ELSEVIER
www.elsevier.com/locate/worlddev

CrossMark

http://dx.doi.org/10.1016/j.worlddev.2017.01.015

World Development Vol. 94, pp. 305–320, 2017

Grain Price and Volatility Transmission from International to Domestic Markets in Developing Countries

FRANCISCO CEBALLOS, MANUEL A. HERNANDEZ, NICHOLAS MINOT and MIGUEL ROBLES*

IFPRI, Washington DC, USA

Summary. — Understanding the sources of domestic food price volatility in developing countries and the extent to which it is transmitted from international to domestic markets is critical to help design better global, regional, and domestic policies to cope with excessive food price volatility and to protect the most vulnerable groups. This paper examines short-term price and volatility transmission from major grain commodities to 41 domestic food products across 27 countries in Africa, Latin America, and South Asia. We follow a multivariate GARCH approach to model the dynamics of monthly price return volatility in international and domestic markets. The period of analysis is 2000 through 2013. In terms of price transmission, we only observe significant interactions from international to domestic markets in few cases. To calculate volatility spillovers, we simulate a shock equivalent to a 1% increase in the conditional volatility of price returns in the international market and evaluate its effect on the conditional volatility of price returns in the domestic market. The transmission of volatility is statistically significant in just one-quarter of the maize markets tested, more than half of rice markets tested, and all wheat markets tested. Volatility transmission seems to be more common when trade (imports or exports) are large relatively to domestic requirements.

Key words — volatility transmission, price transmission, grain commodity prices, domestic markets

1. INTRODUCTION

The global food crisis of 2007–08 was characterized by a sharp spike in grain and other commodity prices. These price increases have been attributed to supply shortages, increased bio-fuel production, reduced stock-to-use ratios, export bans by major grain exporters, and panic buying by some major importers (Garrido, Brummer, M'Barek, Meusissen, & Morales-Opazo, 2016; Gilbert, 2010). Commodity prices rose rapidly again in 2010 and 2011. Overall, since 2007 global grain markets have seen an increase in price volatility, defined as the standard deviation of monthly price returns. For example, comparing the 27-year period before the crisis (1980–2006) with the four-year period during and after the crisis (2007–10), the unconditional volatility of monthly international prices rose 52% for maize, 87% for rice, and 102% for wheat (Minot, 2014).

To the extent that this price volatility is transmitted to markets in developing countries, it may have serious implications for farmers and low-income consumers. As noted by Diaz-Bonilla (2016), producers and consumers alike are affected by both price levels and volatility. Low-income consumers, for example, spend a large share of their income on food in general and on staple foods in particular, making them more vulnerable to food price volatility. In some countries, such as Tanzania, Sri Lanka, and Vietnam, low-income households allocate more than 60% of their budgets to food (Seale, Regmi, & Bernstein, 2003). Food price volatility also affects poor, small-scale farmers who rely on food sales for a significant part of their income and possess limited capacity for timing their sales. In addition, price volatility is likely to distort input allocation, inhibit agricultural investment, and reduce agricultural productivity growth, especially in the absence of efficient risk-sharing mechanisms, with long-run implications for poor consumers and farmers. Martins-Filho and Torero (2011) further note that high volatility might increase the expected losses of producers, affecting their household consumption decisions; similarly, increased volatility through time may promote speculative trading as larger price fluctuations create the opportunity for larger net returns (see also FAO-OECD, 2011). Magrini, Morales Opazo, and Baile (2015) estimate household willingness to pay to eliminate cereal price volatility in five countries. The willingness to pay ranges from 0.06% of income in Bangladesh (where price volatility is low) to above 1% in Niger, Ethiopia, and Malawi (where price volatility is higher).

A key question, however, is whether food price volatility in world grain markets is indeed transmitted to local markets in developing countries. If so, efforts to reduce price volatility should perhaps be focused on concerted regional and international actions through the World Trade Organization or other multilateral bodies. Alternatively, if food price volatility in developing countries is mostly attributed to domestic factors, then the most effective policy remedies would likely include domestic investment to stabilize food production, reduce storage and transport costs, and strengthen safety nets.

One approach to answering this question has been to examine the transmission of prices from world markets to local markets.[1] Although it seems reasonable to assume that markets with high transmission of prices would also be characterized by high transmission of volatility, this may not necessarily be the case. For example, prices from highly volatile world markets may only be transmitted to local markets with a one- to six-month lag, thus insulating local markets from international turmoil and resulting in local prices that exhibit much less volatility. Alternatively, even if there were no direct price transmission, it is possible for local market volatility to be determined by the degree of uncertainty among local traders, which could be influenced by a sudden increase in the volatility of world markets.

* Final revision accepted: January 7, 2017.

The objective of this paper is to estimate both grain price and volatility transmission from world markets to local markets in developing countries. In particular, we focus on the short-term effect of the world price returns of maize, rice, wheat, and sorghum on 41 domestic price returns of grain products in 27 countries in Latin America, Africa, and Asia. The price data are monthly, and most cover the period from January 2000 to December 2013, though there is some variation in starting and ending points. The analysis is based on a multivariate generalized auto-regressive conditional heteroskedasticity (MGARCH) model using the BEKK specification proposed by Engle and Kroner (1995).[2]

We work with price returns (month-to-month price variations) to account for the non-stationarity of the prices in levels. For conceptual clarity, throughout the paper we use the terms "price transmission" and "volatility transmission", which refer to measures calculated from price returns. Hence, the analysis of price transmission corresponds to interactions in price returns at the mean level while the analysis of volatility transmission corresponds to interactions in price returns at the volatility level.

The main contribution of this paper is that it is the first to estimate the transmission of food price volatility from international markets to local markets across several developing countries and regions. As discussed below, other studies have examined the transmission of (mean) price levels from global markets to developing countries, and some have analyzed the transmission of price volatility from one global commodity market to another. Focusing on market interactions in terms of the conditional second moment and allowing for volatility spillovers provides better insight into the dynamic international–domestic price relationship.

The remainder of the paper is organized as follows. Section 2 provides a review of recent research on transmission of prices and volatility. Section 3 details the methodology used in the study. Section 4 describes the data. Section 5 presents and discusses the estimation results while Section 6 summarizes the findings and draws some conclusions for future research.

2. PREVIOUS RESEARCH ON TRANSMISSION OF PRICES AND VOLATILITY

There is a large body of research on the transmission of prices between markets within developing countries (see Abdulai, 2000; Baulch, 1997; Lutz, Kuiper, & van Tilburg, 2006; Moser, Barrett, & Minten, 2009; Myers, 2008; Negassa & Myers, 2007; Rashid, 2004; Van Campenhout, 2007). Most of these studies use cointegration analysis in the form of error-correction models, though some of the more recent ones apply threshold cointegration models and asymmetric response to positive and negative price shocks (e.g., Meyer & von Cramon-Taubadel, 2004). The size of the literature is indicated by a meta-analysis that summarizes the results of 57 cointegration studies with analysis of 1,189 market price pairs (Kouyate & von Cramon-Taubadel, 2016). The results indicate that both distance and an international border between the markets reduce the probability that the prices will be cointegrated and slow the speed of adjustment if it is cointegrated.

Fewer studies have examined the transmission of prices from world markets to local markets. Mundlak and Larson (1992) estimate the transmission of world food prices to domestic prices in 58 countries using annual price data. They find very high rates of price transmission, but the analysis is carried out in levels rather than first differences, so the results probably reflect spurious correlation due to nonstationarity. Quiroz and Soto (1995) repeat the analysis of Mundlak and Larson (1992) using cointegration analysis and an error correction model. They find no relationship between domestic and international prices for 30 of the 78 countries examined. Conforti (2004) examines price transmission in 16 countries, including three in Sub-Saharan Africa, using an error correction model. In general, he finds that the degree of price transmission in Sub-Saharan African countries is less than in Asian and Latin-American countries. Robles and Torero (2010) find empirical evidence of price transmission from international markets to domestic prices of several food products across four countries in Latin America. Minot (2011) analyzes the transmission of prices from world grain markets to 60 markets in sub-Saharan Africa, finding a statistically significant long-term relationship in only 13 of the 62 prices examined. He also finds that rice prices are more closely linked to world markets than are maize prices, presumably because most African countries are close to self-sufficient in maize but import a large share of their rice requirements. Baquedano and Liefert (2014) also examine price transmission from world grain markets to local food markets, using a single-equation error-correction model. They find a long-term relationship in 51 of 61 local prices tested. More recently, Garcia-German, Bardaji, and Garrido (2016) evaluate price transmission between global agricultural markets and consumer food price indices in the European Union member states using error correction models. They find that consumer prices in different member states respond differently to specific world price indices, suggesting some disparities in the structure and efficiency of their food markets.

Another set of studies has focused on the co-movement of world commodity prices. In their seminal paper, Pindyck and Rotemberg (1990) find "excessive co-movement" of seven commodity prices, which they attribute to herd behavior among traders in financial markets. The hypothesis of excess co-movement, however, was challenged by Deb, Trivedi, and Varangis (1996) and Ai, Chatrath, and Song (2006). These studies argue that the Pindyck and Rotemberg results suffer from model misspecification and that fundamental supply and demand factors are sufficient to explain the co-movement.[3] In the case of international agricultural commodity prices, Gilbert (2010) indicates that price shocks for individual commodities are often supply related whereas joint price movement can be explained by macro-economic and monetary conditions.

Fewer studies have examined the co-movement of conditional price volatility. As noted by Gallagher and Twomey (1998), dynamic models of conditional volatility like MGARCH models, widely used in empirical finance, can provide a better understanding of the dynamic price relationship between markets by evaluating volatility spillovers. Volatility transmission between commodity markets may occur through substitution and complementary effects or as a result of common underlying macroeconomic factors, such as uncertainty in financial factors (Saadi, 2011, chap. 9).

Some of the recent studies that evaluate market interactions between agricultural commodities using MGARCH models include Le Pen and Sévi (2010), Zhao and Goodwin (2011), Hernandez, Ibarra, and Trupkin (2014), Beckmann and Czudaj (2014) and Gardebroek, Hernandez, and Robles (2016), with mixed results. Le Pen and Sévi (2010) use different multivariate models, including a factor model and a dynamic conditional correlation (DCC) model, to examine the interrelationship between eight agricultural and non-agricultural commodities and find moderate co-movement in prices and volatility. Zhao and Goodwin (2011) find important volatility spillovers between corn and soybean futures prices based on a BEKK model. Using both a BEKK and a DCC model, Hernandez *et al*. (2014) show significant volatility spillovers within corn, wheat, and soybean futures exchanges in the United States, Europe, and Asia as well as an increase in their interdependence in recent years. Beckmann and Czudaj (2014) also show evidence supporting short-run volatility transmission between futures prices of corn, wheat, and cotton, based on bivariate GARCH-in-mean vector autoregressive (VAR) models. Lastly, Gardebroek *et al*. (2016) implement different MGARCH models and find little evidence of price transmission at the mean level between corn, wheat, and soybean spot markets, but significant transmission in price volatility, particularly at weekly and monthly frequencies.

Overall, there is an extensive literature on the transmission of prices (in levels) between pairs of markets within a country, between international and local markets, and between different international commodity prices. In addition, there is a growing literature on the transmission of price volatility (the second moment of prices) between international commodity markets. However, to our knowledge, there are no studies that examine the transmission of volatility from international grain markets to local markets. This is the gap that we address in this paper.

3. METHODOLOGY

We follow a multivariate GARCH (MGARCH) approach to evaluate the short-term dynamics of volatility in monthly price returns from major agricultural international commodities to key domestic products in Africa, South Asia, and Latin America.[4] In particular, we estimate a bivariate T-BEKK model, proposed by Engle and Kroner (1995), which allows us to measure volatility transmission from international to domestic markets and is flexible enough to account for both volatility spillovers and persistence across markets. The T acronym refers to Student's t density used in the model estimation in order to better control for the leptokurtic distribution of the price returns series.

The T-BEKK approach involves modeling both a conditional mean equation and a conditional variance–covariance equation for each price return series considered in the analysis.[5] In our case, we define price returns as $r_{mt} = \ln(p_{mt}/p_{mt-1})$, where p_{mt} is the price of a certain product (commodity) in market m at month t, and $m = 1$ refers to the domestic market while $m = 2$ to the international market. This logarithmic transformation is a standard measure for net returns (percentage variations in prices) in a market and is generally applied in empirical finance to obtain a convenient support for the distribution of the error term in the estimated model.

We first test for the presence of cointegration between domestic and international (log) prices using the Johansen trace test, with the number of lags (k) selected based on the Schwarz Bayesian information criterion (SBIC). For those cases where the pair of prices are not found to be cointegrated, the conditional mean equation is simply modeled as a vector autoregressive (VAR) process such that

$$r_t = \alpha_0 + \sum_{s=1}^{k} \alpha_s r_{t-s} + \varepsilon_t, \varepsilon_t | I_{t-1} \sim (0, H_t), \qquad (1a)$$

where r_t is a 2×1 vector of price returns for the corresponding product (commodity) in the domestic and international market at month t, i.e., $r_t = \begin{pmatrix} r_{1t} \\ r_{2t} \end{pmatrix}$; α_0 is a 2×1 vector of constants; α_s, $s = 1,\ldots,k$, are 2×2 matrices of parameters capturing own and cross lead–lag relationships between markets at the mean level; and ε_t is a 2×1 vector of innovations with zero mean, conditional on past information I_{t-1}, and conditional variance–covariance matrix H_t.

For those cases where the pair of prices are found to be cointegrated, the conditional mean equation is modeled as a vector-error correction (VEC) model such that

$$r_t = \alpha_0 + \sum_{j=1}^{k} \alpha_j r_{t-j} - \lambda ECT_{t-1} + \varepsilon_t, \varepsilon_t | I_{t-1} \sim (0, H_t), \qquad (1b)$$

where ECT_{t-1} is the lagged error correction term resulting from the cointegration relationship, i.e., $ECT_{t-1} = \ln p_{1t-1} - \beta_0 - \beta_1 \ln p_{2t-1}$; and λ is a 2×1 vector of parameters that measure the adjustment of each (log) price series to deviations from the long-run equilibrium.

The conditional mean equations specified in (1a) and (1b) are generally referred to as *standard* or *reduced* models, as they constitute alternative (though estimable) representations of so-called *structural* models that explicitly allow for contemporaneous effects from cross-price terms. While the reduced representation facilitates the model estimation, it also allows for the estimation residuals to be correlated across equations. This feature invalidates impulse response exercises that rely on a shock on an individual market, assuming the absence of shocks in the remaining markets (thus treating them as independent). As a consequence, in order to obtain valid, causal impulse response functions to a given one-time shock in one market, the estimation errors must be properly orthogonalized.

One common method for orthogonalization is based on the Cholesky decomposition of the reduced model's error variance–covariance matrix. Interestingly, it can be shown that orthogonalizing using this decomposition is akin to imposing a particular recursive structure on the model's equations or, equivalently, to introducing explicit identification restrictions that result in a unique underlying structural model. In the context of our study, the nature of these implicit identification restrictions is to assume away the possibility of contemporaneous transmission of shocks from the domestic market into the international market (while fully allowing for contemporaneous transmission of international shocks into the domestic market).[6] Once orthogonalized, the exercise of introducing a shock of size $\in$ in the international price return equation is valid, and the response in the domestic price return equation after an arbitrary number of time periods can be calculated and assigned a causal interpretation.

As we are interested in the degree of price transmission in the short run, we focus on the domestic price return response after one period (one month) to a shock (the impulse) in the international price return.[7] The size of the shock is equal to one standard deviation of the international price return and the response is reported as a fraction of the shock for comparison across commodities. Given this standardization, the resulting measure is equivalent to the elasticity of price transmission from the international market to the domestic market.

The conditional variance–covariance matrix H_t at time t is, in turn, given by

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'H_{t-1}G, \qquad (2)$$

where C is a 2×2 upper triangular matrix of constants c_{ij}; A is a 2×2 matrix whose elements a_{ij} capture the direct effect of an innovation in market i on the current price return volatility in market j; and G is a 2×2 matrix whose elements g_{ij} measure the direct influence of past volatility in market i on the current volatility in market j (persistence). If we expand Eqn. (2), the resulting conditional variance equation for the domestic market is defined as

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1} \qquad (3)$$

This variance–covariance specification allows us to characterize the magnitude and persistence of volatility transmission from international to domestic markets. [8] Moreover, similar to Gardebroek and Hernandez (2013) and Hernandez *et al.* (2014), we can derive an impulse-response function for the estimated conditional volatility to assess how a shock or innovation in the international market transmits to the domestic market and obtain the elasticity of domestic price volatility with respect to international price volatility.

In particular, to estimate the degree of volatility transmission from international to domestic markets we carry out the following two steps for each estimated model (one per country/commodity):

1. We estimate the size of a shock in the international market ($\bar{\varepsilon}_2$) such that the steady-state standard deviation of the international price return increases in 1% after one period [9]:

$$\frac{\sqrt{h_{22,1}(\bar{\varepsilon}_2)} - \sqrt{h_{22,0}}}{\sqrt{h_{22,0}}} = 0.01$$

2. We introduce shock $\bar{\varepsilon}_2$ in expression (2) and estimate the percentage change in the standard deviation of the domestic price return (with respect to its steady-state value) and compute our volatility transmission VT indicator according to:

$$VT = \frac{\sqrt{h_{11,1}} - \sqrt{h_{11,0}}}{\sqrt{h_{11,0}}} \div 0.01$$

In other words, our volatility transmission indicator shows the reaction after one period of domestic volatility (standard deviation of price returns) to a shock in the international market, assuming the system is initially in steady-state (i.e., $(h_{ii,0})^{0.5} = (h_{ii}^{ss})^{0.5}, i = 1, 2,$ satisfying $H^{SS} = C'C + G'H^{SS}G$). If the volatility transmission indicator is equal to one it means that, after we introduce a shock in the international market, domestic volatility increases in one period in the same proportion as the international volatility. [10] The shocks that we introduce in the international markets are comparable across different commodities in the sense that we force them to be such that the standard deviation of the international market deviates from its steady state by 1% after one period. [11]

4. DATA

The analysis is based on a large dataset of monthly prices due to the lack of wide availability of daily and weekly prices from developing countries. However, it should be noted that the data frequency has implications for the results and their interpretation. First, the frequency of the data affects the measured price volatility. By measuring prices at the monthly level, any analysis will necessarily fail to incorporate relevant information occurring at lower time scales, such as daily and weekly price movements. For example, if monthly prices are generated by averaging weekly prices, the measured monthly volatility will be roughly half the weekly volatility. Second, data frequency may also influence the measurement of transmission of prices and volatility, depending on the speed at which international prices affect local markets (Gardebroek *et al.*, 2016). Finally, there is no unique measure of price volatility, which results in different economic agents relying on alternative definitions of such measure for their decisions. [12] In other words, the relevance of a given measure of price volatility for different economic agents depends partly on the frequency of the underlying data from which it is calculated. For instance farmers, who make planting decisions months before sale, may find observed monthly volatility at planting to be useful for forming their expectations for price at harvest; on the other hand, traders who buy and sell within a particular month would presumably be more influenced by daily or weekly volatility.

Still, being able to rely on a measure of price volatility transmission at a widely available data frequency (i.e., monthly) is beneficial for a number of economic actors, including policymakers planning risk management strategies and value chain actors making investment and stock decisions over medium-term horizons. In addition, even in those cases in which the measure developed in this paper may not be the primary measure of relevance for an economic actor, the overall findings of this study may still provide important broader lessons about price volatility transmission.

The data used in the paper cover 41 domestic prices in 27 countries, including monthly average prices for maize, wheat, rice, sorghum, and some products derived from these grains (see Table A.1). [13] We obtained domestic prices from two sources. Our main source is the Famine Early Warning Systems Network (FEWS NET), a project funded by the United States Agency for International Development (USAID), which compiles data on nominal prices of a number of food commodities across several key domestic markets on a monthly basis. This service is provided as part of their Price Bulletin product and is only available for countries in which the network has a presence—mostly African and Central American economies. Our second source is the Global Information and Early Warning System (GIEWS) of the Food and Agriculture Organization (FAO), which relies on price information from a number of local primary sources across FAO's 190 member countries. We rely on this source to obtain domestic prices for Asian, South American, and some additional Central American countries.

Out of all the price series available from these sources, we work with the domestic prices of the most important food staples in each country, identified as those with the largest contribution to caloric intake according the FAO (2014). Moreover, for each product we use the price from the main local market—generally the capital city. For a few countries, we include prices observed in more than one market (for example, in India we include prices from both the Mumbai and the New Delhi markets). Following standard practice, each series is converted from local currency into U.S. dollars using monthly exchange rates from the IMF's International Financial Statistics (IFS) database. [14] We exclude price series with less than 100 observations or with more than 10% of missing values. [15] Table A.1 in the Appendix shows the details for each of the price series used, including its source (FEWSNET or GIEWS), the corresponding local market, whether it is a retail or a wholesale price, and its unit of measurement.

International monthly price series are compiled by the FAO International Commodity Prices database (FAOSTAT). All prices are expressed in U.S. dollars per tonne. The maize price is for No.2 Yellow Maize, U.S. Gulf; the rice price is for A1 Super, White rice broken, Bangkok, f.o.b.; the sorghum price is for No.2 Yellow Sorghum, U.S. Gulf; and the wheat price is for No.2 Hard Red Winter Wheat (Ordinary Protein), U.S. Gulf, f.o.b. Table A.2 in the Appendix shows the details of each of the international price series used.

Figure 1 shows the evolution of international monthly prices for maize, rice, sorghum, and wheat over the 2000–14 period. In general, prices seem to have been rising in a relatively stable way until the spikes experienced during the food crisis of 2007–08 and the subsequent spikes observed during 2010–11. Interestingly, the figure shows a large degree of comovement between the prices for these four commodities during the past years, with a striking similarity between the prices of sorghum and maize. This is not surprising given that sorghum and maize are close substitutes, particularly in animal feed.

International prices for different food commodities also seem to comove in terms of unconditional volatility. Figure 2 shows the evolution of price volatility (the standard deviation of monthly price returns) for these four commodities over a 2-year moving window from 2000 to 2014.[16] The price volatility of these commodities seems to have followed a similar pattern during most of the period of analysis, with a considerable increase during and following the 2007–08 food crisis, followed by a subsequent decrease—though to higher volatility than that prior to the crisis.

Figure 3 plots the evolution of international and domestic price volatility (the standard deviation of international and domestic price returns) by commodity over a 2-year moving window, in a similar fashion to Figure 2. The results are mixed. In the case of rice and wheat, there seems to be a substantial comovement in the volatility of domestic and international prices, particularly in the case of rice. The volatility of the international price for sorghum also shows some evidence of comovement with domestic volatilities. The pattern of price volatility in domestic maize markets, in contrast, does not generally resemble the pattern of volatility exhibited by the international price of maize. Note also that for maize and sorghum the international price volatility is generally lower than in domestic markets, but for rice and wheat the opposite is true. We examine volatility dynamics between domestic and international price returns more formally in the next section.

Table 1 provides some descriptive statistics for the domestic and international price returns used in the analysis. First, the Jarque–Bera test indicates that the returns for almost every

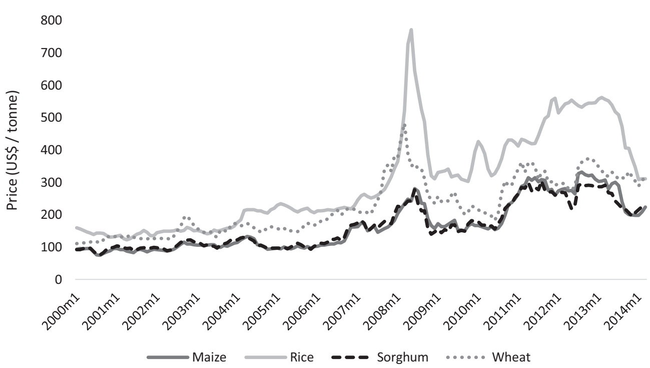

Figure 1. *International Commodity Prices—2000–14. Note: This figure shows the evolution of the monthly international prices of maize, rice, sorghum, and wheat during the 2000–14 period. Prices are expressed in US$ per tonne.*

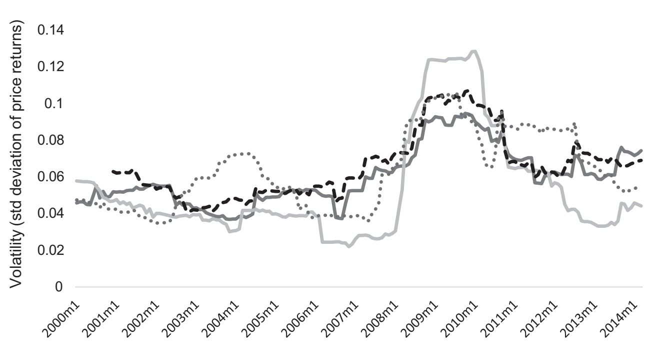

Figure 2. *Volatility of International Grain Prices (2-year moving window)—2000–14. Note: This figure shows the evolution of the volatility of monthly international prices of maize, rice, sorghum, and wheat during the 2000–14 period. The volatility for every month is calculated as the standard deviation of the monthly price returns observed during that and the previous 23 months.*

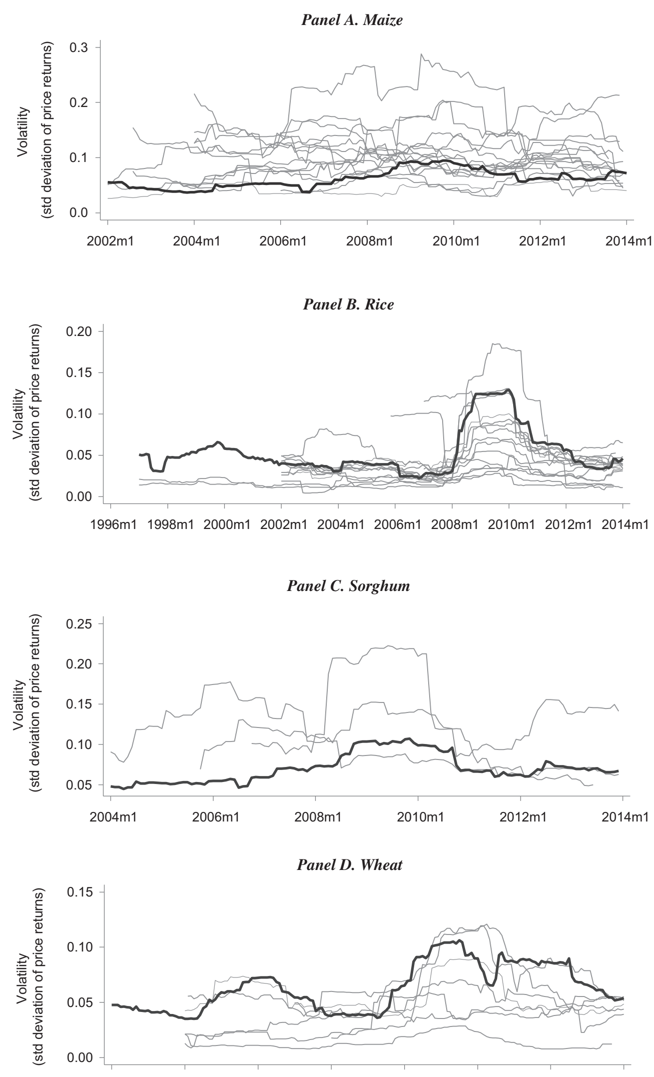

Figure 3. *Volatility (2-year moving window) of domestic and international prices. Note: This figure shows the evolution of the volatility of monthly domestic and international prices of maize, rice, sorghum, and wheat during the 2000–14 period. The volatility for every month is calculated as the standard deviation of the monthly price returns observed during that and the previous 23 months. The line in bold represents the volatility of each international price series.*

Table 1. *Summary statistics and selected normality, autocorrelation, and stationarity tests*

	Maize	Rice	Sorghum	Wheat	Total
Panel A. Domestic price series					
Number of domestic price series	16	15	3	7	41
Mean price returns (in %)	0.42	0.33	0.47	0.46	0.40
% of series with skewness between −1 and 1	87.5	60.0	66.7	100.0	78.0
% of series with kurtosis >3	100.0	100.0	100.0	100.0	100.0
% of series rejecting Jarque–Bera test's H_0	93.8	100.0	100.0	100.0	97.6
% of series rejecting Ljung–Box test's H_0 on squared returns (6 lags)	6.3	66.7	0.0	57.1	36.6
% of series rejecting Ljung–Box test's H_0 on squared returns (12 lags)	18.8	66.7	0.0	71.4	43.9
% of series rejecting LM ARCH test's H_0 on squared returns (6 lags)	12.5	60.0	0.0	57.1	36.6
% of series rejecting LM ARCH test's H_0 on squared returns (12 lags)	6.3	53.3	0.0	57.1	31.7
% of series rejecting ADF test's H_0—Logarithm of price in levels (6 lags)	0.0	0.0	33.3	0.0	2.4
% of series rejecting ADF test's H_0—Price returns (6 lags)	100.0	100.0	100.0	100.0	100.0

	Maize	Rice	Sorghum	Wheat
Panel B. International price series				
Mean price returns (in %)	0.52	0.39	0.54	0.62
Standard deviation of price returns (in %)	6.44	6.18	6.74	6.65
Jarque–Bera's statistic	28.68*	273.10*	39.46*	39.37*
Skewness	−0.41	0.43	−0.33	0.52
Kurtosis	4.84	9.15	5.27	5.11
Ljung–Box's statistic on squared returns (6 lags)	1.71	68.14*	4.42	7.93
Ljung–Box's statistic on squared returns (12 lags)	11.88	81.01*	10.01	12.31
Lagrange multiplier (LM) ARCH test (6 lags)	3.22	60.77*	4.12	7.51
Lagrange multiplier (LM) ARCH test (12 lags)	11.68	70.63*	8.77	10.66
ADF statistic—Logarithm of price in levels (6 lags)	−1.11	−1.21	−1.18	−1.74
ADF statistic—Price returns (6 lags)	−5.08*	−5.02*	−5.31*	−5.28*

Note: This table presents summary statistics and selected normality, autocorrelation, and stationarity tests for domestic (panel A) and international (panel B) price return series for maize, rice, sorghum, and wheat. An asterisk indicates that the null hypothesis is rejected at the 5% level of confidence.

domestic price and all international prices do not follow a normal distribution. The kurtosis in all of the analyzed markets is greater than 3, further pointing to a leptokurtic distribution of returns. Moreover, skewness coefficients are generally close to zero, indicating plausibly symmetrical distributions. These results support the use of Student's t density for the estimation of the BEKK models below.

Second, both the Ljung–Box (LB) and Engle ARCH Lagrange Multiplier (LM) statistics for up to 6 and 12 lags generally reject the null hypotheses of no autocorrelation and no autoregressive conditional heteroscedastic (ARCH) effects in the squared returns. This autocorrelation suggests the existence of nonlinear dependencies in several of the price returns, which combined with the observed high fluctuations in the returns series, motivate the use of methods that account for heteroskedasticity and volatility clustering in the data such as MGARCH models.

Third, the Augmented Dickey-Fuller (ADF) tests suggest that several of the domestic and international prices (in natural logarithms) are non-stationary. As explained in the methodology section, for all these cases a cointegration test is first conducted to determine the need to account for a potential long-run relationship between the corresponding domestic and international price through a vector error-correction model. Finally, the ADF test shows that we reject the null hypothesis of non-stationarity of all the domestic and international price returns. [17]

5. RESULTS

(a) *Price transmission*

This section describes the degree of short-run transmission of prices from international to domestic markets. The first panel of Table 2 presents the relevant VAR and VEC coefficients describing the conditional mean equation for the domestic price returns. Figure 4 shows the corresponding standardized one-period impulse response functions for maize prices (Panel A), rice prices (Panel B), and sorghum and wheat prices (Panel C), which can be interpreted as elasticities. Many of the elasticities are not significantly different from zero at the 5% level of confidence. More specifically, of the 16 maize price transmission elasticities, only one is statistically significant: the Honduran retail price of maize in one of the markets in the capital city (Las Americas or market #1). [18] Over the period covered by the study (2000–13), Honduras imported about 37% of its maize requirements, which helps explain why its prices move with international prices (see Table 3). [19] The importance of maize trade in terms of domestic availability was less than 10% in all nine African countries listed and no more than one-quarter in Mexico and Nicaragua. However, this share is over 50% in Colombia so clearly other factors are at work. One additional factor may be imperfect substitution: the world maize reference price is for No. 2 yellow maize, while many African and Central American countries prefer white maize for human consumption.

Panel B of Figure 4 shows the results for 15 rice prices in Africa, Asia, and Latin America. The figure indicates that, out of the 15 short-run price transmission measures, six of them are statistically significant at the 5% level: Mali, Philippines (regular and well milled), both of Thailand, and Ecuador. The statistical significance of price transmission to Thai rice markets is not unexpected given that the international reference price for rice is the Thai export price. The significance of rice price transmission in Mali, the Philippines and Ecuador is more difficult to explain. Jamora and von Cramon-Taubadel (2016) argue that price transmission may be low if there are quality differences between the export rice and rice consumed in the local market. In these three countries, however, we have

Table 2. *Selected model results and residual tests*

	MAIZE															
	BEN	ETH	KEN	MAW	MOZ	NIG	TAN	UGA	ZAM	ELS	GUA	HON 1	HON 2	MEX	NIC	COL
Panel A																
Conditional mean equation																
Model	VAR	VEC	VEC	VAR	VEC	VAR	VAR	VEC	VAR	VAR	VEC	VAR	VEC	VEC	VEC	VAR
No. of lags	1	0	0	1	0	1	2	0	1	1	0	2	1	0	0	1
α_0	0.006	−0.003	−0.001	0.002	−0.001	0.010	0.003	−0.001	−0.001	0.002	−0.002	0.003	0.000	0.001	0.000	−0.001
	(0.012)	(0.009)	(0.007)	(0.019)	(0.009)	(0.012)	(0.009)	(0.013)	(0.009)	(0.005)	(0.006)	(0.006)	(0.006)	(0.003)	(0.009)	(0.006)
$\alpha_{1,11}$	0.019			0.179*		−0.015	0.221*		−0.019	0.172*		0.206*	0.464*			0.230*
	(0.093)			(0.091)		(0.094)	(0.084)		(0.084)	(0.077)		(0.083)	(0.071)			(0.078)
$\alpha_{1,12}$	0.190			0.319		0.279	−0.134		0.103	0.012		0.244*	0.069			0.133
	(0.179)			(0.267)		(0.174)	(0.145)		(0.135)	(0.081)		(0.100)	(0.092)			(0.092)
Conditional variance equation																
c_{11}	11.813*	−0.029	3.694	19.345*	1.676	4.373*	8.508*	−6.674*	0.211	0.613	0.629	5.493*	6.199*	2.267	−5.438	2.336
	(1.661)	(0.095)	(2.901)	(2.291)	(2.074)	(2.006)	(2.345)	(3.068)	(0.260)	(1.365)	(1.579)	(1.617)	(0.662)	(1.216)	(7.301)	(2.101)
a_{11}	0.346*	0.530*	−0.250	0.336*	0.622	−0.105	0.475*	0.683*	−0.707	0.408	0.798*	−0.938*	0.409*	0.675*	0.789*	0.279
	(0.105)	(0.145)	(0.574)	(0.165)	(0.328)	(0.196)	(0.141)	(0.168)	(0.399)	(0.706)	(0.224)	(0.342)	(0.129)	(0.181)	(0.222)	(0.196)
a_{21}	−0.807*	−0.198	−0.409	0.539*	−0.028	0.738*	−0.260	0.102	−0.146	−0.012	0.084	0.111	0.162	−0.005	−0.290	0.138
	(0.381)	(0.114)	(0.418)	(0.257)	(0.112)	(0.278)	(0.177)	(0.275)	(0.112)	(0.065)	(0.075)	(0.195)	(0.092)	(0.108)	(0.173)	(0.135)
g_{11}	0.002	0.897*	−0.785*	0.001	−0.837*	0.855*	−0.408*	0.565*	0.807*	−0.765*	0.656*	−0.059	0.000	−0.001	−0.384	0.831*
	(0.016)	(0.053)	(0.376)	(0.012)	(0.095)	(0.134)	(0.196)	(0.241)	(0.101)	(0.112)	(0.189)	(0.237)	(0.015)	(0.204)	(0.202)	(0.193)
g_{21}	0.000	−0.102	−0.434	0.000	−0.430	0.067	−0.446	−0.918	−0.388	0.606	−0.300	−0.077	0.000	0.358	0.688	−0.459*
	(0.011)	(0.102)	(1.015)	(0.033)	(0.296)	(0.553)	(0.433)	(0.495)	(0.353)	(0.383)	(0.194)	(0.366)	(0.009)	(0.200)	(1.225)	(0.070)
ν	4.314*	3.717*	4.231*	4.728*	2.813*	3.667*	3.722*	7.037*	3.665*	4.600*	6.029*	3.730*	6.207*	4.051*	4.413*	3.744*
	(1.287)	(0.924)	(1.835)	(1.209)	(0.782)	(0.919)	(0.821)	(2.587)	(1.746)	(1.570)	(2.768)	(1.238)	(1.702)	(0.897)	(0.972)	(0.851)
Wald's test for presence of innovation and persistence effects from international to domestic market (H_0: $a_{21} = g_{21} = 0$)																
Chi-squared	9.083*	7.399*	3.384	4.429	3.507	12.159*	5.663	5.408	2.520	2.506	2.469	0.423	3.287	5.307	4.131	43.095*
p-Value	0.011	0.025	0.184	0.109	0.173	0.002	0.059	0.067	0.284	0.286	0.291	0.809	0.193	0.070	0.127	0.000
Ljung–Box's test for autocorrelation (H_0: no autocorrelation in squared residuals)																
LB(6)	2.522	16.574*	8.201	6.945	10.494	10.843	3.668	3.973	7.967	2.477	3.981	9.137	2.020	4.971	6.578	14.003*
p-Value	0.866	0.011	0.224	0.326	0.105	0.093	0.722	0.680	0.241	0.871	0.679	0.166	0.918	0.547	0.362	0.030
LB(12)	10.152	32.112*	15.799	22.446*	22.996*	20.540	8.285	8.196	13.254	12.784	31.099*	30.716*	12.912	14.728	21.938*	20.610
p-Value	0.603	0.001	0.201	0.033	0.028	0.058	0.763	0.770	0.351	0.385	0.002	0.002	0.375	0.257	0.038	0.056
Lagrange multiplier (LM) test for ARCH residuals (H_0: no ARCH effects)																
LM(6)	1.002	2.442	4.045	1.104	0.654	2.200	2.807	1.833	8.384	3.022	6.344	3.488	2.904	4.138	3.508	0.549
p-Value	0.986	0.875	0.671	0.981	0.995	0.900	0.833	0.934	0.211	0.806	0.386	0.746	0.821	0.658	0.743	0.997
LM(12)	6.154	5.542	6.436	4.294	2.008	4.113	9.094	4.804	8.461	7.299	13.614	4.758	5.117	6.745	6.885	2.162
p-Value	0.908	0.937	0.893	0.978	0.999	0.981	0.695	0.964	0.748	0.837	0.326	0.966	0.954	0.874	0.865	0.999
Hosking's Multivariate Portmanteau test for cross-correlation (H_0: no cross-correlation in squared residuals)																
M(6)	12.367	11.711	18.921	46.859*	5.756	9.724	9.894	9.141	30.430	17.910	15.418	10.739	14.110	15.136	9.683	4.389
p-Value	0.975	0.983	0.756	0.003	1.000	0.996	0.995	0.997	0.171	0.807	0.908	0.991	0.944	0.917	0.996	1.000
M(12)	51.848	30.398	31.940	73.003*	24.924	34.904	44.511	34.225	55.156	43.978	47.272	34.011	34.071	41.570	44.185	38.139
p-Value	0.326	0.978	0.964	0.011	0.998	0.921	0.617	0.933	0.222	0.638	0.503	0.937	0.936	0.732	0.630	0.845
Log Likelihood	−861.8	−770.0	−1,117.1	−892.6	−968.9	−804.3	−975.0	−1,034.8	−977.9	−1,017.8	−637.3	−915.4	−926.0	−989.5	−1,097.6	−969.2
No. of Obs.	123	120	168	120	144	123	144	144	144	161	101	148	148	171	161	154

RICE

	MAL	SEN	IND MUM	IND ND	NEP	PHI REG	PHI WELL	THA 25	THA 5	BRA	COL 1st	COL 2nd	ECU	PER CORR	PER SUP
Panel B															
Conditional mean equation															
Model	VEC	VAR	VAR	VEC	VAR	VEC	VEC	VAR	VAR	VEC	VAR	VAR	VEC	VAR	VAR
No. of lags	1	4	2	1	3	1	1	2	2	1	3	3	1	2	2
α_0	0.002	−0.001	0.003	0.002	0.001	0.002	0.002	0.002	0.003	0.002	0.002	0.002	0.005	0.001	0.001
	(0.005)	(0.007)	(0.002)	(0.002)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
$\alpha_{1,11}$	0.069	−0.498*	0.227*	0.193*	0.484*	0.135	0.219*	0.421*	0.416*	0.203*	0.347*	0.316*	−0.153	0.280*	0.335*
	(0.093)	(0.095)	(0.077)	(0.078)	(0.099)	(0.078)	(0.079)	(0.132)	(0.110)	(0.076)	(0.078)	(0.078)	(0.097)	(0.067)	(0.066)
$\alpha_{1,12}$	0.043	0.105	−0.064	−0.015	−0.267*	0.113*	0.085	0.095	0.078	0.148*	0.018	0.003	0.055	0.019	0.025
	(0.082)	(0.141)	(0.045)	(0.034)	(0.122)	(0.054)	(0.046)	(0.143)	(0.120)	(0.071)	(0.063)	(0.070)	(0.041)	(0.029)	(0.019)
Conditional variance equation															
c_{11}	4.243*	1.638	0.008	0.017	2.357	2.006*	0.743*	1.444*	1.818*	3.029*	1.167	1.852*	0.615*	1.065*	0.767*
	(0.908)	(1.203)	(0.025)	(0.023)	(2.070)	(0.966)	(0.257)	(0.369)	(0.582)	(1.392)	(0.705)	(0.651)	(0.229)	(0.369)	(0.157)
a_{11}	0.440	0.364*	0.091	0.629*	0.343*	0.254	−0.278*	0.487*	0.813*	0.312	−0.039	0.061	0.660*	0.520*	0.474*
	(0.459)	(0.105)	(0.096)	(0.122)	(0.111)	(0.135)	(0.084)	(0.134)	(0.161)	(0.262)	(0.084)	(0.078)	(0.193)	(0.134)	(0.124)
a_{21}	0.252	0.232	0.044	−0.070	0.011	0.204*	0.115	0.118	−0.303*	−0.292	−0.218*	0.179	0.018	−0.047	−0.064*
	(0.323)	(0.128)	(0.038)	(0.057)	(0.177)	(0.076)	(0.083)	(0.087)	(0.120)	(0.186)	(0.071)	(0.094)	(0.039)	(0.036)	(0.018)
g_{11}	−0.123	0.907*	0.997*	0.854*	0.896*	0.742*	0.943*	0.952*	0.854*	0.585	0.890*	0.804*	0.762*	0.676*	−0.678*
	(0.561)	(0.067)	(0.011)	(0.046)	(0.116)	(0.266)	(0.026)	(0.102)	(0.139)	(0.459)	(0.102)	(0.070)	(0.106)	(0.152)	(0.087)
g_{21}	0.109	−0.473*	−0.031*	0.037	−0.012	−0.353*	−0.015	−0.267*	−0.630*	0.530*	0.151	−0.370*	−0.007	−0.011	−0.042
	(0.309)	(0.152)	(0.014)	(0.022)	(0.105)	(0.111)	(0.024)	(0.059)	(0.164)	(0.233)	(0.088)	(0.100)	(0.060)	(0.049)	(0.064)
ν	3.957*	5.166*	5.101*	4.420*	5.229*	9.175*	5.016*	8.985*	8.816*	13.610	132.498	10.599	7.369	4.101*	8.132*
	(1.487)	(1.336)	(1.825)	(1.114)	(2.500)	(3.853)	(1.059)	(3.800)	(3.785)	(10.981)	(330.799)	(6.190)	(4.910)	(0.766)	(2.889)
Wald's test for presence of innovation and persistence effects from international to domestic market (H_0: $a_{21} = g_{21} = 0$)															
Chi-squared	2.198	9.734*	5.435	2.956	0.013	12.546*	2.886	23.040*	21.981*	5.548	9.335*	18.338*	0.211	2.025	12.704*
p-Value	0.333	0.008	0.066	0.228	0.994	0.002	0.236	0.000	0.000	0.062	0.009	0.000	0.900	0.363	0.002
Ljung–Box's *test for autocorrelation (H_0: no autocorrelation in squared residuals)*															
LB(6)	6.794	13.517*	8.398	0.821	8.533	2.908	3.741	4.675	4.998	3.695	6.004	5.095	7.670	1.752	5.119
p-Value	0.340	0.036	0.210	0.991	0.202	0.820	0.712	0.586	0.544	0.718	0.423	0.532	0.263	0.941	0.529
LB(12)	10.996	20.869	13.984	4.935	15.420	8.230	9.706	12.043	13.360	10.083	11.055	12.741	10.466	6.336	9.857
p-Value	0.529	0.052	0.302	0.960	0.219	0.767	0.642	0.442	0.343	0.609	0.524	0.388	0.575	0.898	0.629
Lagrange multiplier (LM) test for ARCH residuals (H_0: no ARCH effects)															
LM(6)	20.121*	6.745	2.583	2.040	1.348	2.239	7.008	2.669	2.198	2.379	9.819	3.467	6.180	2.365	2.191
p-Value	0.003	0.345	0.859	0.916	0.969	0.896	0.320	0.849	0.901	0.882	0.132	0.748	0.403	0.883	0.901
LM(12)	22.214*	15.907	10.044	5.465	3.407	5.564	9.824	4.293	6.550	7.305	10.994	4.501	9.726	4.690	4.816
p-Value	0.035	0.196	0.612	0.941	0.992	0.936	0.631	0.978	0.886	0.837	0.529	0.973	0.640	0.968	0.964
Hosking's Multivariate Portmanteau test for cross-correlation (H_0: no cross-correlation in squared residuals)															
M(6)	31.893	16.927	14.748	43.910*	11.413	14.392	32.630	21.456	15.355	17.461	40.464*	16.529	34.438	41.278*	40.700*
p-Value	0.130	0.852	0.928	0.008	0.986	0.937	0.112	0.612	0.910	0.828	0.019	0.868	0.077	0.016	0.018
M(12)	46.515	32.029	44.182	59.293	22.062	32.705	41.889	38.219	33.908	31.333	58.757	33.401	52.108	52.395	63.919
p-Value	0.534	0.963	0.630	0.127	1.000	0.955	0.720	0.843	0.938	0.970	0.137	0.946	0.317	0.307	0.062
Log Likelihood	−690.8	−695.5	−872.1	−851.1	−641.2	−914.9	−886.4	−865.9	−890.0	−977.4	−908.6	−931.3	−546.1	−1,063.7	−1,018.1
No. of Obs.	122	121	171	171	110	170	170	170	170	171	171	171	111	225	225

	SORGHUM			WHEAT						
	SOR BUR	SOR CHA	SOR NIG	WHE ETH	WHE IND MUM	WHE IND ND	WHE PER	WHE BOL	WHE BRA	BREAD BRA
Panel C										
Conditional mean equation										
Model	VAR	VAR	VAR	VEC	VAR	VAR	VAR	VEC	VEC	VAR
No. of lags	1	1	1	0	2	2	2	1	1	1
α_0	0.005	0.005	0.001	−0.001	0.003	0.002	0.002*	0.003	0.003	0.008
	(0.008)	(0.011)	(0.012)	(0.006)	(0.003)	(0.003)	(0.001)	(0.005)	(0.004)	(0.005)
$\alpha_{1,11}$	0.043	−0.078	−0.126		0.134	0.314*	0.367*	0.063	0.201*	−0.148
	(0.092)	(0.084)	(0.098)		(0.079)	(0.077)	(0.074)	(0.085)	(0.073)	(0.077)
$\alpha_{1,12}$	0.033	0.058	0.299		0.107*	0.077	0.040*	−0.118	0.008	0.085
	(0.103)	(0.153)	(0.163)		(0.044)	(0.044)	(0.016)	(0.067)	(0.064)	(0.077)
Conditional variance equation										
c_{11}	5.253*	9.518*	9.968*	1.016	0.426	0.555	0.746*	−1.361	2.302	2.174*
	(1.764)	(3.785)	(2.708)	(2.573)	(0.878)	(1.251)	(0.259)	(2.123)	(1.892)	(0.816)
a_{11}	−0.140	0.347	0.445*	0.599*	0.294	−0.072	0.174	−0.306*	−0.313*	0.421*
	(0.194)	(0.239)	(0.174)	(0.283)	(0.190)	(0.144)	(0.165)	(0.130)	(0.152)	(0.110)
a_{21}	0.087	−0.172	0.145	−0.428*	0.031	0.033	0.131*	−0.180	−0.305*	0.112
	(0.174)	(0.415)	(0.506)	(0.144)	(0.054)	(0.058)	(0.031)	(0.125)	(0.099)	(0.089)
g_{11}	−0.225	0.443	−0.175	−0.563*	0.962*	0.980*	0.042	0.878*	0.545*	0.734*
	(0.509)	(0.344)	(0.541)	(0.188)	(0.073)	(0.052)	(0.346)	(0.190)	(0.185)	(0.080)
g_{21}	0.849*	−0.617	−0.211	0.345	−0.132*	0.023	0.097*	−0.112	0.420	−0.328*
	(0.285)	(0.699)	(0.739)	(0.279)	(0.050)	(0.036)	(0.042)	(0.092)	(0.217)	(0.074)
ν	4.572*	4.591*	3.675*	4.705*	4.980*	8.305*	7.305*	6.337*	8.857*	9.796*
	(1.306)	(1.381)	(1.485)	(1.271)	(1.470)	(3.979)	(2.634)	(2.123)	(3.750)	(4.273)
Wald's test for presence of innovation and persistence effects from international to domestic market (H_0: $a_{21} = g_{21} = 0$)										
Chi-squared	23.122*	0.869	0.098	29.637*	11.372*	8.677*	24.074*	23.050*	61.000*	21.846*
p-Value	0.000	0.648	0.952	0.000	0.003	0.013	0.000	0.000	0.000	0.000
Ljung–Box's test for autocorrelation (H_0: no autocorrelation in squared residuals)										
LB(6)	1.760	2.548	2.948	5.671	4.266	6.102	3.927	3.064	2.333	3.944
p-Value	0.940	0.863	0.815	0.461	0.641	0.412	0.687	0.801	0.887	0.684
LB(12)	3.521	13.764	13.638	13.769	11.379	11.067	13.213	15.411	8.128	16.633
p-Value	0.991	0.316	0.324	0.316	0.497	0.523	0.354	0.220	0.775	0.164
Lagrange multiplier (LM) test for ARCH residuals (H_0: no ARCH effects)										
LM(6)	1.981	2.248	1.013	3.325	2.113	11.629	10.164	1.720	6.353	1.423
p-Value	0.921	0.896	0.985	0.767	0.909	0.071	0.118	0.944	0.385	0.964
LM(12)	18.856	7.192	2.727	5.745	3.635	22.112*	14.158	5.829	11.153	12.860
p-Value	0.092	0.845	0.997	0.928	0.989	0.036	0.291	0.924	0.516	0.379
Hosking's Multivariate Portmanteau test for cross-correlation (H_0: no cross-correlation in squared residuals)										
M(6)	16.616	5.755	26.227	27.096	15.606	22.684	16.061	10.518	21.972	25.534
p-Value	0.865	1.000	0.342	0.300	0.902	0.538	0.886	0.992	0.581	0.377
M(12)	50.349	35.123	49.785	48.966	29.998	60.651	38.569	18.919	40.587	62.906
p-Value	0.381	0.917	0.402	0.434	0.981	0.104	0.833	1.000	0.767	0.073
Log Likelihood	−815.7	−1,011.5	−720.8	−703.7	−953.8	−969.4	−770.3	−809.3	−1,028.6	−1,052.7
No. of Obs.	123	144	111	120	171	171	165	135	171	170

Note: This table presents selected coefficients from the estimated conditional mean and conditional variance equations for each available country-commodity series, together with goodness of fit tests. Numbers in parentheses are standard errors. An asterisk indicates that the null hypothesis is rejected at the 5% level of confidence. See Section 3 of the main text for details on the estimations and 5(b) of the main text for details on the tests. See Appendix Table A.1 for the full description of the country-commodity acronyms. ν is Student's *t* distribution degrees of freedom parameter used for the BEKK estimation.

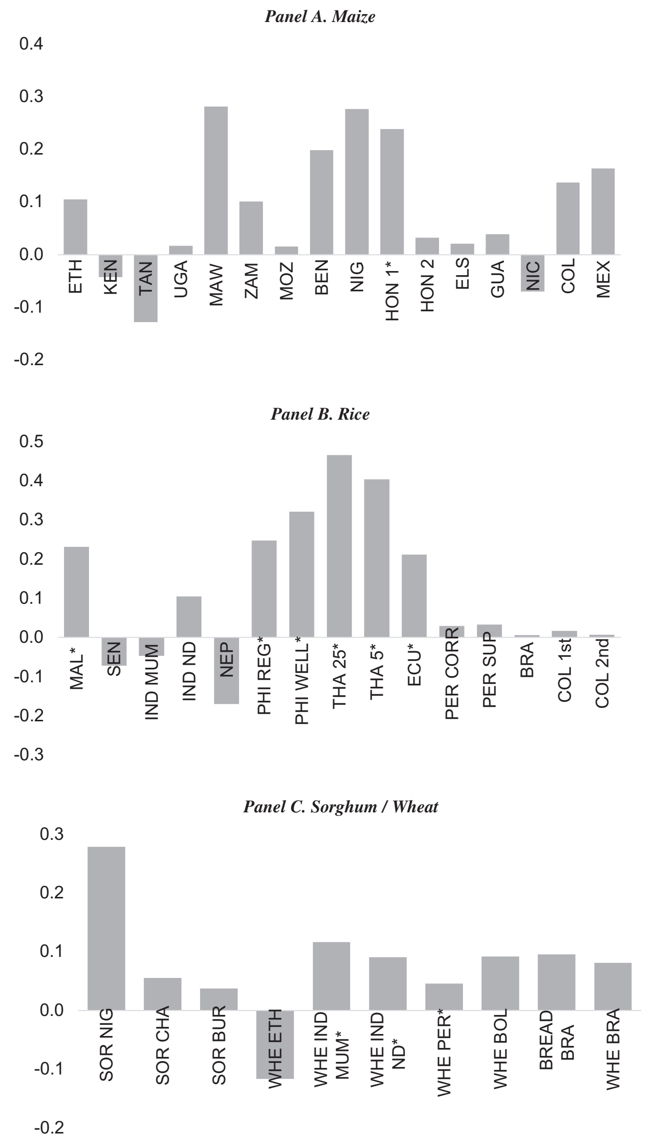

Figure 4. *Price return transmission estimates (at the mean level). Note: This figure shows estimates for the elasticity of price transmission from international markets to domestic markets for each available country and commodity. Panel A focuses on transmission of the international maize price, panel B on transmission of the international price of rice, and panel C on transmission of the international prices of sorghum (first three country-commodities) and wheat. The elasticity of price transmission is defined as the one-period domestic impulse response arising from a one-time shock in the international market (after orthogonalizing the residuals using the Cholesky decomposition), and standardizing it by the size of the shock introduced (equal to one standard deviation of the international price returns, see Section 3 of the main text for details). An asterisk denotes a statistically significant estimate at the 5% level.*

unexpectedly high price transmission. One hypothesis is that the result is due to cross-commodity linkages between rice and other traded grains, such as wheat. Alternatively, government policy may guide local prices to follow international trends, even with minimal trade.

Finally, Panel C of Figure 4 shows the degree of short-run price transmission for three sorghum markets and seven wheat markets. None of the three sorghum markets (Burundi, Chad, and Nigeria) have statistically significant links to world sorghum markets. This is expected since international trade in sorghum is negligible in all three countries (see Table 3). Although the international trade statistics in Table 3 probably exclude informal cross-border trade, this trade would not contribute to linkages with world markets in any case.

In the case of wheat, three of the seven markets show a statistically significant link with world wheat markets: Mumbai, India, New Delhi, India, and Lima, Peru. It is not surprising that wheat prices in Lima are linked to world markets given the country's heavy reliance on imported wheat. On the other hand, it is somewhat surprising to find a link between Indian wheat prices and world prices, given that India is (on average) self-sufficient in wheat. One hypothesis is that the government of India, which maintains large stocks, sets procurement and sales prices taking into account world wheat prices. Brazil and Bolivia depend heavily on wheat imports, but Argentina is the main source of wheat and Argentinian prices are imperfectly integrated with US wheat prices, used as the benchmark for world prices in this study. The lack of linkage between Ethiopian wheat prices and world wheat prices is probably due to the large (but variable) share of wheat imports that are in the form of food aid, and thus less driven by market forces. Indeed, Tadesse and Shively (2009) show that domestic wheat prices in Ethiopia are influenced by the volume of food aid.

In summary, we find just one of 16 local maize prices linked to international markets and none of the three sorghum markets are linked. On the other hand, 6 of the 15 rice markets are linked to international rice markets, and 3 of the 7 wheat mar-

Table 3. *Net imports as a share of domestic availability*

	Maize (%)	Rice (%)	Sorghum (%)	Wheat (%)
Benin	0	85	0	95
Chad	8	2	4	91
Ethiopia	1	49	3	32
Kenya	9	86	10	70
Malawi	0	3	8	108
Mali	1	16	0	103
Mozambique	9	77	1	95
Nigeria	0	37	0	98
Senegal	30	82	1	100
Tanzania	0	9	0	100
Uganda	−2	29	7	94
Zambia	−7	46	35	10
India	−13	−5	−1	−2
Nepal	3	5	109	1
Philippines	4	12	97	104
Thailand	−6	−70	−3	105
Bolivia	1	3	−1	72
Brazil	−18	3	−1	56
Colombia	64	6	52	98
Ecuador	33	−5	44	100
El Salvador	38	72	1	100
Guatemala	32	71	0	97
Honduras	37	83	1	97
Mexico	25	76	32	44
Nicaragua	15	35	−1	100
Peru	50	5	99	88
Mean abs value	16	36	22	72

Note: This table shows the degree of dependence on food imports for each of the countries available in our sample. The degree of dependence on food import is calculated as $(M - X)/A$, where M is the volume of imports, X is the volume of exports, and A is total domestic availability, defined as production plus net imports plus change in stocks. All quantities reflect 2000–13 averages. Data for Burundi are not available.

kets are. These results are similar to those of Minot (2011), who also found that slightly less than one-quarter of the local food markets tested had a long-term relationship with the corresponding international grain market. In contrast, Baquedano and Liefert (2014) found that a large majority of local markets (51 of 61) had a long-term relationship with the international grain price. This difference may be related to the fact that they use single-equation error correction model, while this paper and Minot (2011) use a vector error correction model. However, all three studies find that price transmission is relatively common in wheat and rice markets but rarer in maize and sorghum markets.

(b) *Volatility transmission*

In this section, we describe the volatility transmission estimates from international commodity markets to domestic food markets across countries and commodities. Due to space limitations, we only report in the second panel of Table 2 the estimated coefficients of the BEKK model describing the conditional variance equation of domestic markets (specified in Eqn. (3)).[20] The lower panel of Table 2 also reports different residual diagnostic tests, which generally support the adequacy of BEKK model specification. In particular, the Ljung–Box test yield no or weak evidence of autocorrelation, the Lagrange Multiplier (LM) test suggests no ARCH effects, and the Hosking Multivariate Portmanteau shows no cross-correlation in the standardized squared residuals of the estimated models. All three tests were implemented with up to 6 and 12 lags.[21]

First, we assess the reliability of our estimations by comparing model predictions to sample price volatility statistics (sample standard deviation of domestic price returns) for each domestic price.[22] For model predictions of price volatilities we use (i) the average of the predicted conditional standard deviations of price returns and (ii) the estimated steady-state (or unconditional) price return volatility.[23]

Figure A.1 in the Appendix compares the sample and model estimates of domestic price volatilities. Sample data indicate that maize volatility is on average larger than rice and wheat volatility. Average sample maize volatility is 0.104 while for rice and wheat are 0.047 and 0.048, respectively. Across regions, African countries have the highest sample volatilities (average of 0.113) while in Asia and Latin America the averages are less than half of the African average. Our estimated steady-state and predicted volatilities yield similar conclusions when comparing commodities and regions. When we compare steady-state volatility with sample volatility, the former is consistently lower than the latter. In particular, steady-state volatility estimates are on average 60% of the sample estimates. This is expected as steady-state estimates reflect the standard deviations to be reached over time in the absence of shocks. This finding is also consistent with results reported by Gardebroek *et al.* (2016).

When we compare average predicted volatility with sample volatility, we also observe that our estimated models perform reasonably well. The ratio of the average predicted volatility to the sample volatility is on average 0.99 for the full set of countries and commodities, and our average predicted volatilities further reaffirm that on average maize price volatility is much more volatile (more than two times larger) than rice and wheat price volatility.

Figure 5 presents the resulting volatility transmission estimates for each country and commodity, while Table A.3 in

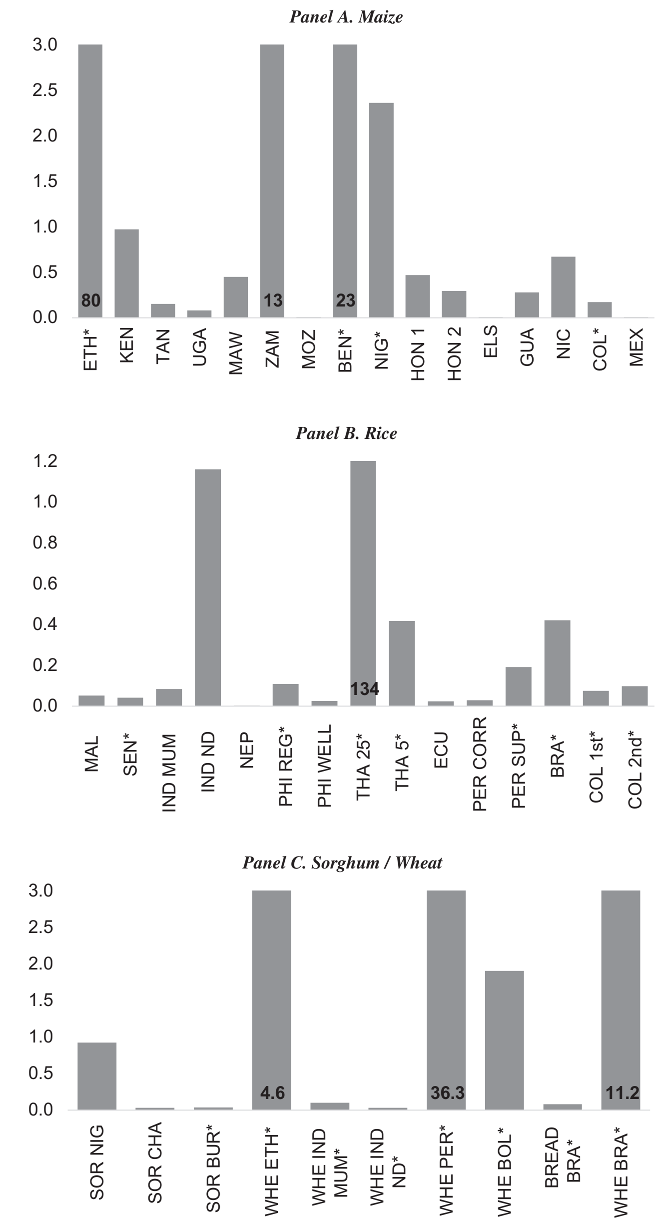

Figure 5. *Price return volatility transmission estimates. Note: This figure shows estimates for the elasticity of price volatility transmission from international markets to domestic markets for each available country and commodity. Panel A focuses on volatility transmission of the international maize price, panel B on volatility transmission of the international price of rice, and panel C on volatility transmission of the international prices of sorghum (first three country-commodities) and wheat. The elasticity of price volatility is defined as the percentage change in the standard deviation of the domestic price return (with respect to its steady-state value), relative to that of the international price return standard deviation (see Section 3 of the main text for details). The figure is truncated to preserve scale, outlier values are indicated in bold. Statistical significance is approximated by a Wald test for the joint significance of* α_{21} *and* g_{21} *in the conditional variance equation specified in Eqn. (3), where* α_{21} *represents the short-term effect of an international price shock on domestic volatility (direct spillover effect), and* g_{21} *represents the short-term effect of changes in international price volatility on domestic volatility (direct persistence effect). An asterisk denotes a statistically significant estimate at the 5% level.*

the Appendix reports the aggregated median values and the distribution of elasticity values by commodity and region. Overall, we find volatility transmission that is statistically significant at the 5% level in about half of the cases, with most of our estimates within values less than 10 (35 out of 41 cases).

An approximate measure of the statistical significance of the relationship between international and domestic volatility is given by the Wald test for the joint significance of α_{21} and g_{21} in the conditional variance equation (see Table 2). α_{21} represents the short-term effect of an international price shock on domestic volatility (direct spillover effect), while g_{21} represents the short-term effect of changes in international volatility on domestic volatility (direct persistence effect).

In the case of maize, 4 of the 16 Wald tests reject the null hypothesis that both coefficients are zero: Benin, Ethiopia, Nigeria, and Colombia. The linkage between international and domestic volatility is easy to understand in the case of Colombia, which imports 64% of its maize requirements over the period under study; in the other five Latin American countries considered in the study, the proportion ranges from 15% to 38%. The linkage for the other three countries is unexpected, given that all three rely on imports for less than 2% of domestic requirements (see Table 3). In addition, as mentioned above, most internationally traded maize is yellow, while African and Central American consumers prefer white maize.

In the case of rice, 8 of the 15 markets show evidence of a statistically significant spillover from international volatility to domestic volatility. This is expected in the case of Senegal, which imports 82% of its domestic requirements, and the two prices in Thailand, for which exports are equivalent to 70% of its domestic requirements (see Table 3). Similarly, the lack of linkage in India, Nepal, Brazil, and Ecuador is explained by small contribution of rice imports in these countries. More surprising is the volatility spillover in Brazil, Colombia, and Peru, where rice imports meet less than 7% of local demand.

In the case of sorghum, one of the three prices shows signs of a statistically significant spillover in volatility from international markets: Burundi. This is surprising given that Burundi is landlocked and has virtually no sorghum imports from world markets. The lack of spillover for Chad and Nigeria is, however, expected given the negligible volumes of traded sorghum.

Wheat markets in developing countries appear to be relatively sensitive to volatility in international wheat markets. All seven of the markets show evidence of a statistically significant link between international and domestic price volatility. This is expected in the case of Peru, Bolivia, and Brazil, given their reliance on imported wheat for more than half of local consumption, and perhaps understandable in the case of Ethiopia, which imports 32% of its requirements (see Table 3). On the other hand, India is largely self-sufficient in wheat in most years, so the volatility linkage with world wheat markets is harder to explain.

Overall, it appears that volatility is (is not) transmitted from international to domestic markets when the ratio of traded volume to domestic requirements is above (below) a significant proportion. In the specific sample of country/commodity cases studied here that proportion seems to be around 40% although this is not necessarily a general rule. In our analysis, 29 of the 41 prices (71%) follow this pattern.

While reliance on international trade seems relevant for explaining the volatility transmission results presented above, in some cases the higher or lower international–domestic interrelationships seem to be explained by other factors. For example, the size of commodity stocks (inventories) may also play a role, with larger stocks tending to dampen volatility transmission. In addition, if a state-owned enterprise has a legal monopoly on imports or exports, it may decide not to transmit international price volatility to local markets for political reasons. If trade transactions occur infrequently (just a few times per year), price volatility transmission is less likely, other things being equal. Other elements that may reduce volatility transmission include long-term contracts, market power, and government regulations (Assefa, Meuwissen, & Oude Lansink, 2016). Time-series data on these variables are not easily available, however, so testing these factors will be left for future research.

Bringing together the results discussed in the previous two sections, Figure 6 compares, for each country and commodity pair, the elasticity of price transmission to the elasticity of volatility transmission. Interestingly, and despite the few statistically significant findings for mean price transmission, the figure shows that the point estimates for both elasticity measures seem to be positively related. In other words, a larger price transmission from the international into the domestic market seems to be associated to a larger volatility transmission, with an overall coefficient of determination (R^2) of 0.08.

(c) *Conditional correlations*

Lastly, we are interested in examining whether the dynamic price relationship between domestic and international markets has changed in recent years, particularly after the global food price crisis of 2007–08. From the BEKK model, we can recover time-varying conditional correlations between the price returns of each domestic market and the international market. This correlation is given by $\hat{\rho}_{12,t} = \frac{\hat{h}_{12,t}}{\sqrt{\hat{h}_{11,t}\hat{h}_{22,t}}}$, where $\hat{h}_{11,t}$ and $\hat{h}_{22,t}$ are the estimated conditional variance equations

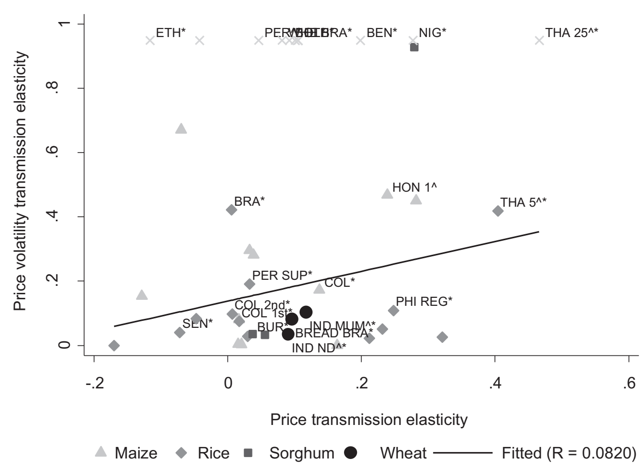

Figure 6. *Price return (at the mean level) and price volatility transmission estimates. Note: This figure shows a scatterplot of the estimates for the elasticity of price return transmission and elasticity of price volatility transmission from international markets to domestic markets for each country and commodity. Estimates for maize, rice, sorghum, and wheat are denoted by different symbols. Labels are shown only for country-commodity pairs with at least one statistically significant estimate. See Sections 5(a) and 5(b) for details on the derivation of the elasticity measures. The figure is truncated on the price volatility transmission axis to preserve scale, outlier values are indicated with an ×. "^" denotes a statistically significant estimate (at the 5% level) for the price return transmission elasticity; "*" denotes a statistically significant estimate (at the 5% level) for the price volatility transmission elasticity.*

Table 4. *Conditional correlation between domestic and international price returns, by commodity and region*

	# of cases positive shift mid−2007	# of cases negative shift mid−2007	Total number of series
Total	9	2	41
By commodity			
Maize	2	1	16
Rice	4	0	15
Wheat	3	1	7
Sorghum	0	0	3
By region			
Africa	1	2	15
Asia	4	0	9
Central America & Mexico	1	0	6
South America	3	0	11

Note: This table portrays the behavior of the estimated conditional correlations between domestic and international price returns around the 2007–08 food crisis. We run separate regressions of the estimated conditional correlations for each available month on trend and trend squared terms, plus a dummy shifter for the period July 2007 onward. The table then reports the number of cases for which the dummy shifter is statistically significant (at the 95% confidence level), by region and commodity (see 5(c) of the main text for details).

and $\hat{h}_{12,t}$ is the covariance equation. We then run separate regressions of these recovered conditional correlations on a trend term, trend squared, and a dummy shifter for the period July 2007 onward, as mid-2007 was the period where the crisis was felt most (food prices peaked).

Table 4 reports the number of cases where we find a statistically significant change after June 2007 in the degree of co-movement between domestic and international price returns by commodity and region (at the 95% confidence level). Overall, we do not observe major changes in the dynamic interrelationship between domestic and international price returns after the food price crisis. Only in nine cases (out of 41) there is a positive shift in the domestic-international conditional correlation and in two cases there is a negative shift. The two negative cases are in Africa (maize in Mozambique and wheat in Ethiopia), while the nine positive cases include four in Asia (rice in Philippines (well milled) and Thailand (25% broken) and wheat in Mumbai and New Delhi), four in Latin America (rice in Ecuador and Peru (milled, standard), maize in Honduras and wheat in Peru), and one in Africa (maize in Ethiopia). Figure A.2 in the Appendix further reports the median change in the domestic–international correlations by commodity and region, confirming that the shifts were generally small, except for Asia with a median shift of 10 percentage points.

6. CONCLUSIONS

Food price volatility in developing countries is economically and politically important. In these economies a large share of household budgets is spent on food, so food prices and volatility have a direct and large impact on welfare. Food price volatility particularly affects poor, small-scale farmers who rely on crop sales for a significant part of their income. It is also likely to inhibit agricultural investment and reduce the growth in agricultural productivity, with long-run implications for poor consumers and farmers. Hence, it is important to better understand the sources of food price volatility and whether it is mostly transmitted from international agricultural commodity markets or largely determined by domestic factors. This in turn can help design better global, regional, and domestic policies to cope with excessive food price volatility and to protect the most vulnerable groups.

In terms of price transmission, we only observe significant interactions from international to domestic markets in few cases. In terms of volatility transmission, however, we observe more interactions across markets. We propose as a volatility transmission estimator (or elasticity) one that shows the reaction (after one period and assuming the system is in steady-state) of the domestic price volatility (the standard deviation of price returns) given a one-percent shock in international price volatility of the commodity. We find that most of our elasticity estimates are within reasonable values, with more than half of them being statistically significant.

Maize markets in developing countries are the least susceptible to volatility in international markets, with just one-quarter of them (4 of 16) showing evidence of a statistically significant effect. Rice markets appear to be more sensitive to volatility in international markets, with more than half the markets tested (8 of 15) having statistically significant spillover. And wheat markets were the most sensitive to international price volatility, with a significant linkage in all seven markets tested. In general terms, this pattern reflects the fact that most of the countries in our sample are relatively self-sufficient in maize: on average, net trade represents 16% of domestic use. In contrast, these countries are more dependent on rice trade (average 38%) and most reliant on international trade in wheat (average 78%).

These patterns extend to individual markets. Colombia is heavily dependent on maize imports and is one of just four markets with significant volatility linkages. Senegal and Thailand are both deeply involved in rice trade, as importer and exporter respectively, and both show volatility spillover from world markets. Similarly, Brazil, Bolivia, Peru, and Ethiopia rely heavily on wheat imports and show transmission of volatility from world markets.

In general, volatility transmission tends to be statistically significant when the traded volume is at least 40% of domestic requirements. This pattern applies to 70% (29 of 41) of the price series tested. Interestingly, all 11 exceptions are markets where trade is minor (less than 40% of domestic requirements) but we do find volatility transmission. Examples include maize in Ethiopia, rice in Peru, sorghum in Burundi, and wheat in India.

These results raise two questions. First, how is price volatility transmitted from world markets to domestic markets in the absence of significant trade? One hypothesis is that the local traders and government trading enterprises monitor international markets and are prompted by international volatility to respond in ways that contribute to local volatility even in the absence of direct trade effects. Another possibility is that price volatility is actually being transmitted through closely related staple grain markets for which there is trade.

Second, why is there no transmission of volatility in cases where trade represents (say) 20–40% of domestic requirements? This is the case for maize in Honduras, El Salvador, Guatemala, and Mexico in our dataset. Since these are coastal countries with relatively free trade in maize, we would expect some volatility transmission. One possible explanation is imperfect substitution between domestic and imported maize, since the international price is for No. 2 yellow maize, while the local prices are for white maize. Another possible explanation is that there is some market power among maize importers, allowing them to dampen the transmission of volatility to local markets. Testing these hypotheses would be a fruitful direction for future research.

NOTES

1. Section 2 discusses the relatively large body of research examining price transmission.

2. The BEKK acronym comes from the synthetized work on multivariate GARCH models by Baba, Engle, Kraft, and Kroner (1990).

3. See Saadi (2011, chap. 9) for an extensive review of commodity price co-movement in international markets.

4. See Bauwens, Laurent, and Rombouts (2006) and Silvennoinen and Teräsvirta (2009) for an extensive overview of different MGARCH models.

5. Similar to most of the previous related studies, we estimate the conditional mean and variance–covariance equations in two steps. The use of monthly data (for 101–225 time periods) difficults the implementation of joint estimation procedures, which present some convergence difficulties. Seo's (2007) joint methodlogy requires, for example, complex maximum likelihood estimation procedures that often leads to convergence problems, which are aggravated by the additional number of parameters to be estimated (see also Serra, Zilberman, & Gil, 2011).

6. We acknowledge that this underlying identification assumption might not be applicable for some cases in the rice market (specifically for important rice exporters such as Thailand, as discussed in Gilbert, 2010, 2011, chap. 7; Jamora & von Cramon-Taubadel, 2016), but we prefer to maintain a common (and standard) orthogonalization approach for comparison purposes across a wide set of countries and commodities. Still as robustness, we reestimated the results for rice imposing the reverse assumption: allowing for contemporaneous domestic-to-international transmission (as well as lagged transmission in any direction) while assuming away contemporaneous international-to-domestic transmission. The results are qualitatively similar to the ones presented below—both in terms of the level and statistical significance of price transmission—for most cases; the notable exception is Thailand, where imposing the reverse assumption results in a much lower (close to zero) degree of international to domestic price transmission.

7. While we focus on one-period responses, it is worth noting that longer term impacts are consistent with short-term impacts. In particular, those countries/commodities with a higher (lower) short-term impact also generally have a higher (lower) long-term impact. This finding is consistent both for price and volatility transmission discussed below. Additional details are available upon request.

8. As in any standard autoregressive process, the state of the process in the previous period (i.e., past variances and innovations) is assumed to account for all relevant information prior to the realization of the variance in the current period, thereby controlling for potentially spurious lead–lag relationships in variance (if any) from international to domestic markets. This also reduces the necessity to account for other variables in the analysis, such as production, harvest, or inventory data, which are not available on a monthly basis.

9. The estimated shocks are around the median historical shock for most cases; more precisely, in all cases they are between percentile 0.45 and 0.67 of the historical shock.

10. It is worth noting that the estimated residuals of the BEKK models are generally uncorrelated across international and domestic markets. We can accordingly consider a change in ε_2 in the modeled system of conditional variances and covariances in Eqn. (2) as a shock originating in the international market (all else equal) and assess the effect of this innovation on the volatility of the domestic market.

11. This procedure, including the normalization, also permits us to account for nonlinearities in volatility impulse response, which was originally raised by Hafner and Herwartz (2006) in the context of BEKK models.

12. We thank an anonymous reviewer for making this point.

13. While the prices used reflect monthly averages, their exact definition (e.g., average of daily prices *vs.* average of weekly prices) varies by source. It is important to note that working with monthly averages would tend to underestimate the measurement of price volatility at a single market as compared to working with end-of-month prices. However, the effect of this feature of the data on the estimated degree of price volatility transmission across markets is ambiguous.

14. We convert local prices to US dollars to make the results comparable across countries. In practice, the measured volatility of local prices is somewhat less when they are expressed in US dollars than when expressed in local currency.

15. Missing values in the remaining series are replaced by linear interpolation between the two closest available data points.

16. For instance, the number for January 2000 reflects the standard deviation of the monthly realized price returns from February 1998 until January 2000.

17. We tested for the presence of seasonality (monthly dummies) in the price returns series and we do not find seasonal patterns in most cases. As a result, we prefer to analyze international–domestic price returns interactions in their purest form.

18. The other maize market considered is Zona Belen (market 2), also in the capital city.

19. Table 3 reports net imports (by country and commodity) as a share of domestic availability defined as production plus net imports plus change in stocks.

20. Wald joint tests indicate that in several cases there are immediate innovation and persistence effects from international to domestic markets.

We discuss in more detail below volatility transmission from international to domestic markets.

21. The estimated degrees of freedom parameter (v) is also small in most cases, which supports the appropriateness of the estimation with Student's t distribution.

22. The sample volatility is equal to $\left(h_{11}^{sample}\right)^{0.5} = \sqrt{\frac{\sum_{t=1}^{n}(r_t - \bar{r})^2}{n}}$.

23. The average of predicted conditional volatilities is equal to $\hat{\bar{h}}_{11} = \frac{\sum_{t=1}^{n}\hat{h}_{11.t}^{0.5}}{n}$, while, as noted above, the steady-state volatility $(h_{11}^{SS})^{0.5}$ satisfies $H^{SS} = C'C + G'H^{SS}G$.

REFERENCES

Abdulai, A. (2000). Spatial price transmission and asymmetry in the Ghanaian maize market. *Journal of Development Economics, 63*, 327–349.

Ai, C., Chatrath, A., & Song, F. (2006). On the co-movement of commodity prices. *American Journal of Agricultural Economics, 88*, 574–588.

Assefa, T. A., Meuwissen, M. P. M., & Oude Lansink, A. G. J. M. (2016). A review of the effects of contextual factors on price volatility. In A. Garrido, B. Brummer, R. M'Barek, M. P. M. Meusissen, & C. Morales-Opazo (Eds.), *Agricultural markets instability: Revisiting the recent food crises*. Oxon, UK: Routledge Press.

Baba, Y., Engle, R., Kraft, D., & Kroner, K. F. (1990). *Multivariate simultaneous generalized ARCH* Mimeo. Department of Economics, University of California, San Diego.

Baquedano, F. G., & Liefert, W. M. (2014). Market integration and price transmission in consumer markets of developing countries. *Food Policy, 44*, 103–114.

Baulch, B. (1997). Transfer costs, spatial arbitrage and testing for food market integration. *American Journal of Agricultural Economics, 79* (May), 477–487.

Bauwens, L., Laurent, S., & Rombouts, J. V. K. (2006). Multivariate GARCH models: A survey. *Journal of Applied Econometrics, 21*, 79–109.

Beckmann, J., & Czudaj, R. (2014). Volatility transmission in agricultural futures markets. *Economic Modelling, 36*, 541–546.

Conforti, P. (2004). *Price transmission in selected agricultural markets*, Commodity and trade policy research working paper no 7. Rome: Food and Agriculture Organization.

Deb, P., Trivedi, P. K., & Varangis, P. (1996). The excess co-movement of commodity prices reconsidered. *Journal of Applied Econometrics, 11*, 275–291.

Diaz-Bonilla, E. (2016). *Volatile volatility: Conceptual and measurement issues related to price trends and volatility*, IFPRI discussion paper 1505. , Washington, D.C..

Engle, R., & Kroner, F. K. (1995). Dynamic conditional correlation-a simple class of multivariate GARCH models. *Journal of Business and Economics Statistics, 20*, 339–350.

FAO (2014). *Food balance sheets*. Rome: FAO (http://faostat3.fao.org/download/FB/FBE/S).

FAO-OECD. (2011). *Price volatility in food and agricultural markets: Policy responses*. Policy report including contributions by FAO, IFAD, IMF, OECD, UNCTAD, WFP, The World Bank, the WTO, IFPRI and the UN HLTF, June. Available at: http://www.ifad.org/operations/food/documents/g20.pdf.

Gallagher, L., & Twomey, C. (1998). Identifying the source of mean and volatility spillovers in Irish equities: A multivariate GARCH analysis. *Economic and Social Review, 29*, 341–356.

Garcia-German, S., Bardaji, I., & Garrido, A. (2016). Evaluating price transmission between global agricultural markets and consumer food price indices in the European Union. *Agricultural Economics, 47*(1), 59–70.

Gardebroek, C., & Hernandez, M. A. (2013). Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn market. *Energy Economics, 40*, 119–129.

Gardebroek, C., Hernandez, M. A., & Robles, M. (2016). Market interdependence and volatility transmission among major crops. *Agricultural Economics, 47*(2), 141–155.

Garrido, A., Brummer, B., M'Barek, R., Meusissen, M. P. M., & Morales-Opazo, C. (Eds.) (2016). *Agricultural markets instability: Revisiting the recent food crises*. Oxon, UK: Routledge Press.

Gilbert, C. L. (2010). How to understand high food prices. *Journal of Agricultural Economics, 61*, 398–425.

Gilbert, C. L. (2011). Grains price pass-through, 2005–09. In A. Prakash (Ed.), *Safeguarding food security in volatile global markets* (pp. 127–148). Rome: Food and Agriculture Organization of the United Nations.

Hafner, C. M., & Herwartz, H. (2006). Volatility impulse responses for multivariate GARCH models: An exchange rate illustration. *Journal of International Money and Finance, 25*, 719–740.

Hernandez, M. A., Ibarra, R., & Trupkin, D. R. (2014). How far do shocks move across borders?: Examining volatility transmission in major agricultural futures markets. *European Review of Agricultural Economics, 41*(2), 301–325.

Jamora, N., & von Cramon-Taubadel, S. (2016). Transaction cost thresholds in international rice markets. *Journal of Agricultural Economics, 67*(2), 292–307.

Le Pen, Y., & Sévi, B. (2010). *Revisiting the excess co-movement of commodity prices in a data rich environment* Economics papers from University Paris Dauphine. France: Paris Dauphine University.

Lutz, C., Kuiper, W. E., & van Tilburg, A. (2006). Maize market liberalisation in Benin: A case of hysteresis. *Journal of African Economies, 16*(1), 102–133.

Magrini, E., Morales Opazo, C., & Baile, J. (2015). *Price shocks, volatility, and household welfare: A cross-country inquiry*. Scientific paper no. 11. ULYSSES project. EU 7th Framework Programme, Project 312182 KBBE.2012.1.4-05. Available at http://www.fp7-ulysses,eu.

Martins-Filho, C., & Torero, M. (2011). *Why food price volatility matters*. Food Security Portal, IFPRI, Available at: http://www.foodsecurityportal.org/why-food-price-volatility-matters.

Meyer, J., & von Cramon-Taubadel, S. (2004). Asymmetric price transmission: A survey. *Journal of Agricultural Economics, 55*(3), 581–611.

Minot, N. (2011). *Transmission of world food price changes to markets in Sub-Saharan Africa*, IFPRI discussion paper 1059. , Washington, D. C..

Minot, N. (2014). Food price volatility in sub-Saharan Africa: Has it really increased?. *Food Policy, 45*, 45–56.

Moser, C., Barrett, C., & Minten, B. (2009). Spatial integration at multiple scales: Rice markets in Madagascar. *Agricultural Economics, 40*, 281–294.

Mundlak, Y., & Larson, D. (1992). On the transmission of world agricultural prices. *The World Bank Economic Review, 6*(3), 399–422.

Myers, R. (2008). *Evaluating the efficiency of inter-regional trade and storage in Malawi maize markets* Report for the World Bank. East Lansing, Mich., U.S.A.: Michigan State University.

Negassa, A., & Myers, R. (2007). Estimating policy effects on spatial market efficiency: An extension to the parity bounds model. *American Journal of Agricultural Economics, 89*, 338–352.

Pindyck, R. S., & Rotemberg, J. J. (1990). The excess co-movement of commodity prices. *Economic Journal, 100*, 1173–1189.

Quiroz, J., & Soto, R. (1995). *International price signals in agricultural prices: Do governments care?*, Documento de investigacion 88. Santiago, Chile: ILADES Postgraduate Economics Program, Georgetown University.

Rashid, S. (2004). Spatial integration of maize markets in post-liberalised Uganda. *Journal of African Economies, 13*(1), 102–133.

Robles, M., & Torero, M. (2010). Understanding the impact of high food prices in Latin America. *Economia, 10*(2), 117–164.

Saadi, H. (2011). Price co-movement in international markets and their impacts on price dynamics. In I. Piot-Lepetit, & R. M'Barek (Eds.), *Methods to analyse agricultural commodity price volatility*. Springer Science.

Seale, J. L., Regmi, A., & Bernstein, J. (2003). *International evidence on food consumption patterns* Technical Bulletin No. 33580. United States Department of Agriculture, Economic Research Service.

Seo, B. (2007). Asymptotic distribution of the cointegrating vector estimator in error correction models with conditional heteroskedasticity. *Journal of Econometrics, 137*, 68–111.

Serra, T., Zilberman, D., & Gil, J. (2011). Price volatility in ethanol markets. *European Review of Agricultural Economics, 38*(2), 259–280.

Silvennoinen, A., & Teräsvirta, T. (2009). Multivariate GARCH models. In T. G. Andersen, R. A. Davis, J.-P. Kreiß, & T. Mikosch (Eds.), *Handbook of financial time series* (pp. 201–229). Berlin: Springer.

Tadesse, G., & Shively, G. (2009). Food aid, food prices, and producer disincentives in Ethiopia. *American Journal of Agricultural Economics, 91*(4), 942–955.

Van Campenhout, B. (2007). Modeling trends in food market integration: Method and an application to Tanzanian maize markets. *Food Policy, 32*, 112–127.

Zhao, J., & Goodwin, B. (2011). *Volatility spillovers in agricultural commodity markets: An application involving implied volatilities from options markets*. Paper prepared for presentation at the Agricultural and Applied Economics Association's 2011 Annual Meeting.

APPENDIX A. SUPPLEMENTARY DATA

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.worlddev.2017.01.015.