Correlation Analysis of Financial Contagion*

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1. INTRODUCTION

The outbreak of the Greek crisis in 2009-2010 and the transmission of financing strains to other countries — such as Portugal, Ireland, and Spain — have once more turned the spotlight on financial contagion. The term 'contagion', generally used in contrast to 'interdependence', conveys the idea that during financial crises there might be breaks or anomalies in the international transmission mechanism, arguably reflecting switches across multiple equilibria, market panics unrelated to fundamentals, investors' herding and the like.

There is still wide disagreement among economists about what contagion is exactly, and how it should be tested empirically. Pericoli and Sbracia (2003), for instance, list five different definitions and related measures of contagion that are frequently used in the literature.[1] A common approach, however, consists of identifying breaks in the international transmission of shocks *indirectly*, inferring them from a significant rise in the correlation of asset returns across markets and countries. In practice, analysts compare cross-country and cross-market correlations of asset returns in 'tranquil' and 'crisis' periods, under the maintained assumption that a significant rise in the correlation of returns can be attributed to a break in their data-generating process. Of course, the importance of the correlation statistics for financial investors

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provides a strong and direct motivation for this type of analysis. As Engle (2009) puts it, the correlation structure of financial assets is the key ingredient to a portfolio choice, because it is instrumental in determining the risk.

Still, these studies share a basic problem. Crises are typically identified as periods in which return volatility is abnormally high. Suppose that a crisis is driven by large shocks to a common factor, affecting all asset returns across the world. Other things equal, a higher variance of the common factor simultaneously causes higher-than-usual volatility *and* stronger comovements in all markets. In other words, holding the parameters of the data-generating process constant (other than the variance of the common factor), so that by definition there is no break in the international transmission of financial shocks, a rise in the magnitude of the common shock mechanically increases cross-country correlations. Consistently with most definitions, however, this would provide no evidence of financial contagion. Meaningful tests of contagion should thus net out the effect of changes in volatility from changes in cross-country correlations.

In this chapter, we first document a small set of stylized facts that motivates the construction of tests of contagion based on correlation analysis (Section 2). Second, drawing on Corsetti et al. (2005), we present a general correlation test for contagion addressing the issue discussed above, and illustrate its properties with an application to the Hong Kong stock market crisis of October 1997 (Section 3). Section 4 concludes.

2. STYLIZED FACTS

We start by documenting a set of four stylized facts characterizing the transmission of shocks across stock markets. The first two are well understood in the literature: (*i*) sharp drops in stock prices tend to cluster across countries, and (*ii*) the volatility of returns rises during financial crises. The other two are often confused in formal and informal discussions of contagion: (*iii*) financial crises are frequently associated with a rise in the cross-country *covariances* of returns; (*iv*) cross-country *correlations* of returns increase often during financial turbulences, but there are many crisis episodes in which correlations fall or remain invariant, relative to tranquil periods.

We document these facts, using weekly stock prices and returns in local currency for 20 countries: the G7, Argentina, Brazil, Mexico, Greece, Spain, Russia, Hong Kong, Indonesia, South Korea, Malaysia, Philippines, Singapore, and Thailand. The sample period runs from January 1990 to May 2010. The data source is Thomson Reuters Datastream.

Sharp falls in stock prices tend to occur in clusters across national markets

Crises are not independently distributed. As noted by Eichengreen et al. (1996), for instance, long phases of tranquility in foreign exchange markets are interrupted by waves of speculative attacks, simultaneously hitting different currencies. Similar patterns characterize stock markets. This is apparent in the two decades spanning the period 1990-2010 (fig. 1). In five episodes of financial turmoil, at least ¾ of the countries in our sample recorded a decline in stock market prices by 20 percent or more. These episodes are the U.S. recession in 1990-1991, occurring contemporaneously to the First Gulf War; the Russian financial crisis and the associated collapse of the U.S. hedge fund LTCM in 1998; the U.S. recession in 2001 and the terrorist attacks on September 11; the period preceding the Second Gulf War; the Great Recession of 2008-2009. In other three episodes, the financial turmoil was somewhat less widespread: the crisis of the European Exchange Rate Mechanism (ERM) in 1992 (which nonetheless affected stock prices in Europe, Asia and Latin America); the crisis in Mexico in 1994-1995; and the stock market crash in Hong Kong in October 1997. It is worth emphasizing that the last two crises severely affected stock prices all over the world, even though they originated in two peripheral economies.

The volatility of stock market returns rises during crisis periods

The major crisis episodes in our sample are characterized by a sharp increase in the volatility of returns (fig. 2). Among them, the Great Recession of 2008-2009 stands out for both its virulence and global nature. In fact, following a period of very low volatility in asset prices between 2004 and 2007 (below 15%), volatility rose to unprecedented levels (up to over 40% for the cross-country median), affecting most countries, as shown by the small interquartile difference.

Covariances between stock market returns frequently increase during crisis periods

The covariances of returns display a somewhat different pattern relative to volatility (fig. 3). A sharp rise in the covariances is apparent during the crisis episodes in 1990-1991, in 1998, in 2001, and especially during the Great Recession. A clear rise in covariances also occurred during the collapse of the Hong Kong stock market in 1997, as well as during the burst of the dot-com bubble in March 2000. But there is virtually no rise in covariances during the ERM crisis or during the Mexican crisis in 1995. Note that covariances remained on a descendent path after September 11, until the eruption of the global crisis in 2007.

Correlations often rise during crises, but are not always higher than in tranquil periods

Looking at the major crisis episodes listed above, a clear rise in correlations can be detected in 1990-1991, during the Mexican crisis in 1995, during the Hong Kong stock market crash in October 1997, in 1998, and during the Great Recession (fig. 4). Correlations instead declined in 1992, during the ERM crisis. In 2001, they rose only after the terrorist attacks of September 11, although many countries had already recorded sharp falls in stock prices since the beginning of the U.S. recession in March. By the same token, there was no rise in correlation before the Second Gulf War, even if at the end of 2002 more than half of the stock markets in our sample had already recorded sharp price falls; correlations only started to rise in February 2003, during the last phase of stock price adjustment, and continued to increase through the spring of 2004 — at a time in which stock prices were already on a rising path.

Note that during the tranquil period 2004-2007, characterized by rising stock prices and low return volatility, the median correlation is often above the peaks observed in crisis episodes, such as those recorded in 1998 and in 2001.

3. CORRELATION ANALYSIS OF CONTAGION: THEORY AND AN APPLICATION

Can we interpret a significant increase in the comovements of asset returns during financial crises as evidence of contagion? More specifically, can we infer contagion via a straightforward application of standard statistical tests for differences in correlation coefficients? As already mentioned, a key problem with this approach is that the correlation between returns is affected by their volatility, which is typically higher during crises. This point was acknowledged early on by seminal contributions on contagion, such as King and Wadhwani (1990).[2]

To illustrate the problem in detail, assume that returns are generated by a standard factor model:

$$\begin{aligned} r_j &= \alpha_0 + \alpha_1 f + \varepsilon_j \\ r_i &= \beta_0 + \beta_1 f + \varepsilon_i \end{aligned},$$

where r_j and r_i denote stock market returns, respectively, in countries *j* and *i*; *f* is a global factor affecting all countries (usually, the market return); ε_j and ε_i are idiosyncratic factors independent of *f* and of each other; α_0, β_0, α_1 and β_1 are constants, with the last two parameters measuring the strength of cross-country-linkages: the higher α_1 and β_1, the stronger the correlation between r_i and r_j. The expressions above can be derived from several models in finance, including the capital asset pricing model and the arbitrage pricing theory.

From the factor model above, the correlation between r_i and r_j, hereafter denoted with ρ, can be written as:

$$\rho = \left[1 + \frac{Var(\varepsilon_j)}{\alpha_1^2 Var(f)}\right]^{-1/2} \left[1 + \frac{Var(\varepsilon_i)}{\beta_1^2 Var(f)}\right]^{-1/2} .$$

Here is the problem: ρ depends on the importance of the terms $\alpha_1^2 Var(f)$ and $\beta_1^2 Var(f)$, capturing how movements in the common factor affect returns, relative to the terms $Var(\varepsilon_j)$ and $Var(\varepsilon_i)$, reflecting country idiosyncratic noise. Suppose we observe a crisis in country *j*, associated with an increase in the volatility of the returns r_j. Holding the parameters α_1 and β_1 constant, the effect of the crisis on the cross-country correlation of returns will depend on the extent to which the rise in the variance of r_j is driven by the variance of the common factor *f*, as opposed to the variance of the country-specific factor ε_j. If movements in the common factors are relatively large, the correlation rises; otherwise, it falls. Two points are worth stressing: correlations may increase or decrease during a crisis, and change with the variance of r_j, *even if the intensity of the cross-country linkages* α_1 *and* β_1 *does not change at all*. These observations suggest that, according to the standard definition of contagion, some fluctuations in correlation are actually consistent with simple interdependence, in the sense that they can occur absent changes in the parameters of the model. To provide evidence in favor of contagion, changes in correlation should be large enough, to point to breaks in the transmission mechanism, i.e. to changes in the structural parameters α_1 and β_1, affecting the intensity of the cross-border transmission of shocks (note that α_0 and β_0 do not affect ρ).

Thus, proper tests of contagion should at least distinguish between breaks due to shifts in the variance of the common factors, and changes in the values of α_1 and β_1. Using the factor model described above, in Corsetti et al. (2005) we have shown that, under the null hypothesis of no contagion, the correlation between r_i and r_j corrected for the increase in the variance of r_j, takes the following form:

$$\phi = \rho\left[\left(\frac{1+\lambda^T}{1+\lambda^C}\right)\frac{1+\delta}{1+\rho^2\psi\left(1+\lambda^T\right)}\right]^{1/2},$$

where

$$\lambda^T = \frac{Var(\varepsilon_j \mid T)}{\alpha_1^2 Var(f \mid T)},\ \lambda^C = \frac{Var(\varepsilon_j \mid C)}{\alpha_1^2 Var(f \mid C)},$$

$$1+\delta = \frac{Var(r_j \mid C)}{Var(r_j \mid T)} \text{ and } \psi = \left(1+\delta\right)\frac{1+\lambda^T}{1+\lambda^C} - 1,$$

and *T* and *C* denote, respectively, the ‘tranquil period’ (a regime characterized by the absence of crisis) and the ‘crisis period’ (a regime of turmoil initiated by the crisis in country *j*). The correlation statistic ϕ depends on the correlation in the tranquil period (ρ), the change in the variance of r_j during the crisis (δ), as well as the relative importance of the idiosyncratic factor relative to the global factor during the tranquil and the crisis period (λ^T and λ^C). Note that, in the special case in which λ^T and λ^C are identical, $\lambda^T = \lambda^C = \lambda$ (i.e. in country *j* the variance of the country-specific factor relative to that of the common factor remains constant during the crisis), ϕ further simplifies as follows:

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

Now, by construction, ϕ is the correlation under the assumption of interdependence — i.e. the assumption that the intensities of the cross-country links α_1 and β_1 do not change between tranquil and crisis periods. Testing for contagion requires verification as to whether the correlation observed during the crisis, call it ρ^c, is significantly larger (or smaller) than ϕ. In other words, instead of comparing ρ^c to ρ (a comparison biased by the increase in the variance of r_j), a proper test for contagion should compare ρ^c to ϕ.

It is important to stress that biases in correlation tests of contagion occur not only if one fails to correct, but also if one *overcorrects* the influence of changes in the variances across regimes. An example of overcorrection can be illustrated as a special case of ϕ (or ϕ'), by setting $\lambda^T = \lambda^C = 0$ — i.e. by arbitrarily and unrealistically imposing that the returns in the country where the crisis originates are not hit by any market-specific shock. In this case, the factor model collapses to an *ad hoc* linear model $r_i = \gamma_0 + \gamma_1 r_j + \upsilon_i$, and the test statistics ϕ becomes $\rho\left[\dfrac{1+\delta}{1+\delta\rho^2}\right]^{1/2}$. This framework — again, a special case of our model for $Var(\varepsilon_j) = 0$ — implies that correlation always increases with the variance of r_j, that is, it always increases during crises. This prediction is clearly inconsistent with the evidence discussed in Section 2. Most importantly, because of *overcorrection*, tests derived from this biased framework tend, not surprisingly, to always yield the same result of no contagion across crisis episodes.

To illustrate our methodology, we reproduce results from early work (see Corsetti et al. 2005), in which we study contagion from the market crisis in Hong Kong in October 1997 — an archetype example in the literature. Based on a subset of 18 of the 20 countries in our sample (excluding Spain and Greece), we compute two-day rolling averages of daily returns in US dollars between January 1 1997 and October 17 1997 (the tranquil period), as well as between October 20 1997 and November 30 1997 (the crisis period).[3] The latter period starts with the crash in the Hong Kong stock index, which lost 25 per cent of its value in just four days from October 20 onwards. Hong Kong stock prices then continued to decline until the end of November, seemingly influencing returns in several other markets.

The parameter δ is estimated by computing the variance of Hong Kong stock returns in the tranquil and the crisis period. The ratios λ^T and λ^C are obtained by regressing returns on the Hong Kong stock market on a common factor, which can be proxied by returns on the world stock market index produced by Thomson Reuters Datastream — a weighted average of the stock indices of several countries. As an alternative, we also use a cross-sectional average return from the full sample, the G7 countries, or the United States only, and further verify our results using principal components and factor analysis.

Results are quite striking. Ignoring the need to correct the correlation coefficient, a standard statistical test of the hypothesis $\rho^c \leq \rho$ would reject the null in favor of the alternative $\rho^c > \rho$ for 8 out of 18 countries. Correcting for changes in the variance of returns makes a difference: using the world stock market index as a benchmark, the hypothesis of interdependence ($\phi \leq \rho$) is rejected for only 5 countries under the maintained assumption $\lambda^T = \lambda^C$, and for 6 countries in the general case $\lambda^T \neq \lambda^C$.[4] Overcorrection can be quite misleading though. A test imposing $\lambda^T = \lambda^C = 0$ on the data, still popular among practitioners, would reject interdependence for just one country (Italy).

5. CONCLUSION

Correlation analysis provides a useful tool for testing for financial contagion. Yet, no correlation measure of interdependence can be derived independently of a model of asset returns. Analysts should note their preferred model, and verify its implications for correlation analysis. Specifically, different models may prescribe different corrections of the standard correlation coefficient in order to check for changes in the variance of returns across tranquil and crisis periods. Our results, however, strongly suggest that country-specific noise should not be arbitrarily ignored in testing for structural breaks in the international transmission of shocks.

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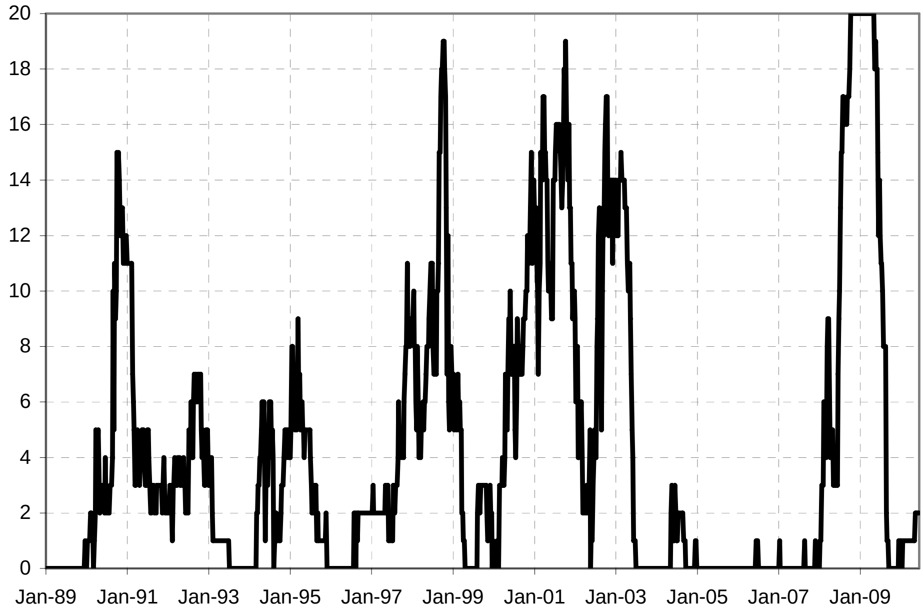
[1] Pericoli and Sbracia (2003) discuss the fact that some studies do not distinguish between contagion and interdependence, but focus on the channels through which negative shocks propagate. In these studies, contagion is defined as an increase in the probability of a crisis following the crisis in another country or as a volatility spillover. More recently, a new wave of studies has made the distinction between contagion and interdependence central, and has developed tests of contagion based on regime switching models or on changes in correlation.

[2] In the first major paper using the correlation approach, King and Wadhwani (1990) acknowledged that volatility affects correlation (see page 20), but implemented no correction for this effect in their empirical tests.

[3] This application uses U.S. dollar returns because they represent profits of investors with international portfolios and two-days rolling averages in order to account for the fact that stock markets in different countries are not simultaneously open. Results are robust, however, to these choices.

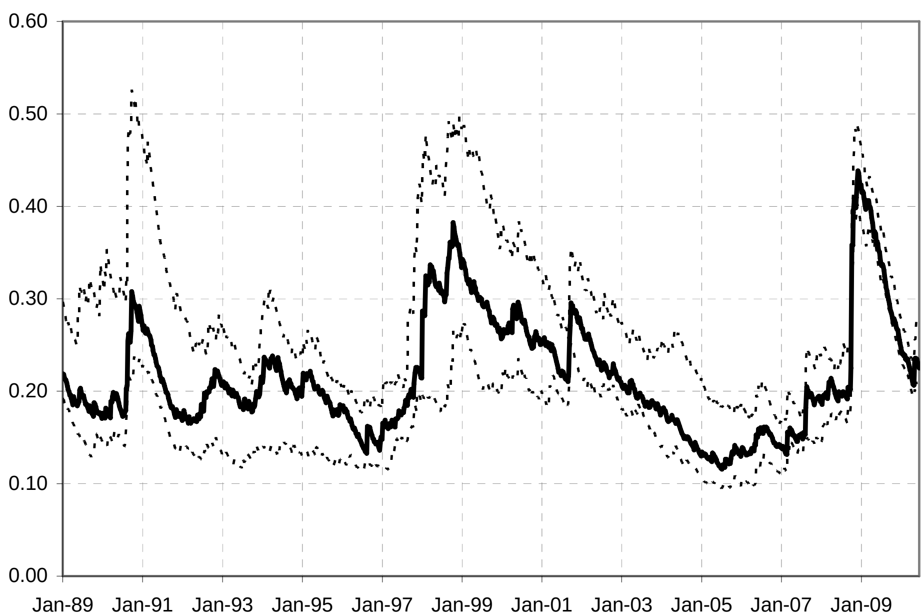
[4] Due to the rapid convergence to the normal distribution, tests for correlation coefficients are generally performed by using their Fisher *z*-transformation (see Corsetti et al., 2005, for details).

Figure 1. Number of countries experiencing stock market distress
(values, weekly data)



Source: elaborations on Thomson Reuters Datastream. The figure shows the number of countries in our sample in which weekly returns on the stock market index recorded a decline of 20 per cent or more with respect to the peak achieved over the previous year.

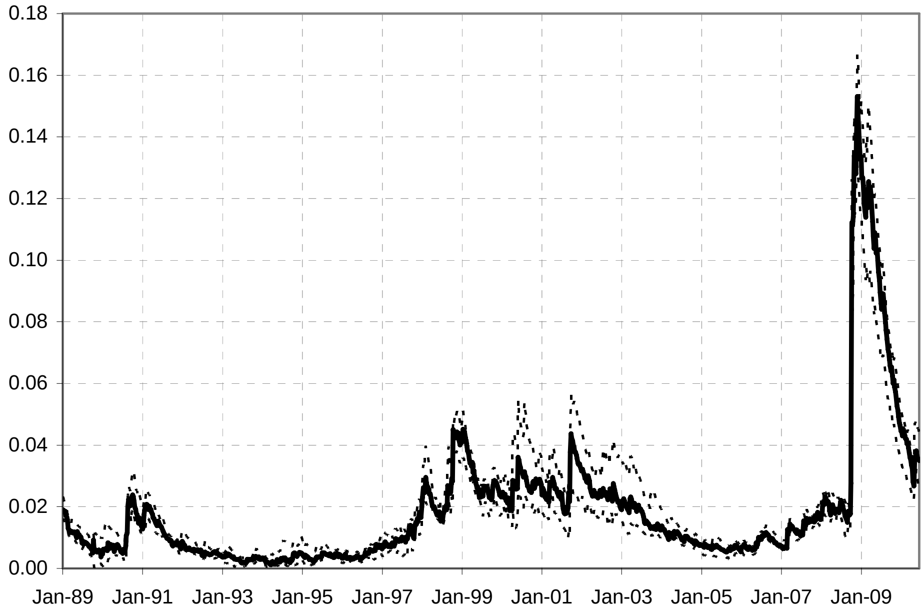
Figure 2. Volatility of stock market returns
(annualized values, weekly data)



Source: elaborations on Thomson Reuters Datastream. The bold line shows the median volatility of weekly stock market returns in local currency; the thin-dotted lines show the first and the third cross-sectional interquartile. Volatilities are computed as exponential moving averages with a decay factor equal to 0.96.

Figure 3. Covariances between stock market returns

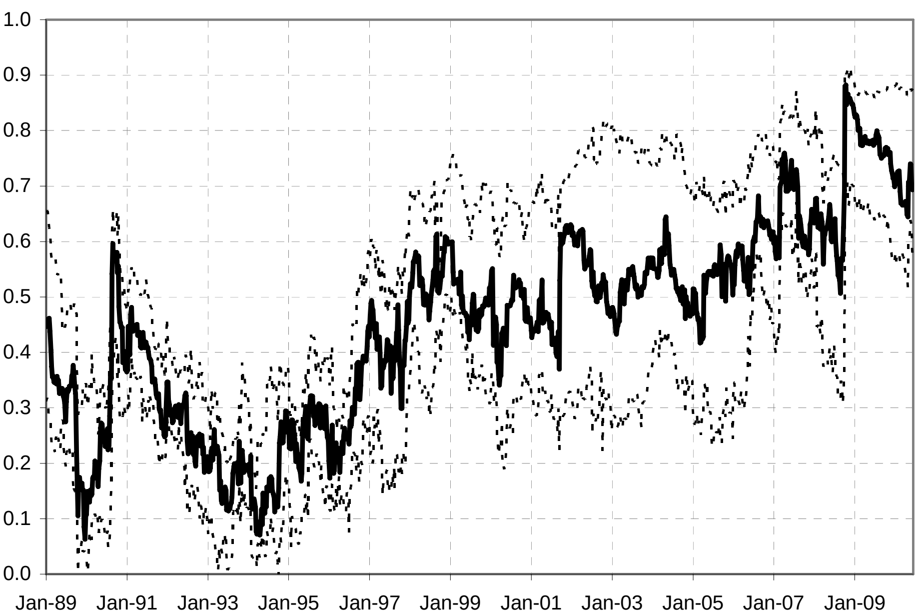
(annualized values, weekly data)



Source: elaborations on Thomson Reuters Datastream. The bold line shows the median of 190 (10×19) bivariate covariances of weekly stock market returns in local currency; the thin-dotted lines show the first and the third cross-sectional interquartile. Covariances are computed as exponential moving averages with a decay factor equal to 0.96.

Figure 4 – Correlations between stock market returns

(weekly data)



Source: elaborations on Thomson Reuters Datastream. The bold line shows the median of 190 (10×19) bivariate correlation coefficients of weekly stock market returns in local currency; the thin-dotted lines show the first and the third cross-sectional interquartile. Correlation coefficients are computed as exponential moving averages with a decay factor equal to 0.96.