argued that while limited spillovers from gold to stocks and bonds respectively

restrict the forecasting capability of the variable, they indicated the presence of an avenue for diversification for investors.

Bubak *et al.* (2011) investigated intra-day volatility transmission in European foreign exchange markets with a multi-step approach, by using non-parametric variation of GARCH along with the dynamic version of Diebold and Yilmaz (2009). The results of the study highlighted extreme volatility surrounding the periods of uncertainty, including the recent financial crisis.

Claeys and Vasicek (2012) employed the Spillovers Index to evaluate the sovereign bond volatility spillovers across European markets besides measuring the impact of ratings news. Heterogeneous volatility spillovers across markets and stronger foreign spillovers than the domestic spillovers were observed. This study also confirmed enhanced and permanent spillovers across European markets. The authors then examined the role of sovereign ratings news in determining the foreign spillovers using event study. The results revealed that the ratings news contributed marginally and asymmetrically to the spillovers; but notably they emphasized that the impact of downgrades news was more severe.

Diebold and Yilmaz (2012) used the Spillovers Index to study the directional spillovers across various asset markets (capital, bonds, foreign exchange, and commodities) in the USA. The method used in this study is a progression of Diebold and Yilmaz (2009). The authors highlighted that the Spillovers Index developed in their earlier study was sensitive to the order of variables, which was rather undesirable. Additionally, the Spillovers Index in its original form only measured total spillovers, even though it was apt to measure directional spillovers also. Besides addressing the methodological weakness, Diebold and Yilmaz (2012) introduced another innovation whereby the Spillovers Index is now capable of estimating spillovers across different classes of assets, like those between bonds and commodities markets. The authors employed range-based volatility to estimate volatility spillovers. The results revealed that capital and bond markets are more volatile than commodities and foreign exchange markets, that volatility persistence is evident, and that the impact of the recent financial crisis is more significant on capital and bond markets. The study also highlighted limited volatility spillovers across four markets in the pre-crisis period, which intensified after the global crisis.

Zhou *et al.* (2012) applied the Spillovers Index to measure spillovers between China and world markets. The results highlight significant volatility interactions between China, Hong Kong, and Taiwan, but limited interactions between China and western markets. Moreover, the authors found that the spillovers among China, Japan and India are more prominent than the spillovers among China, the USA and the UK. The author documented that the spillovers from global markets to China were limited until 2009 due to restricted exposure to inflow and outflow of foreign portfolio investment. In contrast to Fujiwara and Takahashi (2012), the authors found that China's influence on other markets increased after 2005.

Zhang and Wang (2014) employed the Spillovers Index to quantify the returns and volatility spillovers between Chinese and world oil markets[31] during 2001 to 2013. The Spillovers Index highlighted an upward trend in bi-directional spillovers between the two markets, which peaked during the financial crisis of 2008.

Antonakakis and Badinger (2012) used the Spillovers Index to estimate the association between output volatility, economic growth, and spillovers between G7 countries. The results highlighted interdependence between output volatility and growth, with each of these variables affecting each other not only between countries but within countries also. The results also affirmed increased spillovers after liberalization in the 1980s whereby the Spillovers Index more than doubled, as well as the significant influence of the USA in transmitting volatility to other G7 countries. The dynamic rolling window analysis revealed relatively stable output growth and output volatility spillovers before and after 1985; however, it recorded a substantial increase of 66% after the financial crisis.

Sugimoto *et al.* (2014) applied the Spillovers Index to multiple asset classes, such as equity returns of African and developed markets, commodities (gold and petroleum) and foreign exchange. The results of the study highlighted that while African equity markets are significantly affected by crises in the developed markets, they are marginally affected by shocks in the commodity and foreign exchange markets. The results also highlighted limited regional spillovers within African markets, and higher spillovers from the European markets as compared with spillovers from the USA markets.

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[31] China is the second largest consumer of oil after the USA.

Tsai (2014) examined the volatility spillovers across five developed markets (the USA, the UK, Germany, Japan and France) between 1990 and 2013, with respect to fundamental (macroeconomic variables) and non-fundamental (fear) factors, with the help of the Spillovers Index. The author documented increased cross-country transmission of volatility after 1998 and that there is a positive association between fear index and net spillovers in the USA. The author also found that negative fundamental news has a higher impact on the volatility in the USA; however, positive fundamental information relayed higher net spillovers from the USA to other countries.

All the studies using the Spillovers Index for a combination of markets and assets classes acknowledge two findings. First, the volatility spillovers from the USA affect all international markets, although the magnitude of the impact is heterogeneous. Second, the volatility spillovers have considerably amplified in both real and financial sectors of all markets at the time of the recent global financial crisis, highlighting the gravity and scope of this crisis. These findings in general support the argument that countries have integrated due to globalization, and that business cycles and financial markets move in tandem due to bilateral trade, liberalization of financial markets, and increased mobility of capital.

The Spillovers Index sets itself apart from other methods widely used in the literature in several ways. First, it allows for the simultaneous measurement of static and dynamic spillovers across markets, with the help of spillovers tables and plots respectively. Second, the use of rolling windows in the spillover plots to measure the relative spillovers across time makes the need to incorporate dummy variables signifying structural break redundant, which increases the parsimony of the model. Rolling windows incorporate crisis and non-crisis periods endogenously, without forcing the switch from one regime to another by using dummy variables. In other words, in contrast with event study models, the time of the structural break is not enforced a priori, and the sample is not divided into sub-periods to signify the occurrence of an event. Third, the index enables quantification of spillovers from specific countries individually, providing a detailed insight into foreign and self-contributions to mean and volatility. Lastly, the application of the Spillovers Index is especially useful when one country cannot be termed as the center of crisis and a definitive period for crisis cannot be determined (Baur and Fry, 2009). Mierau and Mink (2013) argued that most models used in

available literature lack the capability of simultaneously considering multiple countries as the epicenter of crisis. However, the Spillovers Index is not only capable of capturing evolving crisis linkages, it also removes the need to identify the crisis trigger country (Baur and Fry, 2009).

While the Spillovers Index has its strengths, it also has the following weaknesses:

- The number of lags and sizes of rolling windows: These choices are arbitrary and are not substantiated with theoretical underpinning. Choice of appropriate lags is important as shorter lags may generate noisy estimates while longer lags may fail to capture important information available regarding spillovers in shorter windows.
- Non-parsimonious models: Inclusion of multiple time series and several lags for each variable under consideration results in an expanded system of equations, which may include statistically insignificant variables and lags. This may affect the reliability and consistency of results.
- The distribution of time series data: like many other econometric models, VAR models do not consider the distribution of time series and all the time series are assumed to be normally distributed. The relevant finance literature does not provide remedies to the problems associated with the VAR models; however, some implicit and explicit measures can be helpful in resolving these issues to some extent. For example, the parsimony of the model can be ensured by distributing larger samples into smaller groups, and near normal distribution of the time series can be achieved by including a larger sample size and log normal time series.

Just as the Spillovers Index allows quantification of conditional returns and volatility across markets, an international risk decomposition model developed by Akdogan (1996) also quantifies the integration and segmentation of the markets with the help of the CAPM Model. Akdogan (1996) used a variation of classic CAPM to decompose the risk of several countries relative to a regional or a global benchmark. The market segmentation ranking system designated a score to each of the countries included in the sample, reflecting their contribution to the overall systemic risk of world market index. The measure developed by Akdogan (1996) was rather static in nature and was therefore developed further by Barari (2004) to incorporate the time varying fluctuation in integration estimates. Barari (2004) not only used historic windows but also used moving average windows that allowed the static and time varying measurement of integration across regional and global markets.

However, this method can be differentiated from the Spillovers Index on the basis of the variables under consideration and their execution. While the former measures integration using multivariate regression, the latter not only focuses on providing an estimation of integration across markets through Spillovers tables, but it also allows for the measuring of dynamic volatility spillovers across markets using N-Variable VAR. Albeit, the purpose remains the same – to understand the relationship between markets and the impact of exogenous shocks from regional and global markets.

Another comparable method can be an application of a variation of MVGARCH, which allows for the estimation of the impact of multiple variables on a particular asset jointly. While MVGARCH is widely used in literature to estimate if there are spillovers across markets, the various models that come under MVGARCH only provide information on the statistical significance of the various coefficients included in the models without providing information on the relative contribution from each of the markets in the sample.

3.5 Methods Based on Frequency Domains and Time Scales

While all the methods discussed in the previous sections study the spillovers or interdependence between markets in a time domain, there are some methods that use frequency domains and time scales to examine spillovers across markets. Economists believe that the economic time series are complex incorporating different frequency cycles, and therefore, their dynamics can be better examined using frequency domains (Chan *et al.*, 2008).

The Wavelet Decomposition Analysis (WDA) is an innovative technique, borrowed primarily from engineering (Norsworthy *et al.*, 2000), which considers time and frequency domains simultaneously for the analysis of non-stationery time-series. WDA uses a mathematical transformation to convert the time series from time domain into frequency spectrum and takes into account the importance of time scales in demarcating different modes of behavior and dependence structures between variables. It enables the segregation of variables that change slowly from variables that change rapidly under given conditions, resulting in a cascade of time scales that impact on the decision-making process (Ramsey and Lampart, 1998). For example, the variables under consideration for long-term and short-term investments are different, and the variety of time scales, like hours, days, and months, prompt

different decisions by investors, reflecting their preferences. The processed signal reveals information on the number of frequencies and the amount of energy (volatility in the case of financial assets time series) contributed by each frequency (Gençay *et al.*, 2003). Hence, the WDA can facilitate the examining of the relationship between variables at different time scales without applying the model on multi-frequency data.

Bekiros and Marcellino (2013) claim that simultaneous consideration of temporal and frequency analysis allows better understanding of the complex dynamics of economic time series. The WDA allows the examination of data in smaller windows and enables researchers to identify peculiar traits of the data that might not be visible in larger windows. The technique is particularly useful in examining physical situations where the time series comprises discontinuities and sharp peaks, which are common attributes of financial time series. Though the technique is novel, it has not gained much popularity in the literature (Fernandez, 2004), and has not been used widely in finance and economics literature. The following linkages were explored with the help of WDA:

- Economic variable of consumption and income (Ramsey and Lampart, 1998).
- Systemic risk and time scales (Gençay *et al.*, 2003 and 2005; Galagedera and Maharaj, 2008).
- Financial markets (Fernandez, 2004; Lee, 2004; Castellanos *et al.*, 2011; Dajčman *et al.*, 2012).
- Currencies (Bekiros and Marcellino, 2013).

In a pioneering study, Ramsey and Lampart (1998) used wavelet analysis to empirically explore the importance of the time scale in the relationship between consumption and income. The authors found varied relationship between the two variables in different time scales; interest rates play a role in explaining the long run association between income and consumption while the impact of interest rates is negligible in the short run. Gençay *et al.* (2003, 2005) used wavelet decomposition to estimate systemic risk, represented by β in CAPM model. The authors argue that the frequency of returns impacts the estimates of β, and therefore it is appropriate to disintegrate the return series to reflect different timescales.

Studies like Handa *et al.* (1989) provided evidence that the use of different returns frequencies led to different β estimates for the same asset. To substantiate the argument, Gençay *et al.* (2003) used return series of Dell stocks at different frequencies and found that

the β increased as the frequency of the data was decreased (from daily to monthly). The application of WDA in the study revealed similar results, indicating stable β estimates for a medium to long-term time horizon, and rather instable beta estimates for a short time horizon, which is possible due to noise and presence of day traders and other market anomalies such as thin trading. Gençay *et al.* (2005) used a similar approach to compare the portfolio β estimates for stocks in the USA, the UK, and Germany at different time scales. The results were comparable to Gençay *et al.* (2003). Galagedera and Maharaj (2008) used the WDA to explore the dynamics between portfolio returns and co-skewness and co-kurtosis in 32 Australian industry portfolios. The study attempted to estimate β, systemic skewness, and systemic kurtosis in daily returns at different time scales and to exposit whether the association varies at different scales. The results signified that the risk is timescale dependent and that the systemic co-moments at higher timescales differ from the co-movements estimated at the daily frequency, suggesting that the investors need to consider systemic risk at appropriate timescales aligned with their investment time horizons.

Concerning interdependencies between financial markets, Fernandez (2004) examined the spillovers across eight regional indices using WDA during 1990 and 2002. The results revealed that the most energy, or the variation in returns, mainly exists in the short run and that it disperses at higher timescales. The author found bi-directional spillovers between all regional indices; however, the spillovers from other regions to the G7 countries varied at different timescales. The results of the study were robust even in the presence of asymmetric GARCH effects and autocorrelation in returns. Lee (2004) used WDA to evaluate the interdependencies between the USA and Korean from1995 to 2000, and found significant one-way spillovers from the USA to Korea. Rua and Nunes (2009) found frequency dependent co-movements between their chosen developed, which strengthened at a lower frequency, suggesting that the benefits of diversification in the long-run may be insignificant. In an attempt to evaluate the impact of the recent financial crisis on a large set of financial markets, Castellanos *et al.* (2011) used the WDA. The results highlighted that a limited number of countries were impacted by the innovations in the USA market in the first timescale, that is, two working days; however, the impact was significant at a higher timescale of eight days where all 21 indices included in the study were impacted.

Dajčman *et al.* (2012) performed the cross-correlations wavelet analysis across four developed and three developing European markets. The authors found high correlations between chosen markets at most of the timescales with the exception of the Slovakian market, and also found that the utmost co-movement between the returns of the candidate markets were evident at the highest scales (scale 5 and 6, corresponding dynamics over 32-64 and 64-128 days respectively). Moreover, the authors found that the impact of various financial crises on the developing stock markets are short lived and decayed in maximum 400 days. Dajčman (2013) conducted WDA across four developed European markets with the objectives to evaluate the impact of the financial crisis on return volatilities in Austria, Germany, France and the UK, to explore the lead-lag relationships between the chosen markets, and to understand whether the dynamics of different stock market returns are time-synchronized at particular time scales. The results highlighted that the recent financial crisis had a long-lasting impact on the four markets under consideration. Moreover, most volatility in the returns series was captured by the lowest timescales with two to eight days' horizon. The results also highlighted that the returns were more synchronized in the short-run, and that the returns in the UK led the returns in other European markets.

More recently, Bekiros and Marcellino (2013) explored the dynamics across widely traded currencies with the help of wavelet multi-resolution analysis. The authors first explored the linear, non-linear and spectral causality using appropriate mechanisms. The wavelet-based forecasting was used to examine predictability at different frequencies and at the aggregate level. The results highlighted that the foreign exchange markets demonstrated varied trends in different time horizons and that it is difficult to extract any "global causal behavior" (Ibid, p. 283). The wavelet forecasting mechanism was able to generate a relatively accurate forecast when tested out-of-sample and compared with random-walk analysis. The authors construed no particular lead-lag pattern amongst the time series; however, they suggested that a pattern may appear as traders with different investment time horizons may extract information relevant to their investment preferences.

The band spectrum approach allows for the disintegration of raw time series into frequencies and time scales. Each time horizon in the frequency domain is represented by a unique set of frequencies. Under the frequency domain analysis, the long-run is characterized

by the low frequencies and the short-run is signified by the high frequencies (Andersson, 2011). The band spectrum approach developed by Engle (1974) is borrowed from economics and involves a two-step estimation process (Andersson, 2011). First, all variables are converted to the frequency domain to identify respective time horizons. Second, coefficients for each time horizon are attained by regressing on a sub-set of frequencies rather than the entire raw time series.

Thoma (1992) used the band spectrum approach to understand the causality between money and income. The author attempted to evaluate whether the shocks in money at different frequencies affect the aggregate real activity and whether the money dependent movements in output are huddled at particular frequencies. The results revealed that frequency cycles greater than 18-months determine the causal relationship between outside money and economic activity.

Later, Thoma (1994) used a similar approach to analyze the two-way relationship between growth in money, inflation, and interest rates. The study disintegrated the raw economic time series into various frequencies to identify whether high or low frequencies ascertain the relationships between growth in money and inflation, and growth in money and nominal interest rates. Moreover, the study determined whether the movements caused in each of the above variables are of high or low frequency. The results highlighted that one to two years long cycles of money growth generate higher frequency cycles in inflation, and two discrete higher frequency cycles of changes in the nominal interest rates.

Erol and Balkan (1996) assessed the impact of money-related announcements on the USA financial markets between 1979 and 1982. The results highlighted that the liquidity factor is the main determinant of expectations in the short run in the initial period (1979–1982) and that long-run expectations regarding inflation seem more relevant in the later period of analysis (1982–1988). The results of these studies clearly explicate that the raw time series comprised of multiple frequencies and that the standard OLS estimations are incapable of capturing multiple time horizons with a time series, hence generating inaccurate specifications which have dire consequences for risk management as emphasized by Erol and Balkan (1996) and Andersson (2011).

While the use of the band spectrum approach is becoming more common in economics, the potential for its application to financial assets time series has also been recognized. As in the case of economic variables, the evaluation of financial market interdependencies using the band spectrum approach estimates the association between markets in the frequency domain, instead of the time domain. Chan *et al.* (2008) analyzed the mean spillovers between the Hong Kong and USA markets using the band spectrum regression technique during 1991 and 2006. The sample was classified into smaller windows to exclude the period of extreme volatility during the Asian Financial crisis. Coincidentally, the handover of Hong Kong from Britain to China was also considered a significant event during this period. The results indicated that the causality from Hong Kong to the USA market in the post-crisis and post-handover period were dependent on shorter cycles with higher frequencies, which may have been the result of speculation and short-term investments from investors. Also, the mean spillovers from the USA to Hong Kong increased in the post-hand-over period, due to increased trade.

The most important strength of the frequency domain analysis is its capacity to accommodate non-stationary data, whose presence in most econometric models induces a problem and requires special treatment (Ramsey and Lampart, 1998). Gençay *et al.* (2003) assert that besides being capable of identifying dynamic properties of a process at different timescales, WDA is useful in differentiating seasonalities and revealing structural breaks and volatility clusters, which are common in time series data. Accordingly, the need for data filtering for outliers and event studies to control for structural breaks becomes redundant (Andersson, 2011). The flexibility of the wavelet choice function enables the handling of discontinuities and rapid changes in the time series, without any special treatment. Unlike most econometric models, WDA does not require separate estimation of the long- and short-run relationship between the time series. Moreover, it prevents the need for separate computation of daily, weekly, fortnightly, and monthly returns, which result in the loss of information due to aggregation (Galagedera and Maharaj, 2008).

On the other hand, the method does have some limitations. The length of time scales is subjective. While the wavelet analysis provides information on the number of frequencies and energy contributed by each of the frequencies associated with the raw time series, it does

not give us the time information (where a particular frequency appears in the time domain). In the presence of a stationary signal, the information on the location of the frequency is irrelevant; however, in the case of a non-stationary financial time series, this information is pertinent (Norsworthy *et al.*, 2000).

3.6 Chapter Summary

In summary, it is evident that the significance and implications of the interdependence between markets has prompted tremendous academic interest since the 1970s and has therefore developed into a rapidly expanding body of literature surrounding the topic. Limitations associated with earlier methods, increased availability of data, and enhanced data analysis capabilities have all encouraged researchers to look for a variety of techniques that could quantify the association between markets accurately. This, in turn, has resulted in the evolution of theory and application of new techniques particularly in econometrics.

A comprehensive review of methods adopted in the relevant literature to identify and quantify interdependencies between markets was the focus of this chapter. As discussed earlier, the methods widely used for this purpose can be classified broadly into four categories: correlation estimates, univariate and multivariate statistical methods, ARCH/GARCH models, and Cointegration, VECM and VAR techniques. A detailed review on the prime technique used in this study to measure mean and volatility spillovers between Pakistan and its most active trade partners, the Spillovers Index, was provided under the VAR techniques. Lastly, lesser-known but novel techniques, such as the band spectrum approach and wavelength analysis, were also presented.

Each sub-section in this chapter presented a particular method and discussed its relative strengths and weakness. A large body of literature using different methods encompassing diverse markets in terms of their location (North and South America, Europe, and Asia), country classification (primarily developed and emerging markets), asset classes (stock, bond, currency, gold and oil markets), and spanning several crises (1987 Market Crash, Mexico Currency Crisis, Asian Financial Crisis, and Financial Crisis in 2008) was discussed.

The methods for quantifying interdependence have evolved considerably. Correlation estimates were the stepping-stone for measuring the association between markets, and most

studies published in the 1970s explained the association between markets based on these estimates. With the progression of time, the inherent limitations of these estimates became apparent, and subsequently, OLS estimations became the norm in measuring the association between markets. The ARCH/GARCH models developed in the 1980s, as well as their variations thereafter, changed the way interdependencies across markets were measured. During the same period, that is, the 1980s, cointegration techniques were formulated, followed by VECM and VAR techniques, which also evolved over the period. Spillovers tables and spillovers plots collectively referred to as the Spillovers Index, present static and dynamic measure of spillovers across markets over a certain period. Use of rolling windows negates the need to incorporate special measures for structural break and episodic heteroscedasticity.

Prime considerations in the estimation methods are the choice of distribution of returns, heteroscedasticity, structural breaks and regime switching, linear and non-linear associations, univariate, bivariate, and multivariate relationships, parsimony of the models, and choice of lags. The results of studies using a variety of countries, asset classes, significant economic events, and macroeconomic variables have produced results that are coherent in some cases and are contradictory in other cases. Researchers attribute the difference in results to the choice of data frequency, the markets included in the sample, and the methods used for estimation. It is therefore apparent that even with the availability of vast amount of literature, there are challenges to overcome in data analysis.

Chapters 2 and 3 provided a comprehensive survey of the vast amount of literature published on interdependence between financial markets. While chapter 2 focused on the relevant literature documenting evidence on interdependence between markets and the dynamism interdependence has exhibited over the last four decades, reasons and consequences of amplified cross-market interdependencies; the main theme of chapter 3 was to present the methods that are widely used in literature to quantify the interaction and association of markets.

The next chapter presents the data used for the study, elaborates on the characteristics of the time series under consideration, and treatment to filter and clean the data. Furthermore, the chapter also presents in detail the methods used to analyze the attributes of individual time series as well as estimate the association between them. The

employment of methods, such as, autocorrelations, stationarity, GARCH (p, q) to evaluate the impact of crisis, correlations, causality, multivariate OLS estimation and lastly, the Spillovers Index facilitates answering of all the research questions presented in chapter 1, section 1.2.

4 Data and Methodology

Given the nature of the research questions, this study is positivist in its philosophical stance and is deterministic and reductionist in nature (Creswell, 2009). The primary objective of this thesis is to identify and quantify the interaction between returns and volatility of financial markets, in particular between Pakistan and its key trade partners. The study hypothesizes that linkages exist between financial markets due to trade, geographical proximity, foreign investments and political relationships between countries. The study has a quantitative approach and employs time series analyses to answer the research questions. Time series analysis is the most appropriate technique to answer research questions in this study as it highlights the specific attributes of each market through descriptive statistics, allows analysis of behavior of markets over a period of time, and enables the deduction of reality regarding relationships between means and volatilities across chosen markets. Time series analysis also enables the identification of shocks at various points within the series and allows for the determination of the causes of the shocks. The results attained through time series analysis enhance the external validity of the results and make them easily generalizable to other markets. Various measures are taken to ensure the validity of the study and reliability of results.

The literature validates causality and interdependence between global financial markets as measured by various methods presented in chapter 3 (for example Eun and Shim, 1989; Becker *et al.* 1990; Hamao *et al.*, 1990; Aggarwal *et al.*, 1999; Ng, 2000 amongst many others). Although interdependence between markets relates to many parameters in the finance and economics disciplines, this study considers the definition provided by Bracker *et al.* (1999) as most appropriate to the context. Bracker *et al.* (1999) interpret the returns of two markets to be interdependent when the two markets exhibit "greater co-movement on the same day or (exhibit) a stronger lead/lag relationship across days". In this study, the interdependence between markets extends to co-movements of both returns and volatility.

As discussed in sections 2.2.1 and 2.3, numerous studies provide evidence of increasing interdependence between markets due to trade and geographical proximity (Lin *et al.* 1994; Calvo and Reinhart, 1996; Glick and Rose, 1999; Masih and Masih, 2001; Morana, 2008;), foreign investments (Sachs *et al.*, 1996; Dornbusch *et al.*, 2000; Cheung *et al.*, 2008),

and political relationships (Akdogan, 1992; Akdogan, 1996; Amihud and Wohl, 2004; Choudhry, 2004; Rigobon and Sack, 2005; Aggarwal *et al.*, 2010). Furthermore, studies like Roll (1989), Hamao *et al.* (1990), and King and Wadhwani (1990) provide evidence of amplified interdependence between financial markets during crisis.

In line with the existing literature, this study hypothesizes that cross-market interdependencies exist between the financial markets of frontier markets, particularly Pakistan and its key trade partners due to the above-mentioned widely-cited reasons. Use of various econometric tools to identify and quantify the interdependence between selected markets ensures construct validity. Moreover, the choice of a homogeneous and large sample size, appropriate data frequency and consideration of events, such as the recent financial crisis, which may affect the association between markets, warrants statistical construct validity.

Frontier markets take the center stage in this thesis, with Pakistan market being the market of primary interest. The selection of Pakistan as the principal market in the study is facilitated by various considerations as presented in section 1.3. Other markets included in the study are the USA, the UK, Germany, Singapore, Japan, China, Malaysia, India, Saudi Arabia, Kuwait and the UAE. Factors like bilateral trade and geographical proximity, cross-border foreign investments and political relationships validate the inclusion of these countries in the analysis. The following section briefly discusses the basis for the selection of countries in the sample and for hypothesizing the relationship between their financial markets.

4.1 Reasons for Increased Interdependence Between the Selected Markets

The determinants of interdependence between financial markets are discussed in detail in chapter 2, section 2.3. The selection of financial markets in this study is primarily based on the factors mentioned above. Meaningful results providing deeper insight into the interaction and interdependence between the markets under consideration are expected. The following sub-sections provide details of trade, geographical proximity, foreign investments and political relationships between Pakistan and countries of interest.

4.1.1 Bilateral Trade and Geographical Proximity

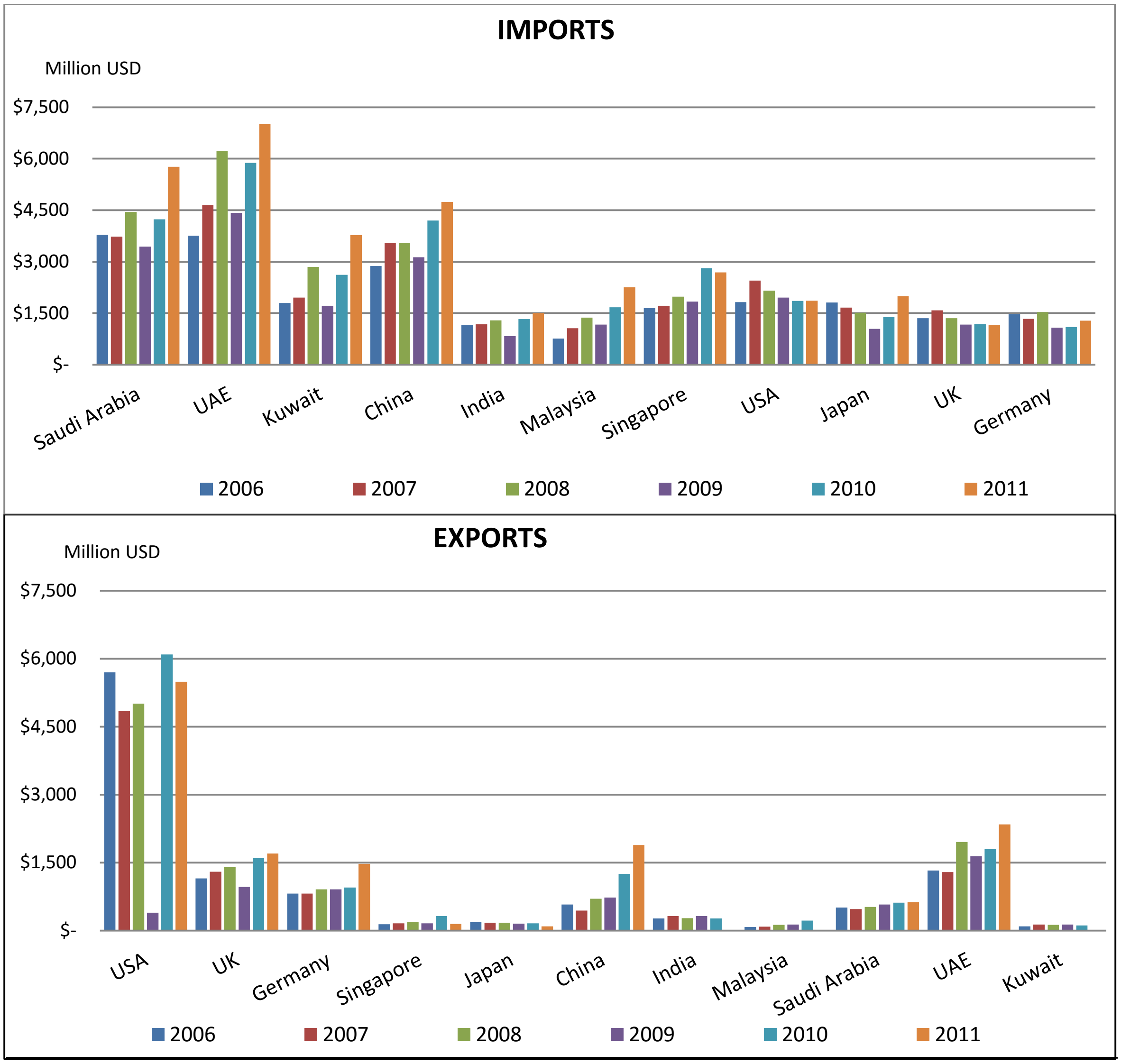
The finance literature provides evidence on positive relationships between trade, geographical proximity and market interdependence (for example Calvo and Reinhart, 1996; Glick and Rose, 1999; Masih and Masih, 2001; Morana, 2008; Johansson and Ljungwall, 2009). Paas and Kuusk (2012) term fundamental economic relationships between countries due to trade as "real links". Morana (2008) argues that financial integration is a product of economic integration and that regional economic factors play a major role in the co-movement of financial markets.

Subsequently, the eleven most active trade partners of Pakistan have been selected for the study. Moreover, most countries in the sample are situated in Asia and have close proximity to Pakistan, with India and China being its closest neighbors. The bilateral trade (in Millions USD) between Pakistan and its trade partners is presented in figures 4.1 and 4.2. As evident from these figures, the GCC countries (Saudi Arabia, Kuwait and the UAE) are the largest import partners of Pakistan due to oil imports. Table 4.1 lists the trade agreements between Pakistan and some of the countries included in the sample.

Figure 4.1 – Total Trade Volume Between Pakistan and its Most Active Trade Partners: 2006-2011

Source: State Bank of Pakistan, 2012b

Figure 4.2 – Imports and Exports Between Pakistan and its Trade Partners: 2006-2011[32]



Source: State Bank of Pakistan, 2012a

China is another large trade partner to Pakistan whereby Pakistan's exports to China have nearly tripled during 2006-2012 and the imports have also increased steadily. In the financial year 2011, China took the first slot in the list of top ten trade partners of Pakistan, followed by the UAE and the USA respectively (Dawn, 2012b). Recently, China and Pakistan signed a trade agreement, assigning each other as the most favored nation in trade and

[32] The trade volumes between Pakistan and the USA are largely due to textile exports (Hameed, 2013).

commerce (Dawn, 2013b). Pakistan's trade with India has also increased in recent times, the volume of imports from India being greater than the exports to India during 2006-2012.

In 2011, seven out of the ten top trading partners of Pakistan were from Asia (Dawn[33], 2012b), highlighting the importance of regional trade and geographical propinquity.

Table 4.1 – Various agreements Between Pakistan and Countries Included in the Study

Trade Agreements		
South Asia Free Trade Area	Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka	1985
Malaysia-Pakistan Closer Economic Partnership Agreement	Pakistan and Malaysia	2007
Pakistan-Gulf Cooperation Council Free Trade Agreement	Pakistan, Saudi Arabia, UAE, Oman, Qatar, Bahrain, Kuwait	2004
Free Trade Agreement in Goods and Investments	Pakistan and China	2006
Free Trade Agreement in Services	Pakistan and China	2007
Cooperation Agreement	Pakistan and EU	2004
Pakistan-Singapore Free Trade Agreement	Pakistan and Singapore	2005 (under negotiation)
Trade and Investment Framework Agreement	Pakistan and USA	2003
Other Agreements and Treaties		
Simla Agreement	Pakistan and India	1972
Non-Attack Agreement	Pakistan and India	1990
Kashmir Accord	Pakistan and India	1974
Central Treaty Organization (CENTO)	Pakistan, USA, UK, Turkey, Iraq, Iran	1955
South-East Asia Treaty Organization (SEATO)	Pakistan and USA	1955

Source: Hameed, 2013; Pakistan Ministry of Commerce, 2013; European Union, 2014; United States Institute of Peace, 2014; Geneva Academy of International Humanitarian Law and Human Rights, 2015; Asia Regional Integration Center, 2015

Besides trade, geographical proximity can also be of importance in enhancing interdependence between financial markets. In the sample, eight out of the eleven key trade partners of Pakistan are situated in Asia (Figure 4.3). As discussed in chapter 2, section 2.3,

[33] The Dawn Newspaper is a widely circulated English daily in Pakistan. Due to limited availability of government documents, newspaper articles are referred to in order to collect relevant information.

the finance literature provides ample evidence of inverse relationships between distance and interdependence between markets. Given the increased trade volume between the candidate countries and their geographical proximity to each other, greater interdependence between the financial markets of these countries is expected.

Figure 4.3 – Pakistan's Key Trade Partners Located in Asia

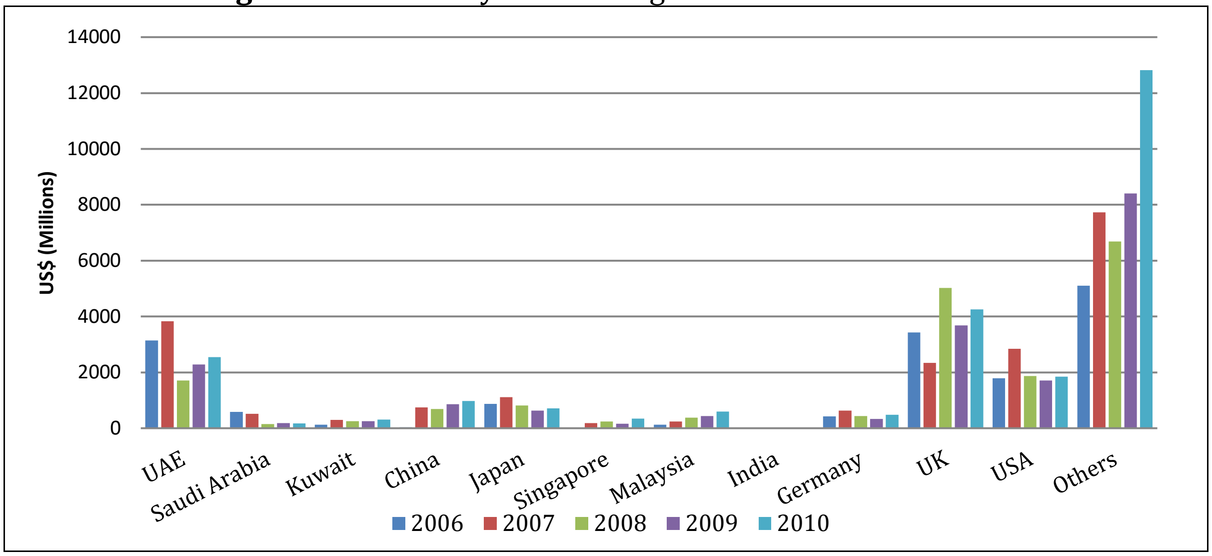
Source: World Atlas, 2015

4.1.2 Foreign Investment

Literature also provides evidence that foreign investment and capital inflows are important determinants of cross-market interdependencies (Sachs *et al.,* 1996; Dornbusch *et al.*, 2000). The countries included in the sample are also the largest foreign investors in Pakistan.

It is evident from figure 4.4 that the UK, the UAE and the USA are the key sources of foreign investment in Pakistan, followed by China, Japan, and Malaysia. It is also evident that India has limited foreign investment in Pakistan as, until recently, Indian companies and investors were not allowed to invest in Pakistan.

Figure 4.4 – Country-wise Foreign Investment in Pakistan



Source: State Bank of Pakistan, 2012

While foreign investments are generally seen as a positive sign for countries, there are some perils associated with foreign investments as well. Dornbusch *et al.* (2000) and Cheung *et al.* (2008) assert that foreign markets provide an opportunity to investors for portfolio diversification; however, in turbulent times, investors treat markets indiscriminately and pull out investments, even from markets which are not affected by the crisis, hence creating a spillover effect from one market to the other. Dornbusch *et al.* (2000) highlight that investors' decisions of pulling out investments from foreign markets may be related to lack of liquidity, whereby investors are forced to liquidate their positions in foreign markets to generate cash flow. The sell-off due to the nervousness of investors and/or liquidity constraints may lead to the transmission of shocks from one market to another. In the presence of evidence of enhanced spillovers during crisis in literature, this study hypothesizes greater mean and volatility spillovers from the markets included in the study to Pakistan and vice versa, especially during the recent financial crisis of 2008.

4.1.3 Political Relationships and Events

As suggested in the finance literature and presented in section 2.3.3, political relationships and events are also important determinants of increased interdependencies between markets. Akdogan (1992, 1996) and Aggarwal *et al.* (2010) found that some political events in the EU led to greater integration of European financial markets. Choudhry (2004) documented

volatility spillovers between countries with strained political relationships, like India and Pakistan, with pronounced spillovers from larger to smaller countries. Similarly, Amihud and Wohl (2004), Rigobon, and Sack (2005) suggest that political crises in one country may affect some macroeconomic variables and the capital markets in other countries.

In general, Pakistan shares friendly political relationship with China and other Asia-Pacific neighbors. However, India and Pakistan do not share a cordial relationship with each other; therefore, it is apparent from Table 4.1 that the agreements and accords between them are mostly related to peacekeeping efforts.

Specifically, Pakistan's relationship with the USA has experienced many ups and downs in the last six decades[34]. Despite having erratic political relationships, both countries are indispensable for each other as Pakistan is a strategic ally of the USA in its war on terror. Kronstadt, (2012) argues that political stability in Pakistan and its willingness to combat religious extremism is crucial for the USA. Beyond the USA, countries such as the UK and Germany are also a part of this alliance. The UK especially has contributed significantly to the operations in Afghanistan (Wallace and Phillips, 2009); hence, it is likely that the political associations between countries induce greater interdependence between markets included in the study.

Based on the evidence provided by the relevant literature regarding cross-market interdependencies due to the factors discussed above, greater interaction between Pakistan and other markets of interest is expected. Subsequently, this study aims to quantify the magnitude of mean and volatility spillovers across the markets under consideration.

4.2 Description of the Sample

Table 4.2 below presents the indices included in the sample along with the methodology used for calculating the relevant indices. Although the indices are calculated using different methods, it does not affect the analysis in the thesis, as all the analysis is performed on returns and volatility series. Table 4.3 provides further insight into the attributes of the candidate markets and classifies each of the countries into developed, emerging, or frontier markets,

[34] For a detailed review of political events between Pakistan and the USA, refer to Hameed (2013).

according to the MSCI classification (2012). HSBC Global Asset Management (2012) defines "emerging market" as a country with low-to-middle per capita income according to the World Bank criteria. In other words, emerging countries are in transition to becoming developed or industrialized countries, and are in the process of developing liquid equity, debt, and foreign exchange markets. On the other hand, Berger *et al.* (2011) define frontier markets as "smaller, less accessible, yet investable countries in the developing world" (p. 227). Standard and Poors (S&P) started to track frontier markets (excluding the GCC countries) in 1996, while the MSCI index representing frontier markets began in 2002 (Berger *et al.*, 2011).

It is apparent from the capital markets' details provided in Table 4.3 that Pakistan is the smallest and the USA is the largest market, as measured by market capitalization. It is interesting to note that the market capitalization of the Pakistan market is one-eighth of that of Saudi Arabia, which is the largest amongst the group of frontier countries in the sample. Similarly, Pakistan and the UAE have the lowest market capitalization to GDP ratio in the sample. With respect to the turnover ratio, China supersedes the USA and in terms of the number of listed companies, India surpasses the USA by nearly 25%. As might be expected, the number of listed companies in the frontier markets is much lower than the number of listed companies in developed and emerging markets, with Pakistan having the highest number of listed companies amongst frontier markets.

Table 4.2 - Countries in the Sample and Representative Indices

Country	Index	Symbol	Methodology***
Developed Markets			
USA	S&P 500 Index	SPX	Capitalization weighted
UK	FTSE 100 Index	FTSE	Capitalization weighted
Germany	Deutsche Borse AG German Stock Index	DAX	Total return
Japan	NIKKEI 225	NKY	Price-weighted
Singapore	Straits Times Index	STI	Capitalization weighted
Emerging Markets			
China**	Shanghai Stock Exchange B Share Index	SSEI	Capitalization weighted
Malaysia	FTSE Bursa Malaysia KLCI Index	KLCI	Capitalization weighted
India	BSE India Sensex 30 Index	BSE30	Capitalization weighted
Frontier Markets			
Pakistan	Karachi Stock Exchange 100	KSE100	Capitalization weighted
Saudi Arabia	Tadawul All Share Index	TDI	Capitalization weighted
UAE	AbuDhabi General Index	ADI	Capitalization weighted
Kuwait	Kuwait Stock Exchange General Index	KSEI	Price-weighted

Notes: **The China index tracks daily price performance of all B-shares listed on the Shanghai Stock Exchange that are available for investment by foreign investors.

***Information on the methodology employed is extracted from Bloomberg.com

Table 4.3– Details of the Capital Markets Included in the Study

	Number of Listed companies	Market Capitalization (million $)	Market Capitalization as %age of GDP	Turnover Ratio *	MSCI Country Classification
Developed Markets					
USA	4102	18,668,333	104.30%	124.6	Developed
UK	2179	3,019,467	118.70%	84	Developed
Germany	665	1,486,314	32.90%	91.8	Developed
Japan	3470	3,680,982	60.30%	99.8	Developed
Singapore	472	414,125	128.60%	43.3	Developed
Emerging Markets					
China	2494	3,697,376	46.30%	164.4	Emerging
Malaysia	921	476,340	137.20%	28.6	Emerging
India	5191	1,263,335	54.20%	54.6	Emerging
Frontier Markets					
Pakistan	573	43,676	15.60%	31.3	Frontier
Saudi Arabia	158	373,379	58.70%	144.4	Frontier
UAE	102	67,950	19.80%	25.3	Frontier
Kuwait	189	97,091	57.10%	23.2	Frontier

Source: The World Bank, 2012a; MSCI Country Classification, 2012

Notes: * According to the World Bank website, the turnover ratio is calculated by dividing total value of shares traded during the period by the average market capitalization for the period

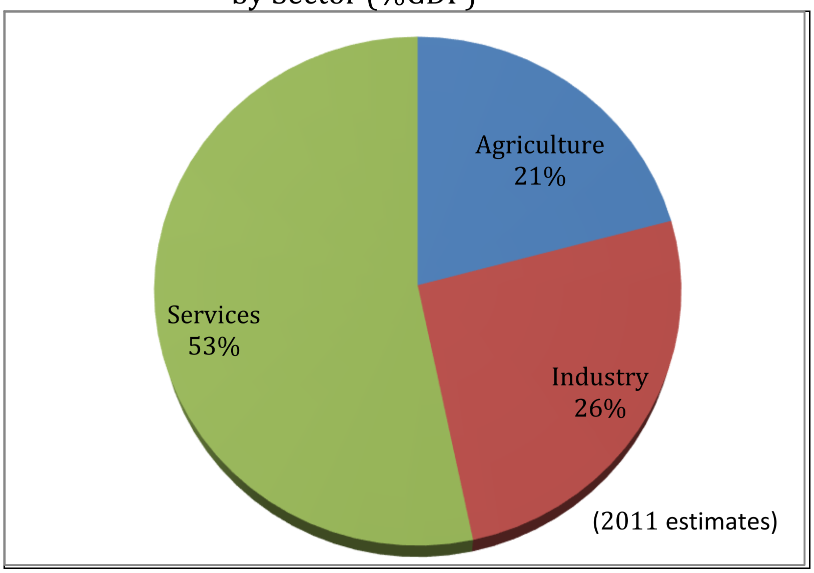
4.3 Background on Countries Included in the Study

The following sub-sections first provide a detailed background of Pakistan and its capital markets, followed by a brief background of the countries and capital markets included in the study. The section also highlights important events that suggest the significance of a particular country for Pakistan, and vice versa.

4.3.1 Pakistan

Pakistan is a South-Asian country, surrounded by China, India, Afghanistan, Iran and the Arabian Sea. Contrary to the belief that Pakistan's economy is agriculture based, it is primarily a service-based economy, as illustrated in Figure 4.5 below.

Figure 4.5 – Distribution of the Pakistani Economy by Sector (%GDP)



Source: CIA Factsheet, 2012

The Karachi Stock Exchange (KSE) is the largest and most liquid exchange among the three stock exchanges in the country. As of December 2012, the 573 listed companies on the KSE have a total market capitalization of more than US$40 billion (The World Bank, 2012a). Pakistan is the second largest market behind India in South Asia (Table 4.4) in terms of market capitalization.

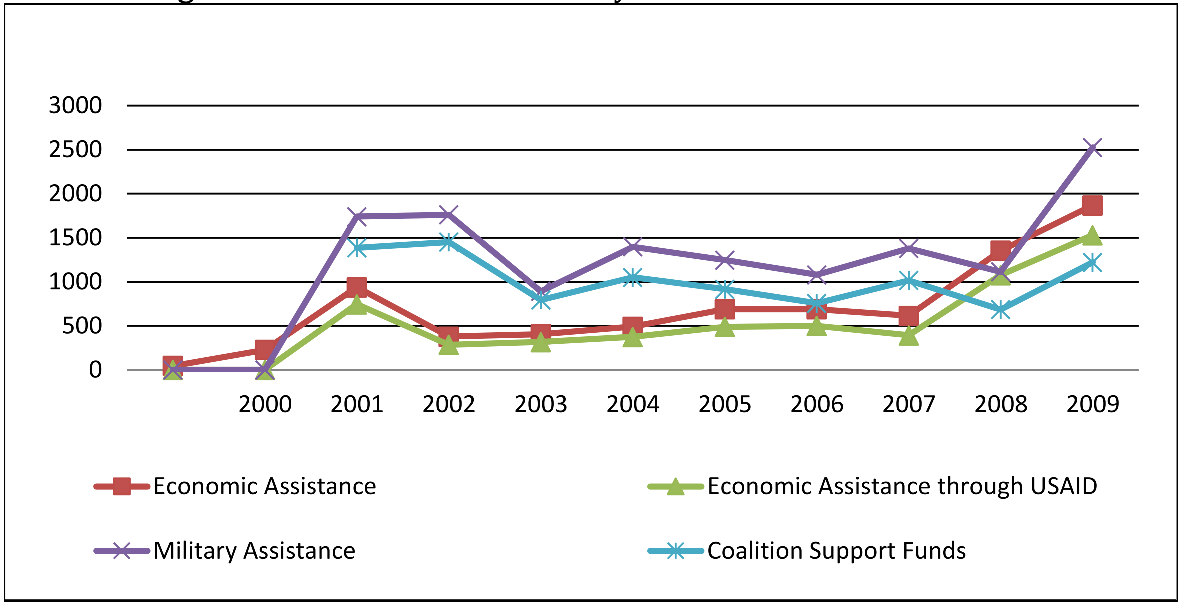
Table 4.4 - Market Capitalization of South-Asian Markets

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
	Billion US$										
India	131.01	279.09	387.85	553.07	818.88	1,819.10	645.48	1,179.24	1,615.86	1,015.37	1,263.36
Pakistan	10.20	16.58	29.00	45.94	45.52	70.26	23.49	33.24	38.17	32.76	43.68
Bangladesh	1.19	1.62	3.32	3.04	3.61	6.79	6.67	7.07	15.68	23.55	17.48
Sri Lanka	1.68	2.71	3.66	5.72	7.77	7.55	4.33	8.13	19.92	19.44	17.05
Note: Data for Nepal not available											

Source: The World Bank, 2012a

The KSE was established in 1948 soon after the inception of Pakistan (KSE, 2012). According to the KSE (2012) website, at the time of establishment, there were only five companies listed on the exchange, with a total paid-up capital of 37million Rupees. Besides the KSE100 index, there are three more indices on the KSE, namely the KSE30 index (free-float weighted), the KSE All Shares Index, and the KMI30 Index (free-float weighted Islamic Index). The KSE was liberalized in 1991 to attract foreign portfolio investment. For the large part of its existence, KSE remained neglected, due to political instability in the country. It received its due share of importance and popularity only in Pervez Musharraf's era in the late 1990s, whereby many reforms were introduced to encourage foreign portfolio investment (SECP, 2012). During the Musharraf era, many state-owned companies were privatized and foreign ownership was encouraged in order to improve the administration of companies and simultaneously increase their credibility (The Privatization Commission of Pakistan, 2011). Additionally, post-9/11, Pakistan received military and economic aid from the USA for being an ally in the war on terror (Figure 4.6). The progress of Pakistan's economy, foreign investments, and some attributes of the KSE over the years are presented in Figures 4.7 to 4.9.

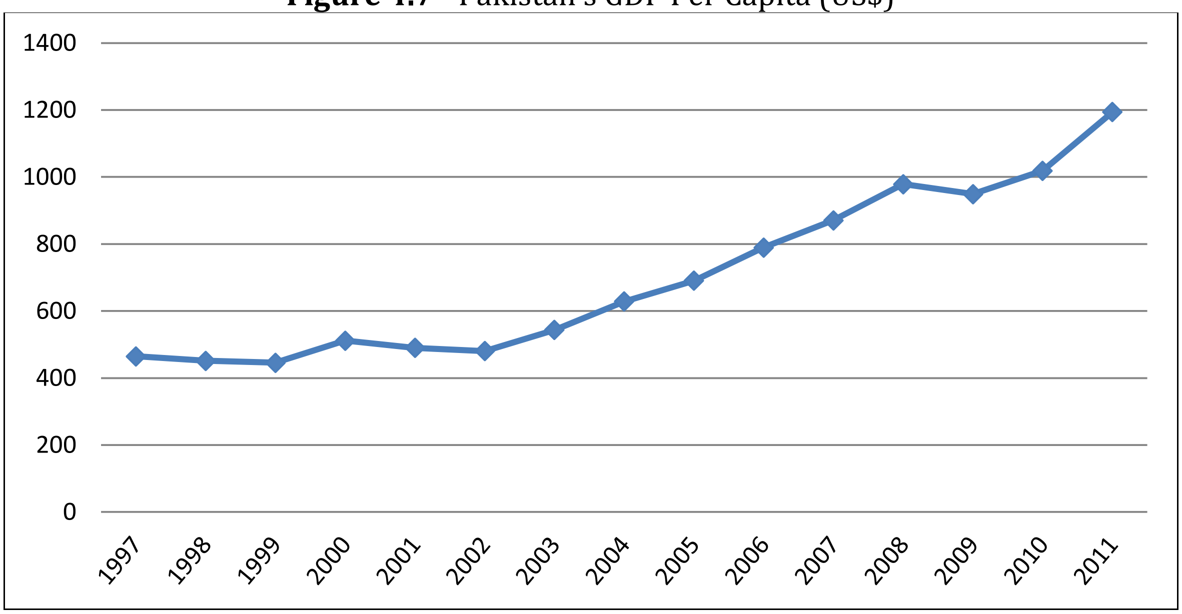
Figure 4.6 - Economic and Military Aid from the USA to Pakistan



Source: The Guardian, 2012

It is evident from figure 4.7 below that the economy of Pakistan grew phenomenally between 2000 and 2008, with GDP per capita recording an average growth rate of 10% between 2003 and 2008.

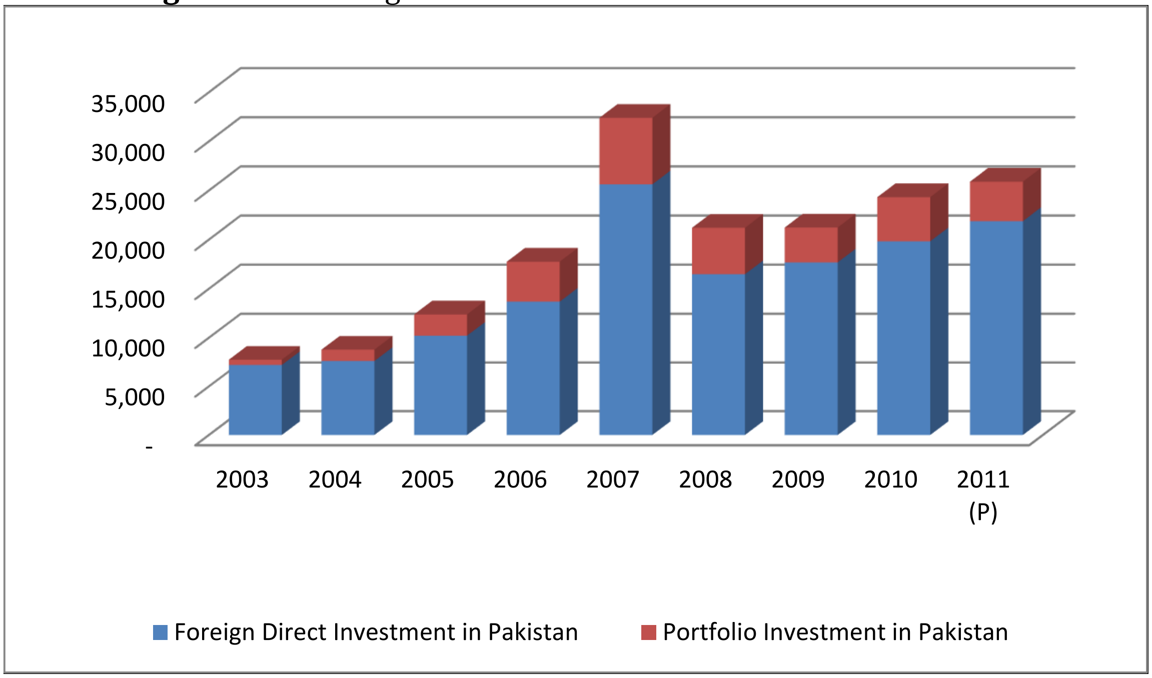
Figure 4.7 - Pakistan's GDP Per Capita (US$)



Source: The World Bank, 2012b

Total foreign investment steadily increased during 2005-2010 (Figure 4.8). While total foreign investment grew three-fold, from US$7,737 million in 2003 to nearly US$ 24,000 million in 2010, foreign portfolio investment grew more than seven times in the same period, from US$ 550 million in 2003 to US$4,500 million in 2010.

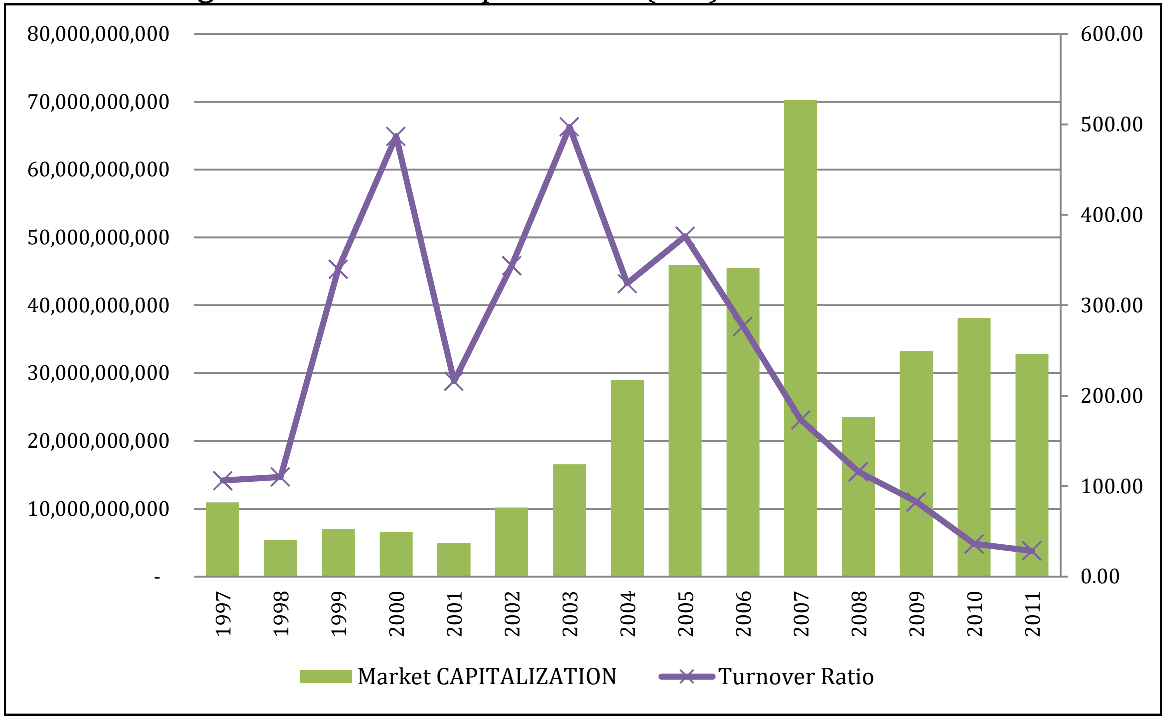
Figure 4.8 – Foreign Direct and Portfolio Investment in Pakistan



Source: State Bank of Pakistan, 2012a

Subsequently, the KSE experienced tremendous growth during these years, as apparent in Figure 4.9 below. The market capitalization and turnover ratio increased immensely until 2007, tapering off in 2008 and beyond. Although the reasons for the decline in market capitalization and turnover ratio remain unexplored, it seems that the financial crisis and some domestic events affected the market greatly and led to amplified volatility in the index.

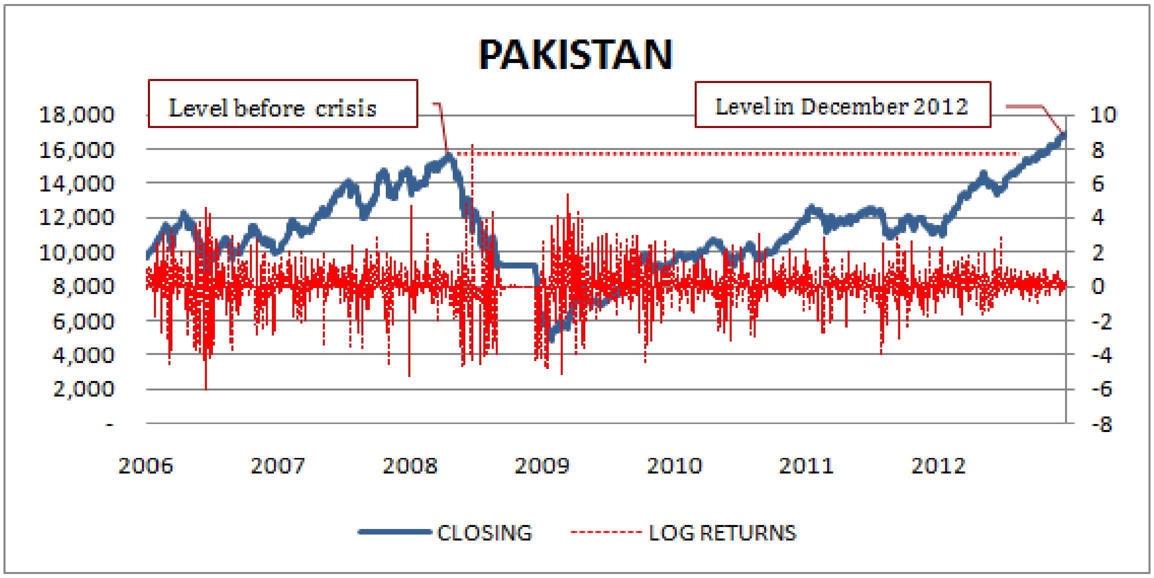
Figure 4.9 - Market Capitalization (US$) and Turnover Ratio



Source: The World Bank, 2012a

The KSE is inherently a volatile market as illustrated in figure 4.10. It has experienced many episodes of exaggerated volatility in the past. The KSE witnessed the worst crash in its history in 2008. After reaching the highest level of 15,670 points in April 2008, the value of the index started declining. A floor was put in place on 20 August 2008 to avoid the free-fall of the market, which restricted the exit of investors, both local and foreign. After the removal of the floor on 14 December 2008, the index fell below 5,000 points and more than 50% of the market capitalization was wiped off from the market within 15 trading sessions (Dawn, 2012a).

Figure 4.10 - Daily Closing and Returns of KSE (Jan 1996 to Dec 2012)



Source: Thomson Reuters

Note: The index level in 2012 has surpassed the level in the pre-crisis period. The floor in the latter half of 2008 is also evident.

The literature provides some evidence on the peculiar traits of Pakistan's market. For example, a study by Bekaert and Harvey (1997) provides evidence on the extreme volatility of the KSE. The authors examined the impact of liberalization on the volatility of nineteen emerging markets including Pakistan, and found that Pakistan was the only country in their sample that exhibited increased volatility after liberalization. Uppal (1998) found similar results, even after controlling for various macroeconomic variables. The market segmentation ranking developed by Bekaert (1995) suggested that smaller markets like Pakistan are quite segmented from the global markets; hence, these markets are attractive avenues for diversification.

Unlike some markets in the sample, the KSE did not suffer a structural break post-crisis and was clearly in recovery by 2010 (Figure 4.9). In December 2012, it was the only market in the sample then trading higher than its pre-crisis level, while the other recovered markets in the sample were trading close to the pre-crisis levels.

As suggested earlier, Pakistan is a frontier market and it was observed in chapter 1 (Figure 1.1), that the returns of the frontier markets have surpassed the returns from their developed and emerging counterparts in recent times. Subsequently, Pakistan may be a

lucrative option for investors who are willing to assume higher risk for higher returns. This may provide further impetus of Pakistan's potential as an avenue for diversification.

The descriptive statistics presented and discussed in chapter 5 clearly suggest that the Pakistan market exhibits traits of typical emerging/frontier markets, such as high volatility, negatively skewed returns and leptokurtosis. The reasons for extreme volatility in the KSE are not explored in the literature and therefore remain largely unknown. Aggarwal *et al.* (1999) and Harvey (1995) found that volatility in emerging markets is caused by domestic, political and economic events, and that global events have minimum impact on emerging markets. With respect to the KSE, it is yet to be examined whether the volatility in the KSE is caused by domestic factors or whether it is a product of regional and/or global spillovers. This study facilitates the understanding of the dynamics of returns and volatility in the KSE and provides an insight into the contributors to its volatility.

The following sub-sections briefly discuss relevant attributes of the other markets included in the sample.

4.3.2 Developed Markets

Five developed markets are included in the study, namely the USA, the UK, Germany, Japan and Singapore, based on their trade volumes with Pakistan. Some key attributes of these markets are presented in Table 4.5.

Table 4.5 - Key Indicators of Developed Markets Included in the Sample

	GDP per Capita (current US$)			**GDP Growth Rate (%age)**			**Ease of Doing Business (Rank)**			**Global Competitiveness Index (Rank)**		
	2010	**2011**	**2012**	**2010**	**2011**	**2012**	**2010**	**2011**	**2012**	**2010**	**2011**	**2012**
USA	48,358	49,855	51,755	2.5	1.8	2.8	5	5	4	2	4	5
UK	36,573	38,927	38,649	1.7	1.1	0.3	4	4	11	13	12	10
Germany	40,408	44,355	42,598	4.0	3.3	0.7	21	22	19	7	5	6
Japan	43,118	46,204	46,548	4.7	(0.5)	1.4	19	18	23	8	6	9
Singapore	46,570	52,871	54,007	15.2	6.1	2.5	1	1	1	3	3	2

Source: The Work Bank Indicators (2014); World Bank Group Doing Business (2011); World Economic Forum (2010 -2011).

The USA

The USA is considered the most influential market in the world, and literature provides evidence (refer to chapters 2 and 3) that the USA exports volatility to most of the markets around the world asymmetrically. Rapach *et al.* (2013) provide evidence that the lagged USA returns have substantial predictive power for many industrialized non-USA countries. Table 2.1 and Table 2.2 clearly indicate that both developed and emerging markets are impacted by volatility in the USA market.

The USA has maintained an average GDP per capita of approximately US$50,000 and an average GDP growth rate of 2.4% during 2010 and 2012. While it has maintained its ranking on the "Ease of Doing Business" index (EDB index), its ranking on the "Global Competitive Index" (GC index) has declined marginally.

The importance of the USA for Pakistan and vice versa is undeniable. Both the countries are trade partners, have foreign investments across borders, and inevitable political relationships. Dooley and Hutchison (2009), Bartram and Bodnar (2009), Korinek *et al.* (2010), and Baur (2012) suggest that extreme volatility in the USA financial market is transmitted heterogeneously to global financial markets, especially during crisis. While developed markets are greatly affected by the volatility in the USA market, the impact on emerging and frontier markets may not be as pronounced. Hon *et al.* (2004) documented that the European markets were greatly affected by the shocks in the USA market due to 9/11, and that these shocks persisted for three to six months after the crisis.

Given the influential role of the USA in deciding the fate of most markets around the world, the political relationship between Pakistan and the USA, and sizeable trade between the two countries, measurable returns and volatility spillovers are expected between the two countries.

The UK

The UK is the second largest economy in Europe after Germany and ranks ninth globally in terms of real GDP (CIA Fact Sheet, 2013). Although the UK is considered to have the most influence on the European markets, it has the lowest GDP per capita amongst the developed countries included in the study. The GDP growth rate has been 1% on average

during 2010 and 2012. The rankings on the GC index have improved, but a significant decline is apparent on the recent EDB index.

The UK capital markets are considered one of the most developed in the world. In the sample, the UK stands fourth both in terms of listed companies and market capitalization. In recent times, financial markets in the UK have experienced exaggerated volatilities, first due to the global financial crisis, and later due to the evolving Eurozone crisis (CIA Fact Sheet, 2013). The relevant literature documents returns and volatility spillovers from the UK to European markets (for example Dajčman, 2013). Moreover, with the formation and expansion of the EU, the financial and economic integration amongst developed and emerging European countries has increased progressively (Christiansen and Ranaldo, 2009; Büttner and Hayo, 2011). Additionally, causality and spillovers between the USA and the UK markets due to trade and investments are widely documented (for example Agmon, 1972; King and Wadhwani, 1990; Malliaris and Urrutia, 1992; Akdogan, 1992; Giannopoulos *et al.*, 2010; Christiansen and Ranaldo, 2009). Beyond trade and investments, both the USA and the UK have shared a cordial political relationship through formal and informal agreements, in the post-Second World War and the Cold War epochs (Wallace and Phillips, 2009). Especially in the post-9/11 era, the UK is a prime ally of the USA in its war on terror and its operations in Afghanistan. According to an estimate, the British contribution to operations in Afghanistan was approximately 80% of that of the USA contribution, with regard to population, and 110% with respect to GDP (Codner, 2008).

Among the countries included in the study, the UK had the highest FDI in Pakistan in 2010 (State Bank of Pakistan, 2012a), followed by the UAE and the USA respectively. In terms of bilateral trade with Pakistan, the trade volume is one third of the volume of trade between Pakistan and the UAE (figures 4.1 and 4.2). Exports to the UK marginally exceed imports from the UK (State Bank of Pakistan, 2012b). In terms of political relationship, Pakistan is a former British colony, a commonwealth country, and a close ally in the collective war against terror (Kronstadt, 2012). Given the importance of the UK within Europe and beyond, bilateral trade, foreign investments, and its political relationship with Pakistan, significant return and volatility spillovers are anticipated between the two countries.

Germany

The CIA factsheet (2013) classifies Germany as the largest European economy, fifth largest global economy and second most populous European country. Services comprise more than 70% of the German economy both in terms of GDP and labor force. The GDP per capita declined in 2012 and the GDP growth rate was less than 1% in the same year. It seems that Germany was affected by the Eurozone crisis, although the impact on Germany was not as severe as it was on the UK. Germany has maintained its ranking on both the EDB and GC indices.

As evident from Table 4.3, Germany's market capitalization is half that of the UK and the number of listed companies is much lower than that in the UK. In addition, the stock market capitalization as a percentage of GDP is much lower as compared to other developed and emerging markets. Siebert (2004) argues that the financial system in Germany is dominated by the banks, which contribute significantly in mobilizing savings, apportioning capital, overseeing corporate investment decisions, and providing risk management vehicles. This might explain the lower contribution of German stock markets to the overall financial system of Germany. However, Borges (2010) found that the German capital markets are amongst the most informationally efficient markets in Europe. During the ongoing Eurozone crisis and the turmoil in European markets in general, the German capital markets have exhibited resilience, even though Germany's close relationship with the UK market in the European countries is well documented in the literature (refer to table 2.1). For example, one of the earliest studies by Agmon (1972) found that a large portion of returns in the German market are a product of innovations in the USA, followed by innovations in the UK.

With respect to trade between Pakistan and Germany, the imports to Pakistan from Germany were significantly higher during most of the period of analysis. However, the trend reversed in 2011, whereby the exports exceeded imports by nearly 15%. There is noticeable FDI from Germany into Pakistan. On the other hand, foreign portfolio investments remained negligible during the period of analysis.

Based on the bilateral trade between the two countries, bi-directional returns and volatility spillovers are expected.

Japan

Japan is considered to be one of the most industrially and technologically advanced countries in the region and in the world, therefore its significance cannot be denied. Moreover, the Japan market is documented to be an influential market in the region and there is some evidence in the literature of volatility transmission from Japan to the other markets in Asia (For example Arestis *et al.*, 2005; Mukherjee and Bose, 2008; Hwang, 2012).

Japan experienced phenomenal growth during the 1960s, 1970s and 1980s; however, Japan's GDP growth has plummeted since the 1990s and the country experienced multiple recessions after the 2008 crisis (CIA Factsheet, 2013). The inflation rate in Japan was amongst the lowest in the world, (0.10%) according to CIA factsheet (2013) estimates. Between 2010 and 2012, the country has experienced a turbulent period. The tsunami and earthquake in March 2011 and the subsequent nuclear disaster has added to the misery and impaired the economy. The problems faced by the country in 2011 are apparent in the declining GDP per capita and negative GDP growth rate. The rankings on the EDB and GC indices have also been affected.

The capital markets in Japan are robust, deep, and liquid, and in the sample, Japan is ranked amongst the top five markets in terms of market capitalization. Japan supersedes the UK both in terms of number of listed companies and overall market capitalization.

The bilateral trade and foreign investments between Japan and Pakistan have seen a marginal increase during the sample period, whereby the imports to Pakistan have outweighed exports from Pakistan to Japan. FDI from Japan is more prominent as compared with portfolio investment, and stands at sixth place (2010) in the sample. The association between the Pakistan and Japan markets is not documented in the finance literature. However, given the trade, foreign investment estimates and geographical proximity between the two countries, significant association between returns and volatility is anticipated, which needs to be further explored and quantified.

Singapore

Singapore is another developed economy of Asia, with high GDP per capita and an extremely high GDP growth rate in last few years. The country has witnessed per capita GDP higher than most of the developed countries across the globe, whereby the real GDP growth

averaged 8.6% between 2004 and 2007 (CIA Factsheet, 2013). Since the economy is primarily dependent on exports of consumer electronics, information technology products, pharmaceuticals and the financial services sector, it experienced a contraction after the financial crisis and recession in Europe. However, the signs of recovery are evident as the GDP growth rate in 2010 was greater than 15%. In 2011 and 2012, Singapore's GDP per capita exceeded that of the USA. The country occupied the topmost spot on the EDB index for a straight three years and is in the top three on the GC index.

The Singaporean government aims to establish Singapore as the most important financial and high-tech hub in Asia. Accordingly, Singapore has one of the most healthy and liquid capital markets in the Asia-Pacific and it is a favored listing destination for many multinational companies. According to the Monetary Authority of Singapore (2012) approximately 40% of the listed companies in Singapore are foreign.

Bilateral trade between Pakistan and Singapore has increased by nearly 60% between 2006 and 2012, and Singapore's foreign investment in Pakistan has ballooned 27 times between 2006 and 2011. Imports to Pakistan far exceed the exports, and portfolio investment in Pakistan is a fraction in comparison to the FDI. Increasing trade and foreign investment, coupled with geographical proximity, is expected to contribute towards interdependence between Pakistan and Singapore.

4.3.3 Emerging Markets

Pretorius (2002, p.94) defines an emerging stock market as:

> "a stock market that is in transition, in other words increasing in size, activity, or level of sophistication. The term is usually defined by a number of parameters that attempt to assess a stock market's relative level of development and/or an economy's level of development."

In 2009, the upper limit of an emerging country's per capita income was US$12,195 (HSBC Global Asset Management, 2012).

The majority of the Asia-Pacific countries emerged stronger after the Asian financial crisis in the 1990s. According to the World Bank (2013b), increased domestic demand in these economies contributed around 40% to global growth in 2012, and it is anticipated that the region's contribution to the world economy will remain paramount in the near future,

resulting in increasing investor confidence and strengthening of financial markets. Moreover, the Asian economies have shown resilience to the recent financial crisis, have exhibited signs of recovery from the crisis since mid-2012 and are anticipated to show further improvement with the recovery of the developed markets (Ibid). This indicates the mounting importance of these economies, not only within the region but also in the global arena. While the importance of all the emerging Asian countries cannot be ignored, the focus of the study is Pakistan and its most active trade partners. Therefore, this study includes only three countries in the region: China, Malaysia, and India. Table 4.6 presents some key characteristics of the emerging markets included in the sample.

Table 4.6 - Key Indicators of Emerging Markets Included in the Sample

	GDP per Capita (current US$)			GDP Growth Rate (%age)			Ease of Doing Business (Rank)			Global Competitiveness Index (Rank)		
	2010	**2011**	**2012**	**2010**	**2011**	**2012**	**2010**	**2011**	**2012**	**2010**	**2011**	**2012**
China	4,433	5,447	6,093	10.4	9.3	7.7	78	79	99	29	27	26
India	1,417	1,540	1,503	10.3	6.6	4.7	135	134	131	49	51	56
Malaysia	8,754	10,058	10,432	7.4	5.1	5.6	23	21	8	24	26	21

Source: The Work Bank (2014); World Bank Group Doing Business (2011); World Economic Forum (2010-2011).

China

China has the largest bilateral trade volume with Pakistan, followed by Malaysia and India respectively (refer to Figure 4.1 and 4.2). In the Asian emerging economies, China experienced tremendous growth from 2005 to 2010, with a real GDP growth rate in the excess of average 8.5% (Eurostat, 2013). In most recent years the GDP per capita (US$) has exhibited a rising trend. The Chinese GDP growth rate in 2012 was 7.7%. Although lower than 2010 and 2011 estimates, it is still much higher than the majority of countries around the world. Since the 1980s, the Chinese government has opted for market-oriented economic development. As a result, the output quadrupled by 2000, making China the world's largest exporter by 2010, and the second-largest economy in the world after the USA in 2012 (CIA Factsheet, 2013). Although the country's ranking on EDB Index has deteriorated, it has maintained its position on the GC Index. This has led to the increased economic importance of China regionally and globally over this period; however, its impact on international financial markets remains relatively limited (Fujiwara and Takahashi, 2012).

During the years of rapid development beginning in the 1980s, the Chinese government has taken initiatives to develop capital markets, and the markets have witnessed expansion in terms of market capitalization, number of listed companies, investors and new investment products (China Securities Regulatory Commission, 2012). In May 2010, the total market capitalization of the two major Chinese exchanges, Shanghai and Shenzhen, reached 3.07 trillion US Dollars, ranking third globally after NYSE and NASDQ respectively (Zhou *et al.*, 2012). The Chinese capital markets are partially liberalized; foreign investors have limited access to the market, primarily through Chinese companies listed on foreign exchanges such as New York and Hong Kong. Subsequently, the impact of the financial crisis may have been limited (Valls, and Chuliá, 2012). However, in the last decade, some Chinese exchanges have developed products specifically for foreign investors, such as the Shanghai Stock Exchange B Share Index, which allows foreign investment in Chinese companies. As of April 2013, shares of 107 Chinese companies were open to foreign investments (CSRC, 2013).

Pakistan and China share cordial political relationships and have Free Trade Agreements (FTAs), which has benefitted Pakistan greatly. Both countries have granted each other "Most Favored Nation" status in 2013 (Dawn, 2013a). In 2013, both countries agreed to develop a master plan to develop Gwadar Port. The port will link China and Pakistan through road, rail, and fibre links and is expected to enhance economic ties between the two countries (Dawn, 2013b). Bilateral trade between China and Pakistan, increasing FDI in Pakistan from the Chinese government and investors, as well as close proximity can all contribute to interdependence between their capital markets.

Malaysia

Malaysia, commonly referred to as the "Tiger Cub Economy of Asia", has progressed in leaps and bounds in the post-Asian financial crisis era. Malaysia's GDP has increased at an average rate of 6% over the last ten years (The World Bank, 2012b). The GDP growth rate has declined by nearly 25% from 2010 to 2012; however, Malaysia has strengthened its position on the EDB and GC indices. According to 2008 estimates, more than 1000 multinational companies have set-up their regional headquarters in Malaysia (Securities Commission Malaysia, 2011). The country is ranked amongst the top 25 countries according to the GC

Index 2011-2012 and 2012–2013 rankings (World Economic Forum, 2013). The relatively superior economic performance of the country is complemented by flourishing capital markets. The market capitalization nearly tripled between 2008 and 2012 (The World Bank, 2012a), and is expected to further double in the next decade (Securities Commission Malaysia, 2011).

The activity in the Malaysian capital markets can be deduced from the highest market capitalization to GDP ratio in our sample, approximately 137%, followed by Singapore, the UK and the USA respectively (refer to Table 4.3). A study by Galagedera (2012) on the relative performance of 22 developed and 18 emerging markets for a period spanning from 2003 to 2010 revealed Malaysia as the best performing market in the complete sample. This gives a good idea of the potential of the Malaysian capital markets for international diversification.

With respect to the relationship between Malaysia and Pakistan, the volume of bilateral trade between the two countries has increased by 170% between 2006 and 2011 (State Bank of Pakistan, 2012b). Foreign investment from Malaysia into Pakistan is significantly lower than most of the countries in the sample; however, it has increased five-fold since 2006. Both the countries have signed several trade and political agreements (Ministry of Foreign Affairs Malaysia, 2013). Given the volume of bilateral trade, steadily increasing foreign investment, geographical proximity and diplomatic relations, interdependence and some degree of spillovers is anticipated between the financial markets of the two countries.

India

The growing importance of India globally, regionally, and especially as Pakistan's closest neighbor cannot be underestimated. Both countries share an approximately 3,000-kilometer-long active border, which is considered to be one of the most dangerous borders between foes (Walker, 2011). The political relationship between India and Pakistan has not been cordial since the partition in 1947. Both countries have fought three major wars (1948, 1965, and 1971) and two minor wars in 1965 and 1999 post-partition (Hussain, 2003). The unresolved issue of disputed Kashmir also has been a bone of contention between the two

countries ever since. Both countries possess nuclear weapons and often blame each other for terrorist activities taking place within their borders.

Just like China, the Indian economy has experience rapid growth in the last decade with an average real GDP growth rate of 8% (The World Bank, 2012b). The growth rate has experienced deceleration from 2010 onwards. Although the country has maintained its position on EDB index, its global competitiveness has been declining gradually.

While China has allowed limited access to foreign investors, India has encouraged foreign direct and portfolio investments. The number of cross listings to encourage foreign investments has increased substantially over the years, with 164 Indian companies getting listed on foreign exchanges by the end of 2006 (Sarkissian and Schill, 2010). As indicated by Table 4.3, the number of domestically listed companies in 2012 surpassed even the USA market. The market capitalization is second to China and is one of the highest amongst the Asian emerging economies.

There are several indices in India; however, this study uses data from the BSE SENSEX 30 index, comprised of the 30 largest companies listed on the exchange based on their free-float and liquidity (Bloomberg, 2012). With enhanced international trade and more foreign companies and investors investing in India, and vice versa, the market has become fairly integrated with the foreign markets (Dicle *et al.*, 2010).

The bilateral trade and foreign investment between India and Pakistan have been limited in the last decade (Figures 4.1, 4.2, 4.3); however, it is anticipated that geographical proximity and the generally strained political relationship between the neighbors might lead to volatility spillovers across borders, which has already been documented in literature. Choudhry (2004) found that news from India affects both returns and volatility in Pakistan, while innovations in Pakistan only affect Indian returns. Mukherjee and Mishra (2010) found evidence of bidirectional contemporaneous returns spillover between India and Pakistan and statistically significant bi-directional volatility spillovers between them. Similarly, Abbas *et al.,* (2013) also documented pronounced volatility spillovers from larger (India) to smaller market (Pakistan). Though these studies provide some evidence on the interdependence between both markets, the phenomenon needs further examination.

4.3.4 Frontier Markets

Frontier markets are small yet investable markets in developing countries. The MSCI Frontier Markets index was established in December 2007 to represent such markets. According to the MSCI (2012) classification, Saudi Arabia, the UAE, Kuwait, and Pakistan are frontier countries[35]. Table 4.7 presents some key indicators of the frontier markets included in the sample.

Table 4.7 - Key Indicators of Frontier Markets Included in the Sample

	GDP per Capita (current US$)			**GDP Growth Rate (%age)**			**Ease of Doing Business (Rank)**			**Global Competitiveness Index (Rank)**		
	2010	**2011**	**2012**	**2010**	**2011**	**2012**	**2010**	**2011**	**2012**	**2010**	**2011**	**2012**
Pakistan	1,023	1,213	1,255	1.6	2.8	4.0	75	83	106	101	123	118
Saudi Arabia	19,327	24,116	25,946	7.4	8.6	5.8	12	11	22	28	21	17
UAE	34,049	39,058	41,692	1.7	3.9	4.4	37	40	26	23	25	27
Kuwait	40,091	51,397	56,367	(2.4)	6.3	6.2	69	74	101	39	35	34

Source: Work Bank Indicators (2014); World Bank Group Doing Business (2011); World Economic Forum (2010 - 2011)

Three GCC markets, namely Saudi Arabia, Kuwait and the UAE, included in the study are major oil exporters to the world and to Pakistan (State Bank of Pakistan, 2012b; CIA Factsheet, 2012). The importance of GCC markets for Pakistan and otherwise cannot be ignored, for various reasons. Cheng et al (2010) argue that from the macroeconomic standpoint, six major oil-producing countries are located in this region, with Saudi Arabia being the largest oil-producing and -exporting country. Moreover, Hamilton (2003) provides evidence that since the Second World War, major global recessions were a result of either oil price shocks or political instability in or originating from the Middle East and North Africa.

According to Cheng et al (2010, p. 414),

> "high (negative) financial market returns have been realized while the MENA area has experienced major political and security instability, the War on Terror, civil war in Iraq, deteriorating relations with the West, and turmoil in world oil markets".

[35] Pakistan was a part of the MSCI emerging markets index between 1997 and 2008. It was downgraded to frontier market status in December 2008 because of a prolonged floor on the capital market from August to December 2008.

Rigobon and Sack (2005) also provide evidence that political crisis in this region has a negative impact on the USA equity markets. While there are some studies exploring the relationships between the GCC and the global markets, especially the USA, (for example Abraham *et al.*, 2001; Hammoudeh and Choi, 2006; Bley and Chen, 2006; Hammoudeh and Li, 2008; Demirer, 2013), the relationships between Pakistan and the GCC countries remain largely unexplored. The methods employed in the study quantify the interaction between Pakistan and the selected GCC markets of Saudi Arabia, the UAE and Kuwait.

Saudi Arabia

Saudi Arabia is an important trade partner of Pakistan, whereby the total volume of trade stands third in the list after the UAE and the USA respectively. While the exports from Pakistan to Saudi Arabia are relatively small, the oil imports from Saudi Arabia are second only to those to the UAE. Saudi Arabia is considered to be the most influential country in the region and a critical global market, for multiple reasons. First, it is the largest oil supplier in the world (USA Energy Information Administration, 2012). Second, along with other oil exporting countries, it is the fourth largest USA debt holder after China, Japan and the Caribbean banking sector (USA Department of Treasury, 2013). Third, after the invasion of Kuwait by Iraq in the 1990s, the USA has made Saudi Arabia its strategic base in the Middle East (Blanchard, 2012). Lastly, being the custodian of the sacred places of Islam, it holds a strong position in the Muslim world (Blanchard, 2012).

The Saudi GDP growth rate averaged 7.3% between 2010 and 2012. During this period, the GDP per capita exhibited a steady increase due to increasing oil prices. Though Saudi Arabia's 2012 ranking on the EDB index deteriorated 10 places from 2010, it fared better on the GC index.

Concerning financial markets in the GCC and the Arab world in general, Saudi Arabia's capital market "Tadawul" is the largest in terms of market capitalization, followed by the UAE, Qatar and Kuwait respectively (The World Bank, 2009).

The present Tadawul exchange was officially established as a joint stock company in 2007 and represents fifteen economic sectors (Tadawul, 2013). The market has experienced episodes of exaggerated volatility in 2006 and 2008. In 2006, the Saudi capital market

experienced a fall of 62% from its historical peak in February 2006, and the market once again lost 57% of its value in 2008 (World Bank, 2009). The shocks from the Saudi markets were transmitted to the neighboring GCC countries, which is evident from figures 5.1 and 5.3 in Chapter 5. While the volatility evident in Tadawul in 2006 is mainly associated with domestic events; the volatility in 2008 and thereafter seems to be a product of the global financial crisis and the real estate crisis in the UAE. In contrast to the evidence regarding the domestic volatility in emerging markets, the GCC markets are affected by global events (Hammoudeh and Li, 2008), which can understandably be associated with the countries being major oil suppliers in the world.

With respect to the interdependence between the Saudi Arabia and Pakistan capital markets, it is anticipated that due to a large oil-based trade volume, the indices may exhibit spillovers during turbulent times and otherwise.

The UAE

Within the GCC countries, the UAE has experienced phenomenal growth during the last decade. Once being an oil-based economy, it has now been successfully diversified into a balanced economy (Abu Dhabi Council for Economic Development, 2009) where the GDP comprises of 43% services sector and 56% industry (CIA Factsheet, 2013). The average GDP growth rate was 3.3% between 2010 and 2012. The GDP per capita was nearly 65% higher than that of Saudi Arabia at an average, during the same period. The UAE in general, and the Emirate of Dubai in particular, has attracted a lot of foreign investment in recent times. Though there are some restrictions in terms of foreign investment in land and capital markets, the investment environment has generally been conducive and is expected to evolve favorably (USA Department of State, 2013b). The country is ranked relatively high on the EDB index and is appreciated for introducing reforms to facilitate starting a new business (The World Bank, 2013a). Moreover, the country has maintained its ranking on the GC index. The UAE has the largest total trade volume with Pakistan, which is largely a reflection of oil imports by Pakistan. In the sample, the UAE is the third largest foreign investor in Pakistan after the UK and the USA (Figure 4.8). The two countries also share cordial political relationships.

The Abu Dhabi Securities Market (ADSM) represents the UAE capital market in this study. The ADSM was established on 15 November 2000 and the index represents all the companies listed on the exchange (Abu Dhabi Securities Exchange, 2013). Table 4.3 clearly indicates that the market capitalization and the number of listed companies are much lower than the Saudi and Kuwait markets. The index demonstrated extreme volatility in 2006 following the downfall of the Saudi markets. However, in 2009, the UAE market transmitted volatility to the rest of the GCC markets. The UAE market suffered turmoil at the end of 2009, when the Dubai government asked for the restructuring of its debt from its international lenders. This also sent jitters to financial markets around the world (Hazelton, 2009), suggesting the UAE's increasing importance in the global arena.

Besides Pakistan's oil imports from the UAE, a large number of Pakistani investors have invested in real estate in the country. Pakistani investors conducted nearly 18% of property transactions in Dubai, worth US$ 1.25 billion, during the first six months of 2014 (Khaleej Times, 2014). Given the level of trade and foreign investment, the two markets are expected to have quantifiable spillovers during tranquil and turbulent times.

Kuwait

Kuwait stands second in the chosen frontier markets in terms of market capitalization. Kuwait is primarily an oil producing country with 8% of world proven oil reserves (USA Department of State, 2013a). Approximately 50% of its GDP is dependent on petroleum; however, not much has been done to diversify the economy (CIA Factsheet, 2013).

Kuwait has the highest GDP per capita (US$) among the frontier markets included in the sample. Kuwait's GDP per capita was nearly twice that of Saudi Arabia between 2010 and 2012. Kuwait GDP surpassed the GDP of the UAE by an average 28% from 2010 to 2012. The country experienced a negative growth rate in 2010, but was able to maintain the growth rate above 6% during 2011 and 2012. While its ranking on the EDB index declined tremendously from 2010 to 2012, it was able to maintain its position on the GC index during this period. Kuwait was ranked fiftieth on the FDI index developed by Groh and Wich (2012), while Saudi Arabia ranked forty-eighth out of 127 countries. Interestingly, other GCC countries like the UAE, Qatar, Bahrain and Oman ranked higher than these two countries (Groh and Wich, 2012).

While Kuwait ranks behind most of its GCC counterparts in terms of overall competitiveness, it has been ahead in developing its financial markets. The Kuwait Stock Exchange is the oldest and fourth largest stock exchange in the Arab world (USA Department of State, 2013a), and has been ahead of its regional counterparts in many aspects. It was the first Arab exchange to start the electronic trading system in 1995, and derivatives like futures and options started trading in 2003 and 2005 respectively (Kuwait Stock Exchange, 2013). It is apparent from Table 4.3 that the market capitalization is less, but the number of listed companies is more when compared to Saudi Arabia.

Given the substantial trade volume between Pakistan and Kuwait, which primarily comprises oil imports by Pakistan, some sizeable returns and volatility spillovers are expected between Pakistan and Kuwait.

This section provided a detailed background of the developments in the Pakistan financial market, followed by a brief background of the other markets selected for the study, classified as developed, emerging and frontier markets. Moreover, this section provided a justification for the inclusion of these countries in the sample by briefly discussing their economic, regional and political association with Pakistan. It is anticipated that bilateral trade, geographical proximity, cross-border foreign investments and political relationships between Pakistan and the countries under consideration would result in greater association and interaction between the conditional returns and volatility of these markets.

4.4 Data Description

Reliability and credibility of data sources is essential to ensure the reliability of the results and the conclusions drawn. Zellner and Sankar (2005) suggest that the application of econometrics tools is dependent on the quality of economic data. However, no econometric technique can overcome any deficiency in the data. Subsequently, the data in this study was extracted from credible sources such as *Thomson Reuters* and stock exchange websites. While daily closing prices in most of the candidate markets for the period January 2006 to December 2012 were extracted from *Thomson Reuters,* the daily data for Saudi Arabia and Kuwait was downloaded from their respective stock exchange websites.

The data included in the analysis is non-synchronous. Non-synchronous data arises due to the illiquidity of the instruments or due to timing effects when the instruments under consideration trade in different time zones or have different trading schedules (Holton, 2014). Markets included in the sample not only trade in different time zones (see table 4.8 below), but also have different weekends. Saudi Arabia, Kuwait and the UAE have Friday and Saturday as the weekend, whilst other markets in the sample, such as the USA and the UK, have Saturday and Sunday as the weekend.

Table 4.8 – Time Zones of Countries Included in the Sample

Country	Time Zone	Country	Time Zone
Pakistan	GMT + 5	India	GMT + 5:30
Saudi Arabia	GMT + 3	USA*	GMT - 4
Kuwait	GMT + 3	UK*	GMT + 0
UAE	GMT + 4	Germany*	GMT + 1
China	GMT + 8	Japan	GMT + 9
Malaysia	GMT + 8	Singapore	GMT + 8

*Countries observe Daylight Saving Times

Trading hours in some markets overlap, such as in the USA and the UK, and in the UK and Pakistan, India, and China. However, the trading hours in the USA do not overlap with the trading hours in most of the Asian markets. Different trading time zones, summarized in table 4.8 and trading days lead to the problem of non-synchronous data. Limitations associated with non-synchronous data plague most of the studies that consider daily data for the markets trading in different time zones. Non-synchronous data presents some challenges to data analysis, and leads to biased and inefficient results (Brown and Warner, 1985). Studies like Longin and Solnik, 1995; Aggarwal *et al.*, 1999; Ng, 2000 and many others use low frequency weekly data to solve this problem. Martens and Poon (2001) argue that the use of low frequency data for analysis resolves the problem of missing data and non-synchronous trading to some extent; however, it results in a smaller sample size, loss of information and inefficient models. Furthermore, smaller sample sizes are insufficient for multivariate analysis (Martens and Poon, 2001; Ng and Lam, 2006).

In the quest for precision in estimates, Martens and Poon (2001) estimated correlations and covariances between the USA, France and the UK, using both synchronous and synchronized data. For synchronous data, the authors used the prices at 16:00 hours

(London time) when all the markets included in their sample were trading. To synchronize non-synchronous data, Martens and Poon (2001) used Riskmetrics (1996) and the Burns *et al.* (1998) methods. The correlations and covariance estimates generated using these methods were different from the ones estimated from synchronous data. The results of the study highlight that even the use of sophisticated methods may not be able to generate precise correlations and covariance estimates if the data is non-synchronized.

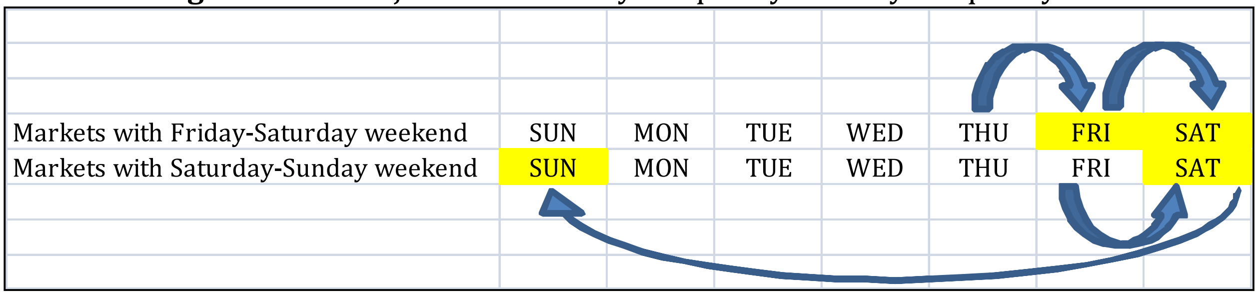
Some authors like Boudoukh, *et al.* (1994) argue that the use of non-synchronous data results in increased autocorrelations between returns, and that comparing prices at different times may result in inaccurate outcomes. Kadlec and Patterson (1999); Atchison *et al.* (1987) and Lo and MacKinlay (1990) estimated the autocorrelations induced by non-synchronous data, and found that a fraction of autocorrelations can be explained by non-synchronous data, also stating that there are other reasons, such as market-maker inventory control, transactions costs, time-varying expected returns and market inefficiency, that possibly result in higher autocorrelation estimates. Brown and Warner (1985) assert that using appropriate measures can minimize the impact of autocorrelations induced by non-synchronous data. However, Ap Gwilym and Sutcliffe (2012) emphasize that the problems with non-synchronous data are more pronounced in high frequency intraday data.

Given the problems associated with non-synchronous data, appropriate measures are considered in this study to deal with non-synchronity, so that unbiased and efficient results can be produced. In this study, it is impossible to adopt the treatment suggested by Martens and Poon (2001) and to take the prices of the time when all the markets are trading, as some of the markets in the sample, such as Pakistan and the USA, do not have overlapping trading hours. Accordingly, in a trade-off between resolving the problem of non-synchronous data versus capturing maximum information with a larger sample size, more emphasis is given to the latter, and appropriate treatment for missing data points is adopted. The use of a larger sample size, which is more than twice the sample size suggested by Ng and Lam (2006) for multivariate models, has resulted in the additional benefits of near-normal distribution.

As suggested by Cheung and Ng (1992); Haniffa and Pok (2010); Kenett *et al.* (2012) and Lui *et al.* (1998) and as illustrated in Figure 4.11, 5-day frequency is adjusted to 7-day frequency to ensure that all the indices possess a value on a particular day. To ensure this, the

missing data on a particular day (for example a weekend) is replaced by the previous day's data.

Figure 4.11 – Adjustment of 5-day Frequency to 7-day Frequency



It is assumed that no new information is incorporated in the prices when the markets are closed and therefore, the prices remain unchanged; hence, it is appropriate to use the previous day's closing prices (Haniffa and Pok, 2010). Although the study employs commonly used methods to minimize the impact of the non-synchronous data, autocorrelations are also estimated for each time series to ensure that the presence of some non-synchronity in the data does not affect the results significantly.

The period of analysis for this thesis is from January 2006 to December 2012. With a 7-day data frequency, the total number of observations is expected to be 2,555. However, the 7-year time series for the markets under consideration includes days with common holidays across the entire sample; hence, the total number of observations in the sample for each market is 2,544 as illustrated in Table 4.9.

Table 4.9 – Calculation for Number of Observations in Each Time Series

Total number of observations	365 x 7	2,555
Common holidays across the sample		11
Sample size		2,544

The data has been analyzed using Eviews-7, and the returns and volatility Spillovers Indices are produced using RATS. The help of a computer programmer is sought to adapt the Spillovers Index programme to the data used in the study.

The closing prices of the indices are considered in local currency and nominal log returns have been calculated for each index. Huyghebaert and Wang (2010), and Lucey and Muckley (2011) suggest that the conversion of indices in US Dollars and nominal returns into

real returns is appropriate when the findings are to extricate the effect of foreign exchange and stock market dynamics. Many studies in the literature (for example Agmon, 1972; Ng, 2000) convert nominal returns into US Dollar returns in order to incorporate the perspective of US investors; however, this is not the objective of this thesis. The findings of the study are useful for international investors who are prone to exchange rate risks while investing in foreign markets.

4.4.1 Returns Time Series

As suggested earlier, time series analysis is most appropriate for a longitudinal examination of the interdependence between candidate financial markets. Time series analysis entails data collection for one or more variables at different but regular periods, and categorizes the characteristics of the change process (Gottman *et al.*, 1969). To initiate the analysis, log returns are calculated for each financial market. In empirical finance, it is common to calculate log returns as compared to simple returns. Hudson and Gregoriou (2014) suggest that if the asset prices follow a Brownian motion, then its log returns are expected to be normally distributed (Hudson and Gregoriou, 2014).

The finance literature provides evidence that the financial time series are non-normal; however, the use of log returns and a large sample size resolve this limitation to a certain extent. The most important assumption associated with log returns is the independent and identical distribution (*iid*) of successive log returns. The consideration of the *iid* invokes the application of the Central Limit Theorem, which suggests that the standardized sum of *n iid* random variables is approximately normally distributed (Wijst and Wijst, 2013). The Central Limit Theorem holds especially when the *n* is sufficiently large and the approximation improves as the sample size grows. Given these considerations, one can assume that the log returns are approximately normally distributed. Gottman *et al.* (1969) argue that a sufficiently long time series has the capability of smoothing undesirable effects that may affect the results. Similarly, Brown and Warner (1985) suggest that the non-normality of returns does not have a major impact in event studies, provided the sample is large.

Chion and Veliz C. (2008) evaluated the daily returns of selected Latin American markets and found that the daily returns series depart from normality; however, the empirical

distribution of longer returns series is close to normal distribution. Peiró (1994) evaluated the empirical distribution of the daily returns of six developed markets, namely the USA, the UK, Japan, France, Germany and Spain. The author found that the distributions of daily returns series ($n \approx 1300$ observations) of the markets under consideration closely resemble the Student's *t*-distribution. Aparicio and Estrada (2001) also found similar results for thirteen European markets, whereby the authors found the distributions of returns series to be Student's *t*-distributed. While the findings of Peiró (1994) and Aparicio and Estrada (2001) are of significance, it is to be noted that with greater degrees of freedom (measured by $n-1$), the Student's *t*-distribution approximates to normal distribution. Hence, it is appropriate to assume that given the large size of the sample, the log return series are approximately normally distributed.

In this study, log returns for each market are calculated by taking the natural log of the price on time t divided by the price on time $t-1$, and the result is then multiplied by 100 to convert the returns into percentage. The calculation of returns is denoted as

$$R_{i,t} = log\ (P_{i,t} / P_{i,t-1}) * 100$$

where $P_{i,t}$ is the daily closing price of the stock market index of country i on day t. The process is repeated for each index to generate twelve individual return series that are assumed to be approximately normally distributed.

4.4.2 Range-based Volatility

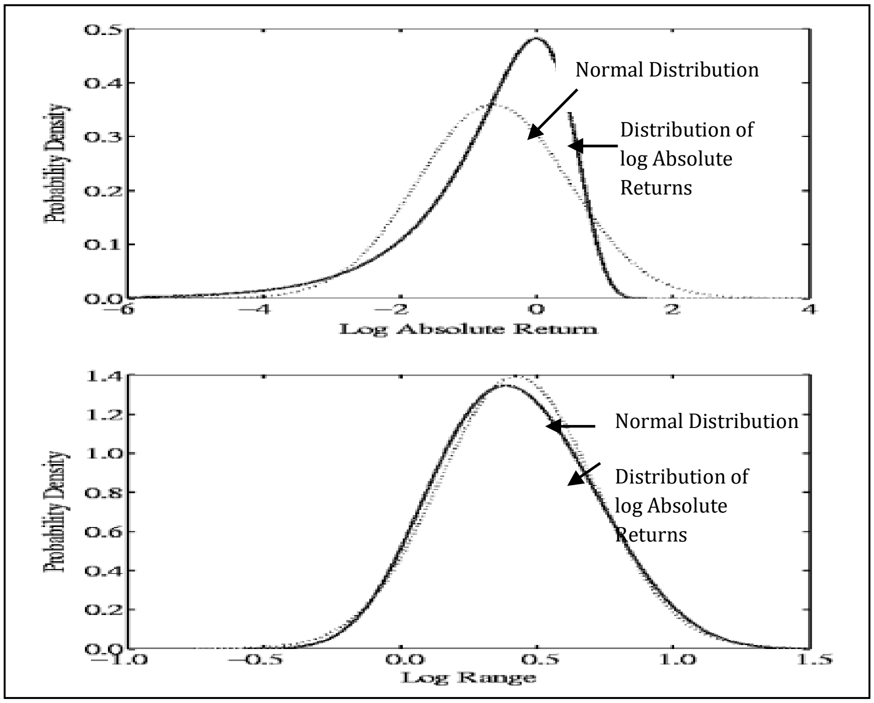
Besides calculating log returns for each market, range-based volatility is calculated for each time series, which considers the "difference between highest and lowest log security prices over a fixed sampling interval" (Alizadeh *et al.*, 2002, p. 1048). Range-based volatility estimation allows for the efficient inference of volatility during a period (Parkinson, 1980; Alizadeh *et al.*, 2002; Poon, 2005; Jacob and Vipul, 2008). The use of range-based volatility assumes that returns exhibit Brownian motion with zero drift in a particular measurement interval (Molnár, 2012). Alizadeh *et al.* (2002) and Brandt and Jones, (2005) argue that volatility is stationary in discrete periods, and that it is conditionally normal and exhibits mean reversion across periods.

Alizadeh *et al.* (2002) argue that the traditional methods of volatility estimation, like log absolute or squared returns, are flawed due to the non-Gaussian measurement error, resulting in inefficient volatility estimates. In their study, Alizadeh *et al.* (2002) provide evidence that the log range is approximately Gaussian, and that log range is less noisy than log absolute or squared returns with respect to measurement errors. Figure 4.12 clearly demonstrates that the log absolute returns are non-Gaussian; on the other hand, log range returns are approximately Gaussian.

Andersen and Bollerslev (1998), Alizadeh *et al.* (2002), and Brandt and Diebold (2006) highlight at least three apparent advantages of range-based volatility, which are listed below:

1. Simple calculation.
2. Unbiased and efficient estimates in comparison with traditional measures, such as squared or absolute daily returns.
3. Resilient to some microstructure noise, for instance, bid-ask bounce.
4. Besides these commonly discussed benefits of range-based volatility estimates, Molnár (2012) provides evidence that the use of range-based volatility estimators using high and low data provides closer estimates to those provided by the models based on high frequency intraday data. Jacob and Vipul (2008) assert that range-based data is capable of capturing the time-varying volatility relatively more precisely. Brandt and Jones (2005) suggest that the benefits of range-based volatility are especially evident when there is greater fluctuation in volatility. Range-based volatility models are useful for univariate as well as multivariate applications. Brandt and Diebold (2006) extended the range-based volatility measure to the multivariate analysis of covariance between foreign exchange markets. The results of the study confirmed the superiority of range-based volatility over realized volatility.

Figure 4.12 - Distribution of Log Range Returns



Source: Alizadeh, Brandt, and Diebold (2002)

In line with Diebold and Yilmaz (2012), this study uses range-based volatility estimates. The method assumes that the periodical returns are normally distributed with conditional volatility σ_t. The method of estimating range-based volatility in Diebold and Yilmaz (2012) is rooted in the extreme volatility model presented in Parkinson (1980). It is widely accepted in literature that security prices depict the Brownian motion and therefore follow a random walk. If the security prices follow a random walk, then the measurement of diffusion is of importance. The diffusion constant represents the random walk of prices and is the same as the variance of returns, traditionally estimated through closing prices. In other words, the diffusion constant measures how far the security prices can go in a random walk. Parkinson (1980, p. 64) asserts,

> "The true variance of the rate of return of a common stock over a unit time interval is precisely the diffusion constant of the underlying random walk".

According to Parkinson (1980), if a particle is at x_0 at $t=0$ and at x_1 at $t=1$, then the D is the variance of displacement and can be denoted by $x_0 - x_1$ after a particular measurement interval. The diffusion constant σ_x^2 for *ith* interval can be presented as:

$$\sigma_x^2 = \frac{1}{n-1}\sum_{i=1}^{n}(d_i - \bar{d})^2$$

For range-based volatility measures, rather than just estimating x(n), where n = 0,1, 2,….., a difference between maximum and minimum values is estimated during each measurement interval. In this scenario, the diffusion constant $\sigma_{i,t}^2$ can be estimated as:

$$\sigma_{i,t}^2 = 0.361[ln(P_{i,t}^{max} - P_{i,t}^{min})]^2$$

where P_{it}^{max} and P_{it}^{min} is the highest price and lowest price in market *i* on day *t* respectively[36]. Parkinson (1980) measured the diffusion constant with the traditional as well as range-based method using high and low intraday prices, and found that the latter provides an estimate that is up to 5 times superior to the former and less noisy than the traditional estimates of volatility.

In this study, the number of data points using closing prices is 2,544; however, the number of data points doubles when both high and low intraday prices are considered for the calculation of range-based volatility. Molnár (2012, p.22) suggests that using a large sample size allows for the consideration of "almost perfectly continuous Brownian motion", and that having a reasonably large number of trading days enhances the precision of estimates of the distributions of range-based volatility estimators. Molnár (2012) ranked the various range-based volatility models and found that the Garman–Klass (1980) volatility estimator using opening, closing, high and low prices provides the best estimates. Parkinson (1980) provides the second best estimates, according to Molnár (2012), but due to the unavailability of opening and closing prices for all the indices for the complete period of analysis, the second best-performing model is chosen to calculate range-based volatility for this study.

4.5 Methods Employed for Data Analysis

The data analysis includes several steps and accordingly relevant tools are employed for the purpose. Figure 4.13 summarizes all the research questions in shaded boxes matching with the specific techniques used in the study to answer them.

[36] For the full derivation see Parkinson (1980).

The data analysis begins by exploring stylized facts about each time series using descriptive statistics of returns and volatility. Tests for serial correlations are employed to evaluate whether there is a correlation between successive returns of individual time series. The estimation of autocorrelations provides an insight into the efficiency of the markets under consideration and it is also important in relation to the non-synchronity in the data. The analysis then proceeds to examine the stationarity of return series as a prerequisite for Granger Causality and Ordinary Least Squares (OLS) estimation to evaluate the association between the chosen markets. Further analysis is performed by using a modified version of GARCH (p, q), whereby the impact of the financial crisis on the markets of interest is captured through inclusion of a dummy variable CRISIS that assumes a value of one during the crisis and a value of zero otherwise.

The association and interaction between markets is evaluated through correlations, Granger Causality, OLS estimation and finally through the Spillovers Index. The initial steps in the analysis provide a foundation for further analysis and quantification of mean and volatility spillovers across the markets under consideration. The cross-market conditional mean and volatility spillovers are estimated with the help of the Spillovers Indices, embracing a VAR method, which was presented by Diebold and Yilmaz (2012). The Spillovers Indices are used in multiple ways with appropriate robustness diagnosis to ensure validity and reliability of results.

The following sub-sections provide details of the techniques used for data analysis to meet the objective of the thesis.

Figure 4.13 - Research Questions and Techniques Employed

What is the direction, duration, and magnitude of conditional returns and volatility spillovers between Pakistan and its most active trade partners?

4.5.1 Methods Employed to Evaluate the Characteristics of Individual Time Series

The data analysis involves simplistic techniques and complex econometric tools to produce meaningful and comprehendible results. This section discusses these techniques and provides justification for their employment. The results are presented in chapter 5.

4.5.1.1 Plots for Closing Prices, Log Returns and Volatility

The analysis begins with the most primitive method of plotting returns and volatility. Closing prices of all the indices are plotted on graphs, along with their log returns, and are presented in chapter 5. The closing prices are plotted on the left axis while the log returns are plotted on the right axis. The range-based volatility exhibited by each index under consideration is also illustrated in chapter 5. These graphs provide an insight into the trend exhibited by the indices, their returns, and volatility during the period of analysis.

4.5.1.2 Descriptive Statistics for Returns and Volatility Estimates

Average daily returns, standard deviation, skewness, kurtosis, and Jarque-Bera statistic for normality for each of the indices is estimated. Similar estimates are generated for the range-based volatility estimates using intraday high and low prices of indices. The use of range-based volatility estimates is found to be appropriate due to the reasons discussed in Section 4.4.2.

4.5.1.3 Autocorrelations

The characteristics of the time series under consideration are examined further using autocorrelation estimates. Autocorrelation arises when the successive errors in a time series are correlated. In this case, the correlations are not between the explanatory variables, but they are between two observations within the same time series at different time lags. Thus, autocorrelation occurs when the errors for period *t* are correlated with the errors for period *t-1*. The autocorrelation can be positive or negative. Positive correlations indicate that positive changes are followed by positive changes, and negative changes by negative changes. On the other hand, negative correlations refer to the state in which positive changes are followed by negative changes, and vice versa.

Presence of autocorrelations is also indicative of the informational efficiency of the markets. If the future returns are dependent on past values, then this indicates that the future returns can be predicted using models like GARCH and its variations. Beyond providing an insight into the informational efficiency of the markets, the test for autocorrelations in the log returns is also appropriate when the data is non-synchronous. Boudoukh *et al.* (1994) suggest that non-synchronous data induces autocorrelations; however, Kadlec and Patterson (1999); Atchison *et al.* (1987) and Lo and MacKinlay (1990) argue that the autocorrelations induced by non-synchronous data are marginal. Given, this study employs non-synchronous data, it is appropriate to evaluate whether the log returns of all the candidate markets exhibit serial correlation.

The autocorrelation of a return series R_i at lag k is estimated by Ljung-Box *Q-statistics* and their associated *p-values*. The *Q-statistic* tests the null hypothesis that there is no autocorrelation up to lag k, and is defined as:

$$Q_{LB} = n\,(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k}$$

where n is the number of observation, $\hat{\rho}$ is the sample autocorrelation at lag k, and h is the number of lags being tested. The choice of lags for autocorrelation estimates in this study is based on the 7-day frequency of data[37].

4.5.1.4 Unit Root Test

Stationarity of the time series is a pre-requisite for most econometric methods. The time series data comprises of three components: trend (increasing or decreasing), seasonal and cyclical patterns and irregular variations. Each of these components introduces some noise in the data series, which if left untreated can lead to inconclusive and inconsistent results leading to inaccurate forecasts. Methods like data transformation (For example utilizing the log of the time series) and calculating differenced time series facilitates the removal of trend and seasonality in the data (detrending), leaving behind only noise associated with irregular variations.

[37] Although autocorrelations are estimated for both seven and thirty lags, the results for seven lags are reported due to the relative parsimony of the model. Moreover, the results for seven and thirty lags do not vary greatly, making it appropriate to report results with fewer lags.

Detrended data is assumed to be stationary. Shocks to a stationary time series are temporary, the values revert back to their long-term constant mean and their variance is constant (Asteriou and Hall, 2007). Unit root tests are necessary to confirm the stationarity of the time series.

Accordingly, it is important to evaluate whether each index is integrated to order one, *I (1)* or, in other words, whether the return series of each index is stationary. It is essential that the time series is evaluated for stationarity; otherwise, the results of the proceeding tests may be inaccurate. For example, lack of stationarity of variables in OLS estimation would lead to high estimates of R^2 and *t*-ratios, although the relationship between the underlying variables may be lacking. Hence it is important to use appropriate tests to first evaluate the time series for stationarity or unit root, and if the unit root exists, then the non-stationary time series should be differenced once, or more than once, until it becomes stationary (Asteriou and Hall, 2007). The first difference of a time series denotes the sequence of changes from current to following period. If R_t denotes the value of the time series R at period t, then the first difference of R at period t is equal to $R_t - R_{t-1}$.

The study uses the ADF test and PP test to analyze the stationarity of the time series. Dickey and Fuller (1979, 1981) formulated a procedure to test non-stationarity or unit root in a time series. The test was based on the simple AR(1) model:

$$R_t = \phi R_{t-1} + \varepsilon_t$$

The Dickey Fuller (DF) test enables examination if $\phi = 1$, and hypothesizes that the time series has a unit root or is non-stationary and that the unit root can be tested using three alternative regression equations:

$$\Delta R_t = \gamma R_{t-1} + \varepsilon_t$$

$$\Delta R_t = \alpha_0 + \gamma R_{t-1} + \varepsilon_t$$

$$\Delta R_t = \alpha_0 + a_2 t + \gamma R_{t-1} + \varepsilon_t$$

where $\gamma = (\phi - 1)$. The first equation does not contain a constant and if $\gamma = 0$ then R_t follows random walk. The second model contains a constant, while the third one allows a non-deterministic time trend in the model. A simple *t*-test is then done to evaluate the coefficient of the lagged variable R_{t-1}. Since the test does not have a conventional *t*-distribution, MacKinnon (1991) suggested appropriate critical values, as summarized in Table 4.10.

Table 4.10 – MacKinnon (1991) Critical Values for DF, ADF and PP Unit Root Tests

Model	1%	5%	10%
$\Delta R_{t-1} = \gamma R_{t-1} + \varepsilon_t$	-2.56	-1.94	-1.62
$\Delta R_{t-1} = \alpha_0 + \gamma R_{t-1} + \varepsilon_t$	-3.43	-2.86	-2.57
$\Delta R_{t-1} = \alpha_0 + a_2 t\gamma + R_{t-1} + \varepsilon_t$	-3.96	-3.41	-3.13
Standard critical values	-2.33	-1.65	-1.28

Source: MacKinnon (1991)

If the DF test value is smaller than the critical value, then the null of unit root is rejected and R_t is considered to be the stationary process.

Dickey and Fuller (1981) augmented the above test to eliminate the problem of high-order autocorrelation by including extra lagged terms of the dependent variable. The ADF test can be written in the following three forms:

$$\Delta R_t = \gamma R_{t-1} + \sum_{i=1}^{p} \beta i \, \Delta R_{t-1} + \varepsilon_t$$

$$\Delta R_t = \alpha_0 + \gamma R_{t-1} + \sum_{i=1}^{p} \beta i \, \Delta R_{t-1} + \varepsilon_t$$

$$\Delta R_t = \alpha_0 + \gamma R_{t-1} + a_2 t + \sum_{i=1}^{p} \beta i \, \Delta R_{t-1} + \varepsilon_t$$

The difference between the three models is the presence of deterministic elements α_0 and a_2t. The critical values for the ADF test are the same as for DF test (Table 4.10). The choice of lags is an important concern in DF and ADF tests. The most appropriate lag is the one in which the Akaike Information Criterion (AIC) or Schwartz Information Criterion (SIC) is minimized. Liew (2004) suggests that the AIC and the final prediction error (FPE) are superior to the other criteria, when the sample size is small ($n \leq 60$). However, in general, the performance of the criteria is greatly improved in large sample sizes. In this study, the choice of lags is based on the SIC values.

Besides ADF, the PP test is also used in the study for testing unit roots in the time series under consideration. The PP test statistics can be termed as generalization of Dickey-

Fuller statistics and is a non-parametric test. While the ADF test assumes normal distribution of the time series under consideration, the PP test does not make any assumption regarding the distribution of the time series, and instead applies the Newey West bandwidth to smoothen the time series.

Asteriou and Hall (2007) present several advantages of the PP test over the ADF test. First, the PP tests are robust to general forms of heteroscedasticity in the error term u_t. Second, the PP test uses an autocorrelation-consistent covariance matrix estimator, making it robust to serial correlation. While ADF corrects for high order serial correlation by including lagged terms, PP makes correction to the *t*-statistic of the coefficient from the AR(1) regression to account for serial correlation in the error term. Lastly, unlike the ADF test, the specification of lag length is not required. The asymptotic distribution of both ADF and PP *t*-statistic are the same; therefore, the critical values presented by MacKinnon (1991) are applicable on both of the tests. Similar to the ADF test, the PP test can include a constant, a constant and a trend, or neither, in the test regression.

The use of multiple unit root tests is important, as the size and power of these tests vary. The size of the test refers to the significance level, which relates to the probability of committing a Type-1 error, and the power of the test refers to the probability of rejecting the null hypothesis when it is false (Gujrati and Porter, 2009). The DF tests are sensitive to the way they are conducted (a constant, a constant and a trend, or neither). Also, these tests are less powerful, as they have a tendency of accepting the null of unit root more often. Given these limitations, it is appropriate to employ multiple unit root tests to ensure the reliability of the outcome.

4.5.1.5 Modified GARCH (p, q) with Gaussian Distribution

A clear understanding and estimation of dynamic volatility in financial markets is very important for asset pricing, risk management, and portfolio management. Finance literature provides ample evidence that volatility in any market can be a product of volatility in other markets. Economics literature documents that volatility in different markets can be due to globalization, bilateral trade, and interdependent business cycles, and political science literature suggests that national and international political events can contribute to volatility in global markets. A large body of literature combines the constructs from various disciplines

to identify the sources of volatility in financial markets and attempts to quantify the contributions to volatility. It has also become common knowledge that exaggerated volatility is episodic and events like the financial crisis of 2008 contribute greatly to the volatility in world markets.

Traditionally, the volatility of the time series is evaluated using standard deviation, which provides an average estimate of spread of returns over the period of analysis and nothing beyond. Additionally, standard deviation for a longer period of analysis makes the estimates irrelevant, as the volatility is time-varying in nature and does not remain constant over the period. Furthermore, consideration of the appropriate period for estimation is subjective and may not be truly informative for investors with varying investment time horizons. There was a progression from standard deviation to OLS estimation in literature in the 1970s; however, the OLS models are considered to be flawed as well.

As discussed in Section 3.2.1, certain assumptions associated with OLS estimations, such as lack of serial correlation, homoscedasticity, and normal and independent distribution of residuals, lead to erroneous estimations, making the OLS models inefficient. Financial time series are primarily leptokurtic, exhibit volatility persistence, and are punctuated with heteroscedasticity. These limitations have implications for the estimation of volatility and therefore, a model incorporating the typical attributes of time series is more apt.

ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) addressed these limitations of OLS estimations. ARCH is a simplistic and parsimonious approach to model volatility (Hansen and Lunde, 2005) that considers the current errors to be dependent on past errors, variance to be conditional on past information, and the variance to be non-constant. On the other hand, the GARCH model states that conditional variance of a return series at time t depends on the squared error term in the previous time period and also on its conditional variance in the previous time period (Gujrati and Porter, 2009). These models and their variations (refer to table 3.1) appropriately incorporate the dynamic nature of volatility and are widely used in finance literature. The GARCH models provide a volatility measure that facilitates risk analysis, portfolio selection, and derivative pricing.

Figures 5.1 and 5.3 in chapter 5 clearly demonstrate that the period under consideration in this study is punctuated with an episode of high volatility, which is primarily associated with the financial crisis of 2008. Some markets, such as China, Japan, Kuwait,

Saudi Arabia and the UAE, experienced structural breaks during this period and are still struggling to recover. To examine whether the financial crisis had an enduring impact on the mean and volatility of the markets included in the sample, further investigation is carried out using appropriate techniques. To achieve this objective, the data for the twelve candidate markets is further analyzed by using a modified version of GARCH (p, q) with Gaussian distribution. In line with Aggarwal *et al.* (1999), Hammoudeh and Li (2008) and Kang *et al.* (2009), the GARCH model is modified to include a dummy variable CRISIS to incorporate the effect of the financial crisis. The period of crisis is chosen according to the timeline in Bartram and Bodnar (2009).

Episodic volatility, clustering and persistence of volatility are evident in all the time series, hence making the application of GARCH suitable, which enables the modeling of these attributes of volatility. The phenomenon of volatility clustering suggests that shocks take longer to decay; however, the volatility eventually returns to its long-run mean value. Zivot (2009) suggests that the GARCH model facilitates an understanding of stylized facts about the volatility of financial and economic time series, like volatility clustering, fat tails, mean reversion, and asymmetry.

The most widely-used specification is the GARCH (1,1). The standard GARCH (1, 1) model can be defined as:

$$x_t = \mu + \varepsilon_t$$

$$e_t \mid I_{t-1} \sim N(0, h_t)$$

$$h_t = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta h_{t-1}$$

where N represents conditional normal density with mean zero and variance h_t. I_{t-1} represents the information available at $t\text{-}1$ and $\omega > 0$, $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$.

This model estimates the variance of return at time t (h_t) as a weighted average of a constant (ω), and yesterday's squared error (ε^2_{t-1}), and yesterday's variance of return (h_{t-1}). Thus, the GARCH models are conditionally heteroscedastic but have a constant unconditional variance. The volatility persistence is estimated by the sum of α and β. If the sum of the two coefficients approaches unity, the volatility is considered to be highly persistent.

The GARCH (1, 1) model considers symmetric response to both positive and negative news by squaring the residuals. Hence, the conditional variance in GARCH depends on the

magnitude of the disturbance term, but not on its sign. Moreover, the distribution of error terms is non-normal, exhibits fat tails, and is asymmetric. This attribute of financial time series is partially captured by heteroscedasticity; however, it needs to be explicitly modeled by allowing the error term ε_t to have a non-Gaussian distribution or by incorporating the asymmetric behavior in the variance equation (Enders, 2010). Although GARCH (1, 1) suffices in mose cases (Zivot, 2009; Hansen and Lunde, 2005), it can be generalized in terms of lags to be used and can be written as GARCH (p, q), where *p* designates the lagged term of the squared error term and *q* signifies the lagged conditional variance (Enders, 2010). The higher order GARCH (p, q) models can be written as:

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 \sum_{k=1}^{q} \beta_k h_{t-k}^2$$

The period of analysis entails a period of turbulence associated with the financial crisis of 2008. Lamoureux and Lastrapes (1990) concluded that when conventional GARCH models are applied to data with sudden changes in variance, the conditional variance is found to be progressively strongly persistent, leading to over-estimation of volatility; therefore appropriate treatment is required to incorporate turbulence. Hamilton and Susmel (1994) used a Switching ARCH (SWARCH) to introduce regime changes, classified as low, moderate and high volatility regimes, to address this limitation of GARCH. Studies conducted by Aggarwal *et al.* (1999), Malik *et al.* (2005), Hammoudeh and Li (2008) and Kang *et al.* (2009) used a varied GARCH model that combined the sudden shifts in variance with GARCH. In the aforementioned studies, change points were detected by using the ICSS algorithm and then dummy variables were introduced into the variance equation of the GARCH model to assimilate sudden changes in variance using dummy variables. These studies documented that the inclusion of dummy variables in the mean and variance equations improved volatility estimates and decreased volatility persistence, as denoted by the sum of α and β in the variance equation.

In line with Aggarwal *et al.* (1999), Malik *et al.* (2005) Hammoudeh and Li (2008) and Kang *et al.* (2009), this study also incorporated the impact of the financial crisis using a dummy variable CRISIS that assumed a value of one during the crisis and a value of zero otherwise. Since the period of exaggerated volatility is known, the application of the ICSS

algorithm is considered to be redundant. Inclusion of the dummy variable in the model allowed for the assumption that a significant event causes either mean or volatility structure break. A statistically significant coefficient associated with the dummy variable provides the evidence that the effect of the event on underlying time series is substantial and durable.

The studies mentioned above employed GARCH (1,1); however, in this thesis, a broader set of model specifications are used to ensure consistency in results. For the GARCH (p, q) model, *p* and *q* assume a maximum value of three and various combinations of *p* and *q* are tested, resulting in nine models for each market of interest. The best-fit model based on the SIC is presented.

The beginning of the crisis is chosen in line with the bankruptcy filing of Lehman Brothers on 15 September 2008. On this day, the Dow Jones experienced a decline of more than 500 points, its largest after 9/11. After that, the financial crisis was unleashed forcefully, bringing turmoil to many markets around the world (Frank and Hesse, 2009). Bartram and Bodner (2009) provide a chronological list of events during the time of crisis, and according to their study, the crisis mellowed in October 2009. Hence, in line with their study, the end date of the crisis is taken as 26 October 2009.

The use of modified GARCH (p, q) provides evidence of whether the impact of the financial crisis was significant on the candidate indices. The variance equation with the dummy variable can be rewritten as:

$$h_t = \omega + \alpha\, \varepsilon^2_{t-1} + \beta h_{t-1} + \nu D_1$$

where ν is the coefficient associated with the dummy variable, and whose statistical significance provides an insight into the impact of structural break. This dummy variable is used in both the mean and the variance equation for each index to evaluate the impact of the financial crisis. Financial assets time series are considered as having a stable long-term mean, which is not affected by a temporary shock. Volatility, on the other hand, is affected by structural changes. While the inclusion of dummy variables in the mean equation reveals limited insight into the dynamics of means, inclusion of dummy variables into the variance equation is particularly meaningful for researchers, as it allows for the estimation of the impact of a significant event on the volatility.

The strengths and weaknesses of the basic GARCH model are discussed in detail in section 3.3. While the traditional GARCH models are simple, intuitive and parsimonious, and are capable of handling large datasets. The restrictions on positivity of all coefficients makes their application unfeasible, especially in considering leverage effect. Limitations of basic GARCH model are addressed by the "second generation" models like EGARCH, TARCH and many other models (McMillan and Speight, 2004), which are concisely presented in table 3.1.

The relevant literature also asserts that the assumptions associated with the normal distribution of the time series makes its application unviable in certain situations. Accordingly, appropriate specification of error distribution, like the Student's *t*-distribution, Generalized Error Distribution (GED), and the Double Exponential Distribution (DED) (Zivot, 2009) leads to better volatility estimates.

Even with all the limitations discussed above, Hansen and Lunde (2005) documented superior performance of GARCH (1, 1) in most situations in terms of their ability to describe the conditional variance. The authors compared the performance of standard GARCH (1, 1) with 330 ARCH-type models and found that the simplistic and parsimonious GARCH model may suffice when examining volatility.

Despite the limitations associated with the traditional GARCH model, the use of the modified GARCH (p, q) with Gaussian distribution in this study is facilitated by the following considerations:

- Large sample size: The sample size of more than 2,500 observations ensures the stability of the model. Similarly, large sample size and log returns address the limitation of non-normal distribution to some extent.
- Consistency: Consideration of a GARCH model with Gaussian distribution enables consistency in all the methods used for data analysis in this thesis. For example, the VAR method employed under the Spillovers Index assumes normally distributed time series.
- Known period of crisis: The finance literature suggests that the classic GARCH model is not capable of capturing asymmetric responses to negative shocks. Since the period of extreme volatility associated with the financial crisis of 2008 is known in the period of analysis, the limitation associated with the extreme values in the time series is addressed by explicitly using a dummy variable in the model.

Besides the above consideration, the main objective of this study is to measure the conditional returns and volatility spillovers across chosen markets using the Spillovers Index. The index captures the turbulence in the time series through rolling windows and does not require the consideration of regime switching through inclusion of dummy variables. Modified GARCH (p, q) with Gaussian distribution is employed only to have an insight into the impact of the financial crisis on markets, as some markets in the sample experienced structural breaks identified in the graphs presented in chapter 5, figure 5.1.

4.5.2 Methods Employed to Measure Association and Interdependence Between Markets

Section 4.5.1 presented the tools that are used in this thesis to examine the attributes of the time series in the sample. Some of the tests employed, such as the unit root tests, are a pre-requisite for further investigation into the interaction between markets. The focus of this section is to identify and quantify the association and interaction between Pakistan and its trade partners. Accordingly, the analysis begins with estimation of correlations, followed by the bivariate Granger causality test, which provides a rudimentary insight into the relationships between markets. Further analysis using OLS estimations and the Spillovers Index is performed to understand the dynamics of the interaction between returns and volatility across markets under consideration.

4.5.2.1 Correlations

The stepping-stone in the analysis of association between candidate markets is the estimation of correlations. Correlation is a statistical measure of the strength and direction of the relationship between two comparable time series. The correlation values range between +1 and -1, whereby +1 suggests a perfect positive correlation and -1 suggests a perfect inverse relationship between the two time series. Mathematically, correlations between return series can be represented as:

$$\rho_{ij} = \frac{Covariance(R_i, R_j)}{\sigma_i \sigma_j}$$

where R_i and R_j are the returns and σ_i and σ_j are the standard deviations of markets *i* and *j*. The measure considers the relationship between returns as well as volatility as denoted by the standard deviations of the time series under consideration.

Section 3.1 clearly indicates the popularity of correlation coefficients in exploring the relationship between returns series due to its simplistic calculation and intuitive interpretation. Event studies and rolling windows are used in the finance literature to accommodate time varying correlations between markets.

Despite the wide use of correlation coefficients in exploring the interdependencies across markets, the method has some limitations. Shadish *et al.* (2002, p. 7) emphasize, "correlation does not prove causation". The variables under consideration might be highly correlated, but there is no assurance that a "cause and effect" relationship exists between them. The limitations of correlations are discussed in detail in section 3.1 and are also listed below:

- Higher correlations estimate during episodic exaggerated volatility in returns can be mistaken as increased integration between markets (Forbes and Rigobon, 2002; Doyle and Faust, 2003; Fernandez, 2004; Bekaert *et al.*, 2005; Carrieri *et al.*, 2007), although the increase in correlations during turbulent times may be statistically insignificant (Doyle and Faust, 2003).
- Correlation estimates are sensitive to the presence of unequal variances or heteroscedasticity and therefore are biased upwards in times of excessive volatility (Forbes and Rigobon, 2002).
- The conditional correlations have limitations that are associated with heteroscedasticity, endogeneity, and omitted variables bias (Rigobon, 2004).
- The information provided by correlations is extraneous for an investor with long-term diversification objectives (Lucey and Muckley, 2011) and a single estimate generated by the correlation coefficient may be inconsequential (Fazio, 2007).
- Correlations estimates are dependent on the nature of inputs. In event studies and rolling window analysis, the classification of sub-periods is arbitrary and the choice of different sub-periods may produce different results (Walti, 2012). Moreover, the estimates are sensitive to the frequency of the data (Billio and Pelizzon, 2003).

Given the limitations associated with correlation estimates, it is appropriate to use them as a primitive measure to analyze the strength and direction of association between the returns

of the markets. The analysis needs to be substantiated further with more sophisticated techniques.

4.5.2.2 Pair-wise Granger Causality

The pair-wise Granger causality test allows for the identification of the linear causal linkages between the time series. According to Granger causality, if a time series *X* "Granger-causes" time series *Y*, then the past values of *X* should help predict *Y*, beyond the information contained in past values of Y alone. The mathematical formulation of Granger causality is based on linear regression modeling of stochastic processes (Granger 1969). For variables R_i and R_j representing returns in markets *i* and *j,* the mathematical illustration can be presented as:

$$R_{it} = \alpha_0 + \alpha_1 R_{it-1} + \ldots\ldots + \alpha_n R_{it-k+} \beta_1 R_{jt-1} + \ldots\ldots + \beta_n R_{jt-k+} \varepsilon_t$$

$$R_{jt} = \alpha_0 + \alpha_1 R_{jt-1} + \ldots\ldots + \alpha_n R_{jt-k+} \beta_1 R_{it-1} + \ldots\ldots + \beta_n R_{it-k+} \varepsilon_t$$

The above equations are used for all possible pairs of R_i and R_j in a group. The selection of lag length *k* has been based on the data frequency or theoretical underpinning. In this study, the causality between the selected markets is examined using multiple lags to ensure consistency in results. The resulting *F*-statistic allows for testing the null if R_i Granger causes $R_{j,}$ and vice versa.

The use of Granger causality and its variations is common in the finance and economics literature. This method to examine the relationship between time series is generally the stepping-stone to further investigation (for example Ng, 2000; Rodríguez-Moreno and Peña, 2013 amongst many others). The method has certain weaknesses, which have been discussed in detail in chapter 3, section 3.4. These limitations are associated with measurement of only bivariate linear causality, incapability to incorporate information on structural breaks, heteroscedasticity and regime switching, and inadequacy in estimating the degree of causation. While the Granger Causality tests are useful in establishing that a unidirectional or bidirectional lead-lag relationship exists between the chosen time series, the quantification of the causal relationship requires application of other techniques.

4.5.2.3 Ordinary Least Squares Estimation

After estimating correlations and Granger Causality between returns, the relationship between markets under consideration is further evaluated using OLS estimations. The OLS estimations are primarily used for the purpose of predicting values of dependent variables with the help of independent variables.

A static model with one dependent variable R_i and one independent variable R_j can be written as:

$$R_{it} = \beta_0 + \beta_1 R_{j1} + u_t, \qquad t = 1,2,3, \ldots\ldots\ldots, n$$

where u_t is the error term.

The above model suggests a contemporaneous relationship between the dependent and independent variables. This means that any change in R_j affects R_i, which can be denoted as:

$$\Delta R_{i\,t} = \beta_1 \Delta R_{j\,t}, \qquad when\ \Delta u_t = 0$$

As noted earlier, some assumptions are associated with OLS estimation:

1. There is a linear relationship between the parameters,
2. Independent variables in the model should not be constant or highly correlated with each other,
3. The expected value of the error term u_t in the model is not correlated with the independent variables,
4. The error term u_t is homoscedastic,
5. The error terms in consecutive periods are uncorrelated, that is, there is no temporal correlation in the error terms, and
6. The errors u_t are independently and identically distributed as Normal $(0, \sigma^2)$.

While the first two assumptions may be satisfied in time series OLS analysis, the third assumption is unrealistic, as the past and future values of the independent variables may have a feedback effect from the values of u_t.. The residuals are evaluated to ensure that they meet the assumptions of homoscedasticity and no serial correlation. If all the above conditions are met, then the OLS estimators are expected to be "BLUE" or Best Linear Unbiased Estimator.

For this study, one dependent and one independent variable are used for OLS estimation; however, multiple lags are taken into consideration. Both dependent and

independent variables are tested for stationarity beforehand using ADF and PP tests. The OLS analysis is performed as follows:

1. Pakistan's log-returns are considered as the dependent variable and are regressed against multiple lag returns of other markets to assess if the coefficients of other markets at different lags are statically significant. Since the hours of operation of the USA and Pakistan markets do not overlap, Pakistan's log returns at *t* are regressed against log returns of the USA at *t-1.*
2. Log-returns of the other candidate markets are considered as dependent variables and are regressed against Pakistan returns to evaluate whether the Pakistan contribution is statistically significant. In this scenario also, the log returns of the USA at *t* are also regressed against the Pakistan log returns at *t-1.*

The resultant OLS model is written as

$$R_{j,t} = \beta_0 + \beta_1 R_{i,t} + u_t, \qquad t = 1,2,3, \ldots\ldots, n$$

where $R_{j,t}$ is the log return of market *j* at time *t*, regressed against $R_{i,t,}$ return of market *i* at time *t* , with an exception of the returns of Pakistan and the USA.

As suggested in section 4.2, the time series in this study comprise non-synchronous data, due to different time horizons and weekends. The trading hours in the USA do not overlap with the trading hours in some emerging markets and any of the frontier markets, including Pakistan. This suggests that the information reflected in the prices of the KSE at time *t* is representative of the information from the USA market at *t-1* and the information from KSE on a particular day may not be reflected in the USA until the next day. Accordingly, the OLS model in this scenario is presented as

$$R_{j,t} = \beta_0 + \beta_1 R_{i,t-1} + u_{t-1}, \qquad t = 1,2,3, \ldots\ldots, n$$

where $R_{j,t}$ is the log return of market *j* at time *t*, regressed against $R_{i,t,-1}$ return of market *i* at time *t-1.*

The results of the model allow for the identification of several important insights. First, it demonstrates whether the coefficients associated with the various independent variables are statistically significant. Second, adjusted R^2 estimates demonstrate the variability in the dependent variable explained by the independent variable. Lastly, the Durbin Watson (DW) statistic associated with OLS estimation is of important consequence, as it indicates the presence or absence of autocorrelation in residuals.

While OLS analysis of time series is widely used in the relevant literature, especially in the context of risk analysis using CAPM, it has its limitations, some of which are related to the assumptions. These limitations are discussed in chapter 3, section 3.2.1 and are associated with distribution of time series, heteroscedasticity, autocorrelations, structural changes and regime shifts in time series data. OLS models also lack the ability to incorporate the time-varying nature of returns and volatility, a limitation that is generally addressed by using event studies for analysis.

The parsimony of the model is also a prime consideration in OLS estimation. While models with limited variables divulge limited information, models with a large number of variables are penalized in terms of degrees of freedom, hence lowering the explanatory power of the model. Accordingly, this study uses step-wise OLS estimation so that only statistically significant lags are retained in the model and the parsimony of the model is not compromised.

Even with all of the above limitations, the OLS model provides an insight into the relationship between markets; however, the decisions of portfolio and risk management cannot be solely based upon the OLS estimates, and further investigation is required to facilitate decision-making or to support policy-making.

4.5.2.4 Spillovers Index

The technique used in this study for analyzing interdependencies between candidate markets was developed by Diebold and Yilmaz (2009, 2012). The method is based on Generalized Forecast Error Variance Decomposition (FEVD), which was first proposed by Pesaran and Shin (1998). The authors named the method as the “Spillovers Index”. Application of the index allows for the identification of the trend and magnitude of mean and volatility spillovers between Pakistan and its most active trade partners. Diebold and Yilmaz (2009) and subsequent publications like Diebold and Yilmaz (2012), Yilmaz (2010), Claeys and Vasicek (2012) used mean and volatility spillovers index on different groups of countries, and found that it indicated that mean spillovers across markets exhibit an upward trend while volatility spillovers across markets devoid trend but demonstrate bursts which indicate shocks associated with various events.

The Spillovers Index quantifies the mean and volatility spillovers across markets with the help of spillover tables and plots. The method uses *N*-Variable Vector Autoregressive (VAR) framework variance decomposition across countries. The method is superior to other existing methodologies as it incorporates both the static and the dynamic nature of return and volatility spillovers. The Spillovers table indicates the average returns and volatility spillovers from market *i* to market *i* (self-contribution to spillovers), from market *i* to market *j* and vice versa (foreign contributions) during the period of analysis, however small or substantial they are. On the other hand, the Spillovers plots exhibit the time-varying nature of returns and volatility spillovers using rolling windows, which allow for the identification of shocks and enable the determination of events associated with them. The rolling window analysis facilitates testing of stability of a model over the period, which is crucial for accuracy in forecasting.

As suggested in chapter 3, section 3.4.5, the most apparent strength of the Spillovers Index is the simultaneous measurement of the static and time-varying nature of mean and volatility spillovers across markets. As suggested by earlier studies, the magnitude of spillovers across markets is heterogeneous and the spillovers effect of negative shocks is more pronounced when compared with positive shocks (Ng, 2000; Martens and Poon, 2001). Moreover, some markets are affected more by global events when compared with regional events, while others respond more to regional shocks and less to global shocks. Accordingly, developing an index for a group of countries provides useful information about the countries that contribute the most towards domestic returns and volatility. The information is apt for portfolio and risk management, as the investors can choose to invest in countries with least foreign spillovers, especially during turbulent times.

Diebold and Yilmaz (2009) estimated the mean and volatility spillovers using VAR model, broadly in line with Engle *et al.* (1990). Their method focused on variance disintegration, which enabled aggregation of spillovers effects across markets. Their method entails the application of *N*-Variable VAR, under which the forecasted error variance of each asset *i* is added to the shocks coming from asset *j*, for all $j \neq i$, and then all the variances are added across all $i=1, 2, 3,\ldots,N$.

Diebold and Yilmaz (2012) define the *self-contribution to variance shares* and *foreign variance shares* as follows:

- *Self-contribution to variance shares:* the fractions of the *H*-step-ahead error variances in forecasting x_i that are a result of shocks to x_i, for *i=1,2,3,4….N*.
- *Foreign variance shares:* the fractions of the *H*-step-ahead error variances in forecasting x_i that are a result of shocks to x_j, for *I,j=1,2,3,4….N*, such that *i≠j*.

The authors, Diebold and Yilmaz (2009) consider a covariance stationary first-order two variable VAR, denoted as

$$x_t = \phi x_{t-1} + \varepsilon_t$$

where $x_t = (x_{1t}, x_{2t})$ and ϕ is a 2 X 2 parameter matrix, and x is either a vector of index returns or a vector of volatilities. Due to covariance stationarity, the moving average representation of VAR can be written as:

$$x_t = \Theta(L)\varepsilon_t$$

where $\Theta(L) = (I - \phi L)^{-1}$. The moving average representation can be written as:

$$x_t = \mathrm{A}(L)u_t$$

where A (L) = $\Theta(L)Q_t^{-1}$, $u_t = Q_t\varepsilon_t$, $E(u_t\acute{u}_t) = I$, and Q_t^{-1} is the unique lower-triangle Cholesky factor of the covariance matrix of ε_t.

Since the ultimate purpose of exploring mean and volatility dynamics is to forecast, one-step forecasting can be considered, in line with Diebold and Yilmaz (2009). The Weiner-Kolmogorov linear least square forecast is given by:

$$x_{t+1,t} = \phi x_t$$

with the subsequent 1-step ahead error vector

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix}$$

with the covariance matrix

$$E\left(e_{t+1,t}\, \acute{e}_{t+1,t}\right) = A_0 \acute{A}_0$$

This suggests that the variance of 1-step-ahead error in forecasting x_{1t} is ${a^2}_{0,11} + {a^2}_{0,12}$ and for x_{2t} is ${a^2}_{0,21} + {a^2}_{0,22}$.

Variance decomposition allows for the determination of the contribution of shocks to a variable from exogenous variables in an autoregressive model. The *H*-step-ahead forecast determines what fraction of the shock is attributable to *i* and what fraction is attributed to x_j for *i, j = 1,2, i≠j*, in the case that there is a shock to x_i. The total spillover ${a^2}_{0,12} + {a^2}_{0,21}$ suggests two possible spillovers in this two-variable scenario: x_{1t} shocks that influence

the forecast error variance of x_{2t} (with contribution $a^2{}_{0,21}$), and vice versa (with contribution $a^2{}_{0,12}$). The total spillovers can be converted into an index, relative to the total forecast error variance $a^2{}_{0,11} + a^2{}_{0,12} + a^2{}_{0,21} + a^2{}_{0,22} = trace\ (A_0 \acute{A}_0)$. The Spillovers Index as a percentage can be denoted as:

$$S = \frac{a^2{}_{0,12} + a^2{}_{0,21}}{trace\ (A_0 \acute{A}_0)} X\ 100$$

The above two-variable scenario can be generalized to a p^{th} order N-variable VAR using H-step-ahead forecast as:

$$S = \frac{\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{h,ij}^2}{\sum_{h=0}^{H-1} trace\ (A_h \acute{A}_h)}$$

Although the original version of the Spillovers Index was capable of highlighting the financial markets that contribute the most to the conditional returns and volatility of a particular financial market, Diebold and Yilmaz (2012) point out the following weaknesses of the original version:

1. Sensitivity of estimates to the ordering of variables due to the use of Cholesky factorization.
2. Inability to measure directional spillovers across markets.
3. Limited application on various assets classes.

Consequently, Diebold and Yilmaz (2012) used the generalized VAR framework presented in Koop *et al.* (1996) and Pesaran and Shin (1998) to overcome the shortcomings of their earlier model. This approach considers correlated shocks but assigns them weightage based on the historical distribution of the errors, rather than orthogonalzing shocks.

The H-step-ahead forecast error variance composition is presented as:

$$\frac{\theta_{ij}^{g}(H) = \sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\acute{e}_{\iota} A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (\acute{e}_{\iota} A_h \sum \acute{A}_h e_i)}$$

where $\sum$ is the variance matrix for error vector ε, σ_{jj} is the standard deviation of the error term for the *jth* equation and e_i is the selection vector, with one is the *ith* element and zero otherwise. The sum of each row in the variance decomposition matrix is not equal to one.

To calculate the Spillovers Index, each entry of the variance decomposition matrix is normalized by the row sum as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}\,(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}\,(H)}$$

where

$$\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\,(H) = 1 \;\text{ and }\; \sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}\,(H) = N$$

After calculating the self and foreign variance share, total spillovers to calculate the spillovers index are calculated as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}\,(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}\,(H)}\;\mathrm{X}\;100$$

or

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}\,(H)}{N}\;\mathrm{X}\;100$$

Lastly, net pairwise spillovers, the difference between the gross shocks transmitted from market *i* to market *j* and vice versa, are calculated as follows:

$$S_{ij}^{g}(H) = \frac{\tilde{\theta}_{ji}^{g}\,(H)}{\sum_{i,k=1}^{N}\tilde{\theta}_{ik}^{g}\,(H)} - \frac{\tilde{\theta}_{ij}^{g}\,(H)}{\sum_{j,k=1}^{N}\tilde{\theta}_{jk}^{g}\,(H)}$$

$$S_{ij}^{g}(H) = \frac{\tilde{\theta}_{ji}^{g}\,(H) - \tilde{\theta}_{ij}^{g}\,(H)}{N}\;X\;100$$

For the purpose of this study, 12-variable VARs with 2 to 10 lags, and 5- and 10-step forecasts are considered. The forecast horizon chosen for this study is in line with Diebold and Yilmaz (2012), although, multiple lags were used to evaluate the consistency of results.

Since the results were not extra-ordinarily different, the choice of lags and H-steps forecast in Diebold and Yilmaz (2012) is followed.

The stationarity and stability of VAR models is of major concern with respect to the validity of the findings. A stable process is one that does not digress to infinity. The eigenvalues provide an insight into the stationarity and stability of the VAR. If the eigenvalues associated with the impulse-responses and variance decompositions are less than 1, the models are meaningful (Lütkepohl, 2006), else they should not be reported.

One of the outcomes of this analysis is the Spillovers tables depicting cross-market conditional returns and volatility spillovers. These tables comprise several rows and columns listing each market of interest. Self-contributions are presented diagonally and the last row and column designate off-diagonal contribution to others and contribution from others respectively and becomes the numerator in the calculation of the Spillovers Index. The denominator to calculate the index is an overall estimate of contributions of mean and volatility across countries included in the sample. The leftover mean and volatility is unconditional.

Besides tables, spillovers plots are also generated that provide insight into the evolution of cross-market spillovers and enable identification of periods of exaggerated spillovers surrounding specific events.

The focus of the study is Pakistan. Therefore, this study focuses on measuring mean and volatility spillovers to and from Pakistan, besides measuring Pakistan's self-contributions to its returns and volatility. The analysis using the mean and volatility Spillovers Indices entails several steps, which are listed in Table 4.11 with their respective outcomes.

Table 4.11 – Application of the Returns and Volatility Spillovers Indices

i.	Generalized Returns and Volatility Spillover Table	*To provide a static measure of returns and volatility spillovers over the period of 7 years across 12 markets included in the sample.*
ii.	Generalized Returns and Volatility Spillover Plot Output: Graphs - 200 days Rolling window analysis with 2 lags and 10 steps forecast horizon	*To evaluate the dynamics of spillovers across time.*

iii.	Change the lags (2 to 6), keeping n-steps constant at 10 Output: Graphs with min, max and median values	*To analyze the sensitivity of the spillovers to different lags.*
iv.	Increase the lags beyond 6 and keep on increasing the lags till the values start falling	*Enables estimation of the lags during which the new information gets absorbed and spillovers go back to normal levels.*
v.	Change the n-steps (5-10), keeping lags constant at 2 Output: Graphs with min, max and median values	*To analyze the sensitivity of the spillovers to different forecast horizons.*
vi.	Groupwise Spillovers Output: Tables and Graphs of spillovers within various groups of countries with Pakistan being part of every group	*To isolate the spillovers within different groups based on different classifications.*
vii.	Net Pairwise spillovers Output: Graphs of net returns spillovers between Pakistan and other countries, in 200-day rolling windows, keeping the lags and n-steps constant (2 and 10 respectively)	*To isolate spillovers between pairs of countries (Total 11 pairs and Pakistan is included in all the pairs).*
viii.	Robustness Check Distribute the whole period into three sub-period (pre-crisis, crisis and post-crisis) and analyze the spillover tables and plots Output: Tables and Graphs for three sub-periods.	*Compare the spillovers in sub-periods and identify whether they are different from the complete period analysis.*

In general, VAR methods are able to capture simultaneous co-movements between time series that may not be captured by univariate or bivariate models. The Spillovers Index in particular exudes several strengths and sets itself apart from other methods widely used in the literature in several ways. First, the combination of spillovers tables and plots allows for the estimation of mean and volatility spillovers at a given point in time as well as its evolution over a certain period. Second, since the spillovers plots endogenously incorporate the dynamic nature of mean and volatility spillovers in rolling windows, the need to incorporate dummy variables signifying structural break becomes redundant. This results in a parsimonious model. With this approach, the need for event studies also becomes superfluous. Third, the index enables the quantification of spillovers from specific countries individually. For example, Fujiwara and Takahashi (2012) measured volatility spillovers from the USA, Japan and China to countries classified in different groups, in order to quantify

the progression of contribution by these countries that in general are assumed to be most important regionally and globally.

While the VAR methods have their strengths, they also have weaknesses. Stock and Watson (2010) highlight some weaknesses inherent in the VAR methods. Some of these weaknesses are related to the attributes of the data, such as volatility persistence, conditional heteroscedasticity, and drift, which may lead to imprecise estimates. Schlegel (1985) points out that since the variables in the time series exhibit autocorrelations as well as correlations with other time series included in the analysis, multicollinearity between variables may pose a challenge when the model is expanded to accommodate several time series. The author argues that the inclusion of a large number of variables in the model makes it difficult to determine which coefficients are statistically significant. Moreover, inclusion of a larger number of lags and smaller sample sizes affects the parsimony of the model. With respect to the Spillovers Index, the choice of lags and the size of rolling windows are arbitrary and are not substantiated with theoretical underpinning or empirical analysis. The choice of appropriate lags is important, as shorter lags may generate noisy estimates while longer lags may fail to capture the important information available regarding spillovers in shorter windows.

This study has used various measures to ensure reliability of results. These measures include the use of large sample size, number of lags that facilitate capturing of maximum information without compromising greatly on parsimony; distributing the sample in smaller groups and pairs.

4.6 Chapter Summary

To summarize, in line with the finance literature the selection of countries in the study based on their bilateral trade with Pakistan. Accordingly, the sample includes the eleven most active trade partners of Pakistan, including five developed (USA, UK, Germany, Japan and Singapore), three emerging (China, India and Malaysia) and three frontier (Saudi Arabia, UAE and Kuwait) markets. Besides trade, the finance literature also highlights the importance of geographical proximity, foreign investments, and political relationships in estimating interdependence between capital markets, which are also given consideration in this study.

As noted earlier, the period of analysis extends from January 2006 to December 2012. Log returns and range-based volatility using high and low intra-day prices are calculated for the markets of interest. The non-synchronity in the data due to different time zones and trading days is addressed by adjusting 5-day data frequency to 7-day data frequency, resulting in 2,544 data points.

Various statistical and econometric methods are employed to examine the characteristics of individual time series. Elementary analysis includes the plotting of returns, closing prices, and range-based volatility on graphs, as well as the calculation of descriptive statistics for returns and volatility. Analysis of autocorrelations and stationarity of the time series at different lags provide further insight into the characteristics of the time series. Confirmation of stationarity of time series is essential for application of econometric methods employed in the study as non-stationary time series exhibit trend, cyclical patterns and irregular variation, which may lead to random noise and inaccurate estimates.

Lastly, a modified version of GARCH (p, q) model with Gaussian distribution is used to analyze each time series. Choice of the GARCH model with Gaussian distribution is facilitated by the use of a large sample size, log returns and the need for consistency across models employed in the study. The modified GARCH (p, q) includes a dummy variable CRISIS to represent the turbulent period during the financial crisis, stretching from 15 September 2008 to 26 October 2009. The dummy variable CRISIS assumes a value of one during the crisis and a value of zero otherwise. The statistical significance of the dummy variable allows for the understanding of the impact of the financial crisis on the markets under consideration. The model is estimated with p and q assuming different values ranging from 1 to 3. The choice of best-fit model is based on the SIC value.

The association and interaction between Pakistan and its trade partners is examined using correlations, Granger causality, OLS estimations, and the Spillover Indices. Correlations and Granger causality provide some primitive insight into the association and causation between markets. Furthermore, stepwise OLS estimation is used to examine whether the returns in Pakistan at different statistically significant lags can be used as predictors for returns in other markets in the sample, and vice versa.

After establishing that there is some association between markets, conditional returns and volatility spillovers across countries are estimated with the help of the Spillovers Indices. The Spillovers tables provide an overall static estimate of spillovers across all the markets in the sample and the Spillovers plots in rolling windows provide a detailed account of evolving cross-market spillovers across time.

The analysis under the Spillovers Indices is carried out in multiple ways. First, the returns and volatility Spillovers Indices is produced for the complete group. Second, the Spillovers Indices are developed for groups comprising Pakistan and markets under different country classification, such as, developed, emerging and frontier markets. Third, the analysis is performed by classifying Pakistan's geographically proximate trade partners into two different groups. One group constitutes countries that share borders with Pakistan and the second group includes those of Pakistan's trade partners that are located in the Asia-Pacific. Lastly, pairw-ise analysis is performed on eleven pairs of countries with Pakistan included in all the pairs. Multi-way analysis allows detailed insight into the dynamics of returns and volatility across markets under consideration.

Multiple robustness checks are also incorporated in the analysis to ensure reliability and consistency of results. Since the choice of lags and n-steps forecast horizon is arbitrary, Spillovers Indices are produced with varied lags and n-steps horizon. First, the number of lags is varied from 2 to 10 while keeping the n-steps forecast horizon constant; then, the n-steps forecast horizon assumes values between 5 and 10, while keeping the number of lags constant at 2.

Another robustness check allows the determination of consistency of results with respect to the financial crisis of 2008. To evaluate whether the cross-market spillovers are altered during tranquil and turbulent periods, the whole period of analysis is distributed into pre-crisis, crisis, and post-crisis periods. The Spillovers Indices is produced for all the three sub-periods to examine varying degrees of the returns and volatility spillovers during both tranquil and turbulent periods.

The chapter also discussed the limitations of the models employed, along with the explicit and implicit measures to produce reasonably accurate results. Additionally, the

employment of various techniques and robustness checks ensures that the results are consistent and reliable. The following chapter, chapter 5 presents the findings of data analysis.

5 Data Analysis and Empirical Results

This chapter presents the results of the data analysis of the chosen time series in this thesis. Before proceeding to evaluate the interaction between the returns and volatility of the various markets, the returns series are evaluated individually to establish stylized facts. The returns and volatility time series are examined with the help of graphs, descriptive statistics, autocorrelations and stationarity, as the results of these tests have some implications for the application of the econometric models used in the thesis. A modified version of GARCH (p, q) model including a dummy variable named CRISIS with several model specifications is used to evaluate the impact of the financial crisis of 2008 on the markets included in the sample.

Once all the relevant analysis is performed on all the individual time series, the association between these markets is evaluated using correlation coefficients, Granger Causality, stepwise OLS estimations and the Spillovers Index. While most of the analysis is performed on the log returns, the Spillovers Index considers both returns and volatility spillovers to estimate the self-contributions of markets and cross-market contributions. For comprehensive insight, the data analysis is performed on different groups based on country classification and geographical proximity, and pairs with Pakistan essentially being a part of every group and pair.

5.1 Characteristics of Individual Time Series

Before evaluating the association and interdependence between the sample countries, it is important to understand the dynamics of returns and volatility of individual time series. For the purpose of visual inspection, the closing prices of indices, log returns and range-based volatility are plotted on graphs. After visual presentation, log returns of all countries are examined with the help of descriptive statistics, autocorrelations and unit root tests. Descriptive statistics reveal details about the volatility and distribution of the time series, autocorrelations provide an insight into the predictability of returns and unit root tests confirm the stationarity of the time series. While most of the analysis in this section is performed on log returns, range-volatility estimates are also evaluated through descriptive statistics.

5.1.1 Plots and Descriptive Statistics

The log returns time series is calculated using daily closing prices of the developed markets (USA, UK, Germany, Singapore, Japan), emerging markets (India, China, Malaysia) and frontier markets (Pakistan, UAE, Saudi Arabia and Kuwait) indices.

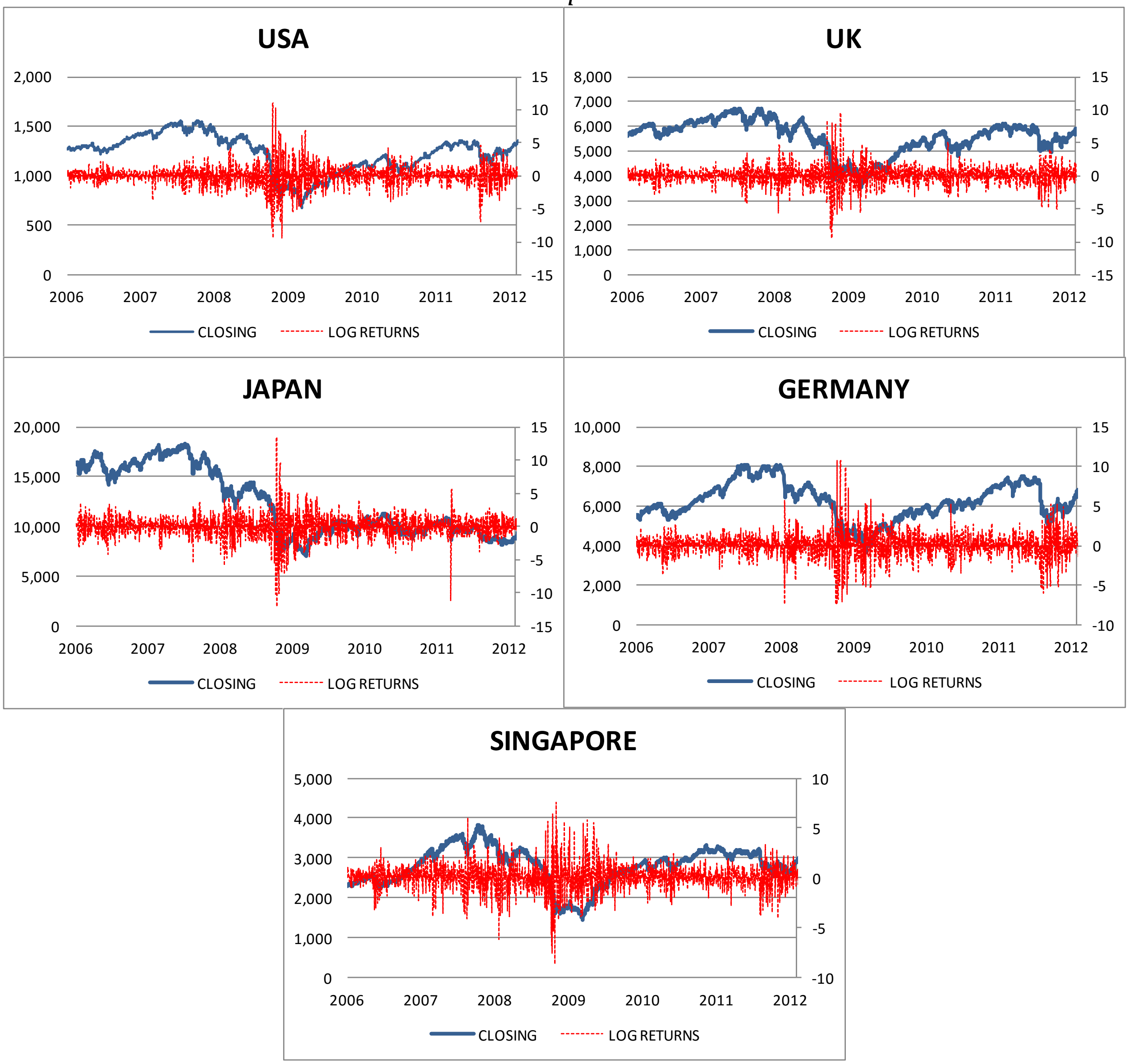
The graphs in Figure 5.1a-5.1c present the closing prices and log returns for each market under the developed, emerging, and frontier markets classifications. The left axis in each graph presents the closing prices and the right axis presents the log returns. Visual inspection of the returns series reveals greater volatility of some markets, such as China, Singapore, Germany, Pakistan and most Middle-Eastern markets. Volatility clustering is evident in all markets, suggesting longevity of both turbulent and tranquil periods. Table 5.1 (later in this chapter) presents the descriptive statistics of the log return series.

In the visual inspection of the graphs of the developed markets, Singapore seems to be the most volatile market. Although Japan does not appear to be as volatile as Singapore, the closing prices of Japan indicate a structural break in the index at the end of 2008 and beginning of 2009, whereby the value of the index declined substantially and has remained at that level ever since. In the emerging markets, China seems to be most volatile and suffered a structural break during the financial crisis of 2008. However, it is to be noted that the Chinese index considered in this sample allows foreign investors to buy shares of local Chinese companies and the structural break may be a reflection of foreign investors' sentiments, instead of being related to domestic fundamentals. India and Malaysia also exhibit volatility clustering; however, the log returns seem to oscillate closely around zero.

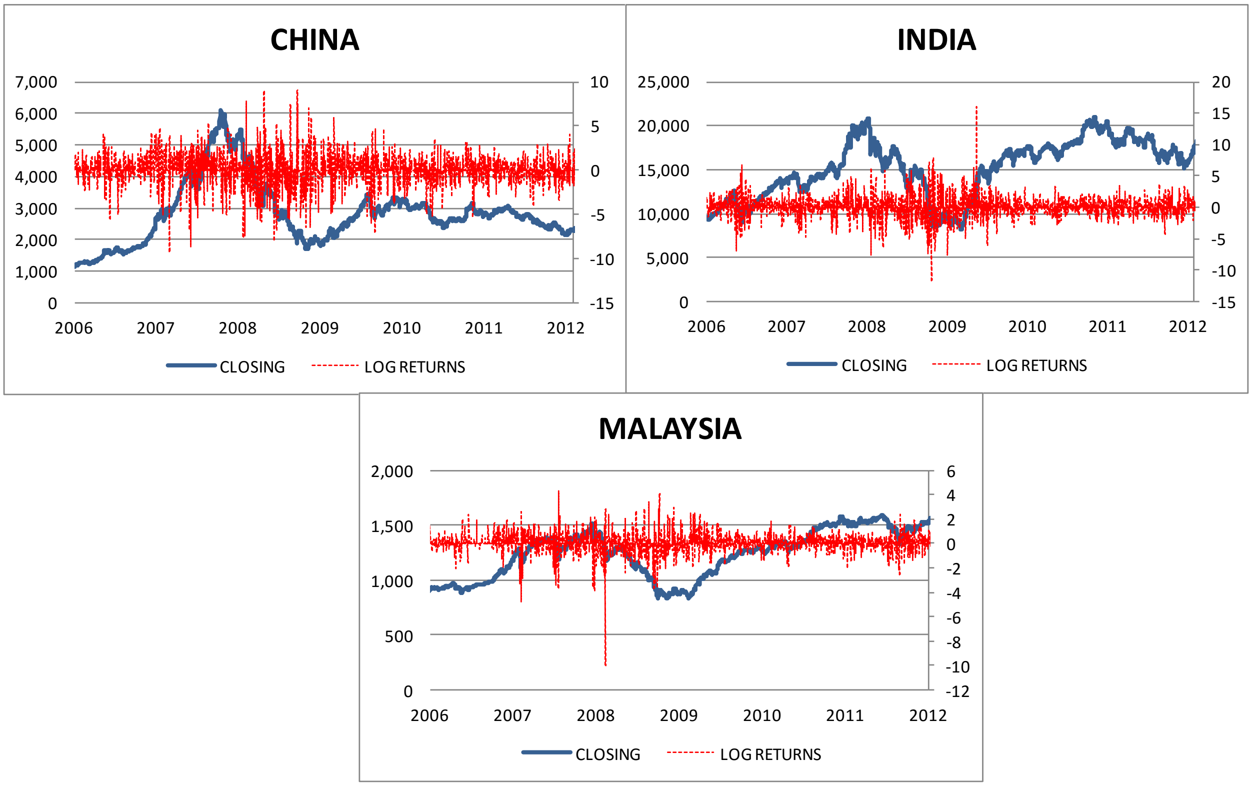
The frontier markets of Pakistan, Saudi Arabia, the UAE and Kuwait exhibit exaggerated volatility, and Pakistan seems to be most volatile in terms of minimum and maximum returns. Saudi Arabia, the UAE and Kuwait exhibit volatility but the returns do not fluctuate outrageously except at the time of a few key events, such as the time around the onset of the global financial crisis in 2008 and the real estate crisis in Dubai at the end of 2009. All the GCC markets in the sample experienced structural breaks at the onset of the financial crisis and have not recovered since then. In fact, the Kuwait index fell further than its value in the pre-crisis era and lost almost two thirds of its value from its peak of nearly 16,000 points at the end of 2008.

Figure 5.1 - Closing Prices and Log Returns of Markets in the Study

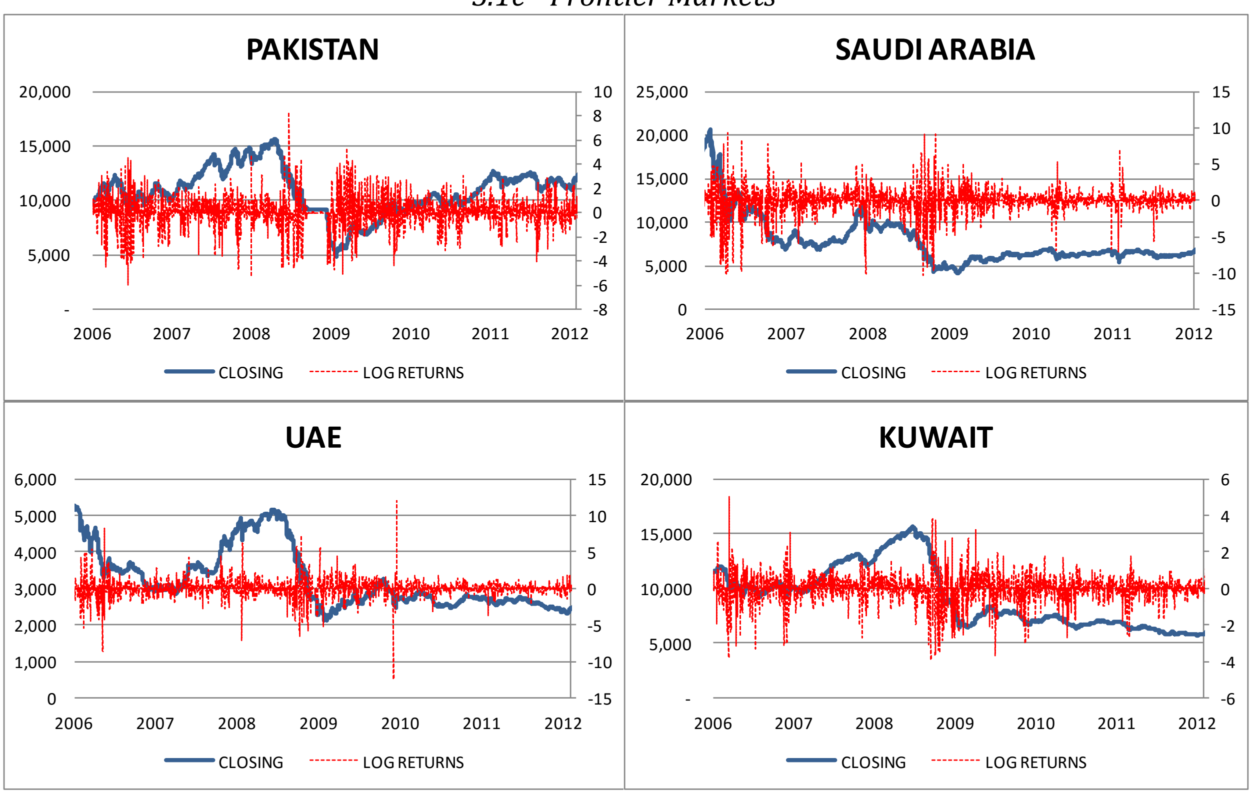
5.1 a - Developed Markets



5.1b - Emerging Markets

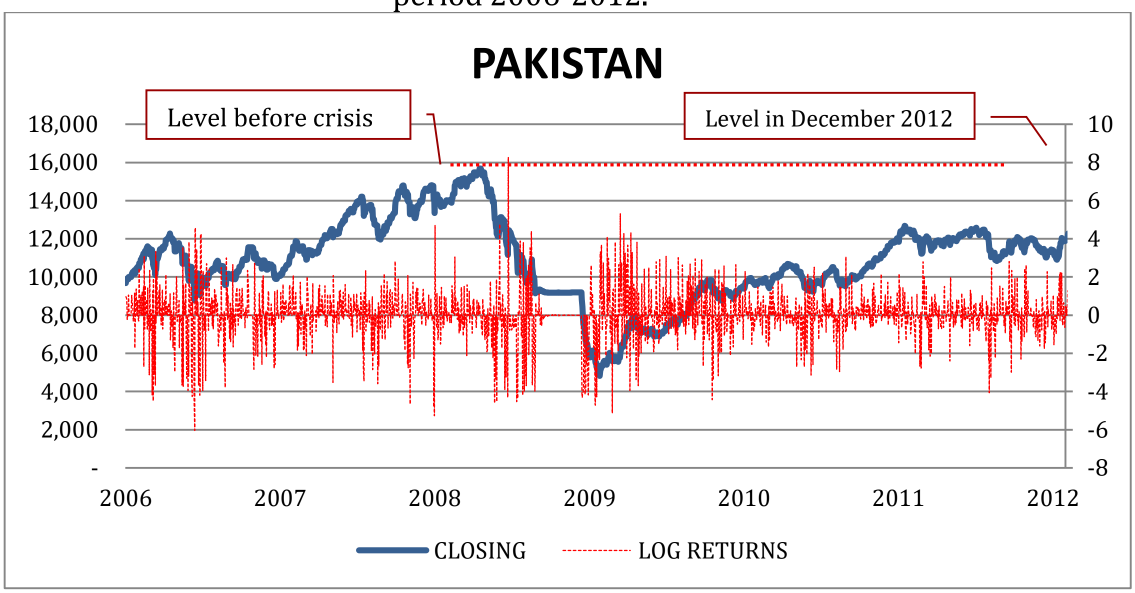


5.1c - Frontier Markets



From September to December 2008, when the world markets were presumably volatile mostly due to the foreign shocks, Pakistan was dealing with its own set of problems. In August 2008, the management of the Karachi Stock Exchange (KSE) and the Securities and Exchange Commission of Pakistan (SECP) mutually agreed to put a floor on the KSE100 index, in order to avoid a free fall of the index. The floor lasted until December 2008. The closing prices and log returns graph for Pakistan is reproduced in figure 5.2 below, which clearly illustrates the imposition of the floor, when closing prices were constant and the returns were zero. Pakistan's index experienced a major decline at the end of 2008 when approximately two thirds of the market capitalization was erased in a few days, bringing the index down to approximately 5,000 points from nearly 16,000 points in April 2008. As seen in figure 5.2, Pakistan appears to be on the path of recovery post-crisis, as the index level has surpassed the level it was trading at before the financial crisis and the index was valued at approximately 17,000 points in December 2012, providing a staggering return of 48% in 2012 (SECP, 2013).

Figure 5.2 - Closing Prices and Log Returns of Pakistan for the period 2006-2012.



Note: The index level in 2012 has surpassed the level in the pre-crisis period. The floor in the latter half of 2008 is also evident.

Comparison across markets reveals volatility clustering in all markets at the end of 2008 and beginning of 2009. The persistence of volatility during this period can be attributed to the financial crisis that started in the USA, then spilled across many markets around the

world asymmetrically. The developed economies appeared to react more aggressively to the crisis as compared to the emerging and frontier markets.

The regional interdependence between several markets is apparent within the sample and is widely documented in literature (see chapter 2 for detailed literature review). The following patterns are observed:

- The UK and Germany exhibited similar patterns of volatility in 2011 and 2012. This volatility can be a result of the Eurozone crisis, which deepened in mid-2011.
- Japan and Singapore exhibited volatility around the time of the earthquake and tsunami of March 2011. This implies association between the two markets that is possibly due to their geographical proximity and trade relationships.
- High volatility in the GCC markets in 2006 appears to have been associated with the crisis that emerged in Saudi Arabia and was then transmitted to other regional markets. At the beginning of 2006, the Saudi Arabia market lost 50% of its value within three months (AME Info, 2006b), followed by the UAE and Kuwait, which declined by 33% and 14% respectively (AME Info, 2006a).

Beyond regional interdependencies, global interdependencies are also evident in the chosen markets. The proliferation of the financial crisis of 2008 is obvious in the return series of the candidate countries, which exhibited exaggerated but varied magnitude of volatilities around the onset of the financial crisis. Another period with exaggerated volatility occurred in late 2009 and early 2010. This episode of enhanced volatilities across markets can be attributed to the Dubai real estate market crash that sent jitters to the USA and European markets, most probably due to the heavy borrowing by the Dubai government and associated entities from world markets. The bonds issued by the Dubai government and its related entities were severely downgraded by Moody's in late 2009 (Moody's, 2009).

Descriptive statistics also provide useful insight into the attributes of the returns and volatility time series. Table 5.1 below presents the descriptive statistics of log returns of developed, emerging, and frontier markets.

In the developed markets, only Japan had negative mean returns in the group. The UK had the lowest positive returns of 0.0019, followed by the USA (0.0046). The highest

positive returns were presented by Germany (0.0131), followed by Singapore (0.0129), although the difference between the returns of Singapore and Germany was marginal. Japan exhibited the highest standard deviation in comparison to its other developed counterparts. On the other hand, Singapore's standard deviation was the lowest (1.1208). Large differences between minimum and maximum values in each time series can also be an indication of volatility. Japan had a positive maximum value of 13 as compared with a minimum value of -12. The range suggests greater fluctuation of returns associated with greater volatility in the time series. Japan's high standard deviation and volatility in returns can be explained by the economic situation in the country, as well as the destruction caused by the natural disaster in March 2011. With respect to skewness and kurtosis of returns, only Germany's returns are positively skewed, while all other developed markets in the sample have negatively skewed returns. Highest kurtosis was presented by Japan (17.2704), followed by the USA (16.3003). Singapore had the lowest kurtosis of 11.

In the group of emerging markets, the mean returns were positive for all emerging markets in the sample and the average returns were marginally different from each other. Minimum standard deviation in the sample was 0.6971 (Malaysia) and maximum was 1.5019 (China). In the sample, India had a maximum value of approximately 16 versus a minimum value of -11.6, which is indicative of greater volatility in India's returns. Malaysia's returns were highly negatively skewed as compared to the other two emerging markets. The estimates of kurtosis for Malaysia were also very high; they were nearly three times the kurtosis of China and approximately twice the kurtosis of India.

Table 5.1 - Descriptive Statistics for Returns[38]

	Sample	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Developed Markets									
USA	2544	0.0046	10.9572	-9.4695	1.2094	-0.2215	16.3003	18771.99	0.00
UK	2544	0.0019	9.3843	-9.2656	1.1491	-0.1309	14.1131	13098.40	0.00
GERMANY	2544	0.0131	10.7975	-7.4335	1.2953	0.1024	12.8105	10206.44	0.00
JAPAN	2544	-0.0178	13.2346	-12.1110	1.3761	-0.6728	17.2704	21778.05	0.00
SINGAPORE	2544	0.0129	7.5305	-8.6960	1.1208	-0.2078	11.1819	7114.28	0.00
Emerging Markets									
CHINA	2544	0.0263	9.0345	-9.2561	1.5019	-0.4544	8.9241	3807.61	0.00
MALAYSIA	2544	0.0249	4.2587	-9.9785	0.6971	-1.4753	25.3428	53837.97	0.00
INDIA	2544	0.0286	15.9900	-11.6044	1.4495	0.1966	14.5063	14050.15	0.00
Frontier Markets									
PAKISTAN	2544	0.0219	8.2547	-6.0418	1.1380	-0.4403	8.6856	3508.81	0.00
SAUDI ARABIA	2544	-0.0364	9.3907	-10.3285	1.5593	-1.0618	14.1295	13607.87	0.00
UAE	2544	-0.0272	11.9944	-12.3128	1.0587	-0.3619	26.9576	60895.92	0.00
KUWAIT	2544	-0.0259	5.0469	-3.8745	0.6732	-0.8577	10.8244	6801.33	0.00

[38] Descriptive Statistics for returns in the pre-crisis, crisis, post-crisis are presented in Appendix 5.1.

The frontier markets of Saudi Arabia, UAE and Kuwait presented the lowest negative returns, not only within the group but also in the entire sample. Pakistan was the only market in the group with positive returns, which were very close to those of its emerging trade partners. Saudi Arabia exhibited the highest standard deviation of 1.56 and Kuwait presented the lowest standard deviation, which were also lowest in the overall sample. The standard deviations of Pakistan and the UAE were comparable. The UAE had a steeper negative minimum value of -12.3 versus a maximum value of 12. All the returns series in this group were negatively skewed, with Saudi Arabia having the highest negative skewness. The UAE had the highest kurtosis estimates in the group and in the sample.

In general, all the time series included in the analysis exhibited the characteristics of a typical financial assets time series, especially negative skewness and high kurtosis estimates. All the countries in the sample exhibited high kurtosis in returns (more than 3). Kurtosis in the sample ranged between 8.6 and 25.3, the lowest being exhibited by Pakistan and the highest by the UAE. Skewness of the time series ranged between -1.475 (Malaysia) and 0.1965 (India). Kurtosis estimates suggest that all the return distributions of all the markets were fat tailed, or leptokurtic. The sample skewness shows that the daily returns had asymmetric distribution with returns having either positive or negative skewness throughout the sample. Ten out of twelve countries in the sample had negatively skewed returns, indicating that the asymmetric tail extended more towards negative values than positive ones. The only exceptions were Germany and India, which exhibited positively skewed returns. This indicates that the return series of all markets were not normally distributed and were fat tailed. The Jarque and Bera (1981) normality test statistics suggest that the daily rates of return were not normally distributed; hence, the null hypothesis of normally distributed series for all the markets included in the sample is rejected as suggested by the *p*-values.

Besides calculating log returns for each market, volatility for each time series is calculated and presented in Figure 5.3. In line with Diebold and Yilmaz (2012), intraday minimum and maximum prices provide range-based volatility for each market and produce separate volatility time series for each of the twelve candidate countries. The authors justify the use of this approach by assuming that volatility is stationary in a period but changes

across periods. Also, the authors assert that considering closing prices only to estimate volatility ignores the time-varying nature of volatility, leading to distorted results.

To estimate volatility in each time series, the natural log of high and low prices is taken and the volatility time series is generated using the following formula:

$$\sigma_{i,t}^2 = 0.361[ln(P_{i,t}^{max} - P_{i,t}^{min})]^2$$

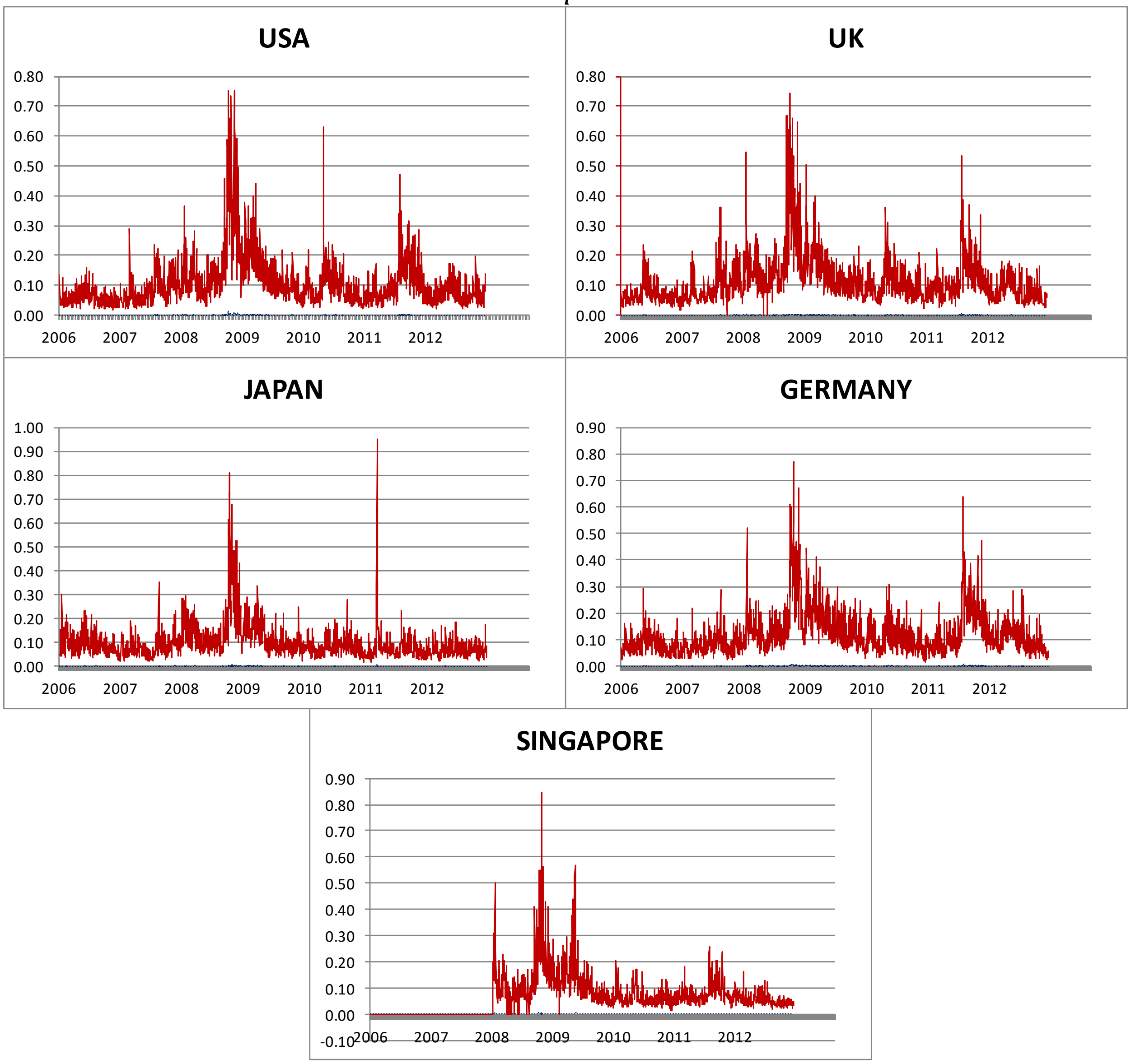
where P_{it}^{max} and $P_{it}^{min}$is the highest and the lowest price in market *i* on day *t* respectively.

The resulting range-based volatility series is then plotted on graphs (Figures 5.3a to 5.3c) to identify periods of extreme volatility across markets. A visual inspection of the volatility plots reveals similar results to the returns plots. Volatility persistence is evident and similar patterns of volatility are apparent in all markets in late 2008 and early 2009, coinciding with the financial crisis. Beyond the financial crisis, peculiar patterns in volatilities can be attributed to regional or local events. For example, Germany and the UK demonstrated increased volatility surrounding the Eurozone crisis in 2011-2012. Japan demonstrated enhanced volatility at the beginning of 2011 possibly due to the devastating Tsunami and subsequent Fukushima nuclear disaster. China exhibited extreme volatility between 2006 and 2009, followed by a relatively tranquil period. India and Malaysia exhibited brief episodes of exaggerated volatility before the crisis, but low volatility after that.

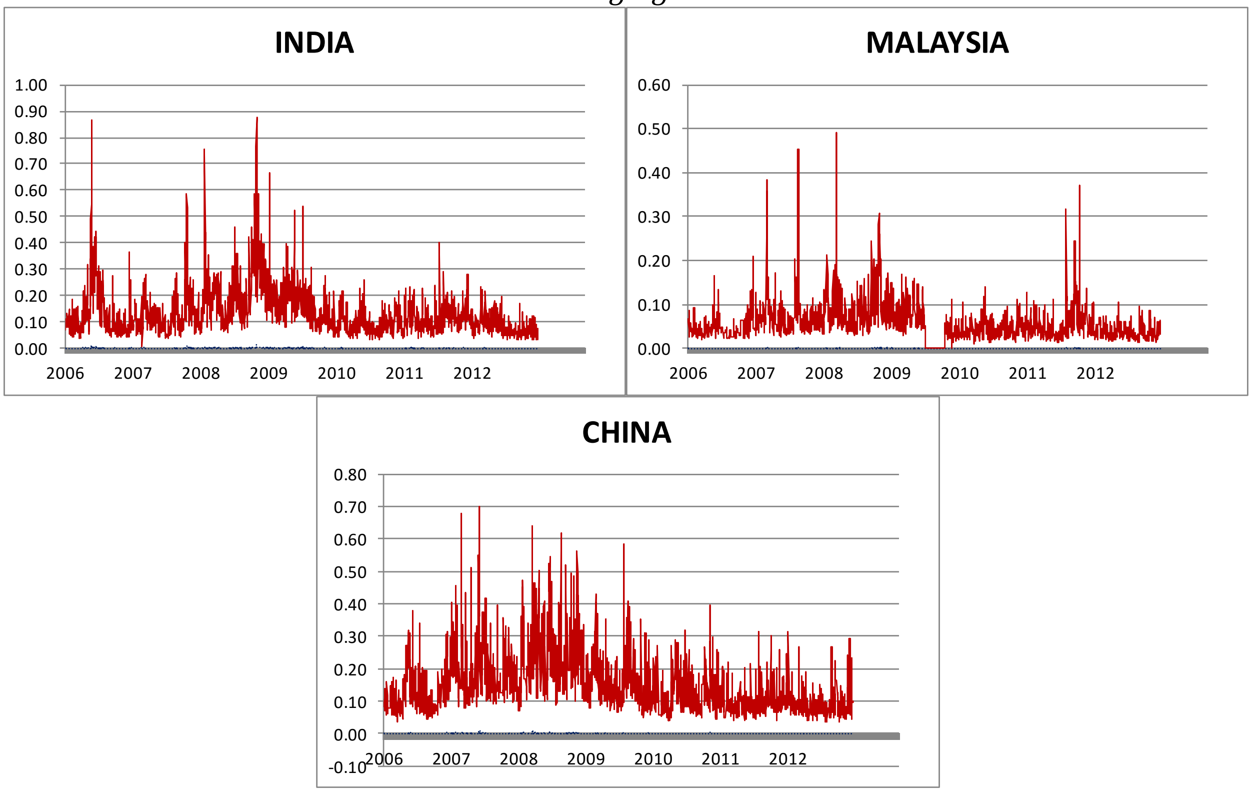
Pakistan's most volatile period was at the end of 2008 and beginning of 2009. Though world markets experienced enhanced volatilities during this period, some domestic events in Pakistan contributed greatly to the turmoil, such as the resignation of President Pervez Musharraf. As discussed earlier, a floor was place on the KSE during August 2008 and December 2008 and it experienced the worst market crash in its history after the floor was removed.

Figure 5.3 – Range-Volatility Graphs of Markets Included in the Sample

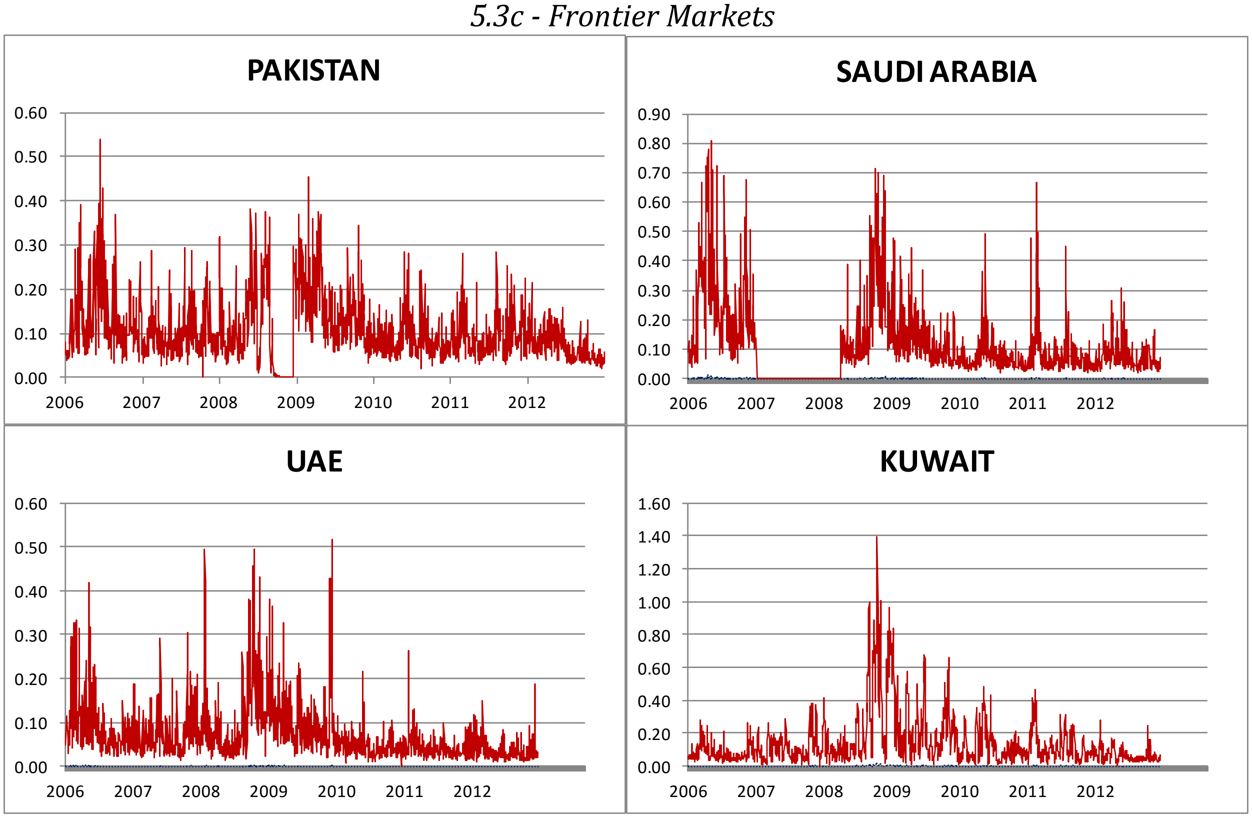
5.3a - Developed Markets



5.3b - Emerging Markets



5.3c - Frontier Markets



Volatility in the Saudi Arabia market was apparent in 2006 and then in 2008. However, the volatility in 2006 was much higher than the volatility in 2008. This indicates that the domestic events caused more turmoil in frontier markets as compared with global events. The UAE demonstrated amplified volatility from 2006 until 2010, which can be associated with the boom and bust of the real estate market, along with the financial crisis. The highest volatility was evident in 2009-2010, when the real estate market collapsed in the UAE (Irwin and Shukurov, 2014). The shock was transmitted to the other GCC markets, and markets like Kuwait demonstrated enhanced volatility following the financial crisis of 2008. Out of the three GCC markets in the sample, Kuwait appears to be the most affected by the financial crisis as its relative volatility jumped to 140% during the period of crisis.

Descriptive statistics for the range-based volatility time series are presented in Table 5.2. Low and high prices for Singapore and Saudi Arabia were not available for the complete period of analysis. Volatility estimates cannot be negative; hence, the mean values and skewness of range volatility cannot be negative. Accordingly, the skewness of the volatility time series can only be evaluated based on high and low values. The skewness and kurtosis estimates are high and are indicative of non-normal time series for all markets of interest. The Jarque-Bera normality test statistics confirm this finding and the null of normality is rejected for all the time series with a *p*-value of zero.

In the developed markets under consideration, the highest mean values were presented by Germany and the UK, and the lowest by Singapore. The standard deviation varied marginally between developed markets, and ranged between 0.0765 (Singapore) and 0.0832 (the USA). Though all the volatility time series are skewed and leptokurtic, Japan exhibited the highest skewness and excess kurtosis in the whole sample.

With respect to emerging markets, the mean volatility ranged between 0.0566 (Malaysia) and 0.1455 (China). Malaysia's standard deviation was the smallest in the group of emerging markets and in the whole sample. China exhibited the lowest estimates for skewness and kurtosis on the sample, with Malaysia's range volatility series exhibiting the highest skewness and kurtosis in the emerging markets under consideration.

Table 5.2 - Descriptive Statistics for Volatility

	Sample	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Developed Markets									
USA	2544	0.1040	0.7520	0.0172	0.0832	3.1360	18.1349	28462.07	0.00
UK	2544	0.1127	0.7417	0.0000	0.0787	3.0344	18.0726	27996.32	0.00
GERMANY	2544	0.1230	0.7684	0.0160	0.0825	2.3804	12.0162	11023.80	0.00
JAPAN	2544	0.0968	0.9492	0.0163	0.0748	4.3225	32.3865	99499.17	0.00
SINGAPORE	2544	0.0639	0.8476	0.0000	0.0765	3.1008	19.2457	32065.02	0.00
Emerging Markets									
CHINA	2544	0.1455	0.7014	0.0344	0.0874	1.7795	7.4027	3398.74	0.00
MALAYSIA	2544	0.0566	0.4897	0.0000	0.0435	3.3121	23.1374	47654.50	0.00
INDIA	2544	0.1342	0.8757	0.0044	0.0906	2.6641	15.2845	19013.28	0.00
Frontier Markets									
PAKISTAN	2544	0.1059	0.5385	0.0000	0.0723	1.4710	5.4918	1576.20	0.00
SAUDI ARABIA	2544	0.1056	0.8097	0.0000	0.1241	2.4517	10.1687	7999.20	0.00
UAE	2544	0.0698	0.5172	0.0000	0.0613	2.8199	14.0553	16333.37	0.00
KUWAIT	2544	0.1415	1.3923	0.0038	0.1628	3.0975	15.4830	20593.76	0.00

In the frontier markets, Kuwait exhibited the highest mean volatility (0.1415) and standard deviation of volatility (0.1628). Pakistan and Saudi Arabia had nearly similar mean volatility estimates and the UAE had the lowest estimates in the group. The UAE had the lowest standard deviation in the group, followed by Pakistan. Similarly, volatility in Pakistan exhibitd the lowest skewness and kurtosis, not only within the frontier markets, but also in the complete sample. The highest skewness in the group was presented by Kuwait. Pakistan's mean volatility and standard deviation of volatility was comparatively lower than some of its developed and emerging counterparts.

Comparison of descriptive statistics of returns and volatility suggests that Pakistan's skewness and kurtosis estimates for both returns and volatility were amongst the lowest in the sample. The standard deviation of volatility was nearly 50% of the standard deviation of returns. In addition, Pakistan had the lowest Jarque-Bera statistic for both returns and volatility time series in the sample.

5.1.2 Autocorrelations

To understand the dynamics of all the returns time series in the sample, serial correlations between returns are calculated. The Ljung Box Q-statistics and associated p-values enable the testing of the null hypothesis that the successive errors are independently distributed and the correlations between the subsequent lags is zero. P-values more than the significance level provide evidence of the lack of serial correlation in the time series. Furthermore, lack of serial correlations suggests that the returns in a particular market follow random walk and that the markets are efficient; hence as observed earlier, the returns in efficient markets cannot be predicted. Positive autocorrelation suggests that an increase in the time series is followed by an increase in value, and negative autocorrelation suggests that an increase in value precedes a decrease in value. Tables 5.3a-5.3c present the correlogram for all the returns series. The serial correlations entail seven lags at the 5% significance level[39].

[39] Autocorrelations were also estimated for 30 lags. Since no significant differences in the results were observed, results up to only seven lags are presented in the thesis.

In the developed markets, the USA returns exhibit positive autocorrelations in all seven lags. Lack of autocorrelations in other developed markets is evident at least in the first two lags. In the case of the UK and Japan, the *p*-values start decreasing and fall below the 5% significance level in the third and fourth lag respectively. For Germany and Singapore, the null of no autocorrelation cannot be rejected for all seven lags.

In emerging markets, China exhibits negative autocorrelation in the first lag and positive autocorrelations in remaining lags. China is the only market in the emerging markets sample and otherwise that exhibits such traits. Malaysia exhibits autocorrelations in all lags as suggested by the *p*-value of zero. In contrast, India exhibits a lack of correlation in all seven lags.

All frontier markets included in the sample provided evidence of autocorrelations in all seven lags, with *p*-values less than the significance level of 5%. Hence, in the case of all frontier markets, the null of no autocorrelation is rejected. There is an evidence of negative autocorrelation in the later lags of the UAE returns. Pakistan exhibits positive autocorrelations in all seven lags with the Q-stat increasing gradually with associated *p*-values of zero. The results are not surprising, as smaller markets are expected to be informationally inefficient[40] and are documented to reflect historical information. This means that their future returns can be forecast using various econometric models (for example, Harvey, 1995a; Kawakatsu and Morey, 1999; Buguka and Brorsen, 2003; Worthington and Higgs, 2006; Omran and Farrar, 2006; Griffin *et al.*, 2010). However, the data analysis in this thesis provides evidence of the inefficiency of some developed markets, which are otherwise considered informationally efficient.

[40] The Efficient Market Hypothesis (EMH) by Fama (1970) is an important concept in finance and forms the foundation of many models used in various studies. The EMH states that the markets are informationally efficient if the prices of securities reflect all available information, hence, it is impossible for investors to "beat the market". Fama (1970) classified market efficiency in three forms: strong, semi-strong and weak. In a strongly efficient market, prices reflect past information as well as current public and private information. In a semi-strong efficient market, the prices reflect both past and current public information, while in a weak form efficient market, prices reflect past information only. In all three forms of efficient markets, prices follow a random walk, and hence, they are unpredictable. If the markets are inefficient, the prospect of making abnormal economic returns using technical analysis arises.

Table 5.3 – Correlograms of Markets Included in the Study

Table 5.3a - Developed Markets

USA

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|******|	|******|	1	0.777	0.777	1538.5	0.000
|***** |	|** |	2	0.739	0.340	2929.4	0.000
|***** |	|* |	3	0.693	0.143	4155.1	0.000
|***** |	|* |	4	0.675	0.130	5316.7	0.000
|***** |	|* |	5	0.662	0.113	6434.7	0.000
|***** |	| |	6	0.626	0.013	7434.4	0.000
|***** |	|* |	7	0.625	0.088	8432.7	0.000

UK

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.024	-0.024	1.4233	0.233
| |	| |	2	-0.004	-0.005	1.4706	0.479
| |	| |	3	-0.052	-0.053	8.4968	0.037
| |	| |	4	-0.033	-0.036	11.267	0.024
| |	| |	5	-0.035	-0.037	14.378	0.013
| |	| |	6	0.053	0.049	21.631	0.001
| |	| |	7	-0.039	-0.041	25.470	0.001

GERMANY

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.020	0.020	1.0628	0.303
| |	| |	2	-0.005	-0.006	1.1308	0.568
| |	| |	3	-0.023	-0.023	2.4521	0.484
| |	| |	4	-0.029	-0.028	4.6195	0.329
| |	| |	5	-0.022	-0.021	5.8220	0.324
| |	| |	6	0.012	0.012	6.2045	0.401
| |	| |	7	-0.025	-0.027	7.8366	0.347

JAPAN

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.025	-0.025	1.6215	0.203
| |	| |	2	-0.002	-0.003	1.6306	0.443
| |	| |	3	-0.034	-0.034	4.5207	0.210
| |	| |	4	-0.052	-0.054	11.539	0.021
| |	| |	5	0.012	0.009	11.928	0.036
| |	| |	6	0.027	0.026	13.758	0.032
| |	| |	7	0.011	0.009	14.060	0.050

SINGAPORE

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.020	0.020	1.0704	0.301
| |	| |	2	0.035	0.035	4.2394	0.120
| |	| |	3	-0.031	-0.032	6.6447	0.084
| |	| |	4	-0.026	-0.026	8.3624	0.079
| |	| |	5	-0.000	0.003	8.3626	0.137
| |	| |	6	0.026	0.027	10.063	0.122
| |	| |	7	0.010	0.008	10.335	0.170

Table 5.3b - Emerging Markets

CHINA

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*| |	*| |	1	-0.066	-0.066	11.088	0.001
| |	| |	2	0.005	0.001	11.161	0.004
|* |	|* |	3	0.078	0.079	26.680	0.000
| |	| |	4	0.000	0.011	26.680	0.000
| |	| |	5	0.031	0.031	29.146	0.000
| |	| |	6	0.048	0.046	34.920	0.000
| |	| |	7	-0.012	-0.007	35.281	0.000

MALAYSIA

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|* |	|* |	1	0.087	0.087	19.364	0.000
| |	| |	2	0.019	0.012	20.299	0.000
| |	| |	3	-0.004	-0.007	20.340	0.000
| |	| |	4	0.020	0.021	21.357	0.000
| |	| |	5	0.069	0.066	33.576	0.000
| |	| |	6	0.020	0.008	34.622	0.000
| |	| |	7	-0.022	-0.027	35.868	0.000

INDIA

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.017	0.017	0.6979	0.403
| |	| |	2	-0.005	-0.006	0.7725	0.680
| |	| |	3	-0.008	-0.008	0.9423	0.815
| |	| |	4	-0.012	-0.012	1.3346	0.855
| |	| |	5	0.017	0.017	2.0346	0.844
| |	| |	6	0.020	0.019	3.0679	0.800
| |	| |	7	-0.039	-0.040	6.9226	0.437

Table 5.3c - Frontier Markets

PAKISTAN

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.063	0.063	10.176	0.001
| |	| |	2	0.049	0.046	16.377	0.000
|* |	|* |	3	0.082	0.077	33.701	0.000
| |	| |	4	0.060	0.049	42.800	0.000
| |	| |	5	0.006	-0.007	42.897	0.000
| |	| |	6	0.008	-0.003	43.074	0.000
| |	| |	7	0.012	0.003	43.437	0.000

SAUDI ARABIA

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|******|	|******|	1	0.821	0.821	1715.9	0.000
|******|	|** |	2	0.783	0.337	3280.5	0.000
|***** |	|* |	3	0.755	0.181	4735.0	0.000
|***** |	|* |	4	0.738	0.133	6122.5	0.000
|***** |	| |	5	0.702	0.025	7381.4	0.000
|***** |	| |	6	0.689	0.069	8595.0	0.000
|***** |	|* |	7	0.699	0.144	9843.4	0.000

UAE

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|* |	|* |	1	0.128	0.128	41.760	0.000
| |	| |	2	-0.003	-0.020	41.780	0.000
| |	| |	3	0.047	0.051	47.520	0.000
| |	| |	4	0.040	0.027	51.533	0.000
| |	| |	5	-0.004	-0.011	51.567	0.000
| |	| |	6	-0.028	-0.028	53.630	0.000
| |	| |	7	0.002	0.006	53.639	0.000

KUWAIT

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|* |	|* |	1	0.156	0.156	61.973	0.000
| |	| |	2	0.024	0.000	63.493	0.000
|* |	|* |	3	0.101	0.099	89.369	0.000
| |	| |	4	0.060	0.030	98.545	0.000
| |	| |	5	0.022	0.008	99.799	0.000
| |	| |	6	0.035	0.022	102.89	0.000
|* |	| |	7	0.076	0.061	117.72	0.000

5.1.3 Unit Root Test

Each time series included in the sample were assessed for stationarity, as non-stationary time series may lead to spurious results in the later stages of data analysis. For this purpose, the ADF test was conducted at *t*, lags two, five, seven, ten, fifteen and thirty. Multiple specifications were used to ensure the reliability and robustness of results. The best-fit model was determined using the minimum SIC, as Liew (2004) suggests that SIC is appropriate for large sample sizes.

The results reveal stationarity of all the log returns series; hence, the null hypothesis of time series having unit root or being non-stationary is rejected at the 5% significance level. The SIC statistic was minimized for *t* for all markets except China, Pakistan, and Kuwait. For these markets, the lowest SIC was reported at lag two. Table 5.4 reports the selective results of the ADF test with the minimum SIC values for all the countries. The full results of the ADF test including all lags are presented in Appendix 5.4.

Given the strengths and weaknesses associated with various unit root tests, the stationarity of each series was also evaluated with the help of the PP test. The PP test is a non-parametric test and does not enforce the assumption of normality on the time series, instead looking for a best-fit model based on the attributes of data. EViews-7 enables the deduction of results based on the Newey-West bandwidth and automatically chooses the most appropriate bandwidth based on the data attributes. The results of the PP test are presented in Table 5.5 and provide evidence that all the return series in the sample are stationary.

Use of parametric (ADF) and non-parametric (PP) simultaneously ensures that the results are robust with and without the forced assumption of normality of time series under consideration.

Table 5.4 – Results of Augmented Dickey Fuller Test

	t-Statistic	Prob.	SIC
Developed Markets			
USA	-56.2791	0.0001	3.2121
UK	-51.6227	0.0001	3.121
GERMANY	-49.3891	0.0001	3.3611
JAPAN	-51.6967	0.0001	3.482
SINGAPORE	-49.3902	0.0001	3.0714
Emerging Markets			
CHINA*	-27.4422	0	3.653
MALAYSIA	-46.189	0.0001	2.1147
INDIA	-49.5918	0.0001	3.5857
Frontier Markets			
PAKISTAN*	-25.5331	0	3.0969
SAUDI ARABIA	-47.7553	0.0001	3.7295
UAE	-44.3185	0.0001	2.9416
KUWAIT*	-24.834	0	2.0249
* Minimum SIC Values at lag 2			

Table 5.5 – Results of Phillips-Perron Test

	Newey-West Bandwith	Phillips-Perron test statistic	Prob.
Developed Markets			
USA	8	-56.4264	0.0001
UK	25	-52.1931	0.0001
GERMANY	15	-49.4541	0.0001
JAPAN	11	-51.8581	0.0001
SINGAPORE	10	-49.3889	0.0001
Emerging Markets			
CHINA	11	-53.7478	0.0001
MALAYSIA	6	-46.3325	0.0001
INDIA	15	-49.585	0.0001
Frontier Markets			
PAKISTAN	15	-48.2393	0.0001
SAUDI ARABIA	10	-47.8218	0.0001
UAE	7	-44.4352	0.0001
KUWAIT	21	-45.9936	0.0001

5.1.4 Modified GARCH (p, q) with Dummy Variable

As suggested earlier in this chapter and as is evident from Figure 5.1, some markets in the sample, like Japan, China, Saudi Arabia, the UAE and Kuwait, experienced a structural break around the time of the financial crisis in 2008. This calls for further investigation into the effects of the financial crisis on all the markets in order to understand whether the crisis had a long-term effect on the candidate markets and whether the impact was statistically significant at 5%.

For this purpose, this study uses a modified version of GARCH (p, q) with Gaussian distribution. Studies using this method of data analysis have used GARCH (1, 1) (for example Aggarwal *et al.*, 1999, Hammoudeh and Li, 2008; and Kang *et al.*, 2009); however, for this study the GARCH (p, q) is used to ensure the robustness of results, with p and q assuming values from one to three. The GARCH (p, q) model is modified by including a dummy variable CRISIS depicting the financial crisis, which assumes a value of one during the crisis period spanning from 15 September 2008 to 26 October 2009 and a value of zero otherwise. The best-fit model for each country with the lowest SIC statistic and the details associated with the CRISIS variable are reported in Tables 5.6a to 5.6c. All the results associated with other model specifications classified under developed, emerging and frontier markets are presented in Appendices 5.4 to 5.16.

Considering the developed markets first, results for the majority of the developed markets under consideration are robust to various model specifications and the results are straightforward to interpret. Singapore is the only market in the sample of developed markets that clearly remained unaffected from the financial crisis of 2008; the CRISIS variable in the model for Singapore remains highly insignificant in all model specifications. While all the models present similar results for Singapore, the best-fit model according to the lowest SIC statistic appears to be GARCH (3, 3). Germany and Japan appear to be clearly affected by the financial crisis. For all model specifications, the CRISIS variable is significant at 5% significance level. The best-fit model for Germany and Japan with the lowest SIC values is GARCH (2, 3) and GARCH (3, 3) respectively.

The results for the USA and the UK are mixed. For the USA, the CRISIS variable is significant for five model specifications and insignificant for the remaining four

specifications. The best-fit model based on the SIC statistic appears to be GARCH (1, 2) for the USA. For the UK, the CRISIS variable is significant for only three model specifications. The best-fit model with the lowest SIC value is GARCH (3, 3) and the model presents the CRISIS variable to be statistically significant at the 2% and 5% significance levels.

With respect to the emerging markets included in the sample, China clearly appears to be unaffected by the financial crisis of 2008, as the CRISIS variable is statistically insignificant for all model specifications. On the other hand, India seemed to be highly affected by the crisis, as the dummy variable included in all models is highly significant at the 5% level. The results for Malaysia are mixed, whereby six models suggest the insignificance of the CRISIS variable. Models with *p=3 and q=1, 2, 3* demonstrate the statistical significance of the dummy variable. The best-fit model for all three emerging markets, as determined by the lowest SIC value, is GARCH (3, 3). In the case of Malaysia, the CRISIS variable in this model is significant at the 10% significance level.

Pakistan and Kuwait in the frontier markets were clearly affected by the financial crisis of 2008 and it is evident in all model specifications, where the dummy variable is statistically significant at the 2% level, with one exception. The only anomaly is observed in GARCH (2, 3) for Kuwait, where the dummy variable is significant at the 10% level. The best-fit models for Pakistan and Kuwait are GARCH (3, 2) and GARCH (1, 2) respectively. For the UAE, the dummy variable is significant at the 5% level in all models except GARCH (2, 3) where the CRISIS variable is highly insignificant. Saudi Arabia demonstrates mixed results and the dummy variable is only significant for three model specifications. However, the best-fit model GARCH (3, 3) for Saudi Arabia indicates that the impact of crisis was significant on Saudi Arabia.

Table 5.6 – Best-fit Modified GARCH (p, q) Models with the Inclusion of Dummy Variable CRISIS for Markets Included in the Study

Table 5.6a - Developed Markets

USA		
GARCH (1,2)		
	z-Statistic	Prob.
C	6.6538	0.0000
RESID(-1)^2	8.9034	0.0000
GARCH(-1)	58.7775	0.0000
GARCH(-2)	-28.1453	0.0000
CRISIS	2.3401	0.0193
SIC		2.6689
Durbin-Watson stat		2.2192

UK		
GARCH(3,3)		
	z-Statistic	Prob.
C	4.3282	0.0000
RESID(-1)^2	13.9285	0.0000
RESID(-2)^2	-16.0544	0.0000
RESID(-3)^2	20.5628	0.0000
GARCH(-1)	338.3518	0.0000
GARCH(-2)	-194.0634	0.0000
GARCH(-3)	143.3919	0.0000
CRISIS	2.7404	0.0061
SIC		2.6032
Durbin-Watson stat		2.0472

GERMANY		
GARCH(2,3)		
	z-Statistic	Prob.
C	7.4701	0.0000
RESID(-1)^2	1.4208	0.1554
RESID(-2)^2	10.4132	0.0000
GARCH(-1)	42.9430	0.0000
GARCH(-2)	-30.0814	0.0000
GARCH(-3)	40.4971	0.0000
CRISIS	2.6537	0.0080
SIC		3.0199
Durbin-Watson stat		1.9589

JAPAN		
GARCH(3,3)		
	z-Statistic	Prob.
C	10.5068	0.0000
RESID(-1)^2	16.5959	0.0000
RESID(-2)^2	-17.6448	0.0000
RESID(-3)^2	17.9816	0.0000
GARCH(-1)	151.9866	0.0000
GARCH(-2)	-86.4156	0.0000
GARCH(-3)	57.0343	0.0000
CRISIS	2.7810	0.0054
SIC		3.0575
Durbin-Watson stat		2.0501

SINGAPORE		
GARCH(3,3)		
	z-Statistic	Prob.
C	6.2599	0.0000
RESID(-1)^2	9.2721	0.0000
RESID(-2)^2	7.6796	0.0000
RESID(-3)^2	20.9738	0.0000
GARCH(-1)	85.1054	0.0000
GARCH(-2)	-121.3876	0.0000
GARCH(-3)	205.9889	0.0000
CRISIS	0.9881	0.3231
SIC		2.6461
Durbin-Watson stat		1.9586

Table 5.6b - Emerging Markets

CHINA		
GARCH(3,3)		
	z-Statistic	Prob.
C	2.6304	0.0085
RESID(-1)^2	4.2921	0.0000
RESID(-2)^2	-0.4271	0.6693
RESID(-3)^2	12.4269	0.0000
GARCH(-1)	68.3516	0.0000
GARCH(-2)	-56.1884	0.0000
GARCH(-3)	116.0051	0.0000
CRISIS	1.2195	0.2227
SIC		3.4257
Durbin-Watson stat		2.1309

MALAYSIA		
GARCH(3,3)		
	z-Statistic	Prob.
C	11.4778	0.0000
RESID(-1)^2	18.9724	0.0000
RESID(-2)^2	-0.4761	0.6340
RESID(-3)^2	22.7445	0.0000
GARCH(-1)	85.3204	0.0000
GARCH(-2)	-110.5272	0.0000
GARCH(-3)	171.6359	0.0000
CRISIS*	1.7870	0.0739
SIC		1.7834
Durbin-Watson stat		1.8233

INDIA		
GARCH(3,3)		
	z-Statistic	Prob.
C	7.8819	0.0000
RESID(-1)^2	11.8479	0.0000
RESID(-2)^2	4.7694	0.0000
RESID(-3)^2	21.1070	0.0000
GARCH(-1)	94.9016	0.0000
GARCH(-2)	-121.9400	0.0000
GARCH(-3)	197.7965	0.0000
CRISIS	2.5103	0.0121
SIC		3.2037
Durbin-Watson stat		1.9657

Table 5.6c - Frontier Markets

PAKISTAN		
GARCH(3,2)		
	z-Statistic	Prob.
C	9.6702	0.0000
RESID(-1)^2	23.4912	0.0000
RESID(-2)^2	19.7428	0.0000
RESID(-3)^2	-15.1190	0.0000
GARCH(-1)	-19.2854	0.0000
GARCH(-2)	256.0982	0.0000
CRISIS	4.1863	0.0000
SIC		2.7503
Durbin-Watson stat		1.8726

UAE		
GARCH (2,1)		
	z-Statistic	Prob.
C	11.7927	0.0000
RESID(-1)^2	10.5631	0.0000
RESID(-2)^2	-8.4598	0.0000
GARCH(-1)	504.5842	0.0000
CRISIS	6.9439	0.0000
SIC		2.4582
Durbin-Watson stat		1.7427

SAUDI ARABIA		
GARCH(3,3)		
	z-Statistic	Prob.
C	24.6990	0.0000
RESID(-1)^2	12.2462	0.0000
RESID(-2)^2	0.4969	0.6193
RESID(-3)^2	23.3564	0.0000
GARCH(-1)	95.8186	0.0000
GARCH(-2)	-95.7996	0.0000
GARCH(-3)	72.6996	0.0000
CRISIS	3.8744	0.0001
SIC		3.0746
Durbin-Watson stat		1.8909

KUWAIT		
GARCH (1,2)		
	z-Statistic	Prob.
C	11.5156	0.0000
RESID(-1)^2	17.4834	0.0000
GARCH(-1)	6.1238	0.0000
GARCH(-2)	38.6081	0.0000
CRISIS	3.0764	0.0021
SIC		1.6685
Durbin-Watson stat		1.6855

5.2 Evaluation of the Association Between Pakistan and its Key Trade Partners

After examining characteristics of all the time series included in the sample, the data analysis focuses on evaluating the association and interdependence between Pakistan and its most active trade partners. Rudimentary analysis using correlation coefficients and Granger Causality provides some insight into the strength and direction of association and causation between the markets of interest; however, it does not provide detailed insight into cross-market interaction. Hence, the data analysis is further supplemented by using step-wise OLS estimation. First, the Pakistan log returns are regressed against the returns of other markets individually to evaluate whether the returns of other markets in the sample affect the Pakistan returns. Next, the returns of other markets are regressed against the Pakistan returns to examine the impact in the other direction. This step reveals useful information regarding the association between the markets of interest and establishes the need for further investigation using sophisticated econometric techniques. For this purpose, a variation of the error decomposition method under VAR, commonly known as the Spillovers Index is used. The Spillovers Indices facilitate the evaluation of static and dynamic spillovers across countries in the sample. As presented in Table 4.11, the returns and volatility spillovers are analyzed in a multitude of ways to ensure that all the details regarding the dynamics of association between the selected countries are captured and that the findings are robust.

While the overall association and interdependence between the chosen markets is discussed briefly, this section primarily focuses on elaborating further on Pakistan and its interaction with its trade partners.

5.2.1 Correlations

Correlation coefficients are a stepping-stone in the analysis of the association between markets. Correlations between the markets included in the sample are presented in Table 5.7. The highlighted column in the table indicates the Pakistan correlations with all the markets included in the sample.

It is observed that all the correlations are positive, suggesting that all markets move in the same direction. However, the strength of the relationships between markets is asymmetric. It is also apparent that most of the correlations between pairs of countries in the study are statistically significant.

The USA and the UK are highly positively correlated, with correlations between them being as high as 0.60. The UK has shown the highest correlation with Germany (0.90). In this case, also, bilateral trade, geographical proximity, and political integration can explain the greater correlation between the markets. The magnitude of correlations between the USA and the Asian developed markets is lower than those between the Asian developed and the European developed markets in the sample. Japan and Singapore exhibit high correlations between themselves.

Among the emerging markets, India demonstrates high correlations with developed as well as emerging markets. This might be an indication of India's increased association with the developed markets, due to enhanced foreign interest in the market. Malaysia demonstrates high correlations with regional markets and also with India.

Frontier markets mostly exhibit statistically significant correlations with all markets in the study, with the exception of Kuwait. Saudi Arabia, being the largest and most influential market in the region, is expected to affect the surrounding GCC markets largely. Accordingly, Saudi Arabia exhibits the highest positive correlation with the UAE. Kuwait exhibits relatively high correlation with the UAE and comparatively lower correlation with Saudi Arabia. The UAE has the highest correlations with all markets except the USA. This can be attributed to the vast amount of foreign investment that the UAE has been able to attract in the last decade from most parts of the world, leading to enhanced correlations with other markets, especially with Europe.

In terms of Pakistan's association with different groups of countries, weak and statistically insignificant correlations between Pakistan and the USA, and Pakistan and Germany, are observed. The association between Pakistan and the UK is weak but statistically significant at 5%. The Pakistan correlations with emerging markets are statistically significant but lower in magnitude.

Table 5.7 - Correlation Matrix[41]

Correlations Coefficients (Post-crisis period: 27 October 2009 - 31 December 2012)

	Pakistan	USA	UK	Germany	Japan	Singpore	China	Malaysia	India	Saudi Arabia	UAE	Kuwait
Pakistan	1.0000											
Developed Markets												
USA	-0.0186	1.0000										
UK	0.0562	0.6826 **	1.0000									
Germany	0.0444	0.7117 **	0.8803 **	1.0000								
Japan	0.1788 **	0.1535 **	0.2575 **	0.2577 **	1.0000							
Singpore	0.1625 **	0.3007 **	0.5082 **	0.4718 **	0.5343 **	1.0000						
Emerging Markets												
China	0.1017 **	0.1375 **	0.2382 **	0.1984 **	0.3261 **	0.3714 **	1.0000					
Malaysia	0.1723 **	0.0738 *	0.2397 **	0.1904 **	0.3809 **	0.4624 **	0.2385 **	1.0000				
India	0.1345 **	0.2634 **	0.4294 **	0.4008 **	0.3040 **	0.5476 **	0.2651 **	0.3004 **	1.0000			
Frontier Markets												
Saudi Arabia	0.0526	0.1128 **	0.1945 **	0.1813 **	0.1338 **	0.1702 **	0.0866 **	0.1274 **	0.1097 **	1.0000		
UAE	0.1882 **	0.0226	0.0550	0.0522	0.1274 **	0.1176 **	0.1054 **	0.1143 **	0.0646 *	0.1629 **	1.0000	
Kuwait	0.1153 **	0.0258	0.0502	0.0385	0.0599 *	0.0642 *	0.0181	0.0930 **	0.0359	0.1596 **	0.2404 **	1.0000

* Significant at the 5% level.
** Significant at the 2% level.

[41] Correlations coefficients between Pakistan and its key trade partners in pre-crisis, crisis and post-crisis periods are provided in Appendix 5.3. The estimates clearly indicate heightened correlations during the crisis.

In the frontier markets, Pakistan exhibits the highest correlation with the UAE, followed by Kuwait. The weakest positive correlation is observed between Pakistan and Saudi Arabia. Saudi Arabia is located in the same region as the UAE and Kuwait, and the volume of trade between Pakistan and these frontier markets is comparable. It appears that the association between these markets is governed by factors other than trade, geographical proximity, foreign investments, and political relationships.

Regional associations are apparent in general. For example, the highest positive correlation is observed between Pakistan and Malaysia, followed by Pakistan and India, Pakistan and the UAE and Pakistan and Singapore, respectively. Correlations between Pakistan and Japan, as well as between Pakistan and Kuwait, are reasonably high as well. The weakest positive correlation in the group is between China and Pakistan. Similarly, China exhibits high positive correlation with regional markets like Singapore, Japan and Malaysia, but low correlations with Saudi Arabia, Kuwait and the UAE.

Some interesting associations are observed in the sample. The correlations between India and China are stronger than the correlations between Pakistan and China. Similarly, the correlations between Pakistan and India are higher than those between Pakistan and China. It appears that tensed political relationships may play a role in determining correlations between financial markets. Political animosity persists between India and China, and the governments of the two countries have avoided close contact and economic integration in the past, assumingly due to potential security threats (Saran, 2013). The political relationship between Pakistan and India is also not very cordial.

It seems that while trade and geographical proximities may explain the association between some markets in the sample, these interpretations cannot be generalized for the whole sample, as observed in the case of Pakistan, India and China. This may suggest that some country-specific factors and other factors such as tensed political relationships may alter the nature of association between financial markets.

The results derived through the correlations estimates are useful but can be described as inconclusive, and therefore there is a need to explore the interaction between these markets further.

5.2.2 Pairwise Granger Causality

The log returns series are further analyzed using the Granger Causality Test to determine whether time series R_i causes time series R_j and vice versa. Although the test does not provide detailed insight into the extent of the causation, it does facilitate an understanding of unidirectional or bidirectional causation between the time series of interest. The test is conducted at lags two, five, seven, ten, fifteen and thirty, to ensure the robustness and reliability of results. Table 5.8 presents the results of the Granger Causality Test for all lags.

Unidirectional causality from all the developed markets to Pakistan, at the 5% significance level, is apparent, suggesting that the returns of developed markets can be useful in predicting the returns of Pakistan; however, the opposite is not true. These results are not unexpected as developed markets, especially the USA, are documented to assume leading position in driving returns in other markets. With respect to the causality between Japan and Pakistan, unidirectional causality from a larger to a smaller market is observed for almost all lags except at thirty lags, where causality from Pakistan to Japan is observed at the 10% significance level. In addition, the causality from Japan to Pakistan at lags ten and fifteen is significant at 10%. While the results of larger lags are pertinent, their significance in examining the association between the two markets may be marginal, due to the 7-day data frequency used in the analysis.

It is clear that correlation estimates could not capture the association between Pakistan and the developed markets. While correlation coefficients suggested weak association between Pakistan and the USA, Pakistan and the UK, and Pakistan and Germany, Granger causality found strong evidence of unidirectional causality from these developed countries to Pakistan.

With respect to the emerging markets included in the sample, the null of no causality could not be rejected for Pakistan and Malaysia for all the lags evaluated in the study. Low volume of bilateral trade during the period of analysis may explain the lack of causality between the two countries. It is interesting to note that the correlation estimates were the highest and statistically significant for Pakistan and Malaysia, while the Granger Causality suggests no causality between the two markets at any of the lags.

Table 5.8 – Granger Causality Between Pakistan and its Trade Partners at Multiple Lags

	2 lags		5 lags		7 lags		10 lags		15 lags		30 lags	
	F-Statistic	p-value	F-Statistic	p-value	F-Statistic	p-value	F-Statistic	p-value	F-Statistic	p-value	F-Statistic	p-value
USA ➔ Pakistan	16.4592	0.0000	7.5737	0.0000	5.7612	0.0000	4.3173	0.0000	3.0174	0.0001	1.9885	0.0011
Pakistan ➔ USA	0.7157	0.4890	0.5329	0.7515	0.4802	0.8496	0.4832	0.9020	0.4455	0.9657	0.7452	0.8398
UK ➔ Pakistan	15.7086	0.0000	7.7575	0.0000	5.6611	0.0000	4.0596	0.0000	3.5438	0.0000	2.1462	0.0003
Pakistan ➔ UK	0.9462	0.3884	0.2441	0.9429	0.4311	0.8832	0.3219	0.9757	0.4325	0.9701	0.8356	0.7209
Germany ➔ Pakistan	15.6164	0.0000	7.5923	0.0000	5.5692	0.0000	4.2038	0.0000	3.2155	0.0000	2.0088	0.0010
Pakistan ➔ Germany	0.4265	0.6528	0.4583	0.8075	0.3895	0.9090	0.3945	0.9496	0.6498	0.8350	0.9992	0.4675
Japan ➔ Pakistan	4.1058	0.0166	2.8696	0.0137	2.1641	0.0345	1.8082	0.0542	1.5177	0.0902	1.1059	0.3164
Pakistan ➔ Japan	1.6766	0.1872	1.1745	0.3192	0.8878	0.5151	0.6862	0.7382	1.0942	0.3558	1.3712	0.0864
Singapore ➔ Pakistan	3.3611	0.0349	3.6335	0.0028	3.0338	0.0035	2.8524	0.0016	2.2190	0.0045	1.4759	0.0464
Pakistan ➔ Singapore	1.3517	0.2590	0.7050	0.6197	0.5774	0.7749	0.5757	0.8351	0.6991	0.7877	0.9322	0.5722
China ➔ Pakistan	1.9451	0.1432	1.0993	0.3586	1.0548	0.3904	0.8046	0.6243	0.9669	0.4881	1.4061	0.0707
Pakistan ➔ China	3.8748	0.0209	2.3052	0.0422	1.7431	0.0947	2.1313	0.0194	1.8641	0.0223	1.4848	0.0439
Malaysia ➔ Pakistan	1.6061	0.2009	1.3643	0.2347	1.2210	0.2873	1.0260	0.4184	1.1123	0.3389	0.9673	0.5169
Pakistan ➔ Malaysia	0.7731	0.4617	0.8176	0.5370	0.8072	0.5812	0.8545	0.5758	0.7277	0.7583	1.0077	0.4546
India ➔ Pakistan	0.0810	0.9222	1.7320	0.1239	2.6586	0.0097	2.1703	0.0170	1.7170	0.0414	1.5615	0.0268
Pakistan ➔ India	1.0927	0.3355	0.4782	0.7928	0.3752	0.9172	0.5752	0.8354	0.6503	0.8345	0.9711	0.5109
UAE ➔ Pakistan	2.5183	0.0808	2.5993	0.0237	2.0636	0.0442	1.7210	0.0705	1.9801	0.0134	1.9298	0.0018
Pakistan ➔ UAE	1.1208	0.3262	2.6081	0.0232	2.5875	0.0117	1.8964	0.0413	1.5108	0.0926	1.4542	0.0530
Saudi Arabia ➔ Pakistan	0.6029	0.5473	0.6851	0.6347	2.1368	0.0369	2.0263	0.0273	2.5458	0.0009	1.6335	0.0165
Pakistan ➔ Saudi Arabia	4.6654	0.0095	2.0890	0.0639	1.6724	0.1112	1.7859	0.0580	2.1413	0.0064	1.8022	0.0049
Kuwait ➔ Pakistan	1.7396	0.1758	1.9358	0.0853	1.5032	0.1614	1.1030	0.3557	0.9235	0.5369	1.0295	0.4220
Pakistan ➔ Kuwait	4.0042	0.0184	2.8090	0.0155	3.2671	0.0019	2.5532	0.0046	1.8041	0.0289	1.9305	0.0018

Unidirectional causality from Pakistan to China was observed at most lags at the 5% significance level, except at seven lags, whereby the one-way causality was statistically significant at the 10% level. At thirty lags, bidirectional causality between the two countries was observed. However, it can be argued that with the use of 7-day frequency data, the results of Granger Causality at thirty lags may not be so meaningful. With respect to causality between traditional foes, Pakistan and India, no causality was observed for lags two and five, but statistically significant causality at the 5% level from India to Pakistan was observed for the remaining lags. Choudhry (2004) and Abbas *et al.* (2013) have reported similar results of causality between India and Pakistan.

With respect to the frontier markets, bidirectional causality was apparent between Pakistan and the UAE for all lags except at lag two. Causality between Pakistan and Saudi Arabia produced mixed results. While unidirectional causality from Pakistan to Saudi Arabia was evident at lags two and five, bidirectional causality was observed at lags ten, fifteen and thirty. Moreover, causality from Saudi Arabia to Pakistan was observed at lag seven. There is evidence of statistically significant unidirectional causality from Pakistan to Kuwait for most lags at the 5% significance level. An anomaly is observed at lag five, whereby bidirectional causality is evident between the two countries, from Pakistan to Kuwait at 5% level, and in the opposite direction at the 10% significance level.

In the case of some emerging and most frontier markets, a delay of causality is observed, which can be attributed to the informational inefficiency of these markets. Literature provides evidence that emerging markets are informationally inefficient and that the prices reflect historical information (for example, Kawakatsu and Morey, 1999; Buguk and Brorsen, 2003; Worthington and Higgs, 2006; Omran and Farrar, 2006; Griffin *et al.*, 2010).

Granger Causality has provided some evidence of causality between the markets of interest. However, these results do not quantify the influence of the markets included in the sample on each other. Hence, OLS estimation is employed below to facilitate understanding and quantification of the interaction between these markets.

5.2.3 Stepwise OLS Estimation

This step in the data analysis further evaluates the association between the log returns of the markets by using stepwise OLS estimation. All markets included in the sample except the USA have overlapping trading hours with Pakistan. Pakistan and the USA operate in time horizons that are nearly nine hours apart (refer to table 4.8 in chapter 4).

Two-way analysis is performed on log returns of Pakistan and its counterparts in the sample. First, Pakistan's log returns at *t* are regressed against the log returns of other markets in the sample. To ensure that all the information is captured, multiple lags are considered for estimations. Since Pakistan and the USA do not have overlapping trading hours, Pakistan's returns at *t* are regressed against lagged returns of the USA, and for this purpose, seven lags are included in the estimation. For other markets where there is an overlap in trading hours, the Pakistan returns at *t* are regressed against the other markets' returns at *t* and against an additional six lags, that is, from *t-1* to *t-6.*

Second, the log returns of all the markets in the sample at *t* are regressed against the Pakistan log returns. For the markets with overlapping trading hours with Pakistan, the returns at *t* are regressed against the Pakistan returns at *t* and its returns at six preceding lags, that is, *t-1 to t-6*. On the other hand, log returns of the USA at *t* are regressed against the Pakistan lagged returns from *t-1* to *t-7,* due to no overlapping trading hours.

The results of the stepwise regression enable an understanding of whether the log returns of regressor markets affect the returns of Pakistan and vice versa. The results are presented in Tables 5.9 and 5.10.

5.2.3.1 Pakistan as Regressand

Tables 5.9a to 5.9c present the results of stepwise OLS estimation where the Pakistan log returns are used as regressand. All the equations in the stepwise OLS estimation include seven regressors, but the choice of regressors is dependent on the trading hours of the markets included in the sample.

Pakistan's returns at *t* were regressed against lagged returns of the USA market *(t-1 to t-7)* as it is expected that the new information from the USA market is reflected in the Pakistan returns the following day. This is apparent in the results, as the USA returns at lags

t-1 and *t-2* were significant, suggesting that the returns in the USA market at *t-1* affect the returns of the Pakistan market when it opens at *t*. The significance of lag *t-2* suggests some lagged effect between the returns of the two markets.

Both of the European markets in the sample open a few hours later than Pakistan. Accordingly, the changes in the UK and Germany returns seem to be partially reflected in the current returns of the Pakistan market. The UK and Germany returns at *t-1* seem to be more pronounced in affecting the Pakistan returns at time *t*. Since these markets open approximately three to four hours later than the Pakistan market, there is a possibility that the information from these European markets does not get fully incorporated into the Pakistan returns on the same day, and that the Pakistan returns at *t* reflect the previous day's information. Interestingly, the Germany returns at *t-4* seem to be more pronounced in affecting the Pakistan returns at *t*, although the coefficients associated with lag *t-4* and time *t* are marginally different. This suggests a 4-day delay in transmission of information from Germany to Pakistan.

The Asia-Pacific markets open a few hours ahead of Pakistan and the difference between the Pakistan and India trading hours is minimal. In all such cases, the returns at *t* are highly significant, with relatively high coefficients. Some delay in the transmission of information from developed Asia-Pacific markets is also observed. For example, the Japan returns at *t-1*, *t-3* and *t-5* have a statistically significant impact on the Pakistan returns at *t*. Similarly, the Singapore returns at *t-4* and *t-3* are more pronounced than at *t-1*. With respect to emerging markets, the China and Malaysia returns at *t* and some later lags are statistically significant at the 5% level. With regard to India, returns at *t* and *t-1* were highly significant.

Table 5.9 - Stepwise OLS Estimation Results with Pakistan as a Regressand

Table 5.9a - Pakistan and Developed Markets

USA			
	Coefficient	**t-Statistic**	**p-value**
t-1	0.1044	5.5741	0.0000
t-2	0.0513	2.7227	0.0065
t-4	0.0369	1.9643	0.0496
t-5	0.0313	1.6604	0.0970
t-7	0.0287	1.5343	0.1251
t-6	0.0261	1.3828	0.1669
t-3	0.0231	1.2280	0.2196
Std Error	1.1304		
F-Statistic	6.3804		
p-value	0.0000		

UK			
	Coefficient	**t-Statistic**	**p-value**
t-1	0.1157	5.9209	0.0000
t	0.0541	2.7668	0.0057
t-4	0.0468	2.3961	0.0166
t-5	0.0404	2.0663	0.0389
t-2	0.0336	1.7187	0.0858
t-3	0.0323	1.6515	0.0988
t-6	0.0223	1.1401	0.2544
Std Error	1.1284		
F-Statistic	7.5249		
p-value	0.0000		

GERMANY			
	Coefficient	**t-Statistic**	**p-value**
t-1	0.0974	5.6274	0.0000
t-4	0.0419	2.4219	0.0155
t	0.0407	2.3482	0.0189
t-3	0.0287	1.6570	0.0976
t-2	0.0286	1.6519	0.0987
t-5	0.0221	1.2750	0.2024
t-6	0.0164	0.9459	0.3443
Std Error	1.1294		
F-Statistic	7.0609		
p-value	0.0000		

JAPAN			
	Coefficient	**t-Statistic**	**p-value**
t	0.0903	5.5372	0.0000
t-1	0.0564	3.4560	0.0006
t-3	0.0374	2.2961	0.0218
t-5	0.0320	1.9632	0.0497
t-6	0.0163	0.9980	0.3184
t-4	0.0151	0.9263	0.3544
Std Error	1.1290		
F-Statistic	7.1325		
p-value	0.0000		

SINGAPORE			
	Coefficient	**t-Statistic**	**p-value**
t	0.1229	6.1583	0.0000
t-4	0.0617	3.0940	0.0020
t-3	0.0595	2.9802	0.0029
t-1	0.0551	2.7610	0.0058
t-6	0.0386	1.9347	0.0531
t-2	-0.0161	-0.8078	0.4193
Std Error	1.1251		
F-Statistic	9.5601		
p-value	0.0000		

Table 5.9b - Pakistan and Emerging Markets

CHINA			
	Coefficient	**t-Statistic**	**p-value**
t	0.0496	3.2958	0.0010
t-4	0.0336	2.2351	0.0255
t-6	0.0192	1.2756	0.2022
t-3	0.0188	1.2427	0.2141
Std Error	1.1353		
F-Statistic	2.7535		
p-value	0.0075		

MALAYSIA			
	Coefficient	**t-Statistic**	**p-value**
t	0.2254	7.0039	0.0000
t-1	0.0656	2.0343	0.0420
t-4	0.0491	1.5331	0.1254
t-6	-0.0337	-1.0505	0.2936
Std Error	1.1267		
F-Statistic	8.3651		
p-value	0.0000		

INDIA			
	Coefficient	**t-Statistic**	**p-value**
t	0.1028	6.6550	0.0000
t-1	0.0278	1.8009	0.0718
t-3	0.0225	1.4553	0.1457
t-4	0.0199	1.2890	0.1975
t-6	0.0157	1.0151	0.3102
Std Error	1.1284		
F-Statistic	7.4154		
p-value	0.0000		

Table 5.9c - Pakistan and Frontier Markets

UAE			
	Coefficient	**t-Statistic**	**p-value**
t	0.1316	6.1592	0.0000
t-5	0.0579	2.6915	0.0072
t-1	0.0338	1.5690	0.1168
t-6	0.0312	1.4635	0.1435
t-2	0.0195	0.9049	0.3656
t-4	-0.0195	-0.9073	0.3643
t-3	0.0177	0.8204	0.4120
Std Error	1.1279		
F-Statistic	8.0051		
p-value	0.0000		

SAUDI ARABIA			
	Coefficient	**t-Statistic**	**p-value**
t-6	0.0467	3.2250	0.0013
t-5	0.0328	2.2642	0.0236
t-3	-0.0209	-1.4352	0.1514
t-1	0.0137	0.9421	0.3462
t-4	0.0105	0.7232	0.4696
Std Error	1.1358		
F-Statistic	2.5953		
p-value	0.0114		

KUWAIT			
	Coefficient	**t-Statistic**	**p-value**
t	0.1747	5.2146	0.0000
t-5	0.0773	2.3080	0.0211
t-2	0.0589	1.7376	0.0824
t-3	-0.0479	-1.4119	0.1581
Std Error	1.1313		
F-Statistic	5.2243		
p-value	0.0000		

With respect to Pakistan and frontier markets, returns at *t* and later lags were observed to be statistically significant. In the case of Saudi Arabia, lag *t-6* is observed to have the highest statistical significance, followed by *t*. However, there is a marginal difference between the coefficients of these lags. For the UAE and Kuwait, lag *t-5* holds the second highest statistical significance after *t,* although the coefficients for lags *t-5* are much lower than those of *t*. Adjusted R^2 for all models are small and range between 0.64% (China) and 2.38% (Singapore).

Some delay in the reaction of the Pakistan returns to new information from all frontier markets and emerging markets is apparent, which can be attributed to the informational inefficiency of these markets, as already documented in literature[42] (for example, Kawakatsu and Morey, 1999; Buguk and Brorsen, 2003; Worthington and Higgs, 2006; Omran and Farrar, 2006; Griffin *et al.*, 2010). With respect to the KSE, several studies conducted on the index level and sectoral level data have confirmed the informational inefficiency of the market (for example Chakraborty, 2006; Hassan *et al.*, 2007).

5.2.3.2 Pakistan as Regressor

In this analysis, the returns of all markets included in the sample were regressed against the 7-day returns of the Pakistan market. The results are presented in Tables 5.10a to 5.10c.

As discussed earlier, the developed markets included in the sample operate in different time zones. Most developed markets under consideration have overlapping trading hours with Pakistan, with the exception of the USA. Since there are no overlapping hours between Pakistan and the USA, returns of the USA market at time *t* are regressed against Pakistan's returns at *t-1* up to *t-7*. Subsequently, the number of regressors in the equation is seven. The data analysis anticipated that any new information from Pakistan at *t-1* would be reflected in the returns of the USA market at *t*. The developed markets in Europe, that is, the UK and Germany, open when the trading is already underway in Pakistan. Subsequently, it

[42] Although some inconsistency in results can be explained by the informational inefficiency of the markets, some of it can be attributed to the arbitrary choice of number of lags in the models. There is no theoretical underpinning that suggests an appropriate method for selection of lags in regression models employing 7-day frequency data. The number of lags and the stepwise regression in this study are facilitated by the need for extracting maximum information while maintaining parsimony of the models.

is anticipated that any new information from Pakistan available at time t is reflected in the returns of these two markets when they open. The Asia-Pacific developed markets, Japan and Singapore, are already open when Pakistan opens, and the trading in these markets is approximately mid-way. Any new information from Pakistan may be reflected during the remaining trading hours in these markets.

It is interesting to note that the Pakistan returns at t are statistically significant at the 2% significance level for all developed markets except the USA. Small coefficients suggest a very weak association between the returns of Pakistan and the developed markets. The adjusted R^2 are very low, ranging from 0.02% (USA market) to 1.4% (Singapore). Coefficients associated with statistically significant lags are positive; however, negative coefficients are associated with some statistically insignificant lags. This suggests that the transmission of information from Pakistan to developed markets is limited to time t only.

For the Asian developed markets that open a few hours earlier than the Pakistan market, time t is statistically significant at the 2% significance level. This may suggest that the impact of the returns in the Pakistan market on the developed markets is negligible and that the developed markets are able to absorb any information from the Pakistan market on the same day. The models for the USA, the UK and Germany are statistically insignificant, with low F-Statistic and high p-values, but the models for Japan and Singapore are statistically significant at the 5% level.

Table 5.10 - Stepwise OLS Estimation Results with Pakistan as a Regressor

Table 5.10a - Developed Markets and Pakistan

USA			
	Coefficient	t-Statistic	p-value
t-2	-0.0232	-1.0922	0.2748
t-5	0.0209	0.9845	0.3249
t-6	0.0167	0.7904	0.4294
Std Error	1.2105		
F-Statistic	0.3701		
p-value	0.9200		

UK			
	Coefficient	t-Statistic	p-value
t	0.0511	2.5424	0.0111
t-2	-0.0248	-1.2340	0.2173
t-1	-0.0203	-1.0094	0.3129
t-6	0.0175	0.8730	0.3827
Std Error	1.1487		
F-Statistic	1.3204		
p-value	0.2362		

GERMANY			
	Coefficient	t-Statistic	p-value
t	0.0542	2.3871	0.0171
t-3	-0.0236	-1.0399	0.2985
t-2	-0.0230	-1.0162	0.3096
t-4	0.0201	0.8863	0.3756
Std Error	1.2948		
F-Statistic	1.1380		
p-value	0.3360		

JAPAN			
	Coefficient	t-Statistic	p-value
t	0.1303	5.4370	0.0000
t-3	-0.0501	-2.0925	0.0365
t-1	0.0340	1.4207	0.1555
Std Error	1.3682		
F-Statistic	4.9486		
p-value	0.0000		

SINGAPORE			
	Coefficient	t-Statistic	p-value
t-2	0.1187	6.0813	0.0000
t-3	-0.0295	-1.5052	0.1324
t-1	0.0269	1.3779	0.1684
t-2	-0.0160	-0.8175	0.4137
t-6	0.0148	0.7614	0.4465
Std Error	1.1136		
F-Statistic	5.9081		
p-value	0.0000		

Table 5.10b - Emerging Markets and Pakistan

CHINA			
	Coefficient	**t-Statistic**	**p-value**
t	0.0929	3.5341	0.0004
t-3	-0.0380	-1.4441	0.1488
t-1	0.0364	1.3850	0.1662
t-2	-0.0322	-1.2245	0.2209
t-5	0.0238	0.9057	0.3652
Std Error	1.4987		
F-Statistic	2.4851		
p-value	0.0153		

MALAYSIA			
	Coefficient	**t-Statistic**	**p-value**
t	0.0863	7.1585	0.0000
t-5	0.0239	1.9796	0.0479
t-1	0.0195	1.6100	0.1075
t-2	-0.0170	-1.4085	0.1591
Std Error	0.6900		
F-Statistic	8.1945		
p-value	0.0000		

INDIA			
	Coefficient	**t-Statistic**	**p-value**
t	0.1719	6.8096	0.0000
t-3	-0.0488	-1.9286	0.0539
t-6	0.0237	0.9384	0.3481
t-2	-0.0207	-0.8195	0.4126
t-1	0.0221	0.8753	0.3815
t-4	-0.0178	-0.7032	0.4820
Std Error	1.4380		
F-Statistic	7.1401		
p-value	0.0000		

Table 5.10c - Frontier Markets and Pakistan

UAE			
	Coefficient	**t-Statistic**	**p-value**
t	0.1137	6.1808	0.0000
t-5	0.0486	2.6439	0.0082
t-6	0.0429	2.3362	0.0196
t-1	0.0286	1.5516	0.1209
t-3	0.0189	1.0264	0.3048
t-4	-0.0174	-0.9440	0.3452
Std Error	1.0483		
F-Statistic	8.2096		
p-value	0.0000		

SAUDI ARABIA			
	Coefficient	**t-Statistic**	**p-value**
t-1	0.0760	2.7825	0.0054
t-1	0.0590	2.1665	0.0304
t-4	-0.0292	-1.0706	0.2845
t-2	0.0282	1.0336	0.3014
Std Error	1.5567		
F-Statistic	1.9787		
p-value	0.0543		

KUWAIT			
	Coefficient	**t-Statistic**	**p-value**
t	0.0551	4.6997	0.0000
t-6	0.0396	3.3845	0.0007
t-2	0.0257	2.1923	0.0284
t-3	0.0247	2.0994	0.0359
t-4	0.0204	1.7422	0.0816
t-1	0.0113	0.9611	0.3366
Std Error	0.6672		
F-Statistic	7.5664		
p-value	0.0000		

All the emerging markets included in the sample open before the Pakistan market. China and Malaysia are in the same time zone and India is just 30 minutes ahead of Pakistan. It is anticipated that any new information from Pakistan affects the returns in the selected markets on the same day. With respect to emerging markets, the Pakistan returns at *t* are highly significant at the 2% significance level for all three markets (China, Malaysia and India). With respect to China, no other lags are statistically significant; however, this is not the case with Malaysia and India. For India, the Pakistan returns at lag *t-3* are also significant at the 10% level. Interestingly, the coefficient for lag *t-3* suggests an inverse association between the returns of the two markets. Similarly, the Pakistan returns at lag *t-5* are significant, with a positive coefficient for the Malaysia market. The statistical significance of later lags may suggest some delay in the reaction of the Indian and Malaysia returns to the information from Pakistan. The adjusted R^2 values range between 0.5% (China) to 2.10% (Malaysia). All the models for the chosen emerging markets are statistically significant at the 5% significance level.

The three GCC frontier markets included in the sample, namely the UAE, Saudi Arabia and Kuwait, open a couple hours later than the Pakistan market. Once again, it is expected that the changes in the returns of Pakistan are transmitted to these frontier markets on the same day. Therefore, the returns of the selected frontier markets at *t* are regressed against the Pakistan same-day returns and some preceding lags. This helps to identify whether there is any delay in market reaction in the frontier markets.

For the UAE, the Pakistan returns are statistically significant at time t*, t-5,* and *t-6*. This suggests an immediate reaction to the information from Pakistan at time t, but some delayed reaction as well. With respect to Saudi Arabia, time t and *t-1* are significant at the 2% and 5% significance level respectively. There is a marginal difference between the positive coefficients of the two lags. The Kuwait market appears to be greatly affected by the returns in the Pakistan market. Pakistan returns at five lags, *t, t-6, t-2, t-3, t-4* are statistically significant. The statistical significance of later lags suggests a delay in the transmission and processing of information in the returns of the frontier markets under consideration.

With respect to the developed markets, the Adjusted R^2 values are higher when the Pakistan returns are regressed against these markets, indicating that returns in developed markets can explain returns in Pakistan to some extent; however, it is also apparent that the values range between 1.5% (USA) and 2.5% (Singapore). Adjusted R^2 values are negligible when the returns of developed markets are regressed against Pakistan. Adjusted R^2 values in the case of Pakistan and emerging markets highlight nearly equivalent values in both scenarios, suggesting that marginal variability in the returns of these markets can be explained by Pakistan, and vice versa. In the frontier markets, the highest variability in the Pakistan returns can be explained by returns in the UAE, followed by Saudi Arabia and Kuwait respectively. In the other direction, the Pakistan returns can only explain 0.4% of variability in the returns of Saudi Arabia, 1.90% variability in the Kuwait returns and 2.02% variability in the returns of the UAE.

It is evident from the findings that the returns of the Pakistan market are affected by the returns of its trade partners at multiple lags; however, the same is not true in the opposite directions. The negligible impact of the Pakistan returns on its trade partners is observed in most cases. It is understandable, as Pakistan is a relatively small market that seems to be affected more by its own political and economic factors than by global factors.

While the findings in this section have provided some insight into the association between Pakistan and its trade partners, some results appear to be inconclusive, For example, in the case of Pakistan and the USA in the first model, lags t-5 is statistically significant but lag t-3 is insignificant. Such results appear inconsistent and inconclusive and and subsequently require further investigation into the association between the selected markets. Accordingly, more sophisticated methods are employed in the next section to appropriately quantify the relationship and interaction between the markets under consideration, which facilitate more elaboration regarding the evolving association between these markets.

5.2.4 Spillovers Index

To facilitate further understanding of the dynamics of association and interaction between Pakistan and its most active trade partners, the Spillovers Index, a variation of the Error

Variance Decomposition VAR is used. This allows for the disintegration of variance into various components, and enables the quantification of variance contributed by various components under consideration. This section not only evaluates the returns but also examines the volatility of each time series. The data analysis in this section also incorporates several robustness checks to ensure the consistency and reliability of results.

As discussed in Section 4.5.2.4 (Table 4.11), the application of the Spillovers Index in the data analysis comprises multiple elements. The Spillovers tables and plots present the static and dynamic measures of returns and volatility spillovers across various group and pairs of markets over the period of seven years.

The sample is divided into several groups based on the following classifications:

i. MSCI Country Classification 2012
   a. Group 1: Pakistan and Developed countries (USA, UK, Germany, Japan, Singapore)
   b. Group 2: Pakistan and Emerging markets (China, Malaysia, India)
   c. Group 3: Pakistan and other Frontier markets (UAE, Saudi Arabia, Kuwait)

ii. Geographical Proximity
   a. Group 4: Pakistan with China and India (closest neighbors sharing borders)
   b. Group 5: Pakistan with Japan, Singapore, Malaysia (Asia-Pacific neighbors)

The spillovers between Pakistan and each group of countries mentioned above provide further insight into the relationships between Pakistan and its trade partners.

To provide further insight into the relationships between the returns and volatility of the countries under consideration, the sample is further classified into pairs to measure net returns and volatility spillovers between two countries, with Pakistan being part of every pair. This step allows isolation of static and dynamic spillovers between Pakistan and other countries in the sample on a one-to-one basis.

For robustness checks, minimum, maximum and median values for returns, as well as volatilities with varying lags (2 to 10) and *n*-steps forecast (5 to 10 days forecast horizon) are extracted, with the objective of capturing sensitivity of return and volatility spillovers to different lags and varying forecast horizons. This step also provides insight into the time that all the markets take to absorb information. Moreover, the whole period of analysis is

classified into three sub-periods (pre-crisis, crisis, and post-crisis) to examine the levels of spillovers in tranquil and turbulent times. The eigenvalues of all estimated full-sample and sub-sample VAR models are less than one, suggesting stationarity and stability of these models. The following sub-sections present the findings of data analysis for returns and volatility spillovers, respectively.

5.2.4.1 Returns Spillovers

This section presents the results of analysis performed on the log returns of the candidate markets for the period 2006-2012. The dynamics between the log returns of various markets included in the sample are evaluated in multiple ways and presented with the help of various tables and figures. This section presents the results as follows:

1. Returns Spillovers Table: Table 5.11 presents the static measure of returns spillovers across the twelve markets included in the sample over seven years.
2. Returns Spillovers Plots: Figure 5.4 incorporates the time-varying nature of returns and presents the overall spillovers across candidate markets over seven years using 200-days rolling windows.
3. Returns Spillovers Plots with Varying Lags and Forecast Horizons: Figures 5.5 and 5.6 present returns spillovers plots associated with changing lags and different forecast horizons respectively, in order to evaluate the sensitivity of spillovers to different lags and n-steps forecast horizons.
4. Groupwise Static and Time-varying Returns Spillovers: Tables 5.13 to 5.17 and Figures 5.7 to 5.11, present the estimates of returns spillovers across groups of countries based on MSCI Classification 2012 and geographical proximity.
5. Net Pairwise Returns Spillovers: Table 5.18 presents the overall static spillovers and the range of evolving cross-market returns spillovers over the period of analysis between Pakistan and its trade partners. Figures 5.12 to 5.14 present returns spillovers between Pakistan and its selected trade partners, in order to isolate the spillovers between two countries from the overall sample.

5.2.4.1.1 Returns Spillovers Table

The overall static returns spillovers across twelve countries from 2006 to 2012 stands at 43% as summarized in Table 5.11. This number provides a relative measure of the contribution of returns spillovers as follows:

- Self-contributions to returns
- Cross-spillovers across countries included in the sample

Since the focus of the study is Pakistan, it has been placed in the upper-most row of the table, followed by groups of developed, emerging and frontier markets. The highlighted diagonal presents self-contribution in each market.

The returns spillovers table provides several interesting insights. The Pakistan self-contribution to its returns is highest in the sample, that is, approximately 90%, followed by Kuwait (84%), Saudi Arabia (83.50%), China (73%) and the UAE (68.5%). Interestingly, three out of four countries with the highest self-contributions are frontier markets. With the exception of Pakistan, the other three largest self-contributors have partially deregulated markets, which limit foreign investment into the domestic capital markets. Higher self-contribution to returns suggests that domestic events are more relevant in these markets and foreign shocks may have a limited impact.

Table 5.11 – Returns Spillovers Table

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	90.10	1.30	1.30	1.20	0.40	0.90	0.30	1.20	1.20	1.10	0.10	0.80	10.00
Developed Markets													
USA	0.10	45.10	19.70	21.70	1.90	4.60	0.30	1.40	3.90	0.70	0.60	0.10	55.00
UK	0.10	17.40	35.20	26.40	3.50	6.80	0.60	2.90	5.80	0.40	0.80	0.10	65.00
GERMANY	0.10	18.50	27.00	36.00	3.20	6.10	0.60	2.40	5.00	0.20	0.90	0.10	64.00
JAPAN	0.20	14.10	11.70	11.70	36.20	11.30	2.10	5.00	5.80	0.90	0.80	0.20	64.00
SINGAPORE	0.40	8.20	8.90	8.10	10.40	37.10	3.50	9.80	11.90	1.30	0.40	0.20	63.00
Emerging Markets													
CHINA	0.40	1.90	2.30	2.00	4.10	6.50	73.20	4.80	3.70	0.70	0.40	0.10	27.00
MALAYSIA	0.70	6.80	7.40	6.00	6.40	13.60	3.20	47.30	7.60	0.60	0.30	0.20	53.00
INDIA	0.60	6.50	8.50	7.40	5.10	14.90	2.10	6.30	46.80	1.10	0.30	0.40	53.00
Frontier Markets													
UAE	0.80	4.10	2.90	2.60	1.20	3.20	0.70	1.20	2.20	68.50	9.10	3.50	31.00
SAUDI ARABIA	0.30	2.40	2.30	2.60	1.00	2.10	0.40	0.80	1.00	2.40	83.50	1.10	17.00
KUWAIT	1.10	1.20	0.80	0.50	0.30	0.50	0.20	0.30	0.50	3.90	6.70	84.20	16.00
Contribution to others	5.00	82.00	93.00	90.00	37.00	70.00	14.00	36.00	48.00	13.00	20.00	7.00	517.00
Contribution including own*	95.00	127.00	128.00	126.00	74.00	107.00	87.00	84.00	95.00	82.00	104.00	91.00	43.10%

*Minor differences due to rounding

Note: Total Spillovers Index -> 517/1200 = 43.10% (1200 is the sum of all numbers in the last row "Contribution including own"). Subsequent tables reporting returns spillovers utilize the same calculation.

In the developed markets, the lowest self-contribution to returns is exhibited by the UK (35%), followed by Germany and Japan (36% each). The USA contributes approximately 45% to its own returns. Exchange of returns spillovers within the developed markets is quite pronounced. For example, the UK, Germany and Japan receive relatively high contributions from the USA, estimated at approximately 17%, 18.50% and 14% respectively. Similarly, the UK contributes 27% to the Germany returns, 20% to the USA returns, and 12% to the Japan returns. Collectively, the USA and the UK contribute 45.50% overall to the Germany returns. Substantially large contributions from the USA to the UK and the German markets may imply that the returns in the USA market are a good predictor for returns in the said European markets. These results are in line with Rapach *et al.* (2013), who found that the lagged USA returns have substantial predictive power for many industrialized non-USA countries. The UK, Germany and Singapore collectively contributed approximately 38% to the Japan returns.

Returns spillovers across Asian countries, especially Japan, Singapore, Malaysia and India are quite evident. India stands out in the sample as it has been on the receiving end, with contributions from both developed and emerging markets amounting to approximately 51%. India also contributes more to the returns of Singapore and Malaysia, as compared to China or Pakistan, which are next-door neighbors to India. These findings may imply the India market's greater integration with developed and emerging markets, as it appears to contribute approximately 46% to the returns of developed and emerging markets collectively, and only 5% to frontier markets.

Regional interdependencies are prominent in Asian markets, with Singapore and Malaysia collectively contributing nearly 12% to returns in China and the GCC markets in the study receiving relatively higher returns spillovers from each other rather than from other markets under consideration.

With respect to Pakistan, the foreign returns spillovers are just 10%, which is the lowest in the sample. Although most countries in the sample contribute marginally to Pakistan's overall returns, contributions from China and Saudi Arabia are close to zero, despite substantial trade volume between Pakistan and these countries. Results provided by

stepwise OLS estimation in section 5.2.3.1 are comparable to the findings presented by the returns spillovers index. The results here contest the existing literature regarding the positive association between trade and market interdependencies. Both Saudi Arabia and China have strong bilateral trade, close geographical proximity and cordial political relationships with Pakistan.

A comparison of total contribution (including self-contribution) and contribution to others reveals that frontier markets in general contribute very little to the returns of other markets. The Pakistan market's contribution to the returns of other markets is the lowest in the sample, at approximately 5%. The contribution of the oil supplier countries (Saudi Arabia, UAE and Kuwait) to other markets is relatively higher in comparison to the Pakistan contribution. This can be attributed to the oil-related trade between the selected countries.

5.2.4.1.2 Returns Spillovers Plots

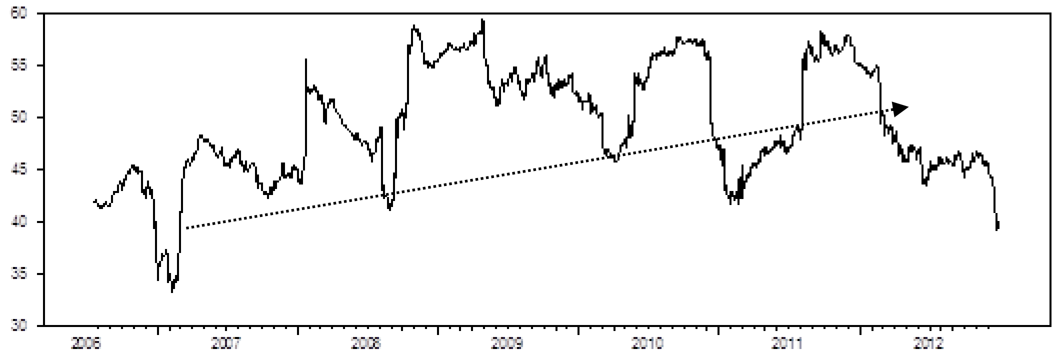
The returns spillovers plot captures the evolving spillovers across countries included in the sample during the period of analysis. The returns spillovers plot (Figure 5.4) provides insight into the overall trend of spillovers, and the upward trend in the returns spillovers is apparent.

It is observed that the Spillovers Index ranges between 33% and 60% over the period of seven years. It stood close to 40% in 2006 and fell to its lowest level (below 35%) in the beginning of 2007, suggesting a period of relative tranquility. The index was at the highest level of nearly 60% in 2008 and 2009, suggesting the onset of the financial crisis and subsequent higher cross-market spillovers. The high spillovers persisted until March 2009 and then treaded between 50% and 55% until December 2009. The spillovers started declining in the first quarter of 2010, demonstrating signs of recovery; however, the spillovers rose again and reached nearly 60% in the third quarter of 2010.

While the financial crisis of 2008 explains the high index levels in 2008 and 2009, the rising spillovers index during 2010 seems to have been a result of the Eurozone crisis. During 2010, the Eurozone experienced uncertainty with respect to Greece, Ireland and Portugal, which was finally resolved by the provision of a bailout package to Greece by the European Union in May 2010, and then to Ireland in November 2010 (European Central

Bank, 2014). This temporary resolution of Eurozone problems resulted in lower spillovers, bringing the index briefly down to approximately 45% by the end of 2010.

Figure 5.4 – Returns Spillovers Plot in 200-days Rolling Windows with 2 Lags and 5-10 Steps Forecast Horizon[43]



The exaggerated returns spillovers in 2011 are evident with a peak in the end of 2011. The period under consideration witnessed many events that were of global significance, which are listed in table 5.12.

Table 5.12 – Significant Events in 2011

January 2011	Egyptian Revolution
February 2011	Eurozone sets-up a permanent bail-out fund, called the European Stability Mechanism, worth 500 billion Euros
February 2011	Libyan Revolution
March 2011	Earthquake and Tsunami in Japan
May 2011	Eurozone and the IMF approve a 78 billion Euro bailout for Portugal
May 2011	Osama bin Laden killed by the US forces
May 2011	Portugal slips into double-dip recession
July 2011	Second bailout package for Greece
August 2011	Muammar al-Gaddafi overthrown
September 2011	Occupy Wall Street Movement begins

Source: European Central Bank, 2014; Stracca, 2013; The Wall Street Journal, 2013.

This period also witnessed the deepening of the USA debt crisis, which resulted in anxiety across international financial markets. During this period, the credit rating agencies, Moody's and Standard and Poor's, indicated possible credit downgrading for the USA debt, resulting in panic among investors worldwide. These significant events in 2011 seem to have driven up the returns spillovers significantly across markets. In 2012, the Spillovers Index

[43] The indicative trend line in Figure 5.4 and subsequent spillovers plots is an indication of the upward (or downward) trend in the index, in general and is not fitted.

gradually declined from 50% to approximately 45%. In December 2012, the index returned to its initial level of 40%, suggesting a return to relative stability in world markets.

It is evident that the returns spillovers plot has captured important global events like the financial crisis of 2008, the Eurozone crisis, and the Arab Spring, as spillovers across markets appear to be elevated during turbulent times. Moreover, the index displays an increasing trend starting from 2008, which may be indicative of a permanent change in the level of cross-market spillovers.

5.2.4.1.3 Returns Spillovers Plots with Varying Lags and Forecast Horizons

In line with Diebold and Yilmaz (2012), further analysis is performed to evaluate the sensitivity of the returns spillovers index to the number of lags and the forecast time horizon included in the analysis in 200-days rolling windows. First, the number of lags varied from 2 to 10, while keeping the n-steps constant at 10, and second, further analysis is performed by changing the n-steps forecast from 5 to 10 days while keeping the number of lags constant at 2.

The extracted time series of minimum, maximum, and median values with varying time lags are presented in Figure 5.5. During the tranquil times the sensitivity of return spillovers to the choice of lags in not so evident. However, during turbulent times, the return spillovers increase as the number of lags increase, suggesting delayed transmission of information across markets, possibly due to non-synchronous trading. For example, all markets included in the sample, except the USA have overlapping trading hours with Pakistan, though some markets open a few hours before Pakistan and some open a few hours after Pakistan. Also, the weekends vary across markets in the sample. In the case of the USA and Pakistan, it is expected that the information from the USA market at *t-1* are only reflected in Pakistan at *t.* Although, to minimize the problem of non-synchronous trading, the study uses 7-day frequency instead of 5-day frequency (for details refer to Chapter 4, Section 4.4), there is a possibility that non-synchronous data may play a role in the delayed transmission of information across markets.

It is also observed that during turbulent times, the returns spillovers keep increasing from two lags until nine lags and then start reducing in lag ten, returning to the levels at lag

two. This may suggest the absorption of information in approximately ten lags. Ratanapakorn and Sharma (2002) found that the emerging markets absorbed the exogenous shocks from developed markets in the ten days, and this is reiterated in this study too. It is also interesting to note that the median values are close to maximum values during the times of high returns spillovers.

Further analysis entails changing the forecast time horizon from five to ten days, keeping the lags constant at two (Figure 5.6). The analysis reveals insensitivity of returns spillovers to the changing forecast horizon. As presented in figure 5.6, the minimum, maximum and median returns overlap each other and hence cannot be differentiated.

Figure 5.5 – Sensitivity of Returns Spillovers to Varying Lags and Constant Forecast Horizon

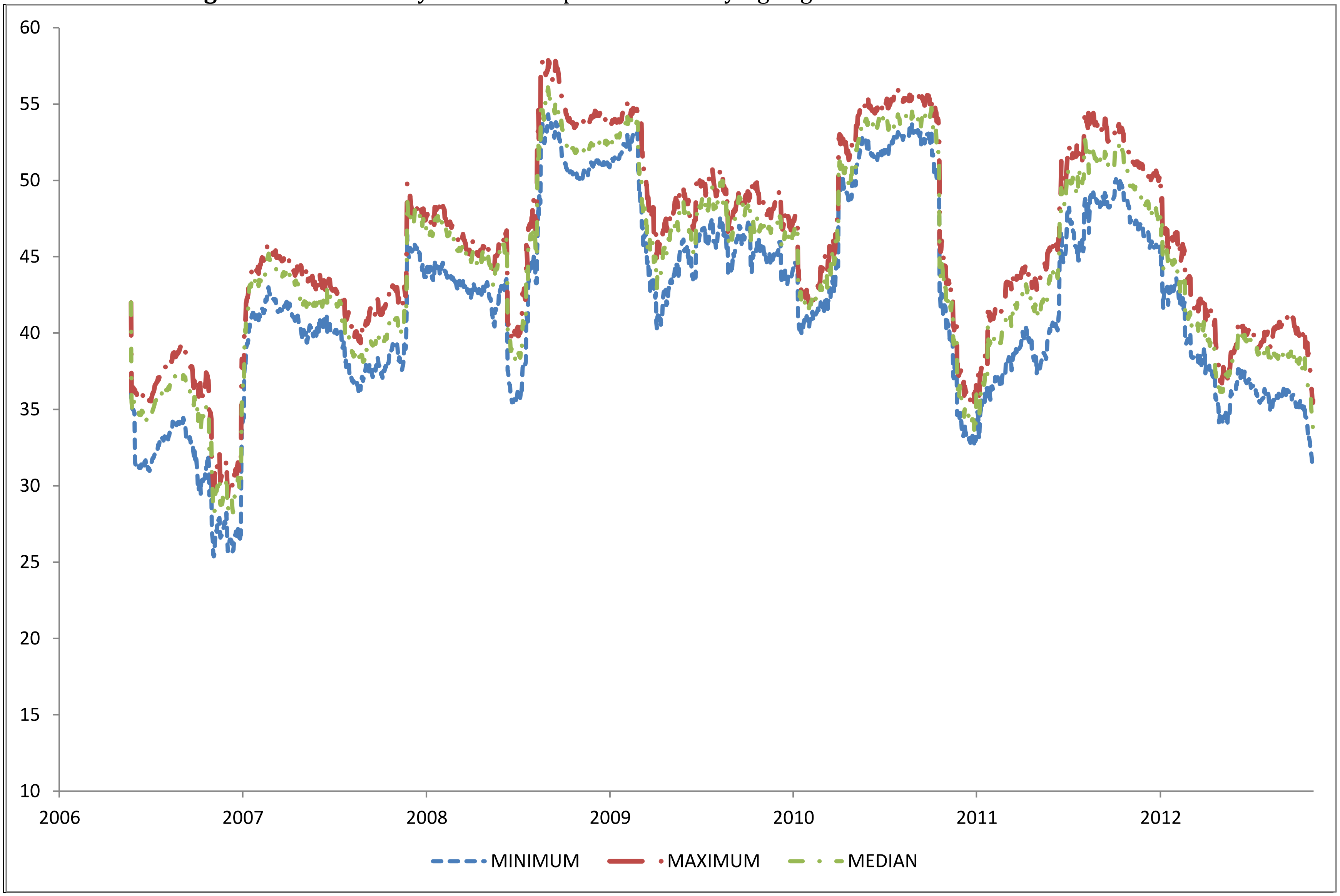
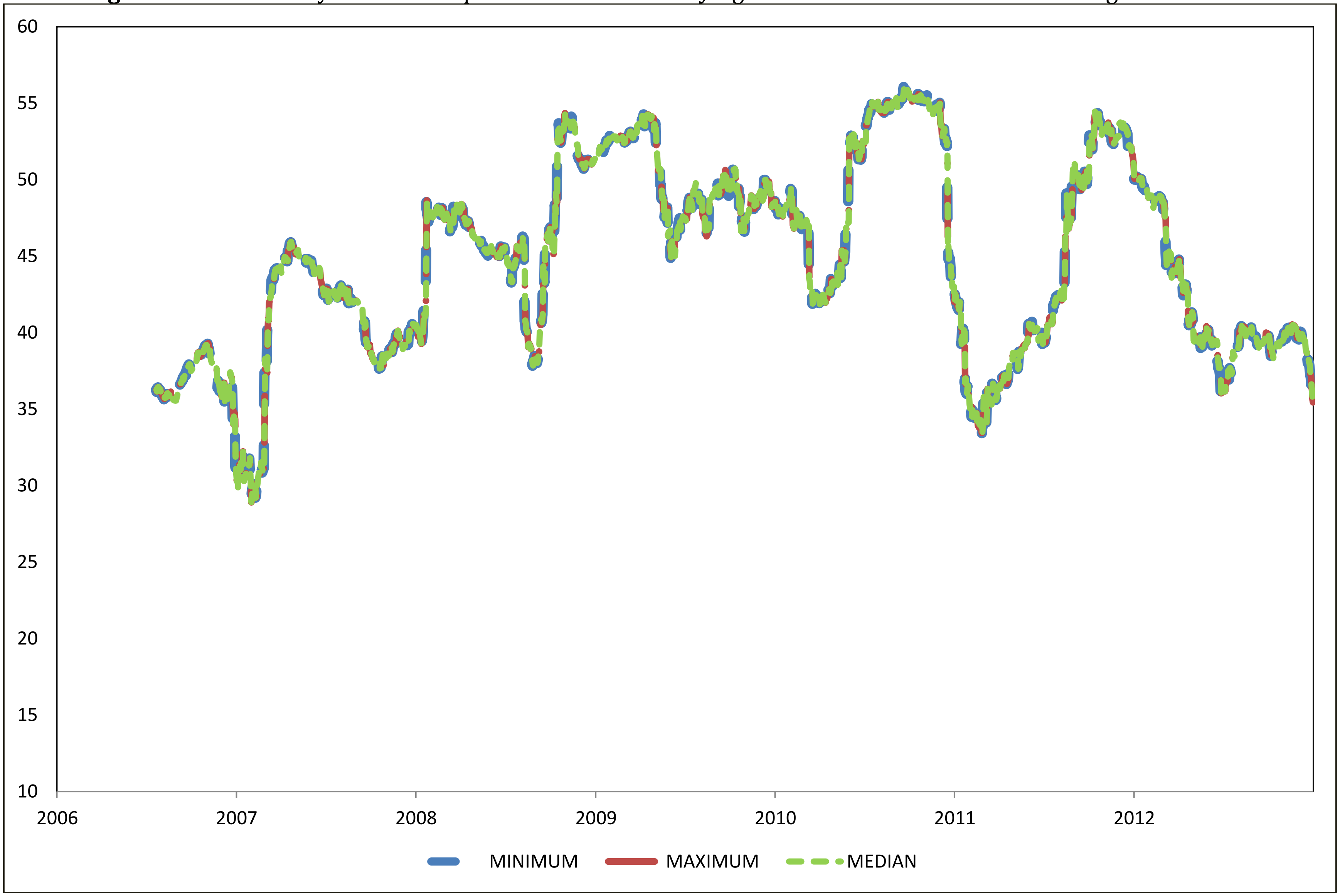


Figure 5.6 - Sensitivity of Returns Spillovers Plot with Varying Forecast Horizon and Constant Lags



5.2.4.1.4 Groupwise Returns Spillovers

To have a thorough understanding of returns spillovers between countries, the sample is divided into five groups using MSCI Country Classification as well as geographical proximity, respectively. Since the study focuses on the interactions of the Pakistan returns with its selected trade partners, Pakistan is included in all the groups under analysis. Both static and dynamic spillovers between countries across various groups are examined to gain detailed insight into their relationships.

i. *Pakistan and Developed Countries*

The overall returns spillovers for the group containing Pakistan and developed countries (the USA, UK, Germany, Japan and Singapore) stands at 47% for the whole period of analysis (Table 5.13). Interestingly, the index is much closer to the index for the whole sample (43%). This may be an indication that the developed countries contribute most of the returns spillovers. A glance at self-contributions and foreign contributions reveals that the Pakistan self-contribution is the highest in the sample, at nearly 95%. The remaining 5% of the contributions come from the five developed countries included in the group. The Pakistan contribution to the developed countries included in the sample is negligible and stands at less than 1%. The Pakistan returns contributed only 0.50% to the Singapore returns, and even less to the returns of the other developed countries in the sample. The USA, the UK and Germany contributed equally to the Pakistan returns followed by Singapore (0.90%) and Japan (0.50%). The results confirm that the USA market exports returns to most markets around the world, although the magnitude is heterogeneous. The influence of the UK and Germany returns on the Pakistan returns is apparent. Regional spillovers are evident, with contributions from Singapore to Japan higher than in the other direction. Literature has provided some evidence on the increased influence of the Singapore market in recent years (For example Lim, 2009; Huyghebaert and Wang, 2010).

The results for this group of countries is in line with the results derived from Granger Causality tests and stepwise OLS estimation, whereby unidirectional causality was observed from all developed markets to Pakistan; OLS estimation models were significant when Pakistan was included as a regressand, and insignificant otherwise.

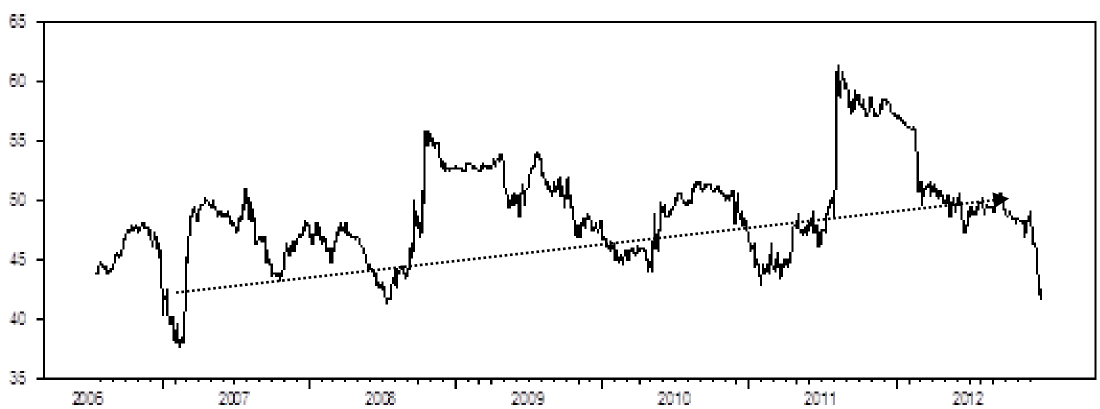
Table 5.13 – Groupwise Returns Spillovers Consisting of Pakistan and Developed Markets

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	From others*
PAKISTAN	94.70	1.30	1.30	1.30	0.50	0.90	5.00
USA	0.10	48.50	21.20	23.30	1.90	5.00	51.00
UK	0.10	19.50	39.50	29.60	3.90	7.50	61.00
GERMANY	0.10	20.30	29.70	39.70	3.40	6.80	60.00
JAPAN	0.20	16.50	13.70	13.70	42.60	13.20	57.00
SINGAPORE	0.50	11.30	12.10	11.20	14.10	50.80	49.00
Contribution to others	1.00	69.00	78.00	79.00	24.00	33.00	284.00
Contribution including own*	96.00	117.00	117.00	119.00	66.00	84.00	47.40%

*Minor differences due to rounding

The spillovers plot in Figure 5.7 provides insight into the dynamic spillovers for Pakistan and the five developed markets over the period of analysis. The index ranged between 37% and 62% over the period of seven years. The index was at its lowest level in the first quarter of 2007 and at its highest level in August 2011. High volatility spillovers of nearly 55% are evident in the last quarter of 2008. A prolonged episode of exaggerated spillovers, ranging between 50% and 56%, follows the peak in September 2008 and lasts until the final quarter of 2009. Another episode of high spillovers begins in August 2011, whereby the spillovers suddenly surge from 52% to nearly 62%. In subsequent months, the spillovers hover between 56% and 62%, and then fall to 52% in February 2011. The index exhibited a further sharp decline in November 2012 falling from 50% to nearly 44%.

Figure 5.7 – Groupwise Returns Spillovers Plot for Pakistan and Developed Markets



It is interesting to note that beyond February 2007 until the end of the period of analysis, the index remained above 41%, indication of an increasing trend in the magnitude of spillovers. However, it is important to note that the group was dominated by developed markets and Pakistan was a very small market in comparison to its developed counterparts. Therefore, the spillover plot may be largely depicting the interaction between developed markets. Greater interdependence between developed markets has been widely documented in the relevant literature since the 1970s and it is not surprising that shocks in one developed market, especially in the USA, are transmitted to other developed markets.

ii. Pakistan and Emerging Countries

The second group includes Pakistan and emerging markets (China, Malaysia and India) in the sample. Coincidentally, two of the emerging markets in the sample are the neighbors closest to Pakistan. The overall spillovers between these countries are presented in Table 5.14.

The returns spillovers plot in this particular group stands at only 14.50%. High self-contributions are evident in the group, with Pakistan having the highest self-contributions of 96%. China follows with self-contributions of 87.40%. Malaysia exhibits the lowest self-contributions at 77.50%. These findings are not surprising as many studies suggest that domestic events affect emerging markets more than global events (for example Aggarwal *et al.*, 1999).

The emerging countries received low returns spillovers from Pakistan and from each other although there is some indication of integration between emerging markets. Despite close geographical proximity, bilateral trade, and political relationships, Pakistan appears to be rather isolated from its emerging counterparts. The highest foreign contribution to Pakistan returns is from Malaysia (2%), followed by India (1.7%), and lastly China (0.40%). With respect to Malaysia, this finding does not correspond with the Granger Causality results as no causality was revealed between the two countries, although stepwise OLS estimation revealed a statistically significant model for association between two countries.

Pakistan contribution to Malaysia returns is highest in the group, although it stands at a mere 1.60%. The Pakistan contributions to India are smaller than what it receives from India.

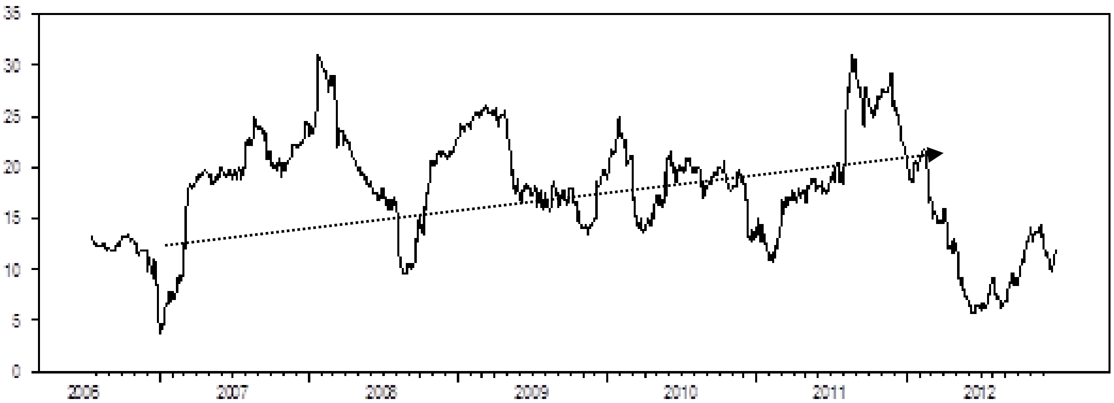
Table 5.14 – Groupwise Net Returns Spillovers Consisting of Pakistan and Emerging Markets

	PAKISTAN	CHINA	MALAYSIA	INDIA	From others*
PAKISTAN	95.90	0.40	2.00	1.70	4.00
CHINA	0.50	87.40	7.10	4.90	13.00
MALAYSIA	1.60	6.40	77.50	14.50	23.00
INDIA	1.40	4.20	13.20	81.20	19.00
Contribution to others	4.00	11.00	22.00	21.00	58.00
Contribution including own*	99.00	98.00	100.00	102.00	14.50%

*Minor differences due to rounding

The returns spillovers plot (Figure 5.8) provides some interesting insights into the relationships between the countries in this group. The index fluctuates between 4% and 32% over the period of seven years. The spillovers rose twice to their highest levels during the period of analysis, once in February 2008 and then in August 2011. The spillovers sustained high levels (ranging between 20% and 32%) until February 2008 and then started descending until they reached 10% in August 2008. Interestingly, the turmoil in developed markets started in September 2008, but it seems that the reaction of the emerging markets to the financial crisis was lagged, as the index started rising in October 2008. The results of GARCH (p, q) model suggested that China and Malaysia remained insulated from the financial crisis and the spillovers index may have been able to capture this.

Figure 5.8 – Groupwise Returns Spillovers Plot for Pakistan and Emerging Markets



The index fluctuated close to 25% between November 2008 and March 2009, and declined close to 20% in April 2009, remaining at the same level for the rest of 2009. This was not the highest level of the index, although the effect of the financial crisis was apparent in other markets.

A brief surge of 25% is visible in February 2010, after which the index remained between 12% and 21% until July 2011. Returns spillovers were high beyond August 2011 and started declining in December 2011. The index hovered between 5% and 10% in 2012. An increasing trend is also visible in this plot; however, it is not as prominent as the developed markets plot.

iii. Pakistan and Frontier Countries

This group includes all frontier markets included in the sample (Saudi Arabia, UAE, Kuwait and Pakistan). Table 5.15 presents the estimates of overall spillovers between the frontier markets. The index measures at 9.5% for all the frontier markets under consideration, over a period of seven years. As observed earlier, frontier markets have high self-contributions and they seem relatively isolated from other markets included in the sample.

Within the frontier markets, Pakistan stands out with the highest self-contributions at 97%, followed by Saudi Arabia (94.70%), Kuwait (87.30%), and the UAE (82.70%). The UAE received the highest spillovers from Saudi Arabia, and vice versa. Kuwait received high spillovers from its GCC counterparts, and marginal spillovers from Pakistan.

In this sample, the UAE contributed the most to the Pakistan returns, followed by Kuwait, and lastly by Saudi Arabia. Simultaneously, Pakistan contributed equally to the UAE and Kuwait returns (1.20%), and marginally to the returns of Saudi Arabia. After performing stepwise OLS estimation, these results are not surprising as the OLS estimation models for Pakistan and Saudi Arabia featured the low *F*-Statistic and relatively high *p*-values, with low adjusted R^2 estimates.

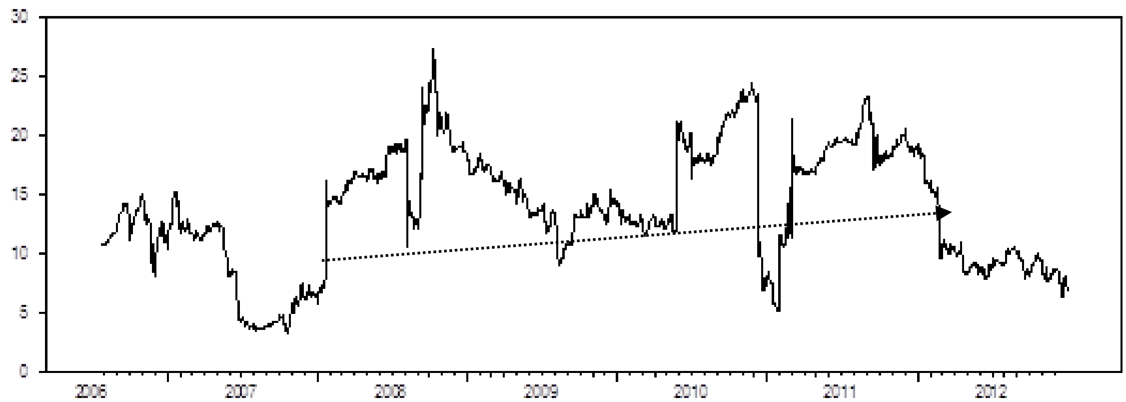
Table 5.15 – Groupwise Net Returns Spillovers Consisting of Pakistan and Frontier Markets

	PAKISTAN	UAE	SAUDI ARABIA	KUWAIT	From others*
PAKISTAN	97.20	1.50	0.20	1.10	3.00
UAE	1.20	82.70	11.30	4.70	17.00
SAUDI ARABIA	0.50	3.40	94.70	1.40	5.00
KUWAIT	1.20	4.60	6.90	87.30	13.00
Contribution to others	3.00	10.00	18.00	7.00	38.00
Contribution including own*	100.00	92.00	113.00	94.00	9.50%

*Minor differences due to rounding

The returns spillovers plot (Figure 5.9) for the frontier markets ranges between 2% and 29%. Sudden peaks and valleys are apparent during the seven-year period of analysis. The highest peak of 29% is visible in September 2008, which coincides with the beginning of the financial crisis. High spillovers of 25% are evident first in November 2010 and then in August 2011.

Figure 5.9 – Groupwise Returns Spillovers Plot for Pakistan and Frontier Markets



The returns spillovers between frontier markets hovered between 7% and 15% in 2006 and the first two quarters of 2007. The index fell to the lowest level of 2% in the latter half of 2007. The index rose sharply in January 2008 from 6% to 16% and then continued to ascend until July 2008. The spillovers declined sharply from 20% to 16%. After attaining a peak of 29% in September 2008, the spillovers declined in the last quarter of 2008 and continued to decline until the third quarter of 2009. A spillovers surge is noticeable in May 2010. The index remained above 20% until November 2010 but then fell sharply to nearly 7% at the end of 2010. However, this fall appeared to be short lived and the spillovers once again ascended sharply to 22% in February 2010. A prolonged episode of high spillovers extended until February 2012. Returns spillovers fluctuated within the bounds of 8% and 10% during the rest of 2012. A subtle upward trend in the plot is visible in this group also.

iv. Pakistan and Countries within Closest Geographical Proximity

This group of countries considers geographical proximity in estimating the returns spillovers between Pakistan and its neighbors. The overall returns spillovers index between Pakistan, China and India stands at a mere 4.80% (Table 5.16), which is very low considering the geographical proximity and volume of trade. All three countries included in the group had high self-contributions, greater than 90%, with Pakistan having been the highest self-contributor at 97.80%. While India and China contributed to each other's returns, the Pakistan contribution to the returns of its neighbors was marginal. It contributed less than 2% to the India returns and a mere 0.60% to the China returns.

Table 5.16 – Groupwise Net Returns Spillovers Consisting of Pakistan and its Border-Sharing Neighbors

	PAKISTAN	CHINA	INDIA	From others*
PAKISTAN	97.80	0.40	1.80	2.00
CHINA	0.60	94.10	5.30	6.00
INDIA	1.70	4.80	93.50	6.00
Contribution to others	2.00	5.00	7.00	15.00
Contribution including own*	100.00	99.00	101.00	4.80%

*Minor differences due to rounding

As presented in Figure 5.10, the returns spillovers plot varied between 1% and 21%. The index exhibited two peaks in the seven-year period of analysis. The highest peak of 21% was apparent in August 2011. The second peak, although lower than the one in August 2011, was visible in January 2008.

The index began at 7.5% in 2006 and remained at that level throughout the year. A sharp decline was evident in December 2006, whereby the index came down to 1%. This was the lowest level of spillovers across the three countries over the complete period of analysis. During the first half of 2007, the index fluctuated within 4% to 5%, starting its journey upwards in the latter half of 2007. A sudden increase in spillovers was witnessed in January 2008 when the index peaked at 17.50%. The decline in the spillovers started in February 2008, reaching nearly 7% in mid-2008.

From July 2008 until July 2011, the spillovers mostly ranged between 5% and 10%, occasionally rising to 12.50%. A sharp ascent was apparent in August 2011, which was probably associated with the Eurozone crisis. High returns spillovers ranging between 16% and 20% were observed in the latter half of 2011. The index declined gradually in 2012, reaching nearly 2.5% in the second quarter of 2012. The index rose moderately in the last quarter of 2012 and hovered between 7.5% and 10% during the last three months of the year.

Figure 5.10 – Groupwise Returns Spillovers Plot for Pakistan and its Border-Sharing Neighbors

v. Pakistan and its Neighboring Countries in the Asia-Pacific

The analysis of spillovers in this group attempts to measure regional returns spillovers between Pakistan and the countries situated in the Asia-Pacific. The overall spillovers between this group of countries are presented in Table 5.17. The spillovers over the period of seven years stood at 29.50%. While the Asia-Pacific countries had high self-contributions of 60% or more, the Pakistan self-contributions were at least 50% higher than those in its peers in the group. The collective contributions from Japan, Singapore and Malaysia to Pakistan stood at 5% only and were equally divided between the three countries. Malaysia appeared to have contributed the most to the Pakistan returns at 2%. On the other hand, the Pakistan contributions to its Asia-Pacific trade partners were a mere 3%, with the highest contribution to Malaysia.

Table 5.17 – Groupwise Returns Spillovers Consisting of Pakistan and its Asia-Pacific Neighbors

	PAKISTAN	JAPAN	SINGAPORE	MALAYSIA	From others*
PAKISTAN	95.00	1.40	1.60	2.00	5.00
JAPAN	0.80	62.90	23.50	12.80	37.00
SINGAPORE	1.00	20.80	59.70	18.50	40.00
MALAYSIA	1.40	13.00	21.40	64.30	36.00
Contribution to others	3.00	35.00	46.00	33.00	118.00
Contribution including own*	98.00	98.00	106.00	98.00	29.50%

*Minor differences due to rounding

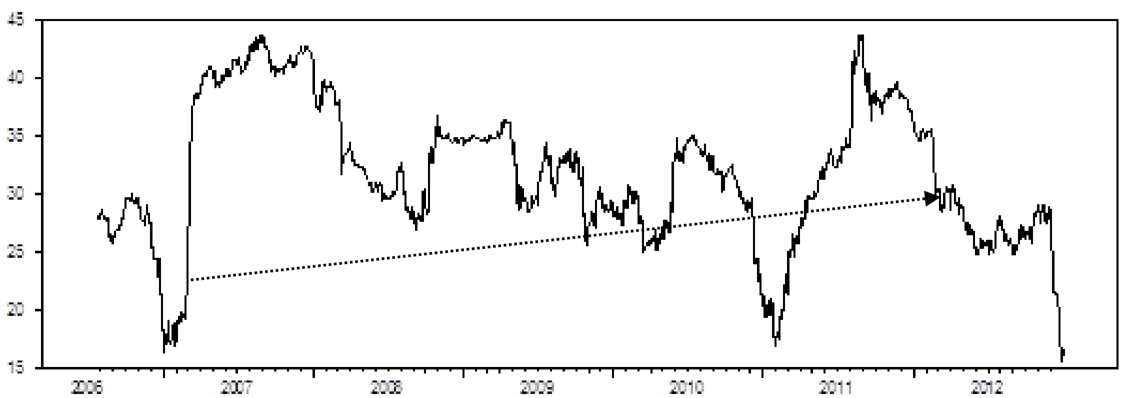
The spillovers plot presented in Figure 5.11 suggests that the spillovers between the four countries varied between 15% and 44% during the period of analysis. However, it

seems that the high spillovers between the countries were a product of regional interdependencies within the Asia-Pacific and that Pakistan had a limited contribution in these varying spillovers.

The plots present two peaks and three troughs. The peaks, one in 2007 and the other in the latter half of 2011, stood close to 44%. The first episode of high spillovers began in February 2007. This period lasted for a year and the spillovers fluctuated between 40% and 44% during this episode. Beyond February 2007, the spillovers decreased moderately and remained within the bounds of 25% and 37% until November 2010. The index descended sharply in December 2010 to nearly 16% and remained there briefly. The spillovers started ascending once again in January 2011 until they reached the highest level of 44% in August 2011. Spillovers started declining thereafter and reached 32% in the first quarter of 2012. In the latter half of 2012, the spillovers oscillated between 25% and 30% and in December 2012 declined sharply to 15%.

While the peak in 2011 could be associated with the Eurozone crisis, the prolonged peak in 2007 was more likely associated with a regional event. In addition, the natural disaster in Japan in March 2011 could have contributed to increased spillovers in the first and second quarters of 2011.

Figure 5.11 – Groupwise Returns Spillovers Plot for Pakistan and its Asia-Pacific Neighbors



The evaluation of cross-country returns spillovers within different groups has provided several interesting insights. A common observation across groups is the upward

trend in returns spillovers during the period of analysis and is highlighted with an upward trend line in spillovers plots. Another observation is associated with amplified spillovers at the times of crises. The spillovers plot capture heightened spillovers during the financial crisis of 2008 and the Eurozone crisis. In all the groups except Pakistan and frontier markets, the magnitude of returns spillovers at the time of the Eurozone crisis were greater than those that occurred at the time of the financial crisis of 2008. In the group of Pakistan and the frontier markets, the index peaked at its highest level during the 2008 financial crisis. The heightened returns spillovers in the recent times surrounding the Eurozone crisis might be indicative of a general trend in transmission of cross-country returns.

5.2.4.1.5 Pairwise Net Returns Spillovers Plots

The analysis so far has provided useful insights into the spillovers across groups of countries; however, it is difficult to isolate the spillovers between two countries, especially in the spillovers plot. It was therefore deemed appropriate to consider pairs of countries. Given the focus of this study, all the pairs included Pakistan in the analysis, resulting in eleven pairs. This step of the analysis facilitated the capturing of both static and dynamic returns spillovers across pairs of countries included in the sample.

The analysis entails 200-day rolling windows with two lags and a 10-step forecast horizon. Table 5.18 presents static and the range of net pairwise spillovers across the eleven pairs of countries over the period 2006 to 2012.

Table 5.18 – Estimates of Pairwise Net Returns Spillovers Between Pakistan and its Key Trade Partners

	Static Returns Spillovers Estimate	Range of Returns Spillovers (Approximate)

Developed Markets		
USA	0.80%	1% to 15%
UK	0.90%	1% to 10%
Germany	0.80%	1% to 11%
Japan	1.30%	0% to 13%
Singapore	1.60%	0% to 19%
Emerging Markets		
China	0.60%	0% and 8%
Malaysia	2.00%	0% to 15%
India	1.80%	0% to 16%
Frontier Markets		
UAE	1.50%	0% to 12%
Saudi Arabia	0.40%	0% to 13%
Kuwait	1.20%	0% to 10%

From the static spillovers estimates across pairs the following observations are evident:

1. The net spillovers between Pakistan and its most active trade partners do not exceed 2%. Lower or near zero net spillovers are indicative of reciprocal of nearly equal magnitude of returns in the pairs under consideration.

2. Net spillovers between Pakistan and the developed countries, excluding the Asian developed countries, are less than 1% over the period of analysis.

3. Returns spillovers between the closest neighbors (China and India) are heterogeneous. Moreover, the spillovers between Pakistan and China are much lower than those between Pakistan and its distant trade partners within the same continent.

4. The spillovers between Pakistan and the oil-exporting countries are inconsistent, with the lowest spillovers demonstrated between Pakistan and Saudi Arabia, which coincidently are the lowest in the sample.

5. The returns spillovers plots do not indicate any trend in returns spillovers; however, peaks and troughs in spillovers can be attributed to some specific events, especially the recent Eurozone crisis.

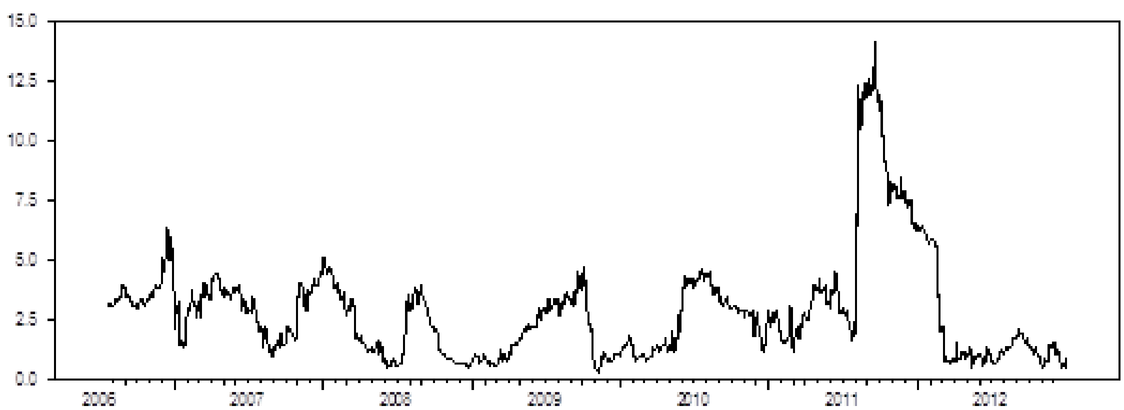
A glance at the net pairwise returns spillovers plots between Pakistan and its key trade partners mostly suggest similarity in patterns of spillovers. Therefore only a representative spillovers plot from each group of countries is illustrated here in Figures 5.12 to 5.14 and all the other plots are included in the appendices 5.17-5.19 An overall evaluation of net returns spillovers amongst the eleven pairs included in the analysis suggests that the

pairwise net spillovers range between 0% and 20%. The highest values of pairwise spillovers are between Pakistan and Singapore (approximately 20%) and the lowest pairwise net spillovers are between Pakistan and China, which do not exceed 8%.

Some typical observations were made in all the pairs irrespective of the country classification. It was observed that the effect of the financial crisis of 2008 is not reflected in the pairwise net spillovers. In all pairs, the index started rising in July 2008, suggesting a transmission of returns between pairs; however, the indices started declining in August/September 2008 and reached their lowest levels, in most cases 0%, in December 2008. The suggested period was marred with a floor on the Pakistan capital market and when global financial markets were experiencing volatility due to foreign shocks; the Pakistan financial market was dealing with its own problems and was probably contributing greatly to its own returns. Hence, the effect of the financial crisis was not so apparent during this period.

Another observation relates to peaks in the pairwise spillovers in mid-2011. This may suggest that global events during this period, for example the Eurozone crisis, the USA debt crisis and the heightening of political instability in some Arab countries led to increased spillovers across countries. The net pairwise returns spillovers surrounding this period reached the highest level in all the pairs.

Figure 5.12 – Pairwise Net Returns Spillovers Plot Between Pakistan and the USA



The Pakistan-USA returns plot is illustrated in Figure 5.12, above and the plots between Pakistan and other developed markets are presented in appendix 5.17. The range

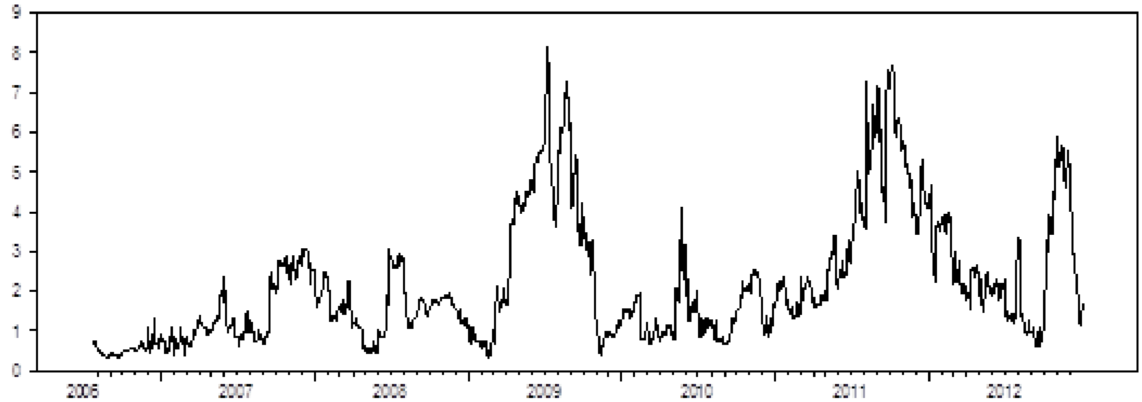
of pairwise spillovers between Pakistan and the developed markets under-consideration clearly suggests that the exchange of spillovers between Pakistan and Singapore exceeded all the other pairs, which appears to have evolved largely during the later period of analysis. Some common traits are worth mentioning:

1. The pairwise net returns spillovers do not demonstrate a trend, and the most plots return close to 0% after a period of heightened spillovers.
2. The pairwise net returns spillovers rose in the end of 2008 and remained high until the last quarter of 2009.
3. The spillovers in 2011 were at least twice as high as the spillovers between 2008 and 2009.
4. The longest period of high returns spillovers across all pairs extended from the beginning of 2011 to mid-2012.
5. A sharp ascent in spillovers was prominent in the third quarter of 2011.

The net returns spillovers between Pakistan and Japan exhibit some peculiarities. The rise in spillovers during 2008-2009 was the highest among all the other pairs in this group. Moreover, the returns spillovers appear to be rising from the last quarter of 2009 until mid-2011, after which spillovers started declining and reached a lower level, which was near to 2%. Another unusual trait that is visible in the Pakistan and Singapore and Pakistan and Japan returns is the heightened spillovers during 2012. It seems that this pattern was peculiar to the Asia-developed markets.

Static estimates of pairwise net returns spillovers between Pakistan and selected emerging countries range between 0.60 (Pakistan-China) and 2.00 (Pakistan-Malaysia). The net returns spillovers plot also demonstrate similar patterns of spillovers across pairs, with the magnitude varying marginally between the countries. Accordingly, all the plots except the one depicting interaction between Pakistan and China are included in Appendix 5.18.

Figure 5.13 - Pairwise Returns Spillovers Plot Between Pakistan and China



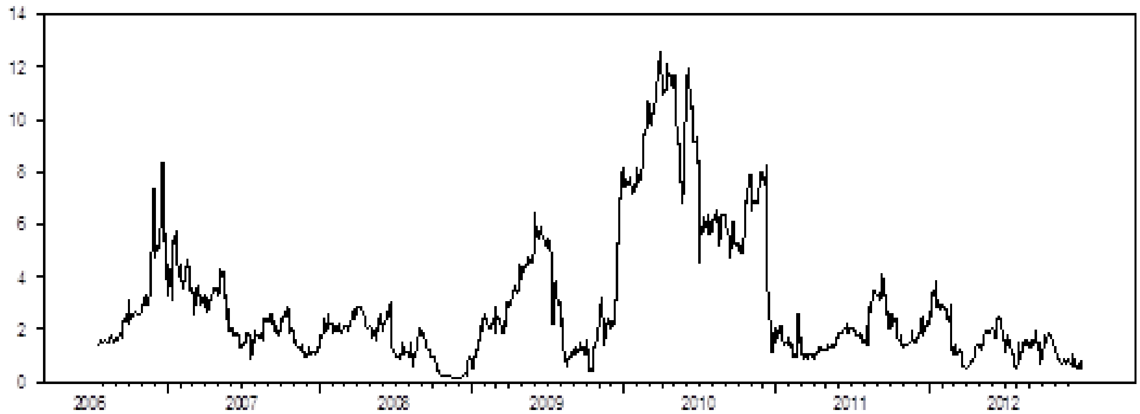
In these plots, peaks and troughs overlapped during the period of analysis, although the magnitude of spillovers varied marginally. The following commonalities in these pairs are observed in the later period of analysis:

1. The returns spillovers do not depict a trend; however, bursts are evident in the spillovers, which can be associated with particular events, such as the on-going Eurozone crisis.
2. The spillovers in the Pakistan-China and Pakistan-Malaysia pairs rose at the beginning of 2009 and fell to the original level of near 0% at the end of 2009.
3. Returns spillovers in all three pairs started rising at the end of 2009 and reached their highest levels at the end of 2011.
4. The spillovers started descending after attaining a peak at the end of 2011 and returned to approximately 0% at the mid of 2012.
5. The rise and fall in returns spillovers across the three pairs appear to have been gradual. Persistence of higher pairwise spillovers is also evident.

Some peculiarity in returns spillovers is observed in the earlier period of analysis. The Pakistan and Malaysia pair indicates heightened spillovers in 2007, whereby the spillovers were nearly as high as the spillovers surrounding the period of the Eurozone crisis. Similarly, exaggerated spillovers are observed between Pakistan and India in 2006. Since these trends are not visible in other pairs, the high spillovers can be attributed to either a domestic or a regional event.

The static spillover estimates between Pakistan and the GCC frontier markets in the sample, range between 0.40% (Pakistan and Saudi Arabia) and 1.50% (Pakistan and the UAE). The variation in the range of spillovers is not so salient (Table 5.18).

Figure 5.14 - Pairwise Returns Spillovers Plot Between Pakistan and the UAE



Spillovers between Pakistan and these markets during the second and third quarters of 2008 are not so prominent, although during this period, oil prices were at their highest levels (nearly $140 a barrel) and one would have expected an impact on oil importing countries such as Pakistan. However, it appears that the floor on the Pakistan market was able to limit the transmission of shocks to the market.

The pairwise returns spillovers plots comprising Pakistan and its GCC-based trade partners appears slightly different from the plots of other pairs comprising Pakistan and developed markets and Pakistan and emerging markets. However, the pattern of pairwise spillovers between Pakistan and its frontier counterparts is comparable; accordingly only the Pakistan-UAE spillovers plot is exhibited in figure 5.14 and the other plots are included in appendix 5.19. The pairwise spillovers plots for Pakistan and the GCC markets present the following commonalities:

1. No particular trend in returns spillovers is observed in these pairs. However, it is noticed that in the later period of analysis, the spillovers have not returned to 0% but have stayed at approximately 1% in all three pairs.

2. The returns spillovers of Pakistan and the selected GCC countries exhibit three peaks, one in December 2006, the second in May 2009 (7%) and then persistent high spillovers between November 2009 and November 2010.
3. The impact of the real-estate crisis in the UAE is apparent as all three pairs exhibit heightened spillovers between November 2009 and November 2010. This illustrates the importance of a regional crisis that can be transmitted to countries located within close proximity.

The Pakistan-UAE pair is the only one in the sample that does not exhibit the significantly increased spillovers during the second half of 2011 that were evident in all the other pairs. The spillovers in the Pakistan-Kuwait pair were the highest during 2009 and were nearly equal to the spillovers in the last quarter of 2010. The peak in spillovers in the Pakistan-Kuwait pair in 2009 is not evident in the rest of the pairs. This is also peculiar to the Pakistan-Kuwait pair as the other two pairs in this group exhibited heightened volatility in mid-2010. A slight increase in the spillovers is apparent; however, the spillovers did not exceed 4%.

5.2.4.2 Volatility Spillovers

Examination of returns spillovers reveals limited spillovers between Pakistan and its trade partners. It is appropriate to evaluate the transmission of volatility across markets, as it is established in the relevant finance literature that volatility in one market propagates quickly to other markets, resulting in high volatility spillovers during turbulent times. This is especially true for negative news, which may create chaos in markets around the world.

This section presents the results of analysis performed on the volatility time series generated using intraday minimum and maximum values. The findings are reported for the overall sample; however, most of the discussion is focused on Pakistan, as it is the market of interest in this thesis.

Analysis of volatility also entails several steps that facilitate the understanding of dynamics between the volatilities of candidate markets. Results of volatility analysis are presented as follows:

1. Volatility Spillovers Table: Table 5.19 presents the static measure of volatility spillovers across twelve candidate markets over the seven-year period of analysis.

2. Volatility Spillovers Plot: Figure 5.15 presents dynamic volatility spillovers in 200-days rolling windows across markets included in the sample. Figure 5.16 highlights the peaks in volatility spillovers and identifies significant events associated with the peaks.
3. Volatility Spillovers Plots with varying lags and forecast horizons: Figures 5.17 and 5.18 present the sensitivity of volatilities to different lags and different n-steps forecast horizons.
4. Groupwise static and dynamic volatility spillovers: Tables 5.20 to 5.24 and figures 5.19 to 5.23 present the estimates of volatility spillovers between Pakistan and groups of countries based on the MSCI Classification 2012 and geographical proximity.
5. Pairwise net spillovers: Table 5.25 presents the estimates of static and range of volatility spillovers across pairs of financial markets. Figures 5.24 to 5.30 attempt to isolate dynamic volatility spillovers between pairs of countries included in the sample over the seven-year period of analysis.

5.2.4.2.1 Volatility Spillovers Table

The static measure of volatility spillovers between candidate markets (Table 5.19) indicates that the overall static volatility spillovers stand at nearly 24%. Some relationships are evident in the volatility spillovers table. For example, spillovers between developed markets stand out clearly. Similarly, regional volatility spillovers are also prominent, such as spillovers between Japan, Singapore, Malaysia and India, and the UAE and Saudi Arabia. It is also evident that frontier markets are not only minimally affected by foreign shocks, but their impact on the volatility of other markets is also negligible. It is not surprising to observe that the frontier markets are among the largest self-contributors to their own volatility. These countries self-contribute approximately 92-99% to their overall volatility with Pakistan having the highest self-contribution at 98.80.

With respect to the contribution to others, developed markets contribute the most to other countries, with the UK taking the lead at nearly 58%, followed by the USA at 52%, and Germany at 50%. Japan and Singapore contribute 24% and 22% respectively to other markets included in the sample. It is interesting to observe that India also contributes significantly to the volatility of other markets (approximately 25%), in particular to the regional markets. Volatility spillovers from Malaysia to its counterparts in the sample are approximately 19%. The remaining markets, China and the frontier markets, contribute marginally to the volatility in other markets, with Pakistan's contribution being the lowest

at approximately 2%. Within the emerging markets, China stands out, with low import and export of volatility. With high volumes of trade between countries around the world, one would expect foreign shocks to affect China; however, China seems to have been resilient to foreign shocks.

As with the returns, the developed markets greatly contribute to each other's volatilities, with the USA being the most prominent exporter of volatility in general. For example, its contribution to the UK, Germany, Japan and Singapore stands at 19.72%, 17.12%, 9.80% and 6.09% respectively. The UK and Germany contribute approximately 17% each to volatility in the USA. The UK and Germany contribute more than 20% to each other's volatility. On the other hand, the above three markets seem to import less than 3% of their volatility from their Asia-Pacific counterparts.

With respect to emerging markets, Malaysia imports more volatility from the UK (5.50%) compared with the USA (3.5%). This is true also for the India market, with the contribution by the UK to the India volatility standing at 4.1%, nearly 50% more than the contribution by the USA. In the case of China, regional spillovers from Malaysia and India are more evident than spillovers from developed markets; however, no market contributes more than 2.5% to the overall volatility in China.

Table 5.19 – Volatility Spillovers Table

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	98.80	0.10	0.00	0.00	0.00	0.10	0.10	0.00	0.30	0.20	0.30	0.00	1.00
Developed Markets													
USA	0.00	58.20	16.90	16.30	2.60	2.40	0.60	1.10	1.60	0.10	0.10	0.20	42.00
UK	0.00	19.70	47.10	21.40	3.00	2.50	0.50	2.90	2.70	0.00	0.10	0.00	53.00
GERMANY	0.00	17.10	24.00	49.30	2.30	3.50	0.10	1.40	1.90	0.10	0.20	0.00	51.00
JAPAN	0.10	9.80	7.00	2.90	66.90	3.00	1.20	3.30	3.90	0.90	0.90	0.10	33.00
SINGAPORE	0.00	6.10	3.90	4.00	2.90	72.20	0.80	3.00	6.60	0.20	0.10	0.30	28.00
Emerging Markets													
CHINA	0.10	1.40	0.90	0.20	1.30	1.90	88.30	2.20	2.30	0.90	0.10	0.40	12.00
MALAYSIA	0.00	3.50	5.50	1.90	2.80	2.80	1.40	77.60	4.20	0.10	0.20	0.10	22.00
INDIA	0.50	2.30	4.10	2.30	4.10	4.20	1.40	3.60	75.70	0.90	0.70	0.10	24.00
Frontier Markets													
UAE	0.90	1.30	0.80	0.10	2.70	0.20	0.60	0.20	1.10	86.50	4.80	0.70	14.00
SAUDI ARABIA	0.60	0.90	0.20	0.00	0.40	0.20	0.10	0.20	0.20	1.20	95.00	0.90	5.00
KUWAIT	0.20	0.50	0.20	0.00	0.20	0.30	0.00	0.00	0.30	0.40	0.40	97.50	3.00
Contribution to others	2.00	63.00	64.00	49.00	22.00	21.00	7.00	18.00	25.00	5.00	8.00	3.00	287.00
Contribution including own*	101.00	121.00	111.00	98.00	89.00	93.00	95.00	96.00	101.00	91.00	103.00	100.00	23.90%

*Minor differences due to rounding

Note: Total Spillovers Index -> 287/1199 = 23.90% (1199 is the sum of all numbers in the last row "Contribution including own"). Subsequent tables reporting volatility spillovers utilize the same calculation.

Amongst emerging markets, China has the highest self-contribution to volatility of 88.30, which is around 93% of the total volatility. Self-contributions by Malaysia and India stand at 81% and 75% of overall volatility, which is also high, compared with developed markets.

The Asia-Pacific developed markets, Japan and Singapore, exhibit higher self-contribution to volatility, compared with the USA, the UK and Germany. Self-contribution to volatility in Japan stands at 75% and the Singapore self-contribution is approximately 78% of the overall volatility. The USA, the UK and Germany contribute 48%, 42% and 50% respectively to their overall volatility, which suggests that the remaining volatility is imported from other markets.

As observed earlier, considerable volatility spillovers from the USA to the developed markets are observed. The USA also contributes significantly to Malaysia and India (2.9% and 1.90% respectively). However, its contribution to volatility in China is rather small (only 1.15%). In frontier markets, the USA contributed approximately 1.07% to the UAE market's volatility and less than 1% to Saudi Arabia and Kuwait. Its contribution to Pakistan remains negligible. Similarly, the UK market's contribution to developed markets is obvious; however, its contribution to Germany is far greater than its contribution to the USA or Asia-Pacific developed markets. Germany also exhibits similar traits and contributes more to the volatility of the UK, compared to other developed markets.

The Japan and Singapore markets' contributions to other developed markets vary between 2% and 3.5%, suggesting that these markets are on the receiving end during turbulent times. Interestingly, Japan and Singapore contribute more to India than to Malaysia. This may seem unusual, as one would expect higher spillovers between close neighbors, compared to neighbors located further away. Also, spillovers from Japan to the UAE are noticeable (2.7%) and are close to spillovers from Japan to Malaysia.

In the case of emerging markets, Malaysia and India seem to transmit more volatility to their counterparts in the sample than China. Malaysia contributes 3% or higher to the UK, Japan, Singapore and India. On the other hand, spillovers from India to the UK amount to nearly 3%, to Singapore approximately 6%, and to Japan and Malaysia nearly 4% each

respectively. China contributes 1.40% each to Malaysia and India, and 1.20% to Japan. Its contribution to other markets in the sample is less than 1%.

The frontier markets seem to receive the lowest overall foreign volatility spillovers. The only noticeable contribution is from Saudi Arabia to the UAE, which stands at 4.80% and is more than 50% of its overall contribution to the markets included in the sample. Contributions from Pakistan, the UAE and Kuwait to other markets remain below 1% and in some cases, close to 0%. The UAE imports approximately 14% of its volatility from the other eleven markets in the sample, followed by Saudi Arabia at 5%, Kuwait at 3% and Pakistan at 1%. Besides importing volatility from Saudi Arabia (4.80%), the UAE imports volatility from Japan (2.7%), the USA (1.30%) and India (1.10%). Volatility spillovers from other countries to the UAE are less than 1% and in some cases negligible. The UAE contributes nearly 1.20% to Saudi Arabia volatility; however, spillovers from other countries to Saudi Arabia remain marginal. Foreign volatility spillovers to Kuwait and Pakistan are minimal.

With respect to Pakistan, minimum volatility spillovers are observed to and from all of its trade partners, suggesting its relative isolation from its key trade partners.

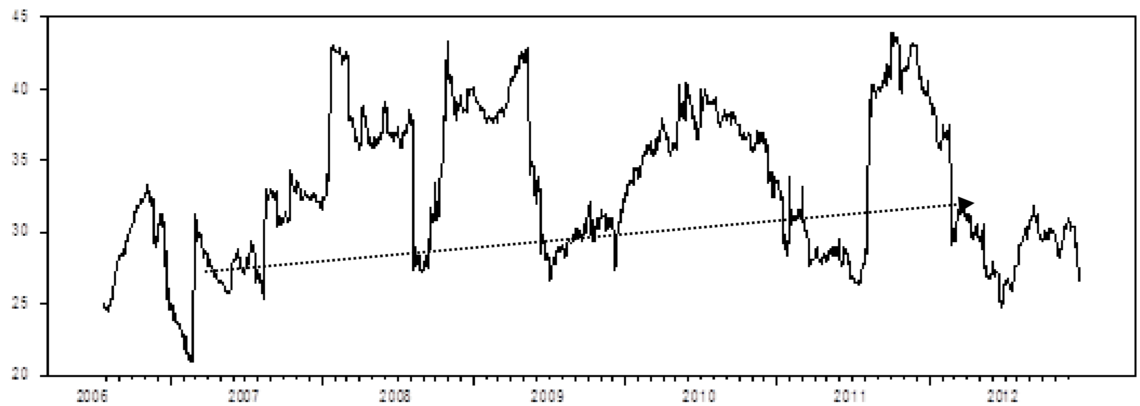
5.2.4.2.2 Volatility Spillovers Plot

Figure 5.15 presents the volatility spillovers plot for twelve markets over the period of seven years. The analysis entails 200-days rolling windows comprising two lags and 5-10 steps forecast horizon. The use of the rolling window allows the evaluation of volatility spillovers over the period without the need for measures to accommodate shocks.

It is evident that the volatility spillovers range between 21% and 44% over the period of seven years. The index reached its lowest level of 21% in February 2007, which was the only time during the period of analysis that the volatility spillovers across candidate markets were so low. The index demonstrates several peaks and valleys. All peaks are associated with some significant global events, as outlined in figure 5.16. Some peaks exhibited gradual increments while others exhibited sharp ascents. It is apparent that the volatility spillovers heightened surrounding particular negative shocks, such as the financial crisis of 2008 and the ongoing Eurozone crisis. The volatility spillovers in general seem to

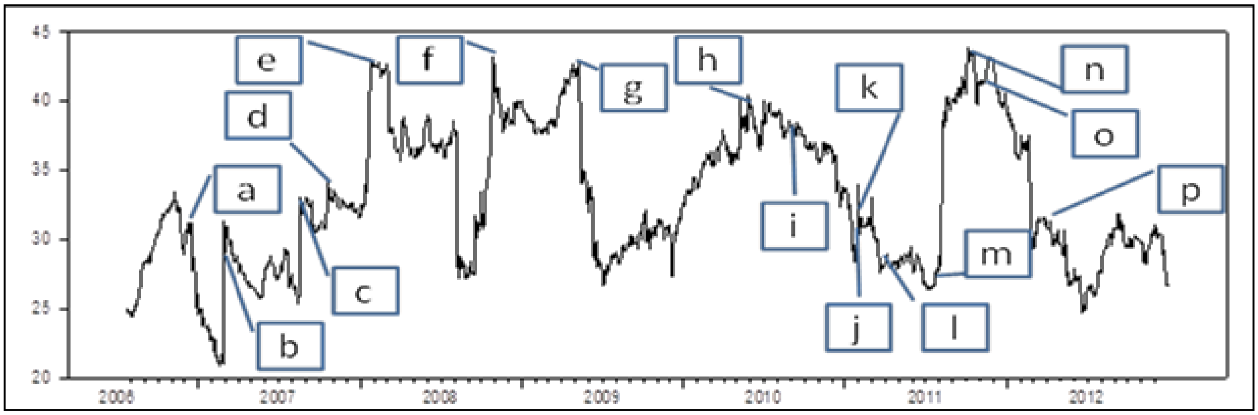
have exhibited an upward trend, which is not as pronounced as the upward trend in returns spillovers.

Figure 5.15 - Volatility Spillovers Plot in 200-days Rolling Windows with 2 Lags and 5-10 Steps Forecast Horizon



The volatility spillovers stood at approximately 25% at the beginning of the period of analysis and then gradually climbed to nearly 35% in October 2006. The index gradually descended to the lowest level in the seven-year period in February 2007, and then soared sharply to 31% in the same month. The volatility spillovers treaded between 25% and 33% until January 2008, and then the index increased suddenly to nearly 44% and stayed there until March 2008. Beyond March 2008, the index fell marginally and hovered between 36% and 40% until June 2008, before taking a sharp dip in July 2008. The volatility spillovers remained at 27% during August 2008 and then started climbing gradually and reached their highest level of 44% in September 2008. This was when Lehman Brothers filed their bankruptcy, setting the world markets on fire. The volatility spillovers remained between 37% and 44% until April 2009. Then, the spillovers sharply fell to 35% in May 2009 and then further to 27% in June 2009.

Figure 5.16 - Volatility Spillovers Plot in 200-days Rolling Windows with 2 Lags and 5-10 Steps Forecast Horizon with Significant Events



	Months and Year	Event
a	Nov-Dec 2006	Saddam Hussain and his allies are sentenced to death.
b	Jan-Apr 2007	During February and March 2007, more than 25 subprime lenders filed for bankruptcy. In April 2007, well-known New Century Financial also filed for bankruptcy.
c	Oct-Dec 2007	Deepening of sub-prime mortgage crisis. Some large banks around the world asked Central banks for emergency funding.
d	Dec 2007	Assassination of Benazir Bhutto, former Prime Minister of Pakistan.
e	Jan-Mar 2008	Evidence of recession in USA economy; Announcement of stimulus package by USA; 2 Fed interest rate drops in 8 days ; The Northern Rock failure in UK; Bear Stearns taken over by JP Morgan. Several banking giants announced huge losses.
f	Sep 2008	Lehman Brothers file bankruptcy
g	Oct-Apr 2009	Banks around the world facing difficulties and governments opted to provide funding to failing banks
h	Jan-Jun 2010	USA economy to get worse. High unemployment rates reported. Negative growth in the UK economy continues. Double-dip recession expected in France, Germany and Italy. Instability in world markets
i	Aug 2010	End of Iraq Operation
j	Jan 2011	Egyptian Revolution begins.
k	Feb 2011	Hosni Mubarak resigns. Uprising in Bahrain and Libya.
l	Mar-Apr 2011	Earth quake and Tsunami in Japan followed by Nuclear disaster.
m	May 2011	Early signs of Euro zone crisis. Portugal slips into double-dip recession.
n	Oct 2011	Greece provided bail-out by European Union members
o	Jan 2012	S&P downgraded nine European countries Austria, Cyprus, France, Italy, Malta, Portugal, Slovakia, Slovenia and Spain
p	Feb-Oct 2012	Euro zone crisis continues

The index climbed gradually in the following months, and remained between 27% and 33% until November 2009, climbing further to 41% in the mid-2010. For the most part of 2010, the volatility spillovers across the selected countries remained between 37% and 41%. The spillovers started decreasing by the end of 2010 and reached nearly 27% in July 2011. The index displayed a sharp incline to 41% in July 2011 followed by a gradual ascent to the highest level of 44% in October 2011. The index sustained its high level for the rest of 2011 and declined to nearly 38% in January 2012. A sharper descent is evident in February 2012, when the index fell to nearly 31%. During the remaining period of analysis, that is, beyond February 2012, the volatility spillovers oscillated between 25% and 32%.

The overall analysis of the volatility spillover plots suggests that after climbing sharply, the index remained at high levels for several months with smaller variations before descending sharply to lower levels. This suggests persistence of volatility and significant spillovers of shocks across countries. The end of 2006 and beginning of 2007 seems to have been the most tranquil period, as suggested by lower volatility spillovers. Beyond this period, the markets seemed volatile, and increased spillovers were progressively more evident. These incremental cross-market spillovers can be attributed to significant global events and enhanced economic and financial integration of markets.

5.2.4.2.3 Volatility Spillovers Plots with Varying Lags and Forecast Horizons

The extracted dynamic volatility spillovers values, using 2 to 10 lags, suggest that the volatility spillovers were sensitive to the choice of lags, with a constant forecast horizon of 10 days. The minimum, maximum and median values of volatility spillovers based on different lags are plotted on the chart and presented in figure 5.17. The volatility spillovers start increasing as the number of lags increases, implying gradual transmission of volatility across markets. The volatility spillovers increase until lag 9 and start falling in lag 10. This indicates that it takes 10 lags for the shocks to be absorbed across markets. It is evident that the median volatility spillovers are close to maximum values, signifying higher values with increasing lags.

The sensitivity of time-varying volatility spillovers to the choice of the forecast horizon is also evaluated and presented in figure 5.18. The analysis is performed using 5 to

10 days forecast horizon, while keeping the number of lags constant at two. Although the values increase with the increasing forecast horizon, the extracted volatility spillovers with 5-days forecast horizon do not differ greatly from volatility spillovers at 10-days forecast horizon. It is interesting to note that during turbulent times, the values at 10-days forecast horizon vary more than they vary during tranquil times. For example, from September 2008 to December 2008, the spillovers varied between 9% and 19%. In contrast, the values fluctuated between 3% and 7% during 2012, which is a relatively tranquil period, as depicted by the volatility spillovers plot in figure 5.18. This indicates that the volatility spillovers are more sensitive to the choice of forecast horizons during volatile times.

Figure 5.17 - Sensitivity of Volatility Spillovers to Varying Lags and Constant Forecast Horizon

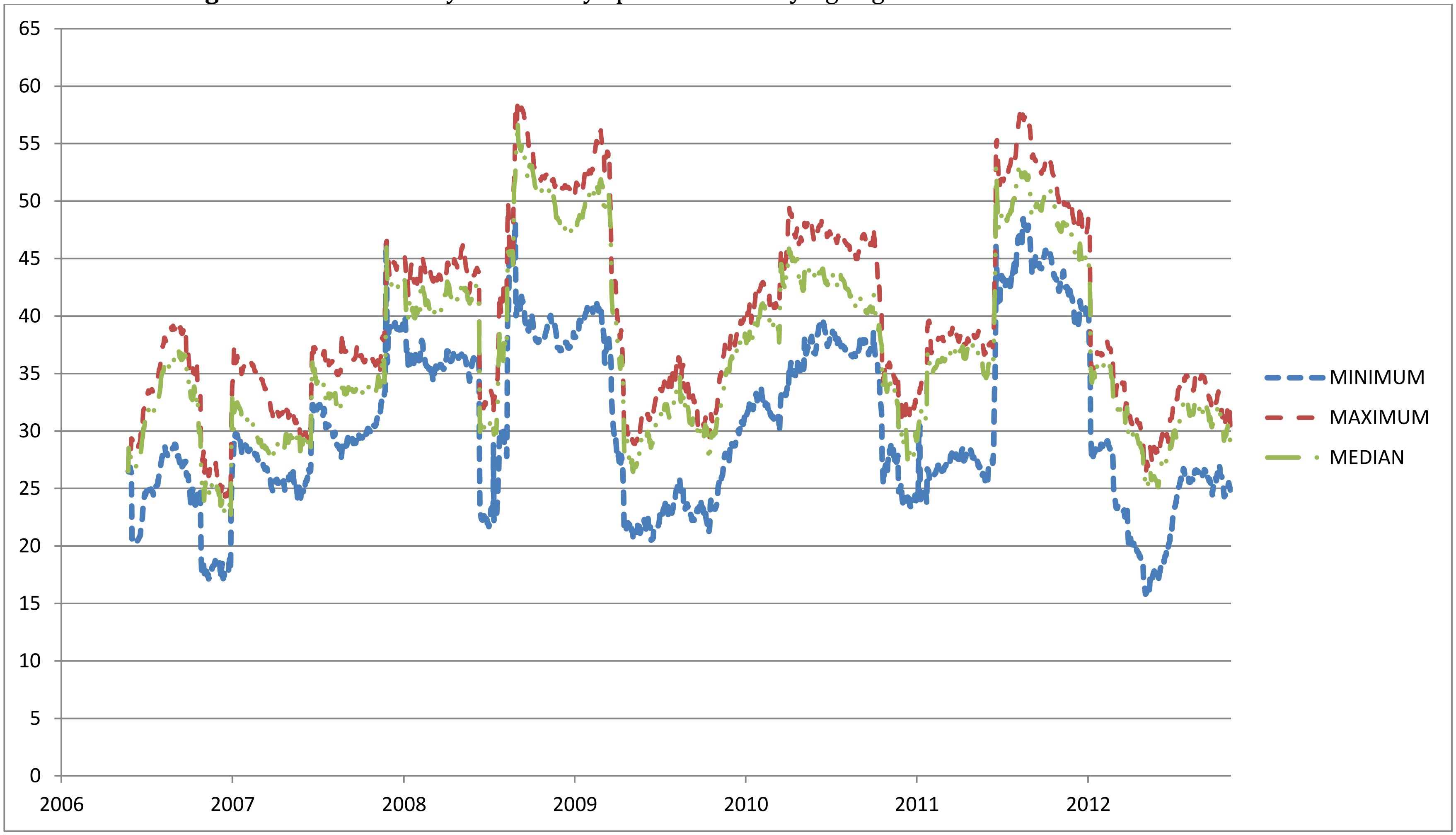


Figure 5.18 - Sensitivity of Volatility Spillovers to Varying Forecast Horizons and Constant Lags

5.2.4.2.4 Groupwise Net Volatility Spillovers Table and Plots

The volatility spillovers are further analyzed by distributing the sample into five different groups based on the MSCI country classification and geographical proximities. Given the focus of the study, Pakistan is included in all the groups in order to understand its interaction with markets belonging to different groups.

i. *Pakistan and Developed Countries*

The overall volatility spillovers between the selected developed countries and Pakistan was 31% (Table 5.20); however, it appears that these represented spillovers across developed markets, with a minimal impact to and from Pakistan. High self-contributions by Pakistan at 99.60% are evident in this group, which leaves little room for contributions from its developed counterparts. Similarly, the Pakistan contributions to developed countries were almost zero. A glance at the last column and last row of table 5.20 confirms that the exchange of volatility spillovers was primarily between developed countries.

Table 5.20 – Groupwise Volatility Spillovers for Pakistan and Developed Countries

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	From Others*
PAKISTAN	99.60	0.00	0.10	0.00	0.10	0.10	0.00
USA	0.00	59.50	17.80	16.50	3.30	2.80	40.00
UK	0.00	21.70	49.20	22.40	3.80	2.90	51.00
GERMANY	0.10	17.90	24.90	50.70	2.60	3.90	49.00
JAPAN	0.00	12.50	8.80	3.50	71.80	3.40	28.00
SINGAPORE	0.00	7.20	4.20	4.40	3.10	81.00	19.00
Contribution to others	0.00	59.00	56.00	47.00	13.00	13.00	188.00
Contribution including own*	100.00	119.00	105.00	98.00	85.00	94.00	31.30%

*Minor differences due to rounding

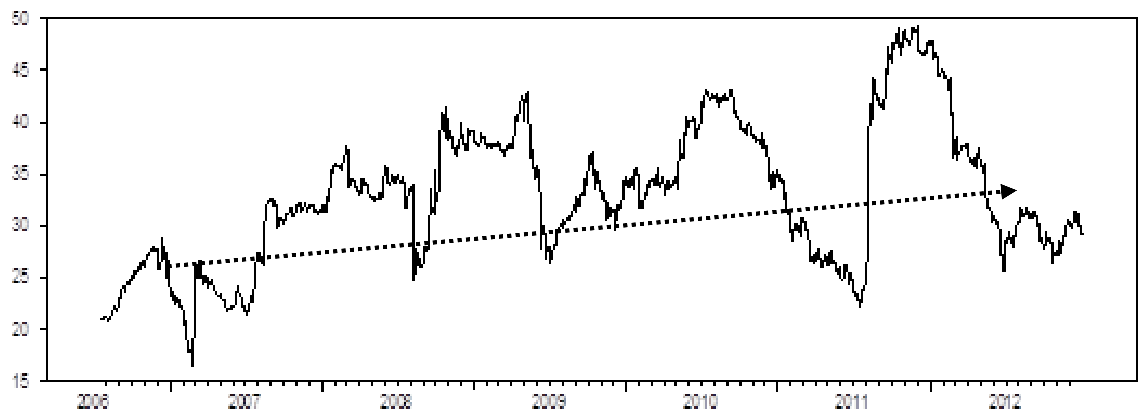
As evident in Figure 5.15, the Spillover Index of this group, including Pakistan and the developed countries, ranged between 15% and 50%. It is also observed that the Spillovers plot for this group was exhibiting an upward trend besides heightened volatility spillovers surrounding specific events.

The spillovers were at their lowest level at the beginning of 2007. The spillovers gradually increased after that and reached nearly 40% in the third quarter of 2008 and

treaded at high levels until mid-2009. In the latter half of 2009, the spillovers declined temporarily to 27% and began to ascend once again, and reached beyond 40% by mid-2011. In August 2011, the index reached close to 50% and remained there for several months, before climbing down to 35% in March 2012, and further declining to 25% in June 2012. It seems that the volatility spillovers in general increased after 2006, as the index did not return to its lower level of 15% after 2007, and sustained levels of 25% or greater in the remaining period of analysis.

Just as in the volatility spillovers table, the spillovers plot appears to reflect the interaction between the developed markets and not their association with Pakistan. Hence, further analysis is required to ensure that the two-way contributions between Pakistan and these countries are presented.

Figure 5.19 – Groupwise Volatility Spillovers Plot Consisting of Pakistan and Developed Countries



ii. Pakistan and Emerging Countries

Table 5.21 exhibits that the overall estimate of volatility spillovers between Pakistan and the selected emerging countries was 6.40%. All the emerging markets in general exhibited high self-contribution to volatility and this is obvious in this group. The Pakistan self-contribution was 99.60%, and subsequently the contributions from other countries were minuscule. India contributed 0.30% and China contributed 0.10% to the Pakistan volatility. Similarly, the Pakistan collective contribution to the selected emerging countries stood below 1%. This indicates the limited influence of Pakistan in transmitting volatility to emerging markets under consideration.

Transmission of volatility from India and Malaysia to China was comparable at 3%, with China contributing close to 94% to its own volatility. With respect to Malaysia, India contributed at least three times more to its volatility as compared with China. Malaysia contributed 90% to its own volatility. India displayed self-contributions of nearly 91% and Malaysia reciprocated by contributing nearly 6% to the India volatility.

It is interesting to note that the volatility transmission between Malaysia and India were far greater than the volatility transmissions to and from China. This may suggest that geographical proximity was less efficient in determining interdependencies between emerging markets. High self-contributions also provided support to the argument that emerging markets were affected more by domestic events and less by events occurring outside their borders.

Table 5.21 – Groupwise Volatility Spillovers for Pakistan and Emerging Countries

	PAKISTAN	CHINA	MALAYSIA	INDIA	From Others*
PAKISTAN	99.60	0.10	0.00	0.30	0.00
CHINA	0.10	93.60	3.20	3.10	6.00
MALAYSIA	0.00	2.40	90.10	7.50	10.00
INDIA	0.60	2.20	5.90	91.20	9.00
Contribution to others	1.00	5.00	9.00	11.00	25.00
Contribution including own*	100.00	98.00	99.00	102.00	6.40%

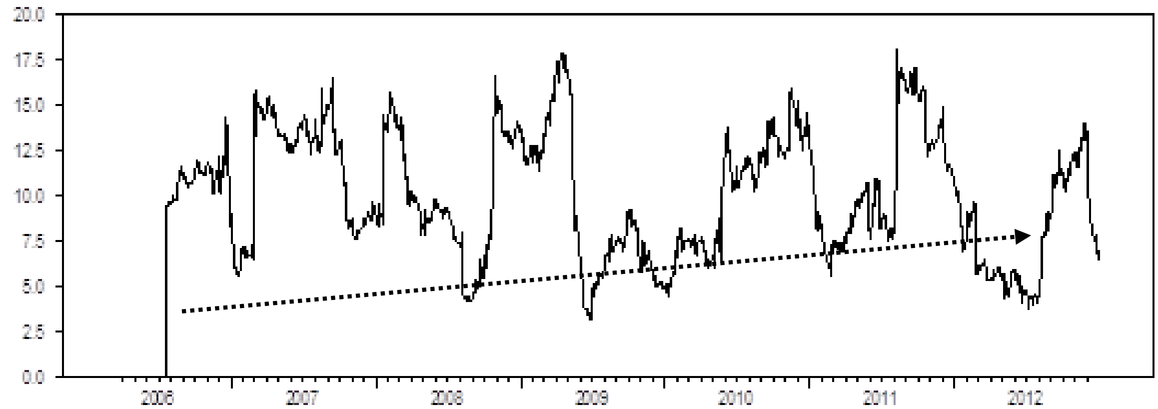
*Minor differences due to rounding

The volatility spillovers plot (Figure 5.20) also indicated low evolving spillovers between the countries in this group. The upward trend in volatility spillovers across time was not as pronounced as in the group of Pakistan and developed markets.

The spillovers ranged between 4% and 19% during the period of analysis. The plot starts from zero due to missing data values in the timeseries and jumps to nearly 10% immediately. Although fluctuations are evident in the index, they are not extraordinary. Unlike the developed markets index, spillovers returned to their lowest levels several times during the period under consideration. Volatility spillovers remained at high levels during the financial crisis of 2008 and then in the latter part of 2011. This suggests some influence

of the turbulent financial markets around the world; however, the spillovers remained below 20% in unstable periods.

Figure 5.20 – Groupwise Volatility Spillovers Plot for Pakistan and Emerging Countries



iii. Pakistan and Frontier Countries

Among all the groups under consideration, this group consisting of frontier markets exhibited the lowest volatility spillovers (Table 5.22). The overall magnitude of spillovers across these four countries stood at a mere 3.50%. The last column and last row of table 5.22 clearly demonstrates marginal exchange of volatility spillovers across frontier markets. This suggests that all these countries were marred with high self-contributions and were rather isolated from each other. Pakistan had the highest self-contributions at 99.50%, followed by Kuwait at 97.80%, Saudi Arabia at 96.60% and the UAE at 92%.

While Pakistan appears relatively secluded from its GCC counterparts with maximum contributions of 0.20% each from Saudi Arabia and the UAE, the GCC markets exhibited interdependence amongst them. Saudi Arabia seems to have been the most influential market, with close to 6% spillovers to the UAE and 2% to Kuwait. On the other hand, it received marginal spillovers from Kuwait and the UAE.

The volatility spillovers plot, including Pakistan and other frontier markets, is depicted in figure 5.21 and ranges between 2.50% and 22%. In this group also, the upward trend in volatility spillovers across markets is less discernible.

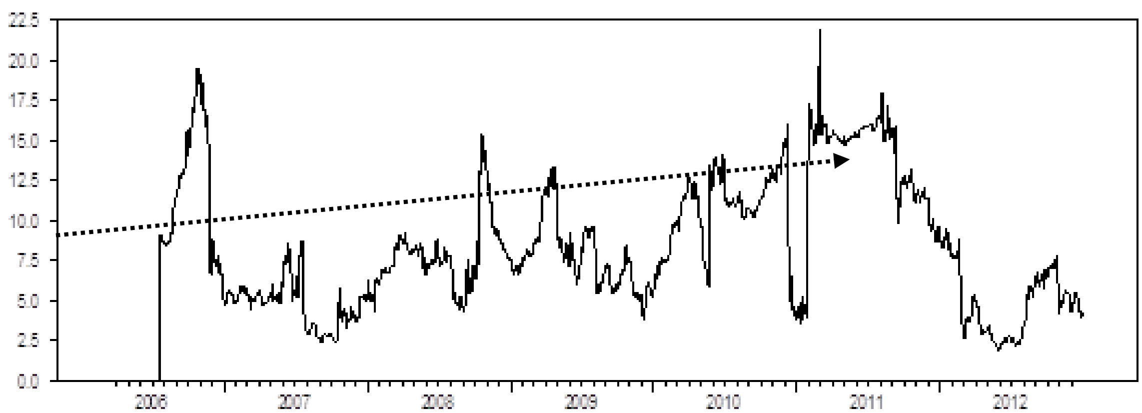
Table 5.22 – Groupwise Volatility Spillovers for Pakistan and Frontier Markets

	PAKISTAN	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	99.50	0.20	0.20	0.00	0.00
UAE	0.80	92.00	5.90	1.30	8.00
SAUDI ARABIA	0.40	1.60	96.60	1.40	3.00
KUWAIT	0.10	1.30	0.70	97.80	2.00
Contribution to others	1.00	3.00	7.00	3.00	14.00
Contribution including own*	101.00	95.00	103.00	101.00	3.50%

*Minor differences due to rounding

Due to missing values in the timeseries, the plot starts from zero and jumps to nearly 9% in May 2006. The first peak of 20% in the index is apparent at the end of 2006. The spillovers remained at less than 10% from the last quarter of 2006 until August 2008, after which they steadily increased to 15% before returning to 7% in December 2008. The spillovers hovered between 5% and 12.50% in mid-2010 and then gradually increased to nearly 17% in December 2010; however, the high level of spillovers was not sustained and a sharp decline was witnessed in the same month. January 2011 presented a subsequent sharp incline, whereby the index reached its highest level during the period of analysis. This episode of high spillovers was prolonged and lasted for nearly seven months. The decline started in August 2011 and since then the spillovers maintained a low level, ranging between 2% and 12.50%. It is interesting to note that while other groups exhibited exaggerated spillovers in August 2011, frontier markets presented a declining trend.

Figure 5.21 – GroupWise Volatility Spillovers Plot Consisting of Pakistan and Frontier Countries



iv. Pakistan and Border-Sharing Neighboring Countries

Regional interdependencies do not seem very apparent in this group comprising Pakistan and its border-sharing neighbors. The overall spillovers across these three countries were only 2.40% (Table 5.23), suggesting marginal exchange of volatility across these three close neighbors.

Self-contributions to volatility in this group were significant, with Pakistan having the largest self-contributions at 99.70%, followed by India at 96.70% and China at 96.40%. While the Pakistan contributions to the volatility of the other two countries were negligible, the India and China volatility contributions to each other were comparable and remained between 3% and 4%.

Table 5.23 – Groupwise Volatility Spillovers for Pakistan and Border-Sharing Neighboring Countries

	PAKISTAN	CHINA	INDIA	From Others*
PAKISTAN	99.70	0.10	0.30	0.00
CHINA	0.10	96.40	3.50	4.00
INDIA	0.60	2.70	96.70	3.00
Contribution to others	1.00	3.00	4.00	7.00
Contribution including own*	100.00	99.00	101.00	2.40%

*Minor differences due to rounding

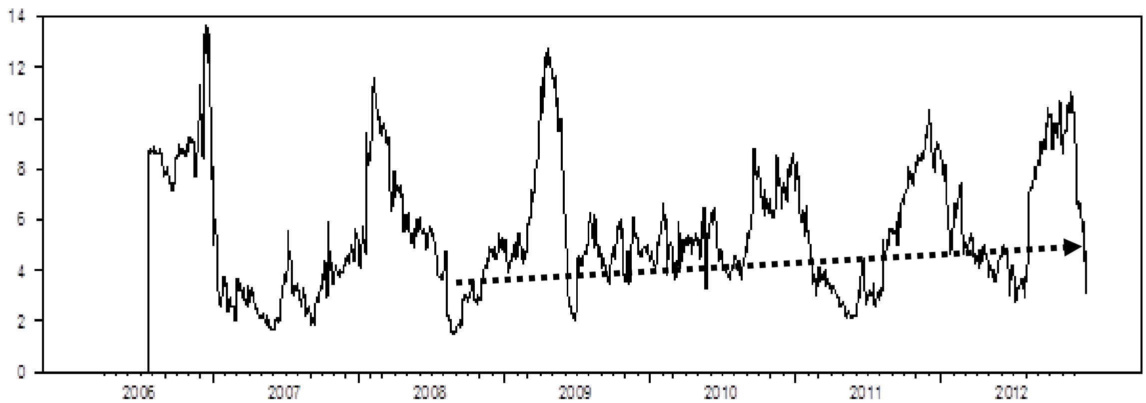
The spillovers plot presented in Figure 5.22 ranged between 2% and 14% with four apparent peaks. The increasing trend in volatility spillovers was observed in the post-financial crisis period. The volatility spillovers attained the following peaks:

1. 14% in the end of 2006
2. 12% in January 2008
3. 13% in March 2009
4. 12% in November 2012

During 2007, the index remained at levels below 6% and after briefly rising to 12% in January 2008, continued to decline until it reached 2% in August 2008. Some effect of the 2008 financial crisis was visible in September 2008 and beyond; however, the spillovers did not exceed 6% in the later part of 2008. In March 2009, spillovers briefly rose to the highest

level of 14%, only to return to 2% in the next quarter. For the next five quarters, until mid-2010, spillovers ranged between 4% and 6%. At the end of 2010, the spillovers increased by nearly 25% and remained close to 8% until December 2010. The first half of 2011 witnessed low spillovers, which ascended in July 2011, coinciding with the Eurozone crisis. In the year 2012, the spillovers declined to nearly 3% in the first half and then increased by at least four times in November 2012.

Figure 5.22 – Groupwise Volatility Spillovers Plot for Pakistan and its Border-Sharing Neighboring Countries



v. Pakistan and Asia-Pacific Neighboring Countries

Table 5.24 presents the static estimate for spillovers between Pakistan and its neighboring trade partners in the Asia-Pacific, and the overall spillovers across seven years stand close to 10%. While Pakistan had a negligible impact on the volatility spillovers in the group, regional exchange of volatility within Asia-Pacific countries was extremely evident.

As demonstrated in other groups, Pakistan exhibited exaggerated self-contributions, standing at 99.80%, with meager contributions from Japan and Singapore. Malaysia also had high self-contributions, close to 90%, with 6% spillovers from Japan and 5% from Singapore. Japan seems to have been more influential in the groups as it transmitted relatively higher volatility to Singapore and Malaysia.

Table 5.24 – Groupwise Volatility Spillovers for Pakistan and its Asia-Pacific Neighbors

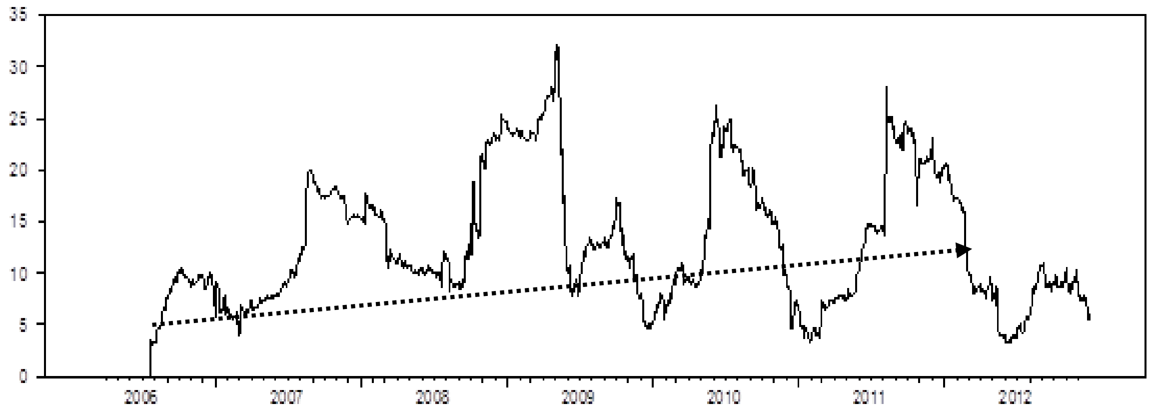
	PAKISTAN	JAPAN	SINGAPORE	MALAYSIA	From Others*
PAKISTAN	99.80	0.10	0.10	0.00	0.00
JAPAN	0.00	85.80	7.50	6.60	14.00
SINGAPORE	0.00	7.40	87.10	5.40	13.00
MALAYSIA	0.10	6.10	5.00	88.90	11.00
Contribution to others	0.00	14.00	13.00	12.00	38.00
Contribution including own*	100.00	99.00	100.00	101.00	9.60%

*Minor differences due to rounding

The spillovers plot (figure 5.23) ranges between 5% and 32% and lacks an increasing trend. Exaggerated spillovers were concentrated beyond July 2008 until the end of the period of analysis. The spillovers ranged between 5% and 20% from 2006 until the first half of 2008. In April 2008, spillovers increased beyond 30% and then declined sharply to less than 10% in May 2009, possibly coinciding with the financial crisis. In the latter half of 2009 and the first quarter of 2010, the index fluctuated between 7% and 15%, and then rose to 26% in May 2010. The spillovers descended gradually and retreated to their lowest level of 5% in the first quarter of 2011. After this, the spillovers steadily increased and attained a level of more than 25% in August 2011, potentially due to the Eurozone crisis. A declining trend was evident beyond this period with the index hovering between 3% and 10% in 2012.

While the spillovers to and from Pakistan were meager in magnitude, the other markets in this group seem to have been affected by volatility spillovers from their regional neighbors, especially during turbulent times.

Figure 5.23 – GroupWise Volatility Spillovers Plot Consisting of Pakistan and Asia-Pacific Neighboring Countries



5.2.4.2.5 Pairwise Net Volatility Spillovers Plots

This sub-section presents insights into the volatility spillovers between the pairs of countries, with a focus on Pakistan. The results so far have provided an insight into the interaction of volatilities across markets, and it is apparent that the Pakistan contribution to the volatilities of other markets is limited. At the same time, it appears remote from the volatility spillovers from other markets. These findings reveal partial information about the Pakistan market's association with the markets under consideration; therefore, the need for further analysis becomes essential. Examining pairwise volatility spillovers allows a clear and detailed understanding of relationships.

Table 5.25 presents the estimates of static volatility spillovers and their ranges between Pakistan and its eleven most active trading partners over a seven-year period of analysis. It is evident that the static volatility spillovers estimates are very low and are below 1%. The pairwise spillovers between Pakistan and developed countries range between 0% and 0.10%, those between Pakistan and emerging markets between 0% and 0.50% and Pakistan and frontier markets between 010% and 0.70%. Static estimates of pairwise net volatility spillovers are marginal; however it is to be noted that these estimates present the net spillovers and not directional spillovers. It appears that the exchange of volatility spillovers between markets is nearly equal in magnitude resulting in lower estimates for net volatility spillovers. Beyond static estimates for volatility spillovers, the need for insight into dynamic association between candidate countries is crucial. Accordingly, pairwise volatility spillovers are plotted. Table 5.25 also presents the range of volatility spillovers across each

pair. Unlike the net pairwise returns spillovers plots, less appears to be common in net pairwise volatility spillovers.

Table 5.25 – Estimates of Pairwise Net Volatility Spillovers Between Pakistan and its Key Trade Partners

	Static Volatility Spillovers Estimate	Range of Volatility Spillovers (Approximate)
Developed Markets		
USA	0.00%	0% to 22%
UK	0.10%	0% to 18%
Germany	0.00%	0% to 17%
Japan	0.10%	0% to 19%
Singapore	0.00%	0% to 19%
Emerging Markets		
China	0.10%	0% and 9%
Malaysia	0.00%	0% to 17%
India	0.50%	0% to 16%
Frontier Markets		
Saudi Arabia	0.70%	0% to 19%
UAE	0.30%	0% to 8%
Kuwait	0.10%	0% to 11%

The following observations are evident from the volatility spillover ranges:

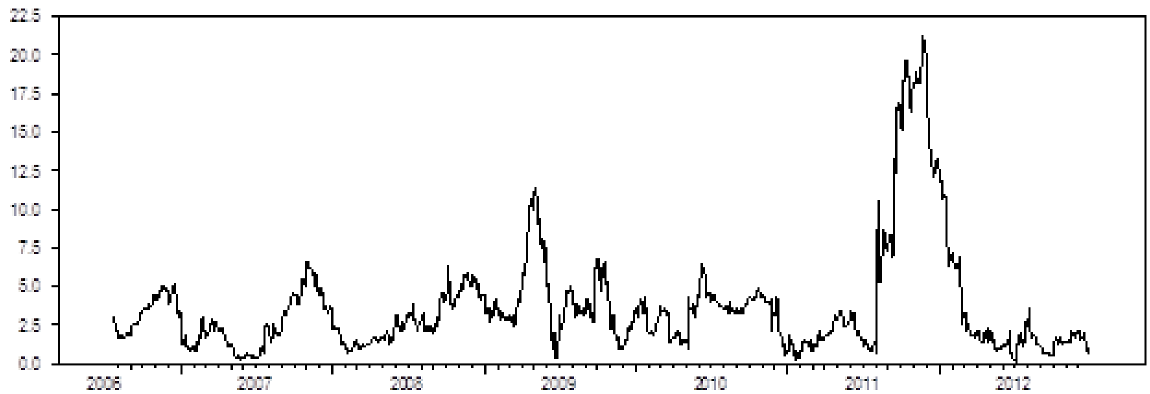
1. The range of volatility spillovers between Pakistan and the USA are the highest, followed by the Asian developed markets. The effect of the developed markets in terms of volatility spillovers is apparent and it is less surprising as developed markets, especially the USA, are documented to transmit shocks to the international markets.
2. In the emerging markets group, it appears that Pakistan and Malaysia have exchanged more volatility as compared with the countries located closer to Pakistan.
3. In the frontier markets group, the range of volatility spillovers is the lowest between Pakistan and the UAE and the highest between Pakistan and Saudi Arabia.

The patterns of volatility spillovers between Pakistan and developed, emerging and frontier markets varies significantly. However, few similarities in patterns of volatility spillovers across pairs are observed, such as:

1. Trend in volatility spillovers is lacking in all pairs and the volatility spillovers have returned to near 0% levels during tranquil times.

2. With a few exceptions, heightened volatility spillovers are noticed in all pairs from mid-2008 to mid-2009. However, volatility spillovers between Pakistan and its eleven trade partners seem to be contained during the financial crisis of 2008, possibly due to the floor placed on the KSE100 index from August to December 2008.
3. Exaggerated volatility spillovers are also prominent in 2011 and their magnitude is greater than those in 2008-2009.

Figure 5.24 - Pairwise Net Volatility Spillovers Plot Between Pakistan and the USA



The plots for Pakistan and developed markets are highly similar; therefore, one illustrative plot between Pakistan and the USA is presented in figure 5.24 above. All the other pairwise net volatility spillovers plots between Pakistan and other developed markets are included in appendix 5.20. These plots exhibit the following parallels:

1. One peak in the volatility spillovers is apparent in the first half of 2009. The height of these peaks in all pairs is approximately similar in magnitude. The highest peak is attained between Pakistan and the UK and stood at 14%.
2. Another episode of exaggerated volatility is observed in the end of 2011. Pakistan and the USA pair have the highest peak in this group, which stands at 21% approximately.
3. Inflated volatility spillovers in the later period of analysis are observed from mid-2011 to end-2011.

Anomalies are observed in the Pakistan-Japan and Pakistan-Singapore pairs. However, the patterns of volatility spillovers are somewhat similar in these pairs. The highest peak in volatility in the Pakistan-Japan pair is evident in the end of 2006, which is the highest for this pair during the period of analysis. Although there is some evidence of

increased spillovers in other pairs during the same period, the increase is not very pronounced. Heightened spillovers in the Pakistan-Japan and Pakistan-Singapore groups are also observed in the end of 2009, whereby the spillovers are equally as high in magnitude as during the first half of 2009. In the Pakistan-Singapore pair, the volatility spillovers in 2011 extend from the beginning till the end, which does not conform to the patterns evident in other pairs.

With respect to pairwise net volatility spillovers between Pakistan and its emerging counterparts, peculiar patterns are observed in all three pairs. Accordingly, all three plots are included here (Figures 5.25 to 5.27). The following typical spillovers patterns in these pairs are apparent:

1. Exaggerated volatility spillovers in the beginning of 2009, primarily associated with the financial crisis are most prominent in the Pakistan-India pair and less apparent in the other two pairs.
2. There is evidence of increased spillovers in the latter half of 2010 in all pairs, but it is most pronounced in the Pakistan-Malaysia pair.
3. Increased spillovers in 2011 are extremely prominent in the Pakistan-Malaysia pair. In this period the plots for the Pakistan-Malaysia and Pakistan-China pairs are at their highest level during the complete period of analysis.

Some atypical characteristics are also observed in pairs comprising Pakistan and its emerging counterparts. In the Pakistan-India pair, the highest volatility spillovers are witnessed in 2006, which are not apparent in the other two pairs. Moreover, in this pair the volatility spillovers have not returned to their lowest levels of 0% since the beginning of 2011. In the Pakistan-Malaysia pair, the volatility spillovers do not exceed 4% until mid-2010 and heightened volatility spillovers are primarily witnessed towards the end of the period of analysis. The Pakistan-China plots demonstrate most variability in volatility spillovers, although the magnitude is less than with the other two pairs.

Figure 5.25 - Pairwise Net Volatility Spillovers Plot Between Pakistan and China

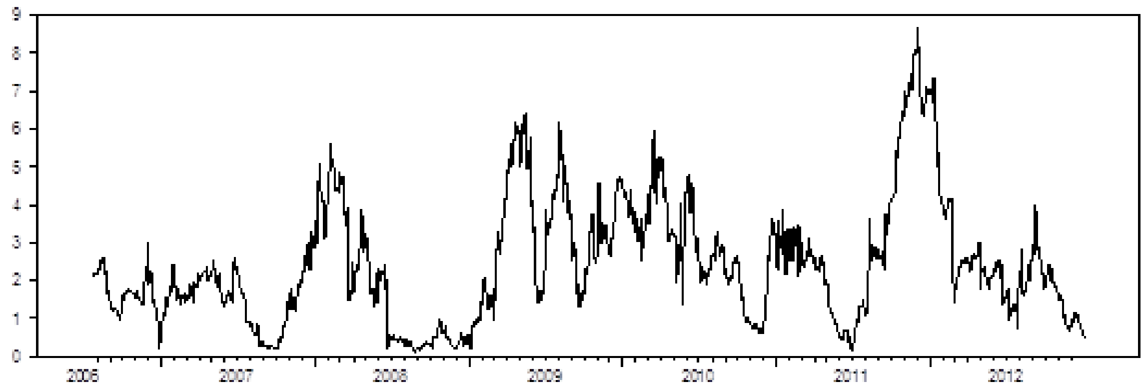


Figure 5.26 - Pairwise Net Volatility Spillovers Plot Between Pakistan and Malaysia

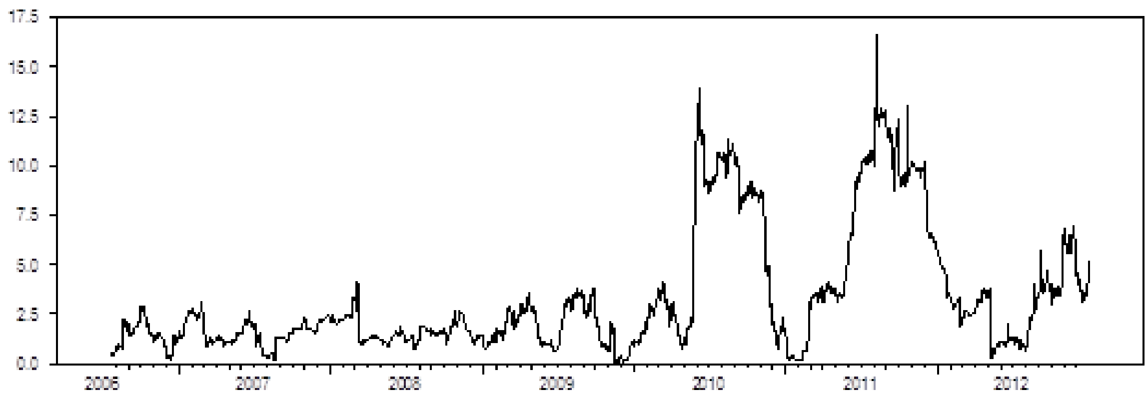
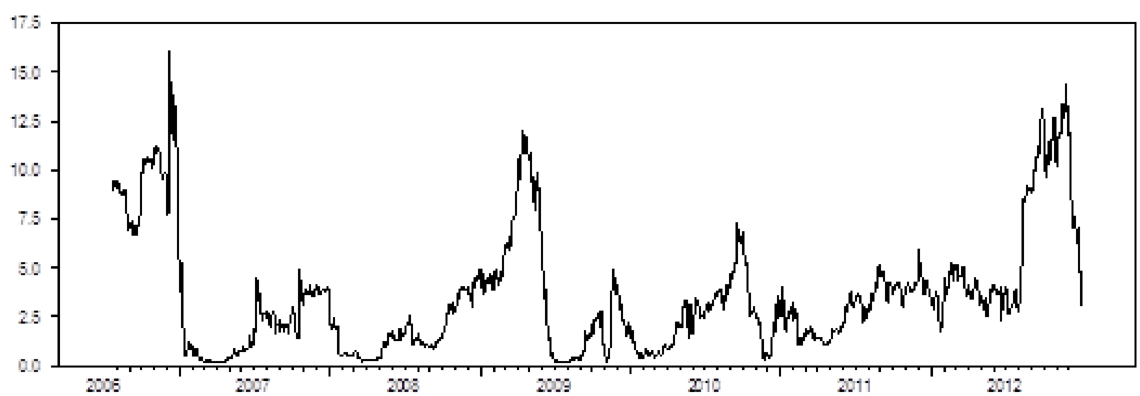


Figure 5.27 - Pairwise Net Volatility Spillovers Plot Between Pakistan and India



The pairwise net volatility spillovers between Pakistan and its frontier counterparts also exhibit peculiar patterns and are therefore presented here in figures 5.28 to 5.30. The plots present the following few similarities:

1. All the plots return to their lowest levels after periods of exaggerated volatility associated with events like the financial crisis, the UAE financial crisis and the prolonged Eurozone crisis.
2. Heightened volatility spillovers surrounding the Eurozone crisis are appropriately captured in the plots; however, the magnitude varies across pairs. Also, the period of amplified volatility spillovers overlaps in all three plots.

Figure 5.28 - Pairwise Net Volatility Spillovers Plot Between Pakistan and the UAE

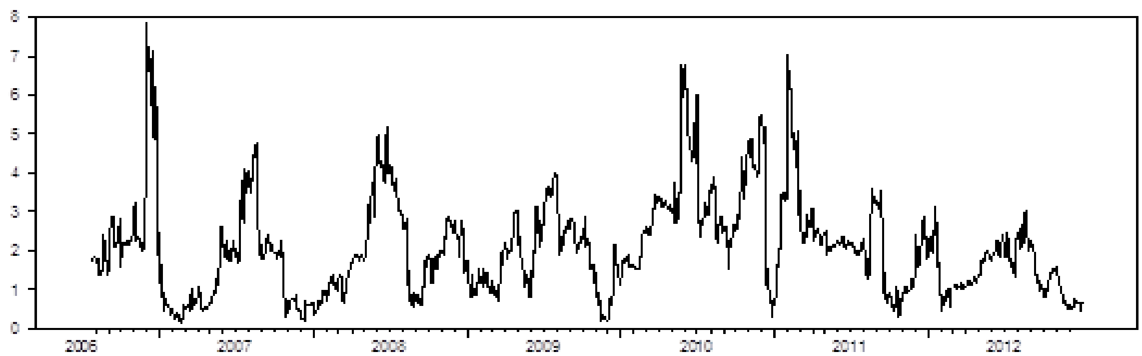


Figure 5.29 - Pairwise Net Volatility Spillovers Plot Between Pakistan and Saudi Arabia

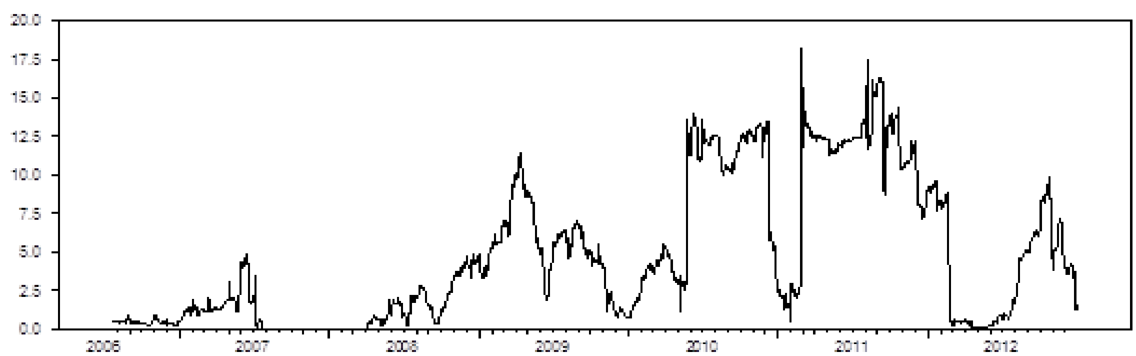
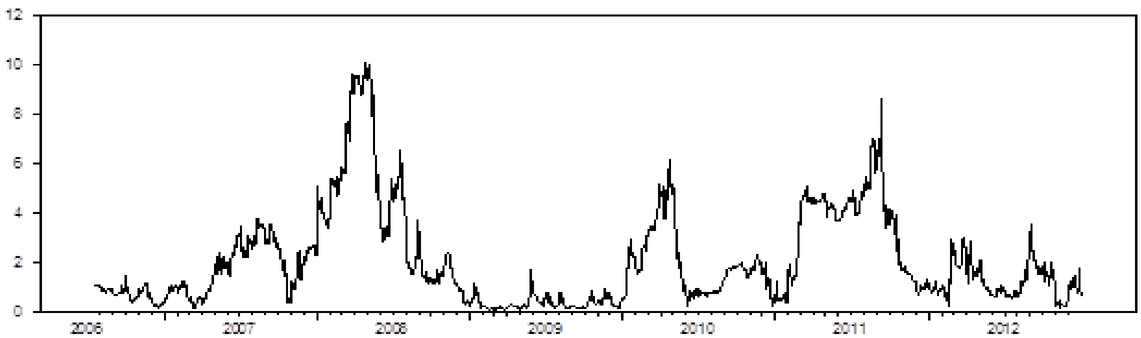


Figure 5.30 - Pairwise Net Volatility Spillovers Plot Between Pakistan and Kuwait



Beyond these similarities, there is less in common across these pairs. The Pakistan-UAE plots exhibit its highest peak in the end of 2006, which is not evident in any other pair. Exaggerated volatility in mid-2008 is evident in the Pakistan-UAE and Pakistan-Kuwait pair. The magnitude of spillovers in the latter pair is double that of the spillovers in the former pair.

High volatility spillovers between the Pakistan-UAE and Pakistan-Saudi Arabia pairs are witnessed in the first half of 2009; however, spillovers between Pakistan and Kuwait were close to 0% during the same period. Similarly, magnified spillovers in 2010 are evident in the Pakistan-UAE and Pakistan-Saudi Arabia pairs but not in the Pakistan-Kuwait pair. This may suggest that although these countries are located in the same region and are closely tied with bilateral and multilateral agreements, the market-specific attributes determine the patterns of volatility spillovers across these markets.

5.2.4.3 Robustness Check

The data analysis in multiple ways has provided ample insight into the interaction between Pakistan and its trade partners; however, it is important to ensure that the findings are robust to various lengths of time series and can perform well in different conditions. Therefore, to ensure robustness and reliability of results, the period of analysis is classified into three sub-periods and the results derived are then compared with the results for the whole period of analysis. The period of analysis is classified as follows:

1. Pre-Crisis Period: From 1 January 2006 to 14 September 2008
2. Crisis Period: From 15 September to 26 October 2009
3. Post-Crisis Period: From 27 October 2009 to 31 December 2012

The fall of Lehman Brothers and their filing of bankruptcy on 15 September 2008 marks the beginning of the crisis period, whilst the end of the crisis period is in line with Bartram and Bodner (2009).

For the purpose of the robustness check, all the countries in the sample are considered collectively in the returns and volatility Spillovers Index. The discussion focuses primarily on Pakistan, with brief insight into the interaction between other markets.

5.2.4.3.1 Returns Spillovers Table and Plot

Table 5.26 presents a comparison of self-contributions to returns in markets of interest during different periods of analysis. Tables 5.27 to 5.29 and figures 5.31 to 5.33 present the returns spillover tables and plots in the pre-crisis, crisis, and post-crisis periods correspondingly. The section provides insight into the behavior of developed, emerging, and frontier markets and specifically sheds light on the Pakistan market's interaction with its trade partners during the sub-periods.

Table 5.26 – Comparison of Returns Self-contributions in Different Periods of Analysis

	Whole Period	Pre-Crisis	Crisis	Post-Crisis
PAKISTAN	90.10	88.00	90.60	81.40
USA	45.10	56.90	39.70	42.50
UK	35.20	38.40	32.00	34.20
GERMANY	36.00	40.50	32.00	35.30
JAPAN	36.20	41.20	27.90	45.10
SINGAPORE	37.10	39.30	33.20	38.90
CHINA	73.20	78.00	70.20	67.20
MALAYSIA	47.30	49.70	38.90	55.60
INDIA	46.80	48.90	40.80	51.00
UAE	68.50	79.50	47.60	79.60
SAUDI ARAE	83.50	92.40	62.80	80.00
KUWAIT	84.20	86.60	74.30	86.00

i. Pre-Crisis Period

The static measure of returns spillovers in the pre-crisis period stands at 38.40% as compared with 43.10% in the full period analysis, indicating lower returns spillovers in tranquil times.

It is evident from table 5.26 that developed markets in the sample exhibit low self-contributions, followed by emerging markets like Malaysia and India. High self-contributions and low foreign contributions are apparent in all the frontier markets and China. A glance at foreign contributions in the pre-crisis period reveals prevalence of regional interdependencies in all the groups.

The following observations regarding the developed markets are made in the pre-crisis period as compared with the whole period analysis:

- The highest self-contributions in both periods are observed in the USA.
- The returns spillovers from the USA to other developed markets are lower in the pre-crisis period when compared with the full period.
- In other developed markets in the sample, the magnitude of self-contributions in the pre-crisis period is slightly higher than those in the whole period of analysis.
- Exchange of returns spillovers among developed markets is pronounced in both the periods. For example, both Germany and the UK contribute equally to the USA returns, amounting to an overall contribution of nearly 35%.
- Reciprocation of returns spillovers between the UK and Germany is apparent.
- The UK contribution to the developed and emerging markets is not very different from its contribution in the full period of analysis, with the exception of Japan. Returns spillovers from the UK to Japan are nearly 40% lower in the pre-crisis period when compared with the full period.
- The returns spillovers from Japan and Singapore to all other markets do not differ significantly in the periods under consideration.
- The Germany market's contribution to the USA in the pre-crisis period is nearly 28% lower than its contribution in the full period analysis. Similarly, its contribution to Japan and Singapore is nearly 33% and 37% lower in the pre-crisis period.

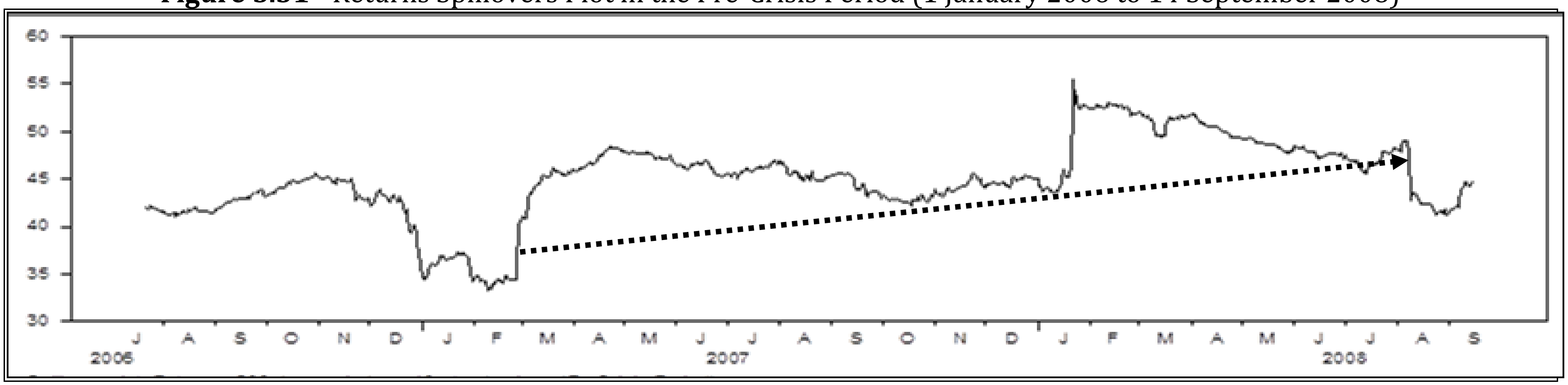
Table 5.27 – Returns Spillovers Table in the Pre-Crisis Period (1 January 2006 to 14 September 2008)

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	88.00	1.30	1.80	1.60	0.80	1.20	0.20	1.50	2.20	0.70	0.40	0.30	12.00
Developed Markets													
USA	0.40	56.90	16.70	16.90	2.20	2.50	0.00	1.40	1.90	0.50	0.10	0.40	43.00
UK	0.30	13.00	38.40	27.30	4.30	7.00	0.40	2.80	5.40	0.30	0.60	0.30	62.00
GERMANY	0.40	13.70	28.60	40.50	4.10	4.70	0.30	2.40	4.10	0.30	0.70	0.20	59.00
JAPAN	0.50	8.30	8.20	8.80	41.20	15.90	1.90	5.70	8.10	0.50	0.50	0.20	59.00
SINGAPORE	0.80	7.00	8.10	5.90	13.90	39.30	2.60	10.70	10.70	0.40	0.40	0.20	61.00
Emerging Markets													
CHINA	0.40	0.80	1.50	1.30	3.80	5.50	78.00	4.30	3.20	0.40	0.30	0.60	22.00
MALAYSIA	1.20	5.90	6.60	5.80	6.70	14.40	2.70	49.70	6.30	0.30	0.20	0.20	50.00
INDIA	1.40	6.50	7.30	6.40	8.20	13.10	1.60	5.70	48.90	0.60	0.10	0.30	51.00
Frontier Markets													
UAE	0.60	0.40	0.70	0.70	0.70	1.00	0.50	0.40	0.40	79.50	10.20	4.90	20.00
SAUDI ARABIA	0.50	0.10	0.10	0.20	1.10	0.90	0.30	0.50	0.30	2.20	92.40	1.40	8.00
KUWAIT	0.40	0.30	0.30	0.30	0.40	0.20	0.10	0.30	0.10	4.00	7.10	86.60	13.00
Contribution to others	7.00	57.00	80.00	75.00	46.00	66.00	11.00	36.00	43.00	10.00	21.00	9.00	460.00
Contribution including own*	95.00	114.00	118.00	116.00	88.00	106.00	89.00	85.00	92.00	90.00	113.00	96.00	38.40%

*Minor differences due to rounding

Note: Total Spillovers Index -> 460/1202 = 38.40% (1202 is the sum of all numbers in the last row "Contribution including own")

Figure 5.31 - Returns Spillovers Plot in the Pre-Crisis Period (1 January 2006 to 14 September 2008)



With respect to emerging markets, it is observed that:

- Contributions from emerging markets to the developed markets are limited. For instance, the total contribution from emerging markets to the Germany spillovers is a mere 7%. Returns spillovers from Germany to emerging markets are similar in both the pre-crisis and the complete periods of analysis.
- China contributes significantly its own returns spillovers in both sub-periods, while India and Malaysia exhibit marginal variation.
- The India contribution to the USA market returns is approximately 100% higher in the full period analysis in comparison to the pre-crisis period.
- Significant bi-directional spillovers between India and Malaysia in the pre-crisis and the full period of analysis are observed.
- Limited interaction between emerging and frontier markets is witnessed, whereby contributions in either direction do not exceed 5% collectively.

With regards to the frontier markets, the estimates in the pre-crisis period suggest the following:

- As Table 5.26 illustrates, high self-contributions are a norm in the group of frontier markets, which suggests their relative isolation from their developed and emerging counterparts. Foreign contributions to frontier markets do not exceed 20%. Similarly, contributions from frontier markets to other markets are restrained to a maximum of 21% (Saudi Arabia).
- The highest foreign contributions are experienced by the UAE, followed by Kuwait, Pakistan and Saudi Arabia respectively.
- Singapore's contribution to the UAE and Saudi Arabia is greater than the contribution from other developed markets, but does not exceed 1%.
- Marginal contribution of overall 1% from emerging markets to the GCC markets is evident.
- The returns spillovers from frontier markets to developed and emerging markets are similar in the pre-crisis and full period analysis.
- India contributed nearly 100% more to the returns of Pakistan in the pre-crisis period, but its contribution to other frontier markets in the sample in the same period was insignificant.

- The frontier markets contributed marginally towards the Pakistan market's returns in the pre-crisis period.
- The returns spillovers from the UK to Pakistan are higher in the pre-crisis period as compared to the whole period.

The spillovers plot in the pre-crisis period ranged between 34% and 57%. An upward trend in the returns spillovers is evident after February 2007. Before this the spillovers ranged between 34% and 36%. The spillovers attained a peak of 57% in January 2008. The index remained above 45% until July 2008, declined moderately to 42% in August 2008, and started ascending once again in September 2008.

ii. Crisis Period

As suggested earlier, this study considers the bankruptcy filing by Lehman Brothers on 15 September 2008 as the starting point of the financial crisis. This sub-section draws a comparison between the pre-crisis, crisis and full period of analysis.

During the crisis period, the returns spillovers across the countries in the sample stood at 51%, which is nearly 33% higher than its pre-crisis level and 18% higher than the spillovers in the full period of analysis. This is not surprising, as exaggerated spillovers during turbulent times have been reported in finance literature (For example Cheung *et al.*, 2008; Dooley and Hutchison, 2009; Huyghebaert and Wang, 2010; Assidenou, 2011; Baur, 2012). During crisis, self-contributions in all markets declined substantially with subsequently higher foreign contributions, except in Pakistan, whereby its self-contributions marginally increased during the crisis when compared with pre-crisis estimates.

The self-contribution of the USA during the crisis was nearly 43% lower than its self-contribution in the pre-crisis period; however, its contribution to developed countries was much higher than the pre-crisis levels, suggesting that the USA exports shocks to other countries, especially during turbulent times. Moreover, it is also evident that the global shocks supersede domestic and regional events, and that a large fraction of returns can be explained through imported shocks during turbulent times.

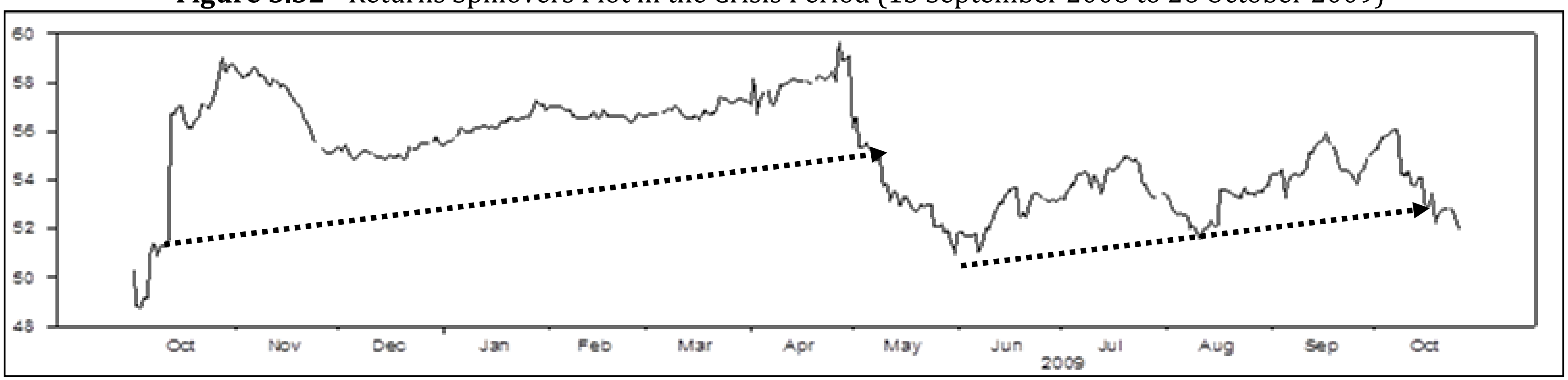
Table 5.28 – Returns Spillovers Table in the Crisis Period (15 September 2008 to 26 October 2009)

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	90.60	1.10	1.00	1.00	0.10	0.40	0.40	0.90	0.40	2.00	0.40	1.80	9.00
Developed Markets													
USA	0.20	39.70	16.90	20.60	2.20	6.30	0.10	3.10	5.30	2.30	2.20	1.20	60.00
UK	0.30	16.20	32.00	24.20	4.60	6.70	0.40	5.20	6.30	1.50	2.00	0.70	68.00
GERMANY	0.20	17.90	24.10	32.00	4.30	6.50	0.60	4.30	5.70	1.60	2.30	0.50	68.00
JAPAN	0.20	16.60	13.50	14.70	27.90	9.70	1.60	6.00	5.50	1.80	1.50	1.00	72.00
SINGAPORE	0.20	9.20	8.30	8.80	9.10	33.20	3.70	10.00	12.00	3.50	0.90	0.90	67.00
Emerging Markets													
CHINA	1.00	2.40	2.30	2.10	2.90	6.10	70.20	5.90	5.20	0.90	0.80	0.30	30.00
MALAYSIA	0.20	8.10	9.00	7.80	7.20	13.20	3.40	38.90	8.90	2.00	0.70	0.70	61.00
INDIA	0.20	7.60	8.80	8.00	4.30	14.70	2.80	7.90	40.80	2.60	1.00	1.40	59.00
Frontier Markets													
UAE	0.60	9.30	6.60	6.40	1.10	6.50	0.60	3.00	4.40	47.60	9.50	4.30	52.00
SAUDI ARABIA	0.40	6.60	6.70	7.50	1.70	4.60	0.20	2.80	2.90	2.40	62.80	1.50	37.00
KUWAIT	1.20	2.70	1.60	1.20	0.60	1.30	0.40	0.70	1.70	6.30	8.00	74.30	26.00
Contribution to others	5.00	98.00	99.00	102.00	38.00	76.00	14.00	50.00	58.00	27.00	29.00	14.00	610.00
Contribution including own	95.00	137.00	131.00	134.00	66.00	109.00	84.00	89.00	99.00	75.00	92.00	89.00	50.80%

*Minor differences due to rounding

Note: Total Spillovers Index -> 610/1200 = 50.80% (1200 is the sum of all numbers in the last row "Contribution including own")

Figure 5.32 - Returns Spillovers Plot in the Crisis Period (15 September 2008 to 26 October 2009)



Further analysis of developed markets during the crisis reveals the following:

- Apparent and significant exchange of returns within developed markets.
- Increase in spillovers from the USA to the emerging markets is evident, which is not extraordinarily high.
- Declined contribution from the UK to Germany and nearly 30% higher contribution from the UK to Japan.
- Extraordinary increase in contributions from the UK to frontier markets.
- Increased contributions from Germany to developed markets, except the UK and emerging markets.
- Heightened spillovers from Germany to the frontier markets, with the exception of Pakistan.
- Noticeable contributions from Singapore to the USA and most of the frontier markets.
- The Japan market's contributions to most of the markets included in the sample remained at pre-crisis levels; however, its contributions to Singapore and India declined substantially during the crisis. This may suggest that the developed markets other than Japan were more influential in transmitting negative shocks to world markets.

Among the emerging markets:

- The China market's contributions to regional returns spillovers were greater when compared with its contributions to developed markets. Subsequently, China was the recipient of higher spillovers from Singapore, which were less than 4%.
- Malaysia and India contributed nearly equally to the China market's returns.
- The frontier markets in the sample collectively contributed only 3% to the China market's returns.
- Spillovers between India and Malaysia were more pronounced than spillovers between India-China and Malaysia-China.

- Malaysia experienced low self-contributions during the crisis and imported nearly 61% of spillovers, out of which nearly 75% was contributed by the developed markets. Malaysia contributed higher spillovers to European markets, compared with the USA market during the crisis, and exchanged an equal amount of returns with Singapore.
- In the case of India, foreign spillovers during the crisis amounted to 59%, with major contributions from developed markets. The India market's emerging counterparts contributed nearly 11% to its returns. The India market's highest contribution was to Singapore, which was nearly double the contribution to other developed markets.

The frontier markets in the GCC experienced the most pronounced increase in foreign spillovers during the crisis. The following pertinent observations were made:

- Foreign contributions to Saudi Arabia increased three-fold and the contributions to the UAE and Kuwait more than doubled during the crisis. For example, the USA contribution to the returns of the UAE increased from a mere 0.4% in the pre-crisis period to nearly 9.5% during the crisis. Similarly, its contribution to Saudi Arabia increased to 7% during the crisis period from close to 0% in the pre-crisis period. Contributions from the USA to Kuwait also increased substantially during the crisis.
- The Saudi Arabia market's contribution to the frontier markets declined considerably during the crisis; in particular, its relative contribution to the UAE declined from 49% in the pre-crisis period to 33% during the crisis. In the frontier markets, the UAE received the highest spillovers from Malaysia (3.4%), and Kuwait experienced the lowest (0.80%).

A comparison of pre-crisis and crisis spillovers estimates reveals a marginal difference in bi-directional spillovers between Pakistan and its trade partners. A few exceptions are observed:

- Pakistan was the only market in the sample that experienced higher self-contribution during the crisis period, compared with the pre-crisis levels, which is comparable to its self-contribution in the full period analysis. Higher self-contribution during the

crisis can be attributed to the problems within the Pakistan market, which led to the placement of a floor on the index in August 2008.

- Spillovers to Pakistan from other developed and emerging countries during the crisis declined in general. For example, the spillovers from the USA to Pakistan declined from 1.30% in pre-crisis to 1.10% during crisis.
- China was the only country in the emerging markets that contributed marginally greater returns to Pakistan during crisis in comparison with pre-crisis level.
- The interaction of returns between Pakistan and the frontier markets altered during the crisis. The contribution from the UAE to Pakistan increased three-fold during the crisis, and spillovers from Kuwait to Pakistan increased from 0.30% in the pre-crisis level to 1.80% during the crisis. Spillovers from Pakistan to Kuwait increased from 0.40% to 1.20% during the crisis; however, the spillovers to other two frontier markets remained unaltered.

The returns spillovers plot suggests high spillovers during the crisis. The index varied between 46% and 60% during turbulent times. The spillovers started increasing in September 2008 with the onset of the financial crisis and reached approximately 60% at the end of October 2008. After October 2008, the index declined moderately; however, it remained above 55% until March 2009. A brief peak at 60% is evident in April 2009, after which the spillovers gradually declined in the latter part of 2009, but still fluctuated between 51% and 56%. An upward trend in returns spillovers is evident in general.

iii. Post-Crisis Period

In line with the chronology presented by Bartram and Bodnar (2009), this study considers 26 October 2009 being the end of the financial crisis. This sub-section presents the findings of the spillovers table and plots in the post-crisis period.

In the post-crisis period, the index fell to nearly 42%, which is not only close to the pre-crisis level of 38%, but also much closer to the index in the full period analysis (43.10%). Self-contributions increased in the post-crisis period with the exception of China and Pakistan, whereby the self-contributions declined. This suggests that cross-market

transmission of shocks exaggerates during crisis but returns to pre-crisis levels during normal times.

The following observations are apparent in developed markets:

- Contributions from the USA, Japan and Singapore to other markets exhibit a decline; however, the contributions from the UK and Germany to other markets remain at the levels witnessed during the crisis. This can be attributed to the prolonged Eurozone crisis, which resulted in instability in several European markets (For example Antonakakis and Vergos, 2013).
- In the post-crisis period, prominent interactions between developed markets are observed, with the USA, the UK and Germany exchanging significant returns. The interaction between the returns of developed markets is evident in all three sub-periods.

In the case of emerging markets:

- Pronounced spillovers between China and its East Asian counterparts (Japan, Singapore and Malaysia) are observed.
- In the case of India, developed markets contribute almost 41% out of 49% total foreign contributions, and 6% is contributed by China and Malaysia, leaving little room for contributions from the frontier markets.

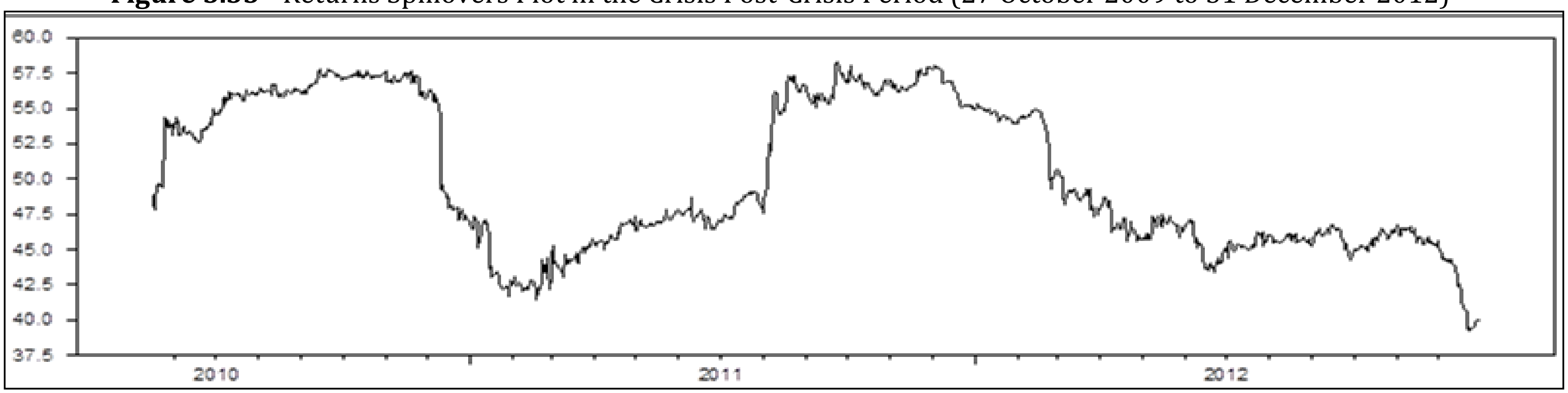
Table 5.29 – Returns Spillovers Table in the Post-Crisis Period (27 October 2009 to 31 December 2012)

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	81.40	3.00	2.10	2.00	1.60	2.00	0.80	1.80	1.70	1.90	0.20	1.20	19.00
Developed Markets													
USA	0.20	42.50	22.30	23.00	1.70	4.70	0.90	0.50	3.30	0.10	0.60	0.20	58.00
UK	0.10	18.90	34.20	26.60	1.90	7.90	1.90	1.20	5.90	0.30	1.00	0.20	66.00
GERMANY	0.20	19.90	27.40	35.30	1.80	7.10	1.30	0.80	5.10	0.20	0.70	0.10	65.00
JAPAN	0.80	12.20	10.00	9.60	45.10	9.60	3.60	3.00	3.90	1.20	0.90	0.10	55.00
SINGAPORE	0.90	8.10	10.90	9.80	8.30	38.90	4.90	5.80	11.00	0.70	0.60	0.10	61.00
Emerging Markets													
CHINA	0.60	2.90	4.50	3.30	5.50	7.90	67.20	2.60	3.70	1.20	0.40	0.20	33.00
MALAYSIA	1.30	8.40	7.40	5.50	3.80	9.20	2.30	55.60	4.80	0.80	0.30	0.50	44.00
INDIA	0.60	6.10	9.40	8.20	3.30	14.30	2.80	3.30	51.00	0.60	0.30	0.10	49.00
Frontier Markets													
UAE	1.80	1.30	1.30	1.20	1.40	1.40	1.50	1.10	1.00	79.60	5.80	2.50	20.00
SAUDI ARABIA	1.10	4.10	3.70	2.60	0.40	1.20	0.40	0.60	1.20	2.60	80.00	2.00	20.00
KUWAIT	1.30	0.90	0.60	0.30	0.10	0.20	0.10	0.70	0.70	1.90	7.10	86.00	14.00
Contribution to others	9.00	86.00	100.00	92.00	30.00	66.00	21.00	21.00	42.00	12.00	18.00	7.00	503.00
Contribution including own	90.00	128.00	134.00	127.00	75.00	104.00	88.00	77.00	93.00	91.00	98.00	93.00	41.90%

*Minor differences due to rounding

Note: Total Spillovers Index -> 503/1198 = 41.90% (1098 is the sum of all numbers in the last row "Contribution including own")

Figure 5.33 - Returns Spillovers Plot in the Crisis Post-Crisis Period (27 October 2009 to 31 December 2012)



In the case of the frontier markets, some interesting observations are apparent, specifically in relation to Pakistan:

- A decline in Pakistan self-contributions is noticeable and is estimated at 10%. Subsequently, foreign contributions to Pakistan, as well as Pakistan contributions to other countries, increased to 19% and 10% respectively. This is peculiar to Pakistan because increased self-contributions in other markets during the post-crisis period are observed.
- Contributions from the developed and emerging markets are approximately similar, with the USA being the highest contributor at 3% and Japan being the lowest at 1.60%. Contributions from India and Malaysia are at least twice the contributions from China.
- Inflated exchange of returns spillovers is evident between Pakistan and the GCC frontier markets in the study. The GCC frontier markets collectively contribute approximately 3.00% to the overall foreign contribution, with the UAE being the highest contributor in the group.
- Pakistan contributed to China and India equally (0.60% each); however, its contributions to Malaysia are higher than the other two emerging markets and stood at 1.30%.

The results associated with the Pakistan market's spillovers suggest its altering association with its trade partners during various sub-periods. In the crisis period, the interaction between Pakistan and oil-producing trade partners is more pronounced as compared with the other two periods. Exchange of spillovers between Pakistan and Malaysia and Pakistan and India vary depending on the sub-period. During crisis, spillovers from these emerging markets to Pakistan decline during crisis as compared to pre-crisis and post-crisis levels.

Comparison between the post-crisis period and the other two sub-periods reveals pronounced exchange of spillovers among developed markets, especially between the USA, the UK and Germany. Singapore stands out in the group, as the exchange of spillovers between Singapore and other developed countries does not fluctuate tremendously in all the

periods of analysis. In the case of the emerging markets, the relative return spillovers from Malaysia to the other markets included in the sample decline significantly. The post-crisis contributions of Malaysia to other markets are nearly 50% lower than their level during the crisis and 36% lower than their pre-crisis levels. The frontier markets of the GCC, which exhibited exaggerated relative contributions to other markets during the crisis, returned to their pre-crisis levels and are close to the full period contributions. Regional spillovers in the emerging and the frontier markets in all the periods are evident, as spillovers across East-Asian markets and across the GCC markets are apparent.

The returns spillovers plot ranges between 39% and 59% in the post-crisis period. During 2010, the spillovers sustain high levels (between 48% and 57%), close to those in the crisis period. In the first half of 2011, the index declines to some extent, but stays above 40% and varies between 42% and 49%. The turbulence in the markets associated with greater returns spillovers cross border is evident in the latter half of 2011, whereby the spillovers jump to the highest levels of close to 59% and sustain a high level until the first quarter of 2012. This can be associated with the Eurozone crisis, the gravity of which increased in August 2011. After the first quarter of 2012, the spillovers gradually decline and finally reach their lowest level of 38% in December 2012.

5.2.4.3.2 Volatility Spillovers Table and Plot

Comparison of self-contributions to volatility in the markets of interest is presented in Table 5.30. Tables 5.31 to 5.33 and Figures 5.34 to 5.36 present the volatility spillovers tables and plots in the pre-crisis, crisis, and post-crisis periods respectively.

Table 5.30 – Comparison of Volatility Self-contributions in Different Periods of Analysis

	Whole Period	Pre-Crisis	Crisis	Post-Crisis
PAKISTAN	98.80	90.90	83.10	90.10
USA	58.20	56.80	46.40	76.20
UK	47.10	45.10	38.00	43.40
GERMANY	49.30	36.10	38.80	45.00
JAPAN	66.90	78.20	53.60	85.50
SINGAPORE	72.20	70.00	61.20	61.50
CHINA	88.30	95.70	66.50	90.20
MALAYSIA	77.60	79.00	53.40	72.90
INDIA	75.70	69.80	50.50	92.40
UAE	86.50	87.00	68.10	97.00
SAUDI ARABIA	95.00	95.40	69.00	90.70
KUWAIT	97.50	96.70	81.60	95.80

i. Pre-Crisis Period

The volatility spillovers table suggests that the overall spillovers across candidate countries stood at nearly 25% in the pre-crisis period, which is also close to the static volatility spillovers estimate in the full period analysis. High self-contribution of close to 90% and beyond are apparent in all frontier markets, as well as China.

The following interesting observations are apparent in the case of developed markets:

- The self-contributions of developed markets vary between 36% (Germany) and 78.20% (Japan).
- Exchange of volatility within developed markets is pronounced. For example, 41% out of 43% of the total foreign contribution to the USA comes from the developed markets.
- Singapore contribution to the USA volatility is nearly 7% higher (17%) than the UK contribution (10%).
- The USA is an apparent volatility exporter to Japan (7.70%), Germany (4.10%) and Singapore (2.90%).

- Developed markets collectively contribute nearly 47.40% to the UK volatility and the remaining volatility comes from the emerging markets of India and Malaysia, at 3% and 3.50% respectively. Singapore contributions to the UK volatility are much higher (20.50%), compared with Germany contributions.
- Germany receives highest foreign contributions from the UK.
- Singapore imports greater volatility from the UK (13.60%) and Japan (8.30%), and much less from the USA (3.80%). Singapore contributions in the pre-crisis period to other countries are nearly twice, compared with the full period estimates.
- Germany self-contribution in the full period analysis is nearly 36% higher than its self-contributions in the pre-crisis period. On the contrary, Japan self-contributions in the full period analysis are nearly 14% lower than its self-contributions in the pre-crisis period.
- In terms of "contributions to others", the estimates vary greatly between the two periods under consideration. The USA and Germany contributions to other countries in the full period analysis were much higher than their contributions in the pre-crisis period.

With regards to the emerging markets, the following observations were made:

- Emerging markets exhibit larger self-contributions to volatility in the pre-crisis period, with China leading the way at 95.70%. China and Malaysia had lower self-contributions in the full period analysis, but the opposite is true for India.
- The contributions to China from Malaysia and India in the full period analysis were moderately high in the pre-crisis period.

Table 5.31 – Volatility Spillovers Table in the Pre-Crisis Period (1 January 2006 to 14 September 2008)

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	90.90	0.10	0.60	0.50	2.00	0.20	1.00	0.00	3.40	0.90	0.30	0.10	9.00
Developed Markets													
USA	0.00	56.80	10.50	6.90	6.20	17.30	0.30	0.20	1.50	0.20	0.20	0.00	43.00
UK	0.50	6.80	45.10	12.50	7.60	20.50	0.10	3.00	3.50	0.10	0.10	0.20	55.00
GERMANY	0.80	7.50	29.30	36.10	5.40	13.30	0.40	4.00	2.80	0.10	0.10	0.20	64.00
JAPAN	1.80	7.70	1.20	4.10	78.20	2.90	0.00	1.60	1.20	0.40	0.00	0.80	22.00
SINGAPORE	0.20	3.80	13.60	1.20	8.30	70.00	0.40	0.00	1.70	0.20	0.10	0.50	30.00
Emerging Markets													
CHINA	0.50	0.90	0.30	0.50	0.00	0.80	95.70	0.30	0.30	0.20	0.40	0.10	4.00
MALAYSIA	0.10	5.10	6.90	7.00	0.80	0.20	0.00	79.00	0.70	0.10	0.20	0.10	21.00
INDIA	3.20	3.20	9.20	1.90	3.60	7.80	0.10	0.40	69.80	0.20	0.30	0.30	30.00
Frontier Markets													
UAE	0.70	0.20	1.80	0.20	1.90	1.30	0.20	0.10	3.30	87.00	3.30	0.00	13.00
SAUDI ARABIA	0.70	0.10	0.20	0.10	0.10	0.00	0.40	0.10	0.70	2.20	95.40	0.10	5.00
KUWAIT	0.10	0.70	0.10	0.20	0.20	0.20	0.40	0.20	0.90	0.20	0.10	96.70	3.00
Contribution to others	9.00	36.00	74.00	35.00	36.00	64.00	3.00	10.00	20.00	5.00	5.00	2.00	299.00
Contribution including own*	99.00	93.00	119.00	71.00	114.00	134.00	99.00	89.00	90.00	92.00	100.00	99.00	24.90%

*Minor differences due to rounding

Note: Total Spillovers Index -> 299/1199 = 24.90% (1199 is the sum of all numbers in the last row "Contribution including own")

Figure 5.34 - Volatility Spillovers Plot in the Pre-Crisis Period (1 January 2006 to 14 September 2008)

Frontier markets primarily exhibit high self-contributions. The following observations are apparent in frontier markets in general and Pakistan in particular:

- The frontier markets exhibit highest self-contributions to volatility as compared with their developed and emerging counterparts.
- The UAE imported volatility spillovers of 13%, mainly distributed between Saudi Arabia and India (3.30% each), Japan (1.90%) and the UK (1.80%).
- Foreign contribution to Pakistan volatility stand at net 9%, with the highest contributions from India (3.40%) and Japan (2%), and marginal contributions from other markets.
- Pakistan self-contribution to its own volatility in the full period analysis is nearly 10% higher than in the pre-crisis level.
- Volatility exchange between Pakistan and the developed countries is less than 4%. Pakistan reciprocated the volatility received from Japan in equal magnitude (nearly 2%).
- Pakistan and India contributed equally to each other's volatility (nearly 3%), followed by China, and a negligible exchange between Pakistan and Malaysia.
- Pakistan contributed equally to the volatility of Saudi Arabia and the UAE; however, spillovers from the UAE to Pakistan were marginally higher and spillovers from Saudi Arabia to Pakistan were nearly 50% of the spillovers in the other direction.

The volatility spillovers plot in the pre-crisis period varies between 20% and 47%, with the lowest spillovers witnessed in the first quarter of 2007, and the highest in the first quarter of 2008. Just before the onset of the crisis in September 2008, the volatility spillovers were close to 30%.

ii. Crisis Period

The overall volatility spillovers during the crisis period stand at nearly 41%, nearly 64% higher than the pre-crisis level and 70% higher than the full period volatility spillovers. Table 5.30 clearly indicates prominent decline in self-contributions and greater exchange of

volatility of varying magnitudes during the crisis without any discrimination between various groups of markets. It is also evident from table 5.32 that in some cases the volatility spillovers from developed markets other than the USA were more prominent during the crisis.

Exchange of volatility between the USA, the UK and Germany is noticeable in this sub-period also. The following observations related to the developed markets during the crisis are apparent:

- Contributions from Germany to the USA increased from 12.50% in the pre-crisis period to nearly 18% in the crisis period.
- Spillovers from Singapore and Japan to the USA decline substantially and remain only one quarter and half of the estimates in the pre-crisis levels, respectively. However, contributions from the USA to Japan nearly double, implying that the Asian developed markets import more volatility from, and export less volatility to, the USA during crisis, compared with normal times.
- Spillovers from India and Malaysia to the USA increase substantially during the crisis and swell from 1.50% and 0.20% respectively to more than 5%.
- Spillovers from the USA to the UK increase by nearly 30% during the crisis. Furthermore, the contributions from Germany, India and Malaysia to the UK increase by 100% during crisis.
- Limited contributions from the frontier markets and China to the USA and the UK are apparent in all periods under consideration.
- Germany self-contributions to volatility are approximately 27% higher in the full period analysis compared with pre-crisis and crisis periods. Contributions from the USA to Germany double during the crisis, with negligible change to contributions from the UK. Contributions from Japan and Singapore to Germany volatility during the crisis reduce considerably. Contributions from emerging and frontier markets to Germany escalate, with Pakistan contribution to Germany increasing three-fold, from less than 1% to 3%.

- Spillovers from emerging markets to Japan increase substantially, especially from China, whereby the volatility spillovers from China to Japan swell from what were 0% before the crisis to 11% during the crisis. Frontier markets play a marginal role in Japan volatility in all periods of the analysis.
- Contributions from the USA and Germany to Singapore increase marginally; however, contributions from the UK to Singapore decline by nearly 30% during the crisis. Malaysia contribution to Singapore increases from 0% before the crisis to nearly 9% during the crisis. Similarly, contributions from India triple from the pre-crisis levels.

In all the emerging markets in the sample, a significant decline in volatility self-contributions during the crisis was observed.

With respect to China, spillovers from most developed countries to China increased many-fold during the crisis. Specifically, spillovers from the USA and Japan increased unprecedentedly, with spillovers from the USA increasing nearly five times and spillovers from Japan increasing from 0% to 6.60%. Spillovers from the UK and Germany increased from less than 1% to more than 4% and spillovers from Singapore increased from 0.80% in the pre-crisis period to nearly 2% during the crisis.

Spillovers between China and its emerging counterparts also increased to some extent. Spillovers from Malaysia to China surged from 1% in the pre-crisis level to 6.40% during the crisis. Contributions from frontier markets to China increased marginally during the crisis.

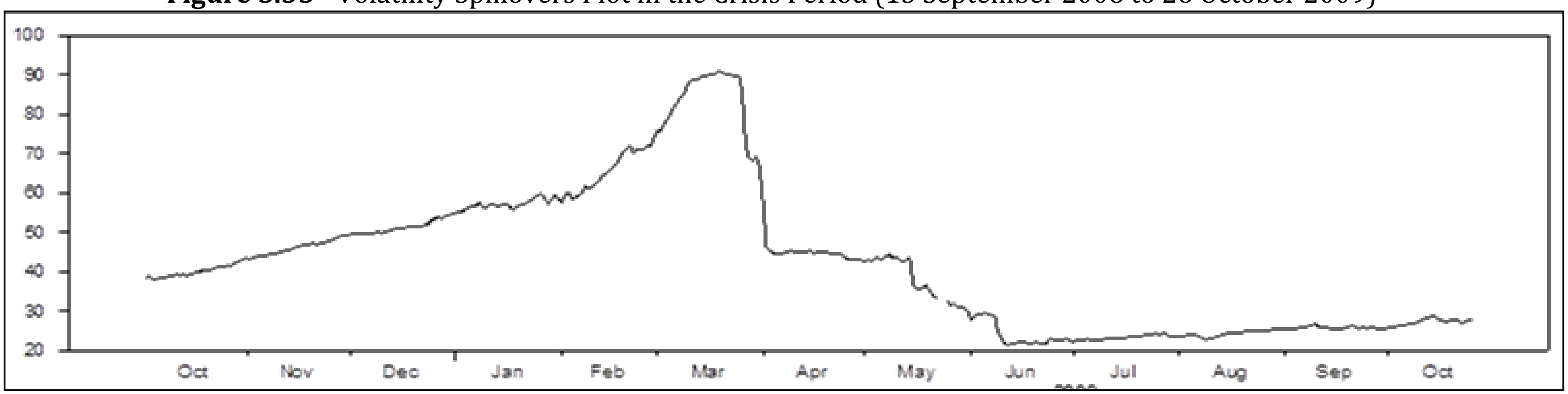
Table 5.32 – Volatility Spillovers Table in the Crisis Period (15 September 2008 to 26 October 2009)

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	83.10	0.70	2.40	4.30	1.80	1.00	1.70	0.20	0.70	1.10	2.20	0.80	17.00
Developed Markets													
USA	1.10	46.40	13.60	17.70	4.30	3.90	1.20	5.10	5.20	0.20	1.00	0.30	54.00
UK	1.80	9.60	38.00	21.50	3.20	3.90	1.30	6.20	8.10	0.50	4.80	1.00	62.00
GERMANY	2.90	13.20	23.60	38.80	2.80	1.20	2.60	5.70	5.90	0.30	2.00	0.90	61.00
JAPAN	1.90	3.90	4.20	5.90	53.60	4.60	10.80	6.30	5.60	0.40	2.30	0.60	46.00
SINGAPORE	1.30	4.00	9.50	4.60	2.40	61.20	0.80	8.70	6.20	0.30	0.40	0.60	39.00
Emerging Markets													
CHINA	1.30	5.10	4.30	4.50	6.60	1.80	66.50	6.40	1.60	0.20	0.20	1.60	34.00
MALAYSIA	3.00	1.40	13.80	6.60	1.20	5.50	2.00	53.40	6.30	3.40	2.40	1.30	47.00
INDIA	1.50	4.00	8.90	8.00	7.00	5.40	4.70	6.50	50.50	0.30	2.50	0.90	50.00
Frontier Markets													
UAE	1.40	9.20	2.70	2.60	3.30	1.30	3.10	1.20	0.90	68.10	4.40	1.70	32.00
SAUDI ARABIA	3.10	8.20	3.40	3.50	2.20	1.40	0.70	2.00	2.00	2.20	69.00	2.30	31.00
KUWAIT	4.60	0.70	0.70	0.10	1.30	0.10	0.30	5.00	2.30	0.50	2.80	81.60	18.00
Contribution to others	24.00	60.00	87.00	79.00	36.00	30.00	29.00	53.00	45.00	9.00	25.00	12.00	490.00
Contribution including own*	107.00	106.00	125.00	118.00	90.00	91.00	95.00	107.00	95.00	78.00	94.00	94.00	40.80%

*Minor differences due to rounding

Note: Total Spillovers Index -> 490/1200 = 40.80% (1200 is the sum of all numbers in the last row "Contribution including own")

Figure 5.35 - Volatility Spillovers Plot in the Crisis Period (15 September 2008 to 26 October 2009)



Spillovers from the USA to Malaysia were reduced to one-third. Additionally, the following observations regarding spillovers from the developed markets to Malaysia were made:

- Spillovers from the UK swell by almost 100% during the crisis.
- Spillovers from Germany and Japan differ marginally in the two periods of analysis.
- Volatility spillovers from Singapore increased from less than 1% to more than 5%.

Spillovers from emerging markets to Malaysia also increased; however, the spillovers from India increased more than the spillovers from China. Frontier markets also contributed higher volatility to Malaysia, with spillovers from Pakistan and the UAE increasing from 0.10% to more than 3% during turbulent times.

The India self-contribution during turbulent times fell by 40% as compared with its pre-crisis self-contributions. Contributions from developed markets to India demonstrate mixed trends. While spillovers from the USA increase marginally, spillovers from Japan double and spillovers from Germany quadruple in magnitude. On the other hand, spillovers from the UK and Singapore decline. Spillovers from China and Malaysia to India increase to nearly 5% and 7% respectively, from less than 1% in the pre-crisis period. Contributions of frontier markets to India volatility vary. While spillovers from Pakistan reduce to half, spillovers from Saudi Arabia increase eight times from 0.30% to 2.50%. Spillovers from the UAE and Kuwait remain unchanged.

While the exchange of spillovers between frontier markets and other markets under consideration appears to be limited in other periods of analysis, the estimates of spillovers vary during crisis and are highlighted here:

- Table 5.30 clearly indicates prominent decline in self-contributions to volatility in frontier markets. Subsequently, volatility spillovers from other markets to the frontier markets in the study increase many-fold, compared with the pre-crisis and full period analysis.

- Contributions from developed countries and China to the UAE increased significantly during the crisis, compared with both full and pre-crisis.
- Foreign volatility contributions to Saudi Arabia increase six-fold, from 5% in the full and pre-crisis periods to 31% during the crisis. Reduced contributions from China to Saudi Arabia during crisis are an exception.
- Pakistan and Malaysia contribute almost 5% each to Kuwait volatility during crisis. Saudi Arabia and India also exhibit increased volatility spillovers to Kuwait during the crisis.

The observations pertinent to Pakistan indicated that developed countries in the sample contributed the most to Pakistan volatility during the crisis, with Pakistan and Germany exchanging an equal amount of volatility. It also appears that the gravity of the crisis altered the interaction between Pakistan and India, and shocks transmitted from global markets to Pakistan became more apparent during turmoil. The following observations are also evident:

- Interestingly, European trade partners transmitted more volatility to Pakistan as compared with its Asian trade partners.
- With respect to its emerging counterparts, while India contribution during crisis declined to nearly one-fifth of its contribution in the pre-crisis period, spillovers to and from China more than doubled in the turbulent period. Also, spillovers from Pakistan to Malaysia increased many-fold during the crisis, although they were negligible in the pre-crisis period.
- Patterns of volatility transmission between Pakistan and its frontier counterparts also altered during the crisis. Pakistan contribution to the volatility of the three frontier markets under consideration amplified substantially. For example, Pakistan contribution to Kuwait volatility surged from 0.10% in the pre-crisis period to 4.60% during the crisis.

The volatility spillovers plot presents a rising trend at the beginning of the crisis period. The index starts at 40% in September 2008 and more than doubles (90%) in March

2009. The increase in spillovers is rather gradual; however, the decline in April 2009 is sharp, whereby the index suddenly falls to nearly half its peak. The spillovers continue to decline until they reach close to 20% in June 2009. From June to October 2009, the spillovers hover between 20% and 30%.

iii. Post-Crisis Period

The post-crisis spillovers table (Table 5.33) suggests that the overall volatility declined to nearly 22% in the post-crisis period, which is nearly half of overall spillovers during the crisis. The estimates of volatility spillovers in the post-crisis period are close to the pre-crisis (25%) and full period (24%) estimates. Higher self-contributions to volatility in the post-crisis period are apparent, suggesting that the domestic or regional events become more relevant in determining volatility in markets during relatively stable times.

In the case of developed markets, there is a visible increase in self-contributions in the post-crisis period, particularly in the USA and Japan. Accordingly, foreign contributions from developed markets under consideration declined considerably and the following was observed:

- Contributions from the UK and Germany to the USA nearly halved in the post-crisis period relative to the crisis period. The UK contributions are nearly 40% lower than its pre-crisis contributions, but Germany contributions to the USA after the crisis are nearly 20% higher than its pre-crisis contributions. After the crisis, contributions from the USA to the UK hovered at the same level as during the crisis, which were nearly 30% higher than the pre-crisis levels, but much lower than the full period estimates.
- Relative to the crisis period, contributions from Germany and Singapore to the UK increased by 33% and 15% respectively, and contributions from Japan declined by nearly 40% in the post-crisis period.
- Japan contributions to the USA became negligible and Singapore contributions declined by nearly one-third after the crisis.

- With respect to the emerging markets, contributions from China to the USA in the crisis and post-crisis periods change marginally; however, they are much higher than the contributions in the pre-crisis and full periods.
- Malaysia contributions to the USA declined by 50% in the post-crisis period, but remained significantly higher than the pre-crisis and 100% more than the full period contributions. Contributions from India declined by nearly 90% after the crisis, and were nearly one-third of its contributions in the pre-crisis and full period.
- Contributions from frontier markets to the USA did not change significantly; however, Pakistan's contributions marginally increased in the post-crisis period as compared with the crisis period.
- China contributed nearly 100% more to the volatility in the UK after the crisis. While the contributions from Malaysia declined marginally in the post-crisis period, contributions from India remained only one-eighth of its contributions during the crisis. It is interesting to note that Malaysia contributions to the UK before the crisis were half of its crisis and post-crisis contributions. In contrast, India contributions were at least three times higher before the crisis and in the full period.
- As with all developed markets, contributions from the frontier markets to the UK were limited but Saudi Arabia's contributions to the UK in the post-crisis period are worth mentioning, as the contributions declined from approximately 5% during the crisis to nearly zero in the post-crisis period.
- Contributions to Germany from the UK declined marginally in the post-crisis period but were lower than the pre-crisis level. It is observed that the UK contributions to Germany mostly remained close to 25% except before the crisis, when the spillovers were approximately 30%. Japan contributions reduced to one-third after the crisis and were nearly one-sixth of the pre-crisis estimates. Contributions from Singapore to Germany nearly doubled after the crisis but remained less than 3%, which coincides with the estimates before the crisis.
- With respect to emerging countries, spillovers from China to Germany reduce to nearly half of its contributions during the crisis, but remain significantly higher than

its contributions in the other periods of analysis. Similarly, contributions from India declined by nearly 80% and 90% in the pre- and post-crisis periods respectively. On the contrary, spillovers from Malaysia to Germany increased moderately (15%) relative to the crisis period, and nearly 63% compared with the pre-crisis spillovers.

- Frontier markets have a limited impact on the volatility in Germany. In all three sub-periods of analysis, Pakistan seems to be the most influential market, with spillovers ranging between 0.80% (pre-crisis) and 2.90% (crisis). Spillovers from Saudi Arabia to Germany are noticeable only in the crisis period.

As suggested earlier, higher self-contributions and lower foreign contributions to volatility are observed in the post-crisis period. In the case of Japan, the following observations were apparent:

- Nearly 60% higher self-contributions than the crisis estimates, and approximately 10% higher than the pre-crisis contributions.
- 31% lower spillovers from the USA in the post-crisis period than during the crisis and nearly 61% lower than the pre-crisis period, which may be indicative of reducing influence of the USA on Japan volatility.
- Spillovers from the UK increased three-fold after the crisis, compared with the pre-crisis level, but the decline from the crisis period was less than 20%.
- Significantly reduced contributions from Germany, compared with other sub-periods.
- Increased spillovers from Singapore during the crisis, but remained at 3% or less in the other periods of analysis.

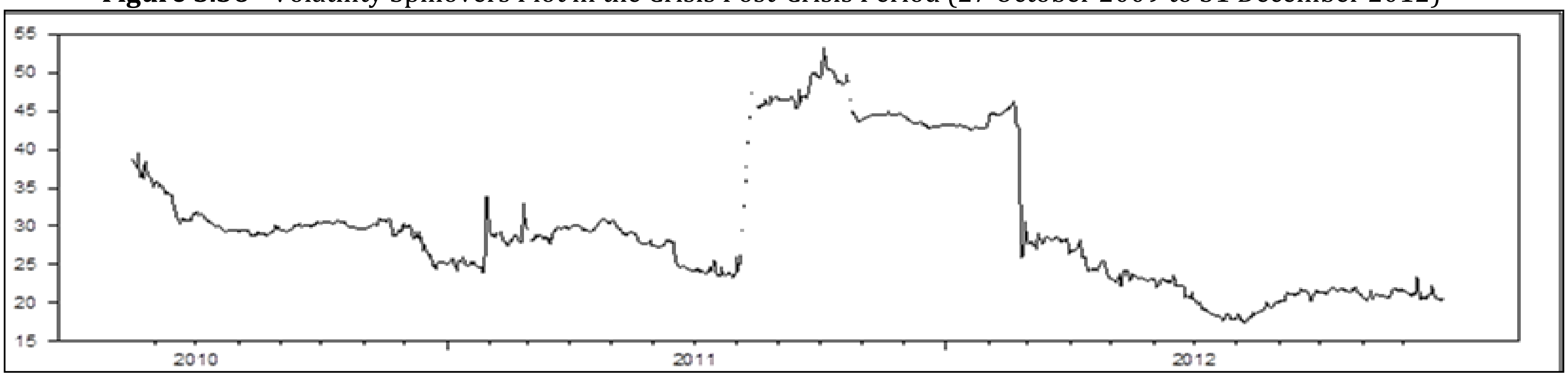
Table 5.33 – Volatility Spillovers Table in the Post-Crisis Period (27 October 2009 to 31 December 2012)

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	UAE	SAUDI ARABIA	KUWAIT	From Others*
PAKISTAN	90.10	1.20	0.60	0.50	0.00	1.30	0.20	0.80	1.00	0.10	1.40	2.80	10.00
Developed Markets													
USA	1.30	76.20	6.00	8.30	0.60	2.70	1.40	2.50	0.60	0.00	0.30	0.10	24.00
UK	1.90	10.10	43.40	28.50	1.80	4.50	2.70	5.70	1.00	0.00	0.20	0.20	57.00
GERMANY	1.90	15.70	22.10	45.00	0.90	5.70	1.40	6.50	0.60	0.00	0.10	0.00	55.00
JAPAN	1.00	2.70	3.40	1.60	85.50	2.50	1.20	1.40	0.30	0.10	0.30	0.10	15.00
SINGAPORE	2.10	10.80	7.00	7.30	1.90	61.50	3.00	4.00	2.10	0.10	0.20	0.10	39.00
Emerging Markets													
CHINA	0.60	2.80	1.10	0.60	0.70	1.80	90.20	0.60	0.40	0.70	0.20	0.30	10.00
MALAYSIA	2.10	5.20	7.00	8.00	1.10	1.70	1.00	72.90	0.80	0.00	0.10	0.00	27.00
INDIA	1.40	0.90	1.10	0.60	0.20	2.00	0.20	0.50	92.40	0.20	0.30	0.30	8.00
Frontier Markets													
UAE	0.10	0.00	0.00	0.00	0.10	0.00	2.20	0.00	0.10	97.00	0.40	0.20	3.00
SAUDI ARABIA	5.60	0.80	0.50	0.50	0.00	0.30	0.20	0.20	0.50	0.10	90.70	0.50	9.00
KUWAIT	0.20	0.00	0.00	0.00	0.00	0.10	1.10	0.10	0.80	0.00	1.80	95.80	4.00
Contribution to others	18.00	50.00	49.00	56.00	7.00	22.00	15.00	22.00	8.00	1.00	5.00	5.00	259.00
Contribution including own*	108.00	126.00	92.00	101.00	93.00	84.00	105.00	95.00	101.00	98.00	96.00	100.00	21.60%

*Minor differences due to rounding

Note: Total Spillovers Index -> 259/1199 = 21.60% (1199 is the sum of all numbers in the last row "Contribution including own")

Figure 5.36 - Volatility Spillovers Plot in the Crisis Post-Crisis Period (27 October 2009 to 31 December 2012)



On the other hand, Singapore self-contributions after the crisis and during the crisis are comparable, although they are nearly 12% less than the pre-crisis estimates. The following mixed trends were observed:

- Contributions from the UK and Japan declined by 50% and 75% respectively; however the contributions from the USA and Germany increased with the progression of time, with the contributions from the USA increased nearly four times and contributions from Germany increased more than six times relative to the contributions in the pre-crisis period.
- In terms of interaction between Singapore and its emerging counterparts, an increase in spillovers from China is also evident. Malaysia contributions were close to zero before the crisis, but increased more than eight times during the crisis, and declined to 4% after the crisis. Spillovers from India, which were otherwise close to 2% in the other sub-periods of analysis, exaggerated during the crisis.
- Volatility spillovers from the frontier markets are limited in all periods, with the exception of Pakistan. Although spillovers from Pakistan declined they remained nearly double in the post-crisis period, compared with the crisis period.

With respect to emerging markets, exchange of volatility spillovers declined in the post-crisis period as follows:

- Spillovers from China to other markets remained only one-ninth of the spillovers during crisis.
- Spillovers from Malaysia remained only 22% of the estimates during crisis.
- Volatility export from India reduced to nearly 0% in the post-crisis period, although the spillovers from India to Japan only were more than 5% during the crisis.

As suggested earlier, higher self-contributions in the post-crisis period are apparent across all groups. Among the emerging markets, China and Malaysia demonstrate high self-contributions post-crisis, which are close to the pre-crisis estimates. After the crisis, China contributions to its own volatility rose more than 35%, and reached 90% from 67% during the crisis. Accordingly, foreign contributions to China declined to less than 10%. With the

exception of Singapore, contributions from developed markets to China declined, although they remained higher than the pre-crisis levels, with an exception of Singapore, where the spillovers during the crisis and in the post-crisis do not vary. Contributions from emerging markets also declined, with Malaysia contributions reducing to one-tenth of its contributions during the crisis. Contributions from frontier markets withdrew close to pre-crisis levels, except for the UAE, where the spillovers marginally increased from their pre-crisis and crisis estimates.

With high self-contributions, foreign contributions to Malaysia decreased. While contributions from some developed markets like the UK, Japan and Singapore declined in the post-crisis period, contributions from the USA and Germany increased relative to the crisis period; however, in both cases the estimates remained close to the pre-crisis levels.

India self-contributions after the crisis amplified by nearly 32% relative to the crisis and almost 83% in comparison with pre-crisis levels. The overall foreign contributions declined to a mere 8% in the post-crisis period, with the highest contributions from Singapore (2%), Pakistan (1.40%) and the UK (1.10%). Contributions from remaining countries in the sample are less than 1% and from some countries only, and spillovers are close to 0%. Spillovers from developed and emerging countries are not only smaller, compared with the crisis period but are also far less than the pre-crisis estimates. Spillovers from the GCC markets in the sample are similar before and after the crisis. Spillovers from Pakistan are comparable in magnitude during and post-crisis.

High self-contributions are also a common trait in frontier markets, except during the crisis. The self-contributions of frontier markets to their own volatility increased post-crisis, which resulted in close-to zero foreign contributions. While Saudi Arabia and Kuwait self-contributions came close to the pre-crisis and full-period estimates, the spillovers of the UAE to its own volatility increased substantially, compared with all other periods of analysis.

The UAE contributed 97% to its volatility after the crisis, with 3% contributions from the other eleven countries in the sample. China is the largest contributor to the UAE volatility with 2.20% spillovers, with the remaining 0.80% contributed collectively by developed, emerging, and other frontier markets. Contributions from all the countries are

much lower than their pre-crisis estimates, with an exception of China, whereby the contributions after the crisis increased eleven times, compared with the pre-crisis level, and are marginally lower than the spillovers during the crisis.

Post-crisis, Saudi Arabia self-contributions increased by nearly 30%, compared with the crisis level, although they were approximately 5% less than the pre-crisis level. Pakistan emerged as the largest contributor with nearly 60% of the overall foreign spillovers to Saudi Arabia in the post-crisis period. Spillovers from most countries to Saudi Arabia returned to the pre-crisis levels, with an exception of spillovers from the UAE, whereby the spillovers remained as a fraction of pre-crisis and during-crisis spillovers. Pakistan is the only country in the sample whose contributions increased by nearly eight-times of its contribution to Saudi Arabia before the crisis.

Beyond the crisis period, Kuwait self-contributions increased to the pre-crisis level, with only 4% collective contribution from its developed, emerging, and frontier counterparts. While other markets did not sustain their spillovers during the crisis, and returned close to their pre-crisis levels, contributions from China and Saudi Arabia stayed well beyond the pre-crisis estimates, although they still ranged between 1% and 2%.

The following observations pertinent to Pakistan self- and foreign-contributions were evident:

- Pakistan self-contributions increased by nearly 7% in the post-crisis period, compared with the pre-crisis period.
- Mixed trends associated with foreign spillovers to Pakistan were apparent. While contributions from the UK and Germany withdrew to the pre-crisis level, contributions from the USA and Singapore exhibited an increasing trend, although these contributions are still very close to 1%. It is interesting to note that spillovers from the USA to Pakistan during the crisis were lower than in the post-crisis period. Spillovers from Japan became negligible in the post-crisis period.
- Among the emerging markets, spillovers from Malaysia to Pakistan post-crisis were higher than the other two sub-periods. Spillovers from Malaysia to Pakistan increased

slightly, although they remained below 1%. Malaysia contribution to Pakistan volatility is higher after the crisis than during the crisis.

- Spillovers from China to Pakistan declined even beyond the pre-crisis estimates, and contributions from India remained one-third of its pre-crisis estimates.
- Spillovers from frontier markets also exhibited varied trends. While contributions from the UAE declined to negligible estimates, contributions from Kuwait increased substantially, from nearly 0% before crisis to approximately 3% after the crisis; this was also four times higher than the spillovers from Kuwait during the crisis. Coincidentally, spillovers from Kuwait were the highest in comparison to all other countries included in the sample.
- Saudi Arabia contributions to Pakistan were nearly 50% lower than during the crisis; however, they were nearly five times greater than the pre-crisis estimates.

The spillovers plot in the post-crisis period ranged between 17% and 53%. The index hovered close to 40% immediately after the crisis. After that, the spillovers declined and fluctuated between 25% and 35% until mid-2011. A sudden incline in spillovers is evident in July 2011, when the spillovers rose to nearly 47%. A prolonged period of high volatility spillovers is apparent thereafter, with the spillovers reaching the highest level of 53% in September 2011. The spillovers declined in February 2012 to 27% and then continued to descend in 2012, reaching their lowest level of 17% in July 2012. The spillovers remained slightly over 20% in the latter half of 2012. It seems that the markets become stable during 2012 and that the period associated with exaggerated volatility spillovers ended at that time.

The results clearly indicate that Pakistan is not a transmitter of returns and volatility to its trade partners, except during a crisis of a larger magnitude.

5.3 Chapter Summary

This section presented and discussed in detail the findings concerning returns and volatility spillovers across the markets under consideration. Greater emphasis was placed on reporting the findings for Pakistan, as Pakistan is the primary focus of this thesis.

The correlation coefficients suggested some association between Pakistan and its counterparts included in the sample. Granger Causality tests using multiple lags highlighted one-way causality from developed markets to Pakistan. The causality results for Pakistan and its emerging counterparts were mixed, whereby unidirectional causality instances from Pakistan to China and from India to Pakistan were observed in most lags. On the other hand, no evidence of causality was found between Pakistan and Malaysia. With respect to the frontier markets, bi-directional causality was observed between Pakistan and Saudi Arabia and Pakistan and the UAE; however, only unidirectional causality from Pakistan to Kuwait was evident in most lags.

The stepwise OLS estimation followed the Granger Causality test. The two-way OLS estimation (Pakistan as regressand and Pakistan as regressor) was performed considering 7-day log returns in each equation. The choice of independent regressors was based on the trading hours in each market. For the USA, the lags *t-1* to *t-7* were considered, as there are no overlapping hours between the USA and Pakistan. On the other hand, returns at time *t* and lags *t-1* to *t-6* were considered for other markets that have overlapping trading hours with Pakistan. Similar considerations were made when Pakistan returns were used as regressors.

A few observations were made for estimations when taking Pakistan as regressand. All models were statistically significant, suggesting the importance of these markets to Pakistan. It was noticed that the first lag *(t-1)* for all the markets opening a few hours later than Pakistan, such as the UK and Germany, was statistically significant. On the other hand, markets that open earlier or around the same time as Pakistan had statistically significant returns at *t*. Some delay in transmission of returns was also observed, with some markets having statistically significant later lags.

The stepwise OLS estimation with Pakistan as regressor presented Pakistan as an insignificant market for the USA, the UK and Germany. The models for all other markets were significant at 2% and 5%, with the exception of Saudi Arabia, in which case the model was significant at the 10% level. The effect of overlapping trading hours was evident, as in all such markets Pakistan returns at *t* had the highest statistical significance. The results for

Pakistan and Saudi Arabia indicate that the two markets are somewhat isolated from each other.

Although the results of the regression analysis provided some insight into the relationships between selected markets, some results appeared to be inconsistent, possibly due to informational inefficiency of markets and subjectivity involved in selection of lags. Subsequently, returns and volatility Spillovers Indices were employed to garner better insight.

The application of the returns and volatility Spillovers Indices was performed in multiple ways to ensure that all relevant details were extracted. All the countries in the sample were analyzed collectively, followed by analysis on smaller groups using country classification and geographical proximity as a criteria. Then, the analysis was performed on pairs of markets, with Pakistan being a part of all the pairs. Finally, to ensure reliable and robust results, the data set was distributed into three sub-periods, depicting pre-crisis, crisis and post-crisis periods. The estimates provided by the spillover tables and plots present the overall spillovers across seven years and provides insight into the evolution of spillovers across countries over the period of analysis. Irrespective of whichever way the analysis was conducted, a few important results were acknowledged. First, Pakistan self-contribution to its returns and volatility was extremely high, implying that local events are more important in determining Pakistan returns and volatility. Second, Pakistan appeared to be relatively isolated from its counterparts in the sample, as the foreign contributions were observed to be marginal. Similarly, Pakistan contributions to the other markets under consideration were discerned to be negligible. Lastly, heightened returns and volatility spillovers were witnessed at the time of the financial crisis of 2008.

The comprehensive data analysis employed in this chapter used a variety of methods to provide insight into the interaction between Pakistan financial markets and those of its key trade partners. In the next chapter, these findings are discussed in relation to the research questions set out in chapter one. In addition, the next chapter compares and contrasts these findings with the existing literature, and discusses the relevance of these findings for researchers, investors, and policy makers.

6 Discussion and Conclusion

The primary objective of this study was to evaluate the magnitude, duration and direction of association and interaction of returns and volatility between frontier markets and their key trade partners, with a focus on Pakistan. Accordingly, the sample comprised of Pakistan and its eleven key trade partners. Although MSCI (2012) identified 35 frontier markets, the selection of Pakistan as the market of primary interest was facilitated by some practical, academic and economic considerations, such as the relative availability of data, limited and inconsistent findings in the literature, peculiar traits that set it apart from other markets, superior returns and potential for diversification.

The financial literature widely cites trade and geographical proximity as key determinants of interdependence between markets; however, several studies provide evidence of segmentation of some markets despite significant trade volume and geographical proximity with other countries. This indicates the complexity of the market interdependence phenomenon and suggests that it may not be appropriate to generalize that the magnitude of trade and distance determine the extent of cross-market interdependence. By using Pakistan as a representative frontier market, this study examined the applicability of trade relationships, geographical proximity and some other consideration in determining the interaction between markets of different statures. Moreover, the study also attempted to quantify the altering relationships between markets during both tranquil and turbulent times.

The study considered the MSCI (2012) typology to categorize the markets of interest into developed, emerging, or frontier markets. Consequently, the markets under consideration were classified as follows:

- Developed markets: the USA, the UK, Germany, Japan and Singapore
- Emerging markets: China, Malaysia and India
- Frontier markets: Pakistan, Saudi Arabia, the UAE[44] and Kuwait

[44] The MSCI elevated the UAE to emerging market in May 2014.

Besides trade relationships, geographical proximity was also considered, as eight out of eleven countries in the sample are located in the same continent as Pakistan. Accordingly, countries were segregated into the following groups:

- Border-sharing Neighbors: China and India
- Asia- Pacific Neighbors: Japan, Singapore and Malaysia

Since Pakistan is the market of primary interest in this thesis, it was included in all the above-mentioned groups to examine its interaction with its trade partners with different statures and geographical proximity. Furthermore, pairwise analysis was performed to examine the Pakistan market's interaction with different markets in the sample. Categorizing countries into groups and then pairs facilitated the comprehensive modeling of returns and volatility interaction between Pakistan and its major trade partners.

The period of analysis extended from January 2006 to December 2012. As presented in chapter 4, section 4.4, different time zones and different weekends across markets induce non-synchronicity in the data. Accordingly, daily data with 5-day frequency was adjusted to 7-day frequency, to ensure the availability of values for each time series on a particular day, resulting in twelve time series, each with 2,544 observations.

In order to effectively address the research objective, a number of specific sub-questions was developed to identify and estimate the magnitude, direction and duration of the interaction between the financial markets of interest. Rudimentary analysis of individual time series preceded the employment of statistical and econometric tools, first to analyze the attributes of each individual time series and then to estimate the interaction between returns and volatility across markets.

To allow visual inspection, graphs of closing prices, log returns, and range volatility were plotted, which provided several interesting insights. Returns in emerging and frontier markets appeared to be more volatile compared with the developed markets under consideration. Volatility persistence was noticeable in all the time series irrespective of the country classification. Exaggerated volatility surrounding the financial crisis of 2008 was apparent in all the markets under consideration, and the majority of the markets demonstrated high volatility surrounding the Eurozone crisis in 2011. Besides these

observations, structural break in the indices of some markets, such as, China, Japan, Saudi Arabia, the UAE and Kuwait, after the financial crisis of 2008, was also evident. This observation called for further analysis of individual time series.

Visual inspection of the graphs was followed by the calculation of descriptive statistics for returns and range volatility for each individual time series included in the sample. Most markets in the study had negative mean returns, high standard deviations, negative skewness and high kurtosis. The results presented by the descriptive statistics were typical to any asset returns series. The descriptive statistics of range volatility also confirmed high volatility and fat tails of the time series under consideration.

Further analysis of the returns series included the estimation of autocorrelations and the evaluation of stationarity with the help of unit root tests. Returns in some markets were found to be autocorrelated; however, this attribute was more common in smaller markets that are documented in literature to be informationally inefficient. The stationarity of all the time series in the study was confirmed by the parametric test, ADF and a non-parametric test, PP. Once the stationarity of time series was established, the application of other models in the study became appropriate.

As discussed earlier, the period of analysis entailed a major financial crisis and consequently world markets experienced episodic exaggerated volatilities. Therefore, it was deemed appropriate to evaluate the impact of the crisis on the selected markets. Accordingly, GARCH (p, q) model with Gaussian distribution was employed with the inclusion of a dummy variable CRISIS to incorporate the impact of the crisis in the model. The findings suggested that only a couple of markets in the sample, namely, Singapore and China, remained insulated from the financial crisis of 2008. The remaining ten markets in the sample were affected by the financial crisis as presented by the statistical significance of the dummy variable CRISIS; however, in the case of Malaysia the results were mixed, with the CRISIS variable being insignificant in some model specifications.

After examining the traits of individual time series and analyzing the impact of the financial crisis on them, techniques like correlation coefficients, Granger Causality, stepwise OLS estimation, and the Spillovers Indices for returns and volatility were employed to assess

the interaction between Pakistan and its counterparts in the sample. While the Spillovers tables provided an overall static estimate of cross-market spillovers, the employment of rolling windows in the spillovers plots exhibited the evolution of spillovers across groups and pairs of countries across time.

The data analysis provided some interesting insights regarding the interaction between the markets included in the sample. Some of these findings are in line with the existing literature, while others challenge them. The discussion below presents the research questions outlined in Chapter 1 with the results associated with them, and compares and contrasts the findings of this thesis with the findings documented in the previous finance literature.

i. Was the impact of the 2008 financial crisis significant on all the markets included in the sample?

The results associated with this research question are discussed in detail in section 5.1.4 and are summarized in table 6.1. Application of GARCH (p, q) model with Gaussian distribution and inclusion of dummy variable CRISIS enable examination of the impact of the financial crisis of 2008 on individual time series in the sample.

The results clearly indicate that the majority of the markets in the study were affected by the crisis. Markets like Singapore and China were exceptions. Moreover, results related to Malaysia are mixed and even the best-fit model is significant at the 10% significance level. This may suggest that the impact of crisis on the Malaysia financial market was not so pronounced.

The findings regarding the European markets are consistent with Dajčman (2013) who provided evidence that the financial crisis had a long-lasting impact on several European economies.

Table 6.1 – Summary of Results of Application of GARCH (p, q) Model with Gaussian Distribution and Inclusion of Dummy Variable CRISIS

	GARCH (p, q) Best-fit Model (SIC)	Significant CRISIS Variable*
Developed Markets		
USA	GARCH (1,2)	Yes
UK	GARCH(3,3)	Yes
Germany	GARCH(2,3)	Yes
Japan	GARCH(3,3)	Yes
Singapore	GARCH(3,3)	No
Emerging Markets		
China	GARCH(3,3)	No
Malaysia	GARCH(3,3)	Yes**
India	GARCH(3,3)	Yes
Frontier Markets		
Pakistan	GARCH(3,2)	Yes
Saudi Arabia	GARCH(3,3)	Yes
UAE	GARCH (2,1)	Yes
Kuwait	GARCH (1,2)	Yes

Note: * at the 5% Significance level, stated otherwise
** at the 10% Significance level

However, the results regarding Singapore are surprising, as literature reports enhanced interdependence between Singapore and the USA (for example Abd. Majid *et al.*, 2008); this is especially evident during turbulent times (for example Ng, 2000). With respect to Malaysia also, literature presents some contradictory findings. For example, Ng (2000) documented that most East-Asian economies, including Malaysia, are affected by negative global shocks. On the other hand, the findings related to China are consistent with the literature, which clearly documents the relative segmentation of China from the western markets (for example, Hwang, 2012; Valls and Chuliá, 2012; Zhou *et al.*, 2012). Results associated with China can also be attributed to the partial deregulation of the Chinese markets, which may act as an insulator in transmitting shocks to the market.

Results regarding Singapore and Asia emerging markets draw attention to the decoupling hypothesis (Kose *et al.*, 2008), which remains an ardently debated topic in the literature (for example, Kose *et al.*, 2008.; Dooley and Hutchison, 2009; Bartram and Bodnar, 2009; Cutrini and Galeazzi, 2012; Wälti, 2012; Levy Yeyati, and Williams, 2012). The

hypothesis suggests that the business cycles in emerging markets have decoupled from developed markets due to strong macroeconomic fundamentals and robust local demand (Kose *et al.*, 2008; Cutrini and Galeazzi, 2012). Although Singapore is not an emerging market, its resilience to the crisis can be attributed to a strong economy and diverse trade links.

A study by Mukherjee and Bose (2008) documented the increased integration of India and the USA, and attributed this to foreign institutional investments into India from western countries. Therefore, it is not surprising that India was affected by the financial crisis that emerged in the USA in 2008. The impact of the crisis is pronounced on the frontier markets. These findings may not be surprising as the literature documents that while frontier markets may seem segmented from developed markets in normal time, negative shocks from developed markets during crisis can be transmitted to these markets (For example, Samarkoon, 2011; Baumöhl and Lyócsa, 2014; Amin and Orlowski, 2014).

With these results, it can be concluded that the financial crisis of 2008 affected most markets around the world, although the impact was heterogeneous. These findings are consistent with the existing literature, which reports that the crisis was asymmetrically transmitted to other countries, leading to greater integration and interdependencies between markets during and after the crisis (For example, Cheung *et al.*, 2008; Dooley and Hutchison, 2009; Huyghebaert and Wang, 2010; Assidenou, 2011; Baur, 2012).

ii. *What is the nature of causality between Pakistan's financial market and those of its most active trade partners?*

The results of Granger Causality associated with research question two are presented in detail in Section 5.2.2. The findings indicate presence of unidirectional causality from all the developed countries to Pakistan. These results are explicable, as all the developed markets included in the sample are considered influential globally and regionally. Recently, Chen *et al.* (2014) documented that the USA returns Granger-cause frontier markets; however, the occurrence of a financial crisis may alter the dynamics of causality between developed and frontier markets. The literature especially documents the importance of the USA in exporting volatility to other markets (For example Becker *et al.* 1990; Koutmos and Booth, 1995; Akdogan, 1996; Huyghebaert and Wang, 2010). The

importance and influence of other developed countries has also been documented in literature (For example Morana, 2008).

In the group of emerging markets, no causality was found between Malaysia and Pakistan. This suggests that the Pakistan market's lagged returns cannot predict the Malaysia returns, and vice versa. On the other hand, unidirectional causality from Pakistan to China as well as from India to Pakistan in most lags indicated the returns to be predictable. While the results regarding China and India are understandable for various reasons, the lack of causality between Pakistan and Malaysia is surprising, as the correlation coefficients provided the highest estimates between these two countries out of the whole sample.

In the frontier markets sample, unidirectional causality from Pakistan to Kuwait is apparent. Bi-directional causality between Pakistan and Saudi Arabia as well as Pakistan and the UAE is apparent, especially in higher lags. The bilateral trade and cross-country foreign investments can explain bi-directional causality between Pakistan, Saudi Arabia and the UAE. Information inefficiency of frontier markets, which has already been documented in the literature (for example, Kawakatsu and Morey, 1999; Buguk and Brorsen, 2003; Worthington and Higgs, 2006; Omran and Farrar, 2006; Griffin *et al.*, 2010) explains the lag in transmission of information and delayed causality between these markets.

iii. Can the Pakistan market's returns at multiple lags explain returns of its trade partners and vice versa?

To enhance the understanding of the interaction of returns of markets under consideration and to answer research question three, OLS estimation was employed. Pakistan returns were used both as regressand and regressor, and appropriate lags were included for estimation. In both cases, the choice of lags was dependent on the hours of operation of the markets. For example, the USA market does not have any overlapping hours with Pakistan; accordingly, the information available in the USA market on one day would be apparent in Pakistan the next day. Hence, the OLS estimation in the case of these two countries included lags from *t-1* to *t-7*. All the other markets in the sample have some overlapping hours with the Pakistan market; therefore, OLS estimation for these markets included returns at time period *t* and returns at lags *t-1* to *t-6*.

Results of the stepwise OLS estimation with Pakistan as a regressand, and significance of the models revealed that Pakistan returns at *t* could be predicted by the returns of all the other markets included the sample irrespective of their classification. However, low values of adjusted R-square suggested that a small fraction of Pakistan's returns could be explained by the 7-day returns of the regressors. It was observed that the *F*-Statistic values for models considering China and Saudi Arabia were the lowest among all the models. This can be associated with partial deregulation of the two markets under discussion, as explained by Valls and Chuliá (2012).

Models with the Pakistan market's 7-day returns as regressors revealed the insignificance of Pakistan in predicting the returns of the developed markets, namely the USA, the UK and Germany. All the other models, except Saudi Arabia, were significant at the 5% level. However, the Saudi Arabia model was significant at the 10% level. The Adjusted R-square values for all models were low, with China and Saudi Arabia exhibiting exceptionally low values. The results suggest that the Pakistan returns are not good predictors of the returns of the developed markets under consideration. The Pakistan returns at different lags can determine only a fraction of returns in other markets.

The results indicate that the significance of Pakistan to other markets and vice versa, is marginal. The results are not surprising as the literature provides ample evidence regarding the segmentation of smaller markets like Pakistan from other markets, implying that their contribution to systemic risk is limited (For example, Akdogan, 1996). Moreover, local events are mostly responsible for returns and volatility in these markets (Ferson and Harvey, 1993; Harvey, 1995a; Aggarwal *et al.*, 1999; Kang *et al.*, 2009). This is not only true for Pakistan but also for other frontier markets included in the sample, such as the UAE, Saudi Arabia and Kuwait (For example, Yu and Hassan, 2008) Similarly, Serwa and Bohl (2005), and Wang and Moore (2008) provide evidence that the smaller markets are less prone, although not completely immune, to the effects of the major financial crisis. Neaime (2012) argues that the strong, real sector of the oil-producing countries may enable their financial markets to absorb foreign shocks quickly. Moreover, Valls and Chuliá (2012) suggest that partial deregulation of financial markets, limited openness, and underdeveloped financial markets can also cushion the financial markets from importing shocks.

The impact of non-overlapping hours was evident. Returns of markets that opened later than the Pakistan market affected its returns the same day and the next day as well. On the other hand, markets that opened a few hours earlier than Pakistan affected its returns on the same day. This indicated that the hours of operation of financial markets have an impact on how soon the information is reflected in the returns of other markets. These findings are in line with Samarkoon (2011).

Lastly, informational inefficiency of smaller frontier markets was also apparent by the greater significance of later lags. This highlighted the importance of historical returns in the predictability of returns of these markets, which has been widely explored and documented in the literature (for example, Kawakatsu and Morey, 1999; Buguk and Brorsen, 2003; Worthington and Higgs, 2006; Omran and Farrar, 2006; Griffin *et al.*, 2010).

The results of correlations, Granger Causality, and OLS estimations provided results that implied association between Pakistan and its trade partners. While the results seem to be consistent, none of these techniques enabled the quantification of the transmission of cross-country returns and volatility spillovers. Hence, more sophisticated econometric models were employed to measure the magnitude, direction, and duration of spillovers between Pakistan and its trade partners under consideration.

iv. What is the magnitude of static and time-varying, mean and volatility spillovers between Pakistan and a group of selected developed, emerging and frontier markets?

Empirical results in relation to research questions four to eight are summarized in table 6.2. The results provided some interesting insights into the relationships between Pakistan and its trade partners, which are classified as developed markets. Evaluation of returns and volatility spillovers estimates across the whole sample, as well as sub-groups revealed 30% higher static estimate for returns spillovers, compared with volatility spillovers. It was observed that Pakistan self-contribution to volatility was greater than its self-contribution to returns. This may imply that Pakistan trade partners, especially developed markets, affect the returns in Pakistan; however, local events largely explain volatility in Pakistan, which is a peculiar trait of frontier and emerging markets and has been documented in literature (Aggarwal *et al.,* 1999; Malik *et al.*, 2005; Kang *et al.*, 2009).

Table 6.2 – Summary of Results for Groupwise Returns and Volatility Spillovers

	Returns Spillovers		Volatility Spillovers	
	Static Estimates	Range	Static Estimates	Range
Whole Group	43.10%	33% to 60%	23.90%	21% to 44%
Pakistan and Developed Markets	47.0%	37% to 62%	31.30%	15% to 50%
Pakistan and Emerging Markets	14.50%	4% to 32%	6.40%	4% to 19%
Pakistan and Frontier Markets	9.50%	2% to 29%	3.50%	2.5% to 22%
Pakistan and its Border-Sharing Neighbors	4.80%	1% to 29%	2.4%	2% and 14%
Pakistan and its Asia-Pacific Neighbors	29.50%	15% to 44%	9.6%	5% to 32%

Note: for detailed results see Tables 5.11-5.17 and 5.19-5.24 and Figures 5.4, 5.7-5.11, 5.15, 5.19-5.23

While the static estimates of spillovers suggest negligible influence to and from Pakistan during the period of analysis, the spillovers plots for the whole sample reflect the impact of the financial crisis of 2008, and then the Eurozone crisis. Both returns and volatility spillovers plots were able to capture heightened volatility during turbulent times.

The finance literature clearly acknowledges the USA as a major exporter of volatility to other markets across the world (for example Becker *et al.* 1990; Koutmos and Booth, 1995; Akdogan, 1996; Huyghebaert and Wang, 2010). This thesis also provides evidence of the transmission of volatility from the USA to other countries. It was also observed that during turbulent times that the returns and volatility spillovers from the USA to other countries increased, although the magnitude of spillovers is asymmetric across countries (For example Dooley and Hutchison, 2009; Huyghebaert and Wang, 2010; Baur, 2012).

The results also provide evidence of the greater interaction of developed markets, not only during turbulent times but also otherwise. Higher spillovers between developed markets became more apparent when the countries were classified into smaller groups. For example, the group comprising Pakistan and the developed countries presented the highest estimates in the spillovers tables and plots, which can largely be attributed to interaction between developed markets themselves. On the other hand the Pakistan contribution to the group was limited. High interdependence between developed markets, especially the USA, the UK and Germany, has been widely documented in literature (for example, Agmon, 1972;

Taylor and Tonks, 1989; Masih and Masih, 1997; Masih, 1999; Fraser and Oyefeso, 2005; Kasibhatla *et al.*, 2006; Rapach *et al.*, 2013). High spillovers between European markets in the sample can be explained by parameters such as bilateral trade, geographical proximity, or by political events such as the formation of the EU (Aggarwal *et al.*, 2010). While the phenomenon of regional interdependencies and geographical proximities seems apparent in European countries, it is not so evident in the Asian developed markets. Japan and Singapore receive more volatility from the USA than they do from each other. Increased integration of the Asian developed markets, such as Japan and Singapore with the USA market has also been documented in the finance literature (For example Chowdhury, 1994; Lin *et al.*, 1994; Phylaktis and Ravazzolo, 2005a; Lim, 2009).

Moreover, significant cross-country spillovers estimates pertaining to Singapore indicate its increasing influence globally. These findings are consistent with Ng (2000), who suggested that Singapore has developed a stronger link with regional and global developed markets.

The results related to the interaction between developed markets and Pakistan are not surprising. The results of OLS estimation also provided evidence that the returns in the developed markets have marginal predictability of returns in the Pakistan market and negligible in the opposite direction. Spiedell and Krone (2007), Logoarde-Segot and Lucey (2007), Kohlert (2011), Samarakoon (2011), Bley and Saad (2012), De Groot *et al.* (2012), and Demirer (2013) have documented low interdependence between developed and frontier markets; therefore, the marginal spillovers between developed markets and frontier markets including Pakistan and the selected frontier markets are understandable.

The finance literature that uses Spillovers Indices to evaluate spillovers across markets provides evidence that the returns spillovers plots generally exhibit upward trend, but a clear trend is lacking in the volatility spillovers plots and exaggerated volatility spillovers appear as burst and the level of volatility spillovers settles back to low levels (For example, Diebold and Yilmaz, 2009; 2012). However, an upward trend was observed in volatility spillovers plots in this study, which was pronounced for the group of developed markets.

This observation can be attributed to two factors. First, it could be due to the prolonged financial crisis of 2008 and beginning of the European sovereign debt crisis while the markets were still recovering from the previous crisis. The uncertainty in the markets has led to higher volatility spillovers on a continued basis, resulting in a higher level of spillovers during the later period of analysis. Second, the choice of data analysis period can explain the difference in findings. The period of analysis in the previous studies did not include the European sovereign debt crisis; therefore, it is possible that the upward trend in volatility spillovers could not be captured earlier.

The returns spillovers index for Pakistan and the group of emerging markets is nearly one-third of the index for Pakistan and the developed countries. On the other hand, the volatility spillovers index is less than half of the returns spillovers index. Regional spillovers in both indices are evident; however, Pakistan stands out in the group with high self-contributions to both returns and volatility. All markets have relatively high self-contributions to returns and volatility, implying that that national events and information are of greater significance to the selected emerging markets.

A detailed analysis of the returns and volatility indices for Pakistan and emerging markets under consideration brought attention to the following:

- China's contributions to Pakistan returns and volatility remain negligible, suggesting that bilateral trade may have little role to play in cross-country spillovers.
- Returns spillovers from Malaysia to Pakistan surpass the returns spillovers from India to Pakistan marginally.
- Pakistan contribution to the returns of both the countries is approximately equal. Volatility contributions from Malaysia to Pakistan and vice versa are non-existent.
- India contributions to Pakistan volatility are also trivial; however, Pakistan contributions to India volatility are double the volatility spillovers in the other direction. Although the spillovers estimates are not substantial, the findings contrast the existing findings in the finance literature, which provides evidence that spillovers in the sub-continent flow from the larger to the smaller market (Choudhry, 2004; Abbas et. Al, 2013; Amin and Orlowski, 2014).

- Lastly, Pakistan self-contributions to volatility outweigh its self-contributions to returns in this group also, suggesting that Pakistan may import returns from its emerging counterparts to some extent, but that its volatility is primarily self-defined.

The results for Pakistan and other frontier markets presented in table 6.2 clearly highlight that the static volatility spillovers estimate is only one-third of the static returns spillovers estimate and that the range of time-varying returns spillovers is greater than the range of volatility spillovers.

The results provided clear evidence that the frontier markets in the sample experienced low foreign contributions and high self-contributions to their returns and volatility, reflecting the importance of national political and economic events. The spillovers between Pakistan and Kuwait, and Pakistan and the UAE, are at least three times higher than spillovers between Pakistan and Saudi Arabia; however, all these estimates are not extraordinarily high. Most markets in the GCC are partially deregulated, limiting their exposure to foreign portfolio investments, which may explain the nominal exchange of returns of volatility spillovers in these markets.

Saudi Arabia and the UAE are the largest Pakistan trade partners. Moreover, these countries are among the largest foreign investors in Pakistan, are located relatively in close geographical proximity, and share cordial political ties with Pakistan. However, it seems that these widely cited determinants of interdependence between markets are not so relevant in the case of Pakistan and the GCC countries included in the sample, as the cross-market spillovers are not so prominent. This may imply that these frontier markets have peculiar traits that may restrict cross-country spillovers. It is important that although the three GCC frontier markets included in the sample are oil-producing and -exporting countries, their relative segmentation from world markets has been documented in the literature (for example, Yu and Hassan, 2008; Cheng *et al.*, 2010).

The returns and volatility spillovers plots exhibit the effect of the financial crisis on the countries included in the group. Exaggerated returns and volatility spillovers in the group surrounding the financial crisis of 2008 were apparent, though the spillovers were otherwise low. These results are consistent with the findings presented by the GARCH (p, q)

model, whereby the CRISIS variable was significant in all model specifications. Although the cross-country contributions by individual countries cannot be isolated here, it can be assumed that the UAE contribution to overall spillovers during the crisis would have been higher, due to large capital inflows into the country.

v. *Is the magnitude of returns and volatility spillovers between Pakistan's financial market and its border-sharing neighbors different from those with its regional neighbors?*

The selection of countries in the sample was primarily based on their bilateral trade with Pakistan; however, geographical proximity was also considered to further understand Pakistan interaction with other markets. Accordingly, sub-question seven took into account the classification of countries into groups based on their geographical proximity with Pakistan. Subsequently, two groups were formed: one included Pakistan and its border-sharing trade partners, and the other included Pakistan and its trade partners in the Asia-Pacific.

In line with the published literature on market interdependencies, trade, and foreign investments, higher spillovers between Pakistan and China and low spillovers between India and Pakistan were expected. However, the returns and volatility Spillovers Index for the group comprising these border-sharing neighbors is merely 4.80% and 2.40% respectively. On the other hand, the returns spillovers plot for this group ranges between 1% and 22% and volatility spillovers plot ranges between 0% and 14%. In this group, it is also evident that the returns spillovers supersede the volatility spillovers, highlighting the importance of local events to domestic volatility.

Higher spillovers between Pakistan and India were observed, as compared with Pakistan and China. Trade volume between Pakistan and China is far greater than the volume of trade between India and Pakistan. This means that bilateral trade, geographical proximity and foreign investments may not be relevant measures to explain the spillovers between these countries. The findings of this thesis challenge the existing findings on market interdependencies due to trade and geographical proximity (for example, Calvo and Reinhart, 1996; Glick and Rose, 1999; Pretorious, 2002; Forbes, 2004; Forbes and Chinn, 2004; Barari, 2004; Campa and Fernandes, 2006, Morana, 2008; Karim and Abd. Majid, 2010; Didier *et al.*, 2010; Dufrénot *et al.*; 2011; Meric *et al.*, 2012; Liu, 2013).

The following arguments offer a potential explanation for the peculiarity of results in this group:

- Partial deregulation of the Chinese market (for example, Wang and Wang, 2010; Zhou *et al.*, 2012; Valls and Chuliá, 2012; Allen *et al.*, 2013) resulting in relatively smaller foreign portfolio investments, and therefore restrained transmission of shocks to the market (For example, Calvo and Reinhart, 1996; Dornbusch *et al.*, 2000; Caramazza *et al.*, 2004; Nissanke, 2010; Cutrini and Galeazzi, 2012).
- Tense political relationships and associated political events may explain the spillovers between Pakistan and India. Literature provides evidence that spillovers between foes take place especially from larger to smaller markets, even if the volume of trade is low (Choudhry, 2004; Abbas *et al.*, 2012).

With respect to spillovers between Pakistan and its Asia-Pacific neighbors, it was observed that the returns spillovers index across these countries was nearly three times that of the volatility spillovers index, which stood at just 10%. The Pakistan market's self-contribution to its volatility was nearly 100%, leaving no room for foreign spillovers from this group of countries. With respect to returns spillovers to Pakistan, approximately 5% was contributed by the Asia-Pacific countries in the group and was approximately equally divided between the three countries. The returns spillovers plots oscillated between 15% and 45% and the volatility spillovers index varied between 0% and 35%.

Amplified returns and volatility spillovers surrounding the financial crisis of 2008 are evident in the plot, suggesting that the group was collectively affected by the crisis. This is consistent with the findings of Cheung *et al.* (2008), who documented amplified regional interdependencies in Asian markets after the 2008 crisis.

It is interesting to note that unlike the volatility spillovers index of the developed markets group, volatility spillovers index of this group does not have any trend, although the group includes two developed markets. This may imply that the volatility spillovers in developed markets, especially the USA, the UK and Germany have soared due to continuity of turbulent times. Moreover, this group includes Singapore, which was not affected by the crisis of 2008 and Malaysia, where the impact of the crisis was not so pronounced.

vi. What is the magnitude of net pairwise returns and volatility spillovers between Pakistan's market and the financial markets of its key trade partners in the sample?

Empirical analysis of association between pairs of countries revealed low net returns spillovers between Pakistan and its individual counterparts, although regional spillovers in most cases outweigh the net spillovers with the USA, the UK and Germany. Marginal net spillovers between Pakistan-China and Pakistan-Saudi Arabia are evident, which suggests that at least in these two markets, market-specific attributes play a major role in limiting the transmission of returns spillovers.

The pairwise net returns spillovers range between 0.40 (Saudi Arabia) and 2.00 (Malaysia). Net spillovers between Pakistan and developed markets ranged between 0.80 (the USA and Germany) and 1.60 (Singapore). Net spillovers between Pakistan and Japan stood at 1.30. The magnitude of net spillovers between Pakistan and developed markets highlighted the importance of Singapore to Pakistan, more than the USA, the UK and Germany. In the emerging markets, net returns spillovers between Pakistan and Malaysia prevail over net returns spillovers between Pakistan and India, and once again, limited spillovers between China and Pakistan become apparent. In the frontier markets, the UAE appeared to be most important to Pakistan with net returns spillovers at 1.50, followed next by Kuwait and lastly by Saudi Arabia.

Pairwise net volatility spillovers suggest negligible impact, as the highest net volatility of 0.70 is observed between Pakistan and the UAE, followed by Pakistan and India (0.50), and then Pakistan and Saudi Arabia (0.30). The net volatility spillovers between Pakistan and four of its trade partners (the USA, Germany, Singapore and Malaysia) are zero, while the other four trade partners (the UK, Japan, China and Kuwait) are 0.10. Exceptionally low estimates of volatility spillovers suggest that in the long run, the impact of shocks across these pairs becomes marginal.

It is apparent in pairwise analysis that the magnitude of net returns spillovers is far greater than the magnitude of net volatility spillovers. This suggests that Pakistan exports returns to and imports returns from other markets, but the volatility is restrained within the domestic boundaries, resulting in high self-contributions to volatility. Amin and Orlowski

(2014) have reported this peculiarity of the Pakistan market, and have also documented the high self-contributions to volatility in Pakistan even during turbulent times.

The analysis of pairwise returns spillover plots and their comparison with each other reveals a larger magnitude of dynamic spillovers between Pakistan and countries located in the same continent, compared with the USA, the UK and Germany. Moreover, it was also observed that the net returns spillovers between Pakistan and non-regional countries are greater in the later period of analysis than is in 2011 and 2012, which can be attributed to the Eurozone crisis.

The patterns of volatility spillovers between Pakistan and its trade partners vary greatly. In most pairs comprising Pakistan and developed markets, the magnitude of volatility spillovers in 2011 and 2012 is much higher than the magnitude surrounding the 2008 financial crisis. The only exception is the Pakistan-Japan pairing, whereby the volatility spillovers in both periods are approximately similar. Volatility spillovers between Pakistan and China are generally low, compared with the other two pairs (Pakistan and Malaysia, and Pakistan and India), whereby the range of volatility spillovers is much higher. The net volatility spillovers between Pakistan and Malaysia are very low during most of the period of analysis; however, the later period is punctuated with episodes of exaggerated volatility, especially in 2011. In the case of Pakistan and India, volatility spillovers seem to have risen at the end of 2008, before reaching the lowest level in mid-2009. Around this time, the political tensions between the two countries were heightened due to the 26/11 massacre in Mumbai, and the escalated spillovers might be an indication of strained political relationships rather than being a result of the financial crisis. Similarly, a surge in the spillover in the later part of 2012 can be attributed to political developments.

The volatility spillovers plots between Pakistan and its GCC trade partners provide some interesting insights. The range of volatility spillovers between Pakistan and the UAE as well as Pakistan and Kuwait is much lower than those between Pakistan and Saudi Arabia. This comes as a surprise as the results so far have indicated that the two markets have limited association. Another important insight is regarding ongoing spillovers between Pakistan and the UAE, suggesting a trend of volatility spillovers between these countries. On the contrary, bursts of volatility spillovers are evident in the interaction between Pakistan

and Saudi Arabia, with exaggerated spillovers witnessed in the later part of analysis. This may mean that the occurrence of specific events may lead to higher spillovers across these markets, which may or may not be associated with the global crisis. The net volatility spillovers between Pakistan and Kuwait were low but exhibited a different pattern as compared to the other two pairs. Enhanced spillovers were evident both in 2008 and 2011 and can be attributed to the turbulent global markets during those times.

The results suggest that while the trade partners might influence the returns, the foreign impact on the volatility of Pakistan might be limited. This was not only evident across groups but also across pairs. Pairwise analysis of returns and volatility spillovers plots suggests higher returns and volatility spillovers in 2011 and 2012, compared with 2008. This peculiarity may mean that although the crisis of 2008 affected Pakistan greatly, its muted reaction during the prime crisis time can be ascribed to the floor that was placed on the index between August 2008 and December 2008. It can also be argued that while many markets around the world were dealing with an imported crisis, Pakistan was struggling to overcome a crisis that was home grown; hence the cross-market spillovers were low during this period.

vii. What was the impact of the financial crisis of 2008 on the returns and volatility spillovers of the financial markets under consideration?

The analysis under the realm of this research question not only helped in reflecting on the transmission of crisis across markets, but it also provided a robustness check to ensure that the results are consistent across groups.

To investigate the impact of the financial crisis, the period of analysis was divided into three sub-periods: pre-crisis, crisis, and post-crisis. The returns and volatility spillovers table provided evidence of amplified returns and volatility spillovers surrounding the crisis. These findings are in line with the relevant finance literature, which widely reports a higher impact of bad news, such as a crisis, on returns and volatility in comparison to the impact of good news (Black, 1976; Hilliard, 1979; Eun and Shim, 1989; King and Wadhwani, 1990; Nelson, 1991; Glosten *et al.*, 1993; Arshanapalli and Doukas, 1993; Lee and Kim, 1993; Wu and Su, 1998; Jang and Sul, 2002; Click and Plummer, 2005; Abd. Majid *et al.*, 2008; Awokuse *et al.*, 2009; and Lim, 2009; Enders, 2010). Ratanapakorn and Sharma (2002) document that short-run association between developed and developing markets such as the USA and the Middle Eastern markets that are apparent during a crisis, may not be evident otherwise. Similar results were found in this thesis, as all groups exhibited increased interaction of returns and volatility during 2008 and 2009.

The analysis of sub-periods provided some interesting results. For example, the contributions from Singapore to developed markets shrink during the crisis but increase in tranquil times. This suggests that larger and more mature developed markets export more volatility during the crisis; however, the significance of other developed markets becomes more evident during normal times.

In the analysis of returns spillovers during the crisis, Pakistan stood out with its peculiar traits. During crisis, Pakistan was observed to follow an opposite direction compared with its developed, emerging, and frontier counterparts. For example, during the crisis, the returns self-contributions of all markets decreased with a subsequent increase in foreign contributions. The Pakistan market's self-contributions, on the other hand, increased during crisis, resulting in reduced foreign contributions to its returns. This peculiarity can

be attributed to the problems that Pakistan financial market found undergoing during 2008 and 2009, which coincided with the financial crisis of 2008.

On the contrary, Pakistan self-contributions to volatility during the crisis followed the same pattern as its developed, emerging, and frontier counterparts. Volatility self-contributions declined during crisis across the board, subsequently foreign contributions to volatility increased during turbulent times. However, Pakistan received higher volatility spillovers from its European counterparts and marginal spillovers from the epicenter of the crisis, that is, the USA. The magnitude of volatility spillovers between Pakistan and the GCC countries in the sample also changed during the crisis, as Pakistan transmitted more volatility to the UAE and Kuwait during crisis.

In the post-crisis period, Pakistan and Japan sustained the level of two-way spillovers, which are much higher than the pre-crisis levels. Moreover, the dynamics of Pakistan interaction with India changed in the post-crisis period, whereby the markets started exchanging equal magnitude of volatility, which is greater than the spillovers in the pre-crisis and crisis period.

The findings highlight that the interdependence between markets in the absence of crisis can potentially be explained by "real links", based on bilateral trade, proximity, and political relations. Rise in returns and volatility spillovers during the crisis may not be indicative of weaknesses in the macroeconomic fundamentals of the country and that they can be a product of foreign shocks to these countries due to foreign investment. Exaggerated volatility around the crisis can be a depiction of the investors' nervousness who penalize markets indiscriminately during uncertain times. During crisis, international investors' expectations may change due to financial cognitive dissonance, endogenous liquidity shock, discernment of political risks (Forbes and Rigobon, 2000), portfolio adjustments (Kodres and Pritsker, 2002), borrowing constraints or illiquidity (Boyer et al., 2006), informational spillovers (Calvo and Mendoza, 2000), and risk and liquidity management (Caramazza et al.,2004). Investors may also react irrationally due to herd behavior and information asymmetries (Dornbusch et al., 2000). As discussed in section 2.4.2, the "wakeup call hypothesis" (Goldstein, 1998 p. 18) appears to be relevant, which may lead to ''discriminating contagion'' (Ahluwalia, 2000, p. 3).

The results regarding Pakistan and emerging countries suggest that the high self-contributions of returns and volatility in smaller markets during normal times has already been documented in the literature, as Ferson and Harvey (1993), Harvey (1995a), Aggrawal *et al.*(1999), Hammoudeh and Choi (2006) argued that volatility in smaller markets is the product of domestic information; hence, a better understanding and quantification of country-specific factors enhances the predictive capability in these markets. However, the finance literature documents exaggerated volatility in these markets surrounding the crisis (for example Samarakoon, 2011; Demirer, 2013). Korkmaz *et al.*, (2012) have also documented generally low contemporaneous returns and volatility spillovers with episodic high spillovers in selected frontier markets.

With respect to Pakistan specifically, its disconnectedness from all the markets in the sample is apparent. Although the magnitude of spillovers exchange changed during the crisis, the change is not significant. Hence it can be concluded that Pakistan is not an important generator of returns and volatility spillovers to the trade partners included in the sample.

The thesis hypothesized that trade, geographical proximity, foreign investments, and political relations determine the magnitude of returns and volatility spillovers. However, a clear connection in the case of frontier markets could not be established in this thesis. The results clearly indicated that while the volume of trade and geographical proximity may explain the level of interdependence and integration in mature and emerging markets, the same may not be applicable on smaller frontier markets. Other factors such as political relations and events and/or market-specific characteristics like the extent of deregulation may explain the level of interdependence between markets.

The findings also implied that a significant crisis alters the magnitude of cross-market returns and volatility spillovers, irrespective of the statures of the markets. During crisis, markets may import and export greater volatility and the self-contributions may decline significantly. This indicates that there is no respite for the investors during the crisis, as the availability of diversification opportunities erode. It is also evident that although the spillovers may reduce after the crisis, they may not return to the pre-crisis levels. Both returns and volatility plots for all the groups demonstrated an increasing trend; however,

the trend was more prominent in some groups, such as, the developed markets. It appears that the onset of the Eurozone crisis immediately after the financial crisis of 2008 has kept the returns and volatility spillovers at higher levels.

6.1 Significance and Implications of Findings

The consideration of frontier markets in this thesis is a major contribution in itself as there is limited published literature on these markets. While ample attention has been paid to emerging and developed markets, smaller yet investable markets remain largely neglected in finance literature. Speidell (2011) highlights the importance of the frontier markets, suggesting that more than 20% of the world's population lives in frontier markets, contributing nearly 6% to the world's nominal GDP and comprising only 3.1% of the world's capitalization. This has been amplified by the reclassification of the UAE as an emerging market. The author suggests that these markets have a lot of potential for growth due to their low GDP to market capitalization ratio. Speidell and Krohne (2007) demonstrate that if the GDP per capita of these countries increases from $1,000 to $5,000, the ratio of market capitalization to GDP will jump from 28% to 66%, which is indicative of the immense growth potential of these markets. Moreover, these markets offer the most viable investment opportunities in the future due to their favorable population dynamics and strengthening macroeconomic variables (Speidell, 2011). Kohlert (2011) argues that although the frontier markets may have under-performed in comparison to their emerging counterparts in the past, they still offer return potential due to their PE ratios, which are low in comparison to emerging markets. De Groot *et al.* (2012) provide evidence that the inclusion of frontier markets in the investment portfolio can relay superior returns for global investors. Baumöhl and Lyócsa (2014) found that asymmetric volatility is not a common phenomenon in the frontier markets, which may indicate the informational inefficiency of these markets. Therefore, predictability and provision of excess returns in these markets is probable. Considering the findings of a handful of studies on frontier markets, it is appropriate to investigate the dynamics of the interaction of a selection of these markets with developed and emerging markets.

Beyond this significant contribution, this thesis contributes to the literature as follows. The focus on Pakistan and its trade partners makes this study unique. Relative

availability of reliable data, high returns and diversification potential, peculiar traits, inadequate attention in literature, and incoherent findings made a market like Pakistan a good candidate for research. No study in the existing literature has paid exclusive attention to a market with peculiar traits (for example, Bekaert and Harvey, 1997; Uppal, 1998; Amin and Orlowski, 2014) and high return potential (Caldwell, 2013). Moreover, contradictory findings in literature regarding integration of Pakistan's financial market with the world markets (Bekaert, 1995; Akdogan 1996) motivated this research.

In terms of method, the employment of the Spillovers Index to estimate and decompose long-run static and dynamic conditional returns and volatility spillovers between Pakistan and its trade partners makes this study unique. The method not only enables the decomposition of returns and volatility, but also captures changes in spillovers during turbulent times. While the use of cointegration (Miles, 2005; Chen *et al.*, 2014), VAR-EGARCH (Amin and Orlowski, 2014), DCC (Baumöhl and Lyócsa, 2014; Amin and Orlowski, 2014), and Granger causality and Logit Regression analysis (Chen *et al.*, 2014) to evaluate interdependence and interactions between developed, emerging, and frontier markets is observed in the finance literature, no study to date has attempted to decompose the conditional returns and volatilities in frontier markets with the help of the Spillovers Index. Furthermore, selection of markets based on theoretical underpinning, their classification according to MSCI (2012) typology, and use of 7-day data frequency sets this thesis apart from the studies conducted earlier.

Significance for Researchers and Practitioners

Table 4.3 clearly highlighted that Pakistan is the smallest market in the sample in terms of market capitalization. However, it has provided superior returns to investors in the past (it was declared the world's best performing market in 2002 by Bloomberg Business Week, 2003) and more recently as well. The Economist (2014) reported that MSCI Index representing Pakistan has risen by 60% in dollar terms since 2012, and is not only ahead of the global indices but has also superseded its frontier counterparts.

While linkages between developed and emerging markets in different regions have been extensively examined using a variety of methods, frontier markets in general remain

largely neglected in literature and only a handful of published studies are found involving these markets (for example Spiedell and Krone, 2007; Logoarde-Segot and Lucey, 2007; Cheng *et al.*, 2010; Berger *et al.*, 2011; Kohlert, 2011; Samarakoon , 2011; Korkmaz *et al.*, 2012; Bley and Saad, 2012; De Groot *et al.*, 2012; Demirer, 2013). Limited attention to the frontier markets in the finance literature can be attributed to unavailability of reliable data, poor regulatory frameworks in these countries, highly prevalent insider trading, and peculiar market microstructures involving price formation and price discovery, transaction and timing costs, information and disclosure, and investor behavior.

As suggested earlier, frontier markets have provided exceptional returns to investors in recent times (for example see figure 1.1) and it is appropriate to consider them as possible avenues for the efficient allocation of resources and diversification. The availability of reliable data is becoming possible as these markets recently have benefitted from systematic data collection from groups like MSCI, S&P, Dow Jones, and FTSE. Each of them now maintains its own set of indices for these markets, hence making the data more accessible. Moreover, the governments in these countries are increasingly making investments to improve the regulatory frameworks and make them more accessible to investors. With diversification opportunities eroding in developed and now in emerging markets (for example Agmon, 1972; Brooks and Del Negro, 2002; Carrieri *et al.*, 2007; Bai *et al.*, 2012; Christoffersen *et al.*, 2012) researchers and practitioners need to identify alternative avenues for diversification. Research involving frontier markets can provide an insight into their viability for the purpose of diversification.

The finance literature typically presents the idea of a positive association between trade and the interdependence of markets. Accordingly, the inclusion of countries in the sample was based on the premise of trade relationships between Pakistan and its developed, emerging, and frontier counterparts. Furthermore, other dimensions like geographical proximity and foreign investments were also considered. However, the results presented in sections 5.4.2.1 and 5.4.2.2 indicated that these factors offer only a limited explanation for Pakistan's lack of interaction with most of its trade partners. This implies that other factors need to be taken into account to explain the interaction, or lack of it, between Pakistan and other markets. Phylaktis and Xia (2006) and Campa and Fernandes (2006) suggest that

monetary and fiscal policies, legal and accounting regimes, economic openness, financial integration, trading activity, industrial concentration, and development can potentially explain different levels of integration across countries. Additionally, factors such as the extent of liberalization, government intervention in financial markets, market microstructures, and regulatory frameworks need to be explored further to explain the interaction between frontier markets and other markets.

Significance for Investors

In a globalized world, deregulated capital markets provide investors an opportunity to allocate the resources efficiently across different country and asset classes, and to take advantage of country-specific risk premia. Enhanced market integration leads to low return-differentials across markets and erodes the opportunity to earn excess returns by portfolio diversification (Akdogan, 1996). Relatively segmented markets are of great interest to investors and portfolio managers as they are a viable option for risk diversification and the maximization of returns.

In line with the relevant literature (for example, Miles, 2005; Chen *et al.*, 2014), the results provide evidence that the frontier markets in the sample receive low foreign contributions to their returns and volatility. Miles (2005) suggests that while some degree of integration between developed and frontier markets are present, the benefits of diversification are not eliminated completely. The author argues that while these markets share the long-run trend with global markets, short-run deviations from these long-run trends may lead to opportunities of getting excess returns. Moreover, the author emphasizes that a smaller coefficient of cointegrating vectors suggests that error corrections in these markets are slow and it may take months and even years before these markets converge back to long-run trends.

The findings in sections 5.4.2.1 and 5.4.2.2 are in line with the literature with respect to the returns in frontier markets, which are greatly dependent on their past returns (for example, Amin and Orlowski, 2014) and have large self-contributions, suggesting that local events are more important in determining their returns and volatility. If these markets are considerably segmented from the developed and emerging markets and from each other,

they provide a viable option for diversification to investors. Berger *et al.* (2011) provide evidence that inclusion of frontier markets in the portfolio enhances returns while limiting risk, which is especially true during a bull period. The authors found that these markets exhibit lower integration with developed markets and that the magnitude of integration has not increased over time. Cheng *et al.* (2010) also documented the segmentation of the frontier markets, especially in the MENA region, emphasizing that these markets can be avenues for diversification. Studies like Samarkoon (2011), Baumöhl and Lyócsa (2014), Chen *et al.* (2014) also document lower interdependencies between the frontier markets and developed markets during tranquil periods. The study by De Groot *et al.* (2012) using company level data across several frontier markets suggests that significant excess returns ranging between 5% and 15% can be generated by employing an appropriate value and momentum strategies in frontier markets. Although there is potential for high returns in these markets, high volatility in individual indices may be of prime concern for investors. Speidell and Krohne (2007) argue that despite high standard deviations in the frontier markets, low correlations with each other and with the developed and emerging markets make them appropriate contenders for portfolio investments.

As observed in chapter 5, section 5.4.2.3, the dynamics of risk and return in these markets may change during turbulent times. Crisis in a global market like the USA may propagate to smaller markets, resulting in increased interdependencies between these markets as documented by Samarkoon (2011). Hence, investors may need to adjust their investment and hedging strategies accordingly.

Speidell and Krohne (2007) argue that the investors need to take into account high domestic volatility and also need to be vigilant about the structural risks that are prevalent in frontier markets. Political risks, lack of disclosures or poor quality of disclosures, lack of infrastructure, language barriers, bureaucracy, inconsistent and ever changing regulations, high transaction costs, and limited depth and breadth of markets may act as impediments in the efficient allocation of resources.

The vulnerability of these countries to local economic and political events cannot be ignored. Most frontier markets, with an exception of the GCC markets, generally rank low on

Euromoney rankings[45], suggesting greater risk attached to these countries. Pakistan was ranked as low as 117 out of 185 countries in 2011 (Euromoney, 2015), suggesting higher risks in all categories mentioned above. For example, in 2008, the Pakistan market's collapse and the subsequent placement of the floor on the market occurred a few weeks prior to the fall of Lehman Brothers, and hence can be attributed to domestic events. However, domestic turmoil coupled with the global crisis can have dire consequences for investors. Hence, investors need to balance out systemic risk with the country-specific risk and make investment choices accordingly.

Significance for Policy makers

The findings of the study have implications for the policy makers. In a globalized world, it is not possible for countries to survive as closed economies. While having economic and financial links between countries contributes to their growth, it also exposes them to the transmission of returns and volatility spillovers from other countries. IMF staff paper (2011, p. 3) suggests,

> "[increased and complex financial linkages induce] latent instability into the global financial system, underscoring the value of a Global Financial Safety Net design that is effective in forestalling the risk that a localized liquidity shock propagates through the global financial network turning into a large-scale systemic crisis".

This became extremely evident during the recent financial crisis, which wreaked havoc even in generally isolated markets. Hence, it is important for policy makers and regulators to identify and measure the interdependence between markets and identify the key markets that transmit most returns and volatility, so that corrective measures can be taken in time in order to restrain the impact of foreign shocks to domestic markets (Giannopoulos *et al.* 2010).

[45] Euromoney ranks countries according to their risk profile every quarter. The ranking process involves an evaluation of economic, political, and structural variables for a country along with debt indicators, credit ratings, and access to bank finance and capital markets. Each of these variables is allocated a weightage for the calculation of a country ranking. Most of the weightage is allocated to political risk (30% weightage), economic performance (30%), and structural assessment (10%). The remaining 30% is equally distributed between the latter three variables.

Dornbusch *et al.* (2000) argue that since the interdependencies between markets are a result of financial and economic integration, spillovers across markets cannot be avoided; however, the impact of these shocks can be minimized through appropriate financial architecture. Fazio (2007) suggests that all policy makers need to appraise the vulnerability of their financial markets to financial crises, by taking into account the macro environmental fundamentals, not only for the country itself but also for the countries located in close proximity.

The policies to manage an imported or locally generated crisis should not only address the issues prevalent during the time of turmoil (for example, intervention by the policy makers in capital markets), but also the issues related to the recovery of markets post-crisis. Lack of appropriate policy in the Pakistan capital market to address the financial crisis in 2008 was apparent. As the effects of crisis started becoming visible in Pakistan in August 2008, the regulatory authority introduced a prolonged floor to the market, which lasted several months. Once the floor was removed in December 2008, the market went into free-fall, eroding millions of dollars in market capitalization. Fazio (2007) argues that such interventions by policy makers may slow down the process of recovery.

Policy makers also need to take into account the impact of foreign capital inflows. When turbulent times prevail, investors become jittery and start penalizing even those countries that may not be the epicenter of the crisis (Dornbusch *et al.*, 2000; Cheung *et al.*, 2008). Samarkoon (2011) provides evidence that countries that may not have strong linkages with the USA during tranquil times can be susceptible to greater shocks during turbulent times. Countries with strong fundamentals can be saved from fundamentals-based contagion or shift contagion (Calvo and Reinhart, 1996; Dornbusch *et al.*, 2000). The results presented in section 5.1.4 indicated that markets, either with strong fundamentals, such as Singapore, or with limited exposure to foreign investments, for example China, remained unscathed from the financial crisis. Hence, policy makers should focus on developing strong macroeconomic fundamentals and at the same time should assess the appropriate levels of foreign capital inflow that may provide the financial markets a buffer during turbulent times. These measures include developing strong macroeconomic fundamentals, such as reducing

fiscal and current account deficits, appropriate exchange rate management, and maintaining a robust and healthy financial sector (Dornbusch *et al.*, 2000).

Lastly, foreign investors prefer to invest in large developed markets, which are liquid, informationally efficient, and have low transaction costs (Thapa and Poshakwale, 2012). Therefore, smaller markets like Pakistan may benefit greatly from the appropriate introduction and implementation of policies aimed towards making these markets liquid and reducing information asymmetry between the companies and the investors.

6.2 Limitations

This section discusses the limitations in terms of data and techniques, and appropriate considerations to address these limitations.

The VAR method used in the study has both strengths and weakness. The method is simple and intuitive, and produces results that are relatively reliable (Schlegel, 1985; Litterman, 1986). The VAR models are also useful in determining simultaneous changes in explanatory and dependent variables, and a distinction between endogenous and exogenous variables is not required (Asteriou and Hall, 2007). Studies like Mahmoud (1984), McNees (1986), Lastrapes and Koray (1990) provide evidence of the superior performance of VAR models in comparison with other simultaneous equation models. Lastrapes and Koray (1990) also documented the capability of the VAR model in capturing the contribution of each explanatory variable to the overall variance of dependent variable.

However, the VAR model used in this particular study is not devoid of limitations. For example, VAR does not take into consideration the non-normality of time series and the assumption of normality is forced. Non-normality of returns time series is the most common and well-documented trait of the asset returns time series. Although a large sample size, log returns, and range-volatility were used to implicitly address this limitation of the method; no explicit measures are yet suggested in the current finance literature to overcome this limitation of the model.

Another problem that can affect the results in VAR estimations is autocorrelations. Use of multiple lags for a particular time series can induce autocorrelations, giving rise to the problem of multicollinearity, which may distort the results. Therefore, autocorrelations were

estimated for each time series prior to applying the VAR methods, to ensure that the results were appropriate.

Parsimonious models are preferred in econometric analysis. However, VAR models are generally not parsimonious in nature. Multiple variables and the addition of time lags compromise the parsimony of the model. Asteriou and Hall (2007) argue that a smaller sample size with a large number of parameters affects the degrees of freedom and may lead to an unstable VAR model. This problem can be addressed by using only statistically significant variables and lags in the final model specification. As noted in chapter 4, this study comprised twelve markets and a maximum of 10 lags with 5 to 10 steps ahead forecast. Subsequently, the number of variables in each VAR model increased significantly, affecting the degrees of freedom. This may pose a challenge in smaller sample sizes; however, in this case, the use of a sufficiently large sample size and the classification of countries into smaller groups and then pairs led to a reduced number of variables in the models, which helped ensure consistent and reasonably reliable results.

The Spillovers Index measures conditional spillovers across markets and it does not take unconditional spillovers into consideration. Besides VAR models, a variety of ARCH/GARCH models, such as CCC, DCC, and ADCC (refer to Table 3.1) estimate conditional correlations between markets. Although unconditional returns and volatility reflect historical information, they are not irrelevant. A simultaneous modelling of both conditional and unconditional spillovers would provide complete understanding of the interaction between markets.

The objective of this thesis was to comprehensively evaluate the interaction and association between Pakistan's financial market and those of its most active trade partners; however, some sample limitations have to be acknowledged.

The selection of the markets in the sample was based on Pakistan's most active trade partners. Data from the State Bank of Pakistan's website regarding imports and exports was extracted and the eleven countries whose markets had the highest trade volume with Pakistan were chosen. A larger set of countries under each classification would have provided an even better comprehension of cross-market spillovers. However, the inclusion

of more trade partners in the model would have resulted in a larger and less parsimonious model and the quality of the results may have been compromised. The period of data analysis was limited from January 2006 up to December 2012, primarily due to the unavailability of data for some markets, particularly the GCC markets. Even during the period under consideration, the missing data for the selected GCC markets posed a challenge. For example, these markets have long Eid holidays twice a year, and during the data filtering process, all such days had to be replaced by the value from the last trading day (for details see section 3.4). An extended period of analysis with fewer missing values would have provided a more detailed insight into the interaction between these markets, if the data were available.

As discussed earlier, high self-contributions were observed in the frontier markets in general and Pakistan in particular. Given high estimates of self-contributions in Pakistan, it was considered appropriate to examine the sectors and industries that contribute the most to the returns and volatility of the overall Pakistan index. To examine this further, data were collected for various sectors and industries. Since the Karachi Stock Exchange does not maintain any sectoral indices, other sources such as MSCI, Dow Jones, and FTSE indices were referred to in order to collect appropriate data. Although the data for sectoral indices were available from these sources, no information was provided on the companies included in the sample and on the methodology of calculating these indices. Moreover, there were many missing values, resulting in an incomplete data set. During the data cleaning process, missing values were replaced with the previous day's values, and subsequently, log returns were calculated for all the sectoral indices. Correlations were calculated for all the time series under consideration, and all the correlation estimates were high, presenting the problem of multi-collinearity in the available data. Nonetheless, with some exclusion, log returns of the Pakistan index were regressed against the log returns of sectoral indices. The results of the multiple regressions were indecisive. Possible reasons for indecisive regressions could be:

- Incomplete data with sizeable missing values,
- Use of multiple sources to collect data leading to inconsistency, and
- An overlap between various sectoral indices, which poses the problem of multi-collinearity.

To further investigate the contribution of various sectors and industries to the overall returns of the index, another attempt was made to examine the contribution of the largest companies (in terms of market capitalization) to the overall market returns. Close examination of the KSE index revealed that fewer than 25 companies represent 75% of the index. Accordingly, the returns of these companies were regressed against the returns of the index. However, meaningful results could not be drawn. The returns of these companies exhibited high correlations primarily because many companies belonged to the same sector. For example, Pakistan's six largest banks were a part of the top 25 companies in the index during the period of analysis. Lack of diversity in the indices of smaller markets like Pakistan is not new. Demirer (2013) documented that the stock markets in the GCC lack diversification benefits for local investors. In this respect it appears that Pakistan is not different from its GCC counterparts in this sense.

6.3 Avenues For Future Research

Several directions can be followed to enable comprehensive understanding of a peculiar market such as Pakistan and other markets similar to Pakistan.

The results clearly indicated that markets like Pakistan contribute significantly to their own returns and volatility. Accordingly, it is important to assess which sectors of the economy contribute the most to the overall returns and volatility of the index. Although an attempt was made to appraise the contribution of different sectors in the economy, meaningful results could not be drawn from the data employed. An attempt to decompose Pakistan's self-contributions to its returns and volatility into various sectors and industries will be a worthwhile future contribution, if and when such data becomes available.

The findings highlighted some peculiar traits of the Pakistan market, such as an increase in returns self-contributions during crisis and the reduced importance of the USA market in determining volatility spillovers during the crisis. These findings may be indicative of the diversification benefits offered by the Pakistan market, especially for investors who invest heavily in the USA market. Further analysis and the formation of an optimal portfolio that includes Pakistan as a possible diversification avenue will provide better insight.

The findings highlighted that frontier markets in general are relatively segmented from other markets, irrespective of the bilateral trade, geographical proximity, foreign investments, and political relationships with other countries. While the role of the former two determinants of interdependence between markets is explored in detail in this thesis, lesser attention is given to international investors' portfolio investments due to limitations associated with the data availability and the length of the thesis. The literature on contagion/cross-market spillovers due to investors' sentiments is extensive and is beyond the scope of this thesis. Future studies can focus on this aspect and examine cross-market spillovers due to investors' reactions during turbulent times.

It can be assumed that for some markets like China and Saudi Arabia, these factors may not play a major role in their interaction with other markets, although these countries are among the world's largest exporters of products and oil respectively. Hence, it would be relevant to investigate the attributes of these markets that keep them insulated from foreign shocks. As discussed in Phylaktis and Xia (2006), and Campa and Fernandes (2006), monetary and fiscal policies, legal and accounting regimes, economic openness, financial integration, trading activity, industrial concentration, and development can potentially explain varying degrees of cross-market interdependencies. Moreover, factors like the extent of liberalization, government intervention in financial markets, market microstructures, and regulatory frameworks can possibly explain the interaction between frontier markets and other markets.

The analysis of pairwise net spillovers indicates a rise in spillovers during 2011 and 2012 in some pairs. In some cases, such as Pakistan and the UK, Pakistan and Germany, and Pakistan and China, the level of volatility spillovers during this time was higher than that during the financial crisis of 2008. This exaggerated volatility might be associated with the Eurozone crisis. The analysis of the impact of this crisis on Pakistan and its trade partners was beyond the scope of this thesis; however, future studies can incorporate the extended Eurozone crisis and subsequent regulatory interventions, and examine whether its impact on developed, emerging, and frontier markets was significant.

The use of OLS in the thesis sufficed the purpose of estimating co-dependence of the markets included in the sample, as other sophisticated econometrics models were also

employed for an in-depth analysis. Future studies could employ quantile regression (Koenker and Bassett, 1978) to model co-dependence between markets under consideration. In contrast to OLS, quantile regression estimates the relationship between independent variables and the conditional quantiles of response variable. Its application is particularly advantageous when the understanding of extreme values is of great significance.

Finally, this thesis quantified conditional returns and volatility spillovers across markets. If future research was to compare conditional and unconditional spillovers, it could potentially provide greater insight into interdependence between markets.

7 References

Abbas, Q., Khan, S. & Shah, S. Z. A. 2013. Volatility transmission in regional Asian stock markets. *Emerging Markets Review*, 16(0), 66-77.

Abd. Majid, M. S., Meera, A. K. M. & Omar, M. A. 2008. Interdependence of Asean-5 Stock Markets from the Us and Japan. *Global Economic Review,* 37(2), 201-255.

Abhyankar, A. 1998. Linear and nonlinear Granger causality: Evidence from the U.K. stock index futures market. *Journal of Futures Markets*, 18(5), 519-540.

Abraham, A., Seyyed, F. J. & Al-Elg, A. 2001. Analysis of Diversification Benefits of Investing in the Emerging Gulf Equity Markets. *Managerial Finance*, 27(10/11), 47-57.

Abu Dhabi Council for Economic Development 2009. The Abu Dhabi Economic Vision 2030. Abu Dhabi, UAE: Abu Dhabi Government.

Abu Dhabi Securities Exchange. 2012. *Abu Dhabi Securities Exchange - Home* [Online]. Abu Dhabi, UAE. Available: http://www.adx.ae/English/Pages/default.aspx#. (Accessed 25 December 2012).

Aggarwal, R., Inclan, C., and Leal, R. 1999. Volatility in Emerging Stock Markets. *The Journal of Financial and Quantitative Analysis,* 34(1), 33-55.

Aggarwal, R., Lucey, B. & Muckley, C. 2010. Dynamics of Equity Market Integration in Europe: Impact of Political Economy Events. *Journal of Common Market Studies,* 48(3), 641-660.

Agmon, T. 1972. The Relations Among Equity Markets: A Study of Share Price Co-Movements in the United States, United Kingdom, Germany and Japan. *The Journal of Finance*, 27(4), 839-855.

Ahluwalia, P. 2000. Discriminating Contagion: An Alternative Explanation of Contagious Currency Crises in Emerging Markets. *IMF Working Papers*. Washington, DC: International Monetary Fund.

Akdogan, H. 1992. Behavior of Systematic Risk in a regionally Integrated model for Stock Prices. *Economic Letters*, 39(2), 213-216.

Akdogan, H. 1996. A Suggested Approach to Country Selection in International Portfolio Diversification. *Journal of Portfolio Management* 23(1), 33-40.

Alizadeh, S., Brandt, M. W. & Diebold, F. X. 2002. Range-Based Estimation of Stochastic Volatility Models. *The Journal of Finance*, 57(3), 1047-1091.

Alkulaib, Y. A., Najand, M. & Mashayekh, A. 2009. Dynamic linkages among equity markets in the Middle East and North African countries. *Journal of Multinational Financial Management*, 19(1), 43-53.

Allen, P. G. & Morzuch, B. J. 2006. Twenty-five years of progress, problems, and conflicting evidence in econometric forecasting. What about the next 25 years? *International Journal of Forecasting*, 22(3), 475-492.

Allen, D. E., Amram, R. & Mcaleer, M. 2013. Volatility spillovers from the Chinese stock market to economic neighbours. *Mathematics and Computers in Simulation*, 94(0), 238-257.

AME Info. 2006a. *Investors bewildered by GCC stock market crash* [Online]. Saudi Arabia. Available at: http://www.ameinfo.com/80316.html. (Accessed 21 September 2012).

AME Info. 2006b. Saudi stock market crash a cause for concern [Online]. Saudi Arabia. Available at: http://www.ameinfo.com/86438.html. (Accessed 21 September 2012).

Amihud, Y. & Wohl, A. 2004. Political news and stock prices: The case of Saddam Hussein contracts*. Journal of Banking & Finance*, 28(5), 1185-1200.

Amin, A. S. & Orlowski, L. T. 2014. Returns, Volatilities, and Correlations Across Mature, Regional, and Frontier Markets: Evidence from South Asia. *Emerging Markets Finance & Trade*, 50(3), 5-27.

Andersen, T. G. & Bollerslev, T. 1998. Dm-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies. *NBER Working Paper.* National Bureau of Economic Research.

Andersson, F. N. 2011. Band Spectrum Regressions using Wavelet Analysis. *Department of Economics Working Papers*. Lund,Sweden: Lund University.

Andrews, D. W. K. 1993. Tests for Parameter Instability and Structural Change with Unknown Change Point. *Econometrica*, 61(4), 821-856.

Ané, T. & Labidi, C. 2004. Return Interval, Dependence Structure, and Multivariate Normality. *Journal of Economics & Finance*, 28(3), 285-299.

Ang, J. B. 2010. Does Foreign Aid Promote Growth? Exploring the Role of Financial Liberalization. *Review of Development Economics*, 14(2), 197-212.

Antonakakis, N. 2012. Exchange return co-movements and volatility spillovers before and after the introduction of Euro. *Journal of International Financial Markets, Institutions and Money*, 22(5), 1091-1109.

Antonakakis, N. & Badinger, H. 2012. Output Volatility, Economic Growth, and Cross-Country Spillovers: New Evidence for the G7 Countries. *Department of Economics Working Paper Series*. Vienna: WU Vienna University of Economics and Business.

Antonakakis, N. & Vergos, K. 2013. Sovereign bond yield spillovers in the Eurozone during the financial and debt crisis. *Journal of International Financial Markets, Institutions and Money*, 26(0), 258-272.

Ap Gwilym, O. & Sutcliffe, C. 2012. Problems Encountered When Using High Frequency Financial Market Data : Suggested Solutions. *Journal of Financial Management & Analysis*, 25(2), 15-28.

Aparicio, F. M. & Estrada, J. 2001. Empirical distributions of stock returns: European securities markets, 1990-95. *The European Journal of Finance*, 7(1), 1-21.

Arestis, P., Caporale, G. M., Cipollini, A. & Spagnolo, N. 2005. Testing for Financial Contagion between Developed and Emerging Markets During the 1997 East Asian Crisis. *International Journal of Finance and Economics,* 10(4)**,** 359-367.

Arshanapalli, B. & Doukas, J. 1993. International Stock Market Linkages: Evidence from the Pre- And Post-October 1987 Period. *Journal of Banking & Finance*, 17(1), 193-208.

Assidenou, K. E. 2011. Cointegration of Major Stock Market Indices during the 2008 Global Financial Distress. *International Journal of Economics and Finance*, 3(2), 212-222.

Asteriou, D. & Hall, S. 2007. *Applied Econometrics*, New York, USA, Palgrave Macmillan.

Atchison, M., Butler, K. & Simonds, R. 1987. Nonsynchronous Security Trading and Market Index Autocorrelation. *Journal of Finance*, 42(1), 111–118.

Awokuse, T. O., Chopra, A. & Bessler, D. A. 2009. Structural change and international stock market interdependence: Evidence from Asian emerging markets. *Economic Modelling*, 26(3), 549-559.

Baek, E. & Brock, W. 1992. A general test for nonlinear Granger causality: bivariate model. *Working Paper*. Iowa State University and University of Wisconsin, Madison.

Baele, L. 2005. Volatility Spillover Effects in European Equity Markets. *Journal of Financial and Quantitative Analysis* 40(2)**,** 373-401.

Bai, Y. & Green, C. J. 2010. International diversification strategies: Revisited from the risk perspective. *Journal of Banking & Finance*, 34(1), 236-245.

Bai, Y., Green, C. J. & Leger, L. 2012. Industry and country factors in emerging market returns: Did the Asian crisis make a difference? *Emerging Markets Review*, 13(4), 559-580.

Barari, M. 2004. Equity Market Integration in Latin America: A Time-Varying Integration Score Analysis. *International Review of Financial Analysis,* 13(5)**,** 649-668.

Bartram, S. M. & Bodnar, G. M. 2009. No Place to Hide: The global Crisis in Equity Markets in 2008/2009. *Journal of International Money and Finance* 28(8), 1246-1292.

Baur, D. G. 2012. Financial contagion and the real economy. *Journal of Banking & Finance*, 36(10), 2680-2692.

Baumöhl, E. & Lyócsa, Š. 2014. Volatility and dynamic conditional correlations of worldwide emerging and frontier markets. *Economic Modelling*, 38(0), 175-183.

Baur, D. G. & Fry, R. A. 2009. Multivariate contagion and interdependence. *Journal of Asian Economics*, 20(4), 353-366.

Bauwens, L., Laurent, S. & Rombouts, J. V. K. 2006. Multivariate GARCH Models: A Survey. *Journal of Applied Econometrics*, 21(1), 79-109.

Becker, K. G., Finnerty, J. E. & Gupta, M. 1990. The Intertemporal Relation between the US and Japanese Stock Markets. *Journal of Finance,* 45(4)**,** 1297-1306.

Beirne, J., Caporale, G. M., Schulze-Ghattas, M. & Spagnolo, N. 2010. Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. *Emerging Markets Review*, 11(3), 250-260.

Bekaert, G. 1995. Market Integration and Investment Barriers in Emerging Equity Markets. *The World Bank Economic Review,* 9(1)**,** 75-107.

Bekaert, G. & Harvey, C. 1995. Time-Varying World Market Integration. *Journal of Finance*, 50(2), 403–444.

Bekaert, G. & Harvey, C. 1997. Emerging Equity Market Volatility. *Journal of Financial Economics,* 43(1)**,** 29-77.

Bekaert, G. & Harvey, C. R. 2003. Emerging Markets Finance. *Journal of Empirical Finance*, 10(1), 3-55.

Bekaert, G., Harvey, C. R. & Lumsdaine, R. L. 2002. Dating the Integration of World Equity Markets. *Journal of Financial Economics,* 65(2)**,** 203-247.

Bekaert, G., Harvey, C. R., Lundblad, C. T. & Siegel, S. 2011. What Segments Equity Markets? *Review of Financial Studies*, 24(12), 3841-3890.

Bekaert, G., Harvey, C. & Ng, A. 2005. Market Integration and Contagion. *Journal of Business*, 78(1), 39-70.

Bekiros, S. & Marcellino, M. 2013. The multiscale causal dynamics of foreign exchange markets. *Journal of International Money and Finance*, 33(0), 282-305.

Bera, A. K. & Higgins, M. L. 1993. ARCH Models: Properties, Estimation And Testing. *Journal of Economic Surveys*, 7(4), 305.

Berg, A. & Pattillo, C. 1999. Predicting Currency Crises: The Indicators Approach and an Alternative. *Journal of International Money and Finance*, 18(4), 561-586.

Berger, D., Pukthuanthong, K. & Jimmy Yang, J. 2011. International Diversification with Frontier Markets. *Journal of Financial Economics,* 101(1)**,** 227-242.

Bhattacharya, U. & Daouk, H. 2009. When No Law is Better Than a Good Law. *Review of Finance*, 13(4), 577-627.

Billio, M. & Pelizzon, L. 2003. Contagion and Interdependence in Stock Markets: Have the Been Misdiagnosed. *Journal of Economics and Business,* 55(5/6)**,** 405-426.

Birkenes, R. M. & Pennell, J. A. 1999. The Russian Financial Crisis: Causes and Effects on ENI Countries. *US Aid Working Papers Series*. US Aid. Available: http://pdf.usaid.gov/pdf_docs/PNACF234.pdf. (Accessed on: 13 December 2014).

Black, R. 1976. Studies in Stock Price Volatility Changes. *In:* Proceedings of the 1976 Meeting of the American Statistical Association, Business and Economics Statistics, 1976. 177-181.

Blanchard, C. M. 2012. Saudi Arabia: Background and U.S. Relations. *CRS Report for Congress*. Congressional Research Service

Bley, J. & Chen, K. H. 2006. Gulf Cooperation Council (GCC) stock markets: The dawn of a new era. *Global Finance Journal*, 17(1), 75-91.

Bley, J. & Saad, M. 2012. Idiosyncratic risk and expected returns in frontier markets: Evidence from GCC. *Journal of International Financial Markets, Institutions and Money*, 22(3), 538-554.

Bloomberg. 2012. *BSE SENSEX Quote* [Online]. Available: http://www.bloomberg.com/quote/SENSEX:IND. (Accessed 25 September 2012).

Bloomberg 2012. Comparison of Returns. *Available:* http://www.bloomberg.com/quote/KSE100:IND/chart. (Accessed 25 September 2012).

Bloomberg. 2015. Comparison of Returns for Frontier Markets, Emerging Markets, Non-US Developed Markets and the US Market. Available at: http://www.bloomberg.com/quote/RFRM:IM (Accessed: 12 June 2015)

Bloomberg Business Week. April 2003. *And World's Top Market Is...Pakistan* [Online]. Available: http://www.businessweek.com/bwdaily/dnflash/apr2003/nf20030410_4232_db039.htm. (Accessed 25 September 2012).

Bodart, V. & Candelon, B. 2009. Evidence of interdependence and contagion using a frequency domain framework. *Emerging Markets Review*, 10(2), 140-150.

Boudoukh, J., Richardson, M. & Whitelaw, R. 1994. A Tale of Three Schools: Insights on Autocorrelations of Short-Horizon Returns. *Review of Financial Studies*, 7(3), 539-573.

Bollerslev, T. 1986. Generalised Conditional Heteroscedasticity. *Journal of Econometrics,* 31(1986)**,** 307-327.

Bollerslev, T. 2010. Glossary to ARCH (GARCH). *Volatility and Time Series Econometrics*. Oxford University Press.

Bollerslev, T. 1990. Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. *Review of Economics & Statistics*, 72(3), 498.

Bollerslev, T., Engle, R. F. & Wooldridge, J. M. 1988. A Capital Asset Pricing Model with Time-varying Covariances. *The Journal of Political Economy*, 96(1), 116-131.

Bollerslev, T. & Ghysels, E. 1996. Periodic Autoregressive Conditional Heteroskedastcity. *Journal of Business and Economic Statistics*, 14(2), 139-151.

Bonham, C., Gangnes, B. & Zhou, T. 2009. Modeling tourism: A fully identified VECM approach. *International Journal of Forecasting*, 25(3), 531-549.

Booth, G. G., Chowdhury, M., Martikainen, T. & Tse, Y. 1997. Intraday Volatility in International Stock Index Futures Markets: Meteor Showers or Heat Waves? *Management Science,* 43(11)**,** 1564-1576.

Booth, G. G. & So, R. W. 2003. Intraday Volatility Spillovers in the German Equity Index Derivatives Markets. *Applied Financial Economics,* 13(7)**,** 487-494.

Borges, M. R. 2010. Efficient Market Hypothesis in European Stock Markets. *The European Jouranl of Finance*, 16(7), 711-726.

Boswijk, H. P. & Franses, P. H. 1995. Periodic Cointegration: Representation and Inference. *Review of Economics and Statistics*, 77(3), 436-454.

Boswijk, H. P., Franses, P. H. & Dijk, D. V. 2009. Cointegration in a historical perspective *UVA Econometrics Discussion Papers*. Amsterdam: Amsterdam School of Economics.

Bowers, C. T. & Heaton, C. 2011. What does high-dimensional factor analysis tell us about risk factors in the Australian stock market? *Applied Economics*, 45(11), 1395-1404.

Boyer, B. H., Kumagai, T. & Yuan, K. 2006. How do crises spread? Evidence from accessible and inaccessible stock indices. *Journal of Finance*, LXI(2), 957-1003.

Bracker, K., Docking, D. S. & Koch, P. D. 1999. Economic determinants of evolution in international stock market integration. *Journal of Empirical Finance*, 6(1), 1-27.

Brailsford, T. J. & Faff, R. W. 1996. An Evaluation of Volatility Forecasting Techniques. *Journal of Banking & Finance*, 20(3), 419-438.

Brandt, M. W. & Diebold, F. X. 2006. A No-Arbitrage Approach to Range-Based Estimation of Return Covariances and Correlations. *Journal of Business*, 79(1), 61-73.

Brandt, M. W. & Jones, C. S. 2005. Bayesian range-based estimation of stochastic volatility models. *Finance Research Letters*, 2(4), 201-209.

Brealey, R. A., Myers, S. C. & Marcus, A. J. 2004. *Fundamentals of Corporate Finance*, New York, McGraw-Hill Company.

Brooks, R. & Del Negro, M. 2002. The Rise in Co-movement across National Stock Markets: Market Integration or IT Bubble? *FBR Atlanta Working Paper Series*. Atlanta, Georgia: Federal Reserve Bank of Atlanta.

Brown, S. J. & Warner, J. B. 1985. Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1), 3-31.

Bubák, V., Kočenda, E. & Žikeš, F. 2011. Volatility transmission in emerging European foreign exchange markets. *Journal of Banking & Finance*, 35(11), 2829-2841.

Buguk, C. & Brorsen, B. W. 2003. Testing weak-form market efficiency: Evidence from the Istanbul Stock Exchange. *International Review of Financial Analysis*, 12(5), 579-590.

Burns, P., Engle, R. & Mezrich, J. 1998. Correlations and Volatilities of Asynchronous Data. *Journal of Derivatives*, 5(4), 7-18.

Burnside, C. & Dollar, D. 2000. Aid, policies, and growth. *American Economic Review*, 90(4), 847-868.

Bussiere, M. & Fratzscher, M. 2006. Towards a New Early Warning System of Financial Crises. *Journal of International Money and Finance*, 25(6), 953-973.

Büttner, D. & Hayo, B. 2011. Determinants of European Stock Market Integration. *Economic Systems*, 35(4), 574-585.

Calvo, G. A. & Mendoza, E. G. 2000. Rational contagion and the globalization of securities markets. *Journal of International Economics*, 51(1), 79-113.

Calvo, S. & Reinhart, C. M. 1996. Capital Flows to Latin America: Is There Evidence of Contagion Effects? *Private Capital Flows to Emerging Markets.* Washington, DC: Institute for International Economics.

Caldwell, K. 2013. The 10 best performing stock markets of 2013. *The Telegraph* [Online]. Available: http://www.telegraph.co.uk/finance/personalfinance/investing/shares/10523334/The-10-best-performing-stock-markets-of-2013.html. (Accessed on; 17 November 2014).

Campa, J. & Fernandes, N. 2006. Sources of Gains From International Portfolio Diversification. *Journal of Emprical Finance*, 13(4/5), 417-443.

Campbell, D. T., Stanley, J. C. & Gage, N. L. 1963. *Experimental and quasi-experimental designs for research*, Houghton Mifflin Boston.

Caporale, G. M. & Spagnolo, N. 2011. Stock Market Integration between Three CEECs, Russia, and the UK. *Review of International Economics*, 19(1), 158-169.

Cappiello, L., Engle, R. F. & Sheppard, K. 2006. Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns. *Journal of Financial Econometrics*, 4(4), 537-572.

Cappiello, L., Kadareja, A. & Manganelli, S. 2010. The Impact of the Euro on Equity Markets. *Journal of Financial and Quantitative Analysis*, 45(2), 473-502.

Caramazza, F., Ricci, L. & Salgado, R. 2004. International financial contagion in currency crises. *Journal of International Money and Finance*, 23(1), 51-70.

Carlson, M. 2007. A Brief History of the 1987 Stock Market Crash with a Discussion of the Federal Reserve Response *Finance and Economics Discussion Series* Washington, DC: Federal Reserve Board.

Carlson, J. B., Hoffman, D. L., Keen, B. D. & Rasche, R. H. 1999. Results of a Study of the Stability of Cointegrating Relations Comprised of Broad Monetary Aggregates. *Journal of Monetary Economics*, 46(2), 345-383.

Carrieri, F., Errunza, V. & Hogan, K. 2007. Characterizing World Market Integration through Time. *Journal of Financial and Quantitative Analysis*, 42(04), 915-940.

Castellanos, A. M., Vacastellanosrgas, F. S. & Rentería, L. G. 2011. The contagion from the 2007-09 US stock market crash. *International Journal of Banking and Finance*, 8(4), 67-81.

Chakraborty, M. 2006. Market Efficiency for the Pakistan Stock Market: Evidence from the Karachi Stock Exchange. *South Asia Economic Journal*, 7(1), 67-81.

Chan, K., Covrig, V. & Ng, L. 2005. What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide. *Journal of Finance*, 60(3), 1495-1534.

Chan, L., Lien, D. & Weng, W. 2008. Financial Interdependence between Hong Kong and the Us: A Band Spectrum Approach. *International Review of Economics and Finance,* 17(4), 507–516.

Chen, M.-P., Chen, P.-F. & Lee, C.-C. 2014. Frontier stock market integration and the global financial crisis. *The North American Journal of Economics and Finance*, 29(0), 84-103.

Chen, G.-M., Firth, M. & Meng Rui, O. 2002. Stock market linkages: Evidence from Latin America. *Journal of Banking & Finance*, 26(6), 1113-1141.

Cheng, A.-R., Jahan-Parvar, M. R. & Rothman, P. 2010. An empirical investigation of stock market behavior in the Middle East and North Africa. *Journal of Empirical Finance*, 17(3), 413-427.

Cheung, Y.-W. & Ng, L. K. 1992. Interactions between the U.S. and Japan Stock Market Indices. Journal of International Financial Markets, Institutions and Money, 2(2), 51-70.

Chesney, M., Reshetar, G. & Karaman, M. 2011. The impact of terrorism on financial markets: An empirical study. *Journal of Banking & Finance*, 35(2), 253-267.

Cheung, L., Fung, L. & Tam, C.-S. 2008. Measuring Financial Market Interdependence and Assessing Possible Contagion Risk in the EMEAP Region. Hong Kong Monetary Authority.

Chiang, M.-H. & Wang, L.-M. 2011. Volatility contagion: A range-based volatility approach. *Journal of Econometrics*, 165(2), 175-189.

Chiang, T. C., Jeon, B. N. & Li, H. 2007. Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance*, 26(7), 1206-1228.

China Securities Regulatory Commission 2012. Reform and Innovation - The Driving Forces Behind China's Capital Markets by CSRC. World Federation of Exchanges.

Chion, S. J. & Veliz C., C. N. 2008. On the Normality of Stock Return Distributions: Latin American Markets, 2000-2007. Journal of CENTRUM Cathedra, 1(2), 90-108.

Choudhry, T. 2004. International Transmission of Stock Returns and Volatility. *Emerging Markets Finance & Trade*, 40(4), 33-52.

Chowdhury, A. R. 1994. Stock Market Interdependencies: Evidence from the Asian NIEs. *Journal of Macroeconomics*, 16, 629-651.

Christiansen, C. & Ranaldo, A. 2009. Extreme Coexceedances in New EU Member States' Stock Markets. *Journal of Banking & Finance*, 33(6), 1048-1057.

Christoffersen, P., Errunza, V. R., Jacobs, K. & Langlois, H. 2012. Is the Potential for International Diversification Disappearing? A Dynamic Copula Approach. *Review of Financial Studies*, 25(12), 3711-3751.

CIA Factsheet. 2013. *Economy – UK, Germany, Japan, Singapore, Malaysia, China, Pakistan, UAE, Kuwait* [Online]. Available: https://www.cia.gov/library/publications/the-world-factbook/ (Accessed 16 June 2013).

Claessens, S. 1995. The Emergence of Equity Investment in Developing Countries: Overview. *The World Bank Economic Review,* 9(1)**,** 1-17.

Claeys, P. & Vašíček, B. 2012. Measuring Sovereign Bond Spillover in Europe and the Impact of Rating News. *CNB Working Paper Series*. Prague, Czech Republic: Czech National Bank.

Click, R. W. & Plummer, M. G. 2005. Stock market integration in ASEAN after the Asian financial crisis. *Journal of Asian Economics*, 16(1), 5-28.

Codner, M. 2008. The Hard Choices: Twenty Questions for British Defence Policy and National Military Strategy. *RUSI Discussion Papers*. London: Royal United Services Institute.

Corhay, A., Tourani Rad, A. & Urbain, J. P. 1993. Common stochastic trends in European stock markets. *Economics Letters*, 42(4), 385-390.

Corsetti, G., Pericoli, M. & Sbracia, M. 2005. 'Some contagion, some interdependence': More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, 24(8), 1177-1199.

Coudert, V. & Gex, M. 2008. Does risk aversion drive financial crises? Testing the predictive power of empirical indicators. *Journal of Empirical Finance*, 15(2), 167-184.

Creswell, J. W. 2009. *Research Design - Qualitatitive, Quantitative, and Mixed Method Approaches*, Thousand Oaks, California, Sage Publications.

CSRC. 2013. *Securities Market Statistics in April 2013* [Online]. Beijing, China. Available: http://www.csrc.gov.cn/pub/csrc_en/marketdata/security/monthly/201305/t20130527_228716.htm. (Accessed 30 May 2013).

Curto, J. D., Pinto, J. C. & Fernandes, J.-a. E. 2006. World Equity Markets: A New Approach for Segmentation. *Czech Journal of Economics and Finance*, 56(7/8), 344-360.

Cutrini, E. & Galeazzi, G. 2012. Can Emerging Economies Decouple from the US Business Cycle? *Working Paper No 41*. Macerata – Italy: University of Macerata.

Dajčman, S. 2013. Interdependence Between Some Major European Stock Markets - A Wavelet Lead/Lag Analysis. *Prague Economic Papers* Prague: University of Economics.

Dajčman, S., Festic, M. & Kavkler, A. 2012. Co-movement Dynamics between Central and Eastern European and Developed European Stock Markets during European Integration and Amid Financial Crises – A Wavelet Analysis. *Inzinerine Ekonomika-Engineering Economics*, 23(1), 22-32.

Darrat, A. F., Elkhal, K. & Hakim, S. R. 2000. On the integration of emerging stock markets in the Middle East. *Journal of Economic Development*, 25(2000), 119-129.

Dawn. 2012a. *Revisiting Stock Market Crash* [Online]. Karachi, Pakistan: Dawn Newspaper. Available: http://dawn.com/2012/01/09/revisiting-stock-market-crash. (Accessed 22 August 2012).

Dawn. 2012b. *Top ten trading partners* [Online]. Karachi, Pakistan. Available: http://dawn.com/2012/01/16/top-ten-trading-partners/. (Accessed 2 May 2013).

Dawn. 2013a. *Pakistan and China accord MFN status to each other* [Online]. Karachi, Pakistan. Available: http://dawn.com/2013/01/06/pakistan-and-china-accord-mfn-status-to-each-other/. (Accessed 2 May 2013).

Dawn. 2013b. *China given contract to operate Gwadar port* [Online]. Karachi, Pakistan. Available: http://dawn.com/2013/02/19/china-given-contract-to-operate-gwadar-port/. (Accessed 2 May 2013).

De Groot, W., Pang, J. & Swinkels, L. 2012. The cross-section of stock returns in frontier emerging markets*. Journal of Empirical Finance*, 19(5), 796-818.

Demirer, R. 2013. Can advanced markets help diversify risks in frontier stock markets? Evidence from Gulf Arab stock markets. *Research in International Business and Finance*, 29(0), 77-98.

Demirgüc-Kunt, A. & Detragiache, E. 1999. Monitoring Banking Sector Fragility: A Multivariate Logit Approach. *IMF Working Papers*. International Monetary Fund.

Demirgüc-Kunt, A. & Detragiache, E. 1997. The Determinants of Banking Crises:Evidence from Developing and Developed Countries. *IMF Working Papers*. International Monetary Fund.

Diamandis, P. F. 2009. International stock market linkages: Evidence from Latin America. *Global Finance Journal*, 20(1), 13-30.

Dickey, D. A. & Fuller, W. A. 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74(366), 427-431.

Dickey, D. A. & Fuller, W. A. 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica*, 49(4), 1057-1072.

Dicle, M. F., Beyhan, A. & Yao, L. J. 2010. Market efficiency and international diversification: Evidence from India. *International Review of Economics & Finance*, 19(2), 313-339.

Didier, T., Love, I. & Pería., M. S. M. 2010. What Explains Stock Markets' Vulnerability to the 2007-2008 Crisis? *World Bank Policy Research Working Paper Series*. Washington, D.C.: World Bank.

Diebold, F. X. 2001. Econometrics: Retrospect and prospect. *Journal of Econometrics*, 100(1), 73-75.

Diebold, F. X. & Nerlove, M. 1989. The Dynamics of Exchange Rate Volatility: A Multivariate Latent Factor ARCH Model. *Journal of Applied Econometrics*, 4(1), 1-21.

Diebold, F. X. & Yilmaz, K. 2009. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal*, 119(534), 158-171.

Diebold, F. X. & Yilmaz, K. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57-66.

Diebold, F. X. & Yilmaz, K. 2015a. *Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring*, Oxford University Press.

Diebold, F. X. & Yilmaz, K. 2015b. Trans-Atlantic Equity Volatility Connectedness: U.S. And European Financial Institutions, 2004–2014. *Journal of Financial Econometrics*, 14 (1), 81-127.

Dolado, J. J. & Lütkepohl, H. 1996. Making wald tests work for cointegrated VAR systems. *Econometric Reviews*, 15(4), 369-386.

Dooley, M. & Hutchison, M. 2009. Transmission of the U.S. subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis. *Journal of International Money and Finance*, 28(8), 1331-1349.

Dornbusch, R., Park, Y. C. & Claessens, S. 2000. Contagion: How it spreads and How it can be stopped. *World Bank Research Observer*.

Doyle, B. & Faust, J. 2003. Breaks in the Variability and Co-Movement of G-7 Economic Growth. *International Finance Discussion Papers*. Washington, DC: Board of Governors of the Federal Reserve System.

Drakos, K. 2010a. Terrorism activity, investor sentiment, and stock returns. *Review of Financial Economics*, 19(3), 128-135.

Drakos, K. 2010b. The determinants of terrorist shocks' cross-market transmission. *Journal of Risk Finance*, 11(2), 147-163.

Dufrénot, G., Mignon, V. & Péguin-Feissolle, A. 2011. The effects of the subprime crisis on the Latin American financial markets: An empirical assessment. *Economic Modelling*, 28(5), 2342-2357.

Dunis, C., Sermpinis, G. & Karampelia, M. F. 2013. Stock market linkages among new EMU members and the euro area: Implications for financial integration and portfolio diversification. *Studies in Economics and Finance*, 30(4), 370-388.

Durlauf, S. N. & Blume, L. E. (eds.) 2010. *Macroeconometrics and Time Series Analysis*, London, UK: Palgrave McMillan.

Easterly, W. 2003. Can foreign aid buy growth? *Journal of Economic Perspectives*, 17(3), 23-48.

Easterly, W., Levine, R. & Roodman, D. 2004. Aid, policies and growth: comment. *American Economic Review*, 94(3), 774-780.

Égert, B. & Kočenda, E. 2007. Interdependence between Eastern and Western European Stock Markets: Evidence from Intraday Data. *Economic Systems,* 31(2)**,** 184-203.

Eichengreen, B., Rose, A. & Wyplosz, C. 1995. Exchange market mayhem: the antecedents and aftermaths of speculative attacks. *Economic Policy*, 10(2), 249-312.

Eichengreen, B., Rose, A. K. & Wyplosz, C. 1996. Contagious Currency Crises. *NBER Working Paper 5681.* The National Bureau of Economic Research.

Enders, W. 2010. *Applied Econometric Time Series*, New Jersey, USA, John Wiley & Sons.

Engle, R. F. 1974. Band Spectrum Regression. *International Economic Review,* 15(1)**,** 1-11.

Engle, R. F. 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica,* 50(5)**,** 987-1007.

Engle, R. F. 1990. Discussion: Stock Market Volatility and the Crash of '87. *Review of Financial Studies*, 3(1), 103-106.

Engle, R. F. 2001. GARCH 101: the use of ARCH/GARCH Models in Applied Econometrics. Journal of Economic Perspectives, 15(4), 157-168.

Engle, R. F. 2002. Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics*, 20(3), 339-350.

Engle, R. F. 2004. Risk and Volatility: Econometric Models and Financial Practice. *The American Economic Review*, 94 (3), 405-419.

Engle, R. F. & Granger, C. 1987. Co-Integration and Error Correction: Representation, Estimation and Testing. *Econometrica,* 55(2)**,** 55, 251-276.

Engle, R. F. & Kroner, K. F. 1995. Multivariate simultaneous generalized ARCH. *Econometric Theory*, 11(1), 122-150.

Engle, R. F., Lilien, D. M. & Robbins, R. P. 1987. Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model. *Econometrica*, 55(2), 391-407.

Engle, R. F., Ng, V. K. & Rothschild, M. 1990. Asset Pricing with a Factor ARCH Covariance Structure: Empirical Estimates for Treasury Bills. *Journal of Econometrics*, 45(1/2), 213-238.

Erol, U. & Balkan, E. M. 1996. How financial markets process money information: A re-examination of evidence using band spectrum regression. *Journal of Macroeconomics*, 18(4), 639-656.

Eun, C. S. & Shim, S. 1989. International transmission of stock market movements. *Journal of Financial and Quantitative Analysis*, 24(2), 241-256.

Eurobank, E. 2012. Global Economic and Market Outlook. *Eurobank Research.* Eurobank EFG.

Euromoney Country Risk. 2015. Pakistan's Wiki |Euromoney Country Risk [Online]. New York, NY, USA: Euromoney Institutional Investor PLC. Available: http://www.euromoneycountryrisk.com/Wiki/Pakistan. (Accessed 21 March 2014).

European Central Bank. 2014. *Timeline of the financial crisis* [Online]. European Central Bank. Available: https://www.ecb.europa.eu/ecb/html/crisis.en.html. (Accessed 5 December 2014).

European Commission. 2010. *Economic and Monetary Union – A timeline*[Online]. Available: http://ec.europa.eu/archives/emu10/timeline_en.pdf. (Accessed on 13 December 2014).

European Union. 2014. *Delegation of the European Union to Pakistan* [Online]. Available: http://eeas.europa.eu/delegations/pakistan/eu_pakistan/chronology/index_en.htm. [Accessed 25 September 2014].

Eurostat. 2013. *Real GDP Growth Rate - Volume* [Online]. Available: http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&init=1&plugin=1&language=en&pcode=tec00115. (Accessed 27 May 2013).

Fama, E. F. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*, 25(2), 383-417.

Fazio, G. 2007. Extreme interdependence and extreme contagion between emerging markets. *Journal of International Money and Finance*, 26(8), 1261-1291.

Fedorova, E. & Saleem, K. 2010. Volatility Spillovers between Stock and Currency Markets: Evidence from Emerging Eastern Europe. *Journal of Economics and Finance*, 60(6), 519-533.

Fernandez, V. 2004. Time-scale Decomposition of Price Transmission in International Markets. Santiago, Chile: Center for Applied Economics, University of Chile.

Fernandez, V. 2006. The impact of major global events on volatility shifts: Evidence from the Asian crisis and 9/11. *Economic Systems*, 30(1), 79-97.

Fernandez, V. 2007. Stock Market Turmoil: Worldwide Effects of Middle East Conflicts. *Emerging Markets Finance & Trade*, 43(3), 58-102.

Fernandez, V. 2008. The war on terror and its impact on the long-term volatility of financial markets. *International Review of Financial Analysis*, 17(1), 1-26.

Ferson, W. E. & Harvey, C. R. 1993. The Risk and Predictability of International Equity Returns. *The Review of Financial Studies*, 6(3), 527-566.

Filardo, A., George, J., Loretan, M., Ma, G., Munro, A., Shim, I., Wooldridge, P., Yetman, J. & Zhu, H. 2010. The International Financial Crisis: Timeline, Impact and Policy Responses in Asia and the Pacific. *BIS Papers*. Basel Bank for International Settlements.

Flannery, M. J. & Protopapadakis, A. A. 2002. Macroeconomic Factors Do Influence Aggregate Stock Returns. *Review of Financial Studies*, 15(3), 751-782.

Forbes, K. J. 2004. The Asian Flu and Russian Virus: The International Transmission of Crises in Firm-Level Data. *Journal of International Economics,* 63(1), 59-92.

Forbes, K. J. & Chinn, M. D. 2004. A Decomposition of Global Linkages in Financial Markets Over Time. *Review of Economics and Statistics*, 86(3), 705-722.

Forbes, K. J. & Rigobon, R. 2002. No Contagion, Only Interdependence: Measuring Stock Market Co-movements. *The Journal of Finance,* 57(5), 2223-2261.

Frank, N. & Hesse, H. 2009. Financial Spillovers to Emerging Markets during the Global Financial Crisis. Working Paper No WP/09/104. Washington, DC: International Monetary Fund.

Frankel, J. & Rose, A. 1996. Currency Crashes in Emerging Markets: An Empirical Treatment. *Journal of International Economics*, 41(3), 351-366.

Fraser, P. & Oyefeso, O. 2005. US, UK and European Stock Market Integration. *Journal of Business Finance & Accounting*, 32(1/2), 161-181.

Friedman, J. & Shachmurove, Y. 1997. Co-movements of major European Community stock markets: A vector autoregression analysis. *Global Finance Journal*, 8(2), 257.

Frijns, B., Tourani-Rad, A. & Indriawan, I. 2012. Political crises and the stock market integration of emerging markets. *Journal of Banking & Finance*, 36(3), 644-653.

Fujiwara, I. & Takahashi, K. 2012. Asian Financial Linkage: Macro-Finance Dissonance *Pacific Economic Review*, 17(1), 136-159.

Gabriel, V. J., Psaradakis, Z. & Sola, M. 2002. A simple method of testing for cointegration subject to mutiple regime changes. *Economics Letters*, 76(2), 213-221.

Galagedera, D. U. A. 2012. Recent trends in relative performance of global equity markets. *Journal of International Financial Markets, Institutions and Money*, 22(4), 834-854.

Galagedera, D. U. A. & Maharaj, E. A. 2008. Wavelet timescales and conditional relationship between higher-order systematic co-moments and portfolio returns. *Quantitative Finance*, 8(2), 201-215.

Galeano, P. & Tsay, R. S. 2010. Shifts in Individual Parameters of a GARCH Model. *Journal of Financial Econometrics*, 8(1), 122-153.

García-Ferrer, A., González-Prieto, E. & Peña, D. 2012. A conditionally heteroskedastic independent factor model with an application to financial stock returns. *International Journal of Forecasting*, 28(1), 70-93.

Garcia, R. & Ghysels, E. 1998. Structural change and asset pricing in emerging markets. *Journal of International Money and Finance*, 17(3), 455-473.

Garman, M. B. & Klass, M. J. 1980. On the estimation of security price volatilities from historical data. *The Journal of Business*, 53(1), 67-78.

Gençay, R., Selçuk, F. & Whitcher, B. 2003. Systematic risk and timescales. *Quantitative Finance*, 3(2), 108-116.

Gençay, R., Selçuk, F. & Whitcher, B. 2005. Multiscale systematic risk. *Journal of International Money and Finance*, 24(1), 55-70.

Geneva Academy of International Humanitarian Law and Human Rights. 2015. *India - International Peace treaties and agreements* [Online]. Geneva, Switzerland. Available:http://www.geneva-academy.ch/RULAC/Peace_treaties.php?id_state=107. (Accessed 2 February 2015)

Giannopolous, K., Nekhili, R. & Koutmos, G. 2010. Volatility Spillovers and Price Dependencies; a Dynamic Non-Parametric Approach. *International Research Journal of Finance and Economics*, 45(1)114-121.

Gilmore, C. G., Lucey, B. M. & Mcmanus, G. M. 2008. The dynamics of Central European equity market co-movements. *The Quarterly Review of Economics and Finance*, 48(3), 605-622.

Glick, R. & Rose, A. K. 1999. Contagion and Trade: Why Are Currency Crises Regional? *Journal of International Money and Finance,* 18(4), 603-617.

Glosten, L. R., Jagannathan, R. & Runkle, D. E. 1993. On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, 48(5), 1779-1801.

Goh, K.-L., Wong, Y.-C. & Kok, K.-L. 2005. Financial Crisis and Intertemporal Linkages Across the ASEAN-5 Stock Markets. *Review of Quantitative Finance & Accounting*, 24(4), 359-377.

Goldstein, M. 1998. *The Asian Financial Crisis: Causes, Cures and Systemic Implications*, Institute for International Economics.

Gottesman, A. A. & Morey, M. R. 2007. Predicting Emerging Market Mutual Fund Performance. *Journal of Investing*, 16(3), 111-122.

Gottman, J. M., Mcfall, R. M. & Barnett, J. T. 1969. Design and Analysis of Research Using Time Series. *Psychological Bulletin*, 72(4), 299-306.

Graham, M., Kiviaho, J. & Nikkinen, J. 2012. Integration of 22 emerging stock markets: A three-dimensional analysis. *Global Finance Journal*, 23(1), 34-47.

Graham, M., Kiviaho, J., Nikkinen, J. & Omran, M. 2013. Global and regional co-movement of the MENA stock markets. *Journal of Economics and Business*, 65(0), 86-100.

Granger, C. W. J. 1969. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, 37(3), 424-438.

Griffin, J. M., Kelly, P. J. & Nardari, F. 2010. Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets. *The Review of Financial Studies*, 23(8), 3226-3277.

Groh, A. P. & Wich, M. 2012. Emerging economies' attraction of foreign direct investment. *Emerging Markets Review*, 13(2), 210-229.

Grubel., H. 1968. Internationally Diversified Portfolios: Welfare Gains and Capital Flows. *The American Economic Review*, 58(5), 1299-1314.

Grubel, H. G. & Fadner, K. 1971. The Interdependence of International Equity Markets. *Journal of Finance*, 26(1), 89-94.

Gujarati, D. N. & Porter, D. C. 2009. *Basic Econometrics*, McGraw-Hill Education.

Gupta, R. & Guidi, F. 2012. Cointegration relationship and time varying co-movements among Indian and Asian developed stock markets. *International Review of Financial Analysis*, 21(0), 10-22.

Hair, J., Black, W., Babin, B. & Anderson, R. 2009. *Multivariate Data Analysis: A Global Perspective*, Upper Saddle River, NJ, Prentice Hall.

Hamao, Y., Masulis, R. & Ng., V. 1990. Correlations in Price Changes and Volatility Across International Stock Markets. *Review of Financial Studies*, 3(2), 281-367.

Hameed, S. 2013. The Future of Cooperation between the United States and Pakistan. *In*: CENTER OF STRATEGIC AND INTERNATIONAL STUDIES (ed.). Washington, DC: Rowman and Littlefied.

Hamilton, J. D. 2003. What is an oil shock? *Journal of Econometrics*, 113(2), 363-398.

Hamilton, J. D. & Susmel, R. 1994. Autoregressive Conditional Heteroskedasticity and Changes in Regime. *Journal of Econometrics*, 64(1), 307-333.

Hammoudeh, S. & Choi, K. 2006. Behavior of GCC stock markets and impacts of US oil and financial markets. *Research in International Business and Finance*, 20(1), 22-44.

Hammoudeh, S. & Li, H. 2008. Sudden Changes in Volatility in Emerging Markets: The Case of Gulf Arab Stock Markets. *International Review of Financial Analysis,* 17(1)**,** 47-63.

Handa, P., Kothari, S. P. & Wasley, C. 1989. The Relation between the Return Interval and Betas: Implications for the Size Effect. *Journal of Financial Economics*, 23(1), 79-100.

Haniffa, M. N. & Pok, W. C. 2010. Intraday Volatility and Periodicity in the Malaysian Stock Returns. *Research in International Business and Finance*, 24(3), 329-343.

Hansen, P. R. & Lunde, A. 2005. A forecast comparison of volatility models: does anything beat a GARCH(1,1)? *Journal of Applied Econometrics*, 20(7), 873-889.

Hargis, K. 2002. Forms of Foreign Investment Liberalization and Risk in Emerging Stock Markets. *The Journal of Financial Research* 25(1)**,** 19-38.

Harvey, C. R. 1995a. Predictable Risk and Returns in Emerging Markets. *Review of Financial Studies,* 8(3), 773-816*.*

Harvey, C. R. 1995b. The Risk Exposure of Emerging Equity Markets. *The World Bank Economic Review*, 9(1), 19-50.

Hassan, A., Abdullah, M., Shah, S. & Zulfiqar Ali, M. 2007. Testing of Random Walks and Market Efficiency in an Emerging Market: An empirical Analysis of Karachi Stock Exchange. *The Business Review, Cambridge*, 9(1), 271-280.

Hazelton, L. 2009. *Dubai debt crisis: Now British banks face fresh crisis after investing billions* [Online]. London, UK. Available: http://www.dailymail.co.uk/news/article-1231320/Dubai-debt-crisis-Fears-second-economic-crash-global-stock-markets-tumble.html#ixzz2UTd0YXvn. (Accessed 27 May 2013).

Hendry, D. F. 1995. *Dynamic econometrics,* London, UK, Oxford University Press.

Herring, R. J. 1994. International Financial Integration: The Continuing Process. *Wharton Working Paper Series*. University of Pennsylvania.

Hiemstra, C. & Jones, J. D. 1994. Testing for Linear and Nonlinear Granger Causality in the Stock Price- Volume Relation. *The Journal of Finance*, 49(5), 1639-1664.

Hilliard, J. E. 1979. The Relationship Between Equity Indices on World Exchanges. *Journal of Finance*, 34(1), 103-114.

Holton, G. A. 2014. *Value-at-Risk: Theory and Practice*. 2nd ed. E-Book. Available: http://value-at-risk.net. (Accessed 26 February 2014).

Hoglund, R. & Ostermark, R. 2003. Size and Power of some Cointegration Tests under Structural Breaks and Heteroskedastic Noise. *Statistical Papers*, 44(1), 1-22.

Hon, M. T., Strauss, J. & Soo-Keong Yong, J. 2004. Contagion in financial markets after September 11: myth or reality? *Journal of Financial Research*, 27(1), 95-114.

Hong, H. & Stein., J. C. 2003. Differences Of Opinion, Short-Sales Constraints, And Market Crashes. *Review of Financial Studies*, 16(2), 487-525.

HSBC Global Asset Management. 2012. What are Emerging Markets? , Available: https://www.emfunds.us.assetmanagement.hsbc.com/investing-in-emerging-markets/content/what-are-em.fs (Accessed 26 September 2014).

Hudson, R. S. & Gregoriou, A. 2014. Calculating and Comparing Security Returns is harder than you think: A Comparison between Logarithmic and Simple Returns. *International Review of Financial Analysis*, (Forthcoming).

Hussain, M. 2003. Pakistan India Relations. *Briefing Papers to Parlimentarians* Lahore, Pakistan: Pakistan Institution of Legislative Development and Transperancy.

Hussain, S. M. & Harju, K. 2008. Intraday Return and Volatility Spillovers Across International Equity Markets. *International Research Journal of Finance and Economics* 22(1), 205-220.

Huyghebaert, N. & Wang, L. 2010. The Co-Movement of Stock Markets in East Asia Did the 1997–1998 Asian Financial Crisis Really Strengthen Stock Market Integration? *China Economic Review,* 21(1)**,** 98-112.

Hwang, J.-K. 2012. Dynamic Correlation Analysis of Asian Stock Markets. *International Advances in Economic Research*, 18(2), 227-237.

IIF. 2012. Capital Flows to Emerging Market Economies. *IIF Research Note.* Institute of International Finance.

IMF 2011. Mapping Cross-Border Financial Linkages: A Supporting Case for Global Financial Safety Nets. *IMF Staff Papers*. International Monetary Fund.

Irwin, T. & Shukurov, B. 2014. IMF Country Report - United Arab Emirates. *IMF Country Report.* Washington, D.C. : International Monetary Fund.

Islam, N. 2003. What Have we Learnt from the Convergence Debate? *Journal of Economic Surveys*, 17(3), 309-362.

Jacob, J. & Vipul 2008. Estimation and Forecasting of Stock Volatility with Range-Based Estimators. *The Journal of Futures Markets*, 28(6), 561-581.

Jang, H. & Sul, W. 2002. The Asian financial crisis and the co-movement of Asian stock markets. *Journal of Asian Economics*, 13(1), 94-104.

Jarque, C. M. & Bera, A. K. 1981. Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte Carlo evidence. Economics Letters, 7(4), 313-318.

Jayasuriya, S. & Shambora, W. 2009. Oops,We Should Have Diversified!. *Applied Financial Economics,* 19(22/24), 1779-1785.

Jeantheau, T. 1998. Strong Consistency of Estimators for Multivariate ARCH Models. *Econometric Theory*, 14(1), 70-86.

Jeon, B. N. & Chiang, T. C. 1991. A System of Stock Prices in World Stock Exchanges: Common Stochastic Trends for 1975–1990. *Journal of Economics and Business,* 43(4)**,** 329-338.

Johansen, S. 1988. Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control,* 12(2)**,** 231-254.

Johansen, S. & Juselius, K. 1990. Maximum Likelihood Estimation and Inference on Cointegration – with Applications to the Demand for Money. *Oxford Bulletin of Economics and Statistics,* 52(2)**,** 169-210.

Johansson, A. C. 2008. Interdependencies Among Asian Bond Markets. *Journal of Asian Economics,* 19(2)**,** 101-116.

Johansson, A. C. & Ljungwall, C. 2009. Spillover Effects Among the Greater China Stock Markets. *World Developmen,t* 37(4), 839-851.

Johnson, R. & Soenen, L. 2003. Economic integration and stock market co-movement in the Americas. *Journal of Multinational Financial Management*, 13(1), 85-100.

Kadlec, G. B. & Patterson, D. M. 1999. A Transactions Data Analysis of Nonsynchronous Trading. *The Review of Financial Studies*, 12(3), 609-630.

Kang, S., Cho, H., and Yoon, S. 2009. Modeling Sudden Volatility Changes: Evidence from Japanese and Korean Stock Markets. *Physics A,* 388(17)**,** 3543-3550.

Karim, B. A. & Majid, M. S. A. 2010. Does Trade Matter for Stock Market Integration? *Studies in Economics and Finance,* 27(1)**,** 47-66.

Kasibhatla, K. M., Stewart, D., Sen, S. & Malindretos, J. 2006. Are Daily Stock Price Indices in the Major European Equity Markets Cointegrated? Tests and Evidence. *American Economist*, 50(2), 47-57.

Kawakatsu, H. & Morey, M. R. 1999. An empirical examination of financial liberalization and the efficiency of emerging market stock prices. *Journal of Financial Research*, 22(4), 385-411.

Kaya, I., Lyubimov, K. & Miletkov, M. 2012. To liberalize or not to liberalize: Political and economic determinants of financial liberalization. *Emerging Markets Review*, 13(1), 78-99.

Kearney, C. 2012. Emerging Markets Research: Trends, Issues and Future Directions. *Emerging Markets Review*, 13(2), 159-183.

Kenett, D. Y., Raddant, M., Lux, T. & Ben-Jacob, E. 2012. Evolvement of Uniformity and Volatility in the Stressed Global Financial Village. *Plos One,* 7(2)**,** 1-8.

Khaleej Times. 2014. *Indians, Brits and Pakistanis lead Dubai property charge* [Online]. Dubai, UAE. Available: http://www.khaleejtimes.com/kt-article-display-1.asp?xfile=data/uaebusiness/2014/August/uaebusiness_August163.xml&section=uaebusiness. (Accessed 27 September 2014).

Khan, S. & Park, K. W. 2009. Contagion in the Stock Markets: The Asian Financial Crisis Revisited. *Journal of Asian Economics*, 20(5), 561-569.

Kim, S. J., Moshirian, F. & Wu, E. 2005. Dynamic stock market integration driven by the European Monetary Union: An empirical analysis. *Journal of Banking & Finance*, 29(10), 2475-2502.

Kim, B.-H., Kim, H. & Lee, B.-S. 2012. Spillover Effects of the U.S. Financial Crisis on Financial Markets in Emerging Asian Countries. Auburn University Department of Economics Working Paper Series. Auburn, USA: Auburn University

King, M. A. & Wadhwani, S. 1990. Transmission of Volatility between Stock Markets. *The Review of Financial Studies,* 3(1), 5-33.

Kodres, L. E. & Pritsker, M. 2002. A Rational Expectations Model of Financial Contagion. *The Journal of Finance*, 57(2), 769-799.

Koenker, R. & Bassett, G. 1978. Regression Quantiles. *Econometrica*, 46(1), 33–50.

Kohlert, D. M. 2011. International Diversification in a Troubled World: Do Frontier Assets Still Improve the Efficient Frontier? *Journal of Investing*, 20(2), 42-49.

Kollias, C., Papadamou, S. & Stagiannis, A. 2011. Terrorism and capital markets: The effects of the Madrid and London bomb attacks. *International Review of Economics & Finance*, 20(4), 532-541.

Komulainen, T. & Lukkarila, J. 2003. What Drives Financial Crises in Emerging Markets? *BOFIT Discussion Papers*. Helenski, Finland: Bank of Finland, Institute for Economies in Transition.

Koop, G., Pesaran, M. H. & Potter, S. M. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1), 119-147.

Korinek, A., Roitman, A. & Vegh, C. 2010. Decoupling and Recoupling. *American Economic Review*, 100(2), 393-397.

Korkmaz, T., Çevik, E. İ. & Atukeren, E. 2012. Return and volatility spillovers among CIVETS stock markets. *Emerging Markets Review*, 13(2), 230-252.

Kose, M. A., Otrok, C. & Prasad, E. S. 2008. Global Business Cycles: Convergence or Decoupling? *NBER Working Paper Series*. Cambridge, USA: National Bureau of Economic Research.

Koutmos, G. & Booth, G. 1995. Asymmetric Volatility Transmission in International Stock Markets. *Journal of International Money and Finance,* 14(6), 747-762.

Kronstadt, K. A. 2012. Pakistan-U.S. Relations. *CRS Report for Congress.* Congressional Research Service.

KSE. 2012. *The Karachi Stock Exchange* [Online]. Karachi, Pakistan: Available: www.kse.com.pk. (Accessed 10 August 2012).

Kuper, G. H. & Lestano 2007. Dynamic Conditional Correlation Analysis of Financial Market Interdependence: An Application to Thailand and Indonesia. *Journal of Asian Economics,* 18(4)**,** 670-684.

Kuwait Stock Exchange. 2012. *Kuwait Stock Exchange* [Online]. Kuwait. Available: http://www.kse.com.kw/en/Pages/default.aspx. (Accessed 25 December 2012).

Lamoureux, C. G. & Lastrapes, W. D. 1990. Persistence in Variance, Structural Change, and the GARCH Model. *Journal of Business & Economic Statistics*, 8(2), 225-234.

Lanne, M. & Saikkonen, P. 2007. A Multivariate Generalized Orthogonal Factor GARCH Model. *Journal of Business & Economic Statistics*, 25(1), 61-75.

Lastrapes, W. D. & Koray, F. 1990. International Transmission of Aggregate Shocks Under Fixed and Flexible Exchange Rate Regimes: United Kingdom, France, and Germany, 1959 to 1985. *Journal of International Money and Finance*, 9(4), 402-423.

Le, Q. V. & Zak, P. J. 2006. Political risk and capital flight. *Journal of International Money and Finance*, 25(2), 308-329.

Lee, B.-S. & Rui, O. M. 2002. The Dynamic Relationship Between Stock Returns and Trading Volume: Domestic and Cross-Country Evidence. *Journal of Banking & Finance*, 26(1), 51-78.

Lee, C., Shie, F. S. & Chang, C. Y. 2012. How Close a Relationship Does a Capital Market have with Other Such Markets? The Case of Taiwan from the Asian Financial Crisis. *Pacific-Basin Finance Journal*, 20(3), 349-362.

Lee, H. S. 2004. International Transmission of Stock Market Movements: A Wavelet Analysis. *Applied Economics Letters,* 11(3)**,** 197-201.

Lee, S. B. & Kim, K. J. 1993. Does the October 1987 Crash Strengthen the Co-Movements Among National Stocks Markets? *Review of Finnacial Economics,* 3(2)**,** 89-102.

Lee, T. H. & Tse, Y. 1996. Cointegration Tests with Conditional Heteroskedasticity. *Journal of Econometrics*, 73(2), 401-410.

Liew, V. K. S. 2004. Which Lag Length Selection Criteria Should We Employ? *Economics Bulletin*, 3(33), 1-9.

Lessard, D. R. 1974. World, National, and Industry Factors in Equity Returns. *Journal of Finance*, 29(2), 379-391.

Levy, H. & Sarnat, M. 1970. International Diversification of Investment Portfolios. *American Economic Review*, 60(4), 668-675.

Levy Yeyati, E. & Williams, T. 2012. Emerging Economies in the 2000s: Real Decoupling and Financial Recoupling. *Journal of International Money and Finance*, 31(8), 2102-2126.

Lim, L. K. 2009. Convergence and Interdependence Between ASEAN-5 Stock Markets. *Mathematics and Computers in Simulation*, 79(9), 2957-2966.

Lin, W.-L., Engle, R. & Ito, T. 1994. Do bulls and bears move across borders? International Transmission of Stock Returns and Volatility. *Review of Financial Studies*, 7(3), 507-538.

Lindgren, C.-J., Baliño, T. J. T., Enoch, C., Gulde, A.-M., Quintyn, M. & Teo, L. 1999. Financial Sector Crisis and Restructuring: Lessons from Asia. *IMF Ocassional Paper Series*. Washington, DC: International Monetary Fund.

Litterman, R. B. 1986. A Statistical Approach to Economic Forecasting. *Journal of Business and Economic Statistics*, 4(1), 1-4.

Liu, L. 2013. International stock market interdependence: Are Developing Markets the Same as Developed Markets? *Journal of International Financial Markets*, *Institutions and Money*, 26(0), 226-238.

Liu, S. Z., Chang, T., Lin, K.-C. & Lai, M.-Y. 2006. Trade Relations and Stock Market Interdependence: A Correlation Test for the U.S. and Its Trading Partners. *Economics Bulletin*, 7(5), 1-15.

Lo, A. & Mackinlay, A. C. 1990. An Econometric Analysis of Nonsynchronous Trading. *Journal of Econometrics*, 45(1), 181-211.

Logoarde-Segot, T. & Lucey, B. M. 2007. Capital Market Integration in the Middle East and North Africa. *Emerging Markets Finance & Trade*, 43(3), 34-57.

Longin, F. & Solnik, B. 1995. Is the Correlation in International Equity Returns Constant: 1960-1990? *Journal of International Money and Finance,* 14(1)**,** 3-26.

Lucey, B. M. & Muckley, C. 2011. Robust Global Stock Market Interdependencies. *International Review of Financial Analysis,* 20(4)**,** 215-224.

Lütkepohl, H. 2005. *New Introduction to Time Series Analysis*, Springer-Verlag Berlin Heidelberg.

Mackinnon, J. G. 1991. Critical values for cointegration tests. In: R. F. Engle AND C. W. J. Granger (ed.) Long-run economic relationships: readings in *cointegration*. Oxford: Oxford University Press

Mahmoud, E. 1984. Accuracy in Forecasting: a Survey. *Journal of Forecasting*, 3(2), 139-159.

Malik, F., Bradley, T., Ewing, T. & James, P. 2005. Measuring Volatility Persistence in the Presence of Sudden Changes in the Variance of Canadian Stock Returns. *Canadian Journal of Economics*, 38(3), 1037-1056.

Malliaris, A. G. & Urrutia, J. L. 1992. The International Crash of October 1987: Causality Tests. The *Journal of Financial and Quantitative Analysis*, 27(3), 353-364.

Marcal, E. F., Valls Pereira, P. L., Martin, D. M. L. & Nakamura, W. T. 2011. Evaluation of contagion or interdependence in the financial crises of Asia and Latin America, considering the macroeconomic fundamentals. *Applied Economics*, 43(19), 2365-2379.

Markwat, T., Kole, E. & Van Dijk, D. 2009. Contagion as a Domino Effect in Global Stock Markets. *Journal of Banking & Finance*, 33(11), 1996-2012.

Martens, M. & Poon, S.-H. 2001. Returns Synchronization and Daily Correlation Dynamics between International Stock Markets *Journal of Banking & Finance,* 25(10)**,** 1805-1827.

Martínez, J. & Santiso, J. 2003. Financial Markets and Politics: The Confidence Game in Latin American Emerging Economies. *International Political Science Review*, 24(3), 363-395.

Masih, A. M. M. & Masih, R. 1997. Dynamic linkages and the propagation mechanism driving major international stock markets: An analysis of the pre- and post-crash eras. *The Quarterly Review of Economics and Finance,* 37(4), 859-885.

Masih, A. M. M. & Masih, R. 1999. Are Asian stock market fluctuations due mainly to intra-regional contagion effects? Evidence based on Asian emerging stock markets. *Pacific-Basin Finance Journal*, 7(3/4), 251-282.

Masih, R. & Masih, A. M. M. 2001. Long and Short Term Dynamic Causal Transmission Amongst International Stock Markets. *Journal of International Money and Finance,* 20(4)**,** 563-587.

Maurent, J. & Joy, O. M. 1976. The Cohesiveness of EEC Equity Markets. *Journal of Common Market Studies*, 14(4), 344.

Mcmillan, D. G. & Speight, A. E. H. 2004. Daily Volatility Forecasts: Reassessing the Performance of GARCH models*. Journal of Forecasting*, 23(6), 449-460.

Mcnees, S. K. 1986. Forecasting Accuracy of Alternative Techniques: A Comparison of U.S. Macroeconomic Forecasts. *Journal of Business & Economic Statistics*, 4(1), 5-15.

Menon, N. R., Subha, M. V. & Sagram, S. 2009. Cointegration of Indian Stock Markets with Other Leading Stock Markets. *Studies in Economics and Finance,* 26(2)**,** 87-94.

Meric, I., Darian, J. C. & Meric, G. 2012. International Trade and National Stock Market Linkages. *The Journal of American Academy of Business*, 17(2), 8-15.

Mierau, J. O. & Mink, M. 2013. Are stock market crises contagious? The role of crisis definitions. *Journal of Banking & Finance*, 37(12), 4765-4776.

Miles, W. 2005. Do frontier equity markets exhibit common trends and still provide diversification opportunities? *International Economic Journal*, 19(3), 473-482.

Ministry of Foreign Affairs Malaysia. 2013. *Bilateral Diplomacy* [Online]. Putrajaya, Malaysia. Available: http://www.kln.gov.my/web/guest/bd-bilateral_treaties. (Accessed 23 June 2013).

Minot, W. G. 1974. Tests for Integration between Major Western European Capital Markets. *Oxford Economic Papers*, 26(3), 424-439.

Mishkin, F. S. 1999. Lessons from the Asian crisis. *Journal of International Money and Finance*, 18(4), 709-723.

Molnár, P. 2012. Properties of range-based volatility estimators. *International Review of Financial Analysis*, 23(0), 20-29.

Monetary Authority of Singapore. 2012. *Singapore Capital Markets - Equity Capital Markets* [Online]. Singapore. Available: http://www.mas.gov.sg/singapore-financial-centre/overview/capital-markets.aspx. (Accessed 15 June 2013).

Moody's. 2009. *Moody's announces further downgrades to Dubai Inc. corporates* [Online]. Dubai, UAE. Available: https://www.moodys.com/research/Moodys-announces-further-downgrades-to-Dubai-Inc-corporates--PR_191579. (Accessed 2 February 2015).

Morana, C. 2008. International Stock Markets Co-movements: The Role of Economic and Financial Integration. *Empirical Economics,* 35(2)**,** 333-359.

Moshirian, F. 1999. New International Financial Structure. *Journal of Multinational Financial Management,* 12**,** 273-285.

MSCI. 2012. MSCI Country Classification [Online]. MSCI. USA. Available: https://www.msci.com/market-classification. (Accessed 10 September 2012).

Mukherjee, P. & Bose, S. 2008. Does the Stock Market in India Move with Asia? Emerging *Markets Finance & Trade*, 44(5), 5-22.

Mukherjee, K. N. & Mishra, R. K. 2010. Stock Market Integration and Volatility Spillover: India and Its Major Asian Counterparts. *Research in International Business and Finance,* 24(2)**,** 235-251.

Müller, U. A., Dacorogna, M. M., Davé, R. D., Olsen, R. B., Pictet, O. V. & Von Weizsäcker, J. E. 1997. Volatilities of Different Time Resolutions — Analyzing the Dynamics of Market Components. *Journal of Empirical Finance*, 4(2/3), 213-239.

Mun, M. & Brooks, R. 2011. The roles of news and volatility in stock market correlation during the global financial crisis. *Emerging Markets Review*, 13(1), 1-7.

Musacchio, A. 2012. Mexico's financial crisis of 1994-1995 *HBS Working Papers Series*. Harvard Business School.

Neaime, S. 2012. The global financial crisis, financial linkages and correlations in returns and volatilities in emerging MENA stock markets*. Emerging Markets Review*, 13(3), 268-282.

Nekhili, R., Altay-Salih, A. & Gencay, R. 2002. Exploring Exchange Rates at Different Time Horizons. *Physica A,* 313(3)**,** 671-682.

Nelson, D. B. 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59(2), 347-370.

Ng, A. 2000. Volatility Spillover Effects from Japan and the Us to Pacific-Basin. *Journal of International Money and Finance,* 19(2)**,** 207-233.

Ng, H. S. & Lam, K. P. 2006. How Does the Sample Size Affect GARCH Model? *In*: 9th Joint Conference on Information Sciences (JCIS), 2006 Kaohsiung, Taiwan.

Nikkinen, J., Omran, M. M., Sahlström, P. & Äijö, J. 2008. Stock returns and volatility following the September 11 attacks: Evidence from 53 equity markets. *International Review of Financial Analysis*, 17(1), 27-46.

Nissanke, M. 2010. The Global Financial Crisis and the Developing World: Transmission Channels and Fall-Outs for Industrial Development. *Research and Statistics Branch Working Paper 06/2009.* Vienna: United Nations Industrial Development Organization.

Norsworthy, J., Li, D. & Gorener, R. 2000. Wavelet-based Analysis of Time Series: An export from Engineering to Finance. *In*, 2000. IEEE, 126-132.

Nyberg, H. 2008. Forecasting the Direction of the U.S. Stock Market with Dynamic Binary Probit Models. *HECER Discussion Papers*. Helenski, Finland: Helsinki Center of Economic Research.

Omran, M. & Farrar, S. V. 2006. Tests of Weak Form Efficiency in the Middle East Emerging Markets. *Studies in Economics and Finance*, 23(1), 13-26.

Ozcicek, O. & Douglas Mcmillin, W. 1999. Lag length selection in vector autoregressive models: symmetric and asymmetric lags. *Applied Economics*, 31(4), 517-524.

Paas, T. & Kuusk, A. 2012. Contagion of Financial Crises: What Does the Empirical Evidence Show? *Baltic Journal of Management,* 7(1)**,** 25-48.

Pahan, J. A. & Soydemier, G. 2000. On the Linkages Between Equity Markets in Latin America. *Applied Economics Letters*, 7(3), 207 - 210.

Pakistan Ministry of Commerce. 2013. *Regional Bilateral Agreements* [Online]. Islamabad, Pakistan. Available: http://www.commerce.gov.pk/?page_id=9. (Accessed 25 September 2013).

Panton, D. B., Lessig, V. P. & Joy, O. M. 1976. Co-movement of International Equity Markets: A Taxonomic Approach. *Journal of Financial and Quantitative Analysis*, 11(3), 415-432.

Park, C. Y. & Lee, J. W. 2011. Financial Integration in Emerging Asia: Challenges and Prospects. *Asian Economic Policy Review*, 6(2), 176-198.

Parkinson, M. 1980. The Extreme Value Method for Estimating the Variance of the Rate of Return. *Journal of Business*, 53(1), 61-65.

Peiró, A. 1994. The distribution of stock returns: international evidence. *Applied Financial Economics*, 4(6), 431-439.

Pentecost, E. J. & Holmes, M. J. 1995. Changes in the extent of financial integration within the European Community between the 1970s. *Applied Economics Letters*, 2(6), 184.

Pesaran, H. H. & Shin, Y. 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1), 17-29.

Phillips, P. C. B. & Perron, P. 1988. Testing for a Unit Root in Time Series Regression. *Biometrika,* 75(2)**,** 335-346.

Phylaktis, K. & Ravazzolo, F. 2005a. Stock Market Linkages in Emerging Markets: Implications for International Portfolio Diversification. *Journal of International Financial Markets, Institutions and Money*, 15(2), 91-106.

Phylaktis, K. & Ravazzolo, F. 2005b. Stock Prices and Exchange Rate Dynamics. *Journal of International Money and Finance*, 24(7), 1031-1053.

Phylaktis, K. & Xia, L. 2006. The Changing Roles of Industry and Country Effects in the Global Equity Markets. *The European Journal of Finance*, 12(8), 627-648.

Pimenta, J. T. & Famá, R. 2002. Interdependence Between the Major Capital Markets of the Emerging Countries of Latin America and Southeast Asia. *Latin American Business Review*, 3(3), 1-25.

Polski, M. M. 2009. Systemic Risk and the U.S. Financial System. *Mercatus on Policy*. Washington D.C.: Mercatus Center At George Mason University.

Poon, S.-H. 2005. A Practical Guide to Forecasting Financial Market Volatility, West Sussex, England, John Wiley & Sons.

Poon, S., Rockinger, M. & Tawn, J. 2003. Modeling Extreme-Value Dependence in International Stock Markets. *Statistica Sinica*, 13(4), 929-953.

Pretorius, E. 2002. Economic Determinants of Emerging Stock Market Interdependence. *Emerging Markets Review,* 3(1)**,** 84-105.

The Guardian. 2012. *Sixty years of US Aid to Pakistan: Get the Data* [Online]. Available: http://www.theguardian.com/global-development/poverty-matters/2011/jul/11/us-aid-to-pakistan. (Accessed 30 September 2012).

Ramsey, J. B. & Lampart, C. 1998. The Decomposition of Economic Relationships by Time Scale Using Wavlets: Expenditure and Income. *Studies in Nonlinear Dynamics & Econometrics*, 3(1), 23.

Rajan, R. G. & Subramanian, A. 2008. Aid and growth: What Does the Cross-Country Evidence Really Show? . *Review of Economic Studies*, 90(4), 643-665.

Ranta, M. 2013. Contagion among major world markets: a wavelet approach. *International Journal of Managerial Finance*, 9(2), 133-149.

Rapach, D. E., Strauss, J. K. & Zhou, G. 2013. International Stock Return Predictability: What is the Role of the United States?. *Journal of Finance*, 68(4), 1633-1662.

Ratanapakorn, O. & Sharma, S. C. 2002. Interrelationships among regional stock indices. *Review of Financial Economics*, 11(2), 91-108.

Ratner, M. & Leal, R. P. C. 1999. Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. *Journal of Banking & Finance*, 23(12), 1887-1905.

Reider, R. 2009. Volatility Forecasting I: GARCH Models. *New York University*. New York, USA: New York University.

Reinhart, C. M. & Rogoff, K. S. 2008. Is the 2007 U.S. Sub-Prime Financial Crisis so Different? An International Historical Comparison. *NBER Working Papers*. Cambridge, USA: National Bureau of Economic Research.

Ripley, D. M. 1973. Systematic Elements in the Linkage of National Stock Market Indices. *Review of Economics & Statistics*, 55(3), 356.

Rigobon, R. 2003. Identification Through Heteroskedasticity. *Review of Economics and Statistics*, 85(4), 777-792.

Rigobon, R. & Sack, B. 2005. The effects of war risk on US financial markets. *Journal of Banking & Finance*, 29(7), 1769-1789.

Riskmetrics 1996. Riskmetrics – Technical Document. 4 ed. New York: Morgan Guaranty Trust Company.

Rodríguez, M. J. & Ruiz, E. 2012. Revisiting Several Popular GARCH Models with Leverage Effect: Differences and Similarities. *Journal of Financial Econometrics*, 10(4), 637-668.

Rodríguez-Moreno, M. & Peña, J. I. 2013. Systemic risk measures: The simpler the better? *Journal of Banking & Finance*, 37(6), 1817-1831.

Roll, R. 1989. Price Volatility, International Market Links, and Their Implications for Regulatory Policies. *Journal of Finance Services Research*, 3(3), 113-246.

Rua, A. & Nunes, L. C. 2009. International Co-movement of Stock Market Returns: A Wavelet Analysis. *Journal of Empirical Finance*, 16(4), 632-639.

Sachs, J., Tornell, A. & Velasco, A. 1996. Financial Crises in Emerging Markets: The Lessons from 1995. *Brooking Papers on Economic Activity,* 1(1)**,** 147-215.

Samarakoon, L. P. 2011. Stock Market Interdependence, Contagion, and the U.S. Financial Crisis: The Case of Emerging and Frontier Markets. *Journal of International Financial Markets, Institutions and Money,* 21(5)**,** 724-742.

Saran, S. 2013. The Curious Case of India and China. International New York Times [Online]. Available: http://india.blogs.nytimes.com/2013/10/28/the-curious-case-of-india-and-china/?_r=0. (Accessed on: 15 December 2013).

Sarkissian, S. & Schill, M. 2010. Cross listing waves. *MPRA Papers*. Munich: University Library of Munich, Germany.

Sarno, L. & Valente, G. 2005. Modelling and Forecasting Stock Returns: Exploiting the Futures Market, Regime Shifts and International Spillovers. *Journal of Applied Econometrics*, 20(3), 345-376.

Schlegel, G. 1985. Vector Autoregressive Forecasts of Recession and Recovery: Is Less More? *Economic Review*. USA: Federal Reserve Bank of Cleveland

Securities Commission Malaysia. 2011. *Malaysia's Capital Market: Transforming Vision Into Opportunities* [Online]. Kuala Lumpur, Malaysia. Available: http://www.sc.com.my/main.asp?pageid=1127&menuid=&newsid=&linkid=&type=. (Accessed 16 June 2013).

Serwa, D. & Bohl, M. T. 2005. Financial contagion vulnerability and resistance: A comparison of European stock markets. *Economic Systems*, 29(3), 344-362.

Shadish, W. R., Cook, T. D. & Campbell, D. T. 2002. *Experimental and Quasi Experimental Designs for Generalized Causal Inference*, Belmont, USA, Wadsworth Cengage Learning.

SECP. 2012. *The SECP Act 1997* [Online]. Securties and Exchange Commission of Pakistan. Islamabad, Pakistan: Available: http://www.secp.gov.pk/secp_act_97.asp. (Accessed 5 October 2012).

SECP. 2013. Annual Report 2012, Securties and Exchange Commission of Pakistan. Islamabad, Pakistan, Available: http://issuu.com/secpbook/docs/final_annual_report_secp?e=7587085/1896305. (Accessed on: 26 April 2013)

Siebert, H. 2004. Germany's Capital Market and Corporate Governance. *Kiel Working Paper*. Kiel, Germany: Kiel Institute for World Economics.

Silvennoinen, A. & Terasvirta, T. 2008. Multivariate GARCH models. *In*: ANDERSEN, T. G., DAVIS, R. A., KREISS, J.-P. & MIKOSCH, T. (eds.) *Handbook of Financial Time Series*. New York: Springer.

Sims, C. A. 1980. Macroeconomics and Reality. *Econometrica*, 48(1), 1-48.

Singh, P., Kumar, B. & Pandey, A. 2010. Price and Volatility Spillovers across North American, European and Asian Stock Markets. *International Review of Financial Analysis,* 19(1), 55-64.

Solnik, B. H. 1974. An International Market Model of Security Price Behavior. *Journal of Financial and Quantitative Analysis*, 9(4), 537-554.

Speidell, L. 2011. *Frontier Market Equity Investing: Finding the Winners of the Future* [Online]. Charlottesville, Virginia, USA: Research Foundation of CFA Institute. Available: http://www.cfainstitute.org/learning/products/publications/rf/Pages/rf.v2011.n2.1.aspx. (Accessed 14 December 2014).

Speidell, L. & Krohne, A. 2007. The Case for Frontier Equity Markets. *Journal of Investing,* 16(3), 12-22.

Spyrou, S. 2013. Herding in financial markets: a review of the literature. *Review of Behavioral Finance*, 5(2), 175-194.

State Bank of Pakistan. 2012a. *Foreign Investment in Pakistan* [Online]. Karachi, Pakistan: State Bank of Pakistan. Available: www.sbp.org.pk/ecodata/NetinflowSummary.pdf. (Accessed 10 August 2012).

State Bank of Pakistan. 2012b. *Import and Export of Goods and Services* [Online]. Karachi, Pakistan: State Bank of Pakistan. Available: http://www.sbp.org.pk/ecodata/ExportsImports-Goods.pdf. (Accessed 10 August 2012).

Stock, J. H. & Watson, M. W. 2010. Dynamic Factor Models. In: CLEMENTS, M. P. & HENDRY, D. F. (eds.) *Oxford Handbook of Economic Forecasting*. Oxford University Press.

Stracca, L. 2013. The Global Effects of the Euro Debt Crisis. *Working Paper Series No 1573 / August 2013*. Frankfurt, Germany: European Central Bank.

Sugimoto, K., Matsuki, T. & Yoshida, Y. 2014. The global financial crisis: An analysis of the spillover effects on African stock markets. *Emerging Markets Review*, 21(0), 201-233.

Sumner, S. W., Johnson, R. & Soenen, L. 2010. Spillover Effects among Gold, Stocks, and Bonds. *Journal of CENTRUM Cathedra*, 3(2), 106-120.

Syriopoulos, T. 2007. Dynamic linkages between emerging European and developed stock markets: Has the EMU any impact? *International Review of Financial Analysis*, 16(1), 41-60.

Tadawul. 2013. *Saudi Stock Exchange (Tadawul) - About us* [Online]. Riyadh, Saudi Arabia. Available: http://www.tadawul.com.sa. (Accessed 8 May 2013).

Taylor, M. P. & Tonks, I. 1989. The Internationalization of Stock Markets and the Abolition of U.K. Exchange Control. *Review of Economics & Statistics*, 71(2), 332.

Thapa, C. & Poshakwale, S. S. 2012. Country-specific equity market characteristics and foreign equity portfolio allocation. *Journal of International Money and Finance*, 31(2), 189-211.

The Economist 2014. Pakistan's stockmarket: Oil on troubled waters. *The Economist.* Mumbai, India. Available: http://www.economist.com/news/finance-and-economics/21627718-despite-constant-political-upheaval-pakistans-stockmarket-doing-well-oil. (Accessed on: 9 November 2014).

The Priviatization Commission of Pakistan. 2011. Completed Transactions: 1991 - 2010 [Online]. Islamabad, Pakistan. Available: http://www.privatisation.gov.pk/about/Completed%20Transactions%20(new).htm. (Accessed 25 September 2012).

The Wall Street Journal. 2013. *Mideast in Motion* [Online]. Available: http://online.wsj.com/article/SB10001424127887324853704578584031255006250.html. (Accessed 5 October 2013).

The World Bank 2009. Corporate Governance Country Assessment - The Kingdom of Saudi Arabia. *Report on the Observance of Standards and Codes (ROSC).* Washington, DC: The World Bank.

The World Bank. 2012a. *Domestic Listed Companies and Market capitalization of listed companies* [Online]. Washington, DC, USA. Available: http://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS. (Accessed 25 September 2012).

The World Bank. 2012b. *GDP Per Capita (US$)* [Online]. Washington, DC, USA. Available: http://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS. (Accessed 25 September 2012).

The World Bank 2013a. Doing Business - Smarter Regulations for Small and Medium-Size Enterprises. *Comparing Business Regulations for Domestic Firms in 185 Economies - 10th Edition*. Washigton DC: The World Bank.

The World Bank. 2013b. *Strong Domestic Demand Drives Increasing Growth in East Asia Pacific* [Online]. Washington, DC, USA. Available: http://www.worldbank.org/en/news/press-release/2013/04/15/strong-domestic-demand-drives-increasing-growth-in-east-asia-pacific. (Accessed 3 June 2013).

The World Bank. 2014. *Economy and Growth Data* [Online]. Washington, DC, USA. Available: http://data.worldbank.org/topic/economy-and-growth#tp_wdi. (Accessed 23 November 2014).

Thoma, M. 1992. The Effects of inside and Outside Money on Industrial Production across Spectral Frequency Bands. *The Review of Economics and Statistics,* 74(4), 737-741.

Thoma, M. 1994. The Effects of Money Growth on Inflation and Interest Rates across Spectral Frequency Bands. *Journal of Money, Credit and Banking,* 26(2), 218-231.

Thupayagale, P. & Molalapata, I. 2012. Dynamic Co-movement and Correlations in Fixed Income Markets: Evidence from Selected Emerging Market Bond Yields. *Investment Analysts Journal*, 41(76), 25-38.

Tsai, I. C. 2014. Spillover of fear: Evidence from the stock markets of five developed countries. *International Review of Financial Analysis*, 33(0), 281-288.

Turgutlu, E. & Ucer, B. 2010. Is global diversification rational? Evidence from emerging equity markets through mixed copula approach. *Applied Economics*, 42(5), 647-658.

UNCTAD 2012. World Investment Report 2012. Geneva, Switzerland: United Nations Conference on Trade and Development.

Uppal, J. 1998. Stock return volatility in an emerging market: A case study of the Karachi Stock Exchange. *Managerial Finance*, 24(3), 34-51.

USA Department of State. 2013a. *Investment Climate Statement - Kuwait* [Online]. Washington, DC, USA. Available: http://www.state.gov/e/eb/rls/othr/ics/2013/204672.htm. (Accessed 27 May 2013).

USA Department of State. 2013b. *Investment Climate Statement - United Arab Emirates* [Online]. Washington, DC, USA. Available: http://www.state.gov/e/eb/rls/othr/ics/2012/191258.htm. (Accessed 21 June 2013).

USA Department of Treasury. 2013. *Major Foreign Holders of US Treasury Securities* [Online]. Washington, DC, USA. Available: http://www.treasury.gov/resource-center/data-chart-center/tic/Documents/mfh.txt. (Accessed 19 June 2013).

USA Energy Information Administration. 2012. *International Energy Statistics - Oil Supply* [Online]. Washington, DC, USA. Available: http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=5&pid=53&aid=1. (Accessed 19 June 2013).

Valls, N. & Chuliá, H. 2012. Volatility Transmission and Correlation Analysis between the USA and Asia: The Impact of the Global Financial Crisis. *Global Economic Review*, 41(2), 111-129.

Van Der Weide, R. 2002. GO-GARCH: A Multivariate Generalized Orthogonal GARCH Model. *Journal of Applied Econometrics*, 17(5), 549-564.

Van Rijckeghem, C. & Weder, B. 2001. Sources of Contagion: Is it Finance or Trade? *Journal of International Economics*, 54(2), 293-308.

Voronkova, S. 2004. Equity market integration in Central European emerging markets: A cointegration analysis with shifting regimes. *International Review of Financial Analysis*, 13(5), 633-647.

Wahab, M. A. & Ahmed, V. 2011. Foreign Assistance and Economic Growth. *World Economics*, 12(4), 137-152.

Wälti, S. 2011. Stock market synchronization and monetary integration. Journal of International Money and Finance, 30(1), 96-110.

Wälti, S. 2012. The myth of decoupling. *Applied Economics*, 44(26), 3407-3419.

Wallace, W. & Phillips, C. 2009. Reassessing the Special Relationship. *International Affairs*, 85(2), 263-284.

Walker, P. 2011. *The World's Most dangerous Borders. Foreign Policy* [Online], Available: http://www.foreignpolicy.com/articles/2011/06/24/the_worlds_most_dangerous_borders?page=0,2. (Accessed on: 26 September 2014).

Wang, P. & Moore, T. 2008. Stock Market Integration for the Transition Economies: Time-Varying Conditional Correlation Approach. *The Manchester School*, 76(1), 116-133.

Wang, P. & Wang, P. 2010. Price and volatility spillovers between the Greater China Markets and the developed markets of US and Japan. *Global Finance Journal*, 21(3), 304-317.

Wiedenbrüg, A. & Post, A. 2012. Perpetual Crisis: A Timeline of 40 Years of Economic Instability. *Global Policy Forum*. Available: https://www.globalpolicy.org/component/content/article/229-world-economic-crisis/51104-financial-and-economic-crises-a-timeline.html. (Accessed on: 13 December 2014)

Wijst, D. V. D. & Wijst, N. V. D. 2013. *Finance: A Quantitative Introduction*, London, Cambridge University Press.

Wong, W.-K., Penm, J., Terrell, R. D. & Lim, K. Y. C. 2004. The Relationship between Stock Markets of Major Developed Countries and Asian Emerging Markets. *Journal of Applied Mathematics and Decision Sciences,* 8(4)**,** 201-208.

World Economic Forum 2010-2011. The Global Competitiveness Report 2010–2011. World Economic Forum. Available: http://www3.weforum.org/docs/WEF_GlobalCompetitivenessReport_2010-11.pdf . (Accessed on: 27 September 2014).

World Economic Forum 2013. Global Competitiveness Report 2012-2013. *In:* SCHWAB, P. K. (ed.). Geneva, Switzerland: World Economic Forum.

Worthington, A. & Higgs, H. 2003. Transmission of Equity Returns and Volatility in Asian Developed and Emerging Markets: A Multivariate Garch Analysis. *International Journal of Finance And Economics,* 9(1)**,** 71-80.

Worthington, A. C. & Higgs, H. 2006. Weak-form market efficiency in Asian emerging and developed equity markets: Comparative tests of random walk behaviour. *Accounting Research Journal*, 19(1), 54-63.

World Atlas. 2014. *Map of Asia* [Online]. Available: http://www.worldatlas.com/webimage/countrys/as.htm. (Accessed 23 December 2014).

Wu, C. & Su, Y.-C. 1998. Dynamic relations among international stock markets. *International Review of Economics & Finance*, 7(1), 63.

Yilmaz, K. 2009. International Business Cycle Spillovers. *Koç University-TUSIAD Economic Research Forum Working Papers*. Istanbul, Turkey: Koç University. Available: http://eaf.ku.edu.tr/sites/eaf.ku.edu.tr/files/erf_wp_0903.pdf (Accessed: 13 December 2012)

Yilmaz, K. 2010. Return and Volatility Spillovers Among the East Asian Equity Markets. *Journal of Asian Economics,* 21(3), 304-313.

Yu, J.-S. & Hassan, M. K. 2008. Global and Regional Integration of the Middle East and North African (MENA) Stock Markets. *The Quarterly Review of Economics and Finance*, 48(3), 482-504.

Zellner, A. & Sankar, U. 2005. On Errors in the Variables In: MYTHILI, G., HEMA, R. (ed.) *Topics in Applied Economics: Tools, Issues and Institutions*. New Delhi: Academic Foundation.

Zhang, K. & Chan, L. 2009. Efficient Factor GARCH models and Factor-DCC models. *Quantitative Finance*, 9(1), 71-91.

Zhang, B. & Wang, P. 2014. Return and Volatility Spillovers Between China and World Oil Markets. *Economic Modelling*, 42(0), 413-420.

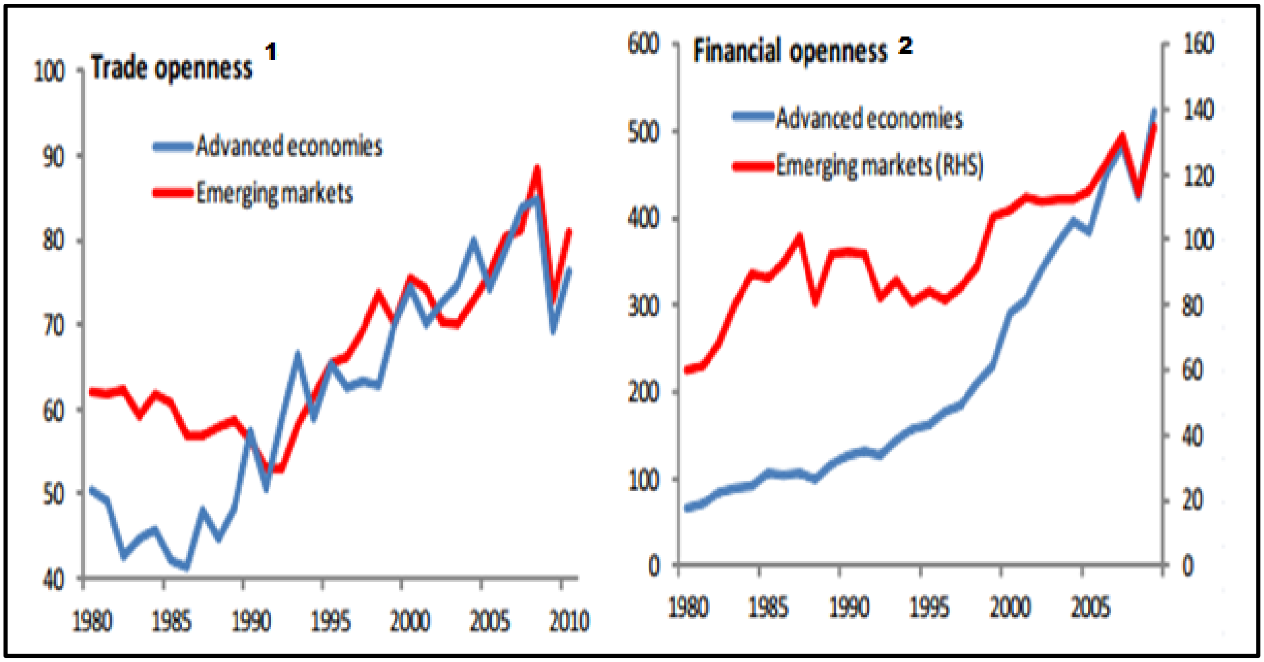
Zhou, X., Zhang, W. & Zhang, J. 2012. Volatility Spillovers Between the Chinese and World Equity Markets. *Pacific-Basin Finance Journal*, 20(2), 247-270.

Zivot, E. 2009. Practical Issues in the Analysis of Univariate GARCH Models. In: MIKOSCH, T., KREIß, J.-P., DAVIS, R. A. & ANDERSEN, T. G. (eds.) *Handbook of Financial Time Series*. Berlin Heidelberg: Springer

Zakoian, J.-M. 1994. Threshold Heteroskedastic Models. Journal of Economic Dynamics and Control, 18(5), 931-955.

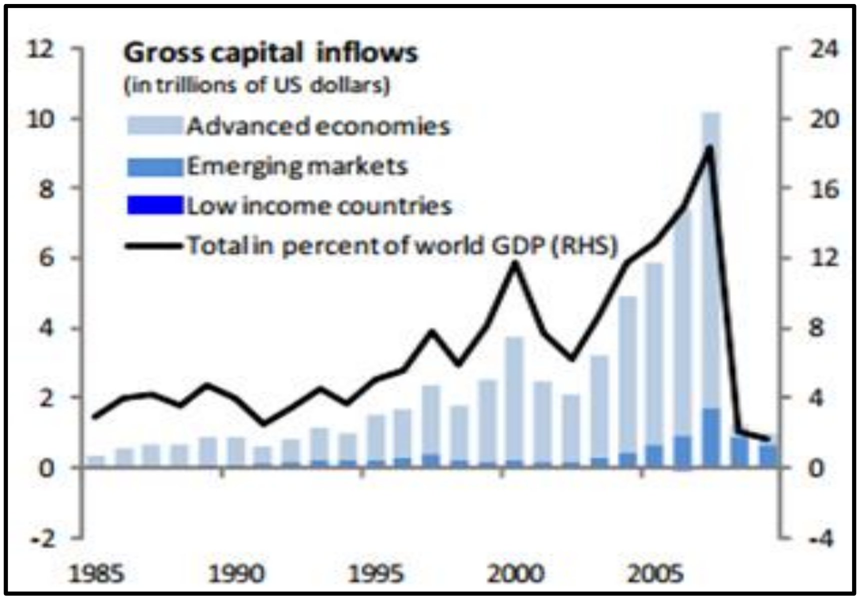
[1]

Appendix 1.1 – Trends in Trade and Financial Openness in Advanced and Emerging Economies*



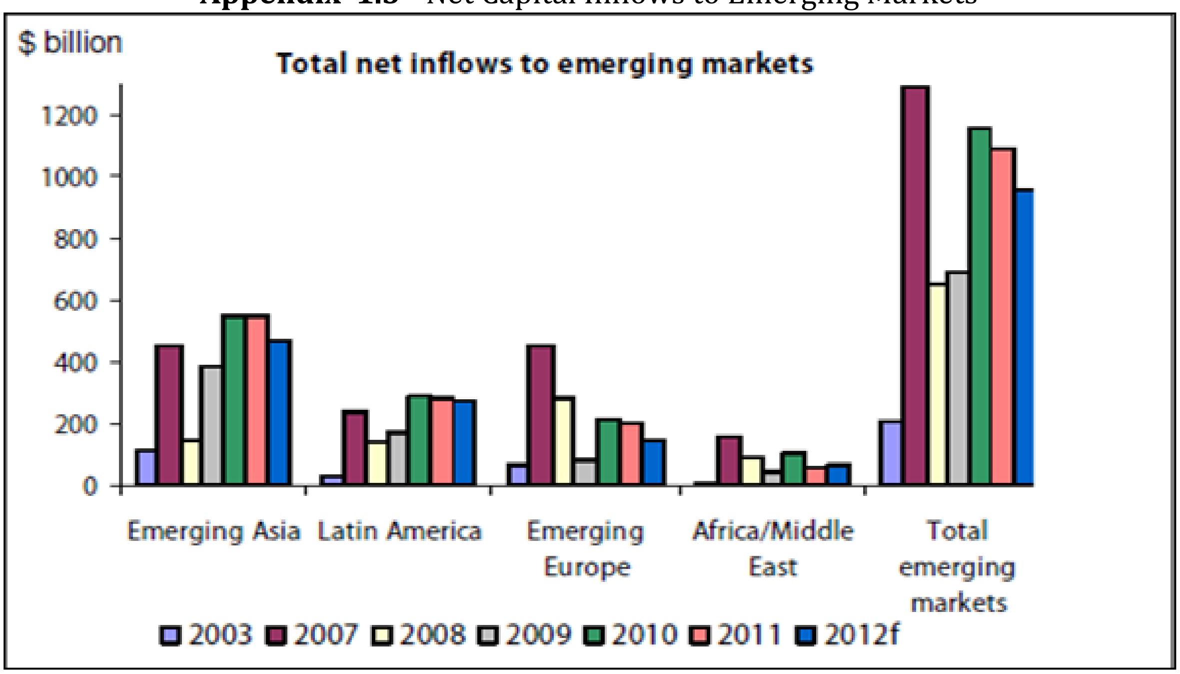
Source: IMF Staff Paper, 2011
Note: *Percentage of GDP
1 Trade openness = sum of imports and exports as a share of GDP.
2 Financial Openness = sum of external assets and liabilities as a share of GDP

Appendix 1.2 – Trends in Gross Capital Inflows in Advanced, Emerging and Low Income Countries



Source: IMF Staff Paper, 2011

Appendix 1.3 - Net Capital Inflows to Emerging Markets



Source: Institute of International Finance, 2012

Appendix 1.4 – Frontier Markets According To MSCI Classification 2012

Americas	Europe and CIS	Africa	Middle East	Asia
Argentina	Bosnia	Botswana	Bahrain	Bangladesh
Jamaica	Herzegovina	Ghana	Jordan	Pakistan
Trinidad and Tobago	Bulgaria	Kenya	Kuwait	Sri Lanka
	Croatia	Mauritius	Lebanon	Vietnam
	Estonia	Morocco	Oman	
	Lithuania	Nigeria	Palestine	
	Kazakhstan	Tunisia	Qatar*	
	Romania	Zimbabwe	UAE*	
	Serbia		Saudi Arabia	
	Slovenia			
	Ukraine			

*Markets upgraded to Emerging Markets status in December 2013

Source: MSCI Country Classification, 2014.

Appendix 1.5 – Market Capitalization of Frontier Markets in 2011 and 2012 (US$)

	2011	2012
Americas		
Argentina	43,579,790,892	34,240,748,272
Jamaica	7,222,699,225	6,390,478,767
Trinidad and Tobago	14,725,159,963	15,165,384,376
Europe and CIS		
Bosnia		
Herzegovinia		
Bulgaria	8,253,157,432	6,666,184,921
Croatia	21,795,617,088	21,559,647,510
Estonia	1,611,200,985	2,331,962,196
Lithuania	4,075,273,250	3,963,704,823
Kazakhstan	43,301,480,000	23,495,736,863
Romania	21,196,718,000	15,925,220,857
Serbia	8,364,824,600	7,450,560,827
Slovenia	6,325,641,677	6,474,886,528
Ukraine	25,558,277,154	20,711,371,700
Africa		
Botswana	4,106,891,988	4,587,518,585
Ghana	3,096,953,399	3,464,538,689
Kenya	10,202,603,924	14,790,720,930
Mauritius	7,666,703,680	7,092,931,403
Morocco	60,088,236,612	52,633,705,236
Nigeria	39,269,936,739	56,389,263,863
Tunisia	9,661,719,481	8,886,882,497
Zimbabwe	10,902,845,012	11,816,165,408
Middle East		
Bahrain	17,152,201,592	16,064,898,555
Jordan	27,183,014,566	26,998,000,000
Kuwait	100,869,323,281	97,091,394,02
Lebanon	10,163,607,439	10,295,670,315
Oman	19,719,430,528	20,107,206,856
Palestine	2,532,469,900	2,634,100,000
Qatar*	125,412,934,586	126,371,321,066
UAE*	71,326,900,000	67,950,505,023
Saudi Arabia	338,873,294,908	373,379,732,299
Asia		
Bangladesh	23,546,000,000	17,479,193,048
Pakistan	32,763,702,675	43,676,289,972
Sri Lanka	19,437,000,000	17,045,987,443
Vietnam	18,316,217,137	32,933,061,036
Total Market Capitalization	1,158,301,827,713	1,078,973,579,864

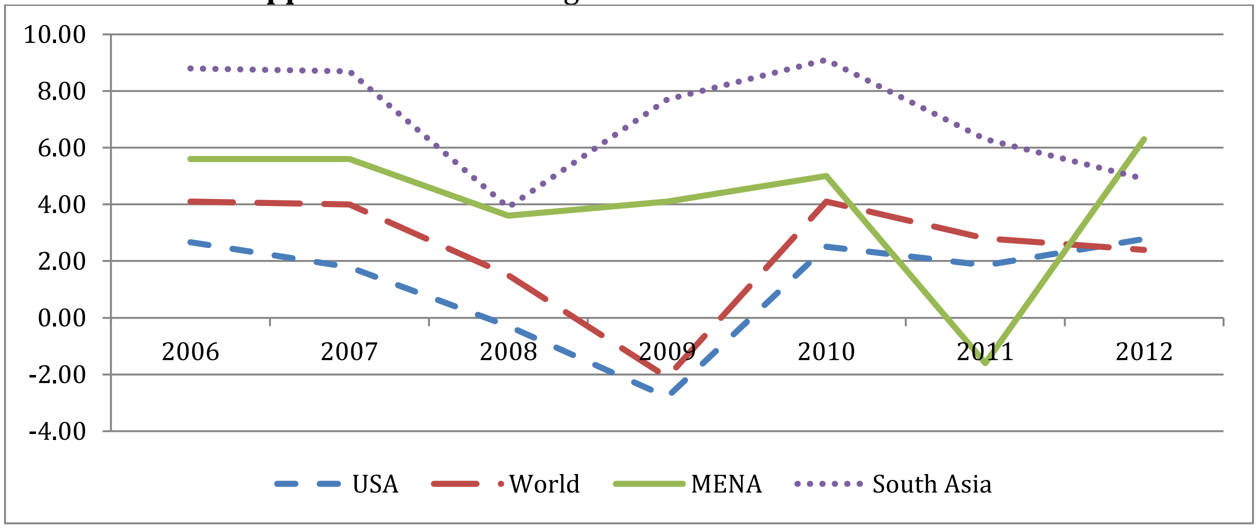
Source: World Bank Indicators, 2014.

Appendix 1.6 – GDP Growth Rate of Frontier Markets 2006-2012

	2006	2007	2008	2009	2010	2011	2012	Average
Americas								
Argentina	8.36	8.00	3.10	0.05	9.14	8.55	0.95	5.45
Jamaica		1.40	-0.71	-4.41	-1.48	1.70	0.72	-0.46
Trinidad and Tobago	13.74	4.75	3.39	-4.39	0.21	-1.60	1.52	2.52
Europe and CIS								
Bosnia and Herzegovinia	6.20	6.84	5.42	-2.91	0.70	1.30	-0.70	2.41
Bulgaria	6.50	6.40	6.20	-5.50	0.40	1.80	0.60	2.34
Croatia	4.94	5.06	2.08	-6.95	-2.27	-0.23	-1.87	0.11
Estonia	10.10	7.49	-4.15	-14.10	2.56	9.56	3.94	2.20
Lithuania	7.84	9.84	2.93	-14.74	1.33	6.00	3.70	2.41
Kazakhstan	10.70	8.90	3.30	1.20	7.30	7.50	5.00	6.27
Romania	8.72	6.26	7.86	-6.80	-0.94	2.31	0.35	2.54
Serbia	3.60	5.40	3.80	-3.51	1.01	1.57	-1.52	1.48
Slovenia	5.85	6.96	3.38	-7.94	1.26	0.71	-2.54	1.10
Ukraine	7.30	7.90	2.30	-14.80	4.20	5.20	0.20	1.76
Africa								
Botswana	7.96	8.68	3.90	-7.84	8.59	6.18	4.26	4.53
Ghana	6.40	6.46	8.43	3.99	8.01	15.01	8.79	8.16
Kenya	6.33	6.99	1.53	2.74	5.80	4.42	4.55	4.62
Mauritius	3.95	5.89	5.51	3.01	4.11	3.85	3.23	4.22
Morocco	7.76	2.71	5.59	4.76	3.64	4.99	2.69	4.59
Nigeria	8.21	6.83	6.27	6.93	7.84	4.89	4.28	6.46
Tunisia	5.65	6.22	4.74	3.61	3.61	-0.23	4.09	3.96
Zimbabwe	-3.46	-3.65	-17.67	5.98	11.38	11.91	5.32	1.40
Middle East								
Bahrain	6.47	8.29	6.24	2.55	4.34	2.10	3.40	4.77
Jordan	8.12	8.18	7.23	5.48	2.34	2.56	2.65	5.22
Kuwait	7.52	5.99	2.48	-7.08	-2.37	6.30	6.19	2.72
Lebanon	1.60	9.40	9.10	10.30	8.00	2.00	2.20	6.09
Oman	5.50	6.80	12.80	1.10	5.60	4.49	4.99	5.90
Palestine								
Qatar	26.17	17.99	17.66	11.96	16.73	14.79	2.56	15.41
UAE	9.84	3.18	3.19	-4.80	1.67	3.88	4.37	3.05
Saudi Arabia	5.58	5.99	8.43	1.83	7.43	8.57	5.81	6.23
Asia								
Bangladesh	6.63	6.43	6.19	5.74	6.07	6.71	6.23	6.29
Pakistan	6.18	4.83	1.70	2.83	1.61	2.79	4.02	3.42
Sri Lanka	7.67	6.80	5.95	3.54	8.02	8.25	6.34	6.65
Vietnam	6.98	7.13	5.66	5.40	6.42	6.24	5.25	6.15

Source: World Bank Indicators, 2014.

Appendix 1.7 – Average GDP Growth Rates 2006-2012



Source: World Bank Indicators, 2014

Appendix 1.8 – Corruption Perception Index of Frontier Markets in 2013

	Rank	Score			Rank	Score
Americas				**Middle East**		
Argentina	106	34		Bahrain	57	48
Jamaica	83	38		Jordan	66	45
Trinidad and Tobago	83	38		Kuwait	69	43
Europe and CIS				Lebanon	127	28
Bosnia	Not Available	Not Available		Oman	61	47
Bulgaria	77	41		Palestine	-	-
Croatia	57	48		Qatar*	28	68
Estonia	28	68		UAE*	26	69
Lithuania	43	57		Saudi Arabia	63	46
Kazakhstan	140	26		**Asia**		
Romania	69	43		Bangladesh	136	27
Serbia	72	42		Pakistan	127	28
Slovenia	43	57		Sri Lanka	91	37
Ukraine	144	25		Vietnam	116	31
Africa						
Botswana	30	64				
Ghana	63	46				
Kenya	136	27				
Mauritius	52	52				
Morocco	91	37				
Nigeria	144	25				
Tunisia	77	41				
Zimbabwe	157	21				

Source: Transparency International, 2013.

Appendix 5.1 - Descriptive Statistics for Returns in Pre-crisis, Crisis and Post-crisis

5.1a - Pre-crisis period: 1 January 2006 to 14 September 2008

	Observations	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Developed Markets									
USA	986	-0.0014	4.1535	-3.5343	0.8329	-0.2865	7.0747	695.5868	0.0000
UK	986	-0.0037	4.6416	-5.6374	0.9345	-0.2342	7.5975	877.4102	0.0000
Germany	986	0.0136	5.7610	-7.4335	0.9547	-0.6672	9.9019	2030.2230	0.0000
Japan	986	-0.0296	4.1823	-5.8157	1.1492	-0.4295	6.0962	424.1644	0.0000
Singpore	986	0.0121	5.9811	-6.2165	1.0658	-0.3291	7.4910	846.4232	0.0000
Emerging Markets									
China	986	0.0591	8.8874	-9.2561	1.7616	-0.6985	7.7423	1004.1160	0.0000
Malaysia	986	0.0159	4.2587	-9.9785	0.8188	-2.2617	29.4346	29549.1100	0.0000
India	986	0.0405	6.6670	-7.6957	1.5157	-0.2931	6.9768	663.8619	0.0000
Frontier Markets									
Pakistan	986	-0.0045	8.2547	-6.0418	1.3273	-0.4725	7.6869	939.1675	0.0000
Saudi Arabia	986	-0.0805	9.3907	-10.0986	1.9201	-0.9720	9.5548	1920.4240	0.0000
UAE	986	-0.0296	8.2500	-8.6484	1.1300	-0.1953	14.5713	5507.1420	0.0000
Kuwait	986	0.0115	5.0469	-3.7365	0.6625	-0.5640	11.5975	3089.0210	0.0000

5.1b - Crisis period: 15 September 2008-26 October 2009

	Observations	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Developed Markets									
USA	404	-0.0395	10.9572	-9.4695	2.2048	-0.0297	7.9721	416.2083	0.0000
UK	404	-0.0105	9.3843	-9.2656	1.9119	-0.0006	9.3633	681.6141	0.0000
Germany	404	-0.0247	10.7975	-7.3355	2.0883	0.4594	8.8221	584.8133	0.0000
Japan	404	-0.0407	13.2346	-12.1110	2.3346	-0.4208	10.3538	922.2533	0.0000
Singpore	404	0.0137	7.5305	-8.6960	1.8656	-0.0391	6.7046	231.1273	0.0000
Emerging Markets									
China	404	0.0996	9.0345	-6.9829	1.8910	-0.0324	6.5547	212.7727	0.0000
Malaysia	404	0.0465	4.0551	-3.6807	0.8864	0.0155	6.9755	266.0651	0.0000
India	404	0.0442	15.9900	-11.6044	2.2828	0.4858	11.1985	1147.3400	0.0000
Frontier Markets									
Pakistan	404	0.0032	5.3012	-5.1349	1.4759	-0.2427	5.5500	113.4226	0.0000
Saudi Arabia	404	-0.0414	9.0874	-10.3285	2.0567	-0.5979	9.5513	746.5444	0.0000
UAE	404	-0.0531	7.2588	-6.6477	1.5632	-0.2779	7.5143	348.2420	0.0000
Kuwait	404	-0.1347	3.8026	-3.8745	1.0428	-0.4947	5.5760	128.1812	0.0000

5.1c – Post-crisis period: 27 October 2009-31 December 2012

	Observations	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
USA	1154	0.0251	4.6317	-6.8958	0.9655	-0.4814	9.5291	2096.1180	0.0000
UK	1154	0.0110	5.0323	-5.0474	0.9422	-0.2838	7.2214	873.1160	0.0000
Germany	1154	0.0259	5.2104	-5.9947	1.1814	-0.2156	7.2953	896.8465	0.0000
Japan	1154	0.0003	5.5223	-11.1534	1.0686	-1.0907	15.4353	7670.9030	0.0000
Singpore	1154	0.0133	3.2896	-4.0873	0.7638	-0.4885	6.8807	770.6957	0.0000
China	1154	-0.0273	4.2336	-5.2941	1.0331	-0.3818	6.6118	655.8752	0.0000
Malaysia	1154	0.0250	2.4037	-2.5311	0.4732	-0.4521	7.1685	875.5687	0.0000
India	1154	0.0129	3.5181	-4.2129	0.9213	0.0744	5.0562	204.5321	0.0000
Pakistan	1154	0.0511	3.0694	-4.0578	0.7666	-0.2312	7.0974	818.2325	0.0000
Saudi Arabia	1154	0.0031	7.0115	-7.0220	0.8545	-1.3320	23.8461	21254.7300	0.0000
UAE	1154	-0.0161	11.9944	-12.3128	0.7254	-0.7309	139.7788	900447.0000	0.0000
Kuwait	1154	-0.0197	1.7486	-3.1023	0.4886	-1.3972	10.5901	3148.2080	0.0000

Appendix 5.2 - Descriptive Statistics for Volatility in Pre-crisis, Crisis and Post-crisis

5.2a - Pre-crisis period: 1 January 2006 to 14 September 2008

	Observations	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Developed Markets									
USA	986	0.0820	0.3651	0.0172	0.0489	1.4102	5.3485	553.3966	0.0000
UK	986	0.0959	0.5471	0.0000	0.0568	2.1772	12.2808	4317.6030	0.0000
Germany	986	0.0957	0.5205	0.0239	0.0523	2.2617	14.6062	6374.7260	0.0000
Japan	986	0.0947	0.3526	0.0211	0.0500	1.4162	6.0737	717.7198	0.0000
Singpore	986	0.0238	0.5019	0.0000	0.0529	2.9113	15.0496	7357.8290	0.0000
Emerging Markets									
China	986	0.1775	0.7014	0.0344	0.0988	1.5273	6.1779	798.2222	0.0000
Malaysia	986	0.0658	0.4897	0.0199	0.0447	4.2532	32.6133	39000.6000	0.0000
India	986	0.1429	0.8668	0.0044	0.0919	2.2494	12.1515	4272.2610	0.0000
Frontier Markets									
Pakistan	986	0.1202	0.5385	0.0000	0.0790	1.4103	4.8952	474.4099	0.0000
Saudi Arabia	986	0.1115	0.8097	0.0000	0.1559	1.9092	6.8103	1195.4740	0.0000
UAE	986	0.0790	0.4949	0.0124	0.0567	2.3679	11.2885	3743.7930	0.0000
Kuwait	986	0.1117	1.0007	0.0038	0.1092	3.8607	25.1654	22633.8500	0.0000

5.2b - Crisis period: 15 September 2008-26 October 2009

	Observations	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Developed Markets									
USA	404	0.1959	0.7520	0.0468	0.1361	1.8456	6.8366	477.1435	0.0000
UK	404	0.1887	0.7417	0.0491	0.1254	2.1285	8.3813	792.5249	0.0000
Germany	404	0.2040	0.7684	0.0542	0.1154	1.7124	6.7070	428.7751	0.0000
Japan	404	0.1638	0.8099	0.0334	0.1322	2.4599	9.6383	1149.2280	0.0000
Singpore	404	0.1616	0.8476	0.0000	0.1169	2.2266	9.0024	940.2866	0.0000
Emerging Markets									
China	404	0.1813	0.5826	0.0643	0.0892	1.4392	5.5978	253.0589	0.0000
Malaysia	404	0.0675	0.3066	0.0000	0.0594	1.0999	4.7999	135.9883	0.0000
India	404	0.2091	0.8757	0.0518	0.1233	2.2232	10.0917	1179.3820	0.0000
Frontier Markets									
Pakistan	404	0.1343	0.4549	0.0000	0.0983	0.3340	2.5134	11.4970	0.0032
Saudi Arabia	404	0.1846	0.7149	0.0382	0.1378	1.7926	5.8529	353.3634	0.0000
UAE	404	0.1193	0.4955	0.0217	0.0795	1.8416	7.0288	501.5770	0.0000
Kuwait	404	0.3141	1.3923	0.0093	0.2780	1.2965	4.3836	145.4031	0.0000

5.2c – Post-crisis period: 27 October 2009-31 December 2012

	Observations	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Developed Markets									
USA	1154	0.0906	0.6291	0.0197	0.0566	2.4250	14.6793	7696.5910	0.0000
UK	1154	0.1004	0.5325	0.0212	0.0549	1.8856	9.3185	2605.7470	0.0000
Germany	1154	0.1180	0.6406	0.0160	0.0711	2.0017	10.0079	3134.7920	0.0000
Japan	1154	0.0752	0.9492	0.0163	0.0453	7.2873	125.1688	728498.7000	0.0000
Singpore	1154	0.0640	0.2592	0.0150	0.0321	2.0939	9.7047	3007.3490	0.0000
Emerging Markets									
China	1154	0.1057	0.3942	0.0345	0.0531	1.7767	6.8644	1326.3310	0.0000
Malaysia	1154	0.0450	0.3705	0.0000	0.0314	4.6768	40.9097	73373.1300	0.0000
India	1154	0.1005	0.4003	0.0296	0.0490	1.4448	6.7570	1081.1260	0.0000
Frontier Markets									
Pakistan	1154	0.0839	0.2848	0.0202	0.0434	1.6235	6.5399	1110.4050	0.0000
Saudi Arabia	1154	0.0729	0.6680	0.0198	0.0574	4.0630	27.6407	32397.5400	0.0000
UAE	1154	0.0447	0.5172	0.0000	0.0423	5.9493	52.1177	122917.3000	0.0000
Kuwait	1154	0.1066	0.6633	0.0043	0.0942	1.9211	7.5050	1687.1240	0.0000

Appendix 5.3 – Correlation Coefficients in Pre-crisis, Crisis and Post-crisis

5.3a - Pre-crisis period: 1 January 2006 to 14 September 2008

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	SAUDI ARABIA	UAE	KUWAIT
PAKISTAN	1.0000											
Developed Markets												
USA	0.0564	1.0000										
UK	0.0758 *	0.4683 **	1.0000									
GERMANY	0.0654 *	0.4770 **	0.8528 **	1.0000								
JAPAN	0.1261 **	0.0899 **	0.3083 **	0.3186 **	1.0000							
SINGAPORE	0.1449 **	0.1225 **	0.4443 **	0.3738 **	0.6342 **	1.0000						
Emerging Markets												
CHINA	0.0289	-0.0275	0.0727 *	0.0734 *	0.2347 **	0.2615 **	1.0000					
MALAYSIA	0.1527 **	0.0599	0.2674 **	0.2643 **	0.4483 **	0.5668 **	0.2527 **	1.0000				
INDIA	0.1755 **	0.0932 **	0.3841 **	0.3483 **	0.4660 **	0.5731 **	0.1936 **	0.3918 **	1.0000			
Frontier Markets												
SAUDI ARABIA	0.0658 *	0.0112	0.0184	0.0329	0.0981 **	0.0594	0.0582	0.0593	0.0161	1.0000		
UAE	0.0839 **	0.0006	0.0092	-0.0148	0.1214 **	0.0978 **	0.0807 *	0.0814 *	0.0816 **	0.1471 **	1.0000	
KUWAIT	0.0620	0.0291	0.0331	0.0152	0.0781 *	0.0466	0.0224	0.0584	0.0262 **	0.1296 **	0.2730 **	1.0000

5.3b - Crisis period: 15 September 2008-26 October 2009

	PAKISTAN	USA	UK	GERMANY	JAPAN	SINGAPORE	CHINA	MALAYSIA	INDIA	SAUDI ARABIA	UAE	KUWAIT
PAKISTAN	1.0000											
Developed Markets												
USA	0.0080	1.0000										
UK	0.0189	0.5883 **	1.0000									
GERMANY	0.0353	0.6867 **	0.8793 **	1.0000								
JAPAN	0.0462	0.1395 **	0.4361 **	0.3841 **	1.0000							
SINGAPORE	0.0682	0.3418 **	0.4860 **	0.4884 **	0.5768 **	1.0000						
Emerging Markets												
CHINA	0.1266 *	0.1194 *	0.2065 **	0.2151 **	0.3474 **	0.4014 **	1.0000					
MALAYSIA	0.0946	0.2431 **	0.4566 **	0.4275 **	0.5881 **	0.6409 **	0.4135 **	1.0000				
INDIA	0.0702	0.3980 **	0.5028 **	0.4775 **	0.3518 **	0.6199 **	0.2908 **	0.4943 **	1.0000			
Frontier Markets												
SAUDI ARABIA	0.0043	0.2232 **	0.2755 **	0.3076 **	0.2254 **	0.2500 **	0.1556 **	0.1850 **	0.2266 **	1.0000		
UAE	0.1491 **	0.1381 **	0.2755 **	0.2520 **	0.3867 **	0.4001 **	0.1980 **	0.3656 **	0.3186 **	0.2913 **	1.0000	
KUWAIT	0.1570 **	-0.0055	0.0947	0.0992 *	0.1951 **	0.2015 **	0.1263 *	0.1763 **	0.1941 **	0.1425 **	0.3998 **	1.0000

5.3c – Post-crisis period: 27 October 2009-31 December 2012

	Pakistan	USA	UK	Germany	Japan	Singpore	China	Malaysia	India	Saudi Arabia	UAE	Kuwait
Pakistan	1.0000											
Developed Markets												
USA	-0.0186	1.0000										
UK	0.0562	0.6826 **	1.0000									
Germany	0.0444	0.7117 **	0.8803 **	1.0000								
Japan	0.1788 **	0.1535 **	0.2575 **	0.2577 **	1.0000							
Singpore	0.1625 **	0.3007 **	0.5082 **	0.4718 **	0.5343 **	1.0000						
Emerging Markets												
China	0.1017 **	0.1375 **	0.2382 **	0.1984 **	0.3261 **	0.3714 **	1.0000					
Malaysia	0.1723 **	0.0738 *	0.2397 **	0.1904 **	0.3809 **	0.4624 **	0.2385 **	1.0000				
India	0.1345 **	0.2634 **	0.4294 **	0.4008 **	0.3040 **	0.5476 **	0.2651 **	0.3004 **	1.0000			
Frontier Markets												
Saudi Arabia	0.0526	0.1128 **	0.1945 **	0.1813 **	0.1338 **	0.1702 **	0.0866 **	0.1274 **	0.1097 **	1.0000		
UAE	0.1882 **	0.0226	0.0550	0.0522	0.1274 **	0.1176 **	0.1054 **	0.1143 **	0.0646 *	0.1629 **	1.0000	
Kuwait	0.1153 **	0.0258	0.0502	0.0385	0.0599 *	0.0642 *	0.0181	0.0930 **	0.0359	0.1596 **	0.2404 **	1.0000

Appendix 5.4 – Results of Augmented Dickey Fuller Test for All Lags

	USA			UK			GERMANY			JAPAN		
Lags	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**
0	-56.2791	0.0001	3.2121	-51.6227	0.0001	3.1210	-49.3891	0.0001	3.3611	-51.6967	0.0001	3.4820
2	-28.9133	0.0000	3.2179	-31.0115	0.0000	3.1247	-29.6526	0.0000	3.3672	-30.3818	0.0000	3.4877
5	-21.6329	0.0000	3.2214	-21.2869	0.0000	3.1299	-21.2279	0.0000	3.3763	-20.9996	0.0000	3.4945
7	-18.4241	0.0000	3.2276	-19.7283	0.0000	3.1334	-18.7026	0.0000	3.3824	-18.5231	0.0000	3.4996
10	-16.3747	0.0000	3.2358	-16.5069	0.0000	3.1391	-16.3032	0.0000	3.3895	-15.7560	0.0000	3.5085
15	-12.4043	0.0000	3.2490	-12.8024	0.0000	3.1546	-12.1852	0.0000	3.3996	-11.7753	0.0000	3.5121
30	-9.2674	0.0000	3.2883	-9.9230	0.0000	3.1933	-9.1751	0.0000	3.4336	-8.8875	0.0000	3.5525

	SINGAPORE			CHINA			MALAYSIA			INDIA		
Lags	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**
0	-49.3902	0.0001	3.0714	-53.8415	0.0001	3.6531	-46.1890	0.0001	2.1147	-49.5918	0.0001	3.5857
2	-29.1384	0.0000	3.0757	-27.4422	0.0000	3.6530	-28.1828	0.0000	2.1205	-29.2671	0.0000	3.5924
5	-20.3278	0.0000	3.0845	-18.4058	0.0000	3.6600	-18.6836	0.0000	2.1259	-20.0886	0.0000	3.6020
7	-18.3535	0.0000	3.0892	-17.1050	0.0000	3.6653	-17.2335	0.0000	2.1315	-18.7505	0.0000	3.6056
10	-14.6900	0.0000	3.0983	-14.4448	0.0000	3.6751	-14.6637	0.0000	2.1416	-16.0507	0.0000	3.6158
15	-11.6941	0.0000	3.1118	-11.7942	0.0000	3.6900	-11.8813	0.0000	2.1571	-11.7990	0.0000	3.6229
30	-7.8537	0.0000	3.1494	-7.9447	0.0000	3.7336	-8.2879	0.0000	2.2003	-8.5049	0.0000	3.6657

	PAKISTAN			UAE			SAUDI ARABIA			KUWAIT		
Lags	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**	**t-Statistic**	**Prob.***	**SIC**
0	-47.3227	0.0001	3.0982	-44.3185	0.0001	2.9416	-47.7553	0.0001	3.7295	-43.0717	0.0000	2.0278
2	-25.5331	0.0000	3.0969	-26.7325	0.0000	2.9446	-27.5791	0.0000	3.7303	-24.8340	0.0000	2.0249
5	-18.6569	0.0000	3.1049	-20.0185	0.0000	2.9526	-18.7619	0.0000	3.7386	-17.9572	0.0000	2.0327
7	-16.5333	0.0000	3.1115	-20.0185	0.0000	2.9595	-18.2890	0.0000	3.7401	-15.0301	0.0000	2.0358
10	-14.1758	0.0000	3.1215	-14.4845	0.0000	2.9629	-15.2147	0.0000	3.7504	-12.5868	0.0000	2.0449
15	-10.9394	0.0000	3.1269	-13.2276	0.0000	2.9745	-12.7401	0.0000	3.7631	-9.8114	0.0000	2.0535
30	-7.2161	0.0000	3.1687	-7.7994	0.0000	3.0007	-8.6591	0.0000	3.7993	-7.5829	0.0000	2.0773

Appendix 5.5 - USA Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

USA								
GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	8.8262	0.0000	C	6.6538	0.0000	C	5.5487	0.0000
RESID(-1)^2	14.4695	0.0000	RESID(-1)^2	8.9034	0.0000	RESID(-1)^2	15.2055	0.0000
GARCH(-1)	196.2125	0.0000	GARCH(-1)	58.7775	0.0000	GARCH(-1)	42.7881	0.0000
CRISIS	1.5266	0.1269	GARCH(-2)	-28.1453	0.0000	GARCH(-2)	-26.4918	0.0000
			CRISIS	2.3401	0.0193	GARCH(-3)	30.2770	0.0000
						CRISIS	1.8491	0.0644
SIC		2.6770	SIC		2.6689	SIC		2.6771
Durbin-Watson stat		2.2192	Durbin-Watson stat		2.2192	Durbin-Watson stat		2.2192
GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	8.7891	0.0000	C	8.7180	0.0000	C	8.8145	0.0000
RESID(-1)^2	2.8601	0.0042	RESID(-1)^2	3.0698	0.0021	RESID(-1)^2	8.9534	0.0000
RESID(-2)^2	2.2083	0.0272	RESID(-2)^2	10.3734	0.0000	RESID(-2)^2	14.5017	0.0000
GARCH(-1)	185.1926	0.0000	GARCH(-1)	1.7704	0.0767	GARCH(-1)	-15.3295	0.0000
CRISIS	1.5333	0.1252	GARCH(-2)	8.5550	0.0000	GARCH(-2)	31.9153	0.0000
			CRISIS	1.7476	0.0805	GARCH(-3)	17.2827	0.0000
						CRISIS	2.1097	0.0349
SIC		2.6794	SIC		2.6792	SIC		2.6753
Durbin-Watson stat		2.2192	Durbin-Watson stat		2.21925	Durbin-Watson stat		2.2192
GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	8.5376	0.0000	C	7.8241	0.0000	C	8.1354	0.0000
RESID(-1)^2	2.8482	0.0044	RESID(-1)^2	3.7094	0.0002	RESID(-1)^2	5.2983	0.0000
RESID(-2)^2	0.8116	0.4170	RESID(-2)^2	8.6059	0.0000	RESID(-2)^2	14.1449	0.0000
RESID(-3)^2	2.0299	0.0424	RESID(-3)^2	-2.4787	0.0132	RESID(-3)^2	1.6779	0.0934
GARCH(-1)	165.9250	0.0000	GARCH(-1)	2.5683	0.0102	GARCH(-1)	-13.0253	0.0000
CRISIS	1.5217	0.1281	GARCH(-2)	8.2414	0.0000	GARCH(-2)	36.9104	0.0000
			CRISIS	1.9390	0.0525	GARCH(-3)	18.9769	0.0000
						CRISIS	2.0515	0.0402
SIC		2.6820	SIC		2.6810	SIC		2.6778
Durbin-Watson stat		2.2192	Durbin-Watson stat		2.2192	Durbin-Watson stat		2.2192

Appendix 5.6 - UK Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

UK

GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	5.3310	0.0000	C	4.3291	0.0000	C	5.5487	0.0000
RESID(-1)^2	14.1622	0.0000	RESID(-1)^2	6.3234	0.0000	RESID(-1)^2	15.2055	0.0000
GARCH(-1)	197.6246	0.0000	GARCH(-1)	3.0618	0.0022	GARCH(-1)	42.7881	0.0000
CRISIS	1.3629	0.1729	GARCH(-2)	1.7975	0.0723	GARCH(-2)	-26.4918	0.0000
			CRISIS	1.3611	0.1735	GARCH(-3)	30.2770	0.0000
						CRISIS	1.8491	0.0644
SIC		2.7332	SIC		2.7359	SIC		2.7296
Durbin-Watson stat		2.0472	Durbin-Watson stat		2.0472	Durbin-Watson stat		2.0472

GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	5.1353	0.0000	C	4.4537	0.0000	C	4.9305	0.0000
RESID(-1)^2	4.8080	0.0000	RESID(-1)^2	6.0315	0.0000	RESID(-1)^2	8.4952	0.0000
RESID(-2)^2	-1.0441	0.2964	RESID(-2)^2	1.4674	0.1423	RESID(-2)^2	-1.4205	0.1555
GARCH(-1)	199.6745	0.0000	GARCH(-1)	0.7763	0.4376	GARCH(-1)	34.9824	0.0000
CRISIS	1.3818	0.1670	GARCH(-2)	4.0112	0.0001	GARCH(-2)	-24.2739	0.0000
			CRISIS	1.3476	0.1778	GARCH(-3)	21.0282	0.0000
						CRISIS	1.8570	0.0633
SIC		2.7360	SIC		2.7387	SIC		2.7324
Durbin-Watson stat		2.0472	Durbin-Watson stat		2.0472	Durbin-Watson stat		2.0472

GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	5.0606	0.0000	C	4.4087	0.0000	C	4.3282	0.0000
RESID(-1)^2	4.9174	0.0000	RESID(-1)^2	4.8748	0.0000	RESID(-1)^2	13.9285	0.0000
RESID(-2)^2	-1.9006	0.0573	RESID(-2)^2	1.2391	0.2153	RESID(-2)^2	-16.0544	0.0000
RESID(-3)^2	1.7919	0.0732	RESID(-3)^2	-0.1450	0.8847	RESID(-3)^2	20.5628	0.0000
GARCH(-1)	177.0309	0.0000	GARCH(-1)	0.5863	0.5577	GARCH(-1)	338.3518	0.0000
CRISIS	1.3965	0.1626	GARCH(-2)	3.2850	0.0010	GARCH(-2)	-194.0634	0.0000
			CRISIS	1.3424	0.1795	GARCH(-3)	143.3919	0.0000
						CRISIS	2.7404	0.0061
SIC		2.7385	SIC		2.7418	SIC		2.6032
Durbin-Watson stat		2.0472	Durbin-Watson stat		2.0472	Durbin-Watson stat		2.0472

Appendix 5.7 - Germany Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

GERMANY

GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	6.8968	0.0000	C	4.4764	0.0000	C	7.0634	0.0000
RESID(-1)^2	12.8057	0.0000	RESID(-1)^2	5.0904	0.0000	RESID(-1)^2	13.8218	0.0000
GARCH(-1)	149.1218	0.0000	GARCH(-1)	15.3048	0.0000	GARCH(-1)	40.1442	0.0000
CRISIS	2.8913	0.0038	GARCH(-2)	-6.0938	0.0000	GARCH(-2)	-23.0673	0.0000
			CRISIS	2.7700	0.0056	GARCH(-3)	24.0189	0.0000
						CRISIS	2.9044	0.0037
SIC		3.0274	SIC		3.0279	SIC		3.0247
Durbin-Watson stat		1.9589	Durbin-Watson stat		1.9589	Durbin-Watson stat		1.9589

GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	7.1190	0.0000	C	2.9363	0.0033	C	7.4701	0.0000
RESID(-1)^2	1.8064	0.0709	RESID(-1)^2	2.1366	0.0326	RESID(-1)^2	1.4208	0.1554
RESID(-2)^2	4.0004	0.0001	RESID(-2)^2	0.6777	0.4980	RESID(-2)^2	10.4132	0.0000
GARCH(-1)	129.7688	0.0000	GARCH(-1)	8.4745	0.0000	GARCH(-1)	42.9430	0.0000
CRISIS	2.8587	0.0043	GARCH(-2)	-3.2295	0.0012	GARCH(-2)	-30.0814	0.0000
			CRISIS	2.3293	0.0198	GARCH(-3)	40.4971	0.0000
						CRISIS	2.6537	0.0080
SIC		3.0283	SIC		3.0308	SIC		3.0199
Durbin-Watson stat		1.9589	Durbin-Watson stat		1.9589	Durbin-Watson stat		1.9589

GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	7.1149	0.0000	C	7.0591	0.0000	C	5.8749	0.0000
RESID(-1)^2	1.7997	0.0719	RESID(-1)^2	1.8285	0.0675	RESID(-1)^2	1.8084	0.0705
RESID(-2)^2	2.5808	0.0099	RESID(-2)^2	8.8322	0.0000	RESID(-2)^2	6.1429	0.0000
RESID(-3)^2	0.2639	0.7918	RESID(-3)^2	4.3287	0.0000	RESID(-3)^2	7.6616	0.0000
GARCH(-1)	126.1242	0.0000	GARCH(-1)	-6.6184	0.0000	GARCH(-1)	-2.7637	0.0057
CRISIS	2.8601	0.0042	GARCH(-2)	85.0555	0.0000	GARCH(-2)	6.1286	0.0000
			CRISIS	3.0525	0.0023	GARCH(-3)	4.4316	0.0000
						CRISIS	2.9184	0.0035
SIC		3.0314	SIC		3.0315	SIC		3.0349
Durbin-Watson stat		1.9589	Durbin-Watson stat		1.9589	Durbin-Watson stat		1.9589

Note: CRISIS variable is significant at 2%, 5% and 10% significance levels

Appendix 5.8 - Japan Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

JAPAN

GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	7.1523	0.0000	C	6.4691	0.0000	C	7.8057	0.0000
RESID(-1)^2	16.3943	0.0000	RESID(-1)^2	11.3393	0.0000	RESID(-1)^2	17.2275	0.0000
GARCH(-1)	125.0323	0.0000	GARCH(-1)	5.9273	0.0000	GARCH(-1)	51.3280	0.0000
CRISIS	2.6782	0.0074	GARCH(-2)	1.4835	0.1379	GARCH(-2)	-29.2869	0.0000
			CRISIS	2.6448	0.0082	GARCH(-3)	28.4505	0.0000
						CRISIS	2.5639	0.0103
SIC		3.1229	SIC		3.1257	SIC		3.1219
Durbin-Watson stat		2.0501	Durbin-Watson stat		2.0501	Durbin-Watson stat		2.0501

GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	6.6479	0.0000	C	7.3118	0.0000	C	7.1289	0.0000
RESID(-1)^2	11.1109	0.0000	RESID(-1)^2	24.1731	0.0000	RESID(-1)^2	12.7703	0.0000
RESID(-2)^2	-1.4741	0.1404	RESID(-2)^2	25.2001	0.0000	RESID(-2)^2	-3.1873	0.0014
GARCH(-1)	102.8906	0.0000	GARCH(-1)	-18.3165	0.0000	GARCH(-1)	52.6854	0.0000
CRISIS	2.6458	0.0081	GARCH(-2)	142.6064	0.0000	GARCH(-2)	-28.9865	0.0000
			CRISIS	2.6655	0.0077	GARCH(-3)	24.1820	0.0000
						CRISIS	2.4912	0.0127
SIC		3.1258	SIC		3.1283	SIC		3.1237
Durbin-Watson stat		2.0501	Durbin-Watson stat		2.0501	Durbin-Watson stat		2.0501

GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	6.2516	0.0000	C	6.2764	0.0000	C	10.5068	0.0000
RESID(-1)^2	11.0079	0.0000	RESID(-1)^2	10.5718	0.0000	RESID(-1)^2	16.5959	0.0000
RESID(-2)^2	-2.1093	0.0349	RESID(-2)^2	-8.7648	0.0000	RESID(-2)^2	-17.6448	0.0000
RESID(-3)^2	1.1474	0.2512	RESID(-3)^2	8.6453	0.0000	RESID(-3)^2	17.9816	0.0000
GARCH(-1)	83.1836	0.0000	GARCH(-1)	34.8763	0.0000	GARCH(-1)	151.9866	0.0000
CRISIS	2.6310	0.0085	GARCH(-2)	-17.1163	0.0000	GARCH(-2)	-86.4156	0.0000
			CRISIS	3.6772	0.0002	GARCH(-3)	57.0343	0.0000
						CRISIS	2.7810	0.0054
SIC		3.1286	SIC		3.1211	SIC		3.0575
Durbin-Watson stat		2.0501	Durbin-Watson stat		2.0501	Durbin-Watson stat		2.0501

Appendix 5.9 - Singapore Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

SINGAPORE

GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	4.4447	0.0000	C	3.7970	0.0001	C	3.7263	0.0002
RESID(-1)^2	13.3568	0.0000	RESID(-1)^2	5.9302	0.0000	RESID(-1)^2	5.5198	0.0000
GARCH(-1)	191.1708	0.0000	GARCH(-1)	24.6099	0.0000	GARCH(-1)	5.0981	0.0000
CRISIS	0.3978	0.6908	GARCH(-2)	-10.5999	0.0000	GARCH(-2)	2.2994	0.0215
			CRISIS	0.7840	0.4331	GARCH(-3)	-4.1742	0.0000
						CRISIS	0.8470	0.3970
SIC		2.6679	SIC		2.6657	SIC		2.6688
Durbin-Watson stat		1.9586	Durbin-Watson stat		1.9586	Durbin-Watson stat		1.9586

GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	4.5039	0.0000	C	2.7823	0.0054	C	4.2129	0.0000
RESID(-1)^2	2.5868	0.0097	RESID(-1)^2	3.0269	0.0025	RESID(-1)^2	3.5946	0.0003
RESID(-2)^2	2.6355	0.0084	RESID(-2)^2	-0.6014	0.5476	RESID(-2)^2	5.9227	0.0000
GARCH(-1)	178.3045	0.0000	GARCH(-1)	19.8926	0.0000	GARCH(-1)	19.3346	0.0000
CRISIS	0.3909	0.6959	GARCH(-2)	-9.0737	0.0000	GARCH(-2)	-12.5940	0.0000
			CRISIS	0.7230	0.4697	GARCH(-3)	24.0052	0.0000
						CRISIS	0.3995	0.6895
SIC		2.6697	SIC		2.6693	SIC		2.6777
Durbin-Watson stat		1.9586	Durbin-Watson stat		1.9586	Durbin-Watson stat		1.9586

GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	4.5043	0.0000	C	4.2021	0.0000	C	6.2599	0.0000
RESID(-1)^2	2.7432	0.0061	RESID(-1)^2	2.6903	0.0071	RESID(-1)^2	9.2721	0.0000
RESID(-2)^2	0.3671	0.7135	RESID(-2)^2	2.8521	0.0043	RESID(-2)^2	7.6796	0.0000
RESID(-3)^2	2.7608	0.0058	RESID(-3)^2	3.2847	0.0010	RESID(-3)^2	20.9738	0.0000
GARCH(-1)	152.9992	0.0000	GARCH(-1)	0.8026	0.4222	GARCH(-1)	85.1054	0.0000
CRISIS	0.5499	0.5824	GARCH(-2)	4.3035	0.0000	GARCH(-2)	-121.3876	0.0000
			CRISIS	0.5342	0.5932	GARCH(-3)	205.9889	0.0000
						CRISIS	0.9881	0.3231
SIC		2.6714	SIC		2.6748	SIC		2.6461
Durbin-Watson stat		1.9586	Durbin-Watson stat		1.9586	Durbin-Watson stat		1.9586

Appendix 5.10 - China Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

CHINA								
GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	5.4475	0.0000	C	5.4689	0.0000	C	4.9655	0.0000
RESID(-1)^2	11.9032	0.0000	RESID(-1)^2	12.3466	0.0000	RESID(-1)^2	8.4790	0.0000
GARCH(-1)	352.9551	0.0000	GARCH(-1)	3.0472	0.0023	GARCH(-1)	0.0405	0.9677
CRISIS	0.4862	0.6269	GARCH(-2)	17.9381	0.0000	GARCH(-2)	16.2334	0.0000
			CRISIS	0.6200	0.5353	GARCH(-3)	1.3547	0.1755
						CRISIS	0.7695	0.4416
SIC		3.4538	SIC		3.4531	SIC		3.4560
Durbin-Watson stat		2.1309	Durbin-Watson stat		2.1309	Durbin-Watson stat		2.1309
GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	5.4491	0.0000	C	5.3124	0.0000	C	1.1065	0.2685
RESID(-1)^2	3.8724	0.0001	RESID(-1)^2	6.5857	0.0000	RESID(-1)^2	4.9650	0.0000
RESID(-2)^2	-0.4262	0.6699	RESID(-2)^2	-0.6608	0.5087	RESID(-2)^2	-1.6683	0.0953
GARCH(-1)	351.9212	0.0000	GARCH(-1)	2.3052	0.0212	GARCH(-1)	4.0058	0.0001
CRISIS	0.4993	0.6175	GARCH(-2)	10.6043	0.0000	GARCH(-2)	7.0746	0.0000
			CRISIS	0.6942	0.4876	GARCH(-3)	-4.5315	0.0000
						CRISIS	0.6539	0.5132
SIC		3.4568	SIC		3.4561	SIC		3.4587
Durbin-Watson stat		2.1309	Durbin-Watson stat		2.1309	Durbin-Watson stat		2.1309
GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	5.5961	0.0000	C	5.2274	0.0000	C	2.6304	0.0085
RESID(-1)^2	4.0744	0.0000	RESID(-1)^2	4.1808	0.0000	RESID(-1)^2	4.2921	0.0000
RESID(-2)^2	-3.4200	0.0006	RESID(-2)^2	-1.4784	0.1393	RESID(-2)^2	-0.4271	0.6693
RESID(-3)^2	4.6185	0.0000	RESID(-3)^2	2.8155	0.0049	RESID(-3)^2	12.4269	0.0000
GARCH(-1)	333.7511	0.0000	GARCH(-1)	2.6887	0.0072	GARCH(-1)	68.3516	0.0000
CRISIS	1.2752	0.2022	GARCH(-2)	5.9510	0.0000	GARCH(-2)	-56.1884	0.0000
			CRISIS	0.9944	0.3200	GARCH(-3)	116.0051	0.0000
						CRISIS	1.2195	0.2227
SIC		3.4561	SIC		3.4580	SIC		3.4257
Durbin-Watson stat		2.1309	Durbin-Watson stat		2.1309	Durbin-Watson stat		2.1309

Appendix 5.11 - Malaysia Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

MALAYSIA

GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	8.1255	0.0000	C	7.1340	0.0000	C	7.5894	0.0000
RESID(-1)^2	18.5405	0.0000	RESID(-1)^2	13.3823	0.0000	RESID(-1)^2	14.8001	0.0000
GARCH(-1)	207.4900	0.0000	GARCH(-1)	4.4872	0.0000	GARCH(-1)	3.8977	0.0001
CRISIS	1.1748	0.2401	GARCH(-2)	5.6209	0.0000	GARCH(-2)	3.8596	0.0001
			CRISIS	1.1930	0.2329	GARCH(-3)	11.7766	0.0000
						CRISIS	0.8558	0.3921
SIC		1.8025	SIC		1.8040	SIC		1.8051
Durbin-Watson stat		1.8233	Durbin-Watson stat		1.8233	Durbin-Watson stat		1.8233

GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	7.3553	0.0000	C	4.6934	0.0000	C	6.1538	0.0000
RESID(-1)^2	7.0464	0.0000	RESID(-1)^2	7.7777	0.0000	RESID(-1)^2	10.1828	0.0000
RESID(-2)^2	-1.4792	0.1391	RESID(-2)^2	-0.2310	0.8173	RESID(-2)^2	0.5358	0.5921
GARCH(-1)	201.7012	0.0000	GARCH(-1)	2.4920	0.0127	GARCH(-1)	1.2090	0.2267
CRISIS	1.0348	0.3008	GARCH(-2)	2.8046	0.0050	GARCH(-2)	3.1193	0.0018
			CRISIS	1.1295	0.2587	GARCH(-3)	6.6462	0.0000
						CRISIS	0.8671	0.3859
SIC		1.8053	SIC		1.8071	SIC		1.8082
Durbin-Watson stat		1.8233	Durbin-Watson stat		1.8233	Durbin-Watson stat		1.8233

GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	7.7766	0.0000	C	5.0293	0.0000	C	11.4778	0.0000
RESID(-1)^2	7.1822	0.0000	RESID(-1)^2	7.1104	0.0000	RESID(-1)^2	18.9724	0.0000
RESID(-2)^2	-5.1417	0.0000	RESID(-2)^2	-5.3427	0.0000	RESID(-2)^2	-0.4761	0.6340
RESID(-3)^2	8.7519	0.0000	RESID(-3)^2	9.5388	0.0000	RESID(-3)^2	22.7445	0.0000
GARCH(-1)	161.7847	0.0000	GARCH(-1)	8.9765	0.0000	GARCH(-1)	85.3204	0.0000
CRISIS	2.0621	0.0392	GARCH(-2)	-2.6066	0.0091	GARCH(-2)	-110.5272	0.0000
			CRISIS	2.4112	0.0159	GARCH(-3)	171.6359	0.0000
						CRISIS	1.7870	0.0739
SIC		1.8024	SIC		1.8035	SIC		1.7834
Durbin-Watson stat		1.8233	Durbin-Watson stat		1.8233	Durbin-Watson stat		1.8233

Appendix 5.12 - India Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

INDIA

GARCH (1,1)		
C	5.7972	0.0000
RESID(-1)^2	14.4474	0.0000
GARCH(-1)	193.6928	0.0000
CRISIS	3.6137	0.0003
SIC		3.2406
Durbin-Watson stat		1.9657

GARCH (1,2)		
C	5.7953	0.0000
RESID(-1)^2	14.5670	0.0000
GARCH(-1)	4.1259	0.0000
GARCH(-2)	12.7515	0.0000
CRISIS	3.7807	0.0002
SIC		3.2423
Durbin-Watson stat		1.9657

GARCH (1,3)		
C	5.3279	0.0000
RESID(-1)^2	7.4765	0.0000
GARCH(-1)	7.0648	0.0000
GARCH(-2)	3.0600	0.0022
GARCH(-3)	-4.4646	0.0000
CRISIS	2.9421	0.0033
SIC		3.2398
Durbin-Watson stat		1.9657

GARCH (2,1)		
C	5.8611	0.0000
RESID(-1)^2	3.2937	0.0010
RESID(-2)^2	3.2297	0.0012
GARCH(-1)	173.4263	0.0000
CRISIS	3.3807	0.0007
SIC		3.2422
Durbin-Watson stat		1.9657

GARCH(2,2)		
C	5.3565	0.0000
RESID(-1)^2	7.5578	0.0000
RESID(-2)^2	0.8719	0.3833
GARCH(-1)	1.4994	0.1338
GARCH(-2)	6.5003	0.0000
CRISIS	3.3720	0.0007
SIC		3.2451
Durbin-Watson stat		1.9657

GARCH(2,3)		
C	6.0020	0.0000
RESID(-1)^2	4.2654	0.0000
RESID(-2)^2	7.7151	0.0000
GARCH(-1)	19.2899	0.0000
GARCH(-2)	-11.4284	0.0000
GARCH(-3)	20.6369	0.0000
CRISIS	2.2855	0.0223
SIC		3.2488
Durbin-Watson stat		1.9657

GARCH(3,1)		
C	6.3471	0.0000
RESID(-1)^2	3.3390	0.0008
RESID(-2)^2	-1.9314	0.0534
RESID(-3)^2	8.0197	0.0000
GARCH(-1)	155.0622	0.0000
CRISIS	3.4389	0.0006
SIC		3.2371
Durbin-Watson stat		1.9657

GARCH(3,2)		
C	4.9320	0.0000
RESID(-1)^2	3.4481	0.0006
RESID(-2)^2	-2.4699	0.0135
RESID(-3)^2	5.2515	0.0000
GARCH(-1)	12.9979	0.0000
GARCH(-2)	-4.2687	0.0000
CRISIS	2.9715	0.0030
SIC		3.2390
Durbin-Watson stat		1.9657

GARCH(3,3)		
C	7.8819	0.0000
RESID(-1)^2	11.8479	0.0000
RESID(-2)^2	4.7694	0.0000
RESID(-3)^2	21.1070	0.0000
GARCH(-1)	94.9016	0.0000
GARCH(-2)	-121.9400	0.0000
GARCH(-3)	197.7965	0.0000
CRISIS	2.5103	0.0121
SIC		3.2037
Durbin-Watson stat		1.9657

Appendix 5.13 - Pakistan Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

PAKISTAN								
GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	10.6861	0.0000	C	8.4938	0.0000	C	9.2208	0.0000
RESID(-1)^2	16.2057	0.0000	RESID(-1)^2	10.6261	0.0000	RESID(-1)^2	12.8767	0.0000
GARCH(-1)	149.8679	0.0000	GARCH(-1)	5.9005	0.0000	GARCH(-1)	7.2933	0.0000
CRISIS	4.3959	0.0000	GARCH(-2)	4.4181	0.0000	GARCH(-2)	1.1456	0.2519
			CRISIS	4.6409	0.0000	GARCH(-3)	7.7033	0.0000
						CRISIS	5.4734	0.0000
SIC		2.7861	SIC		2.7857	SIC		2.7842
Durbin-Watson stat		1.8726	Durbin-Watson stat		1.8726	Durbin-Watson stat		1.8726
GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	8.5430	0.0000	C	5.2750	0.0000	C	9.5246	0.0000
RESID(-1)^2	8.8712	0.0000	RESID(-1)^2	8.8690	0.0000	RESID(-1)^2	14.1915	0.0000
RESID(-2)^2	-5.1724	0.0000	RESID(-2)^2	-5.3565	0.0000	RESID(-2)^2	-6.9747	0.0000
GARCH(-1)	168.2579	0.0000	GARCH(-1)	11.1548	0.0000	GARCH(-1)	92.4810	0.0000
CRISIS	6.3986	0.0000	GARCH(-2)	-0.8392	0.4014	GARCH(-2)	-50.1666	0.0000
			CRISIS	5.4710	0.0000	GARCH(-3)	39.2799	0.0000
						CRISIS	5.4759	0.0000
SIC		2.7816	SIC		2.7845	SIC		2.7732
Durbin-Watson stat		1.8726	Durbin-Watson stat		1.8726	Durbin-Watson stat		1.8726
GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	7.4740	0.0000	C	9.6702	0.0000	C	9.0536	0.0000
RESID(-1)^2	8.8569	0.0000	RESID(-1)^2	23.4912	0.0000	RESID(-1)^2	11.1644	0.0000
RESID(-2)^2	-4.3254	0.0000	RESID(-2)^2	19.7428	0.0000	RESID(-2)^2	13.4678	0.0000
RESID(-3)^2	-1.3913	0.1641	RESID(-3)^2	-15.1190	0.0000	RESID(-3)^2	-0.6353	0.5252
GARCH(-1)	151.5137	0.0000	GARCH(-1)	-19.2854	0.0000	GARCH(-1)	-16.1638	0.0000
CRISIS	6.7476	0.0000	GARCH(-2)	256.0982	0.0000	GARCH(-2)	20.3697	0.0000
			CRISIS	4.1863	0.0000	GARCH(-3)	35.2928	0.0000
						CRISIS	4.8304	0.0000
SIC		2.7844	SIC		2.7503	SIC		2.7819
Durbin-Watson stat		1.8726	Durbin-Watson stat		1.8726	Durbin-Watson stat		1.8726

Appendix 5.14 - UAE Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

UAE

GARCH (1,1)		
C	11.0055	0.0000
RESID(-1)^2	21.4615	0.0000
GARCH(-1)	446.0435	0.0000
CRISIS	5.9793	0.0000
SIC		2.4730
Durbin-Watson stat		1.7427

GARCH (1,2)		
C	11.5738	0.0000
RESID(-1)^2	20.1949	0.0000
GARCH(-1)	4.4704	0.0000
GARCH(-2)	19.4111	0.0000
CRISIS	6.2635	0.0000
SIC		2.4667
Durbin-Watson stat		1.7427

GARCH (1,3)		
C	14.8317	0.0000
RESID(-1)^2	22.5947	0.0000
GARCH(-1)	-17.5673	0.0000
GARCH(-2)	9.6969	0.0000
GARCH(-3)	79.7173	0.0000
CRISIS	2.5184	0.0118
SIC		2.4634
Durbin-Watson stat		1.7427

GARCH (2,1)		
C	11.7927	0.0000
RESID(-1)^2	10.5631	0.0000
RESID(-2)^2	-8.4598	0.0000
GARCH(-1)	504.5842	0.0000
CRISIS	6.9439	0.0000
SIC		2.4582
Durbin-Watson stat		1.7427

GARCH(2,2)		
C	8.9819	0.0000
RESID(-1)^2	10.4996	0.0000
RESID(-2)^2	-4.5276	0.0000
GARCH(-1)	7.3455	0.0000
GARCH(-2)	6.7098	0.0000
CRISIS	3.9033	0.0001
SIC		2.5894
Durbin-Watson stat		1.7427

GARCH(2,3)		
C	18.8577	0.0000
RESID(-1)^2	12.5351	0.0000
RESID(-2)^2	2.1594	0.0308
GARCH(-1)	-3.7874	0.0002
GARCH(-2)	9.7394	0.0000
GARCH(-3)	25.2068	0.0000
CRISIS	0.1377	0.8904
SIC		2.5735
Durbin-Watson stat		1.7427

GARCH(3,1)		
C	13.8678	0.0000
RESID(-1)^2	12.7489	0.0000
RESID(-2)^2	-12.4901	0.0000
RESID(-3)^2	22.3709	0.0000
GARCH(-1)	423.6794	0.0000
CRISIS	5.2259	0.0000
SIC		2.4707
Durbin-Watson stat		1.7427

GARCH(3,2)		
C	7.8550	0.0000
RESID(-1)^2	37.2986	0.0000
RESID(-2)^2	-7.0752	0.0000
RESID(-3)^2	7.5375	0.0000
GARCH(-1)	7.4491	0.0000
GARCH(-2)	-1.9787	0.0479
CRISIS	4.9859	0.0000
SIC		2.6006
Durbin-Watson stat		1.7427

GARCH(3,3)		
C	3.4000	0.0007
RESID(-1)^2	10.5481	0.0000
RESID(-2)^2	-4.1050	0.0000
RESID(-3)^2	3.4786	0.0005
GARCH(-1)	4.0078	0.0001
GARCH(-2)	-0.3974	0.6911
GARCH(-3)	0.1265	0.8993
CRISIS	2.4908	0.0127
SIC		2.5729
Durbin-Watson stat		1.7427

Appendix 5.15 - Saudi Arabia Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

SAUDI ARABIA

GARCH (1,1)			GARCH (1,2)			GARCH (1,3)		
C	16.3468	0.0000	C	7.7739	0.0000	C	8.5669	0.0000
RESID(-1)^2	15.6706	0.0000	RESID(-1)^2	9.3312	0.0000	RESID(-1)^2	10.5779	0.0000
GARCH(-1)	219.0278	0.0000	GARCH(-1)	29.9512	0.0000	GARCH(-1)	16.9191	0.0000
CRISIS	1.7039	0.0884	GARCH(-2)	-12.0590	0.0000	GARCH(-2)	35.7653	0.0000
			CRISIS	1.6136	0.1066	GARCH(-3)	-15.8900	0.0000
						CRISIS	1.4673	0.1423
SIC		3.1382	SIC		3.1363	SIC		3.1356
Durbin-Watson stat		1.8909	Durbin-Watson stat		1.8909	Durbin-Watson stat		1.8909

GARCH (2,1)			GARCH(2,2)			GARCH(2,3)		
C	15.7799	0.0000	C	4.6261	0.0000	C	6.6598	0.0000
RESID(-1)^2	4.6773	0.0000	RESID(-1)^2	5.5653	0.0000	RESID(-1)^2	7.6045	0.0000
RESID(-2)^2	3.2741	0.0011	RESID(-2)^2	-1.1093	0.2673	RESID(-2)^2	-1.3696	0.1708
GARCH(-1)	187.8977	0.0000	GARCH(-1)	24.4823	0.0000	GARCH(-1)	14.6045	0.0000
CRISIS	1.6631	0.0963	GARCH(-2)	-10.8559	0.0000	GARCH(-2)	25.7301	0.0000
			CRISIS	1.6058	0.1083	GARCH(-3)	-18.3624	0.0000
						CRISIS	1.4805	0.1387
SIC		3.1393	SIC		3.1393	SIC		3.1385
Durbin-Watson stat		1.8909	Durbin-Watson stat		1.8909	Durbin-Watson stat		1.8909

GARCH(3,1)			GARCH(3,2)			GARCH(3,3)		
C	15.7015	0.0000	C	16.9884	0.0000	C	24.6990	0.0000
RESID(-1)^2	4.7100	0.0000	RESID(-1)^2	4.9778	0.0000	RESID(-1)^2	12.2462	0.0000
RESID(-2)^2	-0.2881	0.7732	RESID(-2)^2	6.3609	0.0000	RESID(-2)^2	0.4969	0.6193
RESID(-3)^2	6.3220	0.0000	RESID(-3)^2	7.1702	0.0000	RESID(-3)^2	23.3564	0.0000
GARCH(-1)	159.0593	0.0000	GARCH(-1)	2.8419	0.0045	GARCH(-1)	95.8186	0.0000
CRISIS	1.7927	0.0730	GARCH(-2)	34.2542	0.0000	GARCH(-2)	-95.7996	0.0000
			CRISIS	1.3439	0.1790	GARCH(-3)	72.6996	0.0000
						CRISIS	3.8744	0.0001
SIC		3.1382	SIC		3.1363	SIC		3.0746
Durbin-Watson stat		1.8909	Durbin-Watson stat		1.8909	Durbin-Watson stat		1.8909

Appendix 5.16 - Kuwait Modified GARCH (p, q) Models with Dummy Variable CRISIS for all Specifications

KUWAIT

GARCH (1,1)		
C	11.9097	0.0000
RESID(-1)^2	15.3465	0.0000
GARCH(-1)	124.8459	0.0000
CRISIS	3.8777	0.0001
SIC		1.6853
Durbin-Watson stat		1.6855

GARCH (1,2)		
C	11.5156	0.0000
RESID(-1)^2	17.4834	0.0000
GARCH(-1)	6.1238	0.0000
GARCH(-2)	38.6081	0.0000
CRISIS	3.0764	0.0021
SIC		1.6685
Durbin-Watson stat		1.6855

GARCH (1,3)		
C	11.1290	0.0000
RESID(-1)^2	15.5828	0.0000
GARCH(-1)	0.2550	0.7987
GARCH(-2)	30.5628	0.0000
GARCH(-3)	2.8623	0.0042
CRISIS	3.1383	0.0017
SIC		1.6708
Durbin-Watson stat		1.6855

GARCH (2,1)		
C	11.1710	0.0000
RESID(-1)^2	11.2899	0.0000
RESID(-2)^2	-6.4090	0.0000
GARCH(-1)	127.7932	0.0000
CRISIS	3.5884	0.0003
SIC		1.6806
Durbin-Watson stat		1.6855

GARCH(2,2)		
C	11.0188	0.0000
RESID(-1)^2	14.1817	0.0000
RESID(-2)^2	-2.8222	0.0048
GARCH(-1)	5.5612	0.0000
GARCH(-2)	20.0857	0.0000
CRISIS	3.1068	0.0019
SIC		1.6707
Durbin-Watson stat		1.6855

GARCH(2,3)		
C	2.4510	0.0142
RESID(-1)^2	12.0185	0.0000
RESID(-2)^2	-0.4930	0.6220
GARCH(-1)	0.5013	0.6161
GARCH(-2)	9.7531	0.0000
GARCH(-3)	0.0152	0.9879
CRISIS	1.9190	0.0550
SIC		1.6737
Durbin-Watson stat		1.6855

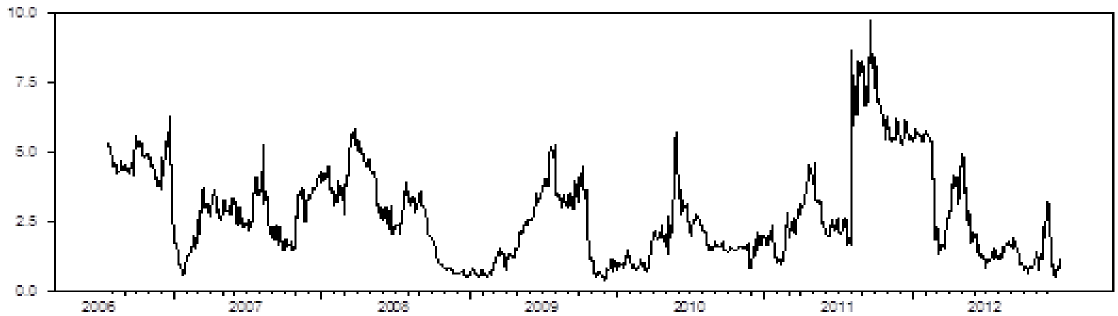
GARCH(3,1)		
C	11.9089	0.0000
RESID(-1)^2	11.7550	0.0000
RESID(-2)^2	-10.4877	0.0000
RESID(-3)^2	10.0328	0.0000
GARCH(-1)	114.5013	0.0000
CRISIS	3.5437	0.0004
SIC		1.6733
Durbin-Watson stat		1.6855

GARCH(3,2)		
C	10.9297	0.0000
RESID(-1)^2	11.9604	0.0000
RESID(-2)^2	-2.5988	0.0094
RESID(-3)^2	-0.0595	0.9526
GARCH(-1)	4.8609	0.0000
GARCH(-2)	16.7201	0.0000
CRISIS	3.0959	0.0020
SIC		1.6737
Durbin-Watson stat		1.6855

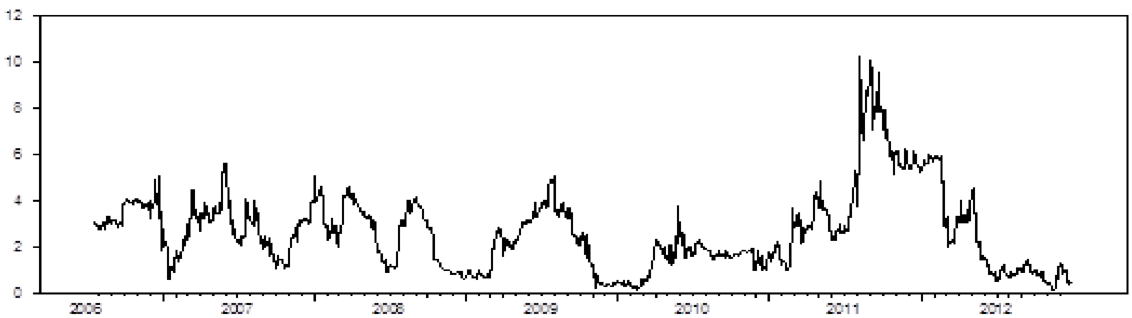
GARCH(3,3)		
C	4.5228	0.0000
RESID(-1)^2	13.9805	0.0000
RESID(-2)^2	-9.2578	0.0000
RESID(-3)^2	4.3070	0.0000
GARCH(-1)	25.6893	0.0000
GARCH(-2)	5.7425	0.0000
GARCH(-3)	-16.3738	0.0000
CRISIS	2.9705	0.0030
SIC		1.6750
Durbin-Watson stat		1.6855

Appendix 5.17 - Pairwise Returns Spillovers Plot Between Pakistan and Developed Markets

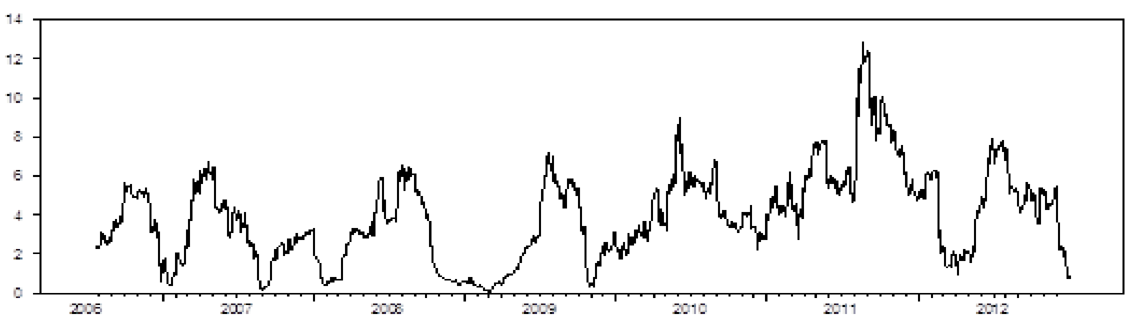
a) Pakistan and the UK



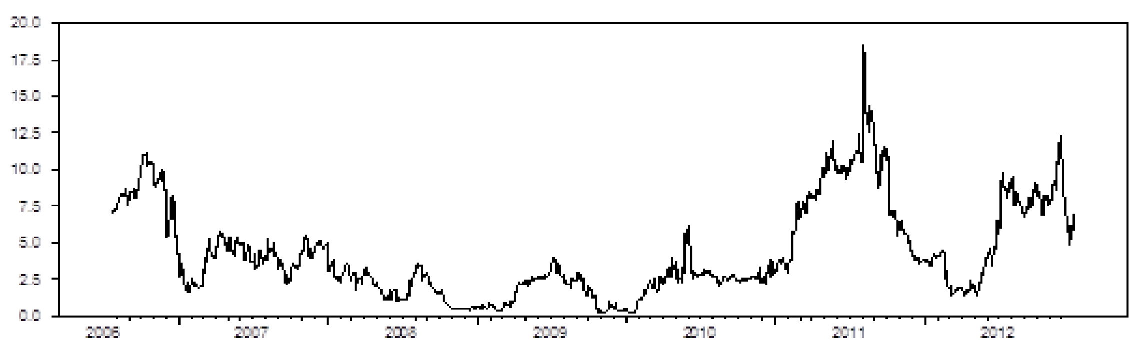
b) Pakistan and Germany



c) Pakistan and Japan

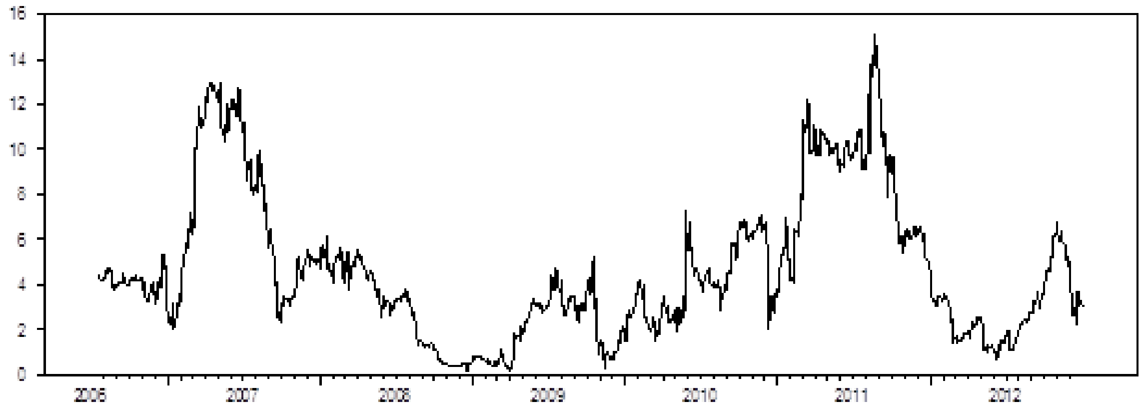


d) Pakistan and Singapore

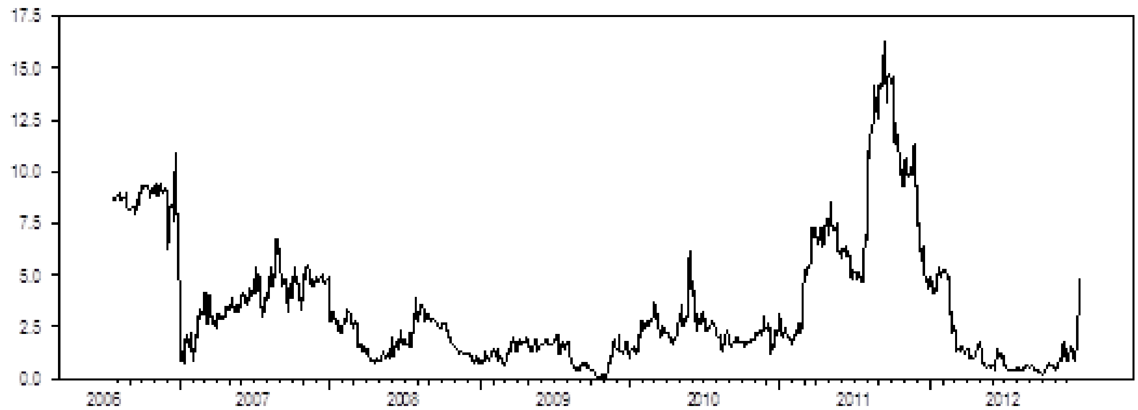


Appendix 5.18 - Pairwise Returns Spillovers Plot Between Pakistan and Emerging Markets

a) Pakistan and Malaysia

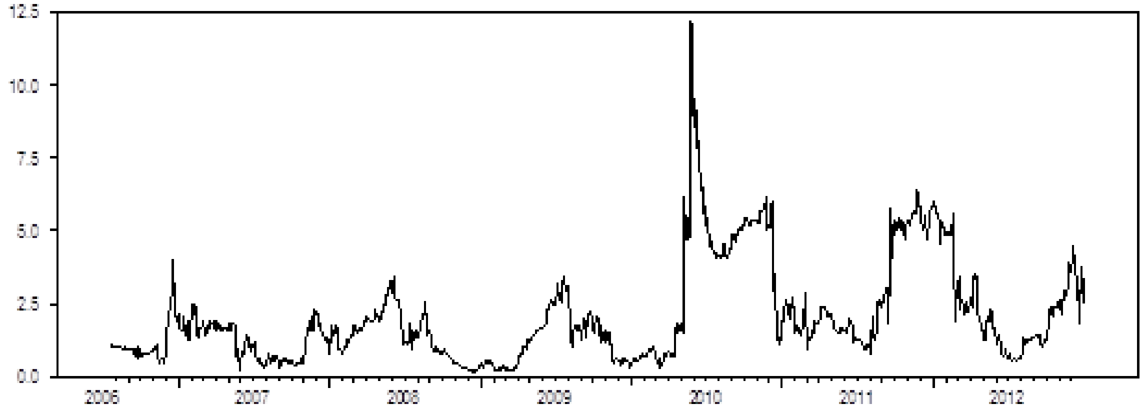


b) Pakistan and India



Appendix 5.19 - Pairwise Returns Spillovers Plot Between Pakistan and Frontier Markets

a) Pakistan and Saudi Arabia



b) Pakistan and Kuwait