Volatility Spillovers in East Asian Financial Markets: A MEM–based Approach

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Abstract

We model the interrelations of equity market volatility in eight East Asian countries before, during and after the Asian Currency Crisis. Using a new class of asymmetric volatility models based on the daily range and the MEM error specification, we find that volatility information in one country spills over into subsequent volatility in other countries. Through the analysis of the system, dynamic propagation of volatility shocks is analyzed to aid understanding of this event. Shocks which originate in one country may be amplified as they are transmitted to linked countries. Thus shocks and risks in such countries pose greater risks to the region than other shocks. Although this partly explains the severity of the currency crisis, we also find evidence that parameters shifted to make the system more unstable during the crisis.

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1 Introduction

When the volatility of a country equity index increases, the risk to investors in that country naturally increases and some are likely to reduce their positions. The cause of the increase can usually be traced to new information on the profitability of the domestic industries. Countries that are linked to this country through trade or other economic relation may find their equity markets disrupted as well. This could be through standard trade theory connections whereby turbulence in the first country will lead to increased uncertainty on the profitability of the linked country and consequently rising equity index volatility as well. However the connection could also be because the information event causing the volatility was regional or global. In this case, the shocks would be contemporaneous so that it would not be possible to see one country leading another.

During a financial crisis these effects generate increased risks throughout linked economic systems. Understanding these links helps to understand the causes and consequences of a crisis. However, if the model changes importantly during the crisis, then the process estimated during stable periods may have little prescription for crisis periods. The Asian currency crisis of 1997-98 provides an interesting example of this spillover effect. The exchange rate uncertainty beginning with the devaluation of the Thai Baht transmitted shocks to equity markets throughout the region. As the risks rose, investors withdrew capital and the economies successively collapsed.

In this paper, we use a sophisticated collection of volatility models for eight East Asian countries from 1995-2006. In order to achieve increased accuracy, the models are based on the daily range and are estimated using the multiplicative error model or MEM as pioneered in Engle(2002) and Engle and Gallo (2006). We examine the transmission or spillover of volatility from one country to another for the system of countries before, during and after the crisis. We analyze the eight countries as a system and find evidence that the structure of the relationships did change in some ways during the crisis. Modelling the transmission mechanism greatly enhances the predictability of volatility throughout the region.

The traditional literature on contagion focuses on variations in these links during crisis periods via an increase of correlations of returns across markets (Forbes and Rigobon, 2002); the multivariate GARCH literature analyzes the behavior of conditional variances and covariances, possibly inserting a Markov switching behavior to account for sudden surges in volatility (Edwards and Susmel, 2001 and 2003). More recently, Diebold and Yilmaz (2009) suggest a spillover index based on the dynamic structure of volatility measures for several international indices estimated by a linear VAR model.

Our goal is to provide an analytical tool to detect significant relationships among markets, the impact of asymmetric effects related to positive and negative market returns and the possible shifts in some coefficients in meaningful subperiods. Our contribution to the debate on the volatility spillover modeling is twofold. First, we focus on the conditional expectation of a volatility proxy (the daily range) rather than deriving it from the returns' conditional variance: one advantage is that we are able to consider more markets relative to multivariate GARCH applications in the area. Second, our nonlinear approach is able to generate momentum in the time–dependent volatility dynamics in the form of hump shaped multiperiod forecast and impulse response functions, allowing the full extent of the transmission of the shocks to occur with a delay.

Our empirical application provides a good example of the evolution of interdependencies among markets around a major crisis. We apply our analysis to eight East Asian markets in the period 1995–2006, devoting particular attention to the treatment of the 1997–1998 turbulent period. We show that markets are significantly interdependent with fairly stable relationships: only for some of the markets did the crisis bring about significant changes in the volatility dynamics. The results indicate an overall crucial role of Hong Kong in influencing other markets. The crisis of October 1997 marks a major diffusion of spillovers to other markets which reach their highest point after a few days: our dynamic forecasts reproduce well the unfolding of the crisis. By contrast, the September 2001 episode shows little evidence of spillovers across markets.

The structure of the paper is as follows: in Section 2 we discuss the literature on volatility spillovers providing a synthetic account of methods and results from papers which analyze the Asian crisis. We enter in the discussion of the volatility proxy chosen and in some stylized facts in Section 3. In Section 4 we present the specification of the vector Multiplicative Error Model used in the analysis with a summary of estimation results and residual diagnostics. In section 5 we present the forecast profiles which can be obtained with the MEM and we analyze the performance of our model in the evolution of two meaningful events, the collapse of the Hong Kong market in October 1997 and the terrorist attacks of September 2001. We introduce MEM impulse response functions in Section 6 analyzing the responses of all markets to a shock in one market and we suggest a measure of volatility spillover balance to evaluate total volatility created by a market relative to the volatility received by other markets. Concluding remarks follow.

2 Volatility Spillovers

The theoretical literature on crises, contagion and volatility spillovers is extensive (Claessens and Forbes 2001; Pericoli and Sbracia, 2003; Dungey and Tambakis, 2005). From an econometric point of view, a variety of methodologies were adopted according to whether a crisis is identified *a priori* or whether the main focus of interest are correlations across markets, possibly subject to a latent regime. Thus, Eichengreen et al. (1996), Caramazza et al. (2004), Van Rijckeghem and Weder (2001) define a dichotomous variable representing the presence of a crisis in a country and adopt Probit/Logit models (explanatory approach where foreign variables may be present); Kaminsky (1999), Kaminsky et al. (1998), Hardy and Pazarbaşoĝlu (1998) focus on the ability of leading indicators representing economic fundamentals (possibly of different countries) in predicting crisis (predictive approach). Engle et al. (1990) use GARCH models where either market activity in one country is present as a predetermined variable in the conditional variance of another country or the full conditional covariances are estimated. Forbes and Rigobon (2002) analyze changes in correlations across markets; Edwards and Susmel (2001, 2003), Fratzscher (2003), Gallo and Otranto (2007) liken the insurgence of a crisis to a switch in regime that is endogenously determined by the data. Generally speaking, the empirical results confirm a certain degree of interdependence among markets, independently of the definition chosen.

A large part of the literature on the 1997-98 Asian financial crisis has discussed volatility spillovers focusing on stock indices, currency prices and interest rates. Table 1 shows a brief summary of the existing empirical analyses. A variety of different econometric approaches have been used to describe how shocks propagate, whether some relationships among different markets exist and how they change, if at all, during a crisis. Results based on these techniques all reach the same conclusion: some dependence between Asian markets exist, Hong Kong plays a very important role in the region (Gallo and Otranto, 2007; Forbes and Rigobon, 2001; In et al., 2001), the cross-market spillovers increased for many countries during the crisis.

Table 1 about here

Following the same scheme of the table, we concentrate our attention on daily volatility in eight Asian markets (Hong Kong (HK), Indonesia (IN), South Korea (KO), Malaysia (MA), the Philippines (PH), Singapore (SI), Taiwan (TA), Thailand (TH)) measured between July 14, 1995 and Oct. 3, 2006 (2754 observations). The novel approach we follow is to specify a vector Multiplicative Error Model where volatilities are modeled directly (rather than conditional variances of returns like in the GARCH approach) as a function of each own's past and the past of other markets' volatilities. Spillovers in our context may be represented by a significant link across markets and the behavior in the crisis will be accommodated by allowing for different dynamics during a specific period.

3 Volatility in the Asian Markets

The devaluation of the Thai Baht on July 2, 1997 is commonly reckoned to have accelerated a wave of foreign capital withdrawals from the whole region. The period of uncertainty was exacerbated by the severe balance of payment crisis that ensued. The role of various macroeconomic imbalances and of the International Monetary Fund intervention in the region has been analyzed at length (Ito, 2007). It is beyond the scope of this paper to look at these causes: from this discussion we retain the consensus that the Thai Baht collapse marks the beginning of the regional crisis with severe downturns in the capital markets in most countries. By the same token, December 1998 is acknowledged to mark the end of the most severe effects of the crisis even if for some countries (e.g. Indonesia; Hill and Shiraishi, 2007) economic contraction lasted longer. We will thus follow this conventional definition of the crisis period as a period common to all markets: this choice is consistent with the evidence produced by Figure 1 where we depict the main stock exchange indices by country (in log–scale for a period between July 1995 and October 2006) with a shaded area identifying the period between July 2, 1997 and Dec. 31, 1998.

Figure 1 about here

We will use the highest and lowest price recorded during the day to build our volatility proxy, the daily range hl_t (Parkinson, 1980):

$$hl_t = \sqrt{\frac{\pi}{8}} \left(\log(\mathrm{high_t}) - \log(\mathrm{low_t}) \right).$$

The range can be interpreted as the maximum intradaily return obtainable on a long position entered at the lowest price and closed at the highest (if the former precedes the latter) or on a short position if the highest price was recorded earlier than the lowest. Parkinson (1980) has established its statistical properties relative to the volatility parameter in an underlying continuous time diffusion process. As it is true with other volatility measures, the range suffers from some limitations if one entertains departures from a pure Brownian motion as the underlying process (e.g the presence of jumps), or if one considers the possible accumulation of information during market closing periods in the form of an overnight surprise (cf. Gallo, 2001, for the impact that overnight returns have on the intradaily GARCH variance). From an empirical point of view, though, range-derived measures have been recognized as a good volatility indicator: Alizadeh et al. (2002) have provided extensive discussion on the properties of the log range; Engle and Gallo (2006) have shown that dynamically the range has good explanatory power in predicting future values of squared returns or realized variance. In a risk management context, Brownlees and Gallo (2009) show that the range has an excellent performance in forecasting close-to-close returns volatility over ultra-high frequency data based measures of realized volatility.

Figure 2 about here

For the Asian markets at hand (cf. Figure 2) the descriptive statistics of the volatility measure are shown in Table 2. We have transformed the values in terms of percent annualized volatility, in order to facilitate their readability and the comparison with the last line of the table, where we report another, noisier, measure of volatility, the standard deviation of the returns.

Table 2 about here

We have chosen to break up the mean of the range by subperiods (Pre–crisis, Crisis and Post–crisis) to provide evidence that will justify some subsequent modeling choices. By and large, the values show a permanent surge in volatility (a high level in the crisis period and a level in the final period higher than the first): an explanation is the effects of the aftermath of the crisis, but also an increased intensity of exchanges within markets and across. The only exception seems to be Taiwan which shows a progressive increase in the average level of volatility.

4 The ME Model for Volatility in East Asia

Partying from the existing literature, we introduce a new model, the Multiplicative Error Model, as a generalization of GARCH-type models applied to non–negative valued processes and estimate it on the range data for the eight markets in a simultaneous structure.

Conditional on the information set I_{t-1}, volatility in market i is modeled as

$$hl_{i,t}|I_{t-1} = \mu_{i,t}\epsilon_{i,t}, \qquad i = 1, \ldots, 8 \tag{1}$$

where the innovation term $\epsilon_{i,t}|I_{t-1}$ is distributed as a Gamma random variable with unit conditional expectation (i.e. with a single parameter ϕ ensuring a large degree of flexibility). The conditional expectation of $hl_{i,t}$, $\mu_{i,t}$, can be specified as a *base* MEM$(1, 1)$,

$$\mu_{i,t} = \omega_i + \beta_i\mu_{i,t-1} + \alpha_{i,i}hl_{i,t-1}, \tag{2}$$

which involves past values of the range and of the conditional expectation (Engle, 2002). Engle and Gallo (2006) show that there are many properties of the MEM which do not depend on the specific shape of the Gamma distribution: neither the first–order conditions of the log-likelihood function nor the robust standard errors calculated following Bollerslev and Wooldridge (1992) involve ϕ. If $\mu_{i,t}$ correctly specifies $E(hl_{i,t}|I_{t-1})$, the expected value of the score evaluated at the true parameters is zero irrespective of the Gamma assumption, making our estimator a consistent Quasi–Maximum Likelihood estimator.

This *base* specification can include other terms which are of interest in the present framework[1]:

1. a second lag on past range $hl_{i,t-2}$ when called for by residual diagnostics;

2. asymmetric effects in which the impact from own lagged volatility is split into two terms according to whether the lagged market returns are negative, respectively, positive (corresponding to dummy variables $D^-_{i,t}$, respectively, $D^+_{i,t}$) ;

3. the lagged daily ranges observed in other markets to link different markets together $hl_{j,t-1},\ j \neq i$;

[1]We use a single subscript when the corresponding effect comes just from the same market and a double subscript for interdependence effects. Also, we prefer not to burden the notation with specifications which have only potential interest. Since they have not received empirical support in our analysis, they would not be considered in what follows.

4. time dummies: DC_t (During Crisis $= 1$ between July 1, 1997 and December 31, 1998) and PC_t (Post–Crisis $= 1$ from Jan. 1, 1999 on);

5. interaction terms between daily ranges of all markets and DC_{t-1} to accommodate the possibility of changing links during the crisis;

6. an interaction between DC_{t-1} and the asymmetric effects.

The general model adopted is thus the following

$$\begin{aligned}\mu_{i,t} &= \omega_i + \beta_i\mu_{i,t-1} + \alpha^-_{i,i} hl_{i,t-1}D^-_{i,t} + \alpha^+_{i,i} hl_{i,t-1}D^+_{i,t} + \sum_{i\neq j}\alpha_{i,j}hl_{j,t-1} + \\ &+ \gamma^-_{i,i}hl_{i,t-1}DC_{t-1}D^-_{i,t} + \gamma^+_{i,i}hl_{i,t-1}DC_{t-1}D^+_{i,t} + \sum_{i\neq j}\gamma_{i,j}hl_{j,t-1}DC_{t-1} + \\ &+ \delta_i DC_{t-1} + \lambda_i PC_{t-1} + \psi_i hl_{i,t-2} \end{aligned} \quad (3)$$

Relative to a Vector Autoregressive model on the same variables, a MEM does not suffer from zeros and ensures non–negative predictions; relative to a VAR on logarithmic transformations, a MEM allows forecasts of volatilities (and not their logs). Since we model expected values of volatility directly, we also note that the number of markets one may consider grows larger. It allows for the analysis of more interdependencies at once, making the MEM preferable to modeling second order moments by multivariate GARCH models which suffer from limitations in the number of variables to be considered.

Based on the equation by equation estimation results, we proceed to select more parsimonious specifications, based either on the significance of zero restrictions or of the absence of asymmetric effects (the equality of the ($\alpha^+_{i,i}$, $\alpha^-_{i,i}$) or ($\gamma^+_{i,i}$, $\gamma^-_{i,i}$) coefficients). The effects which are significant in each market[2] are reported in Table 3.

Table 3 about here

The model selection process is supported by diagnostics on the residuals $hl_{i,t}/\hat{\mu}_{i,t}$

[2]Detailed coefficient estimation results are reported in two different tables at the end of the paper (Tables 6 and 7), but they are not of direct interest in the discussion that follows. Given the large number of coefficients in the most general specification (3) leaving all coefficients irrespective of their significance (as one would do in a VAR) leaves the door open to inefficient estimates and therefore to less precise subsequent analysis. Additional results and the detailed method of selection are available upon request.

shown in Table 4 where we set two different columns for each market with the base specification and the model selected. We report the values of the log–likelihood functions, the Ljung Box test statistics for the null of no autocorrelation in the residuals and squared residuals. Autocorrelation is present only in the *base* specification while there are no traces of it in the selected specification. The estimated Gamma parameter $\hat{\phi}_i$ for the distribution of standardized residuals, $\widehat{\phi_i^{-1}} = \left(\sum_{t=1}^{T}\left(\frac{hl_{i,t}}{\hat{\mu}_{i,t}} - 1\right)^2\right)/T$, turns out to be fairly similar across markets (between 3.5 and 6.5 with many around 4.5) showing similar characteristics of the volatility processes. The last row reports the test statistic of whether coefficients on any link across markets can be constrained to zero (labeled no spillover): we receive confirmation of the inadequacy of the *base* specification, showing that no market can be seen as independent of other markets.

Table 4 about here

What we retain from these results is that all markets show significant interactions with one another in line with Forbes and Rigobon (2001) who cover seven of our markets. The issue of how links changed during and because of the crisis gets market–specific responses: some (Indonesia and Korea) have a more complex dynamics as they exhibit extra interactions during the crisis and shifts in the constant term of the model during and after the crisis: this is in line with the idea that these countries underwent a particular turmoil during the crisis, as documented by Ito *et al.* (2007). In other cases (Hong Kong, Singapore and Thailand), the estimated interaction with other markets did not change profile over the entire period: the only change induced by the crisis is the appearance of a significant reaction of volatility to bad news in their own markets. Taiwan experienced a change in the interactions during the crisis, while Malaysia and the Philippines have some significant effects during the crisis in the form of a shift in the constant term of the equation. In their volatility spillover approach, Diebold and Yilmaz (2009) find asymmetric relationships in the area (e.g. Hong Kong is a dominant market while Taiwan and Thailand do not influence any other Asian markets). Of course the approaches, although similar in spirit (direct modeling of volatilities), are not directly comparable with one another

(Asian versus global, daily versus weekly data, nonlinear versus linear VAR, presence of intervention during and after the Asian crisis).

5 Spillovers from MEM–based Forecasts

Conditional on the information available at time t, the equations (3) for each market can be stacked[3] in a compact form as

$$\boldsymbol{\mu}_{t+1} = \boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t + \mathbf{B}\boldsymbol{\mu}_t + \mathbf{A}^*\mathbf{hl}_t + \boldsymbol{\Gamma}\mathbf{hl}_t DC_t + \boldsymbol{A}_2\mathbf{hl}_{t-1}, \tag{4}$$

Moving further steps ahead, $\mathbf{hl}_{t+\tau},\ \tau > 0$ is not known and needs to be substituted with its corresponding conditional expectation $\boldsymbol{\mu}_{t+\tau}$. The dummies DC and PC are fixed to the value that they had in t. Hence,

$$\begin{aligned}\boldsymbol{\mu}_{t+2} &= \boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t + \mathbf{B}\boldsymbol{\mu}_{t+1} + \mathbf{A}^*\boldsymbol{\mu}_{t+1} + \boldsymbol{\Gamma}\boldsymbol{\mu}_{t+1} DC_t + \boldsymbol{A}_2\mathbf{hl}_t \\ &= \boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t + \left(\mathbf{B} + \mathbf{A}^* + \boldsymbol{\Gamma} DC_t\right)\boldsymbol{\mu}_{t+1} + \boldsymbol{A}_2\mathbf{hl}_t \end{aligned} \tag{5}$$

and, then, for $\tau > 2$

$$\begin{aligned}\boldsymbol{\mu}_{t+\tau} &= \boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t + \left(\mathbf{B} + \mathbf{A}^* + \boldsymbol{\Gamma} DC_t\right)\boldsymbol{\mu}_{t+\tau-1} + \boldsymbol{A}_2\boldsymbol{\mu}_{t+\tau-2}, \\ &= \boldsymbol{\omega} + \mathbf{A}_1\boldsymbol{\mu}_{t+\tau-1} + \mathbf{A}_2\boldsymbol{\mu}_{t+\tau-2}, \end{aligned} \tag{6}$$

which can be solved recursively for any horizon τ.

We use expressions (4) and (6) from a date prior to an event of interest to produce the dynamic predictions of volatility over a horizon of 90 days, that is, a volatility forecast profile for each market. Using the same estimated coefficients we then move the starting date by one day and repeat the same steps. This will move ahead and change the forecast

[3] For the sake of compactness, we resort to a mild abuse of notation by indicating the expressions $\alpha^-_{i,i}D^-_{i,t} + \alpha^+_{i,i}D^+_{i,t}$ as the elements on the main diagonal of $\mathbf{A}^*$.

profile because of the new observed starting values reflecting the market conditions which the forecasts are conditioned on. All profiles converge to the same long run average volatility implied by the model estimates.

We apply this procedure to investigate the evolution of two crucial episodes representing events within the area, respectively, without: October 22, 1997 (collapse of the Hong Kong market) and September 11, 2001 (terrorist attacks in the US). For the sake of legibility, we superimpose in the first graph (Figure 3) only a few forecast profiles, by choosing staggered starting dates (between Oct. 1 and Nov. 19) and drawing vertical lines to identify the week between Oct. 20 and Oct. 24, 1997, when the Hang Seng Index dropped 23%. This picture can be seen as a sequence of video frames which unravel the projected evolution of volatility, starting each time from an updated view of the prevailing situation on all markets.

Figure 3 about here

For the sake of space, we chose to reproduce four, most interesting, markets in Figure 3: Hong Kong, Indonesia, Korea and Thailand. If we trace the evolution of the initial forecasts (beginning of each profile) and the subsequent shape of the profiles themselves, we can look at how the collapse of Hong Kong spilled over to other markets: Hong Kong can be seen as reacting mainly to its own innovations. Reading the profiles along vertical sections (e.g. the vertical line in correspondence with October 24) we see an increase in the progressive volatility forecasts which continues until the beginning of November after which it subsides. Looking at the other three markets, the reaction is much more staggered and the profiles exhibit an interesting hump shape (evidence of a later date at which the volatility is projected to peak) which overshoots the long run volatility level due to the accumulation of the combined interactions across markets. The dominant role of Hong Kong found in the literature (e.g. Forbes and Rigobon, 2001; In *et al.* 2001) finds a confirmation from our results, together with a more detailed evidence of a delayed response to the Hong Kong collapse in the other markets.

Figure 4 about here

The second episode which we report in condensed form is the evolution of volatility as a consequence of the terrorist attacks on Sep. 11, 2001 (Figure 4, vertical lines between Sep. 10 and Sep. 14, 2001). Here the responses are less dramatic, as we find a very moderate reaction in Hong Kong, Indonesia, Korea to the tragic events occurred in the US and a burst in volatility in Thailand the week after the attacks. Overall, the evidence of interdependence in this instance is much weaker.

By contrasting the two sets of results, trade channels and geographical proximity seem to have played a major role in the evolution and interdependence of volatility in the Asian crisis (as already suggested by Forbes, 2004), but not so much in the major uncertainty following the 9/11 episode.

6 Spillovers as Responses to Shocks

Let us recall that the MEM is a system

$$\mathbf{hl_t} = \boldsymbol{\mu_t} \odot \boldsymbol{\epsilon_t} \tag{7}$$

where $\mathbf{hl_t}$ is a vector with stacked $hl_{i,t}$'s, $\boldsymbol{\mu}_t$ is a vector with stacked $\mu_{i,t}$'s, the innovation term $\boldsymbol{\epsilon}_t$ is a jointly multivariate i.i.d. process with unit mean and variance covariance matrix $\boldsymbol{\Sigma}$, and $\odot$ indicates the element–by–element multiplication. We can interpret $\boldsymbol{\mu}_{t+\tau} = E\left(\mathbf{hl_{t+\tau}}|\mathbf{I_t}, \boldsymbol{\epsilon_t} = \mathbf{1}\right)$, i.e. the expectation of $\mathbf{hl_{t+\tau}}$ conditional on $\boldsymbol{\epsilon}_t$ being equal to the unit vector $\mathbf{1}$: this is the basis for the dynamic forecast obtained before. Let us now derive a different dynamic solution $\boldsymbol{\mu}^{(i)}_{t+\tau} = E\left(\mathbf{hl_{t+\tau}}|\mathbf{I_t}, \boldsymbol{\epsilon_t} = \mathbf{1} + \mathbf{s^{(i)}}\right)$, for a generic vector of shocks $\mathbf{s}^{(i)}$. We can build this vector by posing the i-th element equal to the unconditional standard deviation of ϵ_{it} and the other terms $j \neq i$ equal to the linear projection $E(\epsilon_{j,t}|\epsilon_{i,t} = 1 + \sigma_i) = 1 + \sigma_i \frac{\sigma_{i,j}}{\sigma_i^2}$. [4] The element–by–element division ($\oslash$) of the

[4] We exploit the information about the contemporaneous covariation in $\boldsymbol{\epsilon}_t$ *ex–ante*: Dungey and Martin (2007) acknowledge the presence of correlated shocks by estimating them as *contagion*.

two vectors

$$\rho_{t,\tau}^{(i)} = (\boldsymbol{\mu}_{t+\tau}^{(i)} \oslash \boldsymbol{\mu}_{t+\tau}) - \mathbf{1} \quad \tau = 1, \ldots, K. \tag{8}$$

Given the multiplicative nature of the model $\rho_{t,\tau}^{(i)}$ gives us the set of responses (relative changes) in the forecast profile started at time t for a horizon τ brought about by a one standard deviation shock in the i-th market.[5]

Let us take Hong Kong as the market to be shocked, considering October, 22, 1997 as the starting date. Applying our procedure, we obtain the curves in Figure 5.

Figure 5 about here

We observe a high impact on Hong Kong (about 40%) with a monotonically declining response and a one–day ahead lower impact (mostly between 10 and 15%) in the other markets. The latter response grows over time (hump shape or momentum) and reaches its peak between 5 (Indonesia) and 20 days (Taiwan and Thailand) with Korea, Malaysia, Singapore in the middle (after about 15 days). The Philippines exhibit lesser signs of being affected by the shock. The non monotonicity of the response is a peculiarity of our model; for example, in Dungey and Martin's (2007) approach, the individual response of volatility is modeled as a univariate GARCH(1,1) which is not capable of showing momentum.

In general, as many curves would overlap with one another in a graphical representation, we need a synthesis of the impact of the shock from market i to market j at a specific date. We suggest to consider the cumulated responses (the area under the curve) of country j as a way to assess the total change induced by the shock:

$$\phi_t^{j,i} = \sum_{\tau=1}^{K} \rho_{t,\tau}^{j,i} \tag{9}$$

In the example provided in Figure 5, the shock in Hong Kong on Oct. 22, 1997 has a major cumulated impact on Korea, Malaysia, Singapore and Thailand (relative to the Hong Kong area, values between 60% and 70%), an intermediate impact of about 45%

[5] Cf. the impulse response functions described in Engle *et al.* (1990), for news spillovers on volatility. See also Gallant *et al.* (1993), Koop *el.* (1996) for impulse response functions in a nonlinear VAR context.

for Indonesia and Taiwan, and a much lower value for the Philippines (about 28%).

Since the curves in Figure 5 are market and date specific, we can repeat the calculations for all markets and all days in the sample: we obtain results which can be averaged out as in Table 5.

Table 5 about here

In column i, we report the average cumulated effect of a one standard deviation shock to the market i on all markets. Two comments are in order: as one would expect, Hong Kong as an originating market has the biggest impact on all markets; second, there is an apparent asymmetry of responses as for one market the values by column are generally different from the values by row (e.g. for Hong Kong, the volatility generated is bigger than the volatility received). Given the comparability of the figures in the table, we can derive a synthetic index (Volatility Spillover Balance) as the ratio of the average responses 'from' to the average response 'to' (excluding one's own),

$$\zeta_i = \frac{\sum_{j \neq i} \sum_{t=1}^{T} \phi_t^{j,i}}{\sum_{j \neq i} \sum_{t=1}^{T} \phi_t^{i,j}}.$$

A value bigger than one (as in the case of Hong Kong) signals that market as a net creator of volatility spillovers. Korea and Malaysia are fairly balanced (0.95, respectively 0.88), followed by Thailand, Singapore and Taiwan (from 0.82 to 0.74) while the Philippines and, to a much higher degree, Indonesia are "absorbers" of volatility spillovers. Although not directly comparable, the role of Hong Kong, Singapore, the Philippines and Taiwan is in agreement with the results by Diebold and Yilmaz (2009) who identify Indonesia, Korea, Malaysia and Thailand as (mild) volatility spillover providers.

7 Concluding Remarks

In this paper we suggest a novel approach to studying volatility interdependence across markets based on a Multiplicative Error Model: we model directly a volatility proxy for each market inserting other markets' volatilities in the expression of its conditional expectation, allowing for asymmetric effects and for possible changes in the relationships across suitable subperiods: we found relative ease of estimability even with the number of parameters in our specification.

The nonlinear model is capable of generating some interesting dynamics capable of accommodating delays in the transmission of shocks from one market to another through hump–shaped multiperiod forecast and impulse response functions. Although quite general, the model proved well suited to analyze the interdependence and dynamic transmission mechanisms of volatility across East Asian markets during 1990–2006 with a focus on the Asian crisis period (1997–1998). The empirical analysis shows different characterizations for each of the markets considered, although a common feature is the significance of the interdependence for all markets. We find a build-up in the volatility transmission in the case of the major episode of the Asian crisis in Oct. 97, while little or no effects in the case of the terrorist attacks of 9/11. The relative strength of interdependence is confirmed by the analysis of the responses to the shocks, with Hong Kong having a major role as a net creator of volatility, followed by other markets by an increasing degree of volatility absorption (more volatility received than created).

We measured here volatility as daily range, but other proxies can be adopted, such as any of the realized volatility measures. The recent financial crisis and its aftermath may prove an interesting ground on which volatility spillovers can be analyzed along the lines suggested in this paper.

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Author	Variables	Period	Markets Included	Method	Results
Baig and Goldfajth (1999)	Stock market indices, interest rates, exchange rates	1995-1998 (daily)	TH, MA, IN, KO	Correlation Analysis	Cross market correlation increases during the crisis. News affects neighbors.
Dungey and Martin (2007)	Stock market indices, currencies	1997-1998 (daily)	KO, IN, MA TH	Factor model + GARCH	Distinction between spillover and contagion effects during the crisis.
Forbes and Rigobon (2001)	Stock market indices, interest rates	1996-1998 (daily)	HK, IN, KO, MA, SI, TA, TH	Correlation Analysis (heteroskedasticity correction)	No contagion, only interdependence between markets. No increase in correlation, assuming that HK is the dominant market.
In et al. (2001)	Stock market indices	1997-1998 (daily)	HK, KO, TH	VAR-EGARCH (variance)	Reciprocal volatility transmission between HK and KO, unidirectional volatility transmission from KO to TH. HK has a primary role.
Fernandez-Izquierdo and Lafuente (2004)	Stock market indices	1997-2001 (daily)	HK, SI, KO	Factor Analysis, GJR-GARCH (bivariate variance)	Leverage effect existence that is not only due to negative shocks in the market but also to shocks in foreign markets.
Gallo and Otranto (2007)	Stock market indices	1997-2001 (weekly)	HK, KO, MA, SI	Bivariate Multi Chain Markov Switching Model (mean)	Assuming HK dominant, HK has a contagious effect on KO and TH, interdependence between HK and MA.
Forbes (2004)	Stock market indices	1996-1998 (daily)	HK, IN, KO, MA, SI, TA, TH	Probit Models (mean)	Trade links are the most important transmission mechanism.
Kaminsky and Reinhart (1999)	Exchange rates, liabilities, stock prices, mutual fund holdings, exports	1970-1998 (monthly)	TH, MA, IN	Probit Models (mean)	Probability of a crisis increases when more crises occur in other countries, especially in the same geographical area.

Table 1: Summary of the Empirical Literature

Note: We report only the East Asian markets relevant for our analysis, that is: IN (Indonesia), HK (Hong Kong), KO (Korea), MA (Malaysia), SI (Singapore), TA (Taiwan), TH (Thailand). Other markets may have been considered in the corresponding studies but are not mentioned here.

	HK	IN	KO	MA	PH	SI	TA	TH
Mean								
Whole period	15.63	18.00	21.36	14.37	13.94	13.35	17.24	18.99
Pre–crisis	11.77	9.90	13.76	10.04	11.81	8.82	12.95	16.73
Crisis	27.55	31.39	30.54	33.08	22.71	23.18	16.46	30.85
Post–crisis	14.28	17.43	21.48	11.83	12.77	12.58	18.46	17.25
Min	2.84	2.18	2.50	2.20	2.34	2.34	2.95	3.58
Max	136.52	204.20	104.51	279.13	98.63	128.87	94.52	122.63
St.Dev	10.13	14.19	12.53	14.31	9.26	9.68	9.84	12.35
Skewness	2.78	3.38	1.45	6.01	2.73	3.47	1.72	2.52
Kurtosis	18.84	24.41	5.56	74.04	16.14	25.62	7.81	14.20
St.Dev. Returns	26.39	27.68	32.77	25.03	26.15	21.98	25.59	28.90

Table 2: Daily range for the eight Asian markets. Descriptive statistics (standard deviations of returns in the last row). Annualized percentage values. Pre–crisis (July 14, 1995 to July 1, 1997), Crisis (July 2, 1997 to Dec. 31, 1997), Post-crisis (Jan. 1, 1999 to Oct. 3, 2006).

	HK	IN	KO	MA	PH	SI	TA	TH
Other markets	×	×	×	×	×	×	×	×
Other markets during crisis		×	×				×	
Own asymmetric effects			×				×	
Own asymmetries during crisis	×					×	×	×
Shift during crisis		×	×	×	×			
Shift after crisis		×	×					
Lag 2				×		×		×

Table 3: Summary of the selected specification for each market. A cross (×) indicates the presence of significant additional links relative to the own market (base) specification.

Markets	HK – MEM(1,1)		IN – MEM(1,1)		KO – MEM(1,1)		MA – MEM(2,1)	
Models	Base	Selected	Base	Selected	Base	Selected	Base	Selected
Loglik	-3267.975	-3265.314	-3447.357	-3434.800	-3696.633	-3694.599	-3032.638	-3029.500
LB(12)	20.920	13.805	51.230	20.545	23.850	13.335	21.729	15.733
	0.052	0.313	0.000	0.057	0.021	0.345	0.041	0.204
LBSQ(12)	20.212	13.087	18.497	12.647	15.899	10.677	14.488	10.958
	0.063	0.363	0.101	0.395	0.196	0.557	0.271	0.533
$\hat{\phi}$		5.61		3.71		6.51		4.41
No spillovers		2.326		5.978		2.372		3.785
p-value		(0.023)		(0.000)		(0.002)		(0.000)

Markets	PH – MEM(1,1)		SI – MEM(2,1)		TA – MEM(1,1)		TH – MEM(2,1)	
Models	Base	Selected	Base	Selected	Base	Selected	Base	Selected
LogLik	-3155.904	-3149.895	-3036.293	-3032.768	-3446.361	-3444.106	-3549.886	-3546.642
LB(12)	22.307	9.560	11.729	8.651	23.660	16.117	20.586	12.467
	0.034	0.655	0.468	0.732	0.023	0.186	0.057	0.409
LBSQ(12)	2.774	2.215	12.950	7.783	23.288	15.558	15.736	13.496
	0.997	0.999	0.373	0.802	0.025	0.212	0.204	0.334
$\hat{\phi}$		3.57		5.08		4.69		4.68
No spillovers		5.024		4.053		2.249		4.327
p-value		(0.000)		(0.000)		(0.005)		(0.000)

Note: For each market, we indicate the order of the MEM estimated both in the 'Base' and in the retained specifications. LogLik is the value of the log-likelihood. CORR(12) (respectively, CORRSQ(12)) is the LM test statistic for autocorrelation up to order 12 in the standardized residuals $hl_t/\hat{\mu}_t$ (respectively, squared standardized residuals $(hl_t/\hat{\mu}_t)^2$) with the corresponding p-values in parentheses. ϕ is the estimated Method of Moments Gamma parameter (cf. Cipollini et al., 2006). The last two rows report the results of the Wald test statistics from imposing zero constraints on the interaction coefficients (whole period and extra interactions when present) and the corresponding p-values.

Table 4: Model Diagnostics

		From							
		HK	IN	KO	MA	PH	SI	TA	TH
	HK	14.35	0.40	2.33	2.63	0.48	2.27	0.91	2.42
	IN	4.37	1.11	2.01	2.09	0.48	1.78	0.57	1.55
	KO	6.79	0.26	7.18	2.10	0.22	2.07	1.43	1.56
T	MA	10.63	0.27	1.99	9.27	0.69	1.54	0.66	2.60
o	PH	2.87	0.24	0.12	1.87	1.94	1.73	0.86	1.40
	SI	7.84	0.54	2.53	2.41	0.69	6.26	2.39	1.82
	TA	6.47	0.21	2.12	1.13	0.11	1.59	8.78	0.01
	TH	7.07	0.13	2.30	3.01	0.72	1.96	-0.16	6.54
Volatility Spillover Balance		2.39	0.16	0.95	0.88	0.43	0.77	0.74	0.82

Table 5: Summary of the volatility impacts to a one standard deviation shock to the market in the column heading. Last row reports ζ_i, the Volatility Spillover Balance of market i as the ratio of the sum by column ("From") to the ratio of the sum by row ("To"), excluding element (i, i).

Markets	HK		IN		KO		MA	
Models	Base	Selected	Base	Selected	Base	Selected	Base	Selected
ω	0.006	0.006	0.070	0.052	0.018	0.006	0.005	0.002
	(3.334)	(1.710)	(7.791)	(3.426)	(4.713)	(0.849)	(3.497)	(0.568)
μ_{t-1}	0.865	0.835	0.526	0.281	0.763	0.729	0.861	0.783
	(70.559)	(51.814)	(20.222)	(6.415)	(48.674)	(38.010)	(54.847)	(28.237)
DC_{t-1}				0.074		0.064		0.031
				(0.955)		(2.041)		(3.297)
PC_{t-1}				0.077		0.014		
				(6.448)		(3.109)		
HK_{t-1}	0.126	0.120		0.005		0.011		0.036
	(10.547)	(9.640)		(0.218)		(0.827)		(4.048)
$HK_{t-1}DC_{t-1}$				0.067		0.054		
				(0.882)		(1.954)		
IN_{t-1}		0.005	0.387	0.356		0.006		-0.001
		(1.258)	(16.860)	(13.427)		(0.656)		(-0.159)
$IN_{t-1}DC_{t-1}$				-0.055		-0.022		
				(-1.412)		(-1.382)		
KO_{t-1}		0.004		0.054				0.002
		(0.996)		(3.269)				(0.364)
$KO_{t-1}DC_{t-1}$				-0.055		0.021		
				(-1.412)		(1.162)		
MA_{t-1}		0.005		0.038		0.016	0.352	0.320
		(1.145)		(2.031)		(1.448)	(15.670)	(13.889)
$MA_{t-1}DC_{t-1}$				0.006		-0.027		
				(0.150)		(-1.868)		
MA_{t-2}							-0.222	-0.166
							(-8.220)	(-5.565)
PH_{t-1}		0.001		0.023		-0.006		0.008
		(0.220)		(1.204)		(-0.630)		(1.274)
$PH_{t-1}DC_{t-1}$				0.064		0.019		
				(1.144)		(0.800)		
SI_{t-1}		0.009		0.065		0.014		-0.004
		(1.256)		(2.375)		(0.957)		(-0.545)
$SI_{t-1}DC_{t-1}$				0.081		0.008		
				(1.068)		(0.295)		
SI_{t-2}								
TA_{t-1}		0.001		-0.010		0.010		0.000
		(0.213)		(-0.718)		(1.262)		(0.042)
$TA_{t-1}DC_{t-1}$				0.113		-0.055		
				(1.713)		(-1.457)		
TH_{t-1}		0.007		0.040		0.014		
		(2.069)		(2.666)		(1.952)		0.005
$TH_{t-1}DC_{t-1}$				-0.129		-0.051		(1.186)
				(-5.136)		(-3.217)		
TH_{t-2}								
mkt^{+}_{t-1}					0.206	0.188		
					(13.499)	(11.623)		
mkt^{-}_{t-1}					0.231	0.222		
					(15.563)	(14.545)		
$mkt^{+}_{t-1}DC_{t-1}$		-0.036						
		(-2.672)						
$mkt^{-}_{t-1}DC_{t-1}$		0.048						
		(3.132)						

Table 6: Base and Selected MEMs: Estimated Coefficients (Robust t-stats in parentheses) for HK, IN, KO, MA. Jul. 95–Dec. 06.

Markets	PH		SI		TA		TH	
Models	Base	Selected	Base	Selected	Base	Selected	Base	Selected
ω	0.049	0.081	0.007	0.000	0.024	0.021	0.014	0.020
	(6.545)	(5.786)	(3.799)	(0.015)	(5.662)	(3.465)	(4.171)	(2.967)
μ_{t-1}	0.695	0.522	0.854	0.766	0.800	0.789	0.841	0.746
	(24.538)	(11.659)	(44.347)	(26.224)	(51.001)	(44.500)	(47.584)	(25.427)
DC_{t-1}		0.041						
		2.789						
PC_{t-1}								
HK_{t-1}		-0.012		0.020		0.026		0.027
		(-0.866)		(2.309)		(2.212)		(1.959)
$HK_{t-1}DC_{t-1}$						-0.005		
						(-0.249)		
IN_{t-1}		0.015		0.013		0.000		-0.008
		(1.472)		(2.677)		(0.012)		(-1.191)
$IN_{t-1}DC_{t-1}$						-0.005		
						(-0.440)		
KO_{t-1}		-0.023		0.007		0.007		0.015
		(-2.724)		(1.546)		(1.053)		(2.000)
$KO_{t-1}DC_{t-1}$						0.011		
						(1.108)		
MA_{t-1}		0.030		0.004		0.001		0.020
		(1.985)		(0.654)		(0.059)		(2.361)
$MA_{t-1}DC_{t-1}$						0.001		
						(0.106)		
MA_{t-2}								
PH_{t-1}	0.224	0.235		0.012		-0.006		0.019
	(9.086)	(11.112)		(2.021)		(-0.643)		(1.918)
$PH_{t-1}DC_{t-1}$						0.043		
						(2.402)		
SI_{t-1}		0.057	0.333	0.283		0.014		0.015
		(2.971)	(13.111)	(11.801)		(1.062)		(1.111)
$SI_{t-1}DC_{t-1}$						-0.048		
						(-2.502)		
SI_{t-2}			-0.200	-0.140				
			(-6.175)	(-4.644)				
TA_{t-1}		0.010		0.012				-0.011
		(1.064)		(2.689)				(-1.512)
$TA_{t-1}DC_{t-1}$								
TH_{t-1}		0.025		0.004		-0.012	0.276	0.249
		(2.612)		(0.886)		(-2.229)	(11.994)	(10.533)
$TH_{t-1}DC_{t-1}$						0.018		
						(1.621)		
TH_{t-2}							-0.135	-0.080
							(-4.905)	(-2.672)
mkt^{+}_{t-1}					0.148	0.141		
					(9.951)	(9.156)		
mkt^{-}_{t-1}					0.186	0.178		
					(13.093)	(11.849)		
$mkt^{+}_{t-1}DC_{t-1}$				-0.042		-0.083		0.037
				(-2.174)		(-2.535)		(1.749)
$mkt^{-}_{t-1}DC_{t-1}$				0.052		-0.042		-0.028
				(2.772)		(-1.763)		(-1.845)

Table 7: Base and Selected MEMs: Estimated Coefficients (Robust t-stats in parentheses) for PH, SI, TA, TH. Jul. 95–Dec. 06.

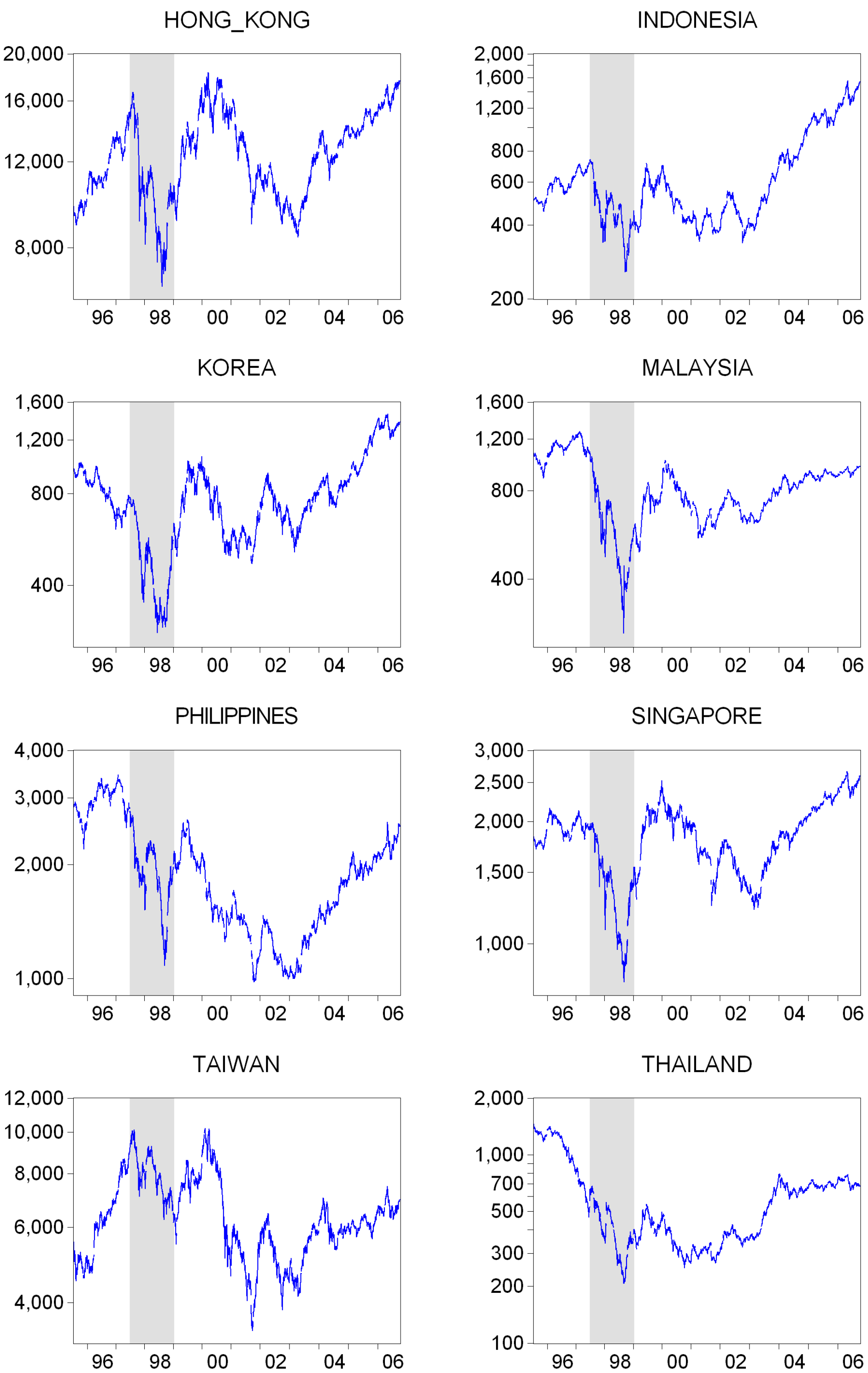

Figure 1: Stock Indices - July 1995 - Oct 2006. Shaded area July, 2, 1997 - Dec. 31, 1998. Log-scale.

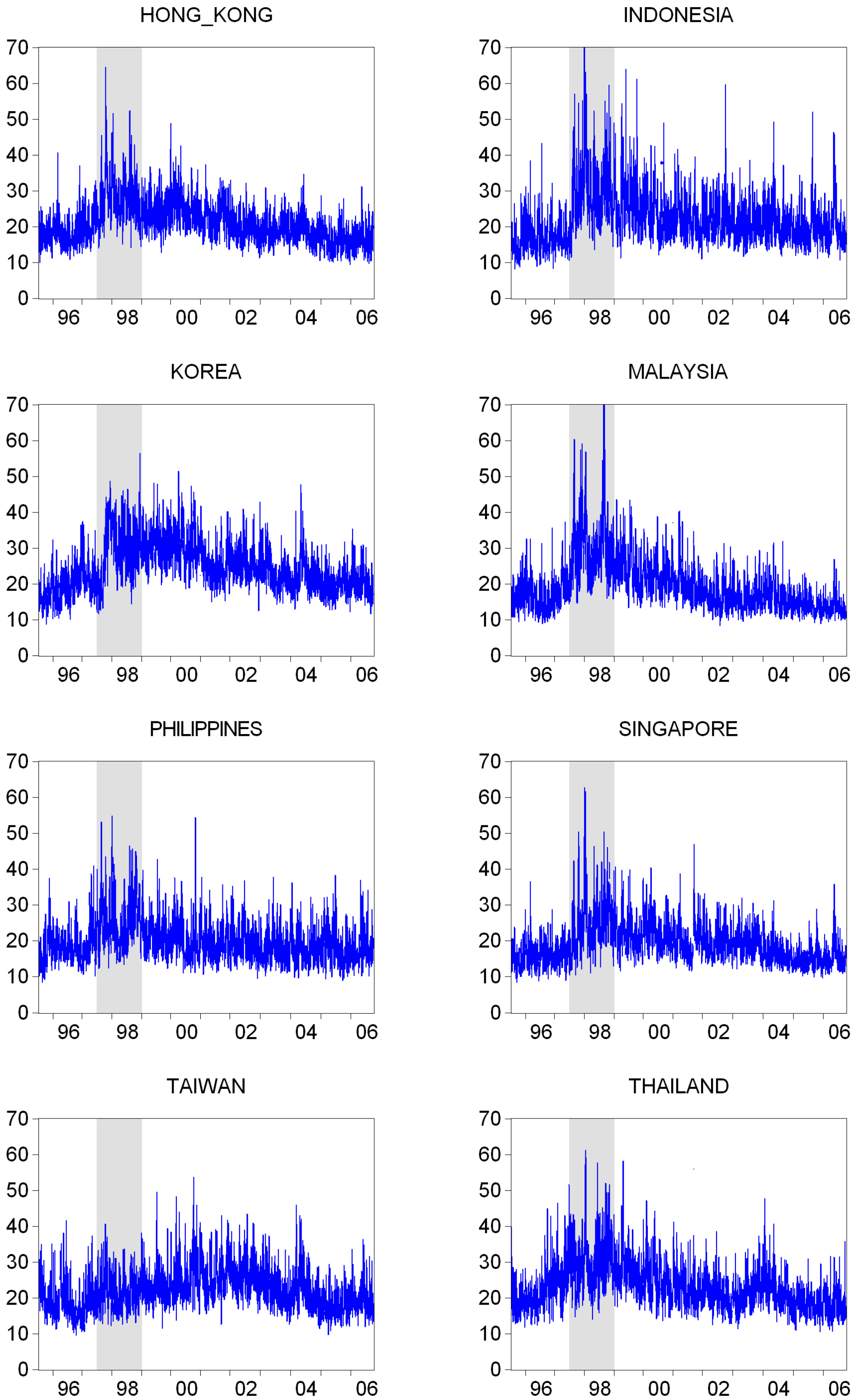

Figure 2: Time series plots of annualized hl_t for all markets (percent). Shaded area between July 2, 1997 and Dec. 31, 1998. Truncated vertical axis leaves out one value for Indonesia (78.92) and one for Malaysia (92.27).

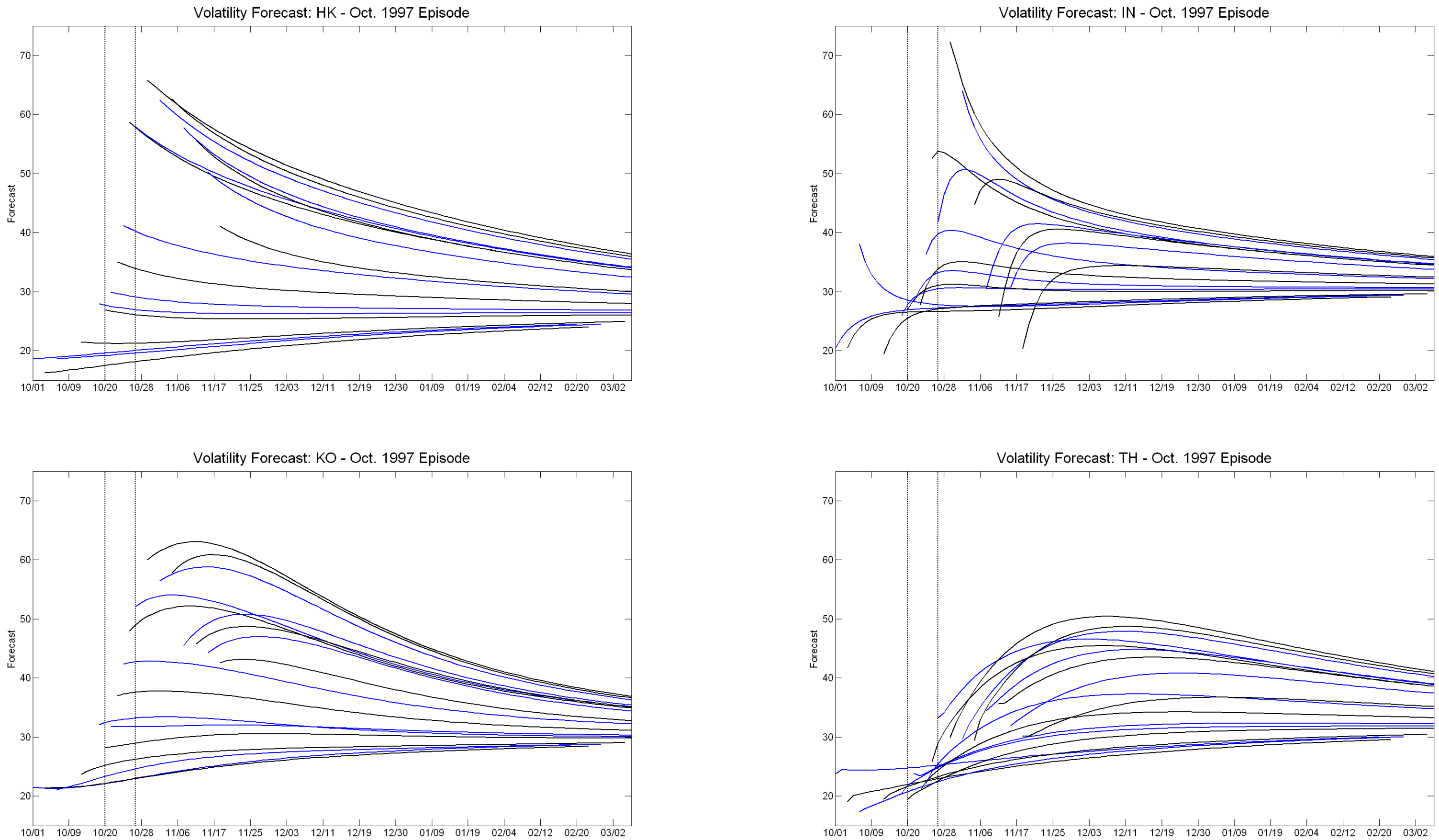

Figure 3: Dynamic volatility forecasts on the whole system (HK, IN, KO, TH reported) computed according to expressions (4) and (6) starting from Oct. 1, 1997 and progressively moving the initial condition ahead. The vertical lines correspond to the week between Oct. 20 and Oct. 24, 1997.

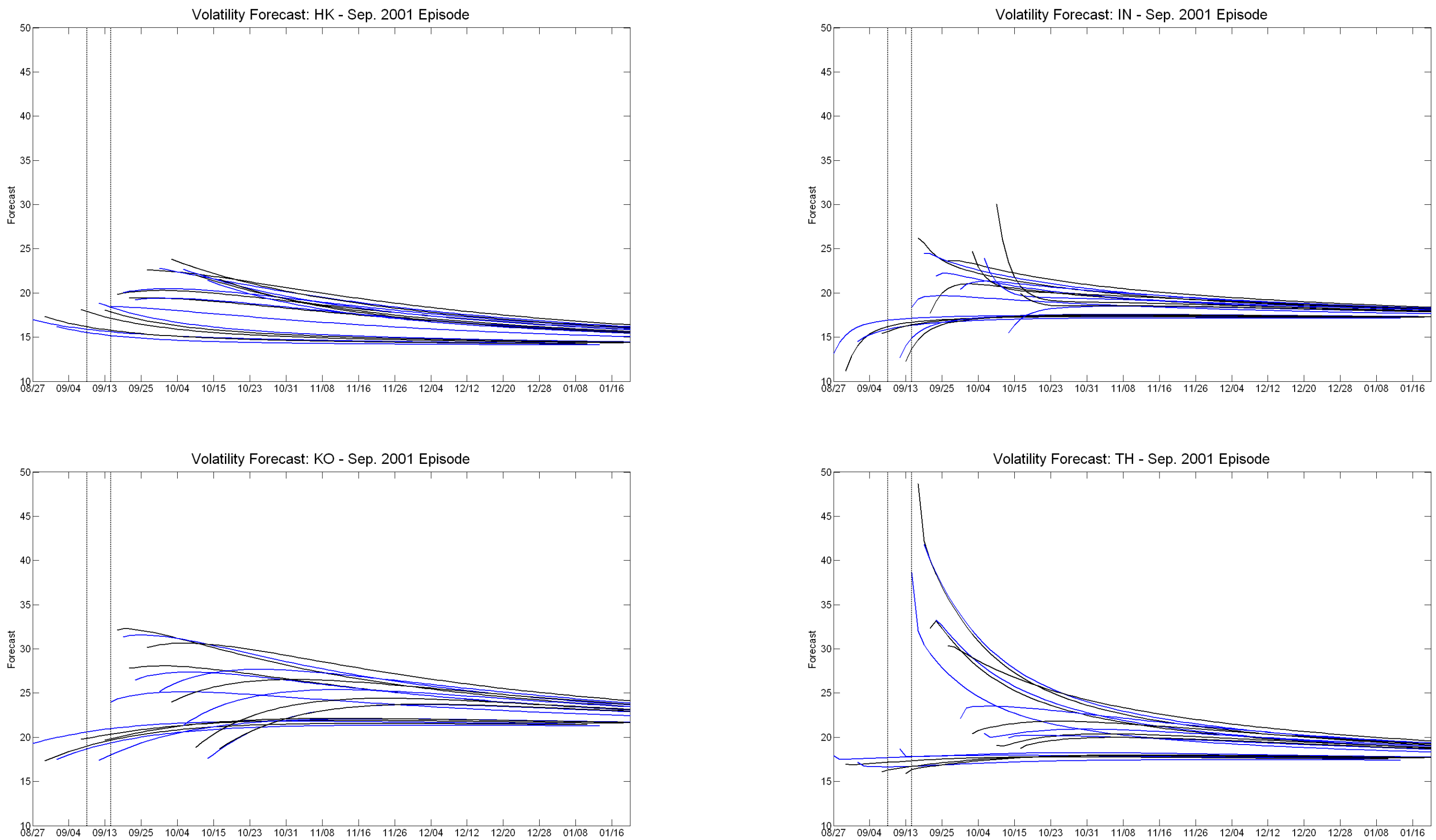

Figure 4: Dynamic volatility forecasts on the whole system (HK, IN, KO, TH reported) computed according to expressions (4) and (6) starting from Aug.27, 2001 and progressively moving the initial condition ahead. The vertical lines correspond to the week between Sep. 10 and Sep. 14, 2001.

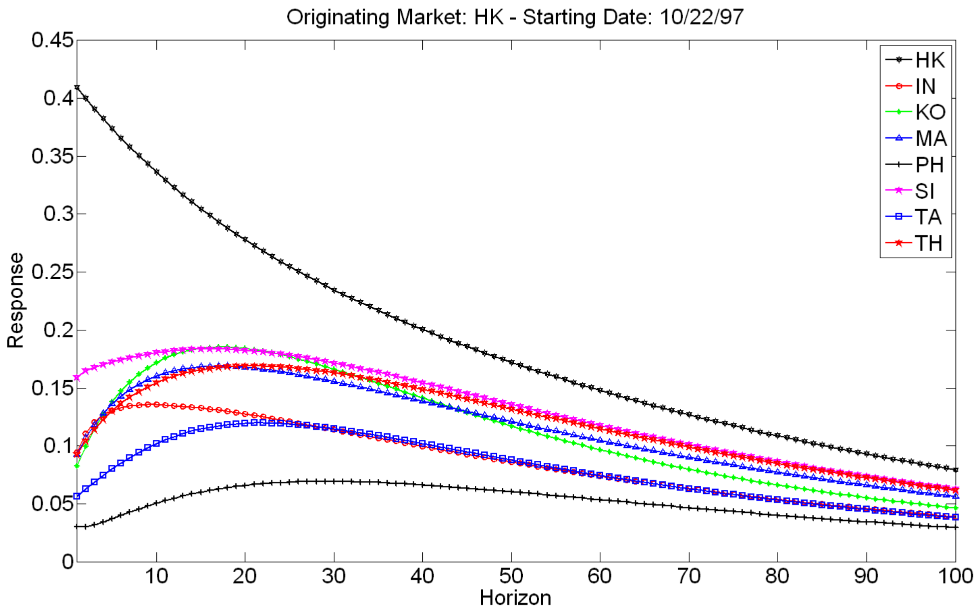

Figure 5: MEM Impulse Response Functions. Each line shows markets relative response to the shock originating in Hong Kong (Oct., 22, 1997).