Measuring common cyclical features during financial turmoil

MEASURING COMMON CYCLICAL FEATURES DURING FINANCIAL TURMOIL: EVIDENCE OF INTERDEPENDENCE NOT CONTAGION

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Abstract

This paper develops a test of contagion in financial markets by considering a measure of co-movement based on the notion of common cycles to detect short run co-movements between a set of time series. We apply our methodology to the international effects of the 1994 Mexican peso crisis and the 1997 Asian crisis. Our results can be interpreted as evidence of a high level of market co-movement during all states of the world and, therefore, question the hypothesis of shift-contagion in the transmission of financial shocks during the 1997 Asian crisis, and to a lesser extend, the 1994 Mexican crisis.

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1 Introduction

The debate regarding the vulnerability of international financial markets and the propagation mechanisms of foreign shocks continues to be an issue of central concern in the international economics literature - see the recent book on international financial contagion edited by Claessens and Forbes (2001), for instance. Probably the most important factor that has generated this considerable interest, is the fact that the process of liberalization of international capital markets has had a direct impact not only on economic science, but also on the economic activity throughout the world; financial crises spread across emerging countries, thereby affecting apparently healthy economies whose policies, only a few months earlier, had been praised by market analysts and the multilateral institutions.

Internationally, capital market liberalization facilitated a greater flow of funds to (emerging) markets around the globe. The wide-ranging financial deregulation made it much easier for banks and domestic corporations to tap into foreign capital to finance domestic investments. On the one hand, such an evolution helps agents to reduce the riskiness of their assets by spreading their portfolios more widely, and creates new markets for domestic investments, which is no more bounded by national saving. Nevertheless, it also induces a rapid rise in financial flows leading to a higher (risk of) financial instability. Moreover, the greater financial interdependencies make countries (or continents) more vulnerable to financial crises via contagion effects.

It is a common belief that the most recent (Asian) financial crisis, that begun with the devaluation of the Thai bath in July 1997, is more widespread than previous crises, and hence is exerting a greater effect on commodity prices, financial markets and economic activity throughout the world; the perception has arisen that the crisis has been more virulent in its impact on the affected economies. In addition, it appears to be the first genuinely global financial crisis to hit the emerging market economies, affecting, as it has, Asia, Russia, South Africa, and Latin America. Furthermore, it appears to be more deeply rooted in financial imbalances in the private sector than in the public sector financial problems that characterized the 1980s debt crisis and the Mexican 1994-1995 crisis. This suggests the fundamental question raised by Kamin (1999), namely, "Have these crises grown increasingly severe in their impact on affected countries, or are we merely more aware of their impact and consequences than was the case in the past?"

As is well documented by extensive empirical work on the impact of high international turmoil, the financial contagion literature demonstrated several empirical contradictions with respect to the existence of contagion, the transmission channels of international shocks and causes of financial turmoil. Moreover, the paradoxes revealed in the data have in turn influenced both the development of new theoretical (transmission) models and the current debate on reforming the international financial architecture.

According to the group of crisis-contingent theories, a number of very different channels through which shocks could be transmitted internationally can be observed: multiple equilibria based on investors psychology, endogenous-liquidity shocks causing a portfolio recomposition and political economy affecting exchange rate regimes. Each of these theories could explain the existence of shift- contagion defined as a significant increase in cross-market linkage after a shock to an individual country (or group of countries). The first mechanism, multiple equilibria, occurs when a crisis in one country is used as a sunspot for other countries. The shift from a good to a bad equilibrium, and the transmission of the initial shock, is driven by a change in investors expectations or beliefs and not by any real linkages and therefore transmit the shock through a propagation mechanism that does not exist during stable periods. In the second model, the liquidity shock leads to an increased correlation in asset prices and this transmission mechanism does not occur during stable periods and only occurs after the initial shock. Finally, according to the political transmission mechanism, exchanges rate crises may be bunched together, and once again, transmission of the initial shock occurs through a mechanism that did not exist before the initial crisis. Although different approaches and models are used to develop these theories, they all share one critical implication: the transmission mechanism during the crisis is inherently different than that before the shock.

In contrast, the remainder of the theories explaining how shocks could be propagated internationally do not generate shift-contagion. These non-crisis-contingent theories assume that cross-market linkages do not increase after a shock; any large cross-market correlations after a shock are a continuation of (real) linkages that existed before the crisis. Examples of so-called "real linkages" transmission mechanism are trade, policy coordination, country reevaluation, country similarities and random aggregate shocks.

In general, any tests based on the concept of shift-contagion avoids taking a stance on how this shift occurs and avoids having to directly measure and differentiate between the various propagation mechanisms, such as real linkages and financial linkages. However, identifying if shift in cross-market linkages exists could provide evidence for or against certain theories of transmission and may indicate which propagation mechanisms are most important.

In addition to these theories, there is extensive empirical evidence on testing for contagion and the transmission of shocks. Four categories of tests have been utilized for evidence of contagion during a number of financial and currency crises: correlation of asset prices, GARCH frameworks (volatility spillovers), cointegration, and probit models. Overall, the findings overwhelmingly favor the conclusion that contagion - no matter how it is defined and given the range of techniques utilized - occurred during the crisis under investigation. For instance, King and Wadhwani (1990) test for an increase in cross-market correlations between the U.S., U.K. and Japan and find that correlations increase significantly after the U.S. stock market crash. Lee and Kim (1993) extend this analysis to twelve major markets and find further evidence of contagion. Calvo and Reinhart (1995) and Baig and Goldfajn (1998) present evidence for contagion after the 1994 Mexican peso crisis and the 1997 Asian crisis; cross-market correlations usually increased significantly during the crises period for many of the countries. Eichengreen et al. (1996) and Kaminsky and Reinhart (1998) estimate probit models to test how a crisis in one country (the exogenous event) affects the probability of a crisis occurring in other countries. The latter study finds that this probability increases when more crises are occurring in other countries (especially in the same region), whereas the former finds that the probability of a country suffering a speculative attack increases when another country is under attack. Taken together, the above evidence suggests that most shocks are transmitted through crisis-contingent channels, such as those based on multiple equilibria, endogenous liquidity, or political economy.

Forbes and Rigobon (2002), however, demonstrated that the presence of heteroscedasticity in market returns can have a significant impact on estimates of cross-market correlations. Therefore, when market volatility increases, which tends to happen during crises, any tests will overstate the magnitude of cross-market relationships and may suggest that contagion occurred, even when the underlying propagation mechanism is constant and shift-contagion does not occur. By using daily data for stock indices of 28 developed and emerging countries to test for evidence of contagion during the 1987 U.S. stock market crash, the 1994 Mexican peso crisis, and the 1997 Asian crisis, Forbes and Rigobon (2002) show that correlation coefficients for multicountry returns are not significantly higher during crisis periods if the problem of changes in the variance of residuals is properly corrected for. The large cross-market linkages after a shock are simply a continuation of strong transmission mechanisms that exist in more stable periods. In addition, Lomakin and Paiz (1999) address the problem of heteroscedasticity in test for contagion in bond markets. When they use the adjustment proposed in Forbes and Rigobon (2002) to correct the variance-covariance matrices, the number of crises and the strength of cross-country linkages are both reduced significantly, suggesting that most shocks are transmitted through non-crisis-contingent channels.

This paper extends the analyses of Forbes and Rigobon (2001, 2002) by considering a stronger measure of co-movements based on the notion of common cycles - see, for instance Engle and Kozicki (1993) and Vahid and Engle (1993). Indeed, in the presence of dynamic systems involving non-stationary variables, we believe that studies based on simple correlations on the variables in level (see inter alia Forbes and Rigobon, 2001, 2002) do not give a relevant measure of a common transmission mechanism. Our analysis relies on the concept of serial correlation common feature (SCCF) to detect short-run co-movements between a set of time series. Within a dynamic multivariate model (cointegrated vector error-correction model, VECM), SCCF enables us to assess a stronger measure for the link between the series. Simultaneously, it allows us to test for the existence of a common response to a shock, called collinear impulse responses (Vahid and

Engle, 1993) or short run attractor regimes (Candelon and Hecq, 2002). Generally, the change in the number of SCCF vectors constitutes a sufficient condition of evidence for or against shift-contagion. However, for those cases that a common factor before and after the crisis has been found, we extend the analysis by considering the ratio of the variance of the common factor to the total variance before and after the crisis. If this ratio does not change significantly, it would mean that there has been no significant change in the transmission mechanism during (or directly after) the crisis under investigation.

However, usual common cyclical feature test statistics, based on canonical correlation analyses (CCA) or on instrumental variables (IV) estimators, are affected by the presence of misspecification such as seasonality, outliers, and conditional heteroscedasticity and exhibit heavy size distortion in these cases - see, for instance Beine and Hecq (1999), and Hecq (1998). Therefore, the attempt to detect common cycles between series with non constant variance or volatile periods, characterizing financial turbulences, is quite hazardous. We evaluate through Monte Carlo simulations the behavior of different procedures for capturing co-movements in short run dynamics in the presence of additional perturbations. In particular, we address the interest of using robust GMM and nonparametric orthogonality tests in order to detect co-movements between economic time series subject to non-normal disturbances. Our tests demonstrated better size and power properties than the traditional instrumental variables (IV) and canonical correlation (CCA) tests in the presence of time-varying volatilities or outliers. We apply our methodology to the analysis of financial contagion during the Mexican crisis of 1994 and the Asian crisis of 1997. We find evidence of a high level of market co-movement during all states of the world and, therefore, question the hypothesis of contagion in the international transmission of financial shocks during the 1997 Asian crisis, and to a lesser extend, the 1994 Mexican peso crisis. This is in line with the findings of Forbes and Rigobon (2002), according to which there is "no contagion, only interdependence"; large cross-market linkages after a shock are merely a continuation of strong transmission mechanisms that already existed in more stable periods, suggesting that most shocks are transmitted through non-crisis-contingent channels, such as those based on trade, policy coordination and random aggregate shocks.

The remainder of this paper is organized as follows. The methodology and models employed to examine the co-movements and cross-market linkages during financial turbulence are explained in Section 2. Section 3 reports the results of the Monte Carlo investigation. Section 4 presents the empirical results and Section 5 contains our concluding comments.

2 Common Cyclical Features

2.1 Model Representation

Let us consider $\Phi(L)Y_t = \varepsilon_t$ a VAR(p) for a n-vector of I(1) time series $Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})'$, $t = 1, \ldots, T$ for fixed values of $Y_{-p+1}, ..., Y_0$ and where $\Phi(L) \equiv I_n - \sum_{i=1}^{p} \Phi_i L^i$, and $\varepsilon_t \sim$

$NIID(0, \Omega_\varepsilon)$ errors . For notational convenience, deterministic terms are omitted at this level of presentation.

We further assume that the process Y_t is cointegrated of order (1,1), so that $rank(\Phi(1)) = r$, $0 < r < n$, and $\Phi(1)$ can be expressed as $\Phi(1) = -\alpha\beta'$, with α and β both $(n \times r)$ matrices of full column rank r. We also rule out the presence of I(2) or explosive processes. The columns of β span the space of cointegrating vectors, and the elements of α are the corresponding adjustment coefficients. Using the identity $\Phi(L) \equiv \Phi(1)L + \Gamma(L)\Delta$ where $\Gamma(L) = I_n - \sum_{i=1}^{p-1} \Gamma_i L^i$, and $\Gamma_i = -\sum_{j=i+1}^{p} \Phi_j$ for $i = 1, \ldots, p-1$ we obtain the VECM (See Johansen, 1995)

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t. \tag{1}$$

Definition 1 *Serial Correlation Common Feature (SCCF). The Series ΔY_t have s SCCF relationships iff there exists a $n \times s$ matrix δ such that δ is full column rank and $\delta' \Delta Y_t = \delta' \varepsilon_t$ is a s dimensional white noise. SCCF implies the following restrictions on the VECM (1) matrix parameters: i) $\delta' \alpha = 0$ and ii) $\delta' \Gamma_i = 0$, $i = 1 \ldots p-1$.*

To stress the smaller number of propagation mechanism when SCCF are detected, the VECM in (1) can be written as a dynamic factor model

$$\Delta Y_t = \delta_\perp A' W_t + \varepsilon_t = \delta_\perp F_t + \varepsilon_t, \tag{2}$$

with $\delta_\perp$ the orthogonal complement of δ and F_t a reduced number of common propagation mechanisms given by the product of a $(n-s) \times (r+n(p-1))$ reduced rank matrix A' and the dynamics in $W_t = (Y'_{t-1}\beta, \Delta Y'_{t-1}, \dots, \Delta Y'_{t-p+1})'$. Importantly enough, the main characteristic of the factor representation (2) is that all the dynamics of the system is included in F_t. This is not generally the case in the traditional dynamic factor modeling where the idiosyncratic terms may be more cyclical than the factor itself. The price to pay with such a SCCF approach however is that such a matrix may not exist.[1]

The equivalence of the SCCF to the presence of common propagation mechanism may also be analyzed through the Wold representation $\Delta Y_t = C(L)\varepsilon_t$, with $\Sigma_{j=1}^{\infty} j|C_j| < \infty$, and $C_0 = I_n$. Indeed, from definition we have $\delta' C(L) = \delta'$, which means that the impulse response functions of the series Y_t are collinear. Based on the polynomial factorization $C(L) = C(1) + \Delta C^*(L)$, where $C_i^* = -\Sigma_{j=i+1}^{\infty} C_j$ for $i \geq 0$, we obtain the multivariate Beveridge and Nelson (1981) representation of the series $Y_t = \tau_t + \mu_t$, where $\mu_t = C^*(L)\varepsilon_t$ is the transitory part and $\Delta\tau_t = C(1)\varepsilon_t$ the first difference of the permanent part. The presence of r cointegrating vectors tells us that there exist $n-r$ common trends and $C(1)$ is of reduced rank $n-r$. On the other hand, the presence of s co-feature vectors implies, for $r+s \leq n$, that there exist $n-s$ common cycles generating Y_t with now $C^*(L)$ of rank $n-s$ and thus with $\delta' C^*(L) = 0$. Consequently we see that common cyclical feature is a way to fully characterize a dynamic system by adding

[1] Notice that we could relax the strong white noise assumption underlying the SCCF approach and use less stringent modeling such as the Codependence Cycle (Vahid and Engle, 1997), the Weak Form reduced rank structure (Hecq, et al., 2000) or the Polynomial Serial Correlation Common Feature (Cubadda and Hecq, 2001) approaches. Non-linear models have also been proposed (Anderson and Vahid, 1998; Candelon and Hecq, 2002).

to the common trends an information concerning the short run, namely the business cycle co-movements. While the cointegrating vectors annihilate the common trends, the common feature vectors annihilate the common cycles.

Besides the grid search procedure originally proposed by Engle and Kozicki (1993) for common serial correlation and common ARCH, there are two main methods to test for co-movements and to estimate common feature vectors: The full system approach based on canonical correlations and regression techniques based on IV, GIVE or GMM estimators. The second class of estimator presents some drawbacks such as the choice a normalization; it may also becomes tricky to apply for more than one cofeature relationship. Nevertheless, they are easier to carry out in the presence of non-linearities (see Anderson and Vahid, 1998 and Candelon and Hecq, 2002).

2.2 Parametric Test Statistics with Constant Variance

The common feature null hypothesis consists of an orthogonality condition between a combination of variables and the past of the series. Consequently the use of IV type estimators and the associated orthogonality tests is straightforward in this context. Let us consider for the VECM in (1), W_t the $1+n(p-1)+r$ vector of instruments composed of lagged variables for the n series, the cointegrating vectors, and an intercept[2], i.e. $W_t = (\Delta Y_{t-1}', \ldots, \Delta Y_{t-p+1}', Y_{t-1}'\beta, 1)'$.

[2] We can choose between, first demeaning all variables or alternatively to keep an intercept both in the cofeature

The condition for $\tilde{\delta} = (1, \theta')'$ being a common feature vector for $(\Delta y_{1t}, \Delta X_t')'$, where $\Delta X_t = (\Delta y_{2t}, \ldots, \Delta y_{nt}, 1)'$, corresponds to the orthogonality of the linear combination $\Delta y_{1t} - \Delta X_t'\theta$ with the past information of the process.[3] In terms of moment conditions, it can be expressed as

$$g_T(\theta; \Delta y_{1t}, \Delta X_t, W_t) = E([\Delta y_{1t} - \Delta X_t'\theta] \otimes W_t') = 0. \tag{3}$$

The GIVE estimator is simply the 2SLS or the IV estimator when the instruments are the past of the series, namely

$$\hat{\theta}_{GIVE} = \left(\Delta \mathbf{X}'\mathbf{W}(\mathbf{W}'\mathbf{W})^{-1}\mathbf{W}'\Delta \mathbf{X}\right)^{-1} \left(\Delta \mathbf{X}'\mathbf{W}(\mathbf{W}'\mathbf{W})^{-1}\mathbf{W}'\Delta \mathbf{y}_1\right), \tag{4}$$

using the obvious temporal concatenation for all $t = 1 \ldots T$, i.e. $\mathbf{W} = (W_1, W_2, \ldots W_T)'$. The validity of the orthogonality condition and consequently the presence of a common feature vector is obtained via an overidentification test *à la* Hansen (see Hamilton, 1994), namely

$$Test = T[g_T(\hat{\theta}_{GIVE}; \Delta y_{1t}, \Delta X_t, W_t]' P_T^{-1} [g_T(\hat{\theta}_{GIVE}; \Delta y_{1t}, \Delta X_t, W_t)],$$

whose empirical counterpart is

$$Test_1 = (\mathbf{u}'\mathbf{W})(\hat{\sigma}_u^2 \mathbf{W}'\mathbf{W})^{-1}(\mathbf{W}'\mathbf{u}).$$

relationship named $\tilde{\delta}$ and in the instruments.

[3] An intercept has been introduced in the regression. Additional components can be considered such as seasonal dummies, outliers, deterministic trends or other exogenous variables.

The variance covariance matrix of the orthogonality condition has under usual regularity properties the sample counterpart $\hat{P}_T = (1/T)\hat{\sigma}_u^2(\mathbf{W}'\mathbf{W})$ with $u_t = \Delta y_{1t} - \Delta X_t'\hat{\theta}_{GIVE}$. $Test_1$ follows asymptotically a $\chi^2_{(v)}$ under the null. The number of degrees of freedom is given by the number of restrictions the null hypothesis imposes, i.e. $v = s \times (n(p-1)+r) - s(n-s)$ or $v = n(p-2)+r+1$ with $s = 1$.

The canonical correlation (CCA) procedure is given by the solution of

$$CanCor \left\{ \Delta Y_t, \begin{pmatrix} \hat{\beta}' Y_{t-1} \\ \Delta Y_{t-1} \\ \Delta Y_{t-2} \\ \vdots \\ \Delta Y_{t-p+1} \end{pmatrix} \mid f_t \right\} \tag{5}$$

where $CanCor(Y, X \mid Z)$ denotes the partial canonical correlations between the elements of Y and X conditional on Z (netting out the effect of Z), $\hat{\beta}$ is a superconsistent estimate of the cointegrating vectors, and f_t is a vector of fixed elements such a constant, a linear trend, and seasonal dummies.

The likelihood ratio (LR) test for the null hypothesis that there exist at least s SCCF vectors is based on the statistic (see *inter alia* Anderson, 1984; Velu *et al.*, 1986)

$$Test_2 = -T \sum_{i=1}^{s} \ln(1 - \hat{\lambda}_i), \qquad s = 1, \dots, n \tag{6}$$

where $\hat{\lambda}_i$ is the $i-$th smallest squared canonical correlation coming from the solution of (5). The test statistic (6) follows asymptotically a $\chi^2_{(v)}$ distribution under the null where $v = s \times (n(p -$

$1) + r) - s(n - s)$, or also $v = n(p-2) + r + 1$ with $s = 1$.

2.3 Robust GMM

Both GIVE and CCA estimators assume homoskedasticity, i.e. that the variance is constant through time. Clearly, this is unsatisfactory for the main purpose of our paper; we try to study common propagation mechanisms during highly volatile periods and, consequently, try to extract common dynamics from the variability feature. However, the presence of (conditional) heteroskedasticity can have a significant impact on t or F tests because the variance-covariance matrices are not properly estimated - see, for instance Hamilton (1994), Hayashi (2000), and Greene (2003). We, therefore, use a robust GMM test statistic and extend the GIVE estimator by the use of White's H.C.S.E. estimator such that

$$\hat{\theta}_{GMM} = \left(\Delta\mathbf{X}'\mathbf{W}(\mathbf{W}'\mathbf{B}\mathbf{W})^{-1}\mathbf{W}'\Delta\mathbf{X}\right)^{-1}\left(\Delta\mathbf{X}'\mathbf{W}(\mathbf{W}'\mathbf{B}\mathbf{W})^{-1}\mathbf{W}'\Delta\mathbf{y}_1\right),$$

where the only difference with the usual $\hat{\theta}_{GIVE}$ estimation is the presence of an additional matrix $\mathbf{B}$ constructed such that

$$\mathbf{B} = \begin{pmatrix} u_1^2 & 0 & \cdots & 0 \\ 0 & u_2^2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & u_T^2 \end{pmatrix},$$

with $u_t = \Delta y_{1t} - \Delta X_t'\hat{\theta}_{GIVE}$, $t = 1 \ldots T$, the residuals obtained under homoskedasticity using the GIVE estimation in a first step.[4] We may then form the following new sequence of residuals

$$u_t^* = \Delta y_{1t} - \Delta X_t' \hat{\theta}_{GMM},$$

and use these to compute a new test robust to heteroscedasticity

$$Test_3 = (\mathbf{u}^{*\prime}\mathbf{W})(\mathbf{W}'\mathbf{B}\mathbf{W})^{-1}(\mathbf{W}'\mathbf{u}^*).$$

The test statistic $Test_3$ follows asymptotically a $\chi^2_{(v)}$ distribution under the null of SCCF where $v = n(p-2) + r + 1$ for $s = 1$.

2.4 Nonparametric Tests

The introduction of nonparametric tests, more robust to some noise in the residuals, will be applied after the estimation of potential common feature vectors via GIVE or CCA. Consequently, we do not use a nonparametric estimation of the common feature space, but we propose non-parametric orthogonality tests to detect the presence of common features. Keeping the notation of Campbell and Dufour (1995, 1997) we analyze the respective behavior of the sign test S_g and two versions of the sign rank test, SR_g and W_g such that

$$S_g = \sum_{i=1}^{T} u((\Delta y_{1t} - \Delta X_t' \hat{\theta})^m \otimes W_t^{c\prime}),$$

[4] Alternatively, the Newey-West estimator can be used.

$$SR_g = \sum_{i=1}^{T} u\left((\Delta y_{1t} - \Delta X_t'\hat{\theta})^m \otimes W_t^{c\prime}\right) R_{2t}^+,$$

$$W_g = \sum_{i=1}^{T} u\left((\Delta y_{1t} - \Delta X_t'\hat{\theta})^m \otimes W_t^{c\prime}\right) R_{1t}^+,$$

where $u(z) = 1$ if $z \geq 0$ and $u(z) = 0$ if $z < 0$, R_{1t}^+ is the rank of $|(\Delta y_{1t} - \Delta X_t'\hat{\theta})^m \otimes W_t^{c\prime}|$ while R_{2t}^+ is the rank of $|(\Delta y_{1t} - \Delta X_t'\hat{\theta})^m|$. The superscript "$c$" means that the variables have been centered where the centering is based only on information available at time t, i.e. for a time series Z_t,

$$Z_t^c = Z_t - median(Z_t, Z_{t-1}, ..., Z_0),$$

while for

$$Z_t^m = Z_t - median(Z_T, Z_{T-1}, ...Z_0),$$

the median is computed on the whole sample.

The standardized statistics

$$\frac{(S_g - 0.5T)}{0.5\sqrt{T}}; \qquad \frac{(SR_g - \frac{T(T+1)}{4})}{\sqrt{\frac{T(T+1)(2T+1)}{24}}}; \qquad \frac{(W_g - \frac{T(T+1)}{4})}{\sqrt{\frac{T(T+1)(2T+1)}{24}}},$$

follow asymptotically a $N(0,1)$ under the null hypothesis of zero correlation between the residuals and the instruments (see Campbell and Dufour, 1995, 1997) for a complete presentation of these test and their asymptotic distributions).

Unfortunately, although nonparametric tests are exact in finite sample when the median is known, their behavior is more complicated when parameters are estimated. Campbell and Dufour (1995, 1997) propose to build a bound test when the median is computed from the data. The situation we face here is still more difficult because we use a two step approach that involves a lot of unknown parameters and to the best of our knowledge, even a bound test can not be set up in this framework. We decide then to illustrate the behavior of these tests as if they were exact. When more than one orthogonality restriction is tested, Bonferoni bounds are used to keep the overall significance test at its nominal level. For instance, in our simulation study, we have four orthogonality conditions. GIVE, GMM and CCA procedures are joint statistics for these restrictions. To be comparable, we take the maximum value of the individual nonparametric tests and confront it with the significance level at $\frac{\alpha}{\#\ of\ ortho\ conditions}$. For instance with 4 orthogonality conditions and with a significance level of 5%, we look at a 1.25% significance level for the largest statistic.

3 Monte Carlo Simulations

Our Monte Carlo experiments are based on a bivariate stationary VAR with two lags and the following Data Generating Process (DGP):

$$
\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} 1.15 \\ -0.25 \end{pmatrix} + \begin{pmatrix} 0.7 & -0.2 \\ -0.7 & 0.2 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix}
$$

$$
+ \begin{pmatrix} -0.2 & 0.5 \\ 0.2 & -0.5 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix},
$$

with the error process given by

$$
\begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \sim NIID \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0.5 \\ 0.5 & 1 \end{pmatrix} \right].
$$

Results are independent of the set of coefficients under the null of common features. The only problem could arise from the presence of weak instruments that would occur if the parameters are too close to zero. It is why we choose coefficient values large enough to avoid that problem and consider a dynamics of order 2 often presented for macroeconomic time series. This process mimics two series whose cyclical fluctuations are countercyclical such as output and unemployment for instance. Indeed, under the null of serial correlation common features, there exists a vector $\delta^{'} = (1\ 1)$ whose premultiplication give $y_{1t} = -y_{2t} + \mu + \nu_t$, where ν_t is a white noise. In each case we generate $T + 100$ observations and we drop the first 100 to let the process be independent of the initial conditions. 10,000 replications with three sample sizes ($T = 50, 200$ and 500) are performed.

Two types of misspecification have then been introduced to mimic the financial turmoil.

First, an innovational outlier on the disturbances of one variable is introduced. More precisely, for two different positions in the sample, $t^* = T/2$ and $t^* = 3T/4$, we have put a large shock such that $\varepsilon_{1t^*} = 20 \times \varepsilon_{1t}$. They are reported as $\text{Shock}_{T/2}$ and $\text{Shock}_{3T/4}$ in Table 1. Second, the consequences of time varying conditional heteroscedasticity are also investigated via a GARCH(1,1), generated from the Bollerslev (1990) multivariate constant GARCH correlation model such that:

$$H_t = D_t C D_t,$$

where

$$D_t = diag(\sqrt{h_{it}}) = \begin{pmatrix} \sqrt{h_{1t}} & 0 \\ 0 & \sqrt{h_{2t}} \end{pmatrix}, \qquad C = \begin{pmatrix} 1 & 0.5 \\ 0.5 & 1 \end{pmatrix},$$

and

$$h_{it} = \omega_i + \alpha_i \varepsilon^2_{it-1} + \beta_i h_{it-1}, \qquad i = 1, 2, \tag{7}$$

$$\varepsilon_t = u_t \bar{H}_t,$$

with $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ and $u_t = (u_{1t}, u_{2t})'$ where u_{it} are two independent $N(0,1)$ and where $\bar{H}_t$ is derived from the Cholesky decomposition of $H_t = \bar{H}_t \bar{H}'_t$. We have considered in (7) numerical values that give unconditional (long-run) variances $\bar{\omega}_i = \frac{\omega_i}{1-\alpha_i-\beta_i}$ equal to 1, that is to say the same one we have under the model without GARCH (iid). Notice that the tests are still valid for integrated GARCH (IGARCH). We choose two sets of parameters often encountered in practice namely a model with a steep news impact curve $(\omega_i, \alpha_i, \beta_i) = (0.01, 0.20, 0.79)$ as well as a model with a less steep impact curve $(\omega_i, \alpha_i, \beta_i) = (0.01, 0.10, 0.89)$.

INSERT TABLE 1

Table 1 reports the rejection frequencies (namely the empirical size) of the different SCCF tests under *iid* disturbances and under various misspecifications. With *iid* disturbances, most tests have an empirical size close to the nominal one (i.e. 5%) except SR_g and W_g which are slightly undersized. Such a behavior has also been noticed by Campbell and Dufour (1995, 1997) and could be amplified in our case for several reasons: First, we do not consider bound tests, which might modified the critical value of individual tests and *à fortiori* the rejection frequencies of the joint test. Second, the number of orthogonality conditions are relatively large. This could lead to an underestimation of the critical value of the tests.

In the presence of an innovational outlier, GIVE and CCA tests present size distortion and are undersized, whereas nonparametric and robust GMM tests behave correctly and have their size around the nominal one. Two remarks can be set up: First, the robust GMM is undersized when the sample size is small (50 observations) which is not the case of non-parametric tests. Such a result is easy to understand as we use asymptotic distribution of the robust GMM test.

Second, the position of the innovative outlier has no effect on the respective size of the SCCF tests.

The major differences between the tests appear in the presence of GARCH in the error process. The sizes of both the GIVE and the CCA procedures increase dramatically with the value of α in the GARCH and, more problematically, with the number of observations. That leads these tests to be unreliable for empirical analyses with volatile series. Both the robust GMM and non parametric test give the correct size. To have a more precise clear-cut, an analysis of the power of the tests is helpful. Table 2 reports the size unadjusted power.[5] It turns out that the parametric test dominates non-parametric ones in term of power. This result is not surprising as non-parametric tests do not use the information on the variance. Furthermore, we do not have finite or asymptotic results for nonparametric tests when several parameters are estimated in a two step approach.

INSERT TABLE 2

This simulation section provides support in favor of the robust GMM procedure. Given the relative few additional computation involved by this test, it is surprising that it is not more often used in empirical works. A more general GMM test is generally used to correct for

[5] These results are obtained by replacing in the first autoregressive matrix of the DGP, the value 0.2 of the second row, second column, by -0.2.

MA component (Codependent cycle approach of Vahid and Engle, 1997), but heteroscedasticity biases are rarely taken into account.

4 Empirical Results

We apply our methodology to the analysis of financial contagion during the 1997 Hong Kong stock market crisis, which is one of the leading case-studies in Forbes and Rigobon (2002), and the 1994 Mexican peso crisis. Using the October crash of the Hong Kong market as the most likely event to drive contagion, we define our period of turmoil as lasting from October 17, 1997 (the crash of the stock market in Hong Kong crash, which plunged by 25 per cent in just four days starting on 17 October 1997) to the end of this month. We define the full period as stretching from 1 January 1996 to 31 December 1998. For the 1994 Mexican peso crisis, we define turmoil and full periods as lasting from 19 December, 1994 (the day the exchange rate regime was abandoned) through 31 December, 1994 and from 1 January, 1993 to 31 December, 1995, respectively. For both crises, the two subperiods before and after the turmoil are also considered separately. The data set consists of end-of-day stock price indexes in local currencies obtained from Datastream.

In our benchmark estimation of the international impact of the October 1997 stock market crisis in Hong Kong and the December 1994 peso crisis in Mexico, we first determine the optimal lag length for each bivariate systems (VAR in level). In order to test for the presence of a cointegrating vector, we perform the Johansen multivariate cointegration test (Johansen, 1995), where the lag length of the bivariate systems relies on the AIC information criterion.

INSERT TABLE 3

From Table 3 , we notice that the optimal lag length for the models in levels varies from 2 to 8, thus supporting all the bivariate systems with an informative dynamic part and suggesting the possibility of a reduction under common feature restrictions. Furthermore, the cointegration analysis rejects the presence of a long run relationship among all bivariate Latin American and Asian systems. It, however, tends to confirm the absence of long-run causality between stock markets, even if the countries belong to the same geographical area. The common feature analysis will thus be performed by using the VAR in first differences with $p-1$ lags in the right-hand-side equations. Table 3 also reports GARCH parameter estimates on excess returns. Interestingly, the GARCH parameters reveal a steeper news impact curve for the Latin American countries ($\alpha \in \{0.086, 0.387\}$), than for Asian countries ($\alpha \in \{0.068, 0.212\}$) whose volatility is more persistent with a higher value of β.

Once the preliminary results are settled, we turn to our common features test and estimation procedures for shift-contagion. As shown before, both GIVE and robust GMM are regression techniques and require a normalization, i.e. the choice of a dependent variable. Tables 4 and 5 present the results for the two normalizations - one on the benchmark country (Hong Kong or

Mexico), and one on the other country. In particular, the $p - values$ of the GIVE and robust GMM tests are reported. Note that we report the estimated coefficients only when the presence of a common feature is not rejected at the 5% significance level. Also, when the null of common feature is rejected with a $p - value$ smaller than 0.01, an entry < 0.01 is introduced in the corresponding cells.

INSERT TABLES 4 AND 5

From the tables, several patterns are immediately apparent. In some cases, the homoscedastic GIVE and robust GMM estimations provide different empirical results concerning the presence of common features. For instance, the GIVE test rejects the presence of common features between Hong Kong and Malaysia and between Hong Kong and Indonesia for all but one subsample, whereas the robust GMM test would lead us to accept the null hypothesis of a common feature. These results confirm our previous simulations, revealing that in presence of GARCH, the GIVE estimation has size distortions in comparison with the robust GMM test. In addition, the choice of the normalization country has only a minor impact on the (GMM) results, especially for the Asian countries. For all but one cases - the Philippines - the empirical test results are robust to altering the normalization. However, for the Latin American countries the GMM test results differ for Venezuela, Colombia and Chile.

Note that we define the absence of shift-contagion ('interdependence') as a system characterized by the same transmission mechanism for both subperiods, namely the pre and post-crisis periods. The transmission mechanism during the crisis, therefore, is not inherently different than that before the shock. Moreover, the acceptance of the serial correlation common feature hypothesis for the full period allows us to assume that there is no structural break in these relationships.

From the tables, it is clear that by using the robust GMM we cannot reject the common cyclical feature null hypothesis for the Asian countries, whereas the results for the Latin American countries are rather mixed depending marginally on choice of the normalization country. For instance, we find some evidence of contagion from the Mexican stock market to the stock markets in Venezuela, Colombia and Chile.

In addition to address the question whether the link (commom dynamics) becomes stronger after a crisis, we argue that the Asian findings based on the existence of a common serial correlation feature suffer from a major drawback; the acceptance of the SCCF hypothesis is a necessary, but not sufficient condition to assume the absence of shift-contagion. We, therefore, extend the analysis by considering the ratio of the variance of the common factor to the total variance before and after the crisis. If this ratio does not change significantly, it would mean that there has been no significant change in the transmission mechanism during (or directly after) the crisis under investigation. We follow Corsetti et al. (2002) principal component models by using the ratio of the variance of the country specific shock to the variance of the common factor weighted by its factor loading. More specifically, we propose a similar R^2 statistic - the ratio of the variance of the cyclical dynamics to the variance of the common factor, or, identically the R^2 of a regression of the most cyclical relationship on the common factor - and test whether this test statistic increases significantly during (or directly after) the crisis under investigation $(R_{s2}^2 - R_{s1}^2) > 0$, where $s_2(s_1)$ represents the post-crisis (pre-crisis) period. We thus consider the null hypothesis $R_{s2}^2 - R_{s1}^2 = 0$ and derive the corresponding test distribution through Monte-Carlo simulations.[6]

INSERT TABLES 6

In Table 6, we present different empirical quantiles of the distribution of $R_{s2}^2 - R_{s1}^2$. We report the "true" difference obtained from historical data together with the median, the 80%, 90%, and 95% confidence intervals obtained from 10.000 Monte-Carlo replications.[7] The results indicate that the proportion of the variance of the common cycle explained by common dynamics has increased in four countries. However, for all cases the test statistic differs not statistically from zero; the weight of the common factor has not significantly increased during the Asian crisis and suggests the absence of shift-contagion ("interdependence").

[6] See Appendix 1 for the derivation of the distribution.

[7] Note that for the Asian countries, the choice of the normalization country has only a minor impact on the (GMM) results. In Table 6, therefore, we only consider Hong Kong as the reference country.

Overall, our findings suggest that there is no longer evidence of a significant change in the transmission mechanism from Hong Kong to any of other country in our sample; most financial shocks are thus transmitted through non-crisis-contingent channels. These results can be interpreted as evidence of a high level of market co-movement during all states of the world and question the hypothesis of contagion in the international transmission of financial shocks during the 1997 Asian crisis, and to a lesser extend, the 1994 Mexican peso crisis.[8]

5 Conclusion

This paper has aimed at proposing a new emphasis in the analysis of contagion in financial markets by considering a measure of co-movement based on the notion of common cycles. In contrast to studies based on simple correlation analysis, as proposed by Forbes and Rigobon (2002), we rely on the concept of serial correlation common feature (SCCF) to detect short-run co-movements between a set of time series. We have shown through Monte Carlo simulations that robust GMM and nonparametric orthogonality tests are very helpful in detecting structural breaks in the mechanism of crisis transmission across countries even in the presence of time-varying volatilities.

In order to test whether international transmission mechanisms change during financial crisis,

[8] Note that Forbes and Rigobon (2002) perform sensitivity analyses with respect to benchmark countries and estimation periods. It turns out that their findings do not change significantly. We perform the same kind of test by extending the turmoil period one month before and one month after. Correspondingly, our findings do not change significantly for these new subperiods.

we apply our methodology to the international effects of the 1994 Mexican peso crisis and the 1997 Asian crisis. Overall, the results can be interpreted as evidence of a high level of market co-movement during all states of the world and, therefore, question the hypothesis of contagion in the international transmission of financial shocks during the 1997 Asian crisis, and to a lesser extend, the 1994 Mexican peso crisis, respectively. In particular, we only find evidence of contagion from the Mexican stock market to the stock markets in Venezuela, Colombia and Chile. Our results are in line with the findings of Forbes and Rigobon (2002), according to which there is 'no contagion, only interdependence'; large cross-market linkages after a shock are merely a continuation of strong transmission mechanisms that already existed in more stable periods, suggesting that most shocks are transmitted through non-crisis-contingent channels, such as those based on trade, policy coordination and random aggregate shocks.

This paper proposes a framework, which can be regarded as a first step in the analysis of the shift-contagion processes. In our view, future work should be directed in two ways. First, it could be interesting to consider multivariate analysis rather than bivariate VAR, where the debatable choice of a benchmark country in no longer valid. Second, our result of 'no contagion, only interdependence' has to be confirmed by using various non-financial indicators and should not only be due to the arbitrary restriction of the exclusive use of stock exchange data. Adopting different real variables, such as industrial production, capital flows and interest rates, may very well lead to a rejection the null hypothesis of 'no contagion', and indicate which propagation mechanisms are thus most important. In this respect, it may be advantageous to determine endogenously the date of the turmoil - see, for instance the MS-VAR approach of Candelon and Hecq (2002).

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Appendix 1: Distribution of the statistics via Monte-Carlo simulations

Let us consider a particular system, composed by 2 countries.

Step A- for the pre-crisis period.

step A1- Draw a sequence $\varepsilon_{1,t1}$ from a $N(0,\hat{\sigma}_1^2)$, where t_1 and $\hat{\sigma}_1^2$ represent the number of observations and $\hat{\sigma}_1^2$ an estimator of the variance.

step A2- Generate a Monte-carlo pseudo-sample (ΔY_t^*) of size t_1 using the centered sequence $\varepsilon_{1,t1}$ and the estimators of the VAR parameters in equation (1). Add also a multivariate constant GARCH correlation structure, estimated on the data.[9]

step A3- Estimate the cofeature vector δ^* and form its orthogonal complement $\delta^*_\perp$ from the pseudo-sample (ΔY_t^*) and a known lag length k.

step A4- Carry out an OLS regression from $\delta^*_\perp \Delta Y_t^*$ on $\Delta Y^{*\prime}_{t-1}, \ldots, \Delta Y^{*\prime}_{t-p+1}$ and an intercept. Compute then $R^{2(m)}_{s1}$, namely the proportion of the variance of the most cyclical relationship explained by the common factor.

Step B1 to B4- Repeat steps A1 to A4 for the characteristics of the post-crisis period, and obtain $R^{2(m)}_{s2}$.

Step C- Repeat A1 to B4 a large number of time (say M), compute at each replication

[9] It turns out that in all cases studied in the empirical part, the estimated GARCH structure presents parameters closed to the ones chosen in the simulation part. The constant correlation coefficient lies between [0.2,0.64].

$St^{(m)} = R_{s2}^{2(m)} - R_{s1}^{2(m)}$ for $m = 1, ..., M$ and build the distribution of S_t.

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Tables

Table 1
Empirical sizes of the different SCCF test statistics (nominal 5 -10,000 replic.)

DGP	T	GIVE	CCA	S_g	SR_g	W_g	GMM
iid	50	6.3	6.3	6.0	4.4	3.3	5.1
	200	5.4	5.4	4.6	3.9	3.2	5.3
	500	5.1	5.1	4.2	3.3	2.8	5.1
$\text{Shock}_{T/2}$	50	2.1	2.5	5.4	4.2	3.4	3.2
	200	3.5	3.6	4.6	4.1	3.3	4.3
	500	4.5	4.5	4.7	3.6	3.2	4.6
$\text{Shock}_{3T/4}$	50	2.1	2.5	5.9	4.2	3.2	2.9
	200	3.7	3.9	5.1	4.3	3.4	4.5
	500	3.9	4.0	4.6	3.6	3.0	4.5
$\text{GARCH}_{(0.01,0.10,0.89)}$	50	8.0	7.6	6.0	4.3	3.5	5.4
	200	8.9	8.9	4.7	4.1	3.3	5.3
	500	11.3	11.3	4.7	3.6	3.0	4.9
$\text{GARCH}_{(0.01,0.20,0.79)}$	50	10.2	9.8	6.1	4.5	3.9	5.3
	200	16.1	16.0	5.3	4.4	3.7	5.0
	500	23.7	23.7	5.9	4.5	4.0	4.5

Table 2

Size Unadjusted Power of SCCF Test Statistics -10,000 replic.

DGP	T	S_g	SR_g	W_g	GMM
iid	50	18.3	21.2	28.7	37.8
	200	64.7	84.1	93.3	97.8
$GARCH_{(0.01,0.20,0.79)}$	50	19.9	23.5	29.8	35.2
	200	62.7	81.3	89.1	88.4

:

Table 3
Descriptive Statistics

VAR	Lag length AIC criterion	Number of cointegration	GARCH(1,1) α	Parameters β
	wrt Mexico	wrt Mexico		
Argentina	2	0	0.086	0.902
Venezuela	2	0	0.387	0.574
Colombia	3	0	0.334	0.636
Chile	5	0	0.227	0.715
Mexico	–	–	0.086	0.878
	wrt Hong-Kong	wrt Hong-Kong		
Philippines	5	0	0.212	0.795
Indonesia	8	0	0.092	0.911
Korea	6	0	0.068	0.933
Malaysia	6	0	0.142	0.877
Singapore	4	0	0.139	0.850
Taiwan	5	0	0.107	0.777
Thailand	4	0	0.148	0.848
Hong-Kong	–	–	0.150	0.849

Table 4

SCCF Test Statistics, normalisation: Country i = fct(Hong Kong or Mexico)

VAR	GIVE						GMM					
	1/01/93-29/12/95		1/01/93-16/12/94		2/01/95-29/12/95		1/01/93-29/12/95		1/01/93-16/12/94		2/01/95-29/12/95	
	pval	β	*pval*	β	*pval*	β	*pval*	β	*pval*	β	*pval*	β
Argentina	0.41	1.89	0.94	1.08	0.98	2.59	0.38	1.86	0.95	1.08	0.99	2.59
Venezuela	< 0.01	–	< 0.01	–	< 0.01	–	< 0.01	–	< 0.01	–	0.11	0.25
Colombia	< 0.01	–	< 0.01	–	< 0.01	–	< 0.01	–	< 0.01	–	0.02	–
Chile	< 0.01	–	< 0.01	–	< 0.01	–	< 0.01	–	0.07	0.68	0.03	–
	1/01/96-31/12/98		1/01/96-16/10/97		3/11/97-31/12/98		1/01/96-31/12/98		1/01/96-16/10/97		3/11/97-31/12/98	
	pval	β	*pval*	β	*pval*	β	*pval*	β	*pval*	β	*pval*	β
Philippines	< 0.01	–	0.87	2.61	0.02	–	< 0.01	–	0.99	2.43	0.03	–
Indonesia	< 0.01	–	< 0.01	–	0.36	0.91	0.22	0.79	0.32	0.89	0.54	0.94
Korea	0.02	–	0.13	1.06	0.42	0.75	0.56	0.78	0.25	1.28	0.43	0.84
Malaysia	< 0.01	–	< 0.01	–	< 0.01	–	0.07	0.13	0.53	0.73	0.13	0.44
Singapore	< 0.01	–	0.52	0.78	0.06	0.55	0.06	0.54	0.78	0.73	0.19	0.56
Taiwan	< 0.01	–	0.30	0.55	0.39	0.47	0.18	0.88	0.22	0.51	0.32	0.51
Thailand	< 0.01	–	0.94	1.99	0.61	0.68	0.46	0.82	0.98	1.75	0.88	0.88

Table 5
SCCF Test Statistics, normalisation: Hong Kong or Mexico =fct(country i)

VAR	GIVE						GMM					
	1/01/93-29/12/95		1/01/93-16/12/94		2/01/95-29/12/95		1/01/93-29/12/95		1/01/93-16/12/94		2/01/95-29/12/95	
	pval	β	*pval*	β	*pval*	β	*pval*	β	*pval*	β	*pval*	β
Argentina	0.41	0.51	0.94	0.92	0.99	0.39	0.53	0.51	0.96	0.93	0.99	0.39
Venezuela	< 0.01	$-$	< 0.01	$-$	< 0.01	$-$	< 0.01	$-$	< 0.01	$-$	0.02	$-$
Colombia	< 0.01	$-$	< 0.01	$-$	0.04	$-$	0.02	$-$	< 0.01	$-$	0.24	-0.3
Chile	< 0.01	$-$	0.12	0.55	0.04	$-$	0.06	0.27	0.45	0.46	0.12	0.25
	1/01/96-31/12/98		1/01/96-16/10/97		3/11/97-31/12/98		1/01/96-31/12/98		1/01/96-16/10/97		3/11/97-31/12/98	
	pval	β	*pval*	β	*pval*	β	*pval*	β	*pval*	β	*pval*	β
Philippines	< 0.01	$-$	0.97	0.21	0.02	$-$	0.43	0.75	0.99	0.25	0.09	0.67
Indonesia	< 0.01	$-$	< 0.01	$-$	0.32	0.59	0.42	0.66	0.20	0.50	0.56	0.64
Korea	< 0.01	$-$	0.74	0.21	0.25	0.62	0.51	0.70	0.81	0.22	0.44	0.64
Malaysia	< 0.01	$-$	< 0.01	$-$	0.11	0.23	0.22	0.38	0.18	0.66	0.34	0.29
Singapore	< 0.01	$-$	0.70	0.67	0.04	$-$	0.23	1.21	0.85	0.83	0.22	1.16
Taiwan	< 0.01	$-$	0.39	0.34	0.43	1.02	0.74	0.75	0.45	0.31	0.40	1.02
Thailand	< 0.01	$-$	0.94	0.43	0.44	0.99	0.56	0.81	0.97	0.48	0.88	0.95

Table 6
Stability of the Factor in the most Cyclical Relationship - Asian Countries

	$R^2_{s2} - R^2_{s1}$	$R^2_{s2} - R^2_{s1}$	$R^2_{s2} - R^2_{s1}$	$R^2_{s2} - R^2_{s1}$	$R^2_{s2} - R^2_{s1}$
	Data Estim.	Median	80%	90%	95%
Philippines	0.018	0.005	[-0.054 : 0.066]	[-0.072 : 0.082]	[-0.087 : 0.097]
Indonesia	-0.067	-0.044	[-0.119 : 0.034]	[-0.140 : 0.057]	[-0.158 : 0.077]
Korea	0.026	0.051	[-0.013 : 0.117]	[-0.031 : 0.137]	[-0.047 : 0.155]
Malaysia	-0.069	-0.024	[-0.096 : 0.056]	[-0.117 : 0.077]	[-0.132 : 0.099]
Singapore	0.034	0.016	[-0.014 : 0.054]	[-0.023 : 0.067]	[-0.032 : 0.079]
Taiwan	0.022	0.012	[-0.022 : 0.049]	[-0.033 : 0.062]	[-0.042 : 0.074]
Thailand	-0.008	-0.005	[-0.048 : 0.037]	[-0.061 : 0.050]	[-0.073 : 0.062]