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A Global Vector Autoregression Model for the Analysis of Wheat Export Prices

Luciano Gutierrez, Francesco Piras, and Pier Paolo Roggero

Food commodity price fluctuations have an important impact on poverty and food insecurity across the world. Conventional models have not provided a complete picture of recent price spikes in agricultural commodity markets, and there is an urgent need for appropriate policy responses. Perhaps new approaches are needed to better understand international spill-overs, the feedback between the real and the financial sectors, as well as the link between food and energy prices. In this article, we present the results from a new worldwide dynamic model that provides the short and long-run impulse responses of the international wheat price to various real and financial shocks.

Key words: Global dynamic models, price analysis, wheat market.

JEL codes: C12, C15, G14, Q14.

During the food crises of 2006–2008 and 2010–2011 there were large increases in the prices of wheat, soybeans, rice, and maize on international markets; these price surges led to substantial increases in domestic prices. High food prices increased the number of people living in poverty because higher prices resulted in consumers spending a larger portion of their income on food (OCDE-FAO 2011). The food crises also led to a significant increase in food insecurity and hunger. The Food and Agriculture Organization of the United Nations (FAO 2008) estimated that, because of higher food prices, an additional 75 million people were eating a diet that was inadequate for meeting their nutritional needs. Thus, understanding key trends in commodity prices plays an important role in formulating food security policies.

Numerous factors have been proposed in the literature for explaining recent commodity price movements, but there is no general consensus on the relative weight that should be attributed to each of these factors. Many authors have stressed that more consideration should be given to the effects of the growing food demand in developing countries, especially in China and India, and also that the lower growth rate in production is among the causes of the recent food price spike (e.g., Trostle 2008; Von Braun 2007; Dewbre et al. 2008; Krugman 2011). Other studies have argued that biofuel programs in the United States and European Union are behind the rise in food prices; these programs provide subsidies for biofuels, which leads to greater use of corn and vegetable oil in non-food applications, and this results in an increase in the price of these commodities (e.g., Mitchell 2008; Headey and Fan 2008). In contrast, Baffes and Haniotis (2010) suggested that the link between food prices and energy prices is the main factor in recent commodity price movements. Indeed, energy prices affect food commodity prices by influencing the cost of inputs such as nitrogen fertilizer and the cost of transport. Besides the abovementioned factors, the list

Luciano Gutierrez is an associate professor in the Department of Agricultural Sciences and Director of the Desertification Research Centre at the University of Sassari, Italy; Francesco Piras is a researcher at the Desertification Research Centre, University of Sassari, Italy; Pier Paolo Roggero is a professor in the Department of Agricultural Sciences and the Desertification Research Centre at the University of Sassari, Italy.
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of possible causes that have been analyzed in the recent literature include the decline of commodity stocks (Abbott, Hurt, and Tyner 2008; Piesse and Thirtle 2009), a weak U.S. dollar (Abbott, Hurt, and Tyner 2008; Mitchell 2008), panic buying (Timmer 2009), bans on exports (Dollive 2008; Headey 2011), and speculation (Irwin, Sanders, and Merrin 2010; Cooke and Robles 2009; Sanders, Irwin, and Merrin 2010; Gilbert 2010a, b; Gutierrez 2013).

The aim of this article is to use a global, dynamic time series model to improve our understanding of wheat price changes. To be precise, we propose a new global wheat market model (GLOWMM) for studying the dynamics of wheat prices through the dependence of each country's export price on all other countries' export prices, and on fundamental real and financial drivers such as supply and demand factors, exchange rates, and oil prices. The GLOWMM model uses the global vector auto regressive (GVAR) methodology originally proposed by Pesaran, Schuermann, and Weiner (2004) and Dées et al. (2007). The GVAR model allows us to evaluate the impact and long-run effects that various shocks have on wheat export prices, for example a reduction of the stock-to-use ratio, an increase in the oil price, and a U.S. currency devaluation relative to the currencies of the main competitors of the United States. We focus on the wheat export price dynamics of the six main exporting countries: the United States, Argentina, Australia, Canada, Russia (including Ukraine and Kazakhstan), and the EU, and allow for the influence of a Rest of the World region to account for the effect of other countries on wheat prices.

We suggest three main reasons why the GVAR model is useful for analyzing worldwide wheat prices. First, the model is specifically designed to analyze market fluctuations and interactions between countries. This is crucial, given the features of the world wheat market and the global dimensions of food price dynamics, which cannot be reduced to one exporter but rather involve multiple countries. Secondly, the GVAR lets us model the dynamism in wheat export prices caused by the effects of country-specific and foreign-specific variables. For country-specific variables, we can use the impact on each country's export price of the usually proposed drivers, such as the stock-to-use ratio, the nominal exchange rate (measured relative to the U.S. dollar) and the cost of inputs. However, export prices can also be affected by what can be labeled foreign-specific variables, that is, variables that are strictly connected to domestic variables such as competitors' export prices, the effective exchange rate, and supply/demand shocks in other countries that may affect the domestic economy. The GVAR model can also account for global shocks such as changes in oil prices and extreme weather events; that is, shocks that will affect all or some countries but can be thought of as strictly exogenous with respect to the wheat market. Thirdly, although the GVAR model is unlike structural models in that it combines a number of atheoretical relationships and does not attempt to impose restrictions based on economic theory, it nevertheless can be easily adapted and used to test well-known economic concepts such as whether the law of one price (LOP) holds in the worldwide wheat market.

The article is organized as follows. In section 2 we provide the motivation for this study and describe the econometric model. In section 3 we present the data, discuss the empirical results, and present the generalized impulse responses of wheat export prices to various shocks. Section 4 concludes.

Motivation and Methodology

This article contributes to the considerable empirical literature on the spatial analysis of commodity price determination, and specifically to the spatial analysis of wheat prices. Wheat, which is among the most important internationally traded grain commodities, is characterized by a market with a limited number of major exporting countries. The six regions mentioned above accounted for more than 88% of total world exports in 2010 (International Grains Council, World Grain Statistics 2010). As shown in figure 1, the logarithms of the wheat export price show a relatively high level of synchronization, especially during the unprecedented market surge in 2007–2008, the sudden market decline in 2009, and the strong market rebound in 2010–2011. The pairwise correlation coefficients for the price of wheat across the six regions from 2000–2012 range between 0.88 and 0.97. Nevertheless, there are differences in the distributions of individual price series, and these may be connected to the heterogenous

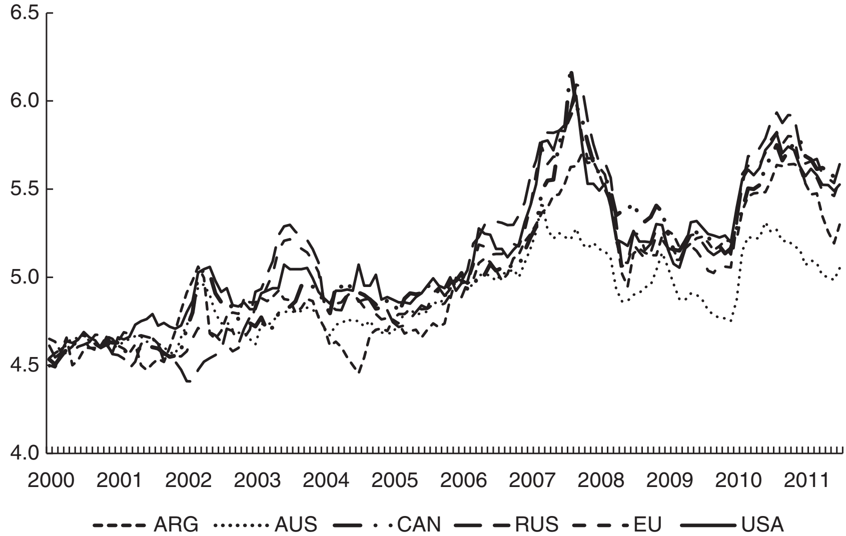

Figure 1. Export price indexes - 2000.7–2012.1 (logarithms, 2000.7–2001.6 = 100)

reactions of countries to shocks. For this reason, considerable attention has been directed to explaining why prices may be imperfectly linked across space, and thus why wheat markets may or may not be imperfectly integrated. For example, Ardeni (1989) and Goodwin (1992) analyzed whether the law of one price holds in international wheat markets. In addition, the market power implications of international wheat price linkages have been investigated, among others, by McCalla (1966); Carter and Schmitz (1979); Alaouze, Watson, and Sturgess (1978); Kolstad and Burris (1986); Scoppola (2007); and more recently by Arnade and Vocke (2013).

Many researchers have proposed using the vector autoregressive methodology (VAR) to analyze spatial wheat prices. Much attention has been devoted to the causality issues among prices (Spriggs, Kaylen, and Bessler 1982; Mohanty, Peterson, and Kruse 1995) or to the analysis of dynamic relationships among wheat prices in the international wheat markets, such as in Bessler, Yang, and Wongcharupan (2003). However, the analysis has usually been confined to investigating spatial wheat price dynamics without connecting them to the main driver factors such as the cost of inputs, demand and supply shocks, or the movement of financial variables such as exchange rates.[1] The reasons for not including the main driver factors in VAR models is connected to a lack of data, which means that a full systematic estimate of a global wheat model would not be feasible for even a limited number of countries.

The global vector autoregressive (GVAR) model can be used to overcome the above-mentioned problems. The GVAR approach, presented in Pesaran, Schuermann, and Wiener (2004), and further developed by Dées et al. (2007), is particularly well-suited to the analysis of the transmission of shocks from one market, country, or region to other markets and economies. The basic idea of the GVAR modeling approach is that each country is individually estimated as a VAR with country-specific variables linked to each other, as in any other VAR model. However, unlike the case of a standard VAR model, each country model can be connected to the others by including foreign-specific variables. These are variables that serve as proxies for the influence of the rest of the world on each country's economy, such as the competitors' wheat export prices and the effective exchange rate, or by including global variables that represent strictly exogenous international factors such as oil prices or climate changes outcomes.[2] After having estimated all the VAR country

[1] Exceptions are Goodwin and Schroeder (1991), where the analysis also considered dynamic relationships between wheat prices and exchange rates and transportation costs, and the work of Pietola, Liu, and Robles (2010), where a conditional mean model for international wheat prices and inventories was analyzed.

[2] Splitting the variables into country- and foreign-specific variables may be preferable to other dimension reduction methods, for example the Factor VAR (FAVAR) method. The FAVAR

models, their corresponding estimates are connected through link matrices, in our case the trade weight of each country or region in the global wheat export market, and then stacked together to build the global model. Below we provide a short presentation of how the GVAR model can be constructed and estimated.[3]

The specification of the GVAR model proceeds in two stages. In the first stage, that is, the estimation stage, the reduced form vector autoregression VAR model, augmented by the exogenous, X, variables, labeled VARX(p,q), is estimated for each country i, and in the second stage all individual country VARX models are stacked and linked using link matrices. To be more precise, for each country $i=1,\ldots,N$, the VARX(p,q) model can be represented as

$$(1) \qquad \Phi_1(L,p_i)y_{it} = a_{i0} + a_{i1}t + \Lambda_i(L,q_i)y^*_{it} + \Psi_i(L,q_i)d_i + \epsilon_{it}$$

where: the index $t=1,\ldots,T$ refers to the time period; a_{i0} is a $(k_i \times 1)$ vector of deterministic intercepts; a_{i1} is a $(k_i \times 1)$ vector of deterministic trends; y_{it} is a $(k_i \times 1)$ vector of country-specific (domestic) variables with a corresponding set of $(k_i \times k_i)$ matrices of lagged coefficients denoted by $\Phi_i(L,p_i) = I - \sum_{p=1}^{p_i} \Phi_i L^i$, where L is the lag operator; y^*_{it} is a $(k_i \times 1)$ vector of foreign variables (i.e., the exogenous X variables in the VARX specification) with a corresponding set of $(k_i \times k^*_i)$ matrices of lagged coefficients denoted by $\Lambda_i(L,q_i); \Psi_i(L,q_i)$ is a matrix of lagged polynomial coefficients associated with the global exogenous variables d_t; and ϵ_{it} is a $(k_i \times 1)$ vector of zero mean, idiosyncratic country-specific shocks, which are assumed to be serially uncorrelated and with time-invariant covariance matrix $\sum_{ii}$, that is, $\epsilon_{it} \sim iid(0,\sum_{ii})$. The weak exogeneity of y^*_{it} in the GVAR model implies no long-run feedback from y_{it} to y^*_{it}, but still allows for lagged short-run feedback between the two sets of variables. Thus, this framework allows country models to be estimated individually, and then at a later stage to be combined in a global model. As discussed in the following section, the weak exogeneity of foreign-specific variables can be tested using the set of country-specific VARX models.

To proceed with the analysis, it is necessary to determine the order of the matrix polynomials $\Phi_i(L,p_i)$, $\Lambda_i(L,q_i)$ and $\Psi_i(L,q_i)$. The Akaike information (AIC), Hannan and Quinn (HQ), and the Schwarz Bayesian criteria (SBC) are used for this purpose. However, prior to making this selection it is useful to show how the GVAR model is constructed for an arbitrary chosen order of the matrix polynomials. Consider a generic country i with $p_i=2$ and $q_i=2$, and assume for the sake of simplicity that $\Psi_i(L,q_i)=0$. Thus, equation (1) can be written as

$$(2) \qquad y_{it} = a_{i0} + a_{i1}t + \Phi_{i1}y_{it-1} + \Phi_{i2}y_{it-2} + \Lambda_{i0}y^*_{it} + \Lambda_{i1}y^*_{it-1} + \Lambda_{i2}y^*_{it-2} + \varepsilon_{it}.$$

We group the domestic and foreign variables for each country as

$$(3) \qquad \mathbf{x}_{it} = \begin{pmatrix} y_{it} \\ y^*_{it} \end{pmatrix}.$$

Therefore, each country's VARX model (2) becomes

$$(4) \qquad \mathbf{A}_{i0}\mathbf{x}_{it} = a_{i0} + a_{i1}t + \mathbf{A}_{i1}\mathbf{x}_{it-1} + \mathbf{A}_{i2}\mathbf{x}_{it-2} + \varepsilon_{it}$$

where

$$(5) \qquad \mathbf{A}_{i0} = (I_{k_i}, -\Lambda_{i0}), \quad \mathbf{A}_{i1} = (\Phi_{i1}, \Lambda_{i1}), \quad \mathbf{A}_{i2} = (\Phi_{i2}, \Lambda_{i2}).$$

In the next step a vector of variables is defined as follows:

$$(6) \qquad y_t = \begin{pmatrix} y_{0t} \\ y_{1t} \\ \vdots \\ y_{Nt} \end{pmatrix}.$$

Now, using the link matrix $\mathbf{W}_i$ constructed from the export weight of each country relative to the exports of all competitor

does not allow a specific set of variables to be defined, and thus is less useful for policy analysis. We thank a referee for having suggested this.

[3] A deeper analysis can be found in Pesaran, Schuermann, and Weiner (2004) and Dées et al. (2007).

countries[4], we obtain the following identity:

$$\mathbf{x}_{it} = \mathbf{W}_i y_t \quad \forall i = 0, 1, \ldots, N. \tag{7}$$

The previous relationship allows each country model to be written in terms of the global vector y_t, and thus it is the fundamental device through which each country's market is linked to the global GVAR model. Using now the identity (7) in each country VARX model (4), we obtain

$$\mathbf{A}_{i0}\mathbf{W}_i y_{it} = a_{i0} + a_{i1}t + \mathbf{A}_{i1}\mathbf{W}_i y_{it-1} + \mathbf{A}_{i2}\mathbf{W} y_{it-2} + \varepsilon_{it}. \tag{8}$$

Finally, by stacking each country-specific model in equation (8), we end up with the Global VAR for all endogenous variables in the system y_t,

$$\mathbf{G}_0 y_{it} = a_0 + a_1 t + \mathbf{G}_1 y_{it-1} + \mathbf{G}_2 y_{it-2} + \varepsilon_t \tag{9}$$

where

$$\mathbf{G}_0 = \begin{pmatrix} \mathbf{A}_{00}\mathbf{W}_0 \\ \mathbf{A}_{10}\mathbf{W}_1 \\ \vdots \\ \mathbf{A}_{N0}\mathbf{W}_N \end{pmatrix}, \mathbf{G}_1 = \begin{pmatrix} \mathbf{A}_{01}\mathbf{W}_0 \\ \mathbf{A}_{11}\mathbf{W}_1 \\ \vdots \\ \mathbf{A}_{N1}\mathbf{W}_N \end{pmatrix},$$

$$\mathbf{G}_2 = \begin{pmatrix} \mathbf{A}_{02}\mathbf{W}_0 \\ \mathbf{A}_{12}\mathbf{W}_1 \\ \vdots \\ \mathbf{A}_{N2}\mathbf{W}_N \end{pmatrix}, \mathrm{a}_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ \vdots \\ a_{N0} \end{pmatrix},$$

$$\mathrm{a}_1 = \begin{pmatrix} a_{01} \\ a_{11} \\ \vdots \\ a_{N1} \end{pmatrix}, \varepsilon_t = \begin{pmatrix} \varepsilon_{0t} \\ \varepsilon_{1t} \\ \vdots \\ \varepsilon_{Nt} \end{pmatrix}.$$

If the $\mathbf{G}_0$ matrix is non singular, it can be inverted, and then multiplying equation (9) by $\mathbf{G}_0{}^{-1}$ we obtain the Global VAR model in its reduced form, that is,

$$y_t = b_0 + b_1 t + \mathbf{F}_1 y_{t-1} + \mathbf{F}_2 y_{t-2} + v_t \tag{10}$$

where

$$\mathbf{F}_1 = \mathbf{G}_0{}^{-1}\mathbf{G}_1, \mathbf{F}_2 = \mathbf{G}_0{}^{-1}\mathbf{G}_2,$$
$$\mathrm{b}_0 = \mathbf{G}_0{}^{-1}a_0, \mathrm{b}_1 = \mathbf{G}_0{}^{-1}a_1, v_t = \mathbf{G}_0{}^{-1}\varepsilon_t.$$

Equation (10) can be solved recursively and used for analyzing the impulse responses, or to compute the forecast error decompositions, or to forecast the y_t variables.

The Empirical Model and its Results

The Dataset

We consider six VARX models, one for each of the main export regions: Argentina, Australia, Canada, EU, Russia, and the United States. We also specify an additional Rest of the World (ROW) regional VARX model to account for the effects exerted by all the other countries. These seven models are estimated at monthly intervals from June 2000 to January 2012. The variables used in the analysis include the logarithm of export prices quoted in U.S. dollars, p_{it}^e, and the wheat stock-to-use ratio z_{it} computed as the fraction of the stocks to total consumption. Instead of using the actual stock-to-use ratio, we use USDA monthly forecasts of stocks and consumption for the upcoming marketing year. Serra and Gil (2011) note that these forecasts are likely to be more effective in explaining price behavior than the actual data, since they are more closely related to actual trading decisions, and thus are more relevant when explaining price behavior. We also include the fertilizer price p_{it}^f expressed in the local currency, the exchange rate e_{it} given by the bilateral exchange rate of the local currency in country i per unit of U.S. dollar, and finally the index of consumer food prices p_{it}^c. This latter variable is included as a benchmark of food inflation in each country i.[5]

As previously stated, the GVAR model accounts for the effects of country-specific

[4] The matrix $\mathbf{W}_i$ can be viewed as the *link* matrix that allows the country-specific models to be written in terms of the global variable vector; see Pesaran, Schuermann, and Weiner (2004).

[5] All of the variables, with the exception of z_{it}, are log of indexes with base year July/2000–June/2001. The data is described in a separate online supplement.

Table 1. Trade Weights Based on Wheat Export Statistics

Countries	Argentina	Australia	Canada	Russia	EU	USA	ROW
Argentina	0.000	0.111	0.147	0.291	0.168	0.193	0.091
Australia	0.045	0.000	0.158	0.313	0.180	0.207	0.098
Canada	0.046	0.124	0.000	0.325	0.187	0.216	0.102
Russia	0.055	0.147	0.196	0.000	0.223	0.257	0.121
EU	0.047	0.127	0.168	0.333	0.000	0.221	0.104
USA	0.049	0.130	0.173	0.343	0.198	0.000	0.107
ROW	0.044	0.116	0.154	0.306	0.176	0.203	0.000
Total	0.040	0.106	0.141	0.279	0.161	0.185	0.088

Source: International Grains Council. Note: Trade weights are computed as averages of shares of exports in total world exports from 2008–2010; they are displayed in column form by export country. Each row, but not each column, sums to 1.

and foreign-specific variables. The foreign-specific variables are constructed as a geometric average of the country-specific variables, using as weights the wheat export-country shares. To be precise, we introduce as foreign-specific variables the average competitors' prices, $p_{it}^{e*} = \sum_{j \neq i} w_j p_{jt}^e$, the effective exchange rate, $e_{it}^* = \sum_{j \neq i} w_j e_{jt}$ (i.e., the average of the country's bilateral exchange rates), the average stock-to-use ratio, $z_{it}^* = \sum_{j \neq i} w_j z_{jt}$, and the average of the food price indexes, $p_{it}^{c*} = \sum_{j \neq i} w_j p_{jt}^c$. Note that each foreign variable is computed under the constraint that $\sum_{j \neq i} w_j = 1$. The choice of weights based on exports is based on the rationale that exogenous shocks, such a stock reduction and/or an exchange rate devaluation, could be passed on to the export prices in all countries through the trade channel. We use fixed weights over time, computed as the average of the years 2008–2010. The weights used in the analysis are presented in table 1.

Finally, each country's system of variables can be influenced by global variables such as the world price of oil, p_t^o, whose importance is common to all countries. The wheat market can be affected by a change in the price of oil in two different ways. The first is the supply-side cost channel, as oil and energy prices are critically important factors for the production of agricultural commodities and foodstuffs. The second channel is connected to the biofuels market. As Piesse and Thirtle (2009) suggested, farmland is in fixed supply, and thus producing more maize and oilseeds for biofuels will reduce the land available for other crops, thereby contributing to price increases in crops such as wheat. The GVAR model will not be able to weigh the importance of the two channels, but it will add new information on the short and long run impact of oil prices on each country's endogenous variable.

Using equation (1) with the United States having an index of $i = 0$ and the ROW countries having an index of $i = 6$, the country-specific (endogenous) variables included in each regional VARX model are as follows:

$$(11) \quad y_{it} = (p_{it}^e, z_{it}, e_{it}, p_{it}^f, p_{it}^c)', \quad i = 1, \ldots, 5;$$
$$y_{0t} = (p_{it}^e, z_{it}, p_{it}^f, p_{it}^c)',$$
$$y_{6t} = (z_{it}, e_{it}, p_{it}^f, p_{it}^c)'.$$

The exchange rate has not been included in the US VARX model, and we do not include the export price among the ROW region variables. The hypothesis for the ROW region is that the wheat price is exogenously determined in the international wheat market, and thus it will not appear in the set of variables that we have previously labeled as country-specific variables. Rather, export prices will exert their effects on ROW regions from the foreign-specific variable.[6] In agreement with equation (1), the set of foreign-specific[7] and global variables included in each VARX model can therefore be described by the following $\tilde{y}_{it}^*$ matrix:

$$(12) \quad \tilde{y}_{it}^* = (p_{it}^{e*}, z_{it}^*, e_{it}^*, p_{it}^{c*})',$$
$$i = 0, \ldots, 6; d_t = (p_t^o).$$

[6] The main reason for this assumption is that wheat export data are not available for the ROW countries. However, we are confident that the exogeneity hypothesis cannot be rejected, given that ROW exports are only a small proportion of the world wheat market.

[7] Note that because we have used the world fertilizer price transformed into local currency as a proxy for local fertilizer prices (using the local currency per unit of U.S. dollar as the exchange rate) we have chosen to not include the foreign counterpart fertilizer variable in the model due to likely multicollinearity problems.

Table 2. Augmented Dickey-Fuller Unit Root Statistics for Home and Foreign Variables

Variables	Argentina	Australia	Canada	Russia	EU	USA	ROW
p^e_{it}	−1.610	−2.530	−1.735	−1.339	−1.484	−1.901	–
z_{it}	−1.100	−3.088	−2.959	−1.489	−2.411	−1.953	−2.040
e_{it}	−2.765	−1.354	−1.036	−2.129	−1.983	–	−2.378
p^f_{it}	−2.235	−1.410	−1.581	−1.707	−1.572	−1.665	−1.512
p^c_{it}	−1.261	−1.724	−0.342	−1.271	−1.107	0.027	−1.385
p^{e*}_{it}	−1.370	−1.324	−1.367	−1.787	−1.386	−1.510	−1.354
z^*_{it}	−1.876	−2.145	−1.659	−2.758	−2.204	−2.792	−2.299
e^*_{it}	−1.914	−2.157	−2.357	−1.619	−2.232	−2.038	−2.038
p^{c*}_{it}	−2.092	−2.227	−2.260	−0.705	−2.177	−2.285	−2.063
p^{o*}_t	−1.109	−1.109	−1.109	−1.109	−1.109	−1.109	−1.109

Notes: The ADF statistics are based on a univariate $AR(p)$ model in the levels, with p chosen according to the Ng and Perron (2001) procedure. The regressions include an intercept. The 95% and 99% critical values of the ADF statistic for a regression with a constant are −2.88 and −3.17, respectively.

The GVAR Estimation

The GVAR methodology can be used for analyzing stationary and/or nonstationary variables. We follow the original work of Pesaran, Schuermann, and Weiner (2004) in assuming that the variables included in the country-specific models are non-stationary. This hypothesis allows us to distinguish between short-run and long-run relationships and interpret the long-run relationships as a cointegrating relationship. We start the analysis by testing the nonstationary properties of the series. Table 2 provides the Augmented Dickey-Fuller (ADF) test statistics for the null hypothesis of the nonstationarity of series.[8,9] Given that the majority of the series are $I(1)$ and thus do not reject the null hypothesis of nonstationarity, the cointegrating model (13) is estimated using the reduced rank restriction (Johansen 1992, 1995).

For each country's VARX model in equation (2), the p_i and q_i orders are estimated using the AIC, SBC, and HQ criteria.[10] Increasing the number of lags in a VAR model quickly reduces the number of degrees of freedom. For this reason, we have imposed the constraint $p_i \geq q_i$; we chose $p_i = 3$ and $q_i = 3$ as maximum values, and $p_i = q_i = 1$ as minimum values. The model with the highest AIC, SBC, or HQ value is chosen. Based on the results reported in table 3, this method provides us with the following values: $p_i = 2, 3$, and $q_i = 1, 2$. Using these values, we found that the modified Lagrange multiplier statistics do not indicate residual auto-correlations in the system of regressions.[11]

Table 3. VARX Order, Case Models, and Number of Cointegrating Relationships

Country	p_i	q_i	Case	Cointegrating Relationships
Argentina	3	1	(III)	2
Australia	3	1	(IV)	2
Canada	2	1	(III)	2
Russia	3	2	(III)	1
EU	2	1	(IV)	1
USA	3	2	(IV)	1
ROW	2	2	(IV)	2

Note: Rank orders are derived using Johansen's trace statistics at the 95% critical value level. The p_i and q_i orders are computed using equation (2).

Given the previous results, and following the GVAR literature, the VARX equation (2) has been rewritten in its Vector Error-Correction (VECMX) form,

$$(13) \quad \Delta y_{it} = c_{i0} - \alpha_i \beta_i' [x_{i,t-1} - \gamma_i (t-1)] + \Lambda_{i0} \Delta \tilde{y}^*_{i,t} + \Gamma_i \Delta x_{i,t-1} + \epsilon_{it}$$

[8] All the procedures used in the following analysis have been written using GAUSS 11.

[9] We do not present the powerful GLS-ADF test statistics proposed by Elliot, Rothenberg, and Stock (1996) because these results are similar to the ADF test statistics.

[10] We follow Dées at al. (2007) and compute the orders of the autoregressive process using the level equation (2) instead of the error-correction form (13).

[11] To be precise, for each regression in each VARX country model we test for the residual auto-correlation using the modified LM statistic proposed in Godfrey (1978a, b). The results do not generally reject the hypothesis of white-noise residual autocorrelations.

where y_{it} and $\tilde{y}^*_{i,t}$ have been previously defined in equations (11) and (12), $x_{it} = (y'_{it}, \tilde{y}^{*\prime}_{it})'$, α_i is a $(k_i \times r_i)$ matrix of rank r_i, and β_i is a $(k_i + k^*_i) \times r_i$ matrix of rank r_i. Before testing for possible cointegration, we investigate how the deterministic component enters the model. We analyze two cases. In the first case we allow for an unrestricted intercept in equation (13), which implies $c_{i0} \neq 0$ and no trend coefficients, that is, $\gamma_i = 0$. In the second case we allow for a model with an unrestricted intercept and a co-trending restriction, that is, $\beta'_i \gamma_i = 0$. According to Pesaran, Shin, and Smith (2000), the former setup is normally referred to as model case III, while the latter setup is normally referred to as model case IV. A test of whether the cointegrating relationships are trended or non-trended was carried out by testing the r_i restrictions $\beta'_i \gamma_i = 0$ in equation (13).[12] The fourth column of table 3 presents the deterministic setup used for each region.

The rank of the cointegrating space for each country/region was computed using Johansen's trace and maximal eigenvalue statistics as set out in Pesaran, Shin, and Smith (2000) for models with weakly exogenous I(1) regressors. The values of the test statistics are reported in table 4. Both statistics are conducted at the 95% significance level using case III or case IV, with the choice depending on the results obtained in the previous likelihood ratio test. Generally speaking, the two rank statistics result in the same rank selection. Where the test statistics report different results, the trace statistic was chosen because this test has better small sample power. For Argentina, Australia, Canada, and ROW countries, the trace test statistics reveal two cointegrating relationships, while for the remaining regions the rank tests suggest only one cointegrating relationship. To exactly identify the cointegrating matrix, a r_i^2 contemporaneous restriction must be imposed. In the case of one cointegrating regression, this is done by normalizing the cointegrating vector with respect to the export price coefficient. In the case of two cointegrating relationships, we compute the exact identity matrix similar to Lütkepohl (2007).

One way of developing a global model with a theoretically coherent foundation is to incorporate long-run structural relationships, as suggested by economic theory, in the otherwise unrestricted country-specific models. In our case, one appealing long-run relationship between export prices is given by

$$(14) \quad p^e_{it} - \sum_{j \neq i} w_j p^e_{jt} \sim I(0) \forall i.$$

This difference between domestic and foreign export prices is a stationary variable, that is, $I(0)$. In other words, once prices are defined in a common currency, perfect arbitrage ensures that the goods traded in different markets have a single price. This hypothesis is usually referred to as the Law of One Price (LOP).

We analyze the previous hypothesis by testing for a set of over-identifying restrictions on the cointegrating vector(s). Assuming, for the sake of simplicity, only one cointegrating vector, from equation (13) the cointegrating unrestricted relationship is given by:

$$(15) \quad \beta_{i1} p^e_{it} + \beta_{i2} z_{it} + \beta_{i3} e_{it} + \beta_{i4} p^f_{it} + \beta_{i5} p^c_{it} + \beta_{i6} p^{e*}_{it} + \beta_{i7} z^*_{it} + \beta_{i8} e^*_{it} + \beta_{i9} p^{c*}_{it} + \beta_{i10} p^o_t \sim I(0).$$

Exact identification of the unrestricted relationship requires one restriction, the standard normalization restriction. If we want to test the validity of the LOP suggested by economic theory, the long-run restrictions admit the following cointegration vector:

$$(16) \quad \beta_i = (1, 0, 0, 0, 0, -1, 0, 0, 0, 0)'.$$

Consequently, the LOP implies ten over-identifying restrictions for each country's VECMX model. The likelihood ratio statistic is used to test whether the over-identifying restrictions are valid. The log-likelihood ratio statistic, LR, is defined by

$$(17) \quad LR = 2\{l(\hat{\theta}_i; r_i) - l(\tilde{\theta}_i; r_i)\} \sim \chi^2_{m_i r_i - r_i^2}.$$

[12] Under the co-trending null hypothesis, $\beta'_i \gamma_i = 0$, the LR test statistic is given by $LR = 2(l(\widehat{\theta}_i; r_i) - l(\widetilde{\theta}_i; r_i)) \sim \chi^2_{r_i}$, where $l(\widehat{\theta}_i; r_i)$ is the maximized value of the log-likelihood function when the cointegrating relations are just identified (i.e., computed under case IV), and $l(\widetilde{\theta}_i; r_i)$ is the maximized log-likelihood when the additional co-trending restrictions have been imposed (the value is obtained by rerunning the model and imposing case III for estimating the individual country models).

Table 4. Cointegration Rank Statistics

	Maximum Eigenvalue Test				Trace Test			
Country	H_0	H_1	Statistics	95% Cr. Values	H_0	H_1	Statistics	95% Cr. Values
Argentina	$r=0$	$r>1$	56.64	50.24	$r=0$	$r=1$	161.63	128.97
	$r<1$	$r\geq 2$	49.54	43.83	$r<1$	$r=2$	104.99	96.78
	$r\leq 0$	$r\geq 3$	22.95	37.27	$r\leq 2$	$r=3$	55.45	68.48
	$r\leq 0$	$r\geq 4$	18.83	30.35	$r\leq 3$	$r=4$	32.51	43.87
	$r\leq 0$	$r\geq 5$	13.68	22.64	$r\leq 4$	$r=5$	13.68	22.64
Australia	$r=0$	$r>1$	65.08	54.14	$r=0$	$r=1$	184.16	145.30
	$r<1$	$r\geq 2$	46.89	47.70	$r<1$	$r=2$	119.08	110.03
	$r\leq 0$	$r\geq 3$	31.03	41.08	$r\leq 2$	$r=3$	72.18	78.52
	$r\leq 0$	$r\geq 4$	25.21	34.09	$r\leq 3$	$r=4$	41.15	50.72
	$r\leq 0$	$r\geq 5$	15.95	26.24	$r\leq 4$	$r=5$	15.95	26.24
Canada	$r=0$	$r>1$	42.10	50.24	$r=0$	$r=1$	140.94	128.97
	$r<1$	$r\geq 2$	36.70	43.83	$r<1$	$r=2$	98.84	96.78
	$r\leq 0$	$r\geq 3$	30.11	37.27	$r\leq 2$	$r=3$	62.13	68.48
	$r\leq 0$	$r\geq 4$	21.43	30.35	$r\leq 3$	$r=4$	32.02	43.87
	$r\leq 0$	$r\geq 5$	10.59	22.64	$r\leq 4$	$r=5$	10.59	22.64
Russia	$r=0$	$r>1$	43.25	50.24	$r=0$	$r=1$	131.74	125.90
	$r<1$	$r\geq 2$	36.29	43.83	$r<1$	$r=2$	88.49	95.14
	$r\leq 0$	$r\geq 3$	23.67	37.27	$r\leq 2$	$r=3$	52.21	66.94
	$r\leq 0$	$r\geq 4$	19.00	30.35	$r\leq 3$	$r=4$	28.53	42.73
	$r\leq 0$	$r\geq 5$	9.53	22.19	$r\leq 4$	$r=5$	9.53	22.19
EU	$r=0$	$r>1$	49.91	54.14	$r=0$	$r=1$	152.54	145.30
	$r<1$	$r\geq 2$	41.97	47.70	$r<1$	$r=2$	102.63	110.03
	$r\leq 0$	$r\geq 3$	24.28	41.08	$r\leq 2$	$r=3$	60.66	78.52
	$r\leq 0$	$r\geq 4$	23.09	34.08	$r\leq 3$	$r=4$	36.38	50.72
USA	$r\leq 0$	$r\geq 5$	13.29	26.24	$r\leq 4$	$r=5$	13.29	26.24
	$r=0$	$r>1$	59.33	47.70	$r=0$	$r=1$	133.77	110.03
	$r<1$	$r\geq 2$	36.57	41.08	$r<1$	$r=2$	74.44	78.52
	$r\leq 0$	$r\geq 3$	25.11	34.09	$r\leq 2$	$r=3$	37.87	50.72
	$r\leq 0$	$r\geq 4$	12.76	26.24	$r\leq 3$	$r=4$	12.76	26.24
ROW	$r<1$	$r\geq 2$	45.67	43.83	$r<1$	$r=2$	116.82	96.78
	$r\leq 0$	$r\geq 3$	37.75	37.27	$r\leq 2$	$r=3$	71.15	68.48
	$r\leq 0$	$r\geq 4$	23.97	30.35	$r\leq 3$	$r=4$	33.40	43.87
	$r\leq 0$	$r\geq 5$	9.43	22.19	$r\leq 4$	$r=5$	9.43	26.64

Note: The null hypothesis (H_0) indicates r cointegration vectors against the alternative hypothesis (H_1) of (at most) $r+1$ cointegration vectors for the maximum eigenvalue (trace) test; r is chosen as the first non-significant statistic, undertaking sequentially the test starting from $r=0$. Critical values are taken from Mackinnon, Haug, and Michelis (1999).

Here, $l(\hat{\theta}_i; r_i)$ is the maximized value of the log-likelihood function under precise identifying restrictions, $l(\tilde{\theta}_i; r_i)$ is the maximized value of the log-likelihood function under over-identifying restrictions, m_i is the number of country-specific and foreign-specific variables, and finally r_i is the rank of cointegrating vector(s). The over-identifying restrictions were imposed on all six countries (accounting for the differences in the cointegration rank and deterministic terms among countries). As shown in table 5, all the test statistics reject the null hypothesis of LOP for wheat prices. This result is at odds with Goodwin (1992), who did not reject the LOP for wheat prices within a set of countries (United States, Australia, Canada, and Japan) when including freight rates in the cointegrating relationships. Unfortunately, freight rate data are not available at monthly intervals for our set of countries, and so we cannot replicate Goodwin's (1992) experiment.

As we have reported, the main assumption underlying the estimation strategy in the GVAR model is the weak exogeneity of $\tilde{y}^*_{it}$ with respect to the long-run parameters of the conditional model (13). In the context of the worldwide wheat market, this hypothesis has important implications. Specifically, it implies that the model does not allow for

Table 5. Likelihood Ratio Test for Overidentifying Restrictions in Cointegrating Vector(s)

Country	*LR* test	*p*-value
Argentina	48.810	0.000
Australia	49.414	0.000
Canada	20.016	0.018
Russia	32.335	0.000
EU	47.460	0.000
United States	56.675	0.000

Note: Likelihood test statistics are distributed as $\chi^2_{m_i r_i - r_i^2}$, where m_i is the number of country-specific and foreign-specific variables, and r_i is the rank of the cointegrating vector(s).

the presence of a leader country, which is equivalent to proposing that the long-run wheat export prices in the world market are jointly determined. This hypothesis does not necessarily rule out the short-run influence of one or more of the main exporting countries on the dynamics of the world wheat price. The weak exogeneity hypothesis can be tested by using the test proposed by Johansen (1992) and Harbo et al. (1998). This test requires that the following regression be performed for each country-specific model and for each l^{th} element of the foreign group of variables $\tilde{y}^*_{it}$:

$$(18) \qquad \Delta\tilde{y}^*_{it,l} = \mu_{il} + \sum_{j=1}^{r_i} \gamma_{ij,t}\widehat{ECM}^{j}_{i,t-1} + \sum_{p=1}^{p_i} \phi_{ip,t}\Delta y_{i,t-p} + \sum_{m=1}^{q_i} \theta_{im,t}\Delta\tilde{y}^*_{i,t-m} + \epsilon_{it,l}.$$

Here, $\Delta y_{i,t-p}$ is the group of home variables expressed in differences, where $p = 1, \ldots, p_i$ and p_i is the lag order of the home component for each $i = 0, \ldots, N$ country model. Moreover, $\Delta\tilde{y}^*_{i,t-m}$ is the set of foreign-specific and global variables in differences, where $m = 1, \ldots, q_i$ and q_i is the lag order of the foreign-specific and global components for each ith country model, $\widehat{ECM}^{j}_{i,t-1}$ is the estimated error correction term, where $j = 1, \ldots, r_i$, and r_i is the number of cointegrating relations, that is, the rank, found in the ith country model. The procedure consists of testing the null hypothesis that $\gamma_{ij,l} = 0$ for each $j = 1, \ldots, r_i$ by means of an F test. The results of table 6 indicate that the hypothesis of weak exogeneity for foreign-specific components cannot be rejected, and thus the GVAR model can be used for comparative studies on the relationships between country-specific and foreign-specific variables, and also for computing GVAR impulse responses.

Estimating the cointegrating VECX models allows us to analyze the effects that foreign-specific variables have on the corresponding domestic variables. In table 7, we present the impact elasticities and their t-statistics. Using these estimates, we can show the short-run relationships between domestic and foreign-specific variables. Looking at wheat export prices, we find that all the estimates are positive and significant. Moreover, the United States and the EU have an impact elasticity close to one. Generally speaking, positive and significant impact elasticities are shown by the exchange rate variable. The only exception is for the ROW countries.

Finally, there is less evidence of short-run co-movements for the stock-to-use ratio variable and consumer food prices because the t-statistics are generally not significant. To summarize, from our analysis it emerges that the impact elasticities of foreign-specific variables on their domestic counterparts are mainly connected to changes in the nominal effective exchange rate and regional wheat prices. As expected, poor relationships were found for the domestic and foreign stock-to-use ratios.[13]

The Generalized Impulse Response Analysis

In the absence of strong a priori information that can identify the short-run dynamics of our system, we use the generalized impulse response function (GIRF) approach proposed by Koop, Pesaran, and Potter (1996) and further developed by Pesaran and Shin (1996). The GIRF has the useful property of being invariant to the ordering of the variables and of the countries.[14] This is of

[13] Finally, we conducted a number of structural stability tests along the lines of Stock and Watson (1996) to analyze whether there is possible parameter instability. Among the tests included in our analysis are Ploberger and Krämers (1992) maximal ordinary least squares cumulative sum (CUSUM) statistics and its mean square variant, and the Nyblom (1989) test statistic. The heteroskedasticity-robust version of the above tests was used. The results, available in the online supplement, show that there is convincing evidence of the stability of the parameters during the period under analysis.

[14] The major weakness of the GIRFs is that they assess the effects of observable-specific rather than identified shocks. However, because our analysis is mainly based on the investigation

Table 6. F Statistics for Testing the Weak Exogeneity of Country-specific Foreign and Global Variables

Country	p_{it}^{*}	z_{it}^{*}	e_{it}^{*}	p_{it}^{c*}	p_{it}^{o}
Argentina	0.499 (0.608)	1.151 (0.320)	0.855 (0.428)	0.682 (0.506)	0.219 (0.803)
Australia	2.227 (0.113)	1.091 (0.339)	0.756 (0.472)	1.774 (0.174)	1.456 (0.235)
Canada	0.463 (0.631)	2.083 (0.130)	1.154 (0.319)	0.846 (0.432)	0.567 (0.569)
Russia	0.240 (.625)	0.112 (0.738)	1.381 (0.244)	1.206 (0.275)	0.234 (0.629)
EU	0.764 (0.384)	1.038 (0.310)	0.877 (0.351)	1.024 (0.314)	0.158 (0.691)
United States	1.670 (0.199)	0.375 (0.541)	1.999 (0.160)	0.613 (0.435)	0.003 (0.956)
ROW	0.219 (0.803)	0.201 (0.818)	0.890 (0.413)	0.258 (0.773)	0.450 (0.639)

Note: The p-values are in parentheses.

Table 7. Contemporaneous Effects of Foreign Variables on Home-specific Counterparts

Country	p_{it}^{e*}	z_{it}^{*}	e_{it}^{*}	p_{it}^{c*}
Argentina	0.439 (6.422)	−0.302 (−0.931)	0.291 (1.824)	−0.342 (−1.214)
Australia	0.558 (7.716)	1.261 (1.490)	1.202 (8.328)	0.118 (0.775)
Canada	0.774 (6.303)	0.544 (1.235)	0.502 (4.692)	0.438 (1.806)
Russia	0.668 (6.786)	−0.077 (−0.683)	0.391 (5.571)	−0.040 (−0.112)
EU	1.041 (10.837)	0.092 (0.600)	1.042 (8.436)	0.744 (3.554)
United States	1.107 (10.570)	0.302 (1.237)	—	0.014 (0.506)
ROW	—	−0.007 (−0.430)	0.012 (0.289)	1.497 (0.619)

Note: The robust t-statistics appear in parentheses and are computed using White's heteroscedastic corrected standard errors.

particular importance in our system, where there is no clear economic a priori knowledge that can establish a reasonable ordering. We analyze the implications of three different external shocks to assess the dynamic properties of the GVAR model and the time profile of the effects of shocks on country-specific and foreign-specific variables and global oil shocks.

More specifically, let us consider the solution of the GVAR model given by equation (9). The GIRFs can be defined as

$$GIRF(y_t; u_{ilt}, n) = E(y_{t+n}|\varepsilon_{ilt} = \sqrt{\sigma_{ii,ll}}, \Im_{t-1}) - E(y_{t+n}|\Im_{t-1})$$

where $\Im_{t-1}$ is the information set at time $t-1$, $\sqrt{\sigma_{ii,ll}}$ is the diagonal element of the variance-covariance Σ_ε corresponding to the lth equation in the ith region, and n is the horizon. From the previous definition it follows that the GIRFs of a unit (one standard error) shock at time t to the lth equation with effects on the jth variable and at time $t+n$ is given by the jth element of

$$(19) \quad GIRF(y_t; \varepsilon_{ilt}, n) = \frac{e_j' \mathbf{A}_n \mathbf{G}_0^{-1} \Sigma_\varepsilon e_l}{\sqrt{e_l' \Sigma_\varepsilon e_l}} \quad n = 0, 1, \ldots; \quad l, j = 1, 2, \ldots, k$$

where $e_l = (0, 0, \ldots, 0, 1, 0 \ldots, 0)'$ is a selection vector with unity as the lth element in case of a country-specific shock.[15] A global shock can also be entertained. In this case the selection vector can be defined as $e_l = (0, w_{i0}, \ldots, 0, w_{i1}, 0, \ldots, 0)'$ with $\sum_{j \neq i} w_{ij} = 1$. For example, a devaluation of the U.S. dollar can be thought of as a weighted shock to the same variable in all countries, using a set of weights reflecting the relative importance of the individual countries in the world wheat export market.

The figures presented below provide bootstrap median estimates of GIRFs and their 90% confidence bounds.[16] The degree of

of the geographical transmission of country-specific or global shocks, we expect that the previous limitation is not important.

[15] The $\mathbf{A}_n$ matrices are calculated recursively as $\mathbf{A}_n = \mathbf{F}_1 \mathbf{A}_{n-1} + \mathbf{F}_2 \mathbf{A}_{n-2} + \ldots + \mathbf{F}_p \mathbf{A}_{n-p}, n = 1, 2, \ldots,$ with $\mathbf{A}_0 = \mathbf{I}_n, \mathbf{A}_n = 0$ for $n < 0$.

[16] Median estimates rather than point estimates were used to account for possibly changing error variances. The confidence interval is calculated using the sieve bootstrap method with

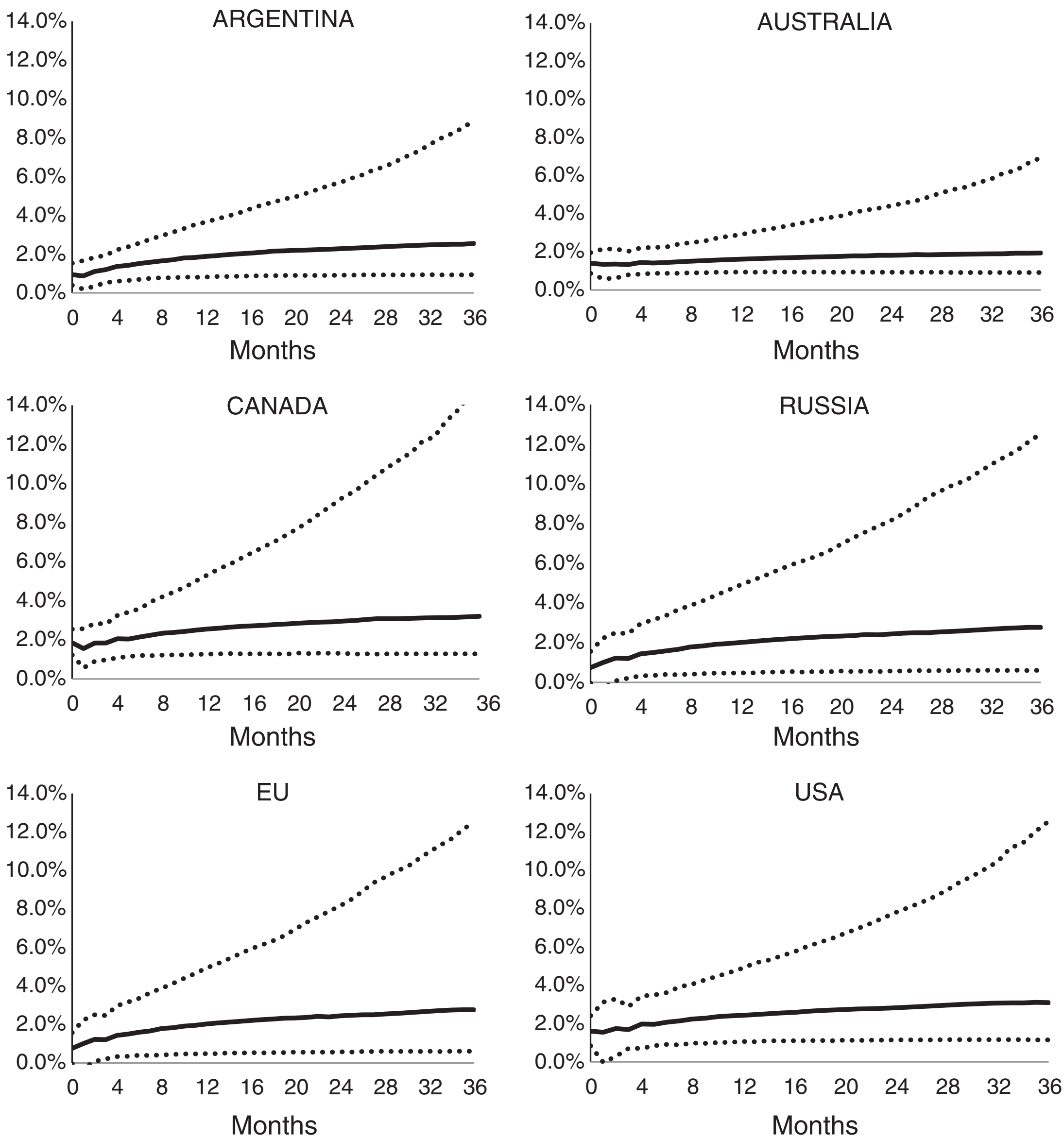

Figure 2. Generalized impulse responses of a negative one-standard-error shock to U.S. stock-to-use ratio on wheat export prices (bootstrap median estimates with 90% bootstrap error bounds)

persistence of GIRFs can be preliminarily assessed by inspecting the eigenvalues of the dynamic system. Since the GVAR includes 33 variables and its maximum lag order is equal to 3, the companion VAR(1) form has 99 eigenvalues, of which 50 (25 pairs) are complex, that is, they originate cyclical behavior in the impulse responses. Given the individual country models and Pesaran Schuermann, and Weiner's theorem (2004), the rank of cointegrating matrix in the global model is not expected to exceed 11 (i.e., the total number of cointegrating relationships in the individual countries' models). Thus, we have to expect that at least 22 eigenvalues (i.e., 33 variables less 11) will fall in the unit circle. The GVAR satisfies this property, with 22 eigenvalues equal to unity and with the remaining moduli less than unity. Hence, the GVAR model is dynamically

1,000 replications. This allows one to account for cross-country correlation. See Smith and Galesi (2011) for a detailed description of the GVAR bootstrapping procedure.

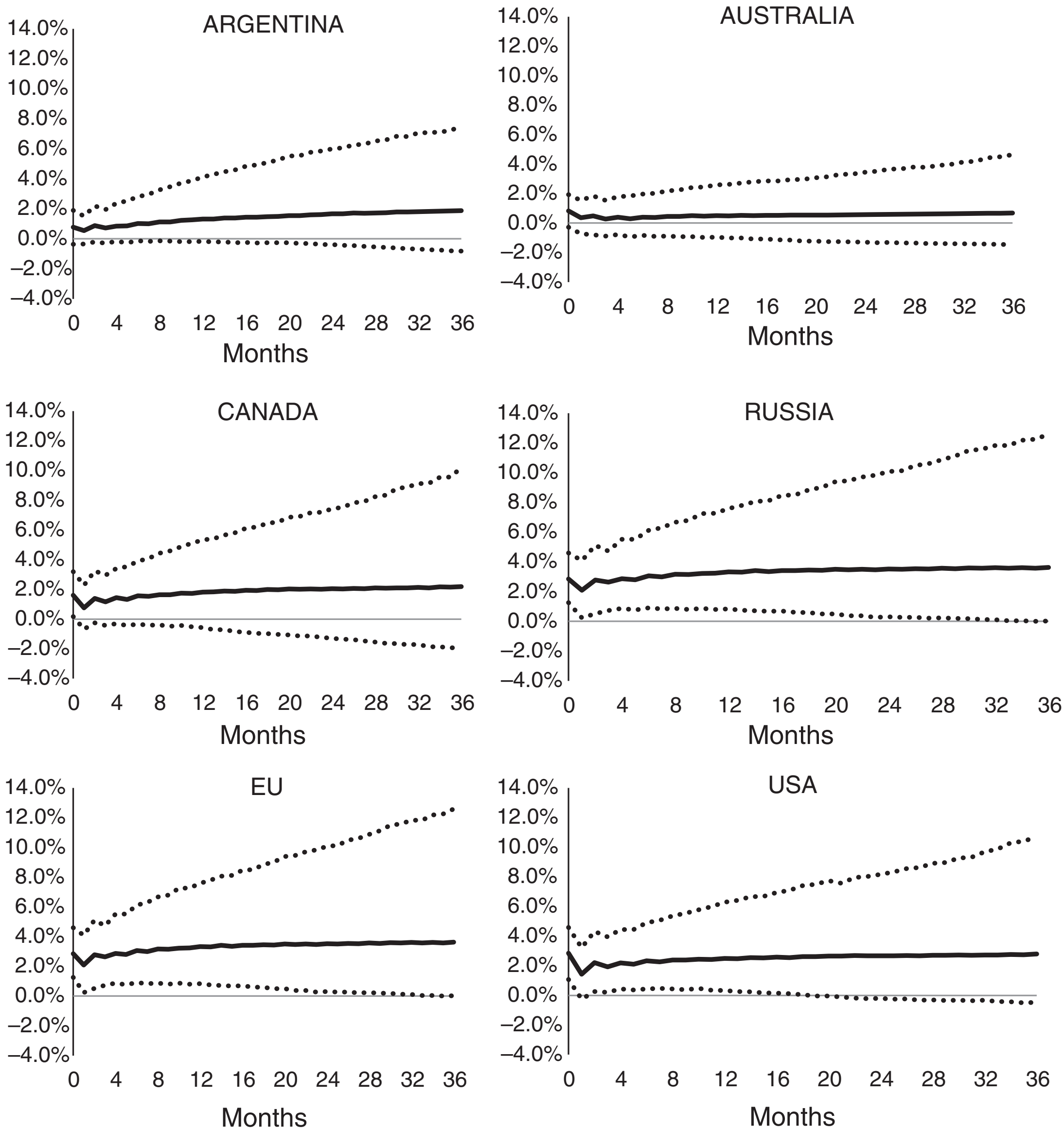

Figure 3. Generalized impulse responses of a negative one standard error shock to U.S. dollar on wheat export prices (bootstrap median estimates with 90% bootstrap error bounds)

stable. The three largest eigenvalues among those which are in moduli less than unity are 0.9826, 0.9436, and 0.8940. Thus, we expect to observe convergence towards a steady-state equilibrium.

The first perturbation we analyze is a reduction in the U.S. stock-to-use ratio. This is a typical shock to a domestic variable that will affect the home market as well as foreign countries. Using the GIRF, we analyze how this shock spreads around the world, manifesting itself in higher wheat prices. The second shock we simulate is a U.S. dollar devaluation against competitor currencies. This can be seen as a global shock that will affect prices (and quantities). The final shock we present is a perturbation in the oil price. Due to space limitations, we only present the GIRF impulse responses of wheat export prices for the various regions analyzed, and we focus on the first three years after the shock.[17]

[17] Naturally the GIRF can be used to analyze the effect of any of the previous (or other) shocks on the other endogenous variables.

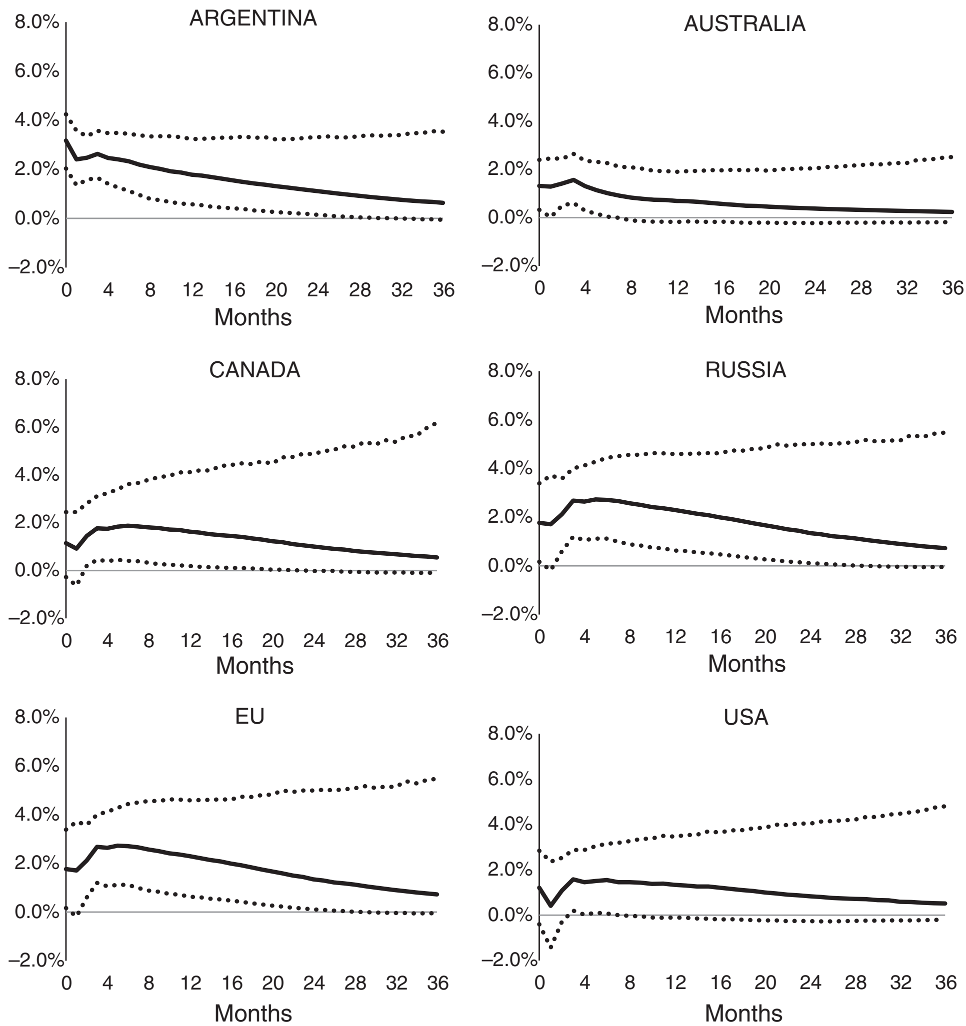

Figure 4. Generalized impulse responses of a positive one standard error shock to oil price on wheat export prices (bootstrap median estimates with 90% bootstrap error bounds)

The first shock we consider is a negative shock to the U.S. stock-to-use ratio. A recent analysis of the possible effects of a reduction of the stock-to-use ratio on price spikes is contained in Trostle (2008); Mitchell (2008); and Abbott, Hurt, and Tyner (2008). In our case, a one standard deviation shock corresponds to a 4.3% decrease in the stock-to-use ratio.[18] In figure 2, we indicate the effects of this shock on the wheat export prices with a solid line, while the 90% bootstrapped confidence intervals are represented by the thinner lines.[19] Not surprisingly, a negative shock to the U.S. stock-to-use ratio raises the export prices in all countries. In the United States the response impact is +1.6%, and after twelve months the rise in the wheat export price is +2.4%. There are similar outcomes for the EU where the response impact is +1.0%, and the rise in the wheat export price is +2.0% after 12 months. The same is true for Australia and Canada.

The U.S. dollar devaluation is considered to be one of the main factors behind the upsurge in commodity prices during the

[18] During the period of analysis, the average value of the variable was 55.1%.

[19] Although for most of countries the confidence intervals are large and some of GIRF are therefore not statistically significant, the impulse response schedules are still informative.

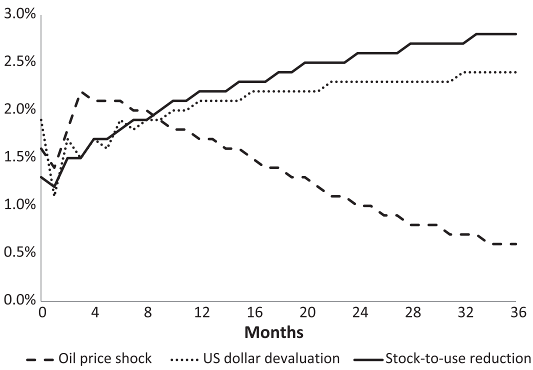

Figure 5. Generalized impulse responses (one standard error shock) of a reduction of US stock-to-use ratio, an increase of oil price, and of a devaluation of the U.S. dollar on global wheat export prices

period we studied. For this reason, we simulate the effects of a U.S. dollar devaluation against all the currencies (see figure 3). This shock can be defined as a typical global perturbation. A one standard error shock in this case is equivalent to a fall of 0.6% in the value of the U.S. dollar against the competitors' currencies. Looking at the impulse responses, the shock is accompanied by a rise in wheat export prices. Thus, with the exception of Argentina and Australia where there was less impact, we note an overshooting response, and in particular elasticity in wheat export that exceeds one. Our results show stronger responses to a U.S. dollar devaluation than do other studies such as Baffes (1997), who estimated the elasticity of commodity prices with respect to the dollar exchange rate at between 0.5 and 1.0, or Sarris (2008), who found a lower elasticity, equal to 0.5, for wheat prices with respect to a U.S. devaluation.[20]

Finally, we analyze the effect of a global oil price shock on the dynamics of the export prices, the results of which are reported in figure 4. A positive one standard error shock to the nominal oil price corresponds to an increase of 8.5% in the oil price index in one month. The impact on wheat export prices varies significantly among countries. For the United States and the EU area, the impact is quite similar, and equal to 1.3%–1.7%. Argentina is the country that seems to be more sensitive to the effect of an oil shock, with an impact on the wheat export price of close to 3.0%. Interestingly, and differently from the other shocks, the effect that an unexpected rise in the oil price has on wheat export prices seems to die out after the first 4 months, with no countries showing persistence of the shock.

To compare the effects of the previous shocks, the GIRFs of each country and type of shock have been aggregated, using the weight of each single country's exports as a share of total world exports. The weighting values in this case are those presented in the last row of table 1. In figure 5 we present the aggregated GIRFs of a one standard error shock. From figure 5 it emerges that the oil price and U.S. dollar devaluation shocks have a higher impact on wheat export prices than does a U.S. stock-to-use reduction. However, after one year the effect of the latter shock on wheat prices is greater and much more persistent. These results seem to be more in line with those of Abbot, Hurt, and Tyner (2008) and Wright (2011), among others, who see the driving force behind the recent food price rises as being mainly related to stock depletion, especially in the cereals market.

Concluding Remarks

In this article we employ the Global Vector Autoregressive (GVAR) methodology to analyze the world wheat market. The aim of the article was not to carry out a structural exercise, but rather to assess what variables are typically associated with wheat price movements. Thus, we focused on the short and long-run responses of wheat export prices to a decrease in the wheat stock-to-use ratio, to an increase in the price of oil, and to a nominal U.S. dollar devaluation. All of these shocks have been proposed in the literature as determinants of recent commodity price movements. The impact effects and time profiles of these shocks are presented using generalized impulse response functions. We find that all these factors have inflationary effects on wheat export prices, although the impact over time and among the countries differs, depending on the type of shock. At a global level, the inflationary effect of a negative shock to the stock-to-use ratio seems to be greater than an oil price or a U.S. dollar devaluation shock. Thus, our results indicate that falling wheat stock levels (relative to consumption levels) should be

[20] Cited from Piesse and Thirtle (2009).

a major concern when analyzing international wheat prices. This finding may have important implications for economic policy. Because of the strong and persistent economic impact of depletions in stock-to-use, agricultural policy makers should monitor the level of wheat stocks.

The model we have outlined in the article can be used for a variety of simulation and forecasting-monitoring exercises that aim to explore different aspects of the global wheat market. The model can also be extended in various directions. First, rolling weights, as in Favero (2012), can be used rather than the simple yearly average that we adopted in the article. This improvement would allow possible changes in the importance of countries to the wheat trade to be appreciated. Moreover, by using rolling weights we could also account for possible bans on exports, such as those experienced in Russia from August 2010 – June 2011. Such bans alter the importance of countries in the wheat trade. Second, regime-switching GVAR models such as those recently proposed by Binder and Gross (2013) can be particularly useful in allowing for possible recurring or non-recurring structural changes, for example different volatility regimes. Finally, the model can be widened to include export-import quantities, with the aim of analyzing changes in trade patterns after shocks in the worldwide wheat market. We leave these as areas for future analysis.

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/online.

References

Abbott, P.C., C. Hurt, and W.E Tyner. 2008. What's Driving Food Prices? Issue Report, Farm Foundation, June.

Alaouze, C.M., A.S. Watson, and N.H. Sturgess. 1978. Oligopoly Pricing in the World Wheat Market. *American Journal of Agricultural Economics* 60 (2): 173–85.

Ardeni, P.G. 1989. Does the Law of One Price Really Hold for Commodity Prices? *American Journal of Agricultural Economics* 71 (3): 661–69.

Arnade, C., and G. Vocke. 2013. Investigating the Divergence in Wheat Prices. Paper presented at AAEA & CAES Joint Annual Meeting, Washington DC.

Baffes, J. 1997. Explaining Stationary Variable with Non-stationary Regressors. *Applied Economics Letters* 4 (1): 69–75.

Baffes, J., and T. Haniotis. 2010. Placing the 2006/08 Commodity Price Boom into Perspective. Policy Research Working Paper no. 5371. Washington DC: The World Bank Development Prospects Group.

Bessler, D.A., J. Yang, and M. Wongcharupan. 2003. Price Dynamics in International Wheat Markets. *Journal of Regional Science* 43 (1): 1–33.

Binder, M., and M. Gross. 2013. Regime-switching Global Vector Autoregressive Models. European Central Bank Working Paper no. 1569.

Carter, C., and A. Schmitz. 1979. Import Tariffs and Price Formation in the World Wheat Market. *American Journal of Agricultural Economics* 61 (3): 517–22.

Cooke, B., and M. Robles. 2009. Recent Food Price Movements: A Time Series Analysis. Discussion Paper no. 942. Washington DC: International Food Policy Research Institute.

Dées, S., F. di Mauro, M.H. Pesaran, and L.V. Smith. 2007. Exploring the International Linkages of the Euro Area: A Global VAR Analysis. *Journal of Applied Econometrics* 22 (1): 1–38.

Dewbre, J., C. Giner, W. Thompson, and M. Von Lampe. 2008. High Food Commodity Prices: Will They Stay? Who Will Pay? *Agricultural Economics* 39: 393–403.

Dollive, K. 2008. The Impact of Export Restraints on Rising Grain Prices. Office of Economics Working Paper No. 2008-08-A. Washington DC: U.S. International Trade Commission.

Elliot, G., T.J. Rothenberg, and J.H. Stock. 1996. Efficient Tests for an Autoregressive Unit Root. *Econometrica* 64 (4): 813–36.

Favero, C. 2012. Modelling and Forecasting Yield Differentials in the Euro Area. A Non-linear Global VAR Model. Innocenzo Gasperini Institute for Economic Research (IGIER) Working Paper no. 431.

Food and Agriculture Organization of the United Nations. 2008. The State of Food Insecurity in the World 2008. Rome: Economic and Social Development Department, Food and Agriculture Organization of the UN.

Gilbert, C. 2010a. How to Understand High Food Prices. *Journal of Agricultural Economics* 61 (2): 398–425.

———. 2010b. Speculative Influences on Commodity Futures Prices 2006–2008. Discussion Paper no. 197, United Nations Conference on Trade and Development (UNCTAD), New York City.

Godfrey, L.G. 1978a. Testing Against General Autoregressive and Moving Average Error Models When the Regressors Include Lagged Dependent Variables. *Econometrica* 46 (6): 1293–302.

———. 1978b. Testing for Higher Order Serial Correlation in Regression Equations When the Regressors Include Lagged Dependent Variables. *Econometrica* 46 (6): 1303–10.

Goodwin, B., and T. Schroeder. 1991. Price Dynamics in International Wheat Markets. *Canadian Journal of Agricultural Economics* 39 (2): 237–54.

Goodwin, B. 1992. Multivariate Cointegration Tests and the Law of One Price in International Wheat Markets. *Review of Agricultural Economics* 14 (1): 117–24.

Gutierrez, L. 2013. Speculative Bubbles in Agricultural Commodity Markets. *European Review of Agricultural Economics* 40 (2): 217–38.

Harbo, I., S. Johansen, B. Nielsen, and A. Rahbek. 1998. Asymptotic Inference on Cointegrating Rank in Partial Systems. *Journal of Business & Economic Statistics* 16 (4): 388–99.

Headey, D. 2011. Rethinking the Global Food Crisis: The Role of Trade Shocks. *Food Policy* 36 (2): 136–46.

Headey, D., and S. Fan. 2008. Anatomy of a Crisis: the Causes and Consequences of Surging Food Prices. *Agricultural Economics* 39: 375–91.

Irwin, S. H., D.R. Sanders, and R.P. Merrin. 2010. Devil or Angel? The Role of Speculation in the Recent Commodity Price Boom (and bust). *Journal of Agricultural and Applied Economics* 41 (2): 377–91.

Johansen, S. 1992. Cointegration in Partial Systems and the Efficiency of Single-Equation Analysis. *Journal of Econometrics* 52 (3): 231–54.

———. 1995. *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press.

Kolstad, C.D., and A.E. Burris. 1986. Imperfectly Competitive Equilibria in International Commodity Markets. *American Journal of Agricultural Economics* 68 (1): 27–36.

Koop, G., M.H. Pesaran, and S. Potter. 1996. Impulse Response Analysis in Nonlinear Multivariate Models. *Journal of Econometrics* 74 (1): 119–47.

Krugman, P. 2011. Soaring Food Prices. New York Times. February 5.

Lütkepohl, H. 2007. *New Introduction to Multiple Time Series Analysis*. New York: Springer.

MacKinnon, J., A. Haug, and L. Michelis. 1999. Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration. *Journal of Applied Econometrics* 14 (5): 563–77.

McCalla, A.F. 1966. A Duopoly Model of World Wheat Pricing. *Journal of Farm Economics* 48 (3): 711–27.

Mitchell, D. 2008. A Note on Rising Food Prices. Policy Research Working Paper no. 4682. Washington DC: World Bank.

Mohanty, S., E.W.F. Peterson, and N.C. Kruse. 1995. Price Asymmetry in the International Wheat Market. *Canadian Journal of Agricultural Economics* 43 (3): 355–66.

Ng, S., and P. Perron. 2001. Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power. *Econometrica* 69 (6): 1519–54.

Nyblom, J. 1989. Testing for the Constancy of Parameters Over Time. *Journal of the American Statistical Association* 84: 223–30.

OCDE-FAO. 2011. Agricultural Outlook 2011. OECD Publishing.

Pesaran, M.H., and Y. Shin. 1996. Cointegration and Speed of Convergence to Equilibrium. *Journal of Econometrics* 71 (1): 117–43.

Pesaran, M.H., Y. Shin, and R. Smith 2000. Structural Analysis of Vector Error Correction Models with Exogenous I(1) Variables. *Journal of Econometrics* 97 (2): 293–343.

Pesaran, M.H., T. Schuermann, and S. Weiner. 2004. Modelling Regional Interdependencies Using a Global Error-Correcting Macroeconometric Model. *Journal of Business and Economics Statistics* 22 (2): 129–62.

Pietola, K., X. Liu, and M. Robles. 2010. Price, Inventories, and Volatility in the Global Wheat Market. Discussion Paper no. 96. Washington DC: International Food Policy Research Institute.

Piesse, J., and Thirtle, C. 2009. Three Bubbles and a Panic: An Explanatory Review of Recent Food Commodity Price Events. *Food Policy* 34 (2): 119–29.

Ploberger, W., and W. Krämer. 1992. The CUSUM Test with OLS Residuals. *Econometrica* 60 (2): 271–86.

Sanders, D.R., Irwin, S.H., and R.P. Merrin. 2010. The Adequacy of Speculation in Agricultural Futures Markets: Too Much of a Good Thing? *Applied Economic Perspectives and Policy* 32 (1): 77–94.

Sarris, A. 2008. Agricultural Commodity Markets and Trade: Price Spikes or Trends? Paper Presented at a Conference on The Food Crisis of 2008: Lessons for the Future, Imperial College, Wye Campus, London.

Scoppola, M. 2007. Economies of Scale and Market Structure in International Grain Trade. *Agricultural Economics* 37: 277–91.

Serra, T., and J.M. Gil. 2011. Price Volatility in Food Markets: Can Stock Building Mitigate Price Fluctuations? *European Review of Agricultural Economics* 14 (3): 122.

Smith, L.V., and A. Galesi. 2011. *GVAR Toolbox 1.1*. www.cfap.jbs.cam.ac.uk/research/gvartoolbox (accessed on May 14, 2014).

Spriggs, J., M. Kaylen, and D. Bessler. 1982. The Lead-Lag Relationship Between Canadian and U.S. Wheat Prices. *American Journal of Agricultural Economics* 64 (3): 569–72.

Stock, J.H., and M.W. Watson. 1996. Evidence on Structural Instability in Macroeconomic Time Series Relations. *Journal of Business and Economic Statistics* 14 (1): 11–30.

Timmer, C.P. 2009. Did Speculation Affect World Rice Prices? Economics and Social Analysis (ESA) Working Paper no. 09-07. Rome: Food and Agricultural Organization of the United Nations.

Trostle, R. 2008. Global Agricultural Supply and Demand: Factors Contributing to the Recent Increase in Food Commodity Prices. Outlook Report no. WRS-0801. Washington DC: U.S. Department of Agriculture, Economic Research Service.

Von Braun, J. 2007. The World Food Situation: New Driving Forces and Required Actions. Washington DC: International Food Policy Research Institute.

Wright, W. 2011. The Economics of Grain Price Volatility. *Applied Economic Perspectives and Policy* 33 (1): 32–58.