DISCUSSION PAPER SERIES

No. 3310

SOME CONTAGION, SOME INTERDEPENDENCE: MORE PITFALLS IN TESTS OF FINANCIAL CONTAGION

Giancarlo Corsetti, Marcello Pericoli
and Massimo Sbracia

INTERNATIONAL MACROECONOMICS

Centre for Economic Policy Research

www.cepr.org

Available online at: www.cepr.org/pubs/dps/DP3310.asp

ISSN 0265-8003

SOME CONTAGION, SOME INTERDEPENDENCE: MORE PITFALLS IN TESTS OF FINANCIAL CONTAGION

Giancarlo Corsetti, Università di Roma III and Yale University and CEPR
Marcello Pericoli, Banca d'Italia
Massimo Sbracia, Banca d'Italia

Discussion Paper No. 3310
April 2002

Centre for Economic Policy Research
90–98 Goswell Rd, London EC1V 7RR, UK
Tel: (44 20) 7878 2900, Fax: (44 20) 7878 2999
Email: cepr@cepr.org, Website: www.cepr.org

CEPR Discussion Paper No. 3310

April 2002

ABSTRACT

Some Contagion, Some Interdependence: More Pitfalls in Tests of Financial Contagion

This Paper develops a test of contagion in financial markets based on bivariate correlation analysis, which generalizes existing tests, and applies it to the international effects of the Hong Kong stock market crisis of October 1997. Contagion is defined as a structural break in the international transmission of financial shocks. For plausible values of the variance of country-specific shocks in Hong Kong, our test finds evidence of contagion for 5 countries out of a sample of 17. This is in sharp contrast with the findings of recent literature, according to which there is 'no contagion, only interdependence'. We show that this strong result in the literature is due to arbitrary and unrealistic restrictions on the variance of country-specific shocks.

JEL Classification: C10, F30, G10 and G15
Keywords: contagion, correlation analysis, factor model and financial crisis

Giancarlo Corsetti
Dipartimento di Economia
Università di Roma III
Viale Ostiense 139
00154 Rome
ITALY
Tel: (39 06) 5737 4056
Email: corsetti@uniroma3.it

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=116499

Marcello Pericoli
Banca d' Italia
Via Nazionale 91
00184 Rome
ITALY
Tel: (39 06) 4792 4167
Fax: (39 06) 4792 4118
Email: pericoli.marcello@insedia.interbusiness.it

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=156320

Massimo Sbracia
Banca d' Italia
Via Nazionale 91
00184 Rome
ITALY
Tel: (39 06) 4792 3860
Fax: (39 06) 4792 4118
Email: sbracia.massimo@insedia.interbusiness.it

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=156321

* This paper is produced as part of a CEPR Research Network on 'The Analysis of International Capital Markets: Understanding Europe's Role in the Global Economy', founded by the European Commission under the Research Training Network Programme (Contract No: HPRN-CT-1999-0067). We thank Fabio Canova, Luca Dedola, Andrea Finicelli, Phil Lane, seminar participants at the Banca d'Italia, ZEI Summer School, XVIII Latin American Meetings of the Econometric Society, XVI Annual Congress of the European Economic Association and CEPR-LBS conference on International Capital Flows, and two anonymous referees for comments. Giovanna Poggi provided valuable research assistance. The opinions expressed in this paper are those of the authors and do not necessarily reflect the position of the Bank of Italy or of any other institution with which the authors are affiliated.

Submitted 18 March 2002

1 Introduction

During currency and financial crises, asset price comovements across markets and across borders tend to increase visibly compared with more tranquil periods. The size of these comovements have led many economists to raise the question of whether 'tranquil periods' and 'crises' are to be interpreted as different regimes in the international transmission of financial shocks; that is, whether there are discontinuities in the international transmission mechanism.[1]

The headline of the theoretical and policy debate on this issue is 'contagion'.[2] Contagion — as opposed to 'interdependence' — conveys the idea that there are breaks in the international transmission mechanism owing to financial panics, herding or switches of expectations across instantaneous equilibria. Although there is no consensus about what exactly contagion is and how we should measure it,[3] several authors have proposed empirical tests in an attempt to address the issue of contagion versus interdependence purely on empirical grounds. Boyer et al. (1999) and Forbes and Rigobon (2001 and 2002), for instance, compare cross-country correlations of asset returns in tranquil and crisis periods, testing for contagion as a structural break in the parameters of the underlying data-generating process.[4]

In these contributions 'tranquil' and 'crisis' periods are identified by different levels of volatility of asset returns. Now, suppose that a crisis is driven by an increase in the variance of a common factor, causing higher-than-usual volatility in several markets. Even if there is no change in the international transmission, larger common shocks would naturally raise the magnitude of cross-country comovements. Hence, an increase in cross-country correlations

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

[2]A partial list of contributions to this debate includes, Buiter et al. (1998), Calvo (1999), Calvo and Mendoza (2000), Caramazza et al. (2000), Claessens et al. (2001), Corsetti et al. (2000a), Edwards (1998), Eichengreen et al. (1996), IMF (1998 and 1999), Jeanne and Masson (1998), Kaminsky and Reinhart (2000), Kaminsky and Schmukler (1999), Kodres and Pritsker (2002), and Schinasi and Smith (2001).

[3]In a related work, Pericoli and Sbracia (2001) discuss a number of definitions of contagion. In early studies on clusters of currency crises, contagion is a significant increase in the probability of a crisis in one country, conditional on a crisis occurring in another country. In works focused on asset prices, contagion is sometimes defined as a volatility spillover from the crisis country to the financial markets of other countries. In models stressing multiple equilibria and herding, contagion is defined as spillovers that cannot be explained in terms of fundamentals. The definition underlying our test is a structural break in cross-market links.

[4]Examples of studies on correlation and contagion also include Baig and Goldfajn (2000), Bordo and Murshid (2001), Goetzmann et al. (2001), King and Wadhwani (1990), Loretan and English (2000).

during a period of financial turmoil is not necessarily evidence of contagion. For contagion to occur, the observed pattern of comovements in asset prices must be too strong (or too weak) relative to what can be predicted when the mechanism of international transmission is constant.

Key to these tests is the specification of a theoretical measure of interdependence that captures the effects on correlation of an increase in the volatility of asset prices for a given transmission mechanism. In general, an increase in volatility of returns during a crisis may be due to either higher variance of some common factor, or to country-specific noise, or both. In this paper, we derive such a measure from a factor model of returns that, in contrast with previous contributions, does not impose restrictions on the variance of common factors relative to the variance of country-specific risks.

We apply our test to the international implications of the Hong Kong stock market crisis of October 1997, which is one of the leading case-studies in Forbes and Rigobon (2002). We find evidence of contagion for at least 5 countries out of a sample of 17. By contrast, the 'adjusted' or 'corrected' correlation tests proposed by Boyer et al. (2000) and Forbes and Rigobon (2002) would reject interdependence for only 1 country. Using our framework, we show that this strong result of 'no contagion, only interdependence' can be attributed to arbitrary assumptions on the variance of the market-specific noise in the country where the crisis originates — assumptions that bias the test towards the null hypothesis of interdependence.

The paper is organized as follows. Section 2 briefly discusses the main pitfalls in testing for the stability of cross-market links using standard correlation analysis. Section 3 introduces our setup and derives a measure of cross-country interdependence. Section 4 reconsiders the literature on contagion in the light of our model, identifying the bias in existing tests. Section 5 assesses the importance of such a bias, applying our methodology to the analysis of financial contagion during the 1997 Hong Kong stock market crisis. Section 6 concludes.

2 Contagion and correlation

The evidence that leads analysts and market commentators to raise the hypothesis of 'contagion' in the international transmission of currency and financial crises, is the apparent increase in comovements of asset prices across markets during periods of financial turmoil. Indeed, although systemic analyses of currency and financial crises emphasize different empirical regularities, most studies agree on the fact that periods of crisis coincide with high *volatility* of asset prices as well as high *covariance* of returns across national markets. Many studies also conclude that, on average, *correlation* between market returns is higher and/or increasing during crises.[5]

However, interpreting any increase in cross-country covariances and/or correlations as evidence of contagion may be misleading. We can illustrate this point by means of a simple example drawing on Forbes and Rigobon (2002). Suppose that the rates of return of the stock market in two countries are linearly related:

$$r_i = \beta_0 + \beta_1 r_j + \nu_i \ ,$$

where r_i and r_j respectively denote stock market returns in countries i and j, ν_i is a stochastic noise independent on r_j, β_0 and β_1 are constants, with β_1 measuring the 'strength' of the link between the two markets. The variance of r_i, the covariance and the correlation between the two rates of return are, respectively:[6]

$$\begin{aligned} Var(r_i) &= \beta_1^2 Var(r_j) + Var(\nu_i) \ ; \\ Cov(r_i, r_j) &= \beta_1 Var(r_j) \ ; \\ Corr(r_i, r_j) &= \beta_1 \sqrt{\frac{Var(r_j)}{\beta_1^2 Var(r_j) + Var(\nu_i)}} \ . \end{aligned}$$

These expressions show that the variance of r_i, the covariance and correlation between r_i and r_j must all increase with $Var(r_j)$, even if the intensity of the cross-country linkage β_1 does not change. Thus, to the extent that a crisis in country j raises the variance of its stock market returns, stronger cross-market comovements are consistent with a stable international transmission of financial shocks. They do not necessarily reflect discontinuities in the transmission mechanism. Can we then conclude that there is 'contagion' even if the international transmission mechanism is exactly the same as in a 'no-crisis' period?

Early contributions on contagion acknowledge this issue. For instance, King and Wadhwani (1990) write that "we might expect that the contagion coefficients would be an increasing function of volatility" (p. 20), but

[5] For a review of the empirical literature, see Pericoli and Sbracia (2001) and Claessens et al. (2001). Corsetti et al. (2000b) present a comprehensive analysis of stylized facts for stock market prices, nominal exchange rates against the US dollar, overnight interest rates, and sovereign spreads of dollar-denominated bonds with corresponding US assets. This study and Corsetti et al. (2001) show that, despite strong market comovements, cross-market correlations are not always higher in crisis periods. In a number of episodes, for instance, correlations actually falls at the outbreak of the crisis. Moreover, there are peaks of correlation in both tranquil and crisis 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 common factors, underlying the increase in market volatility during periods of turmoil. As shown below, country-specific noise plays a key role in testing for discontinuities in the cross-market transmission of shocks.

[6] Hereafter Var stands for the variance operator, Cov the covariance operator and $Corr$ the correlation operator.

they implement no correction for their empirical tests. Recently, two sets of contributions have independently proposed a solution to this problem, that consists in adjusting the sample cross-market correlation coefficient for changes in the volatility of returns in the country where the crisis originates. One set of contributions build on the hypothesis that returns are normally distributed (see Boyer et al. (1999), Loretan and English (2000)), the other draws more directly on regression analysis (see Forbes and Rigobon (2001 and 2002)). Both sets of contributions introduce bivariate tests under the null hypothesis that β_1 does not change during a period of international turmoil.

Somewhat surprisingly, it turns out that applying these tests to different samples always yields the same answer: regardless of the timing of the crisis and the regional and structural features of the countries in the sample, almost no episodes of international spread of financial turmoil should be viewed as 'contagion'. Accordingly, the peaks in cross-country links that emerge in periods of crisis are just an implication of international 'interdependence'. In what follows, we develop a test and investigate whether this strong result can be attributed to pitfalls in the testing procedure developed by this literature.

3 Testing for contagion as instability of cross-market links

3.1 A factor model with period-specific variance of asset returns

This section lays out a simple theoretical framework for testing for structural breaks in the international transmission mechanism. The model consists of two elements. The first one is a data-generating process of stock market returns in country i and country j. As a starting point for the analysis, we choose a standard single-factor model:

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

where α_i and α_j are constants, γ_i and γ_j are country-specific factor loadings, f is a common factor, ε_i and ε_j denote idiosyncratic country-specific factors, with f, ε_i and ε_j mutually independent random variables with finite variance.

The second element is the specification of changes in the variance of f and ε's between tranquil and crisis periods. Specifically, let j denote the country of 'origin' of an international financial crisis; for example, Mexico at the end of 1994, Thailand in July 1997, Hong Kong in October 1997 and Russia in August 1998. Consistently with the evidence of high volatility of returns in periods of instability, a crisis in country j is defined as an increase in the variance of rates of returns. Let $r_j \in C$ denote the event 'crisis in country j' and let δ be the proportional change in the variance of the stock market return r_j relative to the pre-crisis period, namely:

$$Var(r_j \mid r_j \in C) = (1+\delta) \cdot Var(r_j) \ , \ \delta > 0 \ .$$

In general, shocks to the variance of r_j may be due to either the common factor, f, or the country-specific risk, ε_j.

Mutual independence of f, ε_i and ε_j implies that

$$Var\left(\varepsilon_i \mid r_j \in C\right) = Var(\varepsilon_i) \ . \tag{2}$$

In other words, since we are analyzing the spread of the crisis from j to a generic country i, the logic of our test suggests that the change in the variance of r_i during a crisis will only depend on the common factor and the cross-market links between the two countries.

Using model (1), the correlation coefficient between r_i and r_j can be written as:

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

in the tranquil period, and

$$\rho^C = \frac{1}{\left[1 + \frac{Var(\varepsilon_i)}{\gamma_i^2 Var(f|C)}\right]^{1/2} \cdot \left[1 + \frac{Var(\varepsilon_j|C)}{\gamma_j^2 Var(f|C)}\right]^{1/2}}$$

in the crisis period, where for simplicity we write C instead of $r_j \in C$. Comparing these two expressions, we conclude that – if all the parameters in our model are stable across periods – a rise in correlation during a crisis ($\rho^C > \rho$) must correspond to an increase in the variance of the common factor f relative to the variance of the idiosyncratic noise ε_j.

However, if the parameters of the model (1) are not stable, a rise in correlation during a crisis could also correspond to an increase in the magnitude of the factor loadings γ_i and γ_j, or to a strictly positive correlation between the idiosyncratic risks. In line with the literature, we define *interdependence as a change in correlation that is consistent with the data-generating process* (1). As opposed to interdependence, *contagion* occurs if the increase in correlation during a crisis 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 common factor and the country-specific component. In other words, contagion occurs when, conditional on a crisis in country j, correlation is stronger because of some structural change in the international economy affecting the links across markets.

In a related definition, contagion occurs when a country-specific shock becomes 'regional' or 'common'. 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 is provided by the following two-factor model:

$$\begin{aligned} r_i &= \alpha_i + \gamma_i \cdot f + \beta_i \cdot \eta + \varepsilon_i \\ r_j &= \alpha_j + \gamma_j \cdot f + (\eta + \eta_j) \ . \end{aligned} \tag{1'}$$

Under interdependence, we have $\beta_i = 0$, 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 common factor, i.e. when $\beta_i \neq 0$ (so that there is a rise in the covariance of country-specific risk). 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 process (1′) instead of (1). These definitions provide a general framework for the empirical test discussed below.

3.2 Measuring interdependence

How can one test whether changes in the correlation between r_i and r_j are consistent with the data-generating process (1)? The key step in the analysis is the specification of a correlation coefficient under the null hypothesis of interdependence. Let ϕ denote the correlation coefficient between r_i and r_j 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. As shown in Appendix I, ϕ can be written as the following function:

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

where

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

The parameters λ_j and λ_j^C denote the ratio between the variance of the idiosyncratic shock ε_j and the variance of the common factor f, scaled by the factor loading γ_j, during the tranquil and the crisis period, respectively. In what follows, we refer to ϕ as a *theoretical measure of interdependence* and to λ_j and λ_j^C as *variance ratios.*

The correlation coefficient between r_i and r_j observed during the crisis, ρ^C, and the theoretical measure of interdependence, ϕ, are the main elements of our test. 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 common during the crisis in country j), ρ^C will be larger than ϕ. Hence, a statistical analysis of contagion versus interdependence can be performed by testing whether ρ^C is significantly higher than ϕ.

Two features of this test are worth stressing. First, during an international crisis originating in one country, shocks to the common 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 correlation falls during a crisis (as it often does in the data) is by no means evidence against contagion. In other words, testing for contagion needs not be conditional on observing a rise in correlation. Second, the test is symmetrical; that is, 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.

3.3 Building intuition

Clearly, test results will crucially depend on the size of the variance ratios, i.e. on the relative variability of common vs. country-specific factors. To illustrate this point, Figure 1 plots our statistic for a particular case study, that is the spread of financial instability from Hong Kong to the Philippines in October 1997.

To make our graph directly comparable with a similar graph in Forbes and Rigobon (2002), first we simplify our measure of interdependence by assuming that the variance ratio does not vary across periods, that is, $\lambda_j^C = \lambda_j$. This means that the variances of both the common factor and the country-specific risk are assumed to increase by the same proportion during a crisis:

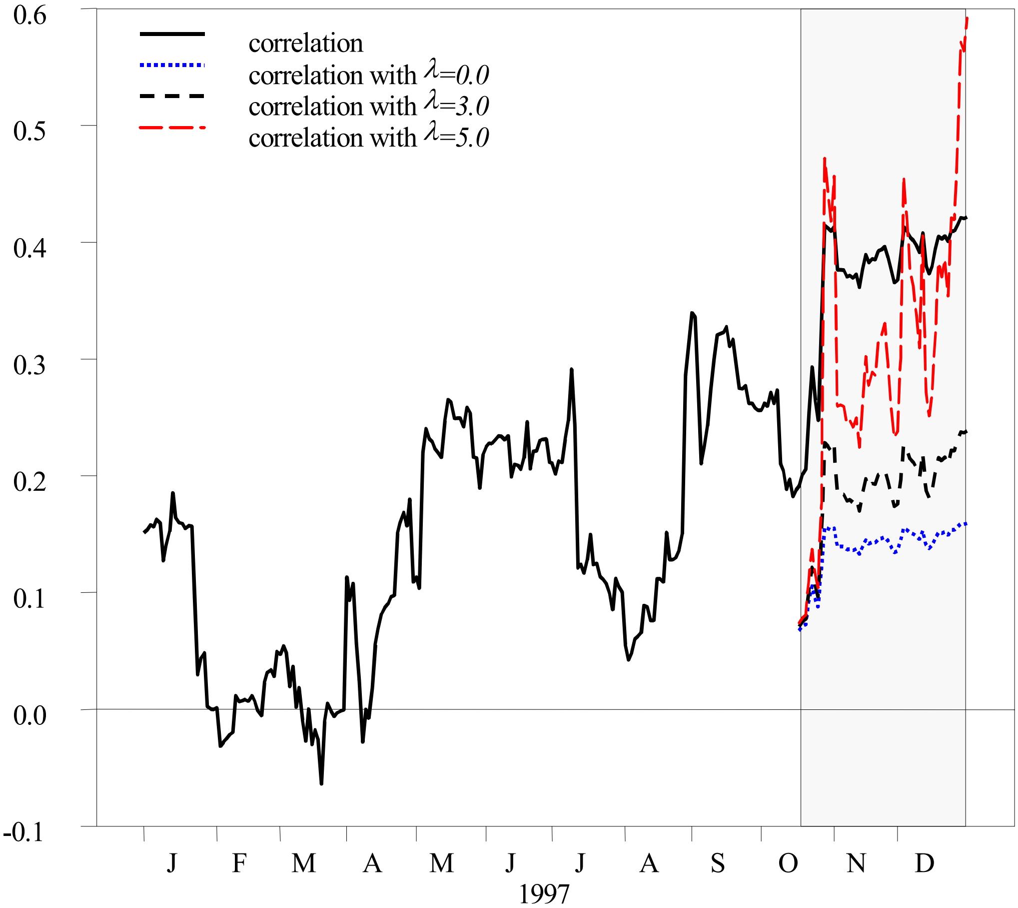
$$\frac{Var(r_j \mid C)}{Var(r_j)} = \frac{Var(f \mid C)}{Var(f)} = \frac{Var(\varepsilon_j \mid C)}{Var(\varepsilon_j)} = 1 + \delta \ .$$

Second, we plot an inverse transformation of (3), instead of (3) itself:[7]

$$\phi_t'(\lambda_j) = \frac{\rho_t^C}{\sqrt{1 + \delta - \delta\left(\rho_t^C\right)^2 - \delta\lambda_j\left(\rho_t^C\right)^2}}\,. \tag{4}$$

Note that, when using ϕ', the null of no contagion becomes $\phi' = \rho$ (as in Forbes and Rigobon (2002)), instead of $\phi = \rho^C$.

Figure 1. Hong Kong and the Philippines: Instantaneous and Adjusted Correlation for Different Values of λ_j



[7]The coefficient ϕ' is obtained by substituting ϕ with ρ^C in equation (3), posing $\lambda_j = \lambda_j^C$, and then solving the resulting expression for ρ. We compute daily correlation as $\rho_t^C = \sum_{t=0}^{T-1} \vartheta^h \widetilde{r}_{i,t-h}\widetilde{r}_{j,t-h}\left(\sum_{h=0}^{T-1}\vartheta^h(\widetilde{r}_{i,t-h})^2 \cdot \sum_{h=0}^{T-1}\vartheta^h(\widetilde{r}_{j,t-h})^2\right)^{-1/2}$, where ϑ is the decay factor (which we set equal to 0.96), T is the length of the moving window (which we set equal to 3 months), $\widetilde{r}_{i,h}$ ($\widetilde{r}_{j,h}$) is the de-meaned return on stock market i (j) at time h.

In Figure 1, the thick line is the daily correlation between stock market returns in US dollars in Hong Kong and the Philippines for 1997. The first $9\frac{1}{2}$ months of the year correspond to the tranquil period (the daily correlation coefficient is a proxy for ρ). The rest of the year, marked by the shaded area, corresponds to the crisis period (the daily correlation coefficient is then a proxy for ρ^C). From October 20 on, three broken lines plot $\phi_t^{'}$, as defined in (4), conditional on three exogenously given values of λ_j ($\lambda_j = 0$, 3 and 5).

The figure shows that when $\lambda_j = 0$, the coefficient $\phi_t^{'}$ is well below ρ^C, while increasing the value of λ_j shifts $\phi_t^{'}$ upwards. Inspection of the graph suggests that $\phi_t^{'}$ is actually close to ρ, the average value of the correlation coefficient during the tranquil period in the first months of 1997. For $\lambda_j = 5$, instead, at many dates $\phi_t^{'}$ becomes close to, or larger than ρ^C, and is well above the average ρ in the tranquil period. Whether or not $\phi_t^{'}$ is significantly different from ρ will crucially depend on the value of the variance ratio λ_j.

Intuitively, the theoretical measure of interdependence adjusts the correlation coefficient for the effect on cross-border comovements of a change in the volatility of stock prices in Hong Kong. A larger λ_j implies a smaller relevance of the common factor, i.e. a larger fraction of the overall change in volatility in Hong Kong is attributed to country-specific noise. Therefore, a larger λ_j entails a smaller 'adjustment' relative to ρ_t^C.

4 The literature reconsidered

4.1 Tests assuming direct and linear cross-market links

To derive their test statistic, Forbes and Rigobon (2001 and 2002) posit a linear relationship between rates of return in countries i and j, namely

$$r_i = \beta_0 + \beta_1 \cdot r_j + \nu_i \ , \tag{5}$$

and they assume:

$$\begin{aligned} Corr(r_j, \nu_i \mid C) = Corr(r_j, \nu_i) = 0 \\ Var(\nu_i \mid C) = Var(\nu_i) \ . \end{aligned} \tag{6}$$

Based on this set of assumptions, they derive the following measure of interdependence:[8]

$$\xi = \rho \left[\frac{1+\delta}{1+\delta\rho^2} \right]^{1/2} \ , \tag{7}$$

which plays the same role as our ϕ. Note that the two measures (ξ and ϕ) coincide when $\lambda_j = \lambda_j^C = 0$.

[8] See Appendix A in Forbes and Rigobon (2002).

Is the linear model (5) in some sense special, or can it be derived from more standard representations of rates of return? To address this question, we rewrite the model by Forbes and Rigobon assuming that the true data-generating process is our factor model (1):

$$r_i = \left(\alpha_i - \alpha_j \frac{\gamma_i}{\gamma_j}\right) + \frac{\gamma_i}{\gamma_j} r_j + \left(\varepsilon_i - \frac{\gamma_i}{\gamma_j}\varepsilon_j\right). \tag{8}$$

This expression reveals two potentially important sources of misspecification in the statistic (7). First, as long as the market return in country j reflects idiosyncratic noise (i.e. $Var(\varepsilon_j) > 0$), the first hypothesis of the linear model (5) is violated: r_j will be correlated with ν_i in both tranquil and crisis periods. Second, if $Var(\varepsilon_j)$ increases during a crisis, the second hypothesis in (6) is also violated: the variance of ν_i will increase during a crisis. In other words, a positive and possibly time-varying $Var(\varepsilon_j)$ implies that the linear model (5) and the set of assumption (6) are not consistent with each other. In light of standard pricing models, the analysis by Forbes and Rigobon is internally consistent only under the (unrealistic) assumption that $Var(\varepsilon_j) = Var(\varepsilon_j \mid C) = 0$ — which is the case where λ_j and λ_j^C are identically equal to zero.

What are the implications of adopting the statistic (7) in a test of contagion? Suppose that $Var(\varepsilon_j)$ is positive but constant. Then, while r_j will still be correlated with ν_i in both the tranquil and the crisis periods, the variance of ν_i will actually be constant, in line with the second assumption in (6). Holding these hypotheses,[9] our measure of interdependence can be written as

$$\phi_{Var(\varepsilon_j|C)=Var(\varepsilon_j)} = \rho\left[\frac{(1+\delta+\delta\lambda_j)^2}{1+\delta}\frac{1}{1+\rho^2\delta(1+\lambda_j)^2}\right]^{1/2}. \tag{9}$$

As long as market idiosyncratic risk is homoskedastic, using (7) instead of (9) will obviously bias the test. Nonetheless, this misspecification per se does not allow us to sign the bias in ξ unambiguously.

By contrast, we can sign the bias from assuming a homoskedastic ν_i when $Var(\varepsilon_j)$ changes during a crisis. In fact, the derivative of ϕ with respect to λ_j^C is negative. In other words, for any given λ_j, higher values of λ_j^C move ϕ towards the region where the null hypothesis of interdependence should be rejected. It follows that, if the country-specific noise increases during a crisis, the tests based on (7) are biased towards the null.[10]

[9] When $Var(\varepsilon_j)$ is constant, we have

$$\frac{1+\lambda_j}{1+\lambda_j^C} = \frac{1+\delta+\delta\lambda}{1+\delta}.$$

[10] The Forbes and Rigobon statistic can be defended under the special (and again un-

4.2 Tests based on linearity and normality of returns

A similar test had been developed earlier by Boyer et al. (1999) and then used by Loretan and English (2000). These authors assume that the vector $(r_i, r_j)'$ is a bivariate normally distributed random variable and analyze cross-country correlation as a function of an increase in the variance of r_j.

To relate this test to our analysis, consider the data-generating process (1) under the assumption that f, ε_i, and ε_j are normally distributed. Specifically, let $(f, \varepsilon_i, \varepsilon_j)'$ be multivariate normally distributed and define a matrix A of rank 2 such that the vector $A \cdot (f, \varepsilon_i, \varepsilon_j)'$ corresponds to our single-factor model (1).[11] By a well-known property of multivariate normal distributions, the vector $A \cdot (f, \varepsilon_i, \varepsilon_j)'$ is bivariate normally distributed.

Clearly, what makes this test different from our specification is not the assumption that r_i and r_j are jointly normal. Rather, what matters is the additional restrictions on the distribution of returns that are invoked by the theorem in Boyer et al. (1999). To see what these restrictions are, it is useful to recall that $(r_i, r_j)'$ can be written as $P \cdot (u_i, u_j)'$, where u_i and u_j are independent and normally distributed random variables, and

$$P = \left[\begin{array}{cc} \sqrt{(1-\rho^2) \cdot Var(r_i)} & \rho\sqrt{Var(r_i)} \\ 0 & \sqrt{Var(r_j)} \end{array} \right]$$

is the Cholesky decomposition of the variance-covariance matrix of $(r_i, r_j)'$. Using this decomposition, the data-generating process of the rates of return can be rewritten as:

$$\begin{aligned} r_i &= \alpha_i + \gamma_i \cdot r_j + \nu_i \\ r_j &= \alpha_j + \gamma_j \cdot \nu_j \quad . \end{aligned} \tag{10}$$

with v_i and v_j independent and normally distributed. This model is clearly equivalent to the linear model (5) of Forbes and Rigobon. Thus, Boyer et al. (1999) and Loretan and English (2000) derive their measure of interdependence from (10), using the same set of restrictions (6) on the correlation between r_j and ν_i and the variance of ν_i.[12] It is therefore no surprise that

realistic) assumption that λ_j is positive in normal times, but there is no component of the change in the variance of r_j that is country-specific during a crisis. In other words, corresponding to $\lambda_j^C = 0$, the crisis in the stock market return in country j is assumed to be a 'global' or 'regional' factor. Under this strong assumption, for any positive λ_j, the statistic (7) is actually biased against the null: if tests based on ξ accept the null, a fortiori tests based on ϕ would also accept the null. Observe that $\lambda_j > 0$ and $\lambda_j^C = 0$ imply that the variance of the global component in r_j increases by more than δ, the increase in the variance of the rates of return.

[11] This matrix is

$$A = \left(\begin{array}{ccc} \gamma_i & 1 & 0 \\ \gamma_j & 0 & 1 \end{array} \right) .$$

[12] See Boyer et al. (1999), page 17.

the statistic derived by Boyer et al. (1999) and Loretan and English (2000) is exactly the same as ξ — which 'adjusts' the sample correlation coefficient by the full increase in the variance of r_j during a crisis. Note that (10) and the set of assumptions (6) imply that both the covariance between r_i and r_j and the variance of r_i are strictly increasing in the variance of r_j; it follows that, during the crisis, the measure of interdependence (7) requires $Cov(r_i, r_j \mid C) > Cov(r_i, r_j)$ and $Var(r_i \mid C) > Var(r_i)$.

The model (10), however, is not the only possible representation of $(r_i, r_j)'$.[13] Specifically, define Q and $(\theta_1, \theta_2)'$ such that:

$$Q = \begin{bmatrix} 1 & \frac{\gamma_i}{\gamma_j} \\ 0 & 1 \end{bmatrix} \text{ and } \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix} = \begin{pmatrix} \varepsilon_i - \frac{\gamma_i}{\gamma_j}\varepsilon_j \\ \gamma_j \cdot f + \varepsilon_j \end{pmatrix}.$$

Then, our data-generating process (1) can be written as $Q \cdot (\theta_1, \theta_2)'$. We stress that this representation of the bivariate normal $(r_i, r_j)'$ is substantially different from (10). By allowing for changes in the variance of both f and ε_j, we obtain a more general model in which all the assumptions in (6) are relaxed. Specifically, $Cov(r_i, r_j \mid C) \gtreqless Cov(r_i, r_j)$ and $Var(r_i \mid C) \gtreqless Var(r_i)$.

The point is that alternative representations of $(r_i, r_j)'$ — implying alternative assumptions on $Cov(r_i, r_j \mid C)$ and $Var(r_i \mid C)$ — lead to different conditional correlation coefficients between r_i and r_j. Hence, our test can be interpreted as an extension of the theorem in Boyer et al. (1999), to the case of a more general structure of the covariance between r_i and r_j and the variance of r_i.

4.3 A summary

We can now summarize our criticism of the literature discussed above: both (5) and (10) imply that r_i depends linearly on r_j. Conditional on a crisis, both models ignore the country-specific component of the change in the variance of r_j. First, this is at odds with standard models of asset returns in financial economics, such as the factor model that we have adopted in our analysis.

Second, to the extent that the increase in the variance of the market in country j is due to its idiosyncratic component, the theoretical correlation coefficient (7) is biased. Such bias is larger, the larger the share of variance in r_j that can be attributed to innovations in country-specific shocks. This could be an important reason why this kind of test hardly finds any evidence of contagion. The question is therefore whether the country specific noise is large enough to bias significantly the test. We address this issue below.

[13]For instance, let $P = P_1 \cdot P_2$. We can then write $(r_i, r_j)'$ as $P_1 \cdot (\omega_1, \omega_2)'$, whereas $(\omega_1, \omega_2)' = P_2 \cdot (u_i, u_j)'$ and the correlation between ω_1 and ω_2 is not necessarily equal to zero.

5 Are existing tests of contagion biased in favor of the null of interdependence?

5.1 A conditional test

In this section, we develop a testing framework aimed at highlighting the sensitivity of test results to different values of the ratio of country-specific vs. common factors in the process generating market returns. Although our test is symmetrical, hereafter we adopt the common practice of focusing on contagion as a phenomenon in which correlation is significantly higher during the crisis period. Hence, our test hypotheses are:

$$\begin{array}{lcll} H_0 & : & \rho^C \leq \phi & \textit{interdependence} \\ H_1 & : & \rho^C > \phi & \textit{contagion .} \end{array} \tag{11}$$

We proceed in two steps. First, we use the statistic ϕ to calculate thresholds for λ_j and λ_j^C at which the test would reject the null of interdependence in favor of contagion at some given confidence level. To clarify the meaning of the critical thresholds for λ_j and λ_j^C, consider first the case in which $\lambda_j^C = \lambda_j$. The statistic becomes

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

By inspecting this equation, 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 also significantly larger than ϕ 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 preset confidence level.

Analogously, in the case $\lambda_j^C \neq \lambda_j$, equation (3) shows that ϕ is monotonically decreasing in λ_j^C. For any given λ_j we can look for *the minimum value of* λ_j^C — denoted with $\bar{\lambda}^C$ — at which the hypothesis of interdependence would be rejected. Thus, while in the case of a constant λ_j we derive a *threshold value* $\bar{\lambda}$, when λ_j is allowed to vary across periods we derive $\bar{\lambda}^C$ as a *threshold function* of λ_j.

Second, we compare the above thresholds with various estimates of the relative volatility of country-specific and common shocks in country j. When the estimated variance ratios are significantly above the thresholds, i.e. above what is required for the test to accept the null hypothesis of interdependence, we interpret such result as evidence in favor of the alternative hypothesis of contagion.

5.2 Critical levels for the variance ratios

Our case-study is the international impact of the October 1997 stock market crisis in Hong Kong. Using data from *Thomson Financial Datastream*, we analyze correlations between Hong Kong stock market returns and those of ten emerging economies (Indonesia, Korea, Malaysia, the Philippines, Singapore, Thailand, Russia, Argentina, Brazil and Mexico) and the G7 countries. For the sake of simplicity, we carry out a test of equality between ϕ and ρ^C by adopting the Fisher z-transformation as our testing framework — details of the test are presented in Appendix II. Adopting alternative testing frameworks would not significantly affect our main results, nor change the central message of this paper.[14]

In our benchmark estimation we calculate two-day rolling averages of daily returns in US dollars and we define tranquil and turbulent periods as stretching from 1 January 1997 to 17 October 1997 and from 20 October 1997 to 30 November 1997 respectively.[15] This definition of the crisis period follows the crash of the stock market in Hong Kong, which plunged by 25 per cent in just four days starting on 20 October 1997. Hong Kong stock prices declined until the end of November, apparently influencing returns in several other markets.

Test results are presented in Table 1. The first two columns of the table report estimates of the correlation of market returns in Hong Kong with the market returns in each country in the sample, in tranquil and crisis periods. Correlation coefficients are calculated using two-day rolling averages of stock market returns in US dollars. The third column of Table 1 reports the threshold level $\bar{\lambda}$ for the case of a constant variance ratio (corresponding to the value of expression (20) in Appendix II). Consistently with the logic of our test, if the variance ratio in Hong Kong during 1997 is constant and lower than $\bar{\lambda}$, the test accepts the null hypothesis of interdependence. From the first three columns in the table, it is apparent that $\bar{\lambda}$ tends to be larger, the smaller the difference between the estimated correlations in crisis and tranquil periods, $\widehat{\rho}^C$ and $\widehat{\rho}$; in other words, if the correlation between two stock markets does not increase sharply during the crisis, the null of interdependence can be rejected only for very high values of the variance ratio. Given the sample size of our case-study, the null of interdependence cannot be rejected at all (so that $\bar{\lambda} = +\infty$) when the correlation in the crisis period is sufficiently low (that is, lower than 0.32 according to expression

[14] Note that, despite the different methodology, the results in Forbes and Rigobon (2002) coincide with our results when we adopt the statistic ξ.

[15] 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. Appendix II shows that these choices do not affect our main results, which are also robust in many other dimensions.

(21) in Appendix II). Conversely, the null of interdependence is rejected for any value of λ_j when the correlation in the tranquil period is close to zero, as in the case of Italy.

The evidence in Table 1 suggests that the null hypothesis of interdependence will be rejected for relatively low values of λ_j in the case of Italy, France, Singapore, the UK and the Philippines. For instance, if $\lambda_j = 3.6$ (a value that we will find in one of our estimates) our test would reject interdependence for all the countries listed above. At $\lambda_j = 7.1$ (that will be our highest estimated value), the test would also reject for Germany and, weakly, for Indonesia.

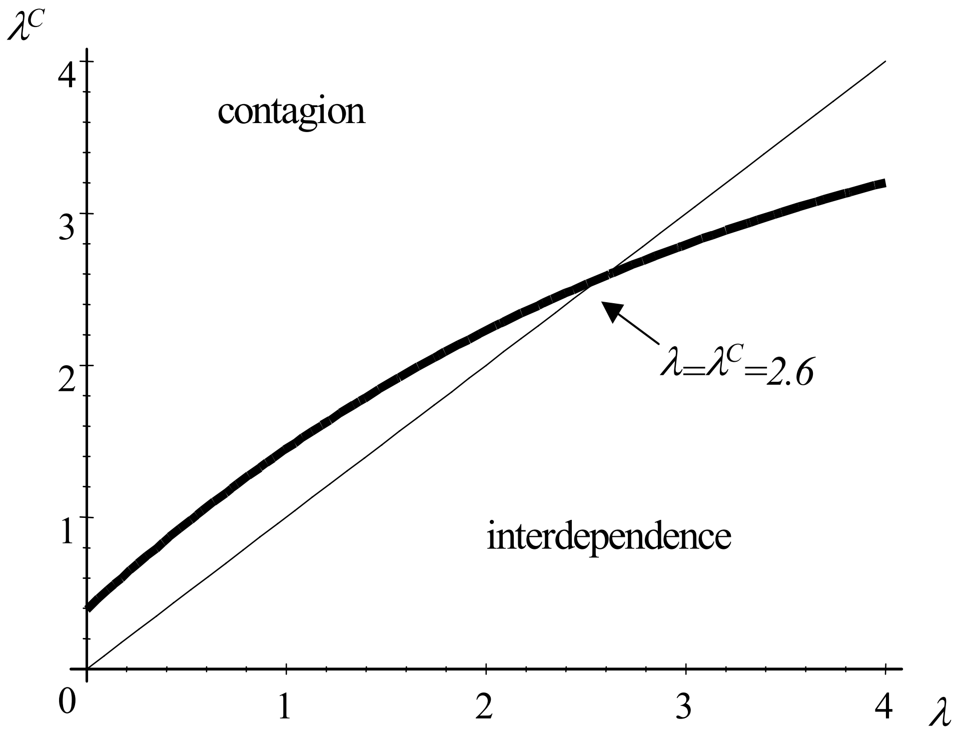
To introduce the discussion of our results in the case of variable variance ratios — i.e. $\lambda_j \neq \lambda_j^C$ — we present a graph that plots $\bar{\lambda}_j^C$ as a function of λ_j for a particular country pair, Hong Kong and the Philippines. The graph (which is based on equation (22) in Appendix II) is shown in Figure 2. 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. At the intersection between the function and the 45° degree line from the origin, both $\bar{\lambda}_j$ and $\bar{\lambda}_j^C$ will coincide with the threshold $\bar{\lambda}$ reported in Table 1.

As for the case of Hong Kong and the Philippines shown in Figure 2, we can analogously calculate $\bar{\lambda}^C$ as a function of λ_j for each of the other 16 countries in our sample. Based on these calculations, the fourth column of Table 1 shows our estimate of $\bar{\lambda}^C$ conditional on setting $\lambda_j = 3$. Note that, for λ_j^C as high as 4.5 (a figure that, together with $\lambda_j = 3$, corresponds to one of estimates below), the test would reject the null hypothesis of interdependence for Italy, France, the UK, Germany, the Philippines and Singapore.

It is instructive to compare our results with the results of a Fisher test of the null hypothesis $\rho^C \leq \rho$, shown in the fifth column of the table. Based on unadjusted sample correlation coefficients, the Fisher test rejects the null hypothesis for about half the countries in our sample: Indonesia, the Philippines, Singapore, Russia and, among the G7, Germany, France, the UK and Italy. Compared with the results of our conditional test, the Fisher test provides some weak evidence of contagion for three countries in addition to those in our 'list of suspects' above (these additional countries are Germany, Indonesia and Russia). The fact that this test rejects interdependence more often is no surprise. As convincingly argued by the literature on contagion tests reviewed above, ignoring that sample correlation coefficients are a function of the variance of returns implies a bias towards contagion.

On the other hand, we can also show the consequences of employing a statistic that 'over-corrects' the sample correlation coefficients, by completely disregarding the market-specific noise in country j. Recall that for $\lambda_j = \lambda_j^C = 0$, our statistic becomes equivalent to ξ, defined by (7). The sixth column of the table shows that applying a test based on ξ would reject interdependence only in the case of Italy — that is, there would be almost no evidence of contagion.

Figure 2. Hong Kong and the Philippines: Threshold Function



5.3 Some evidence on the variance ratios

What do we know about λ_j and λ_j^C? Based on the single-factor model in (1), we estimate these variance ratios using the residuals from univariate regressions of Hong Kong market returns on a composite 'common factor', proxied by the average daily return in a cross section of stock markets. We calculate this cross-section average using both the sample of the G7 countries and our full sample (excluding Hong Kong). As an alternative proxy, we also use the 'world stock market index', an average of the stock indices of about 40 countries produced by *Thomson Financial Datastream*.

After computing the two-day rolling average of returns on the common factor, we regress the two-day rolling average of Hong Kong 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 calculate λ_j. We also report a second set of estimates, in which we include a 'common regional' factor, as proxied by Asian stock markets (with and without Hong Kong), in addition to the global factor.

We show our results in the first half of Table 2. In our sample, the order of magnitude of our point estimates of the variance ratio for Hong Kong is between 2.4 and 5.7: i.e. in the Hong Kong stock market the variance of country-specific shocks is between 2.4 and 5.7 times the variance of the global factor (multiplied by the factor loading γ_j).

Most crucially, while these ratios do not vary substantially between the tranquil and the crisis period, the variance ratio tends to be higher in the latter period than in the former. Using the world stock market index as a benchmark, we obtain $\lambda_j = 3$ and $\lambda_j^C = 4.5$. This is an important piece of evidence contradicting the presumption that during periods of international turbulence, most of the market noise in the country of origin of the crisis becomes systemic, directly affecting other markets. According to our argument, a higher variance ratio during a crisis ($\lambda^C > \lambda$) exacerbate the bias in the tests reviewed in section 3.

Our second estimates of the variance ratio is based on principal component analysis. First, we calculate the principal components for our full sample of rolling averages of returns. Then, we 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 obtained using the composite global factor. The first principal component gives an estimated variance ratio of 7.1. If we include the first five components in the regression (so as to explain 76 per cent 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, $\bar{\lambda} = 4.4$).

In Appendix III, we report a number of robustness tests, whereas we use returns in local currency instead of US dollars, change the definitions of tranquil and crisis periods, replace rolling averages of returns with simple daily returns, and estimate a VAR model of returns using domestic and US interest rates as exogenous variables. None of our results is significantly affected.

Overall, the evidence in this and the previous section suggests that the magnitude of country-specific noise during a crisis is too large for the strong results of interdependence reached by Boyer et al. (1999) and Forbes and Rigobon (2002) to survive.

6 Conclusion

This paper has presented a framework based on correlation analysis to tests for contagion between stock markets in different countries. In the literature, leading tests of contagion are derived from a linear relationship between stock market returns. By contrast, our model moves from a standard model in financial economics, that is a factor model of asset returns. Using this framework, we provide a critique of tests in the literature that use the variance of market returns in the country where the crisis originates as a proxy for the volatility of common factors. We show that failing to distinguish between common and country-specific components of market returns induces a bias towards the null hypothesis of 'no contagion'.

Indeed, focusing on the international transmission of shocks from the Hong Kong stock market crisis in October 1997 as a case study, we find that the strong result of 'no contagion, only interdependence' obtained by previous contributions is quite dubious for a number of countries. In particular, we find evidence of contagion from the Hong Kong stock market to the stock markets in Singapore and the Philippines, among the emerging markets, and France, Italy and the UK, among the industrial countries. Adopting the leading test statistics in the literature would lead us to accept the null hypothesis of 'no contagion' in all cases but Italy.

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. However, our analysis makes a quite general point, as we have shown that there is no single measure of interdependence that can be derived independently of a model of asset returns. Moreover, whatever the model preferred by the analyst, our results suggest that country-specific noise cannot be ignored in testing for structural breaks in the international transmission.

A Appendix I

This appendix derives the expression (3) 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:

$$\frac{Var(\varepsilon_i)}{\gamma_i^2 \cdot Var(f)} = \frac{Var(r_i)}{\gamma_i^2 \cdot Var(f)} - 1 = \frac{\gamma_j^2(1+\lambda_j)Var(r_i)}{\gamma_i^2 Var(r_j)} - 1 \ . \qquad (12)$$

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

$$\rho = \frac{1}{\left[1 + \frac{Var(\varepsilon_i)}{\gamma_i^2 Var(f)}\right]^{1/2} \cdot [1+\lambda_j]^{1/2}} \ . \qquad (13)$$

Substituting (12) into (13), we obtain the unconditional correlation coefficient as a function of the rates of return, the factor loadings and λ_j:

$$\rho = \frac{\gamma_i}{\gamma_j}\left[\frac{1}{1+\lambda_j}\left(\frac{Var(r_i)}{Var(r_j)}\right)^{-1/2}\right] \ . \qquad (14)$$

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:

$$Var(r_i \mid C) = \gamma_i^2 \cdot Var(f \mid C) + Var(\varepsilon_i) \, . \qquad (15)$$

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

$$\frac{Var(r_j \mid C)}{Var(r_j)} = 1 + \delta = \frac{1+\lambda_j^C}{1+\lambda_j}\frac{Var(f \mid C)}{Var(f)} \ . \qquad (16)$$

By solving (16) for $Var(f \mid C)$ and substituting the resulting expression into (15) 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:

$$\begin{aligned}\frac{Var(r_i \mid C)}{Var(r_j \mid C)} &= \frac{Var(r_i) + \psi\gamma_i^2 Var(f)}{(1+\delta)Var(r_j)} = \\ &= \frac{Var(r_i)}{(1+\delta)Var(r_j)} + \frac{\psi\gamma_i^2}{(1+\delta)(1+\lambda_j)\gamma_j^2} \ . \end{aligned} \tag{17}$$

From (14), the correlation coefficient during the crisis period in the hypothesis that only the variances of f and ε_j change, while the factor loadings remain constant — which is our coefficient of interdependence ϕ — can be written as:

$$\phi(\lambda_j, \lambda_j^C, \delta, \rho) = \frac{\gamma_i}{\gamma_j}\left[\frac{1}{1+\lambda_j^C}\left(\frac{Var(r_i \mid C)}{Var(r_j \mid C)}\right)^{-1/2}\right] \ . \tag{18}$$

Substituting (A.6) into (18), 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 (3).

B Appendix II

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 and 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. The threshold values of λ_j and λ_j^C, respectively denoted by $\bar{\lambda}$ and $\bar{\lambda}^C$, can then be derived from:

$$z(\widehat{\rho}^C) - z(\widehat{\phi}(\bar{\lambda}, \bar{\lambda}^C)) = \ell\sigma_z , \tag{19}$$

where $\widehat{\rho}^C$ is the estimated correlation coefficient during a crisis, $\widehat{\phi}(\bar{\lambda}, \bar{\lambda}^C)$ is (3) evaluated using the estimated correlation coefficient in tranquil periods $(\widehat{\rho})$ and the estimated average increase in the variance of returns during a crisis $(\widehat{\delta})$, $\sigma_z = \left(\frac{1}{n-3} + \frac{1}{n^C-3}\right)^{1/2}$, n and n^C denote the sample size of the tranquil and the crisis periods, respectively, and ℓ is a constant depending on the chosen confidence level.

In the case $\lambda_j = \lambda_j^C$, the threshold level of the variance ratio, $\bar{\lambda}$, can easily be found by inverting equation (19). When $\rho > 0$, this yields:

$$\bar{\lambda} = \begin{cases} \left\{\left[\widehat{\rho}\frac{\widehat{\omega}+1}{\widehat{\omega}-1}\right]^2 \left(1 + \hat{\delta}\right) - 1\right\} \frac{1}{\widehat{\delta}\widehat{\rho}^2} - 1 & \text{if } \widehat{\omega} > 1 \\ +\infty & \text{if } \widehat{\omega} \leq 1 \end{cases} , \tag{20}$$

where $\widehat{\omega} = \exp\left[2\left(z(\widehat{\rho}^C) - \ell\sigma_z\right)\right]$. Note that

$$\widehat{\omega} > 1 \;\Leftrightarrow\; \widehat{\rho}^C > \frac{\exp(2\ell\sigma_z) - 1}{\exp(2\ell\sigma_z) + 1} . \tag{21}$$

In the case $\lambda_j^C \neq \lambda_j$, equation (19) 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 $\lambda_j, \widehat{\delta}, \widehat{\rho}, \widehat{\omega}$. We then have:

$$\bar{\lambda}^C = \begin{cases} \bar{\lambda}^C(\lambda_j, \widehat{\delta}, \widehat{\rho}, \widehat{\omega}) & \text{if } \widehat{\omega} > 1 \\ +\infty & \text{if } \widehat{\omega} \leq 1 \end{cases} . \tag{22}$$

A problem in the above procedure is that the assumption of independent samples is violated, since $\widehat{\delta}$ depends on both the tranquil and crisis period samples. To determine the significance level of the test, we resort to Monte-carlo simulation experiments. Setting $\ell = 1.645$ (the value corresponding to a 5 percent significance level in the standard test), 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 (19) with $\ell = 1.645$ 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 $\rho = 0.22$, $\rho^C = 0.66$, which are the observed correlation coefficients between the markets of Hong Kong and the Philippines, the significance level of the test corresponding to (19) is 8.1 per cent.

C Appendix III

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 the 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 Fisher's test, as well as our test procedure with $\lambda_j = \lambda_j^C = \widehat{\lambda}$ (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 whose currencies depreciated sharply in our sample period. In the case of Thailand and Hong Kong, for instance, $\widehat{\rho}$ and $\widehat{\rho}^C$ are equal to 0.10 and 0.01, respectively, when using returns in local currency, whereas they are 0.11 and 0.01 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 $\lambda_j = \lambda_j^C = \widehat{\lambda}$, 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 1996, our test rejects the null for Italy, Singapore, France and the Philippines, but not for the UK. As correlation remained quite high on average at the end of 1997 (see Corsetti et al. (2001)), 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 noticeably, both for $\lambda_j = \lambda_j^C = 0$ and for $\lambda_j = \lambda_j^C = \widehat{\lambda}$. 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 also reject for Singapore, the Philippines, Germany and Russia.

Finally, we have run the same testing procedure as in Forbes and Rigobon (2002), consisting of a VAR model of returns using domestic and US interest rates as exogenous variables. We have also expanded on their test by including oil prices as an exogenous variable. The results from these procedures confirm our conclusions.

D Tables

Table 1. Hong Kong Crisis — Conditional and Fisher Tests

Country	$\widehat{\rho}$	$\widehat{\rho}^C$	$\bar{\lambda}$	$\bar{\lambda}^C(\lambda_j = 3)$	Fisher	if $\lambda = 0$
Indonesia	0.31	0.60	7.1	5.6	C *	I
Korea	0.16	0.07	$+\infty$	$+\infty$	I	I
Malaysia	0.20	0.43	64.5	16.9	I	I
Philippines	0.22	0.66	2.6	2.8	C **	I
Singapore	0.36	0.76	1.5	1.8	C **	I
Thailand	0.11	0.01	$+\infty$	$+\infty$	I	I
Argentina	0.26	0.21	$+\infty$	$+\infty$	I	I
Brazil	0.20	0.31	$+\infty$	$+\infty$	I	I
Mexico	0.29	0.45	49.3	20.0	I	I
Russia	0.19	0.53	13.8	6.4	C *	I
USA	0.15	0.26	$+\infty$	$+\infty$	I	I
Japan	0.28	0.33	7487	361.2	I	I
Germany	0.24	0.63	4.4	3.7	C **	I
France	0.17	0.66	1.2	2.3	C **	I
United Kingdom	0.17	0.63	2.3	2.8	C **	I
Italy	0.00	0.63	0.00	0.0	C **	C
Canada	0.27	0.37	390	61.8	I	I

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 $\widehat{\delta} = 8.72$ and $\lambda_j = \lambda_j^C$); the fourth column reports the threshold for λ_j^C given $\lambda_j = 3$. The fifth column reports the results of the Fisher test: C* (C**) indicates that the hypothesis $\widehat{\rho}^C \leq \rho$ is rejected at the 5 (1) per cent significance level; the sixth column shows the results of a 'contagion' test where we set $\lambda_j = \lambda_j^C = 0$.

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
US and Asia	3.2	3.2	3.2
US and Asia ex Hong Kong	5.7	5.1	6.7
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

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

References

[1] Baig, T., Goldfajn, I. (2000), "The Russian Default and the Contagion to Brazil", *IMF Working Paper*, No. WP/00/160.

[2] Bordo, M., Murshid, A. (2001), "Are Financial Crises Becoming Increasingly More Contagious? What is the Evidence on Contagion?", in: Claessens, S., Forbes, K.J. (eds), *International Financial Contagion*, Kluwer Academic Publishers, Boston.

[3] Boyer, B.H., Gibson, M.S., Loretan, M. (1999), "Pitfalls in Tests for Changes in Correlations", *International Finance Discussion Paper*, No. 597R, Federal Reserve Board.

[4] Buiter, W., Corsetti, G., Pesenti, P. (1998), *Financial Markets and European Monetary Cooperation. The Lessons from the 1992-93 ERM crisis*, Cambridge University Press.

[5] Calvo, G.A. (1999), "Contagion in Emerging Markets: When Wall Street is a Carrier", unpublished paper.

[6] Calvo, G.A., Mendoza, E.G. (2000), "Rational Contagion and the Globalization of Securities Markets," *Journal of International Economics*, Vol. 51, pp. 79-113.

[7] Caramazza, F., Ricci, L., Salgado, R. (2000), "Trade and Financial Contagion in Currency Crises," *IMF Working Paper*, No. 00/55.

[8] Claessens, S., Dornbusch, R., Park, Y. (2001), "International Financial Contagion: How It Spreads and How It Can Be Stopped", in: Claessens, S., Forbes, K.J. (eds), *International Financial Contagion*, Kluwer Academic Publishers, Boston.

[9] Corsetti, G. (1998), "Interpreting the Asian Crisis", *Asian Development Review*, Vol. 16., pp. 18-63.

[10] Corsetti, G., Pesenti, P., Roubini, N. (2000a), "What Caused the Asian Currency and Financial Crisis?", *Japan and the World Economy*, Vol. 3, pp. 305-373.

[11] Corsetti, G., Pericoli, M., Sbracia, M. (2000b), "The Transmission of Financial Shocks", Bank of Italy, May, unpublished paper.

[12] —————————— (2001), "Correlation Analysis of Financial Contagion: What One Should Know before Running a Test", *Temi di discussione*, No. 408, June, Bank of Italy.

[13] Deutsche Bank (2000), "Does Correlation Really Increase in Volatile Markets", Global Market Research, *Fixed Income & Relative Value*, April 17.

[14] Edwards, S. (1998), "Interest Rate Volatility, Capital Controls and Contagion", *NBER Working Paper*, No. 6756.

[15] Eichengreen, B.J., Rose, A., Wyplosz, C. (1996), "Contagious Currency Crises: First Tests", *Scandinavian Journal of Economics*, Vol. 98, pp. 463-494.

[16] Forbes, K.J., Rigobon, R. (2001), "Measuring Contagion: Conceptual and Empirical Issues" in: Claessens, S., Forbes, K.J. (eds), *International Financial Contagion*, Kluwer Academic Publishers, Boston.

[17] ——————— (2002), "No Contagion, only Interdependence: Measuring Stock Market Co-movement", *Journal of Finance*, forthcoming.

[18] Goetzmann, W.N., Li, L., Rouwenhorst, K.G. (2001), "Long-Term Global Market Correlation", *Yale International Center for Finance Working Paper*, No. 00-60, October.

[19] International Monetary Fund (1998), *World Economic Outlook*, IMF, Washington DC, May.

[20] ——————— (1999), *World Economic Outlook*, IMF, Washington DC, May.

[21] Jeanne, O., Masson, P. (1998), "Currency Crises, Sunspots and Markov-Switching Regimes", *CEPR Discussion Papers*, No. 1990.

[22] Kaminsky, G.L., Reinhart, C. (2000), "On Crisis, Contagion, and Confusion", *Journal of International Economics*, Vol. 51, pp. 145-168.

[23] Kaminsky, G.L., Schmukler, S.L. (1999), "What Triggers Market Jitters? A Chronicle of the Asian Crisis", *Journal of International Money and Finance*, Vol. 18, No. 4., pp. 537-560.

[24] King, M.A., Wadhwani, S. (1990), "Transmission of Volatility between Stock Markets", *The Review of Financial Studies*, Vol. 3, No. 1., pp. 5-33.

[25] Kodres, L., Pritsker, M. (2002), "A Rational Expectations Model of Financial Contagion", *Journal of Finance*, forthcoming.

[26] Loretan, M., English, W.B. (2000), "Evaluating 'Correlation Breakdowns' During Periods of Market Volatility" in *International Financial Markets and the Implications for Monetary and Financial Stability*, Bank for International Settlements, Basel, Switzerland, pp. 214-31.

[27] Pericoli, M., Sbracia, M. (2001), "A Primer on Financial Contagion", *Temi di discussione*, No. 407, June, Bank of Italy.

[28] Schinasi, G.J., Smith, R.T. (2001), "Portfolio Diversification, Leverage and Financial Contagion", in: Claessens, S., Forbes, K.J. (eds), *International Financial Contagion*, Kluwer Academic Publishers, Boston.

[29] Stuart, A., Ord, K. (1991), *Kendall's Advanced Theory of Statistics, Volume 2: Classical Inference and Relationship*, Fifth edition, Edward Arnold, London.

[30] ——————— (1994), *Kendall's Advanced Theory of Statistics, Volume 1: Distribution Theory*, Sixth edition, Edward Arnold, London.