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Evidence for Latin America

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Stock Market Volatility Spillovers: Evidence for Latin America*

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Abstract

We extend the framework of Diebold and Yilmaz [2009] and Diebold and Yilmaz [2012] and construct volatility spillover indexes using a DCC-GARCH framework to model the multivariate relationships of volatility among assets. We compute spillover indexes directly from the series of asset returns and recognize the time-variant nature of the covariance matrix. Our approach allows for a better understanding of the movements of financial returns within a framework of volatility spillovers. We apply our method to stock market indexes of the United States and four Latin American countries. Our results show that Brazil is a net volatility transmitter for most of the sample period, while Chile, Colombia and Mexico are net receivers. The total spillover index is substantially higher between 2008Q3 and 2012Q2, and shock transmission from the United States to Latin America substantially increased around the Lehman Brothers' episode.

Key Words. Volatility spillovers; DCC-GARCH model; Stock market linkages; financial crisis.

JEL Classification. G01; G15; C32.

1 Introduction

The recent international financial crisis has clearly shown that national policies and financial events have important cross-border effects. Now-a-days the world is more connected than ever by cross-border financial flows. Policy decisions and relevant news produced in single countries can have significant impacts on other countries. This is particularly true if decisions and news are originated in systemically significant economies.

One of the most notable similarities displayed by financial crises is the occurrence of volatility

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spillovers, i.e. the propagation of negative shocks originated in one economy to other countries' financial markets. Diebold and Yilmaz [2012] developed a volatility spillover measure based on forecast error variance decompositions from vector autoregressions (VAR), useful for measuring the impact that shocks to a particular asset or financial market have on the volatility of other assets or markets.

Their method, which extends the one proposed in Diebold and Yilmaz [2009], has many considerable advantages such as avoiding the necessity of sticking to particular contagion definitions that have to be tested in ad-hoc time periods. Their generalized variance decomposition makes results independent of the ordering of variables in the VAR system. And, additionally, directional and total spillovers can be studied, allowing the identification of individual and systemic volatility effects.

In this paper we present an extension of Diebold and Yilmaz [2009] and Diebold and Yilmaz [2012]. In these two papers the construction of the spillover indexes are performed within a VAR system in which the covariance matrix, estimated under either the Cholesky or the generalized decomposition, is assumed to be time-invariant. However, it is well known that financial series exhibit volatility clusters (see, for instance, Bollerslev [1990] and Engle [1993]). Moreover, asset correlations vary over time, being higher during periods of high volatility (see, for instance, Yang [2005]).

In order to better account for these stylized facts, we propose an extension of the spillover indexes using a DCC-GARCH framework to model the multivariate relationships of the volatility among assets. In our proposal we compute spillover indexes directly from the series of asset returns and recognize the

time-variant nature of the covariance matrix using a multivariate GARCH model. This contrasts with Diebold and Yilmaz [2012], in which the indexes are estimated using volatilities computed using a particular definition involving daily high and low prices.

We apply our method to stock market indexes of the United States and four Latin American countries. We compute both total and directional spillovers for these market indexes for the period spanning between January 2nd, 2003 and January 27th, 2016.

We find several interesting results. Total spillovers vary considerably over time. Particularly, they are substantially higher between the third quarter of 2008 and the second quarter of 2012, a period of ample financial volatility related to the United States subprime crisis and the European sovereign bonds crisis.

Regarding directional spillovers, we encounter that Brazil is a net volatility transmitter for most of the sample period, while Chile, Colombia and Mexico are net receivers. The United States is a net transmitter by construction. Net spillovers exhibit great time-variation as well. For instance, around the Lehman Brothers' episode, shock transmission from the United States to the other four countries increases significantly. Even Brazil becomes a net receiver for that period of time.

The magnitude of volatility spillovers transmitted by Brazil to the other Latin American countries increases after 2012, coinciding with the development of political instability issues of this country that affected negatively several financial markets in the region.

Our contributions to the literature are two-folded. First, we present an extension of Diebold and

Yilmaz [2009] and Diebold and Yilmaz [2012] in which important financial market regularities are better accounted for, as explained above. Second, we study volatility spillovers for a set of major Latin American countries for which the literature on this topic is scarce.

Section 2 shows the methodological framework in which our extension is introduced. Section 3 presents the data used in our empirical application. Results are shown in Section 4, and finally Section 5 concludes.

2 Methodology

In matrix notation, Diebold and Yilmaz [2012] methodology is based on the following VAR(p) model

$$(1) \quad Y_t = \Phi_0 + \sum_{l=1}^p \Phi_l Y_{t-l} + \varepsilon_t$$

where Y_t is a vector of size N , containing all stock market returns at time t , and $\varepsilon_t | t-1 \sim F(0, H_t)$ and F is the multivariate conditional probability distribution of errors. In this way, H_t is the conditional covariance matrix of errors.

Then, Y_t recursion can be expressed like a VMA(∞)

$$(2) \quad Y_t = \Phi_0 + \sum_{p=0}^{\infty} \Theta_p \varepsilon_{t-p}$$

In this way, the h -periods ahead forecast error is

$$(3) \quad e_{t+h}|t = \Theta_0 \varepsilon_{t+h} + \Theta_1 \varepsilon_{t+h-1} + \dots + \Theta_{h-1} \varepsilon_{t+1}$$

whose covariance matrix is

$$(4) \quad \Sigma_{t+h}^e | t = \Theta_0 H_{t+h} \Theta_0' + \Theta_1 H_{t+h-1} \Theta_1' + \dots + \Theta_{h-1} H_{t+1} \Theta_{h-1}'$$

Each element of the diagonal of $\Sigma_{t+h}^e | t$ is a summation that includes terms of its past covariance matrices of the error term ε_t in (1), H_{t+i} for all $i = 1, 2, \dots, h$. Therefore, variance decomposition $\Psi_{ij,t}(h)$ are defined in a way they contain the proportion of the h -step ahead forecast error variance of i coming from j at time t

$$(5) \quad \Psi_{ij,t}(h) = \frac{\sum_{k=0}^{h-1} (d_i' \Theta_k \Sigma_{t+k}^e | t d_j)^2}{\sum_{k=0}^{h-1} (d_i' \Theta_k \Sigma_{t+k}^e | t \Theta_k' d_i)}$$

where d_i and d_j are extraction vectors, i.e. zero vectors that are one in the i^{th} and j^{th} positions, respectively.

It is important to note that we have extended the framework of Diebold and Yilmaz [2012] to allow for a time-varying covariance matrix, H_t . In order to read these indexes as variance shares, it is necessary to normalize them. $\tilde{\Psi}_{ij,t}(h)$ is define as the the h -step ahead forecast error variance share of i caused by shocks in j at time t .

$$(6) \quad \tilde{\Psi}_{ij,t}(h) = \frac{\Psi_{ij,t}(h)}{\sum_{j=1}^N \Psi_{ij,t}(h)}$$

Following Diebold and Yilmaz [2012] and Diebold and Yilmaz [2009] several indexes are computed. The total spillover index measures the contribution of spillovers on the system's forecast error variance.

$$(7) \quad S_t(h) = \frac{\sum_{i=1, i \neq j}^N \sum_{j=1, j \neq i}^N \tilde{\Psi}_{ij,t}(h)}{N}$$

Next, directional spillovers are estimated. Within this type of spillovers, both transmission-directional and reception-directional spillover indexes are calculated for each market. The former contains the

spillover contributions caused by market i on the rest of the system, while the latter incorporates the summation of other markets spillovers on market i . The transmission-directional spillover index is defined as

$$(8) \quad S_{i,t}(h) = \frac{\sum_{j=1, j \neq i}^N \tilde{\psi}_{ji,t}(h)}{N}$$

and the reception-directional spillover index is

$$(9) \quad S_{i,t}(h) = \frac{\sum_{j=1, j \neq i}^N \tilde{\psi}_{ij,t}(h)}{N}$$

After computing these two directional indexes, a net spillover index can be computed straight-forward as the difference between the transmission and reception spillover indexes

$$(10) \quad S_{i,t}(h) = S_{i,t}(h) - S_{i,t}(h)$$

Additionally, another interesting measure is to consider pairwise indexes. The net pairwise spillover index is the difference between the volatility spillover from i to j and the volatility spillover from j to i

$$(11) \quad S_{ij,t}(h) = \frac{\tilde{\psi}_{ji,t}(h) - \tilde{\psi}_{ij,t}(h)}{N}$$

Our extension to this framework consists in modelling the time-varying structure of the covariance matrix of the error term ε_t in (1), H_t . We follow the approach of Engle [2002], namely the DCC-GARCH model. In this multivariate model the conditional covariance matrix of ε_t is given by

$$(12) \quad H_t = D_t R_t D_t$$

D_t is a diagonal matrix of time varying standard deviations of each element in ε_t and R_t is the time varying

correlation matrix.

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} & \cdots & h_{1Nt} \\ h_{21t} & h_{22t} & \cdots & h_{2Nt} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N1t} & h_{N2t} & \cdots & h_{NNt} \end{bmatrix}$$

$$D_t = \begin{bmatrix} \sqrt{h_{11t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22t}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{h_{NNt}} \end{bmatrix}$$

$$R_t = \begin{bmatrix} 1 & \rho_{12t} & \cdots & \rho_{1Nt} \\ \rho_{21t} & 1 & \cdots & \rho_{2Nt} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{N1t} & \rho_{N2t} & \cdots & 1 \end{bmatrix}$$

where h_{iit} is the variance of ε_{it} , h_{ijt} is the covariance of ε_{it} and ε_{jt} , and ρ_{ij} is the Pearson correlation of ε_{it} and ε_{jt} .

In this methodology, squared elements of the diagonal of D_t which are the variances of each ε_{it} are modelled like independent univariate GARCH processes

$$(13) \quad h_{iit} = \omega_i + \sum_{l=1}^{P_i} \alpha_{il} \varepsilon_{it-l}^2 + \sum_{l=1}^{Q_i} \beta_{il} h_{it-l}$$

Now, for the R_t dynamic, the next decomposition is needed

$$(14) \quad R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where Q_t^* is a diagonal matrix whose diagonal is the square root of the diagonal of Q_t and Q_t is a covariance matrix that has the following dynamic

$$(15) \quad Q_t = \left(1 - \sum_{m=1}^M a_m - \sum_{n=1}^N b_n \right) \bar{Q} + \sum_{m=1}^M a_m (\varepsilon_{t-m} \varepsilon'_{t-m}) + \sum_{n=1}^N b_n Q_{t-n}$$

where \bar{Q} is the unconditional expected value of Q_t .

Table 1: Summary Descriptive Statistics on the Daily Series of Stock Market Returns

	Brasil	Chile	Colombia	Mexico	US
Mean	0.04812	0.04358	0.04976	0.11798	0.04804
Std. Dev.	1.75142	1.00405	1.32405	1.81772	1.61961
Skewness	-0.05268	-0.02922	-0.27092	-0.18864	-0.52689
Kurtosis	7.84314	13.11893	14.81702	8.11844	10.77114
LB test	24.214	158.995	184.442	1023.53	662.554
LB2 test	2493.686	1389.364	2175.812	4344.472	5322.24
JB test	3310.306	14438.683	19730.996	3715.514	8672.944

LB stands for Ljung-Box test statistics over the returns, while LB2 does it for Ljung-Box test statistics on the squared returns. JB represents the Jarque-Bera test statistics. All three null hypothesis are rejected for each one of the markets at a 1% level of significance.

3 Data

We examine the daily volatilities of returns on the stock market indexes of five countries. We use daily data on for four major Latin American economies (Brazil - BOVESPA, Chile - IPSA, Colombia - IGBC, Mexico - IPC) and for the United States (S&P 500). Our sample spans the period January 2nd, 2003 to January 27th, 2016. The S&P 500 is included for controlling for global factors in the empirical analysis. Returns are computed taking first differences of the indexes' natural logarithms, they are depicted in Figure 1.

Table 1 shows descriptive statistics of the series of stock market returns for our sample of countries. Information on sample means, standard deviations, skewness, kurtosis, Jarque-Bera (JB) tests for normality and Ljung-Box (LB) tests for autocorrelation are presented. It is important to highlight that all series exhibit a high kurtosis, as usual in this type of

data, and serial correlation.

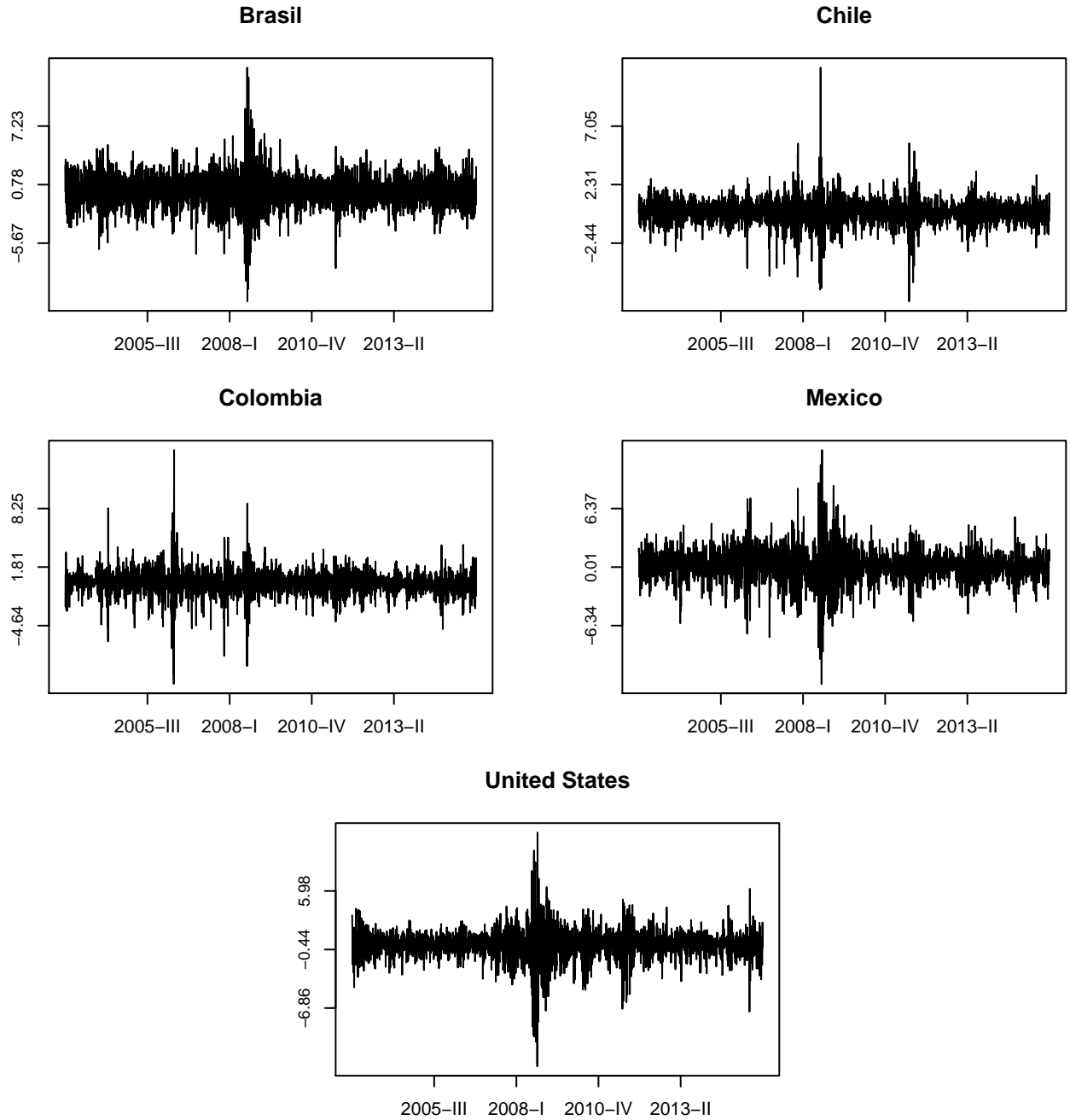
While under the null hypothesis of normal distribution excess kurtosis should be three, for our sample data all kurtosis are way higher. The JB test shows that none of the returns is normally distributed.

Important to notice, Ljung-Box statistics for the squared errors (LB2) of the series show that a GARCH specification can be used in order to control for the presence of volatility clusters in the data.

4 Results

We assume that the S&P 500 returns are weakly exogenous in our system. Additionally, we focus in a ten-day forecast horizon, i.e., $h = 10$ days in our empirical analysis, following Diebold and Yilmaz [2012]. Table 3, in Appendix A, contains tests of adequacy of the DCC-GARCH model specification.

Figure 1: Stock Market Index Returns



The method explained in Section 2 is applied using a rolling window of size 1000, this means that we are computing the spillover indexes for 2379 time periods, spanning from November 10th, 2006 to January 27th, 2016.

Figure 2 shows the total system's spillover. This figure presents the sum of all spillover transmissions and receptions for our sample of countries. It can be seen that the total spillover varies considerably over time. Particularly, it is higher for 2008Q3 - 2012Q2, a period of ample financial volatility related to the United States subprime crisis and the European sovereign bonds crisis.

Figure 2: Total Spillover Index

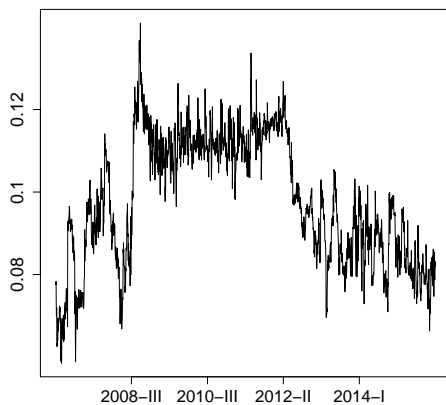


Figure 3 presents total net spillovers for individual countries. In these graphs negative (positive) values at time t correspond to a net receiver (transmitter) position at that time. Clearly, Brazil is a net transmitter for most of the time, while Chile, Colombia and Mexico are net receivers. The United States is a net transmitter for the whole sample period by construction. Net spillovers exhibit great time-variation

as well. For instance, around the Lehman Brothers' episode shock transmission from the United States to the other four countries increases significantly. Even Brazil becomes a net receiver for that period of time.

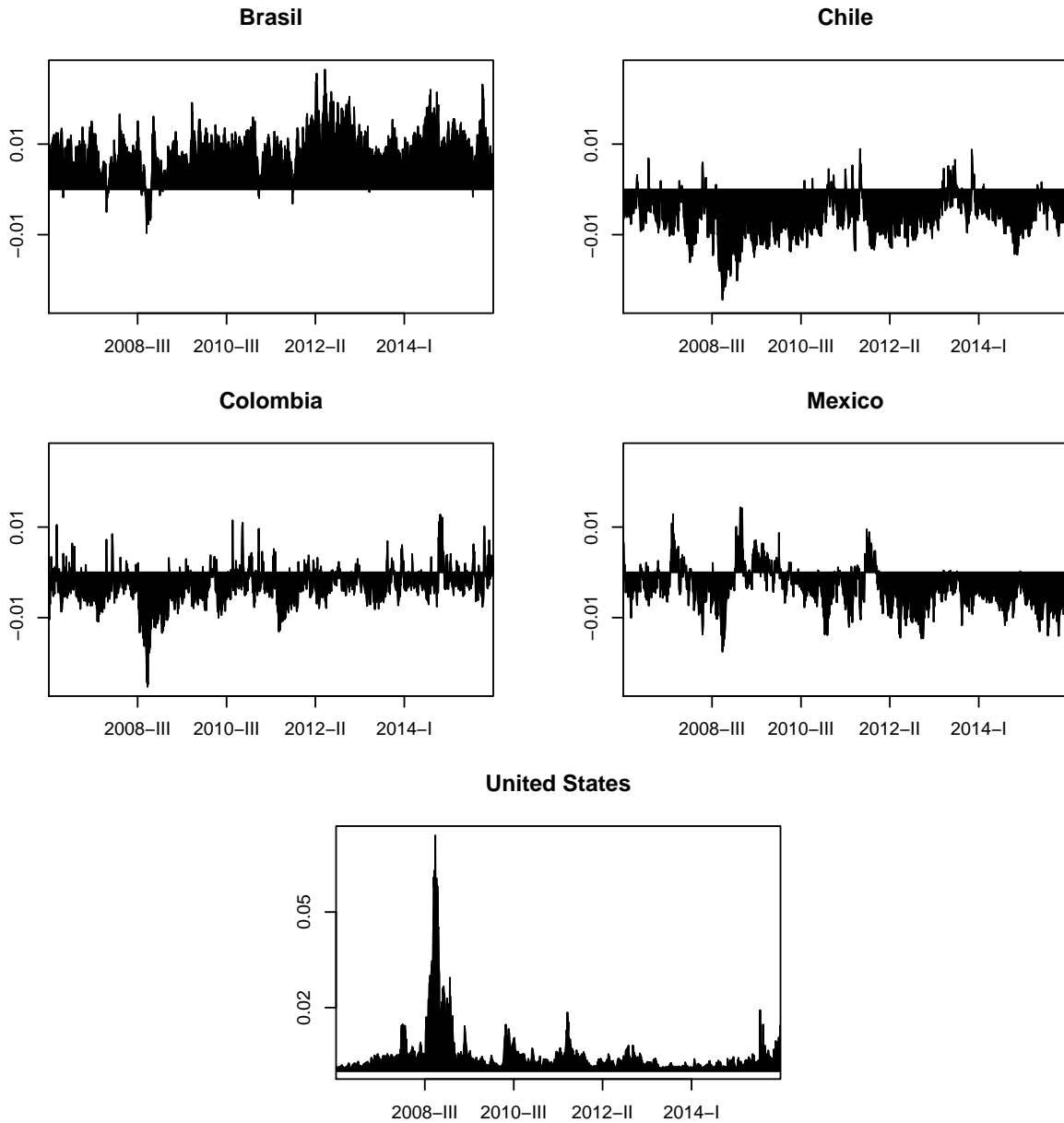
Interestingly, the magnitude of volatility spillovers transmitted from Brazil to the other three Latin American countries increases after 2012. This coincides with the well-known political stability issues of this country that led to Dilma Rouseff's suspension in May 2016, and negatively affected the region's financial markets.

The intensity of reception changed for Colombia and Mexico with a breakpoint in 2012. Before this year, the magnitude of reception was higher for Colombia than for Mexico. After that date, this relation inverted and Mexico became the major recipient of volatility spillovers originating in Brazil and the United States.

Notice that the increase in spillovers received by Mexico during the Lehman Brothers' episode is relatively lower than for the other countries in our sample. This fact, that on a first view may look counter-intuitive due to the close commercial and financial relations between this country and the United States, can be explained. Mexico is the country with deepest financial markets in Latin America and as a consequence it is less affected by international financial shocks. For instance, it was less affected during the bouts of volatility in 2013 and early 2014 (see Mishra et al. [2014]).

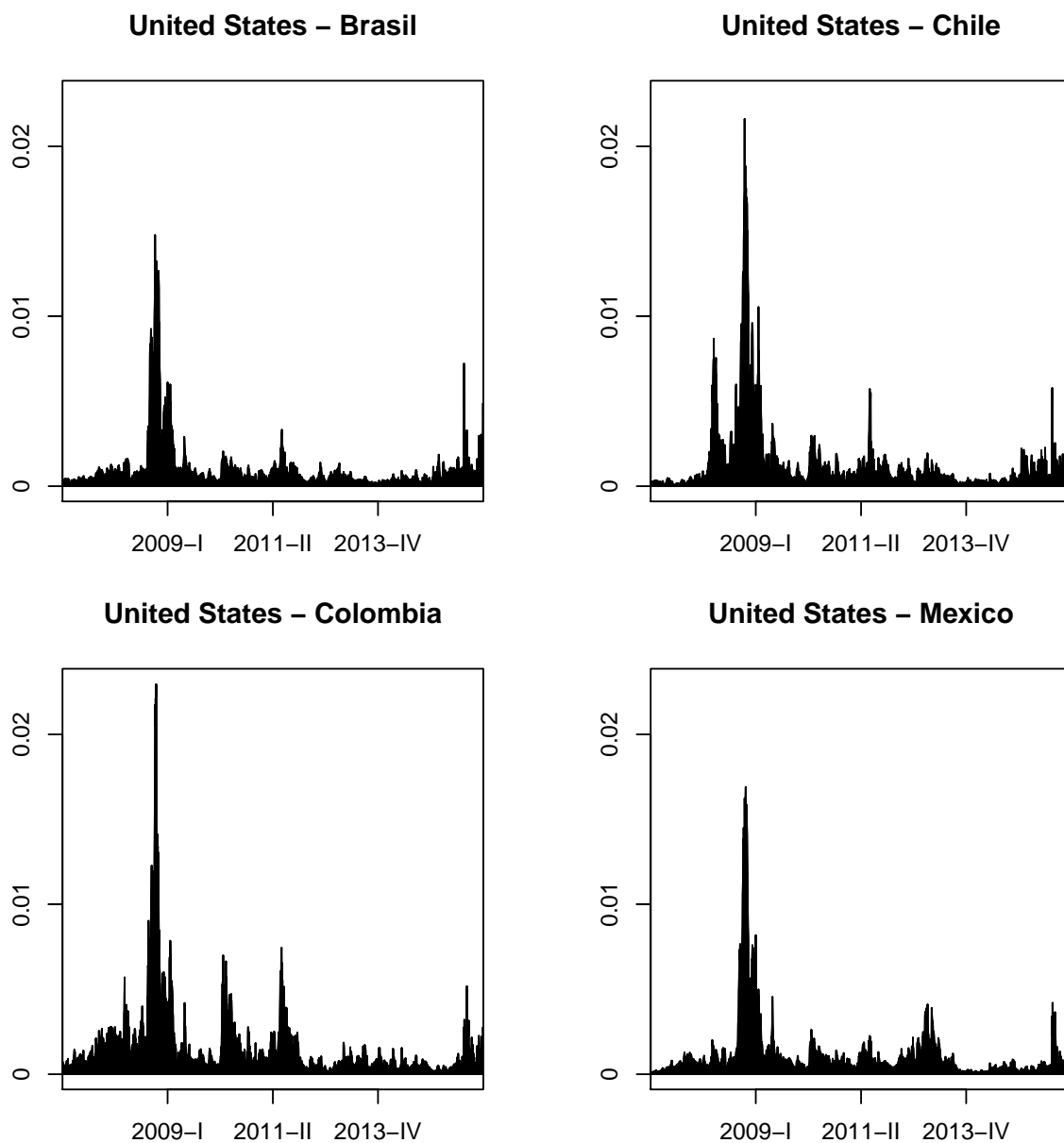
This fact can also be seen from Figures 4 and 5 that depicts pairwise volatility spillovers for the countries included in our system. Notice that, excluding Brazil and the United States, pairwise relations show that there is not a clear structural position among

Figure 3: Net Directional Spillover Index



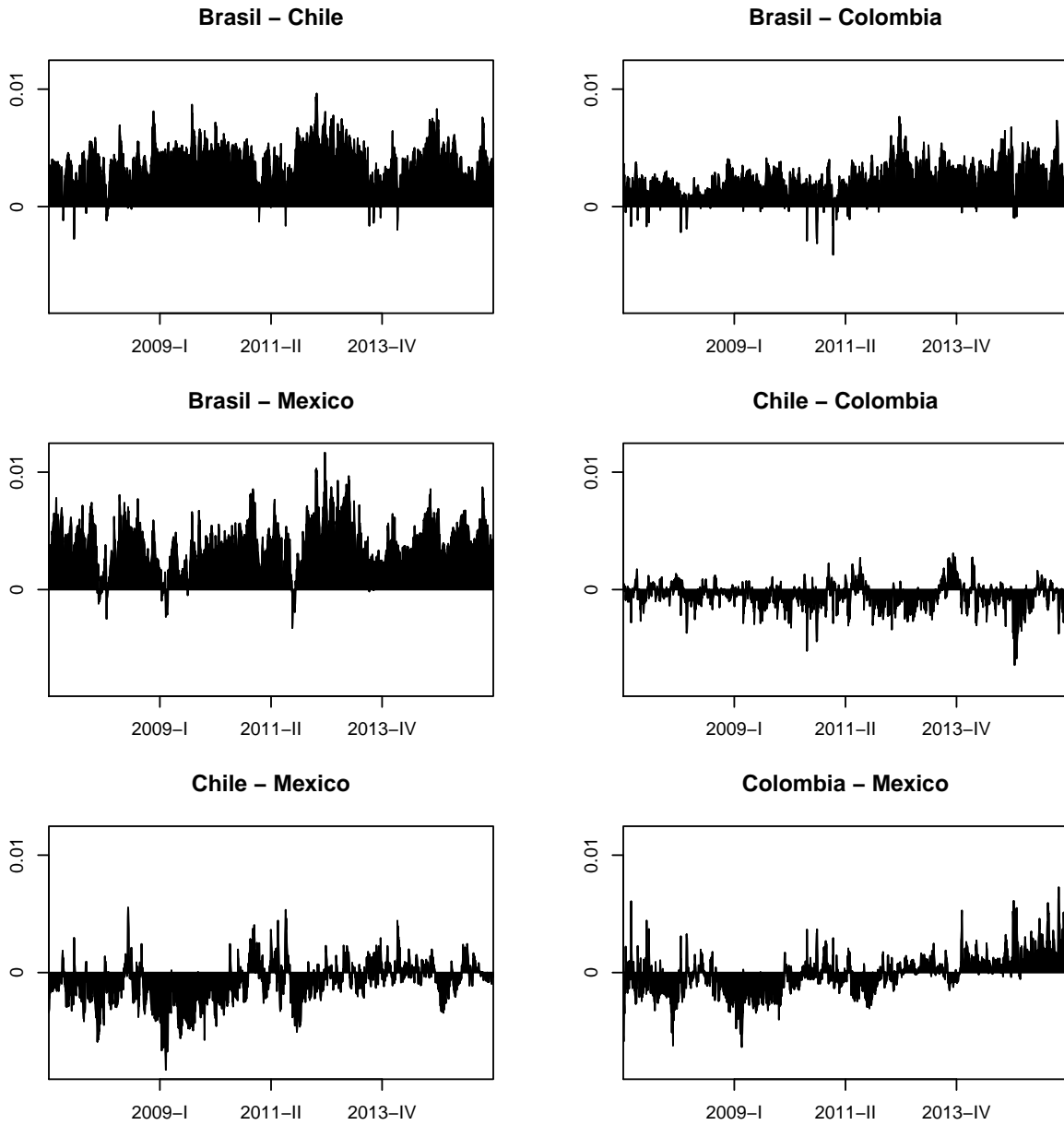
Net directional spillover indexes are the difference between the volatility transmitted from one market to the system and the volatility received by that one market from the system. Hence when the index is positive the market is a net transmitter of volatility, whereas it is negative, it is a net receiver of volatility.

Figure 4: Pairwise Spillover Index of United States and Latin American Countries



Pairwise spillover indexes are the difference between the volatility transmitted from one market to another and the volatility received by that one market from the other. Hence when the index is positive the first market transmits more volatility to the second, whereas it is negative, the second markets send more volatility to the first one.

Figure 5: Pairwise Spillover Index of Latin American Countries



Pairwise spillover indexes are the difference between the volatility transmitted from one market to another and the volatility received by that one market from the other. Hence when the index is positive the first market transmits more volatility to the second, whereas it is negative, the second markets send more volatility to the first one

Table 2: Estimation Results for Testing Changes in United States Pairwise Spillovers

i	ω_{ij}	Subprime Financial Crisis α_{ij}
Brasil	0.614 (0.009)	2.039 (0.026)
Chile	0.722 (0.014)	2.398 (0.042)
Colombia	0.949 (0.018)	2.290 (0.055)
Mexico	0.660 (0.011)	2.013 (0.034)

Standardized errors follow the methodology of Newey and West [1987] for calculating a covariance matrix corrected by heteroscedasticity and autocorrelation. $j = \text{United States}$.

the other three countries. For instance, pairwise relations between Chile and Colombia show that each country has almost the same probability of being either a receiver or a transmitter at each time period.

Regarding Chile and Mexico, during the first part of the sample period Mexico was clearly transmitting volatility to Chile. However, since the beginning of 2011 their relation changed and for the final part of the period became similar to the one between Chile and Colombia. Finally, while Mexico began being a volatility transmitter to Colombia, this relation changed along the sample period up to the point that Colombia became a net transmitter to Mexico in the final part.

An additional exercise consisted in testing whether volatility spillovers from the United States to the

other countries were significantly different during the subprime financial crisis. For doing so, we perform a similar exercise to the one presented in Chiang et al. [2007] and Syllignakis and Kouretas [2011]. We use the following regression equation:

$$(16) \quad S_{ij,t} = \omega_{ij} + \alpha_{ij}DM_t + \eta_{ij,t}$$

where $i = \{Brazil, Chile, Colombia, Mexico\}$ and $j = \{UnitedStates\}$. We regress pairwise spillovers ($S_{ij,t}$) on a constant term (ω_{ij}) and a dummy variables DM_t , taking the value of one during the period of the United States subprime financial crisis and zero otherwise. As the exact period of this (and any other) crisis is not precisely defined, we follow the period chosen by Syllignakis and Kouretas [2011], corresponding to September 26th, 2008 – September 29th, 2009.

Our hypothesis is that spillovers from the United

States to Latin American markets significantly increased during the recent international financial crisis, as the dynamic of capital inflows to Latin American countries during this crisis changed dramatically, responding to changes in risk aversion of international investors. Table 2 shows regression results.

Note that constants are all positive and statistically significant at conventional levels. This result indicates that volatility is increased by spillovers from the S&P 500 during normal times. Linkages are larger for Chile and Colombia.

The dummy variable corresponding to the period of the subprime crisis of the United States is positive and statistically significant for the four countries. This result highlights the fact that during the subprime financial crisis volatility spillovers from the United States to Latin American economies increased importantly. Again, coefficients for Chile and Colombia are the highest for our sample of countries. In line with our results on directional spillovers, the coefficient associated with Mexico is the lowest.

5 Conclusion

In this paper we extend the framework of Diebold and Yilmaz [2009] and Diebold and Yilmaz [2012] and construct volatility spillover indexes using a DCC-GARCH framework to model the multivariate relationships of volatility among assets. We compute spillover indexes directly from the series of asset returns and recognize the time-variant nature of the covariance matrix.

Our approach allows for a better understanding of the movements of financial returns within a framework of volatility spillovers. We apply our method to stock market indexes of the United States

and four Latin American countries, and compute both total and directional spillovers for these market indexes for the period spanning between January 2nd, 2003 and January 27th, 2016.

We find several interesting results. Total spillovers vary considerably over time. Particularly, they are substantially higher between the third quarter of 2008 and the second quarter of 2012, a period of ample financial volatility related to the United States subprime crisis and the European sovereign bonds crisis.

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A Specification Tests

Table 3: Ljung-Box Tests on the DCC-GARCH Errors

Lag	Brasil	Chile	Colombia	Mexico	United States	Multivariate Test
Standardized Errors						
5	0.99961	0.94639	0.99964	0.99797	0.66611	0.99989
10	0.99996	0.99857	0.99990	0.99992	0.90334	1.00000
15	1.00000	0.99991	0.99995	1.00000	0.99001	1.00000
20	1.00000	1.00000	0.99988	1.00000	0.99956	1.00000
25	1.00000	0.99998	0.99999	1.00000	0.99850	1.00000
30	1.00000	1.00000	0.99997	1.00000	0.99847	1.00000
Squared Standardized Errors						
5	0.39094	0.95515	0.85482	0.42257	0.84301	0.92872
10	0.48692	0.87501	0.86031	0.41320	0.53269	0.57665
15	0.41632	0.67391	0.90231	0.38765	0.69224	0.22263
20	0.47633	0.73335	0.93290	0.30353	0.73566	0.21294
25	0.46685	0.72779	0.92603	0.39296	0.62545	0.12111
30	0.64438	0.56982	0.94496	0.53271	0.75341	0.24999

None of the null hypothesis is rejected for each one of the markets at a 10% level of significance.

