Finance Research Letters 20 (2017) 207–216

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Stock market volatility spillovers: Evidence for Latin America[☆]

Santiago Gamba-Santamaria, Jose Eduardo Gomez-Gonzalez[*], Jorge Luis Hurtado-Guarin, Luis Fernando Melo-Velandia

Banco de la República (Central Bank of Colombia), Colombia

ARTICLE INFO

Article history:
Received 22 August 2016
Revised 19 September 2016
Accepted 5 October 2016
Available online 5 October 2016

JEL classification:
G01
G15
C32

Keywords:
Volatility spillovers
DCC-GARCH model
Stock market linkages
Financial crisis

ABSTRACT

We extend the framework of Diebold and Yilmaz (2009b) 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.

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 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 (2009b), 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, ad-

[☆] The errors and omissions are the sole responsibility of the authors. The opinions expressed here are those of the authors and do not necessarily represent those of Banco de la República or its Board of Directors. We are especially grateful to Douglas Cumming and an anonymous referee for excellent comments and suggestions which were very helpful in improving the final version of our document.

[*] Corresponding author.
E-mail addresses: sgambasa@banrep.gov.co (S. Gamba-Santamaria), jgomezgo@banrep.gov.co (J.E. Gomez-Gonzalez), jhurtagu@banrep.gov.co (J.L. Hurtado-Guarin), lmelovel@banrep.gov.co (L.F. Melo-Velandia).

http://dx.doi.org/10.1016/j.frl.2016.10.001
1544-6123/

ditionally, 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 (2009b, 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.

Hence, in this paper we do not have to distinguish between return and volatility spillovers, because our measure of volatility is computed directly from the covariance matrix obtained from a DCC-GARCH model. Our results are therefore comparable to those of Diebold and Yilmaz (2012), with the advantage of avoiding the need of using an artificial definition of volatility.

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 (2009b) 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

$$Y_t = \Phi_0 + \sum_{l=1}^{p} \Phi_l Y_{t-l} + \epsilon_t \tag{1}$$

where Y_t is a vector of size N, containing all stock market returns at time t, and $\epsilon_t|t-1 \sim F(0, H_t)$ 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(∞)

$$Y_t = \Phi_0 + \sum_{p=0}^{\infty} \Theta_p \epsilon_{t-p} \tag{2}$$

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

$$e_{t+h}|t = \Theta_0 \epsilon_{t+h} + \Theta_1 \epsilon_{t+h-1} + \cdots + \Theta_{h-1} \epsilon_{t+1} \tag{3}$$

whose covariance matrix is

$$\Sigma^e_{t+h}|t = \Theta_0 H_{t+h}\ \Theta'_0 + \Theta_1 H_{t+h-1}\ \Theta'_1 + \cdots + \Theta_{h-1} H_{t+1}\ \Theta'_{h-1} \tag{4}$$

Each element of the diagonal of $\Sigma^e_{t+h}|t$ 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