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Spillovers and jumps in global markets: a comparative analysis

Master's Dissertation submitted to the Graduate Program in Economics - Area: Applied Economics from School of Economics, business Administration and Accounting at Ribeirão Preto of the University of São Paulo, to obtain a Master's degree in Sciences. Corrected version. The original is available at FEA-RP / USP.

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Ribeirão Preto

2018

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Abstract

MOURA, R. C. **Spillovers and jumps in global markets: a comparative analysis** 2018. Dissertation (Masters) - School of Economics, business Administration and Accounting at Ribeirão Preto, University of São Paulo, Ribeirão Preto, 2018.

We analyze the relation between volatility spillovers and jumps in financial markets. For this, we compared the volatility spillover index proposed by Diebold and Yilmaz (2009) with a global volatility component, estimated through a multivariate stochastic volatility model with jumps in the mean and in the conditional volatility. This model allows a direct dating of events that alter the global volatility structure, based on a permanent/transitory decomposition in the structure of returns and volatilities, and also the estimation of market risk measures. We conclude that the multivariate stochastic volatility model solves some limitations in the spillover index and can be a useful tool in measuring and managing risk in global financial markets.

Key-words: Multivariate Stochastic Volatility, Jumps, Common Factor, Bayesian Estimation.

Resumo

MOURA, R. C. **Saltos e Spillovers nos mercados globais: uma análise comparativa.** 2018. Dissertation (Master Degree) - School of Economics, business Administration and Accounting at Ribeirão Preto

Analizamos a relação existente entre spillovers e saltos na volatilidade nos mercados financeiros. Para isso, comparamos o índice de spillover de volatilidade proposto por Diebold and Yilmaz (2009), com um componente de volatilidade global, estimado através de um modelo multivariado de volatilidade estocástica com saltos na média e na volatilidade condicional. Este modelo permite uma datação direta dos eventos que alteram a estrutura de volatilidade global, baseando-se na decomposição das estruturas de retorno e volatilidade entre efeitos permanentes/transitórios, como também a estimação de medidas de risco de mercado. Concluimos que este modelo resolve algumas das limitações do índice de spillover além de fornecer um método prático para mensurar e administrar o risco nos mercados financeiros globais.

Palavras-chaves: Volatilidade Estocástica Multivariada, Saltos, Fator Comum, Estimação Bayesiana

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1 Introduction

In recent decades there has been a significant increase in the connections between international financial markets. This interconnectedness among markets allows investors to have access to a significant diversification gains in portfolio allocation and risk management, being also extremely important for external financing of emerging economies.

However, this market integration was also followed by a greater transmission of shocks among economies. Another important consequence of this interconnectedness process is that global crises are becoming stronger and more frequent, e.g. Bordo et al. (2001). Additionally, Forbes (2002) has shown that, with greater international interdependence, a country's specific financial shock spreads rapidly to other countries financial markets. Therefore, an understanding of the correlations and interactions among economies is crucial for portfolio allocation and risk management.

One approach in the analysis of market integration is the estimation of spillover effects among markets, which aims at capturing the patterns of shocks transmission of prices and volatilities. Some initial references in this theme are Engle, Ito and Lin (1988), Hamao, Masulis and Ng (1990), King, Sentana and Wadhwani (1990), Calvo and Reinhart (1996), Edwards (1998) and Nikkinen, Sahlström and Vähämaa (2006), and recent developments in the econometric analysis of international financial markets can be found in Diebold and Yilmaz (2009), Billio et al. (2012), Dungey, Luciani and Veredas (2014), Hautsch, Schaumburg and Schienle (2014) and Barigozzi and Brownlees (2016).

In this context, we highlight the influential work of Diebold and Yilmaz (2009). In this paper, the authors estimated the spillover effects for the global stock market, using a vector autoregressive model (VAR) over the weekly returns and volatilities of nineteen stock indexes for a period of fifteen years. The spillover effects were estimated from the prediction errors of the return or volatility structures, found when disturbances' arising from one asset affect others markets. In this way, the spillover effects between two series were calculated as the ratio between the error variance arising from shocks between these assets and the observed total error of the variance decomposition across all markets.

Although this formulation is very intuitive and easy to estimate, it presents some important limitations. Firstly, the VAR results depend on the order of the variables within it, as usual in VAR decompositions, e.g. Faust (1998). To evaluate the extent of the spillover index that is sensitive to the reordering problem, Diebold and Yilmaz (2009) considered a small number of asset rearrangements. A more robust estimation was proposed by Klobner and Wagner (2013), which considered all possible permutations in the VAR structure to calculate the spillover effects.

Secondly, to build the spillover index, Diebold and Yilmaz (2009) first assumed that connectedness is time-invariant over the sample used, but in fact it is time-variant, as discussed in Diebold and Yilmaz (2015). To obtain a version of the spillover effect, they divide the original sample period into subsamples and estimated this measure over rolling windows of data. The preference over this method relates to its simplicity and consistency with a wide variety of possible data generating processes (DGP) involving time varying parameters, as discussed in Diebold and Yilmaz (2015).

However, this choice can have consequences on the econometric properties of this estimator, since the connectedness is not only time-varying but also time dependent. The use of short rolling windows lowers the efficiency of estimation, increasing the variance of the estimated spillover index and also generates dimensionality problems, e.g. Geraci and Gnabo (2015). In contrast, the use of a long estimation window, biases the results towards time-invariant connectedness estimation, as argued in Clark and McCracken (2009). The rolling sample estimation also increases the sensitivity to outliers in the small subsamples, as these have a larger impact on the estimates e.g. Zivot and Wang (2007). In general, by relying on rolling window estimation, the authors always have a trade-off between the precision and bias in the estimation of interconnectedness.

The use of VAR estimations with constant parameters in each subsample also generates another important limitation. Real-world volatility variations might sometimes be abrupt, with quick and sharp changes in the presence of large shocks or crisis regimes, which cannot be captured by the usual estimation of VAR models. Although it is possible to use versions of this estimator controlling for the presence of variation in the parameters,

such as the use of Markov switching processes or time varying VAR estimation (Geraci and Gnabo (2015)), the most used version is based on the use of rolling sample estimation, as discussed in Diebold and Yilmaz (2015).

Other fundamental aspect, is that the volatility spillover index estimation proposed by Diebold and Yilmaz (2009) is based on an indirect measure of the variance process, i.e., it's obtained through variances estimated using the methodology of Garman and Klass (1980) in a two-stage procedure. This reverberate on the estimator effectiveness to capture rapidly changes in the return and volatility structures. Moreover, this indirect measure makes the use of the index limited to be an indicator of interconnectedness between assets. Thereby, the calculation of risk management measures, such as Value at Risk (VaR) and Expected Shortfall, as well as hedging of positions, isn't possible from the estimated index.

To overcome the problems discussed above, we propose the use of a generalized version of the multivariate stochastic volatility with jumps model created by Laurini, Mauad and Aiube (2017), in which the authors propose an alternative way of identifying the interdependence between financial markets. In this model, the estimation is done without the use of VAR models, it uses all the information available in the sample, avoiding the problems associated with rolling window estimation and is based directly on returns, not requiring indirect estimates of asset volatilities. Furthermore, the model structure can be interpreted as a regime-switching model, where the number of regimes is neither fixed nor determined by the observed sample. In this way, we provide a more informative measure of the interdependence observed in the global stock market.

Complementarily, the model is based on time-varying common factors in the structures of returns and conditional volatilities, which are decomposed into permanent and transient components. The permanent ones are identified as the global factors, whose evolution is performed through a jump structure. These jumps identify the changes in the global volatility pattern, and indicate which shocks are common across markets. The transitory components are associated with the specific effects of each market. Moreover, this structure allows a direct dating of the events related to shock transmissions in global markets.

The model also generates a direct measure of the conditional volatilities of the global market and individual market components, allowing the direct construction of risk management and portfolio allocation measures, such as VaR and Expected Shortfall. We provide on Section 5 a comparison between the VaR estimated by our model and those estimated by traditional conditional volatility models. The results indicate that our model is preferable to the GARCH family in the estimation of tail risks.

It is important to note that, even though Diebold and Yilmaz (2009) and Laurini, Mauad and Aiube (2017) are estimating different measures: while the first measures the average spillover effect of a shock between markets, the later captures the observed jumps in volatilities and conditional returns in global markets. These measures are related, since both capture shocks that alter the market global volatility but are estimated from distinct principles.

The results indicate that our model not only capture well the dynamics of volatility in the period but also identified four additional jumps when compared to the main events found by Diebold and Yilmaz (2009) using a 200 weeks rolling-windows estimation. Thus, as our model is more sensible in identifying unexpected changes in volatility patterns and is still capable of generating risk measurement measures, we conclude that our model complements the results found by Diebold and Yilmaz (2009).

In this context, the present paper will center the discussion on the common factor of global volatility estimated in the stochastic volatility model proposed by Laurini, Mauad and Aiube (2017), comparing it with results obtained by the spillover index, created by Diebold and Yilmaz (2009). To reach this objective, this work have the following structure: Section 2 presents a brief review of the spillover index estimation methodology and a full description of the multivariate stochastic volatility with jumps model. Section 3 presents the analyzed database, and Section 4 presents the comparisons between models. Section 5 presents Value at Risk estimations, comparing it with other estimations based on GARCH volatility models. Finally, the conclusions are presented in Section 6.

2 The Spillover Index and the Multivariate Stochastic Volatility with Jumps Model

2.1 The Spillover Index

Diebold and Yilmaz (2009) created a simple measure of the transmission patterns between financial markets, which they called the Spillover Index. In this methodology, the prediction error of the returns or variances of an asset is decomposed in the disturbances arising from it own and from the other assets in the model. The index represents the average spillover effects of shocks in the global asset market.

For the reader convenience, we will review the basic components of the methodology introduced by Diebold and Yilmaz (2009), presenting a simplified version of this model. First, the authors considered a first-order autoregressive vector with two variables and stationary covariance:

$$\mathbf{x}_t = \Phi \mathbf{x}_{t-1} + \varepsilon_t, \quad (1)$$

In the equation above $\mathbf{x}_t = (\mathbf{x}_{1t}, \mathbf{x}_{2t})$ and Φ represents a 2×2 matrix and $\mathbf{x}$ a vector of returns or volatilities of these stocks. Assuming a stationary covariance structure, the moving average representation of the VAR exists and is given by:

$$\mathbf{x}_t = \Theta(L)\varepsilon_t, \quad (2)$$

where $\Theta(L) = (\mathbf{I} - \Phi(L))^{-1}$. Using the moving average representation, it is possible to rewrite the equation 2 as:

$$\mathbf{x}_t = \mathbf{A}(L)\mathbf{u}_t, \quad (3)$$

in which $\mathbf{A}(L) = \Theta(L)\mathbf{Q}_t^{-1}$, $\mathbf{u}_t = \mathbf{Q}_t\varepsilon_t$, $E(\mathbf{u}_t\mathbf{u}_t') = \mathbf{I}$, and $\mathbf{Q}_t^{-1}$ is the only lower triangular factor of Cholesky's covariance matrix ε_t .

The optimal one step-ahead prediction $\hat{\mathbf{x}}_{t+1,t}$ in the Wiener-Kolmogorov sense for this system is given by:

$$\hat{\mathbf{x}}_{t+1,t} = \Phi \mathbf{x}_t \quad (4)$$

while the vector of one step-ahead prediction errors is:

$$\mathbf{e}_{t+1,t} = \mathbf{x}_{t+1} - \hat{\mathbf{x}}_{t+1,t} = \mathbf{A}_0 \mathbf{u}_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \quad (5)$$

with covariance matrix:

$$E(\mathbf{e}_{t+1,t} \mathbf{e}_{t+1,t}') = \mathbf{A}_0 \mathbf{A}_0' \quad (6)$$

The variance of the one step-ahead forecast error in predicting x_{1t} is $a_{0,11}^2 + a_{0,12}^2$, while the variance of the one step-ahead forecast error of x_{2t} is $a_{0,21}^2 + a_{0,22}^2$. Based on this variance decomposition procedure, it is possible to decompose the variance associated with the shocks occurred in the other variables of this process.

Thus, they define the own variance share, as the fraction of the one step-ahead error variance in forecasting x_i , due to shocks in x_i to $i = 1, 2$ and cross variance share, or spillover, as the fraction of one step-ahead error variance in forecasting x_i due to shocks of x_j for $i, j = 1, 2$ and $i \neq j$. This implies that there will be two possible spillovers: shocks in x_{1t} that affect the prediction error of the variance of x_{2t} with contribution $a_{0,21}^2$ and shocks in x_{2t} affecting the prediction error of the variance of x_{1t} (with contribution $a_{0,12}^2$).

The total spillover will be given by $a_{0,12}^2 + a_{0,21}^2$. This measure becomes an index relative to the total variance forecast error: $a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = \text{trace } \mathbf{A}_0 \mathbf{A}_0'$. Thus, the ratio between total spillover and total error in the prediction of variance generates the spillover index:

$$SOI = \frac{a_{0,12}^2 + a_{0,21}^2}{\text{trace}(\mathbf{A}_0 \mathbf{A}_0')} \times 100. \quad (7)$$

Generalizing this process to an N-variate process of p -th order and a single step ahead forecast, the index can be rewritten as:

$$SOI = \frac{\sum_{i,j=1, i \neq j}^N a_{0,ij}^2}{\text{trace}(\mathbf{A}_0 \mathbf{A}_0')} \times 100. \quad (8)$$

Finally, for the general case of an N-VAR of p -th order and H steps-ahead forecast:

$$SOI = \frac{\sum_{h=0}^{H-1} \sum_{i,j=1, i \neq j}^N a_{h,ij}^2}{\sum_{h=0}^{H-1} \text{trace}(\mathbf{A}_h \mathbf{A}_h')} \times 100. \quad (9)$$

2.2 The Multivariate Stochastic Volatility with Double Jumps Model

The Multivariate Stochastic Volatility with Double Jumps Model (MSVDJ, hereafter) model proposed by Laurini, Mauad and Aiube (2017) is based on a multivariate structure that incorporates the presence of jumps in the mean and conditional volatility. It also performs decomposition between permanent and transient effects in this structure. The permanent effect on the conditional volatility is associated with a common factor among all series, while the transitory effects are associated with specific shocks in each market.

This structure can be used to identify spillover effects in the financial markets, since this common factor can be interpreted as the interdependence among markets. Changes in the level of this common factor are given by a structure of jumps, and this not only identifies, but also date, the relevant events associated with shocks and crises in the global stock market.

The model is based on a multivariate stochastic volatility structure, e.g. Taylor (2008), modified to include the possibility of joint jumps in the mean and conditional volatility. This model has the following structure:

$$Y_{it} = \exp\left(\frac{h_{it}}{2} + \frac{s_i^\nu \mu_t}{2}\right) (\varepsilon_{it}) \quad (10)$$

$$h_{it} = \phi_i h_{it-1} + \sigma_{vi} v_{it} \quad (11)$$

$$\mu_t = \mu_{t-1} + \delta_t^\nu \sigma_\eta \eta_t \quad (12)$$

$$\gamma_{it} = s_i^m \delta_t^m \sigma_\nu \nu_t \quad (13)$$

$$\delta_t^\nu \sim \text{Bern}(p_v) , \delta_t^m \sim \text{Bern}(p_m) \quad (14)$$

$$\varepsilon_{it} \sim N(\gamma_{it}, 1) , v_{it} \sim N(0, 1) \quad \nu_t \sim N(0, 1) \quad (15)$$

In the set of observed series, the log returns, are denoted as Y_{it} , where i denotes an asset index and t the time period. In this model, the dynamics of each series are given by the mean and volatility processes, subject to continuous and jumping components. The conditional volatility process for each asset is obtained as the sum of an asset-specific component h_{it} which is mean reverting, and a common factor μ_t , modeled using a compound binomial process, as in Qu and Perron (2013).

The common factor, which is associated with the mean (global) level of conditional variance, is given by a compound binomial process represented by μ_t , with δ_t^ν being a sequence of independent Bernoulli variables, with common parameter p_v , representing the probability of a jump in variance. In this structure, the process μ_t is constant if there is no jump in the Bernoulli process, and in its occurrence, the process is added to a Gaussian shock of innovations η_t , with standard deviation σ_η .

The transitory component of the volatility of the asset i , given by h_{it} , is modeled as a first-order autoregressive process with zero mean. The persistence parameter of this process is represented by ϕ_i , and the innovations given by a Gaussian variable v_{it} , with volatility σ_{vi} . The conditional volatility of each series is given by the sum of this transitory component with the common factor μ_t multiplied by load factor s_i^ν . As is usual in a factorial model, the identification of the model is obtained by normalizing the load factor s_1^ν to one. In this work, this identification is imposed on the series of United States index returns, since this is the largest market in terms of volume.

This structure can be interpreted as a regime-switching model, where the number of regimes is neither fixed nor determined by the observed sample. Thus, μ_t represents the conditional mean of the volatility process, subject to possible level changes. In this sense, the model can be thought of as a generalization with multiple long-term values for the process of variance decomposition into transitory and permanent components of volatility. Thereby, the model does not suffer from the problems associated with fixed numbers of regimes, such as Markov Switching models (e.g. Hamilton (1989)), allowing a greater flexibility for the evolution of the dynamics of the assets.

It also incorporates a common jump structure in the mean, given by γ_{it} , disposed in the equation 13. In this formulation, the realization of the conditional mean at an instant t , depends on the performance of a jumping process δ_i^m , also formulated as an independent Bernoulli process. If this process is zero, the mean process is given by a standard normal distribution, and in this case, the return dynamics does not depend on the other assets. If this process δ_i^m assumes the value one in the period t , indicating a joint jump in the mean, all series are affected by the same common shock, where the intensity of this jump is transmitted to each series through a factorial load s_i^m .

It is important to emphasize that the process of jump in mean has different characteristics of those occurred in the volatility. While the later are persistent (the impact of the jump remains until the occurrence of the next jump, given by the compound Binomial structure), the mean jump process it is not, impacting the returns only in the period of occurrence of the event. Since the return of each asset is a function of this common factor, γ_{it} , in case of a jump in the mean, it will affect all assets with distinct loads, given by s_i^m , but only in t . If the jump does not happen, this implies that the return of assets will be independent both in time and between assets. Whereas, in occurrence of jump in mean there will be a cross sectional dependence between the assets, but the process will remain independent in time.

Due to the presence of a latent processes, the estimation proposed by Laurini, Mauad and Aiube (2017) for this model is based on Bayesian methods using Markov Chain Monte Carlo simulation (MCMC), combining steps based on the Gibbs and Metropolis-Hastings

samplers.

In addition, to estimate the parameters associated to the jumping processes, a methodology based on the threshold exceedance, proposed by Albert and Chib (1993), is employed. This methodology uses latent auxiliary variables with uniform distributions to generate samples for Bernoulli variables corresponding to the occurrence of jumps. The idea is to generate this continuous latent auxiliary variable, and a threshold calibrated according to the probability of the jump, p_ν and p_m . Consequently, δ_t^m or δ_t^ν assume values equal to one if this auxiliary variable exceeds specific threshold values, and zero otherwise. The data augmenting process determining the Bernoulli threshold is given by a sequence of independent uniform distributions.

For the estimation, we assume the following priors: (i) Beta distribution for the jump probabilities p_ν and p_m , (ii) independent Gaussian Normal distribution for the persistence parameter ϕ_i , as well as for s_i^m , s_i^ν , h_t and μ_t (iii) inverse Gamma distributions for the volatility parameters σ_{vi} , σ_η and σ_ν . The sampling process proposed in Laurini, Mauad and Aiube (2017) can be summarized in the following steps:

1. Initialize the latent variables and parameters: h_{it} , μ_t , δ_t^m , δ_t^ν , ϕ_i , σ_{vi} , p_ν , σ_η , σ_ν , s_i^ν and s_i^m ;
2. Sampling ϕ_i , s_i^ν , σ_η e σ_{vi} conditional on h_{it} , μ_t and the location of the jumps δ_t^ν ;
3. Sampling μ_t ;
4. Sampling h_{it} ;
5. Sampling the process of jumps δ_t^ν ;
6. Sampling the probability of jumps p_ν ;
7. Sampling σ_ν , s_i^ν and s_i^m , conditional on the location of the jumps δ_t^m ;
8. Sampling γ_{it} ;
9. Sampling the process of jumps δ_t^m ;

10. Sampling the probability of jumps p_m ;
11. Go back to step 2;

The above process (from 2 to 11), was done using Gibbs for the steps with analytically known conditional distributions and Metropolis-Hastings for the remaining steps. The sampling process was based on an initial sampling of 4000 discarded iterations (burn-in), and another 8000 simulations used in the construction of the posterior distributions of interest.

As discussed in the introduction, this model can be applied in the estimation of spillover measures because it allows the movements decomposition of returns and volatilities into common and specific components, interpreting their common dynamics, as the movements related to spillover processes. In addition, the model generates a direct measure of global mean volatility, estimated by the common component μ_t , which captures sudden changes in volatility trends associated with the transmission of global shocks. Furthermore, the model allows for the dating of events that alter global volatility patterns, and the common shocks in the returns structure, by estimating the probability of occurrence of jumps in the mean and conditional volatility common to all assets.

3 Database

To perform a direct comparison with the spillover index estimation methodology, proposed by Diebold and Yilmaz (2009), we will use the same database used in his article. This database is composed of 19 stock indices from developed and emerging countries, summarizing the global stock market. The values used are the nominal weekly closing price of these indices in local currency, going from January 10, 1992 to November 23, 2007, comprising 829 observations.

Among the indices, there are seven developed country stock markets: United States (S&P 500 Index), United Kingdom (FTSE 100 Index), France (CAC 40 Index), Germany (DAX Index), Hong Kong (Hang Seng Index), Japan (Nikkei 225) and Australia (S&P

ASX 200), and twelve emerging countries: Indonesia (IDX Composite Index), South Korea (KOSPI Composite Index), Malaysia (FTSE Bursa Malaysia KLCI), Philippines (PSEi Index), Singapore (STI Index), Taiwan (Taiwan Weighted), Thailand (SET), Argentina (Merval Index), Brazil (Ibovespa Index), Mexico (IPC Index), Chile (IGPA Index and IPSA)¹, and Turkey (Borsa Istanbul 100 Index).

Firstly, the return was calculated as the change in the log index price between Fridays. When the index closing data on Friday was not available due to a holiday for example, the value of Thursday was used. Subsequently, the weekly return of nominal rates was converted to real ones, using the IMF's consumer price index (CPI monthly). It is assumed that the inflation rate π_t is constant within the month, thus calculating the real return as the power of a quarter of the monthly inflation rate. Thus, the weekly real return is calculated as $(1 + i_t)/(1 + \pi_t) - 1$, where i_t is the nominal weekly return.

Table 1 shows the descriptive statistics of the returns in the database. We can observe some stylized facts in financial series, as for example, returns have means very close to zero, are asymmetrical and have heavy tails. These observations are consistent with the presence of jumps in the mean and conditional volatility structures.

While we directly use the returns above mentioned to estimate the MSVDJ model, Diebold and Yilmaz (2009) perform a two-step estimation: (1) firstly, the series of variances are constructed using the Garman and Klass (1980) variance estimator and (2) next, they use these variance to estimate the vector autoregressive model and then construct the Spillover index.

The Garman and Klass (1980) variance estimator is based on monday opening prices (O_t), the closing value on friday (C_t), the maximum (H_t) and minimum (L_t) values in the week, and is given by the expression:

$$\sigma_t^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2 \quad (16)$$

¹ IGPA from January-1992 to May-2004 and IPSA from June-2004 onwards

Table 1 – Returns - descriptive statistics

	United States	United Kingdom	France	Germany	Hong Kong	Japan	Australia
Mean	0.001	0.000	0.001	0.001	0.001	-0.001	0.001
Median	0.002	0.001	0.001	0.004	0.003	0.001	0.002
Maximum	0.080	0.099	0.110	0.129	0.136	0.111	0.070
Minimum	-0.154	-0.088	-0.122	-0.140	-0.201	-0.114	-0.053
Standard Deviation	0.021	0.021	0.027	0.029	0.035	0.029	0.016
Asymmetry	-0.727	-0.108	-0.133	-0.277	-0.440	-0.019	-0.186
Kurtosis	7.609	4.790	4.153	5.184	5.884	3.964	3.863
	Indonesia	South Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand
Mean	0.001	0.000	0.001	0.000	0.001	0.000	-0.001
Median	0.002	0.002	0.001	0.000	0.001	0.002	0.001
Maximum	0.182	0.175	0.243	0.160	0.184	0.187	0.218
Minimum	-0.201	-0.218	-0.191	-0.221	-0.243	-0.142	-0.173
Standard Deviation	0.038	0.042	0.032	0.035	0.031	0.036	0.039
Asymmetry	-0.291	-0.333	0.134	-0.312	-0.611	0.012	0.150
Kurtosis	7.594	6.209	11.137	7.128	12.996	5.211	5.429
	Argentina	Brazil	Chile	Mexico	Turkey		
Mean	-0.000	0.002	0.001	0.001	-0.002		
Median	0.003	0.004	0.001	0.004	-0.000		
Maximum	0.243	0.219	0.091	0.170	0.316		
Minimum	-0.202	-0.252	-0.071	-0.178	-0.381		
Standard Deviation	0.051	0.055	0.021	0.036	0.065		
Asymmetry	0.023	-0.296	0.077	-0.306	-0.277		
Kurtosis	5.467	5.077	4.507	5.352	7.147		

Garman and Klass (1980) assumes that the stock return follows a Brownian motion with zero drift to derives a volatility estimator for the diffusion parameter of the Brownian motion. This estimator has a sampling variance which is considerably smaller than the sampling variance of a metric based solely on the closing price, as discussed by Alizadeh, Brandt and Diebold (2002). This metric is very powerful for stocks following pure Brownian motion processes with zero drift and no opening jumps, i.e., opening price is equal to closing price of previous period. Nevertheless, significant differences in this estimator are detected if the asset return distribution involves an opening jump or a large drift, see Shu and Zhang (2006). Consequently, it is inappropriate in the presence of jumps. On the other hand, our model directly captures the jumps, being more suitable for this kind of assets.

We provided in Table 2 the volatility descriptive statistics found by Diebold and Yilmaz (2009) using the Garman and Klass (1980) method for each stock index. In the next section, we'll cover the estimated values for our model.

Table 2 – Volatility descriptive statistics using Garman and Klass (1980) estimator

	United States	United Kingdom	France	Germany	Hong Kong	Japan	Australia
Mean	0.00042	0.00049	0.00075	0.00083	0.00099	0.00072	0.00023
Median	0.00025	0.00024	0.00043	0.00035	0.00050	0.00050	0.00015
Maximum	0.00595	0.00926	0.01013	0.01630	0.00379	0.00798	0.01045
Minimum	0.00002	0.00001	0.00003	0.00001	0.00002	0.00002	0.00001
Standard Deviation	0.00056	0.00079	0.00104	0.00148	0.00204	0.00079	0.00044
Skewness	4.4198	5.4561	4.2555	4.8072	10.2854	3.5656	3.5656
Kurtosis	30.742	44.801	27.337	34.111	156.420	22.417	361.967
	Indonesia	South Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand
Mean	0.00088	0.00128	0.00085	0.00065	0.00045	0.00079	0.00111
Median	0.00036	0.00064	0.00024	0.00033	0.00020	0.00049	0.00056
Maximum	0.02074	0.01869	0.04592	0.01798	0.01050	0.01376	0.02356
Minimum	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00003
Standard Deviation	0.00169	0.00192	0.00287	0.00137	0.00081	0.00099	0.00179
Skewness	5.0567	3.8836	10.5119	8.3102	5.3390	4.7681	5.7314
Kurtosis	39.067	23.236	137.335	92.211	45.602	45.597	52.310
	Argentina	Brazil	Chile	Mexico	Turkey		
Mean	0.00187	0.00210	0.00021	0.00102	0.00317		
Median	0.00085	0.00108	0.00010	0.00053	0.00152		
Maximum	0.03371	0.06133	0.00816	0.02871	0.07689		
Minimum	0.00001	0.00000	0.00000	0.00000	0.00000		
Std. Dev.	0.00327	0.00419	0.00048	0.00180	0.00539		
Skewness	4.9933	7.7243	8.8249	7.8728	6.7978		
Kurtosis	35.897	82.961	113.737	96.061	73.763		

4 Results

We provide in Table 3 the MSVDJ model estimates for the common parameters: the variance jump probability, p_v , the volatility of the jump process in variance σ_η , the probability of common jumps in the mean, p_m , and the volatility associated with this process, σ_η, σ_ν . The specific parameters associated with each market are presented in the appendix of this paper. We can observe a posterior mean of 0.0454 for the probability of jumps in the volatility component, which is equivalent, in average, to some jump every 37.6 weeks. The probability of common jumps in the structure of returns is higher, with a posterior mean of 0.21, indicating that about one-fifth of the observed returns between assets are caused by events of global reach.

Table 3 – Posterior distribution - MSVDJ model common parameters

	2.50%	Mean	97.50%	Standard Deviation
p_v	0.0118	0.0454	0.01051	0.0319
σ_η	1.7136	9.995	25.1757	6.2930
p_m	0.0229	0.2100	0.4298	0.1421
σ_ν	1.0792	47.6692	82.6644	28.4065

We now begin to compare the results found by Diebold and Yilmaz (2009) and the ones obtained by the MSVDJ model. The spillover index is initially calculated using moving windows of 200 weeks from the decomposition of the variance prediction error 10 steps ahead, following the original specification in Diebold and Yilmaz (2009), whereas, as stated in section 2.2, the multivariate model of jumps is estimated using the Bayesian estimation in the whole sample.

We focus on comparing the volatility spillover index and the permanent component of volatility, as they both capture changes in global volatility patterns. Figure 3 shows a panel comparing these components, reporting the posterior mean of the estimated global volatility factor and the Spillover index. We can observe that, although these two measures are constructed using different methodologies, there is a remarkable resemblance between the movements observed between these two estimates. This stems from the fact that both capture the market volatility level. However, they do this in different ways, while the μ_t component is a measure of global mean volatility, the spillover index gives us a measure of market interdependence at an instant of time.

It's clear that both models can capture the main events associated with changes in the pattern of volatility in the global stock market. Furthermore, we can say that they also confirm that volatility responds widely to economic events. Diebold and Yilmaz (2009) perform a visual dating of the relevant events using the estimated index, and indicate as major events:

1. The Asian crisis in three moments: (i) devaluation of the Thai Baht in February 1997, (ii) the arrival of the crisis in Hong Kong in October 1997 and (iii) the spread to other regions such as South Korea, Malaysia and Indonesia until January 1998.
2. The Russian Crises that happened from June to August of 1998.
3. The Brazilian devaluation crisis in January 1999.
4. The 9/11 terrorist attacks occurred in 2001.

Figure 1 – Global volatility factor x Spillover Index (200-week rolling window)

Note: The spillover index graph was calculated using a 200-week rolling window, 10 steps ahead.

5. The dollar crisis in March 2005 due to considerations from some emerging countries that they would not use their reserves to buy dollars.
6. The intense reversal of capital flow from emerging countries, after robust signs that the US central bank (Fed) would increase its interest rates in June 2006.
7. The first sign of final market turmoil, associated with the subprime mortgage market between July and August 2007, as well as the first signs of the problem in March 2007.

A clear limitation in the identification of these critical events, arises from the fact that it is done by visual association of relevant movements in the spillover index and crises that occurred in the financial markets. On the other hand, the methodology of Laurini, Mauad and Aiube (2017) allows to recover the dates of relevant events by estimating the occurrence probability of jumps at each instant of time. Figure 2 and Table 4 report the estimated posterior probability of jumps in the permanent component of variance and the

Figure 2 – Posterior probability of variance jumps

periods with probability of jumps occurrence greater than 0.5 for the whole data base period. These periods represent the moments of large movements in global volatility, and consequently, where a jump in the overall pattern of stock market volatility is more likely.

From this direct dating of jumps, we can explicitly identify the following events:

1. Four jumps were recorded during the Asian crisis period, in February, April, October of 1997 and February of 1998. All these periods have already been interpreted above, apart from April 1997, when some of the largest South Korean companies gone bankruptcy and the speculation about the country's currency reached its peak.
2. The model picks up a jump in July 1998, derived from the Russian Crisis that happened between June and August 1998.
3. In February 1999, the model captures another jump, because of the Brazilian devaluation crisis.
4. There was a jump in June 2000, related to the dot-com bubble burst.

Table 4 – Main Jumps

Date	Jump Probability
18/06/93	0.73
06/05/94	1.00
15/03/96	1.00
21/02/97	1.00
18/04/97	0.54
10/10/97	1.00
06/02/98	0.65
10/07/98	0.50
19/02/99	0.98
30/06/00	0.91
03/08/01	0.91
12/10/01	1.00
04/04/03	1.00
30/06/06	0.62
17/08/07	0.61
31/08/07	0.79

5. In addition, two jumps occurred in 2001: pre and post September 11 terrorist attacks. The first is derived to the feeling of bear market that circulated the period, the second, with the volatility originated by September 11.
6. One jump takes place in April 2003, linked to the beginning of the Iraq war.
7. Another jump happens in June 2006, coupled with rising interest rates in the United States and capital flight from emerging countries.
8. Finally, 2 jumps are captured in August 2007, linked to the first signs of market turmoil associated with the subprime market between July and August 2007.

Comparing the events highlighted above, with the ones capture by Diebold and Yilmaz (2009) for a 200 rolling window, we can observe that some of these periods of high volatility across markets are capture by both models: (i) Asia Crisis, (ii) Russian Crisis, (iii) Brazilian devaluation Crisis, (iv) 9/11 terrorist attacks, (v) capital flight from emerging in 2006 and (vi) the subprime crises. However, some events are only captured by our method. This relies on the fact that the estimation made by the jump model is based

on a dynamic specification of the global volatility factor, being able to correctly identify the other relevant events.

On the other hand, the spillover index in a specific date is based on a rolling window of the 199 weeks prior to this event. This implies that the estimation is using a rolling window sizing almost one quarter of the total sample, generating in loss of sensitivity which results in a clear decrease in the power of event (jump) identification. The spillover index couldn't identify the events that happened in April 1997, shortly after the Baht devaluation crisis, the Dot-com bubble burst, and another moment was in April 2003, related to war in Iraq.

It is worth mentioning that, while the spillover index captured an increase in global volatility during March 2005, the MSVDJ model didn't capture a jump during this period, in fact, the probability of a jump does not exceed 10% during March, April and May of that year. One interpretation about this result is that the event may not have generated permanent changes in global volatility, presenting a rapid reversal to the prior level. Nonetheless, after this period, during 2006 and 2007 the models appear to be overlapping, capturing the same jumps with similar intensities.

In addition, by using a 200-week rolling window, the spillover index cannot be constructed for the events prior to November 1996, missing some major events such as: the crisis of European currencies and the crisis in Mexico. As mentioned in the introduction, the use of rolling windows involves a trade-off between reactivity to detect sudden movements and efficiency. Thus, to obtain a greater sensibility in the spillover index, it's necessary to use a smaller rolling window in its estimation. Following the analysis of Diebold and Yilmaz (2009), we replicate the index constructed using now a 75-week moving window, with a 10-step ahead prediction horizon for the variance decomposition procedure. In Figure 3, we exhibit a comparison between the spillover index for rolling window of 75 weeks, and the permanent factor of volatility obtained by the MSVDJ model, estimated for the same period.

The result, as expected, is that the spillover index loses its smoothness, indicating that there were many more events that increased global volatility than previously verified

Figure 3 – Global volatility factor x Spillover Index (75-week rolling window)

Notes: The spillover index graph was calculated using a 75-week rolling window, 10 steps ahead.

using a 200-week moving window. Among these main events, and additional to those mentioned previously, Diebold and Yilmaz (2009) highlight:

1. The political chaos in Japan between October and November 1993.
2. The Mexican Crisis or "Tequila Effect" that occurred between November and December 1994.

The MSVDJ model, in the new sample period, according to the Table 4, captured three main jumps:

1. The first occurred in June 1993, related to the turbulence of the European market and the currency parities required by the European Unit of Account (ECU).
2. A second jump came in May 1994, in the increase of interest rates made by the Fed and the turmoil generated by the bankruptcy of the Askin hedge fund.

3. Finally, a third jump occurs in March 1996 with heightened concerns about Asian tigers.

Even when a small sample is used, the results demonstrate that the spillover index have a lower power to identify the ruptures that occurred in the global volatility compared to the MSVDJ model. This indicates that the MSVDJ model is more sensitive to capture the jumps occurred in the volatility. This may be related to the fact that it estimates a direct measure of the mean global volatility, whereas the spillover index presents an indirect measure based on the prediction error decomposition.

Analyzing all these turbulent periods, we can see that the MSVDJ model not only captured the moments of greater world volatility, but also indicated the occurrence of a jump before the most documented moments of market turbulence. For example, in 1994, the model indicates that there was a jump in May, when the Fed raised interest rates, long before Mexico's devaluation crisis. In addition to this episode, during the Asian crisis, the model indicated a jump with a probability of one in February of 1997, that is, before it spread to Hong Kong in October of that same year. This result implies that the occurrence of one jump may signal that its effect can still be transmitted to other countries. However, the time and intensity until it reaches another country, depends on the economic structures of those countries, and how the initial crisis was generated.

Additionally, to illustrate the MSVDJ model adjustment for the conditional volatility of specific markets, we show in Figure 4 a comparison between the volatility estimated for the S&P Index by the MSVDJ model and by the methodology of Garman and Klass (1980), used as input in calculating the spillover index. We verified that the volatility estimated by the MSVDJ model follows the pattern of that estimated by Garman and Klass (1980), and thus, the model manages to obtain a good fit when compared to this measure of volatility. Note that the volatility estimated by the MSVDJ model is smoother than the Garman and Klass (1980) estimates, since it estimates the latent volatility free of the measurement errors associated with the Garman and Klass (1980) measure, which is an indirect estimator for true latent volatility.

Figure 4 – Estimated volatility - MSVDJ model vs Garman-Klass method for the S&P Index

5 Risk Management

As mentioned earlier, Diebold and Yilmaz (2009) spillover index can't be directly used in risk management measures such as Value at Risk (VaR) and Expected Shortfall, since it's a index based on an indirect estimation of the market volatility measures. On the other hand, as our model directly estimates volatilities and jumps from returns, risk measures can be directly estimated. To check the risk estimation properties of our model, we conducted a practical test using the MSVDJ model to calculate the VaR, a standard measure used to quantify market tail risk. Following Laurini, Mauad and Aiube (2017) we performed a dynamic VaR estimations using a Gaussian jump corrected approximation. The VaR of the series in period t is calculated as $VaR_t = \hat{y}_{it} - q_\alpha \mathcal{H}_{it}$, where $\hat{y}_{it}$ and $\mathcal{H}_{it}$ are the expected values for the conditional mean and variance of asset i in t .

To show an application of the methodology, we performed the estimation of a VaR with a level of 99% for all series analyzed. In Table 5 we show the proportions of

VaR violations using the MSVDJ model, as well VaR results based on Garch-Normal and Garch with Student-t distributions. Next to the proportion of violations we report the p-value of the Christoffersen (1998) coverage test, which is a test to verify if the empirical coverage obtained by the method is statistically equal to the nominal coverage (proportion of expected violations). The last two rows in the table report the proportion of rejections of the Christoffersen (1998) test at the 5 and 10% significance levels obtained by each estimation method.

Table 5 – 99% Value at Risk Estimation - Proportion of violations and p-value of nominal coverage test

	viol jump 99%	p-value	viol Garch-n 99%	p-value	viol Garch-t 99%	p-value
United States	0.006	0.378	0.018	0.033	0.019	0.013
United Kingdom	0.014	0.216	0.019	0.013	0.019	0.112
France	0.012	0.484	0.014	0.216	0.014	0.112
Germany	0.013	0.296	0.018	0.033	0.019	0.013
Hong Kong	0.014	0.216	0.017	0.053	0.017	0.053
Japan	0.010	1.000	0.011	0.726	0.016	0.112
Australia	0.011	0.726	0.024	0.000	0.025	0.000
Indonesia	0.008	0.860	0.019	0.597	0.018	0.860
South Korea	0.011	0.726	0.019	0.161	0.019	0.161
Malaysia	0.012	0.484	0.010	1.000	0.011	0.726
Philippines	0.012	0.484	0.002	0.022	0.004	0.004
Singapore	0.014	0.216	0.010	1.000	0.010	0.001
Taiwan	0.008	0.860	0.001	0.004	0.002	0.001
Thailand	0.007	0.597	0.001	0.004	0.001	0.004
Argentina	0.012	0.484	0.001	0.004	0.001	0.004
Brazil	0.013	0.296	0.000	0.001	0.000	0.001
Chile	0.006	0.378	0.024	0.000	0.024	0.000
Mexico	0.014	0.216	0.004	0.077	0.004	0.077
Turkey	0.008	0.860	0.000	0.001	0.000	0.001
rejections 5%		0.000		11.000		11.000
rejections 10%		0.000		13.000		13.000

We can observe in the Table 5 that the proportion of violations of the MSVDJ model is consistent with the expected proportion of the violations (1 %), and the Christoffersen (1998) test indicates the acceptance of the null hypothesis of correct specification in the VaR calculation for all analyzed series. The results obtained by the Garch models, both in the Gaussian and Student-t specifications, indicate a high number of rejections of the null hypothesis of correct specification in the VaR calculation, indicating both cases of over and underestimation of VaR values in the sample.

This result is possibly due to the correct handling of the jumps in mean and

Figure 5 – FTSE returns x parametric VaR 99%

Notes: The 99% VaR calculated by Gaussian Garch has values very close to those calculated by t-Garch, so it is not possible to see it with the scale used in this figure.

variance by the MSVDJ model, capturing the pattern of abrupt changes in these financial series. The Garch models only capture the continuous component in the volatility process, being unable to capture the rapidly changing events. This is especially important in the management of tail risks, the fundamental component in the calculation of measures such as VaR.

To illustrate this property, we display at figure 5, the VaR 99% calculated by our model, by the Gaussian Garch and by the Garch with Student t distribution for the FTSE 100 returns. We can see that our model has a good fit calculating the VaR for the series. The Garch models indicate an overestimation in the VaR calculation for this series, while the MSVDJ model captures the correct proportion of expected violations.

6 Conclusion

In this work we compare the spillover index created by Diebold and Yilmaz (2009) with Laurini, Mauad and Aiube (2017) multivariate stochastic volatility with double jumps (MSVDJ) model. The results indicate that both captures well the dynamics of volatility in global stock market in the period under analysis. However, the jumps model is capable of better capturing the unexpected changes in global market volatility, since we have found four additional jumps when compared to main events found by Diebold and Yilmaz (2009).

This can be related to three main advantages of the MSVDJ model. First, it allows us to identify and date the relevant events in the global markets through the estimated posterior probability of jumps. Second, it makes the estimation using all available information in the sample, avoiding the tradeoff between bias and efficiency and in the rolling windows estimation of the spillover index. Finally, it estimates a direct measure of volatility, which makes our model more accurate in the identification of jumps that alter global volatility.

The last advantage allows us to directly estimate risk management measures such as Value at Risk, as presented in section 5. The results indicate that our model is preferable to the GARCH family, as it's rejected in less cases in the VaR specification analysis tests. Thus, our model has several direct practical applications, in contrast to the Diebold and Yilmaz (2009) spillover index, which is only an indicator of market interdependence.

Bibliography

ALBERT, J. H.; CHIB, S. Bayesian analysis of binary and polychotomous response data. *Journal of the American Statistical Association*, Taylor & Francis, v. 88, n. 422, p. 669–679, 1993.

ALIZADEH, S.; BRANDT, M. W.; DIEBOLD, F. X. Range-based estimation of stochastic volatility models. *The Journal of Finance*, Wiley Online Library, v. 57, n. 3, p. 1047–1091, 2002.

BARIGOZZI, M.; BROWNLEES, C. T. Nets: Network estimation for time series. 2016.

BILLIO, M. et al. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, Elsevier, v. 104, n. 3, p. 535–559, 2012.

BORDO, M. et al. Is the crisis problem growing more severe? *Economic Policy*, The Oxford University Press, v. 16, n. 32, p. 52–82, 2001.

CALVO, S. G.; REINHART, C. M. Capital flows to latin america: is there evidence of contagion effects? 1996.

CHRISTOFFERSEN, P. F. Evaluating interval forecasts. *International Economic Review*, JSTOR, p. 841–862, 1998.

CLARK, T. E.; MCCracken, M. W. Improving forecast accuracy by combining recursive and rolling forecasts. *International Economic Review*, Wiley Online Library, v. 50, n. 2, p. 363–395, 2009.

DIEBOLD, F. X.; YILMAZ, K. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, Wiley Online Library, v. 119, n. 534, p. 158–171, 2009.

DIEBOLD, F. X.; YILMAZ, K. *Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring*. [S.l.]: Oxford University Press, USA, 2015.

DUNGEY, M.; LUCIANI, M.; VEREDAS, D. Googling SIFIs. 2014.

EDWARDS, S. *Interest rate volatility, capital controls, and contagion*. [S.l.], 1998. National Bureau of Economic Research.

ENGLE, R. F.; ITO, T.; LIN, W.-L. *Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market*. [S.l.]: JSTOR, 1988. 525–542 p.

FAUST, J. The robustness of identified VAR conclusions about money. In: *Carnegie-Rochester Conference Series on Public Policy*. [S.l.]: Elsevier, 1998. v. 49, p. 207–244.

FORBES, K. J. Are trade linkages important determinants of country vulnerability to crises? In: *Preventing currency crises in emerging markets*. [S.l.]: University of Chicago Press, 2002. p. 77–132.

- GARMAN, M. B.; KLASS, M. J. On the estimation of security price volatilities from historical data. *Journal of Business*, Wiley Online Library, v. 53, n. 1, p. 67–78, 1980.
- GERACI, M. V.; GNABO, J.-Y. Measuring interconnectedness between financial institutions with bayesian time-varying vector autoregressions. 2015.
- HAMAO, Y.; MASULIS, R. W.; NG, V. Correlations in price changes and volatility across international stock markets. *Review of Financial Studies*, The Society for Financial Studies, v. 3, n. 2, p. 281–307, 1990.
- HAMILTON, J. D. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, JSTOR, n. 57, p. 357–384, 1989.
- HAUTSCH, N.; SCHAUMBURG, J.; SCHIENLE, M. Forecasting systemic impact in financial networks. *International Journal of Forecasting*, Elsevier, v. 30, n. 3, p. 781–794, 2014.
- KING, M.; SENTANA, E.; WADHWANI, S. *Volatility and links between national stock markets*. [S.l.], 1990. National Bureau of Economic Research.
- KLOBNER, S.; WAGNER, S. Exploring all VAR orderings for calculating spillovers? Yes, we can! - a note on Diebold and Yilmaz (2009). *Journal of Applied Econometrics*, JSTOR, n. 29, p. 172–179, 2013.
- LAURINI, M. P.; MAUAD, R. B.; AIUBE, F. A. Multivariate stochastic volatility-double jump model: an application for oil assets. 2017. Central Bank of Brazil Working Paper.
- NIKKINEN, J.; SAHLSTRÖM, P.; VÄHÄMAA, S. Implied volatility linkages among major european currencies. *Journal of International Financial Markets, Institutions and Money*, Elsevier, v. 16, n. 2, p. 87–103, 2006.
- QU, Z.; PERRON, P. A stochastic volatility model with random level shifts and its applications to s&p 500 and nasdaq return indices. *The Econometrics Journal*, Wiley Online Library, v. 16, n. 3, p. 309–339, 2013.
- SHU, J.; ZHANG, J. E. Testing range estimators of historical volatility. *Journal of Futures Markets*, Wiley Online Library, v. 26, n. 3, p. 297–313, 2006.
- TAYLOR, S. J. *Modelling financial time series*. [S.l.]: World Scientific, 2008.
- ZIVOT, E.; WANG, J. *Modeling financial time series with S-Plus®*. [S.l.]: Springer Science & Business Media, 2007.

1 Estimated Parameters

Table 6 – United States (S&P 500)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_1	0.756	0.8861	0.9774	0.0641

Note: s_2^ν and s_2^m were normalized to one.

Table 7 – United Kingdom (FTSE 100)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_2	0,3229	0,784	0,9325	0,1461
s_2^ν	0,9357	0,9958	1,0751	0,0334
s_2^m	0,6028	0,7827	1,1287	0,1309

Table 8 – France (CAC 40)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_3	0.0679	0.7093	0.9359	0.2435
s_3^ν	0.8689	0.931	0.9842	0.0332
s_3^m	0.7765	1.0148	1.4713	0.1721

Table 9 – Germany (DAX)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_4	0.739	0.8904	0.9589	0.0592
s_4^ν	0.8484	0.996	0.9824	0.0375
s_4^m	0.6975	1.1006	1.5135	0.1876

Table 10 – Hong Kong (Hang Seng)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_5	0.0148	0.305	0.7851	0.2214
s_5^ν	0.8203	0.9268	0.8988	0.0222
s_5^m	0.9149	1.2037	2.2242	0.3611

Table 11 – Japan (Nikkei 225)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_6	0.6011	0.8297	0.9264	0.0818
s_6^ν	0.8395	0.8695	0.9463	0.0284
s_6^m	0.592	0.8564	1.8215	0.2884

Table 12 – Australia (S&P ASX 200)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_7	0.2448	0.7399	0.9216	0.1791
s_7^ν	0.9728	1.0156	1.1059	0.0282
s_7^m	0.3352	0.5819	1.4665	0.2505

Table 13 – Indonesia (IDX)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_8	0.7771	0.8637	0.9381	0.0422
s_8^ν	0.8114	0.8491	0.9835	0.0389
s_8^m	0.6323	0.987	2.0679	0.4157

Table 14 – South Korea (KOSPI)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_9	0.6778	0.8467	0.9395	0.0784
s_9^ν	0.772	0.8026	0.8352	0.0178
s_9^m	0.8221	1.091	2.1264	0.3088

Table 15 – Malaysia (KLCI)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_{10}	0.9213	0.9647	0.9905	0.0201
s_{10}^ν	0.8051	0.8502	0.8835	0.0211
s_{10}^m	0.4067	0.604	1.3323	0.2279

Table 16 – Philippines (PSEi)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_{11}	0.756	0.4713	0.8384	0.2099
s_{11}^ν	0.8099	0.8376	0.8856	0.019
s_{11}^m	0.6687	0.973	1.8777	0.3378

Table 17 – Singapore (STI)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_{12}	0.5641	0.7576	0.8972	0.0926
s_{12}^ν	0.8856	0.929	1	0.0245
s_{12}^m	0.7981	1.0793	2.0853	0.343

Table 18 – Taiwan (Taiwan Weighted)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_{13}	0.3937	0.7807	0.8969	0.1183
s_{13}^ν	0.8009	0.833	0.948	0.0296
s_{13}^m	0.5765	0.8177	1.9419	0.3072

Table 19 – Thailand (SET)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_{14}	0.6854	0.8219	0.9092	0.0686
s_{14}^ν	0.7841	0.8112	0.87	0.0193
s_{14}^m	0.6913	0.9944	1.9253	0.3059

Table 20 – Argentina (Merval)

	2.50%	Mean	97.50%	Standard Deviation
ϕ_{15}	0.9303	0.9732	0.9942	0.0268
s_{15}^ν	0.7639	0.8459	0.999	0.0542
s_{15}^m	0.7675	1.2224	1.964	0.2548

Table 21 – Brazil (Ibovespa)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_{16}	0.8372	0.9488	0.9824	0.0433
s_{16}^ν	0.7102	0.7502	0.8545	0.038
s_{16}^m	1.1462	1.4852	2.3516	0.2959

Table 22 – Chile (IGPA and IPSA)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_{17}	0.4976	0.8976	0.9652	0.111
s_{17}^ν	0.9029	0.9441	1.0105	0.0261
s_{17}^m	0.3956	0.5557	1.3707	0.2292

Table 23 – Mexico (IPC)

	2.50%	Mean	97.50%	Standard Deviation
ϕ_{18}	0.6863	0.8798	0.9528	0.0886
s_{18}^ν	0.8005	0.8459	0.8976	0.0264
s_{18}^m	0.798	1.1156	1.8223	0.2332

Table 24 – Turkey (Borsa Istanbul 100)

	2.50%	Mean	97.50%	Stand. Deviation
ϕ_{19}	0.6728	0.8107	0.9127	0.0613
s'_{19}	0.6617	0.7052	0.871	0.0443
s^m_{19}	0.3866	0.9496	1.3929	0.2357