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CORRELATION ANALYSIS OF FINANCIAL CONTAGION: WHAT ONE SHOULD KNOW BEFORE RUNNING A TEST

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Abstract

This paper builds a general test of contagion in financial markets based on bivariate correlation analysis – a test that can be interpreted as an extension of the normal correlation theorem. Contagion is defined as a structural break in the data generating process of rates of return. Using a factor model of returns as theoretical framework, we nest leading contributions in the literature as special cases of our test. We show that, while the literature on correlation analysis of contagion is successful in controlling for a potential bias induced by changes in the variance of global shocks, current tests are conditional on a specific yet arbitrary assumption about the variance of country specific shocks. Our results suggest that, for a number of pairs of country stock markets, the hypothesis of 'no contagion' can be rejected only if the variance of country specific shocks is set to levels that are not consistent with the evidence.

Keywords: Contagion, financial crisis, correlation analysis.

JEL classification: F30, C10, G10, G15

1 Introduction

In the past few years, currency and financial crises originating in one country or group of countries have often spread internationally. In periods of instability, asset price movements and comovements across markets and across borders have increased visibly relative to more tranquil periods. The size of these comovements during crises have led many economists to raise the question as of whether 'tranquil periods' and 'crises' are to be interpreted as different regimes in the international transmission of financial shocks; that is, as of whether there are discontinuities in the international transmission mechanism.[1]

The headline of the theoretical and policy debate on this issue is usually 'contagion'.[2] Contagion – as opposed to 'interdependence' – conveys the idea that international transmission mechanism is discontinuous, as a result of financial panics, herding, or switches of expectations across instantaneous equilibria. Although there is considerable ambiguity on what contagion exactly is and how we should measure it, several authors have proposed empirical tests in an attempt to address the issue of contagion versus interdependence on empirical grounds (see Forbes and Rigobon (1999a and 1999b), Boyer et al. (1999), among others).

The idea underlying these studies is to compare cross-market correlation in tranquil and crisis periods and define *contagion as structural breaks in the parameters of the underlying data generating process.* Suppose that a crisis is caused by shocks to some global factors in the world economy. For a given mechanism of international transmission, changes in the volatility of asset prices in one market can be expected to be correlated with changes in volatility in other markets. During a period of financial turmoil, some comovements across markets are therefore an implication of interdependence. Contagion will instead occur when the observed pattern of comovement in asset prices is too strong, relative to what can be predicted when holding constant the mechanism of international transmission.

Using a simple factor model, this paper presents a critical assessment of the empirical literature on correlation analysis of contagion. Key to this literature is the specification of a theoretical measure of interdependence, suitable to capture the international effects of an increase in the volatility of asset prices *for a given transmission mechanism.* We show that many leading contributions derive such measure by (implicitly) making a specific yet arbitrary identification assumption about a key parameter. This is the ratio between the variance of the country-specific shock and the variance of the global factor weighted by its factor loading; we refer to it as the 'variance ratio', and denote it by λ. Tests that are conditional on a low value of λ, tend to accept the null hypothesis of interdependence, while tests that are conditional on a high value of λ tend to reject the null of no contagion. We provide some estimates of λ suggesting

[1] The possibility of such discontinuities are a concern for both investors and policy makers. If correlation across assets is abnormally high during financial crises, diversification of international portfolios may fail to deliver exactly when its benefits are needed the most. By the same token, excessive comovements of asset prices may spread a country-specific shock to other economies, even when these have better domestic fundamentals.

[2] A partial list of contributions to this debate include Baig and Goldfajn (1998), Bordo and Mushid (2000), Buiter et al. (1998), Calvo (1999), Calvo and Mendoza (1999), Caramazza et al. (2000), Claessens et al. (2000),Edwards (1998), Eichengreen et al. (1998), Jeanne and Masson (1998), Kaminsky and Reinhart (2000), Kaminsky and Schmukler (1999), Kodres and Pritsker (1999), and Schinasi and Smith (1999).

that, in a number of cases, the null hypothesis of interdependence would be erroneously accepted when adopting those 'adjusted' or 'corrected' correlation tests proposed by the literature, arbitrarily setting $\lambda = 0$.

The paper is organized as follows. Section 2 presents a few stylized facts about stock market returns in the nineties, comparing their behavior during crisis and tranquil periods. A notable point here is that financial crises are characterized by an increase in the variance and covariance of returns across markets, but not necessarily by an increase in correlation. Section 3 introduces a factor model and derives a general empirical test. Section 4 discusses the existing literature in light of our model. Section 5 carries on a test of financial contagion from the the Hong Kong stock market crisis in October 1997, as a representative case study.

2 Stylized facts

We start our analysis by presenting a set of stylized facts regarding the transmission of shocks across stock markets.[3] We single out four 'stylized facts' characterizing periods of international financial turmoil in our sample. The first two are well understood and extensively discussed by the literature. These are the concentration of sharp downward adjustments in stock prices and the sharp increase in average volatility of daily returns. The other two are often and somewhat surprisingly confused in both formal and informal discussions of contagion: crises are systematically associated with a sharp increase in the cross market *covariance* of assets' returns; yet the direction of the change in cross market *correlation* of asset returns is not homogeneous across countries and crisis episodes — in several cases correlation actually drops during a crisis relative to tranquil periods. This is more than a technical point, as it raises the issue of assessing the relative importance of country-specific factors, as opposed to global factors, underlying the increase in market volatility during periods of turmoil.

Our data set includes 18 countries: the G7 countries, Argentina, Brazil, Mexico, Russia, Hong Kong, Indonesia, South Korea, Malaysia, Philippines, Singapore and Thailand. We use daily and weekly data, from January 1990 to March 2000; the source is *Thomson Financial Datastream*. For each stock market in our sample, we examine levels and volatility of returns, calculated in local currency, as well as covariance and correlation patterns with other markets. We allow for four periods of crisis in international financial markets: from September 1992 to August 1993 (hereafter *ERM crisis*), from October 1994 to June 1995 (hereafter *Mexican crisis*), from July 1997 to January 1998 (hereafter *Asian crisis*), and from May 1998 to March 1999 (hereafter *Russian/Brazilian crisis*). The emphasis of the study is however on stock markets of emerging economies during the second half of the 1990s.

[3] In a companion paper, we present empirical evidence for nominal exchange rates against the U.S. dollar, overnight interest rates, and sovereign spreads of U.S. dollar denominated bonds with corresponding U.S. assets (see Corsetti et al., 2000).

2.1 Four empirical regularities

2.1.1 Sharp falls in stock prices tend to concentrate in periods of international financial turmoil.

In the literature, many authors have observed that financial crises are not randomly distributed. For instance, Eichengreen et al. (1996) noted that clusters of speculative attacks on the exchange rate of several countries in different periods are separated by long phases of tranquillity.

The stock market crises in our sample follow patterns that are consistent with this observation. While referring to IMF (1998 and 1999) for a comprehensive analysis of financial markets in our sample, here we note that, in the second half of the nineties, many *Asian* stock indexes started to decline some time before the eruption of the crisis in 1997 and together stayed on a descending path until the end of 1998 (see Corsetti et al. (2000) and Corsetti (1998)). Stock markets in Asia were not affected by the Mexican crisis, with the exception of Hong Kong. In *Latin America*, stock markets partially survived the Asian crisis, but were all greatly affected by the Mexican crisis and by the Russian/Brazilian crisis. The impact of the last episode was especially strong, bringing about a drop of over 50 per cent in stock indices. At the end of March 2000, stock prices of most emerging market economies had not recovered relative to their historical level. In the *G7 countries*, the impact of the Mexican and the Asian crises was negligible, while the effect of the Russian/Brazilian crisis was much deeper. Yet stock markets recovered quickly also after this crisis.

2.1.2 Volatility of stock prices increases during crisis periods.

Volatility of stock market returns is shown in Figures 1a and 1b. In *Asia* , stock market volatility increases everywhere in 1997-99 relative to 1990-96, with the sole exception of the Philippines.[4] In 1997 and 1998 volatility records two peaks, corresponding to the Asian and the Russian/Brazilian crises.[5] By contrast, Hong Kong is the sole country in the region that is significantly affected by the Mexican crisis. Overall, average volatility in 1997-99 is almost twice than in 1990-96. As regards *Latin American* countries, in the second half of the 1990s stock market volatility either decreases relative to previous record-high levels, as in the case of Argentina, or it remains constant, as in the cases of Brazil and Mexico. Volatility in these two countries is subject to large swings in correspondence with the crisis episodes — yet, it is around its sample average by the end of the decade. In *Russia*, volatility increases in 1997, peaking (dramatically) in

[4] We compute 'instantaneous' volatility of returns for country i at time t as an exponential-weighted moving average given by $\sigma_{i,t} = \sqrt{(1-\vartheta)\sum_{h=0}^{T-1}\vartheta^h(r_{i,t-h}-\overline{r}_i)^2}$, where ϑ is the decay factor (that we set equal to 0.96), T is the length of the moving window (that we pose equal to 3 months), $r_{i,h} = \log(x_{i,h}/x_{i,h-1})$ where $x_{i,h}$ is the value of the country i's stock market index at time h and $\overline{r}_i$ is the average of the variable $r_{i,h}$ in the period $[t-T+1,t]$. Analogously, instantaneous covariance is $\sigma_{ij,t} = (1-\vartheta)\sum_{t=0}^{T-1}\vartheta^h(r_{i,t-h}-\overline{r}_i)(r_{j,t-h}-\overline{r}_j)$ and the instantaneous correlation coefficient is $\rho_{ij,t} = \sigma_{ij,t}/(\sigma_{i,t}\sigma_{j,t})$. Volatility has also been estimated with a simple GARCH(1,1) model, which yields essentially the same results and, hence, it is not shown. Variables computed using daily, weekly and monthly returns give very similar results.

[5] Only in Argentina, Indonesia and Thailand volatility reached higher levels in 1990 than in 1997-99.

the summer of 1998.[6]

In *industrialized countries*, stock market volatility increases gradually from 1990 to 1999, with the exception of Japan, where it decreases, and France, where it shows no trend. In most countries, volatility peaks in 1990-92, then decreases until 1997, when it peaks again, reaching historical heights in 1998.

2.1.3 Covariance between stock market returns increases during crisis periods.

Covariance of weekly returns is presented in Figure 2a-2d. Figure 2a confirms that *Asian countries* are relatively unaffected by the Mexican crisis. Although covariance is never nil during this crisis (as is in most tranquil periods), its level is often lower than the peaks recorded before and after the crisis. Instead, the impact of the Asian and the Russian/Brazilian crises on cross-country comovements of stock returns is much higher. Covariance between weekly returns of Indonesia, Korea, Malaysia, the Philippines and Thailand is record-high during the Asian crisis, diminishes somewhat shortly after, and reaches new peaks in 1998-99. It comes back to pre-1997 levels only by the end of 1999. Covariances between each of these five countries with Hong Kong, Japan, Singapore and the U.S. follow a very similar pattern (Figures 2b and 2c).

In *Latin America*, covariances between returns of Argentina, Brazil and Mexico sharply increase sharply during the three episodes of crisis in the second half of the 1990s (Figures 2d). Comovements of returns in Latin American countries with the *United States* are not significantly different from tranquil periods during the Mexican crisis, but are quite strong during the Asian and the Russian/Brazilian crises. Finally, covariances of Latin American countries and the United States with *Russia* (for which data is available only from January 1996) recorded sizable increments during the Asian and the Russian/Brazilian crises.

2.1.4 Correlation between stock market returns is not necessarily larger during crisis periods than during tranquil periods.

Figures 3a to 3d show correlation coefficients of weekly returns for the stock markets in the sample. For *Asian countries*, a first notable piece of evidence is that, during the Asian crisis, correlation remains below or at the same level of the peaks recorded between 1995 and 1997. That is to say, correlation is not significantly higher during crisis periods than during tranquil periods.

A second notable piece of evidence is that correlation is on an increasing path, both after the beginning of the Asian crisis, and after the Hong Kong crash in October 1997. However, one cannot identify an analogous pattern during other episodes of crisis. For instance, correlation across Asian stock markets during the Russian/Brazilian crisis, either remains stable or decreases. By the same token, there is no single correlation pattern during the ERM and Mexican crises.

In *Latin America*, correlation between the stock markets of Argentina, Brazil and Mexico increases during the Mexican, Asian and Russian/Brazilian crises; during the same crisis episodes, correlation of Latin American countries with the United States increases as well. The magnitude of correlation between the

[6] Volatility of sovereign spreads followed a similar pattern during the period. It strongly increased in 1997 and in 1998, then gradually decreased in 1999 (see Corsetti et al., 2000).

Russian and the U.S. stock markets has gradually increased between 1994 and 2000.

As for *industrial countries*, correlation of the U.S. stock returns *vis-à-vis* France, United Kingdom, Italy and Canada is rising from the low values recorded in 1993-95, reaching a peak in 1999. Somewhat surprisingly, the correlation of both the United States and the European countries with Germany decreases from 1990 until end 1998. No clear trend is observable in the correlation between the Japanese and the US stock prices.

2.2 A synthesis through a case-study

Figure 4 below presents a case-study that summarizes well the typical patterns emphasized in our analysis above. The figure shows the pattern of volatility, covariance and correlation for Hong Kong and the Philippines. In order to disentangle the largest price movements, we also show an indicator of price reversal, calculated as the ratio between the value of the stock market in period t and its maximum value up to period t $(x_t/max\{x_h\}_{h=0}^{t})$ — called $CMAX_t$.

While the Mexican crisis has a limited impact on most Asian countries, stock prices in both Hong Kong and the Philippines record some decline and a rise in volatility. Cross-market linkages between the two countries at first record a decrease in covariance and correlation, due to the sharper movements in the Hong Kong prices. Then, both covariance and correlation follow an inverted V.

During the Asian and the Russian/Brazilian crises, the drop in prices as well as the increase in volatility and covariance are quite striking. In particular, covariance between the two markets rises from nil to its decade-record high, with a sharp step up around October 1997, when the Hong Kong stock market crisis erupts. Covariance remains on high levels until the first quarter 1998, then decreases somewhat, before rising again in correspondence with the Russian turmoil. Correlation increases steadily during the Asian crisis although it does not appear significantly larger than in 1996; it decreases somewhat between May and September 1998 and is fairly stable thereafter.

In light of the stylized facts discussed above, what strikes market participants as evidence of contagion is the magnitude of asset price movements occurring more or less simultaneously in different regions of the world, as measured by the dramatic increase in covariance and volatility. Correlation seldom rises above the level recorded in tranquil periods, even during 'extreme' episodes of international transmission of shocks.

3 A factor-model approach to the analysis of contagion

3.1 The model

This section lays out a simple factor model to approach the issue of testing for structural breaks in the international transmission mechanism. For the purpose of comparison with the current literature, in what follows we focus on correlation analysis, casting our argument in the framework of a single factor model. A meaningful generalization of our argument to multi-factor models is best accomplished without using correlation-based tests — a task that is left to future

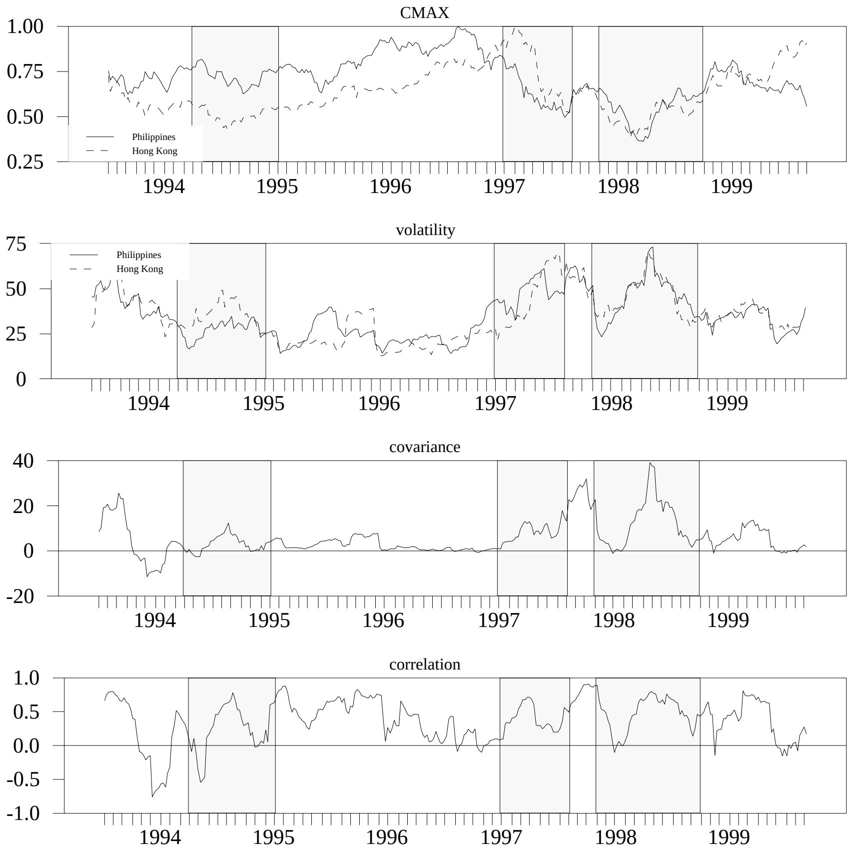

Figure 4: CMAX, instantaneous volatility, covariance and correlation between stock market returns of Hong Kong and the Philippines. Shaded areas correspond to the periods of crisis defined in the text.

contributions.

Assume that the rates of return of the stock markets in country i and country j are generated by the process

$$\begin{aligned} r_i &= \alpha_i + \gamma_i \cdot f + \varepsilon_i \\ r_j &= \alpha_j + \gamma_j \cdot f + \varepsilon_j \end{aligned} \tag{1}$$

where α_i and α_j are constant numbers, γ_i and γ_j are market-specific factor loadings, f is a global factor, ε_i and ε_j denote idiosyncratic risks, and where f, ε_i and ε_j are mutually independent random variables with finite and strictly positive variance.[7]

For simplicity, let both γ_i and γ_j be strictly positive. From the process above, the correlation coefficient between r_i and r_j can be written as:[8]

$$\begin{aligned} \rho &\equiv Corr(r_i, r_j) = \frac{Cov(r_i, r_j)}{\sqrt{Var(r_i) \cdot Var(r_j)}} \\ &= \frac{1}{\left[1 + \frac{Var(\varepsilon_i)}{\gamma_i^2 Var(f)}\right]^{1/2} \cdot \left[1 + \frac{Var(\varepsilon_j)}{\gamma_j^2 Var(f)}\right]^{1/2}} \end{aligned}$$

For given factor loadings γ_i and γ_j, a rise in correlation must correspond to shocks increasing the variance of the global factor f relative to the variance of the idiosyncratic noise ε_i and/or ε_j. Given the variances of the global factor and the idiosyncratic components, however, a rise in correlation could also correspond to an increase in the magnitude of the factor loadings γ_i and γ_j, or to an increase in the correlation between the idiosyncratic risks.

This distinction is at the root of recent empirical studies contrasting contagion to interdependence. Consider a financial crisis in country j. The increase in the variance of the stock market return in such a country may be due to an increase in the variance of either the global factor f, or the country specific component ε_j, or both. It is apparent that, if the change in the variance of the global factor f is large enough relative to the change in the variance of the country specific component ε_j, cross-market correlation must increase during a crisis in country j. This change in correlation is *interdependence*, in the sense that, *conditional on the occurrence of a financial crisis in country j, it is consistent with the data generating process* (1). *Contagion*, as opposed to interdependence, occurs if the increase in correlation turns out to be 'too strong' relative to what is implied by the process (1); i.e. it is too strong to be explained by the behavior of the global factor and the country specific component. In other words, contagion occurs when, conditional on a crisis, correlations are stronger because of some structural change in the international economy — affecting the link across markets.

In a related definition, contagion occurs when a country-specific shock becomes 'regional' or 'global'. This means that there is some factor η for which factor loadings are zero in all countries but one during tranquil periods, and become positive during crisis periods. An illustration of this concept of contagion

[7] Allowing for some covariance across country-specific terms does not substantially modify the main result of our analysis, on the need to adjust correlation coefficients for the variance of country-specific shocks.

[8] We denote with Var the variance operator, Cov the covariance operator and $Corr$ the linear correlation operator.

is provided by the following two-factor model:

$$\begin{aligned} r_i &= \alpha_i + \gamma_i \cdot f + \beta_i \cdot \eta + \varepsilon_i \\ r_j &= \alpha_j + \gamma_j \cdot f + (\eta + \eta_j) \end{aligned}$$

where β_j has been normalized to 1. If interdependence, $\beta_i = 0$, so that the process is equivalent to the data generating process (1) by setting $\varepsilon_j = \eta + \eta_j$. Contagion occurs when the country specific shock η becomes a global factor, *i.e.* when $\beta_i \neq 0$. As shown below, our measure of interdependence is derived under the null hypothesis $\beta_i = 0$. Thus, it will be unaffected by a change in the specification of the process for the rates of return, which uses the above expressions instead of the process (1).

These definitions provide a general framework for the empirical test discussed below.

3.2 Conditional correlation analysis

How can one derive a theoretical measure of correlation suitable to discriminate between contagion and interdependence according to the model presented above? Suppose that we can identify the 'origin' of an international financial crisis in some country j (e.g. Mexico at the end of 1994, Thailand in July 1997, Hong Kong in October 1997). Let δ denote the proportional change in the variance of the stock market return r_j relative to the pre-crisis period. Then, we can write

$$Var(r_j \mid C) = (1+\delta) Var(r_j)$$

where C denotes the event 'crisis in country j'. Note that the observed change in the variance of r_j does not necessarily coincide with an increase in the variance of the global factor, as the variance of the country-specific component may also change during the crisis.

In order to test whether changes in the correlation between r_i and r_j during a crisis in j are consistent with the data generating process (1), we must specify a measure of interdependence under the assumption that γ_i, γ_j, $Var(\varepsilon_i)$ and $Cov(\varepsilon_i, \varepsilon_j)$ *do not* vary with the crisis in country j. In the Appendix we show that, under such an assumption, the correlation coefficient between r_i and r_j can be written as the following function ϕ:

$$\phi(\lambda_j, \lambda_j^C, \delta, \rho) \equiv \rho \left[\left(\frac{1+\lambda_j}{1+\lambda_j^C} \right)^2 \frac{1+\delta}{1+\rho^2 \left[(1+\delta) \frac{1+\lambda_j}{1+\lambda_j^C} - 1 \right] (1+\lambda_j)} \right]^{1/2} \qquad (2)$$

where λ_j (λ_j^C) denotes the ratio between the variance of the idiosyncratic shock ε_j and the variance of the global factor f, scaled by the factor loading γ_j, during the tranquil (crisis) period:

$$\lambda_j = \frac{Var(\varepsilon_j)}{\gamma_j^2 \cdot Var(f)} \text{ and } \lambda_j^C = \frac{Var(\varepsilon_j \mid C)}{\gamma_j^2 \cdot Var(f \mid C)} .$$

In what follows, we will refer to ϕ as a theoretical measure of interdependence. The correlation coefficient between r_i and r_j observed during the crisis, denoted by ρ^C, and the theoretical measure of interdependence ϕ are the main elements of our test.

The coefficient ϕ is derived under the null hypothesis of interdependence: if γ_i, γ_j $Var(\varepsilon_i)$ and $Cov(\varepsilon_i, \varepsilon_j)$ do not change during the crisis, ρ^C and ϕ will coincide. Conversely, if there is contagion in the form of an increase in the magnitude of factor loadings or a positive correlation between idiosyncratic risks (e.g., because some country-specific factor becomes global during the crisis in country j), ρ^C will be larger than ϕ. Then, under the identifying assumption that contagion from international crises does not alter the variance of idiosyncratic shocks in countries other than j (i.e. $Var(\varepsilon_i)$ is constant), a statistical analysis on contagion vs. interdependence can be performed by testing whether ρ^C is significantly higher than ϕ.

We should stress a notable feature of this approach to testing. During an international crisis originating in one country, shocks to the global factor tend to induce large comovements of prices. Yet, the country where the crisis originates may also be subject to large shocks that are and remain country-specific. Overall cross-market correlation may fall. The fact that during a crisis correlation falls (as it often does in the data, see Section 2) is by no means evidence against contagion. In other words, testing for contagion needs not be conditional on observing a hike in correlation. In line with this remark, the test is symmetrical; namely, it can also be applied to structural breaks and contagion consisting in looser interdependence (e.g. falling factor loadings). There is no reason why the concept of contagion should be confined to the hypothesis of stronger than normal ties.

4 A review of the literature

This section analyzes recent empirical contributions on contagion, identifying a set of tests that can be interpreted as special cases of our framework. To introduce our discussion, it is useful to simplify our test statistic ϕ by assuming that the variance ratio defined in the previous section does not vary across periods, $\lambda_j^C = \lambda_j$. Assuming a constant ratio means that the variance of the global factor and the variance of the country-specific risk increase by the same proportion during the crisis in j:

$$\frac{Var(r_j \mid C)}{Var(r_j)} = \frac{Var(f \mid C)}{Var(f)} = \frac{Var(\varepsilon_j \mid C)}{Var(\varepsilon_j)} = 1 + \delta$$

Then, the coefficient of interdependence ϕ simplifies to:

$$\phi(\lambda_j, \delta, \rho) = \rho \left[\frac{1+\delta}{1+\delta\rho^2(1+\lambda_j)} \right]^{1/2} \tag{3}$$

Other things equal, a larger variance-ratio λ_j reduces the effect of an increase in the variance of r_j on the coefficient of interdependence. This is because a larger fraction of this variance is due to the country-specific component, hence weakening cross-market linkages.

To clarify this point, we consider once again the case-study analyzed at the end of Section 2, that is the spread of financial instability in the stock market from Hong Kong to the Philippines on October 1997. Figure 5 below shows the 'instantaneous' correlation coefficient between stock market returns in Hong Kong and the Philippines, both measured in US dollars, during 1997. The daily correlation provides a proxy for ρ (during tranquil periods) and ρ^C (during crises). Note that, before October 20, which is the starting day of the crisis, we only report the instantaneous correlation, ρ_t; from October 20 on, we report both the instantaneous correlation, ρ_t^C, and a set of coefficients of instantaneous correlation under the null hypothesis of interdependence, calculated assuming different values of λ_j.

For the purpose of the graph, we find it useful to calculate and plot an inverse transformation of ϕ, instead of ϕ itself. This transformation, denoted by $\phi_t^{'}(\lambda_j)$, is given below

$$\phi_t^{'}(\lambda_j) = \frac{\rho_t^C}{\sqrt{1+\hat{\delta}-\hat{\delta}\left(\rho_t^C\right)^2-\hat{\delta}\lambda_j\left(\rho_t^C\right)^2}}$$

where $\hat{\delta}$ is estimated from the sample data.[9] According to the logic of our test, this coefficient of correlation is adjusted so as to allow for the fact that changes in the volatility of stock prices in Hong Kong will *per se* affect cross-border comovements during the Hong Kong crisis. Thus, the observed ρ_t^C is adjusted on the basis of the estimated increase in the variance of r_j, that is $\hat{\delta}$. Given $\hat{\delta}$, a smaller λ_j (shifting weight towards an increase in the variance of the global factor) entails a smaller adjusted coefficient.

A visual inspection of figure 5 suggests that the unadjusted correlation coefficient ρ_t^C increased significantly during the Hong Kong crisis in October 1997 relative to the previous months. Is this evidence of contagion? In light of what discussed in the previous section, we can test of contagion vs. interdependence by comparing $\phi_t^{'}(\lambda_j)$ and ρ_t. Specifically, the null hypothesis of interdependence is accepted when $\phi_t^{'}(\lambda_j)$ is not significantly larger than ρ_t. Figure 5 plots different estimates of $\phi_t^{'}(\lambda_j)$ conditional on values of λ_j between 0 and 5. The graph shows that the adjusted coefficient $\phi_t^{'}(\lambda_j)$ is close to ρ_t for low values of the variance ratio, while it gets significantly larger for values of λ_j around 5. The graph thus suggests that the hypothesis of interdependence could be accepted conditional on some λ_j smaller than 5.

The literature provides a few examples of conditional correlation tests of contagion — but in most cases the maintained assumption on the $\lambda's$ is only implicit. In the following section, we will review these tests, nesting them in our framework.

4.1 Tests based on sample correlation coefficient or $\lambda = 1/\rho^2 - 1$

Early contributions on contagion, such as King and Wadhwani (1990), acknowledge the problem of controlling for the relationship between volatility of return and correlation, but implement no correction of their empirical tests.[10] It is

[9] The coefficient ϕ' is obtained by substituting ϕ with ρ^C in equation (2), and then solving the resulting expression for ρ.

[10] King and Wadhwani (1990) are aware of the relationship between volatility and correlation as they write: "we might expect that the contagion coefficients would be an increasing function of volatility" (pp. 20). However, in calculating correlation between markets, they do not correct for the increase in volatility.

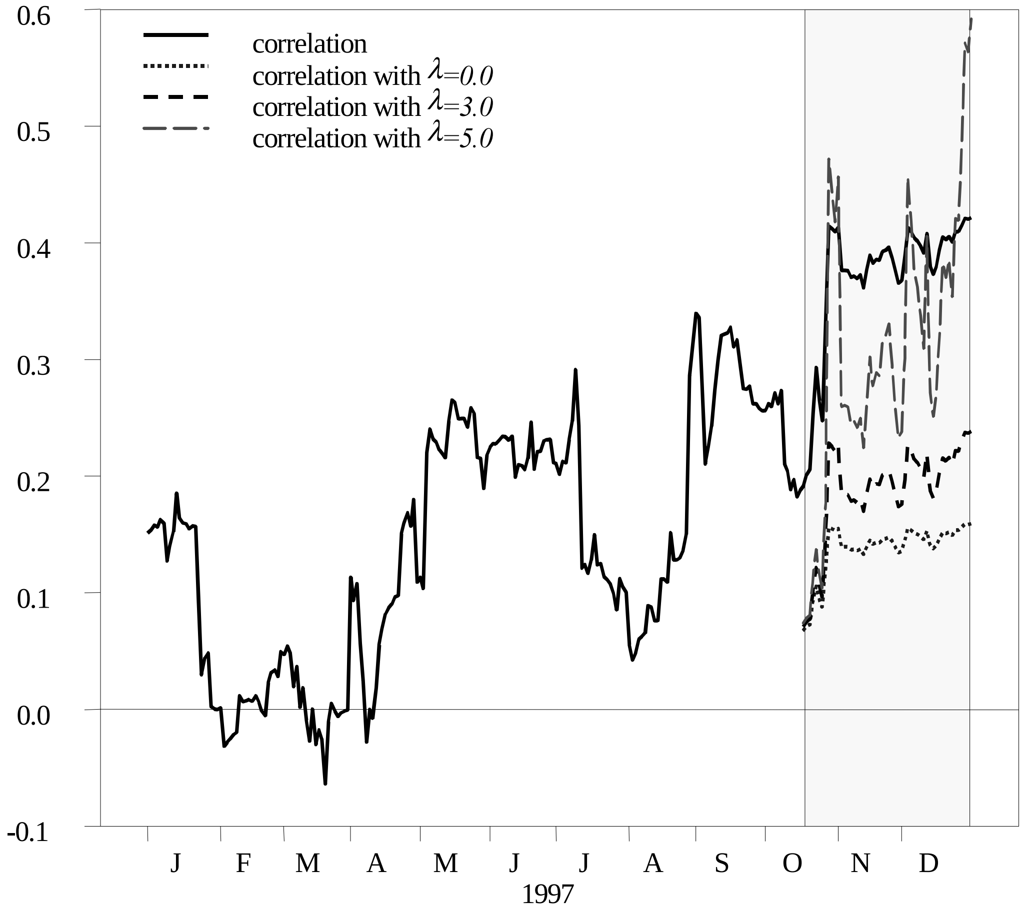

Figure 5: Instantaneous correlation and corrected correlation for different values of λ_j between stock market returns in US dollars of Hong Kong and the Philippines

instructive to use our model in order to highlight the conditions under which a simple test on correlation is consistent with our measure of interdependence. Looking at equation (3), note that ϕ is identically equal to ρ only when

$$\lambda_j^C = \lambda_j = 1/\rho^2 - 1 \ . \tag{4}$$

For this particular value of the variance ratio,[11] interdependence implies that the correlation coefficient should not respond to a crisis in country j. Thus, we can perform a test of contagion just verifying whether the simple correlation coefficient has changed significantly during a crisis.

Interestingly, the implicit assumption in condition (4) is a negative relationship between the correlation coefficient during tranquil period ρ and the variance ratio λ_j: the higher the correlation between r_i and r_j, the higher the importance of the global factor and, in turn, the lower λ_j. This is not an unreasonable assumption in general. However, unless λ_j happens to be exactly equal (or close) to the inverse of the squared correlation coefficient minus one, tests of contagion based on comparing simple correlation will be biased — it could be interesting to explore the loss of accuracy of the test in the region around that value of the variance ratio.

4.2 Tests based on adjusted correlation coefficient with $\lambda = 0$

Consider the approach championed by Forbes and Rigobon (1999a,b). The key to these contributions is the (implicit) assumption that the rate of return of the stock market in country j coincides with a global factor. In terms of our factor model, this is equivalent to assuming that the data generating process of the rates of return is:

$$\begin{aligned} r_i &= \alpha_i + \gamma_i \cdot f + \varepsilon_i \\ r_j &= \alpha_j + \gamma_j \cdot f \end{aligned} \tag{5}$$

so that

$$r_i = \left(\alpha_i - \frac{\alpha_j}{\gamma_j}\right) + \frac{\gamma_i}{\gamma_j} \cdot r_j + \varepsilon_i$$

corresponding to the linear equation at the root of Forbes and Rigobon' estimates:[12]

$$r_i = \beta_0 + \beta_1 \cdot r_j + \varepsilon_i \tag{6}$$

Thus, there is no country-specific shock affecting r_j. In terms of our framework, $Var(\varepsilon_j) = 0$ implies $\lambda_j^C = \lambda_j = 0$.

[11] A similar but more cumbersome expression could be derived for the general case in which $\lambda_j^C \neq \lambda_j$.

[12] Forbes and Rigobon (1999a) filter their data estimating a VAR model with domestic and international interests rates and lagged returns. Then, they analyze the correlation between the residuals of their estimates with the model (6). Note that in the theoretical part of the paper Forbes and Rigobon (1999a) actually write a symmetric model, where r_i and r_j are interdependent. However, the symmetric model is not estimated.

A statistical framework closely related Forbes and Rigobon's test is presented by Boyer et al. (1999) and Loretan and English (2000), who assume that (r_i, r_j) is a normal bivariate random variable. The equivalence between the two approaches can be easily understood by referring to the following property: if (r_i, r_j) is a normal bivariate random variable, one can write[13]

$$\begin{aligned} r_i &= \alpha_i + \gamma_i \cdot r_j + \upsilon_i \\ r_j &= \alpha_j + \gamma_j \cdot \upsilon_j \end{aligned} \tag{7}$$

where υ_i and υ_j are orthogonal and normally distributed random variables. It is apparent that, as in Forbes and Rigobon, the country-specific shock in j is the global factor, up to an affine transformation.

The test statistic adopted by Boyer et al. (1999) and Loretan and English (2000), which follows from the model (7), is the same as the one adopted by Forbes and Rigobon (1999a,b):

$$\rho \left[\frac{1+\delta}{1+\delta\rho^2} \right]^{1/2} \tag{8}$$

This is the correlation between two jointly normal random variables as a function of the increase in the variance of one of them, δ — also known in the literature as 'normal correlation theorem'. Note that (8) coincides with our measure of interdependence (3) when there is no idiosyncratic shock in country j; that is, when $\lambda_j^C = \lambda_j = 0$. Thus, the measures of interdependence (2) and (3) could be interpreted as a generalization of the normal correlation theorem.

In these models, the test strategy consists in verifying whether the statistic (8) is significantly different from ρ^C. The drawback of tests using the statistic (8) is quite clear. In equation (6), r_i depends linearly on r_j, so that there is no component of the variance of r_j that is country-specific. The stock market return in country j is specified as a 'global' or 'regional' factor. The test statistic (8) is therefore only applicable when every single shock in country j has global or regional repercussions. Do we really believe that the rate of return in Hong Kong or Thailand is (or coincide with) a global or even a regional factor both before and after a crisis?

The specification of r_j as a global factor has important implications for the test. To the extent that the increase in the variance of the market in country j is due to idiosyncratic shocks in this country, the theoretical correlation coefficient (8) will be biased. Such bias will be larger, the larger the share of variance in r_j that can be attributed to country-specific shocks. As apparent from equation (6), specifying r_j as a global factor magnifies the theoretical correlation ϕ between the two markets, and increases the chances that its variance will explain the observed correlation during the crisis. Hence, the test will be biased towards the null hypothesis of interdependence. It may not come entirely as a surprise that *this kind of tests hardly find any evidence of contagion.*[14] In the next section, we will indeed provide empirical evidence showing that many strong results in the literature are severely affected by the test bias discussed above.

[13] These tests have been sometimes used by financial market paricipants. See Deutsche Bank (2000).

[14] See for instance Boyer et al. (1999) and Forbes and Rigobon (1999a,b).

5 Empirical evidence

We now present an application of our methodology to the international effects of the October 1997 stock market crisis in Hong Kong.[15] Using data from *Thomson Financial Datastream*, we analyze correlation between stock market returns of Hong Kong with ten emerging economies (Indonesia, Korea, Malaysia, the Philippines, Singapore, Thailand, Russia, Argentina, Brazil and Mexico) and the G7 countries. In our benchmark estimation we calculate two-day rolling averages of daily returns in US dollars and we define tranquil and turbulent periods as starting from January 1 1997 to October 17 1997 and from October 20 1997 to November 30 1997 respectively.[16] This definition of the crisis period follows the crash recorded by the stock market index in Hong Kong, which lost 25 per cent of its value in just four days starting on October 20 1997. Hong Kong stock prices declined until the end of November, apparently influencing returns in several other markets.

Although our test procedure is symmetrical, we adopt the common practice of testing for contagion as a phenomenon in which correlation is significantly higher during the crisis period. Hence, our test hypotheses are:

$$\begin{array}{lcll} H_0 & : & \rho^C \leq \phi & \textit{interdependence} \\ H_1 & : & \rho^C > \phi & \textit{contagion .} \end{array}$$

Looking at the definition (2) of the coefficient of interdependence ϕ, note that ρ and δ, as well as the coefficient ρ^C, can be easily estimated from the data. The main challenge in carrying out this test is to find good estimates of λ_j and λ_j^C.

We will proceed as follows. First, we set up a conditional test fixing the value of variance ratios parametrically; namely, we calculate minimum thresholds for λ_j and λ_j^C at which the difference between ρ^C and ϕ becomes statistically significant. Second, we compare these threshold with empirical estimates of these variance ratios, obtained using different methods.

5.1 Conditional test: identification of threshold values for λ and λ^C

In this section, we identify critical thresholds for λ_j and λ_j^C at which the null hypothesis is rejected at a given confidence level. To clarify the meaning of these thresholds, consider first the case in which $\lambda_j^C = \lambda_j$. By inspecting equation (3), we see that ϕ is monotonically decreasing in λ_j, for given ρ and δ. Suppose we find ρ^C significantly larger than ϕ for a given $\lambda_j = \lambda'$; it follows that ρ^C is significantly larger than ϕ also for any $\lambda_j = \lambda'' > \lambda'$. Therefore, we can look for *the minimum value of* λ_j — denoted with $\bar{\lambda}$ — at which the hypothesis of interdependence would be rejected at some prespecified confidence level. Analogously, in the case $\lambda_j^C \neq \lambda_j$, equation (2) shows that ϕ is monotonically decreasing in λ_j^C. Hence, for any given λ_j we can look for *the minimum value of* λ_j^C, $\bar{\lambda}^C$, at which the hypothesis of interdependence would be rejected. In the first case, the result of the conditional test will be a *threshold* $\bar{\lambda}$; in the second

[15] For a comparison, see Forbes and Rigobon (1999a).

[16] We use US dollar returns because they represent profits of investors with international portfolios. As stock markets in different countries are not simultaneously open, two-day rolling averages of returns have been preferred to simple returns.

case, the result will be a *threshold function*, that gives the threshold $\bar{\lambda}^C$ for any positive λ_j.

Tests of equality between two correlation coefficients can be performed using the *Fisher z-transformation*

$$z(\widehat{\rho}) = \frac{1}{2} \ln \frac{1+\widehat{\rho}}{1-\widehat{\rho}}$$

where $\widehat{\rho}$ is the estimated correlation coefficient. Under the assumption that two samples are drawn from two independent bivariate normal distributions with the same correlation coefficient, Stuart and Ord (1991, 1994) show that the difference between estimated $z(\widehat{\rho})$ in the two samples converges to a normal distribution with mean and variance specified below:

$$N\left(0, \frac{1}{n_1 - 3} + \frac{1}{n_2 - 3}\right)$$

where n_1 and n_2 denote the size of the two samples.

We proceed as follows. We estimate the correlation coefficients during the tranquil period, $\widehat{\rho}$, and during the crisis period, $\widehat{\rho}^C$, as well as the increase in the variance in the Hong Kong stock market, $\widehat{\delta}$. By substituting $\widehat{\rho}$ and $\widehat{\delta}$ into (2), we obtain an estimation of our measure of interdependence as a function of λ_j and λ_j^C, that is $\widehat{\phi}(\lambda_j, \lambda_j^C)$. Given $z(\widehat{\rho}^C)$ and $z(\widehat{\phi}(\lambda_j, \lambda_j^C))$, we derive threshold values of λ_j and λ_j^C from:

$$z(\widehat{\rho}^C) - z(\widehat{\phi}(\bar{\lambda}, \bar{\lambda}^C)) = 1.645\sigma_z \tag{9}$$

where $\sigma_z = \frac{1}{n-3} + \frac{1}{n^C-3}$, with n and n^C denoting the sample size of the tranquil and the crisis period.

A problem in the above procedure is that the assumption of independent samples is violated, since $\widehat{\delta}$ depends on both the tranquil and the crisis period samples: the significance level of the test (9) is not the standard 5 per cent. To assess the significance level of our test, we have resorted to Montecarlo simulation experiments. We have run $1,000,000$ replications for different country pairs, varying the parameter values and sample size. In all our simulations, the significance level of the statistic (9) is comprised between 7 and 9 per cent. For instance, setting $n = 208$, $n^C = 30$ and $\delta = 8.72$, as in our benchmark estimation, and $\rho = 0.219$, $\rho^C = 0,661$, which are the observed correlation coefficients between the markets of Hong Kong and the Philippines, the significance level of the test corresponding to (9) is 8.1 per cent.

5.1.1 The case of a constant variance ratio

Consider first the case $\lambda_j = \lambda_j^C$. The threshold level of the variance ratio, $\bar{\lambda}$, can be easily found by inverting equation (9). This yields

$$\bar{\lambda} = \left\{ \left[\widehat{\rho} \frac{\widehat{\omega}+1}{\widehat{\omega}-1} \right]^2 \left(1 + \hat{\delta}\right) - 1 \right\} \frac{1}{\hat{\delta}\widehat{\rho}^2} - 1 \tag{10}$$

where $\widehat{\omega} = \exp\left[2\left(z(\widehat{\rho}^C) - 1.645\sigma_z\right)\right]$, and (as defined above) $\widehat{\rho}$ and $\widehat{\rho}^C$ are the sample correlation coefficients. Consistently with the logic of our test, if one believes that the variance ratio in Hong Kong during 1997 were constant and lower than the value $\bar{\lambda}$ solving the above equation, one should also accept the null hypothesis of interdependence.

The first two columns of table 1 report the correlation between two-day rolling averages of stock market returns in US dollars of Hong Kong with each country in the sample during the tranquil, $\widehat{\rho}$, and the crisis period, $\widehat{\rho}^C$. The third column of table 1 reports the threshold level of the variance ratio, $\bar{\lambda}$, corresponding to (10). It is apparent that $\bar{\lambda}$ tends to be larger, the smaller the difference between $\widehat{\rho}^C$ and $\widehat{\rho}$; in other words, if the correlation between two stock markets does not increase sharply during the crisis period, the null of interdependence can be rejected only for very high values of the variance ratio. Note also that, when correlation decreases between the tranquil and the crisis period, the null of interdependence cannot be rejected at all ($\bar{\lambda} = +\infty$). When the correlation in the tranquil period is about zero, as in the case of Italy, the null of interdependence is rejected for any value of λ_j.

Table 1 shows that the null hypothesis of interdependence will be rejected for 'low' values of λ_j in the case of Italy, France, Singapore, the UK, and the Philippines. For instance, if one believes that $\lambda_j = 3$ (a value that we will find in one of our estimates), our test would reject interdependence for all the countries listed above. At $\lambda_j = 7$ (that will be our highest estimated value), the test would also reject for Germany.

We stress the consequence of setting $\lambda_j = \lambda_j^C = 0$, as implicitly done in some of the literature reviewed in the previous section. Under such maintained assumption, the test would reject interdependence only in the case of Italy – that is, there would be almost no evidence of contagion. Yet, there are at least four countries for which the strong result of "no contagion" is quite dubious.

Table 1 also reports the results of the Fisher test, based on unadjusted correlation coefficients, so that the null hypothesis is $H_o : \rho^C \leq \rho$. We have shown that this test corresponds to our conditional correlation analysis if λ_j happens to be exactly equal to $1/\rho^2 - 1$.[17] Interpreting the table, observe that this test rejects the null whenever $1/\rho^2 - 1 > \bar{\lambda}$. This is the case for Indonesia, the Philippines, Singapore, Russia and, among the G7, Germany, France, the UK and Italy. Relative to the results from a test conditional on a positive but low λ (say $\lambda = 4$), there is some weak evidence of contagion for two countries that do not appear in our list of 'suspects' above, Indonesia and Russia. So, there is a substantial, although not perfect, overlap of results.

Nonetheless, note that the required variance ratio for the Fisher test on unadjusted correlation coefficients to be consistent with our framework (that is, the magnitude of $1/\rho^2 - 1$) is extremely — and unrealistically — high for most countries. Only in two cases, Singapore and Indonesia, $1/\rho^2 - 1$ is smaller then 10.

[17] Recall that there is only one value of the variance ratio that is true for Hong Kong. Then, the Fisher test will be correct for at most one of the country pairs (or for a set of countries whose stock markets happen to be equally correlated with Hong Kong's).

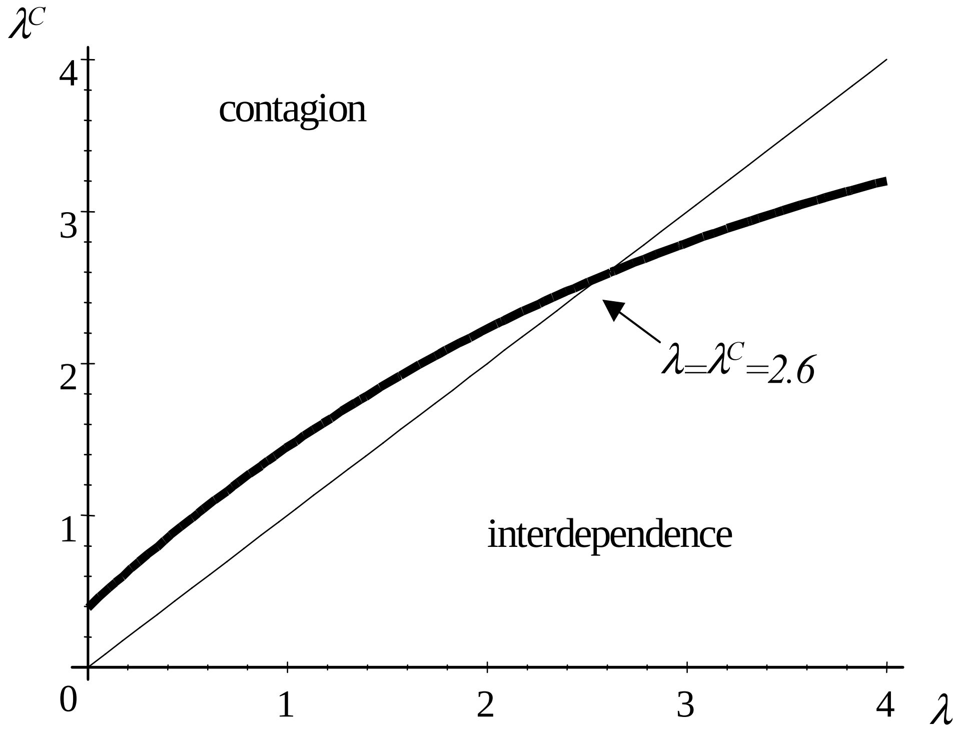

Figure 6: Hong Kong - Philippines threshold function

5.1.2 The case of variable variance ratios

Allowing the variance ratio to vary between the tranquil and the crisis period, i.e. $\lambda_j^C \neq \lambda_j$, equation (9) can be rewritten as

$$\left[1+\widehat{\rho}^2\frac{\widehat{\delta}(1+\lambda_j)+(\lambda_j-\bar{\lambda}^C)}{(1+\bar{\lambda}^C)}(1+\lambda_j)\right]\left(\frac{1+\bar{\lambda}^C}{1+\lambda_j}\right)^2 - \\ -\left(\widehat{\rho}\frac{\widehat{\omega}+1}{\widehat{\omega}-1}\right)^2\left(1+\widehat{\delta}\right)=0.$$

which implicitly defines $\bar{\lambda}^C$ as a function of λ_j. Figure 6 graphs this implicit function for the case of Hong Kong and the Philippines. For any pair (λ_j, λ_j^C) above the function, the test will reject the hypothesis of interdependence. For any pair (λ_j, λ_j^C) below the function, the test will accept the null. The pair at the crossing between the function and the 45° degree line from the origin, identifies the threshold $\bar{\lambda}$ reported in table 1.

5.2 Some evidence on the variance ratio

What do we know about λ_j and λ_j^C? Based on the single factor model in (1), a first, simple approach to obtain estimates of these variance ratios consists of specifying a composite 'global factor', as the daily average return in a cross section of stock markets.[18] We estimate such global factor in different ways: we first use the sample of the G7 countries, then our full sample excluding Hong Kong; finally we adopt the 'world stock market index' produced by *Thomson Financial Datastream*. After computing two-day rolling average of returns on the global factor, we regress the two-day rolling average of Hong Kong's returns on it. The variance of the residuals from this regression gives an estimate of the variance of the country specific shock, from which we obtain an estimate of λ_j.

The results from this procedure are shown in the first half of table 2. In our sample, the order of magnitude of the variance ratio for Hong Kong is between 2 and 4: i.e. in the Hong Kong stock market, the variance of country-specific shocks is between 2 and 4 times the variance of the global factor (multiplied by the factor loading γ_j). Most interestingly, these ratios do not vary substantially between the tranquil and the crisis period.

A second approach to estimating the variance ratio is based on principal component analysis. First, we calculate the principal components for our full sample of rolling averages of returns. We then regress the rolling average of returns in country j on the principal components, using the residual from this regression to estimate the variance of the country specific shocks. Results are shown in the second half of table 2.

Our estimates of λ_j for the full sample are not too distant from what we have obtained by using the composite global factor. The first principal component gives an estimated variance ratio equal to 7.1. If we include the first five components in the regression (so as to explain 76% of the variance in the sample) $\widehat{\lambda}_j$ is equal to 4.1. At the margin, the difference in the estimated value of λ_j is only relevant in the case of Germany (for this country, $\bar{\lambda} = 4.4$). Note however that our test statistic is derived under the maintained assumption of a single factor model, and thus is not directly applicable in a multi-factor world.

A key conclusion from these preliminary (and admittedly rough) estimates based on a single factor model of returns, is that the variance ratio is well below what is needed to justify a test based on unadjusted correlation coefficients (see table 1). At the same time, however, the value of the $\lambda's$ is bounded away from zero. The strong results of interdependence reached by Boyer et al. (1999) and Forbes and Rigobon (1999a) may not survive when the implicit bias in their test is removed.

6 Conclusion

This paper has presented a general framework to approach tests of contagion between stock markets in different countries based on correlation analysis. A number of tests in the literature correct for potential bias due to changes in the variance of global shocks driving returns. By analyzing these tests as special cases of our framework, we show that these tests are conditional on arbitrary

[18] This approach is consistent with more general dynamic factor models, as shown in Forni and Lippi (1997).

assumptions about the variance of country-specific shocks in the market where the crisis originates. When this variance is set equal to zero after the eruption of the financial turmoil — as done in a number of contributions — the chances of accepting the null of interdependence are very high.

Our preliminary empirical estimates suggests that, for the case of the Hong Kong stock market crisis in October 1997, the variance of the country-specific component of returns is not zero. Results from a single factor model show that it is 2 to 7 times higher than the component that can be attributed to the variance of global factor. For most country pairs in our sample, interdependence can be rejected only for larger values of this ratio. Based on our estimates, we find evidence of contagion from the Hong Kong crisis in the case of Singapore and the Philippines, among the emerging markets, and France, Italy, the UK and (weakly) Germany, among the advanced countries. In contrast, the bias in conditional tests arbitrarily setting $\lambda = 0$ is quite severe. For all the countries in our sample but one (Italy), these tests would accept the null of interdependence.

The empirical analysis of this paper has been kept simple (we used a single factor model of returns), and as close as possible to correlation analysis. It should be clear, however, that the issue of controlling for country-specific shocks in contagion analysis is limited neither to correlation analysis, nor to a single-factor model of returns, but should be addressed in all tests identifying contagion as a structural break in the transmission mechanism.

A Appendix

This appendix derives the expression (2) of the coefficient of interdependence ϕ in the general case. From the data generating process of r_i, the unconditional variance of the idiosyncratic shock ε_i can be written as:

$$Var(\varepsilon_i) = Var(r_i) - \gamma_i^2 \cdot Var(f)$$

By the definition of λ_j and the data generating process of r_j, we can also get:

$$Var(f) = \frac{Var(r_j)}{\gamma_j^2(1+\lambda_j)}$$

Therefore, we find:

$$\frac{Var(\varepsilon_i)}{\gamma_i^2 \cdot Var(f)} = \frac{Var(r_i)}{\gamma_i^2 \cdot Var(f)} - 1 = \frac{\gamma_j^2(1+\lambda_j)Var(r_i)}{\gamma_i^2 Var(r_j)} - 1 \tag{A.1}$$

For convenience, we rewrite the expression of the correlation coefficient induced by the process (1):

$$\rho = \frac{1}{\left[1 + \frac{Var(\varepsilon_i)}{\gamma_i^2 Var(f)}\right]^{1/2} \cdot [1+\lambda_j]^{1/2}} \tag{A.2}$$

Substituting (A.1) into (A.2), we obtain the unconditional correlation coefficient as a function of the rates of return, the factor loadings and λ_j:

$$\rho = \frac{\gamma_i}{\gamma_j} \left[\frac{1}{1+\lambda_j} \left(\frac{Var(r_i)}{Var(r_j)}\right)^{-1/2}\right] \tag{A.3}$$

We now turn to the crisis period. From the data generating process of the rate of return of the stock market in country i, the variance of r_i during the crisis is:

$$Var(r_i \mid C) = \gamma_i^2 \cdot Var(f \mid C) + Var(\varepsilon_i) \tag{A.4}$$

Note that by the data generating process (1) and by the definition of λ_j and λ_j^C, it follows that:

$$\frac{Var(r_j \mid C)}{Var(r_j)} = 1 + \delta = \frac{1+\lambda_j^C}{1+\lambda_j} \frac{Var(f \mid C)}{Var(f)} \tag{A.5}$$

By solving (A.5) for $Var(f \mid C)$ and substituting the resulting expression into (A.4) we get:

$$Var(r_i \mid C) = Var(r_i) + \psi \gamma_i^2 Var(f)$$

where ψ is defined as in follows

$$\psi = \frac{\delta(1+\lambda_j) + (\lambda_j - \lambda_j^C)}{1+\lambda_j^C}$$

Hence, we obtain:

$$\begin{aligned}\frac{Var(r_i \mid C)}{Var(r_j \mid C)} &= \frac{Var(r_i) + \psi\gamma_i^2 Var(f)}{(1+\delta)Var(r_j)} = \\ &= \frac{Var(r_i)}{(1+\delta)Var(r_j)} + \frac{\psi\gamma_i^2}{(1+\delta)(1+\lambda_j)\gamma_j^2}\end{aligned} \tag{A.6}$$

From (A.3), the correlation coefficient during the crisis period in the hypothesis that only the variance of f and ε_j change, while the factor loadings remain constant — which is our coefficient of interdependence ϕ — can be written as:

$$\phi(\lambda_j, \lambda_j^C, \delta, \rho) = \frac{\gamma_i}{\gamma_j}\left[\frac{1}{1+\lambda_j^C}\left(\frac{Var(r_i \mid C)}{Var(r_j \mid C)}\right)^{-1/2}\right] \tag{A.7}$$

Substituting (A.6) into (A.7), we finally obtain

$$\begin{aligned}\phi(\lambda_j, \lambda_j^C, \delta, \rho) &= \left[\frac{(1+\lambda_j^C)^2}{(1+\delta)}\frac{\gamma_j^2}{\gamma_i^2}\frac{Var(r_i)}{Var(r_j)} + \frac{\psi(1+\lambda_j^C)^2}{(1+\delta)(1+\lambda_j)}\right]^{-1/2} = \\ &= \left[\frac{(1+\lambda_j^C)^2}{(1+\delta)(1+\lambda_j)^2\rho^2} + \frac{\psi(1+\lambda_j)(1+\lambda_j^C)^2\rho^2}{(1+\delta)(1+\lambda_j)^2\rho^2}\right]^{-1/2} = \\ &= \rho\left\{\frac{(1+\lambda_j^C)^2\cdot\left[1+\psi(1+\lambda_j)\rho^2\right]}{(1+\delta)(1+\lambda_j)^2}\right\}^{-1/2}\end{aligned}$$

which can be rearranged to give equation (2).

B Appendix

Our test results are not sensitive to a number of changes in our sample. In order to show this, we have run our tests using returns in local currency (instead of US dollar), modifying the definitions of tranquil and crisis periods, replacing rolling averages of returns with simple daily returns, and filtering the data with US interest rates. Table 3 summarizes the results, showing the number of countries for which interdependence is rejected under each run of the analysis. For each definition of our sample, we carry out the Fisher's test, as well as our test procedure with $\lambda_j = \lambda_j^C$ (where the constant variance ratio is estimated using the 'world stock market index') and with $\lambda_j = \lambda_j^C = 0$.

Our conclusions are quite robust to a change in the currency of denomination of stock prices. This is true not only for countries that maintained a fixed or quasi-fixed exchange rate with respect to the dollar, but also for countries that experienced a sharp devaluation of their currency in our sample period. In the case of Thailand vs. Hong Kong, for instance, $\widehat{\rho}$ and $\widehat{\rho}^C$ are equal to 0.104 and 0.013, respectively, when using returns in local currency, while they are 0.106 and 0.005 when using returns in dollars. When we run our test setting $\lambda_j = \lambda_j^C = 0$, in our benchmark sample we reject interdependence only for Italy; using returns in local currency we also reject interdependence for the UK. When we set $\lambda_j = \lambda_j^C$, our test rejects the null for Italy, the UK, Singapore, France and the Philippines, regardless of the currency in which we calculate returns.

By the same token, our results are robust to changes in the timing of the tranquil and the crisis periods. When we alter the definition of *tranquil period* to include the year 1996, our test rejects the null for Italy, Singapore, France and the Philippines, but not for the UK. As on average correlation remained quite high at the end of 1997 (see Figures 3a-3d), we have also estimated a model including December 1997 in the *crisis period*. In this case, results are unaffected relative to our benchmark estimation.

Interestingly, if we replace two-day rolling averages with simple *daily returns*, the number of cases in which the conditional tests reject interdependence increases visibly, both for $\lambda_j = \lambda_j^C = 0$ and for $\lambda_j = \lambda_j^C$.[19] In particular, conditional on $\lambda_j = \lambda_j^C = 0$, we reject interdependence for Italy, France, the UK; using the estimated variance ratio together with the hypothesis $\lambda_j = \lambda_j^C$, we reject also for Singapore, the Philippines, Germany and Russia.

Note that we have excluded test results of the United States and Thailand, for which the estimated correlation coefficients during the tranquil and crisis period fall to zero. In this case, tests based on Fisher z-transformation are not appropriate (see Stuart and Ord, 1994).

Finally, we have run the same testing procedure as in Forbes and Rigobon (1999a), consisting in a VAR model of returns using domestic and US interest rates and oil prices as exogenous variables. We have also expanded on their test by including oil prices as exogenous variable. The results from these procedures confirm our conclusions.

[19] Here we have excluded test results of the United States and Thailand, for which the estimated correlation coefficients during the tranquil and crisis period fall to zero. In this case, tests based on Fisher z-transformation are not appropriate (see Stuart and Ord, 1994).

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Table 1: Hong Kong crisis - Conditional and Fisher tests

country	$\widehat{\rho}$	$\widehat{\rho}^C$	$\bar{\lambda}$	Fisher	$\frac{1}{\rho^2}-1$
Indonesia	0.31	0.60	7.1	*	9.7
Korea	0.16	0.07	$+\infty$	-	38.7
Malaysia	0.20	0.43	64.5	-	24.8
Philippines	0.22	0.66	2.6	**	19.8
Singapore	0.36	0.76	1.5	**	6.5
Thailand	0.11	0.01	$+\infty$	-	88.6
Argentina	0.26	0.21	$+\infty$	-	13.5
Brazil	0.20	0.31	30,941.3	-	23.1
Mexico	0.29	0.45	49.3	-	10.8
Russia	0.19	0.53	13.8	*	26.9
USA	0.15	0.26	254.0	-	42.1
Japan	0.28	0.33	7486.5	-	11.4
Germany	0.24	0.63	4.4	**	16.8
France	0.17	0.66	1.2	**	32.3
United Kingdom	0.17	0.63	2.3	**	33.0
Italy	0.00	0.63	0.00	**	732,762
Canada	0.27	0.37	389.8	-	12.8

Note: $\widehat{\rho}$ and $\widehat{\rho}^C$ are estimated correlation coefficients of two-day rolling averages of returns in the tranquil and crisis periods; $\bar{\lambda}$ is the threshold variance ratio as defined in the text (for $\widehat{\delta} = 8.72$). The fourth column reports the results of the Fisher test: * (**) indicates that the hypothesis $\widehat{\rho}^C \leq \widehat{\rho}$ is rejected at the 5 (1) per cent significance level.

Table 2: Estimations of the variance ratio for Hong Kong

	$\lambda = \lambda^C$	λ	λ^C
Cross section:			
G 7	2.8	2.9	3.2
Full sample	2.4	2.6	2.6
World stock market index	3.6	3.0	4.5
Principal components:			
First component	7.1		
First two components	7.0		
First five components	4.1		

Table 3: Robustness - Test results

	Number of countries for which interdependence is rejected		
Test:	Fisher test	$\lambda = \lambda^C = \widehat{\lambda}$	$\lambda = \lambda^C = 0$
Sample:			
Benchmark	8	5	1
Local currency	7	5	2
Tranquil: 3.1.96-17.10.97 Crisis: 20.10.97-28.11.97	8	4	1
Tranquil: 3.1.96-17.10.97 Crisis: 20.10.97-31.12.97	8	5	1
Daily returns	8	7	3

The test $\lambda = \lambda^C = \widehat{\lambda}$ is based on the global factor estimated as the returns on the 'world stock market index'.

Fig. 1a - Stock market volatility *(daily returns, 3M exp. mov. average)*

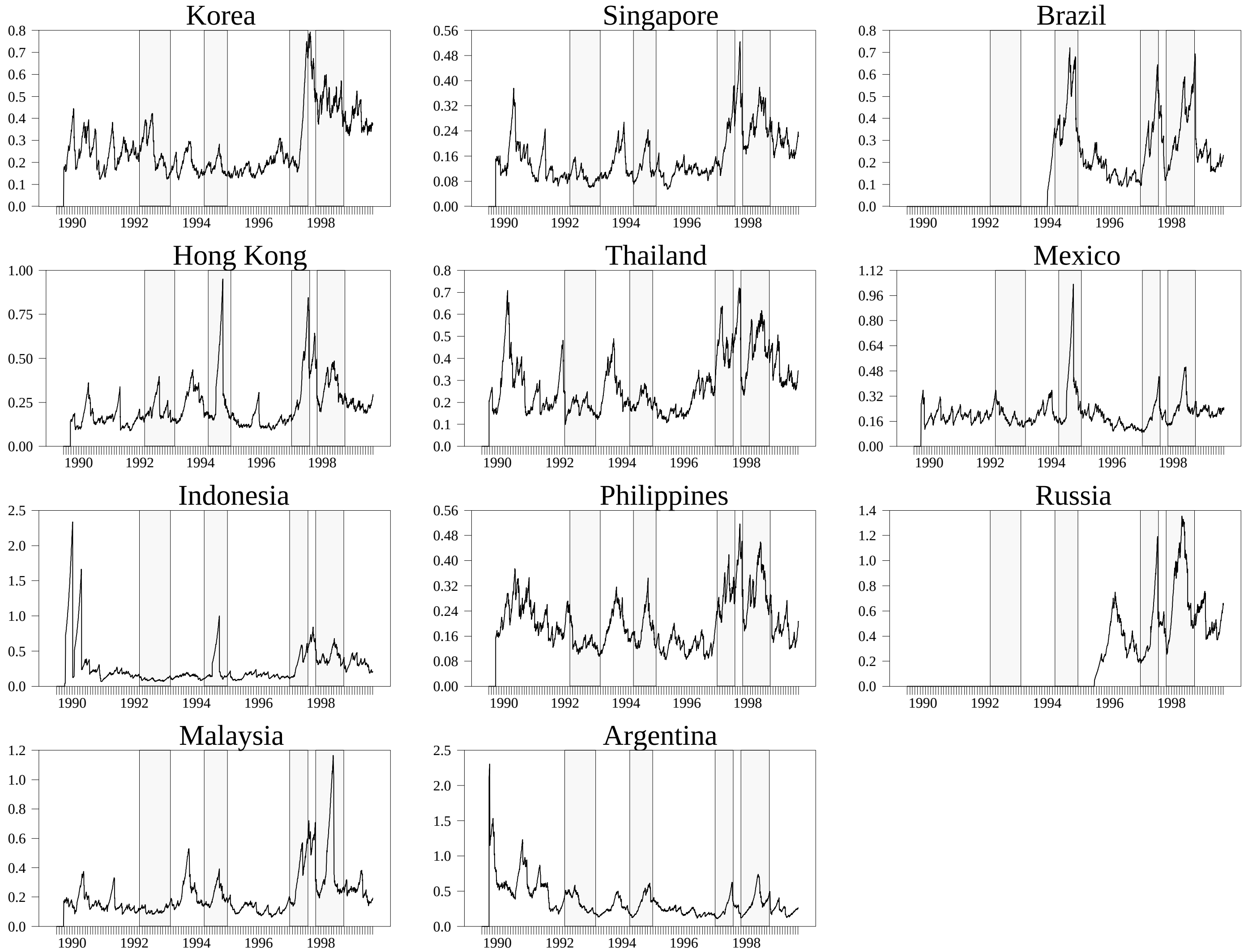

Fig. 1b - Stock market volatility *(daily returns, 3M exp. mov. average)*

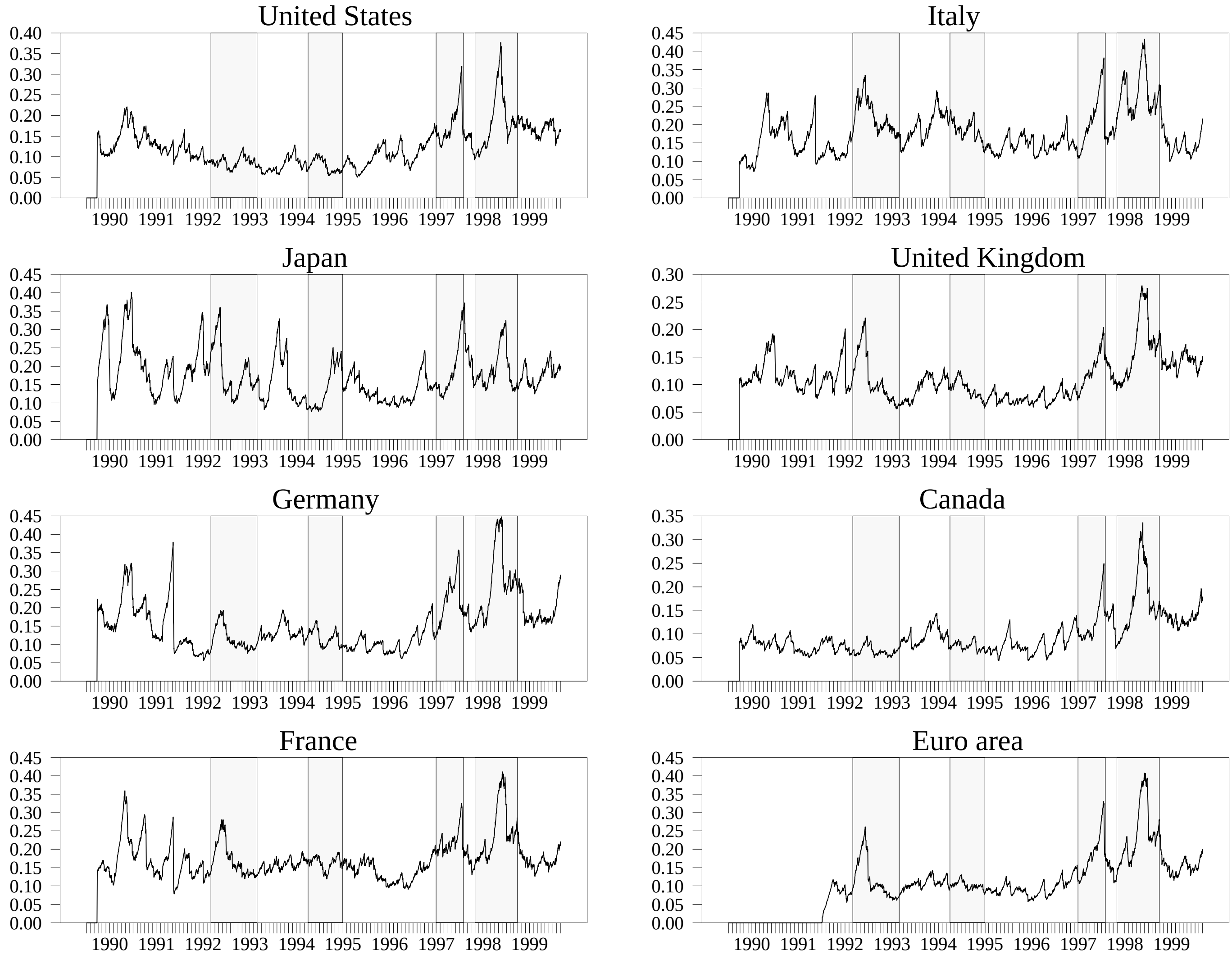

Fig. 2a - Stock market covariance of weekly returns

(Asia; 3 month exp. moving average)

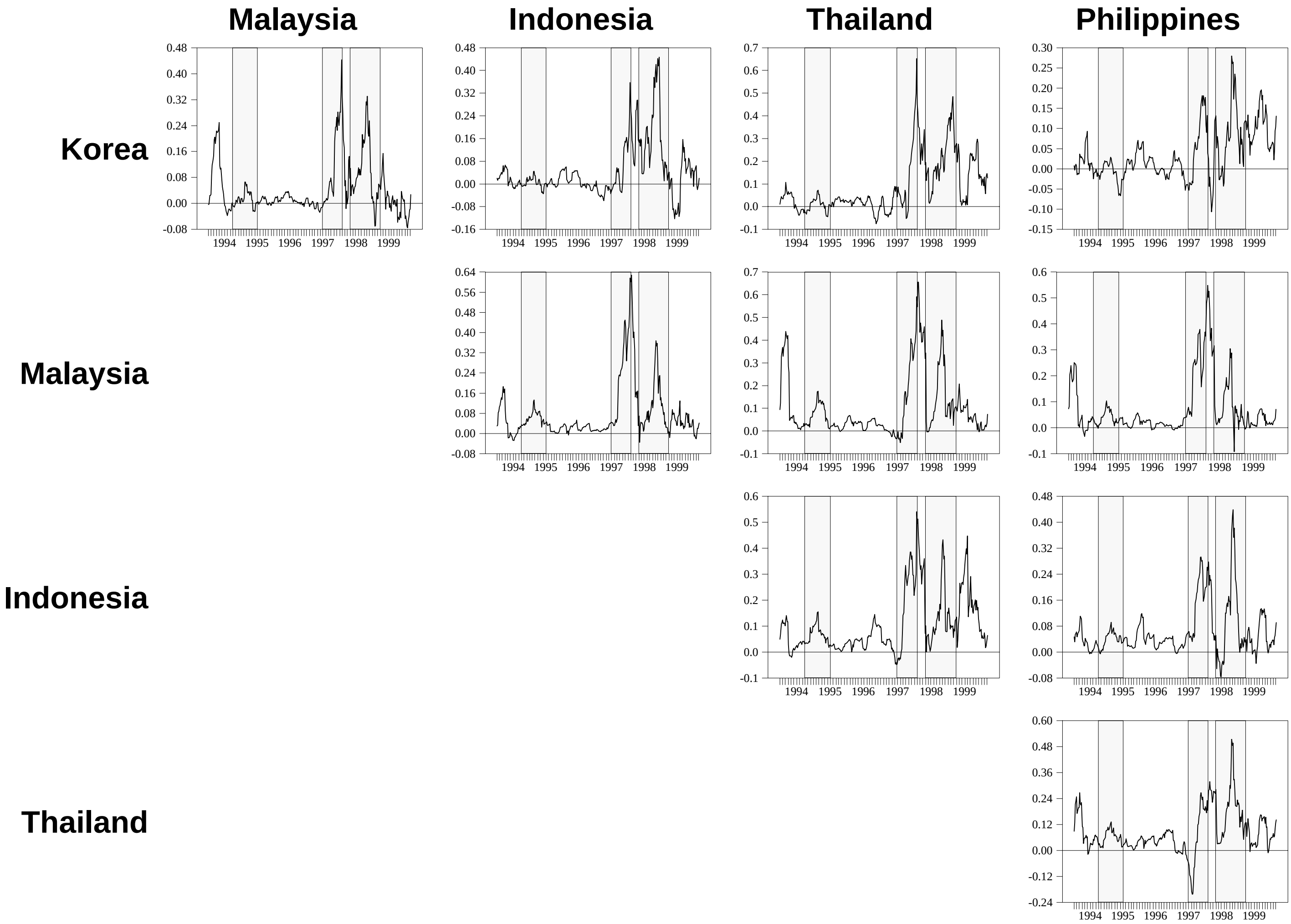

Fig. 2b - Stock market covariance of weekly returns

(Asia vs. Hong Kong and Singapore; 3 exponential month moving average)

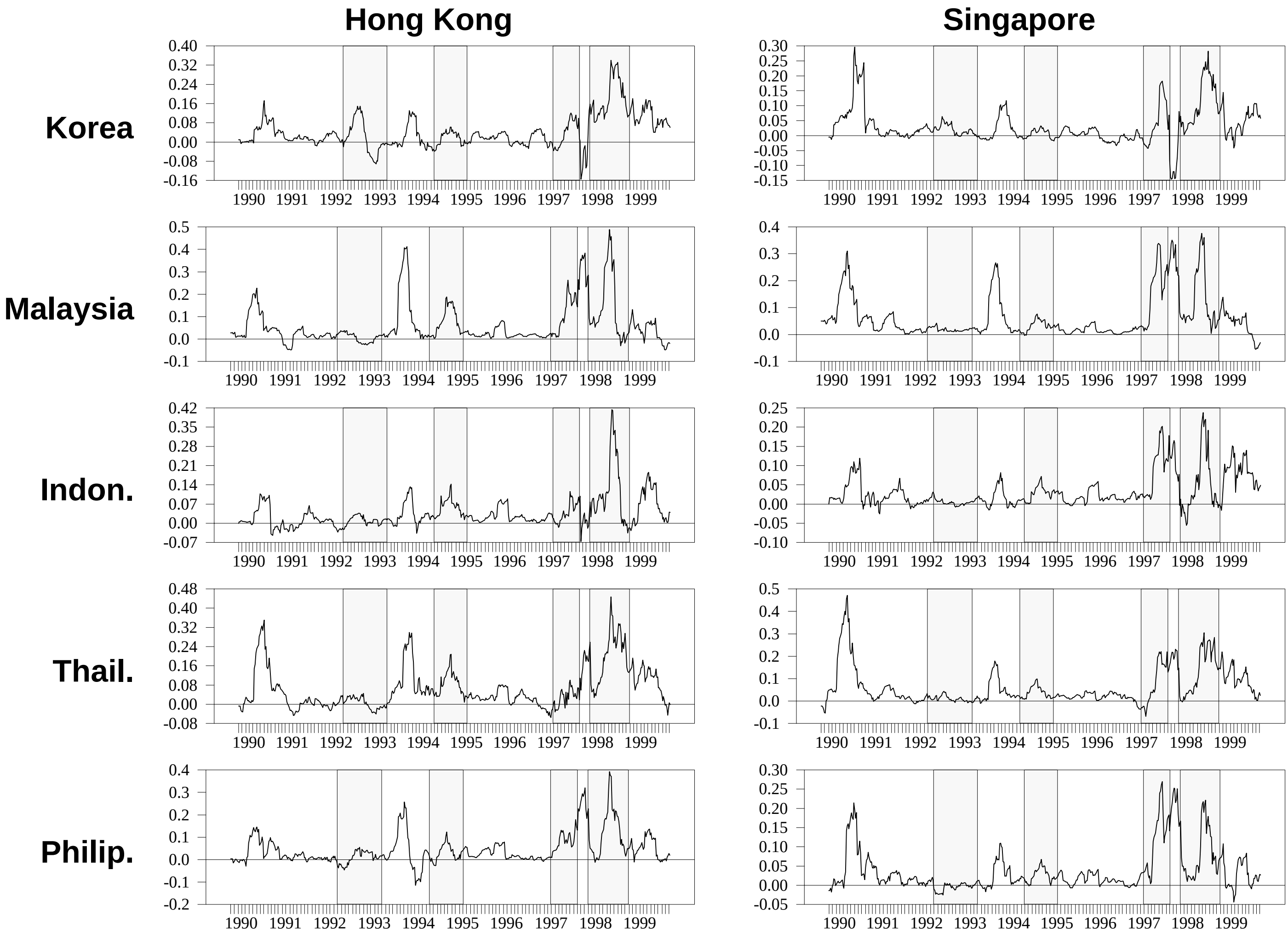

Fig. 2c - Stock market covariance of weekly returns

(Asia vs. USA and Japan; 3 month exponential moving average)

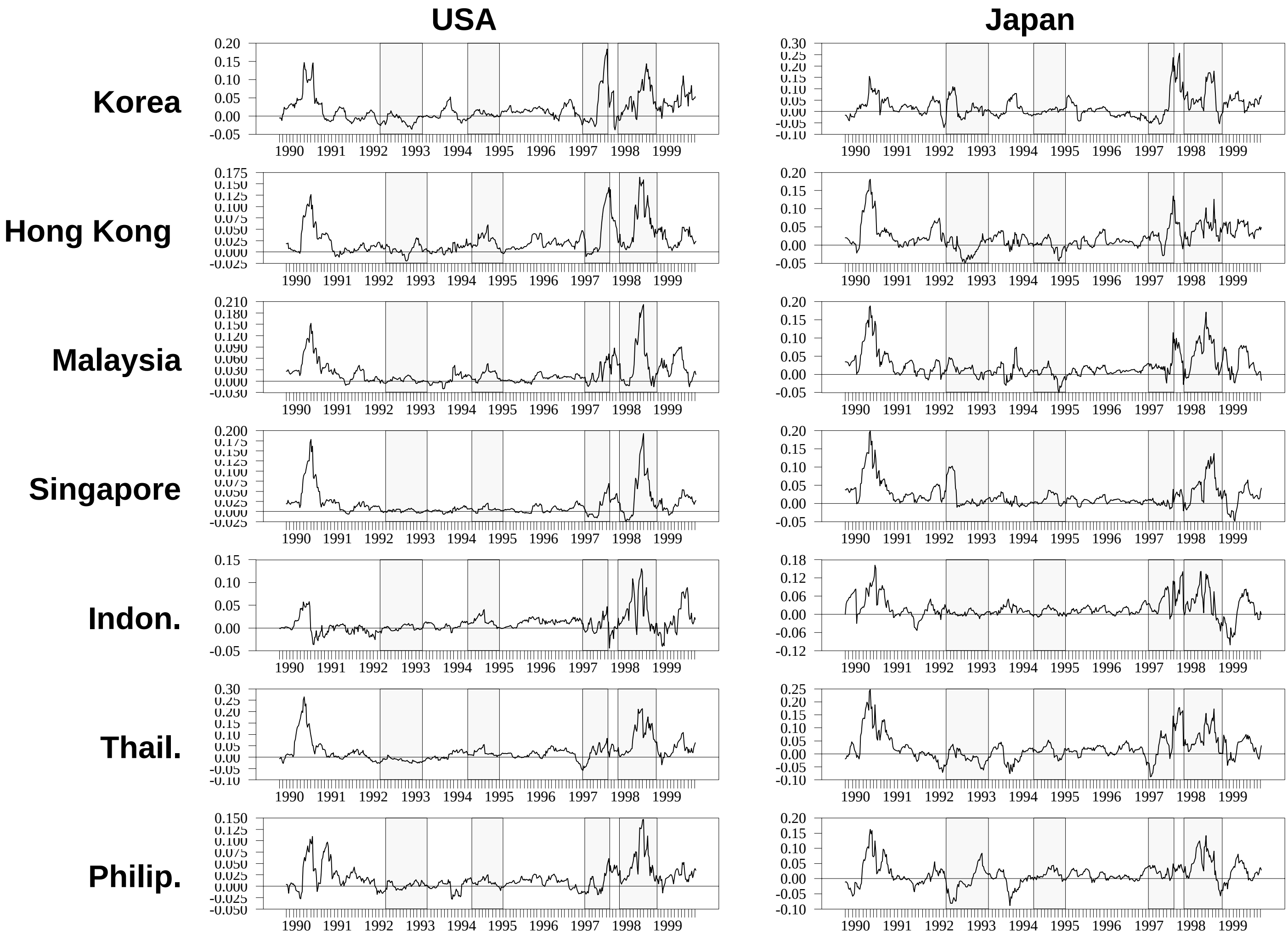

Fig. 2d - Stock market covariance of weekly returns

(Asia; 3 month exp. moving average)

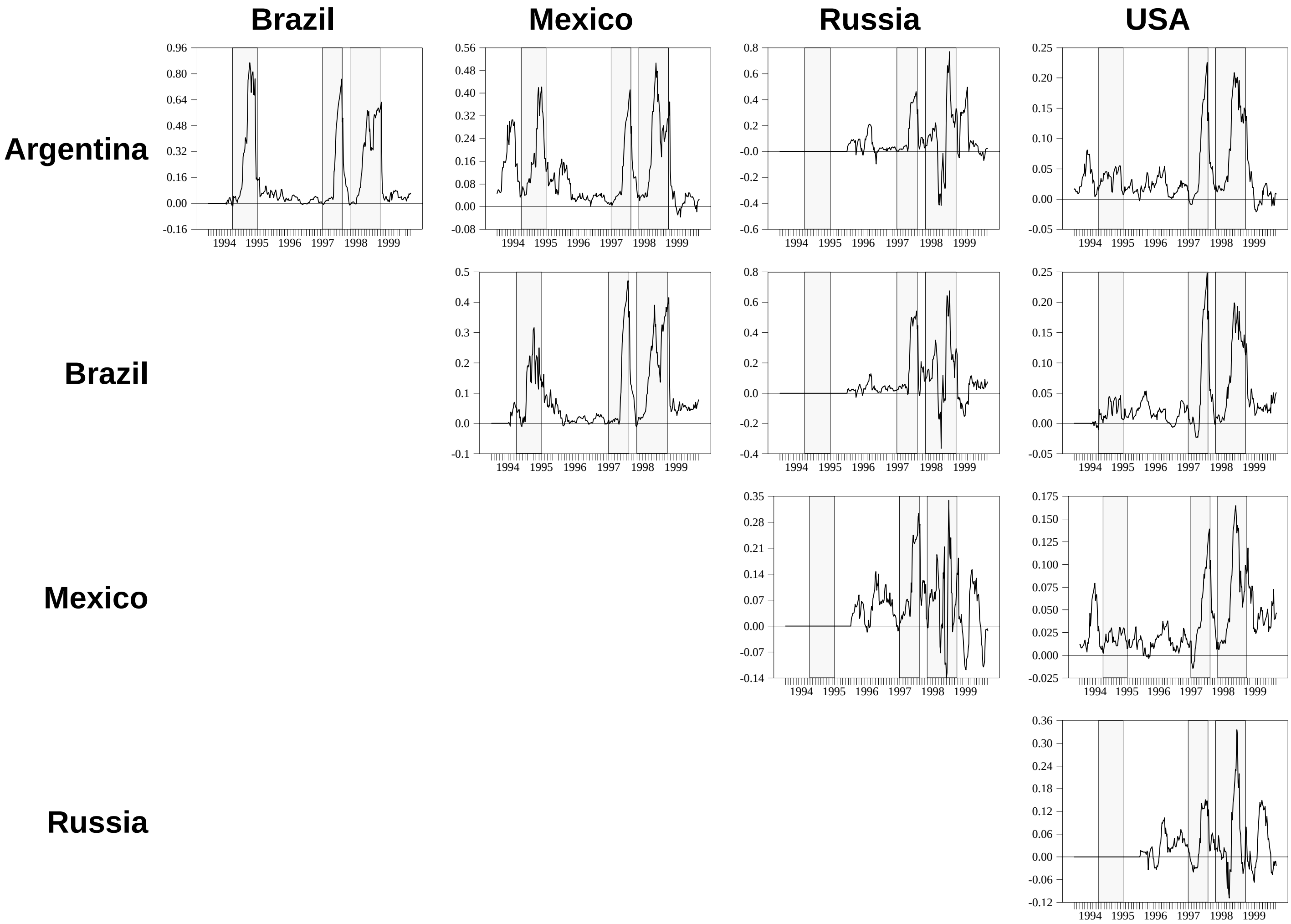

Fig. 3a - Stock market correlation of weekly returns

(Asia; 3 month exp. moving average)

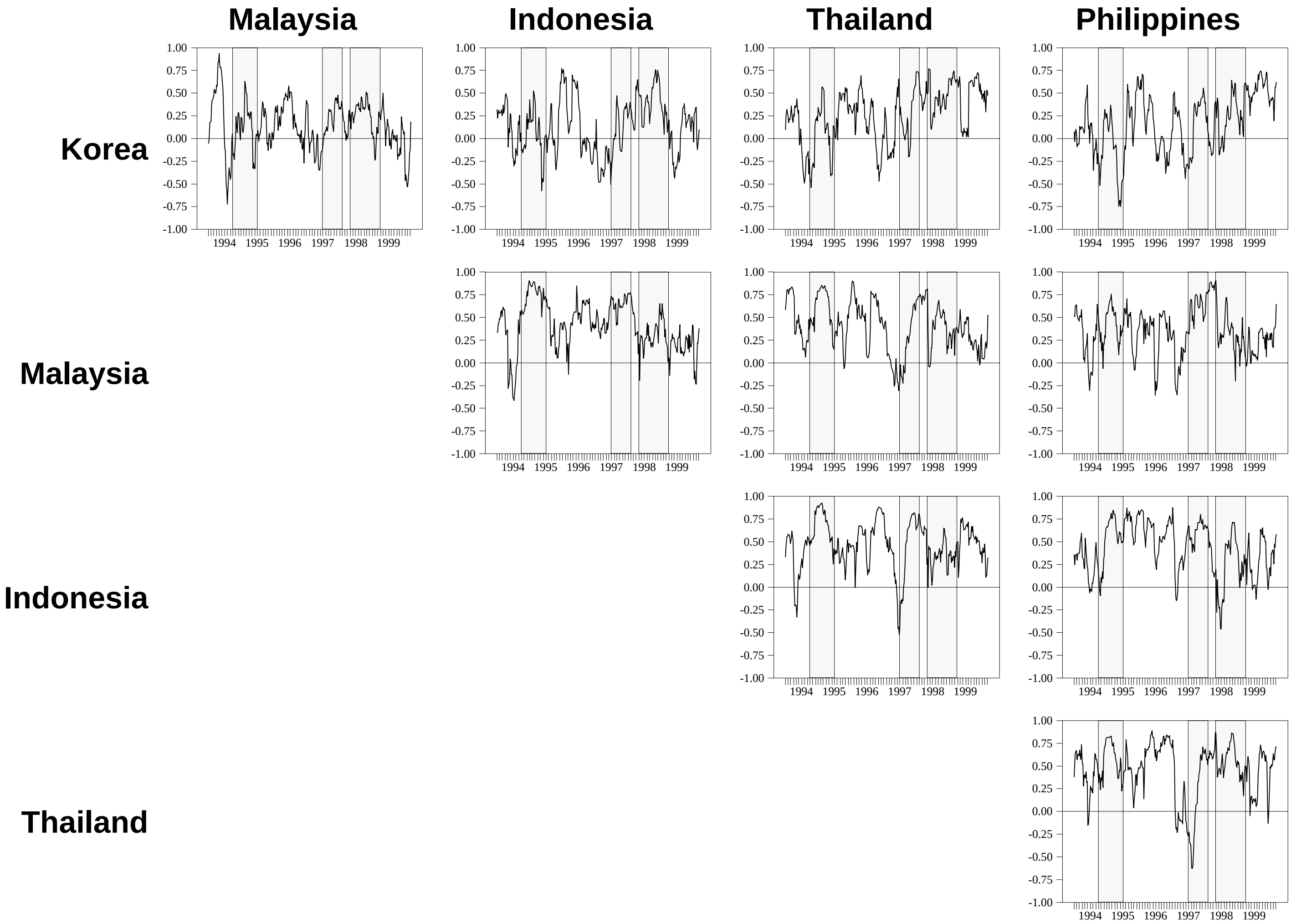

Fig. 3b - Stock market correlation of weekly returns

(Asia vs. Hong Kong and Singapore; 3 exponential month moving average)

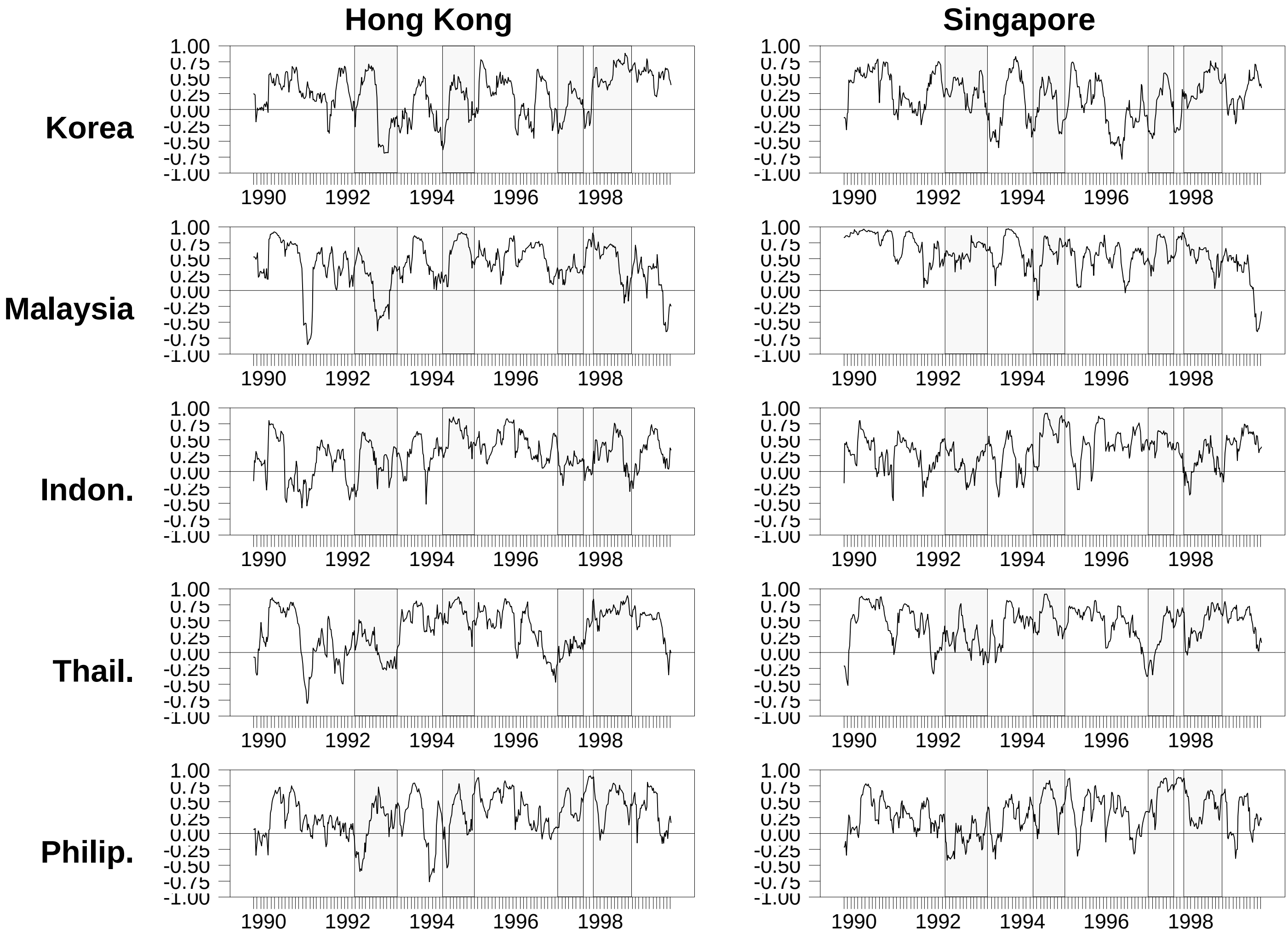

Fig. 3c - Stock market correlation of weekly returns

(Asia vs. USA and Japan; 3 month exponential moving average)

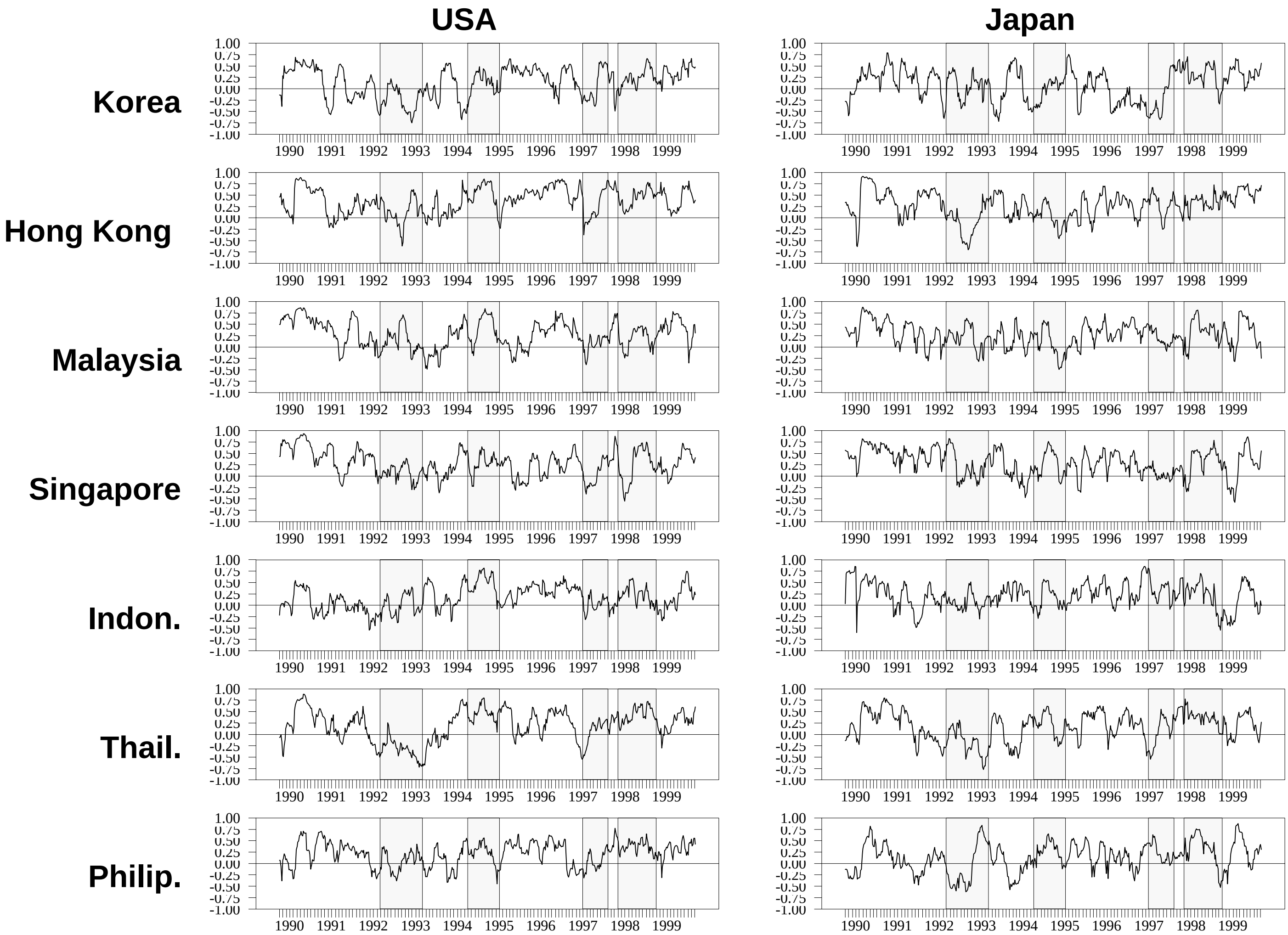

Fig. 3d - Stock market correlation of weekly returns

(Latin America, Russia and the US; 3 month moving average)