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Non-stationary Variance and Volatility Causality

Kamel malik Bensafta
GERCIE, University François Rabelais de Tours, France

Abstract

This paper aims to describe bias estimates when non-stationary variance is not detected. We first present a theoretical multivariate GARCH model with structural changes in variance. Then we describe the non-stationary variance and Volatility Causality in the case of the US and the three developed Asian stock markets Japan, Hong Kong and Singapore. Daily data are used for the period May 30th 2002 until June 29th 2010.

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1. Introduction

A number of empirical studies have been devoted to the study of the relationship between financial markets (King and Wadhawani, 1990 and Edwards, 1998). They look especially at the effects of contagion observed following the American stock exchange crash of October 1987 and the frequent crises of the emergent countries during 1990's (Forbes and Rigobon, 2002; McAleer and Nam, 2005). Studying transmission mechanisms and market co-movement leads to two conclusions: first, market co-movement is important in any strategy of international diversification (King, Sentana and Wadhawani, 1994). This international diversification is based on a weak cross-correlation of geographically spaced markets. Secondly, in the current context of financial globalization, mean and variance spillover reinforce market interdependencies and reduce dramatically any benefit of diversification strategies.

International spillover mechanisms were demonstrated between stock exchange returns and well established by studying volatility (Ng, 2000, Granger et al, 2000, Chakrabarti and Roll, 2002). The volatility spillover was described as "meteor showers" by Engle et *al* (1990); it translates the exogenous part of market turbulence linked to other market-uncertainties. According to this definition, the dependence in variance is a sign of market imperfections and allows risks and returns predictability. It appears that those markets are increasingly dependent in variance (Hamao et *al,* 1990, Koutmos et *al.* 1995), since there is more information in market volatility than market prices (Kyle, 1985).

The GARCH type models are useful for modelling the volatility clustering of high frequency financial series. Under GARCH process, shocks to volatility persist according to ARMA process of squared innovations. Empirical findings show strong persistence of high frequency financial series and this is usually near unity[2]. However, Lamoureux and Lastrapes (1990) show that misspecification in conditional variance processes explain higher persistence measurement. They found that time varying coefficients may exhibit persistence and they proposed time variation of unconditional variance. When taking into account structural change in unconditional variance, they obtained mode reduces persistence value. Theoretically it is hard to detect such structural change but there exist various methods to detect structural change empirically such as regime switching models (Susmel, 2000). In this paper we consider a method based on the CUSUM test, namely the Iterated Cumulative Sum of Squared ICSS algorithm developed by Inclan and Tiao (1994) and Sanso et *al.* (2004).

In this paper, the model of market volatility is a multivariate GARCH process. Short-run Mean and variance spillovers are based on Granger Causality and variance Causality. First, we look for bias estimates in short-run mean spillover when comparing linear VAR and Non-linear VAR. Secondly, we look for bias estimates in volatility spillover estimates between the standard BEKK model (Engle and Kroner, 1995) and the BEKK model with a Structural Break in Variance subsequently called BEKK-BSV (Bensafta and Semedo, 2009). In the last section, we conclude and we provide ways to extend this work.

2 Shock persistence is the measurement of cumulative effects of shocks on volatility. For a GJR-GARCH (p, q) process, persistence is equal to $\varphi_x = \sum_{i=1}^{p}\left(\alpha_{ix} + \frac{1}{2}\gamma_{ix}\right) + \sum_{j=1}^{q}\beta_{jx}$. The measurement of unconditional variance is $(h_t) = \frac{\omega}{1-\varphi}$. A higher unconditional variance leads to highly persistence estimates.

2. The Econometric model

2.1. Detecting a Structural Break in variance

We use an ICSS algorithm based on the CUSUM test to detect the structural change in variance. Following Inclan and Tiao (1994), the variance of a given series shows a structural change due to an exogenous shock. These changes mean a permanent decline in the tendency which continues until the appearance of a new significant shock. This analysis supposes a stationary variance between two points of structural change. Let M series of independent and normally distributed observations: $x_{i,t}$ $(i = \overline{1, M})$. The non-conditional variance of each one of them is $\sigma_{i,t}^2$ and NR_i the number of break point in the variance. On the whole sample of N observations, we have:

$$\sigma_{i,t}^2 = \begin{cases} \sigma_{i,0}^2 & 1 < t < c_{i,1} - 1 \\ \sigma_{i,1}^2 & c_{i,1} < t < c_{i,2} - 1 \\ \vdots & \vdots \\ \sigma_{i,NR_i}^2 & c_{i,NR_i} < t < N \end{cases} \quad (1)$$

Where the $c_{i,j}$ (*j=1…*NR_i) are the dates of break in variance. To estimate the number of changes of variance tendency, the cumulative sum of the square residuals $\mathbb{C}_k = \sum_{t=1}^{k=1,N} u_{i,t}^2$ is calculated. Inclan and Tiao (1994) define the statistics $D_k = \left(\frac{\mathbb{C}_k}{\mathbb{C}_N}\right) - \left(\frac{k}{N}\right)$ with $D_0 = D_N = 0$. When there is no change in variance tendency in the sample, D_k oscillates around zero. Otherwise, when break points exist, D_k is strictly different from zero. Under the null assumption of homogeneous variance $H_0 \colon Var(x_{i,t}) = \sigma_i^2$ (constant), the D_k statistic converges in distribution towards a standard Brownian motion. The null assumption H_0 of non structural break in variance is rejected when $k^* = Max_k\left(\sqrt{N/2}\,|D_k|\right)$ is outside the critical interval ∓ 1.358. Then k^* is a break point at 95%. However, this original version of the ICSS algorithm is defined for a homogeneous variance and does not consider the heteroskedastic nature of the financial series. Sansò et *al.* (2004) make a modification in D_k statistics by taking into account the fourth moment, namely the ICSS-H algorithm. They replace D_k by $G_k = \hat{\delta}_4^{-1/2}\left(\mathbb{C}_k - \frac{k}{N}\mathbb{C}_N\right)$, where $\hat{\delta}_4$ is a consistent estimator of the fourth order moment[3]. The null assumption H_0 is rejected when $k_S^* = \max_k\left|G_k/\sqrt{N}\right|$ is outside the critical interval ∓ 1.405. The k_S^* point is a break point in variance. The ICSS-H algorithm detects $NR_i + 1$regimes of variance for each series. The structural breaks are located by the dummy variables $S_{j,t}^i$. For each series $x_{i,t}$

$$S_{j,t}^i = \begin{cases} 1 \ if \ c_{i,j-1} < t < c_{i,j} - 1 \ \ (j \ from \ \ 1 \ to \ NR_i) \\ 0, else \end{cases} \quad (2)$$

For each series $x_{i,t}$, there are NR_i break points in variance and $NR_i + 1$ régimes of variances.

[3] $\hat{\delta}_4$ is obtained from the non parametric estimator :
$\hat{\delta}_4 = N^{-1}\sum_{t=1}^{N}(\tau_t^2 - \hat{\sigma}^2)^2 + 2N^{-1}\sum_{l=1}^{m} w(l,m)\sum_{t=l+1}^{N}(\tau_t^2 - \hat{\sigma}^2)(\tau_{t-l}^2 - \hat{\sigma}^2)$, where *w(l,m)* is a Bartlett window. The $\hat{\delta}_4$ estimates depend on the choice of m parameter with the Newey-West method. It's usually equal to 2.

2.2.Multivariate GARCH model

The volatility model is a multivariate GARCH process. First, we produce a VAR-BEKK-diagonal estimate (Engle and Kroner, 1995). This standard model is compared to our model which is a VAR-BEKK model increased by a structural break in variance. In the multivariate case, mean transmission is measured by the VAR coefficients of mean equations. Let $r_t = (r_{1t} \quad \cdots \quad r_{Mt})'$ be a vector of logarithmic yields of market indices and $u_t = (u_{1t} \quad \cdots \quad u_{Mt})'$ a vector of dynamic VAR(n_1) residuals, such as:

$$\Phi(L)(r_t - \mu) = u_t \tag{3}$$

Where Φ (L) is the function with lags in the $VAR(n_1)$[4] process. The mean transmission between markets is described by Φ_{ij}^{k} coefficients of the VAR process. These transmissions indicate mean permanent links and dependencies that have combined different channels. Suppose that u_t is a vector of non autocorrelated VAR residuals, and:

$$u_t = H_t^{-1/2}\varepsilon_t \tag{4}$$

Where ε_t is a N-dimension vector of white noise elements such as $\varepsilon_t \leadsto \mathrm{i.i.d}(0, \mathrm{I_t})$ and H_t is the conditional variance-covariance matrix of u_t. H_t is symmetric and defined-positive. Clearly, the u_t have a conditional distribution, given ψ_(t-1)'s information set at time t-1, the conditional distribution is $u_t/\,\psi_{t-1} \leadsto (0, H_t)$, where H_t is a MGARCH process. Several specifications for the matrix Ht exist such as the BEKK and BEKK diagonal (Engle and Kroner, 1995) and Dynamic Conditional Correlation models (Tse and Tsui, 2002, Engle, 2002). Bauwens et al. (2003) give an extensive literature review on the MGARCH model[5]. H_t is defined with equation 5 and the special construction of D_t and R_t matrices :

$$H_t = D_t\mathcal{R}_tD_t = \begin{bmatrix} h_{11t} & \cdots & h_{1Mt} \\ \vdots & h_{ijt} & \vdots \\ h_{1Mt} & \ddots & h_{MMt} \end{bmatrix}, D_t = \begin{bmatrix} \sqrt{h_{11,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{MM,t}} \end{bmatrix},$$
$$\mathcal{R}_t = \begin{bmatrix} 1 & \cdots & \rho_{1M,t} \\ \vdots & 1 & \vdots \\ \rho_{1M,t} & \cdots & 1 \end{bmatrix} \; and \; h_{ij,t} = \rho_{ij,t}\sqrt{h_{ii,t}h_{jj,t}} \tag{5}$$

Where h_{iit} is the conditional variances of M markets ($i = \overline{1, M}$) and h_{ijt} conditional covariances ($i = \overline{1, M}\,, j = \overline{1, M}\; and\; i \neq j$). $\mathcal{R}_t$ is a symmetrical matrix and $\rho_{ij,t}$ the dynamic conditional correlation between i and j markets. The choice of the model must ensure a positive-defined variance-covariance matrix. We use an asymmetrical diagonal BEKK model (Engle and Kroner, 1995), with modifications capturing the Causality in variance and the structural change in the

4 $\Phi(L) = I_m - \Phi^1 L \cdots - \Phi^{n1} L^{n1}$, where n_l is VAR processes order define by the LR sequential test.

5 Engle et *al.* (2001) and Tse et *al.* (2002) DCC models have the attractiveness of a two-step estimation method. These models permit different specifications in GARCH such as Power GARCH and Long-memory FIGARCH. However, these templates provide a linear structure to the correlations dynamics and impose a similar dynamic conditional correlation. In addition, DCC models do not take into account variance spillover.

variance. This model called *VAR-BEKK-BSV* is a different way to introduce an additional movement into the second order moment. The H_t matrix is as follows:

$$H_t = C_B{}' C_B + \sum_{i=1}^{p} A_i' u_{t-i} u_{t-i}' A_i + \sum_{i=1}^{q} B_i' H_{t-i} B_i + \sum_{i=1}^{p} G_i' u_{t-i} u_{t-i}' * D_{Nt-i} D_{Nt-i}' G_i$$
$$+ \sum_{i=1}^{p} \mathbb{T}_i' u_{t-i} u_{t-i}' \mathbb{T}_i + \sum_{i=1}^{q} \mathbb{Z}_i' H_{t-i} \mathbb{Z}_i + \sum_{i=1}^{5} (\delta_i)' D_i \delta_i \quad (6)$$

A_i, B_j *and* G_i are coefficients matrices in the conditional variance-covariance equations. D_{Nt-i} is a M-dimensional vector of dummy variables so that :

$$(d_{i,t}) = \begin{cases} 1 \text{ when } u_{it} < 0 \\ 0, \text{else} \end{cases}$$

C_B is a constant coefficient matrix in conditional variance-covariance equations, * is an element-by-element matrix product, u_t the innovations vector and p and q the GARCH process order. $(C_B)'(C_B)$ is a matrix taking into account structural change in variance[6]. Each diagonal element of C_B is defined as follows:

$$\{C_{Bjj}\} = \omega_{0j} + \sum_{i=1}^{NR_j} \omega_{ji} S_{jt}^i \quad (7)$$

S_{jt}^i are dummy variables for variances schemes (2).

$\mathbb{T}_i$ is a coefficient matrix of elements (tcv^i) for shock to volatility transmission between markets and $\mathbb{Z}_i$ a coefficient matrix of element (tv^i) for volatility transmission between markets. The volatility transmission regressors are defined as follows:

$$\mathbb{T}_i' u_{t-i} u_{t-i}' \mathbb{T}_i = \begin{bmatrix} \left(\sum_{j=2}^{M} (tcv_{j,1}^i) u_{j,t-i}\right)^2 & \cdots & \cdots \\ \vdots & \ddots & \vdots \\ \left(\sum_{j=2}^{M} (tcv_{j,1}^i) u_{j,t-i}\right)\left(\sum_{j=1}^{M-1} (tcv_{j,M}^i) u_{j,t-i}\right) & \cdots & \left(\sum_{j=1}^{M-1} (tcv_{j,M}^i) u_{j,t-i}\right)^2 \end{bmatrix}$$

and

$$\mathbb{Z}_i' H_{t-i} \mathbb{Z}_i = \begin{bmatrix} \sum_{j=2}^{M} (tv_{j,1}^i)^2 h_{jj,t-i} & \cdots & \cdots \\ \vdots & \ddots & \vdots \\ \vdots & \cdots & \sum_{j=1}^{M-1} (tv_{j,M}^i)^2 h_{jj,t-i} \end{bmatrix}$$

Volatility spillover named *Volatility Causality* is measured by the sum $\sum_{i=1}^{p} (tcv^i)^2 + \sum_{i=1}^{q} (tv^i)^2$. The last regressor $\sum_{i=1}^{5} (\delta_i)' D_i \delta_i$ permits « *day of the week effects* » and *« holiday effects »* in variance. D_i is a diagonal matrix whose element $\{D_{jjt}\} = D_{it}$ are :

$$D_{it} = \{D_{1t};\ D_{2t};\ D_{3t};\ D_{4t};\ D_{5t}\} \quad (8)$$

6 H_t construction must satisfy non negativity restrictions and the stationarity condition. In the case of GJR-GARCH, the stationarity condition is $\sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i + 0.5 \sum_{i=1}^{p} \gamma_i < 1$.

Where $D_{1t} = 1$ (resp $D_{2t} = 1, D_{3t} = 1, D_{4t} = 1$ and $D_{5t} = 1$) for Monday (resp, Tuesday, Wednesday, Friday and holiday day) and $D_{1t} = 0$ (resp $D_{2t} = 0, D_{3t} = 0, D_{4t} = 0$ and $D_{5t} = 0$)otherwise. This effect may be present in daily data frequencies (Solnik and Bousquet, 1990, Barone, 1990, Agrawal and Tandon, 1994). δ_i is a vector of coefficients to be estimated.

The standard model and the BEKK-BSV model can be estimated in two ways: firstly a two step estimate, with first VAR coefficient estimates, and secondly, the conditional variance-covariance coefficient estimates. This two-step estimation is allowed because of the block-diagonal character of the variance-covariance coefficients matrix. The one step method considers all coefficients estimates at a time. Errors are conditionally normal and the likelihood function of all distributions is the sum of log-likelihoods of each element. Let L_N the log-likelihood function of the joint conditional distribution:

$$log(L_N) = -\frac{1}{2}\sum_{t=1}^{N}\left[M\,log(2\pi) + log\left(Det(H_{t,\vartheta})\right) + (u_t)'(H_{t,\vartheta})^{-1}u_t\right] \quad (9)$$

Where N is the number of observations, M the number of markets (M=4), $\theta = vech(A, B, C_B, G, J\ and\ \delta\ )$ the vector parameters to be estimated and u_t a normally distributed vector of innovations. Product $u_{it}u_{jt}$ are second order correlated and the joint distribution of $u_{1t};\ u_{2t}; \dots; u_{Mt}$ may not be a normal one. For this reason, θ is estimated by Quasi-Maximum likelihood method *(QML)* of Bollerslev and Wooldridge (1992). Optimization is obtained with the *BHHH algorithm* (Berndt et *al.* 1974) which is well adapted to non linear maximizations (Engle and Kroner, 1995).

3. Empirical results

3.1.Data descriptive

The data cover US and three Asian developed markets Japan, Hong Kong and Singapore. MSCI indices are used since they are better adapted than simple market indices. Indeed they include the mid-cap and the large-cap companies' capitalization. Daily observations from May 30, 2002 to June 29, 2010 are used. Descriptive statistics show the usual characteristics of high frequency financial data: asymmetry, excess kurtosis and non-normality (Table I). Yields MSCI indices for the US market are weak compared to yields in Asian markets. The markets have a similar volatility scale according to standard deviation. The asymmetry is most pronounced on the American market and the Singaporean market. Excess kurtosis shows that extreme values are more frequent than predicted by normality. The Jarque-Bera statistic confirms the non-normality of data.

3.2.Conditional variance model

The Variance regimes detected by the ICSS-H algorithm are given in table II and represented in figure 1. The number of regimes is 7 for Singapore, 8 for the United States and Hong Kong and 10 for Japan. Start and end dates of regimes are not equal although there are some coincidences during the subprime crisis from July 2007 till July 2009:

- 07/2007 – 09/2008: a strong volatility regime which begins with the first phase of the sub-prime crisis.
- 09/2008 – 12/2008: the most turbulent regime and the most volatile during the second phase of the current economic and financial crisis.

- 12/2008 – 07/2009: a third phase of the crisis which is less violent than the two previous phases.
- Return to a calm period around July 2009 for the American market and August 2009 for Asian markets.

These schemes clearly indicate a structural break in the variance during long-run bull and bear market volatility. These distinctions produce a more accurate market volatility model and permit a better comprehension of mean and volatility spillover and interdependences between national stocks markets.

3.3.Mean Causality

It is now accepted that prices and asset returns spillover between stock exchanges markets. It is also shown that market prices are often transmitted unilaterally from US market to stock markets around the world. We produce three measures of the mean transmission coefficient: standard linear VAR model, standard BEKK model and BEKK-BSV model. Coefficients estimates show that most recent information had more impact on returns than older information. The bigger impact came from the US market. One day lagged US returns explain nearly 45% of Asian markets prices. Markets returns are also explained by own lagged returns.

Looking for *Granger Causality GC* between markets shows the following results: *GC* from Asian to the US market is detected with linear VAR only.

Long-Run Mean Spillover *(LRMS hereafter)* is measured by $\Phi = \left(\mathrm{I}_5 - \sum_{\mathrm{i}=1}^{5} \Phi^{\mathrm{i}}\right)^{-1}$. One can see that US market *LRMS* estimates are quite similar for linear and non-linear VAR. Japan returns (resp, Hong Kong and Singapore) $\approx 0.563 *$US returns (resp, 0.523 and 0.536). Contrarily, the *LRMS* estimates from Asian markets to US and between Asian markets are overestimated in the linear VAR. For example, in the linear VAR, the *LRMS* from Japan to Hong Kong (resp Singapore) is -.143 (resp, -.136). In the non-linear BEKK the *LRMS* is only -.049 (resp, -.056). A similar result is obtained by BEKK-BSV: the *LRMS* is only -.054 (resp, -.070). *LRMS* is twice as important in linear VAR and confirms misspecification of the linear VAR compared to the non-linear one (Table III).

These findings are confirmed with Cumulative Impulse-Response Functions *(CIRF hereafter)*. Figure 2 plots *CIRF* for linear VAR and non linear VAR. CIRF of the US market are quite similar for the three models except for a small difference for the US response to own shocks. It is otherwise for the Asian markets where linear VAR overestimate all *CRIF* to shocks: linear VAR *CIRF* is greater than non-linear VAR *CIRF* (in absolute value).

3.4.Conditional Variances-Covariance's Estimates

Table IV provides measures for H_t coefficients estimates, volatility spillover and various measures such as persistence, half-life, long-run volatility spillover and model diagnosis for both standard BEKK and BEKK-BSV.

First, the constant estimated in the conditional variance equation is higher during the sixth regime for the US and Singapore markets and the fifth regime for Japan and Hong Kong markets. Those regimes coincide with the second phase of sub-prime crisis.

Second, all asymmetric coefficients are significant and confirm the asymmetric behavior of market's volatility according to positive and negative shocks. The US market is the most asymmetric one.

Third, in the case of the standard BEKK model, volatility persistence is close to unity (>.9) particularly for US markets (.97). Results show lesser persistence estimates with BEKK-BSV. Half-life of volatility is three times shorter than that estimated by the standard model and varies from 2 days to 8 days. Volatility is much more persistent in the US markets than in the Asian markets. The standard model tends to overestimate the persistence (Lamoureux and Lastrapes, 1994). This overestimation leads to a bias in market spillover estimates and market interdependence estimates.

3.5.Volatility spillover and *Variance Causality*

Volatility spillover is given for both models. The Standard BEKK model underestimates volatility spillover between markets. We emphasize that the share of volatility transmitted by the US market to Asian markets is about half that estimated by BEKK-BSV model. This result was quite expected.

Overall, the share of the volatility of the US market in that of the Asian market varies in the range 2.3% to 8.95%. The Singapore market is the more exposed Asian market to US uncertainties. Feedback from the Asian markets is not significant. In Asia, there is Variance Causality between Hong Kong and Singapore but there is no volatility spillover from Japan to Hong Kong and Singapore.

Concerning days of the week and holiday's effects we found only significant "holiday effects" on the American market. When opening, the US market is much more volatile after closing for a holiday. This effect is not detected in Asian's markets[7].

In terms of maximum log-likelihood, the LR test confirms that BEKK-BSV model is better than the standard BEKK model.

3.6.Dynamic Conditional Correlations DCC

It's now commonly accepted that market interdependences are time-varying (Tse, 2000). The dynamic conditional correlations estimates indicate that market co-movements are highly volatile during turbulent periods. When looking for DCC for both multivariate GARCH models one can see that: the US market is weakly correlated to Asian markets especially to the Japanese market. The Hong Kong market is highly correlated to Japan and Singapore. When comparing standard BEKK and BEKK-BSV we founded that the standard BEKK model overestimates market correlations. This bias is more pronounced during highly volatile periods such as the second phase of the sub-prime crisis (Figure 3). This fact is important when one looks for contagion phenomena based on a significant rise of market correlations during crisis periods. It confirms the well known heteroskedaticity bias during crisis periods (Forbes and Rigobon, 2002).

4. Concluding remark

In this empirical paper, we demonstrate that linear VAR is misspecified because of the significance of second order autocorrelations. This is a serious bias in mean spillover estimates if we consider as here the links between the US and Asian markets. Impulse-Response functions and Granger Causality all confirm these biases.

Additionally, we compare the standard BEKK model to the BEKK-BSV model in which one includes structural breaks in conditional variances. Our empirical results show that the standard

[7] These results are not presented in the paper but can be provide upon request.

BEKK model overestimates volatility persistence. Misspecification in variances leads to Variance Causality biases: first, standard BEKK underestimates volatility spillover effects from US to Asian markets and between Asian markets. Second, Variance Causality is not detected between some Asian markets. Third, market DCC's are biased in the standard BEKK because of volatility persistence overestimation. These biases are much more pronounced during crisis periods.

Finally, of course market volatility is too difficult to be appreciated exactly. However, one can try to take into account all information contained in the data. Non-stationarity in variance seems to be very important in volatility modeling. Thus, we hope to apply non-linear VAR further in economics topics such as the Monetary Transmission Mechanism, which is frequently modeled with linear VAR or linear structural VAR only.

Annexes

Table I: Descriptive statistics of markets returns.

	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	JB		N. Obs
United States	0.62%	11.042	-9.514	1.380	-0.170	12.686	8047.696	***	2108
Japan	0.74%	11.467	-9.513	1.502	-0.137	7.479	1724.682	***	2108
Hong Kong	2.67%	10.448	-12.567	1.450	-0.122	10.592	4942.232	***	2108
Singapore	3.82%	8.563	-9.809	1.463	-0.221	8.249	2376.708	***	2108

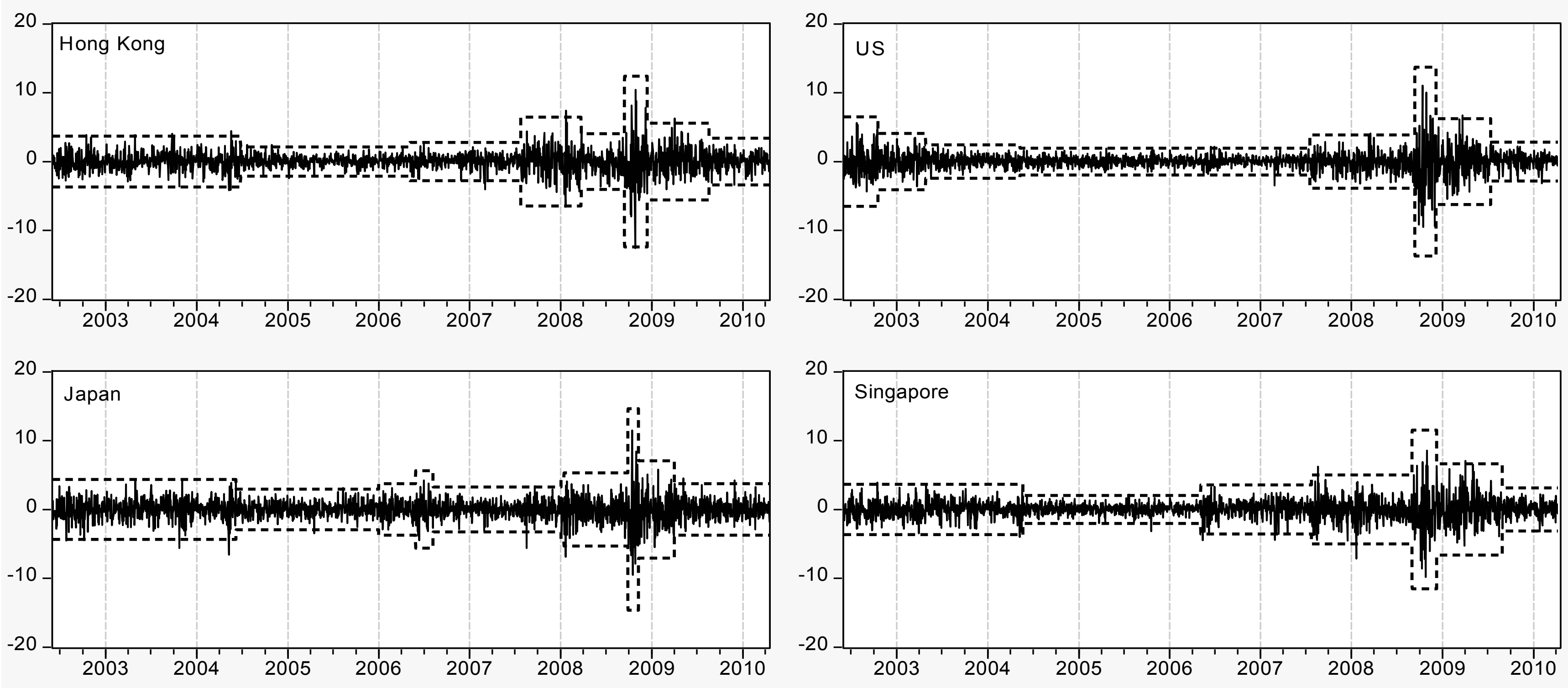
*** Significant at 1%. JB Jarque-Bera statistic.

Table II: Number and date of variance schemes.

US	Start	End	Variance	Hong Kong	Start	End	Variance
1	30/05/2002	16/10/2002	2.171	1	30/05/2002	23/06/2004	1.233
2	17/10/2002	25/04/2003	1.367	2	24/06/2004	04/05/2006	0.706
3	28/04/2003	10/05/2004	0.806	3	05/05/2006	25/07/2007	0.924
4	11/05/2004	18/07/2007	0.649	4	26/07/2007	24/03/2008	2.156
5	19/07/2007	11/09/2008	1.292	5	25/03/2008	12/09/2008	1.348
6	12/09/2008	05/12/2008	4.579	6	15/09/2008	12/12/2008	4.135
7	08/12/2008	14/07/2009	2.072	7	15/12/2008	19/08/2009	1.863
8	15/07/2009	29/06/2010	0.936	8	20/08/2009	29/06/2010	1.128
Japan				Singapore			
1	30/05/2002	04/06/2004	1.452	1	30/05/2002	20/05/2004	1.220
2	07/06/2004	30/12/2005	0.981	2	21/05/2004	04/05/2006	0.676
3	02/01/2006	29/05/2006	1.253	3	05/05/2006	24/07/2007	1.183
4	30/05/2006	07/08/2006	1.871	4	25/07/2007	01/09/2008	1.676
5	08/08/2006	02/01/2008	1.083	5	02/09/2008	09/12/2008	3.847
6	03/01/2008	14/01/2008	1.447	6	10/12/2008	28/08/2009	2.203
7	15/01/2008	26/09/2008	1.772	7	31/08/2009	29/06/2010	1.049
8	29/09/2008	07/11/2008	4.883				
9	10/11/2008	01/04/2009	2.361				
10	02/04/2009	29/06/2010	1.247				

Variance schemes dates obtained by ICSS-H algorithm. Start: the beginning date of the regime. End: end date of the scheme. Variance: the measure of non-conditional variance during the regime.

Figure 1 : Variance schemes (May, 30 2002 – June, 29 2010).



Variance schemes are obtained by ICSS-H algorithm applied to MSCI yields (mid-cap and large-cap) for US, Japan, Hong Kong and Singapore.

Figure 2 : Cumulative Impulse-Response-Function CIRF.

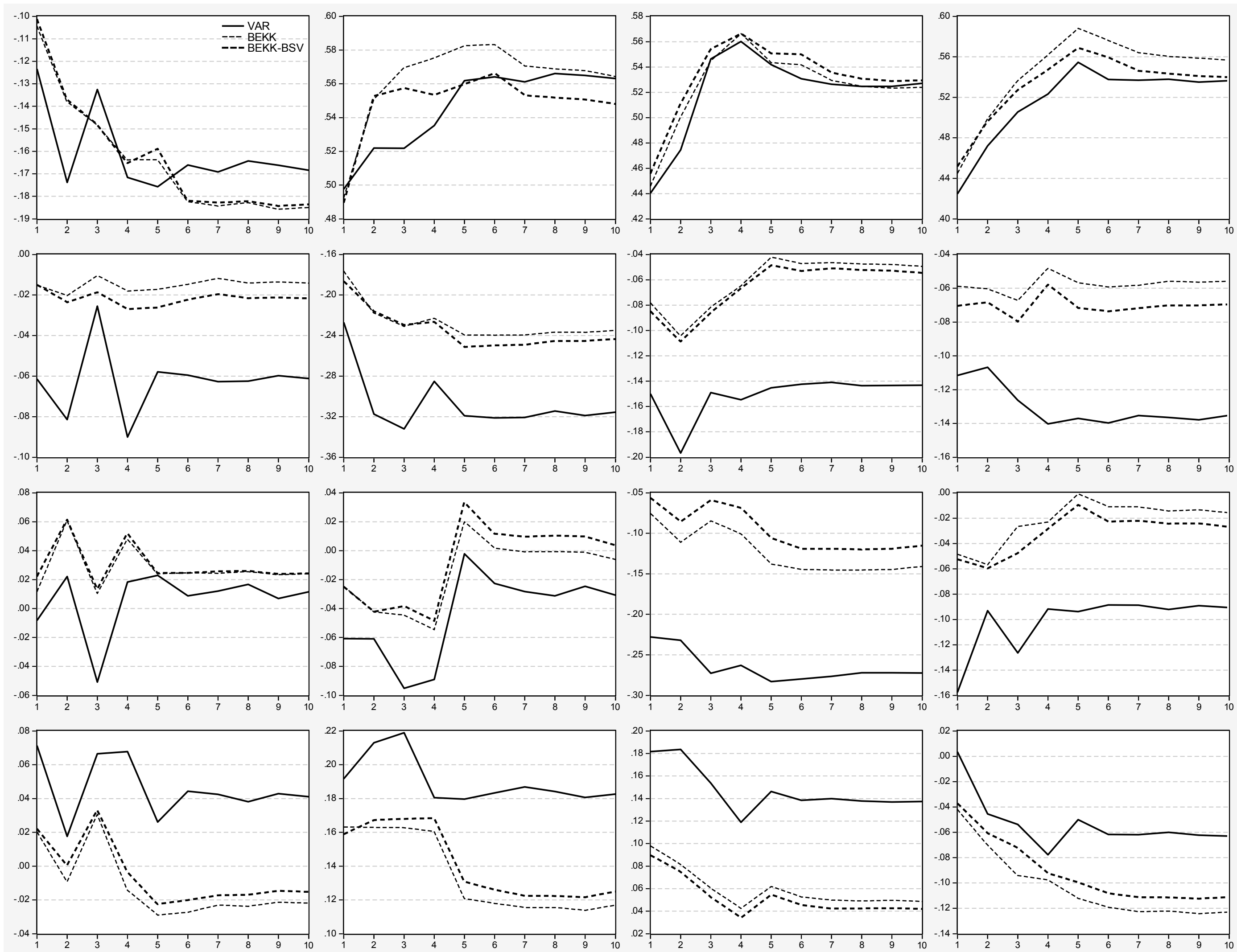
US Responses | Japan Responses | Hong Kong Responses | Singapore Responses

US Shocks

Japan Shocks

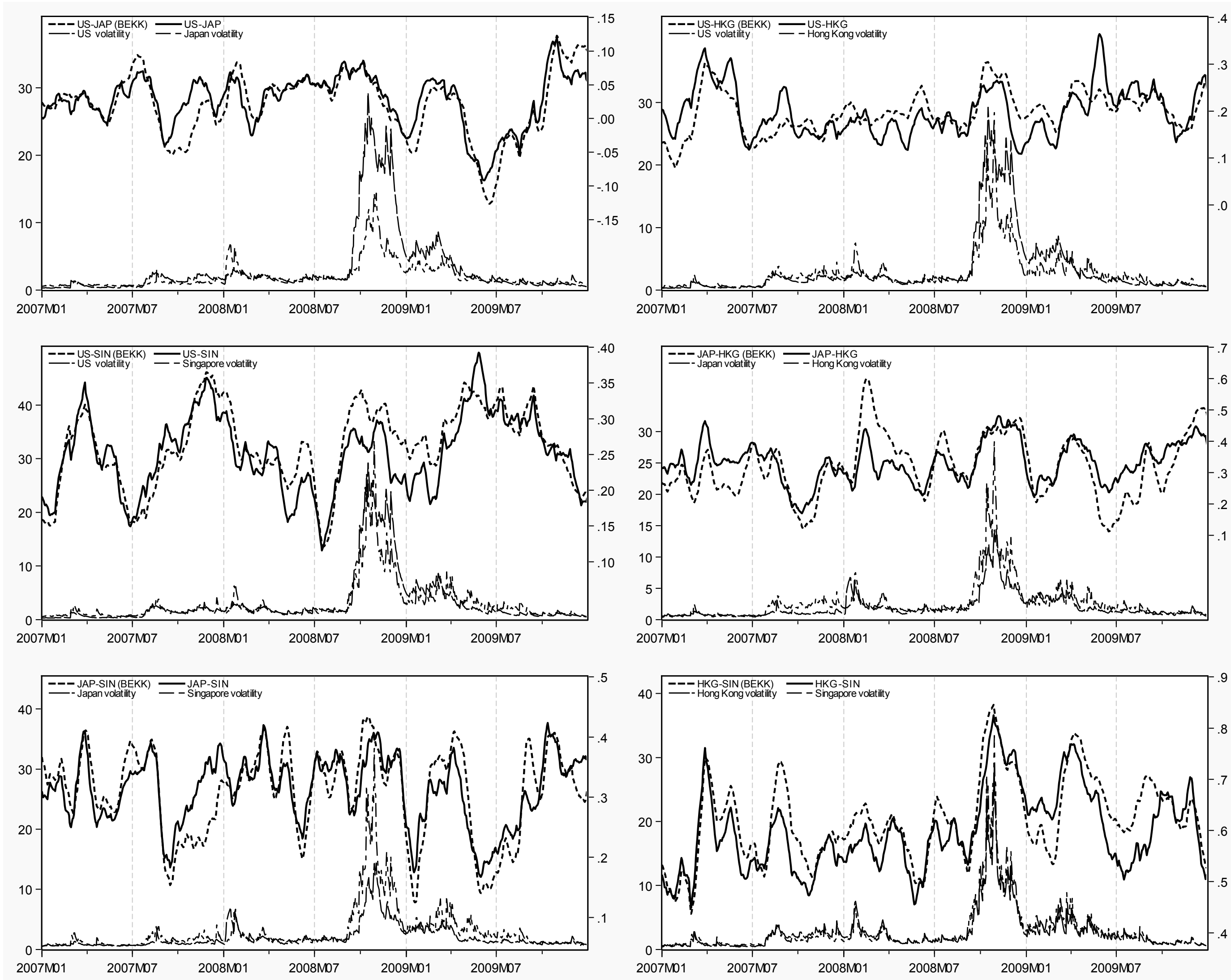
Hong Kong Shocks

Singapore Shocks



CIRF are from linear VAR, BEKK and BEKK-BSV for 10 periods.

Figure 3: Dynamic Conditional Correlations DCC



DCC estimates from Standard BEKK and BEKK-BSV models (May 30, 2002 – Jun, 29, 2010).

Table III: Mean spillover

		Linear VAR				Standard BEKK				BEKK-BSV			
		US	JAP	HKG	SIN	US	JAP	HKG	SIN	US	JAP	HKG	SIN
United States	*(-1)*	-0.123 ***	0.498 ***	0.440 ***	0.425 ***	-0.104 ***	0.492 ***	0.446 ***	0.445 ***	-0.101 ***	0.490 ***	0.456 ***	0.452 ***
	(-2)	-0.062 **	0.144 ***	0.186 ***	0.223 ***	-0.051 *	0.135 ***	0.130 ***	0.170 ***	-0.059 **	0.144 ***	0.128 ***	0.165 ***
	(-3)	0.041	0.071 ***	0.151 ***	0.100 ***	-0.029	0.078 **	0.113 ***	0.104 ***	-0.029	0.062 **	0.112 ***	0.098 ***
	(-4)	-0.041	0.029	0.047 *	0.065 **	-0.024	0.040	0.043	0.066 **	-0.022	0.023	0.032	0.063 **
	(-5)	-0.014	0.046 *	0.032	0.069 **	-0.003	0.029	0.005	0.046 *	0.000	0.021	0.005	0.037
Japan	*(-1)*	-0.061 **	-0.227 ***	-0.150 ***	-0.112 ***	-0.015	-0.176 ***	-0.078 ***	-0.059 ***	-0.015	-0.186 ***	-0.085 ***	-0.070 ***
	(-2)	-0.035	-0.099 ***	-0.068 ***	-0.018	-0.007	-0.057 **	-0.033	-0.011	-0.009	-0.048 *	-0.031	-0.011
	(-3)	0.037	-0.037	0.027	-0.018	0.010	-0.027	0.013	-0.011	0.004	-0.022	0.015	-0.014
	(-4)	-0.054 **	0.010	-0.016	-0.032	-0.006	-0.004	0.015	0.013	-0.009	-0.004	0.021	0.017
	(-5)	0.024	0.001	0.035	0.018	-0.003	-0.018	0.027	-0.001	-0.004	-0.024	0.025	-0.004
Hong Kong	*(-1)*	-0.008	-0.061 **	-0.228 ***	-0.158 ***	0.012	-0.025	-0.075 ***	-0.049 *	0.022	-0.025	-0.056 *	-0.052 *
	(-2)	0.035	0.007	-0.033	0.026	0.052 **	-0.022	-0.044	-0.021	0.044 *	-0.026	-0.040	-0.024
	(-3)	-0.074 **	-0.059 *	-0.070 **	-0.045	-0.042	-0.032	-0.004	0.000	-0.041	-0.022	0.000	-0.015
	(-4)	0.058 *	0.025	0.014	0.040	0.034	-0.001	-0.005	0.017	0.036	0.004	0.004	0.032
	(-5)	0.012	0.051 *	-0.053 *	-0.014	-0.022	0.054 *	-0.056 **	0.009	-0.027	0.061 **	-0.057 **	0.004
Singapore	*(-1)*	0.071 **	0.192 ***	0.182 ***	0.003	0.020	0.163 ***	0.098 ***	-0.042	0.022	0.159 ***	0.090 ***	-0.037
	(-2)	-0.032	0.040	0.040	-0.029	-0.025	0.028	-0.001	-0.024	-0.018	0.035	-0.003	-0.019
	(-3)	0.052	0.054 *	0.012	0.000	0.034	0.028	0.000	-0.014	0.030	0.024	-0.005	-0.003
	(-4)	0.007	-0.037	-0.051 *	-0.033	-0.037	-0.007	-0.036	-0.020	-0.029	-0.005	-0.036	-0.032
	(-5)	-0.032	-0.014	0.014	0.007	-0.021	-0.021	0.031	-0.007	-0.022	-0.020	0.029	-0.005
Constant		0.007	-0.003	0.024	0.040	0.034 *	-0.005	0.023	0.051 **	0.049 **	-0.009	0.032	0.055

Granger Causality tests [b]

	US	JAP	HKG	SIN	US	JAP	HKG	SIN	US	JAP	HKG	SIN
United States		506.868 ***	403.141 ***	356.088 ***		367.457 ***	371.027 ***	315.153 ***		331.629 ***	380.640 ***	302.213 ***
Japan	15.845 ***		46.062 ***	20.922 ***	1.257		19.031 ***	8.024	1.153		19.988 ***	11.219 **
Hong Kong	11.335 **	12.083 **		31.055 ***	10.595 *	5.253		3.938	9.901 *	5.551		5.428
Singapore	11.124 **	47.840 ***	41.854 ***		7.748	31.666 ***	20.107 ***		5.596	27.845 ***	13.611 **	

Long-run Mean spillover [a]

	US	JAP	HKG	SIN	US	JAP	HKG	SIN	US	JAP	HKG	SIN
United States	0.833	-0.061	0.011	0.041	0.816	-0.014	0.025	-0.022	0.818	-0.022	0.025	-0.015
Japan	0.563	0.684	-0.029	0.182	0.565	0.764	-0.005	0.117	0.549	0.756	0.005	0.125
Hong Kong	0.527	-0.143	0.727	0.138	0.525	-0.049	0.859	0.049	0.530	-0.054	0.885	0.043
Singapore	0.536	-0.136	-0.091	0.938	0.557	-0.056	-0.015	0.878	0.540	-0.070	-0.026	0.889

(..) Delay. ***, ** and * Significant coefficients at 1%, 5% and 10%. [a] Long-run mean spillover is measured as $\Phi = (I_m - \Phi^1 \cdots - \Phi^5)^{-1}$. [b] Under null hypothesis of non Granger Causality test statistic follow $\chi^2_{(5)}$.

Table IV: Conditional variances coefficients estimates, Variance spillover and Variance Causality estimates.

	Standard BEKK								BEKK-BSV							
	US		JAP		HKG		SIN		US		JAP		HKG		SIN	
ω_0^2	0.006	**	0.054	**	0.013	*	0.031	*	2.893	**	1.323	***	0.773	***	0.621	***
Regime 2	--		--		--		--		1.338	***	0.737	***	0.356	***	0.306	***
Regime 3	--		--		--		--		0.324	**	1.159	***	0.352	***	0.513	***
Regime 4	--		--		--		--		0.231	***	1.832	***	1.604	***	0.616	***
Regime 5	--		--		--		--		1.112	***	0.544	***	0.804	***	2.361	*
Regime 6	--		--		--		--		13.739	**	7.415	#	2.591	*	1.305	***
Regime 7	--		--		--		--		3.813	**	1.261	***	0.989	**	0.442	***
Regime 8	--		--		--		--		0.426	**	3.700		0.509	***		
Regime 9	--		--		--		--				2.091	**				
Regime 10	--		--		--		--				0.756	***				
α^2	0.000		0.035	***	0.042	***	0.038	***	0.000		0.034	**	0.028	*	0.035	**
γ^2	0.097	***	0.023	**	0.024	***	0.036	***	0.088	***	0.058	***	0.061	***	0.059	**
β^2	0.927	***	0.883	***	0.899	***	0.858	***	0.880	***	0.695	***	0.711	***	0.711	***
Persistence	0.976		0.929		0.953		0.913		0.925		0.758		0.770		0.775	
Half-life	28.518		9.440		14.272		7.640		8.837		2.500		2.648		2.719	
Variance spillover																
	US		JAP		HKG		SIN		US		JAP		HKG		SIN	
$(tcv^1_{US,j})^2$	--		1,31%	**	3,27%	***	3,32%	***	--		2,28%	**	3,16%	***	5,38%	***
$(tv^1_{US,j})^2$	--		0,61%		0,00%		0,97%		--		0,02%		3,37%	#	3,57%	
$(tcv^1_{JAPAN,j})^2$	0,07%		--		0,11%		0,17%		0,54%		--		0,33%		0,00%	
$(tv^1_{JAPAN,j})^2$	0,00%		--		0,00%		0,00%		0,00%		--		0,00%		0,00%	
$(tcv^1_{Hong\ Kong,j})^2$	0,08%		0,15%		--		1,36%	**	0,29%		0,79%		--		1,62%	*
$(tv^1_{Hong\ Kong,j})^2$	0,40%		0,06%		--		0,48%		1,17%		1,22%		--		1,88%	
$(tcv^1_{Singapore,j})^2$	0,15%		0,02%		0,11%		--		0,22%		0,50%		2,60%	***	--	
$(tv^1_{Singapore,j})^2$	0,52%		1,50%	#	0,48%		--		0,34%		3,30%		0,01%		--	
Long-run variance spillover [a] *and Variance Causality* [b]																
	US		JAP		HKG		SIN		US		JAP		HKG		SIN	
United States	--		***1,92%***	***(**)***	***3,27%***	***(***)***	***4,29%***	***(***)***	--		***2,30%***	***(*)***	***6,53%***	***(***)***	***8,95%***	***(***)***
Japan	*0,07%*		--		*0,11%*		*0,18%*		*0,54%*		--		*0,33%*		*0,00%*	
Hong Kong	*0,48%*		*0,21%*		--		***1,84%***	***(**)***	*1,46%*		*2,01%*		--		***3,50%***	***(*)***
Singapore	*0,67%*		*1,53%*		*0,59%*		--		*0,56%*		*3,81%*		***2,61%***	***(**)***	--	
Log-likelihood	**-7717.6**								**-7618.9**							
AIC	**7.656**								**7.592**							
LR test [c]	**197.4**	***														

[a] Long-run variance spillover is the sum $(tcv^1_{i,j})^2 + (tv^1_{i,j})^2$. [b] *(..)* Variance Causality Wald test significance. [c] Under null hypothesis of no break in variance, LR statistic follow $\chi^2_{(29)}$ $(\sum_{i=1}^{4} NR_i = 29)$. ***, **, * and # Significant coefficients at 1%, 5%, 10% and 20%.

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