Contagion in the Presence of Stochastic Interdependence

Clifford A. Ball
Vanderbilt University
Nashville, TN 37203

Walter N. Torous*
UCLA
Los Angeles, CA 90095

Abstract

Contagion represents a significant change in cross-market linkages precipitated by a crisis and is properly measured only after taking into account the interdependence or extant linkages prevailing between markets. Since it is well known that stock return volatilities and correlations are stochastic in the absence of a crisis, interdependence between markets should reflect the time varying nature of these covariances. We measure contagion in the presence of stochastic interdependence using data on stock indices from South East Asian countries around the July 1997 crisis. Since stock return covariances are observed with error, this suggests casting our model in a state space framework which is estimated using a multivariate Kalman filter. In the presence of stochastic interdependence, we find reliable evidence of contagion between Thailand and Indonesia, Malaysia, and the Philippines but not between Thailand and Hong Kong or Singapore.

JEL classification: F30; C10; G15.

Keywords: Contagion, Interdependence, Stochastic Covariance.

* Corresponding author. Fax: +1 310 206 5455; Email address: *wtorous@anderson.ucla.edu*

Contagion in the Presence of Stochastic Interdependence

1 Introduction

The modeling and measurement of the comovement of stock markets continues to attract the attention of economists and policymakers alike. Empirical evidence consistent with volatility in one market spilling over into other markets has been amply documented while links between markets have been shown to change in response to various shocks. As emphasized by previous research, to fully address these issues requires clear definitions of the notions of volatility spillover, contagion, and interdependence across financial markets. Moreover, sound empirical techniques are needed to measure these quantities in the presence of potentially spurious statistical effects.

Forbes and Rigobon (2002) define contagion as a significant change in cross-market linkages following a particular shock or crisis. Of course, this change must be measured relative to the linkages already prevailing between markets. In other words, contagion can only be measured after taking into account the interdependence between markets. Forbes and Rigobon's analysis is couched within a static framework in which the pre-crisis period is assumed characterized by a constant covariance structure in returns. Because of the crisis, however, a potentially different but constant covariance structure may subsequently describe returns. Within this framework, Forbes and Rigobon argue that if cross-market linkages are calibrated by the correlation between the respective stock market returns, then reliably detecting a change in this correlation is problematic. The problem arises because the measured correlation between stock returns is correlated with measured stock return volatilities.[1] Thus, even if the underlying population correlation and volatilities remain fixed, we can expect to see higher measured correlations when measured volatilities are higher. This spurious link may give rise to a potential bias in the estimation of correlation. Forbes and Rigobon derive a correction for this bias and argue that once this bias is taken into account, there is little if any evidence of contagion surrounding a variety of recent crises. By contrast, Chakrabarti and Roll (2002) argue

[1] Loretan and English (2000) also use this fact in their evaluation of correlation breakdowns during periods of market volatility.

that this bias can only arise if the heteroscedasticity in returns is due solely to chance. If, as to be expected, the true underlying volatilities actually increase around the crisis, then Chakrabarti and Roll argue that no such bias exists and applying the Forbes and Rigobon adjustment will spuriously reduce any contagion effect that is actually present in the data.

While it is correct to recognize that stock return volatility can change in response to a crisis, it is also well known that, in general, the covariance of stock returns is time-varying and stochastic.[2] To the extent that correlation is stochastic, a change in correlation *per se* does not necessarily provide evidence of contagion. What is required is a change in correlation exceeding what was expected *ex ante* given its stochastic nature. In other words, if contagion takes into account the interdependence between markets, this interdependence must reflect the time varying nature of covariances arising from the normal arrival of information in the absence of a crisis.

This paper provides a multivariate stochastic covariance model to investigate contagion. We rely on a state-space framework in which measured return covariances - volatilities and correlations - differ from their population counterparts by measurement errors. The state of the system is given by appropriately transformed population return covariances and we model their movement by a first order vector autoregressive (VAR) process in which interdependence across markets is accommodated. The fact that measured correlation is dependent upon measured volatilities can then be explicitly accounted for by allowing correlated errors in measured volatilities and correlation. More importantly, as our state-space framework allows for a stochastically evolving covariance structure, we can investigate contagion in the presence of stochastic interdependence between markets.

The empirical focus of this paper is the South East Asian financial crisis of the summer of 1997. We examine daily returns on market indices from Hong Kong, Indonesia, Malaysia, the Philippines, Singapore and Thailand over the April 1990 through April 2002 sample period. Following others, we date the crisis as July 1997 and assume that Thailand was “ground zero” for the crisis. When estimating the stochastic covariance model, we reject in all cases the null hypothesis that there is no change in the mean levels of population covariances over various post-July 1997 sample periods. However, while we see clear evidence of increases in mean stochastic volatilities, the evidence for in-

[2]See, for example, Solnik, Boucrelle, and Fur (1996).

creases in mean stochastic correlations is mixed. While stochastic correlations of Thailand *versus* the Philippines, Indonesia, and Malaysia, on average, increase post-July 1997, correlations of Thailand with the more developed countries of Hong Kong and Singapore do not change.

Unlike our empirical methodology which follows Forbes and Rigobon and others by relying on changes in correlation to detect contagion, other researchers propose tests that associate contagion with changes in countries' underlying security return data generating processes. For example, Corsetti, Pericoli and Sbracia (2005) posit a factor model of security returns in each country. In their framework an increase in measured correlation between countries' security returns is evidence of contagion only if this increase is due to a structural break in the factor loadings of their respective data generating processes. Corsetti, Pericoli and Sbracia's resultant test statistic rejects the null hypothesis of interdependence in favor of contagion from the Hong Kong stock market in October 1997 to a number of stock markets in both emerging as well as developed economies. By contrast, Candelon, Hecq, and Verschoor (2005) rely on the concept of serial correlation common feature in a cointegrated vector correction model to detect changes in cyclical comovements between countries' security returns around a given crisis. In particular, they define contagion as a change in the cyclical transmission mechanism between the pre- and post-crisis periods, thereby rejecting the serial correlation common feature for the full sample period. Using a generalized method of moments (GMM) procedure shown to be robust to heteroscedasticity in security returns, Candelon, Hecq, and Verschoor cannot reject the common cyclical null hypothesis for the Asian crisis of 1997 but find some evidence of contagion surrounding the Mexican crisis of 1994.

Our paper is organized as follows. Section 2 introduces a multivariate stochastic covariance model to test for volatility spillover and contagion in which the dependence between measured volatilities and measured correlation is explicitly taken into account. Concentrating on the South East Asian crisis, we investigate volatility spillover and contagion within this framework by allowing for a shift in the mean levels of stochastic covariances subsequent to July 1997. Section 3 describes our data while Section 4 provides our empirical results and discusses their economic significance. We conclude in Section 5.

2 Empirical Methodology

An important point raised by Forbes and Rigobon and others is that measured correlation is *not* independent of measured volatilities. That being the case, the dependence between measured volatilities and measured correlation affects joint tests of the null hypothesis of no change in the underlying volatilities and correlation surrounding a crisis. Intuitively, ignoring the fact that these estimates are themselves correlated may result in a misstatement of the statistical confidence with which this null hypothesis is rejected. In other words, we may very well claim to detect a statistically significant shift in the underlying volatilities and correlation around a particular crisis when no such shift actually occurred.

In this section, we detail our methodology to investigate whether contagion has occurred between countries being careful to take into account the dependence between measured correlation and measured volatilities. We must rely on measured volatilities and correlations because data on true population volatilities and correlations are not available. At the same time, we also recognize that volatilities as well as correlations are time-varying or stochastic.[3] To accomplish this, we use a linear state-space framework in which measured variables explicitly differ from their population counterparts by observation errors and the population variables evolve stochastically through time. Estimation is carried out by relying on the Kalman filter. Significantly, we can allow correlated errors in measured volatilities and correlation in this framework. To the extent that correlations are stochastic, a change in measured correlation *per se* does not necessarily provide evidence of contagion. Indeed, contagion requires a change in correlation exceeding that which was expected *ex ante* given its stochastic nature. Intuitively, contagion represents an abnormal change in correlation over and above changes in correlation arising from the normal arrival of information in the absence of the crisis.

We divide the discussion of our methodology into three parts. We first consider the measurement of volatility and correlation (Section 2.1). Next we link the measured variables to their population counterparts within a state-space framework that allows us to detect contagion (Section 2.2). This framework also offers a natural characterization of the movement in covariances arising from

[3]See, for example, Campbell, Lo, and MacKinlay (1997), especially Chapter 12.2 and the references therein.

the normal transmission mechanism prevailing between countries against which contagion must be measured (Section 2.3).

2.1 Measuring Covariances

Stochastic volatility estimation typically relies on daily returns and treats each return as an observation. In a univariate state-space model, for example, the observation is the daily return squared or, alternatively, the *log* daily return squared and this provides a natural estimate of the true *log* volatility but with large error. This large observation error is ameliorated by collecting a sufficiently long time series of daily data and assuming that the parameters governing the model remain constant over the sample period.[4]

More recently, some researchers (see, for example, Anderson, Bollerslev, Diebold and Ebens (2001)) have eliminated almost all measurement error by collecting data at an extremely high frequency, say, every few minutes, and then aggregating this intra day data into a realized daily volatility. This approach shows promise for those markets where much is known about the underlying microstructure. Relying on this approach for cross-market comparisons, however, would require that differences in microstructure and, in particular, the synchronization of price quotes be taken into account.[5]

In this paper, we measure volatilities and correlations by grouping the n available daily returns into m sequential non-overlapping intervals of length k days with $n = m \times k$. We assume that the volatilities of returns to country i and j as well as their correlation are constant across *each* interval but allow these parameters to vary *across* the resultant m intervals.

There is an obvious tradeoff in the choice of k. At one extreme, $k = 1$ day and we have many observations but a large measurement error per observation. Alternatively, we may pick k to be so large that the measurement error becomes negligible but then the number of observations available

[4]Not only is this observation error large but its distribution is not normal (see Mahieu and Schotman (1998)). Various alternative methods have been proposed to handle this non-normality; see, for example, Kim, Shephard and Chib (1998).

[5]In fact, even if higher frequency data were available, the difficulties in obtaining synchronized intra day quotes across countries would severely restrict our ability to adopt this methodology.

for statistical estimation is concomitantly reduced. For example, if we pick $k = n$ days then the latent covariances are assumed fixed over the entire sample period and the model of covariance dynamics degenerates.

Covariance dynamics in our state-space framework will be estimated by relying on the Kalman filter. This approach provides consistent parameter estimates in general and is efficient if the assumption of normality can be justified for the model's resultant measurement errors. As a result, our choice of k must be made in conjunction with normalizing transformations of the data that will ensure that the measurement errors are indeed close to normal. Since we are assuming that the latent covariances are fixed within each interval of length k days, the smallest choice of k to do so will allow us to more accurately characterize covariance dynamics.

For example, if we let v_i^2 denote the sample variance of the returns to country i calculated using k days of returns data, the *log* of v_i^2 approaches normality as k increases. In particular, Bartlett and Kendall (1946) compute the skewness and kurtosis of the *log* chi-squared distribution for a range of sample sizes and recommend the normal approximation for sample sizes from 5 to 10 and above.[6] Also, it is well known that the Fisher transform of the sample correlation, z_{ij}, defined by

$$z_{ij} = \frac{1}{2} log \frac{1 + r_{ij}}{1 - r_{ij}}.$$

where r_{ij} denotes the sample correlation between the returns to country i and country j calculated using k days of returns data, converges to normality at a much faster rate than r_{ij}.[7]

In what follows, we choose $k = 5$ days to balance the amount of data needed to accurately measure covariances while leaving a sufficient number of observations to reliably estimate their dynamics. That is, five trading days of returns to country i and country j are used to calculate sample variances, v_i^2 and v_j^2, and the sample correlation between these returns, r_{ij}. We then rely on the corresponding log variances, log v_i^2 and log v_j^2, and the Fisher transform of the sample correlation z_{ij}.

[6] In particular, see the results tabulated in their Table 1.

[7] See Anderson (1984), page 123 for further details. Johnson, Kotz, and Balakrishnan (1995) summarize information on the distribution of the Fisher transform of the sample correlation. Moments of the distribution are provided by Hotelling (1953) while Winterbottom (1979) points out the variance stabilizing and normalization properties of the Fisher transform. Corsetti, Pericoli and Sbracia also use the Fisher transform in their empirical analysis.

2.2 The Model

We estimate the following model:

$$y_\tau = \alpha_\tau + d + \epsilon_\tau \quad \text{where} \quad var(\epsilon_\tau) = H, \quad \tau = 1, \ldots, m \tag{1}$$

$$\alpha_\tau = T\alpha_{\tau-1} + \eta_\tau \quad \text{where} \quad var(\eta_\tau) = Q, \quad \tau = 1, \ldots, m. \tag{2}$$

Here y_τ is a three-vector of measured *log* variances of returns to countries i and j and the Fisher transform of their corresponding sample correlation, $y_\tau \equiv \{log\ v^2_{i_\tau}, log\ v^2_{j_\tau}, z_{ij_\tau}\}$, all measured over the τ^{th} window, $\tau = 1, \ldots, m$. The state variable at τ, α_τ, is the demeaned population counterpart of y_τ, and d is the mean of the state variable α_τ.

Expression (1) is the measurement equation in which measured volatilities and correlations are explicitly linked to their population counterparts. We denote the corresponding measurement errors by ϵ_τ with covariance matrix H. To the extent that H is non-diagonal, measurement errors in $log\ v^2_{i_\tau}$, $log\ v^2_{j_\tau}$, and z_{ij_τ} are correlated and this correlation is then taken into account when filtering the population parameters from their measured counterparts.

The transition equation, expression (2), models the dynamics of the underlying population volatilities and correlations. To capture their stochastic nature, we assume a vector autoregressive structure for α_τ with transition matrix T and residual errors η_τ with covariance matrix Q. The second moments of the countries' returns are allowed to stochastically vary over time to capture the effects of the arrival of information in the absence of a crisis. While it is plausible to assume that the transition equation errors are multivariate normal, recall from our previous discussion that multivariate normality is only an approximation for the measurement errors.[8]

Contagion in our model represents deviations from this normal relation brought about by a particular crisis. To see this, notice from expression (1) that we can write $E_\tau(y_\tau) = \alpha_\tau + d$ and so the parameter vector d can be interpreted as the mean of the underlying population covariances. If the time

[8]However, this should be a fairly accurate assumption for windows of size $k = 5$ days. This being the case, the linear filter maximum likelihood procedure will provide consistent parameter estimates and any loss of efficiency should be minimal.

period $[\underline{\tau}, \bar{\tau}]$ is posited to be the crisis period, we test whether the levels of underlying population covariances are different in the crisis period versus outside the crisis period, $\Delta d = 0$. Consequently, we test whether the underlying population covariance parameters shift as a result of the crisis while explicitly taking into account their stochastic nature via expression (2). In other words, we measure contagion relative to the covariance dynamics prevailing in the absence of the crisis.

2.3 Interdependence

By explicitly modeling covariance dynamics in the absence of a crisis, we capture the notion of interdependence or "...strong linkages between two economies that exist in all states of the world." (Forbes and Rigobon (2002), page 2224). These linkages reflect the presence of fundamental economic channels along which shocks in one economy are propagated to another, notwithstanding the issue of contagion. Trade, for example, ensures that the effects of, say, a currency devaluation in one economy dissipate to other economies, perhaps with a lag. Alternatively, random global shocks may simultaneously affect the fundamentals of several economies. Interdependence recognizes that economies are linked and this linkage is the mechanism by which shocks are propagated across economies. Contagion occurs when a particular crisis alters these linkages. In our model this manifests itself as a shift in the levels of the underlying population covariances. That is, a statistically significant change in d when estimated over the crisis period as compared to its value estimated outside the crisis period.

To further understand interdependence, it may be tempting to directly apply causality tests[9] to measured volatilities and measured correlations in the hope that the results shed light on the causal relations prevailing between their population counterparts. As expression (2) models the dynamics of the underlying population volatilities and correlations, ignoring measurement error, tests for instantaneous and Granger causality would reduce to tests of rather simple zero restrictions on the corresponding transition matrix T and covariance matrix Q.[10] For example, correlation does not

[9] Granger causality captures lead-lag relations in the population covariance structure in the sense that one element of the covariance structure, say, volatility, may be more accurately predicted if information on, say, correlation, is also taken into account. The notion of instantaneous causality, by contrast, captures contemporaneous linkages as the forecast of one element of the population covariance structure, again say volatility, can be improved when knowledge of the contemporaneous value of another element, correlation, is also included.

[10] See Lütkepohl (1993), especially pages 35-43, for details.

Granger cause volatility only if T is lower triangular while correlation does not instantaneously cause volatility only if Q is diagonal.

Unfortunately, these results will be misleading precisely when measured quantities differ from their population counterparts by correlated measurement errors. In particular, even if there are no causal relations amongst the latent quantities, evidence of both Granger and instantaneous causality will be detected between measured volatilities and correlations.

To see this and investigate the nature of the causal relations prevailing between measured volatilities and correlations, $y_\tau \equiv \{v_{i_\tau}, v_{j_\tau} z_{ij_\tau}\}'$, it is useful to rewrite our linear state-space model, expressions (1) and (2) as follows. Applying the Kalman filter in steady-state gives

$$\hat{\alpha}_{\tau|\tau-1} = (T-K)L\hat{\alpha}_{\tau|\tau-1} + Ky_{\tau-1}$$

where $\hat{\alpha}_{\tau|\tau-1}$ is the optimal forecast of α_τ based on data observed through interval $\tau - 1$ with corresponding steady-state covariance matrix[11] P, L is the lag operator, and K is the Kalman gain matrix defined in steady-state by

$$K = TP(P+H)^{-1}.$$

Provided that the eigenvalues of $(T-K)$ are all inside the unit circle, we can write

$$\hat{\alpha}_{\tau|\tau-1} = [I-(T-K)L]^{-1}Ky_{\tau-1}$$

which implies the following equivalent $VAR(\infty)$ representation for y_τ

$$y_\tau = [I-(T-K)L]^{-1}y_{\tau-1} + \nu_\tau$$

where $var(\nu_\tau) = P + H$. This expression implies that

$$(I - [I-(T-K)L]^{-1}L)y_\tau = \nu_\tau$$

or

$$y_\tau = (I - [I-(T-K)L]^{-1}L)^{-1}\nu_\tau$$

[11] P is obtained as a solution to the algebraic Riccati equation. See Harvey (1990), especially page 118. As noted by Harvey, it is usually difficult to obtain an explicit solution to this equation.

which gives the $VMA(\infty)$ representation or Wold decomposition for y_τ which can be written as

$$y_\tau = \sum_{j=0}^{\infty} \Phi_j \nu_{\tau-j} \text{ where } \Phi_0 = I \text{ and } \Phi_j = T^{\,j-1} K \text{ for } j \geq 1.$$

From the $VMA(\infty)$ representation for y_τ, we see that measured correlation does not Granger cause measured volatility only if the matrices Φ_j are each lower triangular for <u>all</u> values of $j \geq 1$. This represents a series of non-linear restrictions that will, in general, not hold if measurement errors are correlated and H is non-diagonal. In particular, even if T is diagonal (<u>no</u> latent Granger causality) and Q is diagonal (<u>no</u> latent instantaneous causality), a non-diagonal H (correlated measurement errors) gives that in steady-state the gain matrix $K \equiv \Phi_1$ is non-diagonal, consistent with Granger causality amongst the measured volatilities and correlations. Similarly, measured correlation does not instantaneously cause measured volatility only if $var(\nu_\tau) = P + H$ is diagonal. However, for H non-diagonal this condition, in general, will not hold. In other words, correlation between measurement errors will impart correlation, both contemporaneously as well as through time, into measured covariances, implying that the results of causality tests applied to measured covariances will not be informative about the underlying causal relations prevailing between their population counterparts.

3 Data and Summary Statistics

To investigate contagion, we collect daily observations on a number of market indices. Focusing on the South East Asian crisis of the summer of 1997 and relying on Datastream's Total Market Price Indices, we consider the following South East Asian stock markets: Hong Kong (*TOTMHK$*), Indonesia (*TOTMID$*), Malaysia (*TOTMMY$*), Philippines (*TOTMPH$*), Singapore (*TOTMSG$*), and Thailand (*TOTMTH$*).[12] Our sample period begins on Wednesday 4/9/1990 and ends on Wednesday 4/22/2002.

Daily returns, r_t, are calculated as log price relatives, $r_t \equiv 100 \times log(I_t/I_{t-1})$, where I_t denotes the level of an index as of the end of day t.[13] Prior to forming windows, the time series of daily return observations on a particular index are demeaned over the entire sample period. Subsequently,

[12] All data are reported in U.S. dollars. Our conclusions are not altered if these data are converted into local currencies.

[13] There are no weekend observations and Datastream does record observations on holidays as simply that index level

we group these data over each Wednesday to Wednesday time period to form windows each of which contain $k = 5$ demeaned daily returns corresponding to Thursday, Friday, Monday, Tuesday, and Wednesday observations. As a result, for each of our sampled market indices, we have $m = 629$ sequential and non-overlapping intervals of data from which to calculate sample variances and sample correlations.

Figure 1 displays the estimated log variances of the sampled South East Asian country indices. To make any patterns inherent in these data more discernable, we present the raw estimates themselves as well as their exponentially smoothed counterparts. The estimated Fisher transformed correlations, raw and smoothed, of the Thai returns with the returns of the other South East Asian countries are presented in Figure 2.[14]

Before smoothing, we see that the Fisher transformed correlations are far noisier than the log variances. However, after smoothing, a shift in the log variances as well as the correlations is discernable around the 1997 South East Asian crisis. In particular, the smoothed volatilities increase subsequent to the crisis and while the correlations between these countries appear to fall between 1994 and 1996, they increase dramatically around 1997. Taken together, Figures 1 and 2 suggest that log volatilities and correlations are not constant but rather are time varying.

Table 1 provides summary statistics of these estimated covariance measures. From Panel A emerges a picture of changing yet persistent volatility. Among our sampled South East Asian countries, estimated log variances are highest, on average, in Thailand, and are the least stable, as measured by their standard deviations, in Indonesia. With reference to their corresponding sample skewness and kurtosis, estimated log variances are close to being normally distributed for the sampled countries except for Indonesia and Malaysia. Evidence of time series dependence in these estimated log variances can be seen in the pattern of their sample auto-correlations which do not approach zero even at a lag length of $\tau = 8$. In addition, the augmented Dickey-Fuller (ADF) statistics convincingly reject that these estimated series follow a random walk.

prevailing as of the end of the previous day on which trading did occur. We do not delete these observations in light of the infrequency of holidays and the fact that specific holidays may vary across countries. As a result, this gives five daily observations on the level of a particular index per week.

[14]For comparison purposes, we uses a smoothing parameter of $\lambda = 0.93$ throughout.

By comparison, we see little evidence of persistence in the pattern of sample auto-correlations of the Fisher transformed correlation estimates in Panel B of Table 1. The *ADF* statistics also reject that these series follow a random walk. Of course, the true underlying correlations may indeed be persistent, but any noise would significantly reduce our ability to statistically detect persistence in their estimated counterparts. The pair-wise correlation between Thailand and Singapore returns is highest, on average, amongst the sampled South East Asian countries while the correlation between Thailand and Indonesia is lowest, on average.

4 Empirical Results

Specifying when the South East Asian crisis both commenced and concluded, our empirical framework investigates whether a shift in mean population covariances occurred over this time period relative to the mean population covariances characterizing the remaining sampled data. Many, for example, Chakrabarti and Roll (2002), have dated the beginning of the South East Asian crisis as the first week of July 1997 with the devaluation of the Thai bhat, that is, week 378 in our sample. Unfortunately, there is no consensus as to the precise date when it concluded. Of course, there is also the possibility that the crisis may have commenced earlier than July 1997.[15]

To fix matters, we assume that the South East Asian crisis did indeed commence during the first week of July 1997 but we consider a number of alternative dates as to when it concluded. In particular, we fit our model assuming that the crisis concluded one year later, that is, week 429 of our sample period, two years later, week 481, and finally assuming that the crisis concluded three years later, week 533. Fitting the model sequentially over these lengthening contagion horizons allows us to better understand, at least in an *ad hoc* fashion, how covariances changed subsequent to July 1997. As noted earlier, we assume that Thailand was "ground zero" for the South East Asian crisis and our estimation strategy is to sequentially pair Thai returns with the returns to each of the other sampled South East Asian countries. By doing so, we can discern if there are any differences across

[15]As noted by Kaminsky and Schmukler (1999), the Thai bhat was under pressure from July 1996 onwards with the collapse of the Bangkok Bank of Commerce and injections of liquidity by the Bank of Thailand to support the financial system.

countries in how the crisis propagated. The nature of these differences will provide us with a better understanding of contagion. All of our results are tabulated in Table 2, Panels A through E. Details on the implementation of our estimation methodology are summarized in the Appendix.

As a preliminary, we begin by investigating whether the measurement errors surrounding the time-varying log volatilities and the correlation between the respective returns are themselves correlated. For each pair of returns and for every contagion horizon, we fit the model with the H matrix unrestricted and the H matrix restricted to be diagonal. Under the null hypothesis that these measurement errors are uncorrelated (that is, the H matrix is diagonal), twice the resultant log likelihood ratio statistic, $\mathcal{LR}_1$, is asymptotically χ^2 distributed with three degrees of freedom. Notice that in almost every case we can reject this null hypothesis at the 10% significance level or better. Measured volatilities and correlations are indeed correlated even after taking their stochastic nature into account. Clearly, the model with a diagonal H matrix is misspecified and may result in erroneous inferences regarding contagion.

Assuming an unrestricted H matrix, we next fit the model with and without a shift in mean population covariances over the posited contagion horizon. Under the null hypothesis that there is no such shift, twice the resultant log likelihood ratio statistic, $\mathcal{LR}_2$, is again asymptotically χ^2 distributed with three degrees of freedom. In almost every case we can reject this null hypothesis at the 10% significance level or better.

We can also construct this log likelihood ratio statistic under the assumption that the H matrix is diagonal, that is, ignoring the fact that measured volatilities and correlations are correlated, allowing us to investigate the effects of this misspecification on inferences drawn regarding contagion. Notice that in this case the corresponding χ^2 statistics, $\mathcal{LR}_3$, tend to be larger and so we more easily reject the null hypothesis of no mean covariance change under this misspecification. For example, in the case of Thailand *versus* Singapore, at the contagion horizons concluding at months 429 and 481, respectively, assuming a diagonal H matrix gives corresponding χ^2 statistics of 4.43 and 11.76, while the corresponding χ^2 statistics are 1.92 and 3.92 when the H matrix is unrestricted. If we erroneously assume that measurement errors are uncorrelated, we would reject the null hypothesis of no shift in mean population covariances over the contagion horizon through month 481 when no such evidence obtains under the properly specified model.

By being more likely to conclude that mean population covariances have shifted implies that we may falsely provide evidence of contagion when the correlated nature of the measurement errors is ignored. This conclusion emphasizes the need to incorporate the correlated nature of measured variances and measured correlations when investigating contagion. Recall that Forbes and Rigobon rely on a model where covariances are fixed except potentially at a single change point and they recognize the correlated nature of measurement errors surrounding this constant mean. We, by contrast, explicitly account for correlated measurement errors surrounding a random mean, the randomness reflecting the stochastic nature of covariances.

While our χ^2 test provides reliable evidence of a joint shift in mean population covariances over the posited contagion horizons, it does not tell us whether this reflects a shift in either of the mean volatilities or a shift in the mean correlation between returns or both. To do so, we next examine the statistical significance surrounding the shifts in the means of the individual covariance parameters, ∇d_1, ∇d_2, and ∇d_3. In particular, the parameter ∇d_1 measures the shift in the log volatility of Thai returns over a given contagion horizon. The parameter ∇d_2 measures the shift in the log volatility of the other sampled South East Asian returns paired with Thai returns while ∇d_3 measures the shift in the correlation between these returns. Also, as we lengthen the contagion horizon, from concluding at month 429 at one extreme to concluding at month 533 at the other extreme, we can investigate whether the shifts in the individual covariance parameters are short- or long-lived.

The ∇d_1 estimates provided in the different Panels of Table 2 simply give alternative estimates of this shift gotten by pairing Thai returns with a different South East Asian country's returns. Regardless of which of our sampled South East Asian returns we pair with Thai returns, Table 2 provides reliable evidence throughout that Thai log volatility shifts upward post-July 1997. Furthermore, this upward shift is evident at all contagion horizons even the longest suggesting that the South East Asian crisis brought about a permanent increase in Thai log volatility.

Similarly, the parameters ∇d_2 and ∇d_3 measure shifts, if any, in the log volatilities of the other sampled South East Asian returns and their correlations with Thai returns, respectively. For example, in the case of Indonesia and the Philippines, Panels B and D of Table 2, we clearly see that the log volatilities as well as the correlations of these returns with Thai returns shifted dramatically upward in the post-July 1997 sample period. These shifts are evident at all horizons and so the reaction of the Indonesian and the Philippine markets to the South East Asian crisis is long-lived. In other words, if contagion is measured by an upward shift in correlations, we see clear evidence of such an event in the case of Indonesia and the Philippines. By contrast, the behavior of Hong Kong and Singapore volatilities and correlations, Panels A and E of Table 2, is quite different. While there is evidence of Singapore log volatilities increasing throughout the post-July 1997 sample period, in neither case is a shift in correlations statistically evident. That is, consistent with results of Forbes and Rigobon, there is no evidence of contagion between Thailand *versus* Hong Kong and Singapore. Finally, from Panel C of Table 2 we see that the log volatility of Malaysian returns and the correlation of Malaysian and Thai returns initially increase at the outset of the South East Asian crisis, but these shifts are short-lived as these individual covariance parameters are soon back at their pre-crisis levels.

4.1 Discussion

Our empirical results are consistent with Kaminsky, Reinhart, and Végh's (2003)[16] conclusion that Indonesia, Malaysia, and the Philippines "were hit hardest" by the South East Asian crisis precipitated by events in Thailand in July 1997. Not only did the volatility of their stock returns, especially in the cases of Indonesia and the Philippines, increase substantially in the post-July 1997 sample period, contagion, that is, a substantial upward shift in the pairwise correlation of their returns with Thai returns, is also evident. Consistent with Kaminsky, Reinhart, and Végh (2003), "(f)inancial markets in Singapore and Hong Kong also experienced some turbulence". The volatility of their returns, especially in the case of Singapore, do increase substantially in the post-July 1997 sample period. However, we see no evidence of an increase in pairwise return correlations or contagion between Thailand and either Singapore or Hong Kong.

Having reliable evidence of contagion between Thailand and Indonesia, Malaysia, and the Philippines, but not Hong Kong and Singapore, suggests that differences between their respective economies or

[16] See Table 1 of Kaminsky, Reinhart, and Végh (2003).

financial markets may provide clues as to why contagion afflicted some but not all of our sampled South East Asian countries. Firstly, it is unlikely that trade linkages are the source of this contagion.[17] As argued by Baig and Goldfajn (2000), Park and Song (2001) and others, the trade linkages between Thailand and Indonesia, Malaysia, and the Philippines are not striking nor do these countries share very similar third country export profiles. However, quite distinct from Hong Kong and Singapore, each of Thailand, Indonesia, Malaysia, and, to a lesser extent, the Philippines, depended heavily on Japanese commercial bank lending on the eve of the South East Asian crisis (Kaminsky and Reinhart (2000)).[18] The presence of a significant common creditor across these countries is the basis of the common bank creditor channel for the transmission of contagion. That is, different countries are linked by the fact that a common international bank lends to these countries. Confronted by an increase in non performing loans in one country, the bank may reduce its exposure to loans in all countries, thereby transmitting the financial crisis. Our empirical results are consistent with Kaminsky and Reinhart's (2000) conclusion that these common financial linkages can better explain the observed patterns of contagion.

While Japanese bank lending was not particularly important in the case of Hong Kong or Singapore where we see no evidence of contagion, portfolio investors, especially mutual fund investors, played an important role in these two countries. In fact, Kaminsky, Lyons and Schmukler (2002) document that in the two quarters following July 1997, Hong Kong and Singapore suffered the largest mutual fund withdrawals of our sampled South East Asian countries, seven and twelve percent, respectively, of their preceeding quarter holdings. These large mutual fund outflows were prompted, in part, because the Singapore and Hong Kong markets are the most liquid and the most unrestricted of South East Asian markets[19]. Our empirical results suggest that while the crisis did result in an increase in the volatility of Hong Kong and Singapore stock returns, the flexibility and depth of

[17] Eichengreen, Rose, and Wyplosz (1996) argue that trade linkages can result in contagion as currency devaluation in one country reduces competitiveness in partner countries, prompting devaluations to restore this competitiveness.

[18] As tabulated by Kaminsky and Reinhart (2000), fifty-four percent of Thai liabilities were to Japanese banks as of December 1996. The comparable figures were thirty-nine percent and thirty-seven percent for Indonesia and Malaysia. By contrast, only twelve percent of Philippines liabilities were to Japanese banks. However, American banks accounted for nearly thirty percent of Philippine liabilities on the eve of the crisis.

[19] By contrast, for example, in September 1997 the Malaysian government banned short selling on equity markets and imposed restrictions on forward sales of the ringgit.

these markets together with an absence of restrictive government intervention prevented a statistical discernable increase in the correlation of their returns with Thai returns where mutual funds holdings were minimal.

5 Conclusions

Defining contagion as a significant change in cross-market linkages in response to a shock or crisis requires a realistic modeling of these linkages outside of the crisis period. In particular, in the absence of a crisis, it is well known that security returns exhibit stochastic volatility and the correlations between returns are also stochastic. Prior investigations of contagion, unfortunately, have not taken this stochastic nature of covariance into account but rather have relied on static models in which a shift in covariance is permitted only around a particular crisis.

This paper more fully assesses changes in cross-market linkages by explicitly recognizing the stochastic interdependence between markets. We measure contagion and volatility spillover relative to this stochastic interdependence. Concentrating on the South East Asian crisis of July 1997, we find clear evidence of volatility spillover in the equity returns of our sampled countries of Hong Kong, Indonesia, Malaysia, the Philippines, Singapore and Thailand. By contrast, the evidence for contagion is country-dependent. In particular, we see reliable evidence of contagion between Thailand and the lesser developed nations of Indonesia, Malaysia, and the Philippines, but not between Thailand and the more developed nations of Hong Kong and Singapore.

Appendix

Implementation of the Estimation Methodology

All computations are performed in GAUSS. Stable and reliable results are obtained using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm after an appropriate starting value was selected. Each pair of countries generates three times series of observations representing two sample log volatilities and one Fisher-transformed sample correlation.

1. We first fit univariate linear state space models for each of the three series. This is equivalent to fitting the general multivariate model under the restriction that T, Q, and H are diagonal. It is straightforward to implement this estimation.

2. The first step for the multivariate approach was to implement the EM algorithm for 150 iterations using the estimated coefficients from the above restricted model as starting values. See Shumway and Stoffer (1982) for details. This method monotonically increases the likelihood function and works well initially from a variety of starting values. Significantly, Q and H are necessarily positive definite using this technique. Unfortunately the method becomes much slower when nearing the optimum.

3. For the second step we employed the resultant EM estimates as starting values and then implemented the BFGS algorithm. We worked with the Choleski factorization of H and Q to ensure positive definiteness. Experiments revealed that this two-stage approach provided stable results. We obtain standard errors via the outer product method. The resultant standard errors are useful for implementing single restriction t-tests on the parameters. We also ran a number of likelihood ratio statistics based on various restrictions of the model. As a test of the reliability of the method we compared likelihood ratio statistics with one restriction p-values with p-values associated with the individual t-statistics. The matches are good.

Table 1: Summary Statistics

This Table provides summary statistics for the log variances of the returns of the Hong Kong, Indonesia, Malaysia, Philippines, Singapore, and Thailand markets (Panel A) as well as the Fisher transformed correlations of the Thailand returns with Hong Kong, Indonesia, Malaysia, Philippines, and Singapore returns (Panel B). Jq-Bera denotes the Jarque-Bera statistic for testing the null hypothesis of normality, $AC(n)$ denotes the autocorrelation of order n and ADF denotes the Augmented Dickey Fuller test statistic for testing the null hypothesis of a unit root, corrected for serial correlation of order 8. Critical values for the ADF tests are -3.44 (1 percent), -2.87 (5 percent), and -2.57 (10 percent). Our sample period begins on Wednesday 4/9/1990 and ends on Wednesday 4/22/2002.

Panel A: Log Variances

Country	Hong Kong	Indonesia	Malaysia	Philippines	Singapore	Thailand
Mean	0.368	0.695	0.118	0.304	-0.159	0.808
Median	0.371	0.594	-0.035	0.417	-0.174	0.825
Maximum	4.419	7.010	5.610	4.428	4.055	4.706
Minimum	-3.652	-4.278	-3.512	-3.725	-4.253	-2.869
Std. Deviation	1.111	1.582	1.368	1.286	1.152	1.289
Skewness	0.075	0.377	0.614	-0.136	0.105	0.032
Kurtosis	3.410	3.627	3.833	3.140	3.298	2.869
Jq-Bera	4.989	25.181	57.754	2.459	3.489	0.555
(p-value)	(8.3%)	(<1%)	(<1%)	(29.2%)	(17.5%)	(75.7%)
$AC\,(1)$	0.442	0.576	0.545	0.443	0.521	0.484
$AC\,(2)$	0.391	0.576	0.504	0.345	0.426	0.429
$AC\,(3)$	0.353	0.485	0.482	0.321	0.406	0.387
$AC\,(4)$	0.330	0.482	0.461	0.270	0.361	0.313
$AC\,(8)$	0.342	0.451	0.407	0.267	0.319	0.362
$AC\,(13)$	0.235	0.402	0.376	0.227	0.263	0.303
$AC\,(26)$	0.167	0.289	0.285	0.126	0.246	0.270
ADF	-4.068	-3.117	-3.565	-4.616	-4.406	-3.835

Panel B: Fisher Transformed Correlations

Thailand *vs*	Hong Kong	Indonesia	Malaysia	Philippines	Singapore
Mean	0.358	0.255	0.370	0.258	0.395
Median	0.358	0.227	0.310	0.267	0.361
Maximum	2.937	2.609	2.905	2.687	2.469
Minimum	-1.432	-1.575	-1.631	-1.909	-1.427
Std. Deviation	0.661	0.610	0.650	0.658	0.627
Skewness	0.252	0.195	0.135	0.074	0.184
Kurtosis	3.478	3.493	3.349	3.612	3.057
Jq-Bera	12.669	10.338	5.093	10.394	3.619
(p-value)	(<1%)	(<1%)	(7.8%)	(<1%)	(16.4%)
$AC\,(1)$	0.184	0.071	0.126	0.106	0.160
$AC\,(2)$	0.133	0.095	0.083	0.135	0.087
$AC\,(3)$	0.136	0.139	0.066	0.130	0.103
$AC\,(4)$	0.105	0.119	0.037	0.095	0.031
$AC\,(8)$	0.122	0.164	0.063	0.108	0.027
$AC\,(13)$	0.056	0.106	0.019	0.055	0.038
$AC\,(26)$	0.057	0.019	0.010	0.071	0.020
ADF	-5.958	-5.740	-6.666	-5.748	-6.834

Table 2: Test Results

This Table summarizes the tests results obtained by fitting our state-space model to Thai returns paired with the returns of Hong Kong (Panel A), Indonesia (Panel B), Malaysia (Panel C), Philippines (Panel D), and Singapore (Panel E). In each case, the South East Asian crisis is assumed to commence during the first week of July 1997, that is, week 378 of our sample and to conclude either one year later, window=[378,429], two years later, window=[378,481], or three years later, window=[378,533]. The log-likelihood of the resultant model is denoted by $\mathcal{L}$. The likelihood ratio statistic $\mathcal{LR}_1$ tests whether the measurement error covariance matrix H is diagonal, the likelihood ratio statistic $\mathcal{LR}_2$ tests whether there is a shift in any of the covariance parameters over the designated window under the full model, while the likelihood ratio statistic $\mathcal{LR}_3$ tests whether there is a shift in any of the covariance parameters over the designated window under the restriction that the measurement error covariance matrix H is diagonal. Here $***$ indicates significance at the 1% level, $**$ indicates significance at the 5% level, and $*$ indicates significance at the 10% level. The parameter ∇d_1 measures the shift in the log volatility of Thai returns over a given window, the parameter ∇d_2 measures the shift in the log volatility of the other sampled South East Asian returns paired with Thai returns while ∇d_3 measures the shift in the correlation between these returns. Asymptotic standard errors of these estimates are also provided. Our sample period begins on Wednesday 4/9/1990 and ends on Wednesday 4/22/2002.

A: Thailand *vs* Hong Kong

	window=[378,429]		window=[378,481]		window=[378,533]	
	estimate	std. error	estimate	std. error	estimate	std. error
∇d_1	1.13665	0.43835	1.27243	0.27013	1.28203	0.21725
∇d_2	-0.08147	0.36859	0.30332	0.27095	0.59530	0.25074
∇d_3	0.27516	0.16332	0.28905	0.12535	0.17281	0.12133
$\mathcal{L}$	-2310.81923		-2305.72735		-2306.27347	
$\mathcal{LR}_1$	18.6248***		10.3086**		12.13448***	
$\mathcal{LR}_2$	8.89698**		19.08074***		17.9885***	
$\mathcal{LR}_3$	11.3708***		29.8708***		26.95266***	

B: Thailand *vs* Indonesia

	window=[378,429]		window=[378,481]		window=[378,533]	
	estimate	std. error	estimate	std. error	estimate	std. error
∇d_1	1.18859	0.42026	1.16133	0.29435	1.16860	0.23753
∇d_2	1.54759	0.45402	1.21680	0.38832	1.36032	0.29877
∇d_3	0.37462	0.11204	0.38166	0.10418	0.29811	0.09995
$\mathcal{L}$	-2422.98231		-2420.06298		-2421.72714	
$\mathcal{LR}_1$	6.14171		7.21698*		8.03**	
$\mathcal{LR}_2$	13.0195***		18.85812***		15.5928***	
$\mathcal{LR}_3$	22.6436***		27.6824***		23.54106***	

C: Thailand *vs* Malaysia

	window=[378,429]		window=[378,481]		window=[378,533]	
	estimate	std. error	estimate	std. error	estimate	std. error
∇d_1	0.37201	0.46202	1.11832	0.25186	1.25885	0.26494
∇d_2	1.12665	0.43826	1.90310	0.18841	1.30187	0.22530
∇d_3	0.39178	0.12932	0.26674	0.09158	-0.05285	0.09298
$\mathcal{L}$	-2397.19873		-2393.27945		-2393.5481	
$\mathcal{LR}_1$	13.0875***		20.94554***		10.88982**	
$\mathcal{LR}_2$	7.99602**		15.83458***		15.29728***	
$\mathcal{LR}_3$	5.56034		5.54086		15.05928***	

Table 2 (continued)

D: Thailand *vs* Philippines

	window=[378,429]		window=[378,481]		window=[378,533]	
	estimate	std. error	estimate	std. error	estimate	std. error
∇d_1	1.46649	0.38845	1.58128	0.24042	1.52132	0.21318
∇d_2	1.27302	0.29140	1.50279	0.20677	1.00326	0.24327
∇d_3	0.31299	0.13704	0.25858	0.08308	0.34840	0.07227
$\mathcal{L}$	-2452.45669		-2444.18546		-2440.34855	
$\mathcal{LR}_1$	10.20708**		7.33878*		7.05974*	
$\mathcal{LR}_2$	13.54914***		30.0916***		37.76542***	
$\mathcal{LR}_3$	14.57256***		33.983322***		41.93618***	

E: Thailand *vs* Singapore

	window=[378,429]		window=[378,481]		window=[378,533]	
	estimate	std. error	estimate	std. error	estimate	std. error
∇d_1	0.68101	0.57657	0.97693	0.43370	1.11783	0.30166
∇d_2	0.55369	0.48559	0.87145	0.35717	1.07644	0.23732
∇d_3	0.08797	0.13224	0.07701	0.11652	0.14654	0.08686
$\mathcal{L}$	-2259.9259		-2258.91924		-2255.56266	
$\mathcal{LR}_1$	8.5603**		3.24684		1.25458	
$\mathcal{LR}_2$	1.91516		3.92848		10.64164**	
$\mathcal{LR}_3$	4.4288		11.75558***		20.461***	

6 References

1. Andersen, T., Bollerslev, T., Diebold, F. X., and Ebens, H., (2001), "The Distribution of Realized Stock Return Volatility", *Journal of Financial Economics*, Vol. 61, pp. 43-76.

2. Anderson, T. W., 1984, *An Introduction to Multivariate Statistical Analysis*, (Second Edition), Wiley, New York, N. Y.

3. Baig, T., and Goldfajn, I., 1999, "Financial Market Contagion in the Asian Crisis", *IMF Staff Papers*, Vol. 46, pp. 167-195.

4. Bartlett, M. S., and Kendall, D. G., 1946,"The Statistical Analysis of Variance-Heterogeneity and the Logarithmic Transform", *Supplement to the Journal of the Royal Statistical Society*, Vol. 8, pp. 128-138.

5. Campbell, J. Y., Lo, A. W., MacKinlay, A. C., 1997, *The Econometrics of Financial Markets*, Princeton University Press, Princeton, N. J.

6. Candelon,B., Hecq, A., and Verschoor, W. F. C., 2005 "Measuring common cyclical features during financial turmoil: Evidence of interdependence not contagion", *Journal of International Money and Finance*, Vol. 24, pp. 1317 - 1334.

7. Chakrabarti, R., and Roll, R., 2002, "East Asia and Europe during the 1997 Asian Collapse: A Clinical Study of a Financial Crisis", *Journal of Financial Markets*, Vol. 5, pp. 1-30.

8. Corsetti, G., Pericoli, M., and Sbracia, M., 2005, "'Some contagion, some interdependence': More pitfalls in tests of financial contagion", *Journal of International Money and Finance*, Vol. 24, pp. 1177 - 1199.

9. Eichengreen, B., Rose, A., and Wyplosz, C., 1996, "Contagious Currency Crises", NBER Working Paper Number W5681.

10. Forbes, K., and Rigobon, R. , 2002, "No Contagion, Only Interdependence: Measuring Stock Market Comovements", *Journal of Finance*, pp. 2223-2261.

11. Johnson, N. H., Kotz, S., and Balakrishnan, N., 1995, *Continuous Univariate Distributions*,(Second Edition, Volume 2), Wiley, New York, N. Y.

12. Harvey, A. C., 1990, *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, Cambridge, U. K.

13. Hotelling H., 1953,“New Light on the Correlation Coefficient and its Transform”, *Journal of the Royal Statistical Society, Series B*, Vol. 15, pp. 193-225.

14. Kaminsky, G. L., Lyons, R. K., and Schmukler, S., 2001, “Mutual Fund Investment in Emerging Markets: An Overview”, *World Bank Economic Review*, Vol. 15, pp. 315-340.

15. Kaminsky, G. L., and Reinhart, C. M., 2000, “On Crises, Contagion, and Confusion”, *Journal of International Economics*, Vol. 51, pp. 145-168.

16. Kaminsky, G. L., Reinhart, C. M., and Végh, C. A., 2003, “The Unholy Trinity of Financial Contagion”, *Journal of Economic Perspectives*, Vol. 17, pp. 51-74.

17. Kaminsky, G. L., and Schmukler, S., 1999, “What Triggers Market Jitters? A Chronicle of the Asian Crisis”, *Journal of International Money and Finance*, Vol. 18, pp. 537-560.

18. Kim, S., Shephard, N., and Chib, S., 1998, “Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models”, *Review of Economic Studies*, Vol. 65, pp. 361-394.

19. Loretan, M, and English R., 2000, “Evaluating ”Correlation Breakdown” During Periods of Market Volatility”, Board of Governors of the Federal Reserve System, Working Paper

20. Lütkepohl, H., 1993, *Introduction to Multiple Time Series Analysis*, (Second Edition), Springer-Verlag, Berlin.

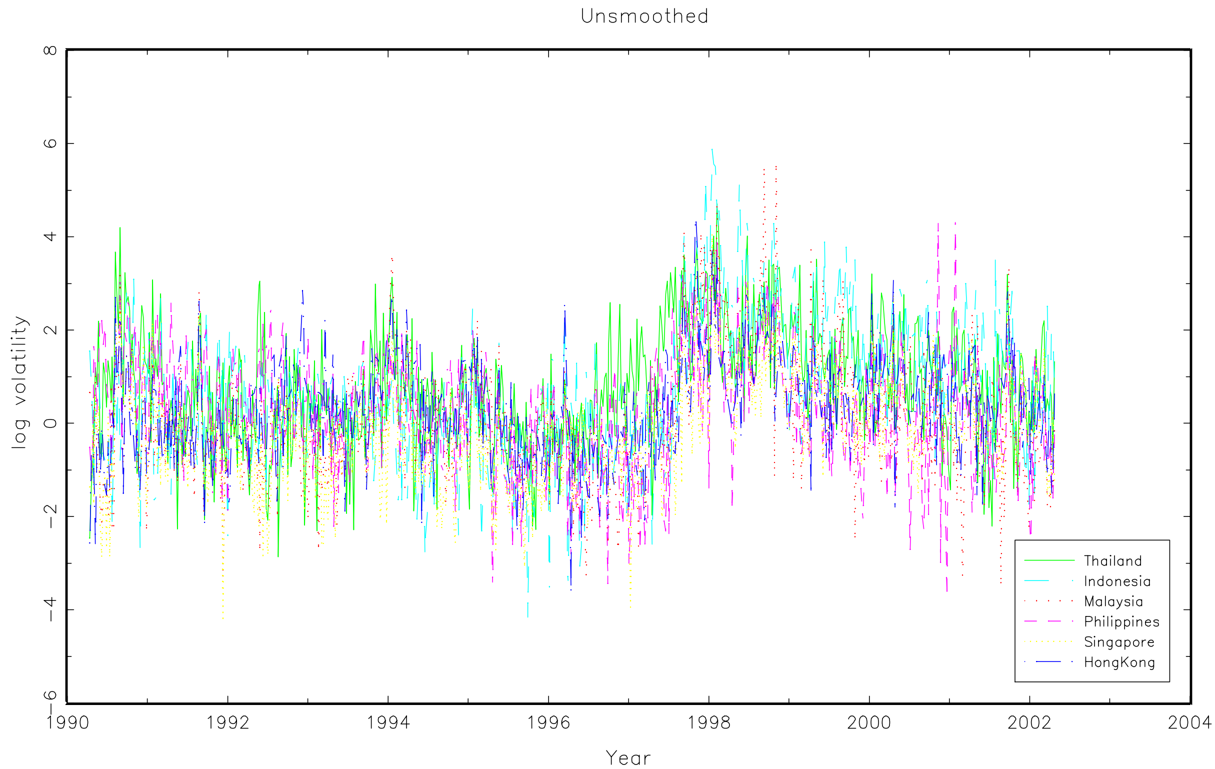
21. Mahieu, R., and Schotman, P., 1998, “An Empirical Application of Stochastic Volatility Models”, *Journal of Applied Econometrics*, Vol. 13, pp. 333-360.

22. Park, Y. C., and Song, C-Y, 2001, “Institutional Investors, Trade Linkage, Macroeconomic Similarities, and Contagion of the Thai Crisis”, *Journal of the Japanese and International Economies*, Vol. 15, pp. 199-224.

23. Solnik, B., Boucrelle, C., and Fur, Y. L., 1996, “International Market Correlation and Volatility”, *Financial Analysts Journal*, Vol. 52, pp. 17-34.

24. Winterbottom, A., 1979,"A Note on the Derivation of Fisher's Transformation of the Correlation Coefficient", *The American Statistician*, Vol. 33, pp. 142-143.

FIGURE 1


Unsmoothed
log volatility
Year
8
6
4
2
0
−2
−4
−6
1990
1992
1994
1996
1998
2000
2002
2004
Thailand
Indonesia
Malaysia
Philippines
Singapore
HongKong

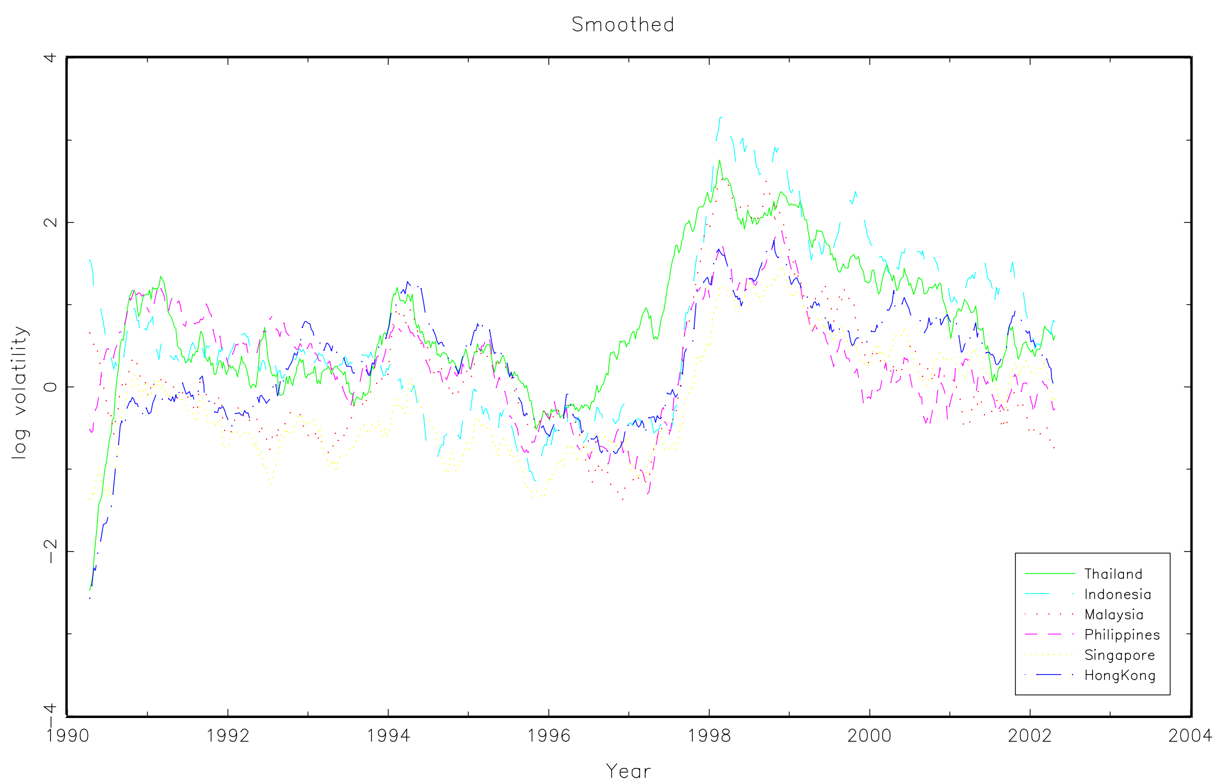
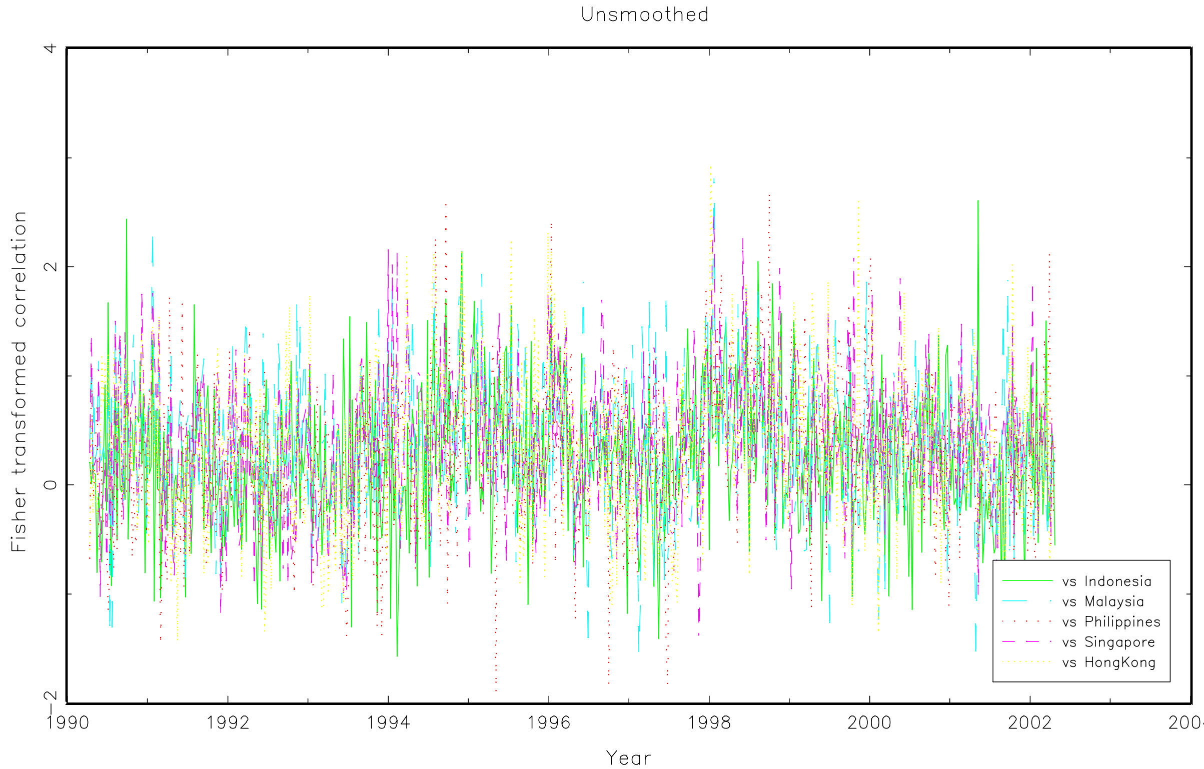
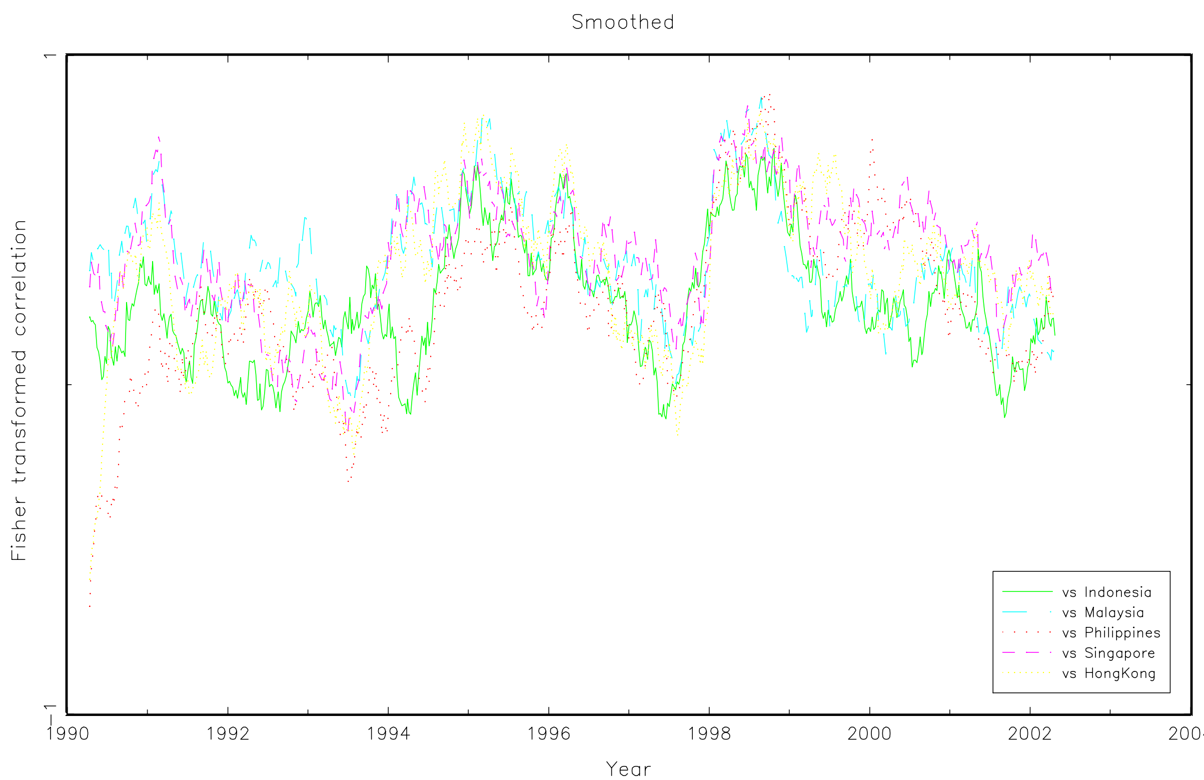

Smoothed
log volatility
Year
4
2
0
−2
−4
1990
1992
1994
1996
1998
2000
2002
2004
Thailand
Indonesia
Malaysia
Philippines
Singapore
HongKong

FIGURE 2


Unsmoothed
Fisher transformed correlation
4
2
0
−2
1990
1992
1994
1996
1998
2000
2002
2004
Year
vs Indonesia
vs Malaysia
vs Philippines
vs Singapore
vs HongKong


Smoothed
Fisher transformed correlation
1
−1
1990
1992
1994
1996
1998
2000
2002
2004
Year
vs Indonesia
vs Malaysia
vs Philippines
vs Singapore
vs HongKong