Part III

Commodity and Financial Market Linkages

Directional Volatility Spillovers Between Agricultural, Crude Oil, Real Estate, and Other Financial Markets

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9.1 Introduction

Portfolio diversification is a principal motive for financial commodity trading (Fortenbery and Hauser 1990). The fundamentals that drive the supply and demand of commodities largely differ from those of other financial assets, suggesting low or negative return correlations. And, like real estate, commodities can serve as an inflation hedge as their prices drive inflation, but holding commodities is not directly associated with inflation-threatened cash flows (Ankrim and Hensel 1993; Huang and Zhong 2013; Bodie and Rosansky 1980; Satyanarayan and Varangis 1996; Anson 1999; Gorton and Rouwenhorst 2006; Daskalaki and Skiadopoulos 2011).

The spread of electronic trading and the creation of commodity index-linked exchange-traded products (ETPs) or mutual funds have made commodity markets more accessible to financial portfolio managers (Conover et al. 2010; Daskalaki and Skiadopoulos 2011). Between 2002 and 2010, assets under the management of commodity ETPs grew from 0.1 billion to 45.7 billion US dollars (BlackRock 2011). Simultaneously, combined open interest for the Chicago Board of Trade (CBOT) corn, soybean, and wheat futures climbed from 0.7 million to 2.7 million contracts (CFTC 2013).

Attractive diversification benefits and facilitated inclusion in portfolios stimulated the use of agricultural commodities in both strategic and tactical portfolio management. While strategic portfolio management may maintain a fixed commodity share [e.g., 4–7 % according to Greer (2007)], tactical portfolio management continuously resets portfolio asset weights due to cross-market arbitrage (Büyükşahin et al. 2010) or as a response to shocks or extreme regimes in selected markets

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(cf. Conover et al. 2010; Jensen et al. 2002). Particularly during financial crises, portfolio managers may shift weights to comparatively less risky and more liquid refuge assets, a phenomenon known as “flight-to-quality” or “flight-to-liquidity” (Beber et al. 2007). Such use of commodities has been suggested, for example, by Silvennoinen and Thorp (2013) and Chong and Miffre (2010), who proposed a shift out of equity and bond markets and into commodities during crisis periods. Finally, the need to meet margin calls in distressed markets may affect weights of all other portfolio assets, if a broad range of assets needs to be sold to obtain liquidity (Büyükşahin et al. 2010).

By any of these channels, tactical portfolio allocation may create or intensify linkages between commodity and financial markets, especially during financial crises. It may also affect linkages between agricultural and energy markets as both commodity groups are included in indices such as the Standard and Poor’s (S&P) GSCI or the Dow Jones UBS (DJ UBS) Commodity index, which are replicated by index-linked products and funds. In any case, volatility, rather than returns, is the more interesting linkage due to its closer relation to information flows (Chiang and Wang 2011; Cheung and Ng 1996). Also, the development of ETP assets suggests a steadily emerging financial interest and motivates the search for a gradual change rather than a sudden structural break in market linkages.

In this chapter, we analyze time-varying short-term volatility spillovers between (1) commodity and financial markets and (2) agricultural and energy markets with rolling volatility spillover indices as introduced in Diebold and Yilmaz (2012) for the period from June 1998 to December 2013. The analyses are based on rolling generalized forecast error variance (FEV) decompositions in a vector autoregressive (VAR) model and allow us to calculate gradually changing directional volatility spillovers between any pair of included assets over the entire observation period. Volatility is measured as the daily range, based on the difference between high and low prices (Parkinson 1980).

Our analysis contributes to existing research in several aspects. First, we investigated the volatility linkages between agricultural commodities and financial assets, which remain scarcely researched. Second, we included a broad market network rather than conducting a bivariate analysis, thereby specifically taking into account the potential substitution between commodity and real estate as a result of the subprime crisis and the aforementioned parallel characteristics between the two asset classes. This also aids the investigation of agriculture-energy linkages as commodity markets are part of the global financial market network; any bivariate relation may thus be affected by the state of third markets. Finally, we do not impose any structural breakpoints; our analysis also goes beyond comparing the selected periods (e.g., before and after the recent financial crisis or before and after the introduction of biofuel mandates), also examining the gradual structural changes.

The remainder of the chapter is structured as follows: The next section focuses on existing empirical evidence on commodity-financial and agricultural-energy linkages, which is followed by a brief description of the methodology. Subsequently, we present and discuss our modeling results and compare them to previous studies. The final section concludes the analysis.

9.2 Previous Empirical Results on Market Linkages

Agriculture-energy market linkages via the use of crops in biofuel production or the use of energy as an agricultural production input are frequently researched. In comparison, research on commodity-financial market linkages is scarce and only recently gaining momentum (Chan et al. 2011).

9.2.1 Agricultural-Energy Market Linkages

We reviewed recent empirical studies which focused on volatility linkages and which covered at least part of the time period after the subprime crisis.[1] The studies typically split their data sample at around either 2006, due to a hypothesized structural change in market linkages after the introduction of biofuel mandates, or 2008, reflecting the potential effects of the financial and food price crises. Most studies used daily data, while Gardebroek and Hernandez (2012) and Du et al. (2011) used weekly data.

To investigate volatility dependencies, Nazlioglu et al. (2013) and Harri and Hudson (2009) conducted Granger causality in variance tests (cf. Cheung and Ng 1996). Nazlioglu et al. (2013) found no linkages between the volatility of daily energy and agricultural spot prices before 2005. The only exception is wheat, which Granger causes the variance of crude oil in that period. Likewise, Harri and Hudson (2009) did not detect any linkages between the volatility of daily corn and crude oil futures prices in the period before 2006. For the period after 2006, Nazlioglu et al. (2013) found volatility spillovers from crude oil to corn and bidirectional spillovers between crude oil and soybeans and between crude oil and wheat. Harri and Hudson (2009) only discovered Granger causality in mean, but not in variance, from crude oil to corn.

Du et al. (2011) used bivariate weekly stochastic volatility models to analyze corn, wheat, and crude oil futures returns for the period 1998–2009. They detected increasing volatility transmission from crude oil to both corn and wheat as well as volatility transmission between corn and wheat in the later subsample 2006–2009.

Several studies employed multivariate GARCH models. Gardebroek and Hernandez (2012) estimated both BEKK and DCC trivariate GARCH models for weekly US corn, crude oil, and ethanol spot prices for the period 1997–2011. There are some short-run volatility spillovers from corn to ethanol but no significant volatility spillovers in the other direction. Structural break tests and subsequent sample splits showed that volatility persistence is stronger in all markets after 2008. Trujillo-Barrera et al. (2011) estimated BECKK GARCH models with daily futures returns for US crude oil, ethanol, and corn for the period 2006–2011. Similar to Gardebroek and Hernandez (2012) they found that the volatility linkages between corn and ethanol increased after 2007, with significant volatility spillovers from corn to

[1] This remains a vibrant field of research. Any omissions are not deliberate.

ethanol but only modest spillovers from ethanol to corn. But they did find strong volatility spillovers from crude oil to both corn and ethanol markets. Ji and Fan (2012) and Chang and Su (2010) employed bivariate E-GARCH models. Chang and Su (2010) used daily returns to examine the relationships between crude oil, corn, and soybean futures during the period 2000–2008. Before 2004, there were no significant volatility spillovers from crude oil to either corn or soybeans; however, this changed in the 2004–2008 period. Ji and Fan (2012) used daily returns of crude oil futures and several Commodity Research Bureau (CRB) indices for the period 2006–2010 and introduced the US Dollar exchange rate as an exogenous shock. They found that volatility spillovers from crude oil to the CRB crop index decrease after the subprime crisis.

9.2.2 (Agricultural) Commodity-Financial Market Linkages

We reviewed recent empirical studies that (1) covered at least part of the period of the subprime crisis and (2) also considered corn, soybeans, wheat, or a relevant commodity index in their sample. Most studies focused on the relationships between selected US commodities and equity markets. Other financial asset classes, especially real estate, are underrepresented. In the past, the emphasis was on return linkages, but volatility dependencies are moving into focus.

Volatility relations are also mostly examined using multivariate GARCH models. Gao and Liu (2014) used bivariate regime switching GARCH models for analyzing the weekly relationships between the S&P 500 index and selected commodity indices from 1979 to 2010. The volatility linkages between the S&P 500 and both the grains and energy indices only slightly increase in the few brief periods whereby the assets shared a high volatility regime. But regime switches in the energy index appeared more closely related to equity volatility than those in the grains index. Mensi et al. (2013) estimated bivariate VAR-GARCH models for pairs of indices for the period 2000–2011; the pairs consisted of the S&P 500 and the following indices: daily wheat, beverage, gold, crude oil, and Brent oil price. Past volatility and unexpected volatility shocks to the S&P 500 have significant effects on oil, gold, and beverage markets, but not on wheat markets. For commodity-foreign exchange relations, Ji and Fan (2012) found that volatility spillovers from the US Dollar index to the CRB crop index were weaker after the subprime crisis than before it; Harri and Hudson (2009) observed Granger causality in mean but not in variance from the US Dollar exchange rate to corn futures prices in the periods before and after 2006.

Diebold and Yilmaz (2012) used their volatility spillover indices to investigate volatility linkages between the DJ UBS Commodity index and the following over the period 1999–2010: the S&P 500, US Treasuries, and the US Dollar index. They found a significant increase in linkages between the DJ UBS Commodity index and the other markets after the beginning of the subprime crisis. Volatility spillovers from the S&P 500 to the commodity index occurred throughout the crisis, while the commodity index volatility spilled over into US Treasuries and the US Dollar index during the middle of and the end of the last decade.

Multivariate GARCH models have also been used to investigate commodity-financial return linkages. Using a bivariate DCC GARCH model for the period 1991–2008, Büyükşahin et al. (2010) found that negative weekly conditional return correlations between (1) the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI), (2) its energy sub-index, and (3) the DJ UBS Commodity index and equities peaked during 2003–2004; the correlations also peaked to a lesser extent at the beginning of the subprime crisis. Correlations between the S&P 500 and the S&P GSCI agricultural index returns appeared unaffected by the crisis. Creti et al. (2013) used bivariate DCC GARCH models to examine the relationship between the daily S&P 500 returns and (1) 25 sampled commodity spot returns, and (2) the CRB index for the period 2001–2011. While they found that dynamic correlations decreased during the subprime crisis for most of the sampled commodities, return correlations between crude oil and the S&P 500 increase in times of increasing, and decrease in times of decreasing stock prices. In contrast, Silvennoinen and Thorp (2013), who used a bivariate DSTCC GARCH[2] model with weekly data between 1990 and 2009, showed that conditional weekly return correlations of equities and two commodities (corn and soybeans) increased in the period 2002–2003, while correlations of equities and two other commodities (wheat and crude oil) peaked in mid-2008. Commodity-bond relations remain relatively constant. Similarly, results from the DCC GARCH model in Huang and Zhong (2013) for the days between 1999 and 2010 and for the months between 1979 and 2010 showed that conditional correlations of the S&P GSCI and US bonds did not considerably increase during the subprime crisis. Yet, conditional rolling return correlations between the S&P GSCI and equities increased from negative to strongly positive. In addition, mean-variance spanning tests revealed that the S&P GSCI, Real Estate Investment Trusts (REITs) and US inflation-linked securities each offered unique portfolio diversification benefits, suggesting relatively weak market linkages. Finally, Bicchetti and Maystre (2013) examined rolling window bivariate intraday return correlations of equities and several commodities (corn, wheat, soybeans, and crude oil) for the period 1996–2011. The authors found an increase in correlations between all sampled commodities and equity returns after September 2008, which declined again in 2011 only in the case of crude oil.

Thus, there are some indications of increased volatility or return linkages between agricultural and energy markets, and between commodity and financial markets around 2006–2008. But, in the case of the agricultural-energy correlation, results are rather mixed. In the case of the commodity-financial correlation, the strongest effects appear to exist between US equities and crude oil. In both cases, the time-dependent dynamics and the direction of influence remain unclear. The majority of the studies focused on using multivariate GARCH models and therefore have to restrict their investigation to a bivariate or at maximum trivariate model.

[2]Dynamic Smooth Transitional Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity model.

9.3 Description of the Methodology and Data

Volatility spillover indices introduced by Diebold and Yilmaz (2009, 2012) allow a larger sample of asset markets to be included while permitting a time-dependent analysis of gradually changing volatility relations. Their computation requires externally calculating a volatility proxy variable, which is then used in the rolling VAR model estimation.

Given that there is no universally accepted best volatility measure (Engle and Gallo 2006), a choice has to be made based on informational content, interpretability, and statistical properties. We expect financial linkages between markets to mostly affect short-term volatility relations. Therefore, we used the range volatility proxy that was described in Parkinson (1980), which has also been shown to have superior statistical properties over the classical volatility proxy. The classical volatility proxy is calculated as the variance of daily returns, which may be associated with large, non-Gaussian measurement errors (cf. Parkinson 1980; Alizadeh et al. 2002; Chiang and Wang 2011). The range is calculated as:

$$\text{Range}_{it} = 0.361\left[\ln\left(\frac{\text{high}_{it}}{\text{low}_{it}}\right)\right]^2, \tag{9.1}$$

where high is the highest and low the lowest price observed on a trading day t.

9.3.1 Data

We use a sample of CBOT corn, soybeans and (soft red winter) wheat futures, New York Metal Exchange (NYMEX) WTI crude oil futures, the S&P 500 US equity index, the Dow Jones Equity all REIT index, CBOT 10-year US Treasury Note futures, and the Intercontinental Exchange (ICE) Futures US Dollar index. The REITs index consists of all US publicly traded companies within the Dow Jones stocks indices that are classified and taxed as equity REITs. The US Dollar Index is a geometrically averaged index of exchange rates of a basket of currencies against the US dollar; the basket comprises the euro, Japanese yen, British pound, Canadian dollar, Swedish krona, and Swiss franc.[3] Price and volume data were obtained from Bloomberg for trading days between 3 June 1998 and 31 December 2013.[4] Missing observations were replaced by a linear interpolation.[5] All futures prices are historical first generic price series, and expiring active futures contracts are rolled to the next deferred contract after the last trading day of the front month.[6]

[3]Weights are as follows: Euro: 57.7 %, Yen: 13.6 %, British Pound: 11.9 %, Canadian Dollar: 9.1 %, Swedish Krona: 4.2 %, Swiss Franc: 3.6 %.

[4]Data for the REIT index is not available prior to that period.

[5]Interpolation implemented with the MATLAB linear interpolation function.

[6]This corresponds to Bloomberg's "relative to expiration" rolling procedure.

9.3.2 Generalized Forecast Error Variance Decompositions

The FEV decompositions split the FEV of the range of each asset i included in a VAR model into shares stemming from own shocks and shares stemming from shocks to the range of another asset j. A VAR model with lag length p (VAR(p)) that consists of range observations for all assets is written as $y_t = A_0 + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \upsilon_t$, where y_t is a $N \times 1$ vector of range volatilities and N corresponds to the number of assets in the system. A_i is a fixed coefficient $N \times N$ matrix (including intercept terms), and u_t is a $N \times 1$ vector of white noise innovations, such that $E(u_t) = 0,\ E(u_t u_t{}') = \Sigma$ and $E(u_t u_{t-s}) = 0$. The equivalent VAR(1) in matrix notation is given as $Y_t = c + AY_{t-1} + U_t$, where

$$
\underset{N \cdot p \times 1}{Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}};\ \underset{N \cdot p \times 1}{c = \begin{bmatrix} c \\ 0 \\ \vdots \\ 0 \end{bmatrix}};\ \underset{N \cdot p \times N \cdot p}{A = \begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_N & 0 & \dots & 0 & 0 \\ 0 & I_N & & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_N & 0 \end{bmatrix}};\ \underset{N \cdot p \times 1}{U_t = \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}}.
$$

The Moving Average (MA) representation of this process is $y_t = \mu + \sum_{h=0}^{\infty} \Phi_h u_{t-h}$ with $\Phi_h = JA^h J'$ and $J = [I_N : 0 : \ldots : 0]$, which is a $N \times N{\cdot}p$ selection matrix (Lütkepohl 2007, pp. 15ff.). The coefficient matrices Φ_h contain the impact multipliers of the system. Their element $\phi_{ij,h}$ describes the response of the ith asset range volatility to a shock in the jth asset range volatility, h periods ago. $\Phi_j(h)$ is the corresponding impulse response function.

The elements in u_t are correlated and estimation of the coefficient matrix Φ_h requires external coefficient restrictions. One possibility is to orthogonalize the shocks, e.g., via a Cholesky decomposition of the covariance matrix (Σ), such that the orthogonalized impulse response function traces the system's response to a *specific ceteris paribus shock* in the range of asset j over time. But this makes impulse responses sensitive to the variable ordering in the VAR model (Enders 2010, p. 309). As we investigate volatility interactions within a system of different asset markets, such an order is difficult to impose and introduces an unwanted element of subjectivity into the estimation.

Generalized impulse responses are an alternative restriction method developed by Koop et al. (1996) and extended by Pesaran and Shin (1998). The generalized impulse response function is computed as $\Phi_j^g(h) = \sigma_{jj}^{-\frac{1}{2}} \Phi_h \Sigma e_j$, where σ_{jj} is the variance of the error term in the equation for the jth range volatility and e_j is a $N \times 1$ selection vector containing 1 as its jth element and is 0 otherwise (Pesaran and Shin

1998). These impulse responses represent how the range of asset i responds to a shock in the range of asset j, taking into account the contemporaneous correlations contained in Σ (Pesaran and Pesaran 1997, p. 428). The impulse response function thus traces the system's response to a *typical composite shock* emanating from the range in asset j (Pesaran and Shin 1998). The responses are independent of variable ordering and are therefore more suitable for use in an analysis of our asset market system. Pesaran and Shin (1998) calculated generalized FEVs (θ_{ij}^{g}) as:

$$\theta_{ij}^{g}(h) = \frac{\sigma_{jj}^{-1} \sum_{l=0}^{h-1} \left(e_i' \Phi_l \Sigma e_j\right)^2}{\sum_{l=0}^{h-1} \left(e_i' \Phi_l \Sigma \Phi_l' e_i\right)}, \; i, \, j = 1, 2, \ldots, N \tag{9.2}$$

where the subscript l denotes the respective forecast period.[7] The correlated shocks lead to a non-diagonal Σ, and elements in the rows of the θ_{ij}^{g} matrix will not sum up to 1.

9.3.3 Volatility Spillover Indices

Time-varying volatility spillover indices require a rolling estimation of the VAR(p) model. A regression window of size w and T observations for the range volatilities will give a total of $T-w+1$ estimates for the θ_{ij}^{g} matrices. For a system of N assets, the elements off the main diagonal in the θ_{ij}^{g} matrices show the contributions of shocks to the range of assets $j = 1, \ldots, N$ to the h-step ahead FEV for the range of assets $i = 1, \ldots, N$, with $i \neq j$ and the diagonal elements denoting the contributions of own shocks. Analogous to the definitions as given by Diebold and Yilmaz (2012), a spillover is defined as the share of the contributions of shocks to the range of assets $j = 1, \ldots N$ in relation to the total FEV of the range of assets i with $i \neq j$. This constitutes the basis for the spillover index calculations.

First, the θ_{ij}^{g} matrices were normalized with the respective row sums such that the entries in each row sum up to 1.[8] Consequently, the total FEV across the range for all assets in the system is equal to N. The definitions and formulas to calculate the individual spillover indices according to Diebold and Yilmaz (2012) are presented in Table 9.1.

[7] The typographical error in Pesaran and Shin (1998, pp. 20 ff.), where σ_{ii} was used instead of σ_{jj}, as pointed out in Diebold and Yilmaz (2011, p. 6), has been corrected.

[8] As suggested in Diebold and Yilmaz (2012), it would also be possible to normalize with the column sums.

Table 9.1 Volatility spillover indices

Total spillover index (TOTAL)	
Sum of spillovers to the range across all asset classes in relation to the total FEV in the system	$\mathrm{TOTAL}(h) = \frac{\sum_{i,j=1, i \neq j}^{N} \theta_{ij}^{g}(h)}{N} \times 100$
Directional spillover index from all other assets (FROM)	
Spillovers received by the range of asset i from the range of all other assets $j = 1, \ldots, N, j \neq i$, in relation to the total FEV in the system	$\mathrm{FROM}_i(h) = \frac{\sum_{j=1, j \neq \mathrm{i}}^{N} \theta_{ij}^{g}(h)}{N} \times 100$
Directional spillover index to all other assets (TO)	
Spillovers transmitted by the range of asset i to all other assets $j = 1, \ldots, N, j \neq i$, in relation to the total FEV in the system	$\mathrm{TO}_i(h) = \frac{\sum_{j=1, j \neq \mathrm{i}}^{N} \theta_{ji}^{g}(h)}{N} \times 100$
Net spillover index (NET)	
Spillovers transmitted by the range of asset i to the range of all other assets $j = 1, \ldots, N, j \neq i$ less spillovers received from the range of all other assets $j = 1, \ldots, N, j \neq i$, in relation to the total FEV in the system	$\mathrm{NET}_i(h) = \mathrm{TO}_i(h) - \mathrm{FROM}_i(h)$
Net pairwise spillover index (PAIR)	
Spillovers transmitted by the range of asset i to the range of one specific asset j, $j \neq i$, less spillovers received from the range of this asset j, in relation to the total FEV	$\mathrm{PAIR}_{ij}(h) = \left(\frac{\theta_{ji}^{g}(h) - \theta_{ij}^{g}(h)}{N} \right) \times 100$

9.4 Empirical Results

We calculated the assets' range volatilities (for detailed results, see Grosche and Heckelei 2014) and used them in the rolling VAR estimation, from which we computed the volatility spillover indices. We also discuss the results and relate the findings to the current literature.

9.4.1 Rolling VAR Estimation and Spillover Index Calculation

We used logged range volatilities and included a total of 3930 observations for each of the eight assets for a window length of 252 trading days. This reflects the volatility movements within one trading year and, at the same time, yields a sufficient number of observations to estimate the VAR. Lag length selection with the Schwartz Bayesian Criterion (SBC) yielded a VAR(5), and the FEV matrices were calculated for a forecast horizon of 10 days. The length of a forecast horizon depends on the underlying assumption regarding the time horizon of asset market

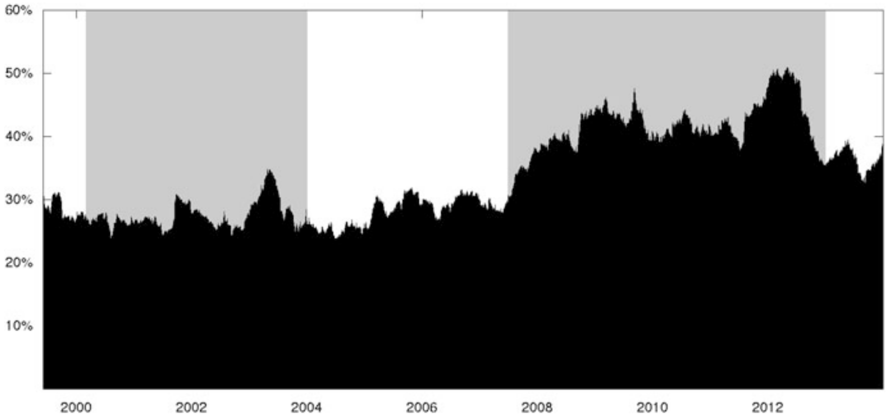

Fig. 9.1 Total volatility spillover index

linkages. A forecast horizon of 10 days is commonly used in calculating financial value at risk (Diebold and Yilmaz 2011). We obtained a total of 3679 observations for each spillover index, and the first observation corresponds to the end of the first regression window (2 June 1999). More details on the rolling VAR estimation, including verification of the robustness of the obtained results, are included in Grosche and Heckelei (2014).

Figure 9.1 shows the total volatility spillover index between 2 June 1999 and 31 December 2013. The areas shaded in gray mark the two major crisis periods of the last decade. The first period of crisis, between March 2000 and December 2003, was characterized by the burst of the dot.com bubble, the NASDAQ crash, and the overall downturn in equity markets. The real economy in the USA and the EU experienced low GDP growth rates. The events of September 11, 2001, and the wars in Afghanistan and Iraq led to political unrest. Agricultural commodity markets were influenced by (1) the continual efforts of the EU to reduce buffer stocks, (2) China's accession to the WTO in December 2001, and (3) growing US soybean exports.

The second period of crisis, between July 2007 and December 2012, started with the early events of the subprime crisis and transformed into a global liquidity crisis; it later evolved into a sovereign bond and state debt crisis. The US Federal Reserve Bank lowered interest rates 12 times successively between August 2007 and December 2008, and the real economy in the US and the EU was hit with low or even negative GDP growth rates. Agricultural commodity markets experienced further growth in soybean exports to China and were affected by the introduction of biofuel mandates in the EU and the USA. At the beginning of the period, the stock-to-use ratios for corn and wheat were at low levels of around 13 % and 18 % respectively, while the stock-to-use ratio for soybeans peaked at 21 % (USDA ERS 2012). Commodity ETP assets under management strongly increased from 6.3 billion US dollars in 2007 to 45.7 billion US dollars in 2010 (BlackRock 2011).

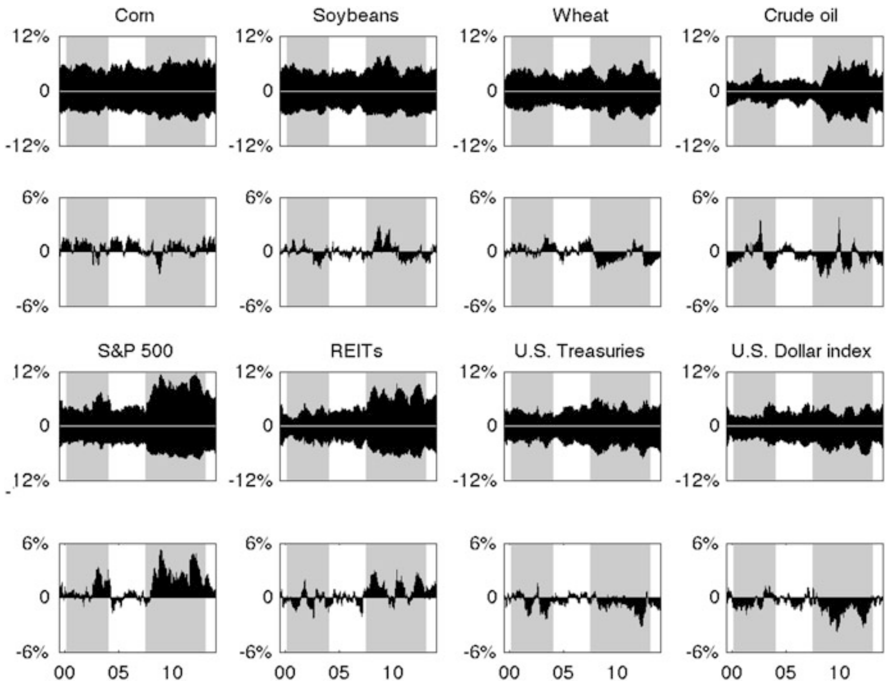

Fig. 9.2 Directional and net spillover indices. *Note*: The *upper graphs* in each pair show the spillovers from and to this asset compared to all other assets in the system. The *lower graphs* are the resulting net volatility spillover indices, where a *positive* (*negative*) value indicates that the asset is a net volatility transmitter (receiver)

Volatility spillovers were at much higher levels in the second period of crisis than the first. While there are two spikes in the first period of crisis (31 % in September 2001 and 35 % in April 2003), the average total spillover between 1 March 2000 and 31 December 2003 amounted to 26 %. In comparison, the average total spillover between 1 July 2007 and 31 December 2012 was 42 %. The index peaked at 51 % on 3 May 2012.

Directional spillovers and the resulting net spillover indices are depicted in Fig. 9.2. During the first crisis, neither of the commodity markets showed a distinct pattern and the indices moved almost horizontally into the tranquil interim period. Only crude oil and, to some extent, wheat futures have spiking directional volatility spillovers. Net spillovers from crude oil peaked at 3.4 % in August 2002, and net spillovers from wheat at 1.8 % in May 2003. In contrast, during the second crisis, volatility spillovers to and from the commodity markets were at higher levels; the net spillover patterns also differ from the previous periods. The changes in the magnitude of volatility spillovers to and from crude oil were, again, most pronounced. And, crude oil was mostly a net volatility receiver during most of the crisis period. Notable spillovers also occurred in wheat and soybean markets. The net volatility transmission from soybeans to other assets reached up to 2.9 % in September 2008. Wheat markets were net volatility receivers and peaked at 1.9 % in June 2008. Only corn market volatility spillovers appeared relatively unaffected by the crisis and showed only a slight increase in level.

Among the financial asset markets, the S&P 500 is the largest net volatility transmitter in the system, with visible increases in the period of crisis (up to 3.4 % in February 2003) and very pronounced peaks in the second crisis period (up to 5.3 % in November 2008). In contrast, the US Treasuries and the US Dollar index were both volatility receivers during the two periods of crisis. Again, the effect was more pronounced in the second crisis, whereby net spillovers to the US Treasuries reach up to 3.2 % in March 2012 and spillovers to the US Dollar index up to 3.7 % in October 2009. The REITs market showed the biggest change in volatility interaction between the two crisis periods. While the REITs market alternated between being a net volatility transmitter and being a net volatility receiver during the first crisis, it almost unexceptionally transmits volatility to of up to 3 % during the later crisis.

The pairwise spillover indices allow for the most detailed investigation of structural changes in volatility interaction between agricultural and energy commodities as well as between commodity and financial asset markets.[9] Figure 9.3 shows the pairwise indices for the agricultural commodities. Over most of the observation period, corn was transmitting volatility to the soybean market at a general magnitude of between 3 and 6 %. There was no marked difference between the first crisis and the interim tranquil period. But during the second crisis, the volatility spillover relationship was reversed. Between 2008 and 2010, soybean markets were transmitting volatility of up to 7.5 % to corn markets in September 2008. In parallel to this development, the volatility spillover relationship between soybeans and wheat also changed. Starting in 2008, soybeans became net transmitters of volatility to wheat, with a peak of 6 % in June 2009. Wheat was mostly a net volatility receiver from corn at a magnitude of up to 4.7 % in September 2002 and 6.5 % in January 2010. There were, however, exceptions occurring (1) towards the end of the first crisis, (2) shortly before the second crisis began, and, most importantly, (3) between 2010 and 2012, when wheat spillovers to corn reach up to 5.3 % in February 2011.

Figure 9.4 shows the indices for the agricultural-crude oil pairs. Corn was transmitting volatility to crude oil during most of the tranquil period, before the first crisis (up to 5 % in March 2000), and during the second crisis (up to 5.3 % in July 2009). This relation was reversed and crude oil transmitted volatility to corn in the following two periods: (1) between November 2001 and January 2003, during the first crisis, and (2) after February 2011, during the second crisis; spillovers reached up to 6.1 % in September 2002 (the first crisis) and 2.6 % in May 2011 (the second crisis). The soybean–crude oil volatility linkages almost perfectly mirrored this development. Soybeans mostly transmitted volatility to crude oil and received volatility of up to 5.2 % in July 2002, during the early crisis, and

[9] Pairwise indices for financial asset markets cannot be discussed in detail in this chapter, but are available from the authors upon request.

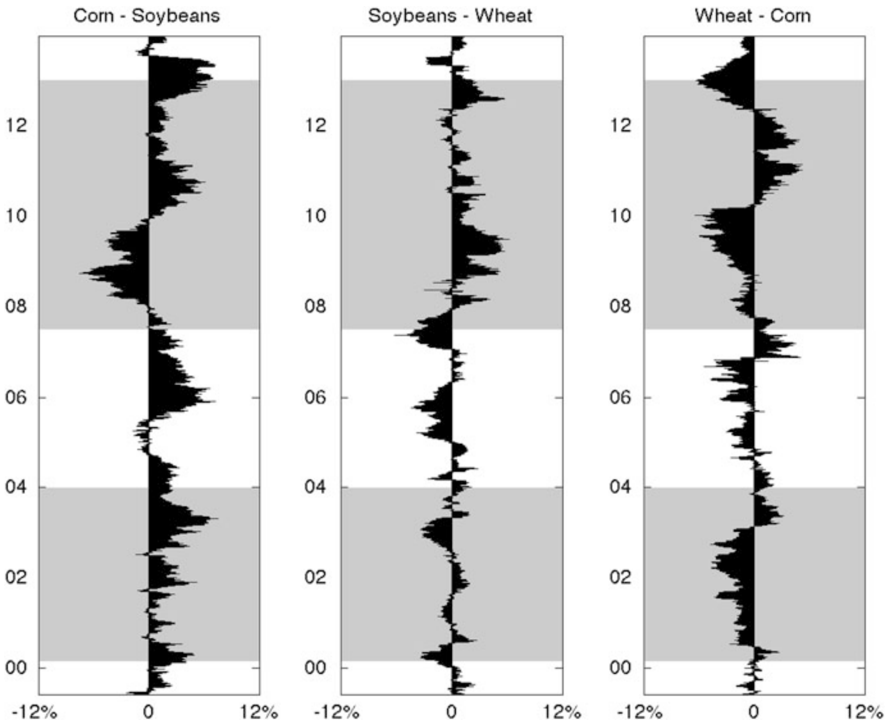

Fig. 9.3 Pairwise spillover indices: agricultural commodities

up to 4.5 % in May 2011, during the later crisis period. While wheat was also mostly transmitting volatility to rather than receiving volatility from crude oil, the magnitude of interaction between the markets' volatility is generally lower than in the case of corn and soybeans. But there was one notable spillover spike of up to 12 % in June 2003. And during the tranquil period, we observed some stronger spillovers from wheat to crude oil of up to 5.4 % in June 2006.

Figure 9.5 shows the pairwise indices for the commodities and the financial asset markets. During the early crisis, volatility from the S&P 500 predominantly spilled over into corn and wheat markets, with a high of 6.4 % in February 2003 for corn and 4.3 % in November 2002 for wheat. Soybean markets, in contrast, were mostly net transmitters of volatility to the S&P 500 during that period. While crude oil markets received some spillovers, they also transmitted volatility to the S&P 500 during November 2001 and October 2002, with a strong magnitude of up to 10.6 % in August 2002. But during and after the second crisis, there was a notable change in this volatility spillover relationship, both in direction and in magnitude. Crude oil mostly received volatility from the S&P 500, peaking at 10.8 % in December 2010. A less pronounced but nevertheless visible change occurred in corn and wheat markets, whereby net spillovers from the S&P 500 increased in magnitude around the time of the subprime crisis, with peaks of 5.3 % in October 2008 for corn and of

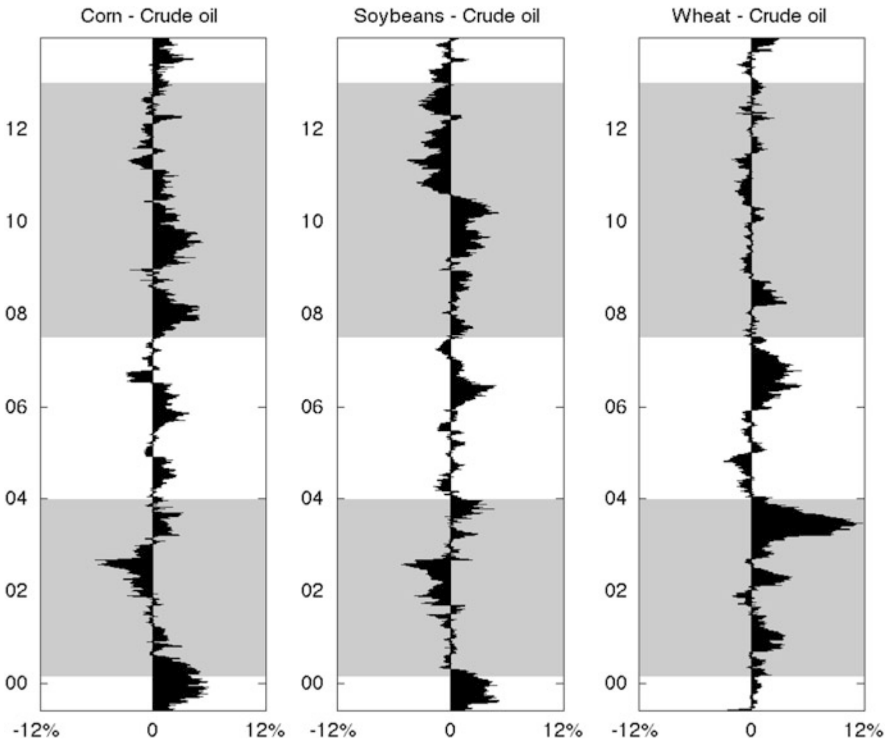

Fig. 9.4 Pairwise spillover indices: agriculture—crude oil

6.7 % in April 2008 for wheat. Soybean markets showed no change in the magnitude of spillover relationships, but in contrast to the crisis in the early 2000s, they became mostly net volatility receivers from the S&P 500.

While the REITs market was a net volatility transmitter to all commodities during parts of the first crisis, this tendency continued for most commodities (except soybeans) into the tranquil interim period. During the crisis, spillovers rose to 4.7 % in January 2003 for corn, 3.8 % in October 2001 for wheat, 4.7 % in January 2003 for soybeans, and 4.5 % in January 2002 for crude oil. For the agricultural commodities, there was no marked difference in spillover patterns during the later crisis. But, in parallel to the developments in the volatility relation with the S&P 500, crude oil started to receive markedly higher net spillovers from the REITs market of up to 9.3 % in February 2009. There was only a short period of reversed transmission between July 2009 and April 2010.

Net spillover between commodities and US Treasuries occurred bidirectionally during both the early crisis and the tranquil period. But there were some exceptions. Around December 2001, there was a period in which volatility of up to 7.2 % spilled over from soybean markets into Treasuries. In the second crisis, corn and wheat markets were almost exclusively net receivers of volatility from the US Treasury

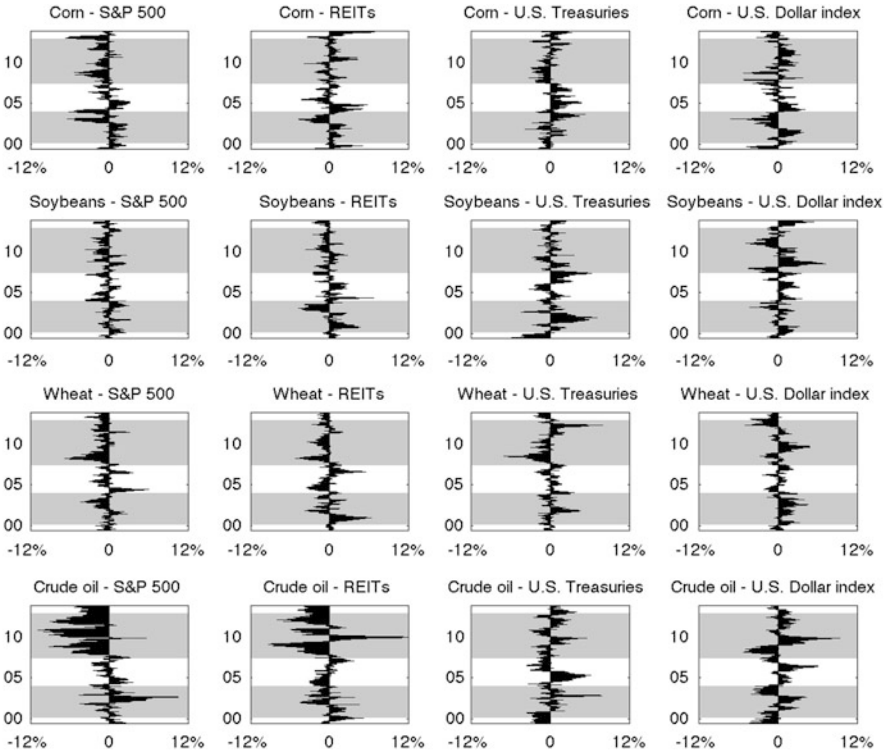

Fig. 9.5 Pairwise spillover indices: commodity—financial assets

(up to 3.2 % in March 2008 for corn and 7 % in July 2008 for wheat), while for soybeans and crude oil, the patterns were less distinct.

Towards the end of the first crisis, the US Dollar index transmitted volatility to the corn, soybean, and crude oil markets: up to 7.1 % in February 2003 (corn), 4.3 % in March 2003 (soybeans), and 4 % in December 2002 (crude oil), while during almost the entire crisis period wheat was a net volatility transmitter to the index with a peak of 4.6 % in August 2002. During the second crisis, however, soybeans, crude oil, and wheat markets transmitted net volatility to the US Dollar index: up to 7.2 % in August 2008 (soybeans), 4.9 % in September 2009 (wheat), and 9.4 % in December 2009 (crude oil), while the net volatility transmission of corn markets was lower and had a less clear direction.

9.4.2 Discussion of Results

The analysis of the above volatility spillover indices does not permit any direct causal attribution of single spillovers. Nevertheless, it is interesting to examine the results in the light of the political and economic developments on the markets and in relation to existing empirical findings about volatility linkages.

The total volatility spillover index shows a distinct increase in range volatility interdependence between the markets during the second period of crisis. While the levels of individual range volatilities were also high at the height of the subprime crisis, the total spillover index peaked only in May 2012, when the volatility levels of individual markets decreased again. In comparison, during the first crisis, there were only two smaller volatility spillover spikes despite high volatility levels in some markets. Thus, over the course of the subprime crisis, the movements of individual volatilities became increasingly synchronized with each other, and they also experienced significant parallel jumps. On the other hand, the period of increased volatility interdependence stretched beyond the period of individual volatility jumps, pointing to a generally higher degree of market interaction.

Directional and net volatility spillover indices showed that the S&P 500 was the strongest volatility transmitter among the assets during the financial crises. Thus, the drivers behind the S&P 500 range volatility would likely also influence the range volatility in other markets. The magnitude of spillovers to and from the other financial asset markets was much lower. Although REITs are also a component of the S&P 500, the stand-alone REITs spillover indices can better illustrate the volatility linkages during the subprime crisis, when REITs were strong net volatility transmitters and remained so until the end of the observation period. US Treasuries, in contrast, are traditionally refuge assets, towards which liquidity is shifted during general economic recessions and individual market crises (e.g., equity or real estate). This effect is visible on the spillover indices, whereby US Treasuries were net volatility receivers during both crisis periods. Unsurprisingly, net spillovers were especially high during the sovereign bond crisis at the end of the second crisis period. The US economy experienced an economic recession during both crisis periods, which affected demand for the US dollar. But the US dollar is also the most important currency for international monetary reserves. While the US Dollar index is a net volatility receiver during both crisis periods, the levels of spillovers increased in the second period, at a time when both the need to adjust monetary reserves and to allocate liquidity to comparably safer US Treasuries was high.

9.4.2.1 Agricultural: Energy Linkages

Corn appeared to be the strongest volatility transmitter among the agricultural commodities, with significant spillovers into both wheat and soybeans. This is plausible as (1) the USA is the world's largest producer of corn and a significant acreage area is allocated to growing corn, and (2) trading volumes of corn futures were much higher on the CBOT than of soybean and wheat futures. Therefore, information is most likely disseminated from corn markets to other affected futures markets rather than in the opposite direction. While seemingly unaffected by the early crisis, the corn–soybean relationship reversed between 2008 and 2010. During that time, soybeans also transmitted volatility to wheat. This effect could be related to China's surging demand for soybeans, which shocked the soybean market and also affected corn and wheat through substitution effects.

The pairwise agriculture-energy spillover indices show that the magnitude of spillovers between both corn and soybeans and crude oil is higher than for wheat. The level of spillovers did not considerably change after 2006; therefore, this effect cannot be clearly attributed to biofuel production. In fact, the spillover indices do not yield any convincing evidence that an increase in spillovers from the energy to relevant commodity markets was a result of the biofuel mandates. While there were some spillovers from crude oil markets to both corn and soybeans markets in the first crisis, between 2006 and 2010, both markets transmitted volatility to crude oil rather than receive it. Only soybeans experienced a clear reversal in that relationship after 2010.

These results are mostly in line with the findings of Gardebroek and Hernandez (2012), who, based on weekly conditional volatility over the period 1997–2011, did not discover evidence of energy volatility spilling over to corn price volatility. And while Ji and Fan (2012) did find significant linkages in the conditional daily volatility between crude oil and the crop index (which includes corn, wheat, soybeans, soft commodities, livestock, and cotton), they also found a decrease in spillovers during the subprime crisis. On the other hand, the results contradict the findings of, e.g., Nazlioglu et al. (2013), Du et al. (2011), and Chang and Su (2010). Using their respective models and volatility measures, they showed that volatility spillovers between crude oil and (1) corn, (2) wheat, and (3) soybeans increased after 2006. But Nazlioglu et al. (2013) also found bidirectional spillovers between (1) crude oil and soybeans and (2) crude oil and wheat after 2006, which is again closer to the results obtained from the spillover indices.

The extraordinary spike (up to 12 %) in the volatility spillovers from wheat into crude oil in June 2003 would merit a closer (causal) investigation. There could be some connection to the end of the UN Iraq oil-for-food program in 2003, which was used by the Iraqi government to secure wheat supplies in exchange for crude oil. It is interesting that Nazlioglu et al. (2013) also found Granger causality in variance from wheat to crude oil before 2005, but it could not be found after 2005.

Thus, there is little indication that short-term daily range volatility linkages in the corn, soybean, and wheat markets were affected by biofuel policies. This is in contradiction to some findings derived using the GARCH-type models. The contradictions could stem from the choice of sample splits and restricting sample size to two or three markets. In this chapter, the volatility spillovers were calculated for a more comprehensive system of asset markets; some of the apparent bivariate volatility spillovers may be absorbed by other markets. Also, structural breaks were not exogenously imposed. Instead, more gradual structural changes were permitted.

9.4.2.2 Commodity: Financial Linkages

The linkages between commodity and financial markets vary strongly depending on the commodity and financial asset class involved. In the first crisis, there were few instances of S&P 500 volatility spilling over to commodities, and the spillovers were low magnitude. However, there were some spillovers from crude oil *into* the S&P 500, which could be explained in terms of fundamentals with the wars in Afghanistan and Iraq. Our findings thus lend strength to the results of Diebold and Yilmaz (2012), who speculated that the range volatility spillover between DJ UBS Commodity index and the S&P 500 during that time were linked to the Iraq war. During and after the second crisis, however, all commodity markets were net S&P 500 spillover receivers. This is again similar to and an extension of the findings in Diebold and Yilmaz (2012) about the DJ UBS Commodity index. Our results generated from data on individual commodity markets allowed for further disaggregation of the spillovers and showed that most net spillovers reached the crude oil market. Yet, corn and wheat also received some transitory spiking net spillovers. All commodities, and especially crude oil, have strong fundamental and financial linkages with US equities because they are inputs in production and components of all important commodity indices, in which crude oil is generally given higher weights than corn, soybeans, or wheat. An increase in short-term range volatility linkages was observed during a time when both commodity index-linked products became more widespread and commodity trading volume increased. This provided evidence in favor of the hypothesis that the financial linkage factor became more important in the second crisis period.

Our results lend strength to the existing results about volatility linkages between the S&P 500 and commodities. Mensi et al. (2013) have shown that volatility shocks to the S&P 500 can significantly affect the oil market; the results of their study are also confirmed for range volatility spillovers. Gao and Liu (2014) found that correlations between energy and grains indices and the S&P 500 increase in periods of volatility, which is also in line with the results above. But, in their model, US energy indices and grains indices did not frequently share common volatility regimes with the S&P 500, and this led the authors to conclude that commodities remain an attractive portfolio diversifier. Yet, the spillover indices show stronger volatility relationships, especially between the S&P 500 and crude oil, which may in fact decrease diversification benefits. In addition, our results for spillovers complement the evidence of increased dynamic conditional return correlations between commodities and the S&P 500 during and after 2008 (e.g., Huang and Zhong 2013; Bicchetti and Maystre 2013; Büyükşahin et al. 2010). The observation made by Creti et al. (2013) that oil-S&P 500 return correlations increase with increasing stock prices could not be confirmed for daily range volatility spillovers (rather, it increase with decreasing stock prices).

The fundamental connection between REITs and commodity markets is much weaker than the connection between commodities and the S&P 500. Nevertheless, volatility spillovers from REITs into crude oil were high in the early 2000s and surged in the late 2000s crisis. This provides additional evidence in favor of the financial linkage hypothesis. But agricultural commodities appear to have much weaker linkages to REITs markets. Volatility spillovers between commodities and US REITs have barely been analyzed in the literature. Somewhat related to our results, Huang and Zhong (2013) showed that commodities and REITs (along with inflation-protected securities) each offer unique diversification benefits that tend to disappear during a financial crisis.

In contrast to the S&P 500 and REITs, the magnitude of range volatility spillovers between commodities and US Treasuries generally appears unaffected by either of the crisis periods. This confirms results of Huang and Zhong (2013), who also found that conditional correlations between the S&P GSCI and US Treasuries did not significantly increase during the subprime crisis. The net spillovers from the DJ UBS Commodity index to US Treasuries identified by Diebold and Yilmaz (2012) were further disaggregated in our model, and they appear to stem mostly from crude oil and soybeans as both wheat and corn markets are net receivers of volatility from US Treasuries during that period.

The US Dollar index receives net volatility spillovers from wheat, soybeans, and crude oil during both crisis periods. But spillovers increased in magnitude during the late 2000s crisis. This could be related to China importing more soybeans and crude oil and the associated changes in the demand for the US dollar. Another explanation is foreign activities on US commodity futures markets. The corn-US Dollar index relationship is less clear, and during the second crisis period, corn transmits less volatility to the US Dollar index than the other commodities. Linkages could have decreased following the drop in US corn exports. Corn was increasingly used for the domestic biofuel production in the USA. The findings of Diebold and Yilmaz (2012) about the spillovers between the DJ UBS Commodity index and the US Dollar index are substantiated for most individual commodities, and crude oil does not appear to be the main driver of the spillover. Ji and Fan (2012) found that volatility spillovers from the US Dollar index to the CRB crop index became weaker after the subprime crisis. When compared with the respective volatility spillover indices, their results only match the ones for corn but not that for soybeans or wheat.

9.5 Conclusions

This chapter has investigated directional time-varying range volatility spillovers using a new method developed by Diebold and Yilmaz (2009, 2012). The chapter focuses on short-term volatility interaction effects within a system which comprises agricultural products, crude oil, and selected financial asset markets over the period between 3 June 1998 and 31 December 2013. We especially emphasized the comparison between the two periods of financial and economic crises, whereby the later crisis period is also characterized by an increased use of commodities as financial investment.

During and after the subprime crisis, individual range volatilities moved increasingly in synchrony, with significant parallel jumps. Also, the total volatility spillover index shows stronger volatility interdependence. This suggests an overall higher degree of market interaction. The S&P 500 was the strongest net volatility transmitter in the system and spillovers peaked during the crisis periods. REITs net volatility transmission starts to rise only with the beginning of the subprime crisis.

The pairwise agriculture-energy volatility spillover indices do not provide significant evidence for an increase in spillovers from the energy to relevant commodity markets as a consequence of biofuel mandates. While this is in line with the findings of some previous studies, such as Gardebroek and Hernandez (2012), it stands in contrast to the results of other related studies. This discrepancy could be because (1) the index uses the full sample rolling approach instead of exogenously introducing structural breaks and (2) the system was extended to include financial assets that could have absorbed some of the volatility spillovers. Yet, our results do not permit the conclusion that biofuel mandates did not have any effects on the volatility (or return) relation between crude oil and biofuel crops. Due to the focus on short-term range volatility, we did not capture any longer-term structural changes arising from events such as reallocating land to be used for biofuel crops as a consequence of a high or volatile oil price.

The pairwise commodity-financial volatility spillover indices show that the volatility interaction between commodity and US Treasury markets appeared relatively unaffected by the crisis periods, but spillovers from commodities to the US Dollar index increased (except in the case of corn). Yet, the most profound shift in volatility interaction occurred between the S&P 500, US REITs, and commodity markets. Crude oil received high net spillovers from both financial asset markets during and after the second period of crisis. Agricultural commodities are less affected than crude oil, although there were some spikes in the spillovers into corn and wheat markets during the second crisis.

The volatility spillover patterns into and from commodities observed in the second period of crisis were more apparent than in the first crisis. While it is not possible to directly attribute causes to the discrepancy, the results do provide evidence in favor of the hypothesis that there were increased financial linkages between the markets. There are two important implications: First, shocks to financial asset markets, which have no direct fundamental connections to commodity markets, may increasingly affect short-term commodity market volatility. Second, if commodities find themselves increasingly being used as portfolio diversifiers and refuge assets, their diversification benefits may be reduced, especially in times of crisis.

Thus, future research should be directed towards investigating the underlying structural relationships behind the volatility linkages. And, as also suggested by Diebold and Yilmaz (2012), a theoretical and empirical comparison of the spillover indices with multivariate GARCH models could be useful. The focus should be put on the relationship between short-term conditional volatility and range volatility. A starting point could be the range volatility-based GARCH models such as the E-GARCH model used in Brandt and Jones (2006) and the conditional autoregressive range model used in Chiang and Wang (2011). In any case, the volatility spillover indices are a useful addition to the hitherto GARCH-centered analysis of volatility relationships. The indices should be further used to investigate alternative asset systems.

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A Roller Coaster Ride: An Empirical Investigation of the Main Drivers of Wheat Price

10

Bernardina Algieri

10.1 Introduction

In recent years, food commodity prices have increased at an unusually rapid pace, and wheat prices in particular have experienced marked upsurges, only briefly interrupted by the global financial crisis. These trends can be particularly detrimental because they could amplify the incidence of poverty (IMF 2011; von Braun and Tadesse 2012; Dethier and Effenberger 2012; Benson et al. 2013), hamper economic growth in poor countries (Jacks et al. 2011), and cause worldwide unrest, such as those documented in several sub-Saharan African regions. Unrest in these regions occur because people living there spend a larger share of their income on food (about 50 %) than urban residents in other parts of the world (about 30 % and 15 % in middle- and high-income countries, respectively) (Portillo and Zanna 2011). Given that Africans depend on a small number of staple crops, increases in cereal prices can be particularly destructive. Spending more consumer money on food means fewer purchases of services, such as sanitation, health, and education (The Economist 2011). In addition, the Middle East and North Africa regions are the world's largest importers of cereals, particularly wheat, making them more vulnerable to higher international cereal prices. This can lead to substantial terms-of-trade shocks, which affect countries' internal and external balances, with higher non-accelerating inflation rates of unemployment and balance of payments deficits.

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In this context, the present study tries to shed light on the main drivers of wheat prices by identifying the influence of the fundamental factors of supply and demand and the behavior of investors in the financial markets. In light of the steep hikes in the price of several commodities, it has become especially important to investigate the underlying factors that exert an influence on the wheat market.

Specifically, the study divides the drivers of wheat prices into market specific variables, broad macroeconomic variables, financial factors, and weather conditions. An empirical analysis was conducted based on monthly data for the period between January 1980 and January 2012 and the subperiod between January 1995 and January 2012. The quadrangulation of the drivers will allow us to better understand commodity price patterns.

The paper makes several contributions to the existing literature. It explicitly examines the case of the wheat market, merging different strands of the literature. Empirical analyses of the factors influencing wheat spot prices are quite scant (Borensztein and Reinhart 1994; Westcott and Hoffman 1999). Some studies about wheat are more descriptive in nature. For instance, Trostle (2008) and Mitchell (2008), after carrying out a graphical inspection, suggested that wheat prices increased due to a large demand for biofuels, high transportation costs, and a severe decline in global wheat supplies. Other analyses considered demand and supply factors while leaving out the role of financialization or other broad macroeconomic factors (Goodwin and Schroeder 1991; Westcott and Hoffman 1999). This study tries to extend the discussion about the wheat market by singling out specific factors behind price swings within a cointegration framework. Another novel contribution is the comparison of two long-run relationships—before and after the "financialization" of the commodity markets—to identify their similarities and differences. The last important element of this study is the ability to analyze price dynamics at a higher resolution through the use of monthly data. Most existing studies based their analysis on annual or quarterly data (Westcott and Hoffman 1999).

The rest of the chapter is organized as follows: Sect. 10.2 reviews literature about the key factors influencing commodity price; Sect. 10.3 introduces the variables of the model; Sect. 10.4 presents the VECM estimation and discusses the results; Sect. 10.5 concludes this chapter.

10.2 Literature Review

The roller-coaster ride experienced by commodity prices over the recent years has triggered a vivacious discussion regarding the causes of these fluctuations.

Some observers argued that the run-ups in commodity prices reflect strong changes in economic fundamentals, with price fluctuations moderated by the participation of nonuser speculators[1] and passive investors in commodity futures markets. Others pointed to the role of broader macroeconomic factors as the main drivers of rising prices. Finally, there are also other observers who argued that commodity prices have been exuberant and divorced from market fundamentals. The first view can be dubbed the "fundamentalist" view, the second the "broad" macro-view, and the third the "financialization" view.

According to the market "fundamentalist" view (Irwin et al. 2009; Irwin and Sanders 2010; Krugman 2010a, 2011; Yellen 2011; Dwyer et al. 2011, 2012), the price of any goods or assets should be driven by demand and supply in the absence of "irrational exuberance." In this context, any shocks to demand and supply which lead to rising global demand and disruption of global supply cause relevant price swings. Negative shocks to agricultural commodity supplies, which cause commodity prices to surge, are mainly the result of adverse weather conditions or collapses in the stock-to-use ratios. In other words, extreme weather conditions are likely to damage existing cropping areas, resulting in greater yield variability and negatively affecting price changes. Additionally, when stock-to-use ratios are low, the market is less able to cope with a significant decline in supply or a drastic increase in demands and thus drives prices significantly upwards (Williams and Wright 1991; Gilbert and Morgan 2011). Preexisting stocks are thus a fundamental source of stability in commodity markets. According to a report by the FAO (2009) about the prerecession spike in food commodity prices, stock levels have been decreasing by an average of 3.4 % per year since the mid-1990s, and the highest prices were registered during a period in which the stock-to-use ratios were at historical lows. Low food stocks and low crop stocks exacerbate the effects of weather disruptions on prices. For instance, wheat prices increased by 47 % in 2010, which was largely attributable to droughts in Russia and China and to floods in Canada and Australia.

With respect to demand, the process of income catch-up (convergence) between developing and advanced countries has triggered a growth in demand for commodities and hence drove up commodity prices. More than 90 % of the augmentation in demand for agricultural commodities in recent years has originated from developing countries, mainly from India and China (Heap 2005; Coxhead and Jayasuriya 2010; Fawley and Juvenal 2011; Cevik and Sedik 2011). In Krugman's words (2010b), rising commodity prices are a sign that "we are living in a finite world, in which the rapid growth of emerging economies is placing pressure on limited supplies of raw materials, pushing up their prices." However, it should be noted that in real terms, the price of food commodities has increased by 75 % between 2003 and 2008 (Erten and Ocampo 2013). This pattern is a reversal of the strong downward trends experienced since the 1980s, but it is still too early to assess if the reversal implies a long-term change (shift) in the direction of the trend, a pronounced short-run food

[1]A rational expectations model predicts that the existence of a futures market would reduce the fluctuation of spot prices for reasonable value of input parameters.

commodity price spike around the long-run trend, or a commodity price super-cycle (Rogers 2004; Heap 2005; Jacks 2013).

According to the "broad" macro-view, other macroeconomic determinants—such as exchange rates, monetary policies, inflation, energy price, global economic activity, and the "thinness" of markets—could have affected price levels and their fluctuations via demand or supply channels. For instance, exchange rates can influence commodity prices through several conduits, such as international purchasing power and the effects on margins for producers with non-US dollar costs (Mussa 1986; Gilbert 1989; Borensztein and Reinhart 1994; Roache 2010; Manera et al. 2013). This means that dollar depreciation increases costs to US producers and consumers in areas where the US dollar is the currency of trade. A change in the US dollar exchange rate thus affects prices measured in US dollar terms, but its effect will be nullified if prices are measured in terms of a weighted basket of currencies. Monetary policies, including interest rate maneuvers, can affect a number of demand and supply channels as well (Orden and Fackler 1989; Frankel 2008; Calvo 2008; Bakucs et al. 2009), leading to greater movements in real commodity prices when changes in real interest rates become frequent. This occurs particularly when interest rates are low and when there is an incentive to hoard physical commodities as an investment vehicle, causing prices to go up. Inflation is a common driver of prices of different commodities. Oil prices have also been mentioned as an additional factor in causing food price shocks via demand channels (Mercer-Blackman et al. 2007; Thompson et al. 2009). This is because a surge in oil prices leads to an increase in demand for grains as biofuels, and this subsequently causes food commodity prices to rise.[2]

Market "thinness," which is defined as the combined share of imports and exports relative to the size of global consumption or production, also significantly affects commodity price movements. In thinner markets, in which domestic prices do not closely follow international market movements, world market prices have to vary more to accommodate an external shock to traded quantities (OECD 2008).

Some observers doubt that fundamental shocks could be used as a reason to fully justify the price run-ups. Instead, they point to the "financialization" of commodity markets and speculation as the main causes of the drifts and fluctuations of commodity prices (Masters 2008; Stewart 2008; Hamilton 2009; Gilbert and Morgan 2011; Tang and Xiong 2012). "Financialization" refers to the large flow of capital into commodity markets, more specifically into long-only commodity index funds (Acworth 2005; Domanski and Heath 2007; Miffre 2011; Miffre and Brooks 2013). Speculation involves buying, holding, and selling of stocks, bonds,

[2] To reduce oil dependence as the main source of energy, several countries, including the USA, have adopted new energy policies to promote the use of biofuel. The 2005 US energy bill mandated that 7.5 billion gallons of ethanol be used by 2012. The 2007 energy bill further raised the mandate to 36 billion by 2022. The mix of increasing ethanol subsidies and high oil prices determined a rapid growth of the ethanol industry, which consumes about one-third of the US maize production. The rise of the ethanol industry might have led prices of maize, and other close substitutes such as soybeans and wheat, to co-move with oil prices (Roberts and Schlenker 2010; EPA 2012).

commodities, or any valuable financial instruments to profit from fluctuations in their price. This is in contrast to market participants buying these assets for use, dividends, interest income, or hedging purposes (Robles et al. 2009). Speculation thus may take the form of speculative stockholding, speculative purchase and the sales of commodity futures, or other derivative contracts.

Similarly, a report by the US Senate's Permanent Subcommittee on Investigations (USS/PSI 2009, p. 2) argued that commodity traders and futures contracts were disruptive forces, pushing prices away from fundamentals, and inducing excessive price movements.

In this context, some believe that a speculative bubble is forming in commodities as a consequence of the highly accommodative stance of the US monetary policy. Some of the accommodative policies include the maintenance of the target federal funds rate at exceptionally low levels (Hamilton 2009) and extremely high flows of investment funds into commodity futures. Loose monetary policies influence commodity prices by reducing the cost of holding inventories or by encouraging "carry trades" and other forms of speculative behavior (Frankel 2013). However, the "fundamentalist" view points to the fact that stocks of agricultural products have generally been falling between 2006 and 2008 as evidence that undermines the hypothesis that speculators contributed to the spike in prices.

The financialization hypothesis suggests that prior to the recession, the surge in commodity prices was accompanied by a large inflow of funds. According to Barclays, index fund investment in commodities increased from $90 billion in 2006 to about $200 billion by the end of 2007; in July 2011, the amount of investment reached a historical peak of $431 billion. In this context, the large-scale speculative buying of index funds during the boom caused commodity future prices to far exceed fundamental values, thus creating a "bubble." However, people who hold the fundamentalist view again argued against the "speculation theory," pointing out that commodities without futures markets have experienced approximately as much fluctuations as commodities with a derivative market.

10.3 Variables and Data

In order to empirically examine the causes of price fluctuation, wheat spot prices were considered. The sample consists of monthly wheat spot prices for the period 1980–2012, and a subperiod is defined as 1995–2012. The subsample starts in 1995 due to the unavailability of some financial data before that year. To identify the key drivers, the different strands of the existing literature were merged, and the driving forces behind wheat prices were divided into four dimensions: market specific variables, broad macroeconomic variables, speculative components, and weather conditions. A detailed description of the data can be found in the Annex.

The focus is on the spot market rather than the futures market for two main reasons. First, it is important to understand the interconnections between the two markets and assess how trading activities in the futures markets affect the patterns of spot prices for their economic and welfare consequences. Second, the existing analyses are mainly focused on commodity futures markets and less on the cash markets.

Wheat spot prices were taken from the IMF International Financial Statistics, via Datastream. The prices are expressed in US dollars, averaged from daily quotations, and have been deflated by the US consumer price index to obtain their real values. The prices were then converted into an index (2000 = 100).

Market Specific Variables include inventory-to-consumption and the "thinness" of markets.

Inventory-to-Consumption
(−)

Inventory stock levels have a crucial role in commodity pricing (Williams and Wright 1991; Pindyck 2001; Krugman 2011). As in manufacturing industries, inventories are used to reduce costs of adjusting production over time in response to fluctuations in demand and to shrink marketing costs by facilitating timely deliveries and preventing stock-outs. Producers can reduce their costs over time by selling out of inventories during high-demand periods and replenishing inventories during low-demand periods. Since inventories can be used to ease production and marketing costs despite fluctuating demand conditions, they lower the degree of short-run market price fluctuations. Therefore, price levels and their fluctuations are expected to increase when the level of inventories is lower.

Because inventory holdings can change, production at any period does not need to be equal to consumption. As a result, the market-clearing price is determined not only by current production and consumption but also by changes in inventory holdings.

Aggregate world stocks at the end of a year were expressed as a proportion of the aggregate world consumption from the previous year. This ratio is also referred to as the stock-to-use ratio (Fig. 10.1). The inventory data are the predicted end-

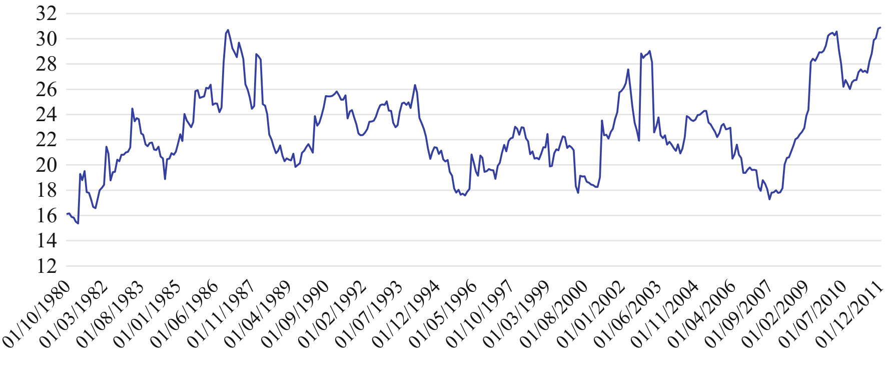


Fig. 10.1 End stock-to-use ratio (in %)

of-season global wheat inventories as published in the monthly USDA reports. Therefore, the inventories are the projected quantities of grain reserves carried over from the ongoing marketing year to the new marketing year. The definition of a marketing year is based on the aggregate of local marketing years. The largest trader of wheat in the international market is the USA, where the marketing season starts at the beginning of June and ends at the end of May. The consumption data are the projected season's consumption levels. The data was obtained from the United States Department of Agriculture (USDA).

International Thinness of Markets
(+)/(−)

The "thinness" of a market refers to the share of the imports and exports of a specific commodity relative to the size of global consumption or production (OECD 2008). This ratio describes the extent to which agricultural products are internationally traded.[3] The thinness of the wheat market can be expressed as follows:

$$TH \equiv \left(\frac{EX_w + IM_w}{Cons_w} \right) \tag{10.1}$$

A low ratio means that the market is "thin," while a high ratio implies "fatness" of the market. Hence, a thin market is characterized by low trading volume.

The thinness of a market could exert two opposite effects on prices. Higher trading volume may lead to higher demand for commodities; this could result in a price run-up. Conversely, trade could help smooth production and consumption across space by moving goods from regions with surplus to those with deficit, thus mitigating the effects of price movements. In this context, more trade implies more stability and price drops, while a lack of trade implies high movements and price increases (Jacks et al. 2011). Increased trade integration would thus facilitate the stabilization of food prices and the reduction of prices for consumers (The World Bank 2012).

In regards to volatility, thin markets, characterized by low trading volumes, tend to show high fluctuations (illiquid), while fat markets display high trading volumes and high liquidity. It is often argued that agricultural markets are "thin"; the ratio of trade flows to global production/consumption is considered low as a consequence of protectionist measures or because a commodity is mostly consumed in their country of production, as in the case of rice (Timmer 2009). This causes price swings that are larger than those expected in more liquid or deeper markets. In the case of wheat,

[3]The construction of this measure includes exports and imports to be conceptually parallel to the degree of openness of an economy. As imports equal exports at a global level, the thinness index could also be represented by either exports or imports.

a change in thinness can be considered as a more direct proxy for changes in trade policy since wheat is consumed independently from where it is produced, and the market dimension is more linked to the existence of restrictive or expansive trade policies.

When markets are thinner and prices in domestic markets do not follow those in international trade because of insulating policies or market imperfections, world market prices must change to better accommodate an external shock to the traded quantities, if all else is equal. Trade thus is an important buffer against localized fluctuations originating from the domestic market and could also be useful for leveling out local supply shocks around the globe.

Broad macroeconomic variables include global economic activity, interest rates, real exchange rates, oil price, and inflation.

Global Economic Activity

(+)

The monthly global industrial production index was considered when measuring the global economic activity. The index was chosen because real world GDP data is not available on a monthly basis but only at quarterly frequency. Initially, industrial production data for advanced and emerging economies were considered separately when analyzing the impact of aggregate demand growth; however, these data are available only at annual frequency, and in any case, world figures have the advantage of including emerging countries such as China and India. This is in line with the study by Frankel and Rose (2009).

Interest Rate and Yield Curve

(−) & (+)/(−)

Real interest rates can influence commodity prices in several ways, as explained by Frankel (2006, 2012, 2013). For instance, the prices of storable commodities rise as interest rates fall because, by decreasing the cost of carrying inventories, lower rates stimulate inventory demand for commodities. On the other hand, a rise in interest rates reduces inventory demand since it increases the cost of carrying inventories. This, in turn, lessens commodity prices.

Another mechanism by which real interest rates affect commodity prices relates to financial speculation in commodity markets. Commodities can be thought of as financial assets; thus when real interest rates are very low, investors are more prone to take open positions in the financial market for commodities, thereby pushing commodity prices up. Conversely, an increase in interest rates encourages speculators to shift from spot commodity contracts to Treasury bills, and this curbs commodity prices. Following this line of thought, Calvo (2008) put forward that increases in commodity prices mostly stem from the combination of low central bank interest rates, the growth of sovereign wealth funds, and the consequent lower demand for liquid assets.

In order to account for the effects of monetary policies, the US money market rate (federal funds) deflated by the consumer price was considered. The interest rate is thus expressed in real values.

In addition, to gain insights into the expected future path of the short-term interest rates, the US interest rate spread has been included, constructed as the difference between the 10-year Treasury bonds and the federal funds. This spread, or difference between long and short rates, is often called the yield curve. It can be considered as an indicator of the stance of monetary policy and general financial conditions because it rises (falls) when short rates are relatively low (high). A negative yield curve (i.e., short rates are higher than long rates) is historically a particularly strong indicator of recession. In short, it is a leading indicator which signals changes in the direction of aggregate economic activity.

The expected relationship between yield spread and commodity prices is uncertain. If risk premiums on Treasury Bond represent a reward to investors for their exposure to economy-wide macroeconomic risks, then we should expect a strong positive linkage between variation in commodity spot prices and measures of risk in Treasury bond markets. This indicates that higher yield spreads, which signal a declining risk tolerance in the Treasury bond market, mean higher commodity prices, which indicate an increasing risk tolerance in the commodity markets. This pattern is consistent with the thesis that asset classes are being treated as substitutes in diversified portfolios.

If risk aversion is instead expressed in a similar way across the Treasury and commodity markets during the period, then rising Treasury yields are correlated with lower commodity prices. This pattern is consistent with the thesis that asset classes are being treated as complements in diversified portfolios.

Oil Spot Price

(+)

The oil price is a critical factor contributing to the increase in production costs of agricultural commodities and food (costs of processing, transportation, and distribution) and consequently to the increase in their market prices. Additionally, an increase in oil price provides an incentive to produce biofuels, thus exerting a further upward pressure on food commodity prices. Therefore, wheat prices and oil prices are expected to be positively related.

Crude oil prices were obtained from Cushing, Oklahoma West Texas Intermediate (WTI) Spot Price FOB (Dollars per Barrel) via Datastream. To obtain the real values, the average petroleum spot price was deflated using the US CPI.

Real Effective Exchange Rate

(+)/(−)

Many agricultural commodities (as with oil) are traded in the US dollar; this implies that the effective exchange rate of the US dollar affects commodity prices as perceived by countries other than the USA. Therefore, a change in the dollar exchange rate can change the demand for and supply of agricultural commodities and consequently their prices. A real exchange rate appreciation (depreciation) can be positively or negatively related to prices.

On the one hand, dollar depreciation tends to reduce the commodity prices in domestic currencies for countries and regions with floating exchange rates, such as the euro area, Japan, the Philippines, and South Korea. This leads to an increase in the demand for commodities in these areas. Therefore, dollar depreciation has a positive impact on the demand for commodities and should contribute to rising commodity prices. Conversely, dollar appreciation makes exports less competitive and decreases the demand for commodities, causing dollar-denominated international commodity prices to diminish. This has a neutral effect for countries that peg their currency to the US dollar, like Oman, Saudi Arabia, Eritrea, and Hong Kong.

On the other hand, if uncertainty increases, both the demand for the dollar and commodities will increase, causing commodity prices to rise.

Inflation

(+)

Since commodities are considered to have the ability to store value, demand for commodities, for use as financial assets or as stocks, increases with inflation. Inflation tends to affect commodity prices through the portfolio choices of financial investors; this occurs because holding commodities can hedge investment portfolios against inflation risks (Roache 2010). The inflation rate is computed using changes in the US consumer price index.

To account for *Financial Variables*, a measure of financialization and speculation in the wheat market has been included.

Financialization and Speculation

(+)/(−)

Commodity markets have seen a progressive financialization over time. This is evident in the evolution of the level of open interest. Open interest describes the total number of long (purchased contracts outstanding) or short (sold contracts outstanding) futures contracts for a given commodity in a delivery month or market that has been entered into but not yet (1) liquidated by an offsetting transaction or (2) fulfilled by the delivery of the commodity.[4] Open interest is hence a widely used measure of the size of a commodity futures market. Specifically, Fig. 10.2 shows the open interest disaggregated by the type of traders and the nature of contracts in the wheat market; that is, it considers the long and short open interests for commercial traders, noncommercial traders, and non-reportables.

Commercial traders, also known as hedgers, hold positions in the underlying commodity and attempt to offset their risk exposure using future transactions. Noncommercial traders, also called speculators, only hold positions in futures

[4]In analytical terms, the market's total open interest is the sum of reporting and non-reporting positions: TOT OI = [NCL + NCS + 2 × NCSP] + [CL + CS] + [NRL + NRS], where noncommercial open interest (NC) is distinguished in long (NCL), short (NCS), and spreading (NCSP), while for commercials (C) and non-reportables (NR) open interest is divided in long and short.

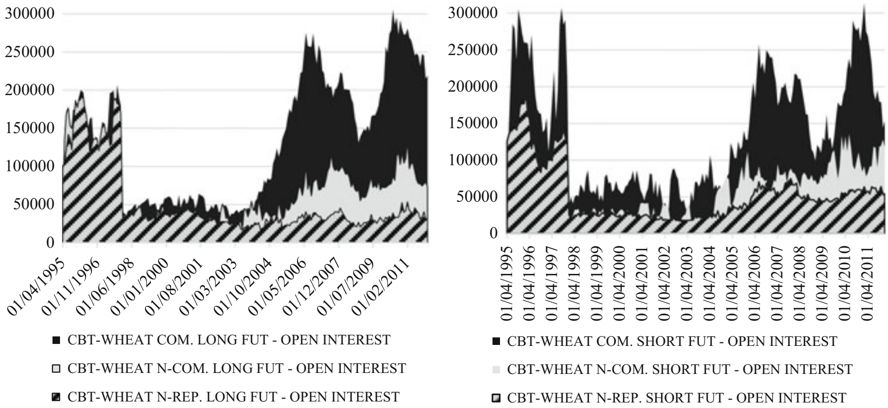


Fig. 10.2 Role of commercials, noncommercials, and non-reportables in wheat market (Chicago Board of Trade). *Source*: Own Elaboration on Datastream

contracts and are not involved in the physical commodity trade. Commercial and noncommercial traders are defined as reportable traders because they hold positions in futures and options at or above specific reporting levels set by the US Commodity Futures Trading Commission (CFTC). Non-reportables refer to small traders who do not meet the reporting thresholds set by the CFTC. Traders could take either long (buy) or short (sell) positions in commodity futures markets, depending on whether commodity prices are expected to appreciate or depreciate.

It is worth noting that although wheat futures can also be traded on the Kansas City Board of Trade (KCBT), and the Minneapolis Grain Exchange (MGEX), figures in this chapter come from the Chicago Board of Trade (CBOT) because it is the world's oldest futures and options exchange and the largest commodity exchange in the world. Founded in 1848, it accounts for about half of the turnover in futures contracts in the USA and the bulk of the world's grain futures trading.

As shown in Fig. 10.2, open interest recorded significant gains from 2003 onward, only registering a drop during the financial crisis but surged again soon afterwards. The fact that the long and short positions of all types of investors in the wheat market have increased over time suggests a rise in the financialization of commodity futures markets.

In a well-functioning futures market, hedgers, who want to lower their exposure to price risks, will have to find a counterparty. In the absence of any speculative activity, long hedgers have to find short hedgers with an equal and opposite position. Since long and short hedgers do not always trade simultaneously or in the same contract amount, there is unmet hedging demand, which speculators can satisfy. Speculators thus reduce searching costs by taking the opposite positions when long and short hedgers do not perfectly match each other's demand (Büyükşahin and Harris 2011). This follows Friedman's (1953) argument: speculators stabilize prices by buying low and selling high so as to bring prices closer to fundamentals. However, it turns out that speculative activities often exceed the level required to offset any unbalanced hedging, thus destabilizing markets. According to De Long et al. (1990), rational speculators set price trend and lead short-term prices away from fundamentals by anticipating the buy/sell orders of trend followers.

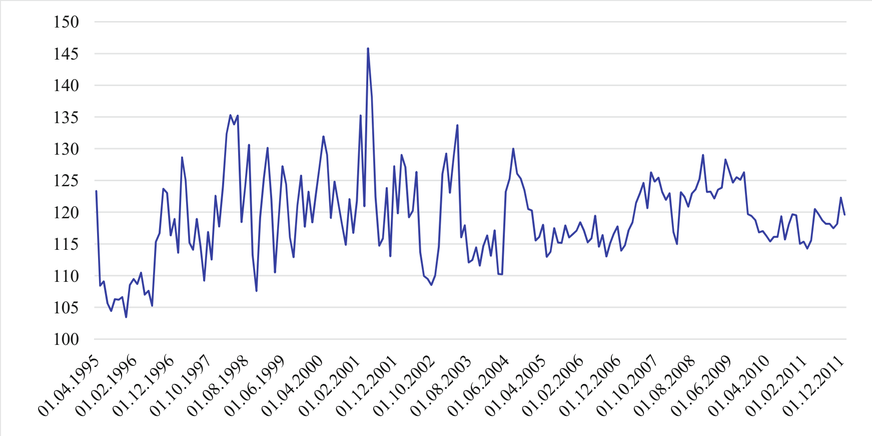
In short, the financialization of commodity markets has brought about an increase in speculative activities, which could have positive or negative effects on commodity markets, and consequently on prices.

Since the share of net long positions of noncommercial traders is frequently used as a variable to capture the activity of financial investors in commodity markets (IMF 2006; Micu 2005; Domanski and Heath 2007), an excessive-speculation index has been constructed following Working (1953). This metrics is a good measure of speculative activities in futures markets since it assesses the relative importance of speculative positions with respect to hedging positions. And as Working suggested, the level of speculation is meaningful only when compared with the level of hedging in the market. The Working index has been used also by Sanders et al. (2010) and Büyükşahin and Harris (2011) to examine the adequacy or excessiveness of speculative participation in the commodity futures markets. The excessive-speculation index is expressed as:

$$\mathrm{ESPI} \equiv \begin{cases} \left[1 + \frac{\mathrm{NC\ OI\ Short}}{(\mathrm{C\ OI\ Short} + \mathrm{C\ OI\ Long})}\right] \times 100 \ \textit{if C OI Short} \geq \textit{C OI Long} \\ \left[1 + \frac{\mathrm{NC\ OI\ Long}}{(\mathrm{C\ OI\ Short} + \mathrm{C\ OI\ Long})}\right] \times 100 \ \textit{if C OI Short} < \textit{C OI Long} \end{cases} \tag{10.2}$$

where NC OI Short = open futures position of short speculators, NC OI Long = open futures position of long speculators, C OI Short = open futures position of short hedgers, and C OI Long = open futures position of long hedgers. In other words, the nominator denotes the short and long speculative positions. The denominator is the total amount of futures open interest resulting from hedging activity.

Figure 10.3 shows the excessive-speculation index in the wheat market and its descriptive statistics.

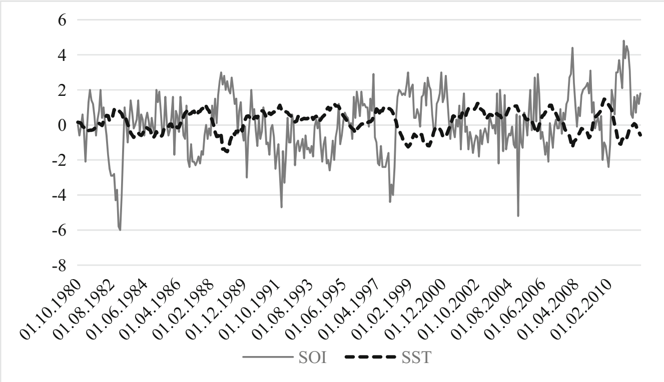


Excessive speculation index					
Mean	119.206	Std. Dev.	6.836	Skewness	0.396
Median	118.429	Sum	24079.670	Kurtosis	3.711
Maximum	145.822	Sum Sq.	9393.373	Jarque-Bera	9.525
Minimum	103.445	Observations	202	Probability	0.008

Fig. 10.3 Excessive-speculation index. Wheat CBOT

Finally, the model controls for *Global weather conditions*. To account for weather conditions, the following two indicators have been considered:

- The sea surface temperature anomalies (SST) for the El Niño region 3.4 (a central region of the Pacific Ocean). This index measures the deviations between the sea surface temperatures in the El Niño region 3.4 and its historical average, and it is calculated by the National Climatic Data Center US Department of Commerce and the NOAA Satellite and Information Service using the extended reconstructed sea surface temperature.
- The Southern Oscillation Index anomalies (SOI), which measures the fluctuations in air pressure occurring between the western and eastern tropical Pacific during El Niño and La Niña episodes (i.e., the state of the Southern Oscillation). It is a standardized index based on the observed sea-level pressure differences between Tahiti, French Polynesia, and Darwin (Australia). In general, a negative phase of the SOI represents below-normal air pressure at Tahiti and above-normal air pressure at Darwin. SOI data are taken from the National Oceanic and Atmospheric Administration National Climatic Data Center.



	SOI	SST		SOI	SST
Mean	0.070	0.164	Std. Dev.	1.693	0.632
Median	0.100	0.290	Coef. of variation	24.052	3.864
Maximum	4.800	1.470	Jarque-Bera	10.292	15.876
Minimum	-6.000	-1.520	Probability	0.006	0.000

Note. Observations: 375

Fig. 10.4 Weather proxies

Although the events described by these indices arise in the Pacific Ocean, they have strong effects on the world's weather and an important influence on the global production and price of primary non-oil commodities (Brunner 2002). Monitoring both the SOI and the SST allows for a better understanding of global climatic fluctuations, enabling us to clearly distinguish between the atmosphere's and the ocean's influence on yield, and thus prices. In addition, evaluating both variables together significantly improves the accuracy of weather forecast when compared to using them separately (Russell et al. 2010).

The dynamics of the SST index and the SOI are reported in Fig. 10.4. With regard to the SST index, positive anomalies (index values above zero) are related to abnormally warm ocean waters across the eastern tropical Pacific typical of an El Niño event, and negative anomalies are related to a cool phase typical of a La Niña episode. Conversely, prolonged periods of positive SOI values (values above zero) coincide with La Niña events during which water becomes cooler than normal; the opposite is true for prolonged periods of negative SOI values. SOI values below zero mirror El Niño episodes, during which water becomes warmer than normal. La Niña events are associated with increased instances of drought throughout the mid-latitudes, where much of the global wheat and other grains (such as corn and soybeans) are produced, thus decreasing their global yield (Hurtado and Berri 1998) and driving up prices. For this reason, La Niña episodes have historically been associated with global food crises. El Niño is associated with an increased likelihood of droughts in tropical land areas, which mainly affects crops such as sugar and palm oil.

It is worthwhile to note that the SST index and the SOI tend to have opposite signs and that the SOI has a higher variability than the SST index as computed by the coefficient of variation shown below.

10.4 Empirical Evidence

10.4.1 Preliminary Unit Root Test

Prior to testing for cointegration, the time series examined in Sect. 10.3 were transformed into logarithms, and their properties were carefully investigated. The transformation of the time series into logarithm is of advantage as the coefficients can be interpreted as elasticities. Inspecting the data graphically (Fig. 10.5) reveals that most of the series resemble a random walk, with some "trending" upward and others downward, and with fluctuations. Therefore, the Augmented Dickey–Fuller (ADF) (1981) and the Philips Perron (P–P) (1988) tests have been conducted for each variable to formally test for the presence of *unit roots*. The critical values for the rejection of the null hypothesis of a unit root are those computed according to the MacKinnon criterion (1991). The lag length for the ADF test is based on the Schwarz information criterion (SIC). The lag structure for the P–P is selected using the Bartlett Kernel with automatic Newey–West bandwidth. The two tests have been carried out with a constant and a linear trend (Table 10.1).

The ADF and P–P tests show that all the independent and dependent variables are integrated of order one I(1), i.e., the series become stationary after being differentiated for the first time. This occurs because the computed values do not exceed the Mac Kinnon critical values. The only exceptions are for the US Fed spread and the SST index, which produced different results according to the two tests.[5] However, it is acceptable to consider the series integrated of order

[5] Although Engle and Granger's (1987) original definition of cointegration refers to variables that are integrated of the same order, Enders (2009) argued that: "It is possible to find equilibrium relationships among groups of variables that are integrated of different orders." Asteriou and Hall (2007) also explained that in cases where a mix of I(0) and I(1) variables are present in the model, cointegrating relationships might exist. Similarly, Lütkepohl and Krätzig (2004) explain: "Occasionally it is convenient to consider systems with both I(1) and I(0) variables. Thereby the concept of cointegration is extended by calling any linear combination that is I(0) a cointegration

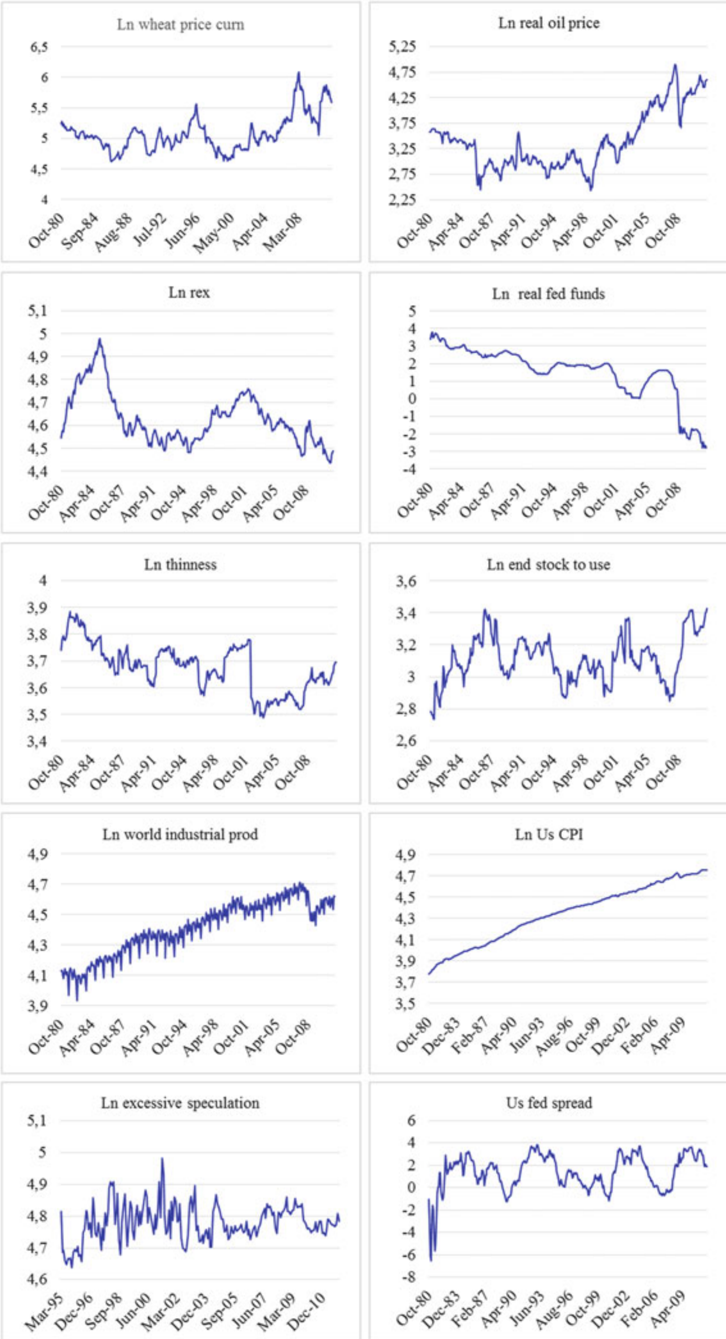


Fig. 10.5 Variables developments

Table 10.1 Unit root tests

	ADF level		ADF first difference		PP Level		PP first difference	
	t-stat	Prob.	*t*-stat	Prob.	*t*-stat	Prob.	*t*-stat	Prob.
ln real p	−2.992	0.1357	−14.911	0.0000	−2.758	0.2142	−14.856	0.0000
ln real poil	−2.431	0.3627	−14.537	0.0000	−2.173	0.5029	−14.026	0.0000
ln real fed fund	−1.068	0.9316	−11.719	0.0000	−0.940	0.9489	−11.642	0.0000
ln rex	−2.355	0.4028	−13.605	0.0000	−2.339	0.4111	−13.544	0.0000
ln end stock to use	−3.066	0.1162	−18.986	0.0000	−3.124	0.1022	−18.986	0.0000
sst	−4.111	0.0066			−3.853	0.0150	−12.365	0.0000
soi	−5.796	0.0000			−9.232	0.0000		
ln us cpi	−2.674	0.2480	−11.595	0.0000	−3.129	0.1010	−10.555	0.0000
ln world ind prod	−1.775	0.7150	−6.058	0.0000	1.850	0.9848	−44.358	0.0000
us fed spread	−4.484	0.0018			−3.363	0.0580	−13.339	0.0000
ln thinness	−2.636	0.2645	−18.783	0.0000	−2.900	0.1637	−18.782	0.0000
ln speculation	−6.668	0.0000			−6.766	0.0000		

Note: test equation includes trend and intercept. Mac Kinnon crit-values. The sample consists of monthly observation spanning the period from 1980 to 2012. The sample refers to the period 1995–2012 only with regard to speculation. Null hypothesis: there is a unit root. Real p = real wheat price, real poil = real oil price, real fed fund = real federal fund, rex = real effective exchange rate, sst = sea surface temperature anomalies, soi = Southern oscillation index anomalies, us cpi = US inflation rate, world ind prod = world industrial production, US fed spread = US bond yield, thinness = thinness of the market, speculation = excessive speculation

one because the series was confirmed by a supplementary Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (1992). The outcomes of the tests are reported in Table 10.1. The presence of non-stationarity implies that standard time-series methods are no longer suitable. And consequently, a cointegration analysis is required (Enders 2009).

To have a broader indication on the variables of interest, the correlation matrix has been computed[6] (Table 10.2).

relation, although this terminology is not in the spirit of the original definition because it can happen that a linear combination of I(0) variables is called a cointegration relation." Therefore, even in the presence of a set of variables which contains both I(1) and I(0) variables, cointegration analysis is applicable, and the presence of a long-run linear combination denotes the existence of cointegrated variables. Hence, it is possible to find long-run equilibrium relationships among a set of I(0) and I(1) variables if their linear combination reveals a cointegrating relationship.

[6]On the basis of the variance inflation factor, the variable ln us cpi was excluded from the model because it is highly correlated with the world industrial production. Further, the inclusion of the inflation rate would have caused a clear problem of endogeneity.

Table 10.2 Correlation matrix

Correlation	ln real poil	ln real fed funds	ln rex	ln end-stock-to-use	SST	SOI	ln us cpi	ind prod	us fed spread	ln thinness	ln speculat.
ln real poil	1										
ln real fed funds	−0.231	1									
ln rex	0.020	0.464	1								
ln end-stock-to-use	−0.066	−0.514	−0.100	1							
SST	−0.114	−0.082	−0.132	0.313	1						
SOI	0.138	−0.216	−0.110	−0.109	−0.678	1					
ln us cpi	0.094	−0.811	−0.540	0.201	0.054	0.242	1				
ln world ind prod	0.020	−0.646	−0.500	0.077	0.011	0.252	0.943	1			
us fed spread	−0.075	−0.510	−0.022	0.600	0.289	−0.160	0.254	0.104	1		
ln thinness	−0.023	0.499	0.439	−0.185	−0.162	−0.289	−0.134	−0.633	−0.139	1	
ln specul.	0.038	−0.079	0.241	0.146	−0.105	0.001	0.167	0.197	0.025	0.117	1

Notes: the monthly observations in the sample were made between 1980 and 2012. The sample refers to the period 1995–2012 only with regards to speculation. Real p = real wheat price, real poil = real oil price, real fed fund = real federal fund, rex = real effective exchange rate, sst = sea surface temperature anomalies, soi = Southern oscillation index anomalies, us cpi = US inflation rate, world ind prod = world industrial production, US fed spread = US bond yield, thinness = thinness of the market, speculat. = excessive speculation

10.4.2 Johansen and Juselius Analysis

The Johansen and Juselius methodology (1990), based on maximum-likelihood estimation, allows for the simultaneous evaluation of equations involving two or more variables and for determining whether the series are cointegrated; that is to say, whether there is a long-term relationship among variables. Furthermore, this technique controls for endogeneity and enables us to assess and test for the presence of more than one cointegrating vector. Finally, this methodology performs better than other estimation methods by including additional lags, even when the errors are non-normal distributed or when the dynamics are unknown, and the model is over-parameterized (Gonzalo 1994).

Consider a p-dimensional vector autoregressive model, which in error correction form is given by:

$$\Delta x_t = \Pi x_{t-p} + \sum\nolimits_{i=1}^{p-1} \Gamma_i \Delta x_{t-i} + \Phi S_t + \xi_t \tag{10.3}$$

where Δ is the difference operator, and $x_t = (k \times 1)$ is the vector of nonstationary I(1) variables, explicitly:

$$\begin{aligned} x_t = {} & [\text{wheat price}_t;\ \text{market specific variables}_t;\ \text{broad macro variables}_t; \\ & \text{weather}_t;\ \text{speculation}_t] \end{aligned} \tag{10.4}$$

and:

$$\Pi = \sum\nolimits_{i=1}^{p} A_i - I \qquad I = a\,(k \times k)\ \text{identity matrix} \tag{10.5}$$

$$\Gamma_i = \sum\nolimits_{j=1}^{i} A_j - I \qquad A = a\,(k \times k)\ \text{matrix of parameters} \tag{10.6}$$

The variable St contains a constant term and a time trend, and ξ is a vector of Gaussian, zero mean disturbances. Γ_i are $(k \times k)$ dimensional matrices of autoregressive coefficients. The long-run matrix $\prod$ can be decomposed as the product of α and β, two $(k \times r)$ matrices each of rank r, such that $\prod = \alpha\beta$', where β' contains the r cointegrating vectors and α represents the adjustment parameters, which reflect the speed of adjustment of the particular variables with respect to a disturbance in the equilibrium relationship. Therefore, Eq. (10.3) becomes:

$$\Delta x_t = (\alpha\beta)\, x_{t-p} + \sum\nolimits_{i=1}^{p-1} \Gamma_i \Delta x_{t-i} + \Phi S_t + \xi_t \tag{10.7}$$

The maximum-likelihood approach makes it possible to test the hypothesis of r cointegrating relations among the elements of x_t,

$$H_0 : \Pi = \alpha\beta \tag{10.8}$$

where the null of no cointegration relation ($r = 0$) implies $\prod = 0$. If $\prod$ is of rank k, the vector process is stationary. If rank $(\prod) = 1$, there is a cointegrating vector; for other cases in which $1 < \text{rank}\ (\prod) < k$, there are multiple cointegrating vectors.

10.4.3 Empirical Results

A VAR system of variables was constructed to test whether real wheat prices are cointegrated with specific market variables, broad macroeconomic factors, speculation, and weather events. To identify the proper model, the five possibilities considered by Johansen (1995) were tested, specifically: (1) the series have no deterministic trends, and the cointegrating equations do not have intercepts; (2) the series have no deterministic trends, and the cointegrating equations have intercepts; (3) the series have linear trends, but the cointegrating equations only have intercepts; (4) both series and the cointegrating equations have linear trends; and (5) the series have quadratic trends, and the cointegrating equations have linear trends. Following the Pantula test (Pantula 1989), the third and the fifth models are the most appropriate for two samples. To identify the lag length, the Aikaike information criterion (AIC) and the SIC were implemented. The chosen lag structure is three (the smallest value) for the complete sample and five for the subsample, following the AIC. A number of dummies have been included in the cointegration test to take into account periods of social and economic instability and structural breaks.[7]

The results of the Johansen test for cointegration are shown in Table 10.3, which reports the hypothesized number of cointegration equations in the first column on the left, the eigenvalue, the trace[8] statistics, the max eigenvalue statistics,[9] and the 5 % critical values. The asterisks indicate the rejection of the hypothesis.

[7]Specifically, outliers were detected by looking at the graphs of the residuals. Five dummies relative to 1998, 2007, 2008, 2010, and 2011 were inserted in the short-sample wheat price equation. The effects of including dummy variables to capture structural breaks in cointegration models have been analyzed in Kremers et al. (1992), and Campos et al. (1996).

[8]The trace statistic of r cointegration relations is a sequence of likelihood ratio tests, computed as $\lambda_{\text{trace}}(r) = -T\sum_{i=r+1}^{k}\ln\left(1-\widehat{\lambda}_i\right)$, where λ_i is the estimated value of the characteristic roots (also called eigenvalue) obtained from the estimated long-run Π matrix, and T is the number of usable observations.

[9]The max eigenvalue statistic is calculated as $\lambda_{t\ \max}(r) = -T\ln\left(1-\widehat{\lambda}_{r+1}\right)$.

Table 10.3 Johansen cointegration tests

Sample (adjusted). Included observations: 365 after adjustments Trend assumption: Quadratic deterministic trend				
Unrestricted cointegration rank test (trace)				
Hypothesized no. of CE(s)	Eigenvalue	Trace statistic	5 % Critical value	Prob.**
None*	0.172	233.630	219.402	0.0090
At most 1	0.111	164.650	179.510	0.2206
At most 2	0.097	121.810	143.669	0.4306
At most 3	0.077	84.592	111.780	0.6913
At most 4	0.050	55.509	83.937	0.8503
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level				
Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized no. of CE(s)	Eigenvalue	Max-Eigen statistic	5 % Critical value	Prob.**
None*	0.172	68.980	61.034	0.0071
At most 1	0.111	42.839	54.966	0.4688
At most 2	0.097	37.219	48.877	0.4742
At most 3	0.077	29.083	42.772	0.6531
At most 4	0.049	18.565	36.630	0.9422
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level				
Sample (adjusted). Included observations: 173 after adjustments. Trend assumption: Linear deterministic trend				
Unrestricted cointegration rank test (trace)				
Hypothesized no. of CE(s)	Eigenvalue	Trace statistic	5 % Critical value	Prob.***
None*	0.362	350.632	285.142	0.0000
At most 1*	0.304	272.774	239.235	0.0006
At most 2*	0.296	210.063	197.371	0.0100
At most 3	0.248	149.364	159.530	0.1561
At most 4	0.167	100.126	125.615	0.5978
Trace test indicates three cointegrating eqn(s) at the 0.05 level				
Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized no. of CE(s)	Eigenvalue	Max-Eigen statistic	5 % Critical value	Prob.***
None*	0.362	77.858	70.535	0.0091
At most 1	0.304	62.711	64.505	0.0736
At most 2*	0.296	60.699	58.433	0.0294
At most 3	0.248	49.239	52.363	0.1010
At most 4	0.167	31.672	46.231	0.6786
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level				

*Denotes rejection of the hypothesis at the 0.05 level
**MacKinnon et al. (1999) *p*-values
***MacKinnon et al. (1999) *p*-values. Estimations include significant dummies

Elaborating on the trace statistic, the first row of the trace statistic tests the hypothesis of no cointegration, the second row tests the hypothesis of one cointegrating relation, the third row tests the hypothesis of two cointegrating relations, and so on. All hypotheses were tested against the alternative hypothesis of full rank (i.e., all series in the model are stationary). For the longer sample, the λ_{trace} test and the λ_{max} statistic indicate the presence of one cointegrating equation at the 5 % level. For the shorter sample, the λ_{trace} test indicates the presence of three cointegrating equations at the 5 % level. The λ_{max} statistic does not confirm this result. The null hypotheses of no cointegrating vector ($r = 0$) can be rejected at the 5 % level, but the null of $r = 1$ cannot be rejected. So, it can be concluded that there is one cointegrating vector in the system at the 5 % level.

Although the results of trace tests and maximum eigenvalue tests point to different outcomes, we can conclude for one cointegrating vector since as Johansen and Juselius note, "one would, however, expect the power of this procedure [the trace test] to be low, since it does not use the information that the last three eigenvalues have been found not to differ significantly from zero. Thus, one would expect the maximum eigenvalue test to produce more clear-cut results" (1990, p. 19).

To extract the cointegrating vectors, a VEC representation has been adopted. Convergence was reached after few iterations for the entire sample and the small sample. The restricted cointegrating vectors and the speed of adjustment coefficients are reported in Table 10.4.

Table 10.4 Vector error correction estimations

Cointegrating vector β	1981:1–2012:1	1995:1–2012:1
ln real poil	0.231(4.44)	0.294(2.84)
ln real fed funds	−0.132(−2.55)	−0.207(−6.03)
ln rex	−0.771(−3.12)	−0.726(−9.77)
ln end-stock-to-use	−0.999(−3.94)	−0.436(−1.99)
sst	−0.244(−3.50)	−0.248(−4.54)
soi	0.166(5.71)	0.104(4.26)
ln world ind prod	3.290(2.80)	1.807(2.63)
us fed spread	0.045(1.99)	0.021(1.09)
ln thinness	−1.008(−2.56)	0.340(1.42)
ln speculation		0.715(7.14)
Constant	27.990	25.800
Trend	0.006(3.51)	0.001(2.01)
Speed of adjustment α		
dln real price index	−0.069(−4.87)	−0.085(−2.07)

Regressand: ln real wheat price index. *t*-stat in brackets. ln stands for logarithm

10.4.4 Discussion of Results and implications

The cointegration analysis suggests that real wheat prices were cointegrated with market specific variables, broad economic variables, weather events, and speculation. In particular, the columns of β in Table 10.4 are interpreted as long-run equilibrium relationships between variables, and the matrix α is used to determine the speed of adjustment towards this equilibrium. The estimated speeds of adjustment coefficients had the expected signs and were statistically significantly different from zero. This means that the cointegrating vectors converged towards their long-run equilibrium in the presence of a shock to the system. Expressly, 6.9 % of the disequilibrium was eliminated in 1 month for the complete sample, and this figure was 8.5 % for the subsample; that is, it took 14.5 months (1/0.069) and 11.7 months (1/0.085), respectively, to restore the equilibrium after a shock.

More specifically, Table 10.4 provides evidence to suggest that higher oil prices have led to an increase in wheat prices due to greater use of petroleum-based inputs in the wheat market. In other words, on the supply side, a rise in oil prices exerts an upward pressure on the input costs (such as fertilizers, irrigation, and transportation costs), which consequently leads to a decline in profitability and production. This results in a shift of the supply curve to the left and a rise in wheat prices. The result provides evidence that energy and agricultural prices are interwoven. A 10 % increase in international oil prices is statistically associated with an approximately 2.3 % rise in wheat prices for the longer sample and a 2.9 % increase for the shorter sample, all other things being equal. This result is in line with the studies by Tang and Xiong (2012) and Chen et al. (2010), who found an increasing correlation between agricultural commodities and oil price.

In addition, wheat prices appear to be sensitive to fluctuations in the real exchange rate. The sensitivity to fluctuation is almost the same for the two samples, both before and after the financialization of the wheat market. Specifically, the elasticity of about -0.7 suggests that a real dollar depreciation causes wheat prices to rise as wheat prices are denominated in the US dollar. The coefficients of the real exchange rate fell in a range between 0 and -1, just as predicted by the economic theory (Gilbert 1989; Borensztein and Reinhart 1994).

The real federal fund variable is negatively linked to the real wheat price, thus confirming the presence of the monetary policy effect. A loose monetary stance (with a lower interest rate of 1 %) implies that the price level will increase by about 0.1 and 0.2 %. When the real interest rate is high, as in the 1980s, money will flow out of commodities and therefore prices shrink. This confirms the studies by Dornbusch (1976), Frankel (2008), Svensson (2008), and Anzuini et al. (2012). The studies highlighted the high responsiveness of agricultural prices to monetary policy changes. The spread variable has a positive sign, signaling that the future expectations of tightened monetary policies do not have a depressing effect on wheat prices and that the Treasury bond market and the wheat commodity market are treated as substitutes asset classes for portfolio diversification. In other words, when the long-term interest rate is higher than the short-term interest rate, it signals an increase in the financial and macroeconomic risk linked to Treasury bonds. This causes investors to shift from the bond market to the commodity market, which in turn raises commodity prices. A 10 % increase in the spread increased prices by about 0.5 %; this value decreased to 0.2 % in the short sample and became insignificant.

The stocks-to-use ratio is used to capture the effects of market supply and demand factors on price determination (Westcott and Hoffman 1999). The variable shows a negative relationship with the wheat price. When usage grows faster than ending stocks, it would imply that demand growth outpaces supply growth, which puts an upward pressure on prices. Specifically, a reduction in the stocks-to-use ratio by 1 % caused real prices to surge by 0.9 % for the longer sample and 0.4 % for the shorter sample. This means that the combined effects of market supply and demand are factors in determining prices. It also means that a rise in the stocks-to-use ratio of a commodity translates into an almost proportional drop in the commodity's price in the longer sample, while the effect is less pronounced in the shorter sample.

As expected, bad weather conditions negatively affected wheat prices. Specifically, La Niña weather patterns tended to lower wheat yields and lift prices. It should be noted that the sea surface temperature anomalies had a larger impact than the fluctuations in air pressure occurring between the western and eastern tropical Pacific during El Niño and La Niña episodes. However, since the variability of SOI is larger than SST, the SOI could have more detrimental effects for wheat production and prices.

A 1 % increase in industrial production produced a significant rise in wheat prices by about 2–3 %. This implies, in accordance with the studies by Svensson (2008) and Wolf (2008), that the global demand is an important determinant of commodity prices.

The thinness of the market, while negative and significant for the longer sample, turned out to be not significant for the shorter sample. This implies that trade restriction policies could exert a detrimental effect as they tend to push wheat prices further up.

Finally, the speculation variable that is included only in the shorter sample indicates that the financialization of markets has contributed to pushing up prices. In traded markets, when futures traders seek exposure to commodities without holding the underlying commodities and speculate on future price movements of the commodity, they amplify price fluctuations on cash markets. This implies that speculative behaviors in the wheat futures market affect the associated spot market. According to our model, a 1 % increase in financial speculation increased cash prices by about 0.7 %.

In summary, the estimated coefficients showed that market specific variables, broad macroeconomic variables, speculative components, and weather conditions have a significant effect on real wheat prices, and thus the existing theories complement rather than contradict one another. The key to understanding the findings of this study is that commodities have multiple uses: they are both consumption goods and financial assets for investments. The positive effect of world demand on wheat commodity prices showed that wheat is used as consumption goods. The positive impact of open interest and yield curve on wheat price demonstrated that wheat is also used as financial assets.

An increasing demand was a dominant factor in driving up wheat prices, together with inventories for the longer sample; excessive speculation turned out to be significant and a relevant factor behind the price swings for the shorter sample. Pressures on real prices were alleviated by restrictive monetary policies, a real dollar appreciation, and, to some extent, expansive trade policies.

The properties of the residuals of the estimated model have been carefully analyzed. A battery of tests revealed that the residuals were stationary, homoskedastic, and uncorrelated. The estimated model was also "dynamically stable".[10]

10.5 Conclusions

The roller-coaster ride which commodity prices have experienced over the last decade has generated considerable interest among academics, policy makers, and investors in its effects on the real economy and thus on economic growth, food security, and investment decisions. In this context, the present study has tried to shed light on the key factors affecting the price movements of wheat, one of the major food grains in the world. The analysis was carried out for the period 1980–2012 and the subperiod 1995–2012, using monthly data.

The results of the study indicated that all the theories about drivers of commodity price do not necessarily contradict, but rather complement, each other. In fact, the results showed that a complex amalgamation of factors have caused prices to rapidly increase in the wheat markets, including speculation in futures markets, macroeconomic fundamentals, market specific variables, and weather conditions.

Wheat prices have been pushed up by a myriad of factors: loose monetary policies (as evident in low real interest rates), higher levels of industrial production (a proxy for strong economic activities), and speculative pressure. An increase in the stock-to-use ratio and a real appreciation has a curbing or dampening effect on

[10]The residual analysis, including details about stability, and the short-run dynamics are not reported for brevity but are available upon request. The impulse response function representation based on the Cholesky decomposition method indicates that short-run wheat price patterns in response to a shock are rich, and the impact of the shock is long-lasting. The variance decomposition based on Monte Carlo repetitions confirmed that there is a long-run relationship between the variables, and that all the determinants are meaningful in predicting real wheat prices when considered as a whole.

wheat prices. The thinness of a market turns out to be insignificant in the short sample, but it plays a role in the long sample, exerting an upward pressure on prices when trade diminishes.

Furthermore, the study has shown that an additional factor behind the rise in wheat prices is the increase in oil prices. Higher oil prices makes wheat production more expensive by raising the cost of inputs like fertilizers, irrigation, and transportation, thereby decreasing the profitability and production of wheat and raising wheat prices.

The variables with the largest effects on price movements over the period 1995–2012 are the global demand, speculation, and the real effective exchange rates. This showed that financial and wheat markets are becoming increasingly interwoven. It also showed that "speculation" which involves trading futures contracts on commodity markets (to profit from price fluctuations) is an important determinant of price dynamics. The wider and more unpredictable price changes are caused by greater possibilities of realizing large gains by speculating on future price movements of the commodity in question. Although the presence of "speculators" on derivatives markets is a necessary condition for a well-functioning market and efficient hedging, price fluctuations can also attract significant speculative activities and destabilize markets, which are both the cause and the effect of increased prices.

The adopted model satisfied the stability conditions as well as other residuals properties, and it indicated that cointegrating vectors will converge towards their long-run equilibrium in the presence of a shock to the system after 14.7 months and 11.7 months for the two sample periods, respectively.

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Annex

Market price for wheat	This is a market price series for wheat, with values expressed in US dollars and averaged from daily quotations. The commodity and market specifications are: US No. 1 hard red winter, ordinary protein, prompt shipment, FOB Gulf of Mexico ports. The series was collected from Datastream
Real effective exchange rate	The US real effective exchange rate series take into account not only changes in market exchange rates but also variations in relative price levels (using consumer prices). The data was taken from Datastream USOCC011
Oil spot prices	This variable has been collected from EIA database and refers to Cushing, Oklahoma WTI (West Texas Intermediate) Spot Price FOB (Dollars per Barrel), Datastream USWTIOIL
Stock-to-use	Data was taken from the USDA http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1194
El Niño region 3.4 sea surface temperature anomalies (SST)	Data was taken from the National Climatic Data Center US Department of Commerce and NOAA Satellite and Information Service using the extended reconstructed sea surface temperature; http://www.ncdc.noaa.gov/ersst/ftp://ftp.ncdc.noaa.gov/pub/data/cmb/ersst/v3b/pdo ftp://ftp.ncdc.noaa.gov/pub/data/cmb/ersst/v3b/pdo/el_nino.dat
The southern oscillation index (SOI)	Data was taken from National Oceanic and Atmospheric Administration National Climatic Data Center;http://www.ncdc.noaa.gov/teleconnections/enso/indicators/soi.php http://www.cpc.ncep.noaa.gov/data/indices/soi
Real federal funds	The US money market rate (federal funds) deflated by the consumer price. The Series refers to the weighted average rate at which banks borrow funds through New York brokers. Monthly rate is the average of rates of all calendar days. Data was collected from Datastream
US interest rate spread	It has been constructed as difference between the 10 year treasury bonds and the federal fund
Global activity	It is measured as industrial production index taken from IMF, IFS, via Datastream
Thinness	It was computed using data provided by the USDA http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1194

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Relative Prices of Food and the Volatility of Agricultural Commodities: Evidence for a Panel of Developing Economies

11

Carlos Martins-Filho and Maximo Torero

11.1 Introduction

Increases in relative prices of food items may have severe negative impact for consumer welfare. This can be particularly acute in low income countries where the share of household expenditure on food items is high. Recently, various time series on prices and returns for major agricultural commodities (rice, maize, soybeans, and wheat) have exhibited periods of increased price variability or high absolute values of returns. Whereas the negative link between high relative food prices and consumer welfare is empirically well documented in low income economies [see, e.g., conceptually (Deaton 1989), and for short-term effects (de Hoyos and Medved 2011; Ivanic and Martin 2008; Ivanic et al. 2012; Jacoby 2013; Wodon and Zaman 2010)], the potential link between high returns on major agricultural commodities and consumer welfare is, to our knowledge, poorly understood. Most of the existing work has focused on traditional measures of transmission of global price volatility to price volatility at the country level (see, e.g., Ceballos et al. 2015; Hernandez et al. 2014; Minot 2014; Zhao and Goodwin 2011). Moreover, the link between high absolute value of returns (volatility) of agricultural commodities at the global level and their impact on local prices of foodstuffs and consumer welfare has not been analyzed in the literature.

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Looking at volatility at the global level is important because although the food price spikes of 2008 and 2011 did not reach the heights of those during the 1970s, price volatility (measured in various ways) has arguably been at its highest level in the past 15 years (see Torero 2012). Wheat and maize prices have been particularly volatile. For soft wheat, for example, there were an average of 41 days of excessive price volatility per year between December 2001 and December 2006 (according to a measure of price volatility recently developed at IFPRI).[1] From January 2007 to June 2011, the average number of days of excessive volatility was more than doubled to 88 per year (see Fig. 11.1).

High and volatile food prices are two different phenomena with distinct implications for consumers and producers. High food prices may harm poorer consumers because they need to spend more money on their food purchases and therefore may have to cut back on the quantity or quality of the food they buy. They may also be

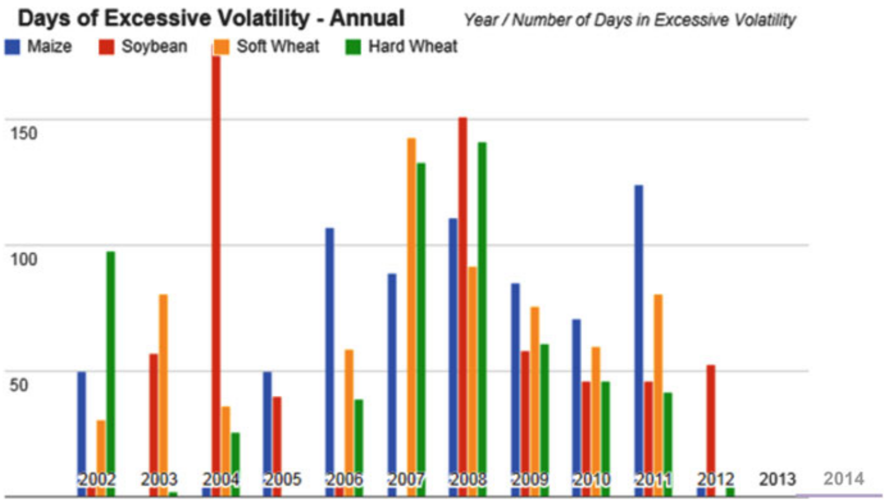

Fig. 11.1 Number of days with excessive volatility in commodity markets. *Source*: The number of days of excessive volatility is calculated using the Nonparametric Extreme Quantile (NEXQ) model for the dynamic evolution of daily returns based on historical data going back to 1954. This model is then combined with extreme value theory to estimate higher-order quantiles of the return series, allowing for classification of any particular realized return (that is, effective return in the futures market) as extremely high or not. A period of time characterized by extreme price variation (volatility) is a period of time in which we observe a large number of extreme positive returns. An extreme positive return is defined to be a return that exceeds a certain pre-established threshold. This threshold is taken to be a high-order (95 %) conditional quantile, (i.e., a value of return that is exceeded with low probability: 5 %). One or two such returns do not necessarily indicate a period of excessive volatility. Periods of excessive volatility are identified based on a statistical test applied to the number of times the extreme value occurs in a window of consecutive 60 days. See Martins-Filho et al. (2015)

[1] See Martins-Filho et al. (2013, 2015).

forced to economize on other needed goods and services. For food producers, higher food prices could raise their incomes—but only if they are net sellers of food—if increased global prices feed through to their local markets, and if the price changes on global markets do not also increase their production costs.

Apart from these effects of high food prices, price volatility also has significant effects on food producers and consumers. Greater price volatility can lead to increased losses for producers because it implies price changes that are larger and occur faster than what producers can adjust to. Uncertainty about prices makes it more difficult for farmers to make sound decisions about how and what to produce. For example, which crops should they produce? Should they invest in expensive fertilizers and pesticides? Should they purchase high-quality seeds? Without a realistic idea of how much they will earn from their products, farmers may become more pessimistic in their long-term planning and dampen their investments in areas that could otherwise improve their productivity. The positive relationship between price volatility and producers' expected losses can be modeled in a simple profit maximization model assuming producers are price takers. Still, it is important to mention that there is no uniform empirical evidence of the behavioral response of producers to volatility. By reducing supply, such a response could lead to higher prices, which in turn would hurt consumers.

It is important to remember that in rural areas the line between food consumers and producers is blurry. Many households both consume and produce agricultural commodities or foodstuffs. Therefore, if prices become more volatile and these households reduce their spending on seeds, fertilizer, and other inputs, this may affect the amount of food available for their own consumption. Even when the households are net sellers of food, producing less and having less to sell will reduce their household income and thus still impact their consumption decisions.

Finally, increased price volatility over time can also generate larger profits for investors, drawing new players into the market for agricultural commodities. Increased price volatility may thus lead to increased—and potentially speculative—trading that in turn can exacerbate price swings further, increasing volatility.

Despite the importance that price volatility may have for consumers, its impact on consumer welfare is notoriously difficult to measure due to income effects associated with price changes. In addition, the fact that in many low income countries economic agents are concomitantly consumers and producers of food creates added concerns and complications. Besides the inherent difficulties in adequately measuring consumer welfare, most empirical models for the dynamic evolution of returns for major agricultural commodities lack flexibility in modeling the conditional volatility (conditional standard deviation) of returns. Restrictive modeling of volatility can produce inconsistent return forecasts and inaccurate assessments and policy recommendations regarding the link between volatility and consumer welfare.

Since the empirical link between high relative food prices and consumer welfare is fairly well established, herein we propose an econometric/statistical model that attempts to model the relationship between conditional return volatility of major agricultural commodities and relative prices of food items/groups in a collection of low income countries. Our goal is to better understand the transmission of global volatility to local relative prices and therefore start to unveil its potential welfare effects.

11.2 Methodology

11.2.1 Relative Food Prices at Country Level

We are interested in understanding if, and how, changes in relative food prices (defined for certain groups of foodstuff) are related to volatility of agricultural commodities in global markets. To construct our variable of interest we use a Laspeyres price index for country $j = 1, \ldots, J$ in time period $t = 0, \ldots, T$. Let N be the number of elements in a collection of goods and services that form a consumption basket and $p_{tj} = \left(p_{tj1} \cdots p_{tjN}\right)'$ be the corresponding vector of prices at time period t in country j. We denote a representative consumption basket for this collection by the vector $q_{tj} = \left(q_{tj1} \cdots q_{tjN}\right)'$. The share of expenditures devoted to the nth element of the consumption basket at time t in country j is given by $s_{tjn} = p_{tjn}q_{tjn}/(p'_{tj}q_{tj})$, where $p'_{tj}q_{tj} = \sum_{n=1}^{N} p_{tjn}q_{tjn}$. Similarly, for a set $I_F = \{i_1, \ldots, i_F\}$ that indexes F elements from the representative basket, we define the share of expenditure on the food group I_F by

$$s_{tj,I_F} = \frac{p'_{tj,I_F}q_{tj,I_F}}{p'_{tj}q_{tj}},$$

where $p_{tj,I_F} = \left(p_{tji_1} \cdots p_{tji_F}\right)$, $q_{tj,I_F} = \left(q_{tji_1} \cdots q_{tjI_F}\right)'$ and $p'_{tj,I_F}q_{tj,I_F} = \sum_{n \in I_F} p_{tjn}q_{tjn}$. We note that $0 \leq s_{tj,I_F} \leq 1$. The Laspeyres price index for country j from time period $t-1$ to time period t can be written as

$$L(p_{tj}, p_{t-1,j}, q_{t-1,j}) = \sum_{n=1}^{N} \frac{p_{tjn}}{p_{t-1,jn}} s_{t-1,jn} \text{ for } t = 1, \ldots, T,$$

and the relative share of the Laspeyres price index associated with food group I_F of the consumption basket is given by

$$Y_{tjI_F} = \frac{\sum_{n \in I_F} \frac{p_{tjn}}{p_{t-1,jn}} s_{t-1,jn}}{L(p_{tj}, p_{t-1,j}, q_{t-1,j})} \text{ for } t = 1, \ldots, T.$$

Clearly, $Y_{tjI_F} \in (0, 1)$ and represents the share of price index variations from time period $t-1$ to t that correspond to the food group defined by the set I_F in the consumption basket. If Y_{tjI_F} is large, say in the vicinity of 1, the set I_F in the consumption basket accounts for a large share of the price variability of the entire consumption basket N. In this case, most of the price changes in the consumption basket from time period $t-1$ to time period t can be attributed to price variations on the elements in I_F.

If the consumption share in period $t-1$ of each element of the food group I_F—$s_{t-1,jn}$—is fixed through time at $s_{0,jn}$ for all n in I_F, then all changes in Y_{tjI_F} can be attributed to changes in relative prices of food items that belong to I_F. Otherwise, the observed variability in Y_{tjI_F} may result from both changes in relative prices and changes in expenditure shares. Throughout this paper, we will fix the share of goods and services through time at $s_{0,jn}$ and take Y_{tjI_F} as our main variable of interest for defined sets of food groups I_F. In Sect. 11.3.1 we define the sets I_F that we consider in our empirical model.

11.2.2 Conditional Global Volatility and Its Relation to Country Level Relative Food Prices

As mentioned above, we are interested in the impact that volatility of returns on agricultural commodities in global markets may have on Y_{tjI_F}. Hence, a key component of our empirical model is a measure of volatility. To obtain such a measure, we follow Martins-Filho et al. (2013) and envision the evolution of a commodity (rice, maize, soybeans, and wheat) price P as a discretely indexed stochastic process $\{P_t\}_{t=0,1,\ldots}$. As such, the observation of a time series of commodity prices that extends from a certain time in the past up to the present time represents a realization of many possible collections of values that a stochastic process may take. We let the one-lag log-returns associated with such time series be denoted by $r_t = \log \frac{P_t}{P_{t-1}}$ and assume that

$$r_t = h^{1/2}(r_{t-1}, \ldots, r_{t-L})\varepsilon_t, \tag{11.1}$$

where $h(r_{t-1}, \ldots, r_{t-L}) = h_0 + \sum_{j=1}^{L} h_j(r_{t-j})$, $L \in \mathbb{N}$ represents the maximum lag on r_t to be included as determinants of the conditional variance (squared volatility) of the process, h_j are smooth non-negative functions that are otherwise unrestricted, $\varepsilon_t \sim IID(0, 1)$ and $E(h_j(r_{t-j})) = 0$ for all j, $h_0 > 0$.[2]

The model in (11.1) assumes that the dynamic evolution of log-returns for agricultural commodities can be described as a conditional location-scale model with conditional mean equal to zero and conditional volatility given by $\left(h_0 + \sum_{j=1}^{L} h_j(r_{t-j})\right)^{1/2}$, which is a function of L lagged returns. Here, rather than assuming that volatility takes on a specific parametric structure, as in autoregressive conditional heteroscedastic (ARCH) or generalized autoregressive conditionally heteroscedastic (GARCH) models (Engle 1982; Bollerslev 1986), we flexibly model the impact of lag returns on volatility via the nonparametric functions h_j as

[2]The requirement that $E(h_j(r_{t-j})) = 0$ for all j is an identification condition for the conditional expectation $E(r_t^2 | r_{t-1}, \ldots, r_{t-L}) = h_0 + \sum_{j=1}^{L} h_j(r_{t-j})$.

in Fan and Yao (1998) and Martins-Filho et al. (2013). In this model, a measure of (conditional) volatility—a function of time—is obtained by estimating h_0, h_j nonparametrically from a time series $\{r_t\}$.

A general stochastic model that relates Y_{tjI_F} to the volatility of agricultural commodities can be expressed as

$$E(Y_{tjI_F}|h^{1/2}(r_{t-1},\ldots,r_{t-L}),W_t) = g^{-1}(m(h^{1/2}(r_{t-1},\ldots,r_{t-L}),W_t)) \qquad (11.2)$$

for $t = L+1,\ldots,T$, where $W_t \in \mathbb{R}^K$ is a collection of suitably defined (exogenous) conditioning variables, g is a strictly monotonic *link* function $g(x) : (0,1) \to \mathbb{R}$, m is a smooth function $m(x) : \mathbb{R}^{K+1} \to \mathbb{R}$. Note that in (11.2) g^{-1} takes values in $[0,1]$, which guarantees that the regression takes values in $(0,1)$, a constraint that must hold given that $Y_{tjI_F} \in (0,1)$. It would be desirable to impose as little structure as possible on the functional m and the link g, however letting m and g be nonparametric functions creates difficulties both for estimation and for deriving practical empirical conclusions. As will be described shortly, we prefer a parametric specification that explicitly accounts for the fact that $Y_{tjI_F} \in (0,1)$, which has important implications for stochastic modeling.

11.2.3 Beta Regression

As described above, our variable of interest—Y_{tjI_F}—takes values in $(0,1)$ and an appropriate parametric statistical model must reflect its range. A flexible univariate parametric (unconditional) density that accounts for such range is the beta density. The beta density associated with a random variable Y is given by

$$\pi(y;p,q) = \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} y^{p-1}(1-y)^{q-1} \text{ for } p,q > 0,\ 0 < y < 1.$$

If $\mu = \frac{p}{p+q}$ and $0 < \phi = p+q$, then $0 < E(Y) = \mu < 1$ and $V(Y) = \frac{\mu(1-\mu)}{1+\phi}$. Here, we follow Ferrari and Cribari-Neto (2004) and consider a *conditional* beta density where $\mu(\cdot)$ is a function of a collection of conditioning variables $X_t' \in \mathbb{R}^K$ with K a natural number, such that for all t

$$g(\mu_t) = \sum_{k=1}^{K} X_{tk}\theta_k = X_t\theta \qquad (11.3)$$

θ is a parameter vector taking values in a compact subset of $\mathbb{R}^K$ and $g(\mu_t) = \log\frac{\mu_t}{1-\mu_t}$. This specific form for g can be promptly recognized as the much used logit-link.

It is easily verified that for a random sample $\{(Y_t, X_t)\}_{t=1}^T$, the log-likelihood function associated with the conditional beta model is given by $\ell(\theta, \phi) = \sum_{t=1}^T \ell_t(\mu_t, \phi)$, where

$$\ell_t(\mu_t, \phi) = \log\Gamma(\phi) - \log\Gamma(\mu_t\phi) - \log\Gamma((1-\mu_t)\phi) + (\mu_t\phi - 1)\log Y_t \\ + ((1-\mu_t)\phi - 1)\log(1-Y_t).$$

The score vectors associated with the parameters of the distribution are given by

$$\ell_\theta(\theta, \phi) = \phi X' D(Y^* - \mu^*),$$

$$\ell_\phi(\theta, \phi) = \sum_{t=1}^T \left(\mu_t(Y_t^* - \mu_t^*) + \log(1-Y_t) - \psi((1-\mu_t)\phi) \right. \\ \left. + \psi(\phi)\right),$$

where Y^* is a vector with tth element given by $Y_t^* = \log \frac{Y_t}{1-Y_t}$, μ^* has tth element $\mu_t^* = \log \frac{\mu_t}{1-\mu_t}$, $\psi(\cdot)$ is the digamma function, $D = \text{diag}\{1/g^{(1)}(\mu_t)\}_{t=1}^T$, and $X' = \left(X_1' \cdots X_T'\right)$, and $g^{(1)}(\cdot)$ denotes the first derivative of g. The values $\hat{\phi}$ and $\hat{\theta}$ that satisfy

$$\ell_\theta(\hat{\theta}, \hat{\phi}) = 0 \text{ and } \ell_\phi(\hat{\theta}, \hat{\phi}) = 0 \tag{11.4}$$

are the maximum likelihood estimators for θ and ϕ. Ferrari and Cribari-Neto (2004) obtained the Fisher Information for this model, which is given by

$$F(\theta, \phi) = \begin{pmatrix} F_{\theta\theta} & F_{\theta\phi} \\ F_{\phi\theta} & F_{\phi\phi} \end{pmatrix},$$

where $F_{\theta\theta} = \phi X' W X$, $F_{\theta\phi} = F_{\phi\theta}' = \phi X' D c$, $F_{\phi\phi} = \text{trace}(D)$ with

$$W = \text{diag}\left\{\phi\left(\psi^{(1)}(\mu_t\phi) + \psi^{(1)}((1-\mu_t)\phi)\right)(g^{(1)}(\mu_t))^{-2}\right\}_{t=1}^T,$$

$$D = \text{diag}\left\{\psi^{(1)}(\mu_t\phi)\mu_t^2 + \psi^{(1)}((1-\mu_t)\phi)(1-\mu_t)^2 - \psi^{(1)}(\phi)\right\}_{t=1}^T, \text{ and}$$

$$c = (c_1, \ldots, c_T)', \text{ with } c_t = \phi\left(\psi^{(1)}(\mu_t\phi)\mu_t - \psi^{(1)}((1-\mu_t)\phi)(1-\mu_t)\right).$$

Following standard arguments for obtaining the asymptotic distribution of maximum likelihood estimators (see Newey and McFadden 1994), we obtain for sufficiently large T the following approximation

$$\begin{pmatrix} \hat{\theta} \\ \hat{\phi} \end{pmatrix} - \begin{pmatrix} \theta \\ \phi \end{pmatrix} \sim N\left(0, F^{-1}(\theta, \phi)\right), \tag{11.5}$$

which allows for asymptotically valid hypothesis testing on the parameters θ and ϕ.

It is desirable to obtain an expression for the first partial derivatives of $E(Y_t|X_t)$ with respect to the conditioning covariates X_{tk}. Given (11.3) and the logit-link, we have

$$\frac{\partial}{\partial X_{tk}} E(Y_t|X_t) = \theta_k \frac{\exp\left(\sum_{k=1}^{K} X_{tk}\theta_k\right)}{1 + \exp\left(\sum_{k=1}^{K} X_{tk}\theta_k\right)}. \quad (11.6)$$

11.3 Data, Empirical Model, and Estimation

11.3.1 Data

We have constructed a panel data set for nine Latin American countries: Costa Rica, El Salvador, Guatemala, Honduras, Ecuador, Peru, Mexico, Nicaragua and Panama, and one Asian country, India. Our variable of interest—Y_{tjI_F}—was constructed for four food groups. They are: (i) Breads and cereals, (ii) meat, (iii) milk and other dairy products, and (iv) other foods. That is, there are four elements in I_F and $I_F = \{\textit{Breads and cereals}, \textit{Meat}, \textit{Milk and other dairy products}, \textit{Other foods}\}$. These food groups were defined based on the international agricultural commodity groups rice, corn and wheat, and on standard grouping for food price indices, which is based on similarities in expenditure shares and market structure. Y_{tjI_F} for (i)–(iv) were constructed using detailed data sets obtained from the national statistical institutes of each country. They included a price index of approximately 200 food and nonfood items that constitute a standard consumption basket, and their corresponding relative importance (weights) in the general consumption price index (CPI).

As components of X_t in the previous section, we included a measure of the overall economic activity in the country given by a “Monthly index of economic activity.” This is a Laspeyres index. It measures the evolution of economic activity, approximating the aggregated value of the industries included in the calculation of the gross domestic product (GDP). The index is given by $I_t = \sum_{i=1}^{n} I_{it} w_{i0}$ where I_t is the general index in period t; I_{it} is the index of industry i (manufacturing, agricultural, etc.) in month t; w_{i0} is the weight associated with industry i in the calculation of GDP in the baseline period; n is the number of industries; GDP is the aggregation of all the aggregated values of the productive activities. Activities included in the calculation of the IMAE (Indice Mensual de Actividad Economica—Monthly Index of Economic Activity) include: agricultural and livestock; mining; manufacturing; construction; water and electricity; trade; transport and communication; services for enterprises; services for financial intermediation; and hotel business. This variable was obtained from the Central Banks from each country. This index measures the total value of all different industries included in the calculation of the GDP. Additionally we included total imports, returns on oil prices, the monetary value (in US dollars) of liquid assets (M1) in circulation, and of course, our main conditioning variables of interest, the estimated volatility of international commodity prices (see the Appendix for a detailed list of sources for these variables in each country).

The volatility of returns for agricultural commodities was estimated using a sequence of returns based on prices for future contracts closest to maturity for: wheat CBOT (Chicago Board of Trade), wheat KCBT (Kansas City Board of Trade), corn, soybeans, and rice. From 01/28/1987 until 8/31/2009, daily data was taken from a historic file bought from the CME Group. From 09/01/2009 to 08/20/2013 daily data was obtained from daily updates, from CME and KCBT. The first observation for the time series estimation is for 01/03/1995.

11.3.2 Empirical Model and Estimation

Since $Y_{tjI_F} \in (0, 1)$, we consider the following empirical specification for $g(\mu_t)$ in Sect. 11.2.3,

$$g(\mu_t) = \theta_0 + \sum_{l=1}^{4} W_{tl}\theta_l + \sum_{l=5}^{9} \theta_l\, h_l^{1/2}(r_{l,t-1}, r_{l,t-2}), \tag{11.7}$$

where $h_l^{1/2}(r_{l,t-1}, r_{l,t-2})$ must be estimated based on a time series of returns $\{r_{lt}\}$ on each of the five agricultural commodities given above, and W_{t1}, W_{t2}, W_{t3}, and W_{t4} represent the monthly indicator of economic activity, total imports, M1 and return on oil prices, respectively. As in Sect. 11.2.3, we specify $g(\mu_t) = \log \frac{\mu_t}{1-\mu_t}$.

Each $h_l^{1/2}(r_{l,t-1}, r_{l,t-2})$ is estimated nonparametrically by noting that from (11.1), we have for each l,

$$E(r_{tl}^2 | r_{l,t-1}, r_{l,t-2}) = h_0 + h_{l1}(r_{l,t-1}) + h_{l2}(r_{l,t-2}).$$

Hence, for each l we conduct a nonparametric additive regression estimation using the procedure discussed in Kim et al. (1999). The data we use on r_{tl} has daily frequency, and all other data has monthly frequency. Thus, we aggregate our daily estimated conditional volatility to produce monthly estimates. We have experimented with the following measures of monthly volatility: (a) monthly means; (b) monthly medians; and (c) monthly inter-quartile ranges. There was little qualitative change in the results from using either of these measures. The results reported in Tables 11.1, 11.2, 11.3, 11.4, 11.5, 11.6, 11.7, 11.8, 11.9, 11.10, 11.11, 11.12, 11.13, 11.14, 11.15, 11.16, 11.17, 11.18, 11.19 and 11.20 in the Appendix are for monthly means. These estimates of (monthly) volatility, denoted by $\hat{h}_l^{1/2}(r_{l,t-1}, r_{l,t-2})$, are then used as covariates for the maximum likelihood estimation of (11.7).

The maximum likelihood procedure requires the numerical solution of the homogeneous system of nonlinear equations given in (11.4). We use the Marquardt algorithm (see Marquardt 1963) to obtain a solution. The procedure requires initial values for the parameters ϕ and θ, which we choose as suggested by Ferrari and

Cribari-Neto (2004).[3] Convergence of the algorithm is attained very quickly for all 40 (four food groups in ten countries) beta-regressions we have estimated. After obtaining $\hat{\theta}$ and $\hat{\phi}$ for all food groups and for all countries we estimated Fisher's information by $F(\hat{\theta}, \hat{\phi})$ using the expressions given in Sect. 11.2.3. $F(\hat{\theta}, \hat{\phi})$ is used to calculate the z-statistics reported in Tables 11.1, 11.2, 11.3, 11.4, 11.5, 11.6, 11.7, 11.8, 11.9, 11.10, 11.11, 11.12, 11.13, 11.14, 11.15, 11.16, 11.17, 11.18, 11.19 and 11.20 that appear in the Appendix. Also reported in these tables are the estimated marginal impact of the various covariates on the conditional expectation of Y_{tjI_F}. These are obtained using the estimates $\hat{\theta}$ to obtain estimated partial derivatives as given in (11.6).

11.3.3 Discussion

We first note that proportion of the variation on the general Laspeyres price index attributed to "Breads and Cereals," "Meats," and "Milk and other dairy products" is fairly small across all countries. These proportions vary from 0.02 to 0.10 for "Breads and Cereals," 0.02 to 0.09 for "Meats," and 0.03 to 0.06 for "Milk and other dairy products." As expected, the price variation of the catchall category "Other foods" is a much larger proportion of the variation on the general Laspeyres price index. It varies from proportion 0.05 to 0.26.

For illustrative purposes, Figs. 11.2 and 11.3 provide Rosenblatt-kernel estimates of the density of the proportion of the general Laspeyres price index attributed to the food group "Bread and cereals" and "Meat" in Honduras and India. Figure 11.4 provides the Rosenblatt-kernel estimate of the density of the proportion of the general Laspeyres price index attributed to the food group "Milk and other dairy products" in Peru, and Fig. 11.5 provides the Rosenblatt-kernel estimate of the density of the proportion of the general Laspeyres price index attributed to the food group "Other foods" in Nicaragua. The estimated unimodal densities presented here are typical across the countries, but cases of bimodal densities do exist.

The results for all regressions are given in Tables 11.1, 11.2, 11.3, 11.4, 11.5, 11.6, 11.7, 11.8, 11.9, 11.10, 11.11, 11.12, 11.13, 11.14, 11.15, 11.16, 11.17, 11.18, 11.19 and 11.20 in the Appendix. The tables contain parameter estimates, z-statistics for the null hypothesis that $\theta_k = 0$ against the alternative that $\theta_k \neq 0$ as well as the estimated marginal impact of each covariate evaluated at its average sample value. In addition, we provide pseudo-R^2 values for each regression. We can perceive some general regularities. For all food groups and for all countries, the precision parameter ϕ and the intercept θ_0 are significant at the 5 % level, with $\phi > 0$ and $\theta_0 < 0$. Also, the pseudo-R^2 for the regressions are generally large, varying from 0.56 to 0.98, indicating a reasonable overall fit for the models we have specified.[4]

[3] All codes for estimation were written using MATLAB and are available upon request.

[4] The exception is the regression for the Meat group in Costa Rica, where the pseudo-R^2 is 0.21.

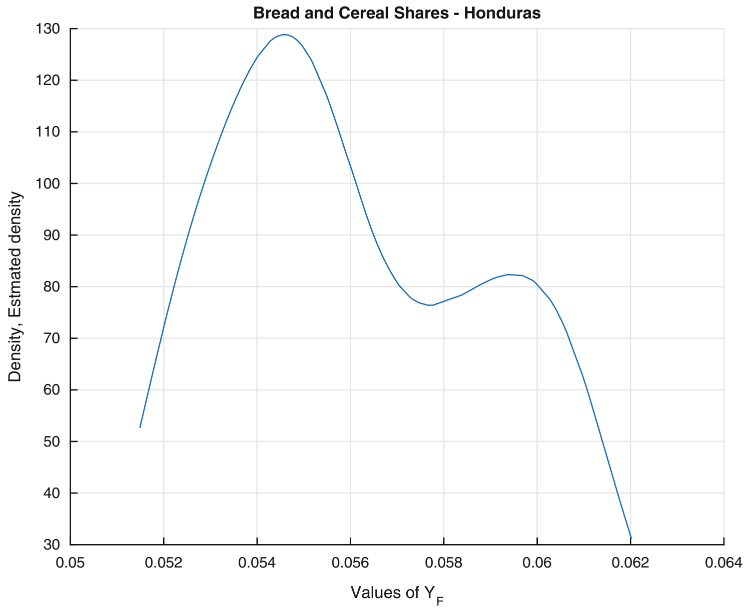

Fig. 11.2 Rosenblatt density estimate of the density of the proportion of general Laspeyres price index attributed to “Breads and cereals” in Honduras

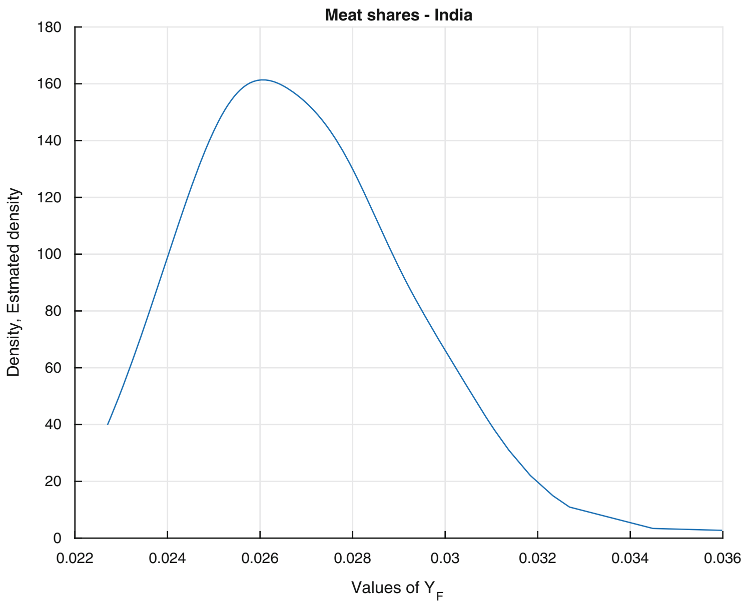

Fig. 11.3 Rosenblatt density estimate of the density of the proportion of general Laspeyres price index attributed to “Meat” in India

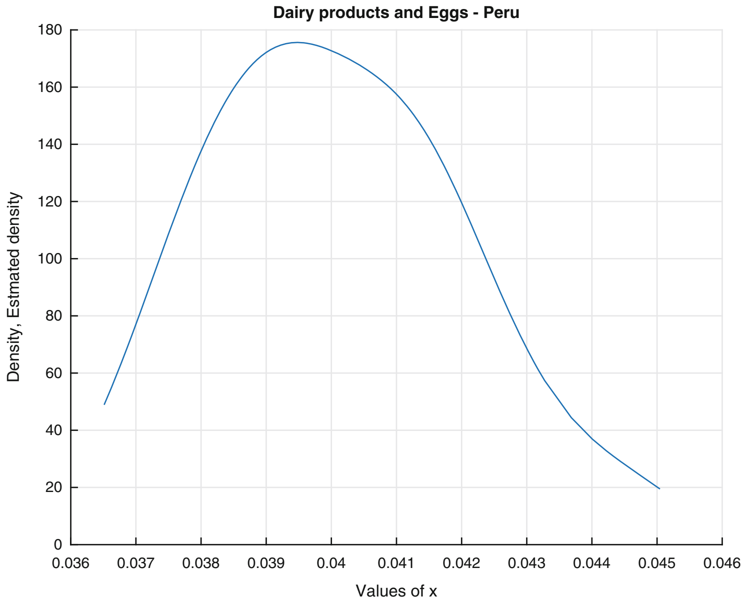

Fig. 11.4 Rosenblatt density estimate of the density of the proportion of general Laspeyres price index attributed to "Milk and dairy products" in Peru

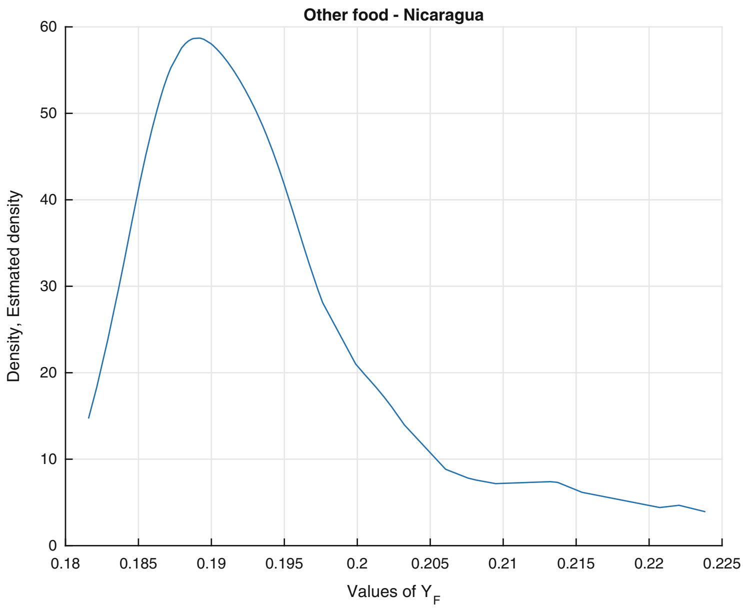

Fig. 11.5 Rosenblatt density estimate of the density of the proportion of general Laspeyres price index attributed to "Other foods" in Nicaragua

In addition, for most regressions, plots of standardized residuals against the indices of the observations show no discernible pattern that may suggest misspecification. Figures 11.6 and 11.7 provide such plots for Honduras and India. The case of Honduras is quite typical, but the figure for India reveals that some observations may have significant leverage on the estimation. We chose to keep these observations in our calculations, but their removal normally boosts the estimated value of ϕ.

For the food group "Breads and cereals" and for all countries, with the exception of El Salvador, Guatemala, and Nicaragua, the parameters associated with the volatility of wheat (either KCBT or CBOT) are positive and significant, mostly at the 5 % level, and in Honduras and Mexico at the 10 % level.[5] Whenever the estimated parameter values associated with either of these volatilities is negative, it is insignificant at either the 5 or 10 % level. Thus, there seems to be evidence that increased volatility of prices of wheat in global markets correlates with an increased proportion of the variation on the general Laspeyres price index that is attributed to the food group "Breads and cereals." Put differently, increased volatility on wheat markets may increase the relative prices of "Breads and cereals" in most countries. Accordingly, policies or market forces that mitigate volatility in these global markets

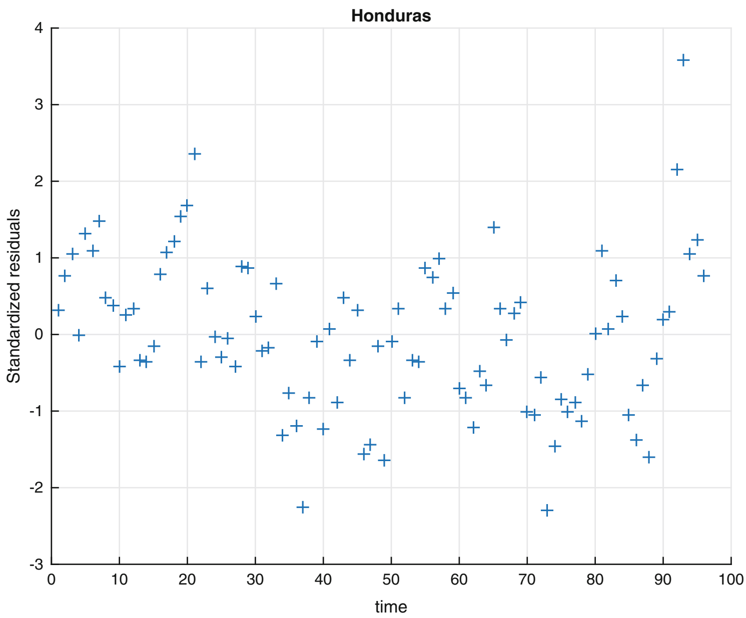

Fig. 11.6 Standardized residuals against the time index of the observations for "Other foods" for Honduras

[5]In El Salvador and Nicaragua the parameters associated with global wheat market volatility are statistically insignificant, and in Guatemala the parameter associated with the volatility of hard wheat (VolWCBOT) is negative and significant at the 10 % level.

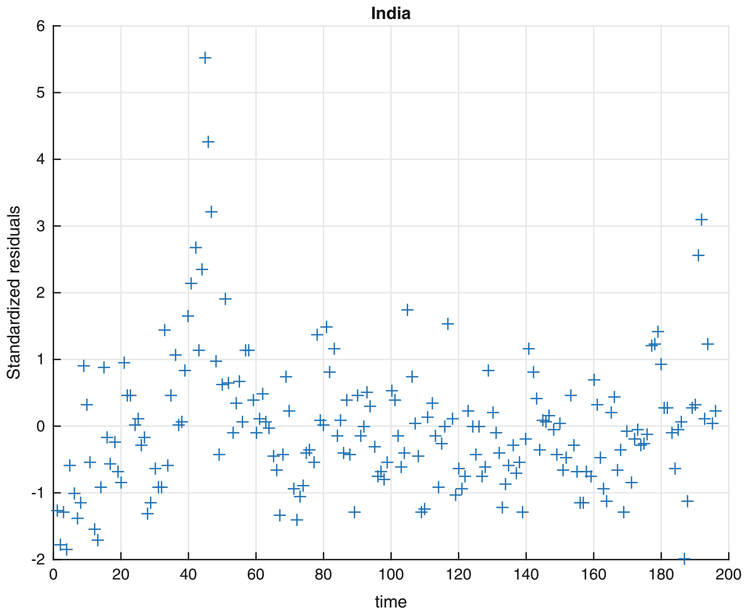

Fig. 11.7 Standardized residuals against the time index of the observations for "Other foods" for India

may help curb the share of general price movements that is attributable to "Breads and Cereals," therefore lessening the impact of changing prices on the budgets of households where this food group accounts for a larger share of expenditures.

The parameter associated with the index of economic activity is, whenever significant, negative for most food groups and countries (19 out of 24 cases). The exceptions are Costa Rica, El Salvador, and Guatemala where the parameter is positive and significant for the food groups "Breads and cereals," "Milk and other dairy products," and/or the catchall category "Other foods." Hence, there seems to be some evidence that increased economic activity dampens the proportion of the variation on the general Laspeyres price index that is attributed to most food groups. Thus, growth seems to lighten the impact of changing prices on the budgets of households where food accounts for a larger share of expenditures.

The parameter associated with the returns on oil prices is insignificant for virtually all food groups across all countries. The exceptions are "Breads and cereals" in India and "Meat" in Ecuador. The parameter associated with M1 is mostly positive and significant, or insignificant in most countries across all food groups. In addition, the absolute value of the estimated parameters associated with M1 is quite small, with values that are less than or equal to 10^{-4}. Similarly, the estimated parameters associated with imports are also very small in absolute value. For this covariate, in most countries in Latin America, it has a statistically significant positive impact on the proportion of the variation on the general Laspeyres price index that is attributed to most food groups. In India the impact of this covariate is significant, but negative.

For the food group "Meats" and for most countries the parameter associated with the volatility of corn is positive and significant at either the 5 or 10 % level. The exceptions are Costa Rica, where the parameter is negative and insignificant, and Nicaragua, Panama, and Peru where the parameters are always positive but not significant at the 10 % level. Hence, there seems to be some evidence that increased volatility of prices of corn in global markets correlates with an increased proportion of the variation on the general Laspeyres price index that is attributed to the food group "Meats."

We note that the marginal impact of changes in covariates on $E(Y_{tjI_F}|\cdot)$ is relatively small across countries and food groups. This impact is rarely above 1 in absolute value, with exceptions for volatility of wheat in India and Costa Rica and volatility of rice in Peru for the "Other foods" group, volatility of rice in El Salvador and volatility of wheat, corn, and soy in Guatemala for the "Breads and cereals" group, and volatility of rice for the "Meat" group in Mexico. Thus, changes in volatility produce, at average values, changes on $E(Y_{tjI_F}|\cdot)$ of smaller magnitude.

11.4 Conclusion

The global food price crises of 2007/2008 and 2010/2011 led to economic difficulties for the poor, contributed to political turmoil in many countries, and in the long run could undermine confidence in global food markets, thereby hampering these markets' performance in balancing fundamental changes in supply, demand, and production costs. More important, food price crises can result in unreasonable or unwanted price fluctuations (volatility) that can harm the poor. Price volatility can have significant effects on food producers and consumers but the potential link between the volatility of returns for major agricultural commodities at the global level and welfare at the household level was not well understood. In this paper we took advantage of the fact that there is already important evidence on the effects of price levels on welfare and therefore focus on reducing the knowledge gap of the relationship between price volatility at the global level and relative prices of food items/groups in low income countries. Specifically, to close this gap we specify an empirical model that describes the dynamic evolution of the relative share of various food items in a Laspeyres price index as a function of the global volatility of returns for major agricultural commodities and a collection of observed covariates and relate it to the volatility of returns of agricultural commodities emerging from a fully nonparametric location-scale stochastic process as in Martins-Filho et al. (2015).

Our results show evidence for most countries of a relationship between relative prices and price volatility for the food group "Breads and cereals" with the volatility of wheat (either KCBT or CBOT). Thus, increased global volatility on wheat markets may increase the relative prices of "Breads and cereals" in most countries.

Similarly, for the food group “Meats” for most countries the parameter associated with the volatility of corn is positive and significant being possibly the transmission mechanism for animal feed based on corn. Hence, and similarly to the case of wheat and breads and cereals, there also seems to be some evidence that increased volatility of prices of corn in global markets correlates with an increased proportion of the variation on the general Laspeyres price index that is attributed to the food group “Meats.”

Accordingly, policies or market forces that mitigate volatility in these global markets may help curb the share of general price movements that is attributable to “Breads and cereals” and “Meat” at the country level lessening the impact of changing prices on the budgets of households where these food groups account for a larger share of expenditures. These results are of extreme relevance for the food price crises of 2007/2008 because volatility was, as initially mentioned, at its highest level during that period of time relative to the past 50 years. Even more the volatility was the highest for wheat and corn. For soft wheat there were an average of 41 days of excessive price volatility per year between December 2001 and December 2006 while from January 2007 to June 2011, the average number of days of excessive volatility more than doubled to 88 per year.

The question is then what countries can do to cope with excessive volatility. In this light, many countries try to stabilize prices through trade policies and management of food reserves. With respect to reserves, international experience in the management and use of so-called strategic grain reserves is mixed, with frequent concerns about operational inefficiencies, financial costs, and disincentives for private traders to perform normal arbitrage functions. Some of the problems with grain reserves can be overcome by establishing clear and open rules for market interventions, including the private sector in the tendering for supplies for the reserves, combining grain and financial reserves to reduce costs. However, instead of domestic buffer stocks, some authors posit the advantages of holding reserves at the international level or regional level. Among other reasons, this type of intervention can reduce storage costs and, if managed by an international intelligence unit, can reduce governments’ political management of the resources. Albeit compelling, an international or regional reserve poses other important obstacles. Politically, it requires multinational coordination and sound governance. Economically, it might disincentive private grain storage. Operationally, it is important to establish clear triggers for market intervention. Similarly, there is important evidence showing that using trade policies to reduce price volatility is not effective and on the contrary could have important welfare costs as shown by Martin and Anderson (2011) and Anderson and Nelgen (2012).

On the other hand, there is evidence that improved transport infrastructure helps reduce price variability. Roads are useful means to spread out regional shocks; if a certain region is hit by a shock (weather or other), it can import food from another region. For example, during the food crisis of 2007/2008, it is shown that regions with better infrastructure in Indonesia were not hit as hard as those poorly connected. In this line, the World Bank (2010) argues that after controlling for exchange rates and world prices, remote provinces appear to have higher levels of price volatility than well-connected provinces. It confirms the importance of investment in infrastructure. In particular, it demonstrates that the constraints created by geography and remoteness to the transmission of price signals can be alleviated by improving the quality of infrastructure. This result is consistent with the fact that in our analysis we also find some evidence that increased economic activity dampens the proportion of the variation on the general Laspeyres price index that is attributed to most food groups. Thus, growth seems to lighten the impact of changing prices on the budgets of households where food accounts for a larger share of expenditures.

In summary, price volatility is likely to remain an important challenge in the medium and long run and, as was shown, a link exists between the volatility of returns for major agricultural commodities and relative prices of certain food groups. It is in this sense that further research is needed to understand alternative policies at the global, regional, and local level that could help countries to cope with excessive volatility.

Appendix

Tables

Table 11.1 Model: Y_{tI_F}—India, $n = 196$

	Breads and cereals			Meat		
Parameter	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	8322.0225	9.8975		8052.0188	9.8966	
θ_0(Intercept)	−3.3859	−45.8605	−0.1181	−3.4186	−40.4528	−0.0918
θ_1(EconAct)	−0.0001	−0.4041	0	−0.0012	−2.9929	0
θ_2(Imports)	0	−4.1538	0	0	−3.8414	0
θ_3(M1)	0	0.8828	0	0	5.1483	0
θ_4(Return on Oil)	0.1347	2.5937	0.0047	0.0363	0.6084	0.001
θ_5(VolCorn)	3.7597	1.6468	0.1311	4.8465	1.8106	0.1302
θ_6(VolSoy)	−7.9867	−2.9294	−0.2785	−11.1097	−3.5301	−0.2985
θ_7(VolRice)	−8.0383	−3.8538	−0.2803	−12.6843	−5.209	−0.3408
θ_8(VolWCBOT)	24.7865	3.972	0.8644	11.699	1.6275	0.3143
θ_9(VolWKCBT)	−7.448	−1.3926	−0.2597	−2.8586	−0.4622	−0.0768
Pseudo-R^2	0.61				0.63	

Table 11.2 Model: Y_{tI_F}—India, $n = 196$

Parameter	Milk and other dairy products			Other foods		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	18,235.638	9.8986		2959.3164	9.8965	
θ_0(Intercept)	−3.3944	−67.3571	−0.115	−2.8103	−27.592	−0.1442
θ_1(EconAct)	−0.0006	−2.5677	0	−0.0012	−2.374	−0.0001
θ_2(Imports)	0	−6.9294	0	0	−1.9511	0
θ_3(M1)	0	5.2652	0	0	2.9808	0
θ_4(Return on Oil)	0.0456	1.2867	0.0015	−0.1576	−2.1992	−0.0081
θ_5(VolCorn)	0.9446	0.5976	0.032	2.2964	0.7103	0.1178
θ_6(VolSoy)	−6.1414	−3.3173	−0.2081	−8.4597	−2.2293	−0.434
θ_7(VolRice)	−0.9646	−0.6754	−0.0327	−12.9179	−4.4025	−0.6627
θ_8(VolWCBOT)	7.9036	1.8516	0.2678	20.5499	2.3618	1.0542
θ_9(VolWKCBT)	2.1534	0.5863	0.073	−5.2261	−0.6984	−0.2681
Pseudo-R^2	0.58				0.58	

Table 11.3 Model: Y_{tI_F}—Costa Rica, $n = 161$

Parameter	Breads and cereals			Meat		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	26,075.522	8.9718		45,212.82	8.9719	
θ_0(Intercept)	−3.6305	−98.3296	−0.1566	−3.173	−106.2465	−0.1228
θ_1(EconAct)	0.0004	1.8016	0	−0.0001	−0.7093	0
θ_2(Imports)	−0.0001	−2.1393	0	0	2.0016	0
θ_3(M1)	0	4.0094	0	0	−0.2263	0
θ_4(Return on Oil)	−0.0237	−0.8253	−0.001	−0.0045	−0.195	−0.0002
θ_5(VolCorn)	−3.0216	−1.7949	−0.1304	−0.1286	−0.0974	−0.005
θ_6(VolSoy)	9.0852	6.4816	0.392	0.2527	0.2246	0.0098
θ_7(VolRice)	2.3734	1.636	0.1024	−0.4263	−0.3762	−0.0165
θ_8(VolWCBOT)	7.5157	2.0229	0.3243	−3.4331	−1.1423	−0.1329
θ_9(VolWKCBT)	8.689	2.2975	0.3749	1.4881	0.4892	0.0576
Pseudo-R^2	0.94				0.21	

Table 11.4 Model: Y_{tI_F}—Costa Rica, $n = 161$

	Milk and other dairy products			Other foods		
Parameter	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	6196.3183	8.9698		10,060.627	8.9724	
θ_0(Intercept)	−4.6539	−56.4141	−0.168	−2.1065	−64.0618	−0.3418
θ_1(EconAct)	0.0034	6.6053	0.0001	0.0009	4.6255	0.0002
θ_2(Imports)	−0.0001	−1.7584	0	−0.0001	−3.7474	0
θ_3(M1)	0	0.1881	0	0	4.0935	0
θ_4(Return on Oil)	−0.0455	−0.7101	−0.0016	−0.0074	−0.2882	−0.0012
θ_5(VolCorn)	3.3943	0.884	0.1225	3.4899	2.3559	0.5663
θ_6(VolSoy)	8.2956	2.633	0.2994	−0.0698	−0.0557	−0.0113
θ_7(VolRice)	9.0529	2.7014	0.3268	2.2767	1.7793	0.3694
θ_8(VolWCBOT)	6.7551	0.8206	0.2438	3.2624	0.9848	0.5294
θ_9(VolWKCBT)	15.4374	1.8353	0.5572	6.8953	2.0505	1.1189
Pseudo-R^2	0.93				0.94	

Table 11.5 Model: Y_{tI_F}—Ecuador, $n = 101$

	Breads and cereals			Meat		
Parameter	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	17,823.992	7.105		17,059.821	7.1061	
θ_0(Intercept)	−4.4994	−40.662	−0.0942	−3.0999	−46.642	−0.1984
θ_1(EconAct)	0.0003	1.3192	0	−0.0003	−2.5424	0
θ_2(Imports)	0	−0.0158	0	0	−0.2144	0
θ_3(M1)	0	0.9764	0	0	3.264	0
θ_4(Return on Oil)	0.0387	0.6157	0.0008	0.0665	1.7533	0.0043
θ_5(VolCorn)	−5.7378	−1.1672	−0.1201	9.0724	3.0926	0.5807
θ_6(VolSoy)	15.704	4.1448	0.3288	−3.8565	−1.6903	−0.2468
θ_7(VolRice)	5.1702	0.8926	0.1083	11.269	3.2368	0.7212
θ_8(VolWCBOT)	−5.5333	−0.6799	−0.1159	3.5782	0.7259	0.229
θ_9(VolWKCBT)	20.9795	2.5906	0.4393	3.5107	0.7179	0.2247
Pseudo-R^2	0.83				0.86	

Table 11.6 Model: Y_{tI_F}—Ecuador, $n = 101$

Parameter	Milk and other dairy products			Other foods		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	91,687.291	7.1062		15,227.761	7.1065	
θ_0(Intercept)	−3.2196	−94.4869	−0.1429	−1.6972	−39.1194	−0.3331
θ_1(EconAct)	0	−0.6612	0	−0.0001	−1.4768	0
θ_2(Imports)	0	4.1872	0	0	2.2185	0
θ_3(M1)	0	0.0493	0	0	8.2742	0
θ_4(Return on Oil)	0.0004	0.0218	0	0.0034	0.1382	0.0007
θ_5(VolCorn)	−1.4647	−0.9732	−0.065	−4.4661	−2.3233	−0.8767
θ_6(VolSoy)	0.0609	0.052	0.0027	2.9095	1.9523	0.5711
θ_7(VolRice)	2.8649	1.6069	0.1272	6.1867	2.7241	1.2144
θ_8(VolWCBOT)	0.1769	0.0699	0.0079	1.1011	0.3418	0.2161
θ_9(VolWKCBT)	4.0488	1.6159	0.1797	1.2828	0.4018	0.2518
Pseudo-R^2	0.85				0.96	

Table 11.7 Model: Y_{tI_F}—El Salvador, $n = 158$

Parameter	Breads and cereals			Meat		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	5561.2261	8.888		12,950.628	8.8873	
θ_0(Intercept)	−2.1186	−28.6153	−0.1978	−2.5586	−36.4601	−0.1052
θ_1(EconAct)	−0.0015	−3.8894	−0.0001	−0.0011	−2.9273	0
θ_2(Imports)	0	0.6865	0	−0.0001	−1.9564	0
θ_3(M1)	0.0001	1.6496	0	0	−0.5514	0
θ_4(Return on Oil)	0.0263	0.5228	0.0025	0.0079	0.1643	0.0003
θ_5(VolCorn)	3.5452	1.8955	0.331	5.0484	2.819	0.2075
θ_6(VolSoy)	4.9424	2.0159	0.4614	−13.2289	−5.384	−0.5438
θ_7(VolRice)	−11.1869	−6.2487	−1.0444	−6.4993	−3.7905	−0.2672
θ_8(VolWCBOT)	2.2313	0.37	0.2083	−11.5973	−2.0402	−0.4767
θ_9(VolWKCBT)	2.9245	0.6448	0.273	5.62	1.3124	0.231
Pseudo-R^2	0.56				0.85	

Table 11.8 Model: Y_{tI_F}—El Salvador, $n = 158$

	Milk and other dairy products			Other foods		
Parameter	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	30,430.033	8.8881		5667.8556	8.8887	
θ_0(Intercept)	−2.549	−70.1824	−0.1738	−1.6938	−30.9319	−0.322
θ_1(EconAct)	0.0005	2.4619	0	0.0001	0.3237	0
θ_2(Imports)	−0.0002	−6.41	0	0.0001	1.0381	0
θ_3(M1)	0	−1.6455	0	0.0001	4.3691	0
θ_4(Return on Oil)	0.0062	0.2515	0.0004	−0.0103	−0.2802	−0.002
θ_5(VolCorn)	−0.9513	−1.0251	−0.0649	−0.2598	−0.1873	−0.0494
θ_6(VolSoy)	−1.1632	−0.9433	−0.0793	4.208	2.3415	0.8
θ_7(VolRice)	−4.3038	−4.8952	−0.2935	−1.2858	−0.9834	−0.2444
θ_8(VolWCBOT)	7.5635	2.5548	0.5157	4.292	0.9573	0.8159
θ_9(VolWKCBT)	−2.8503	−1.2763	−0.1944	−2.7598	−0.8161	−0.5247
Pseudo-R^2	0.88				0.81	

Table 11.9 Model: Y_{tI_F}—Guatemala, $n = 87$

	Breads and cereals			Meat		
Parameter	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	4298.7881	6.5953		146,788.96	6.5954	
θ_0(Intercept)	−2.9855	−24.5471	−0.3232	−2.4889	−96.4172	−0.1709
θ_1(EconAct)	−0.0008	−0.6875	−0.0001	0.0001	0.6322	0
θ_2(Imports)	0.0002	1.7144	0	0	−1.1404	0
θ_3(M1)	0.0002	11.7713	0	0	−6.0762	0
θ_4(Return on Oil)	0.0757	0.9064	0.0082	−0.0175	−1.0212	−0.0012
θ_5(VolCorn)	−11.8679	−3.44	−1.2849	1.8097	2.6906	0.1242
θ_6(VolSoy)	22.4028	7.5817	2.4255	−0.9991	−1.605	−0.0686
θ_7(VolRice)	8.2857	2.5947	0.8971	−1.567	−2.5122	−0.1076
θ_8(VolWCBOT)	−18.6606	−1.9522	−2.0204	1.1373	0.5625	0.0781
θ_9(VolWKCBT)	5.419	0.5968	0.5867	−2.4823	−1.3201	−0.1704
Pseudo-R^2	0.98				0.93	

Table 11.10 Model: Y_{tI_F}—Guatemala, $n = 87$

Parameter	Milk and other dairy products			Other foods		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	65,680.907	6.5953		25,657.83	6.5955	
θ_0(Intercept)	−3.3321	−64.5307	−0.1212	−1.4485	−36.6358	−0.2782
θ_1(EconAct)	0.0002	0.3783	0	0.0009	2.5545	0.0002
θ_2(Imports)	0	−0.7157	0	0	−1.1066	0
θ_3(M1)	0	−1.4175	0	0	−2.6884	0
θ_4(Return on Oil)	−0.0183	−0.5276	−0.0007	0.0335	1.2704	0.0064
θ_5(VolCorn)	0.0587	0.043	0.0021	1.775	1.7126	0.3409
θ_6(VolSoy)	−1.6323	−1.2926	−0.0594	−4.0444	−4.2128	−0.7768
θ_7(VolRice)	−3.3057	−2.6103	−0.1202	0.9904	1.0305	0.1902
θ_8(VolWCBOT)	8.1127	2.0038	0.295	3.9504	1.2751	0.7588
θ_9(VolWKCBT)	2.8203	0.7445	0.1025	−4.0736	−1.4118	−0.7825
Pseudo-R^2	0.58				0.73	

Table 11.11 Model: Y_{tI_F}—Honduras, $n = 96$

Parameter	Breads and cereals			Meat		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	14,598.789	6.9279		48,382.299	6.9281	
θ_0(Intercept)	−2.585	−26.1313	−0.1452	−2.3455	−43.8583	−0.1391
θ_1(EconAct)	−0.0053	−7.3732	−0.0003	−0.0017	−4.43	−0.0001
θ_2(Imports)	0.0005	4.8968	0	0.0001	2.1388	0
θ_3(M1)	0.0001	0.8068	0	0	−1.0715	0
θ_4(Return on Oil)	−0.0571	−1.0855	−0.0032	−0.0273	−0.9683	−0.0016
θ_5(VolCorn)	−1.0199	−0.4448	−0.0573	3.9446	3.212	0.234
θ_6(VolSoy)	−2.084	−0.8758	−0.117	−8.0223	−6.2669	−0.4759
θ_7(VolRice)	−2.5027	−1.2808	−0.1406	−1.8207	−1.7399	−0.108
θ_8(VolWCBOT)	7.9671	0.9622	0.4474	−3.7906	−0.8517	−0.2249
θ_9(VolWKCBT)	10.1606	1.6438	0.5706	−4.2284	−1.2683	−0.2508
Pseudo-R^2	0.75				0.90	

Table 11.12 Model: Y_{tI_F}—Honduras, $n = 96$

Parameter	Milk and other dairy products			Other foods		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	34,209.087	6.928		13,181.435	6.9283	
θ_0(Intercept)	−2.6426	−37.6436	−0.1261	−1.3638	−20.9949	−0.2263
θ_1(EconAct)	−0.0037	−7.2297	−0.0002	−0.0032	−6.957	−0.0005
θ_2(Imports)	0.0003	4.0397	0	0.0003	4.3367	0.0001
θ_3(M1)	0.0002	3.8116	0	0.0001	2.3503	0
θ_4(Return on Oil)	−0.0496	−1.334	−0.0024	−0.0525	−1.5292	−0.0087
θ_5(VolCorn)	−1.5597	−0.9562	−0.0744	1.3954	0.9295	0.2315
θ_6(VolSoy)	−4.8124	−2.8469	−0.2297	−1.6185	−1.048	−0.2685
θ_7(VolRice)	−1.5132	−1.0887	−0.0722	−2.8316	−2.2052	−0.4698
θ_8(VolWCBOT)	−7.0353	−1.1958	−0.3358	0.4223	0.0777	0.0701
θ_9(VolWKCBT)	4.877	1.1178	0.2328	0.2002	0.0496	0.0332
Pseudo-R^2	0.77				0.71	

Table 11.13 Model: Y_{tI_F}—Mexico, $n = 159$

Parameter	Breads and cereals			Meat		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	18,585.355	8.9154		5369.5718	8.915	
θ_0(Intercept)	−3.5081	−32.6184	−0.1168	−1.9976	−13.1078	−0.1125
θ_1(EconAct)	0.0002	0.118	0	−0.0071	−3.3766	−0.0004
θ_2(Imports)	0	2.6326	0	0	3.5931	0
θ_3(M1)	0	−1.9315	0	0	−5.1358	0
θ_4(Return on Oil)	0.0704	1.5813	0.0023	−0.0194	−0.3014	−0.0011
θ_5(VolCorn)	1.8294	1.1281	0.0609	6.605	2.8381	0.3718
θ_6(VolSoy)	−2.6105	−1.2018	−0.0869	−1.784	−0.5532	−0.1004
θ_7(VolRice)	−6.2146	−3.7211	−0.2069	−17.8027	−7.3128	−1.0022
θ_8(VolWCBOT)	9.193	1.8751	0.3061	0.2148	0.0305	0.0121
θ_9(VolWKCBT)	−1.1962	−0.2925	−0.0398	−2.0003	−0.3489	−0.1126
Pseudo-R^2	0.63				0.88	

Table 11.14 Model: Y_{tI_F}—Mexico, $n = 159$

Parameter	Milk and other dairy products			Other foods		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	8191.7135	8.9149		8349.1367	8.9159	
θ_0(Intercept)	−2.5171	−17.6153	−0.1044	−2.2455	−20.5959	−0.1644
θ_1(EconAct)	−0.0065	−3.3301	−0.0003	−0.0024	−1.6152	−0.0002
θ_2(Imports)	0	4.4809	0	0	3.3767	0
θ_3(M1)	0	−6.0912	0	0	−6.1153	0
θ_4(Return on Oil)	0.0212	0.3538	0.0009	-0.0103	−0.2262	−0.0008
θ_5(VolCorn)	3.7388	1.7097	0.1551	2.3254	1.3982	0.1702
θ_6(VolSoy)	−7.3896	−2.4292	−0.3066	−8.1107	−3.5465	−0.5936
θ_7(VolRice)	−14.9432	−6.5592	−0.62	−7.112	−4.1495	−0.5205
θ_8(VolWCBOT)	10.5947	1.6134	0.4396	6.3139	1.2587	0.4621
θ_9(VolWKCBT)	−0.6629	−0.1234	−0.0275	−0.627	−0.152	−0.0459
Pseudo-R^2	0.86				0.81	

Table 11.15 Model: Y_{tI_F}—Nicaragua, $n = 88$

Parameter	Breads and cereals			Meat		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	23,124.049	6.6331		28,388.756	6.6331	
θ_0(Intercept)	−2.9785	−61.2473	−0.2098	−2.557	−55.4856	−0.18
θ_1(EconAct)	0.0002	0.8483	0	0.0001	0.3479	0
θ_2(Imports)	0.0004	4.291	0	0.0001	1.7132	0
θ_3(M1)	0.0005	5.2454	0	0	0.3868	0
θ_4(Return on Oil)	0.0511	1.2112	0.0036	−0.03	−0.7928	−0.0021
θ_5(VolCorn)	−1.4927	−0.8725	−0.1052	2.3858	1.5672	0.1679
θ_6(VolSoy)	7.6796	5.1633	0.541	−3.8797	−2.8563	−0.2731
θ_7(VolRice)	−2.4418	−1.6053	−0.172	3.5647	2.6457	0.2509
θ_8(VolWCBOT)	1.3202	0.2667	0.093	−2.5505	−0.5616	−0.1795
θ_9(VolWKCBT)	4.8302	1.0473	0.3403	−4.9979	−1.2009	−0.3518
Pseudo-R^2	0.94				0.88	

Table 11.16 Model: Y_{tI_F}—Nicaragua, $n = 88$

Parameter	Milk and other dairy products			Other foods		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	8894.0985	6.6327		12,171.234	6.6334	
θ_0(Intercept)	−2.8914	−32.9862	−0.168	−1.6241	−36.4102	−0.3154
θ_1(EconAct)	−0.0002	−0.6858	0	0.0002	0.9527	0
θ_2(Imports)	−0.0005	−2.9821	0	0.0003	3.8202	0.0001
θ_3(M1)	0.0007	4.0906	0	0.0003	4.1596	0.0001
θ_4(Return on Oil)	0.1163	1.5761	0.0068	0.0444	1.1844	0.0086
θ_5(VolCorn)	−10.1085	−3.3629	−0.5872	2.7707	1.8333	0.538
θ_6(VolSoy)	−4.7079	−1.7503	−0.2735	0.3458	0.2589	0.0672
θ_7(VolRice)	−3.62	−1.3816	−0.2103	0.1308	0.0975	0.0254
θ_8(VolWCBOT)	17.1722	1.9661	0.9976	−4.24	−0.9516	−0.8234
θ_9(VolWKCBT)	3.447	0.4277	0.2002	1.7843	0.4344	0.3465
Pseudo-R^2	0.88				0.81	

Table 11.17 Model: Y_{tI_F}—Panama, $n = 79$

Parameter	Breads and cereals			Meat		
	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	42,836.899	6.2847		27,901.146	6.2848	
θ_0(Intercept)	−3.3296	−48.3513	−0.1477	−2.5388	−39.1479	−0.2065
θ_1(EconAct)	−0.0012	−2.3271	−0.0001	0.0008	1.6198	0.0001
θ_2(Imports)	0.0001	3.0469	0	0	−0.6296	0
θ_3(M1)	0.0001	6.2054	0	0	1.0226	0
θ_4(Return on Oil)	0.0334	1.1603	0.0015	0.0145	0.5335	0.0012
θ_5(VolCorn)	−4.9734	−2.2377	−0.2207	3.0768	1.4729	0.2502
θ_6(VolSoy)	3.9587	2.7148	0.1757	−0.2289	−0.1686	−0.0186
θ_7(VolRice)	0.2367	0.1261	0.0105	1.5116	0.8705	0.1229
θ_8(VolWCBOT)	13.9842	3.0451	0.6205	−4.0673	−0.9367	−0.3308
θ_9(VolWKCBT)	−1.0518	−0.2336	−0.0467	−1.3298	−0.3149	−0.1081
Pseudo-R^2	0.95				0.70	

Table 11.18 Model: Y_{tI_F}—Panama, $n = 79$

	Milk and other dairy products			Other foods		
Parameter	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	30,599.764	6.2845		19,812.572	6.285	
θ_0(Intercept)	−3.9488	−41.1289	−0.1244	−2.0358	−34.6196	−0.3042
θ_1(EconAct)	0.001	1.4929	0	0.0006	1.5135	0.0001
θ_2(Imports)	0	0.2854	0	−0.0001	−3.8037	0
θ_3(M1)	0.0001	3.3279	0	0	4.291	0
θ_4(Return on Oil)	−0.0364	−0.9104	−0.0011	−0.037	−1.5032	−0.0055
θ_5(VolCorn)	−12.6476	−4.0779	−0.3984	−1.4221	−0.7495	−0.2125
θ_6(VolSoy)	8.5396	4.2007	0.269	4.6104	3.7345	0.6888
θ_7(VolRice)	1.7534	0.6661	0.0552	0.7373	0.4654	0.1102
θ_8(VolWCBOT)	−0.5952	−0.0932	−0.0187	2.2778	0.5795	0.3403
θ_9(VolWKCBT)	16.9397	2.705	0.5336	3.5562	0.9275	0.5313
Pseudo-R^2	0.94				0.92	

Table 11.19 Model: Y_{tI_F}—Peru, $n = 152$

	Breads and cereals			Meat		
Parameter	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	10,649.305	8.7177		5867.4867	8.7175	
θ_0(Intercept)	−2.2777	−51.2681	−0.2132	−1.7373	−28.2889	−0.1568
θ_1(EconAct)	−0.0007	−2.2116	−0.0001	−0.0031	−6.8838	−0.0003
θ_2(Imports)	0.0001	6.9847	0	0.0003	10.029	0
θ_3(M1)	0	−1.39	0	0	−6.4168	0
θ_4(Return on Oil)	0.0446	1.2385	0.0042	0.0391	0.7958	0.0035
θ_5(VolCorn)	−2.4112	−1.8183	−0.2257	2.2836	1.2644	0.2061
θ_6(VolSoy)	8.627	4.9168	0.8076	−7.3505	−2.9558	−0.6634
θ_7(VolRice)	−5.3316	−3.9281	−0.4991	−12.0382	−6.4187	−1.0865
θ_8(VolWCBOT)	−6.1178	−1.5146	−0.5727	−5.9913	−1.0871	−0.5407
θ_9(VolWKCBT)	7.8244	2.268	0.7325	10.5296	2.2921	0.9503
Pseudo-R^2	0.81				0.87	

Table 11.20 Model: Y_{tI_F}—Peru, $n = 152$

	Milk and other dairy products			Other foods		
Parameter	Estimate	z-statistic	Marginal impact	Estimate	z-statistic	Marginal impact
ϕ	25,927.176	8.7173		4281.78	8.7186	
θ_0(Intercept)	−2.9624	−69.5966	−0.1187	−0.7408	−15.7126	−0.1931
θ_1(EconAct)	−0.002	−6.502	−0.0001	−0.0017	−4.9396	−0.0004
θ_2(Imports)	0.0001	6.299	0	0.0001	3.3777	0
θ_3(M1)	0	−3.1206	0	0	0.4413	0
θ_4(Return on Oil)	0.0555	1.622	0.0022	0.0059	0.157	0.0015
θ_5(VolCorn)	2.0215	1.6189	0.081	3.1737	2.3028	0.827
θ_6(VolSoy)	−1.4678	−0.8619	−0.0588	−3.3824	−1.8061	−0.8814
θ_7(VolRice)	−5.5173	−4.266	−0.2211	−7.4991	−5.2855	−1.9542
θ_8(VolWCBOT)	−1.7307	−0.4505	−0.0694	−1.0336	−0.2425	−0.2693
θ_9(VolWKCBT)	8.6824	2.6816	0.348	−0.681	−0.1887	−0.1775
Pseudo-R^2	0.77				0.70	

Data Sources

For oil prices the source is always U.S. Energy Information Administration (EIA), and for the volatility of international commodities the source is the estimation procedure described in the text.

- Costa Rica—Share of Laspeyres index: Instituto Nacional de Estadistica y Censos de Costa Rica (INEC); Monthly Index of economic activity: Banco Central de Costa Rica; Imports: Banco Central de Costa Rica.
- El Salvador—Share of Laspeyres index: Direccion General de Estadística y Censos (DIGESTYC); Monthly Index of economic activity: Banco Central de Reserva de El Salvador; Imports: Banco Central de Reserva de El Salvador.
- Guatemala—Share of Laspeyres index: Instituto Nacional de Estadistica Guatemala (INE); Monthly Index of economic activity: Banco de Guatemala; Imports: Banco de Guatemala.
- Honduras—Share of Laspeyres index: Instituto Nacional de Estadistica, Honduras (INE); Monthly Index of economic activity: Banco Central de Honduras; Imports: Banco Central de Honduras.
- Ecuador—Share of Laspeyres index: Instituto Nacional de Estadística de Ecuador (INEC); Monthly Index of economic activity: Banco Central del Ecuador; Imports: Banco Central del Ecuador.
- Peru—Share of Laspeyres index: Instituto Nacional de Estadistica e Informatica (INEI); Monthly Index of economic activity: Banco Central de Reserva del Peru; Imports: Banco Central de Reserva del Peru.

- Mexico—Share of Laspeyres index: Instituto Nacional de Estadistica y Geografia (INEGI); Monthly Index of economic activity: Banco de Mexico; Imports: Banco de Mexico.
- Nicaragua—Share of Laspeyres index: Instituto Nacional de Informacion de Desarrollo (INIDE); Monthly Index of economic activity: Banco Central de Nicaragua; Imports: Banco Central de Nicaragua.
- Panama—Share of Laspeyres index: Contraloria General de la Republica; Monthly Index of economic activity: Contraloria General de la Republica; Imports: Contraloria General de la Republica.
- Dominican Republic—Share of Laspeyres index: Oficina Nacional de Estadistica (ONE); Monthly Index of economic activity: missing; Imports: Banco Central de la Republica Dominicana.

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How Strong Do Global Commodity Prices Influence Domestic Food Prices in Developing Countries? A Global Price Transmission and Vulnerability Mapping Analysis

12

Matthias Kalkuhl

12.1 Introduction

Major global food commodities experienced unexpected price spikes in 2007/2008 and again in 2010. This raised serious concerns about the impact of global price shocks and volatility on food security in developing countries. There have been several attempts to investigate the impacts of price shocks on income and poverty as well as nutrition indicators. Some of these papers quantified the number of people who were pushed below the poverty line due to increased food prices (and decreased real incomes) at 105–150 million (de Hoyos and Medvedev 2011; Ivanic and Martin 2008); Tiwari and Zaman (2010) estimated that 63 million people became food insecure, as measured by the number of people who consume less than 1810 calories/day. However, as these studies used either domestic food prices, whereby the linkage to global prices is not directly clear (de Hoyos and Medvedev 2011), or the ad hoc assumption that price transmissions from global markets are uniform (Ivanic and Martin 2008; Tiwari and Zaman 2010), they cannot provide a satisfactory answer about the impacts of global price shocks. The heterogeneous degree of price transmission from international to domestic markets has to be considered explicitly for ex-post impact analysis as well as early warning and information systems, which are aimed at identifying upcoming food security risks.

There are some controversies about the role of international commodity prices in the local food security of developing countries. A common explanation for the low integration of developing countries, in particular African countries, in

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global markets is that many of them import only small amounts of the commodity they consume and that trade does not take place continuously. Additionally, transaction costs due to transportation costs and trade barriers, like tariffs and quotas, are considered to reduce price transmission. Existing research has therefore come to different conclusions regarding the degree of price transmission, depending on the considered domestic market, crop and international reference price.

So far, a comprehensive analysis of the extent of price transmission for the 1.2 billion people worldwide living below the poverty line is missing: We neither have an estimation of how many poor people are affected by global market-induced food price changes nor do we know the heterogeneous extent of price transmission. While the recent FAO report on the State of Food Insecurity in the World (FAO 2013) attempted to provide an aggregate picture of the extent of price transmission, it used regionally aggregated food price indices which showed only weak linkages to global prices and price volatility.[1] The use of regionally aggregated price indices, however, masks the heterogeneity of countries and commodities: combining prices from markets with high market integration and low (or missing) market integration will give an average low transmission that distracts from the serious impacts of international price shocks on *some* markets.

This paper aims to fill this gap by providing a globally comprehensive but nationally differentiated analysis of price transmission which maps transmission elasticities to the size of the vulnerable population. The result will be a Lorenz-type curve showing how many poor people are affected by international price shocks and how strong these effects are. The paper also provides a pragmatic way to deal with the heterogeneity of local food staples by creating a domestic grain price index which is highly relevant to the poor and vulnerable population. Our grain price index is preferable to the food price indices from national statistical agencies used in FAO (2013), Cachia (2014), and Ianchovichina et al. (2012) because the latter often contain processed and luxury food items that are of little relevance to the poor. As for these products, material costs play a minor role; therefore, using official food price indices would likely result in an underestimation of the degree of price transmission to the costs of the food basket of poor people. On the contrary, using individual crop prices instead of price indices – as in most existing studies – inflates the reported results of the empirical analysis, neglects possible substitution effects between grains, and complicates the interpretation of the severity of price transmission.

The market integration of developing countries is a highly relevant topic for policymakers and international organizations. Market integration presents both opportunities and risks. The larger a market is, the better its capability to diversify

[1]Cachia (2014) provides a more detailed overview on methods and data on regional price transmission.

(uncorrelated) shocks; this generally has a stabilizing effect on prices, benefitting producers as well as consumers. In contrast, integration into global markets makes domestic markets vulnerable to "external" shocks that are beyond the control of the national government, in particular, international price volatility (Kornher and Kalkuhl 2013). Market liberalization may further be incompatible with domestic price stabilization schemes, such as buffer stocks.

In this paper, we do not attempt to assess the costs and benefits of market integration. Leaving the normative debate aside, we address the descriptive question of the extent of market integration, which forms the basis of not only further normative analyses but also an appropriate impact assessment of global price shocks. Mapping price transmission with vulnerable population is one important step toward a better understanding of the impacts of recent global food price spikes since 2007. Additionally, our mapping analysis helps to identify the crucial international reference prices that should be monitored carefully in early warning and food security information systems. Finally, the calculated transmission elasticities can be used for forecasting the partial effect of international commodity price dynamics on local food prices and thus food security.

The paper is structured as follows: Section 12.2 provides an overview on existing literature on price transmission and market integration. Section 12.3 establishes the theoretical framework by drawing on basic trade and storage models from the literature. This section in particular helps to explain price transmission when trade is (temporarily) absent.[2] Section 12.4 describes the empirical model to estimate price transmission. Section 12.5 presents the price data used and the calculation of a domestic grain price index as an alternative reference price for the costs of the food basket of the poor. Section 12.6 discusses the results of the transmission analysis, including some robustness checks for different specifications. Section 12.7 summarizes the findings and concludes the chapter with policy and research implications.

12.2 Existing Work on Price Transmission

In the wake of the large swings in international commodity prices, there have been various researches on market integration and price transmission. Using staple prices on several sub-Saharan African markets, Minot (2010) calculated that the price increase in the region was on average 71 % of the corresponding world market increase in 2007/2008. Because static correlations between prices might be spurious and no compelling evidence for market integration exists (Ravallion

[2] Götz et al. (2013) provided an analysis on the price transmission of Ukraine and Russia during different trade regimes. The authors find that price transmission was also present during times of tight export quotas and high export taxes but stronger during liberal trade regimes.

1986), Minot (2010) extended the correlation analysis by applying a vector error correction model (VECM). This model, however, suggests that only one-fifth of the considered domestic price series have a long-run relationship to international prices. The estimated price elasticities range from 16 to 97 %. In general, rice prices seem to be more integrated than maize prices.

Robles (2011) estimated price transmission with an autoregressive distributed lag (ADL) model for some Latin American and three Asian countries using retail prices (Latin America) and wholesale prices (Asia) between 2000 and 2008. Transmission to processed food items is reported to be lower than to raw commodities. The average transmission from international wheat to domestic bread and pasta prices is 20 % and 24 %, respectively. In contrast, transmission of rice and wheat prices in Asia to the raw commodity prices varies a lot among the considered cities, but values higher than 50 % are reported for several cities.

Using a similar econometric approach but considering food price indices instead of commodity prices, Ianchovichina et al. (2012) analyzed price transmission to Middle East and North Africa countries. They report transmission for several countries in the range of 20–40 %. Greb et al. (2012) attempted to investigate price transmission and made some observations about the extent and determinants of market integration by assessing existing literature and by an own analysis based on FAO GIEWS price data. In their meta-analysis, they found that rice markets are more integrated than maize markets. They reported substantial price transmission to domestic markets (long-run price transmission coefficient of 75 %).

Most recently, Baquedano and Liefert (2014) calculated short- and long-run transmission coefficients for several commodities in developing countries within a single-equation error correction model (SEECM). They found that most consumer markets in developing countries are co-integrated with world markets although their speed of equilibrium adjustment is rather low. Cachia (2014) provided an overview of different concepts and models of price transmission and estimated market integrations and price transmission between the FAO (global) food price index and regionally aggregated food price indices (based on consumer price indices from national statistical agencies). His findings suggest limited market integration and rather slow transmission, which might be related to the use of aggregated food price indices as discussed above.

12.3 Theoretical Framework

Domestic prices are linked to world market prices primarily through trade. If a commodity is imported, its domestic price p_t^{D} equals its international price p_t^{G} plus the transaction costs $\tau_t^{I,E}$ for import I and export E. Depending on the trade balance (a positive T_t denotes exports, a negative T_t imports), we can therefore distinguish the three cases (Samuelson 1952)[3]:

$$p_t^{\mathrm{D}} = p_t^{\mathrm{G}} + \tau_t^I \quad \text{if } T_t < 0 \tag{12.1a}$$

$$p_t^{\mathrm{D}} = p_t^{\mathrm{G}} - \tau_t^E \quad \text{if } T_t > 0 \tag{12.1b}$$

$$p_t^{\mathrm{D}} = D\left(Q_t^{\mathrm{D}}, Y_t^{\mathrm{D}}\right) \quad \text{if } T_t = 0, \tag{12.1c}$$

where $D\left(Q_t^{\mathrm{D}}, Y_t^{\mathrm{D}}\right)$ is the inverse of the domestic demand function, which depends on consumption Q_t^{D} and income Y_t^{D}. Equations (12.1a)–(12.1c) imply that the domestic price is independent from the global price if and only if it is neither profitable to export nor to import the commodity, that is if

$$p_t^{\mathrm{G}} - \tau_t^E < D\left(Q_t^{\mathrm{D}}, Y_t^{\mathrm{D}}\right) < p_t^{\mathrm{G}} + \tau_t^I \tag{12.2}$$

Spatial arbitrage through trade links domestic and global prices immediately. There exists, however, also another form of arbitrage through storage which links current prices to expected (future) prices. Assuming rational expectations, current prices are a function of expected futures prices (Wright and Williams 1991):

$$p_t = \beta E_t\left[p_{t+1}\right] \quad \text{if } I_t > 0, \tag{12.3a}$$

$$p_t > \beta E_t\left[p_{t+1}\right] \quad \text{if } I_t = 0, \tag{12.3b}$$

where p_t is the price of the commodity at time t; $\beta = (1-\delta)/(1+r)$ contains the interest rate r and rate of deterioration δ; $E_t[\cdot]$ refers to the expectation at time t; and I_t denotes the inventory of grains. When there are no inventories ($I_t = 0$), current and future prices are not directly linked through intertemporal arbitrage.

Consider now the case of a country which has a zero or negative trade balance (that may change over time) but which is never in an exporting state. Combining Eqs. (12.1a) and (12.3a) for the domestic and global markets and assuming positive storage on both, for exactly s consecutive periods without trade, we obtain:

$$p_t^{\mathrm{D}} = \gamma^s p_t^{\mathrm{G}} + \left[\beta^{\mathrm{D}}\right]^s E\left[\tau_{t+s}\right] \quad \text{if } I_{t+j}^{\mathrm{D,G}} > 0,\ T_{t+j} = 0 \text{ for } 0 < j < s, \tag{12.4}$$

where $\gamma := \frac{\beta^{\mathrm{D}}}{\beta^{\mathrm{G}}} = \frac{\left(1-\delta^{\mathrm{D}}\right)\left(1+r^{\mathrm{G}}\right)}{\left(1-\delta^{\mathrm{G}}\right)\left(1+r^{\mathrm{D}}\right)}$. Equation (12.4) indicates that domestic prices depend on global prices even when there is *no trade* in a sequence of s periods. If

[3]In the subsequent theoretical analysis, we will assume that all transaction costs are unit costs and independent of the price level p_t^{G}. Considering ad-valorem transaction costs ς_t^I (e.g., due to transport insurance, value-added tax, or ad-valorem tariffs), Eq. (12.1a) would change to $p_t^{\mathrm{D}} = p_t^{\mathrm{G}}\left(1+\varsigma_t^I\right) + \tau_t^I$. As the ad-valorem component has no impact on the transmission elasticity (it cancels out after taking the derivatives), we have omitted it to shorten the formal analysis.

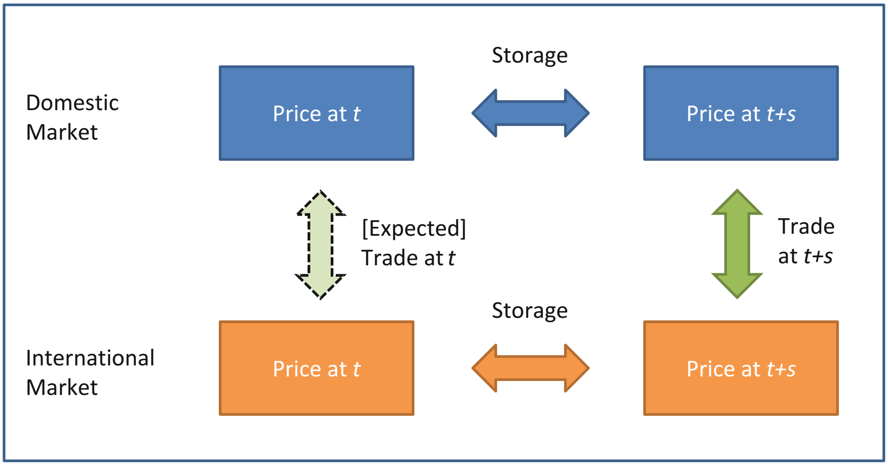

Fig. 12.1 Linkage between domestic and international prices through storage, trade, and expectations. *Source*: Own elaboration, based on Eqs. (12.1)–(12.4)

trade is expected in future periods (which brings domestic and global prices back to equilibrium), current domestic prices are adjusted according to intertemporal arbitrage. The relation between domestic and international markets for the direct trade regime and the indirect transmission regime (expected trade, with storage) is depicted in Fig. 12.1.

In the case of trade, prices at t are directly linked. In the case of no trade at t but expected trade at $t+s$, prices at t are indirectly linked through storage and expected trade arbitrage.

Inserting Eq. (12.4) into the transmission elasticity $\eta := \frac{\partial p^{\mathrm{D}}}{\partial p^{\mathrm{G}}} \frac{p^{\mathrm{G}}}{p^{\mathrm{D}}}$, we get[4]:

$$\eta = \frac{p_t^{\mathrm{G}}}{p_t^{\mathrm{G}} + [\beta^{\mathrm{G}}]^s E[\tau_{t+s}]}$$

Building partial derivatives of η, we obtain $\eta'\left(p_t^{\mathrm{G}}\right) > 0$, $\eta'\left(\beta^{\mathrm{G}}\right) < 0$, $\eta'\left(E[\tau_{t+s}]\right) < 0$, and $\eta'(s) > 0$. Thus, transmission increases in the global price level, and it decreases in the storage discount factor β^G and in expected transaction costs $E[\tau_{t+s}]$. Transmission increases, however, in the distance s to the next trade period: the longer the period of no trade, the stronger domestic prices respond to global prices (if storage domestic and global stocks are strictly positive during that period).

Table 12.1 gives an overview of the different possible trade and storage regimes and how they determine domestic prices and price transmission. In the case of trade,

[4]For $s = 0$, the transmission elasticity collapses to the standard form (direct transmission in case of trade) $\eta = p_t^{\mathrm{G}} / \left(p_t^{\mathrm{G}} + \tau_t\right)$. As argued above, any ad-valorem transaction costs cancel out in the price transmission.

Table 12.1 Domestic prices and price transmission for different trade and storage regimes

Trade T_t	Domestic storage	Global storage	Domestic price p_t^{D}	Transmission elasticity η
Yes	Yes/no	Yes/no	$p_t^{\mathrm{G}} + \tau_t$	$\frac{p_t^{\mathrm{G}}}{p_t^{\mathrm{G}} + \tau_t}$
None, but expected	Yes	Yes	$\gamma^s p_t^{\mathrm{G}} + \left[\beta^{\mathrm{D}}\right]^s E\left[\tau_{t+s}\right]$	$\frac{p_t^{\mathrm{G}}}{p_t^{\mathrm{G}} + \left[\beta^{\mathrm{G}}\right]^s E\left[\tau_{t+s}\right]}$
None, but expected	Yes	No	$\left[\beta^{\mathrm{D}}\right]^s E_t\left[p_{t+s}^{\mathrm{G}} + \tau_{t+s}\right]$	For p_t^{G} : 0 For $E_t\left[p_{t+s}^{\mathrm{G}}\right]$ $\frac{E_t\left[p_{t+s}^{\mathrm{G}}\right]}{E_t\left[p_{t+s}^{\mathrm{G}} + \tau_{t+s}\right]}$
None, but expected	No	Yes/no	$D\left(Q_t^{\mathrm{D}}, Y_t^{\mathrm{D}}\right)$	0
None and not expected	Yes	Yes/no	$\beta^s E_t\left[D\left(Q_{t+s}^{\mathrm{D}}, Y_{t+s}^{\mathrm{D}}\right)\right]$	0
None and not expected	No	Yes/no	$D\left(Q_t^{\mathrm{D}}, Y_t^{\mathrm{D}}\right)$	0

Source: Own elaboration

or in case of expected (future) trade, and positive domestic and global stocks, there is always a positive price transmission from global to domestic markets. However, if global stocks are zero[5] (i.e., if global prices are not in an intertemporal equilibrium), current global prices do not affect current domestic prices. Nevertheless, current domestic prices are in equilibrium with the *expected* global prices (which might, in turn, be a function of current global prices). Only in the remaining cases whereby all stocks are zero or whereby there will never be trade, domestic prices are completely decoupled from global prices. In these cases, domestic prices are solely determined by the conditions of domestic supply and demand, and price transmission is zero.

The theoretical analysis revealed two further interesting insights: For each trade regime, the transmission elasticity η is not affected by ad-valorem transaction costs (which include ad-valorem taxes and tariffs), and it is furthermore independent of the traded amount. In other words, the transmission elasticity will be the same for a country with small and large imports as long as the (unit) transaction costs are the same. Finally, the formal analysis emphasizes the role of storage in price transmission. Traditionally, storage is seen as a buffer against supply shocks, and this buffer reduces price fluctuations. As (private) storage, however, links current and future prices via expectations, it links domestic prices to global prices even if no trade occurs. Hence, storage could make a country more vulnerable against international price shocks because domestic prices are additionally linked to international prices through expectations.

While trade and storage link domestic prices to international prices of the same commodity, substitution effects might also link non-traded commodities to international prices if they are substitutes for traded commodities. The magnitude of substitution effects is expressed in the cross-price elasticity of demand, relating the percentage change in a commodity price to the percentage change in the price of a substitute. Hence, we would also expect price transmission to non-traded local products if they are substitutes for traded commodities. This is in particular the case for staples or different edible oils.

12.4 Empirical Model

As we are interested in the transmission of global shocks to domestic prices, any empirical analysis should consider intra-annual prices. However, many of the variables that determine price transmission (like grain stocks and trade) are only observable on an annual basis and suffer additionally from substantial measurement

[5]Zero stocks refer here to the theoretical model. In real-world settings, stocks become rarely zero because a certain amount of grains will be always stored for operational purposes. This “operational stock,” however, is not part of the intertemporal arbitrage dynamics as it is used to ensure deliveries and does not respond to (expected) prices.

errors and data quality problems.[6] While there are models that allow data of different frequencies to be combined [e.g., GARCH-MIDAS for analyzing volatility, see Engle et al. (2013)], estimating them requires typically a large sample size. Because most of our price series start after the year 2000, we used a pure time-series approach to quantify country- and crop-specific "average" transmission elasticities instead of estimating the underlying fundamental model parameters, like the transaction costs, trade flows, and storage levels.

Time-series models are often confronted with the problem of nonstationary data series, which generates biased estimates and high R^2 due to spurious regression of explanatory variables with trends which leads to the overestimation of t-values in the case of autocorrelation. The typical approach to deal with a nonstationary time series is to differentiate the data until it becomes stationary. If the time series is also co-integrated (i.e., there exists a linear combination of the series that is integrated of order one), it is possible to estimate the long-run relationship between trended variables within an error correction model (ECM) (Engle and Granger 1987). If the time series is integrated to the order of one but not co-integrated, one can analyze the first-differenced, stationary time series within an autoregressive distributive lag model (ADL). If the time series is stationary, the ECM can be made equivalent to an ADL (De Boef and Keele 2008).

An ECM would be the favorable model to test for market integration (i.e., co-integration of domestic and international price series). However, the transmission of short-term shocks in international prices to domestic prices, which is the focus of this paper, does not require co-integrated time series. Relying on co-integrated time series only could exclude countries with significant transmission of shocks.[7] Using an ADL for this set of countries would be one option. As the estimated short-run transmission elasticities of the ADL are not directly comparable to the ECM, which controls for error correction, we prefer to use the same econometric model for all countries and series. Hence, we used an ADL with stationary first-differenced logarithmic prices, which is suitable for all countries and price series.[8] Our basic model estimates the relative change of the domestic food price index as follows:

$$\begin{aligned}\Delta p_{it}^{\mathrm{d}} = &\sum\nolimits_{j=1}^{l} \alpha_i^{dw} \Delta p_{it-j}^{d} + \sum\nolimits_{j=1}^{k} \beta_{ij}^{dw} \Delta p_{t-j}^{w} + \sum\nolimits_{j=1}^{k} \gamma_{ij}^{dw} \Delta e_{it-j} \\ &+ \sum\nolimits_{j=1}^{k} \zeta_{ij}^{dw} \Delta p_{t-j}^{\mathrm{oil}} + \delta_{im}^{dw} + c_i^{dw} + \varepsilon_{i,t}^{dw},\end{aligned} \tag{12.5}$$

[6] Stocks data is, for example, lacking for many countries. Published stock data (e.g. on the USDA-PSD database) is for many developing countries based on rough estimates and balance sheet calculations rather than original survey data.

[7] Additionally, testing for a unit root process, a necessary condition for the ECM, is problematic due to the low performance of unit root tests. Hence, the use of the ADL avoids the risk of using a misspecified ECM.

[8] The stationarity of all domestic and international price series was tested using the Augmented Dickey-Fuller test. While only a few of the original series are stationary, all first-differenced series are stationary with a test statistic below the 1 % critical value. Results are available upon request.

where $\Delta x_t = x_t - x_{t-1}$ is the difference operator, $p^d_{i,t}$ denotes the domestic reference price d (or price index) in country i (all prices in logs) at time t, p^w_{t-j} is a world market reference price (or price index), $e_{i,t-j}$ the exchange rate (in US dollars) of country i, p^{oil}_t is the oil price, $\delta_{i,m}$ a monthly country-specific dummy to account for seasonality, and c^{dw}_i is a (country and commodity specific) constant. We chose the lag structure $l = 3$ and $k = 3$ in our base model, but we also explored different lag structures (including optimal lags using information criteria) as a robustness check. Although oil prices are neglected in most other studies, we considered them important as they influence domestic production and transportation costs as well as import costs (Minot 2010).

Controlling for seasonality (Helmberger and Chavas 1996) and oil prices may allow us to consider important determinants of food and grain prices in particular countries; it might, however, also weaken the reliability of the model due to decreased degrees of freedom for countries in which seasonality or oil prices are irrelevant. Therefore, to automatically select the appropriate model specification for each country and commodity, we applied the Akaike information criterion to (1) the full model, (2) a model which ignores oil prices, (3) a model which ignores seasonality, and (4) a model which ignores both oil prices and seasonality.

We ran the regression in Eq. (12.5) separately for each country i, each international reference price p^w_t and each considered domestic food price p^d_t. With the estimated coefficients, we calculated the short-run transmission $\beta^{dw}_i = \sum_{j=1}^k \beta^{dw}_{ij}$ and the pass-through θ (i.e., the equilibrium effect of a marginal world price change on the domestic food price index) of international price w to domestic price d in country i as:

$$\theta^{dw}_i = \frac{\sum_{j=1}^k \beta^{dw}_{ij}}{1 - \sum_{j=1}^l \alpha^{dw}_{ij}},$$

where $\beta^{dw}_i = \sum_{j=1}^k \beta^{dw}_{ij}$ and $\alpha^{dw}_i = \sum_{j=1}^l \alpha^{dw}_{ij}$; both terms are set to zero if they are not significant at the 5 % level (F-test with Newey-West estimated standard errors).[9] While β^{dw}_i gives the direct (short-term) price transmission within 1–3 months, the autoregressive term α^{dw}_i further amplifies price changes in the subsequent periods. The total effect is therefore given by the pass-through θ^{dw}_i. As we estimated β^{dw}_i and θ^{dw}_i separately for each country and international commodity price (index), we obtained a matrix of transmission elasticities and pass-throughs for every domestic food price index d.

[9]Significance levels of 10 % and 1 % were also employed to check robustness (see below). The Newey-West estimator corrects for heteroskedasticity and autocorrelation. We use a lag length of 6 months. The standard OLS procedure gives similar results (see below).

12.5 Data

This study differs from other related studies because it used an extensive dataset of international commodity prices and price indices, ranging from spot prices at important export destinations to prices of relevant futures contracts.

Table 12.3 in the Appendix lists the prices that were used as international reference prices and price indices. The main sources of information are the FAO and the FAO GIEWS for the international food prices and price indices, the World Bank (2013b) for important international spot prices, and Bloomberg for futures prices. We also calculated indices over futures prices in order to better capture price dynamics on commodity exchanges. For all futures prices, a time series consisting of the respective active contract was used. All price series are monthly data (for daily price series, like futures prices, monthly averages were calculated).

The food price indices (FPI), a part of the national consumer price indices (CPI), served as reference database for the domestic prices. These data are available from the LABORSTA database for 200 countries in the world in a monthly or quarterly frequency (ILO 2013). We drop those countries which only report quarterly food price indices and consider the years 2000–2012.[10] While the LABORSTA database has the advantage of covering many countries, the calculation of the food price indices is not transparent for many countries. In particular, CPIs may suffer from urban bias as price collection in urban area is less expensive than in remote rural areas. Additionally, the weights in a CPI might reflect the consumption and spending patterns of the urban lower-middle class rather than the very poor households that spent up to 70 % of their expenditures on staple food (James 2008). For example, dramatic changes in staple prices, which affect the real income of poor households, might only lead to small changes in the domestic food price index, which consists of processed foods as well as luxury food and beverages.

Because FPI data might be inadequate to monitor the food costs for poor people, we developed an alternative staple grain price index which consists of the retail prices of wheat, maize, rice, sorghum, and millet. We used several sources to compile this retail price database and calculate the national average price in US$ across different markets for each of the commodity prices. We used prices in US$ to avoid the problem of strong inflationary shocks, which are difficult to control for, but provided robustness checks for prices in nominal and CPI-deflated local currencies. We combined the different commodity prices into a price index according to their share of the domestic per capita food supply [taken from FAOSTAT (2013)]:

$$p_{it}^{GPI} = \sum\nolimits_j \alpha_{ij} p_{itj},$$

[10]These countries are (20 in total) AIA, ASM, AUS, BLZ, BTN, COK, CYM, FRO, GUM, JEY, KIR, MHL, MNP, NFK, NIU, PNG, SHN, SPM, TUV, and VUT.

Table 12.2 Domestic food price indices

d	Variable	Description	Source
FPI	Food price index (FPI)	National food price index (nominal); 2000–2012	ILO (2013)
GPI	Domestic grain price index (GPI)	Index of the national average retail prices (nominal US$) of five staple grains for 2000–2012: wheat, maize, rice, sorghum, and millet; weighted according to domestic per capita food supply for 2000–2009	Own calculation; domestic per capita food supply from FAO; retail prices from FEWS NET, FAO GIEWS, WFP Price Monitor, and national sources

Exchange rates were obtained from the IMF database. For the oil price, we consider the "average oil price" of WTI, Brent and Dubai prices quoted at World Bank Commodities Price Database.
Source: Own elaboration

where $\alpha_{ij} = C_{ij}/C_j$ is the j-th crop's share of the total consumption of the considered grains in country i in kg over the period 2000–2009 and p_{itj} is the corresponding crop price at month t in US$ per kg. We used national average prices if available in one of the databases (shown in Table 12.2); otherwise, we calculated an (unweighted) national average price using all the markets price data available (again, using the sources shown in Table 12.2). Our self-constructed grain price index accounts on average for 45 % of the average national calorie consumption in many countries. As the diet of poor people consists of a higher share of staples, our grain price index is likely to cover more than the national average number for poor people which increases its relevancy.

One drawback of the grain price index is the limited data availability. Contrary to the food price index from national statistical offices, retail grain prices were available for 65 countries only. Yet, as will be discussed later, the considered countries are home to more than 90 % of the global poor, who live with an income below $1.25 per day. Thus, the coverage with respect to poor people is much larger than the "geographical" coverage. Another drawback of the grain price index is that it is likely irrelevant to the countries where staples other than those grains considered in this study are consumed as part of their diet (e.g., roots and tubers in Uganda). Because of the advantages and disadvantages of both food price indices and grain price indices, we considered both in our analysis. Table 12.2 summarizes the characteristics and data sources for the domestic price indices.

12.6 Results

This section presents and discusses the calculated transmission elasticities. For policymakers as well as for establishing early warning information systems, it might be relevant to know whether a country's food prices are linked to at least one international commodity price. Subsequently, a country's policymakers can access the database on transmission elasticities to find out which particular commodity prices are transmitted from the international market to the domestic market of that particular country. We therefore calculated a country-specific transmission *vulnerability indicator* V_i^d as the maximum transmission over the pass-throughs of different commodities from the set Ω:

$$V_i^d = \max_{w \in \Omega} \left\{ \theta_i^{dw} \right\} \quad (12.5)$$

If this indicator is zero, domestic food markets are with a high degree of certainty not vulnerable to global price shocks.[11] If the indicator is high, there is high transmission for at least one international commodity price (or price index), which implies that the country is generally vulnerable to global market price changes. As we will see, the vulnerability indicator provides an important benchmark for single international prices or price indices, like the FAO food price index. We further calculated the vulnerability indicator for subsets Ω of commodities, for example, we calculated V_i^d as maximum pass-through overall international rice prices.

12.6.1 Transmission from the FAO Food Price Index

We first considered the transmission from the FAO food price index – an international reference price index – which is often used as an indicator for global food market dynamics. We ran regressions for the transmission to domestic food prices as well as to domestic grain prices. The magnitude of the aggregate transmission elasticity β (if significant at the 5 % level) is depicted in Fig. 12.2 for both the domestic food price index (Fig. 12.2a) and the domestic grain price index (Fig. 12.2b). The maps indicate that there was no significant transmission for several developing countries in Asia, Latin America, and Africa. Where there was statistically significant transmission, it tended to be particularly high. These findings are consistent with the other studies mentioned above but provide a more comprehensive country coverage.

The map showing global transmission to domestic food price indices, for which data is available for almost all countries in the world, reveals another interesting finding: Several developed countries (North America, Europe) show a statistically significant but low price transmission, while transmission to developing countries is either insignificant (i.e., zero) or relatively high. An explanation for this finding is that the food basket in developed countries consists of many processed food items; commodity costs constitute only a very small share of the final price of process food items. Thus, a price increase in a raw commodity translates only into a very small price increase in the final product. This explains why price transmission to the US domestic market is very low – although several of the international reference prices used are quoted from US markets. The transmission from world to domestic

[11] However, they might still be co-integrated with world markets (through rather slow adjustment process) as we do not test for co-integration.

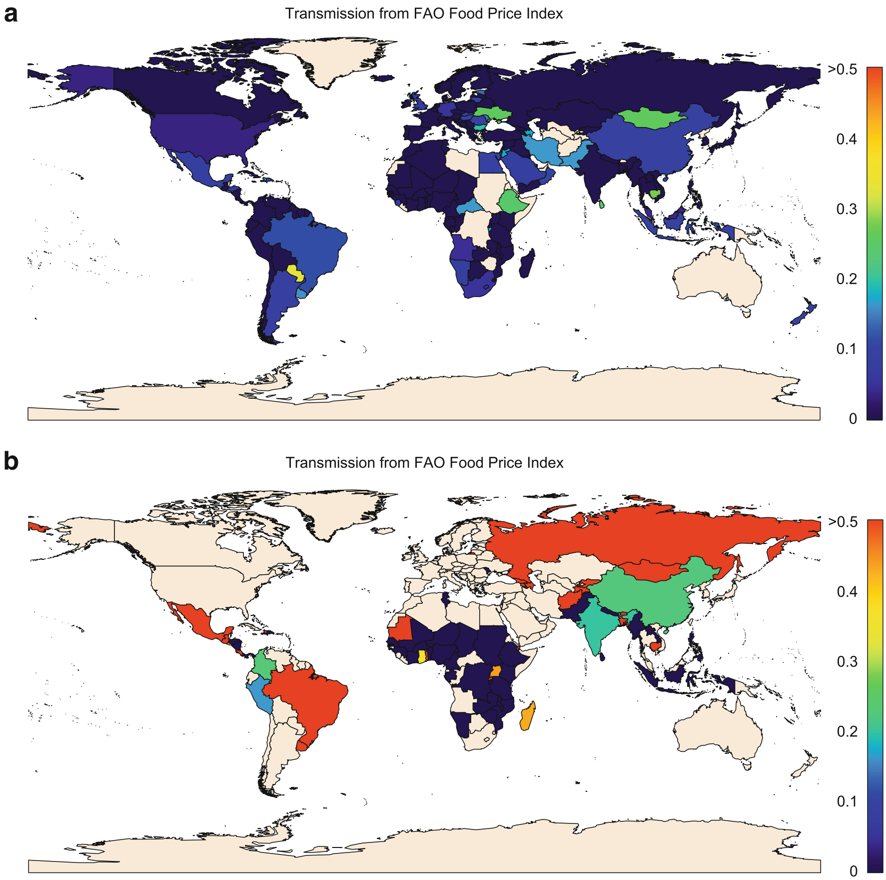

Fig. 12.2 (**a**) Transmission from the FAO food price index to the domestic food price index (FPI). (**b**) Transmission from the FAO food price index to the domestic grain price index (GPI)

markets showed high variance among developing countries because some of them are not integrated into the world market due to high transaction costs. If a country is integrated, price transmission to its domestic market is relatively high because raw commodity costs are a major part of the price of many food items.

The FAO food price index is a much more aggregated price index. It uses weights according to the export share on the global market of the considered commodities. While this gives an appropriate average price index for globally traded commodities, trade patterns may differ greatly among countries. For example, a country might predominantly import rice, but rice prices have a very low weight in the FAO food price index. By adding further international price indices and concentrating on the vulnerability indicator (maximum transmission) for all the grain prices in our database, we got a map which reveals a different result. Many Asian, African, and Latin American countries experience significant and high price transmission

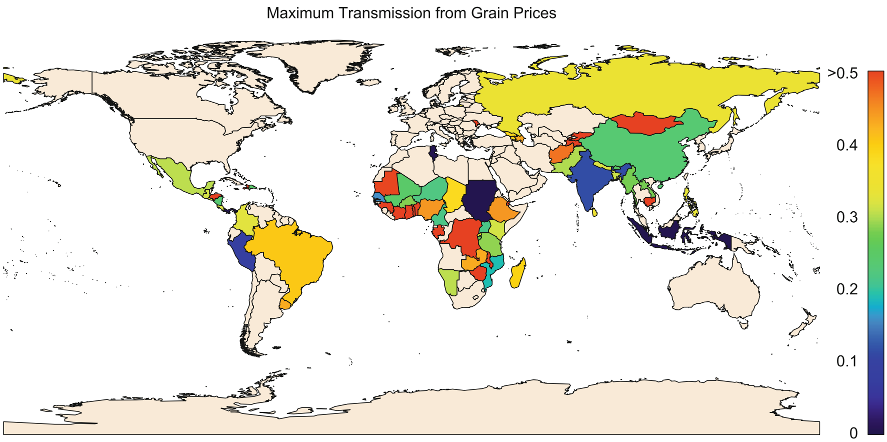

Fig. 12.3 Transmission to the domestic grain price index – vulnerability indicator over international grain prices. *Note*: Maximum transmission to the domestic grain price index using all international grain prices in Table 12.3

(Fig. 12.3). For example, some of the West African countries showed high price transmission to their domestic grain price index, which is primarily driven by international rice prices as these countries import a large amount of rice. Note that a low transmission elasticity of even as low as 20 % may have remarkable implications: doubling of commodity prices (e.g., as was experienced for wheat in 2007/2008) increases the costs of the *entire food or staple commodity basket* by 20 %. This is an important difference when compared with other studies: transmission elasticities for a single commodity do not reveal how important the commodity is for the population. Using a price index, in contrast, weights the price transmission in relation to the importance of the commodity to the diet of a country's population, and it also takes into account any potential substitution effects.

The use of the vulnerability indicator emphasizes that considering the FAO food price index exclusively might lead to serious biases in the assessment of price transmission downward. Thus, it is important to consider a larger set of reference prices and price indices rather than only relying on the FAO food price index. However, the FAO food price index remains a pragmatic alternative when only a single international price (index) can be used.

12.6.2 Vulnerability Mapping: How Many Poor People Are Affected by Global Price Changes?

To assess the impacts of global price changes, it is important to know how many poor people live in countries with high price transmission. Price changes have often heterogeneous impacts on the welfare of households, depending on their production structure and market access (von Braun et al. 2013). High agricultural commodity prices can increase the income of poor rural households who produce cash crops (Tefera et al. 2013). Nevertheless, such beneficial impacts are often realized in the medium or long term when households adjust their production by growing high-value crops. However, existing empirical analyses have concluded that sudden price spikes negatively affect not only poor consumers and the landless but also farmers who buy many food items as they cannot quickly adjust their production in the short run (Aksoy and Isik-Dikmelik 2008; Anríquez et al. 2013).

To assess how strongly poor people are exposed to global price changes, we took the following steps: The transmission elasticities β of the countries (e.g., regarding the Chicago corn price or the vulnerability indicator containing the maximum transmission by grain prices) were sorted in descending order. Next we calculated the number of people living below the extreme poverty line of \$1.25 per day[12] using poverty share and population data from the World Development Indicators (World Bank 2013a).[13]

Figure 12.4 shows the transmission from different international grain prices to the domestic grain price index. We calculated the maximum transmission (vulnerability indicator) according to Eq. (12.1b) for each of the three commodities: wheat, corn, and rice. Hence, the wheat line shows the maximum transmission for each country from all the available wheat price series shown in Table 12.3. We calculated the total vulnerability indicator as the maximum over the commodity indicators (blue line).

Regarding the extent of transmission, Fig. 12.4 clearly shows that rice prices are most strongly transmitted; this has also been highlighted by other studies (e.g., Robles 2011; Baquedano and Liefert 2014). While wheat prices experience lower transmission elasticities than rice prices for many countries, the tail is much longer due to its impact on India, where one-third of the globally poor live. The all-grain vulnerability indicator revealed that more than 1.06 billion poor people live in countries with significant price transmission of 10 % or higher – which constitute 96 % of the poor in the countries studied in this chapter and 89 % of the poor globally. More than 360 million poor people (one-third of the poor) live in countries with transmission elasticities of 30 % or higher; about 44 million poor people live in countries with transmission elasticities of 50 % or higher.

We decomposed the transmission further into the individual price series (see Appendix, Figs. 12.8, 12.9, 12.10, 12.11 and 12.12) to identify the most relevant international reference price for each of the commodities. Prices of futures contracts at the Chicago Board of Trade (CBOT) are the most relevant for wheat, in particular regarding the number of people affected. Transmission elasticities from CBOT prices are, however, topped by transmission rates from Canadian wheat and Argentinian spot prices for some countries (e.g., Nigeria, Ethiopia, or Kenya). For maize, US spot and futures prices were transmitted at rates ranging from 15 to

[12] Using the "moderate poverty line" of \$2 per day gives qualitatively similar results. Quantitatively, however, roughly double as many people are affected.

[13] Poverty rates are not available for every year. We use therefore the most recent number and multiplied it with the 2012 number of total population.

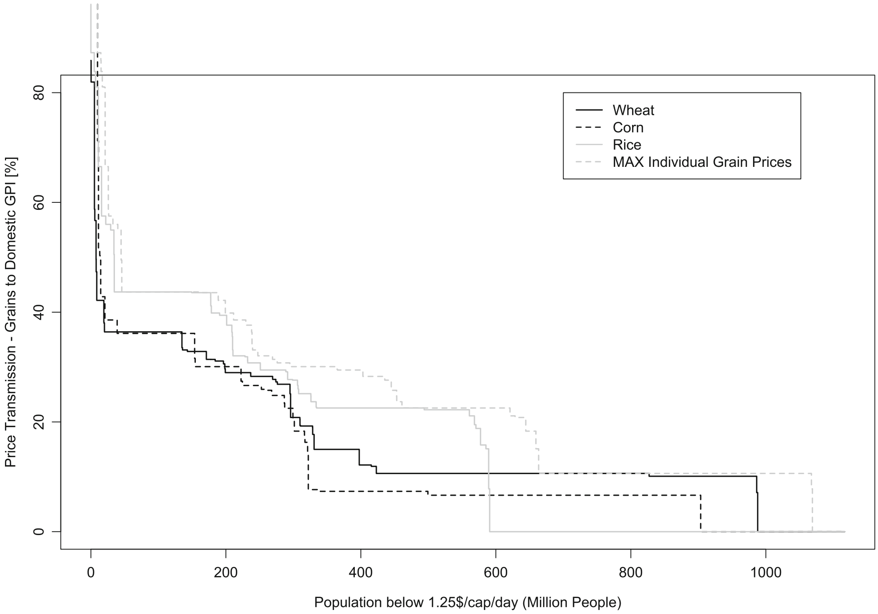

Fig. 12.4 Number and extent of poor people potentially affected by international price changes (change of grain price index). *Note*: The figure shows the transmission elasticities over all countries in descending order mapped to the number of people below the extreme poverty line in the particular country. *Source*: Own illustration

50 % for 150 million poor people. Yellow and white maize prices at the South African Futures Exchange (SAFEX) are strongly transmitted to Malawi at rates higher than 70 %. There is no clear reference price emerging for rice. IGC rice prices and Pakistani and Thai prices transmit at different rates to different countries, with Nigeria experiencing high transmission, in particular from Thai prices and the IGC price index.

Comparing the transmission indicated by the all-grain vulnerability indicator with several other price indices emphasizes that using individual price index alone would cause the size of the affected population to be underestimated. For example, the FAO food price index, a popular international reference price, suggests that 700 million poor could be affected by global price shocks (due to its significant transmission to India and China); the FAO cereals price suggests that 350 million people could be affected – far below the numbers obtained from the all-grain vulnerability indicator. The FAO food price index shows a higher transmission elasticity than most indices that are based only on grain prices because the FAO food price index has a lower variability.[14]

[14]The FAO food price index also contains meat and oils, which are processed food items that typically fluctuate less than commodity prices. Comparing the FAO food price and cereals price

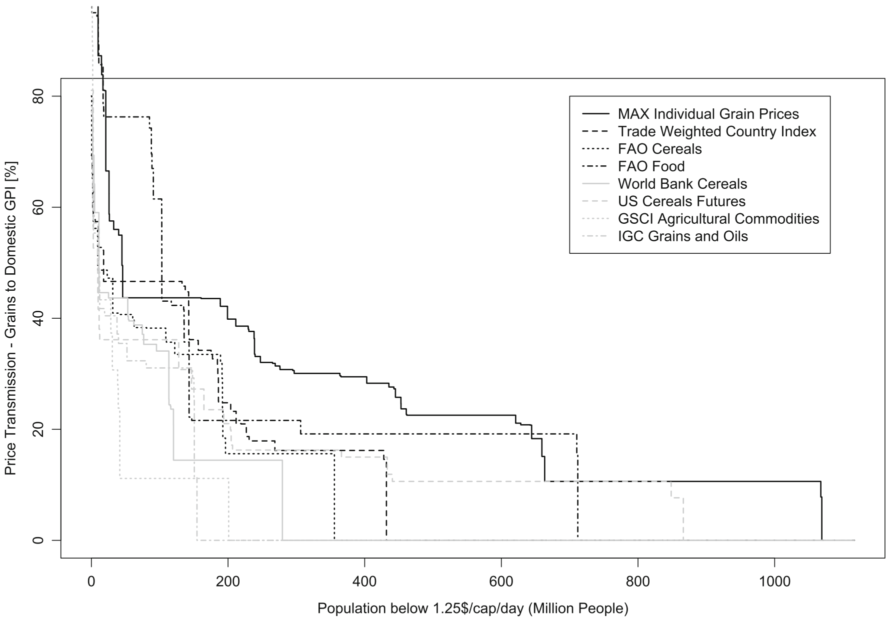

Fig. 12.5 Number and extent of poor people potentially affected by changes of international price indices. *Source*: Own illustration

Figure 12.5 further illustrates that about 850 million poor people might be affected by price changes in US cereals futures contracts (140 million with transmission rates of 30 % or higher), which is particularly relevant for the debate on speculation and financialization (Tadesse et al. 2014; von Braun et al. 2013). The transmission elasticities from commodity prices and price indices for countries with at least one million people living below the poverty line are listed in Table 12.4 in the Appendix.

The calculations shown in Figs. 12.4 and 12.5 require an important qualification: They represent the likely upper bound of the number of people affected. More precisely, they show the number of poor people living in countries affected by a specific price transmission. Not all poor people in a country with positive price transmission experience international price changes. In developing countries, in particular Africa, poor people in remote rural areas lack access to markets due to bad infrastructure (Barrett 2008; Nelson 2008). As discussed previously, food price indices from national statistical agencies could exhibit biases because of their focus on urban centers, making them less relevant for the rural population

index between 1990 and 2011, the former shows an average change rate of ±0.8 % per month, while the latter changes ±1.3 % per month. We would therefore expect a roughly 60 % higher transmission from FAO food prices for an identical commodity composition compared to cereals prices.

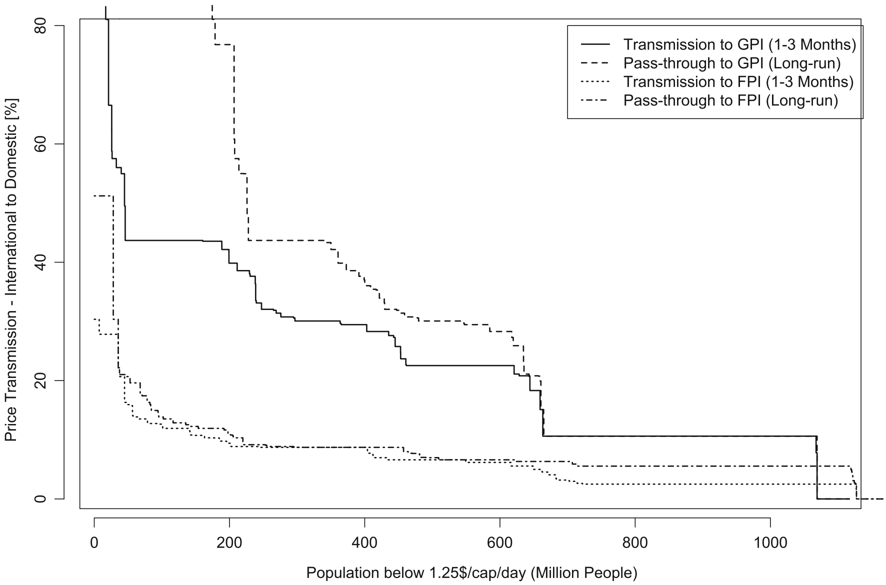

Fig. 12.6 Comparison of transmission and pass-through. *Source*: Own illustration

in remote areas. A transmission analysis based on food price indices from national statistical agencies would overstate the number of affected poor as one would expect lower price transmission from international prices to remote rural markets. The use of the grain price index which also considers grain prices from rural markets is an important alternative because it is constructed independent of the FPI using alternative price data. Nevertheless, the markets considered in this study are far from comprehensive, and prices for many rural areas are missing. The number of poor people in affected countries therefore only indicates the potential number of people affected (which would be the same if domestic markets were perfectly integrated).

12.6.3 Pass-Through and Equilibrium Effects

While the sum of the coefficients of international prices β gives the relative magnitude of price transmission 1–3 months after a spike, the pass-through θ considers long-run equilibrium adjustments due to the autoregressive term (see Sect. 12.4 above). Figure 12.6 depicts the vulnerability indicator (maximum overall international grain prices) for both transmission and pass-through to the domestic food price index as well as to the domestic grain price index. Consistent with Figs. 12.2 and 12.3, we found that transmission elasticities are considerably higher for the domestic grain price index than for the domestic food price index. The long-run equilibrium effect of international price spikes is substantially higher: For high vulnerable countries, the long-run effect is approximately twice as high as the short-run effect. The discrepancy between short-run transmission and long-run pass-though is higher when domestic grain prices instead of domestic food prices are considered. This is due to the more important role of the auto-regressive dynamics.

12.6.4 Robustness Checks

The outcome of our econometric analysis depends on not only the chosen model specification but also the considered significance levels. We therefore discuss the implications of different model specifications for our findings. We confine our discussion only to the vulnerability indicator for grain prices, in particular, with regard to its mapping to affected poor people (as shown in Fig. 12.4).

12.6.4.1 Significance Levels

If the null hypothesis of zero transmission cannot be rejected at the 5 % level, we set the transmission to zero; otherwise, we use the point estimate for the calculation of the transmission. Changing the significance level to 10 % increases the likelihood of erroneously detecting transmission to a country's domestic market when there is none; it reduces, however, the possibility of wrongly concluding that there is no price transmission in the case that the F-test does not reject the null hypothesis of zero transmission. We therefore employed two different significance levels (at 10 % and 1 %) to check the sensitivity of our results. As shown in the Appendix, a significance level of 10 % has only marginal impacts on the extent of price transmission and the number of poor people affected (Fig. 12.7). For a stricter significance level of 1 %, the transmission is lower relative to the poor population: Many countries on the right tail (with low transmission rates) do not pass the stricter significance test. Nevertheless, transmission elasticities for the 550 million poor people in countries with significant transmission hardly changed when compared with the lower significance levels.

12.6.4.2 CPI-Deflated Food Prices

It is often argued that nominal price changes are less relevant because monetary inflation might change the overall price level and therefore the purchasing power of money. To study welfare impacts of price changes, one would ideally deflate nominal prices with (nominal) income for consumers. This information is, however, hardly available.[15] Using the consumer price index (CPI) is a pragmatic alternative, although CPIs do not measure the income or wage of people but rather the costs of goods a consumer who is representative of the population buys. For some countries (e.g., Bangladesh), food items have a share over 50 % of the CPI (ILO 2013). Thus, even without any monetary inflation and without any increases in wages or prices of other consumption goods, an increase in food prices by 10 % would increase the CPI by more than 5 %. Deflating the food price change with the CPI would then

[15]For households with substantial income from selling their agricultural produce, prices of inputs need also to be considered (Dorward 2011).

result in a "real" price change of 5 %, although wages and other consumer prices would remain constant. Deflating the food price index with the CPI would in such cases understate the impact on welfare due to price changes.

Due to the lack of monthly wage or income data, we resorted to deflating food prices by the CPI despite knowing its shortcomings. As our grain price index used prices in the US dollar, which shows very low monthly inflation rates, we performed this robustness check only for the domestic food price analysis. As expected, the transmission to CPI-deflated food price indices was lower than to nominal food prices (Fig. 12.7). The transmission-population curves obtained are similar to our standard model, although slightly lower to the right tail (in particular, for India which experiences high inflation). Using nominal prices in the local currency also gave results similar to our standard model. The robustness of our findings regarding the choice of the currency and deflator is probably due to the use of first differences of log prices, which cancel out inflation, and the use of heteroskedasticity-corrected standard errors by the Newey-West method.

12.6.4.3 OLS Versus Newey-West

To check the robustness of the Newey-West approach with time lags of 6 months, we also included regressions based on the standard OLS, whereby homoskedasticity is assumed for calculating standard errors and thus significance levels. The OLS method allows for a much faster calculation of the standard errors; this becomes important when applying the method to many country and commodity time series. As indicated in Fig. 12.7, OLS gives similar results, although transmission rates were slightly lower as high transmission elasticities for some commodities did not pass the *t*-test at the 5 % level anymore.

12.7 Conclusions

The aim of this paper is to better understand the transmission of shocks from international prices to domestic food prices. Our analytical model emphasized that international price changes can be transmitted through intertemporal arbitrage of storage even if no trade takes place. Our empirical analysis suggests that focusing only on the FAO Food or Cereal Price Indices might cause the vulnerability of the poor to international price changes to be understated. Likewise, food price indices from national statistics might be biased, being more representative of (on average wealthier) urban consumers, who buy and consume relatively more processed staples and luxuries. To avoid these shortcomings, we used a comprehensive database on international reference prices and constructed a domestic grain price index based on retail prices in developing countries and the considered commodities' share of the total consumption. Our price database allows for almost universal country coverage, in particular, with respect to countries where poor people live. For the first time therefore, we were able to estimate how many poor people live in countries where international price changes are transmitted to domestic prices.

Our empirical analysis illustrated that the vast majority of the poor (over 90 %) live in countries where food prices are linked more or less strongly to international prices *in the short term* that is within 1–3 months. For 360 million poor people, international prices transmit to their country at rates of 30 % or higher. The empirical analysis considered seasonality and oil prices (endogenous model selection). The findings were robust at different significance levels and for different price deflators.

Because of our chosen lag structure of 3 months, we expect that international price shocks will translate to domestic price shocks rather quickly. Existing research on the impact of price changes on the welfare of poor consumers has paid more attention to the differentiated and heterogeneous effects of price changes, depending on the production and consumption structure. While higher prices can benefit net sellers of the affected crops, they make poor consumers, net buyer farmers and rural landless worse off in the short term. Several quantitative estimates concluded that the negative effects overweigh the positive effects, for example, with respect to the number of people falling below the poverty line – at least in the short term when production is not able to respond flexibly to higher prices (Ivanic and Martin 2008; Tiwari and Zaman 2010; de Hoyos and Medvedev 2011; Anríquez et al. 2013). There are also concerns that price increases affect poor consumers more than the effect of a symmetric price decrease on producers of food: While poor consumers can run into serious problems because they cannot afford sufficient food, producers may still have enough (self-grown) food to eat, even though their income may be significantly reduced (Kalkuhl et al. 2013).

Although our analysis focused on the transmission of price levels rather than price risk or volatility, one can expect that high international volatility (measured in the fluctuations of *monthly* prices) would also increase domestic food price volatility (see also Chap. 13). While the impacts of price changes on welfare are as yet unclear, higher volatility may have negative effects on welfare because of an increase in the production risks for farmers and, thus, undermining long-term food supply (Haile and Kalkuhl 2013; Haile et al. 2013).

The transmission analysis and the estimated elasticities could be used in early warning systems to detect vulnerable countries in times of high international price swings. It could further be extended to explain the different degrees of price transmission by using other explanatory variables like transportation costs, trade, GDP, or grains stocks.

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Appendix

International Reference Prices and Price Indices

Table 12.3 Considered international reference prices and price indices

w	Variable	Description	Source
1	FAO food price index	Consists of 55 commodity quotations considered as representing the international prices of food commodities; weighted by export share	FAO
2	FAO cereals price index	Consists of wheat, maize, and rice prices; weighted by export share	FAO
3	FAO oil/fat price index	Consists of 12 different oils (including animal and fish oils); weighted by export share	FAO
4	FAO sugars price index	Index form of the International Sugar Agreement prices with 2002–2004 as base	FAO
5	FAO meat price index	Consists of poultry, bovine meat, pig meat, and ovine meat products; weighted by export share	FAO
6	FAO dairy price index	Consists of butter, skimmed milk powder, whole-milk powder, cheese, and casein prices; weighted by export share	FAO
7	WB grain price index	Includes barley, maize, rice, and wheat	World Bank
8	WB fats and oils price index	Includes coconut oil, groundnut oil, palm oil, soybeans, soybean oil, and soybean meal	World Bank
9	Wheat (HRW) US	No. 1, hard red winter, ordinary protein, export price delivered at the US Gulf port for prompt or 30 days' shipment	World Bank
10	Wheat (SRW) US	No. 2, soft red winter, export price delivered at the US Gulf port for prompt or 30 days' shipment	World Bank
11	Wheat CAN	Wheat (Canada), no. 1, western red spring (CWRS), in store, St. Lawrence, export price	World Bank
12	Wheat AUS	Australian soft white, Australia, f.o.b.	USDA/IGC
		Australia Eastern States Standard White Wheat FOB Spot (for 10/2007–09/2008 where USDA/IGC series has missing entries)	Bloomberg
13	Barley	Barley (Canada), feed, western no. 1, Winnipeg Commodity Exchange, spot, wholesale farmers' price	World Bank
14	Sorghum US	Sorghum (US), no. 2 milo yellow, f.o.b. Gulf ports	World Bank
15	Corn US	Maize (US), no. 2, yellow, f.o.b. US Gulf ports	World Bank
16	Soybeans	Soybeans (US), c.i.f. Rotterdam	World Bank
17	Soybean oil	Soybean oil (Any origin), crude, f.o.b. ex-mill Netherlands	World Bank
18	Soybean meal	Soybean meal (any origin), Argentine 45/46 % extraction, c.i.f. Rotterdam beginning 1990; previously US 44 %	World Bank

(continued)

Table 12.3 (continued)

w	Variable	Description	Source
19	Rice Thai A1	Rice (Thailand), 100 % broken, A.1 Super from 2006 onward, government standard, f.o.b. Bangkok; prior to 2006, A1 Special, a slightly lower grade than A1 Super	World Bank
20	Rice Thai 5 %	Rice (Thailand), 5 % broken, white rice (WR), milled, indicative price based on weekly surveys of export transactions, government standard, f.o.b. Bangkok	World Bank
21	Rice Thai 25 %	Rice (Thailand), 25 % broken, WR, milled indicative survey price, government standard, f.o.b. Bangkok	World Bank
22	Rice Vietnam	Vietnamese rice, 5 % broken	World Bank
23	Palm oil	Palm oil (Malaysia), 5 % bulk, c.i.f. N. W. Europe	World Bank
24	Groundnut oil	Groundnut oil (any origin), c.i.f. Rotterdam	World Bank
25	Coconut oil	Coconut oil (Philippines/Indonesia), bulk, c.i.f. Rotterdam	World Bank
26	Fishmeal	Fishmeal (any origin), 64–65 %, c&f Bremen, estimates based on wholesale price, beginning 2004; previously c&f Hamburg	World Bank
27	Beef	Meat, beef (Australia/New Zealand), chucks and cow forequarters, frozen boneless, 85 % chemical lean, c.i.f. US port (East Coast), ex-dock, beginning 11/2002; previously cow forequarters	World Bank
28	Chicken	Meat, chicken (US), broiler/fryer, whole birds, 2½–3 pounds, USDA grade “A,” ice-packed, Georgia Dock preliminary weighted average, wholesale	World Bank
29	Sheep	Meat, sheep (New Zealand), frozen whole carcasses prime medium (PM) wholesale, Smithfield, London, beginning 01/2006; previously Prime Light (PL)	World Bank
30	Wheat/CBT	#2 Soft red winter at contract price, #1 Soft red winter at a 3 cent premium, Chicago Board of Trade	Bloomberg
31	Corn/CBT	#2 yellow at contract price, #1 yellow at a 1.5 cent/bushel premium, #3 yellow at a 1.5 cent/bushel discount, Chicago Board of Trade	Bloomberg
32	Soybeans/CBT	#2 Yellow at contract price, #1 yellow at a 6 cent/bushel premium, #3 yellow at a 6 cent/bushel discount, Chicago Board of Trade	Bloomberg
33	Soybean oil/CBT	Crude soybean oil meeting exchange-approved grades and standards, Chicago Board of Trade	Bloomberg
34	Soybean meal/CBT	48 % protein soybean meal, Chicago Board of Trade	Bloomberg

(continued)

Table 12.3 (continued)

w	Variable	Description	Source
35	Rough rice/CBT	US no. 2 or better long grain rough rice with a total milling yield of not less than 65 % including head rice of not less than 48 %, Chicago Board of Trade	Bloomberg
36	Feeder cattle/CME	650–849 pound steers, medium-large #1 and medium-large #1–2, Chicago Mercantile Exchange	Bloomberg
37	Live cattle/CME	55 % choice, 45 % select, yield grade 3 live steers, Chicago Mercantile Exchange	Bloomberg
38	Lean hogs/CME	Hog (barrow and gilt) carcasses, Chicago Mercantile Exchange	Bloomberg
39	Wheat/KCBT	Hard red winter wheat, no. 2, at contract price; no. 1 at a 1½-cent premium; Kansas City Board of Trade	Bloomberg
40	Wheat/MGEX	Hard red spring wheat, no. 2 or better Northern spring wheat with a protein content of 13.5 % or higher; Minneapolis Grain Exchange	Bloomberg
41	White maize/SAFEX	South African Futures Exchange; starting in 08/1996	Bloomberg
42	Yellow maize/SAFEX	South African Futures Exchange; starting in 08/1996	Bloomberg
43	Wheat/SAFEX	South African Futures Exchange; starting in 11/1997	Bloomberg
44	Soybean/SAFEX	South African Futures Exchange; starting in 04/2002	Bloomberg
45	Sunflower seeds/SAFEX	South African Futures Exchange; starting in 02/1999	Bloomberg
46	Palm oil/MDEX	Malaysia Derivatives Exchange; starting in 03/1995	Bloomberg
47	GSCI agriculture	Price index over active futures with the 2012 S&P GSCI weights on wheat (CBT), wheat (KCBT), corn, soybeans, lean hogs, live cattle and feeder cattle (all CBT)	Own calculation
48	Trade weighted country index	Price index over US corn, US HRW and Thai 5 % spot prices according to the trade shares (imports plus exports of commodity divided by imports plus exports of all three commodities) of each country	Own calculation
49	Rice/Vietnam	Vietnam, rice (25 % broken), export	FAO GIEWS
50	Rice/Vietnam	Vietnam, rice (5 % broken), export	FAO GIEWS
51	Rice/Pakistan	Pakistan, rice (25 % broken), export	FAO GIEWS
52	Rice/Pakistan	Pakistan, rice (Basmati ordinary), export	FAO GIEWS
53	Rice/USA	USA, rice (US long grain 2.4 %), export	FAO GIEWS

(continued)

Table 12.3 (continued)

w	Variable	Description	Source
54	Rice/USA	USA, rice (US California medium grain), export	FAO GIEWS
55	Rice/Thailand	Thailand: Bangkok, rice (25 % broken), export	FAO GIEWS
56	Rice/Thailand	Thailand: Bangkok, rice (5 % broken), export	FAO GIEWS
57	Rice/Thailand	Thailand: Bangkok, rice (fragrant 100 %), export	FAO GIEWS
58	Rice/Thailand	Thailand: Bangkok, rice (glutinous 10 %), export	FAO GIEWS
59	Rice/Thailand	Thailand: Bangkok, rice (parboiled 100 %), export	FAO GIEWS
60	Rice/Thailand	Thailand: Bangkok, rice (Thai 100 % B), export	FAO GIEWS
61	Rice/Thailand	Thailand: Bangkok, rice (Thai A1 Super), export	FAO GIEWS
62	Wheat/Argentina	Argentina, wheat (Argentina, up river, trigo pan), export	FAO GIEWS
63	Maize/Argentina	Argentina, maize (Argentina, up river), export	FAO GIEWS

Source: Own elaboration

Robustness Checks for Transmission to Grain Price Index

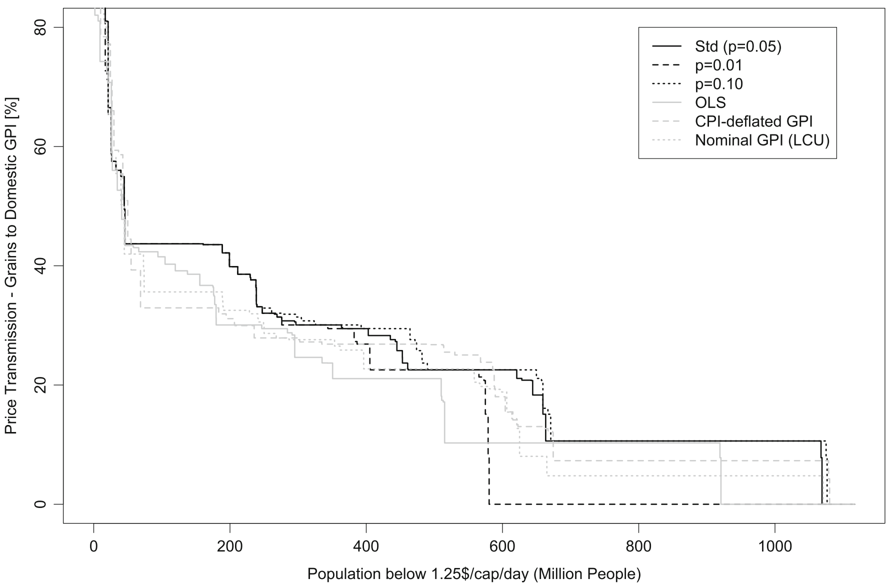

Fig. 12.7 Global price transmission to the domestic grain price index under different significance levels and model specifications. *Source*: Own elaboration

Price Transmission from Individual Grain Prices

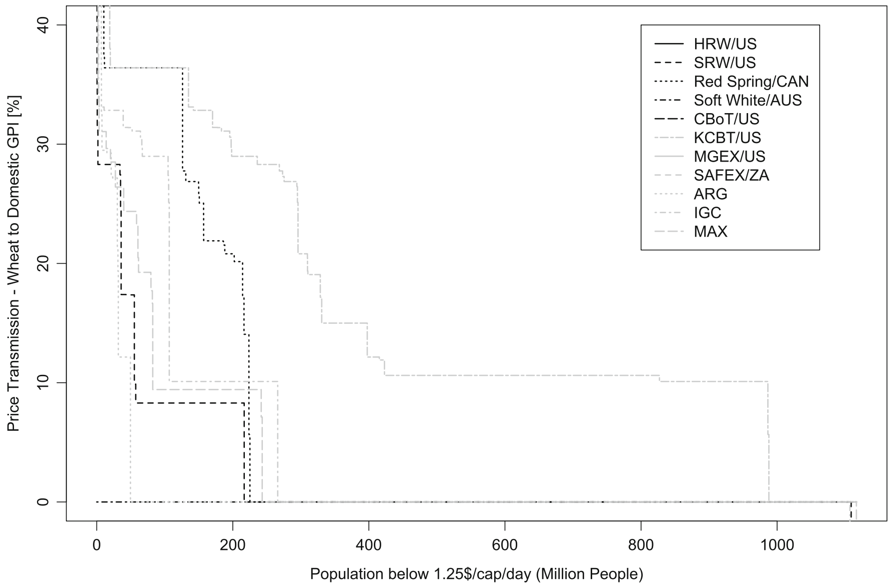

Fig. 12.8 Transmission from several international wheat prices to the domestic grain price index and affected people

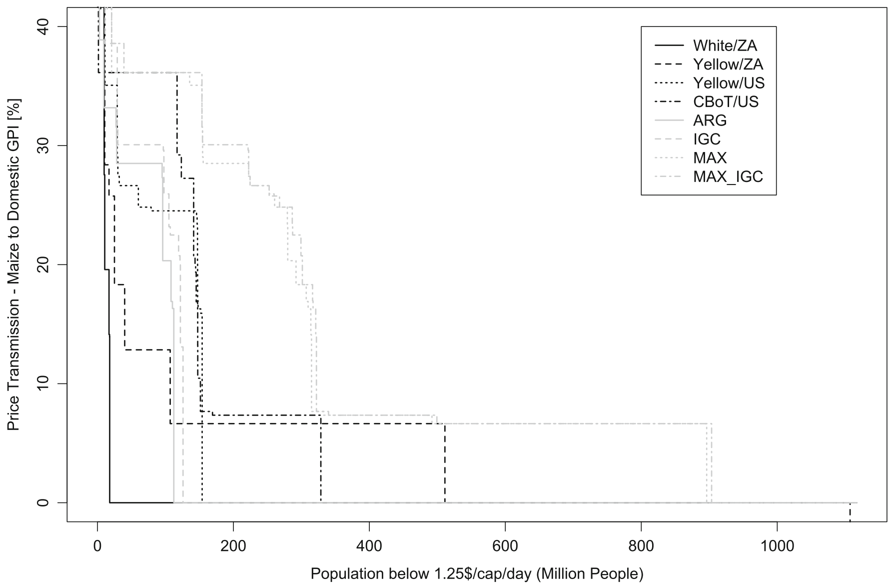

Fig. 12.9 Transmission from several international maize prices to the domestic grain price index and affected people

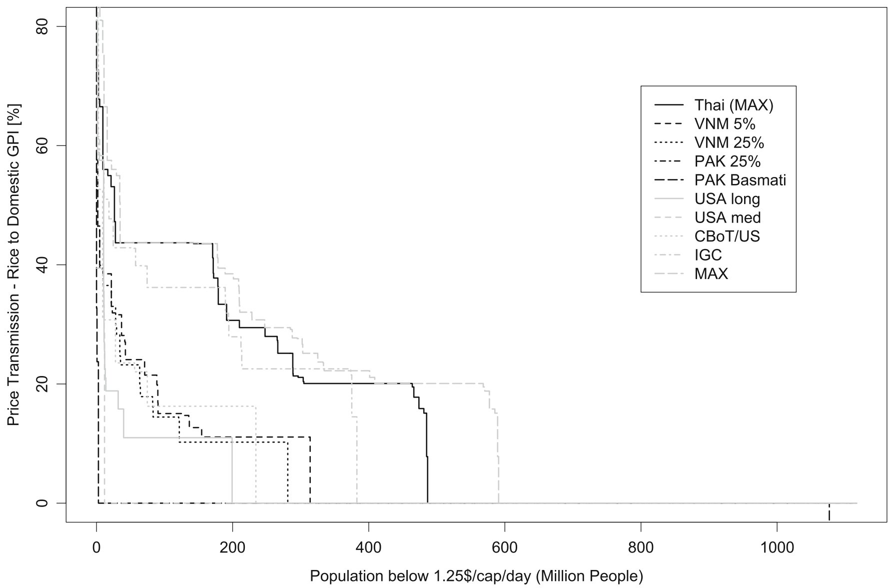

Fig. 12.10 Transmission from several international rice prices to the domestic grain price index and affected people

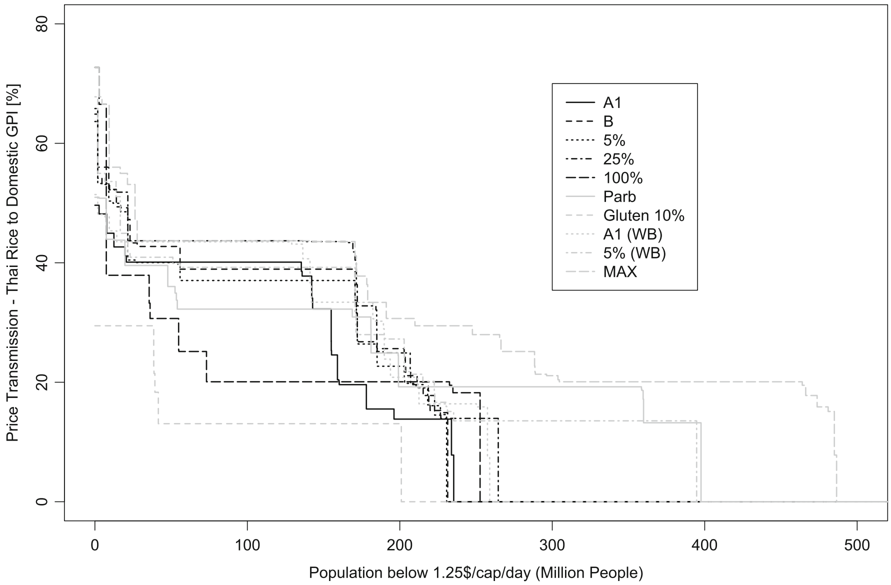

Fig. 12.11 Transmission from Thai rice prices (export) to the domestic grain price index and affected people

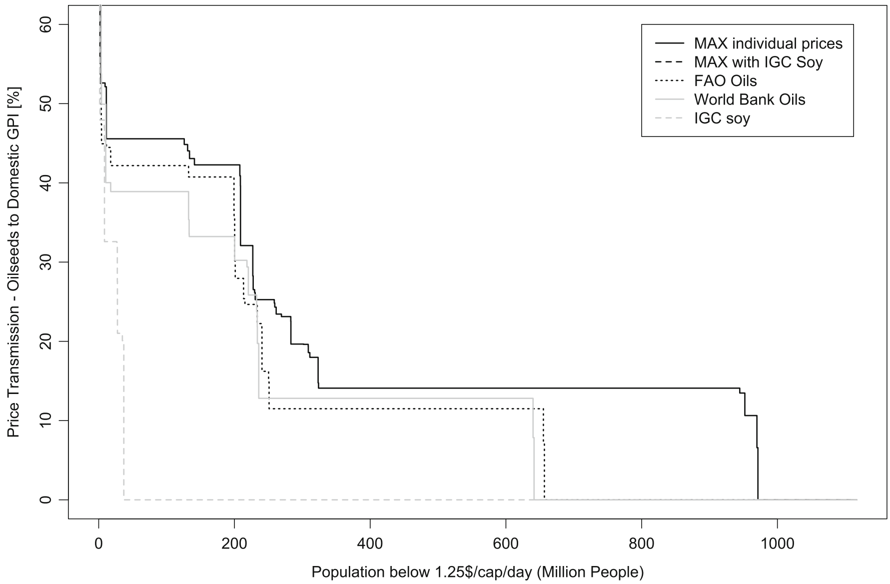

Fig. 12.12 Transmission from several international oilseed prices to the domestic grain price index and affected people

Table 12.4 Transmission elasticities of grain prices and price indices to domestic grain prices for countries with more than one million people below the poverty line

ISO3	Poor pop (Mio)	Wheat	Maize	Rice	Max (grains)	Max (US cereals futures)	FAO food	FAO cereals	WB grains	IGC grains/oils
AFG		0.30	0.46	0.37	0.46	0.28	0.71	0.52	0.50	0.51
BDI	8.0	0.00	0.26	0.16	0.26	0.00	0.00	0.00	0.00	0.00
BEN	4.8	0.28	0.00	0.55	0.55	0.00	0.00	0.00	0.00	0.00
BFA	7.3	0.00	0.00	0.28	0.28	0.00	0.00	0.00	0.00	0.00
BGD	66.9	0.15	0.30	0.22	0.30	0.15	0.76	0.33	0.00	0.31
BRA	12.2	0.31	0.22	0.40	0.40	0.00	0.61	0.36	0.39	0.35
CHN	159.4	0.10	0.07	0.23	0.23	0.16	0.42	0.32	0.32	0.00
CIV	4.7	0.00	0.00	0.67	0.67	0.00	0.00	0.00	0.00	0.00
CMR	2.1	0.18	0.21	0.00	0.21	0.17	0.00	0.32	0.24	0.29
COL	3.9	0.00	0.16	0.32	0.32	0.10	0.22	0.18	0.24	0.11
ETH	28.1	0.33	0.27	0.44	0.44	0.24	0.00	0.71	0.78	0.61
GHA	7.3	0.00	0.00	0.56	0.56	0.00	0.36	0.00	0.00	0.00
GIN	5.0	0.82	0.00	0.87	0.87	0.00	0.00	0.00	0.00	0.00
GTM	2.0	0.31	0.27	0.29	0.31	0.21	0.67	0.40	0.37	0.37
HND	1.4	0.00	0.71	0.81	0.81	0.42	0.00	0.65	0.78	0.77
HTI	6.3	0.31	0.43	0.58	0.58	0.53	0.86	0.56	0.59	0.57
IDN	40.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IND	404.1	0.11	0.07	0.00	0.11	0.11	0.19	0.00	0.00	0.00
KEN	18.7	0.27	0.25	0.31	0.31	0.31	0.00	0.41	0.35	0.00
KHM	2.8	0.00	0.00	0.81	0.81	0.81	0.74	0.00	0.00	0.00
LAO	2.3	0.27	0.00	0.19	0.27	0.00	0.00	0.00	0.00	0.00
MDG	18.1	0.19	0.39	0.25	0.39	0.27	0.42	0.38	0.34	0.40

(continued)

Table 12.4 (continued)

ISO3	Poor pop (Mio)	Wheat	Maize	Rice	Max (grains)	Max (US cereals futures)	FAO food	FAO cereals	WB grains	IGC grains/oils
MLI	7.5	0.12	0.00	0.24	0.24	0.12	0.00	0.00	0.00	0.00
MMR		0.27	0.25	0.27	0.27	0.27	0.00	0.00	0.31	0.34
MNG		0.55	0.37	0.32	0.55	0.34	0.88	0.69	0.53	0.64
MOZ	15.0	0.00	0.18	0.00	0.18	0.00	0.00	0.00	0.00	0.00
MWI	9.8	0.00	1.17	0.00	1.17	0.00	0.00	0.00	0.00	0.00
NER	7.5	0.00	0.00	0.21	0.21	0.00	0.00	0.00	0.00	0.00
NGA	114.8	0.36	0.36	0.44	0.44	0.36	0.00	0.00	0.00	0.00
NPL	6.8	0.31	0.00	0.19	0.31	0.00	0.00	0.00	0.00	0.00
PAK	37.7	0.29	0.00	0.29	0.29	0.00	0.00	0.00	0.00	0.00
PER	1.5	0.07	0.00	0.08	0.08	0.00	0.40	0.00	0.00	0.00
PHL	17.8	0.12	0.08	0.32	0.32	0.08	0.00	0.00	0.00	0.00
RUS		0.33	0.26	0.28	0.33	0.21	0.95	0.47	0.40	0.42
RWA	7.2	0.33	0.26	0.28	0.33	0.21	0.95	0.47	0.40	0.42
SDN	7.4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SEN	4.1	0.00	0.00	0.15	0.15	0.00	0.00	0.00	0.00	0.00
TCD	7.7	0.00	0.00	0.38	0.38	0.00	0.00	0.00	0.00	0.00
TGO	1.9	0.57	0.51	0.84	0.84	0.00	0.59	0.00	0.44	0.38
TZA	32.4	0.28	0.00	0.00	0.28	0.00	0.00	0.00	0.00	0.00
UGA	13.8	0.21	0.00	0.00	0.21	0.00	0.43	0.49	0.45	0.00
ZMB	10.5	0.42	0.00	0.39	0.42	0.00	0.00	0.41	0.00	0.00
ZWE		0.00	0.00	1.54	1.54	0.00	0.00	0.00	0.00	0.00

Note: "Poor pop" refers to the number of people below the poverty line (estimated in 2012) – blank entries denote missing data. Wheat, maize, and rice refer to the maximum transmission of the commodity prices at different international markets or of different types in each of the commodity group; max(grains) is the vulnerability indicator – showing the maximum transmission over the different grain prices; max (US cereals futures) is the vulnerability indicator over commodity prices at US futures exchanges. WB refers to the World Bank's grain price index

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Transmission of Food Price Volatility from International to Domestic Markets: Evidence from Africa, Latin America, and South Asia

13

Francisco Ceballos, Manuel A. Hernandez, Nicholas Minot, and Miguel Robles

13.1 Introduction

The global food crisis of 2007–2008 was characterized by a sharp spike in grain and other commodity prices. These price increases have been attributed to supply shortages, increased biofuel production, reduced stock-to-use ratios, export bans by major grain exporters, and panic buying by some major importers (Gilbert 2010). Commodity prices rose rapidly again in 2010, 2011, and 2012. Since 2007, global grain markets have seen an overall increase in price volatility, which is defined as the standard deviation of monthly price returns. For example, comparing the 27-year period before the crisis (1980–2006) with the 4-year period during and after the crisis (2007–2010), the unconditional volatility of international prices rose by 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. First, low-income consumers spend a large share of their income on food in general and on staple foods in particular, thereby making them more vulnerable to food price volatility. For instance, in some countries, such as Tanzania, Sri Lanka, and Vietnam, low-income households allocate more than 60 % of their budgets to food (Seale et al. 2003). Second, food price volatility 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. Third, price volatility is likely to 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.

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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 excessive 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 be solutions at the local level which are targeted at the most vulnerable groups.

One approach to answering this question is to examine the transmission of prices (in levels) from world markets to local markets.[1] Although it seems reasonable to assume that markets with high transmission of prices could 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 1- to 6-month lag, thus insulating local markets from international turmoil and resulting in less volatile local prices. Alternatively, even if there were no direct price transmission, it would still be 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 on world markets.

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

The main contribution of this paper is that it is one of the first studies to estimate the transmission of food price volatility from international markets to local markets across several developing countries and regions. As will be discussed later, other studies have examined the transmission of (mean) price levels from global markets to developing countries. However, studies on the transmission of price volatility have mainly focused on examining volatility dynamics across different commodities and international markets. In addition, by focusing on market interactions in terms of the conditional second moment and allowing for volatility spillovers, better insight into the dynamic price relationship of international and domestic markets can be gained.

The remainder of the paper is organized as follows. Section 13.2 provides a review of recent research on transmission of prices and volatility. Section 13.3 details the methodology used in the study. Section 13.4 describes the data. Sec-

[1] Section 13.2 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 et al. (1990).

tion 13.5 presents and discusses the estimation results, and Sect. 13.6 summarizes the findings and draws some conclusions for future research.

13.2 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 Baulch 1997; Abdulai 2000; Rashid 2004; Lutz et al. 2006; Negassa and Myers 2007; Van Campenhout 2007; Myers 2008; Moser et al. 2009). Most of these studies used cointegration analysis in the form of error correction models, although some of the more recent studies applied threshold cointegration models and asymmetric response to positive and negative price shocks (e.g., Meyer and von Cramon-Taubadel 2004). Fewer studies have examined the transmission of prices from world markets to local markets. Mundlak and Larson (1992) estimated the transmission of world food prices to domestic prices in 58 countries using annual price data. They found very high rates of price transmission, but the analysis was carried out in levels rather than first differences, so the results probably reflected spurious correlation due to nonstationarity. Quiroz and Soto (1995) repeated the analysis of Mundlak and Larson (1992) using cointegration analysis and an error correction model. They found no relationship between domestic and international prices for 30 of the 78 countries examined. Conforti (2004) examined price transmission in 16 countries, including 3 in sub-Saharan Africa, using an error correction model. In general, the degree of price transmission in sub-Saharan African countries was lower than in Asian and Latin American countries. Minot (2010) analyzed the transmission of prices from world grain markets to 60 markets in sub-Saharan Africa and found a statistically significant long-term relationship in only 13 of the 62 prices examined. He also found that African rice prices are more closely linked to world markets than maize prices, presumably because most African countries are close to self-sufficiency in maize product but import a large share of their rice requirements.

Another set of studies has focused on the co-movement of world commodity prices. In their seminal paper, Pindyck and Rotemberg (1990) found “excessive co-movement” of seven commodity prices, which they attributed to herd behavior among traders in financial markets. The hypothesis of excess co-movement, however, was challenged by Deb et al. (1996) and Ai et al. (2006). These studies argued that the results obtained by Pindyck and Rotemberg suffered from misspecification and that fundamental supply and demand factors were sufficient to explain the co-movement.[3] In the case of international agricultural prices, Gilbert (2010) indicated that shocks to individual commodity prices are often supply related, whereas joint price movement can be explained by macroeconomic and monetary conditions.

[3]See Saadi (2010) for an extensive review of commodity price co-movement in international markets.

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, which are 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 effects or as a result of common underlying factors, such as uncertainty in financial markets.

Some of the recent studies that examined market interactions between agricultural commodities using MGARCH models include Le Pen and Sévi (2010), Zhao and Goodwin (2011), Hernandez et al. (2014), Beckmann and Czudaj (2014), and Gardebroek et al. (2014). Le Pen and Sévi (2010) used different multivariate models, including a factor model and a Dynamic Conditional Correlation (DCC) model, to examine the interrelationship between eight agricultural and nonagricultural commodities and find moderate co-movement in prices and volatility. Zhao and Goodwin (2011) found important volatility spillovers between corn and soybean future prices based on a BEKK model. Using both a BEKK and a DCC model, Hernandez et al. (2014) showed 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 showed evidence supporting short-run volatility transmission between futures prices of corn, wheat, and cotton, based on bivariate GARCH-in-mean VAR models. Lastly, Gardebroek et al. (2014) used different MGARCH models and found little evidence of price transmission in levels between corn, wheat, and soybean spot markets. However, they found significant transmission in price volatility, particularly at weekly and monthly frequencies.

13.3 Methodology

We followed an MGARCH approach to evaluate the 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 estimated a bivariate T-BEKK model, proposed by Engle and Kroner (1995), which allowed us to model volatility transmission from international to domestic markets since the model is flexible enough to take into account both volatility spillovers and persistence across markets.[5]

The T-BEKK approach involves modeling both a conditional mean equation and a conditional variance equation for each price return series considered in the analysis. In our case, we defined price returns as $r_{mt} = \ln(p_{mt}/p_{mt-1})$, where p_{mt} is

[4]See Bauwens et al. (2006) and Silvennoinen and Teräsvirta (2009) for an extensive overview of different MGARCH models.

[5]The T acronym refers to the student's t density used in the model estimation in order to better control the leptokurtic distribution of the price returns series.

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. The logarithmic transformation is a standard measure for net returns 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.

For those cases in which the pair of price returns are not found to be cointegrated, the conditional mean equation is simply modeled as a vector autoregressive (VAR) process such that

$$r_t = a_0 + \sum_{s=1}^{k} a_s r_{t-s} + \varepsilon_t, \ \varepsilon_t \Big| I_{t-1} \sim (0, H_t) \tag{13.1a}$$

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., $r_t = \begin{pmatrix} r_{1t} \\ r_{2t} \end{pmatrix}$; a_0 is a 2×1 vector of constants; a_s, $s = 1,..,k$, 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.[6] In order to determine the number of lags (k), we relied on the Schwarz Bayesian Information Criterion (SBIC). The number of lags in the conditional mean equation varied between zero and two lags, with only one case requiring three lags.

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

$$r_t = a_0 + \sum_{j=1}^{k} a_j r_{t-j} - \lambda \mathrm{ECT}_{t-1} + \varepsilon_t, \ \varepsilon_t \Big| I_{t-1} \sim (0, H_t) \tag{13.1b}$$

where ECT_{t-1} is the lagged error correction term resulting from the cointegration relationship, i.e., $\mathrm{ECT}_{t-1} = lnp_{1,t-1} - \beta_0 - \beta_1 lnp_{2,\,t-1}$, 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.

[6]Other control variables were excluded from the conditional mean (and variance) equations to capture dynamic price relationships across markets in their purest form. As with any autoregressive process, the state of the process (mean or variance) in the previous period is assumed to account for all relevant information prior to the realization of the mean or variance in the current period.

The conditional variance-covariance matrix H_t at time t (with one-time lag) is, in turn, given by

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}A + G'H_{t-1}G, \tag{13.2}$$

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 Eq. (13.2), the resulting conditional variance equation for the domestic market is defined as

$$\begin{aligned} h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} \\ +2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1} \end{aligned} \tag{13.3}$$

This variance-covariance specification allows us to characterize the magnitude and persistence of volatility transmission from international to domestic markets. Moreover, similar to Gardebroek and Hernandez (2013) and Hernandez et al. (2014), we derived impulse response functions for the estimated conditional volatilities to assess how a shock or innovation is transmitted from the international market to the domestic market and obtain the elasticity of domestic price volatility with respect to international price volatility.

13.4 Data

We compiled a large dataset of monthly prices of maize, rice, sorghum, wheat, and wheat products for 41 markets in 27 countries. We obtained domestic price data from two sources. Our main source was the Famine Early Warning Systems Network (FEWS NET), which tracks the nominal prices of several staple 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 was 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 relied on this source to obtain domestic prices in Asian, South American, and some additional Central American countries.

Out of all the price series available from these sources, we considered the domestic prices of the most important food staples in each country, which are defined as those constituting the highest share of the local diet. Moreover, prices from the main local market—generally the capital city—were chosen to be representative of each product. We also included prices observed in more than one market for a few countries (in India, for example, prices from both the Mumbai and the New Delhi markets were considered). As prices are denominated in local currency, each price series was converted into the US dollar using monthly exchange rates from the IMF's International Financial Statistics (IFS) database. Normalizing all prices to the US dollar allowed us to take into account the potential impact of the exchange rate on the international-domestic price transmission analysis. We excluded price series with less than 100 observations (i.e., months) or with a high number of missing or repeated values. Missing values in the remaining series were approximated through linear interpolation between the two closest available data points. Appendix Table 13.3 shows the details for each of the price series used, including its source (FEWS NET 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). These prices are expressed in terms of US dollars per tonne. The maize price is for No. 2 yellow maize, U.S. Gulf; the rice price is for A1 super, white broken rice, 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. Appendix Table 13.4 shows the details of each of the international price series used.

Figure 13.1 shows the evolution of international monthly prices for maize, rice, sorghum, and wheat over the 2000–2014 period. In general, prices had been rising in a relatively stable way until the spikes experienced during the food crisis of 2007–2008; price spikes were subsequently observed between 2010 and 2012. Interestingly, the figure shows a large degree of co-movement between the prices for the four commodities during the past years. The price movement of sorghum

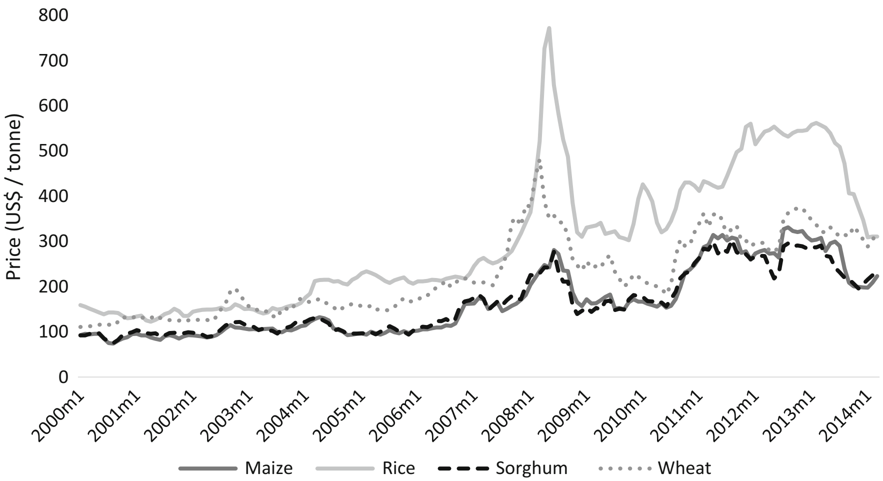

Fig. 13.1 International commodity prices—2000–2014. *Note*: this figure shows the evolution of the monthly international prices of maize, rice, sorghum, and wheat during the 2000–2014 period. Prices are expressed in US$ per tonne

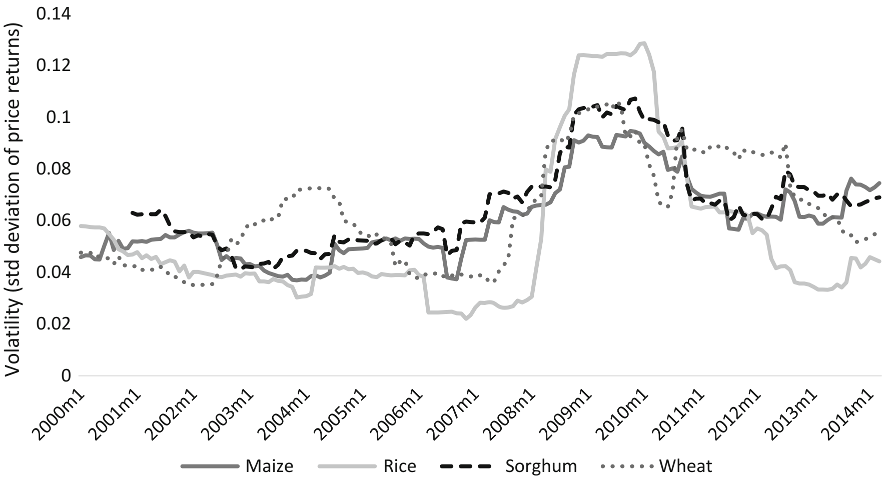

Fig. 13.2 Volatility of international grain prices (2-year moving window)—2000–2014. *Note*: this figure shows the evolution of the volatility of monthly international prices of maize, rice, sorghum, and wheat during the 2000–2014 period. The monthly volatility was calculated as the standard deviation of the monthly price returns observed during that month and the previous 23 months

and maize showed striking similarities; this is also true of wheat price movement—though to a lesser extent.

International prices of different food commodities also seem to co-move in terms of volatility. Figure 13.2 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.[7] 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 2007–2008 food crisis, followed by a decrease—even though price volatility after the decrease was still higher than prior to the crisis. This is more clearly observed in Fig. 13.3, which compares price volatility before (2000–2006) and after the crisis (2008–2014). Except for sorghum, which showed only a moderate increase, sample standard deviations for the rest of the commodities increased by more than 30 % after the crisis, indicating a much higher variation (fluctuation) of international agricultural prices in recent years.

As discussed above, the main purpose of this study is to analyze volatility transmission from international to domestic markets. As a first step, it is useful to analyze the dynamics of the volatility of domestic prices vis-à-vis that of the international reference prices. Figure 13.4a–d plots the evolution of price volatility (the standard deviation of international and domestic price returns) by commodity over a 2-year moving window, similar to Fig. 13.2. The results were mixed. In the

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

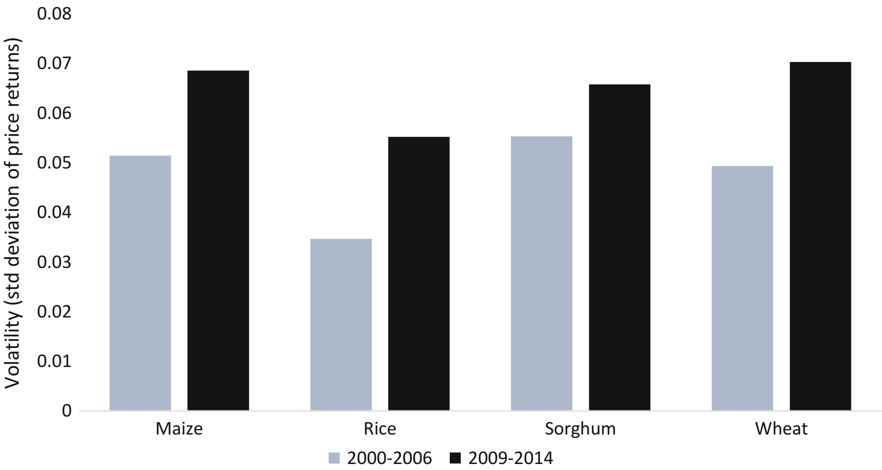

Fig. 13.3 Volatility of international grain prices before and after the 2007–2008 crisis. *Note*: this figure shows the volatility of monthly international prices of maize, rice, sorghum, and wheat before and after the 2007–2008 food crisis. The "before" period spans 2000–2006 while the "after" period spans 2009–2014. The volatility for each period is calculated as the standard deviation of the observed monthly price returns for each commodity

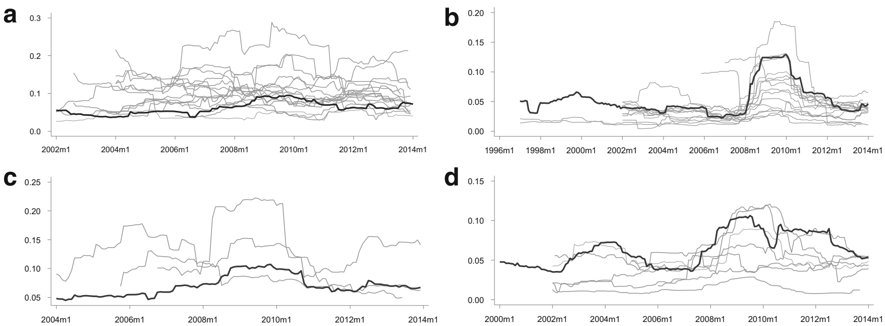

Fig. 13.4 Volatility (2-year moving window) of domestic and international prices for (**a**) maize, (**b**) rice, (**c**) sorghum, and (**d**) wheat. *Note*: Figures (**a**)–(**d**) show the evolution of the volatility of monthly domestic and international prices of maize, rice, sorghum, and wheat during the 2000–2014 period. The volatility for every month is calculated as the standard deviation of the monthly price returns observed during that month and the previous 23 months. The *line* in *bold* represents the volatility of each international price series

case of rice and wheat, there seems to be a substantial co-movement in the volatility of domestic and international prices, particularly in the case of rice. The volatility of international sorghum prices also showed some evidence of co-movement with the volatility of domestic sorghum-related prices. The volatility pattern of prices in domestic maize markets, in contrast, did not generally resemble the volatility pattern exhibited by international maize prices. The volatility dynamics between domestic

Table 13.1 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 (%)	0.42	0.33	0.47	0.46	0.40
% 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 (5 lags)	31.3	66.7	0.0	71.4	48.8
% of series rejecting Ljung-Box test's H_0 on squared returns (10 lags)	31.3	73.3	33.3	71.4	53.7
% of series rejecting AC Q test's H_0 on squared returns (first lag)	37.5	73.3	33.3	71.4	56.1
% of series rejecting AC Q test's H_0 on squared returns (second lag)	43.8	80.0	33.3	85.7	63.4
% of series rejecting ADF test's H_0 on logarithm of price in levels (5 lags)	56.3	13.3	0.0	57.1	36.6
% of series rejecting ADF test's H_0 on price returns (5 lags)	100.0	100.0	100.0	100.0	100.0
Panel B: international price series					
Mean price returns (%)	0.52	0.39	0.54	0.62	
Standard deviation of price returns (%)	6.44	6.18	6.74	6.65	
Jarque-Bera statistic	28.68*	273.10*	39.46*	39.37*	
Kurtosis	4.84	9.15	5.27	5.11	
Ljung-Box statistic on squared returns (5 lags)	1.58	53.74*	4.42	7.25	
Ljung-Box statistic on squared returns (10 lags)	11.86	80.14*	8.71	11.86	
AC Q statistic on squared returns (first lag)	0.09	0.35*	0.08	0.17*	
AC Q statistic on squared returns (second lag)	0.03	0.34	0.01	0.09*	
ADF statistic—logarithm of price in levels (5 lags)	−1.40	−1.58	−1.47	−1.78	
ADF statistic—price returns (5 lags)	−5.88*	−5.74*	−5.74*	−4.68*	

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

and international price returns requires further examination, as will be discussed in the next section.

Table 13.1 provides some descriptive statistics for the domestic and international price returns used in the analysis. First, the Jarque-Bera test indicated that the returns for almost every domestic price and all four international prices did not follow a normal distribution. The kurtosis in all of the analyzed markets was greater than 3, further pointing to a leptokurtic distribution of returns. These results revealed the need to use a Student's t density for the estimation of the BEKK models below.

Second, both the Ljung-Box (LB) statistics for up to five and ten lags and the Portmanteau (Q) statistics for the first- and second-order autocorrelation coefficients generally rejected the null hypothesis of no autocorrelation for the squared returns.

This autocorrelation suggests the existence of nonlinear dependencies in several of the price returns, which motivates the use of MGARCH models to better capture own- and cross-market interdependencies between domestic and international markets.

Third, the Augmented Dickey-Fuller (ADF) test suggested that several of the domestic and international prices (in natural logarithms) were non-stationary. As explained in the methodology section, for all these cases, a cointegration test was first conducted to determine if a potential long-run relationship between the corresponding domestic and international price needs to be taken into account by applying a vector-error correction model. Finally, the ADF test confirms the stationarity of all the domestic and international price returns series.

13.5 Results

In this section, we describe our estimates of volatility transmission from international commodity markets to domestic food markets across countries and commodities. Due to space limitations, we did not provide detailed estimation results of the BEKK model for each of the 41 country-commodity combinations; instead, we assessed the reliability of our estimations by comparing model predictions to sample statistics. In particular, we compared the volatility of each domestic price sample (standard deviation of domestic price returns) with the corresponding predicted volatility from our estimated model. Since the BEKK model explicitly formulates a law of motion for the conditional variance of price returns, the estimated variance are not individual values but rather a series of monthly estimated conditional variances. In addition, we can estimate the implied steady-state (or unconditional) volatility and compare it with the sample volatility. In practice, we estimate the following for each domestic price return:

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

The steady-state volatility $\left(h_{11}^{SS}\right)^{0.5}$ which satisfies the following expression: $H^{SS} = C'C + G'H^{SS}G$

The average of the predicted conditional volatilities: $\overline{\widehat{h_{11}}} = \frac{\sum_{t=1}^{n}\widehat{h}_{11,t}^{0.5}}{n}$

Figure 13.5a–c compare the sample values and model estimates of the domestic price volatility. First, note that the sample volatilities of maize prices are, on average, higher than those of rice and wheat. The sample maize price volatilities ranged from 4.3 % (in Mexico) to 20.8 % (in Malawi), with an average of 10.4 % for our full set of countries. Sorghum also showed volatility levels which are similar to or even higher than maize, although we only obtained data for three countries. In the case of rice and wheat, the sample volatilities are on average 4.7 % and 4.8 %, respectively. Interestingly, African countries have the highest sample volatilities (an average of 11.3 %), while Asia and Latin America countries have averages which are less than half of the African average.

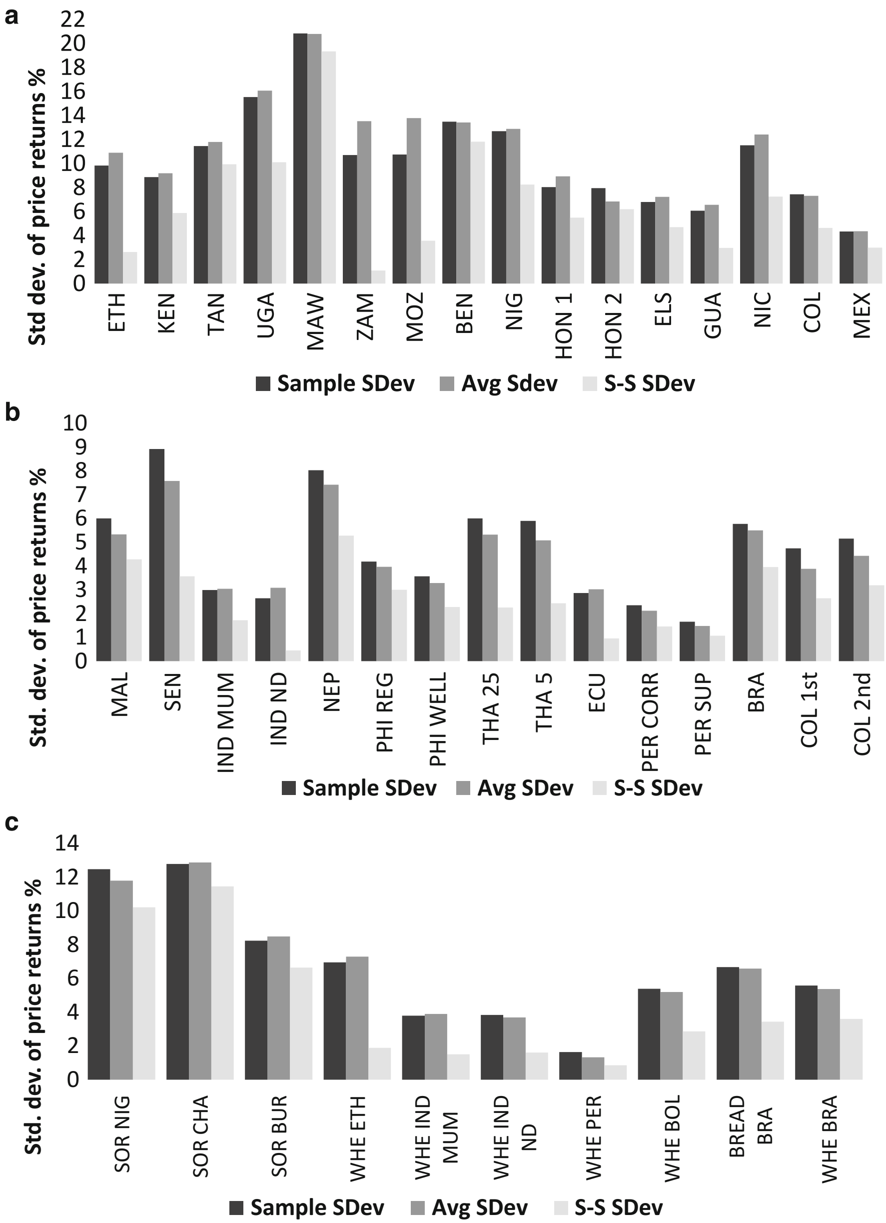

Fig. 13.5 Volatility of monthly prices (in %) sample, average, and steady state for (**a**) maize, (**b**) rice, and (**c**) sorghum/wheat. *Note*: Figures (**a**)–(**c**) compare the sample, average, and steady-state volatilities of monthly price returns. Sample volatility is defined as the standard deviation of the domestic price returns. Average and steady-state volatilities were derived from the results of the conditional variance estimation. The average volatility is the average of the squared roots of the estimated domestic variance terms. The steady-state volatility is the squared root of the domestic variance term after the estimated system reaches a hypothetical steady state. See Sect. 13.5 of the main text for details.

Our estimated steady-state and predicted volatilities yielded similar conclusions when comparing commodities and regions. On average, volatilities estimated by our model for maize prices are larger than those for rice and wheat, with the last two being quite similar. Across regions, estimated food price volatility was around twice as high in Africa than Asia and Latin America. Comparing 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, and these differences range from 10 % for maize in Zambia to 93 % for maize in Malawi. Steady-state estimates are expected to be consistently lower than sample estimates because steady-state estimates reflect the standard deviations to be reached over time in the absence of shocks to price volatility. This finding is also consistent with results reported by Gardebroek et al. (2014).

When comparing the average predicted volatility from the estimated models with the sample volatility, we also observed that our estimated models exhibited a relatively good predictive performance. The ratio of the average predicted volatility to the sample volatility is on average 0.99 for the full set of countries and commodities. This ratio ranged from 0.81 for wheat in Peru (the largest underestimation) to 1.28 for maize in Mozambique (the largest overestimation). Across commodities, the model predictions on average slightly overestimated the sample value in the case of maize (average ratio of 1.05) and underestimate it for rice and wheat (average ratios of 0.92 and 0.96). These average predicted volatilities further reaffirm that maize prices are much more volatile than rice and wheat prices.

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

We estimated the size of a shock in the international market ($\overline{\varepsilon}_2$) such that the steady-state variance of the international price return increases by 1 % after one period:

$$\frac{H_{1,22}\left(\overline{\varepsilon}_2\right) - H_{0,22}}{H_{0,22}} = 0.01$$

We introduced the shock $\overline{\varepsilon}_2$ into Eq. (13.2), estimated the percentage change in the variance of the domestic price return (with respect to its steady-state value), and compute our volatility transmission VT indicator according to:

$$\mathrm{VT} = \frac{H_{1,11} - H_{0,11}}{H_{0,11}} \div 0.01$$

In other words, our volatility transmission indicator compares the reaction (after one period and assuming the system is at a steady state) of the domestic price return variance and the reaction of the international price return variance to a shock in the international market. If our volatility transmission indicator is equal to 1, it means that the domestic price return variance increases by the same proportion as

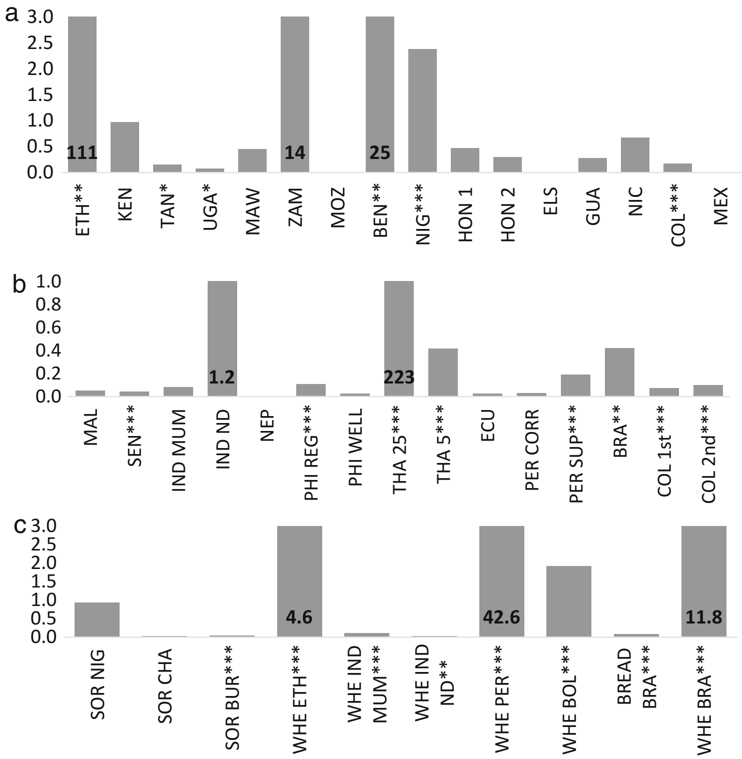

Fig. 13.6 Price return volatility transmission estimates for (**a**) maize, (**b**) rice, and (**c**) sorghum/wheat. *Note*: Figures (**a**)–(**c**) show estimates for the elasticity of price volatility transmission from international markets to domestic markets for each available country and commodity. 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 variance of the domestic price return (with respect to its steady-state value) relative to that of the international price return variance (see Sect. 13.5 of the main text for details). The figure is truncated to preserve scale; outlier values are indicated in *bold*. *, **, and *** denote statistically significant estimates at the 1 %, 5 %, and 10 % level, respectively

the international price return variance in one period, after introducing a shock to the international market.

We present our volatility transmission estimates for each country and commodity in Fig. 13.6a–c, together with a measure of their statistical significance. Aggregated medians and frequencies across commodities and regions are shown in Table 13.2.[8]

[8]We measured statistical significance by implementing the Wald test for the joint significance of α_{21} and g_{21} in the conditional variance equation, where α_{21} is the short-term effect of an

Table 13.2 Price return volatility transmission, by commodity and region

	Median	Volatility transmission (elasticity) Lower than 0.1	Between 0.1 and 1	Higher than 1	Total	Not significant (at 5 % level)
Total	0.172	6	6	8	20	21
By commodity						
Maize	0.372	0	1	3	4	12
Rice	0.082	3	4	1	8	7
Sorghum	0.035	1	0	0	1	2
Wheat	1.919	2	1	4	7	0
By region						
Africa	0.450	2	0	4	6	9
Asia	0.103	1	3	1	5	4
Central America and Caribbean	0.288	0	0	0	0	6
South America	0.172	3	3	3	9	2

Note: This table shows the estimates of the elasticity of price volatility transmission from international markets to domestic markets by commodity and region. The first column presents the median elasticity of all estimates, while columns 2–4 show the number of statistically significant cases (at the 5 % level) for which the estimated elasticity falls between certain values. The last column shows the number of cases for which the estimated volatility transmission was not statistically significant at the 5 % level. The elasticity of price volatility is defined as the percentage change in the variance of the domestic price return (with respect to its steady-state value), relative to that of the international price return variance (see Sect. 13.5 of the main text for details)

Overall, we found volatility transmission that was statistically significant at the 5 % level in about half of the cases, with most of the estimates within reasonable values.[9]

In the case of maize, the median volatility transmission from international to domestic markets was 0.37, but just 4 of the 16 countries exhibited a relationship that is significant at the 5 % level: Ethiopia, Benin, Nigeria, and Colombia.

Our estimates indicated that the volatility transmission of rice prices was lower than that of maize and wheat. The median volatility transmission was less than 0.1, and in seven out of eight statistically significant cases, our volatility transmission estimates are below 0.5. On the other hand, more than half of the estimates of volatility transmission for rice are statistically significant, compared to just one-fourth for maize. Across regions, evidence of transmission was observed mostly in Asia and Latin America, with the highest levels in Thailand and Brazil.

international price shock on domestic volatility (innovation effect) and g_{21} is the short-term effect of changes in international price volatility on domestic volatility (persistence effect).

[9]Our estimates showed extreme values larger than 10 only in 6 of the 41 cases.

In the case of wheat, the median volatility transmission (1.92) is larger than for any other commodity, and all of our estimates are statistically significant. However, there does not seem to be a clear pattern across countries. Volatility transmission was very low (below 0.2) in three of the seven cases: Mumbai wheat, New Delhi wheat, and Brazilian bread. In contrast, volatility transmission was quite high (above 4) in three other cases: wheat in Peru, Brazil, and Ethiopia. Finally, volatility transmission for sorghum was estimated for just three economies, all in Africa, and only one of these (Burkina Faso) was statistically significant.

In terms of regional patterns, while we found no evidence of price volatility transmission in any Central American and Caribbean countries, there was a significant relationship between the volatility of international prices and domestic prices in a large proportion of South American economies. In the case of Africa and Asia, the evidence was mixed, with statistically significant volatility transmission in around one-third of the African cases and one-half of the Asian cases.

13.6 Discussion

We expect price transmission and volatility transmission to be greatest when (1) the international trade in the commodity is large relative to domestic production or consumption, (2) trade restrictions (particularly quantitative restrictions) are low, (3) the government does not intervene to stabilize the domestic price of the commodity, and (4) the transport costs between the country and international markets are low. Some of these factors, particularly the ratio of trade to domestic production, are helpful in explaining the volatility transmission results obtained in this study, but some of the findings were unexpected.

In the case of maize, it is unsurprising that Colombia was the only Latin American country for which our estimate of volatility transmission was statistically significant: Colombian maize imports are equivalent to 64 % of its domestic production, as shown in Appendix Table 13.5. In the other five Latin American countries, the proportion ranges from 15 % to 38 %. And the African countries are not expected to have statistically significant volatility transmission because they are almost self-sufficient in maize production (net trade is 0–9 % of domestic production). The only unexpected finding was the statistically significant volatility transmission in Ethiopia, Nigeria, and Benin.

Turning to rice markets, it is unsurprising that volatility transmission was statistically significant in Thailand, which exports 70 % of its domestic rice production, and Senegal, whose imports are equivalent to 82 % of its domestic output (see Appendix Table 13.5). The lack of volatility transmission to domestic markets in Mali, India, Nepal, and Ecuador is expected given that these countries import an equivalent of no more than 16 % of their domestic production. However, there was evidence of volatility transmission to the domestic markets of Peru, Brazil, and Colombia despite these countries relying minimally on rice imports.

In the case of sorghum, the three countries examined have negligible trade in this commodity, so the volatility transmission in Burundi was unexpected, but the lack of transmission in the other two countries was expected.

As mentioned above, all of the seven wheat prices tested showed statistically significant transmission of volatility. This was expected in the cases of Peru, Bolivia, and Brazil, whose wheat imports are equivalent to 88 %, 72 %, and 56 % of domestic production, respectively. And it is perhaps also understandable in the case of Ethiopia, whose imports are equivalent to 32 % of domestic output. However, it is less clear why international volatility is transmitted to Indian wheat markets given that wheat trade is equivalent to just 2 % of its domestic production.

Overall, it appears that price volatility is (is not) transmitted from international to domestic markets when the ratio of traded volume to domestic production is above (below) 40 %. In our analysis, 29 of the 41 prices (71 %) follow this pattern.

13.7 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 price levels and volatility have a direct and large impact on welfare. Food price volatility also affects poor, small-scale farmers who rely on crop sales for a significant part of their income. Food price volatility 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 the volatility is mostly transmitted from international agricultural commodity markets or largely determined by domestic factors. This in turn will help design better global, regional, and domestic policies to cope with excessive food price volatility and to protect the most vulnerable groups.

The objective of this paper is to estimate the transmission of grain price volatility from world markets to local markets in developing countries, as these estimates have been generally absent in the literature. In particular, we focused on the effect of the world price of maize, rice, wheat, and sorghum on 41 prices of grain products in 27 countries across Latin America, Africa, and Asia. Monthly price data were used, and the data mostly covered the period from January 2000 to December 2013. The analysis was based on a MGARCH approach using a BEKK model.

We assessed the reliability of our estimations by comparing model predictions to sample statistics. In particular, we compared sample food price volatility to average predicted conditional volatility and estimated steady-state volatility. Our model predictions did a good job in replicating sample data patterns. For our full set of commodity/countries, the ratio of the average predicted volatility to the sample volatility was 0.99, and as in the data, the average predicted volatility is higher for maize prices than for rice and wheat prices. Across regions, the estimates showed that the average food price volatility in African countries was around double those in South Asia and Latin America. Furthermore, as expected, our estimated steady-state price volatilities were consistently lower than the sample price volatilities.

We proposed a volatility transmission estimator (or elasticity) that shows the reaction of domestic price return variance relative to the reaction of international price return variance to a one-time shock in the international market (after one period and assuming the system is at steady-state).

We found that most of our estimates were within reasonable values. About half (20 of 41) of the volatility transmission estimates were statistically significant, but the proportion varies by commodity: all seven wheat prices show volatility transmission, but just half of the rice prices and one-fourth of the maize prices did so. Volatility transmission of a commodity's price appears to be linked to the importance of trade in that commodity to the country in question. When the ratio of trade to domestic production is over (under) 40 %, price volatility is (is not) transmitted from world markets to local markets. This rule could explain 29 of the 41 prices examined (71 %). All 12 exceptions to this rule are cases in which trade is minimal but volatility is transmitted from world markets. This could occur through transmission of volatility between closely related commodity markets or perhaps as a result of transmission of "anxiety" from international markets to domestic markets. Further research is needed to examine these alternative explanations.

Acknowledgements The authors acknowledge funding from the European Commission within the FoodSecure Research Project.

Appendix

Table 13.3 Domestic price series' sources and information

International commodity		Country	Local product	Market	Abbreviation	Units	Price type	Start date	End date	Num. of obs.	Region	Source
1	Maize	Benin	Maize (white)	Cotonou	BEN	FCFA/kg	Retail	2003–10	2013–12	123	Africa	FEWSNET
2	Maize	Ethiopia	Maize (white)	Addis Ababa	ETH	ETB/100 kg	Wholesale	2004–01	2013–12	120	Africa	FEWSNET
3	Maize	Kenya	Maize (white)	Nairobi	KEN	KES/90 kg	Wholesale	2000–01	2013–12	168	Africa	FEWSNET
4	Maize	Malawi	Maize (white)	Lunzu	MAW	MWK/kg	Retail	2004–01	2013–12	120	Africa	FEWSNET
5	Maize	Mozambique	Maize (white)	Maputo	MOZ	MZN/kg	Retail	2002–01	2013–12	144	Africa	FEWSNET
6	Maize	Nigeria	Maize (white)	Ibadan	NIG	NGN/kg	Retail	2003–10	2013–12	123	Africa	FEWSNET
7	Maize	Tanzania	Maize (white)	Dar es Salaam	TAN	TZS/100 kg	Wholesale	2002–01	2013–12	144	Africa	FEWSNET
8	Maize	Uganda	Maize (white)	Kampala	UGA	UGX/kg	Wholesale	2002–01	2013–12	144	Africa	FEWSNET
9	Maize	Zambia	Maize (white)	Lusaka	ZAM	ZMW/kg	Retail	2002–01	2013–12	144	Africa	FEWSNET

(continued)

Table 13.3 (continued)

	International commodity	Country	Local product	Market	Abbreviation	Units	Price type	Start date	End date	Num. of obs.	Region	Source
10	Maize	El Salvador	Maize (white)	San Salvador	ELS	USD/pound	Retail	2000–08	2013–12	161	Central America and Caribbean	FEWSNET
11	Maize	Guatemala	Maize (white)	Guatemala City	GUA	GTQ/pound	Retail	2005–08	2013–12	101	Central America and Caribbean	FEWSNET
12	Maize	Honduras	Maize (white, mkt 1)	Tegucigalpa	HON 1	HNL/5 pounds	Retail	2001–09	2013–12	148	Central America and Caribbean	FEWSNET
13	Maize	Honduras	Maize (white, mkt 2)	Tegucigalpa	HON 2	HNL/5 pounds	Retail	2001–09	2013–12	148	Central America and Caribbean	FEWSNET
14	Maize	Mexico	Maize (white)	Mexico City	MEX	Peso/kg	Wholesale	2000–01	2014–03	171	Central America and Caribbean	GIEWS
15	Maize	Nicaragua	Maize (white)	Managua	NIC	NIO/pound	Retail	2000–08	2013–12	161	Central America and Caribbean	FEWSNET

(continued)

Table 13.3 (continued)

	International commodity	Country	Local product	Market	Abbreviation	Units	Price type	Start date	End date	Num. of obs.	Region	Source
16	Maize	Colombia	Maize (white)	Bogotá	COL	Peso/kg	Wholesale	2000–01	2012–10	154	South America	GIEWS
17	Rice	Mali	Rice (local)	Bamako	MAL	FCFA/kg	Retail	2003–11	2013–12	122	Africa	FEWSNET
18	Rice	Senegal	Rice (imported)	Dakar	SEN	FCFA/kg	Retail	2003–10	2013–10	121	Africa	FEWSNET
19	Rice	India	Rice (Mumbai)	Mumbai	IND MUM	Rupee/kg	Retail	2000–01	2014–03	171	Asia	GIEWS
20	Rice	India	Rice (New Delhi)	New Delhi	IND ND	Rupee/kg	Retail	2000–01	2014–03	171	Asia	GIEWS
21	Rice	Nepal	Rice (coarse)	Kathmandu	NEP	USD/kg	Retail	2005–01	2014–02	110	Asia	GIEWS
22	Rice	Philippines	Rice (regular milled)	Metro Manila	PHI REG	USD/kg	Retail	2000–01	2014–02	170	Asia	GIEWS
23	Rice	Philippines	Rice (well milled)	Metro Manila	PHI WELL	USD/kg	Retail	2000–01	2014–02	170	Asia	GIEWS
24	Rice	Thailand	Rice (25 % broken)	Bangkok	THA 25	Baht/tonne	Wholesale	2000–01	2014–02	170	Asia	GIEWS
25	Rice	Thailand	Rice (5 % broken)	Bangkok	THA 5	Baht/tonne	Wholesale	2000–01	2014–02	170	Asia	GIEWS

(continued)

Table 13.3 (continued)

	International commodity	Country	Local product	Market	Abbreviation	Units	Price type	Start date	End date	Num. of obs.	Region	Source
26	Rice	Brazil	Rice	São Paulo	BRA	Real/kg	Retail	2000–01	2014–03	171	South America	GIEWS
27	Rice	Colombia	Rice (first quality)	Bogotá	COL 1st	Peso/kg	Wholesale	2000–01	2014–03	171	South America	GIEWS
28	Rice	Colombia	Rice (second quality)	Bogotá	COL 2nd	Peso/kg	Wholesale	2000–01	2014–03	171	South America	GIEWS
29	Rice	Ecuador	Rice (long grain)	Quito	ECU	Usd/kg	Wholesale	2005–01	2014–03	111	South America	GIEWS
30	Rice	Peru	Rice (milled, corriente)	Lima	PER CORR	Nuevo sol/kg	Retail	1995–01	2013–09	225	South America	GIEWS
31	Rice	Peru	Rice (milled, superior)	Lima	PER SUP	Nuevo sol/kg	Retail	1995–01	2013–09	225	South America	GIEWS
32	Sorghum	Burkina Faso	Sorghum (white)	Ouagadougou	SOR BUR	FCFA/kg	Retail	2003–10	2013–12	123	Africa	FEWSNET
33	Sorghum	Chad	Sorghum (red)	N'Djamena	SOR CHA	FCFA/kg	Retail	2002–01	2013–12	144	Africa	FEWSNET
34	Sorghum	Nigeria	Sorghum (mixed)	Ibadan	SOR NIG	NGN/kg	Retail	2004–10	2013–12	111	Africa	FEWSNET
35	Wheat	Ethiopia	Wheat	Addis Ababa	WHE ETH	ETB/100 kg	Wholesale	2004–01	2013–12	120	Africa	FEWSNET

(continued)

Table 13.3 (continued)

	International commodity	Country	Local product	Market	Abbreviation	Units	Price type	Start date	End date	Num. of obs.	Region	Source
36	Wheat	India	Wheat (Mumbai)	Mumbai	WHE IND MUM	Rupee/kg	Retail	2000–01	2014–03	171	Asia	GIEWS
37	Wheat	India	Wheat (New Delhi)	New Delhi	WHE IND ND	Rupee/kg	Retail	2000–01	2014–03	171	Asia	GIEWS
38	Wheat	Bolivia	Wheat (pealed)	La Paz	WHE BOL	Boliviano/kg	Wholesale	2003–01	2014–03	135	South America	GIEWS
39	Wheat	Brazil	Bread (French)	São Paulo	BREAD BRA	Real/kg	Retail	2000–02	2014–03	170	South America	GIEWS
40	Wheat	Brazil	Wheat (flour)	São Paulo	WHE BRA	Real/kg	Retail	2000–01	2014–03	171	South America	GIEWS
41	Wheat	Peru	Wheat (flour)	Lima	WHE PER	Nuevo sol/kg	Retail	2000–01	2013–09	165	South America	GIEWS

Table 13.4 International price series' sources and information

International commodity	Description	Country	Market	Units	Source
Maize	No. 2 yellow	United States	U.S. Gulf	US$/tonne	FAOSTAT (primary source: USDA)
Rice	A1 super, white broken	Thailand	Bangkok	US$/tonne	FAOSTAT (primary source: Jackson Son & Co. (London) Ltd.)
Sorghum	No. 2 yellow	United States	U.S. Gulf	US$/tonne	FAOSTAT (primary source: USDA)
Wheat	No. 2 hard red winter	United States	U.S. Gulf	US$/tonne	FAOSTAT (primary source: International Grains Council)

Table 13.5 Ratio of imports minus exports over domestic production, average 2007–2013

	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: Data obtained from FAOSTAT online (accessed on May, 2015)

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Part IV

National and Regional Responses to Food Price Volatility