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On the Volatility Spillover between Agricultural Commodities and Latin American Stock Markets

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Received: 21 September 2018; Accepted: 4 October 2018; Published: 10 October 2018



Abstract: Addressing the volatility spillovers of agricultural commodities is important for at least two reasons. First, for the last several years, the volatility of agricultural commodity prices seems to have increased. Second, according to the Food and Agriculture Organization, there is a strong need for understanding the potential (negative) impacts on food security caused by food commodity volatilities. This paper aims at investigating the presence, the size, and the persistence of volatility spillovers among five agricultural commodities (corn, sugar, wheat, soybean, and bioethanol) and five Latin American (Argentina, Brazil, Chile, Colombia, Peru) stock market indexes. Overall, when a negative shock hits the commodity market, Latin American stock market volatility tends to increase. This happens, for instance, for the relationships from corn to Chile and Colombia and from wheat to Peru and Chile.

Keywords: agricultural commodity; volatility spillover; volatility impulse response function

1. Introduction

Since the beginning of the 1990s, the financial literature has displayed remarkable interest in the transmission of volatility, alternatively called volatility spillover, from a source to a recipient. In this regard, how volatility spillover can be estimated and how long it lasts have been largely investigated (Hamao et al. 1990; Engle et al. 1990; Lin et al. 1994, among others). There are two main approaches to estimating volatility spillover. The first method, proposed by Diebold and Yilmaz (2009) and subsequently generalized in a further contribution (Diebold and Yilmaz 2012), lies in the vector autoregressive context and relies on forecast-error variance decomposition. By means of the latter, it is possible to identify a spillover index (and hence the direction), the main sources, and the recipients of the spillovers. A second method uses the multivariate generalized autoregressive conditional heteroskedastic (MGARCH) class of models (surveyed in Bauwens et al. 2006) to firstly estimate the conditional covariance matrices of the variables under investigation, and to then apply the volatility impulse response function (VIRF) methodology proposed by Hafner and Herwartz (2006). The VIRF allows the calculation of the impact, in terms of size and persistence, of shocks on expected conditional volatility. Recently, the MGARCH-VIRF methodology has been applied in different contributions. For instance, Kang et al. (2017) examined the volatility spillovers between the United States and six Asian stock markets (China, Hong Kong, Japan, Korea, Singapore, and Taiwan). Nazlioglu et al. (2015) investigated the volatility transmission between the Dow Jones Islamic equity market and the United States, European, and Asian stock markets. By using only MGARCH models, Mohammadi and Tan (2015) evaluated the interdependencies among the equity markets in the United States, Hong Kong, and China. The work of Allen et al. (2017) uses both of the previously cited methodologies to capture the spillover effects across markets. All of these contributions share the feature of investigating volatility transmission that originates from one stock market and affects

another stock market. However, as pointed out by [Amendola et al. \(2017\)](#) and references therein, the analysis of commodity volatility has recently received significantly increased interest. Within this framework, a rising number of contributions have focused on the volatility spillovers of commodity returns. Moreover, while there are many works examining how energy (or metals) commodity volatilities affect stock markets ([Kang et al. 2015](#); [Arouri et al. 2012](#); [Malik and Ewing 2009](#), for instance), or how these volatilities influence each other ([Vardar et al. 2018](#); [Karali and Ramirez 2014](#); [Jin et al. 2012](#), among others), few contributions focus on volatility spillovers in the context of agricultural commodities. Among these, [Nazlioglu et al. \(2013\)](#), using daily data spanning from January 1986 to March 2011 concerning the spot prices of the world's oil, corn, soybeans, wheat, and sugar, found that, after the Great Recession period, the oil market transferred volatility to three agricultural commodities (corn, wheat, and soybean). Recently, [Hamadi et al. \(2017\)](#) found significant bidirectional volatility spillovers among four agricultural commodities (corn, wheat, soybeans, and soybean oil) by employing daily data covering the period from December 1999 to May 2015. In addition, [Śmiech et al. \(2018\)](#) investigated the volatility spillovers among four agricultural commodities (corn, soybean, wheat and rice) and some financial and energy variables (US dollar, S&P500 futures and crude oil). Interestingly, they found that these latter variables have a limited impact in transferring volatility to food commodities. To the best of our knowledge, there is a gap in this literature regarding the other way around, which is the possible transmission of volatility from agricultural commodities to stock markets. The aim of this work is to fill this gap. In particular, our goal is to analyze the volatility spillovers originating from corn, sugar, wheat, soybean, and bioethanol (log-)returns and affecting the stock markets of five Latin American countries: Argentina, Brazil, Chile, Colombia, and Peru. Interestingly, according to the International Money Fund¹, all of these economies are developing markets (DMs). In this framework, we first apply the recently proposed test for causality in volatility ([Chang and McAleer 2017](#)). Robust to different lagged periods, the test is able to control whether a commodity transfers volatility to a stock market. Afterwards, we adopt the MGARCH-VIRF methodology to verify the size and the persistence of a volatility spillover on a Latin American stock market after a given shock affecting the commodity.

Addressing the volatility spillovers of agricultural commodities is important for at least two reasons. First, during the last several years, the volatility of agricultural commodity prices seems to have increased. As argued by [Hamadi et al. \(2017\)](#), during the period of 2007–2009, agricultural commodity prices exhibited large and unexpected variations. In support of this thesis, the Food Price Index of the Food and Agriculture Organization (FAO) was quite unchanged before 2007, after which it drastically grew until March 2008. This confirms the fact that, during that period, the food prices generally exhibited an uprising trend. In the spirit of [Gilbert and Morgan \(2010\)](#), we perform a preliminary analysis to verify if the five commodity log-returns exhibited different levels of volatility. The results are given in Section 2. In line with the literature, for all the commodities, the hypothesis of variance homogeneity is largely rejected.

There is also a second noteworthy reason for investigating the agricultural commodity spillovers, that is, mainly to determine if the volatility originated from or transferred to Latin American countries. In fact, according to the reports of the [FAO \(2015\)](#) and [OECD and FAO \(2015\)](#), this region has become the largest net exporter of food since 2002, with a projection of 60 billion US\$ in 2024 in terms of net exports of cereals, oilseeds, sugar crops, meats, fish, and dairy products. More specifically, the Latin American countries are grain and sugar net exporters. Nevertheless, the flow of exports is not homogeneous among the five countries considered here, of which the most predominant role is played by Brazil, who, for instance, trades more than half of the global sugar exports. Among the countries under investigation, Peru is not only a DM, but also a net food-importing DM (NFIDM), according to the World Trade Organization (WTO). Thus, it is of great interest to understand to what extent

¹ <https://www.imf.org/external/datamapper/NGDPD@WEO/OEMDC/ADVEC/WEOWORLD>.

the variation in some agricultural commodities can affect both DMs and NFIDMs. One of the key messages in [FAO \(2015\)](#) is the need for understanding the potential (negative) impacts on food security² caused by food commodity volatilities. This contribution attempts to achieve this goal, by studying the interdependencies among food prices and Latin American stock markets. Moreover, according to [Cashin and McDermott \(2002\)](#) and [UNDP \(2011\)](#), higher commodity volatility leads to severe consequences for developing countries, which mostly base their economy on commodity exports ([Bouri et al. 2017](#)). In general, higher food commodity volatilities may induce economic weakness, mainly in food-exporter countries, such as some of those under investigation. Furthermore, in turn, a more fragile economy can heavily undermine the food security. This confirms recent empirical evidence: both the high food prices (from 2007 to mid-2008) and the Great Recession (2007–2009) are intertwined phenomena that have important implications in terms not only of financial, economic and political stability but also in terms of food security, as underlined by [Von Braun \(2008\)](#), among others. Our study assumes particular relevance because it investigates the volatility spillovers originating from commodities primarily generated in Latin American countries (for instance, corn, sugar, soybean and bioethanol are mainly produced in Brazil) and affecting precisely those Latin American stock markets.

The rest of the paper is organized as follows: Section 3 illustrates the econometric methodology used first to verify if there is a volatility spillover from a series to another series. Subsequently, Section 3 presents the bivariate MGARCH model employed to estimate the conditional covariance matrices of the two series where a volatility spillover has been found to exist, and, finally, the VIRF is presented. Section 4 details the data and results of the analysis. The conclusions follow.

2. Change in Volatility of Agricultural Commodities

In this paper, the commodities of interest are: corn, sugar, wheat, soybean, and bioethanol. All of these data were collected from the Datastream database. In line with other contributions, information on commodities are derived from commodity future prices. The first five columns of Table 1 illustrate the beginning and the ending period for the commodity datasets at our disposal, the relative number of daily observations, the Jarque–Bera test and the (full) sample standard deviations (Std. Dev.). As expected, all of the returns are far from being normally distributed, given that the null of the Jarque–Bera test is always rejected. As stated in the previous section, a noteworthy reason for investigating the volatility spillovers of the agricultural commodities is that the latter seem to exhibit high levels of heteroskedasticity, mainly during or after the recent Great Recession period (2007–2009). It can be easily noted that the standard deviations of all the commodities during this period of crisis (identified in the table as sample S6) are larger than the corresponding standard deviations occurring in the full sample periods. Thus, in order to test the homogeneity of variances, we employed the non-parametric Fligner test ([Conover et al. 1981](#)), whose null is that the variances in each of the samples are the same. It results that, for all the commodities, the hypothesis of variance homogeneity is largely rejected.

² The food security definition elaborated in the 1996 World Food Summit ([Clay 2002](#)) is: “Food security, at the individual, household, national, regional and global levels (is achieved) when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life”.

Table 1. Agricultural log-return volatilities over time.

Commodity	BP	EP	Obs.	Jarque–Bera	Std. Dev. (FS)	Std. Dev. (S1)	Std. Dev. (S2)	Std. Dev. (S3)	Std. Dev. (S4)	Std. Dev. (S5)	Std. Dev. (S6)	Fligner
Corn	2 Jan 1973	28 Feb 2018	11,398	0.000	0.017	0.020 (2 Jan 1973/31 Dec 1980)	0.015 (2 Jan 1981/31 Dec 1990)	0.015 (2 Jan 1991/29 Dec 2000)	0.019 (1 Jan 2001/12 Dec 2010)	0.018 (3 Jan 2011/28 Feb 2018)	0.026 (3 Dec 2007/30 Jun 2009)	0.000
Sugar	22 May 1998	28 Feb 2018	4,954	0.000	0.023	0.028 (22 May 1998 /29 Dec 2000)	0.023 (2 Jan 2001/12 Dec 2010)	0.019 (4 Jan 2011/28 Feb 2018)	-	-	0.028 (3 Dec 2007/30 Jun 2009)	0.000
Wheat	27 Aug 1998	28 Feb 2018	4,912	0.000	0.020	0.016 (27 Aug 1998/29 Dec 2000)	0.021 (2 Jan 2001/31 Dec 2010)	0.018 (3 Jan 2011/28 Feb 2018)	-	-	0.030 (3 Dec 2007/30 Jun 2009)	0.000
Soybean	27 Aug 1998	28 Feb 2018	4,912	0.000	0.017	0.013 (27 Aug 1998/29 Dec 2000)	0.019 (2 Jan 2001/12 Dec 2010)	0.014 (3 Jan 2011/28 Feb 2018)	-	-	0.028 (3 Dec 2007/30 Jun 2009)	0.000
Bioethanol	27 Apr 2005	28 Feb 2018	3,230	0.000	0.022	0.021 (27 Apr 2005/31 Dec 2010)	0.022 (3 Jan 2011 /28 Feb 2018)	-	-	-	0.022 (3 Dec 2007/30 Jun 2009)	0.002

Notes: The table reports the standard deviations (Std. Dev.) of the agricultural log-returns over the full sample (FS), and up to five subsamples (S1, . . . , S6). BP and EP stand for begin and end period, respectively. Column labeled Jarque–Bera reports the p -value of the Jarque–Bera test, whose null is of normality. Column labeled Fligner reports the p -value of the Fligner test, whose null is that the variances in each of the groups (samples) are the same.

3. Econometric Methodology

Throughout the paper, let i and j denote the series receiving and originating the volatility spillover, respectively. Moreover, let the expression “ $j \rightarrow i$ ” synthetically indicate the volatility spillover from series j to i . Adopting a standard notation, let $y_{k,t}$ be the log-difference of the commodity price k at time t , that is: $y_{k,t} = \log(P_{k,t}) - \log(P_{k,t-1})$. Moreover, we assume that:

$$y_{k,t} = E(y_{k,t}|I_{t-1}) + \epsilon_{k,t}, \quad \text{with } k = i, j, \quad (1)$$

where $E(y_{k,t}|I_{t-1})$ represents the return expectation conditionally on the information set I_{t-1} , and $\epsilon_{k,t}$ is the heteroskedastic error term, such that $\epsilon_{k,t} = h_{k,t}z_t$. In particular, z_t is a random sequence of i.i.d. normally distributed variables with mean zero and unit variance and $h_{k,t}$ is the conditional standard deviation for series k . The GARCH specification proposed by [Bollerslev \(1986\)](#) to model the conditional variance $h_{k,t}^2$ of commodity k is:

$$h_{k,t}^2 = w_k + \alpha_k \epsilon_{k,t-1}^2 + \beta_k h_{k,t-1}^2, \quad (2)$$

where w_k is the constant and α_k and β_k are the so-called ARCH and GARCH parameters, respectively. In order to test the volatility spillover from commodity j (origin) to series i (recipient), [Chang and McAleer \(2017\)](#) added lagged squared returns and variances of series j to Equation (2), which becomes:

$$h_{i,t}^2 = w_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{i,t-1}^2 + \alpha_j \epsilon_{j,t-1}^2 + \beta_j h_{j,t-1}^2. \quad (3)$$

In this formulation, α_j represents the effect of a shock spillover from series j to series i , while β_j represents the effect of a volatility spillover. Hence, the null of no (shock and) volatility spillover, alternatively defined as Granger non-causality ([Granger 1969](#)), is:

$$H_0 : \alpha_j = \beta_j = 0. \quad (4)$$

In this contribution, we test the null hypothesis by means of a Likelihood Ratio (LR) test, where the (log-)likelihood of the unrestricted model (Equation (3)) is evaluated against that of the restricted model (Equation (2)). Note that both the restricted and the unrestricted models can include specific lagged terms, in addition to or in substitution of $t - 1$.

Let us suppose that a volatility spillover exists between the series i and j . In order to further investigate the interdependencies in volatilities, we use the VIRF methodology proposed by [Hafner and Herwartz \(2006\)](#), which provides the impact (that is: the size and the persistence) of independent shocks on volatility. To make effective the VIRF methodology, the conditional covariance matrix H_t is derived using the BEKK ([Engle and Kroner 1995](#)) model. Generalizing the previous framework to a bivariate conditional heteroskedastic model implies that univariate error term for series k $\epsilon_{k,t}$ becomes bold, namely ϵ_t , which denotes a 2×1 vector of daily-log returns (if $E(y_{k,t}|I_{t-1}) = 0$, for $k = i, j$) or residuals, such that:

$$\epsilon_t = H_t^{1/2} z_t, \quad t = 1, \dots, T, \quad (5)$$

where the random vector z_t is assumed to have zero means ($E(z_t) = \mathbf{0}$) and that $E(z_t z_t') = I_2$, with I_2 indicating a 2×2 diagonal matrix of ones. Moreover, we also assume that the (multivariate) Normal distribution for z_t holds. In Equation (5), $H_t^{1/2}$ a positive definite matrix such that $H_t^{1/2} H_t^{(1/2)'} = H_t = \text{VAR}(\epsilon_t|I_{t-1})$. In other words, H_t is the conditional covariance matrix of returns (or residuals). In the BEKK(1,1) representation, H_t is:

$$H_t = CC' + A\epsilon_t\epsilon_t'A' + GH_{t-1}G', \quad (6)$$

where C , A , and B are, respectively, a lower triangular and 2×2 matrices:

$$\begin{aligned} \begin{bmatrix} H_{ii,t} & H_{ij,t} \\ H_{ji,t} & H_{jj,t} \end{bmatrix} &= \begin{bmatrix} C_{ii} & 0 \\ C_{ji} & C_{jj} \end{bmatrix} \begin{bmatrix} C_{ii} & C_{ji} \\ 0 & c_{jj} \end{bmatrix} + \\ &+ \begin{bmatrix} A_{ii} & A_{ij} \\ A_{ji} & A_{jj} \end{bmatrix} \begin{bmatrix} \epsilon_{ii,t-1}^2 & \epsilon_{i,t-1}\epsilon_{j,t-1} \\ \epsilon_{j,t-1}\epsilon_{i,t-1} & \epsilon_{jj,t-1}^2 \end{bmatrix} \begin{bmatrix} A_{ii} & A_{ji} \\ A_{ij} & A_{jj} \end{bmatrix} + \\ &+ \begin{bmatrix} G_{ii} & G_{ij} \\ G_{ji} & G_{jj} \end{bmatrix} \begin{bmatrix} H_{ii,t-1} & H_{ij,t-1} \\ H_{ji,t-1} & H_{jj,t-1} \end{bmatrix} \begin{bmatrix} G_{ii} & G_{ji} \\ G_{ij} & G_{jj} \end{bmatrix}, \end{aligned}$$

with H_{ii} , H_{jj} , and H_{ij} respectively denoting the conditional variances for series i and j and their conditional covariance. The coefficients A_{ij} and A_{ji} capture the shock spillovers, while G_{ij} and G_{ji} represent the volatility spillovers. Given that the relationship of interest is from series j to series i , attention is mainly devoted to the coefficients (and estimated signs) for A_{ij} and G_{ij} , which contribute to explain $H_{ii,t}$ by the following formulation:

$$\begin{aligned} H_{ii,t} &= C_{ii}^2 + A_{ii}^2 \epsilon_{ii,t-1}^2 + 2A_{ii}A_{ij}\epsilon_{i,t-1}\epsilon_{j,t-1} + A_{ij}^2 \epsilon_{j,t-1}^2 + \\ &C_{ii}^2 H_{ii,t-1} + G_{ii}G_{ij}H_{ij,t-1} + G_{ij}^2 H_{jj,t-1}. \end{aligned} \tag{7}$$

The VIRF methodology identifies independent shocks affecting H_t by computing the Jordan decomposition of the conditional covariance matrix, such that:

$$H_t^{1/2} = \Gamma_t \Lambda_t^{1/2} \Gamma_t', \tag{8}$$

where Λ_t is a diagonal matrix containing the eigenvalues of H_t , and Γ_t is a 2×2 matrix of the corresponding eigenvectors. Hence, the independent shocks z_t are defined as:

$$z_t = H_t^{-1/2} \epsilon_t. \tag{9}$$

As shown in [Hafner and Herwartz \(2006\)](#), if the hypothesis of non-Normal distribution holds, z_t is uniquely defined. This means that z_t may be considered some unpredictable vector of innovations (or shocks) that occurred in the past and affect the future. Finally, in order to identify the VIRF, the *vech* representation of the model in Equation (6) is used:

$$vech(H_t) = vech(C) + R \cdot vech(\epsilon_t \epsilon_t') + F \cdot vech(H_{t-1}), \tag{10}$$

where $vech()$ is the operator stacking the lower fraction of an $N \times N$ matrix into an $N^* = N(N + 1)/2$ dimensional vector, and R and F are matrices with $(N^*)^2$ elements.

Let $E[vech(H_t|I_{t-1})]$ be the baseline expectation, that is, the expectation of H_t , given the available information set (and without any additional shocks). The VIRF h -step-ahead is the difference between the h -step-ahead expected conditional covariance matrix, given a shock at time t , and its history and the baseline expectation, that is:

$$V_h(z_t) = E[vech(H_{t+h}|z_t, I_{t-1})] - E[vech(H_{t+h}|I_{t-1})]. \tag{11}$$

According to our notation, let us suppose that a shock occurred in series j on day t . By Equation (11), it is possible to quantify the impact of the shock both on series j and, more interestingly, on the series receiving the volatility spillover, that is, series i . Following the *vech* representation used in Equation (10), the one-step-ahead VIRF is:

$$V_1(z_t) = R \cdot \left\{ vech\left(H_t^{1/2} z_t z_t' H_t^{1/2}\right) - vech(H_t) \right\}, \tag{12}$$

where z_t is obtained by Equation (9). Finally, for $h \geq 2$, the VIRF becomes:

$$V_h(z_t) = (R + F) \cdot V_{h-1}(z_t). \quad (13)$$

4. Data and Results

As stated in the Introduction, the countries under investigation belong to the Latin America and are: Argentina, Brazil, Chile, Colombia and Peru. Some of these countries play a prominent role in the production of agricultural commodities. According to the FAO, the world's largest producer of corn is the United States of America (in 2016, 384,777,890 tonnes), followed by China (in 2016, 231,673,946 tonnes) and Brazil (in 2016, 64,143,414 tonnes). In terms of sugar production, Brazil has an undisputed global leadership, with its 768,678,382 tonnes of production in 2016. Among the countries under consideration, wheat does not have the same importance. In fact, none of the five countries lie in the FAO's most recent (2016) Top 10 Country Production of Wheat report. As regards the total supply of soybeans, according to the Agricultural Market Information System (AMIS) database³, the top country is the United States (127.73 million tonnes in 2017/2018), followed by Brazil (125.02 million tonnes in 2017/2018). Bioethanol is a hybrid agricultural commodity because it is used as fuel but comes from crop fields. In particular, it derives from corn (in United States, the world's largest producer) and from sugar (in Brazil, who represents the world's second largest producer). Unfortunately, data at our disposal do not cover the same period in the beginning of the samples. Globally, the longest commodity series is that of corn, which starts in January 1973. The shortest series is bioethanol, which begins in May 2005. Interestingly, in 2005, bioethanol production began to be heavily subsidized by the United States and other governments (Tyner 2008). Daily data on Latin American stock markets have been collected from Yahoo Finance. Table 2 synthesizes some summary statistics. All series are not symmetric and not-normally distributed due to their high skewness and kurtosis.

Table 2. Summary statistics of Latin American stock market indexes.

Statistics	Argentina	Brazil	Chile	Colombia	Peru
Symbol	MERV	BVSP	IPSA	GXG	SPBPLPGPT
Begin Period	8 Oct 1996	27 Apr 1993	2 Jan 2002	22 May 1998	31 Mar 1997
End Period	28 Feb 2018				
Obs	5245	6149	4028	4954	5072
Min *	−14.765	−17.208	−7.236	−18.038	−13.291
Max *	16.117	28.832	11.803	23.547	12.816
Mean *	0.077	0.133	0.039	0.008	0.05
Std. Dev.	0.022	0.023	0.01	0.023	0.014
Skew.	−0.307	0.489	0.013	−0.077	−0.416
Kurt.	4.813	10.46	10.206	6.044	10.782

Notes: The table presents the number of observations (Obs), the minimum (Min) and the maximum (Max) observation values, the mean, the standard deviation (Std. Dev.), the skewness (Skew.), and the (excess) kurtosis (Kurt.) for the daily log-returns of the stock market indexes. * means that data have been multiplied by 100.

The patterns of the five commodity prices over time are shown in Figure 1. Even if the samples differ among the commodities, due to different starting periods, some points can be highlighted. First, all the series exhibit a spike during the period 2007–2009. Second, after the Great Recession period, the behavior of the five commodity prices is not homogeneous. For instance, corn price continued to increase until 2014, when it started to decrease.

³ <http://statistics.amis-outlook.org/data/index.html>.

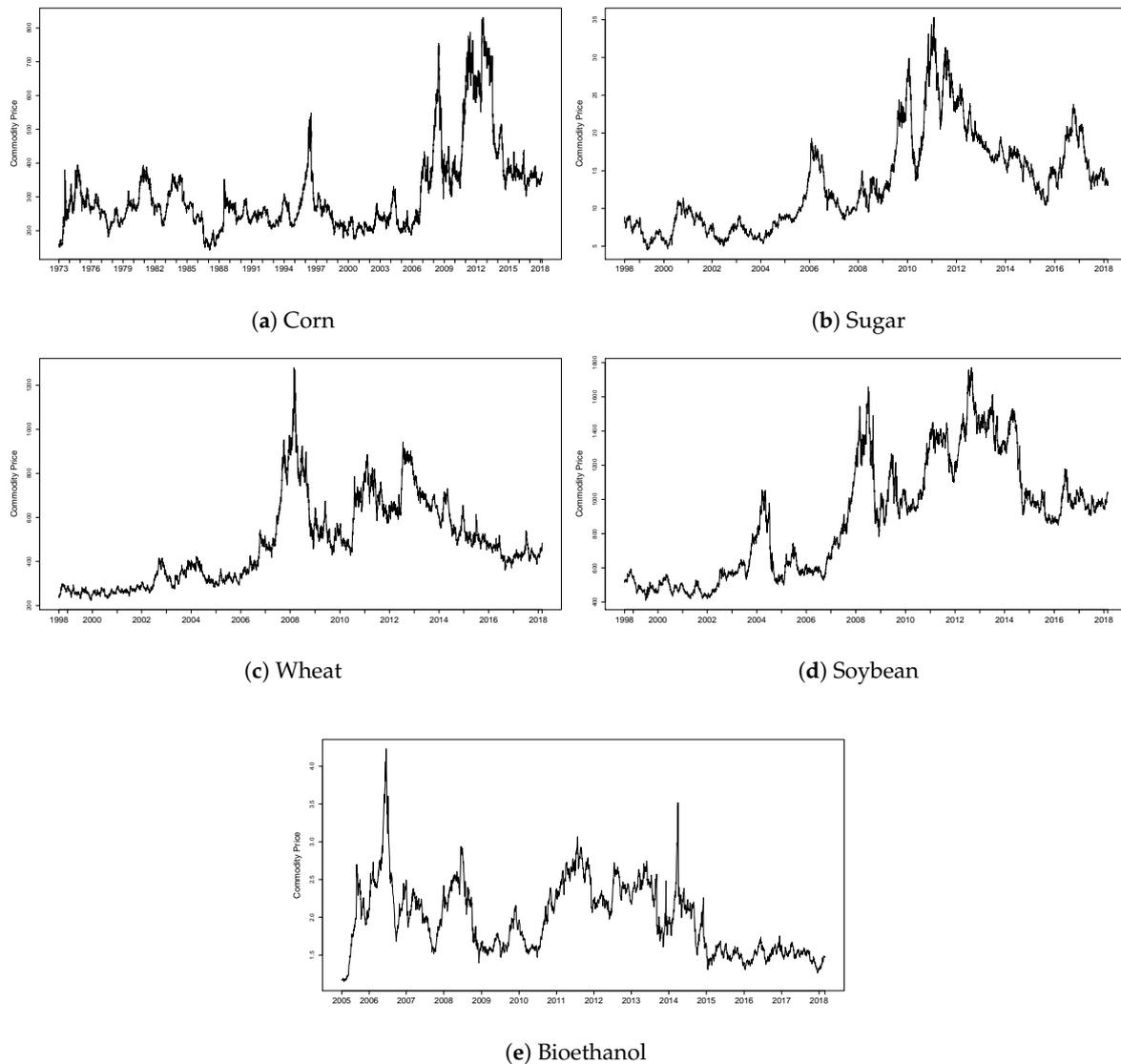


Figure 1. Commodity prices over time.

The results of the LR tests concerning the presence of volatility spillovers are highlighted in Table 3. In particular, series i , the one receiving the spillover, is represented by a Latin American stock market index; series j , the one that originates the spillover, is given by the commodity. To be straightforward in our analysis, we verify the interdependencies between the pair of series i and j for different lagged periods, not only $t - 1$, but also $t - 5$ and $t - 10$. This means that the test deals with commodity transferring volatility up to 10 days ahead. The results are quite unequivocal for the biggest countries. Argentina and Brazil do not receive volatility spillovers from the commodities (and periods) under consideration, at a significance level of at least 10%. Interestingly, Chile, which is a developed country, has to manage with three volatility spillovers in its stock market caused by corn, sugar, and wheat. Colombia, which is a DM, seems to be independent of volatility spillovers caused by sugar, wheat, and bioethanol, while it receives a spillover from corn for $t - 1$ and $t - 5$ at a 10% significance level. Finally, the only NFIDM in our set of countries, that is, Peru, receives strong volatility spillover from corn and wheat, regardless of the lagged period in which the volatility spillover arises.

Table 3. *p*-values of the causality in the volatility test.

Commodity	Time	Argentina	Brazil	Chile	Colombia	Peru
Corn	$t - 1$	0.071	0.115	0.022	0.050	0.000
	$t - 5$	0.324	0.194	0.008	0.084	0.000
	$t - 10$	0.895	0.353	0.003	0.125	0.000
Sugar	$t - 1$	0.351	0.887	0.658	0.000	0.016
	$t - 5$	0.380	0.729	0.876	0.000	0.041
	$t - 10$	0.517	0.911	0.570	0.000	0.481
Wheat	$t - 1$	0.279	0.994	0.081	0.185	0.062
	$t - 5$	0.404	0.997	0.080	0.687	0.048
	$t - 10$	0.577	0.949	0.046	0.619	0.018
Soybean	$t - 1$	0.047	0.607	0.121	0.779	0.736
	$t - 5$	0.266	0.998	0.684	0.142	0.992
	$t - 10$	0.392	0.847	0.833	0.003	1.000
Bioethanol	$t - 1$	0.020	0.381	0.278	0.971	0.606
	$t - 5$	0.846	0.728	0.860	0.465	0.465
	$t - 10$	0.959	0.811	0.981	0.391	0.131

Notes: The table presents the *p*-values of the LR test to detect the volatility spillover originating from series *j* (first column) and transferring to series *i* (first row), for different lagged periods (second column). Dark, medium-dark, and light shades of gray denote significance at the 1%, 5%, and 10% levels, respectively.

Once we analyzed which commodity originated a volatility spillover towards a Latin American country, we focus on the size and persistence of such a spillover by using the MGARCH-VIRF methodology summarized before. Taking advantage of the relationships obtained in Table 3, we estimated the BEKK model only when the test signaled the presence of (shock and) volatility spillover. Results are summarized in Table 4.

Table 4. BEKK estimates.

<i>j</i> (Origin) <i>i</i> (Recipient)	Corn Chile	Corn Colombia	Corn Peru	Sugar Colombia	Sugar Peru	Wheat Chile	Wheat Peru
C_{ii}	−0.003 *** (0.000)	0.007 * (0.004)	−0.002 *** (0.000)	0.009 *** (0.000)	−0.003 *** (0.000)	0.003 *** (0.000)	0.003 *** (0.000)
C_{ji}	0.004 *** (0.001)	−0.002 (0.004)	0.007 * (0.004)	0.008 *** (0.000)	0.003 *** (0.001)	−0.004 *** (0.001)	−0.001 (0.001)
C_{jj}	0.017 *** (0.001)	0.016 *** (0.001)	−0.016 *** (0.002)	0.000 (0.000)	−0.018 *** (0.001)	−0.009 *** (0.001)	0.013 *** (0.000)
A_{ii}	−0.498 *** (0.019)	−0.343 *** (0.026)	0.548 *** (0.020)	1.426 (16.330)	0.498 *** (0.018)	0.496 *** (0.020)	0.475 *** (0.019)
A_{ji}	0.001 (0.011)	−0.011 (0.032)	−0.006 (0.008)	1.426 (16.330)	−0.003 (0.007)	0.002 (0.010)	0.028 *** (0.010)
A_{ij}	0.148 ** (0.058)	−0.011 (0.017)	0.063 ** (0.032)	1.913 (15.307)	−0.024 (0.037)	0.041 (0.049)	0.026 (0.036)
A_{jj}	−0.327 *** (0.040)	−0.404 *** (0.041)	−0.036 (0.033)	1.013 (15.307)	0.343 *** (0.024)	−0.275 *** (0.021)	0.278 *** (0.024)
G_{ii}	0.801 *** (0.018)	0.607 *** (0.052)	−0.758 *** (0.011)	0.339 (0.756)	−0.823 *** (0.012)	0.799 *** (0.020)	−0.828 *** (0.015)
G_{ji}	0.022 (0.024)	−0.963 *** (0.134)	−0.210 *** (0.009)	−0.035 (0.742)	−0.051 *** (0.010)	0.019 (0.021)	0.183 *** (0.014)
G_{ij}	0.419 *** (0.068)	0.205 *** (0.057)	−0.236 *** (0.036)	0.021 (0.757)	−0.144 *** (0.039)	0.709 *** (0.090)	0.189 *** (0.017)
G_{jj}	0.006 (0.025)	−0.091 *** (0.035)	−0.051 (0.043)	0.282 (0.743)	−0.397 *** (0.121)	−0.781 *** (0.040)	0.684 *** (0.013)

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Some interesting points can be underlined. First, there is no evidence of bidirectional (shock and volatility) spillovers between the commodities and Latin American countries under investigation. In fact, we did not find that all the coefficients— A_{ij} , A_{ji} and G_{ij} , G_{ji} —are significant. Second, there is evidence of strong shock and volatility spillovers from corn to Chile and Peru because of the significance of A_{ij} and G_{ij} . For G_{ij} , the coefficient associated with past commodity conditional variance (namely, $H_{jj,t-1}$), considered in squared terms, results in past increased volatility in the corn market increasing today’s volatility in Chile and Peru’s stock market. A third aspect to underline is the presence of volatility spillover from corn to Colombia, from sugar and wheat to Peru, and from wheat to Chile. This derives from the significance of the coefficient G_{ij} for the previous relationships. In summary, the BEKK analysis largely confirms what was found for the causality in the volatility test, except for the relationship “sugar→Colombia”, which is not supported by the significance of the coefficients A_{ij} and G_{ij} . Recall that the causality in the volatility test only focuses on the presence or absence of the volatility (and shock) spillover originating from series j and hitting series i , whereas the subsequent BEKK analysis provides additional details on the interdependencies between the commodities and countries under investigation.

The last step of our analysis consists of investigating the response of volatility to a given shock in the series of the commodity. This step employs the VIRF methodology and is focused on the six relationships previously underlined (corn → Chile, corn → Colombia and corn → Peru; sugar → Peru; and, finally, wheat → Peru wheat → Chile). For each of the previous relationships, we report the volatility impulse responses for three situations. The first situation consists of a calm period, where the commodity log-returns is approximately equal to zero. The second and the third situations occur when the commodity log-returns are (heavily) negative and positive, respectively. We call these situations t_c , t_n , and t_p , where the suffixes c , n , and p stand for “calm”, “negative”, and “positive” periods. All the volatility responses during t_c , t_n , and t_p periods are illustrated in Figures 2–7, which express the variation of the expected conditional variance with and without the shock (as described above), in annualized percentage terms.

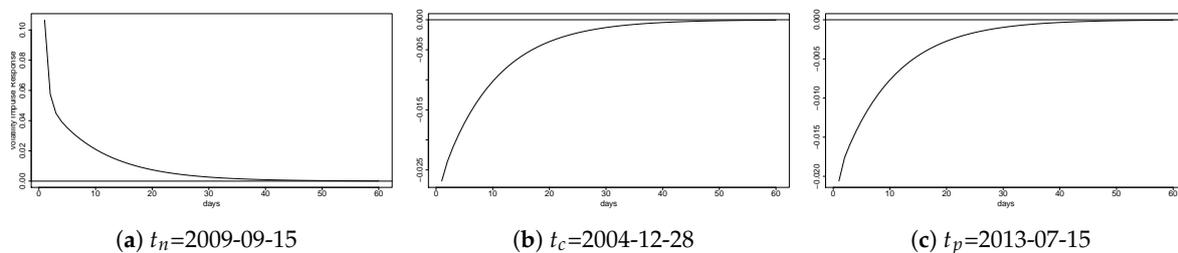


Figure 2. Volatility impulse response from corn to Chile.

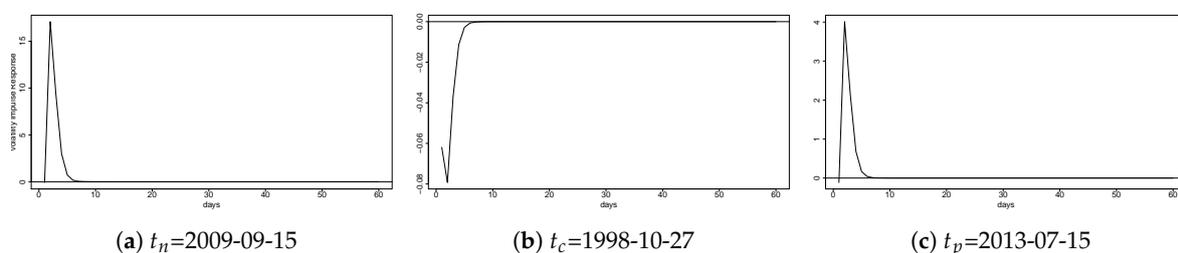


Figure 3. Volatility impulse response from corn to Colombia.

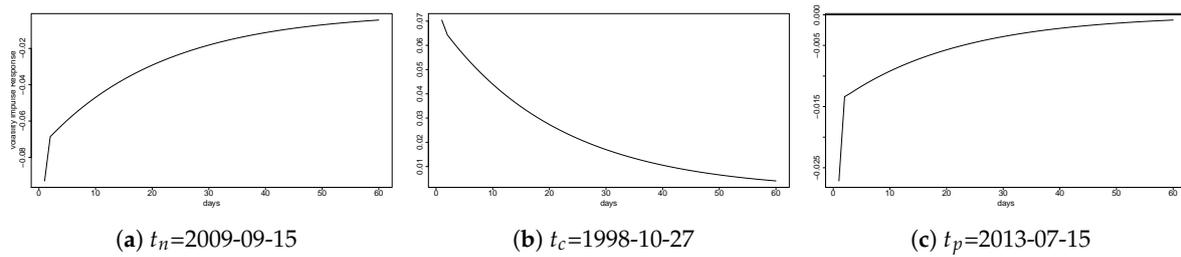


Figure 4. Volatility impulse response from corn to Peru.

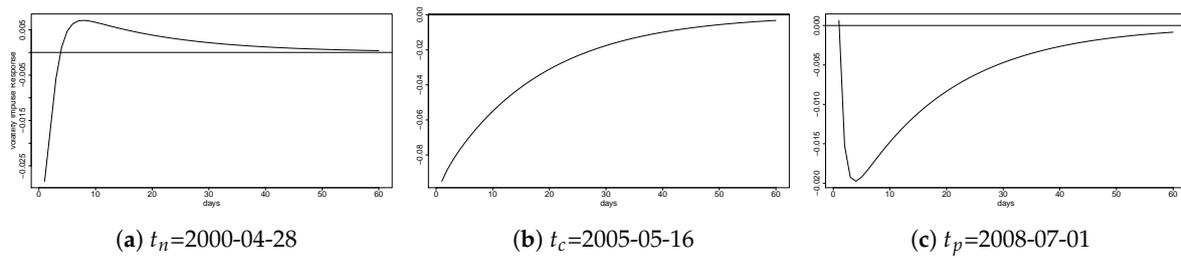


Figure 5. Volatility impulse response from sugar to Peru.

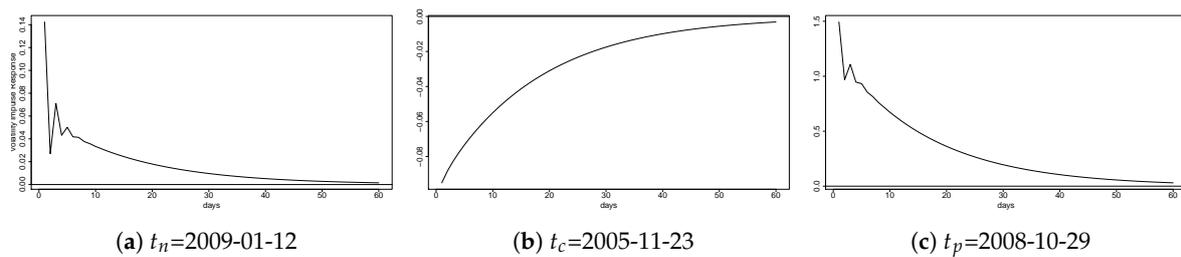


Figure 6. Volatility impulse response from wheat to Peru.

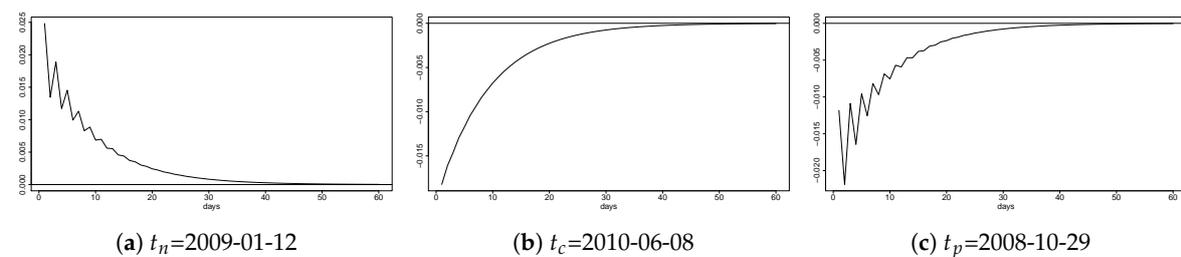


Figure 7. Volatility impulse response from wheat to Chile.

4.1. Volatility Impulse Response from Corn to Chile

Figure 2 depicts the impulse response of Chile’s volatility after a huge decrease and increase in corn daily log-returns (left and right plot), and the response when the daily log-return of corn at time t_c is invariant (middle plot). After a large corn decrease, the volatility of Chile’s stock market increases by a negligible amount (at most, the one-step ahead variance increases by 0.10%). This effect disappears after about 40 days. When the corn price from one day to another exhibits no change, the volatility of Chile’s stock market decreases, this time by an even smaller amount. Interestingly, also when the corn price substantially increases, the volatility of the Chilean stock market decreases, but by relatively less than in the previous case.

4.2. Volatility Impulse Response from Corn to Colombia

With respect to the previous case, the impact of a shock in the corn prices on Colombia's stock market is much more pronounced, as reported in Figure 3. In more detail, both a decrease (left plot) and an increase (right plot) in the corn log-returns lead to greater Colombian stock market volatility. Not surprisingly, the effect of a fall in corn is relatively larger: the volatility is expected to increase by more than 15%. Another interesting aspect to underline is the fact that any volatility response (to a corn decrease, increase, or invariance) vanishes in less than 10 days.

4.3. Volatility Impulse Response from Corn to Peru

Three main points can be highlighted in Figure 4. First, after both a corn price increase and decrease, Peru's stock market decreases in its volatility, while it increases if corn prices are practically invariant from one day to another. Second, the effects on volatility last for at least 60 days. In general, all the volatility responses appear to be of limited importance.

4.4. Volatility Impulse Response from Sugar to Peru

The volatility responses of Peru's stock market to shocks in the sugar log-returns are depicted in Figure 5. Surprisingly, the largest impact on volatility follows a calm period (middle plot). In this case, the volatility of Peru's stock market decreases. In the first days after an increase in the sugar prices, Peru's volatility falls. Moreover, any volatility responses drop off after approximately 60 days.

4.5. Volatility Impulse Response from Wheat to Peru

Figure 6 illustrates the volatility response of Peru's stock market after a given shock in wheat prices. Strangely, the impact of a positive shock (say, a huge sugar price increase) is greater than the impact of a negative shock (say, a decrease in the sugar prices). In both of these circumstances, the volatility of Peru's stock market increases. The effect is much more evident after an increase in wheat returns: this leads to the stock market volatility increasing by 1.5%. Unsurprisingly, calm periods in sugar prices decrease the stock market volatility (middle plot).

4.6. Volatility Impulse Response from Wheat to Chile

The relationship between the wheat prices and Chile's stock market volatility reported in Figure 7 follows a standard and plausible pattern from an economic viewpoint, even if it is not of pronounced importance (0.025% increase). In fact, a turbulent period (say, huge negative returns in the wheat market) results in increased volatility in Chile (left plot). On the contrary, a period characterized by good news (say, positive wheat returns) leads to decreased Chilean volatility (middle plot). Calm periods, meaning wheat prices are invariant over time, induce a fall in Chile's volatility. All of the effects drop off after 30 days approximately.

5. Conclusions

This paper focused on investigating the volatility spillovers from selected agricultural commodity markets (corn, sugar, wheat, soybean, and bioethanol) to five Latin American stock markets (Argentina, Brazil, Chile, Colombia, and Peru). Even though the literature has largely investigated the volatility transmission among countries or among commodities, the effect of volatility produced by agricultural commodities on Latin American stock markets has not received too much attention. Recently, Latin American countries have attracted increased interest because of their status of world leaders as food producers and exporters (Brazil, above all), or because of their status of developing countries as well as food net-importers (for instance, Peru). As pointed out in [OECD and FAO \(2015\)](#), there is a primary need for understanding the impacts on food security determined by food commodity volatilities. Therefore, it is of great interest to study the presence, the size, and the persistence of volatility originating in an agricultural commodity market and transferring additional volatility

to national Latin American stock markets. Moreover, on one hand, in the countries investigated, there is still a lack of diversification in production, and presently few commodities are produced. On the other hand, the five commodities analyzed here are mainly exported from a few countries and are subject to international price variability. To this extent, the agricultural commodity markets have recently experienced remarkable and severe variations, mainly during the period 2007–2009. These variations can be partially explained by the recent growth in Chinese demand for commodities and raw material (Casanova et al. 2016). Additional variability has been induced by the slowdown in international demand (Gruss 2014), which has led to an end to the increase in prices and production that occurred in the first decade of the new millennium. The present work contributes to the literature by employing a three-step analysis devoted to shedding some light on the relationships among agricultural commodities and Latin American countries, which, as pointed out by Delbianco and Fioriti (2018), still depend strongly on commodities. First, the recent causality in the volatility test of Chang and McAleer (2017) was used to verify the presence of volatility spillovers among the markets under consideration. It was shown that there exist some (more precisely, seven) volatility spillovers, robust to different lagged periods, that is: corn → Chile, corn → Colombia, and corn → Peru; sugar → Colombia and sugar → Peru; and, finally, wheat → Chile and wheat → Peru. In summary, neither soybean nor bioethanol produce volatility spillovers towards Latin American countries. Moreover, Argentina and Brazil are not affected by agricultural commodity volatilities, and Peru, which is a net-importer developing country, is the country that more often receives volatility from agricultural markets. In the second step, the BEKK model of Engle and Kroner (1995) was employed to derive the size and the bi- or unidirectional nature of the previous seven relationships. There is clear evidence that there are no bidirectional spillovers. Moreover, among the seven relationships, only that concerning sugar transferring volatility to Colombia stock markets was rejected in terms of statistical significance. These results assume great importance in the light of the primary aim of a volatility model, that is forecasting volatility. Taking into account possible influence of other series, once the volatility spillovers have been ascertained, helps to achieve this aim. In addition, having accurate volatility forecasts is important for a variety of reasons: risk management, portfolio selection, derivative pricing, derivative hedging and so forth. In the last step of our analysis, the VIRF methodology of Hafner and Herwartz (2006) was used to depict the volatility responses to a number of shocks in the commodity markets. More specifically, three types of situations were considered: a negative and positive price shock, such that the commodity return under analysis is respectively very low (say, bad news appears in the market) and high (say, good news affects the commodity), and a situation where the commodity return is invariant. Overall, when a negative shock hits the commodity market, Latin American stock market volatility tends to increase. This happens, for instance, for the relationships corn → Chile, corn → Colombia, wheat → Peru, and wheat → Chile. Among these latter relationships, the largest volatility response (15% increase) concerns the relationship corn → Colombia, which curiously is the relationship having the least persistence: approximately 10 days after a negative corn shock, the effect on the Colombian stock market volatility vanishes. On the other hand, positive commodity returns generally induce a decrease in stock market volatility. This holds for the following relationships: corn → Chile, wheat → Peru, sugar → Peru, and wheat → Chile. In terms of persistence, positive shocks affecting commodity markets last for quite a long time. The decreasing volatility in these circumstances disappears after at least 50 days. The current work could be expanded in many directions. First of all, it would be of interest to also investigate opposite relationships, that is, stock markets exporting volatility to (agricultural) commodities. In this regard, it has to be underlined that some contributions, like Śmiech et al. (2018), find little evidence regarding this aspect even though, during the financial crisis, generally agents seek shelter in alternative and safer markets, as could be some commodity markets. In addition, our analysis confirms the absence of bi-directional spillovers, even though this issue merits to be further investigating, maybe replacing the national stock market indexes by a global stock market index like the S&P500. A second direction to be explored regards the spillovers produced by Brazil and affecting the other Latin American countries. As largely documented, Brazil is

one of the worldwide leaders in producing and exporting some food commodities, such as corn and sugar. However, given our results, Brazil is not affected by the agricultural commodity volatilities. Thus, not only if the agricultural commodities have some volatility spillovers on the Latin American countries, but also if Brazil itself transfers volatility to the other countries could be investigated. Finally, according to [Chevallier and Ielpo \(2013\)](#), aggregate demand variations, usually proxied by the Industrial Production growth rate, influence the commodities. Thus, a possible limitation of our work is that we do not take into account any possible impacts of other volatility determinants in the relationship between series j and i . Therefore, a third possible extension to this work could be evaluating the presence of volatility spillovers including the Industrial Production as an additional volatility determinant, in the spirit of [Engle et al. \(2013\)](#) and [Amendola et al. \(2018\)](#), among others.

Author Contributions: Conceptualization, V.C. and S.F.; Methodology, V.C.; Software, V.C.; Validation, V.C.; Formal Analysis, V.C.; Investigation, S.F.; Data Curation, V.C.; Writing – Original Draft Preparation, V.C. and S.F.; Writing – Review & Editing, V.C. and S.F.; Visualization, V.C.; Supervision, V.C.; Project Administration, V.C. and S.F.; Funding Acquisition, S.F.

Funding: This research received no external funding.

Acknowledgments: We thank the Assistant Editor and two anonymous referees for their helpful suggestions that greatly aided us in improving our work. We also thank Alessandra Amendola for her constructive comments.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MGARCH	Multivariate GARCH
VIRF	Volatility impulse response function
DM	Developing market
NFIDM	Net-food importing developing market
LR	Likelihood ratio

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