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Asymmetric Dynamics in Stock Market Volatility

Indika Karunanayake[1] and Abbas Valadkhani[1]

This paper provides some insight into the asymmetric effects of stock market volatility transmission using weekly stock market return data (January 1992–June 2010) of four countries, namely, Australia, Singapore, the United Kingdom and the United States within a MGARCH (multivariate generalised autoregressive conditional heteroskedasticity) framework. Our results indicate that negative shocks in each market play a more important role in increasing both volatility and covolatilities than positive shocks. In addition, as expected, we identified that all markets (particularly Australia and Singapore) exhibit significant positive mean and volatility spillovers from the US stock market returns, but not the other way around.

Keywords: stock market volatility transmission, asymmetric effect, multivariate GARCH model.

1. Introduction

With the globalisation of international trade and finance, the interactions between international financial markets have increased markedly. It is important to understand the extent and sources of cross-market linkages and interactions. For example, In (2007) argues that the knowledge of market interdependency is important in determining optimal diversification for international investment portfolios. According to Shamsuddin and Kim (2003), the short-run temporal relationships among national stock prices and their long-run co-movements are essential for managing international investment diversification because a low correlation among national stock returns allows investors to minimise their portfolio risk by investing in such international stocks. In addition, Brailsford (1996) stated that the transmission of international stock market volatility is significant for pricing of securities, trading strategies, hedging strategies, and regulatory strategies within and across the markets. Therefore, in recent years, the dynamics of international stock market volatility transmission has emerged as a growing topic of interest.

As to the asymmetry of volatility effects, Bollerslev *et al.* (1994), Brooks (2002) and Patterson (2000) all agree that stock market volatility is more responsive following a large price fall than it is to a price rise of the same magnitude. In addition, Koutmos and Booth (1995) find significant asymmetric volatility effects in the cross-market volatility contexts – indicating that bad news in one stock market increases the volatility of both that market and international markets more than good news tends to decrease volatility. Similarly, Brooks and Henry (2000) and Ng (2000) have found interesting results indicating that both the size and sign of unanticipated shocks within one stock market influence volatility transmission across other stock markets.

[1]School of Economics, University of Wollongong

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Correspondence: Abbas Valadkhani, School of Economics, University of Wollongong, NSW 2522, Australia. Email: abbas@uow.edu.au

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As can be seen from the literature presented above, this issue is becoming increasingly more topical; however, there are limited recent empirical studies capturing such potential asymmetries in a multi-country setting. At an empirical level, Koutmos and Booth (1995) extend Nelson's (1991) univariate exponential generalised autoregressive conditional heteroskedasticity model to multivariate context, whereas Kroner and Ng (1998) propose the use of an asymmetric dynamic covariance model. These two studies are methodologically relevant but they are outdated and do not focus on Australia. There is therefore a gap in the literature for explaining how good or bad news originating in one market has varying volatility implications across different markets interconnected with Australia. On this aspect, far back only Brooks and Henry (2000) included Australia with Japan, and the United States in their asymmetric BEKK model and argue that although it is difficult to explain the asymmetric spillovers of stock returns across markets, the knowledge of such interactions in the stock market volatility transmission dynamics is important for the pricing of securities, and for hedging and trading policies. Therefore, the important contribution of our study is to provide an updated evaluation of asymmetric effects of good and bad news arising from markets interconnected with Australia, particularly in the wake of recent financial turmoils.

Our study applies the Diagonal vector GARCH (DVECH) (Bollerslev *et al.*, 1988) model to determine whether volatility influences on the nature of volatility transmission dynamics across different international stock markets are asymmetric or not. In this regard, we use weekly data from the Australian stock market and three other countries, namely Singapore, the United Kingdom and the United States. The Australian stock market is of particular interest in this study as it is one of the major financial markets in the Asia Pacific region. According to the Standards and Poor's (September 2009), it is the second largest market in the Asia Pacific region and the seventh largest in the world in terms of total market capitalisation. Furthermore, McNelis (1993) and Valadkhani *et al.* (2008) found that the stock market returns of the United Kingdom, Singapore and the United States were highly interrelated with that of Australia. Therefore, this paper enables us to understand how the Australian stock market interacts with highly integrated stock markets in North America, Europe and the Asia Pacific regions. We can then identify the extent to good and bad news from which international stock market impacts on the volatility of Australian stock returns.

Next, we tested whether the estimated asymmetric impacts vary due to the calendar effect, which is the irregularity in stock returns that relate to the calendar such as the month-of-the-year, the week-of-the-month, holidays, weekends and so on. In this regard, the current study focuses on the month-of-the-year and the week-of-the-month. Thus, the current study allows us to identify whether there is any influence from the month-of-the-year and the week-of-the-month towards stock return variations. Hence, we can evaluate how asymmetry of volatility effects varies due to the calendar effect that arises with weekly data.

In portfolio diversification decisions, it is important to identify potential international influence. For instance, as suggested by Kroner and Ng (1998), it is riskier to invest in two assets if they are positively correlated compared with investing in an uncorrelated pair of assets. When two assets move together, shocks in the same direction can then involve higher risk by increasing conditional covolatility than shocks in the opposite direction. Consequently, an investor would be unlikely to benefit from diversifying their financial portfolio, which acquires stocks only from international markets with a high degree of time-varying covolatility. Therefore, this study provides international investors with an updated evaluation of asymmetric volatility effect to manage their portfolio more effectively despite the fact that our results are consistent with the findings of previous studies. In addition, unlike previous studies, testing for calendar effect has enabled us to identify whether asymmetry of volatility effects could have different implications due to the calendar effect that arises with weekly data.

The remainder of this paper is organised as follows. Section 2 presents our DVECH methodology, followed by a description of the data and summary statistics in Section 3. The empirical econometric results and policy implications of the study are set out in Section 4, followed by some concluding remarks in Section 5.

2. Methodology

The major objective of this paper is to examine the interdependence of return and covolatility across four highly integrated international stock markets, with a particular focus on Australia, by using the DVECH proposed by Bollerslev *et al.* (1988). This model is chosen for three reasons. First, it allows us to examine the conditional variance covariance matrix of stock market returns to vary over time. Second, many empirical studies in the literature (e.g. Goeij and Marquering, 2004; Bauwens *et al.*, 2006) suggest that this technique is capable of capturing the interaction effects within the conditional mean and variances of two or more series. Third, as proposed by Goeij and Marquering (2004), our DVECH model can be easily augmented with dummy variables to address the asymmetric nature of volatility of returns. It should be noted that Glosten *et al.* (1993) incorporate the asymmetric volatility for one single market in the context of univariate models, whereas Goeij and Marquering (2004) use the DVECH model in a similar way to examine the asymmetric volatility transmission across different (multi) stock and bond markets.

According to Engle and Kroner (1993), Kroner and Ng (1998), and Brooks and Henry (2000), the empirical implementation of the VECH models is, however, limited due to the difficulty of guaranteeing a positive semi-definite conditional variance covariance matrix. This study uses the unconditional residual variance as the pre-sample conditional variance to overcome this problem, thus guaranteeing the positive semi-definite of conditional variance and covariance matrix (H_t) of the asymmetric DVECH (hereafter ADVECH) model. In addition, we use the Marquardt algorithm to obtain the optimal values of our parameters and Ljung–Box test statistic to test any remaining ARCH effects in the model.

The vector autoregressive stochastic process of asset returns has been specified by Equation 1. Asset returns of country i (r_{iit}) are specified as a function of their own innovations (ε_{it}) and the past own return (r_{ijt-1}), for all $j = 1,\ldots, 4$ and $i = j$ as well as the lagged returns of other countries (r_{ijt-1}) for all $j = 1,\ldots, 4$ and $i \neq j$ as follows:

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

where (in alphabetical order) $i = 1$ for Australia, $i = 2$ for Singapore, $i = 3$ for the United Kingdom and $i = 4$ for the United States; μ_{0i} is the intercept for country i; μ_{ij} (for all $i = 1,\ldots,4$ and $j = 1,\ldots,4$) indicates the conditional mean of stock return, which represents the influence from own past returns of country i (i.e. own-mean spillovers when $i = j$) and the influence from past returns of country j towards country i (i.e. cross-mean spillovers from country j to i when $i \neq j$); and ε_{it} is own innovations (shocks) to country i.

The conditional variance-covariance matrix (H_t) for this study can be written as:

$$H_t = \begin{pmatrix} h_{11t} & h_{12t} & h_{13t} & h_{14t} \\ h_{21t} & h_{22t} & h_{23t} & h_{24t} \\ h_{31t} & h_{32t} & h_{33t} & h_{34t} \\ h_{41t} & h_{42t} & h_{43t} & h_{44t} \end{pmatrix}, \tag{2}$$

where h_{iit} is a conditional variance at time t of the stock return of country i and h_{ijt} denotes the conditional covariance between the stock returns of country i and country j (where $i \neq j$) at time t.

The ADVECH model can be written as follows:

$$\mathrm{vech}(H_t) = C + A^{*}\mathrm{vech}(\varepsilon_{t-1}\varepsilon'_{t-1}) + G^{*}\mathrm{vech}(\eta_{t-1}\eta'_{t-1}) + B^{*}\mathrm{vech}(H_{t-1}), \tag{3}$$

where A^*, B^* and G^* are $(1/2)N(N+1) \times (1/2)N(N+1)$ diagonal matrix of parameter, which satisfies $A^* = \mathrm{diag}[\mathrm{vech}(A)]$, $B^* = \mathrm{diag}[\mathrm{vech}(B)]$ and $G^* = \mathrm{diag}[\mathrm{vech}(G)]$, where A, B and G are $N \times N$ symmetrical matrices; and C is a $(1/2)N(N + 1) \times 1$ vectors of parameters. The vech(·) operator denotes the column-stacking operator applied to 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, whereas 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. In addition, the parameters of matrix G capture the magnitude of asymmetry of volatility effect, where η_{t-1} = max [0, 1] and it is similar to the Glosten *et al.*'s (1993) dummy series. In other words, the term η_{t-1} takes the value of 1 for negative shocks and 0 otherwise (i.e. $\eta_{t-1} = 1$ when $\varepsilon_{t-1} < 0$ and $\eta_{t-1} = 0$ when $\varepsilon_{t-1} \geq 0$). Therefore, the significant positive values of g_{ii} indicate that negative shocks of country i increase the variance. Similarly, the significant positive values of g_{ij} represent the effect from negative shocks between country i and j for rising covariances. Finally, 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 (*bij* where $i \neq j$) capture the cross-volatility spillovers, which are the lagged covolatilities on the current covolatility.

To test calendar effect that arises with weekly data, we evaluated the-month-of-the-year and the-week-of-the-month effects. In this regard, we extended Equation 1, incorporating dummy variables to test the calendar effect. Then, for the-month-of-the-year effects, Equation 1 becomes:

$$r_{iit} = \mu_{0i} + \sum_{j=1}^{4} \mu_{ij} r_{ijt-1} + \sum_{m=1}^{11} \delta_{im} d_{mit-1} + \varepsilon_{it}, \tag{4}$$

where δ is the coefficient of calendar effect that represents the magnitude of influence from the-month-of-the-year when m = 1, 2,…,11, and the dummy variable d takes the value 1 for January when $m = 1$ and 0 otherwise. The dummy variables for other ten months are also defined in a similar way. We use the same method to test the-week-of-the-month effect with m = 1 and 2 for the first week and the last week, respectively.

3. The Data

The data used in this study are weekly average stock market price indices spanning from 6 January 1992 to 28 June 2010 (n = 965 observations) and downloaded from http://au.finance.yahoo.com, which are not in a single currency.[2] Weekly data provide a number of advantages over the use of daily data. First, it avoids the interferences associated with the use of synchronised data as the trading day of one country may coincide with a public holiday in another country. Secondly, it also avoids the time zone differences due to the four countries being located in various time zones with associated different opening and closing times. For the same reasons, Theodossiou and Lee (1993, 1995), Theodossiou *et al.* (1997), Brooks and Henry (2000), and Ng (2000) have also preferred to use weekly data in their studies. Stock market returns are computed based on the stock market price indexes. Let p_t be the stock market price index at time t. The stock market return at time t is then calculated as $r_t = \ln(p_t/p_{t-1})$.

The stock market price data used in this study include the All Ordinaries Index (AORD) of Australia (AU), the Straits Times Index (STI) of Singapore (SI), the Financial Times Stock Exchange Index (FTSE100) of the United Kingdom (UK) and the Standard and Poor's Index (S&P 500) of the United States (US). However, it should be noted that data from Monday, 14 January 2008 to Monday, 21 January 2008 were absent from the Singapore series. Data from Monday, 17 September 2001 to Friday, 21 September 2001 were also missing from the US series. To ensure continuity in the time series data, theses minor gaps were eliminated by interpolating.

Table 1 reports the descriptive statistics for each stock market return series. The mean returns for the four stock markets are all positive and ranging from a minimum 0.0007 (Singapore and the

[2]We tested few other well-accepted website such as http://www.oecd.org, and the dXtime database for weekly data in a common currency. Although both databases have stock market indexes in common currency, they only have monthly, quarterly or annual data. Therefore, we assume that investors can insure against the currency risk.

Table 1. *Descriptive Statistics for Return Series*

	AU	SI	UK	US
Mean	0.0011	0.0007	0.0007	0.0010
Median	0.0026	0.0010	0.0023	0.0027
Maximum	0.0685	0.1278	0.1005	0.0818
Minimum	−0.1189	−0.1440	−0.0973	−0.1747
SD	0.0165	0.0266	0.0193	0.0193
Skewness	−1.0667	−0.2709	−0.4333	−1.2963
Kurtosis	8.5963	8.0645	6.2297	12.6833
Jarque–Bera	1440.81	1042.04	449.14	4036.27
P-value	0.0000	0.0000	0.0000	0.0000
Correlation coefficients				
AU	1.0000			
SI	0.5449	1.0000		
UK	0.6631	0.5406	1.0000	
USA	0.6729	0.5251	0.7813	1.0000

Source: All Ordinaries Index (Australia, AU), the STI (Singapore, SI), the FTSE100 (the United Kingdom, UK) and the S&P 500 (the United States, US) for the period 6 January 1992 to 28 June 2010, containing 965 observations and downloaded from http://www.finance.yahoo.com.au.

UK) to a maximum 0.0011 (Australia). According to the sample standard deviations, Australian stock return is the least volatile series with a standard deviation of 0.0165, whereas the Singapore stock return can be considered as the most volatile series with a standard deviation of 0.0266. The standard deviations for the UK and the US returns are 0.0193, suggesting that the volatility of these two series is almost the same. Figure 1 also confirms this by providing a visual perspective on the volatility of our return series over time during the period January 1992–June 2010.

Based on the estimated skewness statistics, all four return series are skewed to the left. As expected with any high-frequency financial return series, the value of kurtosis is >3.0 for all of the return series, indicating a typical leptokurtic distribution, whereby return series are more peaked around the mean with a thicker tails compared with the normal distribution. Furthermore, the Jarque–Bera statistics and corresponding *P*-values reinforce the above findings by rejecting the null hypothesis of normality at the 1 per cent level of significance.

The pairwise correlations among the four stock market returns are also presented in Table 1. The estimated correlation coefficients are generally >0.5 and consistent with the previous findings of McNelis (1993) and Valadkhani *et al.* (2008); that is, the return series of four stock markets are highly and positively interrelated. The lowest correlation (0.5251) is between the stock market returns of the US and Singapore, whereas the highest (0.7813) is between the stock market returns of the UK and the US. With a correlation coefficient of approximately 0.67, the Australian stock return series is highly correlated with the US stock returns. Finally, the correlation coefficient between the stock returns of Singapore and Australia was also statistically significant (0.54) at the 1 per cent level.

4. Empirical Results

We used three model selection criteria, namely the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan–Quinn Information Criterion (HIC), and adopted ADVECH(1,1) specification in this paper.[3] The results using Equation 3 with the conditional mean equation 1 are given in Table 2. Based on the results presented in Table 2, the own-mean spill-overs (μ_{ii} for all $i = 1,\ldots,4$) are significant at the 1 per cent level of significance, providing evidence

[3]The test results from various ADVECH(p,q) specifications, where p = 1, 2 and 3 and q = 1, 2 and 3 indicate that the ADVECH(1,1) specification has consistently the lowest AIC (−23.17), SIC (−22.98) and HIC (−23.10) with a log-likelihood of 11,192.78.

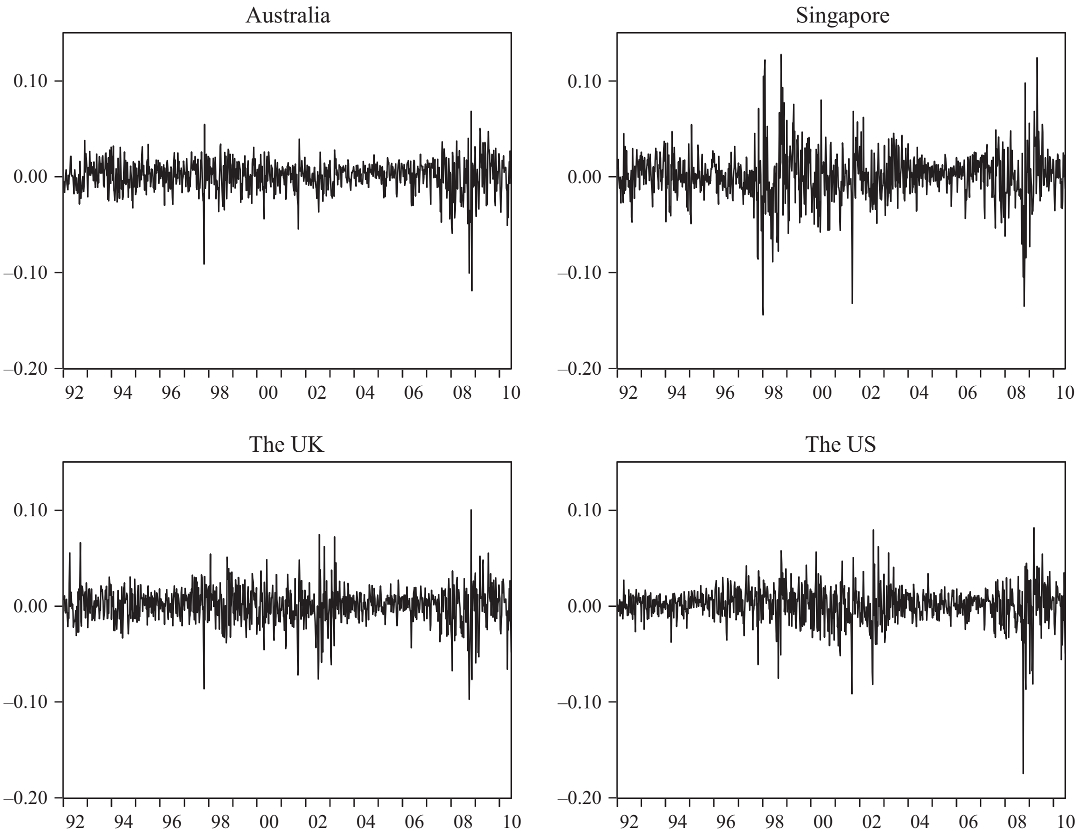

Figure 1. *Weekly Stock Market Returns, January 1992 to June 2010*

of an influence on current returns of each stock market arising from their first lag returns (r_{iit-1}). The own-mean spillovers vary from a minimum of 0.1444 (Australia) to a maximum of 0.2120 (the US). Significant positive cross-mean spillover effects exist from the US to Australia, to Singapore and to the UK. However, an important finding is that there is no positive and significant impact in the opposite direction. The significant cross-mean spillover impact from the US to Australia (0.1376) is higher than that of Singapore (0.1143). In other words, as expected past US stock market returns have greater impact on the Australian stock market.

Own-volatility shocks for all four markets (a_{11}, a_{22}, a_{33} and a_{44}) are significant and vary from 0.0125 (the UK) to 0.0622 (Singapore), indicating the presence of ARCH effects. This means that past shocks arising from the Singapore market will have the strongest impact on its own future market volatility compared with shocks stemming from the other three markets. Based on the magnitudes of the estimated cross-volatility coefficients, a_{ij} $(i \neq j)$, innovations in all of the four stock markets influence the volatility of other markets, but the own-volatility shocks, a_{ij} $(i = j)$, are generally larger than the cross-volatility shocks. This suggests that past volatility shocks in individual markets have a greater effect on their own future volatility than past volatility shocks arising from other markets. Therefore, it appears that the lagged country-specific shocks (ARCH effects) do contribute to the stock market volatility of any given country in a recursive way. According to our results, the degree of cross-volatility shocks is pairwise, with the weakest between UK and US (0.0158) and the strongest between Australia and Singapore (0.0417).

Table 2. *Parameter Estimation for the Mean Equation and the ADVECH(1,1) Equation*

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

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

Parameter	Australia		Singapore		UK		US	
	Coefficient	t-Ratio	Coefficient	t-Ratio	Coefficient	t-Ratio	Coefficient	t-Ratio
μ_{0i}	0.0019***	5.34	0.0017***	3.14	0.0016***	3.99	0.0019***	4.66
μ_{i1}	0.1444***	4.04	−0.0204	−0.45	−0.0196	−0.52	−0.0873**	−2.26
μ_{i2}	−0.0034	−0.16	0.1948***	6.25	−0.0171	−0.81	0.0179	0.84
μ_{i3}	0.0185	0.60	0.1272**	2.58	0.1654***	4.21	0.0199	0.50
μ_{i4}	0.1376***	3.97	0.1143**	2.27	0.0982**	2.46	0.2120***	4.85
c_{i1}	0.00000005	0.72	—	—	—	—	—	—
c_{i2}	0.00000006	0.65	0.00000007	0.48	—	—	—	—
c_{i3}	0.00000008	0.83	0.00000008	0.70	0.00000010	0.75	—	—
c_{i4}	0.00000035	1.24	0.00000038	0.89	0.00000048	1.25	0.00000218***	3.09
a_{i1}	0.0280***	5.36	—	—	—	—	—	—
a_{i2}	0.0417***	6.46	0.0622***	6.19	—	—	—	—
a_{i3}	0.0187***	3.79	0.0279***	4.06	0.0125**	2.57	—	—
a_{i4}	0.0236***	4.55	0.0352***	4.97	0.0158**	3.05	0.0199***	3.28
g_{i1}	0.0189***	3.34	—	—	—	—	—	—
g_{i2}	0.0240***	3.35	0.0305**	2.82	—	—	—	—
g_{i3}	0.0341***	4.64	0.0433***	4.35	0.0616***	6.07	—	—
g_{i4}	0.0308***	4.31	0.0391***	4.09	0.0556***	5.82	0.0501***	4.81
b_{i1}	0.9658***	240.40	—	—	—	—	—	—
b_{i2}	0.9473***	187.99	0.9299***	118.28	—	—	—	—
b_{i3}	0.9609***	284.17	0.9433***	197.54	0.9568***	225.11	—	—
b_{i4}	0.9553***	219.03	0.9377***	173.49	0.9512***	207.40	0.9455***	146.29
$a_{ii} + b_{ii}$	0.9938		0.9921		0.9693		0.9654	

Notes: i = 1 for Australia, i = 2 for Singapore, i = 3 for the United Kingdom and i = 4 for the United States. ***Statistically significant at 1 per cent level, **5 per cent level and *10 per cent level.

The estimated coefficients for the asymmetric impact in the variance equations (g_{ii} for all $i = 1,\ldots,4$) are positive and significant for all four stock markets. As expected, this suggests that negative shocks emanating from each stock market increase volatility to a greater extent than positive shocks. In other words, compared with a rise in price, a drop in stock price tends to increase the volatility more. In this regard, the lowest coefficient belongs to Australia (0.0189) and the highest to the UK (0.0616). Furthermore, coefficients for asymmetric impact in the covariance equations (g_{ij} for all $i \neq j$) are all positive and statistically significant, suggesting that the negative shocks in each stock market have contributed to raise covolatilities across these four markets. The lowest coefficient for asymmetric impact in the covariance equation is between Australia and Singapore (0.0240), whereas the highest figure occurs between the UK and the US (0.0556). In addition, the asymmetric coefficient between Australia and the US is 0.0308, whereas that between Australia and the UK is 0.0341 in the corresponding covariance equation. This is not counter intuitive as this finding indicates that the volatility of smaller markets (Australia and Singapore) will increase when larger markets (the UK and the US) are moving downwards. Therefore, this asymmetry in covariances represents an important implication for portfolio diversification as it is riskier to invest in two stocks if they move in the same direction. More specifically, when investors spread their funds among different international stocks, they can minimise risk if they know how bad news (negative shocks) from one stock market influences other stock markets.

The estimated coefficients for the variance–covariance matrix (Equation 3) have also been presented in Table 2. Similar to Theodossiou and Lee (1993) and Worthington and Higgs (2004), our results indicate statistically significant and positive b_{ij} ($i \neq j$) coefficients for the one-lag conditional variance, thereby suggesting the presence of high volatility persistence. The lowest value for the own-volatility spillovers effect belongs to Singapore ($b_{22} = 0.9299$) and the highest one belongs to the Australian market ($b_{11} = 0.9658$). This implies that past volatility in the Australian market will have the strongest impact on its own future volatility compared with the other three markets. The significant non-zero b_{ij} coefficients (where $i \neq j$ for all i and j) provide further evidence for the presence of high and positive volatility spillovers across these well-integrated markets. The estimated lagged cross-volatility persistence between Australia on the one hand, and Singapore, the UK and the US on the other, are 0.9473, 0.9609 and 0.9553, respectively, supporting the evidence of volatility persistence emanating from all of the other three markets to Australia. Cross-volatility persistence for Singapore, stemming from the UK and the US, are 0.9433 and 0.9377, respectively. Consequently, the UK and the US appear to be the most influential markets for Australia and Singapore. The sum of the lagged ARCH and GARCH coefficients ($a_{ii} + b_{ii}$) for Australia, Singapore, the UK and the US are 0.9938, 0.9921, 0.9693 and 0.9654, respectively. These values are very close to unity, supporting the assumption of covariance stationarity and the volatility persistence in the data.

Next, we tested for the calendar effect. In this regard, first, we estimated the ADEVECH model given in Equation 3 with the mean equation given in Equation 4 including eleven dummy variables for twelve months (the intercept representing the month of December to avoid dummy variable trap). According to the estimated results, all of the dummy variables were insignificant. Second, we tested for January and December effects separately using the same model (Equations 3 and 4). Finally, to examine the-week-of-the-month effect, we executed Equations 3 and 4 for the-first-week-of-the-month and the-last-week-of-the-month. The estimated results from the second and the third stages indicated little evidence for calendar effects. This could be because at an individual market level, the calendar effect could have a significant influence on changing stock returns but at cross-market level, bad news arising in larger markets could have more power than the calendar effect on asymmetry of volatility effect. These results have not been reported in this paper but they are available from the authors upon request.

5. Summary and Conclusion

This paper uses a multivariate ADVECH model and weekly stock market data from 6 January 1992 to 28 June 2010 to evaluate how asymmetric volatility effect influences the volatility spillovers across four international stock markets, namely, Australia, Singapore, the UK and the US. The estimated ADVECH(1,1) model passes the standard diagnostic tests and imposes a restriction on the parameters of a multivariate GARCH model using unconditional residual variance as the presample conditional variance. The resulting estimated coefficients from such a restriction are all positive semi-definite as indicated in the conditional variance and covariance matrix.

We found that the positive return spillover effects are only unidirectional and run from both the US and the UK (the bigger markets) to Australia and Singapore (the smaller markets). These results are consistent with the univariate GARCH application of Brailsford (1996) for Australia, New Zealand and the US, and with the multivariate GARCH application of Brooks and Henry (2000) for Australia, Japan and the US, indicating that the lagged returns of the US stock market heavily influence the returns of the Australian stock market but not vice versa. Brooks and Henry's (2000, p. 509) trope, ''when the US sneezes Australia catches pneumonia'', is therefore supported by our results.

Based on the magnitude of innovation, the shocks arising from the US market can indiscriminately impact on all of the other markets in our sample. According to Sabri (2002), the world's leading stock market would have an influence on the volatility of other markets; our results also support Sabri's argument. As expected, it is also found that the own and cross-volatility persistence exists among these four markets, where Australia and Singapore stock returns exhibit the highest and lowest magnitude of the own-volatility persistence effect (the GARCH effect), respectively. Based on our results, one may also conclude that own-volatility spillovers are generally higher than cross-volatility spillovers in the Australian market. This would suggest that in such markets, changes in volatility are likely to emanate from domestic conditions but their volatility persistence is intertwined with global financial markets.

Finally, unlike previous empirical studies, we take into account potential asymmetries that may exist in both own-volatility spillovers and cross-volatility spillovers. Our results find evidence for such asymmetries. Similar to Kroner and Ng (1998), we also conclude that it is riskier for investors to invest in stocks from only these four markets because a high degree of time-varying covolatility among these four markets makes portfolio diversification less effective.

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