

# EMPIRICAL TESTS ON CRISIS CONTAGION IN 1997/98 ASIA CRISES

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16 June 2004

## Abstract

The objective of this paper is to show how heteroscedasticity due to higher market volatility during crises can bias the conventional test for contagion using conditional cross-market correlation. Using a Markov-switching Vector Autoregressive Model (MS-VAR), we identify that all evidence of contagion disappears except for Thailand and Indonesia case, after correlation coefficients are adjusted to correct for the bias. In other words, the high cross-market correlation amongst most Asian countries during 1997/98 crises are a continuation of strong linkage that exist in all state of the world (interdependence), rather than an increase in these linkages (contagion).

**JEL Classification:** F31, F33

**Keywords:** Currency crisis, Contagion, Markov-switching model

## 1 Introduction

In September 1997, quite suddenly, the newly industrializing countries in East Asia, once regarded as the world's most dramatic economic success, slipped into financial/currency turmoil. The most significant aspect of the crises has been the quick spread of crisis from Thailand to the rest countries in the region. The crisis saw that sharp devaluation in one country's currency can have a powerful impact on the vulnerability of other Asian economies, which may have either similar or different sizes and structures from the source country. Does these episodes of highly correlated exchange market comovements provide evidence of contagion?

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Before answering the question, it is necessary to define the contagion. The mainstream empirical literatures suggest that a contagion occurs when the cross-market correlation coefficient between the source country and vulnerable country increases significantly during crisis period compared with the period of stability. Based on this methodology, many economists find there are evidence suggesting that contagion occurred in several crisis episodes, including the 1997/98 Asia Crises. But as Forbes and Rigobon ([9]) argue, these tests for contagion are biased and inaccurate because the cross-market correlation coefficients are conditional on market volatility.

Here, we follow Forbes and Rigobon's approach to base our contagion test on the unconditional cross-market correlation—after adjusted for heteroscedasticity. The main contribution of this paper lies on the adoption of non-linear Markov-switching VAR model to describe the crisis transmission mechanism for the first time in this area. We focus our research on the recent experiences in Asia—from July of 1991 to December of 1998 for Thailand, Indonesia, Korea, Malaysia and Philippines. Thailand is chosen as the source country due to the well-known fact. Instead of the simple exchange growth rate, we use the Market Pressure Index (MPI) to represent both the successful and unsuccessful attacks in exchange markets. Also following the suggestion by the theoretical models and relevant empirical works, three explanatory variables are included in our regression.

The estimate results show that the Markov-switching VAR model has depicted crisis incidents in Asia during 1990s very well. The hypothesis of linear specification have been rejected at even 1% significant level in all cases. The final results of tests for contagion based on both conditional and unconditional cross-market correlation coefficients are presented. We find that the conditional cross-market correlations increased dramatically during the crises compared with the relatively stable periods for three of four country pairs.

However, the adjustment of correcting for the heteroscedasticity has shown a significant impact on the results. Similar to what Forbes and Rigobon ([9]) find in the return to Asian stock market in 1997/98 crises, all the evidence of contagion no longer exists except for the case of Thailand and Philippines, as the unconditional (adjusted) correlation during the turmoil periods fall down to the same level or even lower level than in more stable periods. The high level of market comovement between Thailand and Malaysia, Philippines during all states of the world, alternatively shows the strong real economic linkage—interdependence amongst these Asian economies.

This paper is organised as follows. The definition of contagion could be given in the first part of the following section before we briefly review the relevant empirical literature. Section III discusses the disadvantage of the conventional technique to test for contagion. One adjustment method by Forbes and Rigobon ([9]) is then suggested to correct the bias due to heteroscedasticity. Section IV gives the interested variables and sources of our data set. Then the new method has been applied in our Markov-switching VAR model to test for contagion in East Asian countries during 1997/98 crises in section V. The final section of the paper presents the final conclusion as well as some suggestions for the future research.

## 2 Literature Reviews

### 2.1 Definition of Contagion

Same as in Forbes and Rigobon ([9]), we define contagion as a significant increase in cross-market linkages after a shock to one country (or group of countries). According to this definition, it is contagion only if two market show a significant increase in comovement during crisis periods compared with periods of stability. If the cross-market comovement does not increase significant after the shock, then any continued level of market correlation only suggests the interdependence between the two economies, which exist in all states of the world.

The advantage of this definition is that it provides a straightforward method of distinguishing between alternative explanations of how crises are transmitted across markets. Some economists would assume that investors behave differently after a crisis, while others argue that most shocks are propagated through stable real linkages between countries, such as trade. This method can provide evidence on which group of theories is more relevant in interpreting the wide spread of crisis in the region. It is then argued that only those countries that are affected by crisis contagion rather than interdependence should qualify for multilateral bailouts.

### 2.2 Review on Recent Evidences on Contagion

The empirical literatures of testing how shocks are transmitted and/or if contagion exists are extensive. Most of them use the same definition of contagion as us. Four different methodology have been utilized to measure how shocks are transmitted internationally: cross-market correlation coefficients, ARCH and GARCH models, cointegration techniques, and direct estimation of specific transmission mechanisms.

The methodology of cross-market correlation coefficients is the most straightforward approach to test for contagion. These tests measure the correlation in exchange market between two countries strengthened after the shock and then contagion occurred.

Calvo and Reinhart ([3]) use this approach to test for contagion in stock prices and Brady bonds after the 1994 Mexican peso crisis. They find that cross-market correlations increased for many emerging markets during the crisis. Baig and Goldfajn ([1]) also found statistically significant increases in the correlation of asset returns during the Asia crises and therefore occurrence of contagion.

However, Forbes and Rigobon ([9]) argue that these tests are biased and inaccurate due to heteroscedasticity. Cross-market correlation coefficients are conditional on market volatility. Therefore, during crises when markets are more volatile, estimates of correlation coefficients tend to increase and be biased upward. When tests do not adjust for this bias, they traditionally find evidence of contagion. In this paper, we will follow Forbes and Rigobon approach to test for contagion in Asia crises, but adopt non-linear Markov-Switching VAR model to get better description about crisis transmission mechanism.

The second approach for analyzing market comovement is to use an ARCH or GARCH framework to estimate the variance-covariance transmission mechanism between countries. Edwards ([7]) examines linkages between bond markets after the Mexican peso crisis. He finds that there were significant spillovers from Mexico to Argentina, but does not explicitly test if this transmission changed significantly after the shock.

A third method of examining cross-market linkages tests for changes in the cointegrating vector between markets over long periods of time. One disadvantage of this method is that cross-market relationships over such long periods could increase for a number of reasons, such as greater trade integration rather than only crisis contagion effects.

The final series of papers examining international transmission mechanisms attempts to directly measure how attack on one country could affect another country's vulnerability to crisis. This literature is extensive and incorporates a range of approaches, including Logit/Probit model (Glick and Rose, [11]), structural approach and etc. Most of these papers find that the probability of a crisis in one country is correlated with a speculative attack on origin country alongside with other factors.

The regime switching approach has been increasingly applied to currency crises over the past few years (Piard, [23] and Jeanne and Masson, [14]). But most of the literatures confine to examination of the effects of certain fundamentals and/or other factors, e.g. contagion, on the probability of transition from a tranquil to a crisis state for one country (or group of countries). This paper is the first one using Markov-switching model to take one step back and ask whether contagion really exists based on unconditional cross-market correlation coefficients.

Before we start to analyze the crisis transmission mechanism amongst Asian countries in 1997/98 crises, it is better to go through the argument about conditional correlation coefficient first in next section.

### 3 Bias in the Conditional Correlation Coefficient

The discussion of how changes in market volatility can bias correlation coefficients was motivated by Ronn ([25]), which addresses this issue in the estimation of intra-market correlations in stocks and bonds. More recently, Boyer, Gibson, and Loretan ([2]) and Loretan and English ([20]) use their statistical frameworks to document this bias in more detail, as well as broader problems about measuring contagion. Forbes and Rigobon ([8] and [9]), by using initiative numerical examples, formal proof and graphs, demonstrate that heteroscedasticity can bias the tests for contagion based on conditional correlation coefficients. They then go further to propose an adjustment to correct the bias.

Assume  $x$  and  $y$  are stochastic variables which represent exchange market pressures in two markets, and they are related according to the equation:

$$y_t = \alpha + \beta x_t + \epsilon_t \tag{1}$$

We also assume the absence of endogeneity and omitted variables:

$$E[\epsilon_t] = 0; \quad E[\epsilon_t^2] = c < \infty \quad (2)$$

$$E[x_t \epsilon_t] = 0 \quad (3)$$

Then we could write the conditional correlation as

$$\rho^* = \rho \sqrt{\frac{1 + \delta}{1 + \delta \rho^2}} \quad (4)$$

$$\text{or } \rho = \frac{\rho^*}{\sqrt{1 + \delta[1 - (\rho^*)^2]}} \quad (5)$$

where  $\rho^*$  is the conditional correlation coefficient,  $\rho$  is the unconditional correlation coefficient, and  $\delta$  is the relative increase in the variance of  $x$ :

$$\delta = \frac{\sigma_{xx}^h}{\sigma_{xx}^l} - 1 \quad (6)$$

Equation (4) clearly shows that the estimated correlation coefficient is increasing in  $\delta$ . In other words, even if the unconditional correlation coefficient remains constant during both stable period and volatile period, the conditional correlation coefficient will be greater during the period when  $x$  is more volatile. That is where the test bias comes from. As markets tend to be more volatile after a shock or crisis, the conditional correlation will tend to strengthen after a crisis, even if the underlying cross-market relationship is the same as during more stable periods.

It is also straightforward to adjust for this bias by using Equation (5). Three criteria are required for the valid adjustment in the empirical implementation: (1) a major shift in market volatility; (2) clear identification of which country generates this shift in volatility; and (3) inclusion of the relevant country as another market in the estimated correlation.

The data we use for testing contagion in Asia crises has suggested that these criteria are satisfied. During the East Asia Financial/Currency Crises, the variance of Market Pressure Index (MPI) in the relevant countries increased by at least 5 times, especially in Thailand and Philippines case where the variance is over twenty times higher. The source country is clear—devaluation in Thai Bhat in September 1997 is always regarded as the beginning of Asia Crises by the mainstream crisis literature. Moreover, we only test for contagion from Thailand to each of other countries in the region each time.

## 4 The Variable and Data Set

### 4.1 The Variables of Interest

We employ the Market Pressure Index (MPI) to represent the volatility in exchange markets, in order to capture not only the large depreciation but also speculative attacks successfully defeated by the authorities increasing interest rates and/or selling international reserves. The MPI is calculated as weighted sum of the nominal exchange rate depreciation, the change in the market interest rate, and the minus percentage change in foreign exchange reserves, according to their relative precision.

Krugman ([19]) suggests in his Moral Hazard Model that lending boom played an important role in 1997/98 Asia Crises, as a main force for bubbles in asset markets. Therefore, we include (1) the Ratio of Domestic Bank Assets to Nominal GDP in our regression as one exogenous variable to explain crises. One period lag of the variable is adopted because at most of the time, asset markets remained at their peaks some time before the crises broke out.

In Chang and Velasco's il-liquidity model ([4]), the il-liquidity problem caused by panicking withdrawal of bank deposit, is also supposed to play a major part in Asia crises. Thus, (2) the Ratio of Bank Loan to Bank Total Deposit is included in our model with three months in advance, to see the aftermath effect of bank il-liquidity on country's vulnerability to crises.

The declining export in some Asian countries has widely been blamed on as deeper cause for Asia crises. As a result, (3) the Growth Rate of Export (% of previous year) has been employed as well. Because of the lagged effect of accumulation in current deficits, we include six month lag of the variable in our regression.

### 4.2 The Data Set

Most of our data is extracted from the on-line IMF's International Financial Statistics (IFS) and the CD of Global Development Finance (GDF). We have also adopted the data published in working papers in World Bank web site to fill in some data gaps, after we got approval from the authors.

The data set consists of monthly observations from July 1991 to December 1998 for Thailand, Indonesia, Korea, Malaysia and Philippines, because we focus on the period of 1990s to see the contagion effect in 1997/98 Asia crises. We do not adopt a longer length of time period also because of the fact that any structural change in markets over that long period would invalidate our test for contagion.

The reason choosing December 1998 as the end point of our sample is that Malaysia started to adopt fixed exchange rate regime with strict capital control at the beginning of 1999.

## 5 Contagion Analysis using MS-VAR model

The popularity of the Markov-switching model in the currency crises literature has increased dramatically over the past few years. It is widely acknowledged that many macroeconomic or financial variables undergo episodes for a long period in which the behavior of the series seems to change quite dramatically, especially when there are wars, currency crises, or significant changes in government policies.

The MS model can allow us to assume that observed data has been drawn from the different distribution conditional on the state-contingent parameter sets. The main advantage of the MS framework compared with Logit/Probit model is that MS model allows for a continuous dependent variable and avoids the arbitrary choice of threshold level to qualify a crisis. Moreover, the non-linear nature of the MS model is also appealing in the time series such as the MPIs, coming from different distributions if the state has switched.

### 5.1 The MS-VAR model

Here, we use Hamilton's Markov-Switching Vector Autoregressive model (MS-VAR)<sup>1</sup> to examine common regime shifts in the stochastic process of the MPIs in pairs of countries, including Thailand and each of the rest countries in the region. It is presumed in Hamilton model that we can not observe these shifts in regimes directly, but instead must draw probabilistic inference about whether and when changes may have occurred based on the observed behavior of the MPIs. Here, our MS model allows for regime shift in the intercept term and also heteroscedasticity in disturbance term. There are obviously two regimes—the model switches from one to another—crisis and more stable state.

A VAR framework has been applied to the two-dimensional vector of MPIs in Thailand and another Asian country so as to control for endogeneity. The MPI is used in the model rather than the simple exchange rate growth so that we could capture all pressure in the foreign exchange market, including unsuccessful speculative attacks. We include three period lags of the MPIs in our regression to control for the serial correlation. We also include three exogenous variables to represent any aggregate shocks and/or fundamental changes in our model. The different period lags have been adopted for different variables according to their different characteristics discussed above.

The specification of our model can be formally expressed as

$$x_t = v(s_t) + \phi(L)x_t + \psi(L)I_t + \eta_t \quad (7)$$

$$x_t = \{x_t^s, x_t^j\}' \quad (8)$$

$$I_t = \{exp_t^s, exp_t^j, lend_t^s, lend_t^j, lndp_t^s, lndp_t^j\}' \quad (9)$$

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<sup>1</sup>Please see Hamilton ([13]), chapter 22, for a detailed statistical review about Markov-switching model and Hamilton ([12]) for an application to US growth.

where  $x_t^s$  is the MPI in the crisis source country;  $x_t^j$  is the MPI in another Asian country;  $\phi(L)$  are vector of lags up to three periods.  $exp_t^s$  and  $exp_t^j$  are export growth rate (% of the same month in the previous year) for the source country and country  $j$  respectively;  $lend_t^s$  and  $lend_t^j$  are domestic bank assets (% of nominal GDP) and  $lndp_t^s$  and  $lndp_t^j$  are the ratio of bank loan to total deposit.  $\psi(L)$  are vector of different period lags for different exogenous variables. Finally, the conditional constant term (intercept)  $v(s_t)$  switches between two states:

$$v(s_t) = \begin{cases} v_1, & \text{if } s_t = 1 \text{ ( 'stable' )} \\ v_2, & \text{if } s_t = 2 \text{ ( 'crisis' )} \end{cases} \quad (10)$$

and  $\eta_t \sim \text{NID}(0, \Sigma(s_t))$ , where  $\Sigma(s_t)$  is also assumed to be different in different regimes. Equation (7)–(9) have formed the measurement equation for the Hamilton's state space model.

The state  $s_t$  is assumed to follow a first order Markov process so that we can write the transition equation as

$$\Pr(s_t = i | \xi_{t-1}) = \Pr(s_t = i | s_{t-1} = j) = p_{ij} \quad (11)$$

where  $\xi_{t-1}$  is a vector representing all the information available at time  $t - 1$  which includes lagged values of  $x_t$  and  $I_t$ . The essence of this scientific method is the presumption that the future will in some sense be like the past. The measurement equation and the transition equation have made up the Hamilton's Markov-switching space model. The value  $p_{ij}$  is known as the transition probability of moving to state  $i$  from state  $j$  and assumed to be independent of time:

$$\begin{cases} p_{12} = \Pr(\text{ stable in } t | \text{ crisis in } t - 1) \\ p_{21} = \Pr(\text{ crisis in } t | \text{ stable in } t - 1) \end{cases} \quad (12)$$

for  $t \in \{1, +\infty\}$ .

As shown in Appendix A, Hamilton ([12]) filter has provided a nonlinear algorithm for generating inference about a discrete-valued unobserved state vector. As a by-product of that algorithm, the log likelihood function for the observed data evaluated at the estimates of parameters can be calculated. Then, the EM method is adopted to obtain maximum likelihood estimates of all the parameters in the MS-VAR model.

In general, the EM method, developed by Dempster, Laird, and Rubin ([5]), maximizes the incomplete-data log likelihood via the iterative maximization of the expected complete-data log likelihood, conditional upon the observable data. Given the observed data and some initial estimate of the parameters in the model, the EM algorithm begins by calculating the smoothed state probabilities (i.e. the unconditional probability of a particular state). With the estimated smoothed state and transition probabilities, the expected complete-data log likelihood function is constructed. This is the "E", expectation part of the algorithm. The expected complete-data log likelihood function is then maximized to obtain an updated parameter estimate. This is the "M", maximization part of the algorithm. Using this

updated estimate, the smoothed probabilities are calculated again and substituted into the expected likelihood function, which is maximized again. This iterative procedure is repeated until convergence (in the parameter estimates or the likelihood function) is obtained. Then we can attain the maximum likelihood estimates of the MS model parameters.

It is also possible to derive estimates of the state vector based on all the sample information. These smoothed estimators represent the best estimate of the probability that the observation of period  $t$  was in state  $s_t$ . Since Markov-switching model includes the possibility that the threshold depends on the last regime, the smoothed probabilities are different from the transition probabilities. Kim ([17]) has developed a backward recursion algorithm to calculate this smoothed inference.

Our analysis focuses on tests for contagion from Thailand to the rest of the region—Indonesia, Korea, Malaysia, and Philippines—during 1997/98 crises. For each set of test, we first estimate the MSIH(2)-VARX(3) model specified in equations (7) through (12) with Thailand as the crisis source country. Using variance-covariance estimates, we calculate the cross-market correction coefficients between the two countries during the stable periods and crisis periods. We then see whether there is a significant increase in the correlation coefficient (not adjusted for heteroscedasticity) during the turmoil period in order to qualify as contagion described in section II.

As Forbes and Rigobon ([9]) argue, these tests for contagion may not be accurate due to the bias in the conditional coefficient resulting from heteroscedasticity. In other words, the estimated increases in the conditional correlation coefficient could reflect either an increase in cross-market linkages and/or increased market volatility. Therefore, we calculate the unconditional correlation coefficients by using equation (5) to adjust this bias. Finally, we see how the test results change after this adjustment.

## 5.2 Results

It is clear from the estimate results (Table 1) that the stable states are depicted by low variances, while the crisis periods are described by much higher variances except for Malaysia. Therefore, the stable periods are times when there are few fluctuation in foreign exchange markets, while markets are highly volatile during crises.

The results also show that the hypotheses of linear specification have been rejected at even 1% significant level in all cases. Countries stayed in stable state much longer than in crisis. The probabilities for countries to stay in the same states (crisis or stable) as in the previous period are much higher than the probabilities to switch between the two different states. In other words, countries that stayed in stable state last month intend to remain in that stable situation this month, while countries where crises broke out last month find themselves dragged into deeper turmoil.

Most of exogenous variables in our model have statistically and economically

Table 1: MSIH(2)-VARX(3) Model <sup>a</sup> Results <sup>b</sup>

	Tha-Mal		Tha-Phi		Tha-Kor		Tha-Ind	
MPI	Tha	Mal	Tha	Phi	Tha	Kor	Tha	Ind
Intercept (Stable)	1.32	-1.10	-0.49	4.15	-6.33	-7.09	-8.55	-6.33
Intercept (Crisis)	1.82	-1.18	0.73	6.45	-5.16	-5.73	-6.12	-3.43
Std. Dev. (Stable)	0.62	0.99	0.40	0.85	0.51	0.40	0.76	0.50
Std. Dev. (Crisis)	1.34	0.30	1.98	1.46	2.19	2.25	2.90	1.19
Transition Prob.								
(Stable → Stable)		0.9404		0.9323		0.9413		0.9583
(Crisis → Crisis)		0.9008		0.7976		0.6088		0.6411
(Stable → Crisis)		0.0596		0.0677		0.0587		0.0417
(Crisis → Stable)		0.0992		0.2024		0.3912		0.3589
Classified	1992:01-1992:04		1992:04-1992:07		1996:07		1997:07-1997:08	
Crisis periods	1995:01-1995:07		1993:08-1993:09		1997:07-1998:01		1997:10-1998:01	
	1996:01-1998:01		1995:02-1995:04		1998:07-1998:09		1998:05-1998:07	
			1997:07-1998:02					
			1998:08-1998:09					
LR Linearity test <sup>c</sup>	54.6458*		79.2336*		102.4552*		101.0320*	

<sup>a</sup> Non-linear Markov-switching estimation with regime-dependent intercepts and heteroscedasticity. Number of regimes: 2. Order of VAR: 3. Number of exogenous variables: 3.

<sup>b</sup> All results were obtained using H-M. Krolzig's MSVAR package for Ox.

<sup>c</sup> "\*" indicates that the null hypothesis of linearity has been rejected at 1% level.

significant effects on country's vulnerability to crisis contagion. <sup>2</sup>

The unconditional smoothed probabilities indicate the probabilities that each pair of countries stay in either stable or crisis state at time  $t$ . <sup>3</sup> A month is classified as a turmoil month if the smoothed probability of being in the crisis state is greater than 50%. Actually, the choice of threshold of 50% does not change the identification of crisis periods at all because these probabilities are all either very close to zero or one. From the results, both Thailand and Indonesia were in the turmoil state at very similar times as Thailand and Korea, while the other two groups share longer and some earlier crisis episodes (Figure ??–Figure ?? show both the filtered and smoothed regime probabilities for each pair of countries). The identification of the crisis months by MS model fits the history fairly well.

The estimated conditional and unconditional correlation coefficients for the stable and turmoil periods are shown in Table 2 and 3 respectively for each pair of countries. <sup>4</sup>

### 5.2.1 Thailand and Malaysia

Several patterns are immediately apparent in our test for contagion from Thailand to Malaysia. At first, cross-market correlation during the relatively stable periods is unsurprisingly high given Thailand and Malaysia, as key members of ASEAN, share similar economic structure. Thailand is highly correlated with Malaysia—0.72 during the stable periods.

<sup>2</sup>Please ask author for relevant results.

<sup>3</sup>Please ask author for relevant results.

<sup>4</sup>Because of the time lagging problem of crisis spreading, we here adopt the absolute value of our estimated correlation coefficients.

Table 2: Conditional Cross-market Correlation Coefficients<sup>a</sup>

	Tha-Mal	Tha-Phi	Tha-Kor	Tha-Ind
Stable periods <sup>b</sup>	0.72	0.26	0.058	0.07
Turmoil periods	0.887	0.508	0.066	0.64
Contagion <sup>c</sup>	C	C	N	C

<sup>a</sup> This table reports conditional (unadjusted) cross-market correlation coefficients for Thailand and each other country in the sample.

<sup>b</sup> Both stable and turmoil periods are defined by Markov-switching Vector Autoregressive model (MS-VAR).

<sup>c</sup> "C" indicates that contagion occurred, while "N" shows no crisis contagion effect.

Table 3: Unconditional Cross-market Correlation Coefficients<sup>a</sup>

	Tha-Mal	Tha-Phi	Tha-Kor	Tha-Ind
Stable periods <sup>b</sup>	0.72	0.26	0.058	0.07
Turmoil periods	0.63	0.12	0.0155	0.33
Contagion <sup>c</sup>	N	N	N	C

<sup>a</sup> This table reports unconditional (adjusted) cross-market correlation coefficients for Thailand and each other country in the sample.

<sup>b</sup> Both stable and turmoil periods are defined by Markov-switching Vector Autoregressive model (MS-VAR).

<sup>c</sup> "C" indicates that contagion occurred, while "N" shows no crisis contagion effect.

Secondly, cross-market correlation increases dramatically to 0.887 during the turmoil periods. This is clear evidence of a strengthened real economic linkage between two countries during crises. Obviously, the prerequisite for contagion is therefore satisfied in this case and contagion occurred from the crash of Thai exchange market to Malaysia.

Thirdly, it is also shown that adjusting for heteroscedasticity has a significant impact on estimated cross-market correlations and the resulting test for contagion. The unconditional correlation (0.63) during the turmoil period is substantially smaller than the conditional correlation and even lower than in the stable period. There is now no evidence of contagion from the Thai crash to Malaysia because of no significant increase in the unconditional correlation coefficient during the crisis periods.

The results exactly highlight how our test methodology defines contagion. The high cross-market correlation between Thailand and Malaysia during volatile periods do not qualify as contagion, because these two markets are correlated in a similarly high degree during more stable periods. These exchange markets are highly interdependent in all states of the world.

## 5.2.2 Thailand and Philippines

The conditional and unconditional correlation coefficients between Thailand and Philippines show the same features as the previous case. During the relatively stable periods, the Thailand exchange market tends to be highly correlated with the market in Philippines (0.26). Secondly, cross-market correlation increases quite significantly to 0.508 during crisis periods. This is a significant increase in the correlation during the turmoil periods and contagion occurred from Thai exchange market to Philippines.

However, this evidence of contagion could result from heteroscedasticity. Therefore, we calculate unconditional correlation to adjust this bias. Once again, this adjustment has a significant impact on estimated correlations and the resulting tests for contagion. The unconditional correlation coefficient is now 0.12 during the turmoil periods, much smaller than the correlation in stable periods (0.26). There is no longer evidence of a significant change in the magnitude of the propagation mechanism from Thailand to Philippines—no contagion according to our definition.

## 5.2.3 Thailand and Korea

Korea, as the fourth biggest economy in East Asia, has entirely different market size and structure from Thailand. This is shown by the relatively low cross-market correlation between Thailand and Korea during the stable periods—0.058. There is no strong economic linkage between Thailand and Korea.

In contrast to the early papers finding contagion effect in Korea, the conditional correlation coefficient in the turmoil periods (0.066) in our model is just slightly greater than in stable periods (0.058). In other words, the prerequisite for contagion to occur is not justified in this case and Thai exchange crash had not been contagious for Korea according to the definition given in section II.

Furthermore, when the correlation coefficient is adjusted for changes in market volatility, there is no evidence of contagion either. The unconditional cross-market correlation is 0.0155 during the turmoil periods, even less than the correlation in stable periods (0.058).

## 5.2.4 Thailand and Indonesia

Surprisingly, our estimated results for Thailand and Indonesia show very different patterns from the former cases. Firstly, the cross-market correlation during the relatively stable periods is surprisingly low (0.07), given two countries share similar market structure. This could be attributed to the different levels of economic development achieved by the two countries, while Thailand stays at the higher level than Indonesia.

The conditional cross-market correlation between Thailand and Indonesia increases dramatically during the 1997/98 East Asia Financial/Currency Crises (0.64). Therefore, it is obvious that the prerequisite for contagion is satisfied and contagion occurred from the crash of the Thai exchange market to Indonesia.

Secondly, it is shown that although adjusting for heteroscedasticity has some impact on estimated cross-market correlation, the test result for contagion keeps unchanged in this case. The unconditional correlation (0.33) during the turmoil periods is smaller than the conditional correlation, but still much higher than in the stable periods (0.07). In other words, there is clear evidence of contagion from the Thai currency crash to Indonesia even after we adjust for heteroscedasticity.

This finding could justify the aids provided by IMF to Indonesia in the very early stage of 1997/98 East Asia Crises. As Forbes and Rigobon ([8]) argue, only countries affected by contagion should qualify for multilateral bailouts. This is because that otherwise during turmoil periods, only a small fluctuation in the source country market could have a damaging effect on the vulnerable country, via a channel that is amplified in crisis.

## 6 Conclusion

This paper has shown that tests for contagion based on conditional cross-market correlation coefficient are problematic due to the bias introduced by increases in market volatility during crises.

The rapid spread of crises from Thailand to the rest of East Asia in 1997 has raised the question: are these highly correlated comovement amongst Asian exchange markets clear evidence of contagion? Here, we focus on a traditional definition of contagion: a significant increase in cross-market linkages after a shock to one country (or group of countries). According to the conventional method of testing for contagion, a significant increase in conditional cross-market correlation (not adjusted for heteroscedasticity) could be interpreted as evidence of contagion. However, as Forbes and Rigobon ([9]) argue, these conditional correlations will be biased upward during a crisis when exchange market volatility increases.

Using the method proposed by Forbes and Rigobon ([9]) to correct for this bias, we calculate unconditional cross-market correlation coefficients instead to test for contagion. The model we employ here is non-linear Markov-switching VAR model. More and more economists argue that it is very unlikely that the economic series can be characterized as drawn from the same distribution conditional on some constant parameter set after a significant event such as currency crisis. This paper, for the first time, adopts a non-linear framework to explore the crisis transmission mechanism. Compared with arbitrary choice of crisis incidences by other models, Markov-switching model does perform well defining crises in the sense of objectiveness and fairness, as it allows the data itself to reveal what move represents abnormal behavior and therefore signals a crisis. In all pairs of countries, the linear hypotheses have been rejected even at 1% significant level, which highlight the better fitness of Markov-switching model than the existing linear models.

The adjustment for heteroscedasticity has shown a significant impact on the original results of test for contagion using conventional (conditional) correlations. Same as what Forbes and Rigobon find in the case of return to stock market, our

research shows that nearly all evidence of contagion based on conditional correlations soon disappears except for Thailand and Philippines case after we adjust for heteroscedasticity. The high level of market comovement during all states of the world, on the other hand, shows close economic linkage–interdependence–between Thailand and Malaysia and Philippines.

However, as Forbes and Rigobon ([9]) point out, it is quite different to quantify the extent of the bias in the conditional correlation coefficient if heteroscedasticity is combined with either endogeneity or omitted variables. Therefore, further work is needed to examine how endogeneity and omitted variables, especially when combined with heteroscedasticity, can affect tests for contagion in Asia after 1997/98 crises.

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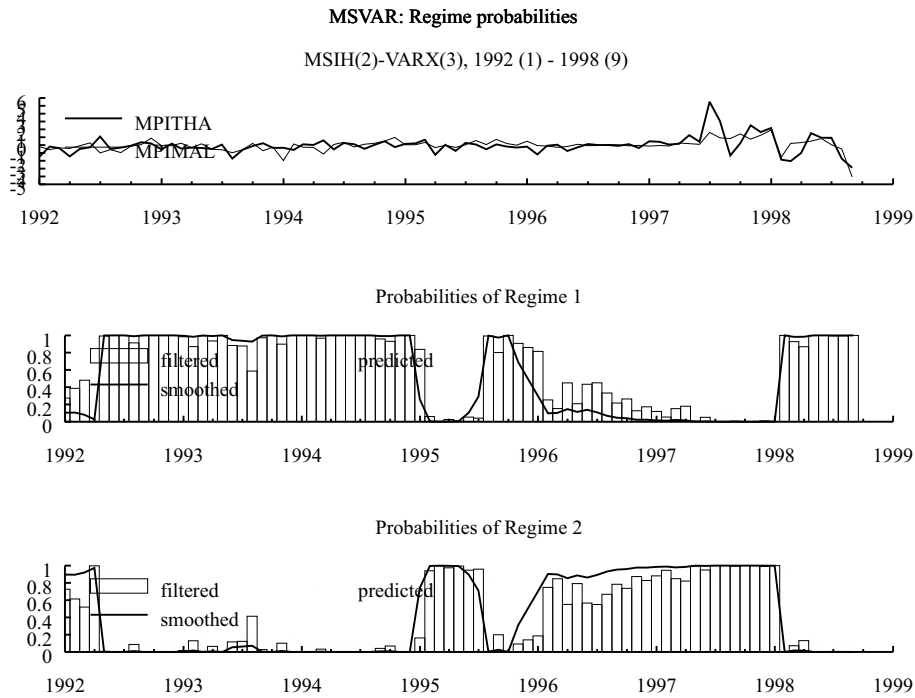


Figure 1: The Filtered and Smoothed Regime Probabilities for Thailand and Malaysia during 1992.1–1998.9

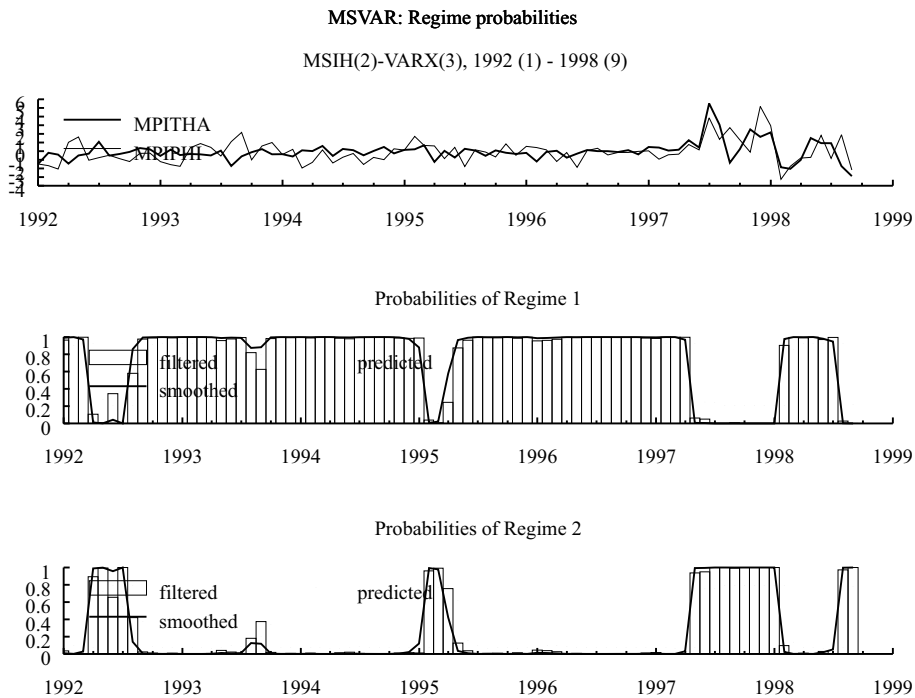


Figure 2: The Filtered and Smoothed Regime Probabilities for Thailand and Philippines during 1992.1–1998.9

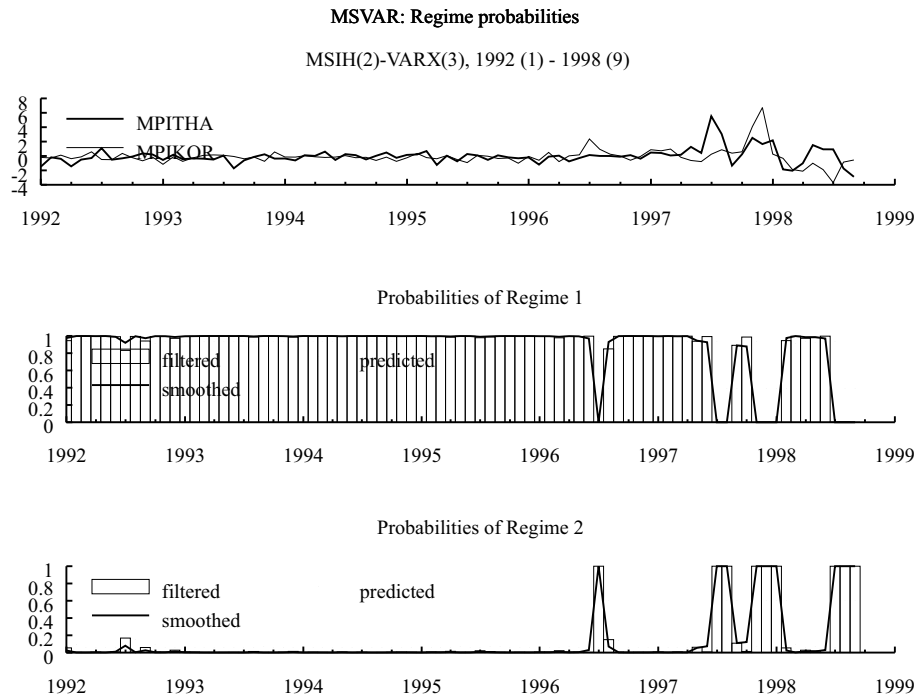


Figure 3: The Filtered and Smoothed Regime Probabilities for Thailand and Korea during 1992.1–1998.9

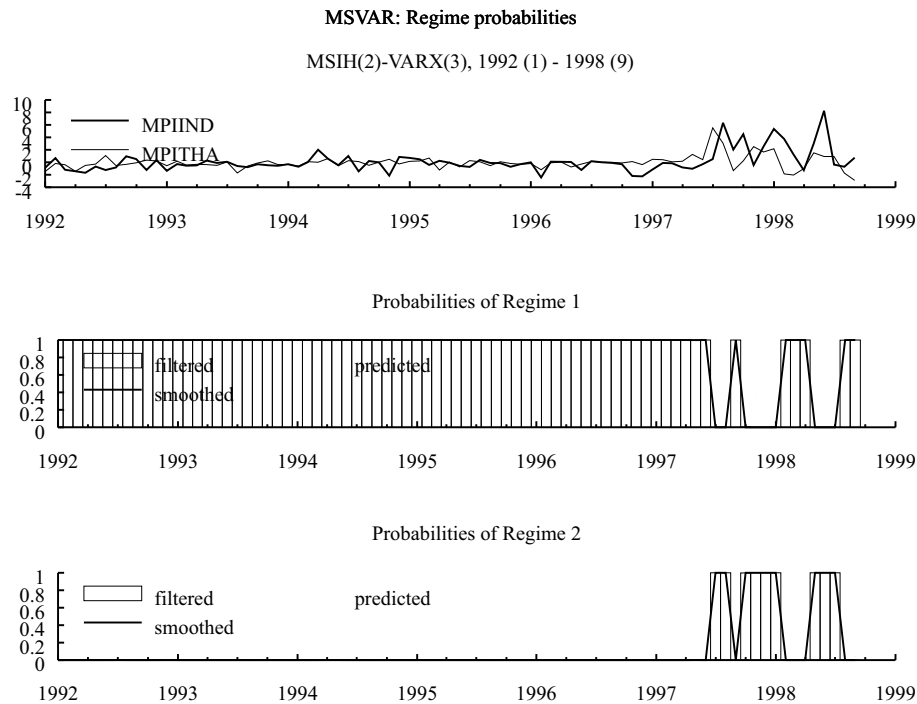


Figure 4: The Filtered and Smoothed Regime Probabilities for Thailand and Indonesia during 1992.1–1998.9

# A Markov-Switching Model Briefing

Many macroeconomic or financial variables undergo episodes for a long period in which the behavior of the series seems to change quite dramatically. Such apparent changes in the time series process can result from events such as wars, financial panics, or significant changes in government policies.

But in econometrics, we usually assume that observed data has been drawn from the same distribution conditional on some constant parameter set. As indicated above, it is very unlikely that economic time series can be characterized in such a way.

The standard econometric way to solve that problem is trying to detect the existence of these changes in regime using different types of parameter constancy tests, and then impost dummy variables to account for these changes. But this procedure might be very rigid and may lead to the use of models with too many dummy variables.

As a result, state space models have been launched to tackle this problem. The general state space model consists of two equations: the measurement equation and the transition equation. The Kalman filter of Kalman [15] and Kalman and Bucy [16] is an algorithm for generating minimum mean square error forecasts in a state space model. But whereas the Kalman filter is a linear algorithm for generating estimates of a continues unobserved state vector, Hamilton [12] presented another approach to provide nonlinear inference about a discrete-valued unobserved state vector.

It is presumed in Hamilton model that econometricians can not observe the shifts in regime directly, but instead must draw probabilistic inference about whether and when changes may have occurred based on the observed behavior of the series.

A variable  $y_t$  is assumed to be a linear function of a vector of variables  $\mathbf{x}_t$  with coefficients that depend on the state or regime in period  $t$ . There are a discrete number of states,  $n$ . Formally

$$y_t = \mathbf{x}'_t \beta_{s_t} + \epsilon_t \quad (13)$$

where  $s_t$  is the state in period  $t$  which can take one of  $n$  possible values,  $1, \dots, n$ . Defining  $\alpha_t$  as the  $n \times 1$  vector with  $i$ th element equal to one when  $s_t = i$  and all other elements equal to zero, we can rewrite the measurement equation (13) as

$$y_t = \mathbf{x}'_t \mathbf{B} \alpha_t + \epsilon_t \quad (14)$$

where  $\mathbf{B} = [\beta_1 : \dots : \beta_n]$  and  $\text{var}(\epsilon_t) = \sigma^2$ .

The state  $s_t$  is assumed to follow a first order Markov process so that we can write the transition equation as

$$\Pr(s_t = i | \xi_{t-1}) = \Pr(s_t = i | s_{t-1} = j) = p_{ij} \quad (15)$$

where  $\xi_{t-1}$  is a vector representing all the information available at time  $t - 1$  which includes lagged values of  $y_t$  and  $x_t$ . The reason for the assumption of Markov

chain is that over a deterministic specification for a process with permanent regime changes, one could generate meaningful forecast prior to the change that take into account the possibility of the regime change. The essence of this scientific method is the presumption that the future will in some sense be like the past. The value  $p_{ij}$  is known as the transition probability of moving to state  $i$  from state  $j$  and is independent of time. If

$$\mathbf{\Pi} = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix}$$

, then we can rewrite (15) as

$$\begin{aligned} E(\alpha_t | \alpha_{t-1}) &= \mathbf{\Pi} \alpha_{t-1} \\ \alpha_t &= \mathbf{\Pi} \alpha_{t-1} + \eta_t \end{aligned} \quad (16)$$

where  $\eta_t$  is uncorrelated with  $\alpha_{t-1}$  or  $\xi_{t-1}$  and is not normally distributed.

The Hamilton filter is an iterative algorithm for calculating the distribution of the discrete state variable  $\alpha_t$ .

Let  $\alpha_t$  be  $E(\alpha_t | \xi_t)$  with  $i$ th element given by

$$\Pr(s_t = i | \xi_t)$$

and  $\alpha_{t|t-1}$  be  $E(\alpha_t | \xi_{t-1})$  with  $i$ th element given by

$$\Pr(s_t = i | \xi_{t-1})$$

Then the Hamilton filter comprises two recursive equations: obtaining an optimal inference about the current state given the past values of the variable that is to be forecast, the updating equation,  $\alpha_t = \mathbf{h}(\alpha_{t|t-1})$ ; the prediction equation, using the outcome of the filter to generate future forecasts of this variable,  $\alpha_{t|t-1} = \mathbf{g}(\alpha_{t-1})$ .

The Hamilton filter prediction equation follows from (16) and is simply

$$\alpha_{t|t-1} = \mathbf{\Pi} \alpha_{t-1} \quad (17)$$

Through the filter introduced by Hamilton [12], the optimal inference of  $\alpha_t$  on the basis of the information set in  $t$  consisting of the observed values of  $\mathbf{Y}_t$ , could be calculated as the following (nonlinear) updating equation.

$$\alpha_t = \frac{\mathbf{v}_t \odot \alpha_{t|t-1}}{\mathbf{v}_t' \alpha_{t|t-1}} \quad (18)$$

where  $\mathbf{v}_t$  is the  $n \times 1$  vector with  $i$ th element given by  $f(y_t | s_t = i, \mathbf{x}_t, \xi_{t-1})$ . The five-step filter weights for each regime the conditional density of the observation  $y_t$ , given the population parameters of regime  $m$ , with the predicted probability of being in regime  $m$  at time  $t$  given the information set  $\mathbf{Y}_{t-1}$ .

The optimal inference and forecast for each date  $t$  in the sample can be found by iterating on the above pair of equations.

Moreover, a starting value  $\alpha_0$  is needed to calculate  $\alpha_t$  through the iterative algorithm. Several options are available for initializing the filter.

If the Markov process is stationary and ergodic, then  $E(\alpha_t) = E(\alpha_{t-1})$  and from the transition equation(12)

$$E(\alpha_t) = \mathbf{\Pi}E(\alpha_t)$$

This can be used to define the vector of unconditional probabilities  $\alpha$  by solving

$$\alpha = \mathbf{\Pi}\alpha$$

Then one approach is to set  $\alpha_0$  equal to  $\alpha$ .

Another option is to set

$$\alpha_0 = \rho$$

where  $\rho$  is a fixed  $(N \times 1)$  vector of nonnegative constants summing to unity, such as  $\rho = \mathbf{N}^{-1} \cdot \mathbf{1}$ .

The population parameters that describe the time series government by (14) and (16) consist of  $\mathbf{B}, \sigma^2$  and the various transition probabilities  $\mathbf{\Pi}$ . Collect these parameters in a vector  $\theta$ .

The log likelihood function  $L(\theta)$  for the observed data  $y_T$  evaluated at the value of  $\theta$  that was used to perform the iterations can also be calculated as a by-product of this algorithm from

$$L(\theta) = \sum_{t=1}^T \log f(y_t|x_t, y_{t-1}; \theta) \quad (19)$$

Then the value of  $\theta$  that maximizes the log likelihood can be found numerically using the EM method, developed by Dempster, Laird, and Rubin [5]. Given the observed data and an arbitrary initial guess for the value of  $\theta$ ,  $\theta^{(0)}$ , the EM algorithm begins by calculating the smoothed state probabilities (i.e. the unconditional probability of a particular state, discussed later in this section). With the estimated smoothed state and transition probabilities, the expected complete-data log likelihood function is constructed, which is the "E", expectation part of the algorithm. The log likelihood function is then maximized to obtain an updated parameter estimate. This is the "M", maximization part of the algorithm. The iterative procedure continues until the change between  $\theta^{(m+1)}$  and  $\theta^{(m)}$  is smaller than some specified convergence criterion. Then the maximum likelihood estimate  $\hat{\theta}$  is equal to  $\theta^{(m)} = \theta^{(m+1)}$ .

Once the unknown parameters of the model  $\mathbf{B}$ ,  $\mathbf{\Pi}$ , and  $\sigma^2$  have been estimated, it is possible to derive estimates of the state vector based on all the sample information. These smoothed estimators, given by  $\alpha_{t|T} = E(\alpha_t|\xi_T)$ , represent the best estimate of the probability that the model was in state  $s_i$  in period  $t$ . since Markov-Switching

Model includes the possibility that the threshold depends on the last regime, the smoothed probabilities are different from the transition probabilities we discussed above.

Developed by Kim [17], the backward recursion algorithm used to calculate smoothed inferences, can be written as

$$\alpha_{t|T} = \alpha_{t|t} \odot \{\Pi'(\alpha_{t+1|T} \oslash \alpha_{t+1|t})\} \quad (20)$$

where  $\odot$  is the element-by-element multiplication operator and  $\oslash$  denotes the element-by-element division. This algorithm is started with  $\alpha_{T|T}$ , iterating on backward for  $t = T - 1, T - 2, \dots, 1$ .

In practice, the Markov-Switching Vector Autoregressive (MS-VAR) models are mostly used for its flexibility. There are two major types of MS-VAR:

- shift in the mean (MSM-VAR): once and for-all jump in the time series

$$y_t - \mu(s_t) = \mathbf{A}_1(s_t)(y_{t-1} - \mu(s_{t-1})) + \dots + \mathbf{A}_p(s_t)(y_{t-p} - \mu(s_{t-p})) + u_t;$$

- shift in the intercept (MSI-VAR): smooth adjustment of the times series

$$y_t = v(s_t) + \mathbf{A}_1(s_t)y_{t-1} + \dots + \mathbf{A}_p(s_t)y_{t-p} + u_t.$$

However, some economists have pointed about that the numerical optimization of a very complicated non-linear function in Hamilton's filter could suffer from several specific types of failures. In particular, the parameter vector may change direction at ever increasing speed toward absurd values, while still increasing log likelihood at each step.