Volatility transmission and financial crises

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Abstract

In this paper we examine the international transmission of financial crises. In particular, the consequences of the 1997 South East Asia crisis for other major stock markets are analysed. We use a bivariate GARCH model, for which a BEKK representation is adopted, and construct LR tests. Appropriate empirical critical values are computed by means of Monte Carlo experiments. Three pairwise models are estimated using data on the US, European, Japanese and South East Asian daily stock market returns. We find evidence of volatility spillovers in all three models. Although the dynamics of the conditional volatilities differ, overall the results suggest that causality links in the variance were strong and bidirectional in normal periods, but following the onset of the crisis become unidirectional, running from the markets in turmoil to the others.

Keywords: Causality-in-variance, Multivariate GARCH, BEKK representation, Stock prices, Volatility, Financial crises.
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1 Introduction

The relative importance of macroeconomic and financial sector linkages in explaining contagion between countries or regions following the onset of a financial crisis is often debated. At the time of the 1997 South East Asia crisis, both the OECD and the IMF tried to quantify its likely adverse effects on output growth in the industrial economies by focusing on trade linkages. For instance, the OECD estimated that a slowdown in trade with Asia could result in a fall of nearly 1 percent in the level of GDP over two years in the OECD area as a whole (see OECD, 1997). Other studies argued that, because trade is mainly regional, contagion tends to be between countries within the same region, be they competitors, because of their export similarity (see Glick and Rose, 1999), or complements, at different stages of economic development (see Diwan and Hoekman, 1998). However, whether trade linkages are a crucial channel for contagion is an empirical matter, and the evidence is not unequivocally supportive of this idea. The OECD itself acknowledged that trade flows are only one of the possible transmission mechanisms - it is vital to take into account spillovers across global financial markets when analysing the possible repercussions of financial turbulence in one region on other regions of the world. In fact a study by the IMF, which tested for financial market contagion within South East Asia, found an increase in the correlations between financial markets during a crisis compared to a tranquil period (see Baig and Goldfajn, 1998).

Admittedly, the nature of the contagion effects is difficult to identify. For instance, although there is evidence that asset prices are highly correlated across South East Asia, it is not clear whether this reflects similarities in fundamentals or is a consequence of spillovers (see Alba et al, 1998). However, there is a growing consensus that analysing financial contagion is essential to understanding financial crises, especially in view of the increasing degree of integration of the international financial markets. For instance, Masson (1999) developed a model in which contagion generates a crisis through its capital account effects (even though the underlying mechanism works through trade channels). Kaminsky and Schmukler (1999) emphasised the possible "herding" behaviour of investors who just follow the market believing that asset prices contain relevant information; as a result, there could be a stock market crisis in one country simply because of the collapse which has occurred in another country. Clearly, a surge in the volatility of stock prices can then have a significant impact on the real economy through, e.g., wealth effects and the cost of capital. Despite this growing emphasis on financial linkages, most empirical studies only investigate feedbacks between developed stock markets, and only consider linkages between first moments. Given the fact that all recent currency and financial crises originated in emerging markets (e.g., Mexico in 1994, and South East Asia in 1997), before a¤ecting the developed economies, and invariably led to substantially more volatile stock prices, it would appear that a study of volatility transmission across emerging and developed stock markets is overdue.

Many of the existing empirical studies look at correlations, i.e. …rst-order dependence in a linear regression framework. Hilliard (1979), Eun and Shim (1989) and Koch and Koch (1991) all examined the contemporaneous and lagged correlation in daily price changes across major stock markets. The possibility of higher-order dependence, arising out of the interactions between the second moments, has hardly been investigated, even though the importance of second conditional moments in modelling high frequency …nancial time series has been recognized ever since Engle (1982) introduced the class of ARCH models. Hamao et al. (1990) employed autoregressive conditionally heteroscedastic models to study the dynamics of spillover e¤ects in price changes and volatility between the US and Japan, and found that shocks that originate in the US are larger and more persistent. Lin et al. (1994), using a signal extraction model with GARCH processes, studied the New York and Tokyo stock markets and found feedback e¤ects between these two markets. Susmel and Engle (1994) analyzed the interrelationship between the New York and London stock markets and did not …nd strong evidence of either mean or volatility spillovers between them. Most recently, Karolyi (1995) examined the dynamic relationship between US and Canadian stock market returns and return volatilities using a bivariate generalized autoregressive conditional heteroscedastic model. He found that the e¤ects of shocks from the S&P 500 index returns on the TSE 300 index returns and volatility are smaller and less persistent than those measured with traditional vector autoregressive models. Theodossiou and Lee (1993) studied the relationship between the US, UK, Canadian, German and Japanese stock markets using a multivariate GARCH-in-mean model and found mean and volatility spillovers between some of those markets.

The present study makes a twofold contribution. First, it puts forward a new approach to testing for volatility spillovers. The concept of causation in the second moments can be thought of as an extension of the well established notion of Granger causality between the …rst moments, and it could be tested empirically by employing the test recently proposed by Cheung and Ng (1996). By contrast, we estimate a bivariate GARCH model, for which a BEKK representation is adopted (see Engle and Kroner, 1995), and then test for the relevant zero restrictions on the conditional variance parameters by means of likelihood ratio (LR) tests, using appropriately computed critical values. Second, we use this framework to analyse the international transmission of …nancial crises. Speci…cally, we focus on the 1997 South East Asia crisis, and ask the question whether its onset a¤ected the volatility transmission mechanism and changed international …nancial linkages. We …nd that, prior to the crisis, there were bidirectional volatility spillovers between the South East Asian, European, Japanese and US stock markets. By contrast, in the post-crisis periods causality links became unidirectional, running only from the South East Asian markets, where the crisis originated, to the others.

The layout of the paper is as follows. The next section outlines the bivariate GARCH model used to study volatility spillovers between stock markets, and reports the results of the Monte Carlo analysis conducted to compute empirical critical values for the LR test. Section 3 describes the data, and reports the empirical estimates. The final section offers some concluding remarks.

2 The model

In this section, we introduce the multivariate GARCH process we will employ to estimate the international transmission of stock returns' volatility. We model the joint processes governing the rates of returns of two stock indices with the following bivariate GARCH model[1]:

$$r_t = \alpha + u_t \tag{1}$$

where the residual vector $u_t = (e_{1,t}, e_{2,t})$ is bivariate and normally distributed $u_t \mid I_{t-1} \sim (0, H_t)$ with its corresponding conditional variance covariance matrix given by:

$$H_t = \begin{bmatrix} h_{1t} & h_{12t} \\ h_{12t} & h_{2t} \end{bmatrix} \tag{2}$$

The parameter vector of the mean return equation (1) is defined by the constant $\alpha = (\alpha_1, \alpha_2)$, while the parameter matrices for the variance equation (2) are defined as C_0, which is restricted to be upper triangular and two unrestricted matrices A_{11} and G_{11}. Therefore, the second moment will take the following form:

$$\begin{aligned} H_t \quad = \quad C_0'C_0 + & \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} e^2_{1,t-1} & e_{1,t-1}e_{2,t-1} \\ e_{1,t-1}e_{2,t-1} & e^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \\ & + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \end{aligned} \tag{3}$$

Equation (2) models the dynamic process of H_t as a linear function of its own past values H_{t-1} as well as past values of the squared innovations $\left(e^2_{1,t-1}, e^2_{2,t-1}\right)$, both of which allow for own-market and cross-market influences in the conditional variance. The important feature of

[1] The model is based on the bivariate GARCH(1,1) BEKK representation form proposed by Engle and Kroner (1995).

this specification is that it allows the conditional variances and covariances of the two series to influence each other, therefore the formulation presented here allows testing of the null hypothesis of no volatility spillover effects in one or even both directions. Furthermore, it does not require the estimation of many parameters (eight for the bivariate system excluding constant, without any loss of generality). Even more importantly, the BEKK model guarantees by construction that the covariance matrices in the system are positive definite.

Given a sample of T observations, a vector of unknown parameters θ and a 2×1 vector of returns r_t, the conditional density function for the model (1) is:

$$f(r_t | I_{t-1}; \theta) = (2\pi)^{-1} |H_t|^{-1/2} \exp\left(- \frac{u_t' \left(H_t^{-1} \right) u_t}{2} \right) \tag{4}$$

The log likelihood function

$$L = \sum_{t=1}^{T} \log f(r_t | I_{t-1}; \theta) \tag{5}$$

is maximized numerically using the Broyden, Fletcher, Goldfarb and Shanno algorithm to yield maximum likelihood estimates. Standard errors are calculated using the quasi-maximum likelihood methods of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals.

2.1 Monte Carlo Analysis

This section reports on Monte Carlo experiments which evaluate the performance of the Likelihood Ratio Test in a BEKK-GARCH(1,1) framework. Several DGPs have been considered, reflecting those commonly found in the literature. We begin by describing the data-generating processes and the experimental design adopted in our simulations. A discussion of the results of the experiments follows.

2.1.1 Experimental Design and Simulation

We assume that u_t follows a martingale difference, dynamically heteroskedastic process as in (1). The BEKK model, once again, has the following specification:

$$H_t = C_0' C_0 + A_{11}' e_{1,t-1} e_{2,t-1}' A_{11} + G_{11}' H_{t-1} G_{11} \tag{6}$$

where

$$C_0 = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}; A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}; G_{11} = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \tag{7}$$

Imposing zero constraints on the odd diagonal coefficient is equivalent to the null hypothesis of no Granger causality from one variable to the other and viceversa.

Our series are generated in such a way as to allow causality in variance in one direction. In particular, under the null hypothesis $H_0 : a_{21} = g_{21} = 0$; we have that h_{2t} does not Granger cause h_{1t}; whereas h_{1t} does cause h_{2t}: Therefore, the equation for H_t will take the following form[2]:

$$\begin{aligned} h_{1t} &= c_{11}^2 + a_{11}^2 e_{1t-1}^2 + g_{11}^2 h_{1t-1} \\ h_{12t} &= c_{12}^2 + a_{11}a_{12}e_{1t-1}^2 + a_{11}a_{22}e_{1t-1}e_{2t-1} + g_{11}g_{12}h_{1t-1} + g_{11}g_{22}h_{12t-1} \\ h_{2t} &= c_{22}^2 + a_{12}^2 e_{1t-1}^2 + 2a_{12}a_{22}e_{1t-1}e_{2t-1} + a_{22}^2 e_{2t-1}^2 + g_{12}^2 h_{1t-1} + 2g_{12}g_{22}h_{12t-1} + g_{22}^2 h_{2t-1} \end{aligned} \tag{8}$$

The likelihood ratio test, LR henceforth, compares the maximum value of the likelihood function under the assumption that the null hypothesis is correct to the maximum value of the unrestricted likelihood function. Then, if the null is true:

$$LR = 2(L_R - L_U) \tag{9}$$

where L_R and L_U are respectively the restricted and the unrestricted maximized likelihood function. Therefore, under the null hypothesis the test is asymptotically distributed as a $\chi^2(j)$ with degrees of freedom j equal to the number of restrictions. We are interested in the percent rejections given by the difference of the test statistics and the chi-squared distribution at the 0.01, 0.05 and 0.10 significance levels.

To ensure the empirical relevance of the simulations, the parameter values for a_{12} are chosen so as to allow for causality effects of different magnitude and sign. Therefore, we take:

$$a_{12} = \pm(0.1; 0.3; 0.6) \tag{10}$$

The values of the sample size are given by the grid: $T \in \{1000; 2000; 3000; 5000\}$ and are representative of the data on stock returns that are typically used in practice. All starting values satisfy the covariance stationary condition[3].

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[2] Similar restrictions can be imposed in the opposite direction; in that case A_{11} and G_{11} would be upper triangular.

[3] As proved by Engle and Kroner (Proposition 2.7), in the BEKK model $\{u_t\}$ is covariance stationary if and only if all the eigenvalues of $A_{11} \otimes A_{11} + G_{11} \otimes G_{11}$ are less than one in modulus.

In all our experiments, 50 + T data points for u_t are generated from (1) by setting $u_t = 0$ ($t \leq 0$) and using the algorithm of Kinderman and Ramage (1976) to obtain Gaussian pseudo-random deviates. However, to attenuate the effect of the initial values, only the last T of these observations are used to carry out the LR test. The number of Monte Carlo replications per experiment is always 1,000. Finally, since the percent rejections at the 0.01, 0.05 and 0.10 significance levels are qualitatively similar and lead to the same conclusions about the relative merits of the test, we focus our discussion on the properties of 0.05-level test.

In this experiment we find that the LR test has finite-sample Type - I error probabilities that differ significantly from the nominal value of 0.05 when $T = 1000; 2000$. The test performance improves rapidly as the sample size increases, requiring $T \geq 3000$ for empirical rejection frequencies to be within a reasonable range of the nominal significance level, where in fact for $T = 5000$ the empirical critical values are reasonably close to the corresponding asymptotic ones, thus producing more reliable inferences.

Insert Table 2

3 An Application to the South East Asia Crisis

In this section we employ the model described above to investigate the casual relations between stock returns volatility in the South East Asian market and other main markets. Testing for causality in the variance is the goal of our analysis. After describing the data, we discuss the results.

3.1 Data

We use daily data (five days per week) for two countries: US and Japan; in addition, two aggregate indices were built, one for Europe (including Italy, France, UK and Germany) and the other for South East Asia (including South Korea, Singapore, Taiwan Philippines, Malaysia, Thailand, Hong Kong and Indonesia). The indices are weighted averages, where the weight is the GDP of individual countries converted to US dollars at market exchange rates[4], averaged over the preceding three years[5] (see Figure 1), over the period 1/1/1986 - 11/10/2000, for a total of 3855 observations. The data were all obtained from Datastream.

[4] The analysis has also been performed with own currency returns. The results have not been reported as they are qualitatively similar and are available from the authors.

[5] We followed the procedure used in the World Economic Outlook Statistical Appendix for constructing aggregate indices.

We de…ne daily returns as logarithmic di¤erences of stock indices. The South East Asian stock returns show an increase in volatility in the middle of 1997. The South East Asian crisis, in fact, began in Thailand in the late spring of 1997 with sustained speculative attacks on the local currency, and continued with its ‡otation in early July 1997. Within days, speculators had attacked the currencies of Malaysia, the Philippines and Indonesia. The Korean currency was attacked later on. Table 1 presents a wide range of descriptive statistics for the four series under investigation, for the full sample and for two sub-periods, namely the pre-1997 and the post-1997 period. The sample moments for the whole sample returns show heavy skewness and kurtosis; consequently, Jarque-Bera Statistics indicate rejections of the null hypothesis that stock market returns are normally distributed. The statistics indicate that the nature of the data is substantially di¤erent for the two sub-samples.

The empirical distributions in fact seem to be dramatically in‡uenced by the break which occurred in the middle of 1997. Visual inspection of the data suggests that GARCH e¤ects are present in the whole sample as well as in the two sub-periods. Ljung-Box portmanteau statistics (LB) to test for serial correlation in the standardized squared returns are also reported. They con…rm that the null hypothesis of white noise residuals can easily be rejected. The magnitude of the autocorrelation values suggests a non linear dependence pattern, indeed, the signi…cant persistence in the squared returns is consistent with the volatility clustering commonly observed in …nancial series. Overall, the summary statistics con…rm the well-known stylized facts for …nancial time series data.

Insert Figure 1

Insert Table 2

3.2 Empirical results

The estimated conditional variances with associated robust standard errors and likelihood function values for the South East Asian and the European, US and Japanese stock market returns are presented in Tables 3, 4 and 5 respectively. For each model, the Akaike, Bayesian and Hannan-Quinn information criteria have been employed to determine the conditional variance lag lengths. They suggest that a BEKK-GARCH(1,1) speci…cation is appropriate for the conditional variance. Hypothesis testing is performed on the models using the likelihood ratio test, and comparing the test statistics with the empirical critical values reported in Table 2. We carry out tests for causality-in-variance for each model, alternatively constraining the matrices A_{11} and G_{11} to be upper triangular or lower triangular, thereby allowing for causality only in one direction at a time. We report the LR statistics and the associated p-values only when the restriction is accepted.

The null hypothesis of unidirectional cross-market spillovers is rejected when the full sample or the pre-1997 period are considered, but it cannot be rejected in the post-1997 period for all the three models. The patterns in the conditional variance coefficients are not substantially different across models. The estimates are for the most part statistically significant, and the covariance stationary condition is also satisfied by all the estimated models, all the eigenvalues of $A_{11} \otimes A_{11} + G_{11} \otimes G_{11}$ being less than one in modulus. In order to test the adequacy of the models, Ljung-Box portmanteau tests were performed on standardized and standardized squared residuals. Overall the results indicate that the GARCH(1,1) specification captures satisfactorily the persistence in squared returns in the series, with the null hypothesis of no autocorrelation being rejected in just one case at the five per cent level. The coefficient values for own market volatilities indicate high persistence in the stock returns, with coefficient estimates that are all bigger than 0.9. Interestingly, though, in the pre-crisis sample the GARCH parameters are less persistent in all the models, with values ranging from 0.77 to 0.93.

Cross-market volatility dependence varies in magnitude and sign across markets. We find feedbacks in variance in both directions in all the models over the whole sample as well as in the pre-crisis sample, a result which is consistent with the growing degree of integration of financial markets over the last two decades. However, there are asymmetries in volatility spillovers across markets. In particular, the South East Asian conditional variance depends positively on shocks originating in the European markets, while innovations in the US market decrease the South East Asian conditional variance. Shocks which occurred in the Japanese market have a positive effect on the South East Asian conditional variance over the full sample, while in the pre-crisis period their influence is negative and smaller. The positive sign found in the cross-market conditional variance suggests that the volatility of South East Asian stock returns has a positive cluster effect on the other markets. In particular, positive South East Asian shocks have a stronger influence in the pre-crisis period compared with the whole sample. On the other hand, in the post-crisis sample cross-market dependence is just in one direction, with the South East Asian market affecting positively the other three markets. The LR statistics associated with the null of zero cross-market volatility spillovers from the US, European, and Japanese to the South East Asian market cannot be rejected. The $\chi^2(j)$ statistics yielded values of 6.36, 7.1 and 8.1, all of which have corresponding p-values bigger than the empirical critical values. Furthermore, the positive sign suggests that financial turbulence, reflected in higher stock returns volatility, has a positive cluster effect on the other markets.

Insert Tables 3, 4 and 5

4 Conclusions

In this paper we have examined volatility transmission across emerging and developed stock markets, which, we have argued, is of crucial importance in understanding how …nancial crises spread (contagion e¤ects possibly re‡ecting the "herding" behaviour of investors, as pointed out by Kaminsky and Schmukler, 1999). In particular, the e¤ects of the 1997 South East Asia crisis on other major stock markets have been analysed. In brief, we have contributed to the literature in two ways. First, we have introduced a suitable framework for analysing causality links among variances. Speci…cally, we have adopted a BEKK representation of a bivariate GARCH model (see Engle and Kroner, 1995), and constructed LR tests for testing for causality-in-variance. Empirical critical values for the LR tests have been obtained by means of Monte Carlo simulations. Second, we have provided some empirical evidence on the transmission of volatility across US, European, Japanese and South East Asian …nancial markets by applying the suggested methodology to daily data on stock returns, and estimating three pairwise models.

The empirical results can be summarised as follows. There is evidence of volatility spillovers in all three models, though the magnitude of the shocks and the nature of the spillovers among these markets vary signi…cantly (the latter not being a surprising …nding, as di¤erences in …nancial linkages among countries are well documented). Also, in all cases bidirectional feedbacks in the second moment are found for the whole sample as well as the pre-crisis sample, though the dynamics of the conditional volatilities di¤er. By contrast, causality links in the variance appear to become unidirectional following the onset of the crisis, running from the markets in turmoil to the others. In other words, it would seem that one important features of …nancial crises is that, whilst there are negative repercussions on other …nancial markets, the countries originally a¤ected become unresponsive to …nancial developments elsewhere. This is consistent with the idea that, though the build-up in vulnerability (due to …nancial weaknesses) in such countries might be gradual (see Alba et al, 1999), the precipitation of the crisis represents a regime switch, with a jump from one equilibrium to another (see Jeanne and Masson, 2000), leading, e.g., to sharp reversals in capital ‡ows, bankruptcies, etc., with devastating e¤ects on both the …nancial and the real sector of the economy.

As a natural extension of the bivariate analysis conducted in the present paper, it would be useful to estimate a k-variate model and to examine volatility spillovers among all four markets;

also, recursive techniques could be used for each market to detect the exact timing of any breaks. This will be the object of future work.

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TABLE 1

Summary Descriptive Stastistics

		Overall sample	Sub-samples	
Country	Statistics	1/1/86-11/10/00	1/1/86-1/7/97	2/7/97-11/10/00
Asia	Mean	0:01605	0:03008	¡ 0:03306
	Std. dev.	0:53464	0:47762	0:696575
	Skewness	¡ 0:27448	¡ 0:54522	0:169311
	Kurtosis	9:29400	9:80966	7:004204
	LM(5)	645:84¤	187:01¤	114:45¤
	LM(10)	868:41¤	223:20¤	147:21¤
	JB	6411¤	5945¤	575¤
Europe	Mean	0:01543	0:01484	0:01822
	Std. dev.	0:42784	0:40628	0:49661
	Skewness	¡ 1:0437	¡ 1:4456	¡ 0:2378
	Kurtosis	14:3436	20:1879	3:89274
	LM(5)	178:59¤	128:11¤	63:770¤
	LM(10)	209:36¤	143:04¤	121:41¤
	JB	21363¤	37973¤	36¤
Japan	Mean	0:00911	0:01432	¡ 0:01035
	Std. dev.	0:68261	0:64541	0:80037
	Skewness	¡ 0:03791	¡ 0:33883	0::54308
	Kurtosis	11:3174	13:7469	6:68692
	LM(5)	223:04¤	481:96¤	40:686¤
	LM(10)	278:17¤	636:79¤	54:312¤
	JB	11110¤	14494¤	526¤
Usa	Mean	0:02132	0:02083	0:02336
	Std. dev.	0:45219	0:42471	0:53773
	Skewness	¡ 3:1209	¡ 4:62630	¡ 0:3741
	Kurtosis	69:116	109:204	6:68662
	LM(5)	231:85¤	180:07¤	57:633¤
	LM(10)	245:65¤	189:97¤	86:168¤
	JB	70823¤	142062¤	504¤

Note: The star indicates rejection at 5% level. LB(r) denoted the Ljung-Box.test of signi…canze of autocorrelations of r lags in the standardized squared residuals.

TABLE 2

Monte Carlo Results

DGP: $C_0 = \begin{bmatrix} :13 & :14 \\ 0 & :13 \end{bmatrix}; A_{11} = \begin{bmatrix} :301 & a_{12} \\ 0 & 321 \end{bmatrix}; G_{11} = \begin{bmatrix} :922 & :009 \\ 0 & :933 \end{bmatrix}$

	T			
a_{12}	1000	2000	3000	5000
¡ :1	:00924	:01098	:01670	:04768
¡ :3	:01011	:01630	:02558	:04698
¡ :6	:01209	:02182	:03114	:04837
:1	:01302	:02287	:03475	:04954
:3	:01092	:01773	:02812	:04675
.6	:01186	:02107	:03211	:04892

Note: Empirical Type-I Error Probability of 0.05-Level are reported.

TABLE 3

Estimated BEKK-GARCH(1,1) models for the Europe and South East Asia Stock Returns Index

	Whole sample 1/1/86-11/10/00		Pre-crisis sample 1/1/86-1/7/97		Post-crisis sample 2/7/97-11/10/00	
Paramaters	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
α_1	$.0245$	$.0056$	$.0177$	$.0068$	$.0303$	$.0145$
α_2	$.0315$	$.0054$	$.0300$	$.0070$	$-.0269$	$.0208$
c_{11}	$-.0573$	$.0125$	$-.1013$	$.0243$	$.0673$	$.0032$
c_{12}	$-.0424$	$.0104$	$-.0159$	$.0400$	$.0151$	$.0071$
c_{22}	$.0607$	$.0149$	$-.0411$	$.0249$	$.1657$	$.0074$
g_{11}	$.9979$	$.0149$	$.7779$	$.0390$	$.9635$	$.0010$
g_{12}	$.4700$	$.0824$	$.3449$	$.1195$		
g_{21}	$-.1670$	$.0635$	$.6911$	$.0540$	$-.0197$	$.0050$
g_{22}	$-.9879$	$.0129$	$.8387$	$.0659$	$.8799$	$.0038$
a_{11}	$.2391$	$.0329$	$.2564$	$.0460$	$.2316$	$.0058$
a_{12}	$.0962$	$.0381$	$.0311$	$.0946$		
a_{21}	$.0048$	$.0260$	$-.1486$	$.0609$	$.1948$	$.0174$
a_{22}	$.2665$	$.0363$	$.2133$	$.0307$	$.3624$	$.0106$
LogLik	2740.021		2557.176		218.779	
LR Test					6.36	
p-value					$(.0415)$	
$LB^2_{E(5)}$	4.5905		15.609^*		3.6088	
$LB^2_{E(10)}$	13.012		20.389^*		14.691	
$LB^2_{A(5)}$	3.2374		6.0582		4.2074	
$LB^2_{A(10)}$	3.8243		6.6242		10.302	

Note: Quasi-maximum likelihood standard errors (S.E.) based on Bollerslev and Wooldridge (1992) are reported.

A * indicates rejection at the 5% level. LR test p-values are in parentheses.

TABLE 4

Estimated BEKK-GARCH(1,1) models for the Usa and South East Asia Stock Returns Index

	Whole sample 1/1/86-11/10/00		Pre-crisis sample 1/1/86-1/7/97		Post-crisis sample 2/7/97-11/10/00	
Paramaters	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
α_1	.0261	.0052	.0234	.0068	.0227	.0167
α_2	.0301	.0069	.0298	.0102	−.0176	.0211
c_{11}	−.0447	.0009	.0315	.0252	.1294	.0417
c_{12}	−.0067	.0019	−.0852	.0474	−.0058	.0242
c_{22}	.0554	.0021	.0000	.0974	.1672	.0561
g_{11}	.9666	.0003	.9272	.0226	.9402	.0319
g_{12}	.0168	.0007	.3832	.0134		
g_{21}	−.0112	.0004	−.2642	.0103	.0045	.0011
g_{22}	.9544	.0006	.8882	.0414	.9023	.0515
a_{11}	.2320	.0015	.1961	.0839	−.2330	.0616
a_{12}	−.0951	.0033	−.1003	.0262		
a_{21}	.0473	.0019	.0959	.0347	.0531	.0149
a_{22}	.2779	.0028	.2264	.0713	.3630	.0905
LogLik	2738.107		2566.087		97.9719	
LR Test					7.1	
p-value					(.0287)	
$LB^2_{U(5)}$	17.657		12.297		6.6488	
$LB^2_{U(10)}$	22.649*		15.276		15.445	
$LB^2_{A(5)}$	7.9737		13.114*		9.3755	
$LB^2_{A(10)}$	9.1776		15.795		9.5730	

Note: Quasi-maximum likelihood standard errors (S.E.) based on Bollerslev and Wooldridge (1992) are reported. A * indicates rejection at the 5% level. LR test p-values are in parentheses.

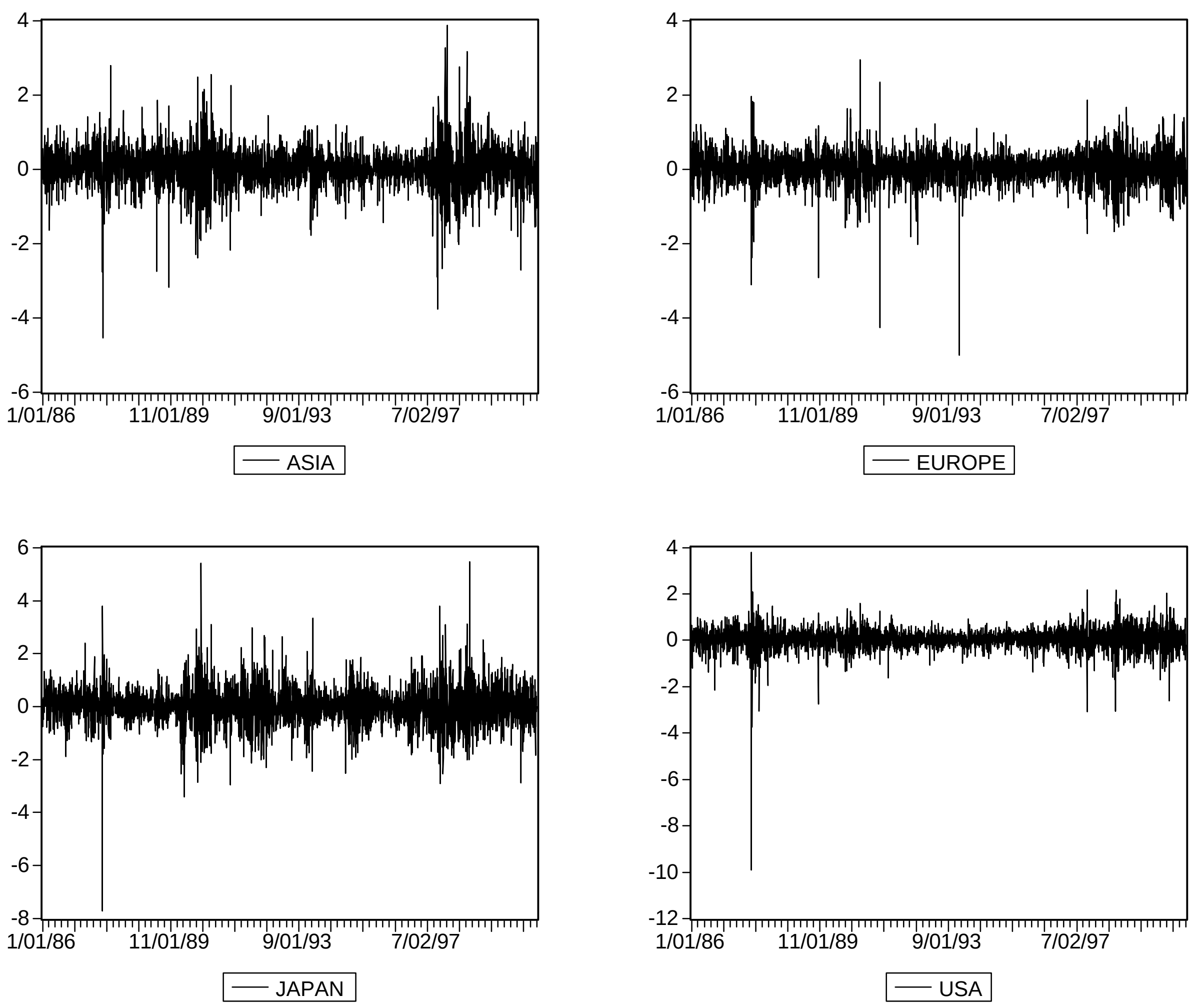
TABLE 5

Estimated BEKK-GARCH(1,1) models for the Japan and South East Asia Stock Returns Index

	Whole sample 1/1/86-11/10/00		Pre-crisis sample 1/1/86-1/7/97		Post-crisis sample 2/7/97-11/10/00	
Paramaters	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
®$_1$	:0289	:0150	:0332	:0120	:0112	:0209
®$_2$	:0341	:0110	:0406	:0085	¡ :0060	:0220
c_{11}	:1036	:0213	:1135	:0180	:0801	:0426
c_{12}	:0432	:1254	:0780	:0573	:0049	:0666
c_{22}	:0778	:0488	:0766	:0116	:1454	:0895
g_{11}	:9503	:0153	:9382	:0162	:9659	:0091
g_{12}	¡ :0004	:0115	¡ :0101	:0071		
g_{21}	¡ :0407	:1641	¡ :0656	:0699	:0499	:0473
g_{22}	:9308	:1127	:9128	:0542	:9168	:0820
a_{11}	:2724	:0376	:3049	:0374	¡ :1586	:0912
a_{12}	¡ :0052	:0173	:0157	:0148		
a_{21}	:1206	:2928	:1315	:1120	:0890	:0599
a_{22}	:3357	:2305	:3454	:0987	:3509	:1521
LogLik	1222:272		1033:967		165:930	
LR Test					8:01	
p-value					(:0182)	
$LB^2_{J(5)}$	0:7754		0:6134		7:1997	
$LB^2_{J(10)}$	1:8023		2:0050		10:336	
$LB^2_{A(5)}$	5:4850		10:295		3:7501	
$LB^2_{A(10)}$	18:126		18:639		12:848	

Note: Quasi-maximum likelihood standard errors (S.E.) based on Bollerslev and Wooldridge (1992) are reported. A * indicates rejection at the 5% level. LR test p-values are in parentheses.

Figure 1:



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ASIA
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-10
-12
USA