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Strohsal, Till; Weber, Enzo

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Identifying Volatility Signals from Time-Varying Simultaneous Stock Market Interaction[1]

Till Strohsal[2]
Department of Economics
Free University Berlin

Enzo Weber[3]
Department of Economics and Econometrics
University of Regensburg

Abstract

In the academic literature, the economic interpretation of stock market volatility is inherently ambivalent, being considered an indicator of either *information* flow or *uncertainty*. We show in a stylized model economy that both views suggest volatility-dependent cross-market spillovers. If higher volatility in one market leads to higher (lower) reactions in another market, volatility reflects information (uncertainty). We introduce a simultaneous time-varying coefficient model, where structural ARCH-type variances serve two purposes: governing the time variation of spillovers and ensuring statistical identification. The model is applied to data of US and further stock markets. Indeed, we find strong nonlinear, volatility-dependent effects.

Keywords: Information, Uncertainty, Spillover, Simultaneous Equations, Identification
JEL classification: G15, C32

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[2]Free University Berlin, Department of Economics, Institute of Statistics & Econometrics, D-14195 Berlin, Germany, till.strohsal@wiwiss.fu-berlin.de, phone: +49 (0)30 838-53399.

[3]University of Regensburg, Department of Economics and Econometrics, D-93040 Regensburg, Germany, enzo.weber@wiwi.uni-regensburg.de, phone: +49 (0)941 943-1952, fax: +49 (0)941 943-4917, and Institute for Employment Research (IAB), Osteuropa-Institut Regensburg.

1 Introduction

The present study proposes a flexible econometric approach to examine the economic interpretation of volatility in financial markets. Firstly, we pinpoint two fundamental understandings of volatility that have emerged from the financial literature during the last decades. On the one hand, the fact that prices vary is interpreted as a sign of *information* flow. On the other hand, high variability is often seen as a mirror image of pronounced *uncertainty* in the market. Both views suggest volatility-dependent stock market interaction, albeit in different directions, and we aim at shedding light on the inherent ambivalence. In a simple economic framework, we show that higher volatility in one market should lead to higher (lower) reactions in another market if volatility reflects information (uncertainty). To the best of our knowledge, these two views of volatility have never been explicitly contrasted and empirically examined. Secondly, we propose a strategy to infer the dominating signal of return variability from the data: we analyse different reactions of investors to observed returns, depending on the prevailing level of volatility. As our econometric framework, we introduce a simultaneous time-varying coefficient model, where time variation is a function of ARCH-type variances. The analysis is based on daily data of major stock indexes from the Americas, Australia and the Asian region.

Let us first provide some background concerning the two signals of volatility we put up for discussion and review some literature we see connected to our line of reasoning. From one point of view, volatility is often associated with uncertainty or risk. Considering the global financial crisis for instance, future market developments are highly uncertain. In the public discussion, the image of labile and disoriented financial markets prevails. Intuitively, the extensive stock market volatility is often interpreted as the reflection of this uncertainty. In the present study this concept of volatility shall be summarized as

the *uncertainty hypothesis*.

Regarding the pricing of assets, it seems natural that investors expect to be compensated for bearing uncertainty in their portfolios. In fact, in academia the understanding of volatility as risk long plays an important role with a prominent example given by the μ-σ-utility function and the CAPM. Originating from Engle et al. (1987), financial econometricians translated this idea into the variance-in-mean model (see also Bali and Engle 2010 and the references therein). Another example for volatility proxying uncertainty is given by interactions between output or inflation uncertainty and the conditional means of these variables (e.g. Grier and Perry 2000). In a further strand of literature, numerous studies analyze how uncertainty about exchange rate movements affects trade volume and foreign direct investment, e.g. Cushman (1985), Chowdhury (1993) and Kiyota and Urata (2004). For instance, volatility might negatively impact the size of trade flows if exchange rate uncertainty renders trade less profitable for risk averse agents.

On the other hand, we will refer to the view of volatility being a measure of information flow intensity as the *information hypothesis*. Some representatives of the literature who elaborate on the volatility-information link are Clark (1973), Epps and Epps (1976) and Ross (1989). Overall, the idea is that no motivation for further trading would exist in a situation where all prices have settled at their equilibrium values. Thus, volatility would be zero in absence of relevant news. If, however, additional information becomes available, price adjustments will generate fluctuations until a new equilibrium is reached. Of course, in reality, shocks are too frequent to allow conventional asset prices to ever settle at some constant consensus value, and perception and handling of information both represent more complicated processes than assumed in stylized model economies. Nonetheless, the line of reasoning exemplifies how volatility is connected to information arrival.

The information content of price movements is normally not observable. This is likely

to be one of the main reasons why information flow was connected to volatility in the first place. By the same token, a strand of literature examined trading volume as an observable variable that is at least partly driven by the information arrival process; see Tauchen and Pitts (1983), Harris (1987), Lamoureux and Lastrapes (1990), Foster and Viswanathan (1993, 1995) and Gagnon and Karolyi (2009). Certainly, volume cannot *explain* volatility, in the sense of an exogenous variable. Instead, both are affected simultaneously by the latent information process. Moreover, many trades are unlikely to be linked to information arrival, such as in the cases of liquidity management (e.g. Andersen 1996), strategic trading under asymmetric information (e.g. Kyle 1985) or differences of opinions on the interpretation of signals (e.g. Kim and Verrecchia 1991). Attempts have been made to proxy information arrival directly by, for example, central bank decisions, macroeconomic news or firm-specific announcements. For studies of corresponding volatility effects, see e.g. Andersen and Bollerslev (1998) or Kalev et al. (2004). Nonetheless, even if important insights into news effects could be gained, such direct observable measures cannot represent more than a fraction of the universe of information arriving in financial markets. Above all, they hardly capture private information, which is a major factor behind volatility (French and Roll 1986).

Our distinct hypotheses serve to fix ideas concerning the character of volatility. Naturally, they are not mutually exclusive. Rather, exploring the "signal of volatility" amounts to asking which effect predominates. In fact, this calls for a mechanism connecting the latent variables information and uncertainty to a measure that is estimable from the data. In the present approach, we propose letting the reaction of market participants decide the character of volatility instead of leaving this task up to the econometrician. Specifically, we make use of the intensity by which shocks feed into actual market prices, thereby connecting a high intensity to high information content, as further explained below. However, given a single observed time series, identifying the size of the shocks

themselves (i.e., volatility) and the size of their impact on the price separately, proves evidently impossible.

We approach this problem by extending the information set to the multivariate case. In particular, we examine the intensity of spillover between two different markets. Logically, while shocks can be identified in the "source" market, transmission intensity is measured in the "target" market. In case observed price changes in the source market are interpreted as highly informative (uncertain) signals by the target market, the latter will incorporate a relatively large (small) fraction of the innovation into its own price. We illustrate this principle in a stylized model economy, based on signal extraction by rational agents. Overall, high volatility in the target market associated with high spillover intensity would support the information hypothesis, while evidence for the uncertainty hypothesis would follow from an inverse linkage.

Econometrically, we measure this nonlinear effect in a time-varying coefficient model governed by the (autoregressive) conditional variance of the source market, i.e., we utilize time variation in volatility to identify its impact on transmission intensity. Such an empirical strategy has not yet been considered in the literature. Our concept does not aim at explaining the mere fact that markets are interconnected, e.g. by trade, policy coordination or common shocks. Rather, we exploit the existing interaction for estimating the spillover intensity and its link to volatility. Furthermore, the a priori division into "source" and "target" markets is an artificial one. In reality, once one introduces spillover effects, one must take a stance on how to resolve endogeneity. Our model setup will generally allow for bi-directional transmission between the US and the second country of interest. Identification is achieved by making use of the heteroskedasticity in the data, which can be exploited to uniquely pin down the structure of simultaneous systems; compare Sentana and Fiorentini (2001) or Rigobon (2003). Therefore, both the direction and the size of spillovers can be determined empirically. These considerations

on simultaneity apply to markets with overlapping trading hours, like in the Americas. For models of the US and the major Asian or Australian stock indexes, the spillover direction is given by the sequence of time, since these markets trade with substantial time shifts. Consequently, identification problems are alleviated in this setting.

Our first major result is that in all countries under investigation spillover intensity significantly depends on volatility. As regards the information content of volatility, our results tell that it crucially depends on the combination of "sender" and "receiver" of volatility signals. For industrial countries, the information hypothesis holds. As for emerging economies, however, the uncertainty hypothesis prevails in their relations to the US.

The rest of the paper proceeds as follows. The next section presents a stylized model of stock market returns and derives the testable hypotheses. Section 3 introduces the econometric model and discusses identification issues and the estimation procedure. Section 4 applies the methodology to daily returns of major stock indexes from the Americas, Australia and the Asian region. The last section concludes.

2 Volatility Signals in a Stylized Model Economy

2.1 The Market Participant: Signal Extraction Problem

First we illustrate the idea of the signal of volatility in a stylized model economy. This should help fix ideas on how stock market interaction could depend on return variability. Moreover, the nature of this interdependence should reveal the character of volatility, i.e., it should indicate whether volatility in one market means information or uncertainty (noise) to the other. A prominent model from the literature, which can be used for this purpose, was considered by King and Wadhwani (1990). We adopt this framework to

demonstrate that in a signal extraction context, the prevailing character of volatility can be identified from the optimal reaction of investors to observed returns.

For the present purpose, it is sufficient to consider two stock markets where price changes are associated with the arrival of relevant information and with noise, i.e., uncertainty. The first consists two parts: directly observed information and a reaction to information that is not fully observed in that market but only in the other:

$$y_{1t} = \iota_{1t} + \alpha_{12}\mathbb{E}[\iota_{2t}|I_{1t}] + \nu_{1t} \tag{1}$$

$$y_{2t} = \alpha_{21}\mathbb{E}[\iota_{1t}|I_{2t}] + \iota_{2t} + \nu_{2t} \quad . \tag{2}$$

Stock returns are given by y_t, information is denoted by ι_t, ν_t refers to noise and $\mathbb{E}[\cdot|I_{jt}]$ represents the expectations operator conditional on the information observed in market j at time t.

When investors form expectations, say in market 1, they face a simple signal extraction problem, since all they can observe from market 2 is the contemporaneous price change. In order to extract the signal from the part of the price movement in market 2 that is not simply due to information in market 1, agents in market 1 have to find β_1 in

$$\mathbb{E}[\iota_{2t}|I_{1t}] = \beta_1(y_{2t} - \alpha_{21}\mathbb{E}[\iota_{1t}|I_{2t}]) \quad . \tag{3}$$

The solution to (3) is given by the minimum-variance estimator:

$$\beta_1 = \frac{\mathrm{Var}[\iota_{2t}]}{\mathrm{Var}[\iota_{2t}] + \mathrm{Var}[\nu_{2t}]} \quad . \tag{4}$$

Evidently, β_1 becomes time varying, i.e., β_{1t}, in case volatility of either ι_{2t} or ν_{2t} changes over time.

Of course, agents in market 2 follow an analogous rationale. Using (3) and (4) to substitute for the conditional expectations in (1) and (2) yields the following simultaneous equations system of stock returns:

$$y_{1t} = A_{12t} y_{2t} + \varepsilon_{1t} \tag{5}$$

$$y_{2t} = A_{21t} y_{1t} + \varepsilon_{2t} \quad , \tag{6}$$

where the spillover coefficients are given by $A_{12t} = \alpha_{12}\beta_{1t}$ and $A_{21t} = \alpha_{21}\beta_{2t}$. The shocks result as $\varepsilon_{1t} = (1 - \alpha_{12}\alpha_{21}\beta_{1t}\beta_{2t})(\iota_{1t} + \nu_{1t})$ and $\varepsilon_{2t} = (1 - \alpha_{12}\alpha_{21}\beta_{1t}\beta_{2t})(\iota_{2t} + \nu_{2t})$.

In our application, we will choose the US as the first country and switch between several other stock markets in y_2. Logically, the model will change according to the choice of the second country. In addition to the second equation, this concerns also (1). Apart from the spillover, the partitioning of the return shock into information and noise, and thus also β and A, depend on the perspective of the second country. In order to keep the notation simple, we write down model (1)-(2) only for a given set of countries.

2.2 The Econometrician: Testable Hypotheses

Following the reasoning from above, the contemporaneous impact from one market to the other depends on the variances of both signal (information) and noise (uncertainty). However, assuming the model in (5) and (6) is identified, the econometrician can only estimate the variance of ε_t. Taking the typical time-varying nature of financial time series volatility into account, we denote the conditional variance of ε_t by $\mathrm{Var}[\varepsilon_t | I_{t-1}] = h_t$ and let the spillover coefficients depend on the variances by

$$A_{ijt} = f_{ij}(h_{jt}) \quad i, j = 1, 2 \;\text{ and }\; i \neq j \,. \tag{7}$$

In view of (4), $\frac{\partial f_{ij}}{\partial h_{jt}} > 0$ would imply that $\mathrm{Var}[\iota_{jt}|I_{t-1}]$ dominates the dynamics of market volatility, i.e., its rate of change is higher than the one of $\mathrm{Var}[\nu_{jt}|I_{t-1}]$. This would favor the information hypothesis. On the contrary, $\frac{\partial f_{ij}}{\partial h_{jt}} < 0$ would represent evidence for the uncertainty hypothesis.

The exact functional form of $f(\cdot)$ is not clear, the more so the α_{ij} from (1) and (2) might also vary over time. As discussed in detail in the next section, we approximate $f(\cdot)$ on an empirical basis. So far, we summarize the following two testable hypotheses:

Information Hypothesis:

The spillover intensity A_{ijt} in (5) and (6) depends *positively* on the level of volatility in the respective other market, i.e., $\frac{\partial A_{ijt}}{\partial h_{jt}} > 0$.

Uncertainty Hypothesis:

The spillover intensity A_{ijt} in (5) and (6) depends *negatively* on the level of volatility in the respective other market, i.e., $\frac{\partial A_{ijt}}{\partial h_{jt}} < 0$.

3 Empirical Approach: Measuring Investors Reaction to Observed Returns

3.1 Simultaneous Model and Identification

In order to explore the signal of volatility, we first discuss our simultaneous model setup. The considered stock returns are collected in the n-dimensional vector y_t. The data generating process is approximated by the following simultaneous system:

$$Ay_t = \mu_t + \varepsilon_t \ , \tag{8}$$

where μ_t represents a vector of predictable components such as lags or a constant term and ε_t is a n-dimensional vector of structural innovations. The contemporaneous impacts are included in matrix A with diagonal elements normalized to one. It is these effects that model the spillovers between returns in the current setting and that we will allow to depend on volatility later on. Common shocks will be accommodated by allowing for correlation of ε_t, as explained below.

The simultaneous specification (8) is not meant to take a stance on *fundamental* causality, in the sense that an impulse say in market j is necessarily the true causal origin of a spillover to market i. Of course, one can think of idiosyncratic events in market j affecting market i, based on economic linkages or psychological effects. However, an impulse in market j may well be initiated by some information that is equally relevant for market i, where investors observe the signal from j. Then it would evidently be the third-party origin of the information, and not market j itself, which would underlie the impact on market i. In summary, spillovers characterize *signals* in one stock index that are incorporated by other markets, but not necessarily based on actual bivariate causality.

Statistically, model (8) as it stands is not identified: In the matrix A with a normalized diagonal, $n(n-1)$ simultaneous impacts have to be estimated, whereas the covariance matrix of the reduced-form residuals $A^{-1}\varepsilon_t$ delivers only $n(n-1)/2$ determining equations due to its symmetry. However, as for instance Sentana and Fiorentini (2001) and Rigobon (2003) show, unobservable factor structures like (8) become unique if heteroskedasticity is present in the stochastic components. The idea is that, although breaks in the structural variances introduce additional unknowns (i.e., the variances in the new regime), they shift the whole covariance matrix in the reduced form, from which available information (i.e., variances and covariances) is doubled. Time-varying volatility is a common feature of financial variables, often modeled as ARCH-type processes. Indeed, the approach

of Sentana and Fiorentini (2001) subsumes the case of regime switches just as other forms of heteroskedasticity such as ARCH. Here, we follow Weber (2010), who specifies multivariate EGARCH processes for the structural shocks.

Formalizing the model setup, first denote the conditional variances of the elements in ε_t by

$$\mathrm{Var}(\varepsilon_{jt}|\Omega_{t-1}) = h_{jt}^2 \qquad j = 1,\ldots,n\,, \tag{9}$$

where Ω_{t-1} stands for the whole set of available information at time $t-1$.

Furthermore, denote the standardized innovations by

$$\tilde{\varepsilon}_{jt} = \varepsilon_{jt}/h_{jt} \qquad j = 1,\ldots,n\,. \tag{10}$$

EGARCH(1,1)-processes are then given by

$$\log h_{jt}^2 = c_j + g_j \log h_{jt-1}^2 + d_j(|\tilde{\varepsilon}_{jt-1}| - \sqrt{2/\pi}) + f_j\tilde{\varepsilon}_{jt-1} \qquad j = 1,\ldots,n\,, \tag{11}$$

where c_j, g_j, d_j and f_j represent the coefficients. The term $\sqrt{2/\pi}$ serves to demean the absolute shock. In addition, going beyond the pure magnitude of shocks, the signed $\tilde{\varepsilon}_t$ introduce asymmetric volatility effects. The logarithmic formulation ensures positive variances without relying on parametric restrictions.

Common shocks are taken into account via the structural constant conditional correlation (SCCC) approach of Weber (2010). The advantage of the SCCC model is to relax the uncorrelatedness assumption for structural shocks on the one hand but to keep up the identification of the simultaneous model achieved through heteroskedasticity on the other. The covariances of structural shocks are recovered by the CCC specification

$$\mathrm{Cov}(\varepsilon_{it},\varepsilon_{jt}|I_{t-1}) = h_{ijt} = \rho_{ij}h_{it}h_{jt} \quad i \neq j\,, \tag{12}$$

where ρ_{ij} denotes the correlation between the ith and the jth innovation.[4] This correlation can be thought of as arising from the exposure of variables i and j to unobserved common factors.

For markets with non-overlapping trading hours identification problems are alleviated. Naturally, a triangular coefficient matrix A_t can be used. Even though the index t then does not refer to the same time for all variables, we keep the notation for simplicity purposes.

3.2 Time-Varying Coefficients

Up to this point, the off-diagonal elements of matrix A in (8) imply spillovers between the endogenous variables that are proportional to the size of shocks with proportionality factors constant over time. While this represents the standard in simultaneous systems, the current research question requires a more complex specification. Therefore, we develop a framework that combines the heteroscedastic structural model introduced above with a time-varying spillover specification. In order to discriminate between the information and uncertainty hypotheses, we allow the transmission intensity to depend on source market volatility as derived in section 2.2.

Strictly speaking, A is substituted by A_t in (8). The elements A_{ijt}, $i \neq j$, denote the coefficients of transmission from variable j to i at time t. As a parsimonious functional form, consider the linear specification of (7):

$$A_{ijt} = a_{ij} + b_{ij} h_{jt} \,, \tag{13}$$

for all i, j. Here, the conditional standard deviation h_{jt} serves as the transition variable. Since A_t stands on the left hand side, negative values represent positive transmission.

[4] We also considered the structural *dynamic* conditional correlation (SDCC) approach. However, empirical evidence was in favor of the SCCC model.

Therefore, a_{ij} is expected to be smaller than zero. Accordingly, a one-unit increase in source market volatility decreases spillover intensity by b_{ij}. Hence, from the above discussion it follows that $b_{ij} < 0$ would favor the information hypothesis, whereas prevalence of the uncertainty hypothesis requires $b_{ij} > 0$. Alternatively, $b_{ij} = 0$ would bring us back to the case of constant parameters.

We note that this specification can be compared to the GARCH-in-mean model, where returns are explained by their own conditional variances. In our approach, the variance series is also employed for an interaction effect with the level. However, we allow the spillover in one mean equation to depend on the conditional variance of another return.

No case can be made, a priori, that the transition function (13), i.e., the volatility effect on spillover intensity, is necessarily linear. While the advantage lies in parametric parsimony, the exact functional form of (7) should be determined on an empirical basis. For instance, let us assume a situation with $a < 0$ and evidence for the uncertainty hypothesis, say $b > 0$. At a certain point, a linear transition function could approach a negative correlation between markets (i.e., with a positive left-hand-side coefficient). Since such a constellation appears rather implausible, the transition effect is likely to exhibit dampening non-linearity for high volatility values. Still, if such realizations are rare in the sample, (13) might work well as approximation of the transition function (7).

As an alternative specification, literature on smooth transition regression (STR) (e.g. Luukkonen et al. 1988) has adopted flexible functions to grasp time variation in coefficients. Specifically, consider

$$A_{ijt} = a_{ij} + \alpha_{ij}/(1 + e^{-\gamma_{ij}(h_{jt} - \beta_{ij})}) \, . \tag{14}$$

The exact form of the transition is determined by the logistic function $(1 + e^{-\gamma(h-\beta)})^{-1}$,

which is monotonically increasing[5] in h_{jt} and bounded between zero and one. The slope parameter γ indicates the speed or smoothness of transition: as $\gamma \to \infty$, the logistic function approaches the indicator function $I(h_{jt} > c)$, i.e., a single threshold. In contrast, $\gamma = 0$ simply gives the linear case. The parameter β represents the location of the transition. In sum, the STR-based specification lets the data decide about the shape of the volatility effect on spillover size.

Nonlinear functional forms are one way of dealing with large realizations of the conditional standard deviation. Another straightforward option is given by transforming the transition variable. While we use the standard deviation, taking logarithms as in (11), for instance, would further dampen extreme volatility spikes. While there is little reason to believe that a "correct" option could be chosen on theoretical grounds, our results proved robust in this respect.

A last comment concerns the testing of statistical significance of the transition variables in the STR setup. Luukkonen et al. (1988) show that straightforward hypotheses like $\alpha_{ij} = 0$ or $\gamma_{ij} = 0$ are inappropriate because of the presence of unidentified nuisance parameters under the null. Instead, for testing purposes the functions are approximated by a Taylor series of a higher order, usually of order three:

$$A_{ijt} = a_{ij} + b_{ij,1} h_{jt} + b_{ij,2} h_{jt}^2 + b_{ij,3} h_{jt}^3 \, . \tag{15}$$

Here, standard likelihood ratio (LR) principles apply to the hypothesis $b_{ij,1} = b_{ij,2} = b_{ij,3} = 0$. Of course, linearization may adversely affect the power of the test. However, as Skalin (1998) points out, simulation-based techniques would be extremely computationally demanding and bootstrapping does not provide superior size and power properties. Therefore, we will rely on the LR test in the transition model (15). Furthermore, if

[5] We think of volatility effects on transmission strength being monotonous, even if they are not necessarily linear. More involved STR functions should thus not be required.

$b_{ij,2} = b_{ij,3} = 0$ but $b_{ij,1} \neq 0$ is found, the transition function can be approximated by the linear specification (13). Estimation is based on (quasi) maximum likelihood.

4 Application: The Signal of International Stock Market Volatility

4.1 Data

We examine a balanced sample from 1/1/1988 to 12/31/2010 of daily returns on major stock indices from the US (S&P 500) and a second country of interest. From the Americas we choose Canada (S&P/TSX 60), Argentina (TOTMKAR[6]), Brazil (Bovespa Index) and Mexico (IPC) as examples for contemporaneous trading. The markets of Australia (S&P/ASX 50), Japan (Nikkei) Korea (KOSPI) and the Philippines (PSEi) are all located overseas from the US and represent markets with non-overlapping trading hours.

Stock returns are depicted in Figure 1. The time variation in volatility appears very pronounced in all series. This is also statistically indicated by significant autocorrelation of squared returns found in preliminary data inspection. The presence of heteroskedasticity is of special importance to our approach, as it allows estimation of volatility effects on spillover intensity.

4.2 Specification Tests

The set of equations to be estimated consists of bivariate simultaneous models with conditional heteroskedasticity for the US and a second country of interest. The empirical application starts with specifying the functional form of the transition function by means

[6]Due to data availability for Argentina we use the TOTMKAR provided by Datastream instead of the MERVAL, see http://product.datastream.com/navigator/HelpFiles/DatatypeDefi nitions/en/3/DSGI_total_market_data.htm.

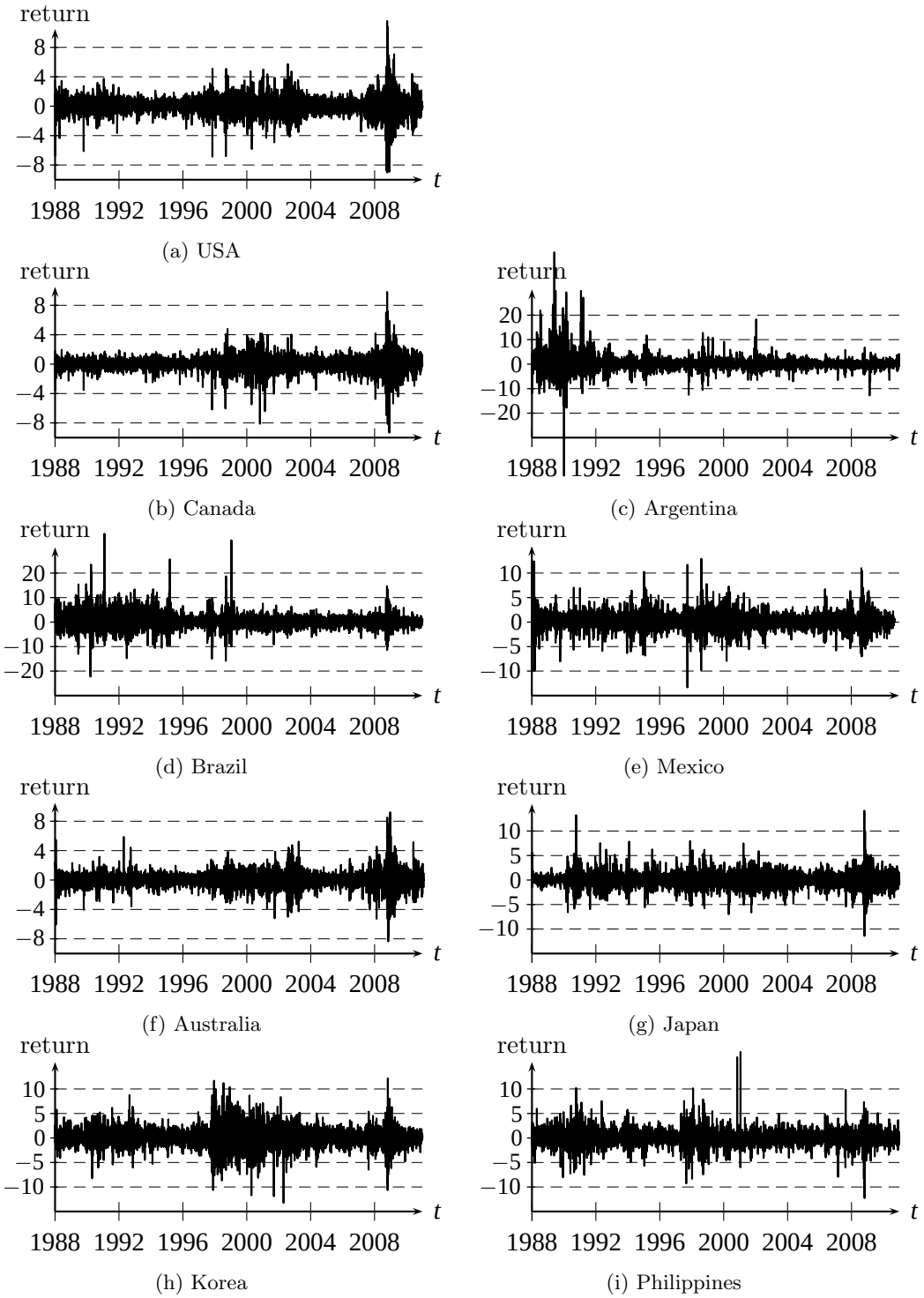


Figure 1: Daily Stock Returns on (a) S&P 500, (b) S&P/TSX 60, (c) TOTMKAR, (d) Bovespa Index, (e) IPC, (f) S&P/ASX 50, (g) Nikkei, (h) KOSPI and (i) PSEi

of likelihood ratio tests. The specification test procedure can be described as follows:

Since stock market trading hours in Canada and the US are exactly the same and those in Argentina, Brazil and Mexico largely coincide with the US, we allow for bi-directional simultaneous effects. Identification is achieved through the SCCC approach. In the Asian region and Australia, stock markets open after those in the US have closed so that identification issues are alleviated due to this chronology. Hence, we only test for the functional form of the transition function in one direction.

Firstly, we test the null of constant coefficients against linearly time-varying coefficients in all countries. Secondly, the null of linear spillover in both directions is tested separately against the alternative of nonlinear (STR) spillover. In view of the third order Taylor approximation this translates into testing two linear restrictions in (15) for each case: H_0: $b_{12,2} = b_{12,3} = 0$ and H_0: $b_{21,2} = b_{21,3} = 0$, respectively.

Columns 2 and 3 of Table 1 include p-values of LR specification tests corresponding to the null given in the first row. Bold numbers reflect rejection of the respective null. Column 4 shows the final model specification.[7] To mention one example, in the case of the US and Canada (second row), we find evidence in favor of linear spillover on the US (not rejecting the null in column 2) and nonlinear spillover on Canada (rejecting the null in column 3).

During estimation we set μ_t constant, as autocorrelation of returns is mostly very close to zero. Results turn out to be insensitive to the inclusion of lagged terms in (8). Furthermore, standardized squared residuals appear free from autocorrelation. Thus, we can be confident that our parsimonious EGARCH(1,1) specification is sufficient to capture the time variation in the volatility series.

[7] In two cases we do not follow the outcome of the specification tests, namely the Argentinian and Brazilian spillover on the US. Even though statistically nonlinear effects are indicated by the p-values, we restrict the spillover to zero. A closer analysis of these two cases revealed that the smooth transition function actually serves as a dummy to capture only very few outliers at the beginning of our sample while the spillover on the US is otherwise constant and close to zero (between 1% and 2%).

X	H_0: linear on US H_1: STR on US p-values for df = 2	H_0: linear on X H_1: STR on X p-values for df = 2	final model specification	coefficient estimates				signal of volatility
Canada	0.54	**0.05**	linear on US	$a_{12} = 0$	$b_{12} = -0.45$			information
			STR on Canada	$a_{21} = 9.16$	$\alpha_{21} = -9.46$	$\gamma_{21} = 9.47$	$\beta_{21} = -0.19$	information
Australia	–	0.25	no spillover on US					-
			linear on Australia	$a_{21} = -0.35$	$b_{21} = -0.08$			information
Japan	–	**0.04**	no spillover on US					-
			STR on Japan	$a_{21} = -0.28$	$\alpha_{21} = -0.18$	$\gamma_{21} = 32.51$	$\beta_{21} = 0.34$	information
Korea	–	**0.00**	no spillover on US					-
			STR on Korea	$a_{21} = -0.20$	$\alpha_{21} = -0.22$	$\gamma_{21} = 25.65$	$\beta_{21} = 0.40$	information
Argentina	0.03	**0.00**	no spillover on US					-
			STR on Argentina	$a_{21} = -11.31$	$\alpha_{21} = 10.73$	$\gamma_{21} = 5.74$	$\beta_{21} = -0.40$	uncertainty
Brazil	0.03	**0.00**	no spillover on US					-
			STR on Brazil	$a_{21} = -13.30$	$\alpha_{21} = 12.58$	$\gamma_{21} = 5.58$	$\beta_{21} = -0.56$	uncertainty
Mexico	**0.00**	0.09	STR on US	$a_{12} = 0$	$\alpha_{12} = -0.04$	$\gamma_{12} = 14.81$	$\beta_{12} = 0.64$	information
			linear on Mexico	$a_{21} = -0.78$	$b_{21} = 0.10$			uncertainty
Philippines	–	**0.00**	no spillover on US					-
			STR on Philippines	$a_{21} = -0.45$	$\alpha_{21} = 0.16$	$\gamma_{21} = 22.49$	$\beta_{21} = 0.72$	uncertainty

Notes: Columns 2 and 3 report p-values of likelihood ratio tests of the indicated null hypotheses with degrees of freedom equal to df. Bold numbers reflect the rejection of the null. In Argentina and Brazil, we restricted the spillover on US to zero even though test statistics point to nonlinear spillovers; see also footnote 7, page 13. The final specification of the functional form for the time-varying spillover is found in column 4. Columns 5 to 8 show the estimated coefficients. The last column lists the signal for market i that emerges from volatility in market j. Linear or STR specifications of the transition function refer to $A_{ijt} = a_{ij} + b_{ij}h_{jt}$ and $A_{ijt} = a_{ij} + \alpha_{ij}/(1 + e^{-\gamma_{ij}(h_{jt} - \beta_{ij})})$ of the simultaneous model:

$$\begin{pmatrix} 1 & A_{12t} \\ A_{21t} & 1 \end{pmatrix} y_t = \varepsilon_t \, .$$

Table 1: Specification Tests and Estimation Results

4.3 Results

The first major result is that we find evidence for time-varying spillover coefficients in all countries under investigation. In particular, LR tests (not presented in Table 1) of constant against linearly time-varying spillover result in p-values of 0.000 (Canada), 0.081 (Australia), 0.031 (Mexico), 0.000 (Argentina), 0.004 (Brazil), 0.018 (Japan), 0.000 (Korea) and 0.031 (Philippines). That is, for all countries test results suggest the rejection of constant parameters.

Estimated coefficients are presented in columns 5 to 8 of Table 1. The hypothesis favored by our evidence is listed in the last column. The results can be divided into two groups. First, the information hypothesis prevails in Australia, Canada, Japan and Korea as US volatility increases the fraction of US shocks that feed into stock prices of these countries. The same holds for Canadian volatility, signaling information for US traders. Second, Argentinian, Brazilian, Mexican and Philippine stock markets seem to understand US volatility as uncertainty since higher volatility leads to a reduction of spillover intensity in these markets. Considering the opposite direction, we find the information hypothesis to dominate in the US with respect to Mexican volatility. However, the small effect from Mexico on the US is economically of minor importance.

The transition functions of these markets are plotted in Figures 2 to 9 (right hand side) together with the spillover intensities (left hand side). We obtain the following results.

Evidence for the Information Hypotheses in Industrial Economies

- In Canada, the effect of US volatility is quite pronounced, indicated by a steep transition function. This results in a transmission that varies between 10% in times of low and approximately 30% in times of high volatility.

- The information signaling effect of Canadian volatility is also substantial. It produces an even higher spillover variation on the US but, of course, with a lower mean.

- In Australia the information signaling US volatility leads to spillover intensity between roughly 36% and 43%. The spike towards the end of the sample resulting from high US volatility during the crisis drives up transmission strength to 50%.

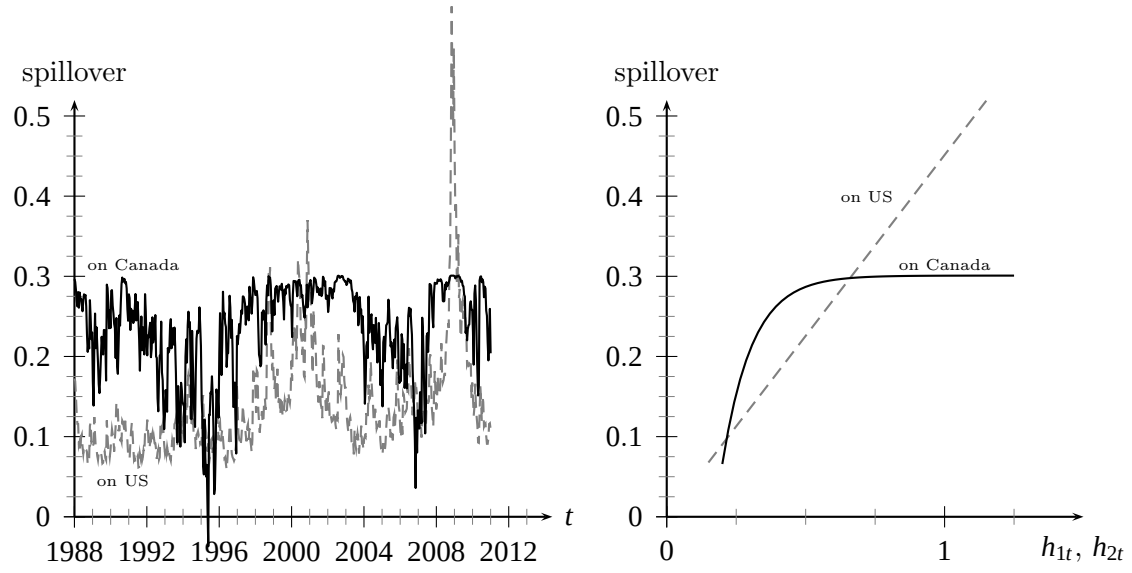
- Transition functions in Japan and Korea are both strongly increasing in a range of low volatility. Spillover intensity increases for higher levels of volatility by up to 20 percentage points.

Evidence for the Uncertainty Hypotheses in Emerging Economies

- The transition functions and spillover intensity for Argentina and Brazil are of similar shape. In Argentina, however, transmission strength varies around a lower level (70%) than in Brazil (80%). US volatility strongly reduces spillover intensity and is thus interpreted as signaling uncertainty. In both cases, the variance of domestic shocks is high compared to the US, and also to Australia and Canada. Thus, despite high spillover, domestic shocks represent a major factor of return variation in Argentina and Brazil.

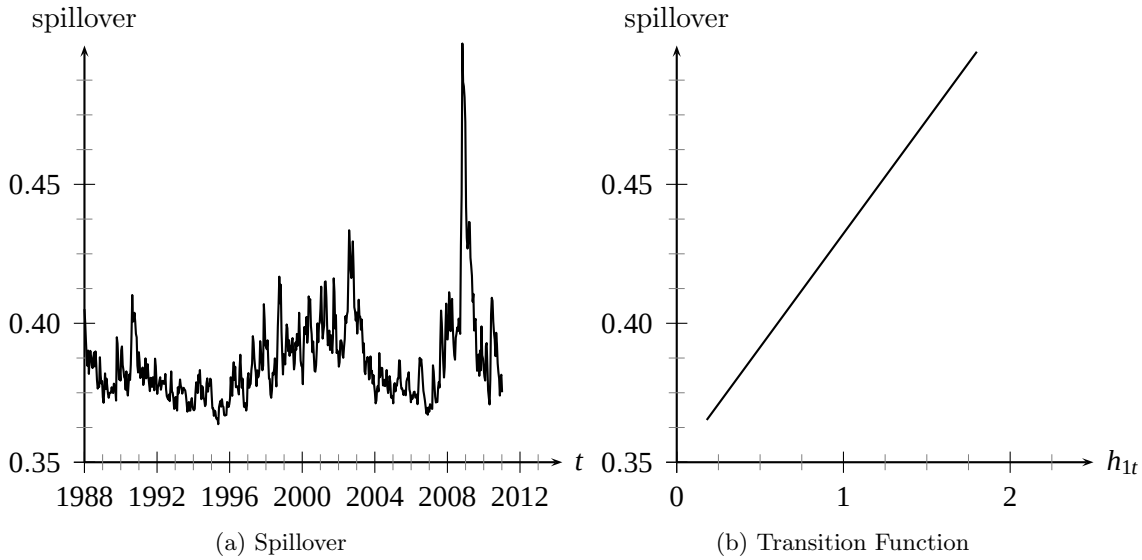
- Analogously, transmission strength takes values between 60% and 76% in Mexico with an average of 73% and US volatility having a negative impact. On the contrary, in the US, Mexican volatility increases spillover. Yet, economically the effect fluctuating between zero and a few percent appears to be of secondary importance.

- The contemporaneous impact from the US on the Philippines equals about 45% during times of low volatility. When volatility approaches 1, spillover strongly decreases and falls below 30%.



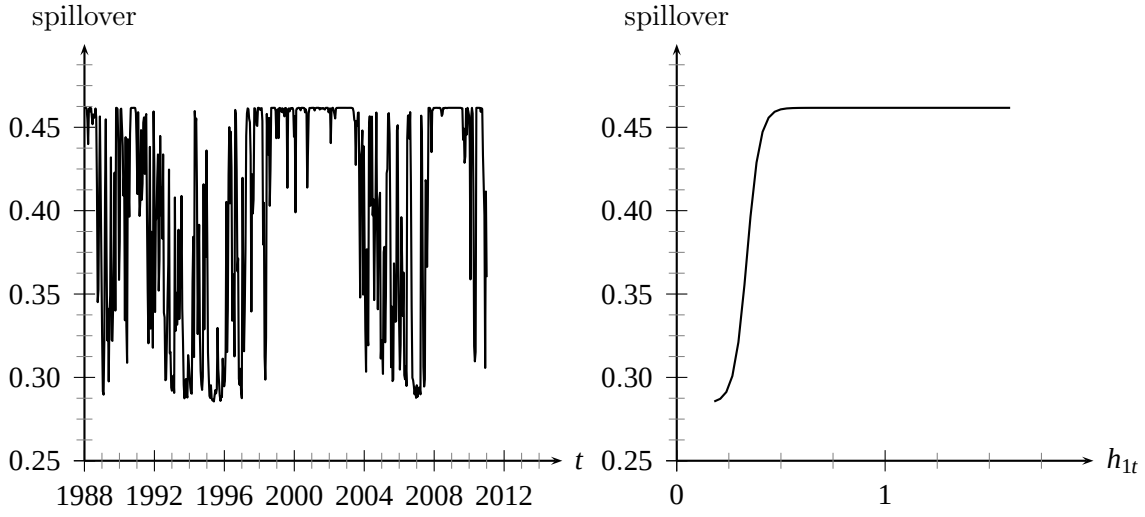
(a) Spillover (b) Transition Function

Figure 2: Spillover and Transition Function for Canada and the US



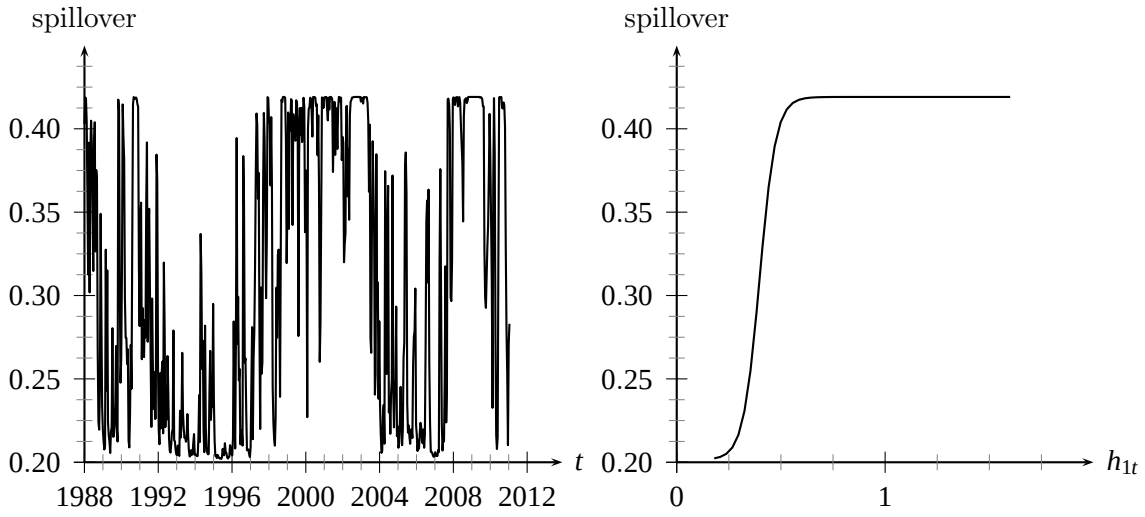
(a) Spillover (b) Transition Function

Figure 3: Spillover and Transition Function for Australia



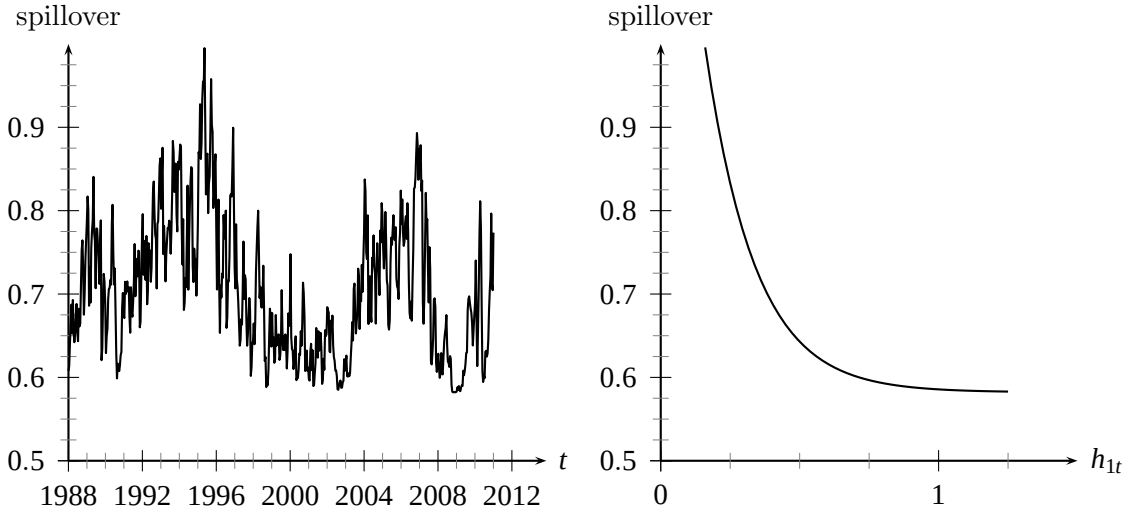
(a) Spillover (b) Transition Function

Figure 4: Spillover and Transition Function for Japan



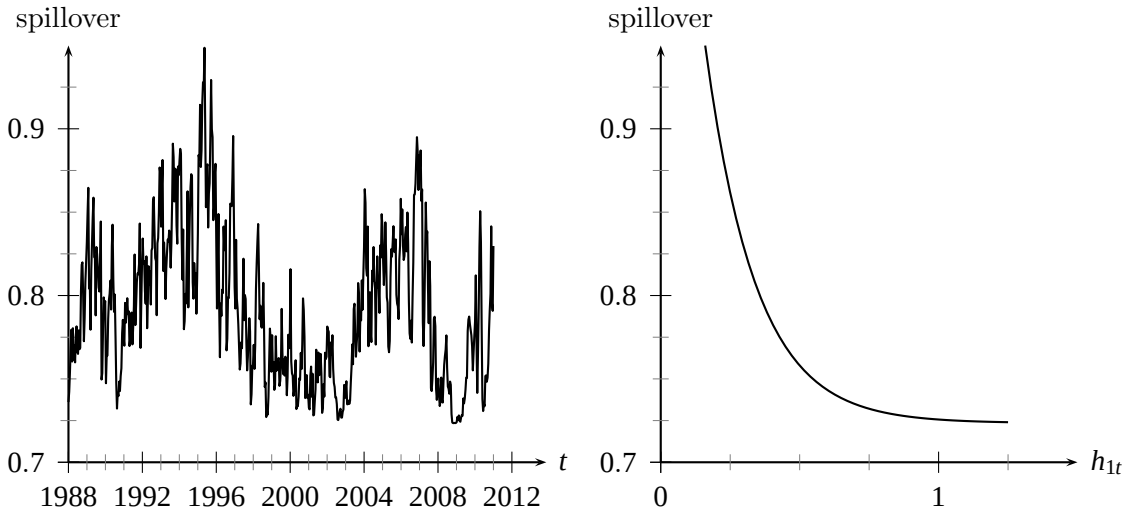
(a) Spillover (b) Transition Function

Figure 5: Spillover and Transition Function for Korea



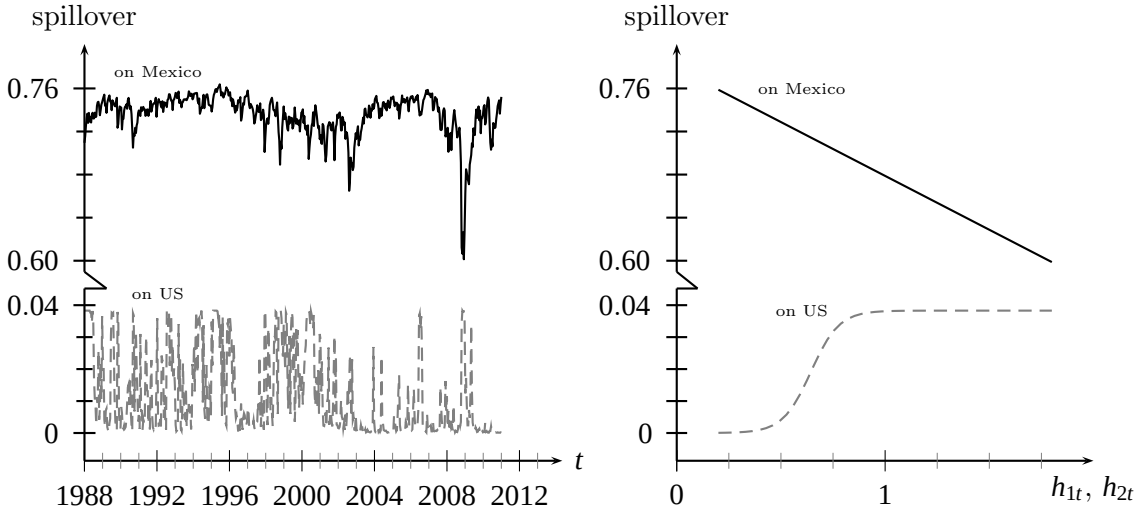
(a) Spillover (b) Transition Function

Figure 6: Spillover and Transition Function for Argentina



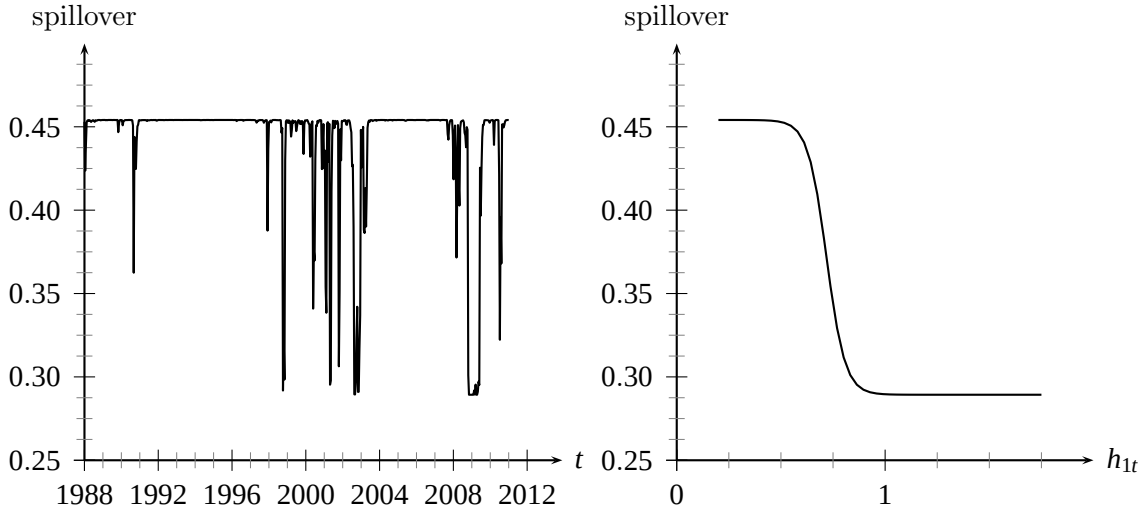
(a) Spillover (b) Transition Function

Figure 7: Spillover and Transition Function for Brazil



(a) Spillover (b) Transition Function

Figure 8: Spillover and Transition Function for Mexico and the US



(a) Spillover (b) Transition Function

Figure 9: Spillover and Transition Function for the Philippines

Interpreting the Stock Market Evidence

Returning to the discussion at the beginning of the paper, the answer to the question whether volatility predominantly signals information or uncertainty is - literally - in the eye of the beholder. On the one hand, identifying shocks in the "source" market and measuring their impact on transmission intensity in the "target" market renders identification and estimation possible. On the other hand, this implies one particular combination of "sender" and "receiver" of volatility signals in each model. The differences in the results across countries show that this combination is crucial. The generally high level of US spillover on the countries under investigation indicates the important role of US stock market developments as a major point of reference. However, even though the "sender of volatility" remains the same in all cases, in times of high volatility this importance decreases for some "receivers", whereas for others it increases.

An intuition for these results might be found in the interconnection and commonalities of each country and the US. Specifically, factors such as trade, policy coordination or institutional similarities might be one reason for the industrial countries Australia, Canada, Japan and Korea to predominantly identify information from stock market fluctuations in the US. The US signal bears highly relevant and well-understood information that outweighs the uncertainty, and, is priced instantaneously. By contrast, the reduction of spillover intensity to the emerging economies Argentina, Brazil, Mexico and the Philippines in times of rising US volatility may be explained in the light of dissimilarities, for instance, in the institutional, legal and regulatory framework and relative political and economic instability. The information content in US price changes becomes less visible during turbulent times, which are perceived as propagating uncertainty instead.

4.4 Crisis, Correlation and Coefficients

During turbulent times, such as the ongoing global financial crisis, stock market co-movement is commonly perceived to be more pronounced. Indeed, splitting the present sample in a pre- and post-Lehman period with break date 9/15/2008 reveals a substantial increase in the empirical return correlation between each country and the US. Yet, at the same time, our previous results showed *decreasing* spillover intensity in some markets (Argentina, Brazil, Mexico and the Philippines). Even though we already specified a time varying coefficient model, these findings suggest that the volatility effect on the transmission strength might exhibit a structural break. So far, our approach implicitly assumed that either the information or the uncertainty hypotheses predominates over the whole sample period. Therefore, we pursue this issue further with emphasis on a pre-crisis and a crisis sample.

It is also well known, however, that a rise in correlation between two variables might very well simply be triggered by an increased variance of the explanatory variable. Forbes and Rigobon (2002), for instance, document this crucial role of volatility changes that can result in biased estimates of correlation coefficients. For the present data we evaluated this effect in a small simulation study. Denoting US returns by x_t and those of the other country by y_t, we simulated $y_t = \beta x_t + \varepsilon_t$ for the pre- and post-Lehman period with parameters according to our empirical estimates from the above models. Thereby, the following rule of thumb was used: We set β to the average spillover intensity and drew ε_t and x_t from normal distributions with zero mean and $\mathrm{Var}(\varepsilon_t)$ and $\mathrm{Var}(x_t)$ equal to the average ARCH variances - before and after 9/15/2008, respectively.

With this parametrization we were able to reproduce the sharp rise in return correlation during the crisis period. Thus, the increasing US volatility turned out to be the major driving force behind the rising correlations with Argentina, Brazil, Mexico and

the Philippines. At the same time, this implies that the transition functions with stable parameters are compatible with the data. Despite the increase in return correlations, our approach is able to identify what we have termed the uncertainty effect, i.e., spillover strength decreases in volatility. The reason is that the variance changes, which affect the correlation coefficients, are explicitly taken into account in our model.

5 Conclusion

The present study motivated volatility-dependent simultaneous stock market interaction by discussing the fundamental character of volatility, which we argue is inherently ambivalent. Regarding the academic literature, volatility is used to proxy two different latent variables: information and uncertainty. We summarize the first view as the information hypothesis referring to studies where volatility is directly related to information flow intensity (see e.g. Ross 1989, Foster and Viswanathan 1993, 1995 or Kalev et al. 2004). The uncertainty hypothesis, on the other hand, has its source in large strands of literature where volatility is functioning as an uncertainty-proxy (see e.g Engle et al. 1987, Grier and Perry 2000, Chowdhury 1993 or Kiyota and Urata 2004).

We propose an econometric approach that consists of a simultaneous equations model with time-varying parameters. The time-variation of the spillover coefficient in one market is driven by the volatility of the other. In this setting it is the effect of volatility on the spillover strength that reflects whether the information hypothesis (positive effect) or the uncertainty hypothesis (negative effect) dominates.

Our main finding is that stock market interaction depends significantly on volatility in all countries under investigation. Evidence for the information hypothesis is found for the industrial countries (Australia, Canada, Japan and Korea), whereas the data of developing countries (Argentina, Brazil, Mexico and the Philippines) support the

uncertainty hypothesis.

This paper reveals that foreign volatility plays a crucial role in the interaction of stock markets. Thereby, the signal of volatility differs substantially across countries. We show that, appart from the well-known capability of conditional variances to capture volatility clusters and ensuring efficient estimation, they constitute a useful tool for further purposes. Namely, conditional variances also help identify simultaneous effects and, especially, describe the time-varying nature of these effects in financial applications.

References

[1] Andersen, T.G. (1996): Return volatility and trading volume: An information flow interpretation of stochastic volatility. Journal of Finance, 51, 169–204.

[2] Andersen, T.G., T. Bollerslev (1998): Deutsche Mark-Dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. Journal of Finance, 53, 219–265.

[3] Bali, T.G., R.F. Engle (2010): The intertemporal capital asset pricing model with dynamic conditional correlations. Journal of Monetary Economics, 57, 377–390.

[4] Chowdhury, A.R. (1993): Does exchange rate volatility depress trade flows? Evidence from error-correction models. Review of Economics and Statistics, 75, 700–706.

[5] Clark, P.K. (1973): A subordinated stochastic process model with finite variance for speculative prices. Econometrica, 41, 135–155.

[6] Cushman, D.O. (1985): Real exchange rate risk, expectations, and the level of direct investment. Review of Economics and Statistics, 67, 297–308.

[7] Engle, R.F., D.M. Lilien, R.P. Robins (1987): Estimating time varying risk premia in the term structure: The ARCH-M model. Econometrica, 55, 391–407.

[8] Epps, T.W., M.L. Epps (1976): The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis. Econometrica, 44, 305–321.

[9] Forbes, K.J., R. Rigobon (2002): No Contagion, Only Interdependence: Measuring Stock Market Comovements. Journal of Finance, 57, 2223–2261.

[10] Foster, F.D., S. Viswanathan (1993): Variations in trading volume, return volatility and trading costs: Evidence on recent price formation models. Journal of Finance, 48, 187–211.

[11] Foster, F.D., S. Viswanathan (1995): Can speculative trading explain the volume-volatility relation? Journal of Business and Economic Statistics, 13, 379–396.

[12] French, K.R., R. Roll (1986): Stock return variances: The arrival of information and the reaction of traders. Journal of Financial Economics, 17, 5–26.

[13] Gagnon, L., G.A. Karolyi (2009): Information, trading volume, and international stock return comovements: Evidence from cross-listed stocks. Journal of Financial and Quantitative Analysis, 44, 953–986.

[14] Grier, K.B., M.J. Perry (2000): The effects of real and nominal uncertainty on inflation and output growth: Some GARCH-M evidence. Journal of Applied Econometrics, 15, 45–58.

[15] Harris, L. (1987): Transaction data tests of the mixture of distributions hypothesis. Journal of Financial and Quantitative Analysis, 22, 127–141.

[16] Kalev, P.S., W.-M. Liu, P.K. Pham, E. Jarnecic (2004): Public information arrival and volatility of intraday stock returns. Journal of Banking & Finance, 28, 1441–1467.

[17] Kim, O., R. Verrecchia (1991): Trading volume and price reaction to public announcements. Journal of Accounting Research, 29, 302–321.

[18] King, M.A., S. Wadhwani (1990): Transmission of Volatility between Stock Markets. Review of Financial Studies, 3, 5–33.

[19] Kiyota, K., S. Urata (2004): Exchange rate, exchange rate volatility and foreign direct investment. The World Economy, 27, 1501–1536.

[20] Kyle, A. (1985): Continuous auctions and insider trading. Econometrica, 53, 1315–1335.

[21] Lamoureux, C.G., W.D. Lastrapes (1990): Heteroskedasticity in stock return data: Volume versus GARCH effects. Journal of Finance, 45, 221–229.

[22] Luukkonen, R., P. Saikkonen, T. Teräsvirta (1988): Testing linearity against smooth transition autoregressive models. Biometrika, 75, 491–499.

[23] Rigobon, R. (2003): Identification through heteroskedasticity. Review of Economics and Statistics, 85, 777–792.

[24] Ross, S.A. (1989): Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy. Journal of Finance, 44, 1–17.

[25] Sentana, E., G. Fiorentini (2001): Identification, estimation and testing of conditionally heteroskedastic factor models. Journal of Econometrics, 102, 143–164.

[26] Skalin, J. (1998): Testing linearity against smooth transition autoregression using a parametric bootstrap. SSE/EFI Working Paper in Economics and Finance 276, Stockholm School of Economics.

[27] Tauchen, G.E., M. Pitts (1983): The price variability-volume relationship on speculative markets. Econometrica, 51, 485–505.

[28] Weber, E. (2010): Structural conditional correlation. Journal of Financial Econometrics, 8, 392–407.