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This paper uses a multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model to provide an insight into the nature of interaction between stock market returns of four countries, namely, Australia, Singapore, the UK, and the US. Using weekly data spanning from January 1992 to December 2008 the results indicate that all markets (particularly Australia and Singapore) display significant positive mean-spillovers from the US stock market returns but not *vice versa*. We also found strong evidence for both own and cross ARCH and GARCH effects among all four markets, indicating the existence of significant volatility and cross volatility spillovers across all four markets. Given a high degree of common time-varying co-volatility among these four countries, investors will be highly unlikely to benefit a reduction of risk if they diversify their financial portfolio with stocks from these four countries only (JEL: G15, F36).

Keywords: Multivariate GARCH, Stock market returns, Australia.

I. Introduction

With the globalization of international trade and finance, the interaction between international financial markets has increased markedly. Therefore, studying financial market linkages has become an important issue among market participants, regulators, and research scholars alike (Chan, Gup and Pan [1997]; Hassan and Malik [2007]; In [2007; Kim and Rogers [1995]; Kanas [1998]; Chou et al [1999]; Reyes [2001]; Li [2007]; Harju and Hussain [2008]). Notably, the importance of this area of analysis has increased markedly since the emergence of the global financial crisis in 2008.

Brailsford (1996) categorized empirical evidence on volatility transmission across several financial markets into two groups: those studying how individual return series are integrated across markets and those studying how volatility transmits in different markets. For example, Eun and Shim (1989) and Peiro et al. (1998) investigated how errors of return series transmit across different markets, while Caporale et al. (2006) and King and Wadhwani (1990) examined how volatilities transmit across different markets. Finally, some other studies have analysed both return and volatility spillovers effects simultaneously in different markets (Kim and Rogers [1995]; Kanas [1998]; Chou, Lin and Wu [1999]; Reyes [2001]; Li [2007]).

In the case of modelling volatility, the existence of a conditional variance within a conditional mean equation makes linear econometric models inappropriate for capturing time varying shocks. However, Engle's (1982) autoregressive conditional heteroskedasticity (ARCH) process and its generalization process or GARCH process (Bollerslev, 1986) can capture the nonlinearity in financial data. Univariate ARCH and GARCH models have been used to capture return and volatility spillovers effects among different markets by incorporating lagged returns, innovations, volatilities, or a combination of these variables from one single market as explanatory variables of the other market (Kim and Rogers [1995]; Kanas [1998]; Reyes [2001]; Harju and Hussain [2008]).

These univariate ARCH/GARCH models have now been extended to encompass multivariate GARCH (MGARCH) models, which are capable of capturing the following salient features of stock market returns: leptokurtosis, volatility clustering and leverage effects, which otherwise cannot be captured using univariate ARCH/GARCH models (Pagan and Schwert [1990]; Higgins and Bera [1992]; Brooks [2002]). As such, MGARCH models have recently been used for the analysis of volatility co-movements and spillovers effects across international stock markets and identifying the evidence of volatility transmission across different stock markets (Chou, Lin and Wu [1999]; Brooks and Henry [2000]; Li [2007]). The most commonly used MGARCH specifications are referred to as the vector GARCH (VECH) model of Bollerslev et al. (1988), the Constant Conditional Correlation (CCC) model of Bollerslev (1990) and the BEKK model of Baba et al. (1990) and Engle and Kroner (1993). Due to the high parameterization issue associated with the estimation of the VECH model, most of these studies have used the BEKK model in which the conditional variance and covariance matrices are positive semi-definite.

In the context of Australia, Brooks and Henry (2000) have used MGARCH models to examine the interplay between the stock market volatility of Australia, the US and Japan. They adopted parametric and non-parametric techniques to test the existence of linear and non-linear transmission of return and volatility across different markets. Brooks and Henry estimated a BEKK model using weekly data covering the period January 1980-June 1998. According to their results, events in the US equity market had significant repercussions on the Australian stock market. In addition, McNelis (1993) and Valadkhani, Chancharat and Harvie (2008) found that the stock market returns of the UK, Singapore and the US were highly interrelated with that of the Australian stock market return, however, none of them applied the MGARCH model in their approach. This paper applies a diagonal VECH model for weekly stock market returns of Australia, Singapore, the UK, and the US to investigate any systematic pattern of return and volatility spillovers. This study contributes to the literature by determining the extent to which the stock market return and volatility in Australia are influenced by external shocks stemming from other major international stock markets using more recent data.

The Australian stock market is of particular interest as it is relatively small compared to the US and the UK but a major player in the Asia-Pacific region. According to the monthly report of Standard & Poor's (November 2008), Australian Securities Exchange (ASX) is the eighth largest in the world in total market capitalization terms and the second largest in the Asia-Pacific region. Although Japanese market is the largest stock market in the Asia-Pacific region, this study excludes Japanese stock market from this analysis because previous studies find that Australian stock market is not highly correlated with the Japanese market (McNelis [1993]; Brooks and Henry [2000)]; Valadkhani et al. [2008]). However, according to the same studies the pair-wise correlation between Australia and the UK, Singapore, and the US are all greater than 0.50.

The diagonal VECH model chosen in this study is of particular interest as it allows the conditional variance covariance matrix of stock market returns to vary over time and is more flexible compared to BEKK model if there are more than two variables in the conditional variance covariance matrix (Scherrer and Ribarits, 2007). Empirical implementation of the VECH model is, however, limited due to the difficulty of guaranteeing a positive semi-definite conditional variance covariance matrix (Engle and Kroner [1993]; Kroner and Ng [1998]; Brooks and Henry [2000]). 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 covariance matrix of the diagonal VECH model.

The rest of this paper is organized as follows; Section II presents our methodology, followed by data and descriptive statistics in Section III. The empirical econometric results and policy implications of the study are set out in Section IV, followed by some concluding remarks in Section V.

II. Methodology

The major objective of this paper is to examine the interdependence of return and co-volatility across four highly integrated international stock markets, with a particular focus on Australia, by using the MGARCH model. The vector autoregressive stochastic process of assets returns is given in 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 $j = 1,\dots,4$ and $i = j$ as well as the lagged returns of other countries (r_{ijt-1}) for all $j = 1, .., 4$ and $i \neq j$ as follows;

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

where $i = 1$ for Australia, $i = 2$ for Singapore, $i = 3$ for the UK and $i = 4$ for the US; μ_{0i} is the intercept for country *i*; μ_{ij} (for all $i = 1, .., 4$ and $j = 1, .., 4$) 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) has four dimensions with the diagonal and non-diagonal elements representing the variance and the covariance terms, respectively. In matrix notation, H_t can be written as:

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

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*.

Even though there are different ways of specifying the MGARCH model, we use a diagonal VECH model (Bollerslev et al., 1988) to better understand the conditional variance and covariance matrix because this model is more flexible when H_t contains more than two variables (Scherrer and Ribarits, 2007). The diagonal VECH representation is based on the assumption that the conditional variance depends on squared lagged residuals and the conditional covariance depends on the cross-lagged residuals and lagged covariances of other series (Harris and Sollis, 2003). The diagonal VECH model can be written as follows:

$$vech(H_t) = C + Avech(\varepsilon_{t-1}\varepsilon'_{t-1}) + Bvech(H_{t-1}) \qquad (3)$$

where A and B are $\frac{1}{2}N(N+1)\times\frac{1}{2}N(N+1)$ parameter matrices and C is a $\frac{1}{2}N(N+1)\times 1$ vector of constants. The diagonal elements of matrix A (a_{11}, a_{22}, a_{33} and a_{44}) measures the influences from past squared innovations on the current volatility (i.e. own-volatility shocks) while non-diagonal elements (a_{ij} where $i \neq j$) determine the cross product effects of the lagged innovations on the current covolatility (i.e. cross-volatility shocks). Similarly, the diagonal elements of matrix B (b_{11}, b_{22}, b_{33} and b_{44}) determine the influences from past squared volatilities on the current volatility (i.e. own-volatility spillovers) and non-diagonal elements (b_{ij} where $i \neq j$) measure the cross product effects of the lagged covolatilities on the current covolatility (i.e. cross-volatility spillovers).

There are two major issues to be considered in the estimation process of this model. First, the number of parameters to be estimated and second, what constraints need to be imposed on the model to ensure that the assumption of positive semi-definiteness of the variance covariance matrix holds (Goeij and Marquering, 2004). To reduce the number of parameters in the estimation procedure, Bollerslev et al. (1988) and Goeij and Marquering (2004) suggest the use of a diagonal version of A and B matrices. According to Bauwens et al. (2006), the conditional variance and covariance matrix in the diagonal VECH model is positive semi-definite if all of the parameters contained in A, B and C are positive and the initial conditional variance and covariance matrix (H_0) is also non-negative. Positive semi-definiteness of the conditional variance and covariance matrix can be easily derived by expressing the model in terms of Hadamard products or imposing conditions using the Cholesky factorization of the parameter.

In this study, a restriction on our model is established in such a way to obtain positive semi-definite values in the variance covariance matrix. We have used the maximum likelihood function to generate these parameter estimates by imposing conditions on the initial values as suggested by Bollerslev et al. (1988). In this regard, let θ be a parameter of interest for a sample of T observations, then the log likelihood function will be:

$$L_T(\theta) = \sum_{t=1}^{T} l_t(\theta) \qquad (4)$$

where $l_t(\theta) = \frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon'_t H_t^{-1}\varepsilon_t$

According to Bollerslev et al. (1988), pre-sample values of θ can be set to be equal to their expected value of zero. However, in this study the unconditional variance of residuals is used as the pre-sample conditional variance to guarantee that H_t is positive semi-definite. The BHHH (Berndt Hall and Hall and Hausman) iterative algorithm is used to obtain the optimal values of our parameters by utilizing the following equation proposed by Engle and Kroner (1993):

$$\theta^{(i+1)} = \theta^{(i)} + \lambda_i \left(\left(\frac{\partial l_t}{\partial \theta} \right)' \frac{\partial l_t}{\partial \theta} \right)^{-1} \left(\frac{\partial l_t}{\partial \theta} \right)' \qquad (5)$$

where $\theta^{(i)}$ denotes the parameter estimate after the i^{th} iteration; $\frac{\partial l_t}{\partial \theta}$ is evaluated at $\theta^{(i)}$ and λ is a variable step length chosen to maximize the likelihood function in the given direction, which is calculated from a least squares regression of a $T \times 1$ vector of ones on $\frac{\partial l_t}{\partial \theta}$.

The Ljung-Box test statistic (Hosking, 1980), which is a multivariate version of the Portmanteau test, is also used to test for any possible remaining ARCH effects in the model. The Ljung-Box test statistic for a multivariate process of order (*p, q*) and a stationary time series $\{ y_t : t = 1, 2, ..., T \}$ is given in the following equation:

$$Q = T^2 \sum_{j=1}^{s} (T - j)^{-1} tj \left\{ C_{Y_t}^{-1}(0) C_{Y_t}(j) C_{Y_t}^{-1}(0) C'_{Y_t}(j) \right\} \qquad (6)$$

where $Y_t = vech(y_t y_t')$; $C_{Y_t}(j)$ is the sample autocovariance matrix of order *j*; *s* is the number of lags being tested and *T* is the number of observations. For large samples, the Ljung-Box test statistic, *Q*, is distributed asymptotically as a Chi-squared distribution under the null hypothesis of no ARCH effect.

III. Data

Average weekly stock market price indices for the period January 1992-December 2008 are used in this paper. Weekly data provide a number of advantages over the use of daily data. Firstly, 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 other similar studies have also preferred to use weekly data (Theodossiou and Lee [1993, 1995]; Theodossiou et al. [1997]; Brooks and Henry [2000]; Ng [2000]).

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:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}} \right) \qquad (7)$$

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), all covering the period from the 13 January 1992 to 8 December 2008 (n = 884 observations). However, it should be noted that the STI did not contain the data for two weeks covering the period from Monday, 14 January 2008 to Monday, 21 January 2008. To ensure continuity in the time series data, this minor gap was eliminated by interpolating the missing two values. Data for the week beginning from Monday, 17 September 2001 to Friday, 21 September 2001 was absent from the US data due to terrorist attack in the US on September 11, 2001. This one week missing value was similarly approximated by interpolating the adjacent two values.

Table 1 presents the descriptive statistics for each stock market return series. The mean returns for the four stock markets are all positive, ranging from a minimum 0.0002 (Singapore) to a maximum 0.0009 (the US). According to the sample standard deviations, Australian stock return is the least volatile series with a standard deviation of 0.0160, while the Singapore stock return can be considered as the most volatile series with a standard deviation of 0.0265. The standard deviations for the UK and the US returns are 0.0188 and 0.0184, respectively, 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-December 2008.

Based on the estimated skewness statistics, all four return series are skewed to left. As expected with any high frequency financial return series, the value of kurtosis is greater than 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 to 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 greater than 0.5 and consistent with the previous findings of McNelis (1993) and Valadkhani et al. (2008) that the return series of four stock markets are highly and positively interrelated. The highest correlation (0.7563) is between the stock market returns of the UK and the US, while the lowest (0.4965) is between the stock market returns of the US and Singapore. With correlation coefficients of approximately 0.64, the Australian stock return series is highly correlated with both the US and UK stock returns. Finally, the correlation coefficient between the stock returns of Singapore and Australia was also statistically significant (0.52) at the 1 per cent level.

The Augmented Dickey-Fuller (ADF) test results presented in Table 2 show that we can reject the null hypothesis of the presence a unit root in the data at the 5 per cent level, suggesting that all of our four return series are all stationary. The Ljung-Box Portmanteau test statistic of four return series and their corresponding squared returns were examined under the null hypothesis of no serial correlation. The calculated Ljung-Box Portmanteau test statistics for both simple and squared versions, which are given in the Table 2, reject the null hypothesis of no serial correlation at the 1 per cent level of significant for all the series. Based on these results using up to 12 lags we found strong evidence of serial correlation in the four series, justifying the inclusion of the lag terms in equation (1).

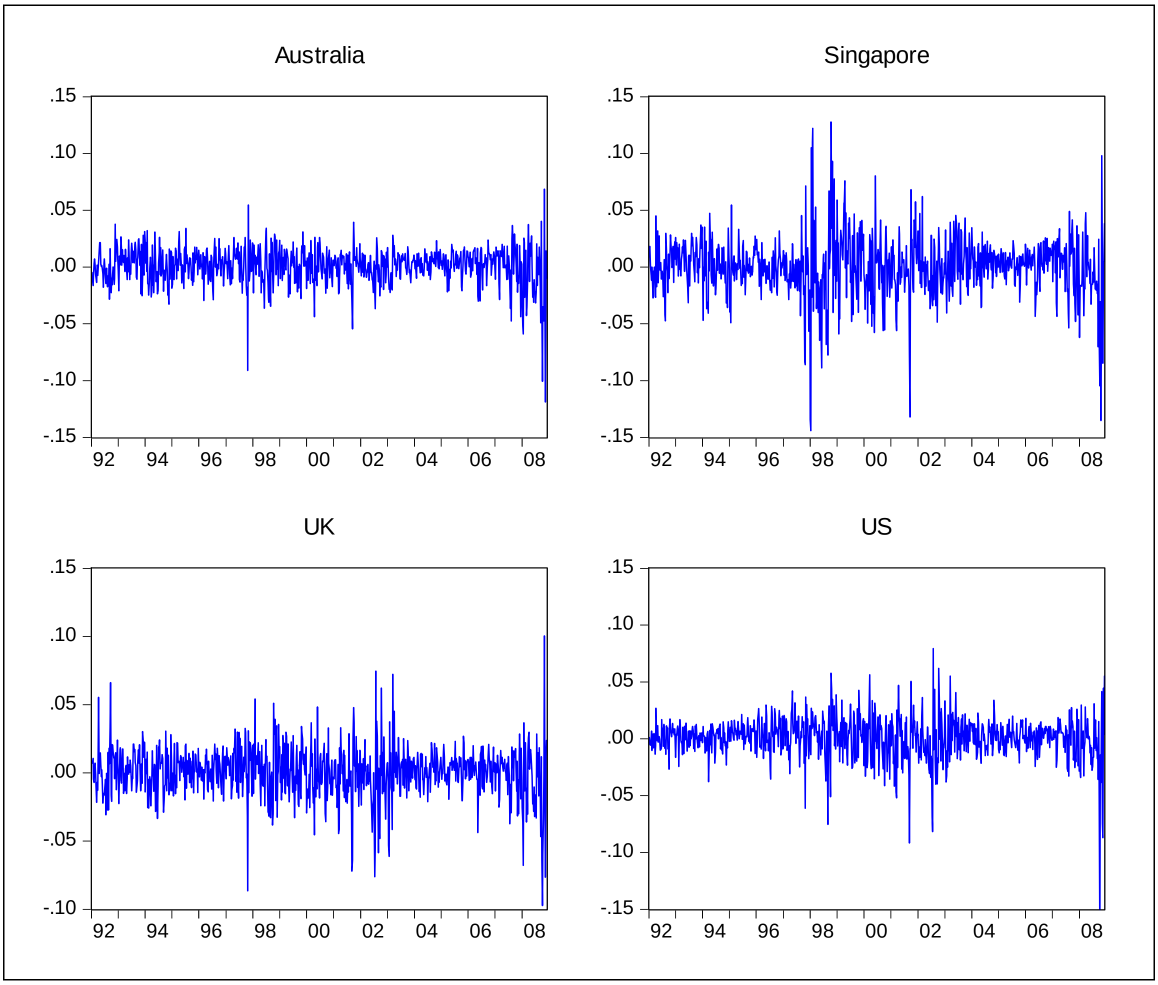

FIGURE 1. Weekly Stock Market Returns, January 1992 to December 2008

TABLE 1. Descriptive Statistics for Return Series

	Australia	Singapore	UK	US
Mean	0.0008	0.0002	0.0006	0.0009
Median	0.0025	0.0009	0.0022	0.0025
Maximum	0.0685	0.1278	0.1005	0.0794
Minimum	-0.1189	-0.1441	-0.0973	-0.1747
Std. Dev.	0.0160	0.0265	0.0188	0.0184
Skewness	-1.2600	-0.3959	-0.4229	-1.4557
Kurtosis	9.8489	8.1765	6.7052	14.7814
Jarque-Bera	1959	1009	531	5419
p-value	0.0000	0.0000	0.0000	0.0000
Correlation Coefficients				
AU	1.0000			
SI	0.5208	1.0000		
UK	0.6394	0.5175	1.0000	
US	0.6473	0.4965	0.7563	1.0000

Sources: S&P/ASX200 index (Australia), the STI (Singapore), the FTSE100 (the UK) and the OEX100 (the US) for the period 13 January 1992- 8 December 2008, containing 884 observations and downloaded from www.finance.yahoo.com.au

TABLE 2. ADF Test Results and Ljung-Box Q-Statistic Results for Weekly Stock Market Returns and Squared Returns

	Australia		Singapore		UK		US	
ADF *t* statistics								
Based on min. AIC	-14.67		-11.39		-19.74		-7.76	
Based on min. SIC	-14.67		-11.39		-24.08		-24.58	
Ljung-Box test statistics for return series								
	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Q(1)	38.05	0.00	54.49	0.00	37.07	0.00	28.39	0.00
Q(2)	38.10	0.00	56.08	0.00	37.21	0.00	28.88	0.00
Q(3)	45.90	0.00	69.84	0.00	37.73	0.00	30.09	0.00
Q(4)	46.04	0.00	71.14	0.00	39.70	0.00	32.95	0.00
Q(5)	46.33	0.00	73.57	0.00	39.72	0.00	34.71	0.00
Q(6)	48.16	0.00	77.56	0.00	40.01	0.00	38.72	0.00
Q(7)	49.78	0.00	77.57	0.00	41.41	0.00	42.09	0.00
Q(8)	49.81	0.00	77.84	0.00	41.99	0.00	45.86	0.00
Q(9)	53.31	0.00	77.86	0.00	42.03	0.00	46.16	0.00
Q(10)	53.32	0.00	78.44	0.00	42.52	0.00	47.22	0.00
Q(11)	53.33	0.00	79.57	0.00	42.52	0.00	53.21	0.00
Q(12)	53.63	0.00	79.61	0.00	42.58	0.00	53.27	0.00
Ljung-Box test statistics for squared return series								
Q(1)	64.20	0.00	141.81	0.00	81.18	0.00	27.59	0.00
Q(2)	112.47	0.00	229.19	0.00	128.89	0.00	33.05	0.00
Q(3)	142.25	0.00	300.72	0.00	153.62	0.00	39.17	0.00
Q(4)	164.79	0.00	367.43	0.00	194.06	0.00	45.23	0.00
Q(5)	179.64	0.00	388.82	0.00	219.37	0.00	70.26	0.00
Q(6)	276.13	0.00	397.16	0.00	244.62	0.00	102.80	0.00
Q(7)	281.19	0.00	400.31	0.00	265.36	0.00	108.21	0.00
Q(8)	284.83	0.00	401.27	0.00	268.38	0.00	108.98	0.00
Q(9)	288.46	0.00	412.80	0.00	270.68	0.00	115.71	0.00
Q(10)	288.82	0.00	422.87	0.00	271.21	0.00	116.10	0.00
Q(11)	289.61	0.00	436.54	0.00	273.25	0.00	117.62	0.00
Q(12)	290.22	0.00	449.15	0.00	274.18	0.00	118.34	0.00

Note: AIC = Akaike information criterion and SIC = Schwarz information criterion. Q(n) is the n^{th} lag Ljung-Box test statistics

IV. Empirical Results

The Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HIC) were used to compare various diagonal VECH(p,q) specifications, where p = 1, 2, and 3 and q = 1, 2, and 3[1]. The results indicate that the diagonal VECH(1,1) specification has consistently the lowest AIC (-23.24), SIC (-22.96) and HIC (-23.13) with a log-likelihood of 10299.72. A multivariate GARCH-M model was also estimated, but similar to Theodossiou and Lee (1993, 1995) we did not find any significant relationship between conditional market volatility and expected returns. Therefore, the diagonal VECH(1,1) specification was adopted in this paper and the results using equation (3) with the conditional mean equation (1) are given in Table 3.

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

TABLE 3. Parameter Estimation for the Mean Equation and the Diagonal VECH(1,1) Equation

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

$$vech(H_t) = C + Avech(\varepsilon_{t-1}\varepsilon'_{t-1}) + Bvech(H_{t-1})$$

Parameter	Australia		Singapore		UK		US	
	Coefficient	*t*-ratio	Coefficient	*t*-ratio	Coefficient	*t*-ratio	Coefficient	*t*-ratio
μ_{0i}	0.0019*	4.72	0.0016*	2.72	0.0016*	3.35	0.0020*	4.49
μ_{i1}	0.1443*	3.65	-0.0138	-0.27	-0.0244	-0.57	-0.0939*	-2.32
μ_{i2}	-0.0053	-0.24	0.1838*	5.36	-0.0150	-0.66	0.0058	0.25
μ_{i3}	0.0229	0.70	0.0846	1.55	0.1494*	3.35	0.0187	0.45
μ_{i4}	0.1214*	3.21	0.1370*	2.45	0.0688	1.56	0.2066*	4.46
c_{i1}	0.000004*	2.62						
c_{i2}	0.000003*	2.26	0.000009*	2.73				
c_{i3}	0.000002*	2.16	0.000002*	2.29	0.000005*	2.78		
c_{i4}	0.000001*	2.10	0.000002*	2.07	0.000003*	2.89	0.000003*	2.93
a_{i1}	0.0557*	5.05						
a_{i2}	0.0361*	3.66	0.0968*	5.91				
a_{i3}	0.0386*	4.56	0.0321*	3.64	0.0528*	5.77		
a_{i4}	0.0368*	5.22	0.0319*	3.80	0.0424*	5.99	0.0515*	6.10
b_{i1}	0.9260*	62.29						
b_{i2}	0.9385*	54.63	0.8870*	49.34				
b_{i3}	0.9429*	68.63	0.9473*	71.39	0.9299*	74.28		
b_{i4}	0.9491*	86.70	0.9503*	77.97	0.9406*	96.68	0.9339*	83.38
$a_{ii} + b_{ii}$	0.9816		0.9839		0.9827		0.9854	
R_i^2	0.0737		0.0784		0.0050		0.0168	

Notes: (a) i = 1 for Australia, i = 2 for Singapore, i = 3 for the UK and i = 4 for the US. (b) * indicates that the corresponding null hypothesis is significant at 5 per cent level. (c) R_i^2 is the percentage change of variation in the returns of market *i* explained by the conditional mean equation

Based on the results presented in Table 3, the own-mean spillovers (μ_{ii} for all i= 1,..,4) are significant at the 5 per cent level of significance, providing evidence 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 0.1443 (Australia) to a maximum of 0.2066 (the US). Positive cross-mean spillovers effects exist from the US to Australia and Singapore and to a lesser extent to the UK. However, an important finding is that there is no positive and significant impact in the opposite direction. The significant cross-mean spillovers impact from the US to Singapore (0.1370) is higher than that of Australia (0.1214). In other words, past US stock market returns have greater impact on the Singapore stock market. The R_i^2 values presented in Table 3, calculated as $1-[\text{var}(\varepsilon_{it})/\text{var}(r_{iit})]$, measure the predictability of variations of future stock market returns due to the conditional mean spillovers. Similar to Theodossiou and Lee (1993), these R_i^2 are less than 8 per cent, indicating very low explanatory power.

Own-volatility shocks for all four markets (a_{11}, a_{22}, a_{33} and a_{44}) are significant and vary from 0.0515 (the US) to 0.0968 (Singapore), indicating the presence of ARCH effects. This means that the past shocks arising from the Singapore market will have the strongest impact on its own future market volatility compared to the 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 the results, the degree of cross-volatility shocks is pairwise the weakest between Singapore-the UK (0.0321) and the strongest between the US-the UK (0.0424).

The estimated coefficients for the variance-covariance matrix (equation 3) have also been presented in Table 3. Our results are consistent with similar studies in the literature (Theodossiou and Lee [1993]; Worthington and Higgs [2004]) with the b_{ij} ($i \neq j$) coefficients for the one-lag conditional variance all statistically significant and positive, thereby indicating the presence of high volatility persistence. The lowest value for the own-volatility spillovers effect belongs to Singapore ($b_{22} = 0.8870$) and the highest one belongs to the US market ($b_{44} = 0.9339$). This implies that the past volatility in the US market will have the strongest impact on its own future volatility compared to the other three markets. The significant nonzero 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 one hand and Singapore, the UK, and the US on the other are 0.9385, 0.9429, and 0.9491, 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 0.9473 and 0.9503, respectively. In this respect, the most influential market would appear to be the US. The sum of the lagged ARCH and GARCH coefficients ($a_{ii} + b_{ii}$) for Australia, Singapore, the UK and the US are 0.9816, 0.9839, 0.9827 and 0.9854, respectively. These values are very close to unity, supporting the assumption of covariance stationarity and the volatility persistence in the data.

TABLE 4. Diagnostic Tests on the Standardized Residuals of the Model

	Australia	Singapore	UK	US
Statistics on standardized residuals				
Skewness	-0.525	-0.227	0.121	-0.7870
Kurtosis	4.6	4.0	3.9	9.9
Jarque-Bera	135	45	31	1836
ADF *t* statistics				
Based on min. AIC	-16.27	-16.28	-21.89	-18.37
Based on min. SIC	-29.52	-28.23	-27.53	-29.20

TABLE 5. The Results of System Residual Portmanteau Tests for Autocorrelations Using the Cholesky Orthogonalization Method

Autocorrelation coefficients	Q-Stat	p-value	Adj. Q-Stat	p-value	d.f
Q(1)	18.63	0.29	18.65	0.29	16
Q(2)	42.61	0.10	42.68	0.10	32
Q(3)	67.27	0.03	67.43	0.03	48
Q(4)	79.52	0.09	79.73	0.09	64
Q(5)	98.60	0.08	98.93	0.07	80
Q(6)	116.26	0.08	116.70	0.07	96
Q(7)	126.36	0.17	126.89	0.16	112
Q(8)	137.77	0.26	138.40	0.25	128
Q(9)	152.59	0.30	153.32	0.28	144
Q(10)	169.05	0.30	170.02	0.28	160
Q(11)	183.91	0.33	185.07	0.30	176
Q(12)	201.12	0.31	202.52	0.29	192

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

Table 4 presents the normality test and the unit root test results on the standardized residuals of the model. According to the ADF test results, all four standardized residual series are stationary. Due to the nature of financial data the resulting residuals are not normally distributed, however, based on the skewness and kurtosis statistics the standardized residuals are closer to a normal distribution than the return series. Table 5 provides the estimated Portmanteau Box-Pierce/Ljung-Box Q-statistics and the adjusted Q-statistics for the system residuals using the Cholesky of covariance Orthogonization method. Both the Q-statistics and the adjusted Q-statistics show that the null hypothesis of no autocorrelations cannot be rejected at the 5 per cent level for various lags of up to 12, with the only exception being the third lag. Thus, one can conclude that there is no significant amount of serial correlation left in the system residuals as the bulk of the serial correlation observed in Table 2 (original return series) has now disappeared in the resulting system residuals in Table 5. This provides further support for the VECH model as it absorbs a great deal of inertia and ARCH and GARCH effects present in the original return series. We have used the unconditional variance of residuals as the initial parameter matrices of the diagonal VECH model to ensure the positive semi-definite of conditional variance and covariance matrix. As stated earlier, all three model selection criteria (i.e. the AIC, the SIC and the HIC) consistently point to a diagonal VECH (1,1) specification as the most acceptable model in explaining the volatility transmission across different markets. Our results show that not only unidirectional positive return spillovers exist from US market to Australia and Singapore but also the own-volatility spillovers are generally higher than cross-volatility spillovers for smaller markets.

V. Summary and Conclusion

Previous studies argue that the Australian stock market return is highly integrated with the stock market returns of the UK, Singapore, and the US (McNelis, [1993]; Valadkhani, Chancharat and Harvie, [2008]). This paper uses a multivariate diagonal VECH model and weekly stock market data from 13 January 1992 to 8 December 2008 to extend this research by identifying the source and magnitude of mean and volatility spillovers across these four markets. We have used a general vector stochastic process of assets returns and allowed the lagged returns of each country to influence the Australian market. The estimated diagonal VECH(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 pre-sample 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 spillovers 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 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. Based on the magnitude of the own innovation effects, it is found that compared to Australia, the UK and the US, the Singapore market is relatively more influenced from its own innovations, however, the shocks arising from the US market can indiscriminately impact on all of the other markets in our sample. As expected, it is also found that the own and cross volatility persistence do exist among these four markets, where the US and Singapore stock returns exhibit the highest and lowest magnitude of the own volatility persistence effect (the GARCH effect), respectively. This suggests that the larger a stock market, the higher would be the magnitude of that market's own volatility persistence. Based on our results one may also conclude that own-volatility spillovers are generally higher than cross-volatility spillovers for smaller markets. This would suggest that in such markets changes in volatility are more likely to emanate from domestic conditions but their volatility persistence is intertwined with global financial markets.

References

Baba, Y.; Engle, R. F.; Kraft, D. and Kroner, K. 1990. *Multivariate Simultaneous Generalized ARCH.* Unpublished manuscript, University of California, San Diego.

Bauwens, L.; Laurent, S. and Rombouts, J. V. K. 2006. Multivariate GARCH models: A Survey. *Journal of Applied Econometrics* 21: 79-109.

Bollerslev, T. 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31: 307-327.

Bollerslev, T. 1990. Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *The Review of Economics and Statistics* 72(3): 498-505.

Bollerslev, T., Engle, R. F. and Wooldridge, J. M. 1988. A Capital asset pricing model with time-varying covariances. *Journal of Political Economy* 96(1): 116-131.

Brailsford, T. J. 1996. Volatility spillovers across the Tasman. *Australian Journal of Management* 21(1): 13-27.

Brooks, C. 2002. *Introductory Econometrics for Finance.* Cambridge University Press.

Brooks, C. and Henry, O. T. 2000. Linear and non-linear transmission of equity return volatility: evidence from the US, Japan and Australia. *Economic Modelling* 17: 497-513.

Caporale, G. M.; Pittis, N. and Spagnolo, N. 2006. Volatility transmission and financial crises. *Journal of Economics and Finance* 30(3): 376-390.

Chan, K. C.; Gup, B. E. and Pan, M. 1997. International stock market efficiency and integration: A study of eighteen nations. *Journal of Business Finance and Accounting* 24(6): 803-813.

Chou, R. Y.; Lin, J. and Wu, C. 1999. Modeling the Taiwan stock market and international linkages. *Pacific Economic Review* 4(3): 305-320.

Engle, R. F. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50(4): 987-1007.

Engle, R. F. and Kroner, K. F. 1993. Multivariate simultaneous generalized ARCH. Discussion Paper No 89-57R.

Eun, C. S. and Shim, S. 1989. International transmission of stock market movements. *Journal of Financial and Quantitative Analysis* 24(2): 241-256.

Goeij, P. D. and Marquering, W. 2004. Modeling the conditional covariance between stock and bond returns: A multivariate GARCH approach. *Journal of Financial Econometrics* 2(4): 531-564.

Harju, K. and Hussain, S. M. 2008. Intraday return and volatility spillovers across international equity markets. *International Research Journal of Finance and Economics* (22): 205-220.

Harris, R. and Sollis, R. 2003. *Modelling and forecasting financial time series*. New York, Wiley.

Hassan, S. A. and Malik, F. 2007. Multivariate GARCH modeling of sector volatility transmission. *The Quarterly Review of Economics and Finance* 47: 470-480.

Higgins, M. L. and Bera, K. A. 1992. A class of nonlinear ARCH models. *International Economic Review* 33(1): 137-158.

Hosking, J. R. M. 1980. The multivariate portmanteau statistic. *Journal of the American Statistical Association* 75(371): 602-608.

In, F. 2007. Volatility spillovers across international swap markets: The US, Japan and the UK. *Journal of International Money and Finance* 26: 329-341.

Kanas, A. 1998. Volatility spillovers across equity markets: European evidence. *Applied Financial Economics* 8: 245-256.

Kim, S. W. and Rogers, J. H. 1995. International stock price spillovers and market liberalization: evidence from Korea, Japan and the United States, Discussion Paper No 499.

King, M. A. and Wadhwani, S. 1990. Transmission of volatility between stock markets. *The Review of Financial Studies* 3(1): 5-33.

Kroner, K. F. and Ng, V. K. 1998. Modeling asymmetric aomovements of asset returns. *The Review of Financial Studies* 11(4): 817-844.

Li, H. 2007. International linkages of the Chinese stock exchanges: a multivariate GARCH analysis. *Applied Financial Economics* 17: 285-297.

McNelis, P. 1993. The response of Australian stock, foreign exchange and bond markets to foreign asset returns and volatilities. Discussion Paper No 9301, Economic Research Department, Reserve Bank of Australia.

Ng, A. 2000. Volatility spillover effects from Japan and the US to the Pacific-Basin. *Journal of International Money and Finance* 19: 207-233.

Pagan, A. R. and Schwert, G. W. 1990. Alternative models for conditional stock volatility. *Journal of Econometrics* 45: 267-290.

Peiro, A.; Quesada, J. and Uriel, E. 1998. Transmission of movements in stock markets. *The European Journal of Finance* 4: 331-343.

Reyes, M. G. 2001. Asymmetric volatility spillover in the Tokyo stock exchange. *Journal of Economics and Finance* 25(2): 206-213.

Scherrer, W. and Ribarits, E. 2007. On the parameterization of multivariate GARCH models. *Econometric Theory* 23: 464-484.

Standards and Poor's 2008. *World by numbers - November 2008.* McGraw Hill.

Theodossiou, P.; Kahya, E.; Koutmos, G. and Christofi, A. 1997. Volatility reversion and correlation structure of returns in major international stock markets. *The Financial Review* 32(2): 205-224.

Theodossiou, P. and Lee, U. 1993. Mean and volatility spillovers across major national stock markets: further empirical evidence. *The Journal of Financial Research* XVI(4): 337-350.

Theodossiou, P. and Lee, U. 1995. Relationship between volatility and expected returns across international stock markets. *Journal of Business and Accounting* 22(2): 289-300.

Valadkhani, A.; Chancharat, S. and Harvie, C. 2008. A factor analysis of international portfolio diversification. *Studies in Economics and Finance* 25(3): 165-174.

Worthington, A. and Higgs, H. 2004. 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.