Are Financial Spillovers Stable Across Regimes?

Evidence from the 1997 Asian Crisis*

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Abstract

We investigate breaks in financial spillovers between the US and eight South-East Asian capital markets before and during the 1997 Asian crisis. We construct threshold vector autoregressive models and apply novel techniques to test whether causality patterns between markets are characterized by one or two regimes. Linkages between the US and Asian markets are shown to follow the threshold model with two regimes, turmoil and tranquility, pointing to

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differences in cross-border return spillovers in stable and crisis periods. The causality analysis shows that spillovers between US and Asian markets become stronger in the turmoil regime.

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1. Introduction

Cross-border spillovers occupy an important place in international finance literature. Interdependencies between capital markets play a significant role for asset pricing and cost of capital calculation, and determine the gains and risks of international portfolio diversification. Macroeconomic policy makers and investors are not only concerned about the existence of the inter-market linkages but even more about sudden breaks in these linkages, for example the breaks caused by currency crises. Such breaks could affect the economy through a change in capital flows or in real linkages between markets, such as trade. They may lower diversification benefits from international investing and change investors' behavior after the break (Ang and Bekaert, 2002, Forbes and Rigobon, 2002, Rigobon, 2003).

In contrast to the contemporaneous interdependencies between markets, as measured by correlation coefficients, focusing on the time structure of spillovers sheds new light on the assimilation of shocks and time-varying patterns of cross-country return causality. Measuring causality provides insight on the speed of information and capital flows between markets. As price-relevant information emerges on one market, it not only generates trades in domestic assets, but can also be relevant for the valuation of foreign assets, hence inducing trades and price movements abroad. However, for information to travel across borders, transmission channels must exist. Real economic linkages between countries, financial markets, and financial institutions, as well as the existence of common lenders have been established in the literature as channels of information flow (Kaminsky and Reinhart, 2000, Kodres and Pritsker, 2002, and Pritsker, 2001, among others).

overwhelming evidence is that, first, US market returns lead both developed and emerging markets around the world. Second, these studies also find other highly capitalized stock exchanges to exert non-negligible international influence, e.g. the Japanese market leads Asian emerging markets. Third, causal relationships between emerging stock markets, albeit weak, also exist. Moreover, the bulk of existing studies shows spillovers to be unidirectional, with newly emerged capital markets found to be lagging behind their mature counterparts, and being themselves not a source of spillovers to the developed markets.

However, the assumption of inter-temporal stability and the unidirectional character of financial spillovers, common in previous studies, can be considered inappropriate in the context of return causality. Given the number of financial crises which occurred repeatedly in the past decade around the world, one would expect causation patterns to differ between calm and crisis periods. Changes in the patterns of causality may take the form of temporal strengthening or weakening of spillovers, or even as a reversal in causality between markets. Increases in the contemporaneous linkages during financial crises have already been reported in the empirical literature, e.g. in the US in the context of the 1987 crisis, and during the Asian crisis of 1997 (Bekaert, Harvey, and Ng, 2005, King and Wadhawani, 1990, Rigobon, 2003).

Furthermore, the relative importance of spillover channels is argued to be time-varying, with some channels being more active in crisis periods. According to Pritsker (2001), channels between financial markets can exist due to 1) real economic linkages, 2) actions of banks operating internationally, and 3) financial market effects. The latter can be driven by common macroeconomic news (King and Wadhwani, 1990), cross-border portfolio rebalancing due to liquidity shock in one country (Calvo, 1999), to hedging of macroeconomic risks (Kodres and Pritsker, 2002), or to wealth changes induced by changing stock prices (Kyle and Xiong, 2001). A wide use of trading strategies such as feedback trading, herding, and application of risk management rules (Schinasi and Smith, 2000), mostly by portfolio investors like mutual funds (Kaminsky, Lyons, and Schmukler, 2001), will magnify these cross-border spillovers.
Theoretical arguments and empirical evidence suggest that the channels discussed above allow initially domestic shocks to spill across borders, inducing reactions of markets abroad. Hence, a change in the interdependence between markets arises. This establishes an economic rationale for the hypothesis investigated in this study that spillover patterns differ across regimes.

In this paper, we extend the existing literature by analyzing changes in spillover patterns between the US market and emerging stock markets in South-East Asia in the period when the latter markets undergo a financial crisis. Specifically, we focus on the severe financial crisis of 1997 that could have reversed spillover patterns between markets, e.g. due to contagion effects. We expect, first, shifts in cross-border causality patterns, and, second, stronger causation effects from the Asian markets to the US market in a crisis regime and much weaker effects in a stable one, due to the notion that specific shock transmission channels are more active during crises. The regime-change hypothesis is often discussed in empirical literature supposing South-East Asia as the source of the 1997 crisis (e.g. Climent and Meneu, 2003, Forbes and Rigobon, 2002, Kaminsky and Schmukler, 1999, Rigobon, 2003, Sander and Kleimeier, 2003). We employ a novel methodology in the context of financial spillovers, namely threshold vector autoregressive (TVAR) models, with estimation and testing procedures developed by Tsay (1998) and Hansen and Seo (2002). Being in general more flexible and avoiding the construction of arbitrary spillover structures and mechanisms, this approach overcomes the severe shortcomings of the previous studies. We discuss this issue in more detail in the next section. Moreover, using the tests for Granger-causality, we explicitly investigate whether the direction and strength of spillovers change significantly as markets move from one regime to another.

We find strong evidence in favor of breaks in causality patterns across regimes, with the US market being a significant source of causality in both regimes. Spillovers from Asia to the US are observable almost exclusively in the crisis regimes, i.e. following large (negative)
return or volatility shocks. These findings are generally in line with results reported by Chen, Chiang, and So (2003), Climent and Meneu (2003), Rigobon (2003), and others using different data samples and methodologies.

The remainder of this paper is organized as follows: Section 2 provides a description of the methodology applied, Section 3 presents data and discusses empirical results as well as their interpretation, and Section 4 summarizes and concludes.

2. Modeling Financial Spillovers

Few approaches have been proposed to model changes in the cross-border return spillovers resulting from switching between tranquil and turbulent regimes. Previous literature uses models with shifts being captured by dummy variables or by arbitrary sample splitting. These studies document significant increases in spillovers during crisis periods (Climent and Meneu, 2003, Malliaris and Urrutia, 1992, Theodossiou, Kahya, Koutmos, and Christofi, 1997). More recently, Chen, Chian, and So (2003) model regime changes within the double-threshold autoregressive GARCH model. The advantage of this method is that the crisis window is not set arbitrarily on the basis of ex-post information, which would give rise to possible data mining (Billio and Pelizzon, 2003), but is estimated from the data. The disadvantage is that one cannot identify where the crisis originates since both countries change regimes simultaneously.

The methodology employed in this paper, threshold VAR models, overcomes several shortcomings common in the empirical literature. First, it does not impose any arbitrary relationship between daily index returns, but allow them to depend on lagged values of the second market returns as well as on autoregressive terms, hence capturing the inter-temporal dynamic structure of spillovers. Our framework allows all variables representing stock index returns on the markets to be explained by the model. In this way we avoid the estimation bias resulting from overlooking the bi-directional spillovers between the US and Asian markets.
Second, we estimate regime changes endogenously and explicitly test for the difference between parameter values in two regimes. We utilize approaches of Tsay (1998) and Hansen and Seo (2002) to compute sample estimates and test statistics as they offer an easy-to-handle treatment to this problem, in contrast to the method of Chen, Chian, and So (2003) consisting of several steps and lacking the simplicity of asymptotic solution.

We first construct the models of financial spillovers between the US market and an emerging East Asian market. Next, we describe the technique to estimate the models and to test for differences in spillovers between markets in calm and crisis regimes.

2.1 Threshold VAR Model

We assume that stock index returns on the emerging market, \( x_t \), depend on their past history and on lagged returns from the US market, \( y_t \). We also allow for feedback spillovers from the Asian to the US market because omitting the bilateral dependencies has been argued to bias the results on spillovers between financial markets (Billio and Pelizzon, 2003, Forbes and Rigobon, 2002).

Under the null hypothesis, the patterns of linkages between the markets are assumed to be constant across regimes. Hence, the vector autoregressive process generating returns in both countries is given by:

\[
z_t = A_0 + \sum_{k=1}^{m} A_k z_{t-k} + \epsilon_t,
\]

where \( z_t \equiv [x_t, y_t]' \), \( A_0 \) is a vector of constant terms, \( A_k \) is the matrix of coefficients corresponding to lagged stock index returns \( z_{t-k} \), and \( \epsilon_t \) is the vector of unobserved innovations on both markets.

Under the alternative hypothesis, the model is the threshold vector autoregression that accounts for possible shifts in causation patterns between the markets due to regime changes.
\[ z_t = I(w_{t-d} \geq q) \left( A_0 + \sum_{k=1}^{m} A_k z_{t-k} \right) + I(w_{t-d} < q) \left( B_0 + \sum_{k=1}^{m} B_k z_{t-k} \right) + \varepsilon_t, \quad (2) \]

where \( I(\cdot) \) is an indicator function equal to one if its argument is logically true and zero otherwise. \( A_k \) and \( B_k \) are the coefficient matrices in the two different regimes of tranquility and crisis, respectively, and \( A_0 \) and \( B_0 \) are the corresponding vectors of constant terms. \( w_{t-d} \) is the threshold variable, lagged by \( d \) periods. It is interpreted as a crisis indicator, which determines the current regime of the model. The stock index returns in \( z_t \) are generated by the linear vector autoregressive processes \( A_0 + \sum_{k=1}^{m} A_k z_{t-k} + \varepsilon_t \) or \( B_0 + \sum_{k=1}^{m} B_k z_{t-k} + \varepsilon_t \) depending on whether the variable \( w_{t-d} \) is above or below the threshold value \( q \), respectively.

### 2.2 Estimation Procedure

An important step in the analysis is the estimation of both VAR models. We apply the algorithm proposed by Hansen and Seo (2002) to estimate parameters of the threshold VAR model. In the matrix notation the linear VAR model (1) can be formulated as:

\[ z_t = AX_t + \varepsilon_t, \quad (3) \]

where \( A \equiv [ A_0, A_1, \ldots, A_k ] \) and \( X_t \equiv [ (z_{t-1})', \ldots, (z_{t-k})' ]'. \) For the two-regime model, let \( A \) denote the matrix of the first-regime coefficients and \( B \equiv [ B_0, B_1, \ldots, B_k ] \) denote the matrix of the second-regime coefficients. Now the threshold VAR model (2) takes the form:

\[ z_t = CX_t(q) + \varepsilon_t, \quad (4) \]

where \( C \equiv [ A, B ] \), \( X_t(q) \equiv [ (X_t)'(w_{t-d} > q), (X_t)'(w_{t-d} \leq q) ]' \). When the parameters \( d \) and \( q \) are known, model (4) becomes linear in relation to the parameters in \( C \), and \( A \) and \( B \) can be estimated using the ordinary least squares (OLS) method.

Hansen and Seo (2002) propose a quasi-Maximum Likelihood (ML) procedure to estimate parameters of the threshold VAR model, when \( d \) and \( q \) are unknown (see also Hansen, 2000). Since the likelihood function is not smooth in the threshold model (4), these
authors use a grid search to find estimates of $d$ and $q$, where $d \in \{1, \ldots, m\}$, with $m$ being the lag length in model (4), and $q \in G$. $G$ is the set of all observation values of $w_{t-d}$ in the sample, constrained by deleting 10% of the highest and 10% of the lowest observation values, as suggested by Andrews (1993) and Hansen and Seo (2002). For each combination of $d$ and $q$ (denoted as $\hat{d}$ and $\hat{q}$) selected from the grid, the OLS estimates of $A$ and $B$, namely $\hat{A}$ and $\hat{B}$, are computed. The estimates \{ $\hat{d}, \hat{q}, \hat{A}, \hat{B}$ \} from the combination that maximizes the concentrated log-likelihood function:

$$L(d, q) = -\frac{n}{2} \log \left| \hat{\Sigma}(d, q) \right| - n$$

(5)

are the ML estimators. $\hat{\Sigma}(d, q)$ is the estimate of the covariance matrix of $\varepsilon_t$ in model (4) and $n$ is the number of observations.

2.3 Statistical Tests

Our econometric approach to investigate the stability of spillovers between capital markets during financial crises relies on two testing procedures for the threshold VAR models. Under the null hypothesis, $H_0$, the process generating $z_t$ is well described by the linear VAR model (1). Alternatively, the hypothesis $H_1$ states that the correct specification is a more general threshold VAR model (2). $H_0$ is nested in $H_1$, because the threshold model (2) satisfying constraint $A = B$ becomes the linear model (1).

If the value of the threshold parameter $q$ were known, one could use the conventional likelihood ratio ($LR$), Lagrange multiplier ($LM$), or Wald ($W$) statistics to test the hypothesis $H_0: A = B$. However, the parameter $q$ is in general not known and it is not identified under the null hypothesis. In this case the statistics $LR$, $LM$, and $W$ do not have their asymptotic standard chi-square distributions under $H_0$ and their true distributions have yet to be derived. Hansen and Seo (2002) consider the $SupLM$ statistic, as in Davies (1987):
\[ SupLM = \sup_{q_{\text{min}} \leq q \leq q_{\text{max}}} LM(q), \]

where \( LM(q) \) is the Lagrange multiplier statistic conditional on the value of \( q \), computed for the estimated models (1) and (2). \( q_{\text{min}} \) and \( q_{\text{max}} \) are the lowest and the highest values in the set \( G \), respectively. To calculate a valid first-order approximation of the asymptotic null distribution of \( SupLM \), Hansen and Seo employ the fixed-regressor bootstrap technique, similarly to Hansen (1996, 2000). They define the new vector of dependent variables \( \tilde{z}_i \equiv \tilde{e}_i u_i \), where \( \tilde{e}_i \) are residuals from the estimated model (1) and the values of \( u_i \) are drawn randomly from the N(0,1) distribution.

The statistic \( SupLM^\ast \) is calculated from the estimates of the models (1) and (2), where \( \tilde{z}_i \) instead of \( z_i \) is set as the vector of dependent variables. The computations of \( SupLM^\ast \) are repeated many times using different draws of \( u_i \) from the N(0,1) distribution. Then, the percentage of the calculated \( SupLM^\ast \) statistics exceeding \( SupLM \) approximates the asymptotic \( p \)-value of the \( SupLM \) statistic under the null hypothesis. In our investigation we derive the \( SupLM \) and \( SupLM^\ast \) statistics using formula (6) from the \( LM(q) \) statistic that is adjusted for possible heteroscedasticity of residuals, as explained in detail by Hansen and Seo (2002):

\[ LM(q) = \text{vec}(\hat{A}' - \hat{B}') (V_1(q) + V_2(q))^{-1} \text{vec}(\hat{A}' - \hat{B}'), \]

where

\[ V_1(q) = [I_2 \otimes X_1(q)'X_1(q)]^{-1} [\xi_1(q)' \xi_1(q)] [I_2 \otimes X_1(q)'X_1(q)]^{-1}, \]

\[ V_2(q) = [I_2 \otimes X_2(q)'X_2(q)]^{-1} [\xi_2(q)' \xi_2(q)] [I_2 \otimes X_2(q)'X_2(q)]^{-1}, \]

and \( I_2 \) is the identity matrix of order two, \( \otimes \) denotes the Kronecker product, \( X_1(q) \) and \( X_2(q) \) are the matrices of stacked rows \( X_i I(w_{i,d} > q) \) and \( X_i I(w_{i,d} \leq q) \), respectively. \( \xi_1(q) \) and \( \xi_2(q) \) are the matrices of stacked rows \( \tilde{e}_i \otimes X_i I(w_{i,d} > q) \) and \( \tilde{e}_i \otimes X_i I(w_{i,d} \leq q) \), respectively.

Tsay (1998) proposes an alternative test for the hypothesis \( H_0 : A = B \), which is based on predictive residuals and the recursive least squares method. Consider the set
\[ G^* = \{w_{i,d}, \ldots, w_{n,d}\} \] of all \( n \) observations of the threshold variable \( w_{i,d} \) in the sample. Let \( w_{(i)} \) be the \( i \)-th smallest element of \( G^* \) and \( t(i) \) denote the time index of \( w_{(i)} \). Arrange the observations in the VAR model (1) in the increasing order of the threshold variable \( w_{i,d} \):

\[
z_{t(i)d} = AX_{t(i)d} + \varepsilon_{t(i)d}, \quad i = 1, \ldots, n.
\] (10)

Let \( \hat{A} \) be the estimate of \( A \) in the model (10) based on the first \( l \) observations from the arranged sample, where \( l < n \). The predictive residual \( \hat{\varepsilon}_{t(i+l)d} \) and the standardized predictive residual \( \hat{\eta}_{t(i+l)d} \) are then defined as:

\[
\hat{\varepsilon}_{t(i+l)d} = z_{t(i+l)d} - \hat{A}X_{t(i+l)d},
\] (11)

\[
\hat{\eta}_{t(i+l)d} = \hat{\varepsilon}_{t(i+l)d} / \left[ 1 + (X_{t(i+l)d})' V_l (X_{t(i+l)d}) \right]^{0.5},
\] (12)

where \( V_l = \sum_{i=1}^l (X_{t(i)d})' (X_{t(i)d}) \). Consider the standardized predictive residuals in the regression:

\[
\hat{\eta}_{t(i+l)d} = \Psi X_{t(i+l)d} + \nu_{t(i+l)d},
\] (13)

where \( l = l_0, \ldots, n - 1 \) and \( l_0 \) is the starting point of the recursive least squares estimation. The appropriate statistic proposed by Tsay (1998) for testing the null hypothesis that the model is linear can be formulated as:

\[
C(d) = (n - l_{10} - (2m + 1)) [\ln |S_0| - \ln |S_1|],
\] (14)

where:

\[
S_0 = \frac{1}{n - l_{10}} \sum_{i=1}^{n-l_{10}} (\hat{\eta}_{t(i+l)d})' \hat{\eta}_{t(i+l)d}, \quad S_1 = \frac{1}{n - l_{10}} \sum_{i=1}^{n-l_{10}} (\hat{\varepsilon}_{t(i+l)d})' (\hat{\varepsilon}_{t(i+l)d}),
\] (15)

and \( \hat{\nu}_{t(i+l)d} \) are the least squares residuals of regression (13). This statistic has an asymptotic chi-square distribution with \( 2(2m + 1) \) degrees of freedom under the null hypothesis.

We use both tests instead of choosing one for several reasons. First, Tsay’s testing statistic has a standard asymptotic chi-square distribution in contrast to the test of Hansen and Seo, where the distribution of the \( \text{SupLM} \) statistic needs to be approximated using a bootstrap
technique. However, the latter test is robust against heteroscedasticity of disturbances, which is important when analyzing financial data. Second, Tsay's statistic is a test of a linear VAR model against a more general nonlinear alternative model, e.g. a Markov switching VAR model, a smooth transition VAR model, or our threshold model. Hansen and Seo provide the statistic that is designed to test directly for the existence of the threshold effect in the VAR model and has higher power in comparison to the test of Tsay (Hansen and Seo, 2002).

3. Data and Empirical Results

In our empirical investigation, we analyze the stability of financial spillovers in tranquil and turmoil regimes by modeling the dependency between the US market and eight emerging capital markets in South-East Asia before and during the Asian crisis of 1997. The turbulent period in Asia started with devaluation and a stock market plunge in Thailand in July 1997. It was followed by Malaysian and Indonesian market declines in July and August, respectively, and the Hong Kong crash in mid-October. Subsequently, the Korean market experienced a downslide starting in mid-December and ending in January 1998. Between mid-August 1997 and mid-January 1998, the majority of Asian stock market indices declined by more than 30 percent, with Hong Kong losing almost 48 percent. The crisis spread to other markets in the region and worldwide.

The sample consists of daily observations of stock index returns from the US market (S&P 500), Hong Kong (HSI), Indonesia (JCI), Malaysia (KLSI), Philippines (PSE), Singapore (STI), South Korea (KOSPI), Thailand (SET), and Taiwan (TWII). These Asian markets suffered most from the financial crisis (Corsetti, Pesenti, and Roubini, 1999). In order to avoid the possible influence of other international crises (Mexico in 1994 and Russia in 1998), our sample covers the period from June 1, 1995 to May 31, 1998.1

1 Data for the Philippines is only available from November 15, 1996.
We start our investigation by testing for the presence of cointegration (long-run relationship) between stock indices on different markets. If the US stock index were cointegrated with an index from an Asian market, we would have to include an appropriate error correction term in model (2). However, using tests of Engle and Granger (1987) and Johansen (1991, 1995), we find no reliable evidence of bi-variate cointegration between the US index and any investigated Asian stock index. Therefore, we use stationary VAR and TVAR models in our study.\(^2\)

Employing the data for national stock indices, we model dependencies between the markets and allow for shifts in spillovers during turmoil periods. We test for the existence of those shifts using the tests described in Section 2. To capture the sluggish adjustment of stock returns to news as well as the day-of-the-week effect, we employ five lags in model (2), i.e. \(m=5\). Next, we analyze the causality patterns between the markets by conducting Granger-causality tests.

An important part of the analysis is the choice of the threshold variable, which depends on the definition of the calm and crisis regimes. Crisis regimes are usually characterized by low returns and high volatility. This definition of the crisis regime is a controversial issue in the literature, with some authors arguing that asset returns are superior crisis indicators, e.g. Chen, Chian, and So (2003), Mishkin and White (2003), and others highlighting the importance of changes in volatility between regimes, e.g. Ang and Bekaert (2002), Fong (2003), Rigobon (2003), and Sola, Spagnolo, and Spagnolo (2002). Therefore, we estimate various threshold vector autoregressive models which employ lagged stock index returns or lagged squared returns from the US and respective Asian market as crisis indicator variables. Then, we choose those threshold variables that maximize the respective likelihood functions.\(^3\)

\(^2\) Toda and Phillips (1994) describe tests of causality in the presence of cointegration.

\(^3\) Since the number of observations and parameters does not change for different threshold variables, the maximum likelihood criterion is equivalent to Akaike and Schwarz criteria.
The results presented in Table 1 show that the stock index returns or variance from the US market are superior crisis indicators in seven out of eight models. These optimal threshold variables are used in the further analysis. The fact that the US variables best indicate regime change during the turbulent period in Asia can be explained by the fact that the US market, characterized by higher capitalization and trading volume, is more informationally efficient than its Asian counterparts. Consequently, it incorporates information concerning the latter quicker than it is being done on each of the Asian markets. Hence, the US variables might predict the switch to a turbulent regime for the US-Asian relationship, even if this is the Asian market that becomes the source of spillovers in a crisis regime. For instance, when crisis hits an Asian market, then returns on this market drop significantly but investors still absorb information from the US market and the regime does not yet change. However, when investors in the US notice the crisis, they react with extreme (low) returns and then start to follow information (and returns) from said Asian market. Thus, extreme returns on the US market become direct indicators of regime change.

Moreover, the change in spillover patterns might be induced by a change in trading strategy by US-based portfolio investors, implementing a new strategy first on the home (US) market and subsequently abroad. Also, it is possible that Asian investors react to a change in investment strategy by US investors with a similar change on their home markets, as they interpret the behavior of US investors as a reaction to unobservable shocks influencing both US and Asian markets.

Furthermore, we perform the tests of Hansen and Seo (2002) and Tsay (1998) to investigate possible breaks in financial spillovers between markets. The results are presented in Table 2. The results of Tsay’s tests are generally in favor of the regime-switching hypothesis.
This can be seen in Table 2 where seven out of eight Tsay statistics reject the linear VAR model at the 5% level of significance, in favor of the regime-switching hypothesis. However, as noted in Section 2, this test approach can suffer from several weaknesses. Therefore, to obtain additional and more reliable evidence, we further conduct a test by Hansen and Seo which is robust to heteroscedastic errors and has higher power. As in the previous case, Hansen and Seo’s test clearly indicates that the null hypothesis of inter-temporal stability in cross-border causation patterns between returns can be rejected at high significance levels, as indicated by high values of the test statistics. This shows that all spillover models are non-linear.

Table 2 about here

This finding suggests that spillover patterns change between crisis and tranquil regimes in the majority of linkages investigated. Only the outcome for Taiwan (TWII) is mixed, but at least one test rejects the null hypothesis of stability in the spillover patterns. The estimated threshold parameters indicate that markets enter the crisis regime after the returns on the selected (generally US) market fall below some negative threshold value (e.g. -0.8036 for the pair US-Hong Kong (HSI)), or the return volatility, estimated by squared returns, increases beyond some high threshold value, e.g. 1.4971 for the pair US-Thailand (SET). These high absolute values of threshold variables suggest that crisis regimes are infrequent in the sample, since it is hard for the respective market to surpass the threshold. Indeed, only exceptionally low returns or highly volatile returns on one of the markets lead into a crisis regime. This fact is mirrored by both the high percentage of observations in the calm regime, as well as the short duration of crisis regimes in comparison to turbulent ones. More specifically, in all but one (two) models, over 69 (85) percent of observations are in a calm regime (Table 2).
Furthermore, the estimated average length of a crisis regime is usually shorter than two days while tranquil regimes last on average more than seven days for all but two models. A distinctive exception is the relationship between Philippines (PSE) and the US, where a more volatile regime dominates in the sample. Generally, the results on the frequency of regime changes and the duration of regimes indicate that regime changes are not of the structural break type. Markets are characterized by multiple and random swings into crisis and rapid jumps back to a calm regime rather than by a single regime change and long regime duration.

In order to investigate the changes in causality patterns, we conduct tests of Granger-causality for the relationship between the US and Asian markets for each market and regime separately. From the results displayed in Table 2, it is reasonable to assume that two regimes are present and that threshold parameters are estimated precisely in each analyzed relationship. Therefore, we can employ the Wald statistics which are robust toward a general form of heteroscedasticity to test whether lagged returns from one market provide important information for modeling current returns on the other market. As a robustness check, we also employ the standard F and the likelihood ratio (LR) tests in models where autoregressive conditional heteroscedasticity (ARCH) is explicitly accounted for. In order to control for ARCH effects in residuals, we estimate GARCH, EGARCH, and TARCH models of Bollerslev (1986), Nelson (1991), and Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994), respectively, as suggested by Cheung and Fujii (2001). We select the optimal models using the Schwarz information criterion. Results from Granger-causality analysis are presented in Table 3.

Table 3 about here

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4 The adjustment for the ARCH effects is justified by the presence of conditional heteroscedasticity in residuals in model (2) – results not reported here. As Cheung and Fujii (2001) show, F and LR tests lack power if the ARCH effects are not explicitly accounted for. We thank the referee for suggesting this methodology.
In accordance with the hypothesis presented in the introduction, spillovers between capital markets are found to be unstable and to change across regimes, as reported in Panel A of Table 3. The US market leads six Asian markets in a calm regime (Hong Kong, Indonesia, Malaysia, the Philippines, Singapore, and Thailand), as indicated by the significant test statistics. Moreover, we observe additional causation effects to South Korea and Taiwan in a crisis regime. However, the difference between causality from the US market in crisis and calm regimes is modest. The results obtained by Chen, Chian, and So (2003), Climent and Meneu (2003), and Malliaris and Urrutia (1992) also suggest stronger spillovers from the US market to other markets in turmoil periods. Last, the shocks originating on the US market are found to spill over to the Asian markets in all but one (KOSPI) case, regardless of the regime.

The weak causality for the pair US-Korea deserves additional attention. We believe that this effect is due to the regulations of Korean market, specifically to restrictions on capital flows, asset ownership, as well as governmental interference with the security pricing process, which weakened Korean linkages with the world market (also found e.g. by Baig and Goldfajn, 1999, Climent and Meneu, 2003, and Kaminsky and Reinhart, 2000). The special position of industrial agglomerates, cheabols, probably also contributed to this outcome.  

We now proceed with the novel finding emerging from the results presented in Table 3, Panel A. As expected, past returns on the Asian markets are of little importance for the current development of US index returns in a tranquil regime. Only limited causality from Asian markets to the US market is found in the sample. However, in a crisis regime the causation effects from Asian markets to the US market are stronger and statistically significant in five out of eight cases. This result suggests that information from less developed markets is transmitted to the US market, albeit mostly in turbulent periods. These periods are relatively short, as

5 For the chronology of economic and political events in Korea and other countries, see an excellent database by Geert Bekaert and Campbell R. Harvey: http://www-1.gsb.columbia.edu/faculty/gbekaert/other.html
presented in Table 2, which in turn explains the lack of causation from emerging markets to the US market detected in some earlier studies (e.g., Chau-Lau and Ivaschenko, 2003, Hu, Kholdy, and Sohrabian, 2000, Masih and Masih, 2001).

To highlight the importance of our finding of regime-dependent causality between markets, we also estimate linear VAR models and present the results in Panel B of Table 3. As can be seen, the VAR methodology is unable to differentiate between regimes. As a result, the hypothesis of causality running from Asia to the US is rejected in all but one case. This is in contrast to the results from the TVAR analysis as presented in Panel A, where significant spillovers from Asian markets to the US market are detected in a crisis regime. This outcome can be explained by the short duration of the turbulent regime, and constitutes a justification of the employment of the threshold VAR models that allow for regime changes.

In general, our results from the threshold models suggest that there is evidence of significant spillovers from Asian markets to the US market during the Asian crisis in 1997. In contrast to the results from linear VAR models, the two-regime threshold VAR models are able to detect significant spillovers from Asian markets at least in one regime in seven out of eight cases. Moreover, both regimes are significant in all cases, which suggests that linear models describing dependencies between markets during the Asian crisis may be misspecified.

If a turmoil regime is primarily characterized by the “contagious” financial crisis in South-East Asia, then our results provide important insight into the direction and speed of spillovers from the crisis region to the US market. This finding well fits two definitions of financial contagion widely used in the literature. First, financial spillovers from one market to another can be defined as contagion, as in Claessens, Dornbusch, and Park (2001) and Pritsker (2001), among others. We find evidence in favor of such spillovers from the US to Asia and in the opposite direction during crisis regimes. Second, contagion can be understood as a break in the interdependency structure between countries, a definition introduced by King and Wadhwani (1990) and favored by e.g. Edwards (2000) and Rigobon (2003), among others. In
the paper, we find a significant difference in spillover patterns between regimes. Hence, our results support both definitions of financial contagion as presented above. Obviously, some information transmission mechanisms are at work mainly during turbulent periods, e.g. actions of bank lenders (Allen and Gale, 2000; Kaminsky and Reinhart, 2000) or hedge and mutual funds (Schinasi and Smith, 2000, Kaminsky, Lyons, and Schmukler, 2001) responding to macroeconomic, liquidity, or wealth shocks, as discussed in the introduction. This induces changes in spillover patterns between markets.

The economic rationale for spillovers between US and Asian markets might be discussed in the framework of Pritsker’s (2001) contagion channels. First, in the presence of real economic linkages, be it via trade or foreign direct investment, values of companies in one country will react to changes in comparative advantages of companies in the other country induced by changes in interest rates, currency value, taxes and other contributions, property rights protection, etc. Second, involvement of US banks in Asia might establish a channel for spillovers. For instance, in case of shocks deteriorating the profitability of their Asian customers, US banks will at the beginning suffer directly from unpaid and delayed loans and then will try to maintain their liquidity by tightening their credit policy (e.g. reducing credit provision) at home. Third, portfolio rebalancing by US investors as a response to macroeconomic, liquidity, or wealth shocks, will exert impact on stock prices in many countries, an effect magnified by asymmetric information by feedback trading, herding, and use of certain risk techniques by portfolio investors worldwide. In sum, there are several channels through which Asian markets can influence the US one, and vice versa, especially following a shock originating in one country and spilling abroad in turbulent periods.

4. Summary and Conclusions

Earlier studies in international finance assumed the stability of cross-border causation patterns or focused on breaks in instantaneous interdependencies between financial markets
without analyzing the direction of information flows during turmoil periods. In this paper, we extend the existing literature by employing a novel methodology to answer the questions of causation stability as well as the nature and directions of spillovers between US and Asian stock markets.

The results from our analysis suggest that causal relationships between the US and eight Asian markets are not stable and change significantly across regimes. Returns and squared returns from the US market are usually better crisis indicator variables, and dominate as optimal threshold variables. Capital markets seldom enter a crisis regime and leave it after only one or two days. Spillovers from the US market to Asia exist in both regimes and become more intensive in turmoil. On the other hand, causation from Asian capital markets is decent in a calm regime but strong in a crisis regime. These results are in accordance with the literature finding some transmission channels to be more active during crisis than tranquil regimes, a result of changing behavior of bank lenders and portfolio investors. These breaks in spillover patterns may be interpreted as evidence of financial contagion.

From an economic perspective, we learned that the US market was influenced by Asian markets performance when these emerging markets were hit by financial crisis. All other times, information from the emerging markets played a minor role in the behavior of US stock index returns. On the other hand, the US market is an important determinant of Asian stock returns in both regimes.

International investors can use the knowledge regarding the driving forces behind changes in causality patterns for more accurate return forecasting rather than rebalancing their portfolios. This is due to the short duration of the crisis regimes found by applying the methodology of Hansen and Seo (2002). For instance, the policy of reallocating capital during a two-day turmoil period would imply high portfolio turnover and, hence, extraordinary costs of asset management. Similarly, from the policymakers’ perspective, the regime changes were too frequent and crisis periods too short to adjust policy each time they emerge. Short-term
changes in macroeconomic policy would be costly, ineffective, and increase market uncertainty. Nevertheless, the results presented in this paper show that modeling spillovers in a double regime framework provides an approach for better understanding and forecasting information and capital flows between capital markets during crisis periods.
References


Calvo, G. A., 1999, Contagion in emerging markets: When Wall Street is a carrier, manuscript, University of Maryland.


Davies, R. B., 1987, Hypothesis testing when a nuisance parameter is present only under the alternative, Biometrika 74, 33-43.


Hansen, B. E., 1996, Inference when a nuisance parameter is not identified under the null hypothesis, Econometrica 64, 413-430.


Table 1: Log-likelihood values in the threshold models

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<thead>
<tr>
<th>Threshold variable $w_{t-k}$</th>
<th>HSI</th>
<th>KOSPI</th>
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<th>STI</th>
<th>SET</th>
<th>JCI</th>
<th>KLCl</th>
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<tbody>
<tr>
<td>$x_{t,1}$</td>
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<td>-1099.35</td>
<td>-904.77*</td>
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<td>-930.55</td>
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<tr>
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<td>-1052.36</td>
<td>-546.20</td>
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Note: The highest log-likelihood values are marked with *. $x_{t-k}$ denotes stock index returns on the US market at time $t-k$ and $y_{t-k}$ denotes stock index returns on the respective Asian market at time $t-k$. 
Table 2: Tests for stability of financial spillovers

<table>
<thead>
<tr>
<th></th>
<th>HSI</th>
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<th>SET</th>
<th>JCI</th>
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</thead>
<tbody>
<tr>
<td>Statistic of Tsay</td>
<td>40.2116* (0.010)</td>
<td>61.8050** (0.000)</td>
<td>16.1517 (0.808)</td>
<td>60.9487** (0.000)</td>
<td>36.4349* (0.027)</td>
<td>44.1894** (0.003)</td>
<td>35.7576* (0.032)</td>
<td>25.2134 (0.287)</td>
</tr>
<tr>
<td>Statistic of Hansen and Seo</td>
<td>37.6420** (0.000)</td>
<td>29.7121** (0.000)</td>
<td>27.1726** (0.002)</td>
<td>31.4391** (0.002)</td>
<td>33.4605** (0.001)</td>
<td>36.3683** (0.001)</td>
<td>30.3096** (0.000)</td>
<td></td>
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<tr>
<td>Estimated threshold parameter</td>
<td>-0.8036</td>
<td>1.4168</td>
<td>-0.8036</td>
<td>-0.806</td>
<td>1.4971</td>
<td>-1.1901</td>
<td>-0.2582</td>
<td>1.2033</td>
</tr>
<tr>
<td>Threshold variable</td>
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<td>$x_{t-5}^2$</td>
<td>$x_{t-1}^2$</td>
<td>$x_{t-4}^2$</td>
<td>$y_{t-4}$</td>
<td>$x_{t-2}$</td>
<td>$x_{t-5}$</td>
<td></td>
</tr>
<tr>
<td>Percentage of observations in the calm regime</td>
<td>89.17</td>
<td>86.02</td>
<td>89.14</td>
<td>89.18</td>
<td>86.02</td>
<td>85.14</td>
<td>69.82</td>
<td>11.51</td>
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<tr>
<td>Average duration of the crisis regime [in days]</td>
<td>1.25</td>
<td>1.23</td>
<td>1.22</td>
<td>1.21</td>
<td>1.27</td>
<td>1.48</td>
<td>1.56</td>
<td>8.97</td>
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<tr>
<td>Average duration of the calm regime [in days]</td>
<td>10.17</td>
<td>7.52</td>
<td>9.89</td>
<td>9.85</td>
<td>7.81</td>
<td>8.38</td>
<td>3.61</td>
<td>1.16</td>
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</table>

Note: *, ** denote significance at the 5% and 1% levels, respectively. P-values are presented in parentheses. For both tests, the $H_0$ hypothesis is that there is no difference in the causality patterns across regimes, against $H_1$ of structural break in causality patterns due to regime change. $x_{t-k}$ denotes stock index returns on the US market at time $t-k$ and $y_{t-k}$ denotes stock index returns on the respective Asian market at time $t-k$. 
Table 3: Tests for Granger-causality between markets

<table>
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<th>Null hypothesis</th>
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<td>Panel A: Results from the TVAR models</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P 500 does not cause y in calm regime</td>
<td>44.052***</td>
<td>5.974</td>
<td>5.501</td>
<td>19.138***</td>
<td>12.534**</td>
<td>18.131***</td>
<td>12.089**</td>
<td>23.851***</td>
</tr>
<tr>
<td>y does not cause S&amp;P 500 in calm regime</td>
<td>11.538***</td>
<td>5.096***</td>
<td>7.119***</td>
<td>4.636***</td>
<td>2.803*</td>
<td>0.727</td>
<td>0.000</td>
<td>0.237</td>
</tr>
<tr>
<td>y does not cause S&amp;P 500 in any regime</td>
<td>46.029***</td>
<td>32.217***</td>
<td>27.948***</td>
<td>17.419***</td>
<td>8.593</td>
<td>4.034</td>
<td>2.197</td>
<td>3.028</td>
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<tr>
<td>Panel B: Results from the VAR models</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P 500 does not cause y in any regime</td>
<td>58.074***</td>
<td>6.885</td>
<td>22.482***</td>
<td>29.607***</td>
<td>12.111**</td>
<td>29.678***</td>
<td>11.941**</td>
<td>22.251***</td>
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<tr>
<td>y does not cause S&amp;P 500 in any regime</td>
<td>33.161***</td>
<td>0.877</td>
<td>6.134***</td>
<td>12.189***</td>
<td>2.771*</td>
<td>8.204***</td>
<td>3.467***</td>
<td>4.113***</td>
</tr>
<tr>
<td>y does not cause S&amp;P 500 in any regime</td>
<td>166.269***</td>
<td>5.375</td>
<td>20.305***</td>
<td>58.698***</td>
<td>17.538***</td>
<td>49.991***</td>
<td>33.333***</td>
<td>29.664***</td>
</tr>
</tbody>
</table>

Note: W is the heteroscedasticity-adjusted Wald statistic, F and LR are the ARCH-adjusted F and likelihood ratio statistics, respectively. P-values are presented in parentheses. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively. It is possible that some values of the F statistic in ARCH models are negative – in this case we enter 0.000 in the table.