Unobservable shocks as carriers of contagion

March 2, 2009

Abstract

We propose an identified structural GARCH model to disentangle the dynamics of financial market crises. We distinguish between the hypersensitivity of a domestic market in crisis to news from outside non-crisis markets, and the contagion imported to a tranquil domestic market from foreign crises. The model also enables us to connect unobserved structural shocks with their source markets using variance decompositions and to compare the size and dynamics of impulses during crises periods with tranquil period impulses. To illustrate, we apply the method to data from the 1997-1998 Asian financial crisis which consists of a complicated set of interacting crises. We find relatively little hypersensitivity in these markets, but significant contagion. Impulse response functions for an equally weighted equity portfolio show the increasing dominance of Korean and Hong Kong shocks during the crises.

Keywords: Contagion, Structural GARCH

JEL Classification: F37, C51

1 Introduction

An important unanswered question concerning financial crises, is whether, given the complex contemporaneous transmissions between markets, it is possible to separately identify and measure shocks emerging from a particular source market. As well as disrupting markets in the country where trouble begins, financial crises may spread turmoil into foreign markets, in a phenomenon often labelled 'contagion'.[1] Here we develop a method for separating these increased crisis-period linkages into two categories. The first category is hypersensitivity to information from elsewhere during a local crisis, in other words, where turmoil at home changes the way a domestic market reacts to news from foreign markets. The second category is the increased impact of news from a troubled foreign market on (potentially non-crisis) domestic markets - we restrict the label 'contagion' to this second effect. These categories can be separately measured whenever domestic and foreign crises are not totally coincident.[2]

This distinction is not an unnecessary abstraction since each category supports different crisis management and prevention policies. While the domestic policy makers of a country in crisis are likely to be interested in preventing hypersensitivity, that is preventing their own troubled market from over-reacting to external news, they have little incentive to prevent their crisis spreading to foreign markets. On the other hand, such a crisis may generate externalities to other countries in the form of contagion, so that governments and market participants in non-crisis countries may want to protect their markets from foreign-sourced trouble if possible. The existence of these externalities is consistent with the agenda for coordinated global reforms in regulation, financial infrastructure and instrument design following major incidents (see, for example, Mishkin (1998) on Latin America, Eichengreen (2002) on East Asia and Alexander, Eatwell, Persuad and Reoch (2007) on the sub-prime crisis).

We model contemporaneous linkages between financial markets during normal times, as well as changes during crisis periods. In order to capture the well-known clustering of financial returns, we base our analysis in a multivariate GARCH model of asset market interaction. We allow different regimes within the framework, corresponding to periods of tranquility and

[1] Consistent with recent literature, we here refer to 'pure' contagion in the terminology of Dornbusch, Park and Claessens (2000) and Kaminsky and Reinhart (2002), as distinct from crisis-driven changes in fundamental linkages.

[2] Theoretical models of contagion propose mechanisms such as information asymmetry and portfolio rebalancing (Kodres and Pritsker, 2002; Yuan, 2005), institutional and regulatory linkages, and relationship complexity (Allen and Gale, 2000; Brusco and Catiglionesi, 2007; Pavlova and Rigobon, 2007; Kiyotaki and Moore, 2002). Recent network theory tallies particularly well with the empirical framework developed here, see Allen and Babus, (2008).

to a series of crises experienced in the sample period. We estimate structural parameters using identification by heteroskedasticity, extending the work of Caporale et al. (2005) and Rigobon and Sack (2004).

We also propose an innovative approach to classifying and interpreting structural shocks, by attributing them to a specific source market using variance decompositions. Unlike previous approaches, this method is data-driven and does not rely on arbitrary restrictions such as market hierarchies or orthogonalizations. Having identified underlying structural shocks by their market of origin, it is possible to track the size and duration of innovations from any particular source and compare their relative importance under different regimes (that is in the different crises or tranquil periods). The rich interactions captured in our model contribute to the developing empirical literature on cross-country and cross-asset-market crisis models.[3]

To illustrate the approach, we take the perspective of an international investor, and model daily U.S. dollar returns to major equity market indices during the complex series of interrelated crises in Asia over the period 1997-1998. The sample consists of Hong Kong, Indonesia, Korea and Thailand, each of which had their own crises and potentially also received transmissions from other crisis countries. The results show statistically significant contagion between a number of countries but, in most cases, the evidence for hypersensitivity is not significant. Our findings suggest that during this period, the crisis countries themselves had at best weak incentives to slow down the spread of turbulence. Therefore, from a policy perspective, it appears that nearby markets under the threat of contagion had cause to take a more proactive role in curbing the crisis of an affected neighbor, or once a crisis has developed, to look for protection either via domestic regulation or international policy coordination.

Further analysis using innovation accounting for an equally-weighted portfolio of equity indices shows the rise in importance of the Hong Kong-sourced shocks during the crisis. On the other hand, foreign markets seemed to have been shielded from shocks originating in Indonesia during the crisis there.

In Section 2 we set out the modelling strategy and Section 3 explains the dynamic analysis. The Asian data and estimation results are reported in Sections 4 and 5. Section 6 concludes.

---

[3] We also avoid the demonstrated difficulties caused by modelling contagion as changes in correlation (Dungey and Martin, 2007; Hartmann, Straetmans and de Vries, 2004).

2 Modelling Strategy

Consider a vector of k de-meaned asset returns $\mathbf{Y}_t$ that are all potentially contemporaneously interlinked in tranquil periods, so that the system can be described as

$$\mathbf{B}^*\mathbf{Y}_t = \mathbf{u}_t \tag{1}$$

where $\mathbf{B}^*$ is a $k \times k$ matrix of coefficients representing these non-crisis linkages, b_{ij}, normalized on the diagonal elements of $\mathbf{B}^*$. The $k \times 1$ vector $\mathbf{u}_t$ represents the idiosyncratic shocks in the system,

$$\mathbf{u}_t = \mathbf{g}_t \boldsymbol{\varepsilon}_t \tag{2}$$

$$\varepsilon_{it} \sim iidN(0, 1) \tag{3}$$

where $\mathbf{g}_t$ is a $k \times k$ diagonal matrix. (Scaled structural innovations $\mathbf{u}_t$ are uncorrelated.) The underlying shocks themselves, given by $k \times 1$ vector $\boldsymbol{\varepsilon}_t$, are distributed *i.i.d.* standard normal. Appendix A gives a detailed $k = 2$ dimensional example of the model and dynamics.

Here, we capture hypersensitivity and contagion by a change in the strength of linkages between asset returns during a crisis, consistent with the approach of Forbes and Rigobon (2002), Favero and Giavazzi (2002), and Pesaran and Pick (2007) amongst others. We explicitly model both the ability of countries to transmit contagion abroad, and any supersensitivity to foreign shocks during periods of domestic crisis. In the past, these two effects have not been separately distinguished nor empirically quantified, both being captured in a single measure. We model tranquil and crisis periods as follows:

$$\mathbf{B}\mathbf{Y}_t = \mathbf{u}_t, \text{ where } \mathbf{B} := (\mathbf{B}^* + \mathbf{B}_{c,s}\mathbf{D}_t), \tag{4}$$

with $\mathbf{B}_{c,s}\mathbf{D}_t$ representing the linkages present in crisis periods. *Contagion* (indicated by subscript c) is modelled as the additional impact on the asset market in home country i during a crisis in foreign country j, given by the parameters $b_{c,ij}$ in each equation. *Hypersensitivity* (indicated by subscript s), is given by the parameter $b_{s,ij}$ in each equation measuring the additional impact of foreign shocks during a domestic crisis. Each period of crisis is identified using an indicator variable $D_{i,t}$ which is one during the crisis in home country i and zero otherwise. The relevance of each instance of contagion and hypersensitivity is tested by the significance of the parameters $b_{c,ij}$ and $b_{s,ij}$. In the case of no contagion or hypersensitivity in the system $b_{c,ij} = b_{s,ij} = 0$ for all i, j.

We also model the known fat-tailed characteristics of the financial markets returns in $\mathbf{Y}_t$. Given the structure of (2) to (4) it is straightforward to see that

$$\mathbf{B}\mathbf{Y}_t \sim (0, E[\mathbf{G}_t]), \tag{5}$$

where $\mathbf{G}_t = \mathbf{g}_t \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' \mathbf{g}_t'$ is a $k \times k$ diagonal matrix of the squares of the elements of the matrix $\mathbf{g}_t$.

The conditional covariance matrix of the structural shocks is a GARCH(1,1), specified for $\mathbf{G}_t$ as

$$\mathbf{G}_t = diag[\boldsymbol{\psi} + \boldsymbol{\lambda}\left(\mathbf{u}_{t-1} \circ \mathbf{u}_{t-1}\right)] + \boldsymbol{\zeta}\mathbf{G}_{t-1}, \tag{6}$$

where $\boldsymbol{\psi}$ is a $k \times 1$ vector of constants, ψ_i, $\boldsymbol{\lambda}$ is a $k \times k$ diagonal matrix of ARCH coefficients and $\boldsymbol{\zeta}$ is a $k \times k$ diagonal matrix of GARCH coefficients.

Since both $\mathbf{G}_{t-1}$ and $\mathbf{u}_{t-1}$ are unobservable, we specify the system as a reduced form.

$$\mathbf{Y}_t = \boldsymbol{\kappa}_t, \text{ where } \boldsymbol{\kappa}_t := \mathbf{B}^{-1}\mathbf{u}_t = \mathbf{A}\mathbf{u}_t. \tag{7}$$

The joint conditional distribution of the vector of de-meaned returns is

$$\mathbf{Y}_t \sim (0, \mathbf{H}_t), \tag{8}$$

and we work with this reduced form covariance matrix, $\mathbf{H}_t$, which can be estimated as a multivariate GARCH process in the de-meaned returns vector $\mathbf{Y}_t$, $\mathbf{H}_t = \mathbf{A}\mathbf{G}_t\mathbf{A}'$.

Identification of the structural parameters in $\mathbf{B}$ from the estimated value of $\mathbf{H}_t$ depends on establishing the link between the structural parameters and the reduced form. The lower diagonal elements of the reduced form covariance matrix $\mathbf{H}_t$ can be expressed as [4]

$$vech\left(\mathbf{H}_t\right) = \mathbf{C}_0 + \mathbf{C}_1\left(\boldsymbol{\kappa}_{t-1} \circ \boldsymbol{\kappa}_{t-1}\right) + \mathbf{C}_2\mathbf{h}_{t-1} \tag{9}$$

[4] In the case of non-zero mean data the following expressions would be complicated by the additional interactions of any common factors with the independent factors.

where $\mathbf{C}_0$ is a $k(k+1)/2 \times 1$ vector of constant coefficients, $\mathbf{C}_1$ is a $k(k+1)/2 \times k$ matrix of ARCH coefficients , $\mathbf{C}_2$ is a $k(k+1)/2 \times k$ matrix of GARCH coefficients and $\mathbf{h}_t$ is a $k \times 1$ vector of the diagonal elements of $\mathbf{H}_t$.

To establish the relationship between the coefficients of $\mathbf{H}_t$ and the structural parameters we begin with the vector of ARCH terms. Relying on the independence of structural shocks, we set cross products to zero, and write

$$(\mathbf{A} \circ \mathbf{A})^{-1} \boldsymbol{\kappa}_{t-1} \circ \boldsymbol{\kappa}_{t-1} = (\mathbf{u}_{t-1} \circ \mathbf{u}_{t-1}) . \tag{10}$$

Next we can make a similar transformation of the GARCH terms:

$$(\mathbf{A} \circ \mathbf{A})^{-1} \mathbf{h}_{t-1} = vecd\left(\mathbf{G}_{t-1}\right), \tag{11}$$

where $vecd$ is the vector of the diagonal elements of the matrix.

If we again rewrite $\mathbf{H}_t = \mathbf{A}\mathbf{G_t}\mathbf{A}'$ in $vech\,(\cdot)$ form and define the required transformation of the $\mathbf{A}$ matrix as $\mathbf{A}^v$, a $k(k+1)/2 \times k$ matrix of products of the elements of $\mathbf{A}$, then the reduced form covariance matrix is comprised of structural shocks and structural parameters,

$$vech\left(\mathbf{H}_t\right) = \mathbf{A}^v\boldsymbol{\psi} + \mathbf{A}^v\boldsymbol{\lambda}\left(\mathbf{u}_{t-1} \circ \mathbf{u}_{t-1}\right) + \mathbf{A}^v\boldsymbol{\zeta} vecd\left(\mathbf{G}_{t-1}\right). \tag{12}$$

Finally by substituting equation (10) and equation (11) we can link the $\mathbf{C}$ matrices of the reduced-form MGARCH and the structural parameters,

$$vech\left(\mathbf{H}_t\right) = \mathbf{A}^v\boldsymbol{\psi} + \mathbf{A}^v\boldsymbol{\lambda}\left(\mathbf{A} \circ \mathbf{A}\right)^{-1}\left(\boldsymbol{\kappa}_{t-1} \circ \boldsymbol{\kappa}_{t-1}\right) + \mathbf{A}^v\boldsymbol{\zeta}\left(\mathbf{A} \circ \mathbf{A}\right)^{-1}\mathbf{h}_{t-1}. \tag{13}$$

Estimation and identification of structural form parameters therefore depends on the estimation of the reduced form covariance matrix expressed in terms of structural parameters. The coefficients from the reduced form in equation (9) provide $k(k+1)/2$ parameters in the $\mathbf{C}_0$ matrix, $k^2(k+1)/2$ parameters in each of the $\mathbf{C}_1$ and $\mathbf{C}_2$ matrices for a total of $(2k+1)(k+1)k/2$. The structural model contains $3k(k-1)$ parameters in the $\mathbf{B}$ matrix and $3k$ GARCH parameters for a total of $3k^2$. (In the four-country example estimated below there are 48 structural parameters and 90 reduced form parameters.)

Structural parameters are non-linear transformations of the reduced form parameters in this model, so an analytical proof of identification is difficult.[5] However we have evidence for local numerical identification since we consistently achieve convergence in the maximization of the structural likelihood function from a range of starting values. We also confirmed the numerical identification and optimization procedure by estimating the model using simulated data.

3 Dynamics

Innovation accounting within the SGARCH model gives a mapping of the dynamics of transmissions between markets. We introduce a new approach to connecting each structural shock to a source market without resorting to standard identifying restrictions such as Choleski decomposition or long-run variance assumptions. Our method relies on an interpretation of variance decomposition: we treat the shocks which contribute the largest part of each domestic-market forecast error variance during the tranquil period as emanating from that market. This interpretation is possible because we estimate the entire (normalized) structural model and can thus work with the structural innovations directly, rather than their reduced form counterparts. Consequently we do not need to apply arbitrary restrictions to the structural model to trace turbulence during crises back to a specific source.

We make tranquil period dynamics the benchmark, then examine the dynamics of both contagion and hypersensitivity effects during periods of crisis. We take the position of an international investor holding an equally weighted portfolio of each of the market indices in the model, and track the impact of structural impulses on the volatility of this naive portfolio. While this is a convenient application of the processes and effects, the potential for exploring contagion dynamics in this model are much wider than this simple portfolio example. The model can be used to track individual transmission paths for shocks from all domestic and foreign sources under each of the four crises in the sample, separating hypersensitivity and contagion effects.[6]

[5] Rothenberg (1971, Theorem 7) shows that for non-linear systems of equations, under weak regularity conditions, an 'overly strong sufficiency condition' for global identification of structural parameters is met when the Jacobian matrix of second order partial derivatives with respect to the structural parameters has a positive determinant.

[6] One could ask, for example, 'What is the effect on the volatility path of returns to the Thai stock market of a shock emerging from Hong Kong, during the Indonesian market crisis?', and derive an impulse response

The 1−step ahead conditional forecast error variance for $\mathbf{Y}_t$ is the fitted value of the reduced form conditional covariance matrix:

$$\begin{aligned} var_t\left[\mathbf{Y}_{t+1} - E_t\left(\mathbf{Y}_{t+1}\right)\right] &= var_t\left[\mathbf{A}\mathbf{u}_{t+1} - E_t\left(\mathbf{A}\mathbf{u}_{t+1}\right)\right] \\ &= \mathbf{H}_{t+1|t}, \end{aligned} \tag{14}$$

treating all estimated parameter values as known with certainty.

The conditionally heteroskedastic properties of the model mean that forecast errors vary with realized volatility at time t, and consequently each forecast error depends on the specific history of volatility at time t and more generally on the forecast horizon (see Gallant et al. 1993 and Engle and Ng 1993). Since this process generates as many forecast errors at the 1-step horizon as there are observations in the sample, we need a way of summarizing the information without losing the value of conditioning. Here we compute the forecast errors for both tranquil and crisis periods for each time t, and stack them by size, creating an empirical distribution of conditional forecast error variances, effectively based on a series of random draws from the structural error distributions. We then select empirical quantiles from the tranquil and crisis period distributions and compare the forecast error variances and decompositions.

The forecast error variance is a non-linear function of structural parameters and structural shocks, however the identification of structural parameters during estimation means that it is possible to numerically identify the structural errors via the relationship $\mathbf{B}\mathbf{Y}_t = \mathbf{g}_t\boldsymbol{\varepsilon}_t$ so that $\mathbf{g}_t^{-1}\mathbf{B}\mathbf{Y}_t = \boldsymbol{\varepsilon}_t$. The percentage of the forecast error variance at time t, $VD_{i,j|t}$, for market return y_i that is due to each structural shock ε_j is computed as

$$VD_{i,j|t} = \frac{\left(\mathbf{A}\mathbf{g}_{j,t+1|t}\mathbf{g}'_{j,t+1|t}\mathbf{A}'\right)_{ii}}{\left(\mathbf{A}\mathbf{g}_{t+1|t}\mathbf{g}'_{t+1|t}\mathbf{A}'\right)_{ii}} \times 100, \tag{15}$$

where $\mathbf{g}_{j,t+1|t}$ is the jth column of the 1−period ahead forecast standard deviation matrix $\mathbf{g}_{t+1|t}$. Each of the structural shocks ε_j is linked to the ith market if $VD_{i,j|t} > VD_{i,m|t}$ for $m = 1, ..., k$.[7]

function to estimate the size and duration of this specific effect.

[7]This ordering would not be complete or unique if there were more than one market to which the shock ε_j contributed the majority of forecast error variance or if any two structural shocks accounted for the same

Further, in the event that an investor holds an equally-weighted portfolio across the k markets, the forecast error variance decomposition for the portfolio indicates the shift in portfolio risk associated with exposure to a particular market during a crisis. The proportion of portfolio volatility associated with each structural shock component can be computed as

$$VD_{p,j|t} = \frac{w'\mathbf{A}\mathbf{g}_{j,t+1|t}\mathbf{g}'_{j,t+1|t}\mathbf{A}'w}{w'\mathbf{A}\mathbf{g}_{t+1|t}\mathbf{g}'_{t+1|t}\mathbf{A}'w} \times 100 \tag{16}$$

where w is a $k \times 1$ vector of portfolio weights, in our example, the unit vector. Using (16) we can compare the mean contribution of each shock to portfolio variance during the tranquil and crisis periods.

Conditional impulse responses for the variance of the individual returns can be computed using the approach of Lin (1997). For the equally-weighted portfolio the response is the expectation at time t of the partial derivative of $w'\mathbf{H}_{t+n}w$ with respect to $\partial\varepsilon^2_{j,t}$, given by

$$E_t\left[\frac{\partial w'\mathbf{H}_{t+n|t}w}{\partial\varepsilon^2_{j,t}}\right] = E_t\left[\frac{\partial w'\mathbf{A}\mathbf{G}'_{t+n|t}\mathbf{A}'w}{\partial\varepsilon^2_{j,t}}\right]. \tag{17}$$

As for the variance decompositions, we compute an impulse response conditioning on each time t volatility history, stack each time path into an empirical distribution and draw out specific quantiles for comparison.

4 The Asian Crisis

The Asian crisis of 1997-1998 exemplified the complexities which can arise between financial markets. There were multiple crises in a number of countries in the region, and across several different classes of assets. The debate over the causes of, and links between, these crises remains unresolved.

The discursive literature at the time of the Asian crisis viewed pressure in the Hong Kong equity market around October 1997 as leading to pressure on equity markets in other countries, and particularly in precipitating crisis in Korean markets. Four of the major countries involved in the turmoil during 1997-1998 were Thailand, Indonesia, Korea and Hong Kong. However empirical evidence on contagion during this period is mixed. On one

proportion of variance for one market. Neither of these cases arise in this application.

hand, Forbes and Rigobon (2002) and Kleimeier, Lehnert and Verschoor (2003) find little evidence for contagion in these equity markets using bivariate correlation tests. On the other hand, each of Baig and Goldfajn (1999), Caporale et al. (2003) and Baur and Schulze (2005) find statistically significant contagion effects.[8] However the dynamic properties of the SGARCH model set out above allow us to go further than testing for contagion effects. We can also identify the main sources of turbulence for each country's crisis and gauge their relative importance to a diversified investor.

Returns are constructed as the residuals from a VAR(1) on the log changes in the daily US dollar-valued equity market indices for each country, including also the change in the 3-month U.S. Treasury Bill rate as a proxy for an exogenous common shock, following Forbes and Rigobon (2002).[9] Figures 1 to 4 show the time series of returns.

The model proposed in Section 2 requires an exogenous identification of the indicator variables, D_i for $i = 1, ..., k$, where k is the total number of equity indices involved. The crisis dates for each individual country are collated from existing sources. The Hong Kong crisis period is set as 27 October 1997 to 17 November 1997 (Billio and Pelizzon, 2003; Rigobon, 2003). The Indonesian crisis period is set as 1 January 1998 to 27 February 1998 encompassing the period of high volatility in returns associated with political uncertainty and IMF negotiations. The Korean crisis occurs in the lead up to successful renegotiation of its debt moratorium with the IMF on 24th December. Clearly (Panel C in Figure 1) the volatility in this market began in late November; we designate the Korean crisis period from 25 November 1997 to 31 December 1997. The Thai crisis in equity markets dates from 10 June 1997 to 29 August 1997 (Billio and Pelizzon, 2003; Rigobon, 2003). The crisis periods are shown as the narrow shaded areas in each of the panels of Figure 1.

Table 1 gives some descriptive statistics for the returns series. The first panel is for the entire sample. The following four panels give the crisis periods chronologically, confirming that, in general, the volatility of returns rises when a market is in crisis.

[8] The role of contagion emanating from Hong Kong equity markets is highlighted in Corsetti, Pericoli and Sbracia (2005), Baur and Schulze (2005) and Bond, Dungey and Fry (2006) and statistically significant contagion from Korea to Thai equity markets is noted in Baig and Goldfajn (1999) and Cerra and Saxena (2002). Baig and Goldfajn (1999) also find links from Korea to Indonesia and Indonesia to Thailand.

[9] Before estimation we removed all observations where any market was not trading. This reduced the number of observations in the sample period from 3951 to 3608.

5 Estimation Results

The results of applying the model of Section 2 to the Asian dataset are given in Table 2. Estimation was performed using quasi-maximum likelihood techniques (QML) via numerical methods in Ox. The tranquil period coefficient estimates are shown in the top panel of Table 2. There are significant linkages between a number of the equity markets. The returns to the Hong Kong index exhibit a significant positive relationship with returns in Indonesia and Korea while the Korean returns are positively related to Indonesia's during periods of tranquility. Indonesian index returns are also significantly affected by Hong Kong and Korea. The Thai market appears to import a positive impact from all three neighbors in the tranquil period, but does not influence the other markets.

Hypersensitivity occurs when the connection between domestic markets and foreign markets changes during a domestic crisis period. Results are shown in the second panel of Table 2. Here only one linkage is statistically significant and is also negative, indicating that Korean returns covaried negatively with Indonesian returns during the Korean crisis.

The negative coefficient represents an interesting addition to the literature, in that it suggests that during periods of crisis, links between two markets are sometimes weaker rather than stronger. This is consistent with Forbes and Rigobon (2002) who find a fall in conditional correlation in many instances.

Contagion occurs when a local market is affected by crisis in other countries. The strength of these effects are shown in the third panel in Table 2. Indonesia experienced contagion from the Hong Kong and Korean crises. During the Hong Kong crisis, the Korean market sensitivity to shocks from Hong Kong increased substantially by 0.645 over the tranquil measure of -0.125. There is also negative covariance between Thai and Hong Kong returns during the Hong Kong crisis.

Table 3 provides the parameter estimates for the GARCH behavior of the underlying shocks. In each of the cases there is a small positive and significant constant and significant ARCH and GARCH effects. The combined ARCH and GARCH parameters sum close to one in each case.

In summary we find evidence for shifts in the relationships between the equity markets of Hong Kong, Indonesia, Korea and Thailand during the crisis period, but these effects are not uniform in direction or significance across countries and crises. In terms of strengthening effects, the Hong Kong crisis had a large impact on regional markets, generating significant contagion in Indonesia and Korea but creating a weakening link with Thailand, where correlation fell. Korean links with Indonesia became significantly weaker during Korea's own crisis, but otherwise hypersensitivity did not appear to change links with other external markets. Overall we find evidence of significant contagion, but less of hypersensitivity.

5.1 *Variance decomposition*

The first panel of Table 4 gives the tranquil period decomposition at one step ahead, with 5th and 95th quantile measures.[10] These results are used to allocate the shocks to their source market. In each case, we label the shock that makes the greatest contribution to volatility in each of the tranquil-period decompositions as the own-country shock.[11] These contribute at least 80% of forecast error variance in each case. The maximum impact from another country at the mean is 16% (the link from Korean shocks to the Hong Kong market). The final column in Table 4 gives the variance decompositions for the equally weighted portfolio, which also account for covariance between the returns. In the tranquil period, Korean and Indonesian shocks are dominant, at 39% and 31% of the total whereas Hong Kong and Thailand contribute around 15% each.

The variance decompositions relating to links due to hypersensitivity during crisis periods are shown in the second panel of Table 4.[12] The only decomposition which changes substantially from that in the tranquil period is for Korea, where the contribution of domestic shocks is diminished by approximately 20 percentage points and the impact of Indonesia increases commensurately. For the equally-weighted portfolio, results show an increased contribution of 17 percentage points from Korea (56%), 14 percentage points from Thailand (21%) and a small increase from Hong Kong. The contribution from Indonesia is reduced, most likely due to the changing link between Indonesia and Korea.

However during an external crisis, contagion links create dramatic changes, where local market effects are swamped by news from crisis-markets abroad. The third panel of Table 4 shows that the contribution of domestic market shocks to the one-step-ahead variance decomposition is greatly reduced under foreign crises compared with the tranquil period.

[10] The variance decomposition is constructed for all t possible conditionings in the sample. A histogram of these outcomes gives the mean and quantiles reported in Table 4.

[11] The results at 5 steps ahead confirm our classification.

[12] All insignificant parameters are set to zero when variance decompositions and impulse response functions are computed.

Change is most dramatic for Indonesia where the contribution from domestic shocks drops by 70 percentage points to a mean contribution of 28%; contagion from Korea (43%) and Hong Kong (28%) account for this. The contribution of the domestic shock for Hong Kong falls by about 10 percentage points to 70% in favour of an increase in Korean contribution to 26%. The contribution of domestic shocks for Korea decreases by about 20 percentage points, and the influence of Hong Kong rises from less than 1% to almost 20%. There is no real change in the Thai decomposition. Hence, Hong Kong shocks are clearly important in all countries apart from Thailand. This is also evident in the portfolio results, where the contribution of Hong Kong increases by 16 percentage points to 32% and the Korean contribution increases to 52% due to contagion effects. However, there are falls in the percentage contributions of Indonesia and Thailand to portfolio variance.

5.2 *Impulse response functions*

Figure 2 presents impulse responses in the variance of the equally weighted portfolio to unit (one standard deviation) shocks from Hong Kong, Indonesia, Korea and Thailand respectively. The left column shows the impulse response in the tranquil period, and the right column shows the responses with contagion effects. Using the unconditional (sample) portfolio variance as a basis for calculation, a 0.1 increase in portfolio variance on the vertical axis is approximately equal to a 0.6 percentage point increase in annualized portfolio volatility.

A structural shock associated with Hong Kong in the tranquil period is the smallest of those investigated here, and takes about two months to dissipate half the initial impact. When we account for contagion, however, the effect of a one standard deviation shock is to raise variance by a factor of 10 over the tranquil period, with increases persisting above the tranquil level for well over six months.

Patterns for impulses to structural shocks from Indonesia are remarkably different. The initial impact of a one standard deviation shock in the tranquil period is very large and the distribution of responses is also very dispersed. By contrast, contagion effects are small in this case, so that unlike Hong Kong, impulse responses for shocks from Indonesia in tranquil and contagion periods are very alike.

The impact of Korean shocks in the tranquil period is greater than for Hong Kong, but not so large as for the Indonesian case already discussed. During the tranquil period there are statistically significant linkages with all the other countries in the sample, as shown in Table

2. The contagion effects are substantial, with the size of the initial shock in the external crisis scenario being six-fold the tranquil period shock, necessitating a differing scale on this panel to the other panels in the figure. Half of this impact has dissipated by 47 days after the shock, but some effect is still present nearly a year after the initial shock.

As a result of the lack of linkages from Thailand to other markets, the impulse responses to shocks originating from Thailand are the same in each of the tranquil and contagion periods.

Overall, the largest contributors to volatility are the Hong Kong and Korean crises. Shocks from these events increase portfolio variance by between six and ten times and persist for a number of months.

6 Conclusion

This paper develops a model which contributes an important refinement to the taxonomy of crises: we distinguish between hypersensitivity and contagion. A local market may experience contagion from a foreign market in distress, either as the recipient of an increase in pre-existing links with, or via the opening of a new channel of transmission. A local market in crisis may also experience hypersensitivity to shocks from foreign markets. Contagion and hypersensitivity map into policy discussions of crisis prevention and management, in the sense that policies need to be incentive compatible with the actively operating links.

In particular, results here suggest that during the Asian crisis, the crisis countries themselves had at best weak incentives to slow the spread of turbulence, while the nearby markets had reason to look for protection either via domestic regulation or through international policy coordination.

The modelling framework separates hypersensitivity and contagion based on a multivariate GARCH framework with regimes and exogenously defined crisis periods. An advantage is that structural parameters can be identified from the reduced form. Unlike past work, which has relied on arbitrary restrictions to classify the sources of unobservable structural shocks, we use variance decompositions to label the structural shocks and connect them to source markets. This approach enables an economic interpretation of risk transmission in tranquil and crisis periods.

Applying this model to four Asian equity markets during the East Asian crisis period of 1997-1998, we observe statistically significant contagion links, but little in the way of hypersensitivity. We also estimate the changes in portfolio volatility for an equally-weighted portfolio of the four equity assets due to shocks originating in each country during both tranquil and crisis periods. Impulse response analysis shows the increasing dominance of Korean and Hong Kong shocks during the crisis and the diminishing influence of Indonesian sourced shocks.

The modelling framework proposed here has many similarities with the recent network literature on linkages between financial institutions, where those institutions care about both inflow from, and outflow to, counterparties, see Allen and Babus (2008) for an overview. Future work linking the empirical framework developed in this paper and network theory should provide insights into the credit crunch of 2007-2008.

Appendix

Here we present a two-dimensional illustration of the main features of the model and dynamics.

The tranquil period model for de-meaned returns for asset markets 1 and 2 is:

$$y_{1t} = b_{12}y_{2t} + g_{11,t}\varepsilon_{1t} \tag{18}$$

$$y_{2t} = b_{21}y_{1t} + g_{22,t}\varepsilon_{2t}, \tag{19}$$

which can be extended for crisis periods to

$$y_{1t} = b_{12}y_{2t} + b_{s,12}D_{1t}y_{2t} + b_{c,12}D_{2t}y_{2t} + g_{11,t}\varepsilon_{1t} \tag{20}$$

$$y_{2t} = b_{21}y_{1t} + b_{s,21}D_{2t}y_{1t} + b_{c,21}D_{1t}y_{1t} + g_{22,t}\varepsilon_{2t}, \tag{21}$$

where the binary dummy variables, D_{1t} and D_{2t} take the value 1 during periods of crisis experienced in y_{1t} and y_{2t} respectively, and 0 otherwise. For the rest of the example, we work with the simpler tranquil period model. The matrix of contemporaneous market linkages is normalized on the diagonal to give,

$$\mathbf{B} = \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \tag{22}$$

and

$$\mathbf{B}^{-1} := \mathbf{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}. \tag{23}$$

The GARCH processes on ε_i in this case are:

$$\begin{bmatrix} g_{11t}^2 & 0 \\ 0 & g_{22t}^2 \end{bmatrix} = diag\left\{ \begin{bmatrix} \psi_1 \\ \psi_2 \end{bmatrix} + \begin{bmatrix} \lambda_{11} & 0 \\ 0 & \lambda_{22} \end{bmatrix} \begin{bmatrix} u_{1t-1}^2 \\ u_{2t-1}^2 \end{bmatrix} \right\} + \begin{bmatrix} \zeta_{11} & 0 \\ 0 & \zeta_{22} \end{bmatrix} \begin{bmatrix} g_{11t-1}^2 & 0 \\ 0 & g_{22t-1}^2 \end{bmatrix}. \tag{24}$$

so that $g_{ii,t}\varepsilon_{it} = u_{it}$.

To estimate the simple model structure in (18) and (19) we need to account for the covariance between y_{it} and u_{jt} and the identification of structural parameters, and we resolve both estimation issues by working with the reduced-form covariance matrix.

For two assets, the reduced form covariance matrix $vech\mathbf{H}_t = \mathbf{A}^v vecd\left(\mathbf{G}_t\right)$ from equation (9) can be expressed as

$$\begin{bmatrix} H_{11,t} \\ H_{21,t} \\ H_{22t} \end{bmatrix} = \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{11}a_{21} & a_{12}a_{22} \\ a_{21}^2 & a_{22}^2 \end{bmatrix} \times \left\{ \begin{bmatrix} \psi_1 \\ \psi_2 \end{bmatrix} + \begin{bmatrix} \lambda_{11}u_{1t-1}^2 \\ \lambda_{22}u_{2t-1}^2 \end{bmatrix} + \begin{bmatrix} \zeta_{11}g_{11t-1}^2 \\ \zeta_{22}g_{22t-1}^2 \end{bmatrix} \right\} \tag{25}$$

From (10) above we can write

$$\begin{aligned} \boldsymbol{\kappa}_{t-1} \circ \boldsymbol{\kappa}_{t-1} &= \mathbf{A}\mathbf{u}_{t-1} \circ \mathbf{A}\mathbf{u}_{\mathbf{t-1}} \\ &= \begin{bmatrix} \left(a_{11}u_{1t-1} + a_{12}u_{2t-1}\right)^2 \\ \left(a_{21}u_{1t-1} + a_{22}u_{2t-1}\right)^2 \end{bmatrix} \\ \begin{bmatrix} \kappa_{1t-1}^2 \\ \kappa_{2t-1}^2 \end{bmatrix} &= \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{21}^2 & a_{22}^2 \end{bmatrix} \begin{bmatrix} u_{1t-1}^2 \\ u_{2t-1}^2 \end{bmatrix} \\ \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{21}^2 & a_{22}^2 \end{bmatrix}^{-1} \begin{bmatrix} \kappa_{1t-1}^2 \\ \kappa_{2t-1}^2 \end{bmatrix} &= \begin{bmatrix} u_{1t-1}^2 \\ u_{2t-1}^2 \end{bmatrix} \end{aligned} \tag{26}$$

using the assumption that the structural shocks are independent so that cross products in

u_{1t} and u_{2t} can be set to zero. From equation (11)

$$\mathbf{h}_{t-1} = \begin{bmatrix} H_{11t-1} \\ H_{22t-1} \end{bmatrix} = \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{21}^2 & a_{22}^2 \end{bmatrix} \begin{bmatrix} g_{11t-1}^2 \\ g_{22t-1}^2 \end{bmatrix}$$

$$\begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{21}^2 & a_{22}^2 \end{bmatrix}^{-1} \begin{bmatrix} H_{11t-1} \\ H_{22t-1} \end{bmatrix} = \begin{bmatrix} g_{11t-1}^2 \\ g_{22t-1}^2 \end{bmatrix} \tag{27}$$

If we rewrite $\mathbf{H}_t$ in $vech\left(\cdot\right)$ form and define the requisite transformation of the $\mathbf{A}$ matrix as $\mathbf{A}^v$ then

$$\begin{bmatrix} H_{11,t} \\ H_{21,t} \\ H_{22t} \end{bmatrix} = \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{11}a_{21} & a_{12}a_{22} \\ a_{21}^2 & a_{22}^2 \end{bmatrix} \left\{ \begin{array}{c} \begin{bmatrix} \psi_1 \\ \psi_2 \end{bmatrix} + \begin{bmatrix} \lambda_{11} & 0 \\ 0 & \lambda_{22} \end{bmatrix} \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{21}^2 & a_{22}^2 \end{bmatrix}^{-1} \begin{bmatrix} \kappa_{1t-1}^2 \\ \kappa_{2t-1}^2 \end{bmatrix} \\ + \begin{bmatrix} \zeta_{11} & 0 \\ 0 & \zeta_{22} \end{bmatrix} \begin{bmatrix} a_{11}^2 & a_{12}^2 \\ a_{21}^2 & a_{22}^2 \end{bmatrix}^{-1} \begin{bmatrix} H_{11t-1} \\ H_{22t-1} \end{bmatrix} \end{array} \right\} \tag{28}$$

Dynamics

The proportion of the forecast error variance for return to domestic market one, $y_{1,}$ that is due to structural shock ε_1 is

$$VD_{1,1|t} = \frac{a_{11}^2 g_{1,t+1|t}^2}{a_{11}^2 g_{1,t+1|t}^2 + a_{12}^2 g_{2,t+1|t}^2} \tag{29}$$

and due to structural shock ε_2 is

$$VD_{1,2|t} = \frac{a_{22}^2 g_{2,t+1|t}^2}{a_{11}^2 g_{1,t+1|t}^2 + a_{12}^2 g_{2,t+1|t}^2} \tag{30}$$

The proportion of portfolio error variance for an equally weighted portfolio ($w = 1/k$) includes the impact of diversification, and error sourced in ε_1 would be represented by the following expression,

$$
\begin{aligned}
VD_{p,1} = & \left[g^2_{1,t+1|t}\left(a^2_{11} + a_{12}a_{11} + a_{21}a_{11} + a_{21}a_{12}\right)\right] / \\
& \left[g^2_{1,t+1|t}\left(a^2_{11} + a_{12}a_{11} + a_{21}a_{11} + a^2_{21}\right) + g^2_{2,t+1|t}\left(a^2_{12} + a_{12}a_{22} + a_{12}a_{22} + a^2_{22}\right)\right]. \quad (31)
\end{aligned}
$$

Impulse responses in this case are

$$
\begin{aligned}
E_t\left[\frac{\partial \mathbf{w}'\mathbf{H}_{t+1}\mathbf{w}}{\partial\varepsilon^2_{1,t}}\right] &= \partial[\left\{(1/2)^2\left[\begin{array}{c} g^2_{1,t+1|t}\left(a^2_{11} + a_{12}a_{11} + a_{21}a_{11} + a^2_{21}\right) \\ +g^2_{2,t+1|t}\left(a^2_{12} + a_{12}a_{22} + a_{12}a_{22} + a^2_{22}\right)\end{array}\right]\right\}/\partial\varepsilon^2_{1,t} \\
&= (1/2)^2\left(a^2_{11} + a_{12}a_{11} + a_{21}a_{11} + a^2_{21}\right)\frac{\partial g^2_{1,t+1|t}}{\partial\varepsilon^2_{1,t}} \quad (32)
\end{aligned}
$$

which creates a recursion in the structural parameters so that for an initial shock $\varepsilon^2_{1,t} = \sqrt{\varepsilon^2_{1,t}} = 1$ in period t,

$$
\begin{aligned}
g^2_{1,t+1|t} &= \psi_1 + \lambda_1 u^2_{1,t} + \zeta_1 g^2_{1,t} \quad (33) \\
\frac{\partial g^2_{1,t+1|t}}{\partial\varepsilon^2_{1,t}} &= \lambda_1 g^2_{1,t} \quad (34)
\end{aligned}
$$

and

$$
E_t\left[\frac{\partial w'\mathbf{H}_{t+1}w}{\partial\varepsilon^2_{1,t}}\right] = (1/2)^2\left(a^2_{11} + a_{12}a_{11} + a_{21}a_{11} + a^2_{21}\right)\lambda_1 g^2_{1,t}. \quad (35)
$$

References

Alexander, K., Eatwell, J., Persuad, A., Reoch, R., 2007. Financial supervision and crisis management in the EU. EU Policy Department Economic and Scientific Policy Document IP/A/ECON/IC/2007-069.

Allen, F., Babus, A., 2008. Networks in Finance. Wharton Financial Institutions Centre Working Paper 08-07.

Allen, F., Gale, D., 2000. Financial contagion. Journal of Political Economy 108, 1-33.

Baig, T., Goldfajn, I.,., 1999. Financial market contagion in the Asian crisis. IMF Staff Papers 46, 167-195.

Baur, D., Schulze, N., 2005. Co-exceedances in financial markets: a quantile regression analysis of contagion. Emerging Markets Review 6, 21-43.

Billio, M., Pelizzon, L., 2003. Contagion and interdependence in stock markets: have they been misdiagnosed? Journal of Economics and Business 55, 405-426.

Bond, S., Dungey, M., Fry, R., 2006. A web of shocks: crises across Asian real estate markets. Journal of Real Estate Finance and Economics 32, 253-274.

Brusco, S., Castiglionesi, F., 2007. Liquidity coinsurance, moral hazard and financial contagion. Journal of Finance 62, 2275-2302.

Caporale, G., Cipollini, A., Spagnolo, N., 2005. Testing for contagion: a conditional correlation analysis. Empirical Finance 12, 476-489.

Cerra, V., Saxena, S. C., 2002. Contagion, monsoons and domestic turmoil in Indonesia's currency crisis. Review of International Economics 10, 36-44.

Corsetti, G., Pericoli, M., Sbracia, M., 2005. Some contagion, some interdependence: more pitfalls in tests of financial contagion. Journal of International Money and Finance 24, 1177-1199.

Dornbusch, R., Park, Y. C., Claessens, S., 2000. Contagion: understanding how it spreads. The World Bank Observer 15, 177-197.

Dungey, M., Martin, V.L., 2007. Unravelling financial market linkages during crises. Journal of Applied Econometrics 22, 89-119.

Eichengreen, B., 2002. Toward a new international financial architecture: a practical post-Asia agenda. Institute for International Economics, Washington.

Engle, R.F., Ng, V.G., 1993. Measuring and testing the impact of news on volatility. Journal of Finance 48, 1749-1778.

Favero, C., Giavazzi, F., 2002. Is the international propagation of financial shocks non-linear? Evidence from the ERM. Journal of International Economics 57, 231-46.

Forbes, K., Rigobon, R., 2002. No contagion, only interdependence: measuring stock market co-movements. Journal of Finance 57, 2223-2261.

Gallant, A.R., Rossi, P.E., Tauchen, G., 1993. Nonlinear dynamic structures. Econometrica 61, 871-907.

Hartmann, P., Straetmans S., de Vries, C., 2004. Asset market linkages in crisis periods. Review of Economics and Statistics 86, 313–326.

Kaminsky, G., Reinhart, C., 2002. Financial markets under stress. Journal of Development Economics 69, 451-470.

Kiyotaki, N., Moore, J., 2002. Balance-sheet contagion. American Economic Review 92, 46-50.

Kleimeier, S., Lehnert T., Verschoor, W., 2003. Contagion versus interdependence: A re-examination of Asian-crisis stock market co-movements. LIFE Working Paper 2003-05.

Kodres, L., Pritsker, M., 2002. A rational expectations model of financial contagion. Journal of Finance 57, 769-799.

Lin, W-L., 1997. Impulse response function for conditional volatility in GARCH Models. Journal of Business and Economic Statistics 15, 15-25.

Mishkin, F., 1998. The Mexican financial crisis of 1994-59: an asymmetric information analysis, in: Scheherazade S. R., (Ed.), Financial Crisis Management in Regional Blocs, Kluwer, Norwell, pp. 149-182.

Pesaran, H., Pick, A., 2007. Econometric issues in the analysis of contagion. Journal of Economic Dynamics and Control 31, 1245-1277.

Pavlova, A., Rigobon, R., 2007. The role of portfolio constraints in the international propagation of shocks. Review of Economic Studies, forthcoming .

Rigobon, R., 2003. On the measurement of the international propagation of shocks: is the transmission stable? Journal of International Economics 61, 261-283.

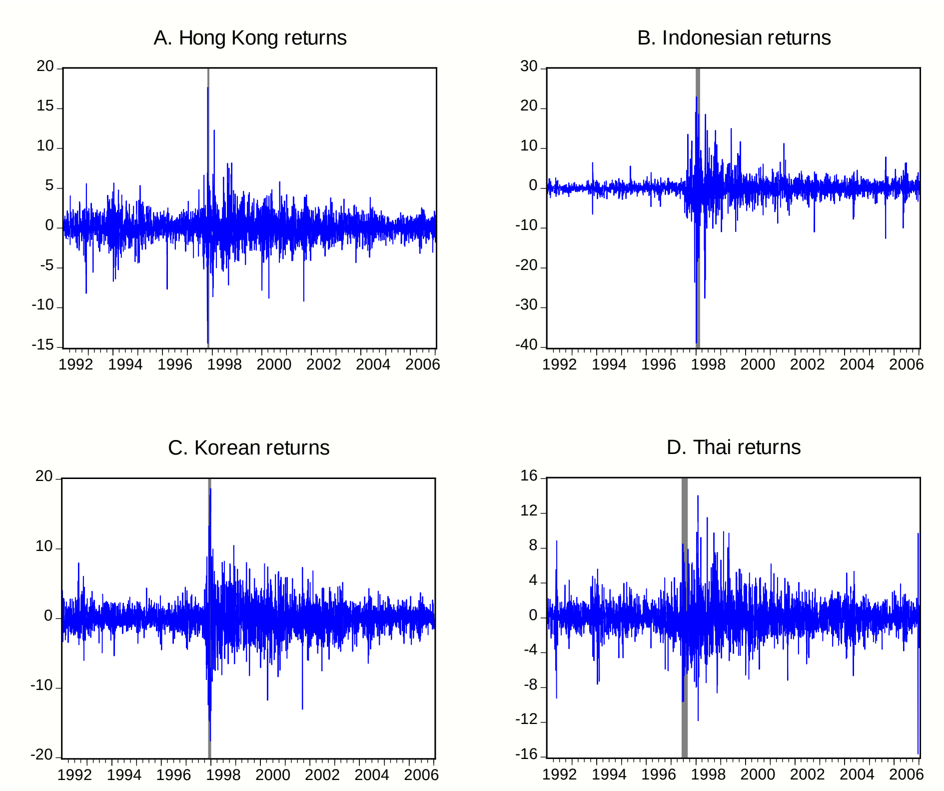
Rigobon, R., Sack, B., 2004. Impact of monetary policy on asset prices. Journal of Monetary Economics 51, 1553-1575.

Rothenberg, T., 1971. Identification in parametric models. Econometrica 39, 577-591.

Yuan, K., 2005. Asymmetric price movements and borrowing constraints: a rational expectations equilibrium model of crises, contagion, and confusion. Journal of Finance 60, 379-411.

Figure 1: Time Series of Daily Returns to Asian Equity Price Indices,

January 1992 to January 2007.

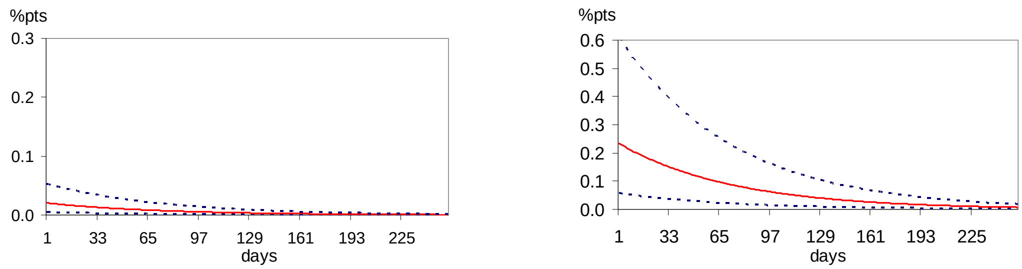


Note: Each series is the residuals from a VAR(1). Grey bars indicate the period designated as crisis period in each country. Data sources are described in Table 1.

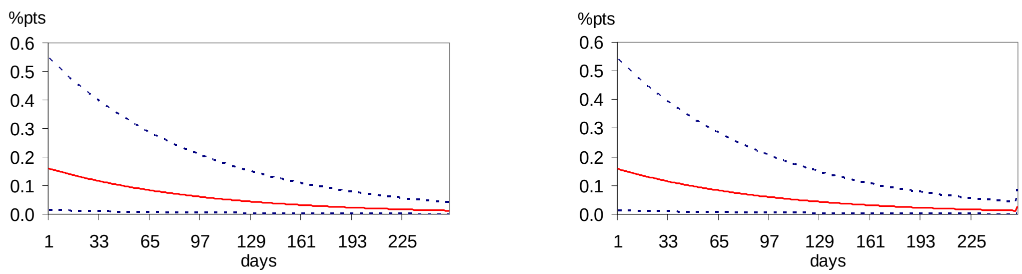
Figure 2: Impulse Response Functions of Equally Weighted Portfolio Variance to a Standard Deviation Shock for Periods of Tranquility and Contagion

Tranquil Period **Contagion**

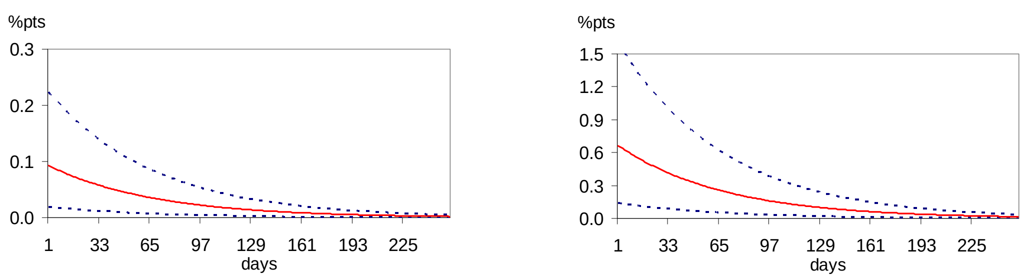
Hong Kong sourced shock



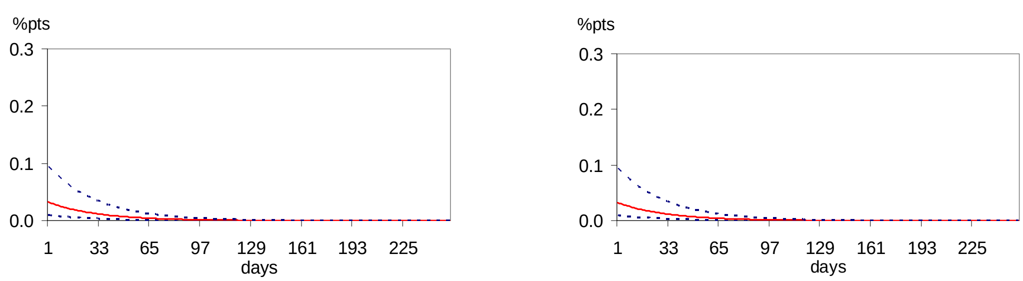
Indonesian sourced shock



Korean sourced shock



Thai sourced shock



Note: Vertical axes show the absolute increase in the daily variance of an equally-weighted portfolio of the equity indices n-days after a one standard deviation structural shock from each equity market. Impulse response functions are calculated conditioning on volatility at every time $= t$ in the sample. The dashed lines represent the 5th and 95th quantiles of the empirical distribution of the conditional impulse responses and the solid line represents the median.

Table 1:
Descriptive Statistics for Equity Returns: Tranquil Period and Crisis Periods

	Hong Kong (HK)	Indonesia (IN)	Korea (KO)	Thailand (TH)
Total Period: 1 January 1992-9Janaury 2007				
Mean	0.000	0.000	0.000	0.000
Max	17.673	22.961	18.647	14.039
Min	-14.467	-38.888	-17.572	-15.622
Std dev.	1.606	2.456	2.169	1.885
J-B p-val	0.000	0.000	0.000	0.000
Thai crisis: 10 June 1997 - 29 August 1997				
Mean	-0.061	-0.642	-0.053	-0.500
Max	4.828	4.504	2.191	8.485
Min	-5.071	-7.515	-2.592	-9.629
Std dev.	1.662	2.487	1.062	3.832
J-B p-val	0.001	0.007	0.884	0.930
Hong Kong crisis: 27 October 1997 - 17 November 1997				
Mean	-0.353	-0.168	-0936	-0.450
Max	17.673	11.881	8.832	6.335
Min	-14.467	-8.285	-8.764	-5.733
Std dev.	6.767	5.155	4.936	3.776
J-B p-val	0.129	0.226	0.810	0.734
Korean crisis: 25 November 1997 - 31 December 1997				
Mean	0.137	-0.723	-1.191	-1.002
Max	4.698	19.060	18.647	5.486
Min	-5.649	-23.663	-17.572	-7.328
Std dev.	2.435	7.671	10.916	2.942
J-B p-val	0.612	0.016	0.477	0.841
Indonesian crisis: 5 January 1998 to 27 February 1998				
Mean	-0.019	-1.599	0.496	1.166
Max	12.295	22.961	9.957	14.069
Min	-8.612	-38.888	-13.244	-11.813
Std dev.	3.982	11.600	5.193	5.310
J-B p-val	0.112	0.069	0.520	0.872

Note: Returns are computed as percentage log changes in the price indices for Hong Kong (Hang Seng HNGKNGI), Indonesia (Jakarta Composite JAKCOMP), Korea (Korea Composite KORCOMP) and Thailand (Bangkok SET BNGKSET) using daily series from Datastream, translated to US dollars before returns are computed. Sample runs from 2 January 1990 to 9 January 2007 but observations where there is a zero return from any series are removed before de-meaning, leaving 3608 days. Returns are de-meaned using a VAR(1) in the returns and the contemporaneous change in the daily 3-month US Treasury Bill secondary market mid-rate (FRTBS3M).

Table 2:
Parameter Estimation Results

	i	Hong Kong (HK)	Indonesia (IN)	Korea (KO)	Thailand (TH)
			Tranquil		
Hong Kong	$b_{i,HK}$		0.103	-0.125	0.268
			(0.003)	(0.156)	(0.000)
Indonesia	$b_{i,IN}$	0.086		0.056	0.154
		(0.001)		(0.006)	(0.000)
Korea	$b_{i,KO}$	0.296	0.002		0.094
		(0.000)	(0.032)		(0.039)
Thailand	$b_{i,TH}$	0.027	0.953	0.031	
		(0.595)	(0.457)	(0.561)	
			Hypersensitivity		
Hong Kong	$b_{s,i,HK}$		-2.050	-1.981	0.440
			(0.212)	(0.253)	(0.464)
Indonesia	$b_{s,i,IN}$	0.309		-0.758	0.230
		(0.512)		(0.033)	(0.187)
Korea	$b_{s,i,KO}$	-0.627	-0.636		-0.689
		(0.160)	(0.532)		(0.431)
Thailand	$b_{s,i,TH}$	0.431	1.351	0.903	
		(0.449)	(0.373)	(0.478)	
			Contagion		
Hong Kong	$b_{c,i,HK}$		0.554	0.645	-0.500
			(0.038)	(0.007)	(0.049)
Indonesia	$b_{c,i,IN}$	0.131		0.133	-0.127
		(0.266)		(0.538)	(0.589)
Korea	$b_{c,i,KO}$	-0.150	0.741		-0.002
		(0.299)	(0.001)		(0.973)
Thailand	$b_{c,i,TH}$	-0.174	-0.038	-0.098	
		(0.150)	(0.692)	(0.205)	

Note: Parameter estimates for the model $BY_t = u_t$, where $B := (\mathbf{B}^{*}+\mathbf{B}_{c,s}\mathbf{D}_t)$ with $B_{c,s}D_t$ representing the linkages present in crisis periods. Contagion (indicated by subscript c) is modelled as the additional impact on asset markets in home country i during a crisis in foreign country j, given by the parameters $b_{c,ij}$ in each equation. Hypersensitivity (indicated by subscript s) is given by the parameter $b_{s,ij}$ in each equation measuring the additional impact of foreign shocks during a domestic crisis. Each period of crisis is identified using an indicator variable $D_{i,t}$ which is one during the crisis in home country i and zero otherwise. The relevance of each instance of contagion and hypersensitivity is tested by the significance of the parameters $b_{c,ij}$ and $b_{s,ij}$ where the columns represent the equations for each domestic market and the rows represent the impact of the foreign market. Estimation is by QML over daily de-meaned returns to equity market indices, sampling 2 January 1990 to 9 January 2007. P-values are in brackets.

Table 3:
GARCH parameter estimates

		Structural Shocks			
	i	Hong Kong	Indonesia	Korea	Thailand
Constant	ψ_i	0.029	0.073	0.078	0.113
		(0.035)	(0.025)	(0.003)	(0.037)
ARCH	λ_i	0.090	0.187	0.125	0.169
		(0.000)	(0.000)	(0.000)	(0.003)
GARCH	ζ_i	0.897	0.803	0.860	0.800
		(0.000)	(0.000)	(0.000)	(0.000)

Note: Parameter estimates for the conditional covariance matrix of the structural shocks, $G_t = diag[\psi + \lambda(\mathbf{u}_{t-1} \circ \mathbf{u}_{t-1})] + \zeta G_{t-1}$,where ψ is a 4×1 vector of constants, ψ_i, λ is a 4×4 diagonal matrix of ARCH coefficients and ζ is a 4×4 diagonal matrix of GARCH coefficients. Estimation is by QML over daily de-meaned returns to equity market indices, sampling 2 January 1990 to 9 January 2007. P-values are in brackets.

Table 4:
Mean Conditional Forecast Error Variance Decomposition (One Step Ahead)

ε_i	Hong Kong	Indonesia	Korea	Thailand	portfolio
			Tranquil		
Hong Kong	80.23	1.11	0.79	5.26	15.63
	[61.80 - 95.23]	[0.12-3.56]	[0.20-2.38]	[1.63-12.48]	[4.87-39.38]
Indonesia	3.18	98.73	2.20	5.50	31.25
	[0.43-9.56]	96.16-99.84]	[0.44-6.16]	[0.96-15.85]	[10.53-63.95]
Korea	16.59	0.16	97.01	4.62	39.20
	[4.06-33.40]	[0.03-0.41]	[92.60-99.19]	[1.19-11.12]	[15.81-63.98]
Thailand	0.00	0.00	0.00	84.62	13.92
	[0.00-0.00]	[0.00-0.00]	[0.00-0.00]	[68.78-94.93]	[4.25-29.12]
			Hypersensitivity		
Hong Kong	81.48	1.11	1.75	5.06	19.09
	[63.91-95.51]	[0.12-3.56]	[0.43-5.38]	[1.53-12.10]	[7.63-43.13]
Indonesia	1.61	98.73	23.82	0.85	4.10
	[0.21-4.85]	[96.16-99.84]	[7.21-53.55]	[0.13-2.44]	[0.87-4.10]
Korea	16.91	0.16	74.43	4.78	56.16
	[4.09-33.93]	[0.03-0.41]	[45.34-91.42]	[1.16-11.65]	[28.00-78.96]
Thailand	0.00	0.00	0.00	89.31	20.66
	[0.00-0.00]	[0.00-0.00]	[0.00-0.00]	[78.50-96.55]	[7.34-40.81]
			Contagion		
Hong Kong	70.29	28.62	19.35	0.04	31.53
	[47.64-91.68]	[9.78-61.58]	[6.58-45.62]	[0.01-0.09]	[12.82-64.30]
Indonesia	3.43	28.09	3.54	5.01	13.63
	[0.51-10.18]	[8.61-60.00]	[0.73-10.01]	[0.88-14.48]	[3.33-35.11]
Korea	26.27	43.29	77.11	9.11	52.06
	[7.40-48.26]	[18.56-67.49]	[51.07-91.41]	[2.42-21.15]	[25.03-74.97]
Thailand	0.00	0.00	0.00	85.54	2.79
	[0.00-0.00]	[0.00-0.00]	[0.00-0.00]	[68.76-96.05]	[0.82-6.14]

Note: Conditional one-step ahead error variance decompositions, computed for individual assets and an equally-weighted portfolio of market indices. Rows show the mean of empirical histogram of the conditional variance decompositions, conditioning on each standard deviation $g_{ii,t}$ in the sample, and figures in square brackets are the 5th and 95th quantiles.