# Time-Varying International Stock Market Interaction and the Identification of Volatility Signals[1]


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**Abstract**

This paper investigates the dependency of international stock market interaction on financial volatility. We show in a stylized economic model that volatility-dependent cross-market spillovers can be interpreted in two different ways, as indicating *information* flow or *uncertainty*. If higher volatility in one market leads to higher (lower) reactions in another market, volatility reflects information (uncertainty). We apply a simultaneous time-varying coefficient model, where structural ARCH-type variances serve two purposes: governing the time variation of spillovers and ensuring statistical identification. We analyze data of US and further stock markets. Indeed, we find strong nonlinear, volatility-dependent spillovers.



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# 1 Introduction

The present study investigates international stock market interaction and its dependency on financial volatility. We apply a flexible econometric approach to estimate and to interpret volatility-dependent cross-market spillover. Considering the public and academic discussion, we argue that two basic understandings of volatility could be distilled. On the one hand, the fact that prices vary can be 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. We aim at empirically testing whether such a relation exists and to shed light on the role of volatility. We use a simple economic framework to motivate that higher volatility in one market should lead to higher (lower) reactions in another market if volatility reflects information (uncertainty). Secondly, we propose a strategy to infer the role of return variability from the data: we analyze different reactions of investors to observed returns, depending on the prevailing level of volatility. As our econometric framework, we apply 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 interpretations 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 fragile 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 $\mu$-$\sigma$-utility function and the CAPM. Originating from Engle et al. (1987), financial econometricians translated this idea into the variance-in-mean model (see also French et al. 1987, 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 contrary, a second view interprets volatility as a measure of information flow intensity. We refer to this perception as the *information hypothesis*. Some representatives of the literature who elaborate on the volatility-information link are Clark (1973), Epps and Epps (1976), Ross (1989) and Fleming et al. (1998). Overall, as in the mixture-of-distribution hypothesis, 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 economic models. 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), 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), Kalev et al. (2004) or Goeij and Marquering (2006). 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 help to fix ideas concerning the character of volatility. Naturally, they are not mutually exclusive. Rather, exploring how volatility affects stock market interaction 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.

In the empirical analysis, we will also allow for leverage effects, i.e. positive (good news) and negative shocks (bad news) may have different effects on volatility. The distinction we make between the *information hypothesis* and the *uncertainty hypothesis* is, however, different from asymmetric volatility reactions. While accounting for possible leverage effects, we analyze how the level of volatility influences the spillover of shocks between markets. Thereby, for instance information can equally result from both good and bad news.

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 economic model, 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 set-up to analyze international stock market interaction 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 most 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 Economic Model

## 2.1 The Market Participant: Signal Extraction Problem

First we discuss a stylized economic model to 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 of 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 $\iota_t$, $\nu_t$ refers to noise and $\mathbb{E}[\cdot|I_{jt}]$ represents the expectations operator conditional on the information observed in market $j$ at time $t$. The model reflects the usually positive correlation of international stock returns, i.e. $\alpha_{12} \geq 0$, $\alpha_{21} \geq 0$ .

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 $\beta_1$ 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:

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

According to equation (4), the larger the information shock variance $\mathrm{Var}[\iota_{2t}]$, the higher $\beta_1$ and, as it will become immediately evident below, the higher the spillover. Moreover, if the volatility of returns changes, either due to a change in the variance of $\iota_{2t}$ or of $\nu_{2t}$, $\beta_1$ becomes time varying, i.e., $\beta_{1t}$.

Of course, to extract the information from price movements in market 1, agents in market 2 follow an analogous rationale. The model is completed by using (3) and (4) to substitute for the conditional expectations in (1) and (2). This 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 $\varepsilon_{2t} = (1-\alpha_{12}\alpha_{21}\beta_{1t}\beta_{2t})(\iota_{2t}+\nu_{2t})$.

From equations (4) and (5)-(6) it is evident that the variances of foreign information and uncertainty shocks enter the spillover coefficients $A_{ijt}$ through $\beta_{it}$. It is precisely this mechanism which identifies the prevailing signal of volatility by investors reactions to foreign returns. If return volatility, i.e. the volatility of the total shock, increases, spillovers change. They increase if information dominates the volatility change and they decrease if uncertainty dominates the volatility change.

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 $\beta$ 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

The model (1), (2) cannot be estimated directly since all four shocks are unobservable. Otherwise, we could simply estimate their variances to see which volatility effect dominates. However, we have shown that under the assumption that the model in (5) and (6) is identified, one could exploit the time variation in the spillovers in order to measure volatility signals. 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). The econometrician can approach the problem of measuring volatility signals by estimating the variance of $\varepsilon_t$, i.e. the entire shocks to the returns. Taking the typical time-varying nature of financial time series volatility into account, we denote the conditional variance of $\varepsilon_t$ by $\mathrm{Var}[\varepsilon_t|I_{t-1}] = h_t$ and let the spillover coefficients depend on the variances by

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

As can be seen in (4), beta would be constant if the variation, i.e. the rate of change in $\mathrm{Var}[\iota_{jt}|I_{t-1}]$ and $\mathrm{Var}[\nu_{jt}|I_{t-1}]$, was exactly identical. Assume, for instance, that $\frac{\partial f_{ij}}{\partial h_{jt}} > 0$, so that $\mathrm{Var}[\iota_{jt}|I_{t-1}]$ dominates the dynamics of market volatility in the sense that its rate of change is higher than the one of $\mathrm{Var}[v_{jt}|I_{t-1}]$. This would favor the information hypothesis. On the contrary, $\frac{\partial f_{ij}}{\partial h_{jt}} < 0$ would represent evidence for the uncertainty hypothesis. In sum, examining the time variation in spillover strength can provide us with decisive information on which of the shocks contributes more to the volatility dynamics.

While the theoretical model in the previous section serves as a motivation, we argue that empirically the functional form of $f(\cdot)$ over the whole value range is not known a priori. As discussed in detail in the next section, allow for flexibility by approximating $f(\cdot)$ 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 volatility-dependent stock market interaction, 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 $\mu_t$ represents a vector of predictable components such as lags or a constant term and $\varepsilon_t$ is a $n$-dimensional vector of structural innovations. As it will turn out in the empirical application, however, significant lagged effects do not occur – a result which one would expect since financial market reactions usually appear quite quickly. 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 $\varepsilon_t$, 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.

For the present application, we propose a generalization of the model in Weber (2010), who specifies EGARCH processes for the structural shocks. Firstly, we also account for a possible leverage effect, which is commonly observed in return data (Nelson 1991). The logarithmic formulation ensures positive variances without relying on parametric restrictions, which is an advantage compared to alternative asymmetric volatility models as the threshold model of Glosten at al. (1993). Secondly, we use an extended version of the original univariate EGARCH specification by allowing for variance interactions between countries.

Formalizing the model setup, first denote the conditional variances of the elements in $\varepsilon_t$ by

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

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

Furthermore, denote the $n \times 1$ vector of standardized innovations by $\tilde{\varepsilon}_t$ with typical element

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

The multivariate EGARCH(1,1)-process is then given by

$$\log h_t^2 = c + g \log h_{t-1}^2 + d(|\tilde{\varepsilon}_{t-1}| - \sqrt{2/\pi}) + f \tilde{\varepsilon}_{t-1} \qquad , \tag{11}$$

where $\log h_t^2$ and $c$ are vectors of dimension $n \times 1$. The $n \times n$ coefficient matrices $g$, $d$ and $f$ include the GARCH, ARCH and leverage coefficients with variance interaction terms as off-diagonal elements. Subtraction of $\sqrt{2/\pi}$ serves to demean the absolute shock. The signed $\tilde{\varepsilon}_t$ takes asymmetric volatility effects (good vs. bad news) into account.

Since the variables $i$ and $j$ could be exposed to unobserved common factors, we consider a generalization of the heteroskedasticity based identification of Sentana and Fiorentini (2001) and Rigobon (2003) proposed by Weber (2010). That is, the shocks are allowed to be correlated as in classical simultaneous systems. As it turns out in the empirical analysis below, however, the contemporaneous correlation of shocks plays only a limited role in the sense that our results are robust to this specification.

In principle, the presence of heteroskedasticity represents only a necessary condition for statistical identification. As discussed in Sentana and Fiorentini (2001) and Weber (2010), a sufficient condition is that the variances are linearly independent across states. By now, we are not aware of an appropriate statistical test for two univariate GARCH processes. However, from visual inspection of GARCH processes, linear dependence seems quite unlikely.

For markets with non-overlapping trading hours identification problems are alleviated. The fact that country $i$ is only trading while the stock exchange in country $j$ is closed implies that contemporaneous spillovers do not appear. In our model setup, this amounts to specifying a triangular coefficient matrix $A_t$. 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 characterize the stock market interaction in terms of 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):

$$A_{ijt} = a_{ij} + b_{ij} h_{jt} \ , \tag{12}$$

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. To clarify this notation, consider the bivariate case with $\mu_t = 0$, where equation (8) takes the form:

$$\begin{pmatrix} 1 & a_{12} + b_{12} h_{2t} \\ a_{21} + b_{21} h_{1t} & 1 \end{pmatrix} \cdot \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \varepsilon_t \quad \Leftrightarrow \quad y_t = \begin{pmatrix} -a_{12} - b_{12} h_{2t} \\ -a_{21} - b_{21} h_{1t} \end{pmatrix} y_t + \varepsilon_t \ . \tag{13}$$

The most plausible correlation between international financial markets is a positive one. Therefore, in view of (13), we expect $a_{ij}$ to be smaller than zero. Moreover, with the above notation, a one-unit increase in source market volatility decreases spillover intensity by $b_{ij}$. It follows that $b_{ij} > 0$ would favor the uncertainty 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 (12), 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, (12) 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[4] in $h_{jt}$ and bounded between zero and one. The slope parameter $\gamma$ 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 $\beta$ 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. These effects of volatility might change over time, e.g. with regard to crisis periods. We address this issue in Appendix A.

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. The relevant literature usually employs a third order

[4] 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.

approximation:

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

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 $b_{ij,2} = b_{ij,3} = 0$ but $b_{ij,1} \neq 0$ is found, the transition function can be approximated by the linear specification (12). We maximize the likelihood function under the assumption of normally distributed shocks. As the normality assumption is usually too restrictive for financial time series data, we rely on quasi maximum likelihood.

# 4 Evidence on the Volatility-Dependency of International Stock Market Interaction

## 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[5]), 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.

[5]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.

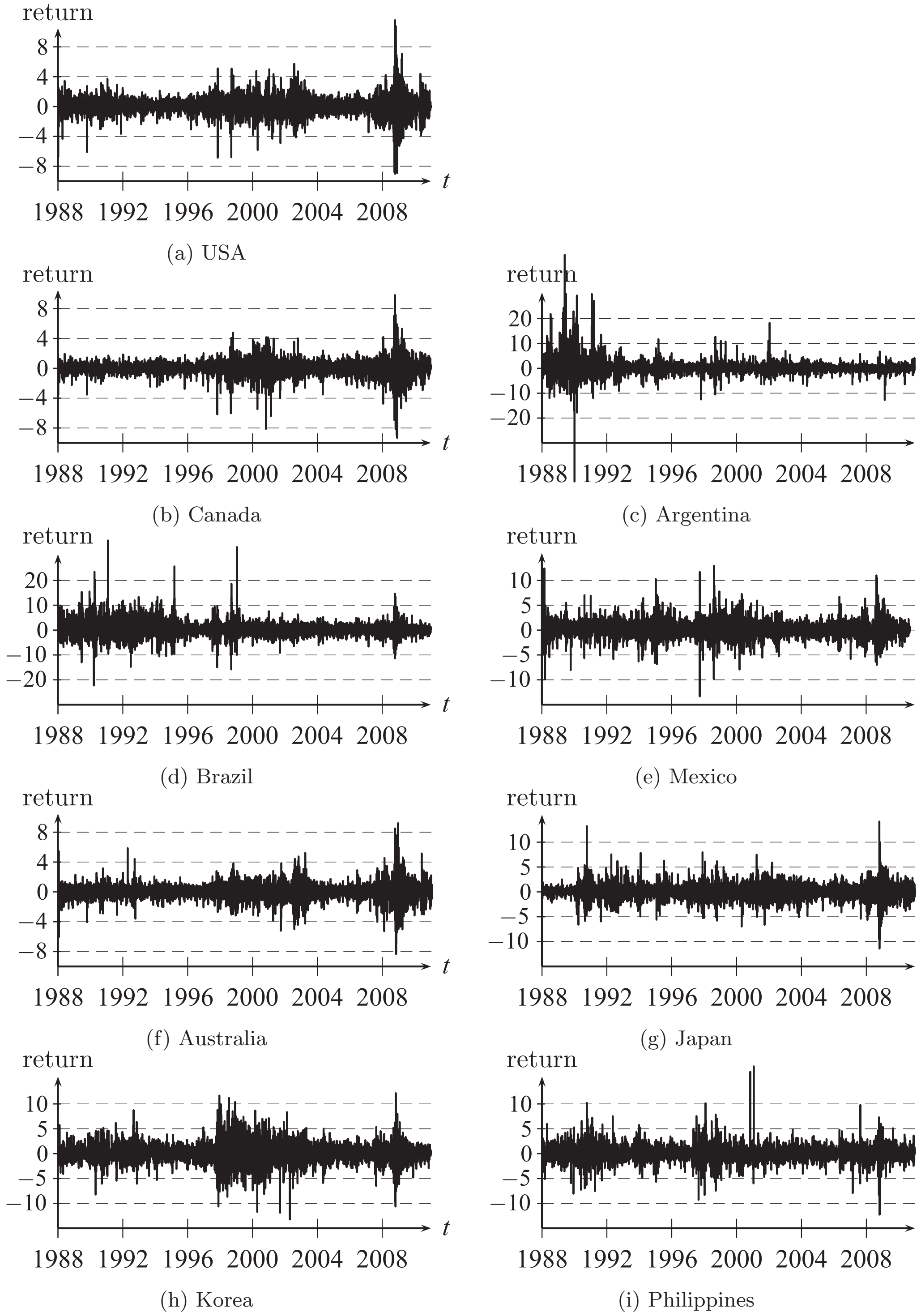



Figure 1: Daily Stock Returns on (a) S&P 500, (b) S&P/TSX 60, (c) TOTMKAR, (d) Bovespa Index, (e) IPC, (f) S&P/ASX 50, (g) Nikkei, (h) KOSPI and (i) PSEi

## 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. Since we are allowing not only for linear but also for smooth transition type non-linear spillovers, we face the problem that under the null some parameters are not identified. This is a well-known problem which inflates standard errors. Therefore, our inference is based on likelihood ratio testing in the Taylor approximation rather than on $t$-tests in the smooth transition formulation.

The LR test procedure to specify the functional form of the transition function represents the starting point of our empirical analysis and, based on Section 3.2, can be described as follows:

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.

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. In the Asian region and Australia, stock markets open after those in the US have closed so that the contemporaneous effect, i.e., on the same day is restricted to appear only in one direction.

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.[6] 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 linear spillover on Canada (not rejecting the null in column 3).

During estimation we set $\mu_t$ 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).

[6] 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%).

Our multivariate EGARCH specification finds highly significant leverage effects and variance interactions. This indicates that both features of the variance model are clearly present in the data. 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.

### 4.3 Results

The first major result is that we find strong evidence for time-varying spillover coefficients in all countries under investigation. In particular, LR tests (not presented in Table 1) of constant against time-varying spillover result in $p$-values of 0.000 (Canada), 0.002 (Australia), 0.010 (Japan), 0.000 (Korea), 0.000 (Mexico), 0.000 (Argentina), 0.003 (Brazil) and 0.000 (Philippines). That is, for all countries test results suggest a clear 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, Korea and Mexico as US volatility increases the fraction of US shocks that feed into stock prices of these countries. In that sense, stock market interaction is stronger in times where returns are more volatile. The same holds for Canadian and Mexican volatility, signaling information for US traders. Second, Argentinian, Brazilian and Philippine stock markets seem to understand US volatility as uncertainty since higher volatility leads to a reduction of spillover intensity in these markets.

For two examples, one from the information hypothesis group and one from the uncertainty hypothesis group, we plotted the spillovers as a function of the variance $h_{jt}$ (i.e. the transition functions) in order to visualize which hypothesis is supported, see Figures 2 to 3 (right hand side). The development of the spillovers over time is shown on the left hand side. The spillover intensity, which lies between 0% and 100%, measures the fraction of a shock that is transmitted from one market to the other. We obtain the following results.

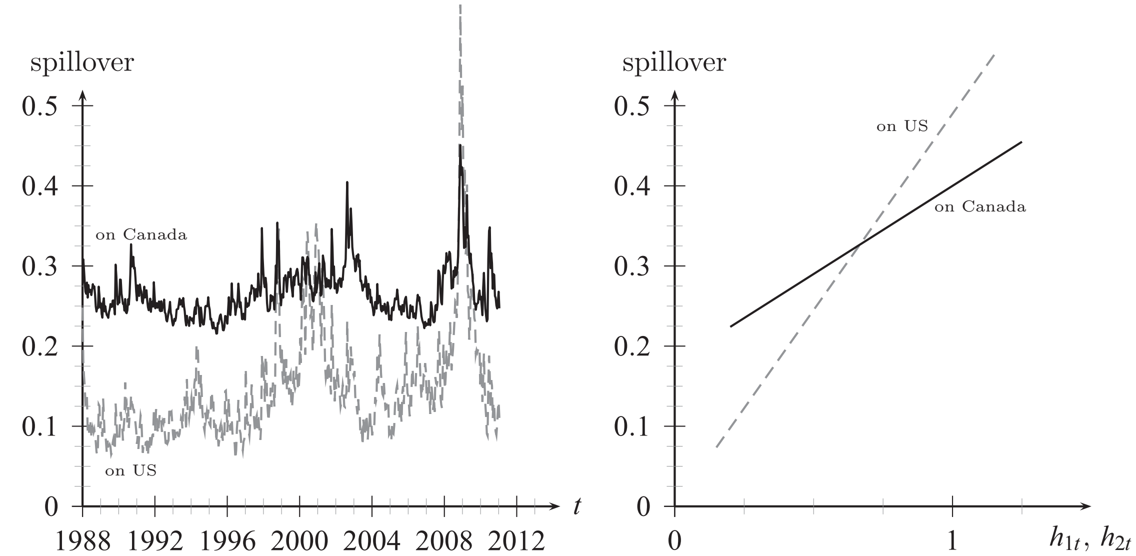
| X | $H_0$: linear on US<br>$H_1$: STR on US<br>$p$-values for df $=2$ | $H_0$: linear on X<br>$H_1$: STR on X<br>$p$-values for df $=2$ | final specification of time-varying spillovers | coefficient estimates | | | | signal of volatility |
|---|---|---|---|---|---|---|---|---|
| Canada | 0.32 | 0.09 | linear on US | $a_{12}=0$ | $b_{12}=-0.49$ | | | information |
| | | | linear on Canada | $a_{21}=-0.18$ | $b_{21}=-0.22$ | | | information |
| Australia | – | 0.07 | no spillover on US | | | | | - |
| | | | linear on Australia | $a_{21}=-0.34$ | $b_{21}=-0.16$ | | | information |
| Japan | – | 0.10 | no spillover on US | | | | | - |
| | | | linear on Japan | $a_{21}=-0.36$ | $b_{21}=-0.15$ | | | information |
| Korea | – | **0.00** | no spillover on US | | | | | - |
| | | | STR on Korea | $a_{21}=-0.18$ | $\alpha_{21}=-0.27$ | $\gamma_{21}=10.68$ | $\beta_{21}=0.38$ | information |
| Mexico | **0.00** | **0.00** | STR on US | $a_{12}=0$ | $\alpha_{12}=-0.04$ | $\gamma_{12}=3.73$ | $\beta_{12}=0.53$ | information |
| | | | STR on Mexico | $a_{21}=-0.66$ | $\alpha_{21}=-0.06$ | $\gamma_{21}=7.47$ | $\beta_{21}=0.27$ | information |
| Argentina | 0.00 | **0.03** | no spillover on US | | | | | - |
| | | | STR on Argentina | $a_{21}=-1.49$ | $\alpha_{21}=0.86$ | $\gamma_{21}=23.01$ | $\beta_{21}=0.18$ | uncertainty |
| Brazil | 0.04 | **0.01** | no spillover on US | | | | | - |
| | | | STR on Brazil | $a_{21}=-1.17$ | $\alpha_{21}=0.42$ | $\gamma_{21}=14.86$ | $\beta_{21}=0.19$ | uncertainty |
| Philippines | – | **0.00** | no spillover on US | | | | | - |
| | | | STR on Philippines | $a_{21}=-0.45$ | $\alpha_{21}=0.16$ | $\gamma_{21}=25.44$ | $\beta_{21}=0.70$ | uncertainty |

Notes: Columns 2 and 3 report $p$-values of likelihood ratio (LR) tests of the indicated null hypotheses with degrees of freedom equal to df. The inference is base on LR tests only, since in the smooth transition case we have unidentified parameters under the null which inflates standard errors. 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 3. 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:

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

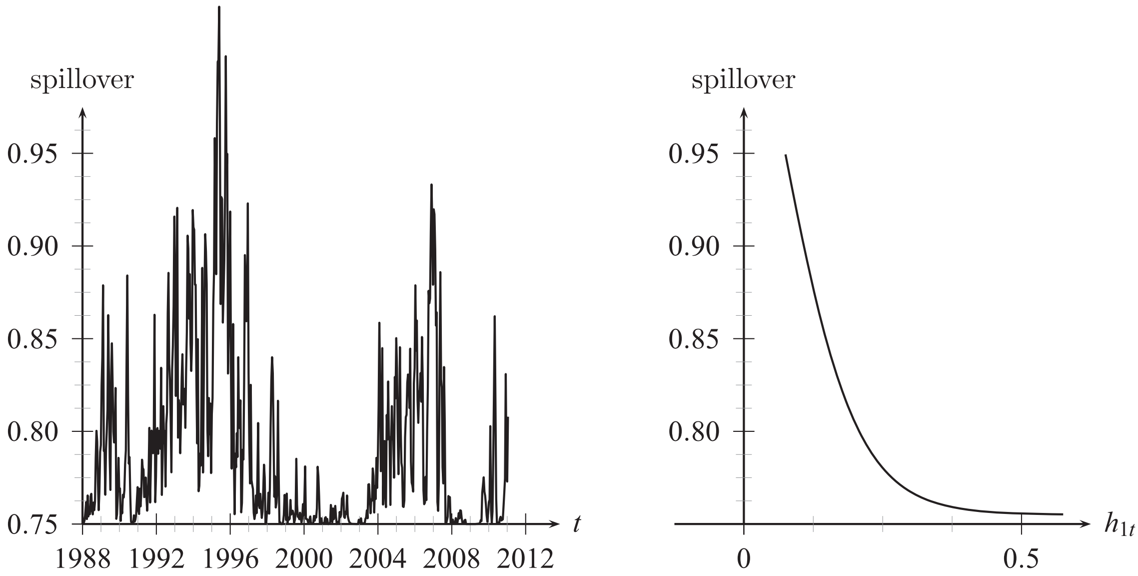
Table 1: Estimation Results: The Effect of Volatility on Time-Varying Spillovers

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




(a) Spillover (b) Transition Function

Figure 3: Spillover and Transition Function for Brazil




(a) Spillover (b) Transition Function

**Evidence for the Information Hypotheses in Industrial Economies**

- In Canada, the effect of US volatility is quite pronounced. We find a transmission that varies between 20% in times of low and approximately 45% 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 the remaining industrial economies (as well as Mexico), spillovers from the US play a similar or even stronger role.

**Evidence for the Uncertainty Hypotheses in Emerging Economies**

- Transmission strength for Brazil varies around a level of 80%. US volatility strongly reduces spillover intensity and is thus interpreted as signaling uncertainty. The variance of domestic shocks in Brazil is high compared to the US. Thus, despite high spillovers from the US, domestic shocks represent a major factor of return variation in Brazil.
- Argentinian and Philippine returns are similarly strongly and also negatively affected by US spillovers.

**Interpreting the Stock Market Evidence**

Returning to the discussion at the beginning of the paper, the answer to the question how volatility shapes international stock market interaction 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, Korea as well as Mexico[7] 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 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.

# 5 Conclusion

The present study motivated volatility-dependent simultaneous interaction between international stock markets 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, Kiyota and Urata 2004, Bekaert et al. 2009 or Li 2011).

As econometric approach, we propose 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 international 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, Korea) and Mexico, whereas the data of emerging economies (Argentina, Brazil and the Philippines) support the uncertainty hypothesis.

[7]While not counting as a typical industrial country, for Mexico factors such as large bilateral trade shares and proximity to the US are likely to play an important role.

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, apart 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.

# A Appendix: Crisis, Correlation and Coefficients

Particularly during the sample period under investigation it is important to pursue the possibility of structural breaks. 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 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 take a closer look at a pre-crisis and a crisis sample.

Specifically, we check whether our model is sufficiently flexible to represent the main features of the data or we should rather allow for a structural break at the beginning of the crisis. For this purpose, we conduct a small simulation experiment based on parameters according to our empirical estimates from the above models. The following steps indicate this experiment. Denoting US returns by $x_t$ and those of the other country by $y_t$, we generated $y_t = \beta x_t + \varepsilon_t$ for the pre- and post-Lehman period. As a rule of thumb, we set $\beta$ to the average spillover intensity and drew $\varepsilon_t$ 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. That is, the rise in return correlation is not due to presence of a structural break but only triggered by an increased variance of the explanatory variable, similar to the considerations in Forbes and Rigobon (2002). This also shows that our approach does not suffer from what is known as the heteroskedasticity bias.

For our empirical analysis, this implies that the increasing US volatility is the major driving force behind the rising correlations with Argentina, Brazil 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.

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