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Identifying the pattern of international stock return co-movements

Abbas Valadkhani
University of Wollongong, abbas@uow.edu.au

Surachai Chancharat
University of Wollongong, sc983@uow.edu.au

Charles Harvie
University of Wollongong, charvie@uow.edu.au

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Keywords
Identifying, pattern, international, stock, return, movements

Disciplines
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Identifying the Pattern of International Stock Return Co-movements

Abbas Valadkhani*, Surachai Chancharat** and Charles Harvie***

Abstract

This paper investigates the relationships between stock market returns of 13 countries based upon monthly data spanning December 1987 to April 2007. Specifically, the principal component (PC) and maximum likelihood (ML) methods are used to examine any discernable patterns of stock market co-movements. Factor analysis provides evidence that stock returns in a number of Asian countries are highly correlated and, based on the resulting robust factor loadings, they form the first well-defined common factor. We also find consistent results (based on both the PC and ML methods) suggesting that the stock returns of all global developed economy stock markets are also highly correlated, and constitute our second factor. We conclude that, inter alia, geographical proximity and the level of economic development do matter when it comes to co-movements of stock returns and that this has important implications for financial portfolio diversification if the aim is to reduce systematic risks across countries.

Keywords Stock Markets, Factor Analysis, Portfolio Diversification

1. Introduction

Since the time that Grubel (1968) extended the concepts of modern portfolio analysis to international capital markets, a large number of empirical studies have examined the advantages of international diversification. Early studies, such as Levy and Sarnat (1970), Lessard (1973), Ripley (1973) and Eun and Resnick (1988), investigated the performance of ex-post efficient portfolios and demonstrated that the benefits of internationally diversified portfolios stem from the fact that co-movements between different national stock markets are low.

More recently there has been a growing interest in international portfolio diversification, exemplified by a number of empirical studies examining various aspects of stock market co-movements. Previous studies have adopted different methodologies in the context of international equity market integration. The traditional approach has been to look at the estimates of correlation coefficients between national stock prices, with the argument being that if the correlation structure demonstrates instability over time then, assuming that the correlation is on an upward trajectory, this indicates greater integration. Based upon this approach Bailey and Stulz (1990) and Meric and Meric (1997) find that international diversification is possible, however the preponderance of

* A/Professor Abbas Valadkhani (corresponding author), School of Economics, University of Wollongong, NSW, Email: abbas@uow.edu.au

** Surachai Chancharat, PhD Student, School of Economics, University of Wollongong, NSW. Email: sc983@uow.edu.au

*** A/Professor Charles Harvie, School of Economics, University of Wollongong, NSW. Email: charles_harvie@uow.edu.au

the literature indicates that there is instability in the relationship (Wahab and Lashgari, 1993; Longin and Solnik, 1995).

A second approach emphasizes the cointegration technique to evaluate the degree of international integration in stock markets. Arshanapalli and Doukas (1993), Chaudhuri (1997), Narayan and Smyth (2004) and Syriopoulos (2004) find some evidence of a long-run relationship among all countries in their studies, implying that attempts by investors to diversify risk and attain superior portfolio returns by investing in different markets may have limited potential. Nevertheless, DeFusco *et al.* (1996), Kanas (1998), Worthington *et al.* (2003), Phylaktis and Ravazzolo (2005) and Valadkhani and Chancharat (2008) argue that the long term relationships between stock markets are much weaker indicating that investors have opportunities for reducing risk and enhancing returns through portfolio diversification investment in different countries.

A third approach employs the generalized autoregressive conditional heteroscedasticity (GARCH) model to capture potential asymmetric effects of innovations on volatility. Bekaert and Harvey (1995), Fratzscher (2002) and Fernandez-Izquierdo and Lafuente (2004) find that a number of stock markets exhibit a high degree of integration. Similar results were found by Longin and Solnik (1995) and Christofi and Pericli (1999) who use correlation and covariance matrix estimates that provide evidence of increased integration, implying fewer opportunities to diversify risk and increase returns across various stock markets.

A final approach involves the use of factor analysis to search for systematic variation patterns among stock markets. An early study by Ripley (1973) found evidence that major stock markets moved together. Subsequently, Hui and Kwan (1994), Naughton (1996) and Hui (2005) employed factor analysis to examine the systematic variation patterns among the US and Asia-Pacific stock markets. Illueca and Lafuente (2002), Fernandez-Izquierdo and Lafuente (2004) used the same technique to investigate the systematic covariation of stock prices for four international areas, *i.e.* Europe, Asia, North and South America. Consistent with our findings their results mostly reveal that the computed factor loadings are in accord with international geographic clustering.

The main objective of this paper is to investigate the relationships between stock market returns of 13 countries, namely Australia, Germany, Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Taiwan, Thailand, the UK and the US, using factor analysis to investigate the systematic covariation of stock market returns. The results shed light on the scope for risk diversification and increased returns through international diversification of stock across developed and developing countries.

The remainder of this paper is organized as follows. Section 2 presents briefly the empirical methodology utilized in the paper. Section 3 describes the summary statistics of the data employed. Section 4 discusses the empirical results and the last section provides some concluding remarks.

2. Empirical Methodology

Traditional factor analysis assumes that series have no unit root in time series data. Thus, the empirical results indicate that with or without capturing the endogenously-determined one or two structural breaks, the stock price indices (P_t) are mainly I(1) and the stock market returns $ln(P_t/P_{t-1})$ are I(0). The results have not been reported in this paper but they are available from the authors upon request. As mentioned previously correlation analysis has been used in earlier studies of stock market integration, where the higher the correlation coefficient, the greater the evidence of stock market linkages across countries.

Factor analysis is one of the most well known methods of classical multivariate analysis (Hair *et al.*, 1998; Tabachnick and Fidell, 2001; Tsay, 2002). The objective is to obtain a reduced set of uncorrelated latent variables using a set of linear combinations of the original variables, so as to maximize the variance of these components. Specifically, for a given multivariate set of k variables, the model can be described as follows:

$$\begin{cases} r_1 - \mu_1 = \ell_{11} f_1 + \ell_{12} f_2 + \ldots + \ell_{1m} f_m + \varepsilon_1 \\ r_2 - \mu_2 = \ell_{21} f_1 + \ell_{22} f_2 + \ldots + \ell_{2m} f_m + \varepsilon_2 \\ \quad \vdots \; = \; \vdots \\ r_k - \mu_k = \ell_{k1} f_1 + \ell_{k2} f_2 + \ldots + \ell_{km} f_m + \varepsilon_k \end{cases} \tag{1}$$

or in matrix notation we can write:

$$\boldsymbol{r} - \boldsymbol{\mu} = \boldsymbol{LF} + \boldsymbol{\varepsilon} \tag{2}$$

with $m < k$ and where $\boldsymbol{r} = (r_1, r_2, \ldots, r_k)$ denotes the multivariate vector of stock returns, = ($_1$, $_2$,…, $_k$) is the corresponding mean vector, $\boldsymbol{F} = (f_1, f_2, \ldots, f_k)$ is the resulting common factor vector, $\boldsymbol{L} = [\ell_{ij}]_{k \times m}$ is the matrix of factor loadings, ℓ_{ij} denotes the loading of the i^{th} variable on the j^{th} factor and $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_k)$ is the specific error of r_i.

2.1 Factor Estimation Methods

The two most widely used methods to estimate the orthogonal factor model. The first method is the principle component (PC) analysis which does not require the normality assumption of the data and the prior specification of the number of common factors. Depending on the measurement scale of the variables included, this method can be used based on both the covariance and correlation matrixes. The maximum likelihood (ML) method is the second most widely used estimation method, and is based, on the other hand, on the normal density function and requires a pre-specification of the number of common factors.

We first briefly discuss the PC method. Let us assume that $(\hat{\lambda}_1, \hat{e}_1), (\hat{\lambda}_2, \hat{e}_2), \ldots, (\hat{\lambda}_k, \hat{e}_k)$ are pairs of the eigenvalues and eigenvectors of the sample covariance matrix $\hat{\Sigma}_r$, where $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \ldots \geq \hat{\lambda}_k$ and $m < k$ meaning that the number of latent common factors should be less than the number of original variables. We can then define the matrix of factor loading as follows:

$$\hat{\boldsymbol{L}} \int [\hat{\ell}_{ij}] = \left[\sqrt{\hat{\lambda}_1}\hat{\boldsymbol{e}}_1 \,|\, \sqrt{\hat{\lambda}_2}\hat{\boldsymbol{e}}_2 \,|\, \ldots \,|\, \sqrt{\hat{\lambda}_m}\hat{\boldsymbol{e}}_m \right] \tag{3}$$

The diagonal elements of the matrix $\hat{\Sigma}_r - \hat{\boldsymbol{L}}\hat{\boldsymbol{L}}'$ consist of the estimated specific variances. This means that $\hat{\Psi} = \text{diag}\{\hat{\Psi}_1, \hat{\Psi}_2, \ldots, \hat{\Psi}_k\}$, where $\hat{\Psi}_i = \hat{\sigma}_{ii,r} - \sum_{j=1}^{m} \hat{\ell}_{ij}^2$, and $\hat{\sigma}_{ii,r}$ is the $(i, i)^{\text{th}}$ element of $\hat{\Sigma}_r$. We can estimate the communalities by $\hat{c}_i^2 = \hat{\ell}_{i1}^2 + \hat{\ell}_{i2}^2 + \ldots + \hat{\ell}_{im}^2$. Using this method the error matrix associated with our approximation is equal to $\hat{\Sigma}_r - (\hat{L}\hat{L}' + \hat{\Psi})$, which should ideally be a null matrix. The sum of squared elements of $\hat{\Sigma}_r - (\hat{L}\hat{L}' + \hat{\Psi})$ is always less than or equal to $\hat{\lambda}_{m+1}^2 + \hat{\lambda}_{m+2}^2 + \ldots + \hat{\lambda}_k^2$. Hence the resulting approximation error is determined by the sum of squares of the excluded eigenvalues. According to the solution in equation (3), as the number of common factors or m increases the computed factor loadings remain unchanged

In the ML method, on the other hand, it is assumed that the common factors (or $\boldsymbol{F}$) and the specific factors (or $\boldsymbol{\varepsilon}$) are jointly normal. We can then conclude that $\boldsymbol{r}$ is multivariate normal with mean and covariance matrix $\Sigma_r = \boldsymbol{LL}' + \Psi$. Therefore, one can use the ML method to estimate $\boldsymbol{L}$ and Ψ subject to $\boldsymbol{L}'\Psi^{-1}\boldsymbol{L} = \Delta$, which is a diagonal matrix. The sample mean can be considered as a proxy for . For a detailed account of this method, see Johnson and Wichern (2002). In this method the number of common factors should be known *a priori*.

2.2 Factor Rotation

If $\boldsymbol{P}$ is a $m \times m$ orthogonal matrix, the following relations can be written: $\boldsymbol{LL}' + \varnothing = \boldsymbol{LPP}'\boldsymbol{L}' + \varnothing = \boldsymbol{L}^*(\boldsymbol{L}^*)' + \varnothing$ and $\boldsymbol{r} - \mu = \boldsymbol{LF} + \varepsilon = \boldsymbol{L}^*\boldsymbol{F}^* + \varepsilon$ in which $\boldsymbol{L}^* = \boldsymbol{LP}$ and $\boldsymbol{F}^* = \boldsymbol{P}'\boldsymbol{F}$. Under an orthogonal transformation the communalities and the specific variances do not change. Thus, it is possible to find $\boldsymbol{P}$ (an orthogonal matrix) to transform the factor model in such a way that the loadings on the common factors are easier to interpret. This transformation involves rotating the common factors in the m-dimensional space. In practice there are many ways for rotating the common factors. The varimax method is a rotation method which is widely used in the literature and works well in many applications. Let the rotated matrix of factor loadings be $\boldsymbol{L}^* = [\ell_{ij}^*]$ and the i^{th} communalities are shown by c_i^2. We can then define $\tilde{\ell}_{ij}^* = \ell_{ij}^* / c_i$ as the rotated coefficients scaled by the (positive) square root of communalities. In the varimax method the orthogonal matrix $\boldsymbol{P}$ is chosen in such a manner that it maximizes the quantity of:

$$V = \frac{1}{k}\sum_{j=1}^{m}\left[\sum_{i=1}^{k}(\tilde{\ell}_{ij}^*)^4 - \frac{1}{k}\left(\sum_{i=1}^{k}\tilde{\ell}_{ij}^{*2}\right)^2\right] \tag{4}$$

The interpretation of this relation is straightforward. When V is maximized it means that the squares of the loadings on each factor are spread out as much as possible. The aim is to facilitate the interpretations of common factors by finding groups of very large and very small coefficients in any column of the rotated matrix of factor loadings.

Table 1 Descriptions of the data employed, December 1987-April 2007

Country	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	p-value	Communalities	
										PC	ML
Australia	0.007	0.007	0.157	-0.166	0.052	-0.265	3.478	4.927	0.085	0.561	0.467
Germany	0.008	0.012	0.202	-0.279	0.063	-0.742	5.669	90.142	0.000	0.609	0.520
Hong Kong	0.008	0.009	0.284	-0.344	0.075	-0.222	5.563	65.420	0.000	0.614	0.593
Indonesia	0.007	0.011	0.662	-0.525	0.141	0.373	7.539	204.508	0.000	0.518	0.383
Japan	0.000	-0.002	0.217	-0.216	0.065	0.068	3.591	3.562	0.168	0.411	0.280
Korea	0.006	-0.001	0.534	-0.375	0.108	0.301	6.213	103.268	0.000	0.339	0.260
Malaysia	0.006	0.009	0.405	-0.361	0.088	-0.253	7.000	157.156	0.000	0.626	0.542
Philippines	0.005	0.006	0.360	-0.347	0.094	-0.064	4.810	31.832	0.000	0.648	0.562
Singapore	0.007	0.011	0.228	-0.231	0.069	-0.560	5.513	73.188	0.000	0.755	0.758
Taiwan	0.004	0.002	0.381	-0.410	0.109	-0.037	4.392	18.777	0.000	0.321	0.261
Thailand	0.003	0.007	0.359	-0.416	0.116	-0.405	4.974	44.025	0.000	0.668	0.615
UK	0.006	0.005	0.138	-0.111	0.044	0.015	3.227	0.505	0.777	0.792	0.850
US	0.008	0.011	0.106	-0.151	0.040	-0.580	4.079	24.275	0.000	0.650	0.567

Source: Morgan Stanley Capital International, http://www.msci.com/equity/index2.html.

Table 2 Correlation and anti-image correlation coefficients for 13 selected stock markets

Country	AU	GE	HK	IN	JA	KO	MA	PH	SG	TA	TH	UK	US
Correlation Coefficients													
Australia	1.000												
Germany	**0.458**	1.000											
Hong Kong	**0.476**	**0.408**	1.000										
Indonesia	0.287	0.219	**0.398**	1.000									
Japan	**0.406**	**0.322**	**0.342**	0.146	1.000								
Korea	**0.414**	0.235	**0.332**	**0.340**	**0.453**	1.000							
Malaysia	**0.306**	**0.337**	**0.558**	**0.479**	0.248	**0.319**	1.000						
Philippines	**0.400**	0.291	**0.537**	**0.496**	0.221	0.272	**0.543**	1.000					
Singapore	**0.514**	**0.440**	**0.714**	**0.515**	**0.386**	**0.389**	**0.659**	**0.606**	1.000				
Taiwan	0.260	**0.307**	**0.389**	0.181	0.220	**0.313**	**0.396**	**0.388**	**0.430**	1.000			
Thailand	**0.482**	**0.335**	**0.537**	**0.463**	**0.326**	**0.502**	**0.558**	**0.614**	**0.645**	**0.407**	1.000		
UK	**0.568**	**0.655**	**0.484**	0.161	**0.467**	**0.313**	**0.318**	0.245	**0.492**	0.171	0.298	1.000	
US	**0.504**	**0.608**	**0.506**	0.269	**0.348**	**0.360**	**0.336**	**0.376**	**0.547**	0.299	**0.437**	**0.645**	1.000
Anti-image Correlation Coefficients													
Australia	**0.931**[b]												
Germany	-0.061	**0.871**[b]											
Hong Kong	-0.063	0.042	**0.943**[b]										
Indonesia	-0.022	-0.073	-0.017	**0.876**[b]									
Japan	-0.066	-0.002	-0.019	0.090	**0.892**[b]								
Korea	-0.129	0.117	0.031	-0.200	-0.299	**0.837**[b]							
Malaysia	0.149	-0.070	-0.122	-0.159	0.027	-0.026	**0.915**[b]						
Philippines	-0.107	0.019	-0.116	-0.209	-0.003	0.147	-0.122	**0.914**[b]					
Singapore	-0.075	0.045	-0.319	-0.197	-0.097	0.071	-0.273	-0.101	**0.915**[b]				
Taiwan	0.004	-0.188	-0.090	0.182	-0.022	-0.158	-0.117	-0.121	-0.112	**0.874**[b]			
Thailand	-0.158	-0.038	-0.035	-0.027	-0.012	-0.281	-0.146	-0.272	-0.180	-0.039	**0.912**[b]		
UK	-0.267	-0.395	-0.136	0.132	-0.223	-0.039	-0.080	0.085	-0.114	0.195	0.153	**0.822**[b]	
US	-0.025	-0.265	-0.077	0.001	0.057	-0.103	0.127	-0.062	-0.134	-0.037	-0.079	-0.298	**0.916**[b]

Notes: (a) Boldfaced figures in the correlation coefficient matrix are significant at 5 per cent level. (b) The boldfaced elements on the main diagonal of the anti-image matrix are referred to as the measures of sampling adequacy (MSA) and computed as $MSA_i = \sum_{i \neq j} r_{ij}^2 \Big/ \left(\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} a_{ij}^2 \right)$ where r_{ij} is the simple correlation coefficient between variables i and j and a_{ij} is the partial correlation coefficient between variables i and j. The minimum acceptable value of MSA is usually above 0.50.

3. Data and Basic Statistics

The data in this paper include the stock prices (P) of the following 13 countries: Australia (AU), Germany (GE), Hong Kong (HK), Indonesia (IN), Japan (JA), Korea (KO), Malaysia (MA), the Philippines (PH), Singapore (SG), Taiwan (TA), Thailand (TH), the UK and the US. Monthly data span from December 1987 to April 2007 with a base value of 100 in December 1987. All stock indices were obtained from Morgan Stanley Capital International.

Table 1 presents the descriptive statistics of the data, containing sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis as well as the Jarque-Bera statistics and p-values. The price return is defined as $ln(P_t/P_{t-1})$. The highest mean return is 0.008 in Hong Kong, Germany and the US, while the lowest is 0.000 in Japan. The standard deviations range from 0.040 in the US (the least volatile) to 0.141 in Indonesia (the most volatile). The standard deviations of stock returns are least volatile in developed economies (*i.e.* the US, the UK, Australia, Germany, and Japan, respectively), and the most volatile in developing countries (namely Indonesia, Thailand, Taiwan, Korea and the Philippines). Most monthly stock returns have excess kurtosis which means that they have a thicker tail and a higher peak than a normal distribution. The calculated Jarque-Bera statistics and corresponding p-values are used to test for the normality assumption. Based on the Jarque-Bera statistics and p-values this assumption is rejected at 5 per cent level of significance for all stock returns, with the only three exceptions being the monthly stock returns in Australia, Japan and the UK.

4. Empirical Results

Table 2 illustrates the extent to which 13 stock market returns are correlated pairwise in a matrix. Out of 78 cells below the main diagonal there are 61 correlation coefficients (shown in boldface letters) above +0.30 which are also statistically significant. The highest correlation coefficients belong to Singapore-Hong Kong (0.714); Singapore-Malaysia (0.659); Thailand-Singapore (0.645); US-UK (0.645). It is interesting that pairwise the highest correlation coefficients are between the countries in the same region and/or at a similar stage of economic development.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was as high as 0.898 and the Bartlett test of sphericity rejected the null hypothesis that the correlation matrix was an identity matrix. The anti-image correlation coefficient matrix has also been reported in the bottom of Table 2 to provide detailed assessment of the sampling adequacy for the individual variables included in factor analysis. As can be seen the elements on the main diagonal of this matrix are above 0.822, which is larger than the acceptable level of 0.50.

In order to obtain a clearer picture of groupings of stock markets based on the co-movement of returns, a factor analysis of correlation matrix can now be conducted. The resulting eigenvalues for only the first two common factors were greater than unity. We reached the same conclusion using the Scree plot (not reported but available from the authors upon request) as a criterion to determine the number of common factors. The proportion (per cent) of variance explained by each factor is also shown in Table 3, indicating that these two factors altogether account for about 58 per cent of the total variance using the PC method (first factor = 46 per cent, second factor = 12 per cent) and 51 per cent of the total variance using the ML method (first factor = 42 per cent, second factor = 9.5 per cent).

We then rotate the resulting factors by the varimax method to facilitate the interpretation of the results presented in Table 3. As can be seen the first factor has relatively large weights for all eight Asian countries (the Philippines, Malaysia, Thailand, Singapore, Indonesia, Hong Kong, Taiwan and Korea), but relatively lower loadings for all of the developed countries including Japan being the only country from Asia. Thus one can argue that the first factor relating to the eight Asian countries in the sample is geographic proximity. Therefore, an investor may not be able to reduce risk and increase returns substantially by diversifying their financial portfolios through purchasing only the stocks of these countries because these returns are highly correlated. The second factor, which represents the co-movements of the stock returns in developed countries, has the highest loadings for the UK, Germany, the US, Australia and Japan (all classified as more advanced countries) while at the same time having relatively lower weights for the remaining countries.

Table 3 Factor analysis of correlation matrix

Country	Rotated factor loadings		Country	Rotated factor loadings	
	Factor 1	Factor 2		Factor 1	Factor 2
Principal Component Method			Maximum Likelihood Method		
Philippines	**0.789**	0.159	Singapore	**0.746**	0.449
Malaysia	**0.767**	0.194	Thailand	**0.740**	0.260
Thailand	**0.763**	0.293	Philippines	**0.726**	0.187
Singapore	**0.744**	0.449	Malaysia	**0.693**	0.248
Indonesia	**0.718**	0.042	Hong Kong	**0.624**	0.452
Hong Kong	**0.637**	0.456	Indonesia	**0.609**	0.108
Taiwan	**0.528**	0.206	Taiwan	**0.482**	0.170
Korea	**0.422**	0.401	Korea	**0.406**	0.308
UK	0.101	**0.884**	UK	0.101	**0.916**
Germany	0.176	**0.760**	Germany	0.207	**0.691**
US	0.289	**0.752**	US	0.325	**0.679**
Australia	0.334	**0.670**	Australia	0.365	**0.578**
Japan	0.171	**0.618**	Japan	0.230	**0.476**
% of variance	45.917	11.859	% of variance	41.741	9.463
Cumulative %	45.917	57.775	Cumulative %	41.741	51.203

Note: The highest factor loadings in each common factor are shown in boldface figures.

The results are robust and consistent for both the PC and ML methods. Even excluding countries with communalities less than 0.5 (see Table 1) produces highly robust results in that the remaining developing countries (Hong Kong, Malaysia, the Philippines, Singapore and Thailand) and developed countries (Germany, the UK and the US) exhibit a factor loading distribution similar to that shown in Table 3.

5. Conclusions

This study has used monthly data (1987:M12-2007:M4) to examine the extent to which returns in 13 selected international stock markets (Australia, Germany, Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Taiwan, Thailand, the UK and the US) are correlated, and whether these relationships can be analysed in a meaningful manner for the purpose of cross-country financial diversification. The results derived from a factor analysis, using both the PC and ML procedures, indicate that stock markets are integrated among Asian countries. More specifically, the rotated factor loadings of the first common factor provide ample evidence that the returns in Singapore, Thailand, the Philippines, Malaysia, Hong Kong, Indonesia, Taiwan and Korea enjoy a high degree of linear association. Based on the rotated loadings of the second factor using both the PC and ML methods it was found that the stock returns in all five developed countries (the UK, Germany, the US, Australia and Japan) can be represented by a well separated common factor in terms of their co-movements during the period December 1987 to April 2007.

Overall, we conclude that the cross country co-movements of stock market returns, defined as $ln(P_t/P_{t-1})$, depend, *inter alia,* on geographical location and/or the level of economic development. Therefore, if the aim of an astute investor is to reduce systematic investment risk across countries, his or her financial portfolio should include a diversified range of international stocks from various continents and form both developed and developing countries with varying degrees of stock market maturities.

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