Empirical Evidence on Financial Spillovers and Contagion to International Stock Markets

by
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INTRODUCTION

As stock markets around the world become increasingly open to foreign investors, overseas capital, and external information, new forces start driving asset prices and asset price volatility on local markets. These forces are often identified as financial inter-market linkages or financial spillovers, i.e. information and capital flows between stock markets. Spillovers are observed when changes in asset prices or in return volatility on one stock market cause movements of asset prices or their volatility on a different market. Inter-market linkages cover various types of relationships between stock prices on separate markets, which include causation effects, feedback dependencies, and reliance on common or global factors.

For both economists and investors it is particularly important to learn and measure quantitatively the relationships between stock markets in order to assess integration of local markets with the world market, discover new investment opportunities, analyze the risk of investing on local markets, and evaluate the scope of international portfolio diversification. Effectiveness of capital markets can also be examined by measuring how quickly markets assimilate important news from abroad.

Excessive information and capital flows between markets are observed during financial crises and other turbulent events, e.g. explosions of stock market bubbles, terrorist attacks, bankruptcies of large companies, parliamentary elections. Depressing news from important international markets often causes a rapid fall of stock prices on the local market. In this way financial crises may expand from one market to other countries or regions. Extreme events such as crises are occasionally blamed for breaking or boosting ordinary linkages between stock markets. Intensive relationships between a crisis market and calm markets can lead to the spread of the crisis, which is often called 'financial contagion.

Alternatively, contagion can be interpreted as an increase in the probability of a crisis in one country, conditional on a crisis occurring in another country (e.g. Eichengreen, Rose, and Wyplosz, 1996). Sola, Spagnolo, and Spagnolo (2002) suggest an extreme version of this definition, where the probability of having a crisis at home equals one if the crisis hits another market. Another branch of studies explores changes in the correlation of international stock returns (King and Wadhawani, 1990, Forbes and Rigobon, 2002) or defines contagion as excessive spillovers from one market to another during turbulent periods beyond structural linkages between these markets (Corsetti, Pericoli, and Sbracia, 2005). Yet one more group of investigations focuses on coincidence of extreme return shocks across countries as evidence of contagion (e.g. Bae, Karolyi, and Stulz, 2003).

In this thesis different definitions of financial contagion are explored. These definitions are applied to test for evidence of contagion on a number of stock markets and during several turbulent periods. First, we investigate the question whether emerging stock markets are more or less vulnerable to large financial shocks than developed capital markets. Second, this study analyzes how significant financial turmoil can change the direction and strength of spillovers between a mature calm market and emerging crisis markets. Additionally, we explore the direction of spillovers and contagion effects between two crisis markets during the same turbulent period. Third, dynamic dependencies between mature stock markets are explored to learn how the strength of spillovers changes in tranquil and turbulent times and how crisis markets are influenced by the leading stock market. Economists, investors and even policymakers are concerned about directions of spillover and breaks in inter-market linkages that could disturb investments in calm countries and increase the risk of crises. Although the above issues related to financial contagion are important, they are only recently introduced in the academic literature. Therefore, approaches dealing with these issues need to be novel and are often unique.

In order to measure quantitatively the evidence of financial contagion and spillovers during crises, we apply and extend some techniques recently introduced in the literature

(Corsetti, Pericoli, and Sbracia, 2005, Forbes and Rigobon, 2002, Sola, Spagnolo, and Spagnolo, 2002) and propose new methods based on the Markov switching framework, threshold vectors autoregressive models, and Granger-causality methodology (Granger, 1980, Hansen and Seo, 2002, Phillips, 1991).

The remainder of this thesis comprises four interrelated chapters and a final section with concluding remarks. The following chapters focus on several aspects of measuring dependencies between stock markets in calm and turbulent times. The first part investigates contagion to European stock markets associated with seven big financial shocks between 1997 and 2002. Methods using heteroscedasticity-adjusted correlation coefficients are applied to discriminate between contagion, interdependence, and breaks in stock markets relationships. The analysis focuses on a comparison between developed Western European markets and emerging stock markets in Central and Eastern Europe. Only modest evidence of significant instabilities in cross-market linkages after the crises is found. The Central and Eastern European stock markets are not more vulnerable to contagion than Western European markets.

In the second chapter, we examine breaks in financial spillovers between the U.S. and eight Southeast Asian capital markets before and during the 1997 Asian crisis. Threshold vector autoregressive models are constructed and novel techniques are utilized to test whether causality patterns between markets are characterized by one or two regimes. Linkages between the U.S. and Asian markets are shown to follow the threshold model with two regimes: turmoil and tranquility, pointing to differences in cross-border return spillovers in stable and crisis periods. The causality analysis reveals that spillovers between the U.S. and Asian markets become stronger in the turmoil regime. We discuss possible channels of increased spillovers from the crisis markets to the U.S. market.

In the third chapter, the concept of causality in the Markov switching framework is introduced into the analysis of financial inter-market dependencies. This study extends the methodology of testing for financial spillovers between capital markets by explicitly defining contagion, spillovers, and independence, and providing statistics to test for the existence of causality. We apply the methodology to stock index returns on the Japanese (Nikkei 225) and the Hong Kong (HSI) markets during the Asian crisis and no evidence of contagion between the markets is found, rather strong evidence of feedback spillovers between them.

The fourth chapter analyzes asymmetric spillovers between mature stock markets during calm and turbulent times. Financial spillovers and financial contagion are defined in accordance with chapter 3 and statistical models corresponding to these definitions are constructed. Applying the new testing methodology based on transition matrices, this study finds that spillovers from the U.S. stock market to the U.K., Japanese, and German markets are more frequent when the latter markets are in a crisis regime. However, the hypothesis of strong financial contagion from the U.S. market to the other markets is rejected.

The chapters of this thesis are interrelated not only due to the common subject of all analyses, i.e. contagion and financial spillovers, but also due to the fact that novel methods to test for contagious spillovers are presented in each chapter. Chapters 1 and 2 focus on changes in inter-market linkages during crises, while chapters 3 and 4 direct attention to probability measures of contagion. Chapters 2, 3, 4 consider closely lagged spillovers in contrast to chapter 1, which examines contemporaneous financial linkages. Chapter 3 introduces causality to the presented type of Markov switching models, and chapter 4 extends this methodology by providing tests for asymmetric causality. Finally, all analyses consider different relationships between stock markets, e.g. linkages between mature and developing markets, spillovers to markets in another region, contagion effects during various crises.

1. FINANCIAL CONTAGION VULNERABILITY AND RESISTANCE: A COMPARISON OF EUROPEAN STOCK MARKETS

There has been great interest in empirical and analytical studies on cross-country and cross-market transmission of financial crises over the last decade. Most of the empirical work has been undertaken to measure the extent of financial spillovers to mature and emerging markets and to find channels of transmission of shocks to foreign countries. Earlier studies have often focused on contagion to emerging stock markets in South America and Asia due to the crises in the U.S. in 1987, Mexico in 1994, East Asia in 1997, and Russia in 1998.[1]

Recently, the discussion regarding the enlargement of the European Union (EU) shifted attention to transition countries in Central and Eastern Europe (CEE). However, until now very few empirical studies have concentrated on contagion to CEE markets. Darvas and Szapáry (2000) provide evidence that spillovers from the Russian crisis to CEE were due to shifts in market sentiments and Krzak (1998) argues that the CEE countries have been hit by the Russian crash most heavily through trade rather than through any financial linkages. Gelos and Sahay (2001) outline that the behavior of the emerging CEE markets after the Russian crisis was similar to that of their counterparts in Asia and Latin America during the Asian crisis. Furthermore, they observe increasing correlations across CEE stock markets during the 1994 – 1999 period. Fries, Raiser, and Stern (1999) find that CEE stock markets were generally not as vulnerable to financial contagion during the Asian and Russian crashes as the less developed stock markets from the former Soviet Union.

Contagion has been commonly defined as a transmission of shocks from a crisis-country to other countries, which can be observed through co-movements of different

[1] Surveys on this issue can be found in Claessens and Forbes (2001), Goldstein, Kaminsky, and Reinhart (1999), Calvo, Goldstein, and Hochreiter (1996), and IMF (1999).

financial indices on multiple markets or rising probabilities of default. In this chapter, we apply the definition put forward by Forbes and Rigobon (2002) and distinguish between common shocks and contagion.[2] Accordingly, contagion requires a change in the structure of stock market linkages. The increase in cross-market linkages during the crisis must be significant to be called contagion, not just interdependence. Contagion is then an excessive transmission of shocks from one crisis stock market to others, beyond any idiosyncratic disturbances and fundamental links among them. Fundamental financial links constitute interdependence.

Many empirical methods measuring contagion are based on cross-market correlation coefficient estimates.[3] Forbes and Rigobon (2002) demonstrate that the rise in correlation does not necessarily imply contagion as defined above. The authors propose a test to distinguish between contagion and co-movement of stock index returns driven by bilateral linkages. Their most striking empirical result from using this procedure is that in the majority of countries one cannot observe contagion during the 1987 U.S. crash, the 1994 Mexican collapse, and the 1997 Asian crisis. Gelos and Sahay (2001) also apply a simplified version of this methodology and find no contagion from the Czech Republic, Asia, and Russia to CEE stock markets. The method is attractive because it does not assume any specific structure of financial spillovers and allows for a straightforward interpretation of empirical results on cross-market interdependence. Furthermore, some recent testing methodologies extend or are

[2] See also Masson (1998), Kaminsky and Reinhart (2000), Karolyi (2003), and Moser (2003). Discussions on different definitions of contagion may be found in Edwards (2000), Forbes and Rigobon (2001), and Pericoli and Sbracia (2003).

[3] See, for example, King and Wadhwani (1990), Lee and Kim (1993), Longin and Solnik (2001). An overview of most methods can be found in Forbes and Rigobon (2001, 2002), Rigobon (2001), Claessens and Forbes (2001), and Pericoli and Sbracia (2003).

based on the Forbes-Rigobon approach (e.g., Corsetti, Pericoli, and Sbracia (2005), Bekaert, Harvey, and Ng (2003), Rigobon (2003))[4].

Although some new definitions and approaches to test contagion have appeared in the literature (for example, Chan-Lau, Mathieson, and Yao (2002) and Bae, Karolyi, and Stulz (2003)), we concentrate on a correlation based analysis. As noted by Billio and Pellizon (2003) and Forbes and Rigobon (2002) this concept suits better than other approaches the issues of international diversification, the role of international institutions and bail-out funds, as well as propagation mechanisms. We utilize the methodologies introduced by Forbes and Rigobon (2002) and Corsetti, Pericoli, and Sbracia (2005) and extend their empirical investigation in three directions. First, a different timeframe to explore new crises is used. To our best knowledge, no investigation has focused on spillover effects of new financial crashes to transition countries in CEE. Studying these crises provides new evidence on financial spillovers to emerging stock markets.

Second, it is of considerable interest to investors and financial market regulators to examine how vulnerable the European stock markets are to different financial shocks. Therefore, in contrast to most previous studies related to contagion, we provide additional evidence on breaks in linkages between crisis and non-crisis capital markets (Billio and Pellizon (2003)). Third, our investigation focuses on a comparison between emerging CEE and mature Western European stock markets. The process of integration between the fast developing and well-developed markets in Europe is an example of successful financial liberalization in terms of macroeconomic and institutional fundamentals. Thus, the emerging stock markets appear as an interesting option for diversification of international capital

[4] Ronn (1998), Boyer, Gibson, and Loretan (1999), and Loretan and English (2000) investigated adjusted correlation measures analogous to the one proposed by Forbes and Rigobon.

portfolios (Chen, Firth, and Rui (2002), Bekaert and Harvey (2002, 2003)). Our empirical results offer new evidence of whether emerging stock markets in Europe are more vulnerable to financial crises than well-developed European markets and which recent crises were most contagious.

In the next section we describe the methods applied to investigate the existence of contagion following Forbes and Rigobon (2002) and Corsetti, Pericoli, and Sbracia (2005). In section 1.2 we explain the extension of the model proposed by Corsetti, Pericoli, and Sbracia. In section 1.3 we present the data and a method to identify the crises. Section 1.4 contains our empirical results and section 1.5 summarizes this chapter.

1.1 Methodology

Forbes and Rigobon (2002) and Corsetti, Pericoli, and Sbracia (2005) propose alternative models of inter-market dependencies that allow for constructing measures of correlation between stock returns on the crisis and calm stock market during crisis periods. These correlation measures, adjusted for volatile periods, are functions depending on the specification of the proposed models. Forbes and Rigobon consider a model, where stock returns on the crisis market, y_t, are exogenous and influence returns on the calm market, x_t:

$$\begin{aligned} x_t &= a_1 + c_1 y_t + \varepsilon_t^x \\ y_t &= \varepsilon_t^y \end{aligned}, \tag{1.1}$$

where ε_t^x and ε_t^y are idiosyncratic shocks to the respective stock markets. Forbes and Rigobon assume that volatility of stock returns on the crisis market increases during turbulent periods, but the parameters in the model and the volatility of idiosyncratic shocks in the non-crisis market, ε_t^x, remain constant.

High volatility of stock returns on the crisis market, which is transferred to the non-crisis market through stable fundamental linkages, induces higher correlation between the stock markets even when contagion does not occur. Correlation is conditional on the volatility of stock returns in the crisis market and, therefore, an increase in correlation is not necessarily caused by contagion, but may be due to higher volatility of stock returns as well. Analytical and empirical results confirm this hypothesis (King and Wadhwani (1990), Corsetti, Pericoli, and Sbracia (2005), Longin and Solnik (2001), Forbes and Rigobon (2002)).

Forbes and Rigobon (2002) show that under the assumption of no omitted disturbances to a non-crisis country or any feedback shocks from the non-crisis market to the turmoil country the adjusted correlation coefficient, which does not depend on the volatility of returns in the crisis market, satisfies:

$$\rho^{FR} = \frac{\rho^{crisis}}{\sqrt{1+\delta[1-(\rho^{crisis})^2]}}. \tag{1.2}$$

ρ^{crisis} is the correlation coefficient between the crisis and the non-crisis market observed during the crisis period. The parameter δ represents the relationship between the variances of stock returns from the crisis country during the turmoil period, $Var^{turmoil}(y_t)$, and during the calm period, $Var^{stable}(y_t)$:

$$\delta = \frac{Var^{turmoil}(y_t)}{Var^{stable}(y_t)} - 1. \tag{1.3}$$

Forbes and Rigobon compare the correlation coefficient in the stable period, ρ^{stable}, with the adjusted correlation measure in the crisis period, ρ^{FR}, to test for a change in linkages between stock markets during crises. A significant positive (negative) difference between both correlation values is interpretable as evidence of contagion (a break in inter-market linkages).

In a more general model presented by Corsetti, Pericoli, and Sbracia (2005) stock returns of two markets consist of a factor common for both markets (e.g., a global factor), f_t, and idiosyncratic factors independent of any non-domestic influences, ε_t^x and ε_t^y:

$$\begin{aligned} x_t &= a_1 + c_1 f_t + \varepsilon_t^x \\ y_t &= a_2 + c_2 f_t + \varepsilon_t^y \end{aligned} \tag{1.4}$$

In this model volatilities of idiosyncratic and common shocks on the crisis market may increase during turbulent periods, but only the common factor influences stock returns on the non-crisis market.

As argued by Corsetti, Pericoli, and Sbracia, empirical results show that the volatility of idiosyncratic shocks ε_t^y on the crisis market, independent from the common factor, is different from zero. If model (1.4) is correct, then y_t is correlated with the residual factor in the first equation of model (1.1) and variance of this residual factor increases always when the volatility of ε_t^y increases. The above facts violate the assumptions of the Forbes-Rigobon approach. Thus, the adjusted correlation measure proposed by Forbes and Rigobon will usually be biased.

Instead, Corsetti, Pericoli, and Sbracia propose a formula for the correlation between markets during a crisis period that would be generated by the model with stable inter-market linkages:

$$\rho_{crisis}^{CPS} = \rho^{stable}\left[\left(\frac{1+\lambda_y^{stable}}{1+\lambda_y^{crisis}}\right)^2 \frac{1+\delta}{1+\left(\rho^{stable}\right)^2\left[(1+\delta)\dfrac{1+\lambda_y^{stable}}{1+\lambda_y^{crisis}}-1\right]\left(1+\lambda_y^{stable}\right)}\right]^{\frac{1}{2}}, \tag{1.5}$$

where:

$$\lambda_y^{stable} = \frac{Var^{stable}(\varepsilon_t^y)}{(c_2)^2 Var^{stable}(f_t)}, \tag{1.6}$$

$$\lambda_y^{crisis} = \frac{Var^{crisis}(\varepsilon_t^y)}{(c_2)^2 Var^{crisis}(f_t)}. \tag{1.7}$$

$Var^{stable}(\cdot)$ and $Var^{crisis}(\cdot)$ denote variances of argument variables computed in stable and crisis periods, respectively. Corsetti, Pericoli, and Sbracia compare the correlation coefficient, ρ_{crisis}^{CPS}, with the sample correlation coefficient, ρ^{crisis}, computed in the turbulent period between a crisis and a non-crisis market, to test for the existence of contagion or breaks in linkages.

Recent empirical studies find a dependence of stock returns on mature and emerging markets on returns from other markets or regions even after controlling for the impact of the global market (e.g., Eun and Shim (1989), Malliaris and Urrutia (1992), Masih and Masih (2001), Scheicher (2001), Climent and Meneu (2003)). In fact, our empirical investigation also shows that different measures of a common factor like world market stock returns, US market stock returns, and factors derived from the principle component analysis (Corsetti, Pericoli, and Sbracia (2005)) are unable to reduce the correlation between idiosyncratic shocks on the crisis and non-crisis markets to zero. Taking into account direct inter-market dependencies leads to an extension of the Corsetti-Pericoli-Sbracia approach:

$$\begin{aligned} x_t &= a_1 + c_1 f_t + b_1 y_t + \varepsilon_t^x \\ y_t &= a_2 + c_2 f_t + b_2 x_t + \varepsilon_t^y \end{aligned}, \tag{1.8}$$

where f_t denotes a measure of a global factor or a common factor after excluding direct interdependencies. After controlling for the direct inter-market relationship, idiosyncratic shocks ε_t^x and ε_t^y remain independent. The parameters b_1 and b_2 are measures of direct dependences between stock markets beyond the influence of the global market. The attractive feature of specification (1.8) is that its reduced form:

$$\begin{aligned} x_t &= a_1^* + c_1^* f_t + \eta_t^x \\ y_t &= a_2^* + c_2^* f_t + \eta_t^y \end{aligned} \qquad (1.9)$$

is analogous to the one proposed by Corsetti, Pericoli, and Sbracia. The non-zero correlation between residuals of the reduced-form specification, η_t^x and η_t^y, is the sole but crucial difference. It implies that the adjusted correlation function derived by Corsetti, Pericoli, and Sbracia, although theoretically appealing, may be biased in empirical exercises, as shown in section 1.2.

From the discussion above we can draw the following conclusion. The adjusted correlation coefficients of Forbes and Rigobon (2002) and Corsetti, Pericoli, and Sbracia (2005), independent from calm and crisis periods, may in some situations be biased. However, the latter approach is more general and requires fewer assumptions. The test of Corsetti, Pericoli, and Sbracia rejects the hypothesis of stable inter-market linkages more often than the test of Forbes and Rigobon in empirical studies. Similar test results from both specifications provide more robust evidence in favor or against the hypothesis of contagion.

In our empirical investigation we report results from both correlation measures to check how robust the findings are with respect to different model specifications. Additionally, we compute correlation coefficients using the reduced-form residuals of specification (1.9). We interpret these residuals as unpredictable stock returns or excess stock returns beyond any external and lagged domestic influence. The estimated correlation coefficients between excess stock returns allow for testing how the direct linkages between stock markets (beyond those with a global factor) change during crisis periods. The correlation measures between reduced-form residuals, adjusted for crisis and calm periods, can be computed using the Forbes-Rigobon method under condition that $b_2 = 0$ in model (1.8). Thus, we test stability of the following data-generating process:

$$\begin{aligned}\eta_t^x &= b_1\varepsilon_t^y + \varepsilon_t^x \\ \eta_t^y &= \varepsilon_t^y\end{aligned} \quad . \tag{1.10}$$

This approach assumes that any direct dependences between markets beyond the influence of the global factor (or some measure of a common factor) are allowed only in the direction from the crisis market to the non-crisis market. Volatility of ε_t^x is required to be constant in stable and crisis periods. [5] The other assumptions are analogous to the Forbes-Rigobon approach, but they consider residual returns instead of market returns here. We add lagged returns from both stock markets to the equations in (1.9) to adjust for autocorrelation in stock returns, spillovers and causality between markets, analogously to Forbes and Rigobon (2002).

After calculation of the correlation coefficients for the stable period and the correlation coefficients for the crisis period, ρ^{crisis}, ρ^{FR}, and ρ_{crisis}^{CPS}, all coefficients are converted using a Fisher transformation into approximately normally distributed variables and can be compared by employing standard tests (Gelos and Sahay (2001), Corsetti, Pericoli, and Sbracia (2005)). We investigate the null hypotheses of no increase and no decrease in the relationship between crisis and non-crisis countries using standard one tail t statistics. The corresponding alternative hypotheses are that there is an increase (a decrease) in correlation coefficients. A significant positive change in correlation coefficients between the stable period and the turmoil period is interpreted as a shift in the structure of those relationships and, hence, provides evidence in favor of contagion. Furthermore, a significant decrease in

[5] Alternatively, a method of Corsetti, Pericoli, and Sbracia (2005) could be used. Forbes and Rigobon (2002) show that their test is also valid for sufficiently low (but different from zero) values of b_2. We expect b_2 to be close to zero, because the global factor has a major impact on local stock index returns.

correlation between stock markets returns can be interpreted as a break in links between them (Billio and Pellizon (2003), Corsetti, Pericoli, and Sbracia (2005)).

Billio and Pellizon (2003) and Dungey and Zhumabekova (2001) raise problems of omitted variables, feedback dependencies between stock markets, different time zones, and arbitrary choices of the crisis window, which all can affect tests of contagion. We deal with these aspects by employing different model specifications, different tests, different measures of global shocks, inclusion of lagged stock returns into the models, and using daily as well as two-day stock indices denominated in local currencies and in U.S. dollars. Moreover, different crisis windows from two weeks up to three months are investigated.

1.2 Extending the Model of Corsetti, Pericoli, and Sbracia

In this section, we explain the extension of the model presented by Corsetti, Pericoli, and Sbracia (2005), where additional direct inter-market dependencies are allowed. Typical measures of common factors like world stock market returns, U.S. stock market returns, factors estimated using the principal component analysis fail to reduce the correlation between residual factors to zero. We show that omitting this direct relationship between the crisis and the non-crisis market in any measure of the common factor, f_t, used in the model of Corsetti, Pericoli, and Sbracia (2005) can lead to a bias in their test of contagion, because the residual factors on both markets are correlated.

Let f_t be a measure of a global or common factor after excluding direct interdependencies between stock markets. The model controlling for these linkages takes the following form (1.8):

$$\begin{aligned} x_t &= a_1 + c_1 f_t + b_1 y_t + \varepsilon_t^x \\ y_t &= a_2 + c_2 f_t + b_2 x_t + \varepsilon_t^y \end{aligned}.$$

The parameters of the structural form are not identified, but the reduced form of the model can be constructed. In matrix notation it takes the following form:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \frac{1}{1-b_1 b_2} \begin{bmatrix} 1 & b_1 \\ b_2 & 1 \end{bmatrix} \begin{bmatrix} a_1 & c_1 \\ a_2 & c_2 \end{bmatrix} \begin{bmatrix} 1 \\ f_t \end{bmatrix} + \frac{1}{1-b_1 b_2} \begin{bmatrix} 1 & b_1 \\ b_2 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^y \end{bmatrix}. \tag{1.11}$$

After re-writing the equations, the reduced-form model satisfies (1.9):

$$\begin{aligned} x_t &= a_1^* + c_1^* f_t + \eta_t^x \\ y_t &= a_2^* + c_2^* f_t + \eta_t^y \end{aligned},$$

where:

$$a_1^* = \frac{a_1 + a_2 b_1}{1-b_1 b_2},\ a_2^* = \frac{a_2 + a_1 b_2}{1-b_1 b_2},\ c_1^* = \frac{c_1 + b_1 c_2}{1-b_1 b_2},\ c_2^* = \frac{c_2 + b_2 c_1}{1-b_1 b_2} \tag{1.12}$$

and:

$$\begin{aligned} \eta_t^x &= \frac{1}{1-b_1 b_2}\varepsilon_t^x + \frac{b_1}{1-b_1 b_2}\varepsilon_t^y \\ \eta_t^y &= \frac{b_2}{1-b_1 b_2}\varepsilon_t^x + \frac{1}{1-b_1 b_2}\varepsilon_t^y \end{aligned}. \tag{1.13}$$

Expression (1.9) is analogous to the one used by Corsetti, Pericoli, and Sbracia. However, formula (1.13) implies that the residuals η_t^x and η_t^y are in general correlated, because η_t^x can be written as a linear function of η_t^y:

$$\eta_t^x = b_1 \eta_t^y + \frac{1 - b_1 b_2 (1 - b_1 b_2)}{1 - b_1 b_2} \varepsilon_t^x. \tag{1.14}$$

The reduced-form residuals η_t^x and η_t^y are uncorrelated only if the parameters b_1 and b_2 are equal to zero. However, the empirical literature suggests the existence of strong direct (e.g., regional or interregional) linkages between stock markets, as discussed in section 1.1. Additionally, model (1.13) is equivalent to model (1.10) in the main text, when $b_2 = 0$:

$$\begin{aligned} \eta_t^x &= b_1 \varepsilon_t^y + \varepsilon_t^x \\ \eta_t^y &= \varepsilon_t^y \end{aligned}.$$

Corsetti, Pericoli, and Sbracia (2005) show that the correlation coefficient between stock returns on two markets, generated by the model (1.9) under assumptions of no contagion, no breaks in linkages between the markets, and no correlation between idiosyncratic factors η_t^x and η_t^y (i.e. the model of Corsetti, Pericoli, and Sbracia), is given by:

$$\rho_{crisis}^{CPS} = \rho_{stable}^{CPS} \left[\left(\frac{1+\lambda_y^{stable}}{1+\lambda_y^{crisis}} \right)^2 \frac{1+\delta}{1+\left(\rho_{stable}^{CPS}\right)^2 \left[(1+\delta) \frac{1+\lambda_y^{stable}}{1+\lambda_y^{crisis}} - 1 \right] \left(1+\lambda_y^{stable}\right)} \right]^{\frac{1}{2}}, \quad (1.15)$$

or equivalently by:

$$\rho_{crisis}^{CPS} = \frac{\dfrac{Cov^{crisis}(x_t, y_t)}{\sqrt{(c_1^*)^2 Var^{crisis}(f_t)}\sqrt{(c_2^*)^2 Var^{crisis}(f_t)}}}{\left[1+\dfrac{Var^{crisis}(\varepsilon_t^x)}{(c_1^*)^2 Var^{crisis}(f_t)}\right]^{\frac{1}{2}} \left[1+\dfrac{Var^{crisis}(\varepsilon_t^y)}{(c_2^*)^2 Var^{crisis}(f_t)}\right]^{\frac{1}{2}}} = \quad (1.16)$$

$$= \frac{1}{\left[1+\dfrac{Var^{crisis}(\varepsilon_t^x)}{(c_1^*)^2 Var^{crisis}(f_t)}\right]^{\frac{1}{2}} \left[1+\dfrac{Var^{crisis}(\varepsilon_t^y)}{(c_2^*)^2 Var^{crisis}(f_t)}\right]^{\frac{1}{2}}} = \frac{c_1^*}{c_2^*} \left(\frac{1}{1+\lambda_y^{crisis}} \right) \left(\frac{Var^{crisis}(x_t)}{Var^{crisis}(y_t)} \right)^{-\frac{1}{2}}$$

,

where ρ_{stable}^{CPS} is assumed to be the same as ρ^{stable}. In the presence of correlated residuals η_t^x and η_t^y the correlation between stock returns x_t and y_t becomes:

$$\rho_{stable}^* = \left(1+\frac{Cov^{stable}(\eta_t^x, \eta_t^y)}{c_1^* c_2^* Var^{stable}(f_t)} \right) \left[\frac{c_1^*}{c_2^*} \left(\frac{1}{1+\lambda_y^{stable}} \right) \left(\frac{Var^{stable}(x_t)}{Var^{stable}(y_t)} \right)^{-\frac{1}{2}} \right] \quad (1.17)$$

during tranquil periods and

$$\rho^*_{crisis} = \left(1+\frac{Cov^{crisis}(\eta_t^x,\eta_t^y)}{c_1^* c_2^* Var^{crisis}(f_t)}\right)\left[\frac{c_1^*}{c_2^*}\left(\frac{1}{1+\lambda_y^{crisis}}\right)\left(\frac{Var^{crisis}(x_t)}{Var^{crisis}(y_t)}\right)^{-\frac{1}{2}}\right] \quad (1.18)$$

during crisis periods. c_1^* and c_2^* are assumed to be positive here. The linkages between stock returns beyond the world market influence are often positive, i.e., $Cov^{crisis}(\eta_t^x,\eta_t^y)>0$ (see also Figure 1.1). When $Cov(\eta_t^x,\eta_t^y)>0$ during the stable or the crisis period, the correlation generated by the model (1.9) is larger than the correlation generated by the model that assumes $Cov(\eta_t^x,\eta_t^y)=0$ in this period (i.e. the model of Corsetti, Pericolli, and Sbracia).

Note that the ratio of volatilities on both markets during crises can be expressed as:

$$\frac{Var^{crisis}(x_t)}{Var^{crisis}(y_t)} = \frac{Var^{stable}(x_t)+(c_1^*)^2\psi Var^{stable}(f_t)}{(1+\delta)Var^{stable}(y_t)} =$$

$$= \frac{Var^{stable}(x_t)}{(1+\delta)Var^{stable}(y_t)} + \frac{(c_1^*)^2\psi}{(1+\delta)(c_2^*)^2(1+\lambda_y^{stable})}, \quad (1.19)$$

as in the Corsetti-Pericoli-Sbracia approach, where

$$\psi = \frac{\delta(1+\lambda_y^{stable})+(\lambda_y^{stable}-\lambda_y^{crisis})}{1+\lambda_y^{crisis}}.$$

Hence, the correlation between returns on both markets during crises becomes:

$$\rho^*_{crisis} = \left(1+\frac{Cov^{crisis}(\eta_t^x,\eta_t^y)}{c_1^* c_2^* Var^{crisis}(f_t)}\right)\left(\frac{(c_2^*)^2(1+\lambda_y^{crisis})^2 Var^{stable}(x_t)}{(c_1^*)^2(1+\delta)Var^{stable}(y_t)}+\frac{(c_2^*)^2(1+\lambda_y^{crisis})^2(c_1^*)^2\psi}{(c_1^*)^2(1+\delta)(c_2^*)^2(1+\lambda_y^{stable})}\right)^{-\frac{1}{2}} =$$

$$= \left(1+\frac{Cov^{crisis}(\eta_t^x,\eta_t^y)}{c_1^* c_2^* Var^{crisis}(f_t)}\right)\left(\frac{(1+\lambda_y^{crisis})^2}{(1+\delta)}\frac{(c_2^*)^2 Var^{stable}(x_t)}{(c_1^*)^2 Var^{stable}(y_t)}+\frac{(1+\lambda_y^{crisis})^2\psi}{(1+\delta)(1+\lambda_y^{stable})}\right)^{-\frac{1}{2}}.$$

(1.20)

After substituting (1.17) into (1.20) we get:

$$\rho^{*}_{crisis}=\left(1+\frac{Cov^{crisis}(\eta_t^x,\eta_t^y)}{c_1^* c_2^* Var^{crisis}(f_t)}\right)\left(\frac{(1+\lambda_y^{crisis})^2(1+\phi^{stable})}{(1+\delta)(\rho^{*}_{stable})^2(1+\lambda_y^{stable})^2}+\frac{(1+\lambda_y^{crisis})^2\psi(\rho^{*}_{stable})^2(1+\lambda_y^{stable})}{(1+\delta)(1+\lambda_y^{stable})^2(\rho^{*}_{stable})^2}\right)^{-\frac{1}{2}}=$$

$$=\left(1+\phi^{crisis}\right)\rho^{*}_{stable}\left(\frac{(1+\lambda_y^{crisis})^2[(1+\phi^{stable})+\psi(\rho^{*}_{stable})^2(1+\lambda_y^{stable})]}{(1+\delta)(1+\lambda_y^{stable})^2}\right)^{-\frac{1}{2}}= \qquad (1.21)$$

$$=\left(1+\phi^{crisis}\right)\rho^{*}_{stable}\left[\left(\frac{1+\lambda_y^{stable}}{1+\lambda_y^{crisis}}\right)^2\frac{1+\delta}{1+\phi^{stable}+\left(\rho^{*}_{stable}\right)^2\left[(1+\delta)\frac{1+\lambda_y^{stable}}{1+\lambda_y^{crisis}}-1\right]\left(1+\lambda_y^{stable}\right)}\right]^{\frac{1}{2}},$$

where $\frac{Cov(\eta_t^x,\eta_t^y)}{c_1^* c_2^* Var(f_t)}$ is denoted by ϕ to simplify notation.

Since the test of Corsetti, Pericolli, and Sbracia (2005) typically derives the correlation for the tranquil period ρ^{CPS}_{stable} from the sample correlation, then the estimate of the true correlation generated by the model (1.9) in the stable period is not biased. The correlation in the crisis period ρ^{CPS}_{crisis} is obtained using formula (1.15) and the unbiased estimate of the correlation from the stable period. ρ^{CPS}_{crisis} is likely to be different from the true ρ^{*}_{crisis} if residuals η_t^x and η_t^y are correlated, i.e. $\phi^{stable}\neq 0$ or $\phi^{crisis}\neq 0$. The direction of the bias depends on values of ϕ^{stable} and ϕ^{crisis}. Thus, the test of Corsetti, Pericolli, and Sbracia may be biased, but the direction of the bias is difficult to assess *a priori* without knowing the values of suitable parameters in (1.21).

1.3 Data and Identification of Crises

In our empirical analysis we utilize time series returns from 17 stock markets, calculated in both U.S. dollars and local currencies. We concentrate on the four largest markets in CEE (The Czech Republic, Hungary, Poland, and Russia) and on selected West European markets, which are members of the EU. They range from the biggest and most developed financial centers (France, Germany, and The United Kingdom) to less developed stock markets (Greece, Ireland, Portugal, and Spain). The latter four represent the countries that entered the EU in the seventies and eighties as emerging markets and may now be considered – according to MSCI measures – as developed stock markets. Thus, we are able to investigate differences in vulnerability to financial crises depending on the development and importance of the stock market. In addition, six stock markets in which crises took place (Argentina, Brazil, Hong Kong, Korea, Turkey, and the U.S.) are selected.

Seven crises are analyzed. We start with the Asian crisis, the Russian financial failure and its expansion to Brazil. We then continue with the investigation on financial turmoil in Turkey at the beginning of 2001, the terrorist act on the U.S., and the Argentinean insolvency collapse in 2002. Our analysis ends with the American stock market crash after the Enron and WorldCom bankruptcies. The five non-American crises are significant with respect to their extent. The indices in crisis markets in each case fell more than 40% during the turmoil. The two American crashes in 2001 and 2002 are included in line with Mishkin and White (2003) who found that the 2000 – 2001 crisis was among the fifteen biggest crashes in the U.S. during the last century.[6] We separately investigate two important events within this long-term downturn, namely the terrorist act which caused the U.S. index to fall by about 18% and the second accounting scandal when the same index fell by an additional 20%.[7]

It is obvious from the discussion of our methodology that an important step in the analysis is the identification of the crisis interval. It requires a separation of a turmoil period

[6] The actual decline lasted until September 2002. Crashes are defined in Mishkin and White as a 20% drop in the market index value during a period which may range from one day to one year.

[7] The Morgan Stanley Capital International database of standardized country equity indices is used as a proxy for the U.S. stock index.

from a stable period in order to accurately investigate the existence of contagion. We use two approaches for identifying stable and turmoil periods. First, starting dates of the crises are known and reported in the literature. The lengths of the turmoil intervals are chosen to be one or two months depending on the crisis' development.[8]

Table 1.1 Duration of the crises

Crisis Name	Crisis Country	Stable Periods	Crisis Periods
Asian "Flu"	Hong Kong Korea	**1997:9:1 – 1997:10:22** 1997:9:1 – 1997:10:16 1997:9:17 – 1997:12:14	**1997:10:23 – 1997:11:22** 1997:10:17 – 1998:1:12 1997:12:15 – 1998:1:12
Russian "Virus"	Russia	**1998:6:6 – 1998:8:5** 1998:2:1 – 1998:6:19 1998:2:1 – 1998:6:19	**1998:8:6 – 1998:10:5** 1998:6:30 – 1998:9:30 1998:7:20 – 1999:10:5
Brazilian Crisis	Brazil	**1998:11:1 – 1998:12:31** 1998:10:6 – 1998:11:26 1998:10:6 – 1998:11:26	**1999:1:1 – 1999:3:1** 1998:11:27 – 1999:1:14 1998:11:27 – 1999:1:26
Turkish Collapse	Turkey	**2000:12:5 – 2001:2:14** 1999:5:1 – 2000:11:3 2000:9:6 – 2000:11:3	**2001:2:15 – 2001:3:13** 2001:2:15 – 2001:4:03 2000:11:6 – 2000:12:4
Terrorist Acts and Economic Slowdown	U.S.	**2001:6:27 – 2001:8:26** 2001:7:14 – 2001:9:13 2001:4:14 – 2001:9:13	**2001:9:14 – 2001:10:13** 2001:8:27 – 2001:9:21 2001:9:14 – 2001:10:13
Argentinean Crisis	Argentina	**2001:10:13 – 2001:12:12** 2001:11:4 – 2002:1:3 2001:10:14 – 2002:1:3	**2001:12:27 – 2002:2:26** 2002:1:4 – 2002:1:17 2001:1:4 – 2002:3:4
Accounting Scandals	U.S.	**2002:4:25 – 2002:6:24** 2002:3:20 – 2002:5:20	**2002:6:25 – 2002:7:24** 2002:6:25 – 2002:7:23

Note: The samples used for the main analysis are reported in the first rows in bold. These dates are applied to calculate correlation coefficients between crisis and non-crisis markets using a VAR model.

[8] We have also experimented with shorter periods of two weeks and longer periods of three months. The results do not change our general conclusions.

Second, the starting date is the day when a country index has its local maximum and the ending date is the local minimum during the crisis. Using this criterion we analyze periods when indices fell at the highest rate and the downfall was significant (Mishkin and White (2003)). Similarly, the stable intervals start two months before the initial shock. As a check of robustness we choose as the stable period the maximum possible length from the end of the last crisis to the beginning of the next one. The results (not reported but available on request) do not change our general conclusion. All analyzed periods are presented in Table 1.1.

The crisis intervals denoted with a bold font in Table 1.1 are based on dates reported in the literature. All empirical results presented in this chapter rely on these dates.[9] The Asian crisis periods are similar to those chosen by Rigobon (2001). The crisis in East Asia started in Thailand in June 1997, but the most remarkable collapse was observed on the Hong Kong capital market a few months later and persisted there for about two weeks. October 23, 1997, is the day of the drastic increase (over 30 percentage points) of short-term interest rates in Hong Kong. The dates for the financial collapses in Russia and Brazil are based on Rigobon (2001, 2003) and Baig and Goldfajn (1998). The initial shock to the Russian financial markets took place on August 6, 1998, and persisted till the end of September.[10] The Brazilian collapse, which has been often associated with contagion from the Russian crisis, lasted from October 1998 till March 1999, but the capital market suffered mostly during the period from the end of November 1998 to January 1999.

The duration of the Turkish crisis was chosen following Alper (2001) and Yeldan (2002) and an interval for the Argentinean collapse is based on information from daily newspapers. The Turkish financial crisis started already in November 2000, but it developed

[9] The findings from the other intervals are also discussed in our sensitivity analysis in the next section.

[10] The initial shock was to the bond market and the stock market reacted one week later.

after a dispute between the Turkish Prime Minister and President on February 15, 2001. The central bank stopped defending the Turkish lira against capital outflows on February 21, 2001, and let it float freely. In Argentina martial law was declared on December 18, 2001, after some protests, violent demonstrations and looting of supermarkets. Two days later the Argentinean President resigned. On February 1, 2002, a decree restricting bank withdrawals was brought into force.

The starting dates of the two American market crashes are taken from daily newspaper headlines (Mishkin and White (2003)). The terrorist acts in New York and Washington took place on September 11, 2001, and WorldCom revealed its great accounting fraud on June 25, 2002. Nevertheless, as mentioned by Mishkin and White (2003) the prolonged downturn of the U.S. stock market was also heavily influenced by a slowdown of the American economy.

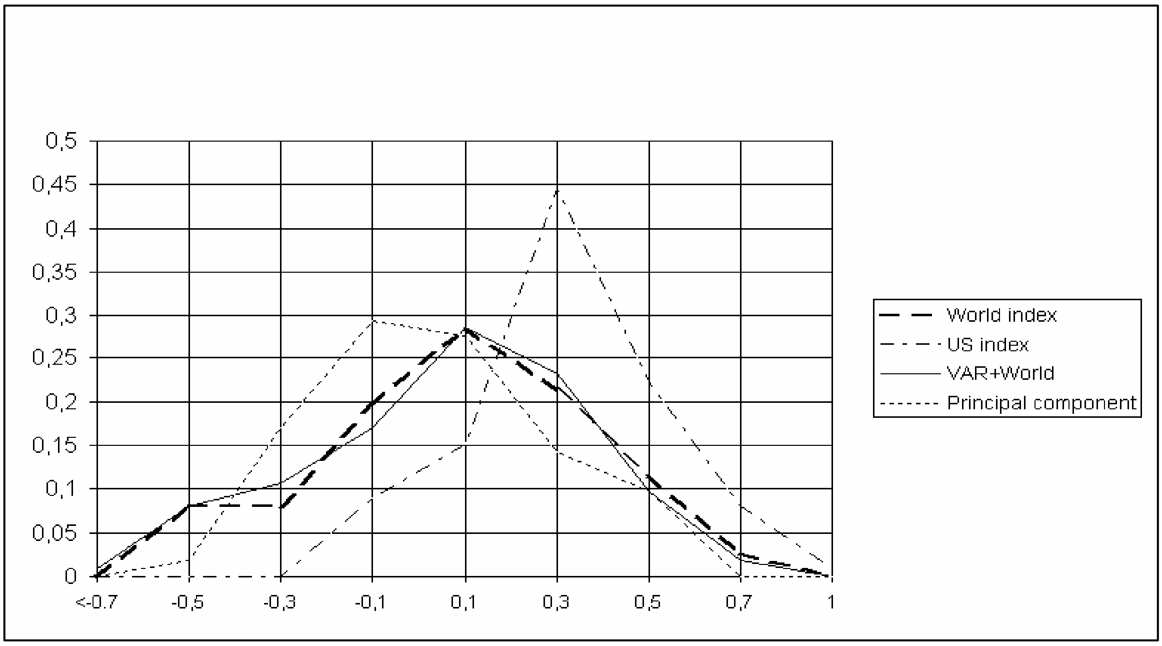
The standardized, comparable time series on stock market returns were obtained from the MSCI internet database (www.msci.com). Due to the crises analyzed, the time series used in the study range from September 1997 to September 2002.

1.4 Empirical Results

In this section, we compare correlation coefficients between stock returns of crisis countries and selected European stock markets during stable and turmoil periods. This part of our investigation is based on the methodology outlined in section 2 and uses the crisis periods described in section 3. The models of Forbes and Rigobon (2002), Corsetti, Pericoli, and Sbracia (2005), and additionally model (1.9) are employed to estimate the correlation coefficients among crisis and non-crisis stock markets. Following Forbes and Rigobon (2002) we use two-day average rolling log stock returns to control for different opening hours of national stock exchanges around the world. Corsetti, Pericoli, and Sbracia (2005) propose different measures of a common factor influencing both crisis and non-crisis stock markets.

Similarly, we employ world market and US index returns from the MSCI database, and the first principal component computed from a group of all investigated stock markets. We check which of these measures of the common factor reduces the absolute value of correlation measures between idiosyncratic shocks on the crisis and non-crisis markets to minimum. Empirical distributions of correlation coefficient estimates between idiosyncratic shocks for the different measures of the common factor are presented in Figure 1.1.

Figure 1.1 Empirical density functions of correlations between residual factors



Note: World index returns, U.S. index returns, World returns and lagged returns from both markets, and principle component are measures of the common factor employed in the model of Corsetti, Pericoli, and Sbracia (2005). We compute the correlations for all investigated stable periods between all crisis and non-crisis markets.

For each measure, we find cases of significant deviations of the estimated correlation coefficients from zero. However, the best results are obtained with the principal component measure. Therefore, we employ this measure in our main investigation and discuss results from other measures in a sensitivity analysis.

Table 1.2 Correlation coefficients between crisis market and non-crisis markets before and during the crisis

Crisis Market	Date of the Crisis	Explanation of Results			Poland			Czech Republic			Hungary			Russia			United Kingdom			France		
		FR	CPS	RES	FR	CPS	RES	FR	CPS	RES	FR	CPS	RES	FR	CPS	RES	FR	CPS	RES	FR	CPS	RES
Hong Kong	1997:10:23	ρ^{stable}	$\rho^{stable}_{residuals}$	0.19	0.19	0.30	0.12	0.12	0.06	0.25	0.25	0.23	0.34	0.34	0.37	0.30	0.30	0.23	0.44	0,44	0,40	
	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.56	0.56	0.76	-0.12	-0.12	-0.21	0.56	0.56	0.80	0.70	0.70	0.85	0.72	0.72	0.59	0.74	0,74	0,65
	1997:11:22	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.28	0.44	0.48	-0.05	0.30	-0.10	0.28	0.52	0.54	0.39	0.61	0.60	0.41	0.58	0.33	0.43	0,67	0,36
		Test Results (– / / +)							–													
Russia	1998:08:06	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.55	0.55	0.54	0.57	0.57	0.57	0.61	0.61	0.55				0.57	0.57	0.44	0.44	0,44	0,25
	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.44	0.44	0.39	0.58	0.58	0.56	0.53	0.53	0.49				0.51	0.51	0.52	0.55	0,55	0,56
	1998:10:05	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.38	0.52	0.27	0.51	0.53	0.41	0.46	0.56	0.35				0.44	0.54	0.39	0.48	0,43	0,40
		Test Results (– / / +)																				
Brazil	1999:01:01	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.49	0.49	0.13	0.01	0.01	-0.06	0.43	0.43	0.13	0.35	0.35	0.03	0.23	0.23	-0.15	0.40	0,40	0,03
	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.30	0.30	0.01	0.21	0.21	0.05	0.35	0.35	0.16	0.37	0.37	0.19	0.59	0.59	0.45	0.39	0,39	0,14
	1999:03:01	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.21	0.61	0.01	0.14	0.02	0.02	0.25	0.57	0.08	0.27	0.50	0.09	0.45	0.36	0.23	0.28	0,54	0,07
		Test Results (– / / +)				–												+				
Turkey	2001:02:15	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.30	0.30	0.44	0.36	0.36	0.20	0.30	0.30	0.39	0.33	0.33	0.36	0.17	0.17	-0.25	0.23	0,23	-0,07
	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.04	0.04	-0.23	-0.14	-0.14	0.04	0.25	0.25	0.22	0.35	0.35	0.09	-0.21	-0.21	-0.37	0.20	0,20	0,27
	2001:03:13	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.03	0.00	-0.21	-0.12	0.00	0.04	0.21	0.00	0.21	0.30	0.00	0.08	-0.18	0.00	-0.33	0.17	0,00	0,25
		Test Results (– / / +)					–	–							+							
U.S.	2001:09:14	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.26	0.26	0.01	-0.03	-0.03	0.03	0.27	0.27	0.10	0.40	0.40	0.33	0.63	0.63	0.56	0.47	0,47	0,28
	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.26	0.26	0.20	0.31	0.31	0.25	0.45	0.45	0.32	0.28	0.28	0.47	0.66	0.66	0.58	0.63	0,63	0,55
	2001:10:13	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.13	0.61	0.10	0.16	-0.12	0.13	0.24	0.63	0.20	0.14	0.71	0.26	0.40	0.77	0.32	0.37	0,74	0,30
		Test Results (– / / +)				–			+						–							
Argentina	2001:12:27	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.03	0.03	-0.09	0.04	0.04	-0.03	0.04	0.04	-0.16	0.03	0.03	-0.04	0.36	0.36	0.21	0.35	0,35	0,20
	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	-0.17	-0.17	0.14	-0.10	-0.10	-0.15	-0.19	-0.19	-0.09	0.00	0.00	0.06	0.00	0.00	0.22	0.11	0,11	0,25
	2002:02:26	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	-0.09	0.00	0.07	-0.05	0.00	-0.06	-0.10	0.00	-0.04	0.00	0.00	0.02	0.00	0.06	0.10	0.06	0,06	0,11
		Test Results (– / / +)															–					
U.S.	2002:06:25	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	-0.17	-0.17	-0.16	-0.19	-0.19	-0.19	-0.07	-0.07	-0.04	0.20	0.20	0.34	0.29	0.29	0.30	0.49	0,49	0,44
	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.19	0.19	0.25	0.25	0.25	0.13	0.06	0.06	-0.08	0.33	0.33	0.23	0.45	0.45	0.40	0.53	0,53	0,50
	2002:07:23	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.12	-0.32	0.18	0.16	-0.35	0.09	0.04	-0.15	-0.06	0.21	0.36	0.15	0.29	0.45	0.31	0.36	0,57	0,42
		Test Results (– / / +)				+			+													

Table 1.2 (Continued) Correlation coefficients between crisis market and non-crisis markets before and during the crisis

Crisis Market	Date of the Crisis	Explanation of Results			Germany			Spain			Ireland			Portugal			Greece		
					FR	CPS	RES	FR	CPS	RES	FR	CPS	RES	FR	CPS	RES	FR	CPS	RES
	1997:10:23	ρ^{stable}	$\rho^{stable}_{residuals}$	0.33	0.33	0.12	0.48	0.48	0.29	0.23	0.23	0.09	0.72	0.72	0.63	0.62	0.62	0.57	
Hong Kong	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.84	0.84	0.88	0.70	0.70	0.63	0.76	0.76	0.88	0.72	0.72	0.73	-0.12	-0.12	-0.24
	1997:11:22	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.55	0.60	0.66	0.39	0.69	0.35	0.45	0.49	0.75	0.40	0.75	0.42	-0.05	0.73	-0.11
		Test Results (– / / +)				+	+					+	+	–			–	–	–
	1998:08:06	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.62	0.62	0.55	0.56	0.56	0.53	0.40	0.40	0.23	0.48	0.48	0.47	0.42	0.42	0.31
Russia	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.54	0.54	0.55	0.50	0.50	0.52	0.28	0.28	0.24	0.48	0.48	0.51	0.39	0.39	0.39
	1998:10:05	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.47	0.57	0.39	0.43	0.53	0.40	0.23	0.39	0.17	0.41	0.46	0.40	0.33	0.40	0.29
		Test Results (– / / +)																	
	1999:01:01	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.36	0.36	-0.07	0.51	0.51	0.07	0.12	0.12	0.13	0.38	0.38	0.10	0.40	0.40	0.06
Brazil	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.35	0.35	0.12	0.56	0.56	0.37	0.39	0.39	0.29	0.36	0.36	0.23	0.39	0.39	0.24
	1999:03:01	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.25	0.51	0.06	0.42	0.62	0.19	0.28	0.21	0.14	0.26	0.52	0.11	0.28	0.55	0.12
		Test Results (– / / +)																	
	2001:02:15	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.25	0.25	-0.13	0.27	0.27	0.12	0.36	0.36	0.35	0.28	0.28	0.05	-0.12	-0.12	-0.06
Turkey	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	-0.08	-0.08	-0.11	0.01	0.01	-0.21	-0.24	-0.24	-0.28	-0.28	-0.28	-0.04	-0.64	-0.64	-0.33
	2001:03:13	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	-0.07	0.00	-0.10	0.01	0.00	-0.19	-0.21	0.00	-0.26	-0.24	0.00	-0.04	-0.58	0.00	-0.30
		Test Results (– / / +)									–		–	–			–	–	
	2001:09:14	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.64	0.64	0.54	0.41	0.41	0.21	0.07	0.07	-0.10	0.28	0.28	0.20	0.10	0.10	0.06
U.S.	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.75	0.75	0.69	0.60	0.60	0.57	0.76	0.76	0.74	0.26	0.26	0.48	0.72	0.72	0.70
	2001:10:13	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.49	0.78	0.42	0.35	0.72	0.32	0.50	0.24	0.46	0.13	0.64	0.25	0.46	0.34	0.44
		Test Results (– / / +)									+	+	+		–		+	+	+
	2001:12:27	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.35	0.35	0.22	0.41	0.41	0.25	0.23	0.23	-0.02	0.41	0.41	0.35	0.14	0.14	0.21
Argentina	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	-0.07	-0.07	0.01	0.24	0.24	0.28	-0.29	-0.29	-0.22	0.17	0.17	0.20	-0.01	-0.01	-0.19
	2002:02:26	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	-0.04	0.05	0.00	0.13	0.07	0.12	-0.15	0.03	-0.09	0.09	0.08	0.08	-0.01	0.02	-0.08
		Test Results (– / / +)			–						–	–							
	2002:06:25	ρ^{stable}	ρ^{stable}	$\rho^{stable}_{residuals}$	0.53	0.53	0.51	0.51	0.51	0.52	-0.16	-0.16	-0.09	0.08	0.08	0.19	-0.01	-0.01	0.13
U.S.	–	ρ^{crisis}	ρ^{crisis}	$\rho^{crisis}_{residuals}$	0.73	0.73	0.78	0.56	0.56	0.47	0.08	0.08	-0.14	0.44	0.44	0.44	0.37	0.37	0.06
	2002:07:23	$\rho^{crisis}_{adjusted}$	$\rho^{stable}_{adjusted}$	$\rho^{crisis}_{adjusted}$	0.55	0.58	0.77	0.39	0.58	0.38	0.05	-0.30	-0.12	0.29	0.16	0.32	0.24	-0.01	0.04
		Test Results (– / / +)										+						+	

Note: The calculation of the correlation coefficients follow the approaches by Forbes and Rigobon (FR), Corsetti, Pericoli, and Sbracia (SPC), and from the extended model (9) (RES). "+" and "–" denote evidence of contagion and a break in financial linkages, respectively. $\rho^{crisis}_{adjusted}$ denotes an appropriate adjusted correlation coefficient for the crisis period

In case of the extended model (1.9), we compute correlation coefficients ($\rho^{stable}_{residuals}$ for tranquil periods and $\rho^{crisis}_{residuals}$ for turbulent periods) between excess returns (reduced-form residuals) from both markets. In this specification, we include the first lag of stock returns as explanatory variables to control for serial correlation in stock returns, causality, and lagged spillovers between markets. Moreover, stock returns from the U.S. market as a proxy for shocks from the global market are used.

In Table 1.2 we present correlation coefficients from stable and crisis periods and the results of all three test statistics. The 5% significance level is throughout used in our tests, except for the Corsetti-Pericoli-Sbracia tests which are computed at the 10% significance level to approximate the true 5% level and to show that our results are robust. The main finding from Table 1.2 is that in the majority of cases there was neither contagion to the CEE nor to the West European markets. Hence, linkages between the stock markets of the crisis and the non-crisis countries remained stable during turmoil periods. Contagion is rather a rare phenomenon. Gelos and Sahay (2001), using a similar methodology, also found weak evidence in favor of contagion to CEE markets during the Czech crisis in 1997 and crashes in Asia and Russia. According to our results, there is some evidence of contagion to Western European markets during the Asian crisis (to Germany and Ireland), during the Brazilian crisis (to the United Kingdom), and after both shocks to the U.S. (to Ireland and Greece). There are only four cases of contagion to CEE markets, namely to Polish and Czech markets after shocks to the U.S., and to Russia during the Turkish crisis. Only two cases of contagion are robust to the model and test specification (Ireland and Greece).

Other interesting findings are the cases of significant negative changes in linkages between crisis and non-crisis stock markets. Some evidence of structural breaks in linkages can be found during the Hong Kong collapse for Greece, Portugal, and the Czech Republic, during the Brazilian crisis for Poland, and during the Turkish crisis for Greece, Portugal, Ireland, the Czech Republic, as well as Poland. Moreover, breaks of linkages can be found after the terrorist acts in the U.S. for Portugal, Russia, and Poland, during the Argentinean crisis for Ireland, Germany, and the United Kingdom. However, only one case of a break in linkages is robust to the model specification. During the "Russian virus" there was also a negative shift in adjusted correlations between almost all studied countries and Russia, but the change was not statistically significant.

In contrast to Glick and Rose (1999), our results related to the crisis in Russia indicate that geographical proximity is not always an important driver of contagion. The causality tests implemented by Gelos and Sahay (2001) provide evidence of strong interdependence between Russia and Central European countries at the time of collapse in 1998, but their correlation analysis results are in line with ours.[11] A decline in linkages with crisis stock markets during different crashes is as common as contagion overall.

We can observe a few patterns of stock market behavior regarding contagion and breaks in linkages. The crises in Russia, Brazil, and Argentina induce less contagion compared to the rest of the crises under investigation. Relatively few cases of breaks in linkages can be found for the Russian and the Brazilian crisis as well as the second U.S. scandals. During most downfalls the CEE stock markets acted similarly to the Western European ones. Our sensitivity analyses show approximately the same relative number of cases of contagion to CEE and Western European countries, i.e., 10% and 12%, respectively. Moreover, a similar picture appears with respect to breaks in linkages. These results indicate that the CEE stock markets were not more vulnerable to contagion than the developed European markets during the analyzed period.

[11] See also Krzak (1998), Darvas and Szapary (2000) for studies on contagion from Russia to CEE.

Interestingly, correlations between residual returns from the extended models are significantly greater (lower) than zero in 33% (25%) cases during tranquil times and in 38% (30%) cases during turbulent periods at the 0.05 significance level. This could suggest that in some cases the bias in the Corsetti-Pericoli-Sbracia approach is not severe. Moreover, the residual correlation increases in 54% cases (in 16% cases significantly) and decreases in 46% cases (in 22% cases significantly) during turmoil. These outcomes also indicate limited evidence of contagion.

We checked the robustness of our results by using daily and two-day returns of stock indices, denominated in local currencies and in U.S. dollars, in our tests of contagion. We also applied different model specifications and tests. The findings of our sensitivity analysis are not reported but available on request. As expected, using the approach proposed by Corsetti, Pericoli and Sbracia (2005) we find more evidence of contagion and less evidence of breaks in inter-market linkages. Nevertheless, we find that CEE stock markets are usually not more vulnerable to financial crises than Western European markets.

Our results are also robust against many different settings of stable and turmoil periods. It is interesting to note that any contagion effects in Europe are usually strongest within the first two-week periods, but still rare in comparison to cases of interdependence. Generally, either the CEE stock markets are no more vulnerable to contagion than Western European markets or contagion is limited in all investigated stock markets.

1.5 Contagion, Interdependence, and Breaks in Linkages

Forbes and Rigobon (2002) showed that higher stock return volatility on a crisis market induces higher correlation between this market and other non-crisis markets even when there is no shift in fundamental relationships between any of them (Ronn (1998), Boyer, Gibson, and Loretan (1999), Loretan and English (2000)). They call such behavior of international stock market returns “interdependence”. In contrast, “contagion” is caused by a significant change in fundamental linkages between the crisis market and non-crisis markets. We utilize the methodologies introduced by Forbes and Rigobon (2002) and Corsetti, Pericoli, and Sbracia (2005) as well as an extension of the Corsetti-Pericoli-Sbracia approach to determine whether several financial shocks have any impact on linkages between crisis markets and European stock markets. We focus our investigation on a comparison between the behavior of Western and CEE stock markets during the period prior to the entrance of the first CEE countries to the EU. Crises in East Asia (1997), Russia (1998), Brazil (1999), Turkey (2000), Argentina (2001), and the U.S. (2001, 2002) are analyzed. They originate from macroeconomic fundamentals as well as from political affairs (e.g., terrorist acts).

Our main conclusion is that contagion to CEE stock markets was not more frequent than to Western European stock markets. Depending on the model specification, contagion occurred hardly ever or not frequently during the investigated crises and it is rather interdependence than contagion that characterizes co-movements between the crisis and non-crisis stock markets. This result is important for investors willing to allocate their financial capital to emerging markets in Europe.

During the analyzed period the CEE stock markets appeared to be quite robust against different external shocks. One explanation of this result could be poor integration of CEE stock markets with world capital markets. Measures of integration like the rate of volatility on the local market explained by U.S. or world market volatility (Baele (2005)), indicate that Portugal, Greece, and Ireland were not notably more integrated with the world stock market, but the other Western European markets were. In the analyzed period, CEE emerging stock markets did not always react in the same manner to important financial shocks as more developed markets in Western Europe. However, the direction of change in heteroscedasticity adjusted correlation coefficients between crisis and non-crisis markets is common for both groups of countries. In this sense, the behavior of CEE stock markets had a regional character. The examples of Russia and Argentina show that crises in some emerging capital markets may have an opposite effect on other developing countries. The main reason for the lack of financial contagion between these countries might be the limited importance of the crisis markets.

The crises on financial markets in the U.S. and Hong Kong had the most significant impact on the non-crisis European stock markets. In addition, we investigate breaks in relationships between crisis and non-crisis capital markets during turmoil periods. The results for European stock markets show that cases of breaks in linkages are usually as frequent as cases of contagion. This evidence may suggest that some stock markets are independent of certain crises or even benefit from crises elsewhere. The explanation of this phenomenon could be the flow of capital from the crisis market to the non-crisis market and, therefore, further studies in this direction are certainly needed.

2. ARE FINANCIAL SPILLOVERS STABLE ACROSS REGIMES? EVIDENCE FROM THE 1997 ASIAN CRISIS

Cross-border spillovers occupy an important place in the international finance literature. Interdependencies between capital markets play a significant role for assets 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, financial institutions, and the existence of common lenders have been established in the literature as channels of information flows (Kaminsky and Reinhart 2000, Kodres and Pritsker 2002, and Pritsker 2001, among others).

Empirical studies on the causal relationship between capital markets traditionally focused on the return spillovers between mature markets (Chen, Chiang, and So 2003, Eun and Shim 1989, Karolyi 1995, Malliaris and Urrutia 1992, Peiró, Quesada, and Uriel 1998), between mature and emerging markets (Hu, Kholdy and Sohrabian 2000, Masih and Masih 2001, Ng 2000), and across emerging capital markets (Gelos and Sahay 2001, Scheicher 2001). The 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 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. Change in the patterns of causality may take a 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 2003, King and Wadhawani 1990, Rigobon 2003).

Furthermore, the relative importance of spillover channels is argued to be time-variable, with some channels being more active in crisis periods. Due to the reliance of emerging countries on common bank creditor and cross market portfolio re-balancing by hedge and mutual funds, financial markets and institutions have been shown both theoretically and empirically to act as shock transmission mechanisms in turmoil rather than in calm regimes

(Calvo 1999, Kaminsky, Lyons, and Schmukler 2001, Kaminsky and Reinhart 2000, 2001, Kodres and Pritsker 2002). These theoretical arguments, as well as empirical evidence, establish a background for the hypothesis investigated in this study that spillover patterns differ across regimes.

In the study presented in this chapter, 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 the crisis regime and much weaker effects in the stable one, due to the notion that specific shock transmission channels are more active during crises. The regime-change hypothesis is often discussed in the empirical literature describing 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 the other.

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 only in the crisis regimes, i.e. for large (negative) return or volatility shocks. These findings are generally in line with results reported by Chen, Chiang, and So (2003), Climent and Meneu (2002), Rigobon (2003), and others using different data samples and methodologies.

The remainder of this chapter is organized as follows: Section 2.1 provides a description of the methodology applied, Section 2.2 presents data and discusses empirical results as well as their interpretation, and Section 2.3 summarizes this chapter.

2.1 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 chapter, 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 (Billio and Pelizzon 2003, Forbes and Rigobon 2002). 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.

2.1.1 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:

$$z_t = \sum_{k=1}^{m} A_k z_{t-k} + \varepsilon_t \,, \tag{2.1}$$

where $z_t \equiv [x_t \quad y_t]'$, A_k is the matrix of coefficients corresponding to lagged stock index returns z_{t-k}, and ε_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:

$$z_t = I(w_{t-d} \geq q)\left(\sum_{k=1}^{m} A_k z_{t-k\,t}\right) + I(w_{t-d} < q)\left(\sum_{k=1}^{m} B_k z_{t-k\,t}\right) + \varepsilon_t \ , \tag{2.2}$$

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. 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 $\sum_{k=1}^{m} A_k z_{t-k} + \varepsilon_t$ or $\sum_{k=1}^{m} B_k z_{t-k} + \varepsilon_t$ depending on whether the variable w_{t-d} is above or below the threshold value q, respectively.

2.1.2 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 (2.1) can be formulated as:

$$z_t = AX_t + \varepsilon_t \, , \tag{2.3}$$

where $A \equiv [\, A_0 \; A_1 \ldots A_k \,]$ and $X_t \equiv [1 \; (z_{t-1})' \ldots (z_{t-k})' \,]'$. 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 (2.2) takes the form:

$$z_t = CX_t(q) + \varepsilon_t \, , \tag{2.4}$$

where $C \equiv [\, A \;\; B \,]$, $X_t(q) \equiv [\; (X_t)' I(w_{t-d} > q) \quad (X_t)' I(w_{t-d} \le q) \;]'$. When the parameters d and q are known, model (2.4) 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 (2.4), these authors use a grid search to find estimates of d and q, where $d \in \{1, ..., m\}$, with m being the lag length in model (2.4), 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:

$$L(d,q) = -\frac{n}{2} \log \left| \hat{\Sigma}(d,q) \right| - n \tag{2.5}$$

are the ML estimators. $\hat{\Sigma}(d,q)$ is the estimate of the covariance matrix of ε_t in model (2.4) and n is the number of observations.

2.1.3 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 (2.1). 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 (2.1).

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):

$$SupLM = \sup_{qmin \leq q \leq qmax} LM(q), \tag{2.6}$$

where $LM(q)$ is the Lagrange multiplier statistic conditional on the value of q, computed for the estimated models (2.1) and (2.2). $qmin$ and $qmax$ 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 $z_t^* \equiv \tilde{\varepsilon}_t u_t$, where $\tilde{\varepsilon}_t$ are residuals from the estimated model (2.1) and the values of u_t are drawn randomly from the N(0,1) distribution.

The statistic $SupLM^*$ is calculated from the estimates of the models (2.1) and (2.2), where z_t^* instead of z_t is set as the vector of dependent variables. The computations of $SupLM^*$ are repeated many times using different draws of u_t from the N(0,1) distribution. Then, the percentage of the calculated $SupLM^*$ statistics exceeding $SupLM$ approximates the asymptotic p-value of the $SupLM$ statistic under the null hypothesis. In our investigation we derive the $SupLM$ and $SupLM^*$ statistics using formula (2.6) from the $LM(q)$ statistic that is adjusted for possible heteroscedasticity of residuals, as explained in detail by Hansen and Seo (2002):

$$LM(q) = vec(\hat{A}' - \hat{B}')'(V_1(q) + V_2(q))^{-1} vec(\hat{A}' - \hat{B}'), \tag{2.7}$$

where

$$V_1(q) = [I_2 \otimes X_1(q)'X_1(q)]^{-1}[\xi_1(q)'\xi_1(q)][I_2 \otimes X_1(q)'X_1(q)]^{-1}, \tag{2.8}$$

$$V_2(q) = [I_2 \otimes X_2(q)'X_2(q)]^{-1}[\xi_2(q)'\xi_2(q)][I_2 \otimes X_2(q)'X_2(q)]^{-1}, \tag{2.9}$$

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 $X_t I(w_{t-d} > q)$ and $X_t I(w_{t-d} \leq q)$, respectively. $\xi_1(q)$ and $\xi_2(q)$ are the matrices of stacked rows $\tilde{\varepsilon}_t \otimes [X_t I(w_{t-d} > q)]$ and $\tilde{\varepsilon}_t \otimes [X_t I(w_{t-d} \leq q)]$, 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 $G^* = \{w_{1-d}, ..., w_{n-d}\}$ of all n observations of the threshold variable w_{t-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 (2.1) in the increasing order of the threshold variable w_{t-d}:

$$z_{t(i)+d} = AX_{t(i)+d} + \varepsilon_{t(i)+d}, \qquad i = 1, ..., n. \tag{2.10}$$

Let $\hat{A}_l$ be the estimate of A in the model (2.10) based on the first l observations from the arranged sample, where $l < n$. The predictive residual $\hat{\varepsilon}_{t(l+1)+d}$ and the standardized predictive residual $\hat{\eta}_{t(l+1)+d}$ are then defined as:

$$\hat{\varepsilon}_{t(l+1)+d} = z_{t(l+1)+d} - \hat{A}_m X_{t(l+1)+d}, \tag{2.11}$$

$$\hat{\eta}_{t(l+1)+d} = \hat{\varepsilon}_{t(l+1)+d} \big/ [1 + (X_{t(l+1)+d})' V_m (X_{t(l+1)+d})]^{0.5}, \tag{2.12}$$

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

$$\hat{\eta}_{t(l+1)+d} = \Psi X_{t(l+1)+d} + \upsilon_{t(l+1)+d}, \tag{2.13}$$

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:

$$C(d) = [n - l_0 - (2m+1)][\ln|S_0| - \ln|S_1|], \tag{2.14}$$

where:

$$S_0 = \frac{1}{n-l_0}\sum_{m=l_0}^{n-1}(\hat{\eta}_{t(l+1)+d})(\hat{\eta}_{t(l+1)+d})', \qquad S_1 = \frac{1}{n-l_0}\sum_{m=l_0}^{n-1}(\hat{\upsilon}_{t(l+1)+d})(\hat{\upsilon}_{t(l+1)+d})', \tag{2.15}$$

and $\hat{\upsilon}_{t(l+1)+d}$ are the least squares residuals of regression (2.13). 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 *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).

2.2 Data and Empirical Results

In our empirical investigation, we analyze the stability of financial spillovers in tranquil and turmoil regimes. Moreover, we model the dependency between the US market and four emerging markets in South-East Asia before and during the Asian crisis of 1997. The turbulent period in Asia started with a devaluation and stock market plunge in Thailand in July 1997. It was followed by the Malaysian and the Indonesian market decline 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.[12]

On the basis of these time series, we model dependencies between the markets that allow for shifts in spillovers during turmoil periods. We test for the existence of those shifts using the tests described in Section 2.1. 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 (2.2), i.e. m=5. Next, we analyze the causality patterns between the markets by conducting Granger-causality tests.

The central 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

[12] Data for the Philippines is only available from November 15, 1996.

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.[13]

The results presented in Table 2.1 show that the stock index returns from the US market are superior crisis indicators in six out of eight models. Squared returns are optimal threshold variables in four out of eight models. The lag one is selected four times, which suggests that the dependencies between capital markets usually change quickly after the threshold variable enters a new regime. In the other four cases, threshold variables with lag one generate likelihood values very close to the optimal ones. The optimal threshold variables are used in the further analysis.

[13] 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.

Table 2.1 Log-likelihood values in the threshold models

Threshold variable w_{t-d}	HSI	KOSPI	TWII	STI	SET	JCI	KLCI	PSE
x_{t-1}	-903.76*	-1099.35	-904.77*	-736.85*	-1035.59	-994.45	-3132.71	-2646.21
x_{t-2}	-918.33	-1119.49	-930.55	-767.69	-1026.93	-1008.52	-3135.93	-2653.64
x_{t-3}	-926.35	-1113.76	-928.93	-765.88	-1040.27	-1010.12	-3142.60	-2643.66
x_{t-4}	-922.40	-1118.85	-926.88	-760.48	-1025.61	-1009.65	-3139.58	-2648.79
x_{t-5}	-934.17	-1104.28	-937.57	-742.91	-1022.56	-1027.88	-3147.92	-2656.30
y_{t-1}	-911.99	-1125.07	-923.60	-768.09	-1026.04	-1022.31	-3144.36	-2637.98
y_{t-2}	-929.06	-1104.07	-934.65	-752.85	-1029.54	-1007.72	-3139.33	-2644.60
y_{t-3}	-924.48	-1107.98	-921.37	-750.57	-1030.08	-1015.21	-3142.36	-2657.62
y_{t-4}	-905.38	-1117.50	-934.51	-759.67	-1050.24	-994.13*	-3152.94	-2656.10
y_{t-5}	-928.87	-1112.38	-937.24	-758.26	-1029.94	-1024.55	-3153.00	-2651.95
x_{t-1}^2	-913.79	-1121.03	-940.66	-764.26	-1042.14	-1017.18	-3145.31	-2631.29*
x_{t-2}^2	-938.57	-1110.03	-939.12	-742.72	-1028.92	-1013.75	-3151.88	-2653.37
x_{t-3}^2	-954.81	-1118.95	-931.13	-774.64	-1040.51	-1022.58	-3152.52	-2644.55
x_{t-4}^2	-908.83	-1124.14	-939.57	-768.42	-1020.74*	-1013.94	-3125.03	-2646.39
x_{t-5}^2	-938.21	-1093.39*	-937.52	-764.91	-1044.43	-1016.54	-3144.68	-2657.29
y_{t-1}^2	-922.59	-1106.08	-931.11	-781.79	-1025.75	-1018.10	-3141.46	-2646.14
y_{t-2}^2	-917.96	-1114.42	-921.78	-757.50	-1028.22	-1013.05	-3149.68	-2649.52
y_{t-3}^2	-912.24	-1117.17	-935.22	-745.19	-1035.59	-996.58	-3147.31	-2657.66
y_{t-4}^2	-914.92	-1106.01	-934.20	-752.06	-1044.72	-1025.48	-3143.99	-2652.53
y_{t-5}^2	-939.04	-1123.77	-937.39	-746.59	-1023.80	-1017.85	-3124.99*	-2651.76

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 2.2 Tests for stability of financial spillovers in crisis periods

	HSI	KOSPI	TWII	STI	SET	JCI	KLCI	PSE
Statistic of Tsay	40.2116* (0.010)	61.8050** (0.000)	16.1517 (0.808)	60.9487** (0.000)	36.4349* (0.027)	44.1894** (0.003)	23.1705 (0.392)	39.8360* (0. 011)
Statistic of Hansen and Seo	37.6420** (0.000)	29.7121** (0.000)	27.1726** (0.002)	31.4391** (0.002)	33.4605** (0.001)	36.3683** (0.001)	25.2618* (0.042)	32.9588** (0.000)
Estimated threshold parameter	-0.8036	1.4168	-0.8036	-.8006	1.4971	-1.1901	.01932	3.0390
Threshold variable	x_{t-1}	x^2_{t-5}	x_{t-1}	x_{t-1}	x^2_{t-4}	y_{t-4}	y^2_{t-5}	x^2_{t-1}
Percentage of observations in the calm regime	89.17	86.02	89.14	89.18	86.02	85.14	10.84	83.60
Average duration of the crisis regime [in days]	1.25	1.23	1.22	1.21	1.27	1.48	9.41	1.30
Average duration of the calm regime [in days]	10.17	7.52	9.89	9.85	7.81	8.38	1.16	6.64

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 $t-k$.

Furthermore, we perform the tests of Hansen and Seo (2002) and Tsay (1998) to investigate possible breaks in financial spillovers between markets during turbulent periods. The results are presented in Table 2.2. The results of Tsay's tests are generally in favor of the regime-switching hypothesis. This can be seen in Table 2.2 where six out of eight Tsay's statistics reject the linear VAR model at the 5% level of significance. However, as noted in section 2.1, 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 signals that all spillovers models are non-linear.

This finding suggests that spillover patterns change between crisis and tranquil regimes in the majority of linkages investigated. The outcomes for Malaysia and Taiwan are mixed, but at least one test rejects the null hypothesis in each case. The estimated threshold parameters indicate that markets enter the crisis regime after the returns on the selected market fall below some negative threshold value, e.g. -0.8036 for the pair US-Hong Kong, or the squared returns increase beyond some high threshold value, e.g. 1.4971 for the pair US-Thailand. 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 the crisis regime. This fact is mirrored by both the high percentage of observations in the calm regime, as well as the short duration of the crisis regimes in comparison to the turbulent ones. More specifically, in all but one of the models above 75 percent of observations are in the calm regime, as reported in Table 2.2.

Table 2.3 Heteroscedasticity-adjusted Wald tests for Granger-causality between markets

Null hypothesis	y							
	HSI	KOSPI	TWII	STI	SET	JCI	KLCI	PSE
S&P 500 does not cause y in crisis regime	53.013*** (0.000)	6.018 (0.304)	16.315*** (0.006)	19.491*** (0.002)	10.229* (0.069)	38.642*** (0.000)	14.739** (0.012)	131.678*** (0.000)
S&P 500 does not cause y in calm regime	44.052*** (0.000)	5.974 (0.309)	5.501 (0.358)	19.138*** (0.001)	12.534** (0.028)	18.131*** (0.003)	1.186 (0.946)	103.556*** (0.000)
S&P 500 does not cause y in any regime	97.066*** (0.000)	11.992 (0.286)	21.816** (0.016)	38.629*** (0.000)	22.763** (0.012)	56.773*** (0.000)	15.926 (0.102)	235.233*** (0.000)
y does not cause S&P 500 in crisis regime	35.170*** (0.000)	7.805 (0.167)	10.632* (0.059)	18.181*** (0.003)	11.214** (0.047)	7.228 (0.204)	312.373*** (0.000)	7.603 (0.179)
y does not cause S&P 500 in calm regime	9.173 (0.102)	7.397 (0.192)	4.672 (0.457)	2.480 (0.780)	5.161 (0.397)	6.708 (0.243)	6.057 (0.301)	2.597 (0.762)
y does not cause S&P 500 in any regime	44.343*** (0.000)	15.202 (0.125)	15.304 (0.121)	20.661** (0.024)	16.375* (0.089)	13.936 (0.176)	318.430*** (0.000)	10.201 (0.423)

Note: P-values are presented in parentheses. *,**, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Furthermore, the estimated average length of the crisis period is usually shorter than two days while the tranquil period lasts on average more than seven days for all but one model. One exception is the relationship between Malaysia and the US where a more volatile regime dominates in the sample. Generally, the results on the frequency of regimes changes and the duration of regimes indicate that regime changes are not of the structural break type. They are characterized by infrequent, multiple, and random swings into crisis and rapid jumps back to the calm regime rather than by unique regime changes 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 2.2, 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 standard heteroscedasticity-consistent Wald statistics to test whether lagged returns from one market provide important information for modeling current returns on the other market. Results are presented in Table 2.3.

In accordance with the hypothesis presented in the introduction, spillovers between capital markets are found to be unstable and to change across regimes. The US market leads five Asian markets in the calm regime (Hong Kong, Indonesia, the Philippines, Singapore, and Thailand), as indicated by the significant test statistics. Moreover, we observe additional causation effects to Taiwan and Malaysia in the crisis regime. Interestingly, almost all causation effects from the US market are stronger in the crisis regime than in the tranquil regime, which can be seen from the higher Wald statistic values. 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.

The lack of significant causality for the pair US – Korea deserves additional attention. We believe that this effect is due to the regulations of the Korean markets, 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.[14]

We now proceed with the novel finding emerging from the results presented in Table 2.3. As expected, past returns on the Asian markets are of little importance for the current development of US index returns in the tranquil regime. No significant causality from the Asian markets to the US market is found in the sample. However, in the crisis regime the causation effects from the eight Asian markets to the US market are stronger and in five out of eight cases statistically significant. This result suggests that information from less developed markets is transmitted into the US market, albeit only in the turbulent periods. These periods are relatively short, as presented in Table 2.2, 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).

If the 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 into the US market. This finding fits well the concept of financial contagion understood both as financial crisis spilling over from one market to other markets and as a break in the interdependency structure between countries. Obviously, some information transmission mechanisms are at work mainly during the turbulent periods, e.g.

[14] 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

actions of common bank lenders or hedge and mutual funds. They induce changes in spillover patterns between markets.

2.3 Unstable spillovers across regimes

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 the study presented in this chapter, 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 the 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, but neither dominates as an optimal threshold variable. Capital markets seldom enter the 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 the turmoil. On the other hand, causation from the Asian capital markets is non-existent in the calm regime but strong in the 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 the Asian markets performance when these emerging markets were hit by the financial crisis. Otherwise, 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 by more accurate return forecasting rather than by changing weights in their international asset 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 days turmoil period would imply high portfolio turnover and, hence, extraordinary costs for assets managers. 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 chapter 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 the crisis periods.

3. FINANCIAL CONTAGION, SPILLOVERS, AND CAUSALITY IN THE MARKOV SWITCHING FRAMEWORK*

The Markov switching framework enables the construction of models of stock index returns that switch between multiple regimes. The empirical literature suggests that such models outperform their one-regime counterparts in explaining the movements of asset prices (Cecchetti, Lam, and Mark (1990), Turner, Stratz, and Nelson (1990), Rydén, Teräsvirta and Åsbrink (1998), Timmermann (2000)). Recently, Markov switching models have been employed to analyze the inter-market dependencies during calm and tumultuous periods (Ang and Bekaert (2002), Sola, Spagnolo, and Spagnolo (2002)). In this context, Sola, Spagnolo, and Spagnolo (2002) have introduced the idea of independence and contagion (contagious volatility spillovers) as types of relationships between capital markets in calm and crisis regimes.

Typically the ideas of spillovers or dependencies between financial markets are related to an instantaneous inter-market relationship (e.g. King and Wadhwani (1990), Forbes and Rigobon (2002), Hartmann, Straetmans, and de Vries (2004)). Nevertheless, there exists a significant number of studies covering inter-market spillovers understood as stock returns or volatility on one market causing the specific behavior of returns or volatility on the second market in subsequent periods (Eun and Shim (1989), Malliaris and Urrutia (1992), Karolyi (1995), Cheung and Ng (1996), Booth, Martikainen, and Tse (1997), Climent and Meneu (2003), Sander and Kleimeier (2003) among others). In this thesis we follow this latter branch of literature where causality is interpreted as the evidence of inter-market spillovers.

In this chapter we augment the framework of inter-market dependencies by introducing the concept of Granger causality into the Markov switching models of stock index returns (see also Granger (1969, 1980), Psaradakis, Ravn, and Sola (2003)). The notion of one market Granger-causing the other market can be interpreted as evidence of information or

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capital flows between the markets. In contrast to previous studies, we explicitly define contagion, independence, and causality between capital markets. Furthermore, we develop a procedure to estimate the Markov switching model under the no-causality hypothesis and propose a statistic to test the null hypothesis of no-causality against the alternative of causality between stock index returns on two markets. In addition, we calculate the probabilities of crisis and calm regimes for each market, dependent upon different information sets. These probabilities could be important for international investors and capital market authorities interested in avoiding financial turmoil on the local market when a crisis hits elsewhere. Finally, we present an empirical example of the relationship between the Japanese and Hong Kong markets during the 1997 Asian crisis. We find evidence of feedback spillovers between the markets. The volatility on both markets and the correlation between stock index returns increase when both markets enter the crisis regime.

In the next section we describe the Markov switching model, the estimation procedure and tests for the hypotheses of contagion, independence, and causality. In section 3.2, we present an empirical analysis of the relationship between the Japanese and Hong Kong markets. Section 3.3 concludes the discussion on the methodology presented in this chapter.

3.1 Methodology

In this section we present the general framework for testing of inter-market dependencies based on the idea of Markov switching models. We introduce the definition of causality into the Markov switching models of financial markets and describe the definitions of contagion and independence in the form of mathematical expressions. Although the mathematical formulations were avoided in earlier descriptions of contagion and spillovers, they are especially useful in clarifying statistical assumptions underlying these economic phenomena. We use the definitions of causality and no-causality to construct a test of inter-market spillovers. In addition, we demonstrate the formulas for the probabilities of entering the crisis or calm regime by a market, conditional on different information sets, which are useful for forecasting the future state of a market. Finally, we apply the results from our general framework to the Markov switching mixture of normal distributions with constrains on means, extending the models of Phillips (1991), Ravn and Sola (1995), and Sola, Spagnolo, and Spagnolo (2002). We show the estimation procedure of our model under the assumption of no-causality, which is different from the procedures presented by Phillips (1991) to estimate models under the contagion and independence hypotheses.

3.1.1 The Markov switching framework

Define two time series R^X and R^Y describing daily index returns on two separate markets *X* and *Y*. Each of the markets is allowed to switch between two regimes denoted by *l* and *h* (e.g. calm and turmoil). The regimes correspond to the states of two hidden processes, S_t^X and S_t^Y, respectively. Both of them have the same state spaces described by the set $A=\{h,l\}$.

In order to examine the relationship between two markets, we construct the Markov chain S_t with its state space defined by the set $K=\{(i,j): i,j \in A\}$. By definition:

$$S_t = \begin{cases} 1 & (S_t^X = l) \wedge (S_t^Y = l) \\ 2 & (S_t^X = l) \wedge (S_t^Y = h) \\ 3 & (S_t^X = h) \wedge (S_t^Y = l) \\ 4 & (S_t^X = h) \wedge (S_t^Y = h) \end{cases}. \tag{3.1}$$

The transition matrix assigned to the process S_t is given by:

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{pmatrix}, \tag{3.2}$$

where p_{ij} denotes the probability of entering the state *j* from state *i*; $i, j = 1 \dots 4$.

In the context of financial markets undergoing calm and turbulent periods, we are able to distinguish four different states that the two markets can enter. The first state of the process S_t corresponds to the situation where both markets are in the calm regime. In the second state, market X is in the calm regime, while market Y suffers in the crisis regime. In the third state, X is in the crisis regime and Y is in the calm regime. Finally, in the fourth state both markets are in the crisis regime.

The four-state framework has already been employed to investigate dependencies between two macroeconomic or financial variables that are allowed to switch between two alternative regimes (Phillips (1991), Hamilton and Lin (1996), Ravn and Sola (1995), Sola, Spagnolo, and Spagnolo (2002)). These studies typically set restrictions on the transition matrix **P** to analyze various types of dependencies between the variables.

3.1.2 Independence, causality, contagion

In our work, we apply restrictions to the transition matrix to define the three types of relationships between capital markets that have recently met an increasing attention in the literature on international finance, namely independence, spillovers, and contagion. In order to analyze these inter-market relationships, we introduce the concept of Granger causality into the Markov switching framework (Granger (1969, 1980)). In the context of financial markets, causality is usually interpreted as evidence that some information or capital flows between capital markets exist that push stock returns on one market to follow returns on the other market with some lag. Our approach to causality is analogous to the definitions presented by Psaradakis, Ravn, and Sola (2003), but we distinguish between the lack of causality and independence. In the following definitions we are interested whether there exists causality or contagion from market X to market Y. However, market Y is not restricted from influencing market X. The definitions where causality and contagion from Y to X is considered are analogous.

Definition 1. S_t^X causes S_t^Y in the Granger sense if

$$\exists i, j, k \in A \quad P(S_t^Y = i \mid S_{t-1}^X = j, S_{t-1}^Y = k) \neq P(S_t^Y = i \mid S_{t-1}^Y = k)$$

Definition 2. S_t^X does not cause S_t^Y in the Granger sense if

$$\forall i, j, k \in A \quad P(S_t^Y = i \mid S_{t-1}^X = j, S_{t-1}^Y = k) = P(S_t^Y = i \mid S_{t-1}^Y = k)$$

or equivalently

$$P(S_t^Y = i \mid S_{t-1}^X = h, S_{t-1}^Y = h) = P(S_t^Y = i \mid S_{t-1}^X = l, S_{t-1}^Y = h)$$

$$P(S_t^Y = i \mid S_{t-1}^X = h, S_{t-1}^Y = l) = P(S_t^Y = i \mid S_{t-1}^X = l, S_{t-1}^Y = l).$$

The idea of these two alternative definitions is as follows. The market X has an influence on the market Y, when the magnitude of the conditional probability $P(S_t^Y = i \mid S_{t-1}^Y = j, S_{t-1}^X = \cdot)$ for all $i, j \in A$, depends on the regime of market X with one lag. The magnitude of this probability should change depending on the state of S_{t-1}^X. If the magnitude of probability remains unchanged independently of the regime of market X, one concludes that market X has no lagged impact on Y. Definition 2 implies a set of restrictions on the transition matrix **P**:

$$\begin{aligned} p_{11} + p_{13} &= p_{31} + p_{33} \\ p_{21} + p_{23} &= p_{41} + p_{43} \\ p_{22} + p_{24} &= p_{42} + p_{44} \\ p_{12} + p_{14} &= p_{32} + p_{34} \end{aligned} . \tag{3.3}$$

Thus, the matrix **P** takes on the following form, when S_t^X does not cause S_t^Y :

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{42}+p_{44}-p_{24} & p_{41}+p_{43}-p_{21} & p_{24} \\ p_{31} & p_{12}+p_{14}-p_{34} & p_{11}+p_{13}-p_{31} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{pmatrix}. \tag{3.4}$$

Finally, it is worth mentioning that the set of conditions (3.3) and the conditions obtained for the case where market Y does not cause X are necessary and sufficient for the processes S_t^X and S_t^Y to be first-order Markov chains. This is obtained from a theorem providing a condition for a Markov chain to be lumpable with respect to a partition. For a detailed discussion see Kemeny and Snell (1960).

Definition 3. Contagion from X to Y is present if

$$\forall k \in A \quad P(S_t = (\cdot, k) \mid S_{t-1} = (k, \cdot)) = 1$$

or equivlently

$$\forall j \in A \quad P(S_t^Y = j \mid S_{t-1}^X = j) = 1.$$

Definition 3 describes a situation where the process S_t^Y replicates realizations of the process S_t^X with a one-period delay. If the market X was in the calm (crisis) regime yesterday, the state of the market Y is calm (crisis) today. This definition is less restrictive than the analogous definition presented by Sola, Spagnolo, and Spagnolo (2002), in this sense that it allows for the influence of market Y on market X, when there is contagion from X to Y. It must be highlighted that contagion is a very restrictive form of inter-market relationships, because it imposes the following constraints on the transition matrix $\mathbf{P}$:

$$\mathbf{P} = \begin{pmatrix} p_{11} & 0 & p_{13} & 0 \\ p_{21} & 0 & p_{23} & 0 \\ 0 & p_{32} & 0 & p_{34} \\ 0 & p_{42} & 0 & p_{44} \end{pmatrix}. \tag{3.5}$$

Definition 4. Time series R^X is regime-independent of time series R^Y if process S_t^X is independent of process S_t^Y. Therefore, a sufficient condition for regime-independence is $\forall i, j, k, l \in A \quad P(S_t = (i,k) \mid S_{t-1} = (j,l)) = P(S_t^X = i \mid S_{t-1}^X = j)P(S_t^Y = k \mid S_{t-1}^X = l)$.

The relationship defined here assumes independence between the processes S_t^X and S_t^Y, but does not exclude dependence between R^X and R^Y. Index returns R^X and R^Y on the two separate markets can be correlated even though the regimes of the markets are independent. Therefore, we call such returns regime-independent. Independence implies the following form of the transition matrix **P**:

$$\mathbf{P} = \begin{pmatrix} \pi_{11}^X \pi_{11}^Y & \pi_{11}^X (1-\pi_{11}^Y) & (1-\pi_{11}^X)\pi_{11}^Y & (1-\pi_{11}^X)(1-\pi_{11}^Y) \\ \pi_{11}^X (1-\pi_{22}^Y) & \pi_{11}^X \pi_{22}^Y & (1-\pi_{11}^X)(1-\pi_{22}^Y) & (1-\pi_{11}^X)\pi_{22}^Y \\ (1-\pi_{22}^X)\pi_{11}^Y & (1-\pi_{22}^X)(1-\pi_{11}^Y) & \pi_{22}^X \pi_{11}^Y & \pi_{22}^X (1-\pi_{11}^Y) \\ (1-\pi_{22}^X)(1-\pi_{22}^Y) & (1-\pi_{22}^X)\pi_{22}^Y & \pi_{22}^X (1-\pi_{22}^Y) & \pi_{22}^X \pi_{22}^Y \end{pmatrix}, \quad (3.6)$$

where π_{ij}^X denotes the probability that the process S_t^X switches from state *i* to state *j* and π_{ij}^Y denotes the probability that the process S_t^Y moves from state *i* to state *j*, where $i, j \in A$. It is worth noting that the regime-independence described by definition 4 is the special case of the no-causality definition 2. In order to see this, it is enough to check that the elements of the matrix **P** in (3.6) fulfill the set of conditions (3.3).

3.1.3 The probability of crisis and calm regimes

Knowing the parameters in the transition matrix of the process S_t enables us to calculate the probabilities that are especially interesting from the international investor's perspective. We compute the probability that the particular market *Y* enters a regime of crisis or calm, conditional on the information that this market and the market *X* were in their respective regimes yesterday. These probabilities can be obtained by summing suitable elements of matrix **P**. For example $P(S_t^Y = h \mid S_{t-1}^X = l \wedge S_{t-1}^Y = l) = p_{12} + p_{14}$.

Computation of the probability that market Y enters state i, conditional only on the information that the market X was in state j one period earlier may also be of interest to analysts. It shows how the lack of information about the past state of Y influences forecasts of its present state. For example, the probability $P(S_t^Y = h \mid S_{t-1}^X = l\,)$ can be found in the following way. Let us notice that

$$\begin{aligned}
&P(S_t^Y = h \wedge S_{t-1}^X = l\,) = \\
&= P(S_t^Y = h \wedge S_{t-1}^X = l \wedge S_{t-1}^Y = l) + P(S_t^Y = h \wedge S_{t-1}^X = l \wedge S_{t-1}^Y = l) = \\
&= P(S_t^Y = h \mid S_{t-1} = 1)P(S_{t-1} = 1) + P(S_t^Y = h \mid S_{t-1} = 2)P(S_{t-1} = 2) = \\
&= \pi_1(p_{12} + p_{14}) + \pi_2(p_{22} + p_{24}),
\end{aligned} \tag{3.7}$$

where $\pi' = (\pi_1, \pi_2, \pi_3, \pi_4)$ is a vector of ergodic probabilities for the Markov chain S_t and p_{ij} are elements of the transition matrix **P**. Thus,

$$P(S_t^Y = h \mid S_{t-1}^X = l\,) = \frac{P(S_t^Y = h \wedge S_{t-1}^X = l)}{P(S_{t-1}^X = l)} = \frac{\pi_1(p_{12} + p_{14}) + \pi_2(p_{22} + p_{24})}{\pi_1 + \pi_2}. \tag{3.8}$$

3.1.4 The specific model

In this subsection, we construct the model of inter-market dependencies, which applies the four-state Markov chain described above, and present tests for restrictions on the transition matrix **P**. These restrictions satisfy the conditions for regime-independence, no-causality, and contagion. The unrestricted version of the model corresponds to bi-directional causality between the markets.

Our model is a Markov switching mixture of bivariate normal distributions. It is an extended version of the models examined by Phillips (1991), Sola, Spagnolo, and Spagnolo (2002) with respect that it imposes fewer restrictions on the means and volatilities of stock index returns in each regime. We consider the Markov switching model with two time series and four states. Each of the states corresponds to one bivariate normal distribution. The only constraints that have to be imposed are the ones that enable us to differentiate between different states. In this study, we propose the following restriction on means

$$\boldsymbol{\mu}_1 = \begin{pmatrix} \mu_1^X \\ \mu_1^Y \end{pmatrix}, \quad \boldsymbol{\mu}_2 = \begin{pmatrix} \mu_1^X \\ \mu_2^Y \end{pmatrix}, \quad \boldsymbol{\mu}_3 = \begin{pmatrix} \mu_2^X \\ \mu_1^Y \end{pmatrix}, \quad \boldsymbol{\mu}_4 = \begin{pmatrix} \mu_2^X \\ \mu_2^Y \end{pmatrix}. \tag{3.9}$$

Hence, the vectors of means in the second and third states are completely defined after the means in the first and fourth states are estimated. The model takes on the form

$$\mathbf{y}_t = I_{\{S_t=1\}}\boldsymbol{\mu}_1 + I_{\{S_t=2\}}\boldsymbol{\mu}_2 + I_{\{S_t=3\}}\boldsymbol{\mu}_3 + I_{\{S_t=4\}}\boldsymbol{\mu}_4 + \boldsymbol{\varepsilon}_t \tag{3.10}$$

where $\boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_t)$,

$$\Sigma_t = I_{\{S_t=1\}}\boldsymbol{\Sigma}_1 + I_{\{S_t=2\}}\boldsymbol{\Sigma}_2 + I_{\{S_t=3\}}\boldsymbol{\Sigma}_3 + I_{\{S_t=4\}}\boldsymbol{\Sigma}_4, \tag{3.11}$$

and $I_{\{S_t=i\}}$ is defined as

$$I_{\{S_t=i\}} = \begin{cases} 1, & S_t = i \\ 0, & S_t \neq i \end{cases}.$$

The mean and variance parameters are usually not known a priori, therefore we outline the procedure to estimate these parameters using the maximum likelihood (ML) approach. The log-likelihood function is given by the formulae

$$L(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log(\xi_{t|t-1} \times \mathbf{f}_t), \tag{3.12}$$

where

$$\xi_{t|t-1} = (P(S_t = i \mid \boldsymbol{\Lambda}_{t-1}; \boldsymbol{\theta}))'_{i=1,2,3,4}, \qquad \mathbf{f}_t = (f(y_t \mid S_t = j; \boldsymbol{\Lambda}_{t-1}; \boldsymbol{\theta}))'_{j=1,2,3,4}, \tag{3.13}$$

and

$$f(\mathbf{y}_t \mid S_t = j; \boldsymbol{\Lambda}_{t-1}; \boldsymbol{\theta}) = \frac{1}{2\pi|\boldsymbol{\Sigma}_j|^{1/2}} \times \exp\left(-\frac{1}{2}(\mathbf{y}_t - \boldsymbol{\mu}_j)'(\boldsymbol{\Sigma}_j)^{-1}(\mathbf{y}_t - \boldsymbol{\mu}_j)\right). \tag{3.14}$$

The symbol $'$ and $\times$ denotes a transposition of a vector, and the scalar product, respectively. $\boldsymbol{\theta}$ is the vector of all unknown parameters in the model, $\boldsymbol{\Lambda}_t = \{\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_T\}$ and T is the sample size.

The parameters are computed using the Expectation-Maximization (EM) algorithm (Hamilton (1990), Kim (1994)). In the (l+1)th step of iteration, the following maximum likelihood estimators are used.

$$\hat{p}_{ij}^{l+1} = \frac{\sum_{t=2}^{T} P(S_t = j, S_{t-1} = i \mid \boldsymbol{\Lambda}_T; \hat{\boldsymbol{\theta}}^l)}{\sum_{t=2}^{T} P(S_{t-1} = i \mid \boldsymbol{\Lambda}_T; \hat{\boldsymbol{\theta}}^l)} \tag{3.15}$$

is the approximation of the p_{ij} parameter in the transition matrix **P**. The estimator given by (3.15) is defined in terms of smoothed probabilities $P(S_t = i \mid \boldsymbol{\Lambda}_T; \hat{\boldsymbol{\theta}}^l)$, where $i \in \{1,2,3,4\}$. In order to identify and examine persistence of regimes in a Markov-switching framework, it is enough to plot smoothed probabilities against time.

The estimates of the vectors μ_j in the (l+1)th step, for j=1 and 4, are given by

$$\hat{\boldsymbol{\mu}}_j^{l+1} = \frac{\sum_{t=1}^{T} \mathbf{y}_t \cdot P(S_t = j \mid \boldsymbol{\Lambda}_T; \hat{\boldsymbol{\theta}}^l)}{\sum_{t=1}^{T} P(S_t = j \mid \boldsymbol{\Lambda}_T; \hat{\boldsymbol{\theta}}^l)} = \begin{pmatrix} \hat{\mu}_j^X \\ \hat{\mu}_j^Y \end{pmatrix}, \tag{3.16}$$

and for j=2,3

$$\hat{\boldsymbol{\mu}}_2^{l+1} = \begin{pmatrix} \hat{\mu}_1^X \\ \hat{\mu}_4^Y \end{pmatrix}, \ \hat{\boldsymbol{\mu}}_3^{l+1} = \begin{pmatrix} \hat{\mu}_4^X \\ \hat{\mu}_1^Y \end{pmatrix}. \tag{3.17}$$

The estimators of covariance matrices $\boldsymbol{\Sigma}_j$ for each state of the hidden Markov chain (j=1,2,3,4) are given by

$$\hat{\boldsymbol{\Sigma}}_j^{l+1} = \frac{\sum_{t=1}^{T} (\mathbf{y}_t - \hat{\boldsymbol{\mu}}_j^{l+1})(\mathbf{y}_t - \hat{\boldsymbol{\mu}}_j^{l+1})' \cdot P(S_t = j \mid \boldsymbol{\Lambda}_T; \hat{\boldsymbol{\theta}}^l)}{\sum_{t=1}^{T} P(S_t = j \mid \boldsymbol{\Lambda}_T; \hat{\boldsymbol{\theta}}^l)} \tag{3.18}$$

The iteration procedure begins with choosing random starting values for all parameters and continues computing approximations of the ML estimates until $\| \hat{\boldsymbol{\theta}}^l - \hat{\boldsymbol{\theta}}^{l+1} \| < 10^{-8}$. Then, the EM procedure is repeated a large number of times (e.g. 200) to ensure that the local maximum of the likelihood function is a global one.

However, estimation of the model with the constrained transition matrix is different for each type of the relationship between the markets. For example in case of contagion (definition 3), Phillips (1991) argues that it is enough to set the starting values of the respective parameters in **P** to zero to receive the valid ML estimates of the contagion model. One property of the EM algorithm described by Hamilton (1990) and Kim (1994) is that once transition probabilities are set to zero they remain equal to zero through all iterations. The method of determining the ML estimators when elements of the transition matrix are a function of the other parameters (as in regime-independence case) was developed by Phillips (1991). The details on estimation of the likelihood function under no-causality constraints are available upon request.

The likelihood ratio (LR) tests have usually been used to test for the existence of restrictions on transition matrix **P** (Phillips (1991), Raven and Sola (1996), Sola, Spagnolo, and Spagnolo (2002)). Phillips (1991) uses LR tests to check the null hypothesis of contagion given by definition 3 against the alternative hypothesis of no restrictions on the transition matrix (i.e. causality between markets) and to test the null hypothesis of regime independence given by definition 4 against the alternative of no restrictions on transition matrix **P**. Similarly, we propose using the LR statistic to test the null hypothesis of no-causality from *X* to *Y*, described in definition 2, against the alternative hypothesis of causality between the markets.

The LR statistic for testing the contagion hypothesis can be approximated by $\chi^2(8)$ distribution, because eight elements have to be equal to zero in matrix **P** under the null hypothesis. The statistic for testing regime-independence is asymptotically $\chi^2(12)$ distributed, because twelve constraints are imposed on transition matrix **P** in the formula (3.6). The test statistic for no-causality effect has an asymptotic $\chi^2(2)$ distribution, because two elements of the transition matrix are subject to constraints.

3.2 Empirical Example

In order to present empirical results using our approach, we investigate the relationship between the Japanese and Hong Kong capital markets during the East Asian crisis in 1997. The Asian crisis is well-suited to our multi-regime framework presented above, because it provides an excellent economic interpretation for the crisis regime in the Markov switching model. Corsetti, Pesenti, and Roubini (1999) provide an extensive description of the dependencies between financial markets during the Asian crisis.

During the crisis in October, 1997, the Hong Kong market underwent one of the most significant declines among the Asian markets. In the six-month period following the beginning of July, Hong Kong lost over 30% of its stock market value in both dollar and local terms (Chakrabarti and Roll (2002)). After the crash in Hong Kong, events in Asia became headline news and the spread of the crisis to the markets worldwide, i.e. contagion, was discussed (Forbes and Rigobon (2002)). The Japanese economy also suffered from the crisis. The Nikkei 225 index fell by 26% in the second half of 1997, and by 8% in October 1997, when the crisis in Hong Kong erupted. Corsetti, Pesenti, and Roubini (1999) argue that the Japanese macroeconomic conditions were still deteriorating in September 1998.

In our study we employ the main indices from the Hong Kong and Japanese markets, namely the HSI and the Nikkei 225. The series are daily returns of these indices covering the three-year period from June 1, 1995 to May 30, 1998. Since we want to avoid the influence of other turmoil events on the relationship between the two markets, we set the sample period to start after the Mexican crisis of 1994 and to end before the Russian crisis in the summer of 1998.

We estimate the bivariate Markov switching model in several versions. The first one is the unconstrained model fulfilling the hypothesis of causality between capital markets. The second version, with constrained parameter space in transition matrix **P**, assumes that the states of both markets are independent, i.e. the markets are regime-independent. Next, we set constraints on the transition matrix in order to estimate the models satisfying the hypotheses that HSI does not lead Nikkei 225 and that Nikkei 225 does not lead HSI, respectively. Finally, we separately estimate the models under the hypotheses of contagion from Nikkei 225 to HSI and contagion from HSI to Nikkei 225. We compare all constrained models with the unconstrained version using the LR tests. The results are presented in Table 3.1.

Table 3.1 Test of linkages between markets

Test	Nikkei225 (X) and HSI (Y)	HSI (X) and Nikkei225 (Y)
Independence	134.56^{**}	134.56^{**}
No spillovers	44.28^{**}	62.74^{**}
Contagion	24.43^{**}	18.10^{*}

Note: * and ** denote rejection of the null hypothesis at 5% and 1% levels respectively.

Our first result suggests that the hypothesis of regime-independence between the two markets is much too restrictive in comparison to the general hypothesis allowing for bi-directional spillovers between the Hong Kong and Japanese markets. The LR test strongly rejects the independence hypothesis at a 1% level of significance, which can be interpreted as evidence of dependence between the regimes on the two markets. We also find that the no-causality hypothesis is rejected in each case. This result indicates that causality from the Hong Kong to the Japanese market and from the Japanese to the Hong Kong market takes place. Granger (1969, 1980) calls such a bi-directional leading relationship a feedback causality.

Similarly, the hypotheses of contagion from the Japanese market and from the Hong Kong market are rejected at a 5% level. Forbes and Rigobon (2002) using a correlation approach also find no evidence of contagion from Hong Kong to Japan during the Asian crisis. However, we observe that the statistic for contagion hypothesis is higher in the case of contagion to the Hong Kong market. This result may indicate that causality from Hong Kong to Japan is more significant than causality in the opposite direction. This assumption is backed by the result from the no-causality tests, where the no-causality hypothesis from the Hong Kong market is more strongly rejected than the hypothesis of no-causality from Japan.

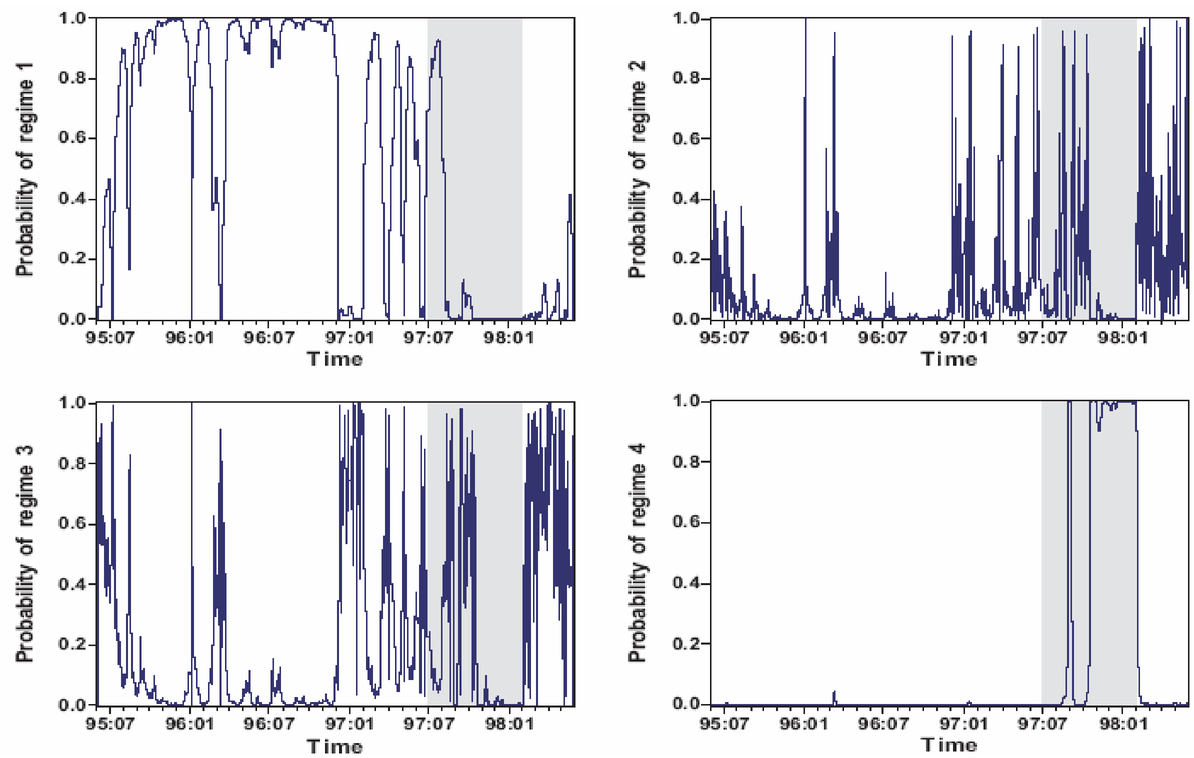
Table 3.2 Parameter estimates

States			Parameters					Transition matrix $\mathbf{P}$			
S_t	S_t^X	S_t^Y	μ_1^X	σ_X^2	μ^Y	σ_Y^2	ρ^{XY}	(l,l)	(l,h)	(h,l)	(h,h)
1	calm(l)	calm(l)	0.049	1.021	0.123	0.874	0.194	0.969	0.031	0.000	0.000
			(0.005)	(0.128)	(0.009)	(0.094)	(0.066)				
2	calm(l)	crisis(h)	0.049	0.849	-0.466	2.438	0.381	0.000	0.174	0.826	0.000
			(0.005)	(0.081)	(0.101)	(0.394)	(0.083)				
3	crisis(h)	calm(l)	-0.055	1.798	0.123	1.137	0.239	0.072	0.294	0.620	0.014
			(0.008)	(0.201)	(0.009)	(0.121)	(0.025)				
4	crisis(h)	crisis(h)	-0.055	2.469	-0.466	4.814	0.476	0.000	0.032	0.000	0.968
			(0.008)	(0.237)	(0.101)	(0.315)	(0.051)				

Note: Standard errors in parentheses.

In Table 3.2 we present the estimated parameters from the model that satisfies the hypothesis of feedback causality between capital markets. The means on both markets are positive in the calm regime and they are negative in the crisis regime. This suggests that the market indices were falling on average during the crisis and growing during the calm periods. Similarly, the volatility of both index returns is the highest when both markets are in a crisis regime and the volatility is always higher on the specific market when the particular market enters a crisis regime. It must be noted that the latter result was obtained despite the lack of any constraints on the variance parameters in our model.

Figure 3.1 Smoothed probabilities of different regimes during the Asian crisis



Note: The shaded area includes the period from July 1, 1997, to January 31, 1998.

From the estimated parameters in the transition matrix one can infer that regimes where both markets are in the same state of calm or crisis are very persistent. Once the markets enter one of these regimes, they stay there for a longer period. The other two regimes, 2 and 3, are less persistent. Figure 3.1 confirms these observations. It presents the smoothed probabilities of being in the particular state conditional on information from the entire sample. State 1, where both markets are in the calm regime, dominates in the period from June, 1995 till the end of 1996. State 4 is persistent in the period from July, 1997 to January, 1998, which corresponds to the crisis period described in the literature (e.g. Corsetti, Pesenti, and Roubini (1999)). In contrast, the states 2 and 3 are not stable, but are frequently visited and left in the period from the beginning of 1997 till the period from the beginning of 1997 till the beginning of the crisis in July 1997 and after the crisis in 1998.

All regimes together reveal some interesting patterns of shock transmission between the markets. First, when both markets are in a calm regime, they will either stay in this regime (p_{11}=0.969) or switch to a regime where Japan is still in a calm state and Hong Kong is in a state of turmoil (p_{12}=0.031). This suggests that Hong Kong enters the crisis first and it is followed by the Japanese market on the next day. Then, Hong Kong sometimes stays in the crisis (p_{22}=0.174), but usually it switches to a calm state while Japan replicates the move of Hong Kong from the preceding day and enters a crisis (p_{23}=0.826). Japan usually stays longer in the crisis (p_{33}=0.620), sometimes exchanges regimes with Hong Kong (p_{32}=0.294), or follows Hong Kong into a calm regime (p_{31}=0.072). It is rare that Hong Kong accompanies Japan into crisis when Japan is already there (p_{34}=0.014), but it is the only way for both markets to get into the crisis (p_{14}=p_{24}=0.000). Once the markets are in a crisis regime, they will, with a high probability, stay there till the next period (p_{44}=0.968) or the Japanese market will leave first (p_{42}=0.032).

Generally, the Hong Kong market enters a crisis first, but it often switches between calm and crisis. Japan follows Hong Kong into crisis and remains in this state much longer. Eventually, both markets are in crisis and stay there until Japan leaves it first. These findings show that the behavior of both markets during the Asian crisis was more complicated than the contagion hypothesis assumes (Sola, Spagnolo, and Spagnolo (2002)).

Table 3.3 Probabilities conditional on information from the foreign market

Conditional probabilities			
HSI on Nikkei225		Nikkei225 on HSI	
$P(S_t^Y = l \mid S_{t-1}^X = h)$	0.105	$P(S_t^X = l \mid S_{t-1}^Y = h)$	0.482
$P(S_t^Y = h \mid S_{t-1}^X = h)$	0.850	$P(S_t^X = h \mid S_{t-1}^Y = h)$	0.518
$P(S_t^Y = h \mid S_{t-1}^X = l)$	0.055	$P(S_t^X = h \mid S_{t-1}^Y = l)$	0.191
$P(S_t^Y = l \mid S_{t-1}^X = l)$	0.945	$P(S_t^X = l \mid S_{t-1}^Y = l)$	0.809

Financial investors are interested in the probability of one market entering crisis when the other market was there one period earlier. In Table 3.3 we present such conditional probabilities. We observe that the markets tend to replicate the regimes of the other market from the preceding period. It seems that the Japanese market more often avoids entering a crisis regime despite the other market being there one period earlier. Similarly, there is a higher probability that the Japanese market enters a crisis than that the Hong Kong market enters the crisis conditional on the information that the other market was in a calm regime one day earlier. However, most market participants additionally possess the information about the state of the domestic market from one day earlier, which can dramatically change the estimates of the conditional probabilities. We present the calculations in Table 3.4.

Table 3.4 Probabilities conditional on information from home and foreign market

Conditional probabilities			
HSI on Nikkei225		Nikkei225 on HSI	
$P(S_t^Y = h \mid S_{t-1}^X = h \wedge S_{t-1}^Y = h)$	1.000	$P(S_t^X = h \mid S_{t-1}^X = h \wedge S_{t-1}^Y = h)$	0.968
$P(S_t^Y = h \mid S_{t-1}^X = l \wedge S_{t-1}^Y = h)$	0.174	$P(S_t^X = h \mid S_{t-1}^X = h \wedge S_{t-1}^Y = l)$	0.634
$P(S_t^Y = h \mid S_{t-1}^X = h \wedge S_{t-1}^Y = l)$	0.308	$P(S_t^X = h \mid S_{t-1}^X = l \wedge S_{t-1}^Y = h)$	0.826
$P(S_t^Y = h \mid S_{t-1}^X = l \wedge S_{t-1}^Y = l)$	0.031	$P(S_t^X = h \mid S_{t-1}^X = l \wedge S_{t-1}^Y = l)$	0.000
$P(S_t^Y = l \mid S_{t-1}^X = l \wedge S_{t-1}^Y = l)$	0.969	$P(S_t^X = l \mid S_{t-1}^X = l \wedge S_{t-1}^Y = l)$	1.000
$P(S_t^Y = l \mid S_{t-1}^X = h \wedge S_{t-1}^Y = l)$	0.692	$P(S_t^X = l \mid S_{t-1}^X = l \wedge S_{t-1}^Y = h)$	0.174
$P(S_t^Y = l \mid S_{t-1}^X = l \wedge S_{t-1}^Y = h)$	0.826	$P(S_t^X = l \mid S_{t-1}^X = h \wedge S_{t-1}^Y = l)$	0.366
$P(S_t^Y = l \mid S_{t-1}^X = h \wedge S_{t-1}^Y = h)$	0.000	$P(S_t^X = l \mid S_{t-1}^X = h \wedge S_{t-1}^Y = h)$	0.032

Based on these results, we can more precisely forecast the future state of each market. the Japanese market will almost never enter a crisis when both markets are in a calm state the day before. The Hong Kong market will enter a crisis with the probability 0.031. Analogously, both markets will with a very hogh probability remain in crisis regimes provided that they were in crisis regimes in the preceding period. Generally, the probabilities from Table 3.4 differ significantly from those presented in Table 3.3, which suggests that the information about the past states of the local market is important for forecasting its future state. Nevertheless, the information about the performance of the Japanese market today is relevant for the state of the Hong Kong market tomorrow and the state of the Hong Kong market today determines the future state of the Japanese market.

In this study we assume that all information is transferred between markets at the latest on the next working day, which is reasonable at the time when even emerging markets are fully computerized and most public information is available immediately. However, in general it is possible that one market is followed by another market with a lag of two days or more. Hamilton and Lin (1996) and Sola, Spagnolo, and Spagnolo (2002) propose specifications which allow for testing independence and contagion with two lags. However, these methods require a transition matrix to be twice as large or a more complicated set of restrictions. Therefore, we leave development of tests for causality at higher lags for future research.

3.3 Comments on the Markov Switching Framework

In chapter 3, we present a methodology to construct different types of relationships between financial markets using a bivariate Markov switching model. We explicitly define the hypotheses of causality, regime-independence, and contagion, describe estimation of the model, and present likelihood ratio tests for the hypotheses of causality, regime-independence, and contagion. In this way we introduce the Granger causality approach to the Markov switching model of asset returns, which is related to the methodology of Psaradakis, Ravn and Sola (2003).

This methodology has several advantages over other approaches used to estimate links between the markets. First, it allows testing of various hypotheses of dependencies between financial markets. The models do not assume any specific linear or nonlinear links between stock index returns. All hypotheses of causality, contagion, and independence are defined in relation to probability measures. Second, this approach differentiates between calm and crisis periods, which are modeled as multiple random events rather than the dates assumed to be known a priori or structural changes taking place in the sample (Psaradakis, Ravn, and Sola (2003)). The causality patterns are allowed to be asymmetrical with respect to states of calm and crisis, as argued by Sola, Spagnolo, and Spagnolo (2002). Using the Markov switching model, we are able to calculate the probability that one market enters a particular regime conditional on information about the past states of this and the other market.

Finally, the testing procedure enables us to differentiate between extreme types of inter-market dependencies (independence, contagion) and more frequently observed relationships (causality, feedback causality, dependence without causality). Naturally, the presented model provides a simplified description of dependencies between financial markets. There are surely other factors that impact both of the investigated markets and influence the inter-market relationship (Frankel and Rose (1996), Portes and Rey (1999), Billio and Pelizzon (2003), Wälti (2003) among others). For example, if one of the investigated markets absorbs some external information more quickly than the second market, one could wrongly conclude that the first market leads the second. Adding a variable representing common shocks to both markets, e.g. a third market or macroeconomic policy variable, to our model is possible, but increases the number of parameters and the size of the transition matrix. It also complicates the construction of restrictions in the transition matrix imposing causality or contagion. We leave this issue for further research.

As an empirical application, we model the relationship between the Japanese and Hong Kong markets during the Asian crisis in 1997. We find evidence of feedback causality between stock index returns on these markets, but we reject the hypotheses of contagion as defined by Sola, Spagnolo, and Spagnolo (2002). The characteristics of index returns on both markets are found to be typical for calm and crisis regimes. Lower index returns, higher volatility of returns, and higher correlation between markets are often observed during international financial crises and tumultuous periods (King and Wadhawani (1990), Longin and Solnik (2001), Forbes and Rigobon (2002)).

In contrast to previous studies, our clinical examination of the Asian crisis enables us to investigate the sequence of market crisis entrance. Additionally, for each market we calculate the probability of entering the specific regime conditional on the past performance of this and the other market. We note that estimated probabilities allow for an accurate prediction of the future states of the markets.

4. TESTING FOR FINANCIAL SPILLOVERS IN CALM AND TURBULENT PERIODS

The importance of cross-market linkages and spillovers between international stock markets is well established. The literature on this issue allows to draw at least two main conclusions. First, the empirical studies find that the US stock market is the dominant capital market influencing other mature and developing stock markets (Eun and Shim (1989), Hamao, Masulis, and Ng (1990), Lin, Engle, and Ito (1994), Peiró, Quesada, and Uriel (1998), Ng (2000)). International stock markets are strongly correlated with the US market and past US stock returns affect present returns on other markets. Lagged spillovers are particularly interesting to investigate, because stock markets with some delay assimilate important news from other markets. The most likely reasons may be inefficiencies of international stock markets, different opening hours on those markets, and non-synchronous trading (Cheung and Ng (1996), Peiró, Quesada, and Uriel (1998)). Analyzing lead-lag effects enables investors to learn about the structure and direction of financial spillovers, which is important for effective portfolio allocation and risk management (e.g., Ang and Bekaert (2002, 2003)).

Second, investigations in the field of stock market linkages suggest that stock returns are more volatile and more correlated with each other during turbulent periods compared to tranquil periods (King and Wadhwani (1990), Karolyi and Stulz (1996), Longin and Solnik (2001), Forbes and Rigobon (2002)). A rising positive correlation may suggest a decrease of capital diversification opportunities across markets during financial crises (Ang and Bekaert (2002), Bekaert and Harvey (2003)). The differences in financial spillovers during calm and turmoil periods are of special interest to agents who want to learn about the chance of having a crisis at the home market today, when there was a negative shock to another market yesterday. International investors can adjust their portfolio strategies to a changing structure of spillovers in different regimes. Moreover, financial market regulators are concerned about the vulnerability of home capital markets to international crises.

Despite the importance of both aspects only a few studies investigate changes in lead-lag effects of financial spillovers during calm periods and financial crises. The scarce findings suggest that spillovers from one market to other markets are found to be stronger when the former market is hit by some negative shock (Malliaris and Urrutia (1992), Sola, Spagnolo, and Spagnolo (2002), Chen, Chiang, and So (2003), Climent and Meneu (2003), Sander and Kleimeier (2003)). However, whether stock markets undergoing financial distress are still vulnerable to spillovers from other markets is an open question. Finding an answer to this issue may help in analyzing sources of financial crises. Stronger spillovers to turmoil stock markets could point to contagion as the main source of crises, while weaker spillovers could suggest an individual character of financial distress. We attempt to answer this question in this chapter.

Most studies analyzing spillovers between stock markets during tranquil and crisis times do not take into account that the two analyzed markets can be in two different regimes of crisis or calm, i.e., for example, the stock market following the other market can be in the state of crisis independently of the state of the leading market. Another drawback of some studies is the ad hoc method used to identify crisis and calm periods (e.g., Malliaris and Urrutia (1992), Forbes and Rigobon (2002), Dungey and Zhumabekova (2001)). For example, in Chen, Chiang, and So (2003) the two regimes are explicitly defined as past stock returns exceeding (or falling below) an estimated threshold level. Moreover, earlier studies usually concentrate on specific events.

In this chapter, we consider spillover effects from the US stock market to three major markets in Japan, the United Kingdom, and Germany over the period from 1984 to 2003 as well as sub-samples. We compare spillover effects during tranquil and turbulent periods and address the problems expressed above by extending the Markov switching model proposed by Phillips (1991). Phillips developed a bivariate Markov switching model to evaluate the transmission of business cycles between countries. Sola, Spagnolo, and Spagnolo (2002) applied this approach in the framework of financial markets to test their specific hypothesis of contagion across stock markets during the Asian crisis in 1997. Edwards and Susmel (2001) added lagged returns and conditional autoregressive heteroscedasticity into the model specification and investigated tests of independence and co-movements between international emerging stock markets in 1990s.

We construct a model of stock index returns for two markets analogous to the one proposed by Sola, Spagnolo, and Spagnolo (2002) and develop a test to investigate the hypotheses that, first, one market leads the other in both turmoil and tranquil periods and, second, one market leads the other only when the latter is already in a turmoil (calm) period. In this way we extend the methodology proposed by Edwards and Susmel (2001) and Sola, Spangolo, and Spagnolo (2002), used to test financial contagion and independence by applying tests for financial spillovers in a Markov switching framework (see also Ravn and Sola (1995), Hamilton and Lin (1996), Psaradakis, Ravn, and Sola (2004)).

Our testing procedure has several advantages over other approaches to analyze the transmission of spillovers across stock markets. First, for each stock market it differentiates between calm and turbulent regimes. Thus, the method allows for a measurement of spillovers depending on the state of the market. The empirical literature suggests that multi-regime switching models of stock returns perform better than one-regime models (Cecchetti, Lam, and Mark (1990), Turner, Stratz, and Nelson (1990), Rydén, Teräsvirta, and Åsbrink (1998), Ang and Bekaert (2002)). Second, our procedure does not require an ad hoc identification of periods to examine spillovers between stock markets. Instead it estimates the probabilities of being in the crisis in a joint framework with all parameters of the model. Third, correlation and regression measures often fail to explore non-linear relations between variables. We offer a test on cross-market spillovers which does not depend on a specific linear or non-linear structure of linkages between stock returns. Fourth, Sola, Spagnolo, and Spagnolo (2002) provide a test of extreme spillovers, which they call a test of contagion. Our test is more flexible than the one applied there, since it examines a wider range of possible spillovers between the stock markets.

Finally, as an additional characteristics, most of the studies do not explicitly define spillovers between stock markets. In this chapter, we provide a definition of one market leading other market that allows for distinguishing between lead-lag relations in calm and turbulent periods. This definition is consistent with the notion of causality, while in the context of financial crises it suits well the concept of contagion. To distinguish between extreme cases of spillovers we provide explicit definitions of independence (no spillovers) and contagion, which are in line with Sola, Spagnolo, and Spagnolo (2002), and compare the empirical results for tests based on those definitions.

The remainder of this chapter is organized as follows. In the next section (4.1) we describe the model based on the idea of Phillips (1991) to estimate stock index returns on two markets. Section 4.2 discusses our definitions of financial spillovers and discusses the tests for dependencies between the markets. Data and empirical results on spillovers from the US stock market to the Japanese, British, and German stock market are presented in section 4.3. Section 4.4 summarizes results of using the presented methodology to test for asymmetric spillovers.

4.1 Modeling Index Returns on Two Markets

Our econometrical starting point is a Markov switching model of index returns on two markets. Let Z be the vector $[X, Y]'$, where $X = \{x_t,\ t \in N\}$ and $Y = \{y_t,\ t \in N\}$ are the two time series that can be interpreted as stock market index returns on two separate markets.

Both index returns are allowed to enter one of the two complementary states of "crisis" and "calm" periods. Using all four combinations of these states we construct a Markov process with four regimes and we use the index s to denote these regimes. "X and Y are in the calm states" defines the first regime $(s=1)$. "X is in the calm state and Y is in the crisis state" denotes the second one $(s=2)$. The third regime indicates that "X is in the crisis state and Y is in the calm state" $(s=3)$. "X and Y are in the crisis states" defines the fourth regime $(s=4)$.

At each point in time, the state s is determined by an unobservable Markov chain. The dynamics of the Markov chain are described by a 4×4 transition matrix P:

$$P=\begin{pmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{pmatrix}, \tag{4.1}$$

where p_{ij} denotes the probability of changing the state from i to j. Assume that the 2×1 vector $z_t=[x_t, y_t]'$ is driven by the four-state regime switching process:

$$z_t=\mu_s+\Theta_s u_t, \tag{4.2}$$

where u_t is a Gaussian process with zero mean and positive-definite covariance matrix Σ. The vector z_t is generated by the mixture of normal distributions with the mean μ_s and the covariance matrix Σ_s, both depending on the state s:

$$z_t \mid (s_t=s) \sim N(\mu_s, \Sigma_s) \tag{4.3}$$

and:

$$\Sigma_s=\Theta_s'\Sigma\Theta_s \tag{4.4}$$

for $s=1,2,3,4$. Thus, the model is called a (four-state) Markov switching mixture of normal distributions and it consists of 32 independent parameters, namely two parameters of means for each state, three independent parameters from Σ_s for each state, and twelve independent parameters from the transition matrix P. In this model no constraints are imposed on the parameters of means, variances, correlations, and parameters from the transition matrix P.

Economists highlight the significance of changes in return volatility during crisis periods. The high variance of index returns characterizes turmoil periods and the low variance characterizes tranquil periods. Additionally, the correlation coefficients between returns on different markets tend to increase when one of the markets enters the crisis regime (e.g. King and Wadhwani (1990), Karolyi and Stulz (1996), Longin and Solnik (2001), Forbes and Rigobon (2002)). However, some authors define crisis regimes as low average returns observed over longer periods or appearance of unusually low returns (Longin and Solnik (2001), Chen, Chiang, and So (2003), Mishkin and White (2003), Hartmann, Straetmans, and de Vries (2004)).

Therefore, in this study we highlight the importance of changes in the variance and correlation by allowing them to take different values in all four regimes. Moreover, we restrict the parameter space by assuming that the mean of returns on each market switches between its high and low value depending on the state of this market. The high value of mean describes a market in the calm regime and the low value of mean describes a market in the tranquil regime. We expect low mean returns, high variances, and high correlation when both markets are in the crisis regime and high means, low variances, and low correlation when both markets are in the tranquil regime. The parameter space for means, variances, and correlations between returns on the two markets is defined as follows:

$$\mu = \left\{ \mu_{s=1} = \begin{bmatrix} \mu_T^X \\ \mu_T^Y \end{bmatrix}, \mu_{s=2} = \begin{bmatrix} \mu_T^X \\ \mu_C^Y \end{bmatrix}, \mu_{s=3} = \begin{bmatrix} \mu_C^X \\ \mu_T^Y \end{bmatrix}, \mu_{s=4} = \begin{bmatrix} \mu_C^X \\ \mu_C^Y \end{bmatrix} \right\}, \tag{4.5a}$$

$$\sigma = \left\{ \sigma_{s=1} = \begin{bmatrix} \sigma_{T_1}^X \\ \sigma_{T_1}^Y \end{bmatrix}, \sigma_{s=2} = \begin{bmatrix} \sigma_{T_2}^X \\ \sigma_{C_1}^Y \end{bmatrix}, \sigma_{s=3} = \begin{bmatrix} \sigma_{C_1}^X \\ \sigma_{T_2}^Y \end{bmatrix}, \sigma_{s=4} = \begin{bmatrix} \sigma_{C_2}^X \\ \sigma_{C_2}^Y \end{bmatrix} \right\}, \tag{4.5b}$$

and

$$\rho = \{\rho_{s=1} = \rho_{TT}^{XY}, \rho_{s=2} = \rho_{TC}^{XY}, \rho_{s=3} = \rho_{CT}^{XY}, \rho_{s=4} = \rho_{CC}^{XY}\}. \quad (4.5c)$$

Symbols T, T_1, and T_2 denote the state of tranquility on the respective market (the numbers are to distinguish between different values of a particular parameter in different regimes). Symbols C, C_1, and C_2 denote the crisis state. The transition matrix remains unconstrained, therefore we call this model a "general" or "unconstrained" model.

In order to examine how our model fits the data we use several tests proposed by Breunig, Najarian, and Pagan (2003). We compare the means, variances, and peaks of the empirical distributions of the original data and the data simulated from our model. Additionally, we investigate a "leverage effect" for both sets of data. The leverage effect is a common feature of stock returns indicating higher volatility of returns when past returns are negative (e.g. Black (1976), Engle and Ng (1993)). We find that our models are consistent with the original data in all cases and for all tests.

4.2 Independence, Spillovers, and Contagion

In addition to the Markov switching model we need definitions of regime-independence, contagion and spillovers. These definitions enable us to assess the strength of shock transmission between the markets during stable and turmoil periods. Moreover, the definitions provide us the basis to distinguish between spillovers when one of the markets is in the crisis or in the calm state. We also describe the tests for no spillovers and contagion and propose our testing procedures to analyze the hypotheses of, first, one market leading the other during calm periods and, second, one market leading the other during crisis periods. The null hypothesis is that a spillover effect exists between the markets in both periods.

There exist several definitions of contagion and methods to test them. The definitions presented in this chapter are strongly related to the original description of contagion discussed in Eichengreen, Rose, and Wyplosz (1996) (Pericoli and Sbracia (2003), Hartmann, Straetmans, and de Vries (2004), and Fontaine (2005) among others). Contagion is defined there as "a significant increase in the probability of a crisis in one country, conditional on a crisis occurring in another country". Sola, Spagnolo, and Spagnolo (2002) suggested an extreme case of this definition, where the probability of having a crisis at home equals one if the crisis hits another market. We explore their methodology (Definitions 1 and 2) and propose a modest alternative that suits more closely the description presented above (Definition 3).

Another branch of studies explore changes in the structure of inter-market linkages, i.e. “shift-contagion” hypothesis (Forbes and Rigobon (2001)). They usually analyze changes in the correlation of international stock returns (e.g. King and Wadhawani (1990), Forbes and Rigobon (2002), Pericoli and Sbracia (2003)) or define contagion as excessive spillovers from one market into another during turbulent periods beyond structural linkages between these markets (Rigobon (2003)). Although we concentrate on the tests of financial spillovers based on the probability measures, our modeling framework provides evidence on changing correlation of stock returns on different markets in stable and turbulent regimes.

Yet one more group of investigations focus on coincidence of extreme return shocks across countries as evidence of contagion (Longin and Solnik (2001), Bae, Karolyi, and Stulz (2003), Hartman, Streatman, and de Vries (2004)). Bae, Karolyi, and Stulz express the concern that correlations which give equal weight to small and large shocks are not appropriate for an evaluation of the impact of large (possibly negative) returns. Similarly to their study, our model allows to evaluate the likelihood of joint occurrence of low and large returns on different markets. The low and large returns are distinguished here using multiple regimes and changes in the correlation structure are conditional on these regimes.

Other strategies to empirically study contagion include testing whether markets respond to news from other markets, analyzing the significance, size, and changes of coefficients in (limited dependent variable) regressions, VAR, and GARCH models, and studying inter-market correlation after controlling for market fundamentals. Many definitions of contagion and their applications are surveyed in Dornbusch, Park, and Claessens (2000), Claessens and Forbes (2001), Billio and Pelizzon (2003), Karolyi (2003), Moser (2003), Pericoli and Sbracia (2003), and on World Bank web pages.

Definition 1. Let $Z = [X \;\; Y]'$ be described by the Markov switching model introduced above. Y is said to be "regime-independent" of X if the event that Y enters the state i at time t is independent of the present and past states of X, where i is the crisis or calm regime in our Markov switching model.

Sola, Spagnolo, and Spangolo (2002) employ the definition of regime-independence of X and Y to test for contagious spillovers between financial markets. In case Y and X are regime-independent the following restrictions are imposed on the transition matrix P:

$$P = \begin{pmatrix} \pi_{TT}^{X}\pi_{TT}^{Y} & \pi_{TT}^{X}(1-\pi_{TT}^{Y}) & (1-\pi_{TT}^{X})\pi_{TT}^{Y} & (1-\pi_{TT}^{X})(1-\pi_{TT}^{Y}) \\ \pi_{TT}^{X}(1-\pi_{CC}^{Y}) & \pi_{TT}^{X}\pi_{CC}^{Y} & (1-\pi_{TT}^{X})(1-\pi_{CC}^{Y}) & (1-\pi_{TT}^{X})\pi_{CC}^{Y} \\ (1-\pi_{CC}^{X})\pi_{TT}^{Y} & (1-\pi_{CC}^{X})(1-\pi_{TT}^{Y}) & \pi_{CC}^{X}\pi_{TT}^{Y} & \pi_{CC}^{X}(1-\pi_{TT}^{Y}) \\ (1-\pi_{CC}^{X})(1-\pi_{CC}^{Y}) & (1-\pi_{CC}^{X})\pi_{CC}^{Y} & \pi_{CC}^{X}(1-\pi_{CC}^{Y}) & \pi_{CC}^{X}\pi_{CC}^{Y} \end{pmatrix}, \qquad (4.6)$$

where π_{ij}^{Q} denotes the probability of entering the state j by the time series Q at time t when it was in the state i at time $t-1$. $Q \in \{X, Y\}$, $i, j \in \{T, C\}$, and T and C denote the calm and crisis regimes, respectively. It should be noted that regime-independence does not imply independence of X and Y, since they are still allowed to be correlated with each other.

Definition 2. Contagion from X to Y is present when the probability that Y enters the state i at time t conditional on the information that X was in this state at time $t-1$ is equal one, where i denotes the crisis or calm regime in our Markov switching model.

According to this definition the stock index return Y has to enter a specific regime, e.g. the crisis regime, if the stock index return X was there one period earlier. Thus, the sum of conditional probabilities p_{11} and p_{13} in the transition matrix P can be formulated as:

$$p_{11} + p_{13} = 1. \tag{4.7}$$

Calm and crisis are complementary events and we can express the sum of the probabilities as:

$$p_{11} + p_{13} = \Pr(Y_t \text{ in calm } | \ X_{t-1} \text{ in calm } \textit{and } Y_{t-1} \text{ in calm}) \tag{4.8}$$

because:

$$p_{11} = \Pr(X_t \text{ in calm and } Y_t \text{ in calm } | \ X_{t-1} \text{ in calm and } Y_{t-1} \text{ in calm}), \tag{4.9}$$

$$p_{13} = \Pr(X_t \text{ in crisis and } Y_t \text{ in calm } | \ X_{t-1} \text{ in calm and } Y_{t-1} \text{ in calm}). \tag{4.10}$$

Analogously, the other constraints on the transition matrix are:

$$p_{21} + p_{23} = 1, \tag{4.11}$$

$$p_{32} + p_{34} = 1, \tag{4.12}$$

$$p_{42} + p_{44} = 1 \tag{4.13}$$

and the transition matrix P takes on the form:

$$P = \begin{pmatrix} p_{11} & 0 & 1-p_{11} & 0 \\ p_{21} & 0 & 1-p_{21} & 0 \\ 0 & p_{32} & 0 & 1-p_{32} \\ 0 & p_{42} & 0 & 1-p_{42} \end{pmatrix}. \tag{4.14}$$

Our definition of contagion is a less restrictive version of the one put forward by Sola, Spagnolo, and Spagnolo (2002) and is inspired by the work of Phillips (1991). Sola, Spagnolo, and Spagnolo set additional constraints assuming that $p_{11} = p_{21}$ and $p_{32} = p_{42}$, i.e. the probability that both markets, X and Y, enter the crisis or the calm regime does no depend on the regime of Y in the previous period. Thus, the past realizations of Y do not influence X when there is contagion from X to Y. Such an additional restriction has been criticized in the financial contagion literature due to the possibility of an estimation bias coming from overlooking the bi-directional transmission of shocks between the markets (Forbes and Rigobon (2002), Billio and Pelizzon (2003), Moser (2003), Rigobon (2003)).

Additionally, the idea of contagion is usually associated with financial crises spilling over from one market to other markets. One can expect that one market infects the other market only when it is in the crisis regime. Such a definition of "contagion in the crisis regime" corresponds to the transition matrix:

$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ 0 & p_{32} & 0 & 1-p_{32} \\ 0 & p_{42} & 0 & 1-p_{42} \end{pmatrix}. \tag{4.15}$$

The important characteristics of these definitions are identification of direction of contagion and financial spillovers from one market to another occurring with a lag, which allows for identification of delays in information or capital flows between markets (Climent and Meneu (2003), Sander and Kleimeier (2003)). Our contagion definitions in the spirit of Sola, Spagnolo, and Spagnolo (2002) are very restrictive. Even rejecting them does not imply that one market does not lead the other (Ravn and Sola (1995)). Therefore, we propose a weaker form of inter-market dependency that fits well the idea of increased probability of a crisis at home, given the crisis occurred abroad and is based on the notion of financial spillovers and causality (e.g., Geweke (1984)).

Definition 3. X leads Y by one period if the magnitude of the probability that Y enters the state i at time t depends on whether X was in the state j at time $t-1$, where i and j are allowed to be the crisis or calm regimes in our Markov switching model.

We understand dependence as evidence of the difference in conditional probabilities of Y entering the state i, when X was in the calm state or in the crisis state at time $t-1$, respectively. The case of X leading Y is interpreted in the context of inter-market linkages as a presence of financial spillovers from one market to the other. For example, the definition of spillovers comprises the situation when the probability of one market entering the crisis regime depends not only on whether this market was in the state of crisis one period earlier, but also on whether the other market was there in the previous period:

$$\Pr(Y_t \text{ in crisis } | X_{t-1} \text{ in crisis and } Y_{t-1} \text{ in crisis})$$

$$\neq \Pr(Y_t \text{ in crisis } | X_{t-1} \text{ in calm and } Y_{t-1} \text{ in crisis}), \qquad (4.16)$$

which can be expressed in terms of parameters from the transition matrix P as:

$$p_{22} + p_{24} \neq p_{42} + p_{44}. \qquad (4.17)$$

Analogously, the following inequalities must be valid if X leads Y in all regimes:

$$p_{11} + p_{13} \neq p_{31} + p_{33}, \qquad (4.18)$$

$$p_{21} + p_{23} \neq p_{41} + p_{43}, \qquad (4.19)$$

$$p_{12} + p_{14} \neq p_{32} + p_{34}, \qquad (4.20)$$

$$p_{22} + p_{24} \neq p_{42} + p_{44}. \qquad (4.21)$$

If one assumes that no spillovers exist between the markets in any regimes, the inequalities (18) to (21) become equalities and then the transition matrix P is defined as:

$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{42} + p_{44} - p_{24} & p_{41} + p_{43} - p_{21} & p_{24} \\ p_{31} & p_{12} + p_{14} - p_{34} & p_{11} + p_{13} - p_{31} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{pmatrix}. \qquad (4.22)$$

It can be shown that the constraint $p_{22} = p_{42} + p_{44} - p_{24}$ is equivalent to $p_{23} = p_{41} + p_{43} - p_{21}$ and that the constraint $p_{32} = p_{12} + p_{14} - p_{34}$ is equivalent to $p_{33} = p_{11} + p_{13} - p_{31}$. Therefore, the parameters p_{23} and p_{33} can be set unconstrained in the estimation process.

Additionally, one can assume that no spillovers from X to Y will be present at time $t+1$ in case Y is in the crisis state at time t. For example, the influence of the US market on the Japanese market could strongly diminish, when the Japanese market is hit by the strong internal crisis. In this case the transition matrix P will be defined as follows:

$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{12} + p_{14} - p_{34} & p_{11} + p_{13} - p_{31} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{pmatrix}. \tag{4.23}$$

Alternatively, the opposite hypothesis of no spillovers from X to Y when Y is in the calm regime may be denoted by:

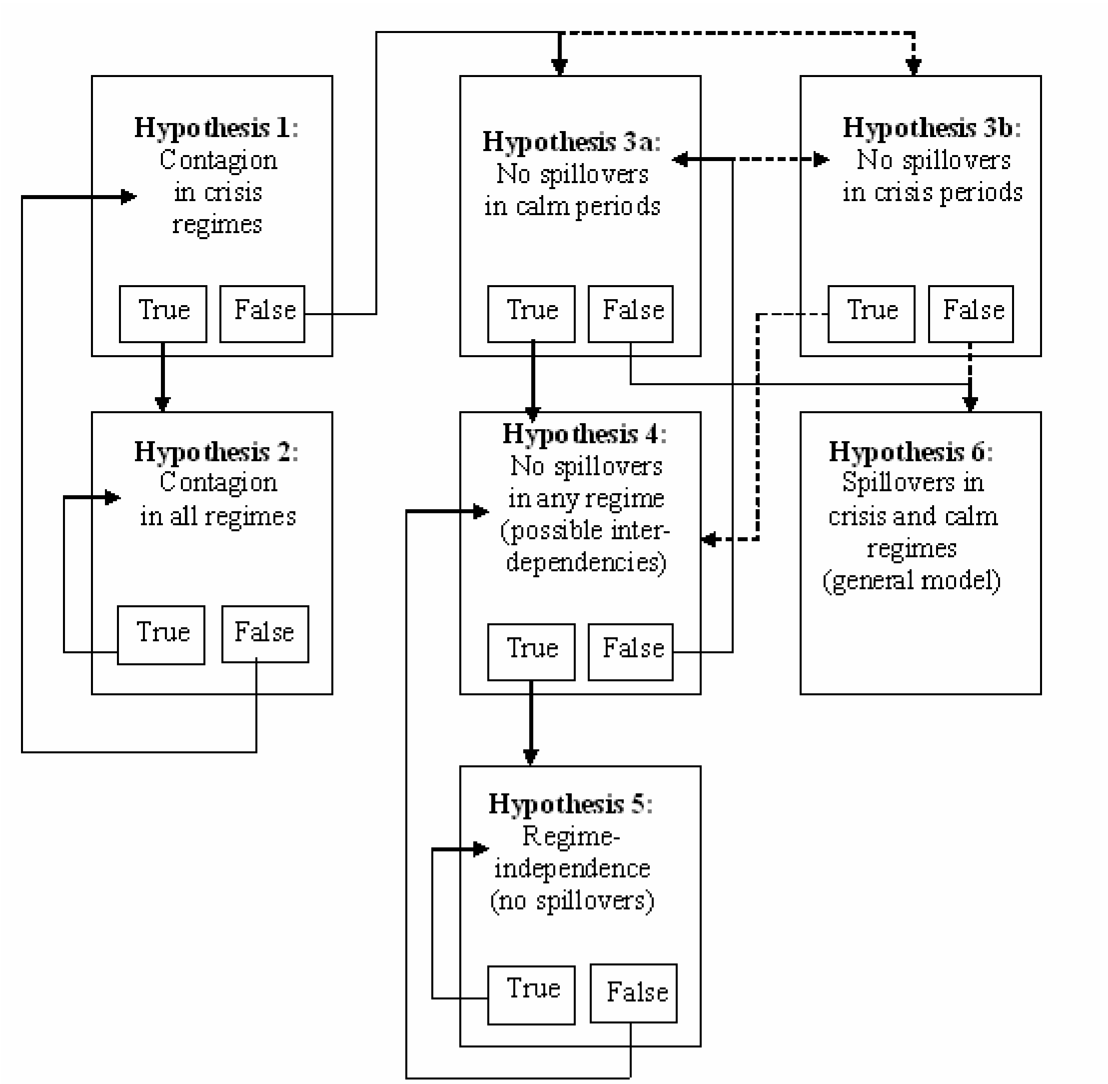
$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{42} + p_{44} - p_{24} & p_{41} + p_{43} - p_{21} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{pmatrix}. \tag{4.24}$$

Generally, the Markov switching approach fits well the idea of investigating spillovers and contagion between the markets during stable and turmoil periods. Analyzing differences between spillovers to calm and crisis markets is made possible by setting the suitable restrictions on parameters from the transition matrix. Thus, one does not need to assume any specific linear or nonlinear structure of spillovers between the markets, like in autoregressive and ARCH models, since both contagion and spillovers are introduced directly through the probability measures.

The definitions introduced above are helpful in building tests of financial contagion, spillovers, and independence between the markets. The general model, described by the equations (4.1) to (4.5), imposes no restrictions on the transition matrix P and assumes financial spillovers in both stable and turbulent regimes. It can be estimated using the standard Expectation-Maximization (EM) algorithm, similarly to Hamilton (1989, 1990). A similar technique is applied to estimate the contagion models, employing equations (4.2) to (4.5) and transition matrices (4.14) and (4.15). The models assuming regime-independence (no spillovers), no spillovers in crisis periods, no spillovers in calm periods, and no spillovers in any regime use the transition matrices (4.6), (4.23), (4.24), and (4.22), respectively.

These models with constrained transition matrices are estimated using an algorithm analogous to the one described by Phillips (1991). Details are available upon request. The log-likelihood values corresponding to the estimates are denoted by $L_{SPILLOVERS}$ for the general model with no constraint on the transition matrix P, $L_{INDEPENDENCE}$ for the regime-independence model, $L_{CONTAGION}$ for the contagion model, $L_{CONTAGION\ IN\ CRISIS}$ for the "contagion during crises" model, and $L_{NO\ SPILLOVERS}$, $L_{NO\ SPILLOVERS\ IN\ CRISIS}$, $L_{NO\ SPILOVERS\ IN\ CALM}$ for the no-spillover models with the transition matrices (4.22), (4.23), and (4.24), respectively.

Figure 4.1 The Financial Spillovers Hypotheses and Their Testing Sequence



We describe now our testing procedure used to explore possible interdependencies between capital markets. In Figure 4.1 the testing hypotheses are ordered in the general-to-specific sequence. Exceptions are Hypotheses 3a and 3b, which are not nested in Hypothesis 2. We start with testing the null hypothesis assuming that there is contagion from X to Y when both markets are in the crisis regime (Hypothesis 1) against the alternative of no contagion. Under the null hypothesis, the likelihood ratio statistic:

$$LR = 2(L_{SPILLOVERS} - L_{CONTAGION\ \ IN\ CRISIS}) \sim \chi^2(4) \tag{4.25}$$

has the standard asymptotic χ^2 distribution with four degrees of freedom. If the null hypothesis can be accepted, we continue with testing the hypothesis that contagion exists in both calm and crisis regimes (Hypothesis 2). We use the likelihood ratio statistic:

$$LR = 2(L_{SPILLOVERS} - L_{CONTAGION}) \sim \chi^2(8), \tag{4.26}$$

which has the asymptotic χ^2 distribution with eight degrees of freedom (Sola, Spagnolo, and Spagnolo (2002)).

If the Hypothesis 1 is rejected then no contagion exists in any regimes and we follow the procedure by analyzing the hypothesis that no spillovers from X to Y are present in cases Y was in the calm regime at time $t-1$ (Hypothesis 3a). Alternatively, one can test the hypothesis of no spillovers to Y in case Y was in the crisis regime at time $t-1$ (Hypothesis 3b). The respective statistics are:

$$LR = 2(L_{SPILLOVERS} - L_{NO\ \ SPILLOVERS\ \ IN\ CALM}) \sim \chi^2(1) \tag{4.27}$$

and:

$$LR = 2(L_{SPILLOVERS} - L_{NO\ \ SPILLOVERS\ \ IN\ CRISIS}) \sim \chi^2(1). \tag{4.28}$$

If the both hypotheses are rejected, we conclude that financial spillovers from X to Y are present in both regimes (Hypothesis 6) and finish the procedure here. When one of the above hypotheses, 3a or 3b, is accepted, we utilize the following statistic to test the Hypothesis 4 of no spillovers between the markets in any regime:

$$LR = 2(L_{SPILLOVERS} - L_{NO\ SPILLOVERS}) \sim \chi^2(2). \tag{4.29}$$

When this hypothesis is accepted, we conclude that X does not lead Y by one period, but some interdependencies between stock index returns on both markets, which take place simultaneously (e.g. on the same day) may still be present. The probability of one market entering the crisis or calm regime may still depend on the regime that the other market will enter collaterally. To rule out such dependencies between the markets we test the hypothesis that markets are regime-independent (Hypothesis 5) by applying the following test statistic:

$$LR = 2(L_{SPILLOVERS} - L_{INDEPENDENCE}) \sim \chi^2(12). \tag{4.30}$$

If this hypothesis is accepted, the markets enter any regimes independently of other markets (Phillips (1991), Sola, Spangolo, and Spagnolo (2002)). The flexibility of the test rests on the fact that both markets are still allowed to be correlated in each regime. This characteristic can almost always be observed between financial markets (e.g., Forbes and Rigobon (2002)).

The Markov switching models, employed by testing different hypotheses, differ only in parameters of the transition matrix P. In this way we avoid the problem of existence of some nuisance parameters that would be unidentified under the null hypotheses – a typical obstacle in testing multi-regime models. Therefore, our likelihood ratio statistics have their standard asymptotic distributions, as in Phillips (1991), Ravn and Sola (1995), and Sola, Spagnolo, and Spagnolo (2002).

The testing procedure outlined here is not meant to compare spillovers between the markets depending on the regime of the leading market. The important feature of the hypotheses 3a, 3b, and 4 is that they enable us to analyze the question raised in the introduction, whether markets undergoing a financial distress are more or less vulnerable to spillovers from other markets.

4.3 Data and Empirical Results

In this section, we report the results obtained from the testing methodology outlined above and present the calculated probabilities of a crisis on each market when there was a crisis on the US market one day earlier. In our analysis we employed the standard capital market indices from the four largest markets in the world. The S&P 500 index represents the US market, the NIKKEI 225 is the index for the Japanese market, the FTSE 100 index corresponds to the UK market, and the DAX stands for the German index. The index returns are computed as first differences of logged daily closing prices from the four markets and cover the period from April 3, 1984 to May 30, 2003, which corresponds to 4423 observations.

As argued in the introduction, the US is believed to be the dominating market leading other stock markets independently of crisis and calm periods. Therefore, in the empirical analysis we concentrate on spillovers from the US market to the other three markets, although the model applied here complies bi-directional interdependencies. Using the proposed algorithm, we check whether the structure of dependencies of the British, German, and Japanese markets on the US market should be called spillovers or rather contagion. In addition, we test for possible changes in the linkages between the markets during turbulent and calm periods. Next, we present the final models obtained from the testing procedure and compute the probabilities of the potential turmoil on the British, German, and Japanese market individually conditional on the information that the US market was in the turmoil regime one period earlier.

In order to analyze whether linkages between the markets have varied over time independently of crisis and calm regimes, we additionally calculate all tests for three non-overlapping sub-periods from April 3, 1984 to December 28, 1988, from January 4, 1989 to December 29, 1995, and from January 4, 1996 to May 30, 2003. The 1996 – 2003 sub-sample is characterized by a considerable high variance of index returns on all markets in comparison to previous periods, which could eventually influence the general results. We also divide the rest of the time series into the two sub-periods, where the 1989 – 1995 interval is a relatively stable period and the 1984 – 1988 period comprises the great crash of the 1987 that has been found to influence spillovers from the US to other markets (Malliaris and Urrutia (1992)).

Table 4.1 Log-likelihood values of the estimated markov switching models

	S&P 500 and NIKKEI 225	S&P 500 and FTSE 100	S&P 500 and DAX
$L_{SPILLOVERS}$	– 13222.11	– 11780.00	– 12957.88
$L_{NS\ IN\ CRISIS}$	– 13238.43	– 11834.50	– 12988.96
$L_{NS\ IN\ PROSPERITY}$	– 13235.73	– 11821.00	– 12979.50
L_{NS}	– 13247.70	– 11863.07	– 13006.06
$L_{INDEPENDENCE}$	– 13390.40	– 11858.60	– 13062.95
$L_{CONTAGION}$	– 13386.00	– 11840.58	– 13069.87
$L_{CONTAGION\ \ IN\ CRISIS}$	– 13331.62	– 11816.13	– 13003.45

Note: The log-likelihood values corresponding with the estimates are denoted by $L_{SPILLOVERS}$ for the general model, $L_{INDEPENDENCE}$ for the independence model, $L_{CONTAGION}$ for the contagion model, $L_{CONTAGION\ \ IN\ CRISIS}$ for the "contagion during crises" model, and L_{NS}, $L_{NS\ IN\ CRISIS}$, $L_{NS\ IN\ PROSPERITY}$ for the no-spillover models with the transition matrices (23), (24), and (22), respectively.

Each model of the bilateral linkages between the US market and the other market is estimated in seven different versions. The first version corresponds to the general model with no restrictions on the transition matrix P, which allows for potential spillovers between the markets. The second model assumes that both markets are regime-independent from each other and the third one assumes no spillovers from the US market to the other market. The fourth model is estimated under the constraint that no spillovers exist when the dependent market is in the state of crisis and the fifth one assumes no spillovers when the dependent market is in the calm regime. The sixth and seventh cases are the models of contagion from the US to the other market and contagion only in the crisis periods, respectively.

In Table 4.1 the log-likelihood values from the estimated models are presented. The general model has the highest likelihood value for each pair of markets, since all other models are restricted versions of the general model. Additionally, the "regime-independence" models are special cases of the "no-spillovers" models, which in turn set additional constraints in comparison to the "no-spillovers in crisis" and "no-spillovers in calm periods" models. Finally, the both "contagion" models are restricted forms of the general model.

Table 4.2 Tests of linkages between the markets

Null hypothesis	S&P 500 and NIKKEI 225	S&P 500 and FTSE 100	S&P 500 and DAX
Regime-independence	336.58**	157.20**	210.14**
No spillovers during calm	26.64**	82.00**	43.24**
No spillovers during crises	33.24**	109.00**	62.16**
No spillovers at any regimes	51.18**	127.19**	96.36**
Contagion	327.78**	121.16**	223.98**
Contagion during crises	219.02**	72.26**	91.14**

Note: * and ** denote rejection of the null hypothesis at the 5% and 1% levels, respectively.

To distinguish which models are statistically justified and which are too restrictive we employ the likelihood ratio statistics described in the previous section. All the results from our testing procedure are presented in Table 4.2. For all pairs of markets, the hypotheses of contagion and a weaker hypothesis of contagion in the crisis regime is rejected, which corresponds to the result of Sola, Spagnolo, and Spangolo (2002). Hence, we continue the procedure by testing the null hypotheses of no spillovers in crisis periods, no spillovers in calm periods, and no spillovers in any regimes. All of them are also rejected and we interpret these results as existence of spillovers from the US to the Japanese, British, and German markets independently of whether these latter markets are in crisis or calm regimes.

It is interesting to note that the test statistics for the hypothesis of no spillovers during crises always have higher values than the statistics for the hypothesis of no spillovers during calm periods. Assuming no spillovers when the Japanese, British, and German markets are in crisis regimes would be a more likely choice than assuming no spillovers in calm regimes. However, these both hypotheses, and models, are rejected as too restrictive. Finally, the regime-independence is also rejected in all cases, which confirms that some interdependencies are present between the US and other markets.

According to our results the best models of dependencies between the markets are the general unconstrained models allowing for spillovers in all regimes, but not restricting these spillovers only to contagion effects. We present the parameters of these final models in Table 4.3. It is important that all the models match the main empirical patterns found on international capital markets. First, the regime with low average index returns on both markets is characterized by higher volatility of index returns than the regime with both markets in calm periods. It is interesting to note that the highest (lowest) volatilities are always obtained in the same regime for both markets. Moreover, in each model the regime with highest volatilities on the two markets is the one with one market in the state of crisis and the other market in the state of calm.

Table 4.3 Final models of dependencies between the markets

State of X	State of Y	μ^X (%)	σ^X (%)	μ^Y (%)	σ^Y (%)	$corr(X,Y)$	Transition matrix P			
S&P 500	DAX									
calm	Calm	0.080 (0.007)	0.670 (0.023)	0.107 (0.013)	0.845 (0.035)	0.175 (0.066)	0.982	0.002	0.001	0.015
calm	crisis	0.080 (0.007)	5.944 (1.891)	0.019 (0.001)	4.994 (1.044)	0.315 (0.092)	0.000	0.566	0.043	0.391
crisis	calm	0.037 (0.004)	1.842 (0.495)	0.107 (0.013)	3.007 (0.747)	0.684 (0.171)	0.000	0.000	0.972	0.028
crisis	crisis	0.037 (0.004)	1.127 (0.297)	0.019 (0.001)	1.493 (0.444)	0.378 (0.092)	0.025	0.007	0.005	0.962
S&P 500	FTSE 100									
calm	calm	0.082 (0.006)	0.666 (0.084)	0.065 (0.005)	0.732 (0.091)	0.315 (0.024)	0.978	0.000	0.022	0.000
calm	crisis	0.082 (0.006)	8.717 (2.110)	– 0.088 (0.007)	5.250 (1.417)	0.493 (0.067)	0.000	0.513	0.382	0.105
crisis	calm	– 0.064 (0.009)	1.222 (0.195)	0.065 (0.005)	1.138 (0.214)	0.444 (0.072)	0.035	0.005	0.953	0.007
crisis	Crisis	– 0.064 (0.009)	1.946 (0.280)	– 0.088 (0.007)	2.174 (0.540)	0.517 (0.091)	0.000	0.000	0.037	0.963
S&P 500	NIKKEI 225									
calm	calm	0.099 (0.010)	0.738 (0.135)	0.099 (0.095)	0.640 (0.140)	0.066 (0.009)	0.970	0.014	0.000	0.016
calm	crisis	0.099 (0.010)	0.637 (0.102)	– 0.027 (0.012)	1.659 (0.342)	0.154 (0.033)	0.016	0.969	0.008	0.007
crisis	calm	– 0.005 (0.002)	3.066 (0.980)	0.099 (0.095)	3.289 (0.917)	0.142 (0.024)	0.000	0.057	0.850	0.092
crisis	crisis	– 0.005 (0.002)	1.234 (0.123)	– 0.027 (0.012)	1.363 (0.202)	0.176 (0.053)	0.017	0.000	0.018	0.965

Note: For further explanations see text.

Second, when both markets are in the crisis regime they become more correlated with each other than when they are in their calm regimes (e.g., Longin and Solnik (2001), Forbes and Rigobon (2002)). Finally, from the elements of the transition matrices it can be observed that the probability of staying in the same regime is always highest for all regimes and all estimated models. This result can be interpreted as evidence of persistence of high (low) volatility in stock market index returns in line with the well-known characteristics of conditional heteroscedasticity in stock index returns (e.g., Rydén, Teräsvirta, and Åsbrink (1998)). Moreover, comparing the estimated transition matrices in Table 4.3 with constraints proposed in equations (4.14) and (4.15) leads to the conclusion that the high values of the parameters p_{22} and p_{33}, which can be interpreted as indicators of persistence of the states 2 and 3, are main reasons for rejecting both contagion hypotheses in the spirit of Sola, Spagnolo, and Spagnolo (2002).

Our results, suggesting that the spillovers hypothesis is true, are consistent with the literature defining contagion as an increase in the probability of having a crisis at home when there is a crisis on the other market. Eichegreen, Rose, and Wyplosz (1996) and Hartmann, Streatmans, and de Vries (2004) also find evidence of contagion when they apply the same definition of contagion.

Having estimated transition matrices for each model we are able to compute the probabilities of some market entering the state of crisis or calm, conditional on the information that this market and the US market were in their respective states yesterday. These results are of special importance for international investors and the great advantage of the model is that they can be obtained directly using standard computations on the elements of the transition matrix. We additionally provide results on the probability of one market entering the crisis (calm) regime conditional on the state of the US market one day earlier. The results are presented in Table 4.4.

Table 4.4 Probability of a crisis or calm today and the information from yesterday

X represents the S&P 500 index returns and Y represents:	NIKKEI 225	FTSE 100	DAX
Probabilities conditional on the information from X_{t-1} and Y_{t-1}			
Pr(Y_t in calm | Y_{t-1} in calm and X_{t-1} in calm)	0.970	1.000	0.983
Pr(Y_t in calm | Y_{t-1} in calm and X_{t-1} in crisis)	0.850	0.988	0.972
Pr(Y_t in calm | Y_{t-1} in crisis and X_{t-1} in calm)	0.024	0.382	0.043
Pr(Y_t in calm | Y_{t-1} in crisis and X_{t-1} in crisis)	0.035	0.037	0.030
Pr(Y_t in crisis | Y_{t-1} in calm and X_{t-1} in calm)	0.030	0.000	0.017
Pr(Y_t in crisis | Y_{t-1} in calm and X_{t-1} in crisis)	0.150	0.012	0.028
Pr(Y_t in crisis | Y_{t-1} in crisis and X_{t-1} in calm)	0.976	0.618	0.957
Pr(Y_t in crisis | Y_{t-1} in crisis and X_{t-1} in crisis)	0.965	0.963	0.970
Probabilities conditional only on the information from X_{t-1}			
Pr(Y_t in calm | X_{t-1} in calm)	0.564	0.929	0.967
Pr(Y_t in calm | X_{t-1} in crisis)	0.149	0.206	0.231
Pr(Y_t in crisis | X_{t-1} in calm)	0.436	0.071	0.033
Pr(Y_t in crisis | X_{t-1} in crisis)	0.851	0.794	0.769

Note: For further explanations see text.

The main conclusion from the calculated probabilities is that entering one regime by the market is most likely and even close to one when this market and the US market were in the same regime one period earlier. If the US market was not in that regime one period earlier then the probability of entering the regime by the other market drops in almost all cases. The probability is close to zero that the market enters the state of calm (crisis) when the US market and this respective market were in the opposite regime one period earlier. This finding illustrates how the past information about the US market spills over to other mature markets on the next day. Furthermore, we are able to forecast the future state of the market more accurately having the information about the present state of both markets rather than having the information only about the US market. This in turn explains why the hypothesis of contagion is rejected in our analyses. The past information about each market is significant for its present performance.

Table 4.5 Tests of linkages between the markets in sub-samples

Sub-periods	Null hypothesis	S&P 500 and NIKKEI 225	S&P 500 and FTSE 100	S&P 500 and DAX
1984/04/03 – 1988/12/28	Regime-independence	93.18**	53.12**	63.24**
	No spillovers during calm	3.20	7.23**	0.94
	No spillovers during crises	7.02**	15.77**	4.28*
	No spillovers at any regimes	53.24**	25.52**	4.52
	Contagion	105.38**	87.82**	66.42**
	Contagion during crises	22.58**	71.88**	61.88**
1989/01/04 – 1995/12/29	Regime-independence	61.98**	56.96**	65.00**
	No spillovers during calm	8.96**	1.16	9.42**
	No spillovers during crises	19.14**	2.76	24.04**
	No spillovers at any regimes	25.98**	5.84	37.42**
	Contagion	56.14**	71.30**	61.24**
	Contagion during crises	40.58**	56.02**	31.52**
1996/01/04 – 2003/05/30	Regime-independence	94.56**	112.26**	95.46**
	No spillovers during calm	3.00	12.48**	8.82**
	No spillovers during crises	5.86*	23.04**	11.80**
	No spillovers at any regimes	7.76*	56.64**	20.90**
	Contagion	41.94**	42.68**	24.04**
	Contagion during crises	28.96**	27.30**	9.14

Note: * and ** denote rejection of the null hypothesis at the 5% and 1% levels. respectively.

We continue the analysis with studying the relations between the markets in the selected three non-overlapping sub-samples to learn how the dependencies between international capital markets change over time. The results from testing all hypotheses of contagion, spillovers, and regime-independence are presented in Table 4.5. The general findings from this exercise are that the US leads Japan, the UK and Germany, but the patterns of spillovers from the US to those markets vary over time (Rydén, Teräsvirta, and Åsbrink (1998)).

Some evidence of asymmetry in spillover effects between calm and crisis regimes is present the investigated sub-samples. In the 1984 – 1988 period we can accept the hypothesis that the S&P 500 index returns do not lead the DAX and NIKKEI 225 index returns when the latter indices are in the calm regimes. Similarly, from 1996 to 2003 returns on the Japanese market follow the US market returns only in the state of crisis and any spillover effects to Japan are quite weak in this period. The lack of spillovers in any regime to the UK is accepted in the 1989 – 1995 sub-sample. Since regime-independence is also rejected there, we interpret this result as evidence of the inter-dependencies between the US and UK capital markets, which take place without delay. One possible explanation for the lack of spillovers to the UK from the US could be the ERM currency crisis of 1992 that affected most strongly the British market. In the most recent period 1996 – 2003, S&P 500 index returns lead very strongly the DAX returns and one can observe the contagion effect when the German index is in the crisis regime. Likely reasons for this contagion effect could be recent shocks which took place on the US market and spread to other markets after the terrorist attack on September 11 and after the burst of the "dot.com" bubble. In all other cases there are significant spillovers from the US to the other markets independently of the crisis and calm regimes.

From Table 4.5 one can observe that spillovers between capital markets evolve over time independently of changing regimes. There are naturally some factors other than changing states of the markets which can influence the strength of spillovers and future applications may extend the proposed models by introducing additional elements or varying parameters. Nevertheless, our results show that spillovers between the four big stock capital markets exist in all periods.

There is less evidence of spillovers to the markets in the calm regime than to the stock markets which are in the crisis regime in the sub-periods. This finding could indicate that the market not involved in some international crash often remains resistant to spillovers from the US stock market. As soon as it allows for the high volatility regime at home it becomes more vulnerable to the influence of the US market, because concerned investors observe more carefully the performance of the US market in the context of the international turmoil.

This could also suggest that in some periods the analyzed markets are robust to any contagion from the US market, because they enter crisis regimes independently of the US market or simultaneously with the US market. If the latter case was true, then the direction of contagion would be toward the US market rather than from the US market due to possible crises on other not investigated markets that could cause the US market and other analyzed markets to enter the crisis regime in the same time. Additionally, the US market has less influence on the European and Asian markets on the same day because of different trading hours on the stock exchanges in Asia, Europe, and America. American stock markets open and close after the European and Asian markets each day, although some trading hours overlap. In contrast, European and Asian stock index returns may influence the American index returns on the same day (e.g., Cheung and Ng (1996)).

4.4 Summarizing Asymmetric Spillovers

In chapter 4, we investigate international financial spillovers from the US stock market to the Japanese, British, and German markets. We introduce a statistical framework to deal with the problem of asymmetries in financial spillovers in calm and turbulent regimes. Spillovers and contagion to stock markets during crisis and calm periods are explicitly defined and new tests are proposed to distinguish between financial spillovers in crisis and calm regimes.

Our testing framework is capable of distinguishing between different types of relations connecting two markets, i.e., contagion, spillovers, and independence. Thus, we compare the results from testing financial spillovers with outcomes from the tests of contagion and independence and obtain evidence that the Japanese, UK, and German stock markets are dependent on the past performance of the US market, but encounter almost no indication of contagion in the spirit of Sola, Spagnolo, and Spangolo (2002). We find that spillovers taking place when the dependent markets are in the crisis regime are more frequent than spillovers to the markets in the state of calm, which is in line with the results of Chen, Chiang, and So (2003). This result suggests that financial crashes on the US market do not always directly cause turmoil on the Japanese, UK, and German markets. However, the crashes on the US market increase the probability of a crisis on the three other mature markets, which is in line with the hypothesis of contagious crises introduced by Eichengreen, Rose, and Wyplosz (1996).

Additionally, we present the probabilities for the Japanese, UK, and German stock markets individually entering the states of calm and crisis periods, conditional on the information about the past performance of those markets and the US market. Information from both markets is found to be relevant for efficient forecasting of future stock market index returns on those markets, therefore further research could incorporate our framework in testing for diversification benefits from asset allocation on international markets, as in Ang and Bekaert (2002, 2003).

CONCLUSIONS

This thesis contains four studies on financial linkages between stock markets in different countries during calm and turbulent times. It explores various definitions of financial spillovers and contagion and different methods are used here to test these definitions on a number of international stock markets. The studies are presented separately in four chapters.

In the first study we investigate contagion to European stock markets associated with seven big financial shocks between 1997 and 2002. Developed Western European markets and emerging stock markets in Central and Eastern Europe are compared and only modest evidence of significant instabilities in cross-market linkages after the crises is found. The Central and Eastern European stock markets are not more vulnerable to contagion than Western European markets.

The second analysis contributes to the discussion on increase of financial spillovers during crises. We construct threshold vector autoregressive models to test whether causality patterns between the U.S. and eight Southeast Asian capital markets are characterized by one or two regimes during the 1997 Asian crisis. Linkages between the markets follow the threshold model with two regimes, where spillovers between the U.S. and the Asian markets become stronger in the turmoil regime. Possible explanations for more intensive relationships during tumultuous periods are reliance of emerging countries on common bank creditors and cross market portfolio rebalancing by hedge and mutual funds.

The third chapter introduces the concept of causality in the Markov switching framework in the analysis of spillovers and contagion between stock markets. This methodology is applied to stock index returns on the Japanese (Nikkei 225) and the Hong Kong (HSI) markets during the Asian crisis and no evidence of contagion between the markets is found, rather strong evidence of feedback spillovers between them.

The final study deals with the problem of asymmetries in financial spillovers during calm and turbulent times. Causality from the U.S. stock market to the U.K., Japanese, and German markets is more frequent when the latter markets are in a crisis regime. Although, the results show that past states (calm or turbulent) of the U.S. and local market are both relevant for predicting the future state of the local market, they also reject the hypothesis of strong financial contagion from the U.S. market to the analyzed markets.

The new methods to explore contagion and spillover effects proposed in the previous four chapters may be of interest to economists analyzing dependencies between stock markets. Our new empirical results confirm on the one hand that contagion is a rather rare phenomenon, but patterns of capital and information flow to stock markets change during turbulent periods. From policymakers' and international investors' perspectives, the changes in spillover patterns are often too frequent to adjust macroeconomic policy or reallocate capital between markets, respectively. However, international investors could consider our outcomes to improve the quality of forecasts and increase returns from their short-term investments.

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