A Test for Volatility Spillovers[*]

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Abstract

This paper proposes a new procedure for analyzing volatility links between different markets based on a bivariate Markov switching model. An empirical application of this procedure to three emerging markets is examined and discussed.

Keywords: Markov switching, GARCH, Volatility, Financial crises.
JEL Classification: C32, G15

1 Introduction

During recent years we have witnessed several financial crises which have originated in an emerging economy and have then, after a short period of time, spread across to other markets. The transmission mechanism could either be explained as the natural consequence of the real and financial interrelations between these economies, or (and) as a result of the action of institutional investors which have long positions in emerging markets financial instruments and, whenever a crises takes place, want to reduce their portfolios' risk by selling their high return high risk positions (e.g. Kaminsky and Schmukler, 1999).

A popular approach used to test the transmission of shocks across financial markets has been based on generalized autoregressive conditionally heteroscedastic (GARCH) models (see Reinhart (2001) for a survey). Nevertheless, tests for contagion based on GARCH models do not allow us to distinguish whether the interaction takes place in periods of calm (low volatility) or crises (high volatility). These models are typically symmetric both in the parameterization (an economy affects the other in the same way in periods of calm and in periods of crises) and in the temporal causality (an economy affects the other future volatility both in calm and in crises). In that respect, these models do not seem rich enough to accommodate the economic and financial explanations of the crises presented above.

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This paper proposes an alternative way of detecting the transmission of high volatility periods from one economy to another. We consider a parameterization of the Markov switching model used in Phillips (1991) and Ravn and Sola (1995) which allows for four possible states of nature (consisting of combinations of either low or high volatilities) and test whether a country leads the other in and out of a period of crises (defined as periods of high volatility). An attractive feature of this approach is that it accounts for the fact that a crises (and its transmission) is better characterized as a sporadic event (which only take place a few times in a sample), rather than a structural relationship between stock markets as in a multivariate GARCH.

An empirical application of this procedure to three emerging markets recently affected by severe financial crises is examined and discussed. For the Asian countries considered in the paper, we cannot reject the hypothesis that Thailand leads South Korea and therefore the volatility spillovers appear to be unidirectional following the onset of the crisis, running from the markets in turmoil (Thailand) to the other (South Korea). Only weak evidence of volatility spillover was found between South Korea and Brazil.

2 The Model

Consider the following model for the 2×1 vector $z_t = [x_t; y_t]'$:

$$z_t = \mu + \Phi_{s_t} u_t, \tag{1}$$

where $\mu = [\mu_x; \mu_y]'$ and u_t is a Gaussian process with zero mean and positive-definite covariance matrix Σ; $\{s_t\}$ is modelled as a time-homogeneous Markov chain on $\{1; 2; 3; 4\}$, independent of $\{u_t\}$, with s_t indicating the state that the system is in at date t. The time series $\{z_t\}$ (the vector of stock market returns of country x_t and y_t) satisfies therefore a four-state Markov process

$$z_t|(s_t = s) \sim N(\mu; \Omega_{s_t}), \tag{2}$$

for $s = 1; 2; 3; 4$; with $\Omega_{s_t} = \Phi'_{s_t} \Sigma \Phi_{s_t}$. Accordingly, the variance-covariance matrices are:

$$\Omega = \left\{ \begin{array}{ll} \Omega_{s=1} = \begin{bmatrix} \sigma^2_{xh} & \sigma_{xh;yh} \\ \sigma_{yh;xh} & \sigma^2_{yh} \end{bmatrix}; & \Omega_{s=2} = \begin{bmatrix} \sigma^2_{xh} & \sigma_{xh;yl} \\ \sigma_{yl;xh} & \sigma^2_{yl} \end{bmatrix}; \\ \Omega_{s=3} = \begin{bmatrix} \sigma^2_{xl} & \sigma_{xl;yh} \\ \sigma_{yh;xl} & \sigma^2_{yh} \end{bmatrix}; & \Omega_{s=4} = \begin{bmatrix} \sigma^2_{xl} & \sigma_{xl;yl} \\ \sigma_{yl;xl} & \sigma^2_{yl} \end{bmatrix} \end{array} \right\}; \tag{3}$$

where the indices h and l refer to high or low volatility. In the general case the transition matrix will be given by a 4×4 matrix, Π (with elements $\pi_{ij} = \Pr(s_t = i|s_{t-1} = j)$, $i; j = 1; 2; 3; 4$), where each column sums to unity and all elements are nonnegative. We can impose various restrictions on the transition matrix to test particular hypotheses. For example, if the volatility of each country's return follows an independent regime-shifting process, the four states transition matrix will be given by

$$\Pi^{indep} = \begin{pmatrix} \pi_{xh}\pi_{yh} & \pi_{xh}(1-\pi_{yl}) & (1-\pi_{xl})\pi_{yh} & (1-\pi_{xl})(1-\pi_{yl}) \\ \pi_{xh}(1-\pi_{yh}) & \pi_{xh}\pi_{yl} & (1-\pi_{xl})(1-\pi_{yh}) & (1-\pi_{xl})\pi_{yl} \\ (1-\pi_{xh})\pi_{yh} & (1-\pi_{xh})(1-\pi_{yl}) & \pi_{xl}\pi_{yh} & \pi_{xl}(1-\pi_{yl}) \\ (1-\pi_{xh})(1-\pi_{yl}) & (1-\pi_{xh})\pi_{yl} & \pi_{xl}(1-\pi_{yh}) & \pi_{xl}\pi_{yl} \end{pmatrix}. \tag{4}$$

We can then test the validity of the restricted version by using a likelihood ratio (LR) test that under the null hypothesis is distributed as $\chi^2(8)$: We will refer to this as the hypothesis of independence (or no financial contagion) between x and y. Contagion, as opposed to independence, occurs whenever one of the countries leads (or lags) the other one in and out periods of high volatility. This would be the case, for example, if y is always in the same state that x was one period before. The appropriateness of this hypothesis can be verified by testing (using LR tests distributed as $\chi^2(10)$) if we can reduce the transition matrices to

$$\Pi_1^{xly} = \begin{pmatrix} \pi_{xh} & \pi_{xh} & 0 & 0 \\ 0 & 0 & (1-\pi_{xl}) & (1-\pi_{xl}) \\ (1-\pi_{xh}) & (1-\pi_{xh}) & 0 & 0 \\ 0 & 0 & \pi_{xl} & \pi_{xl} \end{pmatrix} \tag{5}$$

where Π_1^{xly} indicates x leads y one period. It is also possible to allow for expected leads of longer than one period; the matrix Π_2^{xly} below illustrates the case where the expected lead is two periods:

$$\begin{pmatrix} \pi_{xh}\pi_{xh}+(1-\pi_{xh})(1-\pi_{xl}) & \pi_{xh}\pi_{xh}+(1-\pi_{xh})(1-\pi_{xl}) & 0 & 0 \\ 0 & 0 & (1-\pi_{xl})\pi_{xh}+\pi_{xl}(1-\pi_{xl}) & (1-\pi_{xl})\pi_{xh}+\pi_{xl}(1-\pi_{xl}) \\ (1-\pi_{xh})\pi_{xl}+\pi_{xh}(1-\pi_{xh}) & (1-\pi_{xh})\pi_{xl}+\pi_{xh}(1-\pi_{xh}) & 0 & 0 \\ 0 & 0 & \pi_{xl}\pi_{xl}+(1-\pi_{xl})(1-\pi_{xh}) & \pi_{xl}\pi_{xl}+(1-\pi_{xl})(1-\pi_{xh}) \end{pmatrix}. \tag{6}$$

Similar matrices can be constructed for the case where y leads x.

Whenever the results are inconclusive (say more than one of the restricted models presented above is not rejected), the models can be compared using selection criteria which weight fit, measured by the maximized log-likelihood, and complexity, measured by the number of parameters. Two popular criteria, the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC), are employed in the next section.

3 Empirical Results

As an empirical illustration of the testing procedure outlined before, we investigate for the presence of volatility spillovers across three emerging stock markets which have recently been hit by a severe financial crises, namely Thailand, South Korea and Brazil. The popular view is that the East Asian crisis began in Thailand during the late spring of 1997 with sustained speculative attacks on the local currency and as a result the Korean currency was attacked later that year[1]. The crisis then spread to other emerging economies including Brazil.

To assess the plausibility of the contagion interpretation of the crises, we apply our methodology to countries with similar fundamentals and economic links, such as Thailand and South Korea. Contagion for these economies is consistent with both the real interrelation and the portfolio interpretation transmission channel.

[1] See Corsetti et al (1998) for a detailed review.

We also consider countries without substantial economic and direct ¯nancial linkages (such as South Korea and Brazil). For these countries, evidence of contagion running from South Korea to Brazil would be supportive of the hypothesis that, as Asian markets tumbled, international investors had to liquidate positions in Brazil in order to balance their portfolio.

Statistical inference in the context of Markov switching models described in the previous section is carried out by making use of the non-linear algorithm of Hamilton (1994, Ch. 22). Figure 1 plots the logarithmic di®erences of stock market indices for Thailand and South Korea over the period 1980:I-2001:II and shows that the volatility has substantially increased in both countries as a consequence of the 1997 crisis. Maximum likelihood estimates[2] of the general model for the two countries, reported in Table 1, provide evidence of the magnitude of the changes in volatility between periods calm and crisis. Figure 2 plots the ¯lter probabilities of being in each state of the four regimes from the general model. It is clear from the plot that state 4 (low volatility) is associated with the period 1980-1985, while state 1 (high volatility) is associated with 1987-1988 (in correspondence with the Black Wednesday) and 1997-2001 (in correspondence to the Asian ¯nancial crisis). For (most of) the remaining of the sample, Thailand is characterized by periods of high volatility and Korea by periods of low volatility. Table 2 reports maximized log-likelihood values for the models described in the previous section. The restriction of independence of the Markov processes which dictate the switches of the volatilities in the two countries is rejected at the conventional level of 5%. While the hypothesis of volatility spillovers running from South Korea to Thailand is ¯rmly rejected from the data, the test statistic for the hypothesis that Thailand leads South Korea by two periods is not rejected by the data at the 5% signi¯cant level. Furthermore, both the AIC and the SBC favour Thailand leading South Korea by two periods.

Turning to South Korea and Brazil, Figure 3 plots the logarithmic di®erences of stock market indices for 1984:II-2001:II. From Table 1, the estimated parameters show signi¯cant evidence of shifts between regimes, with the estimated volatility being on average ¯ve times larger in periods of crises than in periods of calm. The inferred ¯lter probabilities shown in Figure 4 identify the years 1986-1988 and 1998-2000 as associated with periods of crises (state 1), and 1994-1995 with periods of calm (state 4). Notice that the stock returns of both countries are highly volatile starting from the middle of 1998 in correspondence to the beginning of the Brazilian crisis. In contrast with the case of Thailand and South Korea, the results presented in Table 2 show little evidence in favor of the contagion hypothesis. Even though we do not reject the hypothesis that South Korea leads Brazil by two periods, this is not strong evidence in favour of that hypothesis since we also cannot reject the hypothesis of independence. When we compare the restricted models, both AIC and the SBC criteria suggest that the independent model is preferred to the contagion interpretation.

4 Summary

This paper has introduced a new method for testing volatility spillovers which characterize the transmission of the crises as a sporadic event which typically involve a country going from a period of low volatility to high volatility, and being followed by the other in the subse-

[2]All the ¯tted models considered in this section have standardized residuals which exhibits no signs of linear or nonlinear dependence.

quent(s) period. The appealing feature of our specification is that it enables us to identify the probabilistic structure, the timing and the duration of the volatility transmission mechanism from one country to another. The potential applicability of the proposed procedure has been illustrated through an analysis of Thailand, South Korea and Brazil data.

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Table 1. General Model[a]

	Thailand (x) South Korea (y)	South Korea (x) Brazil (y)
$¹_x$	¡ 0:00501 (0:01625)	0:11688 (0:03066)
$¹_y$	0:00182 (0:01486)	0:03202 (0:01494)
$¾^2_{xh}$	0:08324 (0:02623	0:10152 (0:03853)
$¾^2_{xl}$	0:01143 (0:00224)	0:01596 (0:00331)
$¾^2_{yh}$	0:08153 (0:03446)	0:16253 (0:04459)
$¾^2_{yl}$	0:07554 (0:02436)	0:03252 (0:01374)
$¾_{xh;yh}$	0:04815 (0:02258)	¡ 0:02718 (0:05612)
$¾_{xh;yl}$	¡ 0:00367 (0:00690)	0:00826 (0:00776)
$¾_{xl;yh}$	0:07687 (0:02755)	0:05200 (0:02210)
$¾_{xl;yl}$	0:00228 (0:00190)	0:03673 (0:00893)

[a]Figures in parentheses are estimated standard errors.

Table 2. Maximized Log-Likelihood and Complexity-Penalized Likelihood Criterion[a]

	Thailand and South Korea			South Korea and Brazil		
Model	Log-L	AIC	SBC	Log-L	AIC	SBC
General	234.18	-424.36	-370.62	133.61	-223.22	-174.40
Independent	226.11 (*)	-424.22	-390.02	129.63	-231.26	-200.19
Korea leads Thailand (1Q)	209.49 (**)	-394.98	-365.67			
Korea leads Thailand (2Q)	216.23 (**)	-408.46	-379.15			
Thailand leads Korea (1Q)	216.67 (**)	-409.34	-380.03			
Thailand leads Korea (2Q)	227.65	-431.30	-401.99			
Brazil leads Korea (1Q)				122.28 (*)	-220.56	-193.92
Brazil leads Korea (2Q)				123.55 (*)	-223.10	-196.46
Korea leads Brazil (1Q)				120.91 (**)	-217.82	-191.18
Korea leads Brazil (2Q)				125.02	-226.04	-199.41

[a](1Q) and (2Q) indicate leading by one and two quarters. (*) and (**) indicate signi¯cance at 5% and 1% respectively, on the basis of a LR test. AIC and SIC are de¯ned as -2logL+2k and -2logL+ln(T)k, respectively, where k is the number of estimated parameters, T is the sample size and logL is the maximized log-likelihood.

Figure 1: Quarterly Returns for Thailand and South Korea

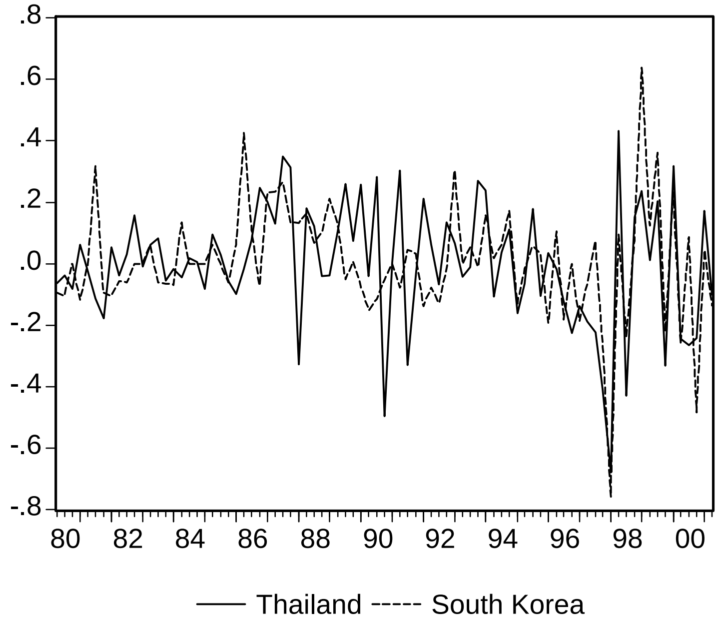

Figure 2: Filter Probabilities for Each State in the General Model

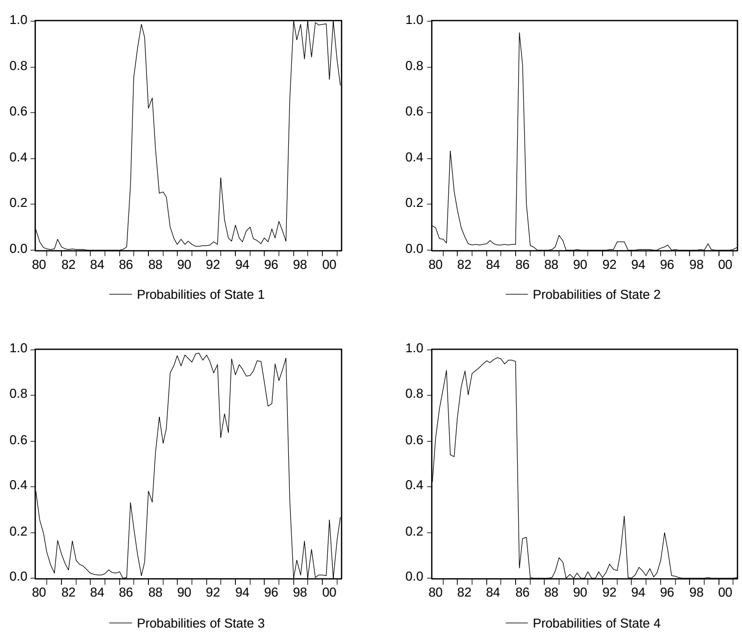

Figure 3: Quarterly Returns for South Korea and Brazil

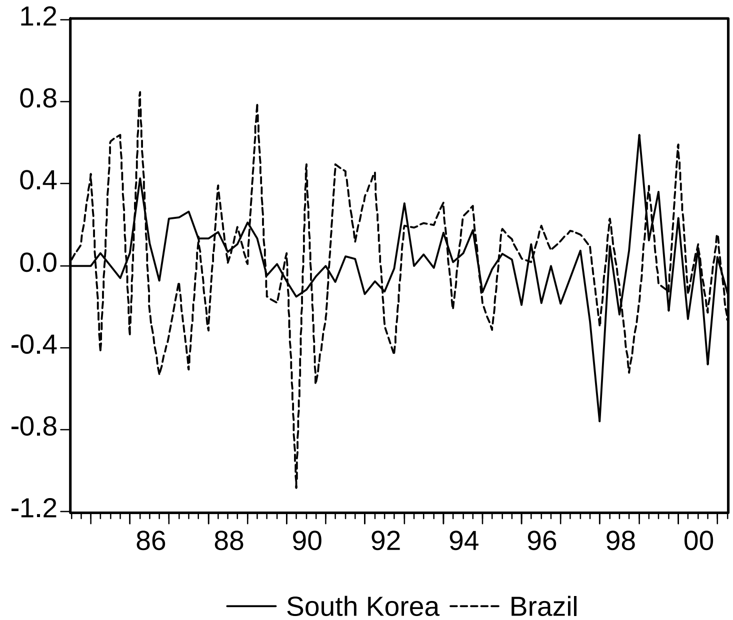

Figure 4: Filter Probabilities for Each State in the General Model