Measuring Stock Market Contagion with an Application to the Sub-prime Crisis
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Mark Mink and Jochen Mierau *

* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.
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Mark Mink* and Jochen O. Mierau†

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Abstract

We present a new method to examine financial contagion, defined as a sudden strengthening of shock transmission between financial markets. In particular, we develop a correlation-like measure of synchronicity between markets that is straightforward to implement while being insensitive to heteroskedasticity of market returns. In fact, synchronicity would perfectly coincide with the dynamic conditional correlation (DCC) coefficient if the latter could be calculated using the ‘true’ models for the variance and covariance of the market returns. When analysing the 1997 East Asian crisis and the current sub-prime mortgage crisis, we find no evidence that stock market returns are more contagious during periods of turmoil than during tranquil times.

Keywords: Contagion, Heteroskedasticity, Dynamic Conditional Correlation, Sub-prime Crisis, East Asian Crisis.

JEL codes: C14, F36, G15.

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1 Introduction

Financial crises are characterised by the sudden and simultaneous materialisation of risks that in times of tranquility were believed to be independent. As a result, the opportunities for risk spreading are diminished when they are most needed, which can pose a substantial threat to the stability of the international financial system. In more popular terms, during financial crises all correlations tend to one.

The behaviour of international stock markets provides quite a literal example of this effect. While in tranquil times returns across markets correlate only mildly, these correlations often increase when sudden price drops occur. This break-down of risk spreading opportunities in times of stock market crashes has induced investors to fear that during financial crises shift-contagion occurs, which Rigobon (2002) defines as “a shift in the strength of the transmission of shocks from one country stock market to another” (p. 36).

Although an increase in market return correlations implies that opportunities for risk spreading have diminished, such an increase is not necessarily caused by an increase in the strength of shock transmission between stock markets. Forbes and Rigobon (2002) show that an increase in the correlation can also be a purely statistical phenomenon, resulting from the fact that the (squared) correlation coefficient is defined as the proportion of return variance that both markets have in common. For example, when we assume that returns in stock market A are driven by fifty percent of the returns in stock market B plus an idiosyncratic component, an increase in the variance of the returns in B will increase the proportion of market volatility in A driven by the returns in B, so that the correlation between both markets increases. The mechanism of

\[\text{Allen and Gale (2001), Rigobon (2002), and Pericoli and Sbracia (2003) provide overviews of alternative definitions and taxonomies of contagion that have been proposed in the literature.}\]
shock transmission between both markets has, however, remained unchanged. Since volatility increases are especially likely to occur during financial crises, an increase in correlation at times of sudden price drops does not by itself provide evidence for the presence of shift-contagion.\footnote{Boyer et al. (1999), Loretan and English (2000), and Forbes and Rigobon (2002) were among the first to notice the bias in the correlation coefficient.}

Several measurement methods have been proposed to distinguish between the effects of shift-contagion and heteroskedasticity on the correlation between market returns. These approaches generally rely on strong assumptions regarding the mechanism of shock transmission or the statistical properties of the market returns, while they yield mixed results (see Dungey et al., 2005). We therefore propose a new measure of synchronicity between stock market returns that is insensitive to heteroskedasticity of the market returns. In addition, the measure follows a standard binomial distribution and is easy to implement in a multivariate setting as well. Using the synchronicity measure to examine stock market contagion during the 1997 East-Asia crisis and the 2007 sub-prime mortgage crisis, we find no evidence that stock market returns are more contagious during periods of turmoil than during tranquil times.

The remainder of the paper is set up as follows. Section 2 presents the standard model of shift-contagion while section 3 introduces the synchronicity measure. In sections 4 and 5 we apply the measure to the East-Asian crises and to the sub-prime crisis, while the final section concludes.

## 2 Modeling contagion

As discussed in Dungey et al. (2005), most empirical approaches to model financial contagion (implicitly) adopt the same latent factor model of market returns. In this model, returns in market $i$ are driven by an autonomous component $\mu_i$, 

\begin{align*}
\text{Return}_i &= \mu_i + \epsilon_i \\
\epsilon_i &\sim N(0, \sigma_i^2)
\end{align*}
an idiosyncratic factor $u_{it}$, a common factor $w_t$, and, only when contagious shock transmission occurs, the idiosyncratic factor of the foreign market. For the two-market case the model is given by

$$y_{it} = \mu_i + \lambda_i w_t + u_{it} + \gamma_{it} u_{jt}$$

$$y_{jt} = \mu_j + \lambda_j w_t + u_{jt} + \gamma_{jt} u_{it}$$

(1)

where $E(u_i) = E(w) = 0$ and $E(u_i u_j) = E(w u_i) = 0$. The strength of the common factor is determined by the $\lambda$ parameters, which are constant over time as they represent the normal interdependence between markets $i$ and $j$. Shift-contagion is defined as a sudden increase in one or both of the $\gamma$ parameters, which in normal times are equal to zero. To arrive at a structured discussion we assume that the values of the parameters lie in non-negative real space. This can always be achieved by a monotonic transformation of the latent factors.

### 3 Measuring contagion

The parameters of the latent factor model above can only be identified when additional restrictions are imposed on the model’s structure. To this end Dungey et al. (2005) equate the common factor to the US interest rate while modeling the idiosyncratic factors as GARCH processes. For the two-market case, in addition one of the $\gamma$ parameters can be set equal to zero for all time periods, which however assumes that the source of any contagion effects is known and that there are no feedback between markets. As also Corsetti et al. (2005) show, no single measure of contagion can thus be derived independent of a model for the dynamics of the latent factors.

An alternative to direct identification of the model is to focus on the correlation between market returns, which is for instance advocated by King and Wadwhani (1990) and Lee and Kim (1993). The sample correlation between
standardised market returns $x_i$ and $x_j$ reads

$$E(x_{it}x_{jt}) = E\left(\lambda_i\lambda_jw_{it}^2 + \gamma_{jt}u_{it}^2 + \gamma_{it}u_{jt}^2\right),$$

which is indeed increasing in the value of the $\gamma$ parameters. However, as is also discussed by Boyer et al. (1999), Loretan and English (2000), and Forbes and Rigobon (2002), the sample correlation can also increase due to changes in the values of $w^2$ and $u^2_i$ even when the $\gamma$ parameters are equal to zero. Therefore, a sudden increase in the sample correlation between market returns during crisis periods can only be considered a necessary condition, rather than a sufficient condition, for contagion to have occurred.

Analysis of the sample correlation between $x_i$ and $x_j$ shows that the correlation measure can also be written as

$$E(x_{it}x_{jt}) = E(\phi_{ijt}|x_{it}x_{jt}|),$$

where $\phi_{ijt} = x_{it}x_{jt}/|x_{it}x_{jt}|$. To see this, note that when substituting for $\phi_{ijt}$ in Equation (3), the terms between absolute value bars drop out. The parameter $\phi_{ijt}$ can be interpreted as the synchronicity between contemporaneous market returns, and is equal to 1 when $x_{it}$ and $x_{jt}$ have the same sign while it equals $-1$ when their signs are opposite. Synchronicity at time $t$ thus indicates whether or not stock markets $i$ and $j$ contemporaneously move in the same direction (i.e. up or down).

Equation (3) shows that the correlation coefficient can be interpreted as a weighted average over time of the synchronicity measure $\phi_{ijt}$, with weights equal to $|x_{it}x_{jt}|$. These weights are calculated on the basis of the amplitudes of the market returns, but they do not indicate whether these returns are of the same size. After all, multiplying one time series with returns by one hundred does
not affect correlation with the other. It is therefore not a priori clear why using this particular weighting scheme is appropriate in analysing contagion between market returns. One reason for this approach could be that more extreme market returns deserve a larger weight because they are relatively prone to contagion effects or because they have a larger impact on the stock market index, but also from this perspective there are at least four reasons to question whether applying the above weighting scheme is appropriate.

First, as the weights are based on the standardised returns $x_t$ rather than the actual returns $y_t$, they do not contain information on the actual magnitude of the returns but only reflect information on their magnitude relative to each other. Especially during tranquil periods, finding an extreme standardised return therefore does not imply that the actual return was extreme as well. Second, standardisation requires that the actual returns are de-meaned and scaled using the population means and standard deviations, which are estimated using the observed sample means and standard errors. Unfortunately, especially during crises periods standardisation is less appropriate since these sample estimates cannot be interpreted due to the non-stationarity of stock market returns (see Figure 2 below). Third, Bae et al. (2003) show that to give particular attention to days with extreme returns, one should analyse these returns in isolation from the rest of the sample period so as to measure the synchronicity between them directly. Fourth, by combining a measure of return similarity $\phi_{ijt}$ with a measure of return importance $|x_{it}x_{jt}|$, the calculated correlation statistics become difficult to interpret. This difficulty is illustrated in Table 1.

The table shows how extreme (standardised) observations influence the correlation between market returns of Hong Kong and eight other East Asian countries during the month following October 17th 1997.\footnote{At this date the Hang Seng index lost 27 percent of its value, so that Forbes and Rigobon (2002) decide to classify the subsequent month as a crisis period during which contagion could have taken place.} While the first column
Table 1: Correlation with Hong Kong between October 17th and November 14th 1997

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<td>Thailand</td>
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The stock market indices used are the Hang Seng, Jakarta SE Composite, Nikkei 225 Stock Average, Korea SE Composite, KLCI Composite, Philippine SE I, MSCI Singapore, Taiwan SE Weighted, and the Bangkok SET.

shows that correlations during this period were indeed rather high, several of these correlations decrease in size dramatically when the one, two, or three most extreme returns are removed from the sample. By calculating return correlations as a weighted rather than a simple average of return synchronicity, the obtained results can thus be largely driven by just a couple of extreme standardised observations in the examined time interval. As a result, while one thinks one is examining contagion over the full one-month period, one’s results turn out to be mainly driven by developments on a handful of trading days. Although these days might indeed be of a particular interest, Bae et al. (2003) show that such events are better analysed by focusing on the synchronicity of extreme returns directly.

The impact of extreme returns on the correlation coefficient can be reduced by focusing on conditional correlation coefficients defined as $E_{t-1}(x_{it}x_{jt})$. The Constant Conditional Correlation (CCC) proposed by Bollerslev (1990) is calculated over a particular time interval, and is defined as the covariance between market returns that were standardised using conditional standard deviations ob-
tained from estimating a GARCH model. The Dynamic Conditional Correlation (DCC), proposed by Engle (2002), estimates a GARCH model for the covariance between standardised returns as well, so that a conditional correlation can be obtained for each individual trading day. Conditional correlations thus only take into account the market returns’ variance and/or covariance to the extent that these could be predicted by means of a statistical model, generally chosen to be a GARCH(1,1) specification, conditional upon the information available at time \( t - 1 \). In the context of Equation (3), using this approach translates into less heteroskedasticity of the weights \(|x_{it}x_{jt}|\) and thus leads to smoother correlation patterns (see Chiang et al. (2007) for an application of DCC to the East Asian crisis).

Although conditional correlations \( E_{t-1}(x_{it}x_{jt}) \) can be useful in forecasting correlation during the next trading days, and thus can prove valuable in modeling expectations of market participants, it is important to realise that they do not measure the actual correlation at these dates\(^4\). An increase in forecasted or expected correlation \( E_{t-1}(x_{it}x_{jt}) \) is therefore neither a necessary nor a sufficient condition for shift-contagion to have occurred. This only changes when the conditional correlations are calculated using the ‘true’ models for the returns’ variance and covariance, so that forecasted and actual values coincide perfectly. Although these ‘true’ models are unknown, they would by definition yield conditional variances \( E_{t-1}(y_{it} - \bar{y}_i)^2 = (y_{it} - \bar{y}_i)^2 \), so that the standardised returns would be given by \( x_{it} = (y_{it} - \bar{y}_i) / \sqrt{(y_{it} - \bar{y}_i)^2} = \pm 1 \) and \(|x_{it}x_{jt}| = 1\). The weights would thus drop out of Equation (3), and for each time \( t \) the conditional correlation coefficient would coincide with synchronicity \( \phi_{ijt} \).

In summary, we have shown that the appropriateness of using correlation coefficients to analyse contagion between markets can be questioned for at least

\(^4\)Engle (2002) is very clear about this as well, as he states that “the conditional correlation is based on information known the previous period” and thus provides a “forecast of the [actual] correlation” (p. 340).
four reasons, which all have to do with the inclusion of the weights $|x_{it}x_{jt}|$ in Equation (3). Addressing one of these issues by calculating conditional correlations introduces the problem that conditional correlations only provide information about forecasted rather than actual changes in shock transmission between markets. However, adopting the conditional correlation approach does imply that if market participants had been able to use perfect forecasts of the returns’ variances and covariances, they would only focus on the returns’ synchronicity $\phi_{ijt}$ and ignore any information about their amplitudes. Popularly speaking, this finding suggests that one can sometimes get more information out of a measure that requires less information to be put into it.

Bearing this in mind, we propose to focus directly on the synchronicity between markets $i$ and $j$, which as in Mink et al. (2007) can be calculated as

$$\phi_{ijt} = \begin{cases} 
1 & \text{if the sign of } y_{it} \text{ is equal to the sign of } y_{jt} \\
0.5 & \text{if } y_{it} = 0 \text{ and/or } y_{jt} = 0 \\
0 & \text{if the sign of } y_{it} \text{ is opposite to the sign of } y_{jt}
\end{cases} \quad (4)$$

As we use the actually observed returns $y_{it}$ rather than standardised returns $x_{it}$, average synchronicity $\bar{\phi}_{ij}$ over a $(1,T)$ interval indicates the proportion of time that stock markets contemporaneously moved in the same direction. This measure is not affected by extreme market returns, as is illustrated in Figure 1. While one-month moving averages of correlation and DCC-GARCH(1,1) between Hong Kong and Indonesia increase substantially at times of higher market volatility, synchronicity $\bar{\phi}_{ij}$, for comparison expressed on a $(-1,1)$ scale as well, remains much more stable. At times where volatility is lower all three measures follow roughly identical patterns.

The synchronicity measure can easily be extended to compare interdependencies between returns within a group of $N > 2$ stock markets. This can be
done without first having to identify the source market of any contagion effects, which will in many cases be unknown. Within a group of $N > 2$ markets we define synchronicity at time $t$ as

$$
\phi_t = 2 \max \{ \text{share of pos. returns at } t, \text{share of neg. returns at } t \} - 1
$$

$$
= \frac{1}{N} \sum_{i=1}^{N} \phi_{it},
$$

(5)

where

$$
\phi_{it} = \begin{cases} 
1 & \text{if the sign of } y_{it} \text{ equals the sign of the majority of returns} \\
0.5 & \text{if } y_{it} = 0 \text{ or exactly half of the returns is positive/negative} \\
0 & \text{if the sign of } y_{it} \text{ equals the sign of the minority of returns}
\end{cases}
$$

(6)

Denoting $\phi_t = \frac{1}{T} \sum_{i=1}^{T} \phi_{it}$, synchronicity $\phi_t$ indicates the proportion of time
that stock market $i$ moves in the same direction as the majority of the stock
markets in the group (notice the similarity between $\phi_{it}$ in Equation (6) and $\phi_{ijt}$
in Equation (4)). As the above synchronicity measures can be calculated on a
per-observation basis, they are particularly suited for an analysis in real-time.

The measures $\phi_{ij}$ and $\phi_i$ indicate the proportion of time that stock market
$i$ moves into the same direction as stock market $j$, or into the same direction as
the majority of stock markets. Both measures can therefore be interpreted as
the probability of success (i.e. synchronicity) in a binomial drawing experiment
with $T$ drawings. This favourable distributional property of the synchronicity
measures is valid for all processes generating the market returns, as long as they are not serially correlated (which is not the case in our sample). When
calculating correlations, in contrast, standard statistical inference is only valid
when the market returns are normally distributed. Especially during financial
crises this assumption is unlikely to hold due to the fat tails of the returns’
empirical distributions, as is illustrated by the discussion around Table 1. The
multivariate synchronicity measure in Equation (5) does not follow a binomial
distribution, so that testing hypotheses concerning this particular measure re-
quires performing for instance a simulation analysis.

To test whether a significant increase in synchronicity has taken place, we
can partition our data into tranquil and crisis periods based on an exogenous
(to be identified) criterion of crises, and compare the difference between $\phi^T_{ij}$ and
$\phi^C_{ij}$ or between $\phi^T_{i}$ and $\phi^C_{i}$ using a two-proportion $z$-test. The test allows us
to compare two binomial proportions (i.e. two values of $\phi_{ij}$ or $\phi_i$) calculated
for samples which differ in size (i.e. in number of observations) but which have
equal variances under the null hypothesis of no contagion (i.e. when $\phi^C_{ij} = \phi^T_{ij}$.
or \( \phi_C^j = \phi_T^j \). Omitting the subscripts \( i \) and \( j \), the test-statistic is defined as

\[
z = \frac{\phi_C - \phi_T}{\sqrt{\hat{\phi} \left(1 - \hat{\phi}\right) \left(\frac{1}{N_C} + \frac{1}{N_T}\right)}} \sim N(0,1),
\]

where \( \hat{\phi} = \frac{N_C \phi_C + N_T \phi_T}{N_C + N_T} \) (i.e. the pooled estimator of \( \phi \)), \( N_T \) equals the number of observations in the tranquil period, and \( N_C \) equals the number of observations in the crisis period. D’Agostino et al. (1988) show that even in the small sample case this test is robust in the sense that the actual significance levels are usually close to the nominal ones.

We can use the above procedure to examine whether the observed value of \( \phi_C \) is significantly higher than \( \phi_T \). However, although it disregards the amplitude of the market returns, an increase of the synchronicity measure can still be caused by a change in the volatility of the latent factors instead of by an increase in the contagion parameters \( \gamma \). Analogous to the interpretation of the correlation coefficient, we therefore conclude that the degree of synchronicity between financial markets being significantly higher during times of financial crisis than during times of financial tranquility, is a necessary but not a sufficient condition for shift-contagion to have occurred.

### 4 Contagion during the East-Asian crisis

Many analyses into financial contagion have focused on the East Asian crisis of 1997, in case of Forbes and Rigobon (2002) with specific attention for the month following the 27 percent fall of the Hang Seng on October 17th. Figure however shows that cumulative returns during this month were indeed negative.

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5 Using a similar test to compare standard correlations requires a Fisher transformation of these correlations in order to achieve a distribution closer to the normal. However, as Dungey and Zhumbabayeva (2001) show, this is an asymptotic result so that especially for small samples with \( N_C < 50 \) this transformation seriously affects the power of the test.
on about all markets, but that they were not substantially lower than many monthly returns observed in other periods. As a result, if the decision whether or not to classify a one-month period as a ‘crisis period’ depends on the magnitude of the observed stock market declines, several other one-month periods classify as crises as well. During these months many other stock markets experienced declines larger than or comparable to the 27 percent fall of the Hang Seng. Therefore it also is not a priori clear which stock market should be classified as the source of any contagion effects.

We overcome the issue of having to select a source country by focusing on synchronicity between stock markets in the region as a whole through calculating $\phi_t$ as specified in Equation (5), while we focus on synchronicity between individual stock markets and the rest of the region by calculating $\phi_{it}$ as in Equation (6). To avoid having to select a particular crisis period we present one-month moving averages of the synchronicity values. Figure 3 does so for synchronicity between individual countries and the region, where the vertical
line again indicates the month starting on October 17th 1997. When the moving average of synchronicity lies outside the shaded areas, it differs from average synchronicity over the 1996–1998 period at the 95-percent level of significance.\footnote{The boundaries of the shaded areas are defined as the 95-percent critical values from the $B(n, \phi)$ distribution, with $n = 21$ being the number of trading days inside the window and $\phi$ being average synchronicity over the full 1996–1998 interval. Calculating these critical values from Equation (7) would yield virtually identical results due to the large number of observations in the tranquil period $N^T$.}

The main message to be inferred from the figure is that synchronicity fluctuates substantially over time, although there are not many months during which it was significantly higher than the sample average. Around the crash of the Hang Seng, only synchronicity for the Philippines is marginally significant, but this level is not higher than several spikes observed at earlier or later dates in the sample. For several other countries, notably Indonesia, Japan, Taiwan, and Thailand, synchronicity during the month following October 17th 1997 was relatively low.

The volatility of individual stock markets’ synchronicity patterns could be caused by fluctuations of a common factor driving all stock markets in the region. If so, this would cloud our contagion analysis. However, if such a volatile regional factor existed, changes in the intensity of this common factor would be reflected by changes in synchronicity for the East Asian region as a whole. Figure 4 shows that this is not the case. Synchronicity for the region as a whole $\phi_t$, again calculated within a one-month moving window, is not volatile enough to explain fluctuations of synchronicity between individual stock markets and the region. Moreover, also the U.S interest rate, which is often used as a proxy for any common shocks in the region, hardly fluctuated over time as it was virtually constant at 5.20% until September 1998. Since synchronicity for the region as a whole also does not peak around especially the crash of the Hang Seng or any other dates, our findings provide no evidence that shift-contagion has occurred.
Figure 3: One-month moving average of synchronicity between individual stock markets and the region, 1996-1998
between East Asian stock markets during the 1997 financial crisis.

5 Contagion during the Sub-prime crisis

The sub-prime mortgage crisis started during the middle of 2007 with the burst of the US housing bubble accompanied by rising default rates on mortgages sold in the sub-prime market segment. While this first affected mortgage originators themselves, the crisis quickly spread through financial markets because these parties had transferred default risk on originated mortgages to third party investors on a large scale by selling mortgage backed securities. Since such securities were also widely used as collateral in markets for wholesale funding, the increasing mortgage default rates and the rise in risk premia caused by this triggered a global credit crunch (see Brunnermeier (2009) for an extensive discussion of the chain of events). Also stock markets were affected, especially for

\footnote{Focusing on synchronicity between individual countries and Hong Kong leads us to find similar patterns to those in Figures 3 and 4 and therefore does not affect our conclusions.}
The stock market indices used are the BEL 20, CAC 40, DAX 30, OMX Iceland All-share, ISEQ Overall Index, AEX Index, SMI, FTSE 100, and S&P 500.

countries with relatively large financial sectors such as Belgium, France, Germany, Iceland, Ireland, the Netherlands, Switzerland, United Kingdom and the United States. Figure 5 shows that since mid-2007 these countries’ stock market indices declined almost in parallel.

Figure 6 shows that one-month moving synchronicity between individual stock markets and the group as a whole is not elevated during the period following the outbreak of the crisis. The vertical lines in the figure now indicate the months starting at the days when Bear Stearns received an emergency loan from
the FED (March 14th 2008) and when Lehman Brothers collapsed (September 15th 2008). Around these dates systemic risk was perceived to be especially high. However, also during the months following these events synchronicity generally lies below its upper critical value and is not markedly higher than during many other one-month periods. This finding is confirmed by the pattern of monthly synchronicity within the group of stock markets as a whole, which is depicted in Figure 7. In fact, there is no evidence whatsoever of a structural break in stock market synchronicity after the outbreak of the sub-prime crisis, so that also in this case our findings do not provide evidence for the occurrence of shift-contagion between national stock markets.
Although we do not find evidence of shift-contagion, this result does not mean that there was no shock transmission between markets. What our findings do suggest, however, is that the intensity of shock transmission has not changed relative to more tranquil periods. Given this observation, the simultaneous decline of stock market indices depicted in Figure 5 is most likely caused by the common factor in Equation (1) having become negative for a larger part of the time. On itself, this effect would not lead to a higher level of synchronicity between markets. In addition, the increase in return volatility observed during the crisis, which is illustrated in Figure 2 for the East Asian crisis, is probably due to a simultaneous increase in the variance of the common as well as the idiosyncratic factors. Again, this would not lead to higher synchronicity. All in all, while during financial crises market returns for many countries are generally found to be volatile and negative during a prolonged period of time, the model in Equation (1) implies that this can also happen without shock transmission between markets having increased. Our empirical results support this explana-
tion, as they suggest that for the two crises periods examined above any such increases have indeed not taken place.

6 Conclusion

In this paper we contribute to the literature on contagion of financial crises by focusing on ‘shift-contagion’, which is defined as an increase in the strength of the transmission of shocks from one stock market to another. While we model contagion using the same latent factor model as many other researchers have adopted, we depart from the literature in how we measure this phenomenon. In particular, whereas traditional approaches have relied on restrictive assumptions regarding the shock transmission process and the statistical properties of the market returns to identify the model directly, we use a correlation-like measure of synchronicity between stock markets. The main advantages of our synchronicity measure are that it is insensitive to heteroskedasticity of the market returns, follows a standard binomial distribution, and can straightforwardly be implemented also in a multivariate setting.

Using our synchronicity measure we examine whether contagion between stock markets occurred during the 1997 East Asian crisis and during the 2007 sub-prime mortgage crisis. We find that changes in the degree of synchronicity between markets occur regularly during the years under consideration, while there is no evidence that the transmission of shocks strengthens only or especially during financial crises. This result suggests that during the East Asian crisis as well as the sub-prime crisis stock markets have not been affected by shift-contagion.
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References


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