# Are 1997 Asian Twin Crises Contagious?

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## Abstract

Until recently, currency and banking crises (twin crises) have been largely treated as separate phenomena, but the recent experiences of several Southeast Asian countries indicate that both banking and currency crises can occur jointly. However, most of empirical literature has focused on the determinants of each type of crisis in isolation and little empirical work to date has systematically investigated the association of the twin crises. In particular, no study has tested if the is a pure contagion effect between the twin crises. This paper tries to fill this gap by examining the pure contagion effect both *within* a country and *across* countries using data from Japan and Thailand. The empirical results indicate that within a country there is a positive feedback relation between Thai banking sector and its currency market, indicating a within-country bi-directional contagion-in-mean effect between the twin crises. Across countries there are unidirectional relations between Thai banking sector and Japanese currency market and between Japanese banking sector and Thai currency market, suggesting a unidirectional cross-country contagion-in-mean effect between the twin crises. As for contagion-in-volatility, it is not significant, implying that there is no incremental increase in volatility during the 1997 Asian crisis. Finally, the global banking industry risk is significantly priced.


## I. Introduction

Because banking and currency crises (the *twin* crises) have often been extremely costly in terms of reduced income and increased unemployment to their own countries as well as others, the joint occurrence of twin crises associated with the recent 1997 Asian financial turmoil has drawn renewed attention to the interrelationship between these two phenomena. There are several theoretical reasons to explain why there is a link between the twin crises. However, most of empirical literature has focused on the determinants of each type of crisis in isolation and little empirical work to date has systematically investigated the association of the twin crises with a few exceptions (e.g., Kaminsky and Reinhart, 1999; Glick and Hutchison, 2000). Kaminsky and Reinhart (1999) find that problems in the banking sector typically precede a currency crisis, which in turn deepens the banking crisis. In other words, banking and currency crises can generate a vicious circle by amplifying each other. Similarly, Glick and Hutchison (2000) conclude that the linkage between the onset of currency and bank crises in emerging markets is strong, indicating that currency crises feed into the onset of banking problems and vice versa. However, none of the above-mentioned two studies explicitly tests whether there is a "pure" contagion effect between the twin crises. Masson (1999) argues that there are three main channels that financial markets turbulence can spread from one country to another: monsoonal effects, spillovers and pure contagion effects. 'Monsoonal' effects, or 'contagions from common causes' tend to occur when affected countries have similar economic fundamentals or face common external shocks. The second type of financial market inter-linkages arises from spillover effects, which may be due to trade linkages or financial interdependence. The first two channels of financial crises can be categorized as fundamentals-driven crises since the affected countries share some macroeconomic fundamentals, which implies that the transmission of financial crises is due to the interdependence among those countries and not necessarily due to

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contagion. The third transmission channel is the pure contagion effect. Contagion here refers to the cases where crisis in one country/market triggers a crisis elsewhere for reasons unexplained by macroeconomic fundamentals. For instance, a crisis in one country may lead creditors and investors to pull out from other countries over which they have a poor understanding resulting from information asymmetries. The linkages between the twin crises studied by Kaminsky and Reinhart (1999) and Glick and Hutchison (2000) are considered to be fundamentals-driven crises, which are due to the interdependence and not necessarily due to contagion. Consequently, it will be interesting to see if there are any pure contagion effects between banking and currency crises. Forbes and Rigobon (2002) recently test contagion using national stock market data, and conclude that there is no contagion during the 1997 Asian crisis, 1994 Mexican devaluation, and 1987 U.S. market crash.[1] However, they also point out that their empirical results will be biased if the assumptions of no omitted variables (i.e. no exogenous global shocks) and endogeneity (i.e. no feedback from one market to another market) do not hold in their model. As a result, it deserves another look whether there is really no contagion during the 1997 Asian crisis if possible exogenous global shocks and feedback effects are controlled. To achieve that, the current paper makes the following contributions in contagion literature. First, I define 'contagion' as significant spillovers of country- or market-specific idiosyncratic shocks during the crisis after economic fundamental or systematic risk has been accounted for. In testing for contagion, its existence depends on the economic fundamentals used. Unfortunately, there is disagreement on the definitions of the fundamentals. To control for the economic fundamentals, most empirical studies tend to choose those fundamentals arbitrarily, such as by using macroeconomic variables, dummies for important events, and time trends. The problem with these control variables is that contagion is not well defined without reference to a theory. To overcome this problem, I rely on an inter-temporal capital asset pricing model (ICAPM), which provides me a theoretical basis in selecting the economic fundamentals. The economic fundamentals under ICAPM are the global banking industry and world market risks, so the evidence of contagion is based on testing whether idiosyncratic risks - the part that cannot be explained by the global banking industry and world market risks, are significant in describing the dynamics of conditional means and volatilities of banking sector and currency returns during the 1997 Asian crisis period. Second, in addition to the contributions in overcoming the drawback of arbitrarily choosing economic fundamentals in testing contagion effects in previous studies, the methodology used in this paper is also unique. In particular, I utilize an asymmetric Multivariate General Autoregressive Conditional Heteroscedastic in Mean (MGARCH-M) approach to model the conditional mean spillovers during the crisis period, in addition to capturing the time dependencies in the second moments of asset returns, a stylized property found in most financial time-series. Finally, this paper tests contagion between twin crises not only *within* a country, but also *across* countries. In other words, I can examine whether there is contagion not only between a country's banking sector and its currency market, but also between a country's banking sector (currency market) and another country's currency market (banking sector).

The remainder of the paper is organized as follows. Section II presents the theoretical

[1]Forbes and Rigobon (2002) define contagion as a significant increase in cross-market linkages after a shock to one country or group of countries, and find that there was virtually no increase in unconditional correlation coefficients during the 1997 Asian crisis and thus conclude that there was no contagion but interdependence. However, they also point out that their definition of contagion is not universally accepted, and therefore it warrants another examination of whether contagion did occur during 1997 Asian crisis.

asset pricing model used to control for systematic risks, and the econometric methodology employed to estimate the model. Several test hypotheses are presented in Section III. Section IV describes the data and empirical results are reported in Section V. Some conclusions are offered in the final section.

## II. The Model and Methodology

In this paper, I consider a two-factor model where the two factors are global market and industry risks. In particular, I test the following model:

$$R_{i,t} = \beta_i + \lambda_{mkt,t-1} Cov_{t-1}(R_{i,t}, R_{mkt,t}) + \lambda_{ind,t-1} Cov_{t-1}(R_{i,t}, R_{ind,t}) + \varepsilon_{i,t} \quad \forall i \qquad (1)$$

where $R_{i,t}$ is the gross return of asset $i$ at time $t$, "$mkt$" denotes global market risk and "$ind$" is the global industry risk.

The conditional ICAPM in equation (1) has to hold for every asset. However, the model does not impose any restrictions on the dynamics of the conditional second moments. Several multivariate GARCH (MGARCH) models have been proposed to model the conditional second moments. Among popular MGARCH models, the BEKK model is better suited for the purpose of this paper because it not only guarantees that the covariance matrices in the system are positive definite, but also allows the conditional variances and covariances of different markets to influence each other, which is very important for testing contagion in this paper. As a result, a BEKK structure with asymmetric volatility effects is selected over the other MGARCH specifications to model the conditional second moments of banking sector returns and to test contagion effects among them. Specifically, the dynamic process for the conditional variance-covariance matrix of asset returns is specified as:

$$\begin{aligned} H_t &= C'C + A' \cdot H_{t-1} \cdot A + B' \cdot \varepsilon_{t-1}\varepsilon'_{t-1} \cdot B + D' \cdot \eta_{t-1}\eta'_{t-1} \cdot D \\ &+ G' \cdot \psi_{t-1}\psi'_{t-1} \cdot G + K' \cdot \xi_{t-1}\xi'_{t-1} \cdot K + L' \cdot \mu_{t-1}\mu'_{t-1} L + M' \cdot \nu_{t-1}\nu'_{t-1} \cdot M + N' \cdot \theta_{t-1}\theta'_{t-1} \cdot N \qquad (2) \\ &+ P' \cdot \varsigma_{t-1}\varsigma'_{t-1} \cdot P + Q' \cdot \tau_{t-1}\tau'_{t-1} \cdot Q + S' \cdot \upsilon_{t-1}\upsilon'_{t-1} \cdot S + V' \cdot \zeta_{t-1}\zeta'_{t-1} \cdot V + Y' \cdot \rho_{t-1}\rho'_{t-1} \cdot Y \end{aligned}$$

where $H_t$ is $6\times 6$ time-varying variance-covariance matrix of asset returns; $C$ is restricted to be a $6\times 6$ upper triangular matrix and $A$, $B$, $D$, $G$, $K$, $L$, $M$, $N$, $P$, $Q$, $S$, $V$, and $Y$ are diagonal matrices. The $6\times 1$ vector, $\eta_{t-1}$, captures the asymmetric impact that the vector of past negative shocks has on the conditional covariance matrix in a manner similar to that of Glosten et al. (1993). The effects of past shocks of other markets on a market's conditional variance or conditional covariances (volatility spillovers) are captured by the vectors $\psi_{t-1}$, $\xi_{t-1}$, $\mu_{t-1}$, $\nu_{t-1}$, and $\theta_{t-1}$.

Several papers in the literature show that volatility spillovers between markets are asymmetric in the sense that negative innovations in a market increase volatilities in other markets more than do positive innovations in that market. Consequently, it will be interesting to see whether such asymmetric volatility spillovers do occur during the crisis. The vectors $\varsigma_{t-1}$, $\tau_{t-1}$, $\upsilon_{t-1}$, $\zeta_{t-1}$, and $\rho_{t-1}$ capture this asymmetry. The difference between the first set of innovation vectors ($\psi_{t-1}$, $\xi_{t-1}$, $\mu_{t-1}$, $\nu_{t-1}$, $\theta_{t-1}$) and the second set of innovation vectors ($\varsigma_{t-1}$, $\tau_{t-1}$,

$\upsilon_{t-1}$, $\zeta_{t-1}$, $\rho_{t-1}$) is that the first set captures overall volatility spillovers during the *entire* sample period, while the second set captures the asymmetric volatility spillovers during the *crisis* period. By including vectors $\varsigma_{t-1}$, $\tau_{t-1}$, $\upsilon_{t-1}$, $\zeta_{t-1}$, and $\theta_{t-1}$, I can then test the incremental influences of volatility shocks on the banking sectors and currency markets, which is a true test of contagion-in-volatility.

The parameterization of the conditional covariance matrix can therefore be viewed as an extension of the diagonal BEKK representation of Engle and Kroner (1995) that allows for past shocks from other markets to influence conditional variances and covariances, for asymmetries in the impacts of these shocks. This representation of the conditional covariance matrix differs from the most general BEKK form in that conditional variances are not permitted to depend on cross-products of lagged shocks, lagged conditional variances of other markets, and lagged conditional covariances with other markets. Similarly, conditional covariances are not influenced by lagged squared shocks and lagged conditional variances in other markets. The parameterization presented here facilitates testing of the null hypothesis of no volatility spillover effects against the alternative that conditional variances depend on other markets only through their past squared shocks. Even with this diagonal BEKK parameterization, it still requires the estimation of 78 parameters in the conditional covariance matrix.

Under the assumption of conditional normality, the log-likelihood to be maximized can be written as:

$$\ln L(\varpi) = -\frac{TN}{2}\ln 2\pi - \frac{1}{2}\sum_{t=1}^{T}\ln|H_t(\varpi)| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t(\varpi)'\ H_t(\varpi)^{-1}\varepsilon_t(\varpi) \qquad (3)$$

where $\varpi$ is the vector of unknown parameters in the model. Since the normality assumption is often violated in financial time series, I use quasi-maximum likelihood estimation (QML) proposed by Bollerslev and Wooldridge (1992) which allows inference in the presence of departures from conditional normality. Under standard regularity conditions, the QML estimator is consistent and asymptotically normal and statistical inferences can be carried out by computing robust Wald statistics. The QML estimates can be obtained by maximizing equation (3), and calculating a robust estimate of the covariance of the parameter estimates using the matrix of second derivatives and the average of the period-by-period outer products of the gradient. Optimization is performed using the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm.

## III. Hypothesis Testing

### A. Testing time-varying risk premium

The conditional ICAPM with a constant (positive) price of risk is usually rejected by the data. These rejections could be driven by the fact that in some periods realized return is a bad proxy for expected return, even if realized return is a reasonable proxy over longer periods of time. The increased flexibility provided by a time-varying price of risk allows the conditional ICAPM to better accommodate such periods and, as a consequence, the model is not rejected. This time-varying price of risk is economically appealing in the sense that investors use all available information to form their expectations about future economic performance, and when the information changes over time, they will adjust their expectations and thus their expected risk premia when holding different risky assets. However, this does not come without a cost. In some periods the estimated price of risk is inevitably negative and in addition it is probably a very noise estimate of the true price of risk and hence it is not surprising if the estimate occasionally is negative. An estimated negative price of market risk is equivalent to a negative expected return on the world market portfolio. In other words, in periods when the price of market risk is negative, the world market portfolio is not conditionally efficient. This is evidence against the theoretical model developed, for example, by Merton (1980) only if we believe that expected return sometimes is negative in equilibrium. The competing intrepretation is that estimeted negative expected returns simply reflect that the econometric model adopts to negative realized returns. A typical suggestion in the literature is to impose the additional restriction $\lambda_{mkt,t-1} > 0$ during the estimation. However, this auxiliary restriction appears to assume the difficulty away rather than solve it. For example, De Santis and Gerard (1997) argue that the rejection of one of their asset pricing tests is a consequence of the positivity restriction or the rejection is indeed driven by the inability of their model to accommodate negative expected returns. As a result, in this paper I allow time-varying price of both world market and global industry risks, but do not impose positivity restriction on $\lambda_{mkt,t-1}$. Specifically, both $\lambda_{mkt,t-1}$ and $\lambda_{ind,t-1}$ are modeled as linear functions of the predetermined information variables, and are parameterized as follows.

$$\lambda_{mkt,t-1} = \varphi'_{mkt} z_{t-1} \tag{4}$$

$$\lambda_{ind,t-1} = \varphi'_{ind} z_{t-1} \tag{5}$$

where $Z_{t-1}$ is a vector of information variables observed at the end of time $t-1$ and $\varphi$'s are time-invariant vectors of weights. Given the dynamics of prices of risks, I can then test the whether the world prices of market and industry risks are significantly priced and change over time by testing whether the information variables in $Z_{t-1}$ are significant in addition to significant GARCH parameters.

### B. Testing Contagion in Mean[2]

To test whether a country's (or a market's) past idiosyncratic shocks have significant impact on the other markets' condition returns (contagion-in-mean) during the Asian crisis, I incorporate past market-specific innovations into equation (1). Specifically, the equation (1) can be modified as:

$$R_{i,t} = \beta_i + \lambda_{mkt.t-1} Cov_{t-1}(R_{i,t}, R_{mkt,t}) + \lambda_{ind,t-1} Cov_{t-1}(R_{i,t}; R_{ind,t}) + \sum_{i,j} \phi_{ij} \varepsilon_{j,t-1} + CD(\sum_{i,j} \omega_{ij} \varepsilon_{j,t-1}) + \varepsilon_{i,t}; \forall i, j \tag{6}$$

where "$CD$" is a dummy variable, which is equal to one during the crisis and zero otherwise. In testing the contagion-in-mean effects, I allow the past market-specific innovations to affect banking sector and currency returns in the *entire* sample period, and then test whether there are any incremental influences of past innovations on these returns during the *crisis* period. Thus, the contagion-in-mean hypothesis can be examined by testing whether the coefficients, $\omega_{ij} (i \neq j)$ are individually or jointly significant after the systematic risks have been accounted for.

[2]Due to the space constraint, I do not present the test results for volatility spillover and contagion-in-volatility but they are available upon request.

## IV. Data and Summary Statistics

According to Table 2 in Kaminsky and Reinhart (2001), Japanese banks were lending four times as much as U.S. banks to emerging Asia, and the five crisis countries – Indonesia, Malaysia, Philippines, South Korea, and Thailand listed in their Table 2 accounted for two-third of all loans to emerging markets. In addition, Japanese banks were most exposed to Thailand--which is the first country to experience a crisis. Consequently, I examine the pure contagion effects between the twin crises using data from Japan and Thailand. In particular, I use weekly returns on Thai and Japanese banking sector total return (dividend included) indices denominated in local currency and their bilateral exchange rates with respect to U.S. dollar. U.S. dollar denominated global banking industry ($BANK$) and world market total return indices ($WORLD$) are used to proxy global industry and world market risks, respectively. Weekly returns are calculated by taking the logarithmic first differences of the total return indices and bilateral exchange rates.

I select a set of information variables that have been widely used in the international asset pricing literature. They are excess dividend yield measured by the dividend yield on $WORLD$ in excess of the 7-day Eurodollar interest rate ($DIV$), the change in the U.S. term premium, measured by the first difference of the yield difference between 10-year Treasury constant maturity rate and 7-day Eurodollar rate ($\Delta USTP$), the U.S. default premium, measured by the yield difference between Moody's Baa-rated and Aaa-rated U.S. corporate bonds ($USDP$), the lagged return on $WORLD$, and a constant ($CONSTANT$).

The weekly data ranges from April 6, 1990 to March 23, 2001, which is a 573-data-point series. However, I work with rates of return and use the first difference of information variables, and finally all the information variables are used with a one-week lag, relative to the return series; that leaves 571 observations expanding from April 20, 1990 to March 23, 2001. All the data are extracted from Datastream.

Table 1 presents summary statistics of the data and the correlation matrix for the returns. As can be seen, among all the return series $WORLD$ has the highest weekly mean return of 0.164%, and, Japanese banking sector returns ($BJP$), on the other hand, has the lowest weekly mean return of -0.165%. Regarding the currency returns, the weekly mean return is negative for Thai bhat (-0.094%). This negative mean return is due to the significant depreciation of Thai bhat during the 1997 Asia crisis. For comparison, Table 1 also reports the same summary statistics during the 1997 Asian crisis period. As can be seen, all the weekly mean returns are negative except $WORLD$, implying both Thai and Japanese banking sectors and their currency markets and global banking industry were negatively affected by the crisis. In addition, almost all the pair-wise unconditional correlation coefficients are significantly higher during the crisis period than those for the entire sample period, indicating a strong market comovements between banking and currency markets during the crisis. Based on these increases in market comovements, it will be interesting to examine if these increases during the crisis are due to interdependence or contagion.

Table 1 also reports Bera-Jarque and Ljung-Box statistics. Bera-Jarque test rejects normality for all return series for any standard level of confidence. The Ljung-Box test statistics for raw returns ($LB(16)$) are significant at the 1% level only for Thai banking sector and currency market. However, for squared returns, $LB^2(16)$ is significant at the 1% level in all cases, indicating strong nonlinear dependencies in the sample. This is consistent with the volatility clustering observed in most stock markets, suggesting that the use of a conditional heteroscedasticity model is advisable.

**Table 1: Summary statistics of banking sector, currency, and factor returns**

| **Returns** | *BTH* | *BJP* | *CTH* | *CJP* | *BANK* | *WORLD* |
|---|---|---|---|---|---|---|
| ***Full sample*** | | | | | | |
| Mean (%) | 0.08 | -0.17 | -0.09 | 0.04 | 0.13 | 0.16 |
| Std. Dev. (%) | 6.54 | 3.66 | 1.69 | 1.70 | 2.37 | 1.86 |
| Minimum (%) | -26.78 | -14.84 | -19.36 | -5.96 | -8.93 | -9.01 |
| Maximum (%) | 37.16 | 13.12 | 9.83 | 14.60 | 10.37 | 7.71 |
| *BJP* | 0.19 | | | | | |
| *CTH* | 0.19 | 0.14 | | | | |
| *CJP* | 0.09 | 0.14 | 0.17 | | | |
| *BANK* | 0.35 | 0.65 | 0.15 | 0.26 | | |
| *WORLD* | 0.35 | 0.46 | 0.13 | 0.24 | 0.84 | |
| ***Crisis period*** | | | | | | |
| Mean (%) | -1.20 | -0.86 | -0.60 | -0.02 | -0.07 | 0.11 |
| Std. Dev. (%) | 10.76 | 4.83 | 4.41 | 2.68 | 3.10 | 2.24 |
| Minimum (%) | -20.99 | -13.84 | -19.35 | -4.43 | -8.51 | -5.31 |
| Maximum (%) | 27.42 | 12.45 | 9.83 | 14.60 | 10.37 | 7.71 |
| *BJP* | 0.28 | | | | | |
| *CTH* | 0.21 | 0.26 | | | | |
| *CJP* | 0.25 | 0.32 | 0.25 | | | |
| *BANK* | 0.61 | 0.63 | 0.28 | 0.18 | | |
| *WORLD* | 0.61 | 0.53 | 0.26 | 0.01 | 0.94 | 1.00 |
| $B-J$ | 397.57** | 78.83** | 37459.81** | 2372.68** | 82.66** | 164.54** |
| $LB(16)$ | 34.81** | 23.18 | 86.45** | 17.65 | 13.87 | 11.46 |
| $LB^2(16)$ | 302.73** | 36.27** | 100.68** | 30.69* | 139.42** | 110.09** |

* and ** denote statistical significance at the 5% and 1% level, respectively.

## V. Empirical Results

### I. The evidence of time-varying risk premia

First, considering the test results for the existence of time-varying risk premia for global industry and market risks. The results are very encouraging. For example, the joint hypothesis of zero prices of industry and market risks is strong rejected by Wald statistic ($Wald$ = 966.970) with a p-value of zero. The joint hypothesis of constant prices of industry and market risks is also significantly rejected ($Wald$ = 957.779). Next, the joint hypothesis of constant price of industry risk is strongly rejected by Wald test ($Wald$ = 35.741), and the joint hypothesis of constant price of market risk is also rejected ($Wald$ = 88.268). These test results imply that both industry and market risks are not only priced but also time varying. The information variables useful in predicting the dynamics of the risk prices include excess dividend yield ($DIV$), the default premium ($USTP$), and the lagged world market return ($WORLD$) as evidenced from the hypothesis tests (#7, #9 and #10) reported in Table 3, and the statistically significance of individual parameter estimates, $\varphi$, depicted in Panel A of Table 2. The significant time-varying industry risk premium found here shed a new light on the pricing of global banking industry risk since previous studies conclude that it is not priced.

## II. Evidence of mean spillover and contagion in mean

After controlling the systematic industry and market risks, I can then test contagion-in-mean effects among two national banking sectors and their currency markets. However, before that, I need to control for the overall mean spillovers in the entire sample period, so any incremental mean spillover effects can be tested during the crisis period. It can be seen from Table 4 that the hypothesis of no mean spillover (#1 - #4) is rejected at the 1% level for Thai banking sector ($BTH$) and two currency markets ($CTH$ and $CJP$). To find out the sources of mean spillover for these three markets, one can check statistical significance of individual mean spillover parameter, $\phi$, reported in Table 2. Table 2 indicates that the source of mean spillover for Thai banking sector ($BTH$) basically comes from its currency market ($CTH$) and Japanese banking sector ($BJP$) since $\phi_{BTH,CTH}$ = -0.479 and $\phi_{BTH,BJP}$ = 0.091 are statistically significant at the 1% level based on the robust standard errors. This finding indicates that the chain of causality, as stressed by Miller (1996), can run from currency crises to the onset of banking crises. Miller (1996) shows that a speculative attack on a currency can lead to a bank crisis if deposit money is used to speculate in the foreign exchange market and banks are “loaned up.” In addition, both Rojas-Suarez and Weisbrod (1995) and Obstfeld (1994) argue that a currency crisis may lead to problems in a vulnerable banking sector if policy makers respond to the pressure on the exchange rate by sharply raising interest rates. As for $CTH$, the source of mean spillover comes from $CJP$ ($\phi_{CTH,CJP}$ = 0.086). Similarly, the source of spillover for $CJP$ is $CTH$ ($\phi_{CJP,CTH}$ = 0.084), suggesting a feedback relation between these two currency markets. These results can also be confirmed by the significant Wald statistics for the hypothesis tests (#6 to #8) reported in Table 4. By comparing the magnitude of the three Wald statistics, it appears that the two currency markets are responsible for generating return shocks for the other markets during the sample period.

Now, considering the test results of contagion-in-mean effects, as shown in Table 4, similar to the findings for mean spillovers, these effects are statistically significant at the 1% level in three cases: $BTH$, $CTH$, and $CJP$. For example, the joint hypothesis of no contagion in return shocks for $BTH$ ($H0: \omega_{BTH,j} = 0; \forall j = BJP, CTH, CJP$) during the crisis is strongly rejected by the Wald statistic ($Wald$ = 35.319) at the 1% level. The same rejection also applies to the other two cases. To find out the sources of contagion in return shocks for $BTH$, one can again examine the individual significance of contagion-in-mean parameter, $\omega_{BTH,j}$, reported in Table 2 based on the robust standard errors. Basically, the current returns in $BTH$ are affected by past return shocks in $CTH$ ($\omega_{BTH,CTH}$ = 0.247). For $CTH$, its current returns are affected by the past return shocks in the two banking sectors. Finally, the current returns for $CJP$ are influenced by the past return shocks from Thai banking ($\omega_{CJP,BTH}$ = 0.038) and currency markets

($\omega_{CJP,CTH}$ = -0.096). By examining the significance of these individual contagion-in-mean parameters, several findings emerge between twin crisis during the 1997 crisis period. First, within a country there is a positive feedback relation between Thai banking sector and its currency market. Second, across countries there are unidirectional relations between Thai banking sector and Japanese currency market with return shocks running from $BTH$ to $CJP$, and between Japanese banking sector and Thai currency market with return shocks running from $BJP$ to $CTH$, suggesting a shock in a country's banking sector has significant impact on the other country's currency market. Finally, there is also a unidirectional relation between two currency markets with return shocks running from $CTH$ to $CJP$. This feedback and unidirectional relations among two banking sectors and two currency markets during the crisis can be further confirmed by the hypothesis tests (#13 - #16) reported in Table 4. Although all the markets can be sources of contagion-in-mean effects as Wald test statistics reject all the hypotheses, both banking sector and currency market in Thailand seem to be the major sources in generating those contagion-in-mean effects because its two Wald test statistics are relatively higher than those for Japanese banking sector and currency market. The significant pure contagion effects found here imply that the link between the twin crises can not be explained beyond the common fundamentals shared by both banking sector and currency market. One possible explanation for this finding is a liquidity shortage of international investors. Whenever international investors face large losses in one crisis country (e.g. because of margin calls) they may be forced to rearrange their portfolio thereby redrawing money from other countries. The smaller the referring market is the more likely such transactions will influence market prices. Thus, contagion effects because of international liquidity shortages are likely to happen in small markets like they are present in emerging markets. Another possible explanation for contagion is that a group of countries might be perceived by market participants as very similar with respect to aspects like e.g. culture though in fact being quite heterogeneous. If one country of this group is suffering a currency crisis market participants might wrongly expect that other countries of the group are also likely to suffer a crisis and start to attack their currencies. This wrong misperception might be due to incomplete or wrong information as well as to unobservable characteristics of the referring countries. Finally, in an inefficient foreign exchange market a speculative attack might also be started by so-called herding behavior. The term "herding" in general describes the phenomenon that market participants mimic the behavior of other market participants. Such a herding behavior in foreign exchange markets can easily lead to a currency crisis.

**Table 2: Quasi-Maximum Likelihood estimation of the conditional ICAPM**

| | | | | | |
|---|---|---|---|---|---|
| ***Panel A: Conditional mean process*** | | | | | |
| **Prices of world market and industry risks** | | | | | |
| | *CONSTANT* | *DIV* | $\Delta USTP$ | *USDP* | *WORLD* |
| $\varphi_{mkt}$ | -9.90 | -2.38 | 33.51 | 59.17 | -456.51 |
| | (4.26)* | (1.25) | (44.72) | (19.90)** | (82.37)** |
| $\varphi_{ind}$ | -6.23 | 9.87 | -45.76 | 117.46 | 252.24 |
| | (1.06)** | (2.13)** | (34.60) | (46.20)* | (65.82)** |
| **Mean spillovers** | | | | | |
| | $j = BTH$ | $j = BJP$ | $j = CTH$ | $j = CJP$ | |
| $\phi_{BTH,j}$ | 0.05 | 0.09 | -0.48 | -0.02 | |
| | (0.02)* | (0.03)** | (0.11)** | (0.06) | |
| $\phi_{BJP,j}$ | -0.01 | -0.0 | -0.08 | 0.01 | |
| | (0.01) | (0.03) | (0.05) | (0.04) | |
| $\phi_{CTH,j}$ | 0.00 | 0.00 | -0.24 | 0.09 | |
| | (0.00) | (0.01) | (0.02)** | (0.02)** | |
| $\phi_{CJP,j}$ | -0.01 | 0.00 | 0.08 | 0.02 | |
| | (0.01) | (0.02) | (0.02)** | (0.03) | |
| **Contagion in mean** | | | | | |
| | $j = BTH$ | $j = BJP$ | $j = CTH$ | $j = CJP$ | |
| $\omega_{BTH,j}$ | -0.03 | -0.12 | 0.25 | 0.46 | |
| | (0.04) | (0.14) | (0.09)** | (0.35) | |
| $\omega_{BJP,j}$ | -0.01 | -0.16 | 0.03 | 0.21 | |
| | (0.02) | (0.04)** | (0.04) | (0.12) | |
| $\omega_{CTH,j}$ | 0.06 | -0.05 | 0.06 | -0.03 | |
| | (0.02)** | (0.021)* | (0.06) | (0.06) | |

| | | | | | | |
|---|---|---|---|---|---|---|
| ***Panel B: Conditional variance process*** | | | | | | |
| | *BTH* | *BJP* | *CTH* | *CJP* | *BANK* | *WORLD* |
| $a$ | 0.95 | 0.96 | 0.81 | 0.94 | 0.96 | 0.97 |
| | (0.02)** | (0.02)** | (0.02)** | (0.02)** | (0.01)** | (0.01)** |
| $b$ | 0.14 | 0.23 | 0.61 | 0.23 | 0.21 | 0.18 |
| | (0.07)* | (0.06)** | (0.06)** | (0.06)** | (0.04)** | (0.04)** |
| $d$ | 1.38 | 1.09 | -1.18 | 1.64 | 1.54 | 1.85 |
| | (1.21) | (0.73) | (1.45) | (3.30) | (0.91) | (0.89)* |
| **Volatility spillovers** [a] | | | | | | |
| | $i = BTH$ | $i = BJP$ | $i = CTH$ | $i = CJP$ | $i = BANK$ | $i = WORLD$ |
| $j = BTH$ | | 0.04 | 0.01 | -0.02 | 0.01 | -0.01 |
| | | (0.03) | (0.00)** | (0.01)** | (0.01) | (0.01) |
| $j = BJP$ | 0.12 | | -0.01 | 0.04 | 0.01 | -0.00 |
| | (0.14) | | (0.01) | (0.01)** | (0.02) | (0.01) |
| $j = CTH$ | 0.36 | -0.10 | | 0.02 | -0.00 | 0.01 |
| | (0.46) | (0.14) | | (0.05) | (0.00) | (0.01) |
| $j = CJP$ | -0.11 | -0.04 | 0.02 | | -0.01 | -0.00 |
| | (0.28) | (0.04) | (0.02) | | (0.04) | (0.03) |
| $j = BANK$ | 0.04 | 0.03 | 0.01 | -0.08 | | -0.01 |
| | (0.09) | (0.05) | (0.01) | (0.04) | | (0.02) |
| $j = WORLD$ | 0.01 | -0.05 | -0.04 | 0.02 | -0.05 | |
| | (0.16) | (0.05) | (0.02)* | (0.04) | (0.04) | |

| **Contagion in asymmetric volatility** [a] | | | | | | |
|---|---|---|---|---|---|---|
| | $i = BTH$ | $i = BJP$ | $i = CTH$ | $i = CJP$ | $i = BANK$ | $i = WORLD$ |
| $j = BTH$ | | -0.11 | -0.59 | -0.13 | 0.04 | 0.02 |
| | | (0.29) | (0.56) | (0.17) | (0.12) | (0.06) |
| $j = BJP$ | 1.09 | | 1.20 | 0.13 | 0.09 | 0.08 |
| | (2.49) | | (1.39) | (1.07) | (0.49) | (0.37) |
| $j = CTH$ | -0.25 | 0.25 | | -0.01 | -0.03 | 0.07 |
| | (2.27) | (0.45) | | (0.35) | (0.09) | (0.23) |
| $j = CJP$ | 1.99 | -0.49 | 6.83 | | -0.64 | -0.11 |
| | (27.55) | (5.46) | (13.01) | | (7.99) | (1.90) |
| $j = BANK$ | -12.98 | -4.86 | -1.18 | 4.22 | | 0.45 |
| | (14.22) | (3.33) | (2.51) | (2.41) | | (0.42) |
| $j = WORLD$ | 14.69 | 2.01 | -4.08 | -5.88 | 1.68 | |
| | (23.25) | (8.11) | (4.75) | (8.58) | (2.26) | |

[a] The reported parameter estimates for both the volatility spillover and contagion-in-asymmetric-volatility coefficients can be interpreted as follows. For example, if $x_{ij}$ represents the volatility spillover coefficient from market $j$ to market $i$, then the volatility spillover coefficient estimate from $BJP$ to $BTH$ is 0.121. Similarly, the volatility spillover coefficient estimate from $CTH$ to $BTH$ is 0.361. The reported parameter estimates for the contagion-in-asymmetric-volatility coefficients have the same interpretation as those for volatility spillover coefficients. Robust standard errors are given in parentheses. * and ** denote statistical significance at the 5% and 1% level, respectively.

**Table 3: Hypothesis tests concerning prices of risks and predictability of conditioning variables**

| Null Hypothesis | Wald | d.f. | P-Value |
|---|---|---|---|
| **1. Are the prices of industry and market and risks equal to zero?** $H0: \varphi_{ind} = \varphi_{mkt} = 0; Z_{t-1} = \{CONSTANT, DIV, \Delta USTP, USDP, WORLD\}$ | 966.97 | 10 | 0.00 |
| **2. Are the prices of industry and market risks constant?** $H0: \varphi_{ind} = \varphi_{mkt} = 0; Z_{t-1} = \{DIV, \Delta USTP, USDP, WORLD\}$ | 957.78 | 8 | 0.00 |
| **3. Is the price of industry risk equal to zero?** $H0: \varphi_{ind} = 0; Z_{t-1} = \{CONSTANT, DIV, \Delta USTP, USDP, WORLD\}$ | 64.03 | 5 | 0.00 |
| **4. Is the price of industry risk constant?** $H0: \varphi_{ind} = 0; Z_{t-1} = \{DIV, \Delta USTP, USDP, WORLD\}$ | 35.74 | 4 | 0.00 |
| **5. Is the price of market risk equal to zero?** $H0: \varphi_{mkt} = 0; Z_{t-1} = \{CONSTANT, DIV, \Delta USTP, USDP, WORLD\}$ | 286.53 | 5 | 0.00 |
| **6. Is the price of market risk constant?** $H0: \varphi_{mkt} = 0; Z_{t-1} = \{DIV, \Delta USTP, USDP, WORLD\}$ | 88.27 | 4 | 0.00 |
| **7. Is there no predictability from excess dividend yield?** $H0: \varphi_{ind,k} = \varphi_{mkt,k} = 0; \forall k = DIV$ | 25.67 | 2 | 0.00 |
| **8. Is there no predictability from the change in term premium?** $H0: \varphi_{ind,k} = \varphi_{mkt,k} = 0; \forall k = \Delta USTP$ | 2.45 | 2 | 0.29 |
| **9. Is there no predictability from the U.S. default premium?** $H0: \varphi_{ind,k} = \varphi_{mkt,k} = 0; \forall k = USDP$ | 23.86 | 2 | 0.00 |
| **10. Is there no predictability from the world market portfolio?** $H0: \varphi_{ind,k} = \varphi_{mkt,k} = 0; \forall k = WORLD$ | 30.82 | 2 | 0.00 |

**Table 4: Hypothesis tests concerning mean spillover and contagion in mean**

| Null Hypothesis | Wald | d.f. | P-Value |
|---|---|---|---|
| **1. Is there no mean spillover for** $BTH$ **?** $H0:\phi_{BTH,j}=0;\forall j=BJP,CTH,CJP$ | 37.57 | 3 | 0.00 |
| **2. Is there no mean spillover for** $BJP$ **?** $H0:\phi_{BJP,j}=0;\forall j=CTH,CJP,BTH$ | 3.25 | 3 | 0.36 |
| **3. Is there no mean spillover for** $CTH$ **?** $H0:\phi_{CTH,j}=0;\forall j=CJP,BTH,BJP$ | 39.63 | 3 | 0.00 |
| **4. Is there no mean spillover for** $CJP$ **?** $H0:\phi_{CJP,j}=0;\forall j=BTH,BJP,CTH$ | 16.70 | 3 | 0.00 |
| **5. Is there no mean spillover from** $BTH$ **?** $H0:\phi_{i,BTH}=0;\forall i=BJP,CTH,CJP$ | 2.37 | 3 | 0.50 |
| **6. Is there no mean spillover from** $BJP$ **?** $H0:\phi_{i,BJP}=0;\forall i=CTH,CJP,BTH$ | 10.54 | 3 | 0.01 |
| **7. Is there no mean spillover from** $CTH$ **?** $H0:\phi_{i,CTH}=0;\forall i=CJP,BTH,CTH$ | 30.94 | 3 | 0.00 |
| **8. Is there no mean spillover from** $CJP$ **?** $H0:\phi_{i,CJP}=0;\forall i=BTH,CTH,CTH$ | 31.27 | 3 | 0.00 |
| **9. Is there no contagion in return shocks for** $BTH$ **?** $H0:\omega_{BTH,j}=0;\forall j=BJP,CTH,CJP$ | 35.32 | 3 | 0.00 |
| **10. Is there no contagion in return shocks for** $BJP$ **?** $H0:\omega_{BJP,j}=0;\forall j=CTH,CJP,BTH$ | 3.35 | 3 | 0.34 |
| **11. Is there no contagion in return shocks for** $CTH$ **?** $H0:\omega_{CTH,j}=0;\forall j=CJP,BTH,BJP$ | 23.41 | 3 | 0.00 |
| **12. Is there no contagion in return shocks for** $CJP$ **?** $H0:\omega_{CJP,j}=0;\forall j=BTH,BJP,CTH$ | 31.23 | 3 | 0.00 |
| **13. Is there no contagion in return shocks from** $BTH$ **?** $H0:\omega_{i,BTH}=0;\forall i=BJP,CTH,CJP$ | 22.50 | 3 | 0.00 |
| **14. Is there no contagion in return shocks from** $BJP$ **?** $H0:\omega_{i,BJP}=0;\forall i=CTH,CJP,BTH$ | 15.94 | 3 | 0.00 |
| **15. Is there no contagion in return shocks from** $CTH$ **?** $H0:\omega_{i,CTH}=0;\forall i=CJP,BTH,CTH$ | 21.87 | 3 | 0.00 |
| **16. Is there no contagion in return shocks from** $CJP$ **?** $H0:\omega_{i,CJP}=0;\forall i=BTH,CTH,CTH$ | 14.05 | 3 | 0.00 |

## VI. Conclusion

Until recently, currency and banking crises have been largely treated as separate phenomena, but the recent experiences of several Southeast Asian countries indicates that both banking and currency crises can occur jointly. However, most of empirical literature has focused on the determinants of each type of crisis in isolation and little empirical work to date has systematically investigated the association of the twin crises. In particular, no study has tested if there is a pure contagion effect between the twin crises. This paper tries to fill this gap by examining the pure contagion effect both within a country and across countries using data from Japan and Thailand. The empirical results indicate that within a country there is a positive feedback relation between Thai banking sector and its currency market, indicating a within-country bi-directional contagion-in-mean effect between twin crises. Across countries there are unidirectional relations between Thai banking sector and Japanese currency market with return shocks running from Thai banking sector to Japanese currency market, and between Japanese banking sector and Thai currency market with return shocks running from Japanese banking sector to Thai currency market, suggesting a unidirectional cross-country contagion-in-mean effect between the twin crises. As for contagion-in-volatility, it is not significant, implying that there is no incremental increase in volatility during the crisis. Finally, in contrast to previous studies, the global banking industry risk is significantly priced, suggesting the importance of including the industry risk when testing asset pricing models using industry returns.

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