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This paper examines the dynamics of cross-country GDP volatility transmission and their conditional correlations. We use quarterly data (1961-2008) for Australia, Canada, the UK and the US to construct and estimate a multivariate generalised autoregressive conditional heteroskedasticity (MGARCH) model. According to the results from the mean growth equations, we identified significant cross-country GDP growth spillover among these countries. Furthermore, the growth volatility between the US and Canada indicates the highest conditional correlation. As expected, we also found that the shock influences are mainly exerted by the larger economies onto the smaller economies.

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JEL classification: C59, F43, O47.

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1. Introduction

The volatility of output growth is profoundly important in assessing economic growth: the high volatility of output growth causes random shocks, makes the economy contract and can trigger a recession (Simon 2001). There is a consensus in the literature that output growth and its volatility have declined during the past few decades (Barrell & Gottschalk 2004; Perez, Osborn & Artis 2003; Stock & Watson 2005). Fountas and Karanasos (2006, p. 639) state that this decline in macroeconomic volatility is known in the literature as 'the Great Moderation' . According to Barrell and Gottschalk (2004), the Great Moderation could be due to rising openness to trade and holdings of financial wealth, along with reductions in inflation volatility.

Many studies have focused on different aspects of output growth. One group of studies, such as Artis, Kontolemis and Osborn (1997), Baxter (1995) and Otto, Voss and Willard (2001), has examined cross-country output correlations. For instance, Baxter (1995) identified a pair-wise positive correlation between US output and that of nine OECD countries using a two-country model to evaluate one pair of countries at a time.[3] Otto et al. (2001) found a bilateral output growth correlation for 17 OECD countries arising from common shocks and transmission of shocks between countries via trade and monetary policy. Boone and Hall (1999) identified a positive correlation in GDP among G5 countries (Italy, Japan, Germany, the UK and the US) during the post-war period.[4]

Similar to these output-growth correlations, other studies have documented the evidence of output volatility and changes in cyclical co-movements of output volatilities across different countries (Backus & Kehoe 1991; Perez et al. 2003; Stock & Watson 2005). For instance, Backus and Kehoe (1991) identified that the output volatility fluctuations of 10 countries were larger before World War I than after World War II.[5] The extent of these volatility fluctuations differed from country to country. Perez et al. (2003) examined the volatility shocks of GDP growth and their transmission across G7 countries, including the US. They identified that the business cycles of all G7 countries were influenced by the changes in the transmission of GDP shocks over time.

In addition, some empirical studies have documented the common properties of business cycles and common international volatility shocks (Kose, Otrok & Whiteman 2003a; Stock & Watson 2005). Using data from 61 countries over seven world regions, Kose et al. (2003a) identified the common dynamic properties of business-cycle fluctuations.[6] They found that countries with less-volatile GDPs were synchronised with the world business cycle (i.e. common world factors), while less-developed and more-volatile economies followed country-specific cycles. Using the per-capita real GDP volatilities of G7 economies, Stock and Watson (2005) identified the common international shocks, country-specific idiosyncratic shocks and country-specific effects of international idiosyncratic shocks. They also provided some evidence that these countries experienced a reduction in GDP volatility due to the declining magnitude of the common international shocks.

It is evident that output-volatility interdependencies have increased with the high synchronisation of business cycles across countries. One can argue that shocks emanating from one country are having greater ramifications for other economies than in the past because of these cross-border economic interdependencies (Kose, Prasad & Terrones 2003b). Although some empirical studies, such as Ahn and Lee (2006), Caporale and Spagnolo

[3] Australia, Austria, Canada, France, Germany, Italy, Japan, Switzerland and the UK.
[4] Sample periods were 1950-1986 for Germany, 1950-1985 for Italy, 1952-1986 for Japan and 1950-1983 for the UK and the US.
[5] Australia, Canada, Denmark, Germany, Italy, Japan, Norway, Sweden, the UK and the US.
[6] Africa, Asia (Developed), Asia (Developing), Europe, Latin America, North America and Oceania.

(2003), Diebold and Yilmaz (2008) and Leon and Filis (2008), have attempted to establish the link between financial variables and output growth in individual countries, the motivation of the current study is to provide an evaluation of cross-country spillovers of GDP growth rates and their volatilities across four major industrialised countries using more sophisticated techniques.

The current study first investigates the nature of any systematic patterns of GDP growth across individual countries, and examines how the GDP growth of one country can interact with the others. Second, we explore GDP volatility spillovers across countries by evaluating how country-specific shocks and volatilities, as well as cross-country shocks and volatility co-movements, affect GDP volatility within one country, and the transmission of shocks among countries. Finally, we investigate the GDP volatility correlations to shed some light on how constant-conditional correlations relate to time-varying conditional variance and covariance. Specifically, we use quarterly GDP data (1961-2008) from Australia, Canada, the UK and the US for the multivariate framework of generalised autoregressive conditional heteroskedasticity (MGARCH) models.

Unlike previous studies, our methodology simultaneously estimates time-variant, country-specific volatility spillovers, as well as cross-country volatility spillovers, across all the countries in our sample.[7] This will permit us to analyse single- and multi-country influences on other countries. As Bollerslev, Chou and Kroner (1992) and Bollerslev, Engle and Nelson (1994) suggested, these MGARCH models have been developed for analysing volatility transmission across different markets and assets, since the volatility of financial markets moves together across assets and markets. According to Theodossiou et al.(1997), Goeij and Marquering (2004), Bauwens, Laurent and Rombouts (2006) and Caporin and McAleer (2009), MGARCH models are the most appropriate methodology to capture interaction effects within the time-varying conditional mean and variances of two or more series. Although MGARCH models have predominantly been used for analysing the interaction effects of volatility and covolatility across international financial markets in the past, MGARCH models also represent the most suitable methodology for examining the interaction effects of GDP volatility and covolatility and, therefore, economic growth across various countries.

The rest of this paper is organised as follows: Section 2 presents the methodology, which is built upon the diagonal vector GARCH (DVECH)[8] model and the Constant Conditional Correlation (CCC)[9] model. The data and preliminary findings are set out in Section 3, followed by the empirical econometric results in Section 4. The last section provides some concluding remarks.

2. Methodology

This paper evaluates the interplay between GDP growth rates and their volatilities among four industrialised Anglo-Saxon countries: Australia, Canada, the UK and the US. We use the DVECH model to study the volatility spillovers within and across these countries. We also employ the CCC model to evaluate how time-varying conditional variances and covariances link to the constant-conditional correlations. Furthermore, we apply the vector autoregressive stochastic process to GDP growth rates to obtain the mean equations, which allows us to examine the nature of GDP growth-rate interdependencies. The mean equation and the two models used in this paper are as follows.

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[7] One group of studies evaluated pairs of countries at a time or incorporated effects from a single country to their model (for example, see Baxter 1995 and Otto et al. 2001), while another group used multivariate methodology based on factor modelling (examples include Stock and Watson 2005 and Kose et al. 2003a).

[8] Diagonal vector GARCH (DVECH) (Bollerslev et al. 1988).

[9] Constant Conditional Correlation (CCC) (Bollerslev 1990).

2.1 The Mean Equation

Equation (1) gives the vector autoregressive stochastic process of GDP growth rates. This serves as the mean equation for the DVECH and CCC models. The GDP growth rate of country i (r_{iit}) is specified as a function of its own innovations (ε_{it}) and its own lagged growth rates (r_{ijt-1}), for all $j = 1,\ldots, 4$ and $i = j$, as well as the lagged growth rates of other countries (r_{ijt-1}), for all $j = 1, .., 4$ and $i \neq j$ as follows:

$$r_{iit} = \mu_{0i} + \sum_{j=1}^{4} \mu_{ij} r_{ijt-1} + \varepsilon_{it} \tag{1}$$

where $i = 1$ for Australia, $i = 2$ for Canada, $i = 3$ for the UK and $i = 4$ for the US; μ_{0i} is the intercept term for country i; μ_{ij} (for all i = 1, .. , 4 and j = 1, .. , 4) indicates the conditional mean of GDP growth rate, showing the influence from country i's own past growth rates (i.e. own-mean spillovers) when $i = j$ and the cross-mean spillovers from country j to i when $i \neq j$; and ε_{it} is country i's own innovations (shocks) and is assumed to be independently and identically distributed (IID) with zero mean and variance.

2.2 The DVECH Model

Since the conditional variance and covariance matrix (H_t) contains four variables, this study uses the DVECH model, as it is more flexible for more than two variables (Scherrer & Ribarits 2007). Furthermore, this model is based on the assumption that the conditional variance depends on squared lagged own residuals and the lagged own variances while the conditional covariance depends on the cross-product of the lagged residuals and lagged covariances of other series (Harris & Sollis 2003). In addition, we impose conditions on the initial values as suggested by Bollerslev et al. (1988), and use the maximum likelihood function to generate the parameter estimates. Therefore, this paper uses the unconditional residual variance as the pre-sample conditional variance to guarantee the positive semi-definite of H_t of the DVECH model. The corresponding DVECH model is incorporated into our framework; it can be written as follows:

$$vech(H_t) = C + A^{*} vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + B^{*} vech(H_{t-1}) \tag{2}$$

where A^{*} and B^{*} are $\frac{1}{2}N(N+1) \times \frac{1}{2}N(N+1)$ diagonal matrices of parameters, which satisfies $A^{*} = diag[vech(A)]$ and $B^{*} = diag[vech(B)]$ where A and B are $N \times N$ symmetrical matrices; and C is a $\frac{1}{2}N(N+1) \times 1$ vector of parameters. The $vech(\cdot)$ operator denotes the column-stacking operator applied to the upper portion of the symmetric matrix. The diagonal elements of matrix A (a_{11}, a_{22}, a_{33} and a_{44}) measure the own-volatility shocks, which represent the impacts arising from past squared innovations on the current volatility. The non-diagonal elements (a_{ij} where $i \neq j$) determine the cross-volatility shocks, which can be shown as the cross-product effects of the lagged innovations on the current covolatility. Similarly, the diagonal elements of matrix B (b_{11}, b_{22}, b_{33} and b_{44}) determine the own-volatility spillovers that can be considered as the past volatilities on the current volatility, and the non-diagonal elements (b_{ij} where $i \neq j$) capture the cross-volatility spillovers, which are the lagged covolatilities on the current covolatility.

2.3 The CCC Model

Since the CCC model contains time-varying conditional variance and covariance with the constant-conditional correlations, we use this model to evaluate how time-varying conditional variance and covariance influence the constant-conditional correlations. It also allows univariate analyses for each of the data series, assuming the GARCH(1,1) structure for conditional variances and non-zero constant-conditional correlations across series (Bollerslev, 1990). Suppose ε_{it} is the i^{th} elements of the residuals, the CCC model can be written as follows:

$$h_{iit} = \alpha_i + \beta_i \varepsilon_{it-1}^2 + \gamma_i h_{iit-1}$$
$$\rho_{ij} = h_{ijt} \Big/ \left(h_{iit} h_{jjt} \right)^{1/2} \qquad (3)$$

where h_{ijt} is the ij^{th} element in H_t; α_i is the intercept term for country *i*; β_i measures the own-volatility shocks; γ_i determines the lagged own-volatility; and ρ_{ij} is the conditional correlation between growth of country *i* and *j*, where $-1 < \rho_{ij} < 1$ and $i \neq j$.

Furthermore, we use the BHHH (Berndt, Hall, Hall, & Hausman 1974) algorithm to obtain the optimal values for the parameters, and the Ljung-Box test statistic to test any remaining ARCH effects in these two models.

3. Data and Preliminary Findings

Quarterly GDP data from Australia, Canada, the UK, and the US for the period spanning from 1961:Q4 to 2008:Q4 (*n* = 189 observations) were obtained from OECD Main Economic Indicators (OECD 2009) for this study. Based on these GDP values, the growth rate (r_t) at time *t* is calculated as $r_t = \ln\left(p_t / p_{t-1} \right)$, where p_t is the GDP value at time *t*.

Table 1 presents the descriptive statistics for the GDP growth series for Australia, Canada, the UK and the US. All four countries show positive mean growth rates during the sample period, ranging from a minimum of 0.006 per cent (the UK) to a maximum of 0.009 per cent (Australia). Based on the sample standard deviations, the US (0.0085) and Canada (0.0086) indicate the lowest output volatility, while Australia exhibits the highest output volatility, with 0.011 (Figure 1). A cursory look at the figure also reveals a decline in output beginning in the early 1980s. Several recent studies have confirmed this decline (Barrell & Gottschalk 2004; Blanchard & Simon 2001; Dijk et al. 2002; Kose et al. 2003b).

The estimated skewness statistics for all the countries except the US exhibit positive skewness. The kurtosis value is greater than 3.0 for all series except Canada. This indicates a typical leptokurtic distribution, whereby growth series are more peaked around the mean, with thicker tails than a normal distribution. The Jarque-Bera statistics for Australia, the UK and the US also support rejecting the null hypotheses of normality at the 5 per cent level of significance.

Table 1 reports the pair-wise unconditional correlations among the four countries. The estimated pair-wise correlation coefficients suggest that the countries are positively interrelated. The lowest correlation (0.348) is between the GDPs of Australia and the UK, while the highest (0.71) is between Canada and the US. The Australian data indicates a correlation coefficient of 0.55 with both the US and the UK series. Table 1 also gives the results of the Augmented Dickey-Fuller (ADF) test for the GDP growth rate series, which suggest that that all four series are stationary.

Figure 1
Quarterly GDP growth rates from 1961:Q4 to 2008:Q4

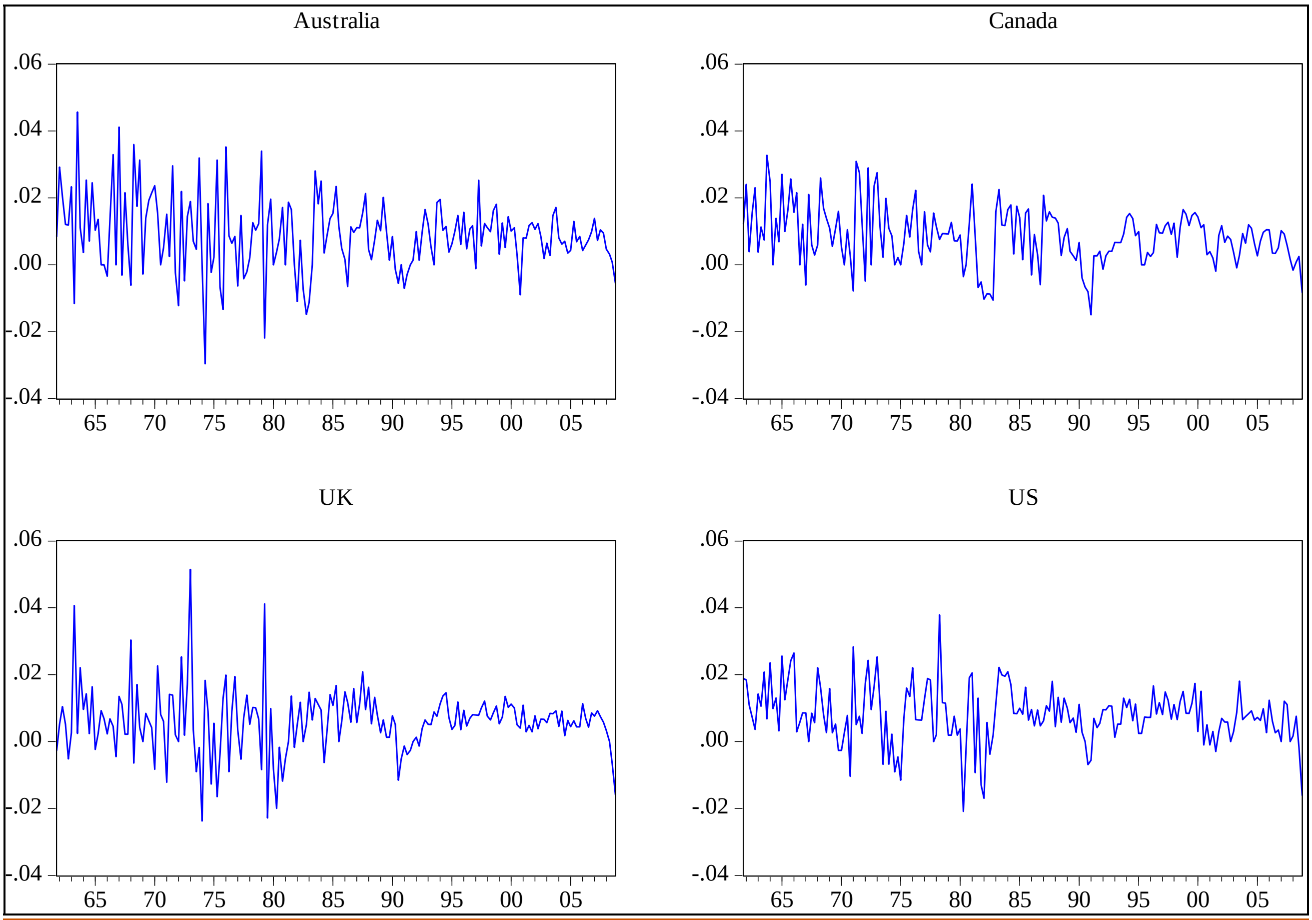

Table 1
Descriptive statistics for GDP growth

Descriptive Statistic	Australia	Canada	UK	US
Mean	0.0090	0.0084	0.0060	0.0079
Median	0.0086	0.0087	0.0062	0.0075
Maximum	0.0456	0.0328	0.0515	0.0379
Minimum	-0.0296	-0.0149	-0.0237	-0.0209
Std. Dev.	0.0111	0.0086	0.0095	0.0085
Skewness	0.1810	0.1700	0.5315	-0.1163
Kurtosis	4.1455	3.2477	7.3702	4.3628
Jarque-Bera	11.3663**	1.3933	159.2991***	15.0512***
	(0.0034)	(0.4982)	(0.0000)	(0.0005)
Correlation Coefficients				
Australia	1.0000			
Canada	0.5498	1.0000		
UK	0.3481	0.5205	1.0000	
US	0.5540	0.7112	0.5245	1.0000
ADF t Statistics				
Based on min. AIC	-3.80	-10.04	-6.04	-6.74
	(0.0106)	(0.0000)	(0.0000)	(0.0000)
Based on min. SIC	-14.58	-10.04	-13.76	-10.03
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Sources: Quarterly GDP data of Australia, Canada, the UK and the US for the period 1961Q4 to 2008Q4 (n = 189 observations) are obtained from OECD Main Economic Indicators (OECD, 2009).

4. Empirical Results

We adopted the DVECH(1,1) and CCC(1,1) specifications for this study as discussed for Equations (2) and (3) respectively, and for the mean structure in Equation (1).[10] This section reports three main findings: the transmission of GDP growth across countries, international co-movements of GDP growth volatility and the nature of cross-country volatility correlations.

4.1 Transmission of GDP Growth Rates

Table 2 presents the estimated results for the mean equation. Panel A reports the parameter estimation of the mean structure using the DVECH(1,1) model, and Panel B represents the results of the mean equation based on the CCC(1,1) model. According to the estimated coefficients, the constant terms in the mean equation in both models are statistically significant at the 1 per cent level for all the countries except Canada, which is significant at the 10 per cent level. The own-mean spillovers (μ_{ii} for all i= 1,..,4) are statistically significant only for Canada, providing weak evidence for the influence of own lagged GDP growth effects on current growth rates.

[10] We tested various DVECH(p,q) and CCC(p,q) specifications (where p = 1, 2, and 3 and q = 1, 2, and 3) using three model-selection criteria: the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HIC). The results indicated that the DVECH(1,1) specification consistently has the lowest AIC (-27.55), SIC (-27.04) and HIC (-27.34), with a log-likelihood of 2647.22, while the CCCH(1,1) specification consistently has the lowest AIC (-27.64), SIC (-26.97) and HIC (-27.37), with a log-likelihood of 2651.29.

Table 2:
Parameter estimation for mean equation

$$r_{iit} = \mu_{0i} + \sum_{j=1}^{4} \mu_{ij} r_{ijt-1} + \varepsilon_{it}$$

Panel A: Mean structure of DVECH(1,1)

	Australia	Canada	UK	US
μ_{0i}	0.0056***	0.0015*	0.0035***	0.0044***
	(5.03)	(1.87)	(4.99)	(5.43)
μ_{1i}	-0.0184	0.1595***	0.0532	0.0030
	(-0.28)	(3.32)	(1.19)	(0.06)
μ_{2i}	0.0488	0.2350***	0.1683**	0.1728**
	(0.55)	(4.09)	(2.31)	(2.23)
μ_{3i}	0.1843**	0.1333**	0.1233	0.2260***
	(2.38)	(2.34)	(1.52)	(3.43)
μ_{4i}	0.2184**	0.2910***	0.1060	0.1162
	(2.36)	(5.04)	(1.36)	(1.46)

Panel B: Mean structure of CCC(1,1)

	Australia	Canada	UK	US
μ_{0i}	0.0045***	0.0017**	0.0032***	0.0041***
	(4.11)	(2.12)	(4.08)	(4.84)
μ_{1i}	0.0036	0.1601**	0.0580	0.0062
	(0.04)	(3.15)	(1.11)	(0.12)
μ_{2i}	0.1620	0.2398***	0.1880**	0.1934**
	(1.54)	(3.19)	(2.22)	(2.43)
μ_{3i}	0.2301**	0.1878***	0.1108	0.2652***
	(2.66)	(3.26)	(1.22)	(3.71)
μ_{4i}	0.1839*	0.2290***	0.1020	0.0762
	(1.79)	(3.80)	(1.07)	(0.81)

Notes: (a) i = 1 for Australia, i = 2 for Canada, i = 3 for the UK and i = 4 for the US. (b) *** indicates statistical significance at the 1 per cent level, ** indicates statistical significance at the 5 per cent level and * indicates statistical significance at the 10 per cent level.

However, there exist significant positive cross-mean spillovers effects from the UK and the US to both Australia and Canada, indicating a positive influence running from the larger economies towards the relatively smaller economies. Based on the magnitude of cross-mean lagged effects presented in Panel A of Table 2, Australian GDP growth rates are heavily influenced by the lagged growth rates of the UK (0.183) and US (0.218). In addition, our results indicate a positive and significant impact on the US GDP growth rates from the UK (0.226) and Canada (0.173). The GDP growth of Canada is positively influenced by the cross-lagged GDP growth effects of the other three countries in the sample. A bidirectional relationship can be identified between Canada and the UK on the one hand and the US and Canada on the other. Based on the magnitude of the coefficients, this bidirectional relationship is stronger between Canada and the US than between Canada and the UK. Very similar results emerge from the results in Panel B of Table 2.

4.2 International Co-movements of GDP Growth Volatility

Table 3 reports the estimated ARCH and GARCH coefficients of the DVECH(1,1) model. The estimated values of all intercept terms are insignificant and close to zero; thus they are not reported. The significant own-volatility shocks for all four countries (a_{11}, a_{22}, a_{33} and a_{44}) range from 0.033 (Canada) to 0.127 (the US), indicating the presence of ARCH effects. According to Table 3, one can conclude that the shocks arising from the US will have a stronger impact on its own future volatility than those from the other three countries.

Besides own-volatility shocks, the estimated cross-volatility coefficients, a_{ij} $(i \neq j)$, in all four countries are significant at the 1 per cent level. These cross-volatility shocks are generally higher than the own-volatility shocks. This suggests that cross-volatility shocks have a stronger effect on future covolatility than do country-specific volatility shocks. Based on the estimated cross-volatility coefficients, the degree of cross-volatility shocks pair-wise is the weakest between Australia and Canada (0.043) and the strongest between the US and the UK (0.109). In addition, there is evidence of growth-volatility shocks emanating from both the UK and the US to Australia. This cross-output volatility persistence between Australia on the one hand and the UK and US on the other are 0.072 and 0.084, respectively. This suggests that output shocks originating from the US influence the Australian output volatility more than shocks stemming from Canada and the UK. This finding also confirms the findings in the previous section, since GDP growth rates and their volatilities are intertwined with the performance of larger economies.

Table 3 also presents the estimated coefficients for the variance and covariance matrix of DVECH model using equation 2. The own-volatility coefficients b_{ij} $(i = j)$ for the lagged conditional variance of all four countries are again positive and statistically significant. These own-volatility spillovers effects vary from its lowest in the US (0.890) to the highest in Canada (0.956). Similar to the results presented in Table 2, the past volatility in Canada will have the strongest impact on its own future volatility compared to the other three countries while the US has the lowest influence on its own future volatility from the past volatility.

Table 3:
Parameter estimation for variance and co-variance equation

$$vech(H_t) = C + A^{*}vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + B^{*}vech(H_{t-1})$$

	Australia	Canada	UK	US
a_{1i}	0.0554** (2.40)			
a_{2i}	0.0425*** (3.64)	0.0326** (2.55)		
a_{3i}	0.0720*** (3.63)	0.0552*** (3.52)	0.0935** (3.18)	
a_{4i}	0.0840*** (3.80)	0.0644*** (3.63)	0.1091*** (4.10)	0.1272** (3.15)
b_{1i}	0.9378*** (53.22)			
b_{2i}	0.9468*** (90.94)	0.9560*** (83.06)		
b_{3i}	0.9215*** (63.03)	0.9304*** (68.91)	0.9055*** (43.31)	
b_{4i}	0.9133*** (54.52)	0.9222*** (53.71)	0.8975*** (46.53)	0.8895*** (30.77)
$a_{ii} + b_{ii}$	0.9932	0.9886	0.999	0.983

Notes: See Table 2.

The estimated non-zero b_{ij} coefficients (where $i \neq j$ for all i and j) are all significant at the 1 per cent level, providing further evidence for high and positive volatility-spillover persistence across these four industrialised countries. In contrast to the cross-volatility shocks (a_{ij}), the magnitude of the cross-volatility spillovers (b_{ij}), is, pair-wise, the lowest between the UK and the US (0.898), and highest between Australia and Canada (0.947). Furthermore, the significant cross-volatility effects between Australia and the UK and US are 0.922 and 0.913, respectively. These results support the view that volatility initially stemming from the US and the UK affects Australian output almost equally. Furthermore, our findings provide convincing evidence that volatility persistence usually emanates from larger economies towards smaller economies. In addition, the sum of the lagged ARCH and GARCH coefficients ($a_{ii} + b_{ii}$) for Australia (0.993), Canada (0.989), the UK (0.999) and the US (0.983) are close to unity, supporting the assumption of co-variance stationarity and volatility persistence in the data.

4.3 The Nature of Cross-country Volatility Correlation

Table 4 summarises the estimated results from the CCC(1,1) model, which allows non-zero constant-conditional correlations across these four output growth series. In terms of GDP volatility correlations, our interest here is to identify how constant conditional correlations relate to the time-varying conditional variance and covariance. Thus, we do not report the estimated values of constant parameters, which are insignificant and close to zero. As shown in Table 4, all the parameters in the time-varying conditional variances are individually significant. In addition, the Wald test results for all $\beta_i = \gamma_i = 0$ and for all i confirm the presence of lagged ARCH and GARCH effects on the GDP growth volatility of each country.

Table 4:
Parameter estimation for constant conditional correlations

$$h_{iit} = \alpha_i + \beta_i \varepsilon_{it-1}^2 + \gamma_i h_{iit-1}$$

$$\rho_{ij} = h_{ijt} \big/ \left(h_{iit} h_{jjt}\right)^{1/2}$$

	Australia	Canada	UK	US
β_i	0.0795* (1.67)	0.3201** (2.44)	0.1057** (2.63)	0.1521* (1.89)
γ_i	0.9259*** (21.23)	0.6616*** (5.76)	0.8828*** (26.74)	0.8297*** (10.86)
ρ_{i2}	0.1333 (1.60)	-		
ρ_{i3}	0.1792* (1.98)	0.1844* (1.99)	-	
ρ_{i4}	0.1648* (1.79)	0.3408*** (4.40)	0.2180** (2.56)	-

Notes: See Table 2.

According to Table 4, all conditional correlations except for that between the GDP growth volatility of Australia and Canada are statistically significant. The existence of non-zero conditional correlations is also confirmed by the Wald test for $\rho_{ij} = 0$ for all $i \neq j$. The smallest conditional correlation is between Australia and the US (0.1648), and the highest is between Canada and the US (0.341). Similar to our findings, Artis et al. (1997) and Perez et al. (2003) also found a strong association between the US and Canada. Furthermore, the countries with lower own-volatility also have the highest conditional correlations. For instance, Canada and the US have the lowest own-volatilities but the highest conditional correlation. The conditional correlations reported in Table 4 are much smaller (closer to zero) than those reported in Table 1. This could be because the correlation coefficients presented in Table 1 are based on the raw output growth rates, as with most cross-country studies. We further calculated correlation coefficients for residuals estimates obtained from the mean equation (Equation 1) using both the DVECH and CCC models. These correlation coefficients for residual series are similar to those reported in Table 4 (close to zero), with the highest correlation coefficient between Canada and the US (approximately 0.37) from both models.[11]

Finally, we perform several diagnostic tests on standardised residuals to validate our findings. Panel A of Appendix A reports the system-generated portmanteau test results for the DVECH(1,1) model, and Panel B reports the results for the CCC(1,1) model. The estimated results from the Portmanteau Box-Pierce/Ljung-Box Q-statistics and the adjusted Q-statistics for the standardised system residuals generated from the DVECH and CCC models support the null hypothesis of no autocorrelations at the 5 per cent confidence level. This provides further support for both the DVECH model and the CCC model, as they absorb a great deal of the ARCH and GARCH effects present in the original series.

5 Summary and Conclusion

This research uses the DVECH model to identify the magnitude of volatility spillovers across four sample countries, namely Australia, Canada, the UK and the US and the CCC model to evaluate the cross-country conditional correlations. We employ a general vector stochastic process of GDP growth rates to find any discernable pattern in cross-country mean spillovers. Our results indicate that: (1) there is a significant amount of spillover and a high degree of volatility persistence in GDP growth rates across these four countries; (2) the significant positive GDP growth spillovers from the UK affect the other three countries; (3) based on the results of the DVECH model, both domestic and external shocks give rise to volatility in individual countries.

We found convincing evidence that that both own-country volatility and cross-country volatility increase the future volatilities within and across countries. However, the unanticipated country-specific shocks are generally lower than the country-specific volatilities in each of these countries. According to the results from the CCC model, the cross-country conditional correlation between the US and Canada is higher than the other pair-wise cross-country conditional correlations. Finally, we find that the significant positive cross-mean spillovers effects originating in the UK and the US can affect both Australia and Canada, leading to our final conclusion that positive spillover effects from larger economies can influence the GDP growth rates of relatively smaller economies.

Although this study identifies the shocks and volatility spillovers of GDP growth rates across Australia, Canada, the UK and the US, one can argue that these shocks and volatility spillovers cannot be transmitted and recorded through GDP growth alone. Therefore, in terms of an agenda for future research, it would be interesting to evaluate various sources of financial shocks by including additional variables and splitting the periods corresponding to financial and economic crises. However, given the number of countries, the inclusion of more financial variables increases the number of estimated parameters geometrically in the mean, variance and covariance equations, and complicates the interpretations of the results. Thus, due to the nature of the multivariate GARCH modelling framework, these points cannot be implemented, but could serve as interesting topics for research using alternative modelling methodologies such as simultaneous equation systems.

[11] These results have not been reported in this paper; they are available from the authors upon request.

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Appendix A: Diagnostic Test Results for Standardised System Residual

Table A1:
Portmanteau test results for autocorrelations obtained from the DEVEC(1,1) model

Autocorrelation coefficients	Conditional Correlation Orthogonalisation		Conditional Covariance Orthogonalisation	
	Q-Statistic	Adjusted Q-Statistic	Q-Statistic	Adjusted Q-Statistic
Q(1)	8.1660 (0.94)	8.2092 (0.94)	8.2258 (0.94)	8.2693 (0.94)
Q(2)	24.7176 (0.823)	24.9370 (0.81)	24.9874 (0.81)	25.2093 (0.80)
Q(3)	43.6295 (0.65)	44.1522 (0.63)	44.0363 (0.64)	44.5637 (0.61)
Q(4)	73.7992 (0.19)	74.9707 (0.16)	74.0370 (0.18)	75.2096 (0.16)
Q(5)	87.3663 (0.27)	88.9044 (0.23)	87.7628 (0.26)	89.3063 (0.22)
Q(6)	99.9951 (0.37)	101.9451 (0.32)	100.1297 (0.37)	102.0766 (0.32)
Q(7)	113.2711 (0.45)	115.7289 (0.38)	113.4535 (0.44)	115.9100 (0.38)
Q(8)	134.1034 (0.34)	137.4769 (0.26)	134.3003 (0.33)	137.6731 (0.26)

Note: Q(n) is the n^{th} lag Ljung-Box test statistics.

Table A2:
Portmanteau test results for autocorrelations obtained from the CCC(1,1) model

Autocorrelation coefficients	Conditional Correlation Orthogonalisation		Conditional Covariance Orthogonalisation	
	Q-Statistic	Adjusted Q-Statistic	Q-Statistic	Adjusted Q-Statistic
Q(1)	10.1716 (0.86)	10.2257 (0.85)	10.2348 (0.85)	10.2893 (0.85)
Q(2)	23.6941 (0.86)	23.8928 (0.85)	23.7892 (0.85)	23.9887 (0.84)
Q(3)	36.4312 (0.88)	36.8354 (0.88)	36.4445 (0.89)	36.8481 (0.88)
Q(4)	69.2361 (0.31)	70.3495 (0.27)	69.1065 (0.31)	70.2162 (0.28)
Q(5)	82.3226 (0.41)	83.7917 (0.36)	82.2234 (0.41)	83.6895 (0.37)
Q(6)	93.6163 (0.55)	95.4557 (0.50)	93.4044 (0.56)	95.2372 (0.50)
Q(7)	106.5193 (0.63)	108.8550 (0.57)	106.3296 (0.63)	108.6595 (0.57)
Q(8)	129.5399 (0.45)	132.8931 (0.37)	129.4114 (0.45)	132.7615 (0.37)

Notes: See Table A1.