Testing the Sensitivity of Spillover Effects Across Financial Markets

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Abstract: Although market interdependence would seem to be conceptually straightforward, being based on international fundamentals, there are no generally accepted testing strategies. This paper tests for the sensitivity of the empirical results reported in Veiga and McAleer (2004), who use the vector autoregressive moving average asymmetric generalised autoregressive conditional heteroskedasticity (VARMA-AGARCH) model of Chan, Hoti and McAleer (2002) to test for the existence of volatility spillovers among FTSE 100, S&P 500 and Nikkei 225. The existing literature is extended to analyse the robustness of the empirical results reported in Veiga and McAleer (2004) to: (1) the choice of currency used to denominate asset prices, where it is found that the results are not affected by the choice of currency; (2) the inclusion of another asset in testing for volatility spillovers, where it is found that the results can be changed substantially following the inclusion of another asset; (3) the choice of the conditional mean specification, where it is found that the results are sensitive to the choice of conditional mean specification; and (4) the stability of the conditional correlation matrix over time through the use of rolling windows, where it is found that the conditional correlations tend to be time-varying.

Keywords: Multivariate GARCH, Asymmetries, Volatility, Spillovers, Risk, Sensitivity.

1. INTRODUCTION

There are several fundamental issues in volatility modelling. In financial econometrics, forecast errors can be costly as they may lead to sub-optimal hedge-ratios, incorrect risk assessments and mis-pricing of derivative securities. Therefore, a critical issue in volatility modelling is the robustness of the estimates and forecasts to variations in the assumptions of the underlying model. The literature on volatility spillovers has focused on analysing the robustness of the parameter estimates in two directions: (1) the presence of outliers and extreme observations; and (2) the choice of currency used to denominate asset prices.

Veiga and McAleer (2004) tested 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. In this paper, the existing 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). The empirical results based on the VARMA-AGARCH model 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.
The literature is extended to analyse the robustness of the empirical results reported in Veiga and McAleer (2004) to the: (1) choice of currency used to denominate asset prices; (2) inclusion of another asset in testing for volatility spillovers; (3) choice of the conditional mean specification; and (4) stability of the conditional correlation matrix over time through the use of rolling windows.

2. Impact of Alternative Currency Denominations

The aim of this section is to analyse the sensitivity of the empirical results to the use of alternative currency denominations. In examining stock market interdependencies, a currency must be chosen to denominate the stock price. In a survey of eleven papers examining such interdependencies (see Table 1), one paper used the US dollar as the base currency, three papers expressed stock prices using local currencies, four papers used both the local currency and US dollar denominated prices, while three papers simply did not report the currency used. When a common currency is used, it is always the US dollar, but a complicating factor is that the US market is always included in the empirical analysis.

Table 1:
Classification of Papers by Choice of Base Currency

Local currency	US dollar	Both US dollar and local currency	Not reported
(i)Eun and Shim (1989), (ii)Koutmos (1992), (iii)Theodossiou and Lee (1993)	(i)Karolyi and Stulz (1996)	(i)Hamao, Masulis, and Ng (1990), (ii)Koch and Koch (1992), (iii)Lau and Diltz (1994), (iv)Lee, Rui and Wang (2001).	(i)Hamao, Masulis and Ng (1991), (ii)Susmel and Engle (1994), (iii)In, Kim, Yoon and Viney (2001).

Changes in the US dollar are largely influenced by changes in US fundamentals, which also drive financial returns. Thus, it is likely that some of the co-movements observed among returns in different markets expressed in a common currency are caused by changes in the fundamentals driving the US dollar exchange rate.

In order to test this hypothesis empirically, the VARMA-AGARCH model is estimated using five different currencies to denominate stock returns, namely US dollar, Swiss franc, British pound, Japanese yen and the local currency. The choice of currency does not appear to alter the estimates of the own effects, with all significant parameter estimates having the same sign and similar magnitudes. Thus, in testing for the presence of own ARCH, GARCH and asymmetric effects, the choice of currency does not appear to alter the results appreciably. In testing for the existence of volatility spillover effects, there is evidence of spillovers of ARCH effects from S&P 500 to Nikkei 225 when the returns are expressed in yen or local currencies, but not when the other currencies are used. These results suggest that tests of volatility spillovers are largely invariant to the choice of base currency.

3. Choice of Multivariate Effect

In this section the sensitivity of the results to the choice of multivariate effects included in the conditional variance equation is tested. Various papers, such as Lin, Engle and Ito (1994), have tested for volatility spillovers between pairs of countries. An interesting issue is whether the inclusion of a third country in the analysis changes the results substantially from those obtained in the bivariate framework. The VARMA-AGARCH model is estimated under two regimes, as follows:

(1) regime A omits the most distant (in trading time) multivariate effect from the conditional variance equation for each index; and

(2) regime B omits the most recent (in trading time) multivariate effect from the conditional variance equation for each index.

The empirical results are presented in Tables 2 and 3 below. A comparison of the results obtained under regimes A and B with those from the unrestricted model show that testing for the presence of volatility spillovers is sensitive to the choice of the included multivariate effect. Under regime A, we find evidence of spillovers of both ARCH and GARCH effects from S&P 500 to Nikkei 225 and from FTSE 100 to S&P 500. Regime B suggests that spillovers of both ARCH and GARCH effects occur from FTSE 100 to Nikkei 225. Using the unrestricted model, we find evidence of spillovers of GARCH effects from FTSE 100 to Nikkei 225, from FTSE 100 to S&P 500, and from S&P 500 to FTSE 100. Finally, using the unrestricted model, we find evidence of spillovers of ARCH effects from FTSE 100 to S&P 500.

4. Choice of Conditional Mean

The choice of conditional mean specification is an important, yet largely ignored, issue in tests for volatility spillovers. This section provides an analysis of the impact of different conditional mean specifications on the empirical results. The four conditional mean specifications used in this section are: AR(1), VAR(1), ARMA(1,1) and VARMA(1,1). Tables 4 and 5 present the results for each index using the four conditional mean specifications.

The results appear to be sensitive to the conditional mean specification. When a VAR or VARMA is chosen, we find evidence of spillovers of GARCH effects from FTSE 100 to Nikkei 225 and from S&P 500 to FTSE 100. However, when an AR or ARMA specification is used, no such spillover effects are found.

5. Constant Conditional Correlations

The VARMA-AGARCH model has constant conditional correlations. Engle (2002) and Tse and Tsui (2002) have recently proposed similar multivariate GARCH models with time-varying conditional correlations. Chan, Hoti and McAleer (2003) extend each of these models to the generalized autoregressive conditional correlation (GARCC) model, and derive the theoretical and statistical properties of a wide range of dynamic conditional correlation models.

In the constant conditional correlation framework, Γ is no longer a matrix of constant conditional correlations, but follows a restricted multivariate GARCH(1,1) specification. Specifically, Γ is the correlation matrix of the standardised shocks, η_t, which is assumed to be a vector of independent and identically distributed (iid) random variables. If Γ is assumed to be time varying, a more general multivariate GARCH structure would be required to generalize the iid assumption for η_t. This difficulty would render existing proofs of consistency and asymptotic normality of the QMLE for the constant conditional correlation GARCH model invalid for its time-varying counterpart. Such deficiencies would also prevent the models from testing for the presence of volatility spillovers.

Using rolling windows, we can examine the time-varying nature of the conditional correlations using the VARMA-AGARCH model. If the rolling conditional correlations are found to vary substantially over time, the assumption of constant conditional correlations may be too restrictive. Such a result may be used to estimate a variety of dynamic conditional correlation models, and may also question existing results based on constant conditional correlation models. In order to strike a balance between efficiency in estimation and a viable number of rolling regressions, the rolling window size is set at 1800 for all three data sets.

Figures 4, 5 and 6 plot the dynamic paths of the conditional correlation matrices for VARMA-AGARCH. All the conditional correlations display significant variability, which suggests that the assumption of constant conditional correlations may not be valid, and hence may lead to biased inferences.

The existence of time-varying conditional correlations may also suggest time-varying volatility spillovers. To date, no paper in the literature on volatility spillovers has tested the null hypothesis of constant conditional correlations against the alternative of dynamic conditional correlations. Moreover, a maintained hypothesis in all empirical analyses in the spillovers literature has been the presence of constant, rather than time-varying, volatility spillovers.

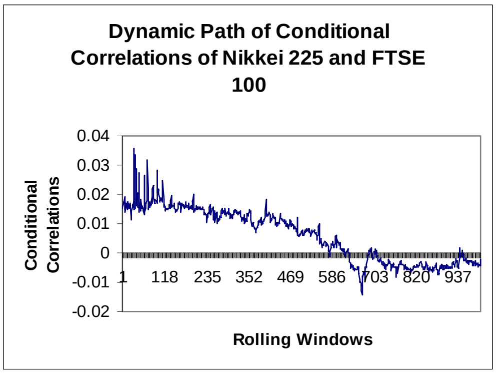

Figure 4

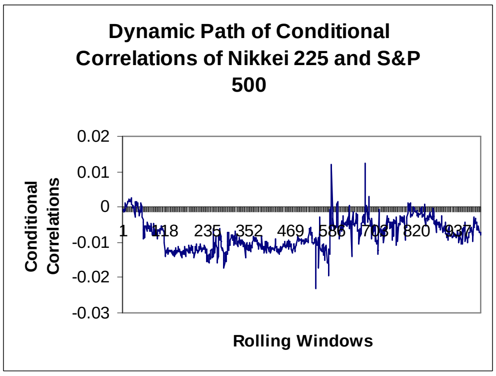

Figure 5

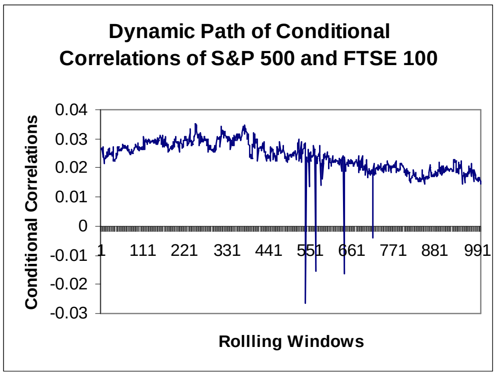

Figure 6

6. Conclusion

The empirical analysis in the paper examined three fundamental issues. First, the sensitivity of the empirical results to the choice of base currency was examined by estimating the VARMA-AGARCH model using five base currencies, namely the local currency, US dollar, Swiss franc, British pound and Japanese yen. This approach extended previous attempts at testing the sensitivity of the results by using a single base currency, namely the Swiss franc, which is not the local currency of one of any indexes used. The empirical analysis suggested that the choice of currency does not change the results significantly.

Second, the sensitivity of the estimates to the choice of multivariate effects was tested by estimating two restricted variants of the VARMA-AGARCH model, with the first specification omitting the more distant multivariate effects and the second omitting the most recent multivariate effects. The results suggested that the testing procedure was sensitive to the choice of multivariate effects. Finally, the sensitivity of the results to the choice of conditional mean specification was tested, and the results were found to be sensitive to the choice of conditional mean.

Finally, on the basis of rolling windows, the assumption of constant conditional correlations inherent in the CCC, VARMA-GARCH and VARMA-AGARCH models was shown not to be consistent with the data.

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Table 2: Regime A
Omitting the Most Distant Multivariate Effect

Returns	□	□	□	□	□̃R	□-R
Nikkei 225	**0.032**	**0.026**	**0.063**	**0.919**	**0.042**	**-0.035**
	9.866	4.307	6.369	122.401	6.777	-5.049
	1.992	2.290	2.915	44.704	2.828	-2.678
FTSE 100	**0.008**	**0.023**	**0.074**	**0.932**	0.003	-0.003
	3.121	2.488	7.299	126.862	1.333	-1.090
	2.495	2.056	3.385	96.901	1.156	-0.858
S&P 500	**0.013**	-0.003	**0.126**	**0.900**	**0.049**	**-0.024**
	6.949	-0.409	8.583	76.751	10.773	-4.358
	4.373	-0.278	5.742	51.393	3.652	-2.315

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. Entries in **bold** are significant at the 5% level.
3. □̃R denotes the coefficient of the most recent ARCH effect from another market.
4. □-R denotes the coefficient of the most recent GARCH effect from another market.

Table 3: Regime B
Omitting the Most Recent Multivariate Effect

Returns	$\square$	$\square$	$\square$	$\square$	$\tilde{\square}$D	$\square$-D
Nikkei 225	**0.036**	**0.026**	**0.062**	**0.919**	**0.034**	**-0.031**
	8.942	4.502	6.175	116.755	5.550	-4.801
	2.404	2.172	3.136	51.592	2.690	-2.999
FTSE 100	**0.007**	0.015	**0.092**	**0.918**	-0.002	0.015
	3.192	1.445	6.875	78.057	-0.368	1.737
	3.037	1.410	4.279	66.723	-0.350	1.735
S&P 500	**0.015**	-0.002	**0.137**	**0.925**	0.004	-0.006
	6.129	-0.310	12.327	146.733	2.890	-2.542
	3.402	-0.236	6.113	87.758	1.053	-1.402

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. Entries in **bold** are significant at the 5% level.
3, $\tilde{\square}$D denotes the coefficient of the most distant ARCH effect from another market.
4, $\square$-D denotes the coefficient of the most distant GARCH effect from another market.

Table 4: Conditional Variances For Nikkei 225
with Four Conditional Mean Specifications

Conditional Mean for Returns	. $\square$	$\square_N$	$\square_{\square}$	$\square_{\square}$	$\square_S$	$\square_S$	$\square_F$	$\square_F$
AR	**0.035**	**0.023**	**0.067**	**0.918**	**0.038**	-0.024	0.012	-0.016
	9.975	3.921	6.484	119.588	5.730	-2.429	1.553	-1.942
	2.149	1.956	3.109	46.306	2.009	-1.459	1.128	-1.391
VAR	**0.031**	**0.023**	**0.061**	**0.924**	**0.031**	-0.019	0.017	**-0.022**
	10.195	3.997	6.240	124.671	4.602	-1.954	2.342	-2.754
	1.979	2.138	2.973	49.173	2.009	-1.265	1.678	-2.143
ARMA	**0.035**	0.023	**0.067**	**0.918**	**0.038**	-0.024	0.012	-0.016
	9.974	3.913	6.495	119.631	5.729	-2.429	1.542	-1.933
	2.147	1.944	3.107	46.205	2.012	-1.458	1.124	-1.386
VARMA	**0.031**	**0.023**	**0.060**	**0.924**	**0.031**	-0.018	0.018	**-0.023**
	10.169	4.067	6.202	124.279	4.567	-1.907	2.414	-2.889
	1.990	2.161	2.960	49.369	2.012	-1.235	1.742	-2.222

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

Table 5: Conditional Variances for FTSE 100
with Four Conditional Mean Specifications

Conditional Mean for Returns	. $\square$	$\square_F$	$\square_F$	$\square_F$	$\square_N$	$\square_N$	$\square_S$	$\square_S$

AR	**0.008**	0.015	**0.083**	**0.928**	**0.005**	-0.006	-0.002	0.012
	2.851	1.577	6.950	93.826	1.746	-1.758	-0.352	1.517
	2.215	1.360	3.923	79.268	2.035	-1.665	-0.288	1.361
VAR	**0.009**	0.018	**0.094**	**0.911**	0.004	-0.005	-0.005	**0.020**
	2.589	1.623	6.762	70.855	1.459	-1.274	-0.720	2.138
	2.175	1.566	4.015	62.902	1.488	-1.098	-0.665	2.125
ARMA	**0.009**	0.019	**0.079**	**0.924**	**0.005**	-0.007	-0.002	0.013
	2.989	1.946	6.748	88.999	1.815	-1.840	-0.267	1.528
	2.274	1.629	3.625	76.037	2.105	-1.740	-0.217	1.406
VARMA	**0.009**	0.018	**0.094**	**0.911**	0.004	-0.005	-0.005	**0.020**
	2.594	1.618	6.762	70.660	1.452	-1.271	-0.751	2.156
	2.179	1.559	4.013	62.961	1.468	-1.095	-0.693	2.145

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. Entries in **bold** are significant at the 5% level.
3. The parameters in the conditional variance equation associated with S&P, Nikkei and FTSE returns are denoted by subscripts S, N and F, respectively.