Multivariate Volatility and Spillover Effects in Financial Markets

Bernardo Veiga and **Michael McAleer**

School of Economics and Commerce, University of Western Australia
(Bernardo@student.ecel.uwa.edu.au, Michael.McAleer@uwa.edu.au)

Abstract: The relationship between volatility and risk has been one of the main factors underlying the interest in volatility modelling. An important question for international diversification is whether shocks in one market influence, or have spillovers into, returns and volatility in other markets. This paper tests for the existence of volatility spillovers among the S&P 500, FTSE 100 and Nikkei 225 stock indexes using intra-daily data from 12/10/1992 to 7/7/2003. Existing work is extended through the application of the vector autoregressive moving average asymmetric generalised autoregressive conditional heteroskedasticity (VARMA-AGARCH) model of Chan, Hoti and McAleer (2002). The results suggest the presence of volatility spillovers from FTSE 100 to both S&P 500 and Nikkei 225, and from S&P 500 to FTSE 100.

Key words: Multivariate GARCH, Asymmetries, Volatility, Spillovers, Risk.

1. INTRODUCTION

The seminal work of Tobin (1958) and Markowitz (1959) showed that the efficiency of portfolios could be optimised by combining assets based on the correlation in their returns. Grubel (1968) extended the portfolio selection problem by considering portfolios that contain asset holdings in other countries, and showed that portfolio efficiency could be improved through international diversification. This has led to a vast body of research into the degree of co-movements among returns in different financial markets.

Engle's (1982) research on time-varying volatility models has added a new dimension to the analysis of market co-movements. The relationship between volatility and risk has been one of the main factors underlying the interest in volatility modelling. An important question for international diversification is whether shocks in one market influence, or have spillovers into, returns and volatility in other markets.

This paper tests for the existence of price and volatility spillovers among three major stock market indexes, namely S&P 500, FTSE 100 and Nikkei 225. Existing empirical research is extended through an application of the vector autoregressive moving average asymmetric generalised autoregressive conditional heteroskedasticity (VARMA-AGARCH) model of Chan, Hoti and McAleer (2002). This general model has not previously been applied to test for volatility spillovers.

Chan et al. (2002) derived the necessary and sufficient conditions for strict stationarity and ergodicity, sufficient conditions for the existence of the log-moment and of all moments, and sufficient conditions for consistency and asymptotic normality of the quasi-maximum likelihood estimator (QMLE) of the VARMA-AGARCH model. Their proofs are based on the derivation of the causal expansions, which do not require the existence of moments. The structural and asymptotic properties of all nested special cases follow by the imposition of appropriate restrictions, which allows the various special cases of the VARMA-AGARCH model to be tested.

2. Data

The data used are the daily opening prices (PO_t) and closing prices (PC_t) from 12/10/1992 to 7/7/2003 for the Nikkei 225, FTSE 100 and S&P 500 stock indexes

expressed in the local currencies. At the time of collecting the data, this was the longest series available from DataStream. The rationale for employing intra-daily frequency data for modelling stock returns and volatility transmission is three-fold.

First, market efficiency would suggest that news is quickly and efficiently incorporated into stock prices. Therefore, while information generated yesterday may be significant in explaining prices today, it is less likely that information generated last week would have any relevance today.

Second, changes in rates of return are news driven. Announcements such as declarations of war, profit forecasts and changes in interest rates are factors that drive equity prices in the short run. However, since investors have heterogeneous beliefs and expectations, their responses to such news can vary widely. Using daily stock data permits an analysis of how a market's "psychology" can be transmitted from one market to another.

Finally, if the returns in market i at time t are calculated as the log difference between the closing prices of market i in calendar days t and t-1, these 24-hour returns of market i will overlap in real time with the 24-hour returns of other markets in calendar time t. The use of intra-daily data should assist in reducing the non-synchronous trading problem, as highlighted in Scholes and Williams (1977), because the open-to-close (o-c) returns of Tokyo do not overlap with the o-c returns of New York or London, while the o-c returns in London have only a 2-hour overlap with the o-c returns in New York.

The o-c returns in market i at time t ($R_{o-c,it}$) are defined as:

$$R_{o-c,it} = \ln(PC_{it} / PO_{it})$$

where PC_{it} and PO_{it} are the closing and opening prices in market i at time t, respectively. Several definitions of volatility are available in the literature. This paper adopts the measure of volatility proposed in Pagan and Schwert (1999), who define the *true* volatility in o-c returns as:

$$V_t = (R_{o-c,it} - E(R_{o-c,it}))^2.$$

Statistics	Nikkei 225	FTSE 100	S&P 500
Mean	1.684	1.183	1.096
Median	0.527	0.316	0.278
Maximum	55.005	34.818	66.269
Minimum	0	0	0
Std. Dev.	3.599	2.654	2.819
Skewness	6.652	5.71	10.813
Kurtosis	71.301	48.835	188.463
CoV	2.137	2.243	2.572

Table1:
Descriptive Statistics for the Volatilities of Nikkei 225, FTSE 100 and S&P 500.

The plots of the volatility of the o-c returns of the three indexes are given bellow:

2

| 60 |
| 50 |
| 40 |
| 30 |
| 20 |
| 10 |
| 0 |

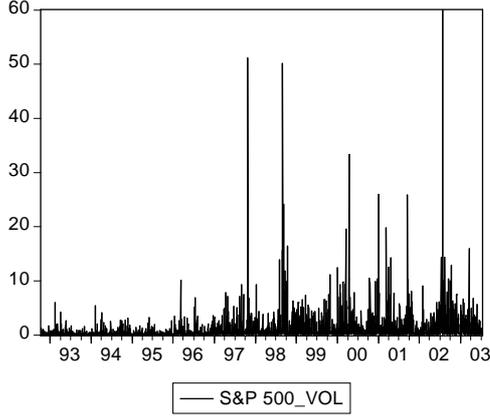93 94 95 96 97 98 99 00 01 02 03

—— S&P 500_VOL
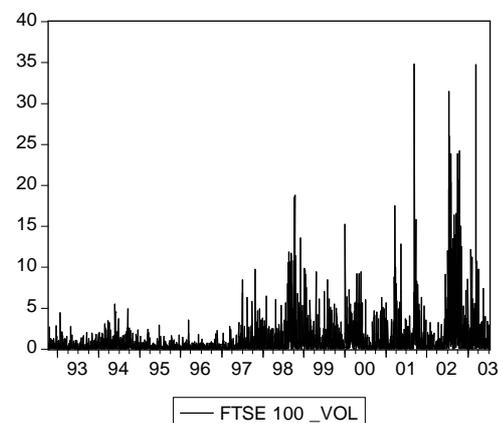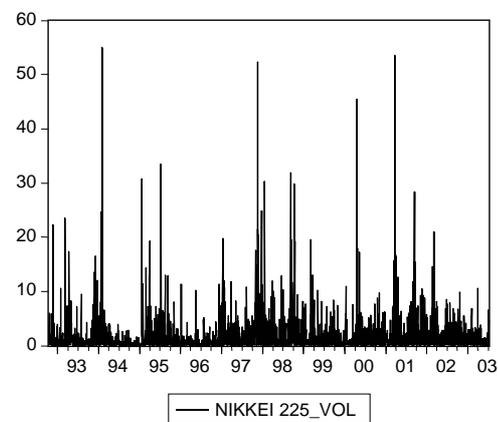
Table 1 gives the descriptive statistics for the volatility of the o-c returns of the three indexes. Each of the volatility series exhibits clustering, which needs to be captured by an appropriate model. Furthermore, all series appear to contain a number of observations which might legitimately be regarded as outliers.

The volatility in all series appears to increase dramatically around 1997, corresponding to the Asian economic and financial crises. This increase in volatility persists until the end of the sample, and is likely to have been affected by the September 11, 2001 terrorist attacks and the conflicts in Afghanistan and Iraq. It is interesting to note that this increase in volatility is much more pronounced for S&P 500 and FTSE 100 than for Nikkei 225, which may arise because the USA and UK have been more directly involved in the 'war on terror' than has Japan.

3. Model

This paper uses the vector autoregressive moving average asymmetric generalised autoregressive conditional heteroskedasticity, or VARMA-AGARCH, model of Chan, Hoti and McAleer (2002) to test for the existence of volatility spillovers. The general model is given by:

$$Y_t = E(Y_t / F_{t-1}) + \varepsilon_t$$

$$\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t$$

$$\varepsilon_t = D_t \eta_t$$

$$H_t = W + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-l} + \sum_{l=1}^{r} C_l I(\eta_{t-l}) \vec{\varepsilon}_{t-l}$$

$$+ \sum_{l=1}^{s} B_l H_{t-l}$$

where $H_t = (h_{1t},...,h_{mt})'$, $W = (\omega_1,...,\omega_m)'$, $D_t = diag(h_{it}^{1/2})$, $\eta_t = (\eta_{1t},...,\eta_{mt})'$, $\vec{\varepsilon}_t = (\varepsilon_{1t}^2,...,\varepsilon_{mt}^2)$, A_l, C_l and B_l are $m \times m$ matrices with typical elements α_{ij}, γ_{ij} and β_{ij}, respectively, for $i, j = 1,...,m$, $I(\eta_t) = diag(I(\eta_{it}))$ is an $m \times m$ matrix, $\Phi(L) = I_m - \Phi_1 L - ... - \Phi_p L^p$ and $\Psi(L) = I_m - \Psi_1 L - ... - \Psi_q L^q$ are polynomials in L, the lag operator, F_t is the past information available to time t, I_m is the $m \times m$ identity matrix, and $I(\eta_{it})$ is an indicator function, given as:

$$I(\eta_{it}) = \begin{cases} 1, \varepsilon_{it} \leq 0 \\ 0, \varepsilon_{it} > 0 \end{cases}$$

The time subscripts in the model correspond to trading time and not calendar time. For example, in the conditional mean and conditional variance models for FTSE 100, the information set of traders in London includes the past information from London as well as information from Tokyo for the same calendar day, and information from New York for the previous calendar day. The coefficients α_{ij} and β_{ij} for i≠j measure the extent to which the lagged unconditional shock and lagged conditional variance in market j, respectively, influence the conditional variance in market i.

An attractive feature of the VARMA-AGARCH model is its ability to capture multivariate asymmetries concerning the impact of positive and negative unconditional shocks to market i on the conditional variance in market i through the coefficient γ_i. If γ_i is positive, it implies that negative shocks increase the conditional volatility in market i to a larger extent than positive shocks.

4. Method

There is no overlap between trading hours in the Tokyo market and the other two markets. However, a two-hour overlap in trading exists

between London and New York. In order to simplify the analysis, it is assumed that the three markets do not overlap. Non-overlapping trading implies that the mean and variance in each market can be conditioned upon any information which has already been observed in a particular market, as well as in the other two markets. The possible biases arising from overlapping trading hours between the London and New York stock markets have been investigated in Hamao et al. (1990) and Koutmos and Booth (1995), where it has generally been found that the parameter estimates are not significantly affected.

Due to the non-synchronous nature of the intra-daily data used in this paper, joint estimation is not appropriate. The sequential estimation procedure used for non-synchronous data is as follows:

(1) For each financial index return series, the univariate GARCH (1,1) model with a VAR mean specification is estimated, and the unconditional shocks and standardized residuals of the three financial index returns are saved.

(2) For each return, the univariate AR(1)-GARCH(1,1) and AR(1)-AGARCH(1,1) models are estimated, including the lagged squared unconditional shocks and the lagged conditional variances of the other two financial indexes, where the lags refer to trading rather than calendar time.

The tests of interdependence and asymmetry are valid under the null hypothesis of independent and symmetric effects, so that step (2) is valid under the joint null hypothesis. The primary purpose of the structural and asymptotic theory is to demonstrate that such testing is straightforward and valid. This is in contrast to, for example, the univariate and multivariate EGARCH models, for which the asymptotic theory has yet to be established.

5. Results

The results reported in Table 2 suggest that all markets experience positive and significant returns spillovers from the other two markets, such that a positive (negative) shock to one market increases (decreases) returns in the following two markets to open.

Returns	Constant	MA(1)	Nikkei (-1)	FTSE (-1)	S&P (-1)
Nikkei	**-0.050**	-0.148	0.064	**0.104**	**0.158**
	-2.582	-1.458	0.631	4.548	6.998
	-2.806	-1.522	0.664	4.210	5.963
FTSE	0.004	0.059	**0.073**	-0.141	**0.144**
	0.260	0.591	5.972	-1.438	7.770
	0.270	0.581	5.643	-1.426	7.039
S&P	0.018	**-0.154**	0.024	0.326	0.124
	1.493	-2.648	2.047	18.750	2.251
	1.525	-2.774	2.068	17.462	2.403

Notes:
1. The three entries for each parameter are their respective estimate, the asymptotic t-ratio and the Bollerslev-Wooldridge (1992) robust t-ratio.
2. Nikkei (-1), FTSE (-1) and S&P (-1) denote the lagged returns for each index.
3. Entries in **bold** are significant at the 5% level.

Table 2:
Conditional Mean

Generally, the more recent is information in trading time, the more likely will that information be significant in explaining the conditional mean. In the conditional mean equation for Nikkei 225 (S&P 500), the most recent information in trading time used to explain the returns at time t are the returns to S&P 500 (FTSE 100) on the previous (same) calendar day. The most recent return has a larger impact on the conditional mean than on the returns to FTSE 100 (Nikkei 225) on the previous (same) calendar day, or the own one-period lagged returns. For FTSE 100, the biggest impact comes from the returns to S&P 500 on the previous calendar day, followed by the own lagged returns, while the smallest impact arises from the returns to Nikkei 225 on the same calendar day.

It is interesting to note that the own lagged returns are not significant for Nikkei 225 and FTSE 100, suggesting that the own long run persistence is dominated by spillover effects. As expected, information generated by S&P 500 has the strongest spillover effects on the returns of the other two markets, while Nikkei 225 has the weakest spillover effects.

The short run persistence of shocks to index i in the same market is given by ($_{.i}$ $\tilde{}_i$□), where $_i$ is the short run persistence of positive shocks and $_{.i}$ $_i$ is the short run persistence of negative shocks. The empirical results reported in Table 3 show that the conditional volatility of Nikkei 225 is affected by both its short run positive and negative shocks. The conditional volatility of FTSE 100 and S&P 500 are affected only by their own short run negative

		N	F	S		N	F	S
Returns								
Nikkei 225	**0.031**	**0.023**	0.021	0.018	**0.060**	**0.924**	**-0.023**	-0.018
	10.169	4.067	2.562	2.414	6.202	124.279	-2.889	-1.907
	1.990	2.161	1.940	1.742	2.960	49.369	-2.222	-1.235
FTSE 100	**0.009**	0.004	0.018	-0.005	**0.094**	-0.005	**0.911**	**0.020**
	2.594	1.452	1.618	-0.751	6.762	-1.271	70.660	2.156
	2.179	1.468	1.559	-0.693	4.013	-1.095	62.961	2.145
S&P 500	**0.017**	0.001	**0.048**	-0.004	**0.127**	-0.003	**-0.024**	**0.900**
	5.032	0.344	10.270	-0.449	8.510	-1.113	-4.113	78.736
	3.883	0.264	3.658	-0.312	5.835	-0.999	-2.292	52.003

Notes:
1.   The three entries for each parameter are their respective estimate, the asymptotic t-ratio and the Bollerslev-Wooldridge (1992) robust t-ratio.
2.   The parameters in the conditional variance equation associated with S&P, Nikkei and FTSE returns are denoted by subscripts S, N and F, respectively.
3.   Entries in **bold** are significant at the 5% level.

Table 3
Conditional Variance

shocks, while the conditional volatility of S&P 500 is affected by short run shocks to FTSE 100 and by its own short run negative shocks.

The long run persistence of shocks to index i in the same market is given by ($._i$ ˜ $_i$☐ $_i$. All indexes are affected by the long run persistence of own shocks. Table 3 shows that the conditional volatility of Nikkei 225 is negatively affected by the long run persistence of shocks from FTSE 100. The conditional volatility of FTSE 100 is positively affected by the long run persistence of shocks from S&P 500. Finally, the conditional volatility of S&P 500 is negatively affected by the long run persistence of shocks from FTSE 100.

react differently to positive and negative shocks. A positive   suggests that the conditional volatility of each market increases more from a negative than from a positive shock, which is consistent with the stylised fact that volatility reacts more strongly to bad news than to good news.

The results reported in this paper differ from those available in the literature. For example, Hamao et al. (1990) find evidence of volatility spillovers from S&P 500 to both FTSE 100 and Nikkei 225, and from Nikkei 225 to FTSE 100. Theodossiou and Lee (1993) report evidence of volatility spillovers from S&P 500 to all other indexes. In comparison, this paper finds evidence of volatility spillovers from

For the conditional variance equation, the timing of multivariate effects does not appear to be a significant factor. The strongest effect always comes from the sum of the own ARCH and GARCH effects, which in real time constitutes the most distant information.

A comparison of the two multivariate effects shows that, for FTSE 100, the most distant multivariate effect has a stronger effect than the most recent, while the opposite is true for S&P 500. In fact, the most recent multivariate ARCH and GARCH effects for the conditional variance equations of Nikkei 225 and FTSE 100 are not significant at the 5% level.

The asymmetric coefficient   is positive and significant for S&P 500, FTSE 100 and Nikkei 225 in Table 3, suggesting that these markets

FTSE 100 to both S&P 500 and Nikkei 225, and from S&P 500 to FTSE 100.

Hamao et al. (1991) report evidence that volatility spillover effects can be time varying. If this is correct, then the differences in the reported findings can be attributed to differences in the samples used in the empirical studies. Hamao et al. (1990) use data for the period 01/04/1985 to 31/05/1988, while Theodossiou and Lee (1993) use data from 11/01/1980 to 27/12/1991.

A second possible explanation lies in the use of only asymptotic t-ratios in these two studies. As can be seen in Table 2, the asymptotic t-ratios are typically higher in absolute value than their robust counterparts, which is likely

due to the inclusion of extreme observations in the samples. Thus, the asymptotic t-ratios reject the null hypothesis of no spillover effects more frequently than do their robust counterparts.

6. Conclusion

In this paper, open-to-close returns of the FTSE 100, S&P 500 and Nikkei 225 stock indexes were used to test for returns and volatility spillovers. The VARMA-AGARCH model of Chan, Hoti and McAleer (2002) was used to model the multivariate conditional volatilities and to test for the existence of volatility spillovers. Open-to-close returns were intended to reduce the degree of overlap among the returns, and hence reduce the measurement errors inherent in using non-synchronous data. Due to the non-synchronous nature of the stock market data, a sequential estimation procedure was used. Testing for returns and volatility spillovers across markets is important for a variety of theoretical and empirical problems. As existing tests have largely been based on symmetric models, which are typically misspecified, asymmetric multivariate models were estimated to test for the presence of asymmetries.

The VARMA-AGARCH model and sequential estimation permit valid statistical inference because the structural and statistical properties of the model have been established in Chan, Hoti and McAleer (2002). Significant evidence of returns spillovers were found across all pairs of stock indexes, as well as volatility spillovers from FTSE 100 to both S&P 500 and Nikkei 225, and from S&P 500 to FTSE 100. These results differ from those in the literature, where volatility originating in S&P 500 has generally been found to have spillover effects to all other indexes, and Nikkei 225 volatility has been found to have spillovers effects to FTSE 100.

7. Acknowledgements

8. References

Bollerslev, T. and J.M. Wooldrige (1992), "Quasi-Maximum Likelihood Estimation of Dynamic Models with Time Varying Covariances", *Econometric Reviews*, 11, 143-173.

Chan, F., S. Hoti and M. McAleer., "Structure and Asymptotic Theory for a Multivariate Asymmetric Volatility: Empirical Evidence for Country Risk Ratings", Paper presented to the Australasian Meeting of the Econometric Society, Brisbane, Australia, July 2002.

Engle, R.F., "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", *Econometrica*, 50, 987-1007, 1982.

Grubel, H.G., "Internationally Diversified Portfolios: Welfare Gains and Capital Flows", *American Economic Review*, 58, 1299-1314, 1968.

Hamao, Y.R., R.W. Masulis and V.K. Ng.,"Correlations in Price Changes and Volatility Across International Stock Markets", *Review of Financial Studies*, 3, 281-307, 1990.

Hamao, Y.R., R.W. Masulis and V.K. Ng., "The Effect of the 1987 Stock Crash on International Financial Integration", in W.T. Ziemba, W. Bailey and Y.R. Hamao (eds.), *Japanese Financial Market Research,* Elsevier, 483-502, 1991.

Koutmos, G. and G.G. Booth., "Asymmetric Volatility Transmission in International Stock Markets", *Journal of International Money and Finance*, 14, 747-762, 1995.

Markowitz, H., *"Portfolio Selection: Efficient Diversification of Investments"*, Blackwell, New York. 1959.

Pagan, A.R., and G.W. Schwert., "Alternative Models for Conditional Stock Volatility", *Journal of Econometrics*, 45, 267-290, 1990.

Scholes, M., and J. Williams., "Estimating Betas from Nonsynchronous Data", *Journal of Financial Economics*, 5, 309-327, 1977.

Theodossiou, P. and U. Lee., "Mean and Volatility Spillovers across Major National Stock Markets: Further Empirical Evidence", *Journal of Financial Research*, 16, 327-350, 1993.

Tobin, J., "Liquidity Preference as a Behavior Towards Risk", *Review of Economic Studies*, 25, 65-86, 1958.