International Review of Applied Economics, 2015
Vol. 29, No. 3, 403–434, http://dx.doi.org/10.1080/02692171.2014.1001325

The relationship between agricultural commodity prices, crude oil prices and US dollar exchange rates: a panel VAR approach and causality analysis

Anthony N. Rezitis*

University of Patras, Department of Business Administration of Food and Agricultural Enterprises (Agrinio), 2 G. Seferi Str., Agrinio 30 100, Greece

(*Received 14 August 2014; final version received 16 December 2014*)

This study examines the relationship between crude oil prices, US dollar exchange rates and 30 selected international agricultural prices and five international fertilizer prices in a panel framework. The study uses panel VAR methods and Granger causality tests on panel data sets of agricultural commodity prices (as well as specific agricultural commodity sub-groups) and fertilizer prices with monthly observations of the period from June 1983 to June 2013. The empirical results of the present study indicate that crude oil prices as well as US dollar exchange rates affect international agricultural commodity and fertilizer prices. Furthermore, contrary to the findings of several studies in the literature, the present study supports bidirectional panel causality effects between crude oil prices and international agricultural prices as well as between US exchange rates and international agricultural prices.

Keywords: agricultural commodity prices; oil prices; exchange rates; panel VAR; panel causality

JEL Classifications: O13, C01, C32

1. Introduction

Since 2006, agricultural commodity prices have started rising with some fluctuations in a dramatic fashion after several decades of low levels and relative stability. Agricultural commodity prices show similar pattern to those of world oil prices but an opposite pattern to those of the US dollar. In other words an increase (decrease) in agricultural commodity prices has coincided with an increase (decrease) in world oil prices and a decline (increase) in the value of the US dollar (Figure 1). In particular, past increases of world oil prices may have resulted in higher agricultural commodity prices through cost-push effects since their production may depend on the use of crude oil. Moreover, the higher demand for biofuels has further reinforced the relation between agricultural commodities and crude oil. This is because higher crude oil prices may have led to a higher demand for agricultural commodities to substitute biofuel for crude oil. More specifically, high crude oil prices make biofuel production more profitable and this causes increases in the prices of grain, sugar and vegetable oils, which are used not only in food production but also in biofuel

*Email: arezitis@upatras.gr

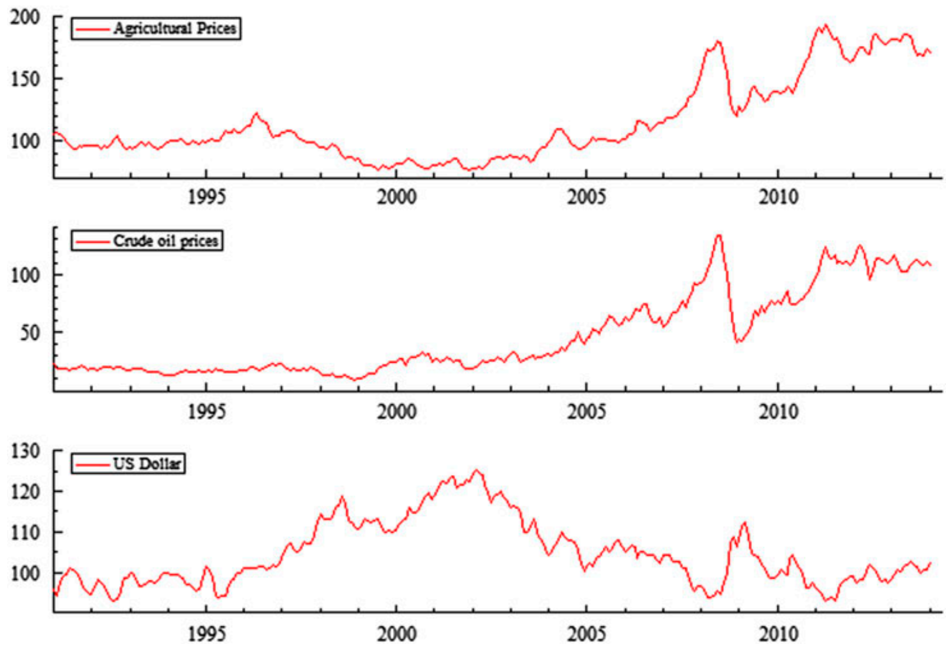

Figure 1. Agricultural commodity price index (2005 = 100), crude oil price (US dollar per barrel), US dollar exchange rate index (2010 = 100).

production. The US dollar is the main currency for the global trade of most agricultural commodities and other goods. Thus, agricultural commodity prices measured in US dollars increase when the US dollar depreciates against other currencies and decrease when the US dollar appreciates. Furthermore, the inverse relationship between the agricultural commodity prices and the US dollar exchange rate may also be attributed to inflation. This is because when the US dollar depreciates, investors and speculators concerned about higher inflation rates invest in commodities futures, such as grains, thereby driving up commodity food prices (Rezitis and Sassi 2013).

The purpose of this study is to examine the extent to which crude oil prices and the strength of the US dollar are related to the prices of 30 selected world agricultural commodities (as well as five sub-groups of those agricultural commodities) and five fertilizer commodities. In order to analyze the relation between the crude oil prices, the US exchange rates and the agricultural commodity prices (as well as the fertilizer prices), panel vector autoregression (VAR) methods are employed on panels of commodity price data sets based on monthly observations from June 1983 to June 2013. The panel VAR methodologies used in the present study capture the dynamics as well as the possible feedbacks between the three series under consideration, i.e. crude oil prices, US exchange rates and agricultural commodity prices (and fertilizer prices). The empirical results indicate that significant price dynamics and feedbacks exist between the series under consideration.

This study contributes to the related literature in several ways. First, it is the first study to use panel VAR models to examine the price dynamics and causality between 30 agricultural commodity prices (and five fertilizer prices) as well as subgroups of these commodities, crude oil prices and US dollar exchange rates. Among the previous studies, only the study by Nazlioglu and Soytas (2012) conducts a panel cointegration and causality analysis to examine the relationship between 24 agricultural commodity prices, world oil prices and the US dollar. However, the aforementioned study indicates that 'the results do not show a uniform conclusion that the null of unit root can be rejected for the levels of the variables.' Moreover, it is worth stating that we reached the same conclusion by applying similar panel unit root tests to the data set used in the present paper. Taking into consideration the studies by Sims (1980) and Sims, Stock, and Watson. (1990), which recommend avoiding differencing even if the variables contain a unit root (Enders, 2010), the present study uses a panel VAR approach in the levels of the variables. Furthermore, as Enders (2010) indicates, 'the main argument against differencing is that it "throws away" information concerning the co-movements in the data.' Second, the current study presents Granger causality test results for groups (panels) of agricultural commodity prices as well as individual commodity prices. The previous literature presents causality tests only at the specific commodity level since it employs time series data, while the study by Nazlioglu and Soytas (2012) presents only panel-level causality tests. Third, the current study presents estimates of the impulse response functions as well as cumulative effects of the right-hand lagged variables of the VAR model. The aforementioned estimates provide measures of the impacts between the variables. Finally, the panel data approaches provide increased power information than the simple time series methods because the former derive information from both time and cross-sectional dimensions, and the latter only from the time dimension.

The remainder of this paper is organized as follows. Section 2 presents and discusses the literature on the causes of agricultural commodity price increases, focusing mainly on the relationship between the agricultural commodity prices, the oil price and the US dollar exchange rate. Section 3 presents the empirical model and the data, while Section 4 provides the econometric methods and the empirical results. The conclusions are drawn in Section 5.

2. Literature review

A number of previous studies have endeavored to analyze the relationship between agricultural commodity prices, the world oil price and the US exchange rate. In particular, Rezitis and Sassi (2013) review the literature that examines the possible causes of the recent food and agricultural commodity spikes. Moreover, they use a structural time series approach to examine the behavior of the monthly commodity food price index for the period from January 1992 to October 2012. Based on the international literature, Rezitis and Sassi (2013) indicate several factors considered to influence food prices, among which are: (1) shocks in production (Schnepf 2008); (2) energy and fertilizer prices (Abbott, Hurt, and Tyner. 2008; Mitchell 2008; Trostle 2008); (3) export policies (Trostle 2008); (4) a low level of global inventories (Wright 2009, 2011); (5) neglected investment in R&D and infrastructure (Abbott, Hurt, and Tyner., 2008); (6) emerging economies and structural change in the global demand (Headey and Fan 2008); (7) high oil prices (Abbott, Hurt, and Tyner., 2008); (8) global biofuel production (Abbott, Hurt, and Tyner .2008, 2011; Headey and Fan 2008; Mitchell 2008; Wright 2009); (9) import policies (Abbott, Hurt, and Tyner.2011; Wright 2009); (10) depreciation of the US dollar (Abbott, Hurt, and Tyner., 2011; Mitchell 2008; Trostle 2008); and (11) inelastic markets

(Abbott, Hurt, and Tyner., 2011). Furthermore, this paper, based on the related literature (Cooke and Robles 2009; Gilbert 2010; Robles, Torero, and von Braun. 2009; Timmer 2009), discusses in detail the role of biofuels and speculation on food and agricultural commodity markets. The empirical part of the study by Rezitis and Sassi (2013) indicates that commodity food prices present seasonality and cyclicality and that crude oil has a positive effect on commodity food prices while the US real effective exchange rate has a negative effect.

Nazlioglu and Soytas (2012) examine the dynamic relationship between oil prices, 24 world agricultural commodities and US dollar exchange rates in a panel framework using panel cointegration and causality analysis for the period from January 1980 to February 2010. The empirical findings provide strong evidence of the impact of the oil prices on the agricultural commodity prices and a positive impact of a weak dollar on the agricultural prices. The results from the panel causality analysis support causal linkages from the oil prices and from the US dollar exchange rates to the agricultural prices but also from the agricultural prices to the oil prices and to the US dollar.

More recently, Alquist and Coibion (2014) provide a new empirical approach for identifying the driving forces of global economic activity and commodity prices. The proposed model predicts the existence of a factor structure for commodity prices that has a direct economic interpretation. The first component of the factor structure is related to idiosyncratic price movements, the second to global economic forces and the third to commodity-specific shocks. Alquist and Coibion (2014) suggest a way to interpret the common factors driving commodity prices and offer a new perspective on the historical behavior of a broad cross-section of internationally traded commodities since the early 1970s.

Pala (2013) investigates the linkage between the crude oil price index and the food price index, using the Johansen cointegration test, and Granger causality, using the vector error correction model (VECM), for the period from January 1990 to August 2011. The empirical results indicate the presence of two structural breaks, after August 2008 and November 2008. The empirical results of the Granger causality tests between the crude oil price index and the food price index show that the causation between these two variables is in two directions. Furthermore, the cointegration regression coefficient between the crude oil and the food price variables is negative in the period from January 1990 to August 2008 and positive in the period from November 2008 to August 2011.

Du and McPhail (2012) examine the dynamic relation between ethanol, gasoline and corn prices during the period from March 2005 to March 2011 using a structural VAR model. The empirical results show a structural change around March 2008 and support a more closely linked relation between the aforementioned prices in the more recent period, during which the relation between corn prices and ethanol prices is found to be the strongest.

Ciaian and Kancs (2011) investigate the interdependencies between energy, bioenergy and food prices. They use a time series cointegration mechanism for nine major agricultural commodity prices – corn, wheat, rice, sugar, soybeans, cotton, banana, sorgum and tea – along with one average crude oil price for the period January 1994 to December 2008. The empirical findings show that energy prices affect the prices of agricultural commodities. In particular, the prices of all nine aforementioned agricultural commodities are cointegrated with the crude oil prices, especially during the sub-period from January 2004 to December 2008. The Granger causality tests show that there is causality from oil to agricultural prices but not vice versa. The impulse response analysis indicates that all the agricultural prices are affected by energy prices, including those that are not directly used for bio-energy production.

Saghaian (2010) presents empirical results obtained using a vector error correction (VEC) system and Granger causality to investigate the relationship between the prices of oil, ethanol, corn, soybeans and wheat. More specifically, the empirical results show that there is a strong correlation among oil and commodity prices and that crude oil prices Granger cause corn, soybean and wheat prices.

Zhang et al. (2010) use price data on fuels, such as ethanol, gasoline and oil, and agricultural commodities, such as corn, rice, soybeans, sugar and wheat, to investigate the long-run cointegration of these prices using a VECM. The results indicate no direct long-run price relations between fuel prices and agricultural prices and a limited short-run relationship between fuel and agricultural prices.

Chen, Kuo and Chen. (2010) investigate the relationship among the prices of corn, soybeans and wheat and the crude oil price. The empirical results indicate that the change in each grain price is significantly influenced by the change in the crude oil price as well as by the change in other grain prices.

Frank and Garcia (2010), using weekly data from 1998 to 2008, examine the linkages between several agricultural commodity prices (i.e. wheat, corn, cattle and hogs), oil prices and exchange rates by employing VAR and VECM procedures. They identify a break point that divides the sample period into two sub-periods (i.e. 1998–2006 and 2006–2009). The empirical results indicate that for the first sub-period the exchange rate and the crude oil price have a limited effect on the agricultural commodity prices, while for the second sub-period the effects of the exchange rate and the crude oil price on the agricultural prices are more pronounced.

Akram (2009) investigates the relationship between commodity prices (i.e. crude oil, food, metals and industrial raw materials), real interest rates and US dollar exchange rates. The empirical analysis is based on quarterly data of the period 1990q1–2007q4 using structural VAR models and indicates that a weaker dollar and a reduction in the real interest rates lead to higher commodity prices.

Harri, Nalley, and Hudson (2009) examine the relationship between agricultural commodity prices (i.e. corn, soybeans, soybean oil, cotton and wheat), oil prices and exchange rates using cointegration analysis for the period from January 2000 to September 2008. The empirical results show that corn, cotton and soybean prices are linked to oil prices, but wheat prices are not. Exchange rates are linked to all of the aforementioned prices.

Arshad and Hameed (2009) investigate the relationship between cereal prices (i.e. maize, rice and wheat) and crude oil prices. They use the Engle–Granger two-stage estimation approach and Granger causality tests with a data set of the period from January 1980 to March 2008. The empirical results support the presence of unidirectional long-run causality from crude oil prices to the three cereal prices. Hameed and Arshad (2009) examine the relationship between petroleum prices and vegetable oil prices (i.e. palm oil, soybean oil, sunflower oil and rapeseed oil) for the period from January 1983 to March 2008 using the Engle–Granger two-stage estimation approach and Granger causality tests. The empirical results show that in the long run there is a one-directional relationship from the crude oil price to the prices of each of the four vegetable oils. The reverse is not true, i.e. the crude oil price is not influenced by the price of any of the vegetable oils under consideration.

3. Model and data

Based on the previous discussions, agricultural commodity prices are expected to be related to world crude oil prices and US dollar exchange rates. The empirical analysis is based on panel vector autoregression (VAR) models, which are useful for examining the dynamics of the variables under consideration. As in the case of the simple VAR models, all the variables of the panel VAR are assumed to be endogenous and independent, but a cross-sectional element is added to the representation of the panel VAR. Panel VARs have been used to create average effects across heterogeneous panel units and to examine unit-specific differences relative to the average. Furthermore, panel VAR models help to study a variety of transmission issues across individual panel units (members) that cannot be dealt with in simple VAR models. The study by Canova and Ciccarelli (2013) presents a detailed review of panel VAR models.

The panel VAR model used in the present paper is based on the panel VAR approach developed by Canova and Ciccarelli (2009) and Canova, Ciccarelli, and Ortega. (2007) and is presented as:

$$\begin{aligned} y_{it} = \alpha_{it} + A_{it}(L)Y_{t-1} + u_{it} \quad u_{it} \sim \left(0, \sigma_i^2\right) \\ \text{for} \quad i = 1, \ldots, N \quad t = 1, \ldots, T \end{aligned} \tag{1}$$

where $Y_t = (y'_{1t}, y'_{2t}, \ldots y'_{Nt})'$ is a stacked version of y_{it}, which is a vector of G variables for each unit i=1,…,N. α_{it} is a G×1 vector of intercepts, $A_{it,l}$ are G×NG matrices for each lag l and u_{it} is a G×1 vector of random disturbances. It is assumed that there are p lags for the G endogenous variables. Note that Y_t includes variables that account for cross-sectional interdependencies and $E\left(u_{it}u_{j\tau}\right) = 0 \quad \forall i \neq j, \quad \text{all} \quad t, \tau$ Furthermore, model (1) exhibits three important characteristics: first, the coefficients of the model are allowed to vary over time; second, the dynamic relationships are allowed to be unit-specific; and third, dynamic feedback across units is possible and this allows for cross-unit lagged interdependencies. Model (1) can be written in a simultaneous equation format as follows:

$$Y_t = X_t\delta_t + E_t \quad E_t \quad \sim \quad N(0, \Omega) \tag{2}$$

where $\delta_t = (\delta_{1t}, \delta_{2t}, \ldots, \delta_{Nt})$ stocks together matrix A_{it} and vector α_{it} so that each δ_t is of dimension G(NGp+1)×1. Since δ_t varies across cross-sectional units in different time periods, it cannot be estimated using classical methods. It is assumed that δ_t can be factored as:

$$\delta_t = \Xi_1\lambda_t + \Xi_2\gamma_t + \Xi_3\rho_t + \varepsilon_t \tag{3}$$

where Ξ_1, Ξ_2, Ξ_3 are lower dimensional matrices, λ_t captures variations in the coefficient vector that are common across units and variables, λ_t captures unit-specific variations in the coefficient vector and ρ_t captures variable-specific variations in the coefficient vector. Note that equation (3) can be written compactly as:

$$\delta_t = \Xi\theta_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, \Sigma \otimes V) \tag{4}$$

where $\Xi = [\Xi_1, \Xi_2, \Xi_3], \quad \theta_t = [\lambda_t, \gamma_t, \rho_t]$, V is a k×k matrix and θ_t evolves over time as a random walk as:

$$\theta_t = \theta_{t-1} + \eta_t \quad \eta_t \sim N\left(0, \bar{B}\right) \tag{5}$$

It is assumed that $\sum = \Omega$ and $V = \sigma^2 I_k$, where σ^2 is known. Note that $\bar{B}$ is a block diagonal matrix. Factorization (3) transforms an overparameterized panel VAR into a parsimonious SUR model, with the regressors as the averages of the right-hand side variables of the VAR model. Substituting equation (4) into equation (2), the estimated empirical model has the following state space structure:

$$\begin{aligned} Y_t &= (X_t \Xi)\theta_t + v_t \\ \theta_t &= \theta_{t-1} + \eta_t \end{aligned} \tag{6}$$

Where $v_t \sim \left(0, \sigma_t \Omega = \left(1 + \sigma^2 X_t^{'} X_t\right)\Omega\right)$. Model (6) can be estimated with both classical and Bayesian methods. The latter approach is employed in the present study because it provides more accurate estimates given the relatively small N in the case of the present study.

The data used in this study consist of monthly observations of the period from June 1983 to June 2013 for the world prices of 35 agricultural commodities, five fertilizer prices, the world crude oil prices and the real effective US dollar exchange rates. Table 1 provides a detailed description of the data. It is worth stating that the agricultural commodity and fertilizer price data have been converted into the same unit of measurement, i.e. dollars per metric ton, in order to avoid potential data inconsistency generated for measuring prices in different units. Summary statistics and unit root tests of the variables used in the estimated models can be provided by the authors upon request.

4. Methods and findings

4.1. Univariate autoregression and findings

First, the univariate autoregression case is considered, where y_{it} corresponds to the agricultural commodity price i. In other words, $G = 1$. Furthermore, six different groups of commodities are considered: *CERL* with N = 6, *VOPM* with N = 10, *CBOS* with N = 4, *MASE* with N = 6, *BEVE* with N = 4 and *FERT* with N = 5 (Table 1). For example, in the case of *CERL*, model (1) becomes:

$$\begin{gathered} \ln CERL_{it} = \alpha_i + \sum_{l=1}^{p} \beta_{li} \ln CERL_{i,t-l} + u_{it} \\ for\ l = 1, \ldots, 6;\ \ t = 1983{:}06 \text{ to } 2013{:}06 \end{gathered} \tag{7}$$

Note that similar models to equation (7) are developed for the rest of the commodity groups (*VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*). Six numbers of lags are supported by the Akaike information criterion (AIC) and the Schwarz Bayesian criterion (SBC). The estimation of the aforementioned models is based on the shrinkage estimators for univariate autoregression presented by Doan (2012). This approach is based upon the literature on Bayesian VARs using a prior (Minnesota prior) on the difference between β_i and the common β (pooled estimate). One of the advantages of the Bayesian panel VAR approach used in the present study is that it is more feasible compared with classical panel VAR approaches in the case of small N. In the univariate autoregression case, the lag coefficients are independent of the scale of the variable; for this reason, the univariate autoregression model is relatively easy to estimate. It also provides univariate impulse response functions (*IRF*), which show the price responses to unit shocks to the (Gibbs) mean estimates for each commodity group.

Table 1. Data description: Agricultural commodity, fertilizer, petroleum prices and exchange rates.

No.	Commodity	Description	Unit
1–30: Agricultural Commodity (AGCP)			
1–6: Cereals (CERL)			
1	Barley (BARL)	Canadian no. 1 Western Barley	US Dollars per Metric Ton
2	Corn (CORN)	U.S. No.2 Yellow, FOB Gulf of Mexico	US Dollars per Metric Ton
3	Rice (RICE)	5 percent broken milled white rice, Thailand nominal price quote	US Dollars per Metric Ton
4	Sorghum (SORG)	U.S. No. 2 milo yellow, FOB Gulf ports	US Dollars per Metric Ton
5	Wheat (WHEH)	U.S. No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico	US Dollars per Metric Ton
6	Soft Red Winter Wheat(WHES)	U.S. No. 2, export price delivered at the US Gulf port for prompt or 30 days shipment	US Dollars per Metric Ton
7–16: Vegetable oils and Protein Meals (VOPM)			
7	Coconut Oil (COCO)	Coconut oil (Philippines/Indonesia), bulk, c.i.f. Rotterdam	US Dollars per Metric Ton
8	Fishmeal (FISM)	Peru Fish meal/pellets 65% protein, CIF	US Dollars per Metric Ton
9	Groundnuts (GRON)	40/50 (40 to 50 count per ounce), cif Argentina	US Dollars per Metric Ton
10	Olive Oil (OLIO)	extra virgin less than 1% free fatty acid, ex-tanker price U.K.	US Dollars per Metric Ton
11	Palm Oil (PALO)	Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA	US Dollars per Metric Ton
12	Peanut Oil (PEAO)	Any origin, c.i.f. Rotterdam	US Dollars per Metric Ton
13	Soybean Meal (SOYM)	Chicago Soybean Meal Futures (first contract forward) Minimum 48 percent protein	US Dollars per Metric Ton
14	Soybean Oil (SOYO)	Chicago Soybean Oil Futures (first contract forward) exchange approved grades	US Dollars per Metric Ton
15	Soybeans (SOYB)	Chicago Soybean futures contract (first contract forward) No. 2 yellow and par	US Dollars per Metric Ton
16	Sunflower (SUNF)	US export price from Gulf of Mexico	US Dollars per Metric Ton
17–20: CBOS			
17	Cotton (COTT)	Cotlook 'A Index', Middling 1-3/32 inch staple, CFR Far Eastern ports	US cents per Pound
18	Bananas (BANA)	Central American and Ecuador, FOB U.S. Ports	US Dollars per Metric Ton
19	Oranges (ORAN)	Miscellaneous oranges, CIF French import price	US Dollars per Metric Ton
20	Sugar (SUGA)	Free Market, Coffee Sugar and Cocoa Exchange (CSCE) contract no.11 nearest future position	US cents per Pound

(*Continued*)

Table 1. (*Continued*).

No.	Commodity	Description	Unit
1–30: Agricultural Commodity (AGCP)			
21–26: Meat & Seafood (MASE)			
21	Beef (BEEF)	Australian and New Zealand 85% lean fores, CIF U.S. import price	US cents per Pound
22	Lamb (LAMB)	Lamb, frozen carcass Smithfield London	US cents per Pound
23	Pork (PORK)	51-52% lean Hogs, U.S. price	US cents per Pound.
24	Poultry (POUL)	Whole bird spot price, Ready-to-cook, whole, iced, Georgia docks	US cents per Pound
25	Fish (salmon) (SALM)	Farm Bred Norwegian Salmon, export price	US Dollars per Kilogram
26	Shrimp (SHRI)	No.1 shell-on headless, 26-30 count per pound, Mexican origin, New York port	US cents per pound
27–30: Beverages (BEVE)			
27	Cocoa Beans (COCB)	International Cocoa Organization cash price, CIF US and European ports	US Dollars per Metric Ton
28	Coffee Arabica (COFA)	International Coffee Organization New York cash price, ex-dock New York	US cents per Pound
29	Coffee Robusta (COFR)	International Coffee Organization New York cash price, ex-dock New York	US cents per Pound
30	Tea (TEA)	Mombasa, Kenya, Auction Price. From July 1998, Kenya auctions, Best Pekoe Fannings. Prior, London auctions, c.i.f. U.K. warehouses	US cents per Kilogram
31–35: Fertilizer (FERT)			
31	DAP (diammonium phosphate)	Standard size, bulk, spot, f.o.b. US Gulf	US Dollars per Metric Ton
32	Potassium chloride (muriate of potash) (POTA)	Standard grade, spot, f.o.b. Vancouver	US Dollars per Metric Ton
33	Phosphate rock (Morocco)(PHOS)	70% BPL, contract, f.a.s. Casablanca	US Dollars per Metric Ton
34	TSP (triple superphosphate)	Up to September 2006 bulk, spot, f.o.b. US Gulf; from October 2006 onwards Tunisian, granular, f.o.b.	US Dollars per Metric Ton
35	Urea (UREA)	Bulk, spot, f.o.b. Black Sea (primarily Yuzhnyy) beginning July 1991; for 1985-91 (June) f.o.b. Eastern Europe	US Dollars per Metric Ton
36. Crude Oil (OILP)			
	Crude Oil (petroleum)(OILP)	Simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh	US Dollars per Barrel
37. Exchange Rate (EXCR)			
	Exchange Rate (EXCR)	Real effective US dollar exchange rate	Narrow index (2010=100)

Source: Items 1– 36 are obtained from: http://www.indexmundi.com/commodities/
Item No. 37 is obtained from http://www.bis.org/statistics/eer/

4.1.1. Univariate impulse response functions (IRFs)

Figures 2–7 provide the *IRFs* obtained from the estimation of univariate autoregression models, such as equation (7). Figures 2–7 correspond to the *CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT* commodity groups, respectively.

Cereals (CERL). Figure 2 shows the *IRFs* for each commodity price of the *CERL* group and indicates that in the 12 months from the initial shock, the highest price response is attributed to *CORN* (corn) with about 116.3%, followed by *WHEH* (wheat) with about 115.1% and *RICE* (rice) with about 104.3%. Furthermore, the greatest persistence of the price change is shown by *BARLEY* (barley), followed by *CORN* (corn) and *RICE* (rice), which retains, in the 96 months after the initial shock, about 48.7%, 36.4% and 25.8% of the initial response, respectively.

Vegetable oils and protein meal (VOPM). With respect to the *VOPM* (vegetable oils and protein meals) commodity group, Figure 3 indicates that in the 12 months after the shock the highest response of about 151.2% is shown by *FISM* (fishmeal), followed by *PEAO* (peanut oil) with about 138.7% and *COCO* (coconut oil) with about 125.1%. The greatest persistence is shown by *FISM* (fishmeal), *SOYB* (soybeans), *SOYO* (soybean oil), *SOYM* (soybean meal) and *OLIO* (olive oil), which retain in the 96 months after the initial shock about 57.7%, 27.4%, 22.6%, 16.1% and 15.4% of the initial response, respectively.

Cotton, bananas, oranges and sugar (CBOS). Figure 4 indicates that in the five months after the shock, the highest response of about 157.9% is shown by *COOT* (cotton), followed by *SUGA* (sugar), which is about 116.9%. Among the members of the *CBOS* commodity group, the greatest persistence is presented by *SUGA* (sugar), which shows a response of about 12.5% 96 months after the initial shock.

Meat and seafood (MASE). Figure 5 shows the *IRFs* corresponding to the *MASE* (meat and seafood) commodity group. This figure indicates that in the four months after the initial shock, *POUL* (poultry) shows the highest response of about 164.1%, followed by *LAMB* (lamb) with about 131.3% and *SAML* (salmon) with about 125.5%. In this commodity group, *POUL* (poultry) and *BEEF* (beef) show the

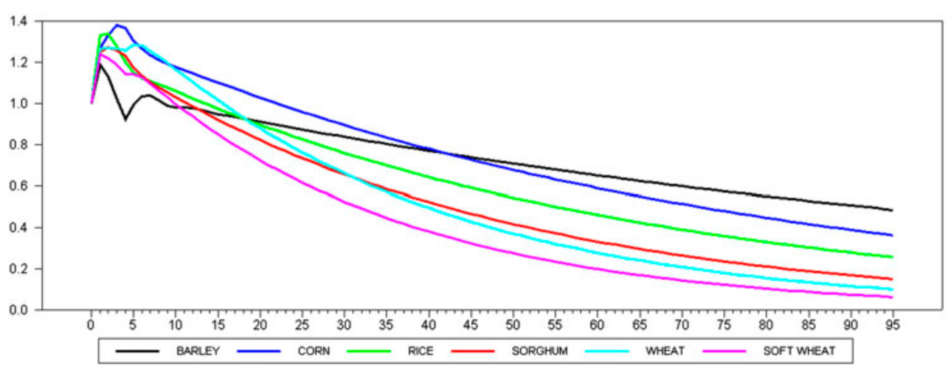

Figure 2. Univariate IRF comparison in the *CERL* commodity group.

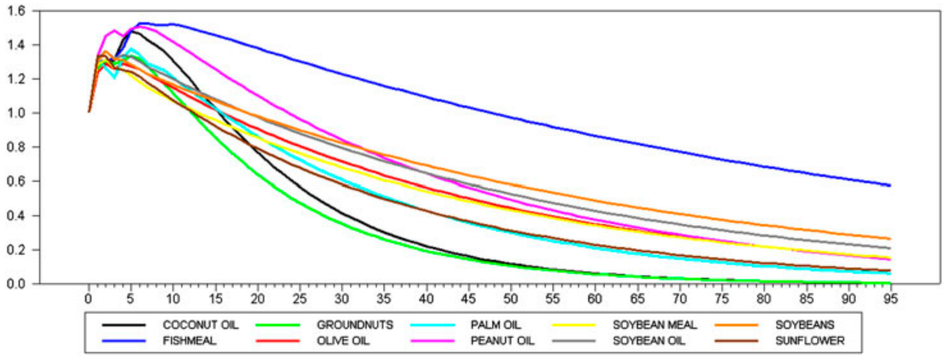

Figure 3. Univariate IRF comparison in the *VOMP* commodity group.

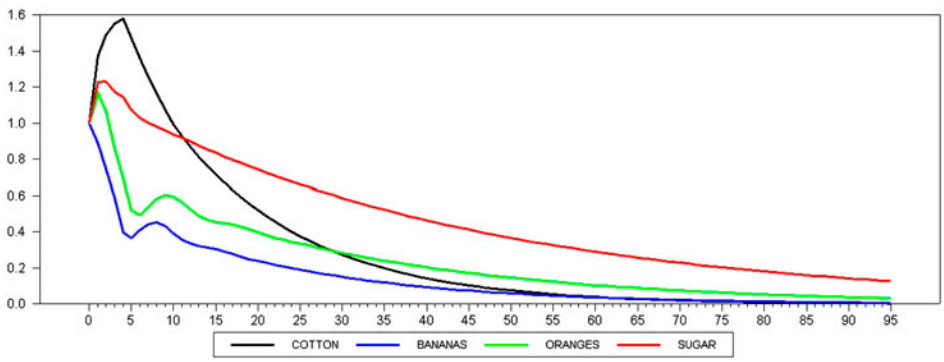

Figure 4. Univariate IRF comparison in the *CBOS* commodity group.

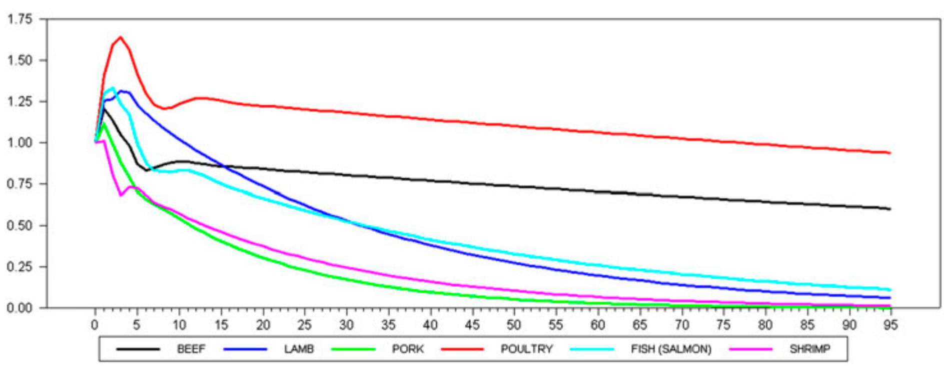

Figure 5. Univariate IRF comparison in the *MASE* commodity group.

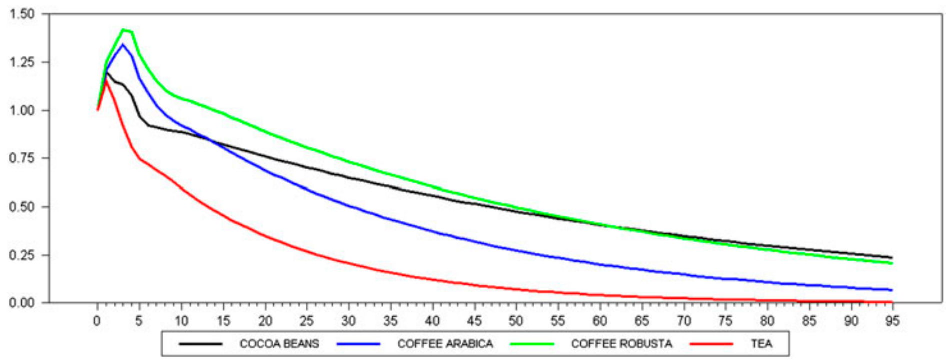

Figure 6. Univariate IRF comparison in the *BEVE* commodity group.

greatest persistence, with about 93.8% for the former and 60.5% for the latter, in the 96 months since the initial shock.

Beverages (BEVE). With respect to the *BEVE* (beverages) commodity group (Figure 6), the highest response of about 141.7% is shown by *COFR* (coffee Robusta), followed by *COFR* (coffee Arabica) with about 134% and then by *COCB* (cocoa beans) with about 113.2%, in the four months after the shock. Furthermore, the greatest persistence is shown by *COCB* (cocoa beans) and COFR (coffee Robusta) with about 23.6% for the former and about 20.8% for the latter, in the 96 months after the initial shock.

Fertilizers (FERT). Finally, Figure 7 presents the *IRFs* for the group of *FERT* (fertilizers), indicating that in the twelve months after the initial shock, *POTA* (potassium) shows the highest response of about 247%, followed by *TSP* (triple superphosphate) with about 215.2% and *PHOS* (phosphate rock) with about 204.9%. Moreover, the greatest persistence is shown by *POTA* (potassium), *UREA* (urea) and *PHOS* (phosphate rock), with about 92.7%, 30.4% and 26.9% in the 96 months since the initial shock, respectively.

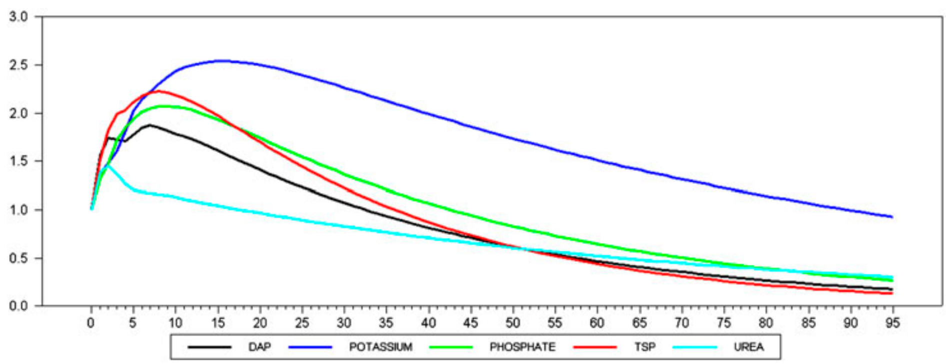

Figure 7. Univariate IRF comparison in the *FERT* commodity group.

4.2. Full panel VAR and findings

Turning now to the full panel VAR case, the same aforementioned six groups of commodities are considered but in this case $G = 3$ (commodity price, crude oil price (*OILP*) and US exchange rate (*EXCR*)). Thus, for example, model (7) becomes as follows:

$$
\begin{aligned}
\ln CERL_{it} &= \alpha_i + \sum_{l=1}^{p} \beta_{11li} \ln CERL_{i,t-l} + \sum_{l=1}^{p} \beta_{12li} \ln OILP_{i,t-l} + \sum_{l=1}^{p} \beta_{13li} \ln EXCR_{i,t-l} + u_{1it} \\
\ln OILP_{it} &= \alpha_{1i} + \sum_{l=1}^{p} \beta_{21li} \ln CERL_{i,t-l} + \sum_{l=1}^{p} \beta_{22li} \ln OILP_{i,t-l} + \sum_{l=1}^{p} \beta_{23li} \ln EXCR_{i,t-l} + u_{2it} \\
\ln EXCR_{it} &= \alpha_{3i} + \sum_{l=1}^{p} \beta_{31li} \ln CERL_{i,t-l} + \sum_{l=1}^{p} \beta_{32li} \ln OILP_{i,t-l} + \sum_{l=1}^{p} \beta_{33li} \ln EXCR_{i,t-l} + u_{3it} \\
& \textit{for } l = 1, \ldots, 6;\ t = 1983{:}06 \textit{ to } 2013{:}06
\end{aligned}
\tag{8}
$$

Similar models to equation (8) are developed for the rest of the commodity groups (*VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*). The empirical results of the present paper were obtained based on the ordering of variables presented in model (8). A change of the ordering of the variables does not alter significantly the main conclusions of the present paper. Six numbers of lags are supported by the Akaike Information Criterion (AIC) and the Schwarz Bayesian criterion (SBC). The estimation of model (8) is based on the shrinkage estimators of the full panel VARs presented by Doan (2012). In this case, as opposed to the univariate autoregression, the coefficients are scale-dependent. Again, the Minnesota prior is used and it starts with an (OLS) univariate autoregression on each of the dependent variables in order to adjust the scale.

Table 2 shows the cumulative effects of each of the autoregressive right-hand variables of the VAR model, estimated using OLS. For example, the cumulative effect of the β_{11} coefficient of model (8) on the dependent variable *ln CERL* is given by the sum: $\sum_{l=1}^{p} \beta_{11l}$, where $p = 6$ (six numbers of lags are considered). The *IRFs* are created by generating unit shocks to all the variables. Figures 8–13 present the *IRFs* corresponding to the *CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT* commodity groups, respectively. The variable shocked is presented in the column, while the target variable is in the row.

Table 3 presents panel Granger causality tests between each agricultural commodity sub-group (*CERL*, *VOPM*, *CBOS*, *MASE* and *BEVE*), oil prices (*OILP*) and exchange rates (*EXCR*). Note that the same table presents Granger causality tests between each individual commodity price, oil prices and exchange rates. In the same manner, Table 4 presents panel Granger causality tests for fertilizer prices, oil prices and exchange rates, while Table 5 provides overall panel Granger causality tests between the agricultural commodity price group (*AGCP*), oil prices (*OILP*) and exchange rates (*EXCR*). The aforementioned Granger causality test results are obtained following Doan (2012). The null hypothesis is that there is no Granger causality in an individual member of the panel, while the alternative is that there is Granger causality in at least one. In the case of model (8), the null hypothesis that oil prices (*OILP*) Grange cause cereal prices (*CERL*) could be described by the following joint test: $\beta_{12li} = 0$ for all $i = 1,2,\ldots,6$. Meanwhile, the alternative hypothesis holds when at least one of the β_{12li} for i = 1,2,…,6 is different from zero. Rejection

Table 2. Cumulative effects of the right hand lagged variables of the VAR model (8) and their corresponding F-statistics and p-values for six groups.

Equations	Cumulative Effects and F-statistics [p-values]		
Cereals (*CERL*) Ln*CERL*	$\sum_{l=1}^{6} \beta_{11l} = 0.9864$ F-statistic=15782.5 [0.0000]	$\sum_{l=1}^{6} \beta_{12l} = 0.0068$ F-statistic=4.0097 [0.0005]	$\sum_{l=1}^{6} \beta_{13l} = 0.0439$ F-statistic=4.5508 [0.0001]
Ln*OILP*	$\sum_{l=1}^{6} \beta_{21l} = 0.0019$ F-statistic=4.2484 [0.0003]	$\sum_{l=1}^{6} \beta_{22l} = 0.9931$ F-statistic=17900.3 [0.0000]	$\sum_{l=1}^{6} \beta_{23l} = 0.0284$ F-statistic=6.4988 [0.0000]
Ln*EXCR*	$\sum_{l=1}^{6} \beta_{31l} = 0.0006$ F-statistic=2.2017 [0.0402]	$\sum_{l=1}^{6} \beta_{32l} = 0.0004$ F-statistic=7.1461 [0.0000]	$\sum_{l=1}^{6} \beta_{33l} = 0.9821$ F-statistic=15541.4 [0.0000]
	Vegetable Oils and Protein Meal (*VOPM*) Cumulative Effects and F-statistics [p-values]		
Ln*VOPM*	$\sum_{l=1}^{6} \beta_{11l} = 0.9957$ F-statistic=90636.3 [0.0000]	$\sum_{l=1}^{6} \beta_{12l} = 0.0023$ F-statistic=6.0780 [0.0000]	$\sum_{l=1}^{6} \beta_{13l} = 0.0308$ F-statistic=6.4073 [0.0000]
Ln*OILP*	$\sum_{l=1}^{6} \beta_{21l} = 0.0010$ F-statistic=1.6466 [0.1302]	$\sum_{l=1}^{6} \beta_{22l} = 0.9939$ F-statistic=35972.6 [0.0000]	$\sum_{l=1}^{6} \beta_{23l} = 0.0333$ F-statistic=10.3701 [0.0000]
Ln*EXCR*	$\sum_{l=1}^{6} \beta_{31l} = 0.0003$ F-statistic=2.5193 [0.0196]	$\sum_{l=1}^{6} \beta_{32l} = 0.0004$ F-statistic=11.4813 [0.0000]	$\sum_{l=1}^{6} \beta_{33l} = 0.9826$ F-statistic=27196.9 [0.0000]
	Cotton-Bananas-Orange-Sugar (*CBOS*) Cumulative Effects and F-statistics [p-values]		
Ln*CBOS*	$\sum_{l=1}^{6} \beta_{11l} = 0.9887$ F-statistic=8867.8 [0.0000]	$\sum_{l=1}^{6} \beta_{12l} = 0.0039$ F-statistic=0.3325 [0.9200]	$\sum_{l=1}^{6} \beta_{13l} = 0.0337$ F-statistic=0.7565 [0.6042]
Ln*OILP*	$\sum_{l=1}^{6} \beta_{21l} = 0.0010$ F-statistic=1.4601 [0.1884]	$\sum_{l=1}^{6} \beta_{22l} = 0.9941$ F-statistic=14797.9 [0.0000]	$\sum_{l=1}^{6} \beta_{23l} = 0.0341$ F-statistic=4.2150 [0.0003]

(*Continued*)

Table 2. (*Continued*).

Equations	Cumulative Effects and F-statistics [*p*-values]		
Ln*EXCR*	$\sum_{l=1}^{6} \beta_{31l} = 0.0002$	$\sum_{l=1}^{6} \beta_{32l} = 0.0006$	$\sum_{l=1}^{6} \beta_{33l} = 0.9819$
	F-statistic=0.4938 [0.8134]	F-statistic=4.4348 [0.0002]	F-statistic=10639.5 [0.0000]
	Meat & Seafood (*MASE*) Cumulative Effects and F-statistics [*p*-values]		
Ln*MASE*	$\sum_{l=1}^{6} \beta_{11l} = 0.9980$	$\sum_{l=1}^{6} \beta_{12l} = 0.0027$	$\sum_{l=1}^{6} \beta_{13l} = 0.0073$
	F-statistic=75667.9 [0.0000]	F-statistic=3.1092 [0.0049]	F-statistic=2.0631 [0.0545]
Ln*OILP*	$\sum_{l=1}^{6} \beta_{21l} = 0.0003$	$\sum_{l=1}^{6} \beta_{22l} = 0.9944$	$\sum_{l=1}^{6} \beta_{23l} = 0.0383$
	F-statistic=0.8759 [0.5117]	F-statistic=23409.6 [0.0000]	F-statistic=6.4939 [0.0000]
Ln*EXCR*	$\sum_{l=1}^{6} \beta_{31l} = 0.00005$	$\sum_{l=1}^{6} \beta_{32l} = 0.0005$	$\sum_{l=1}^{6} \beta_{33l} = 0.9824$
	F-statistic=0.3841 [0.8896]	F-statistic=6.6533 [0.0000]	F-statistic=16622.4 [0.0000]
	Beverage (*BEVE*) Cumulative Effects and F-statistics [*p*-values]		
Ln*BEVE*	$\sum_{l=1}^{6} \beta_{11l} = 0.9793$	$\sum_{l=1}^{6} \beta_{12l} = 0.0078$	$\sum_{l=1}^{6} \beta_{31l} = 0.0071$
	F-statistic=7318.9 [0.0000]	F-statistic=2.3735 [0.0276]	F-statistic=1.0570 [0.3865]
Ln*OILP*	$\sum_{l=1}^{6} \beta_{21l} = 0.0033$	$\sum_{l=1}^{6} \beta_{22l} = 0.9954$	$\sum_{l=1}^{6} \beta_{23l} = 0.0372$
	F-statistic=1.4797 [0.1814]	F-statistic=13920.5 [0.0000]	F-statistic=4.4143 [0.0002]
Ln*EXCR*	$\sum_{l=1}^{6} \beta_{31l} = 0.0304$	$\sum_{l=1}^{6} \beta_{32l} = 0.0005$	$\sum_{l=1}^{6} \beta_{33l} = 0.9822$
	F-statistic=2.0304 [0.0588]	F-statistic=4.2511 [0.0003]	F-statistic=11012.4 [0.0000]
	Fertilizer (*FERT*) Cumulative Effects and F-statistics [*p*-values]		
Ln*FERT*	$\sum_{l=1}^{6} \beta_{11l} = 0.9902$	$\sum_{l=1}^{6} \beta_{12l} = 0.0081$	$\sum_{l=1}^{6} \beta_{13l} = 0.0353$
	F-statistic=28134.9 [0.0000]	F-statistic=4.6740 [0.0001]	F-statistic=4.6740 [0.0001]
Ln*OILP*			

(*Continued*)

Table 2. (*Continued*).

Equations	Cumulative Effects and F-statistics [*p*-values]		
	$\sum_{l=1}^{6}\beta_{21l}=0.0016$	$\sum_{l=1}^{6}\beta_{22l}=0.9932$	$\sum_{l=1}^{6}\beta_{23l}=0.0334$
	F-statistic=2.1732 [0.0429]	F-statistic=12799.0 [0.0000]	F-statistic=5.3281 [0.0000]
Ln*EXCR*	$\sum_{l=1}^{6}\beta_{31l}=0.0003$	$\sum_{l=1}^{6}\beta_{31l}=0.0002$	$\sum_{l=1}^{6}\beta_{33l}=0.9836$
	F-statistic=1.9999 [0.0626]	F-statistic=5.3999 [0.0000]	F-statistic=13214.8 [0.0000]

Number in brackets are *p*-values.

of the null of non-causality means that causality is found in some (although not necessarily all) of the individual members of the panel. For this reason, it is worth displaying the results of both the joint test and the individual tests. Furthermore, it is possible for all the individual tests to be insignificant at conventional significance levels while the joint test is strongly significant. According to Doan (2012), this is not unexpected, since the joint test is based on the whole panel and thus provides more and better information than the individual tests, which are based on individual members (samples) of the panel.

4.2.1. Multivariate impulse response functions (IRFs)

Figures 8–13 show the *IRFs* for the commodity prices (*CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*), *OILP* (oil prices) and *EXCR* (exchange rates). The greatest response of each variable is attributed to its own shock. This is also supported by the cumulative effects presented in Table 2, in which all these effects are statistically different from zero at any conventional level of significance and greater than the value of 0.98. Among the *CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT* commodity groups, the greatest persistence is shown by *BARLEY* (barley), *FISM* (fishmeal), *COOT* (cotton), *POUL* (poultry), *COFR* (coffee Robusta) and *POTA* (potassium), respectively. These results are in accordance with those obtained in the univariate autoregression case (model 7).

IRFs of commodity prices due to one unit shock in OILP. In general, the *IRFs* of the commodity prices (*CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*) due to one unit shock in *OILP* (oil prices) indicate a positive response for most of the commodities in each commodity group. Specifically, Figures 8–13 indicate that the highest response is shown by *BARLEY* (barley), *OLIO* (olive oil), *ORAN* (oranges), *POUL* (poultry), *COCB* (cocoa beans) and *POTA* (potassium) for the commodity groups *CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*, respectively. The positive responses of the commodity prices to the *OILP* (oil prices) are also supported by the corresponding positive cumulative effects $\left(\sum_{l=1}^{6}\beta_{12l}\right)$ presented in Table 2.

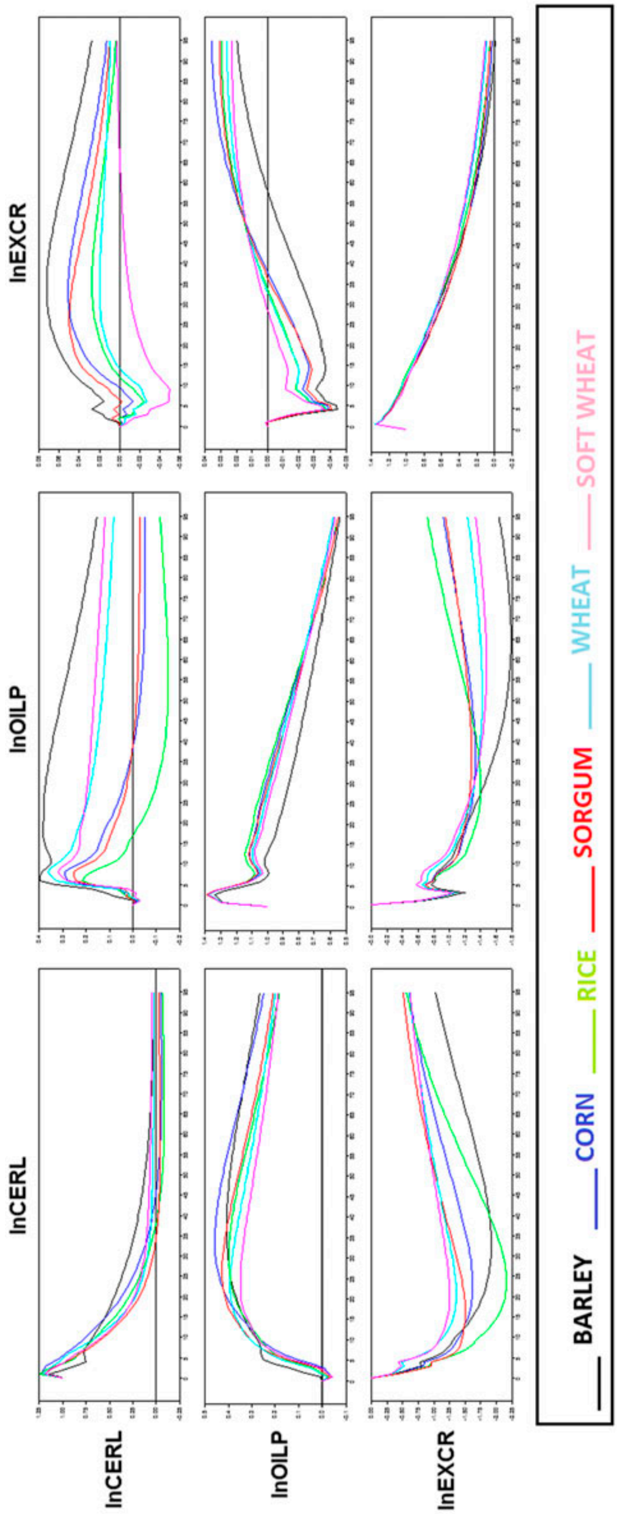

Figure 8. Full VAR-IRF comparison in the *CERL* commodity group.

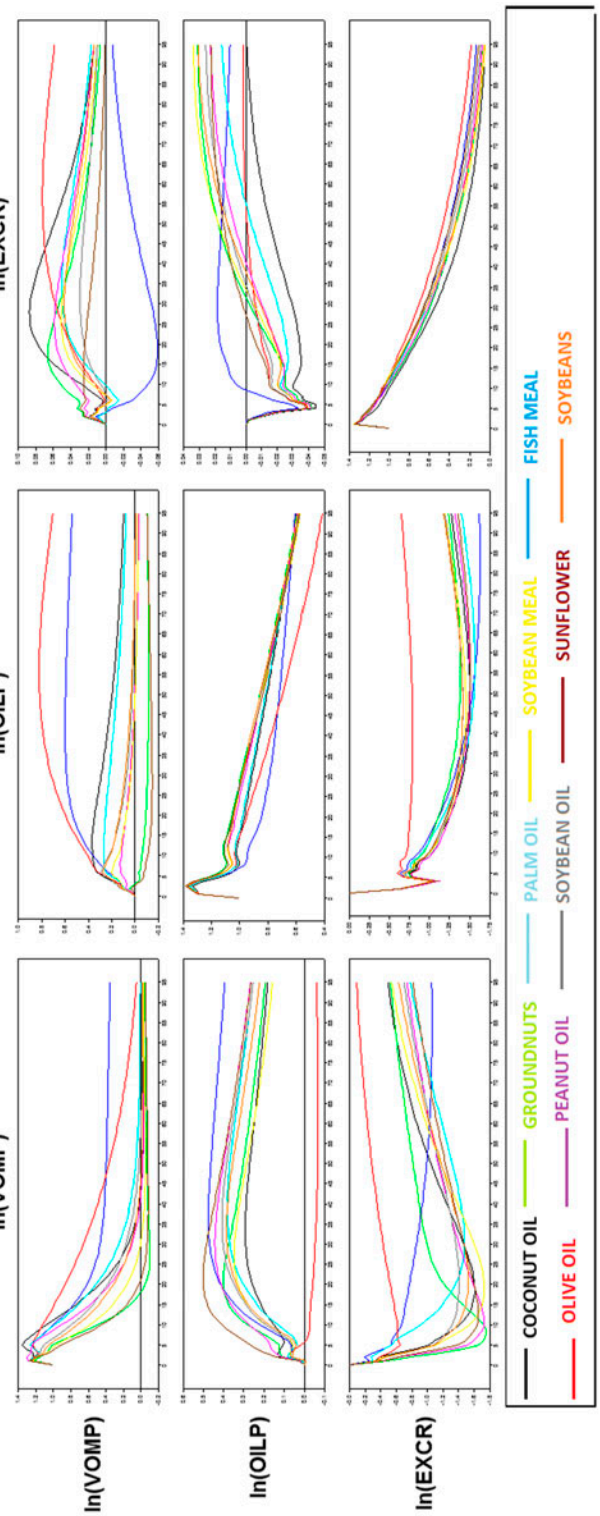

Figure 9. Full VAR-IRF comparison in the *VOMP* commodity group.

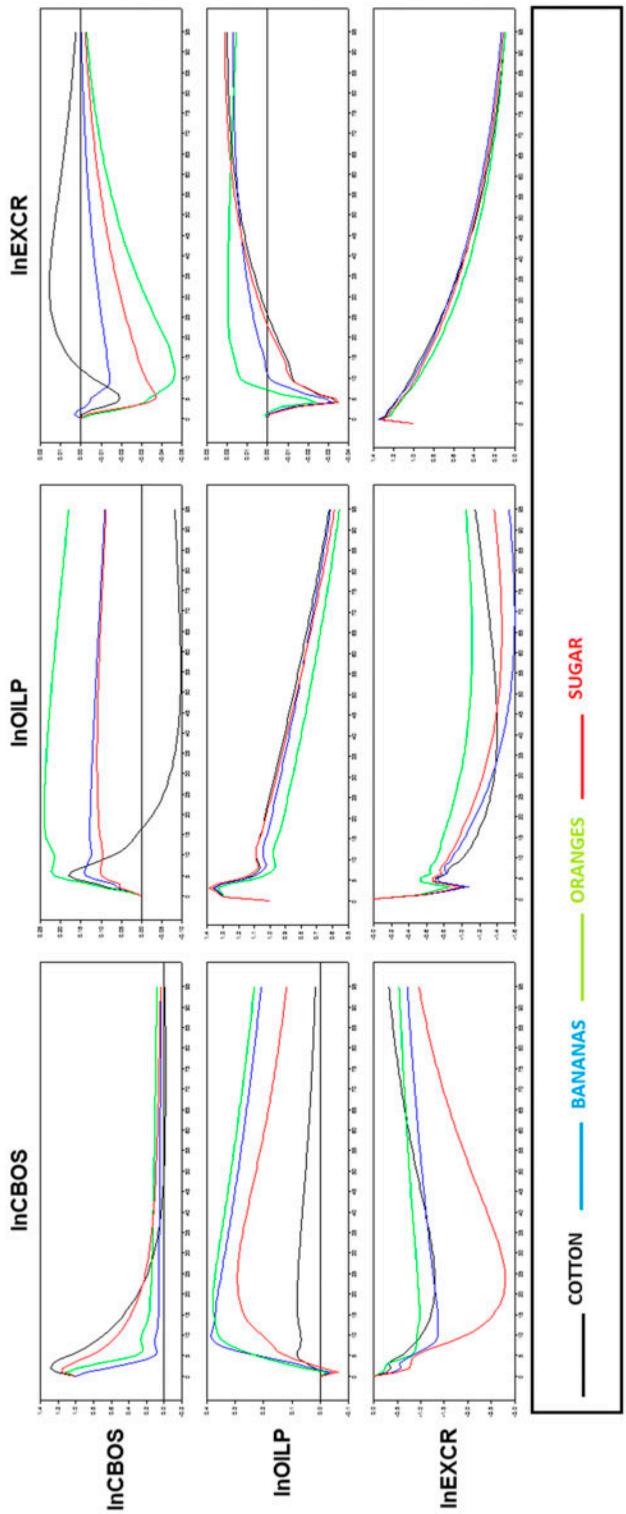

Figure 10. Full VAR-IRF comparison in the *CBOS* commodity group.

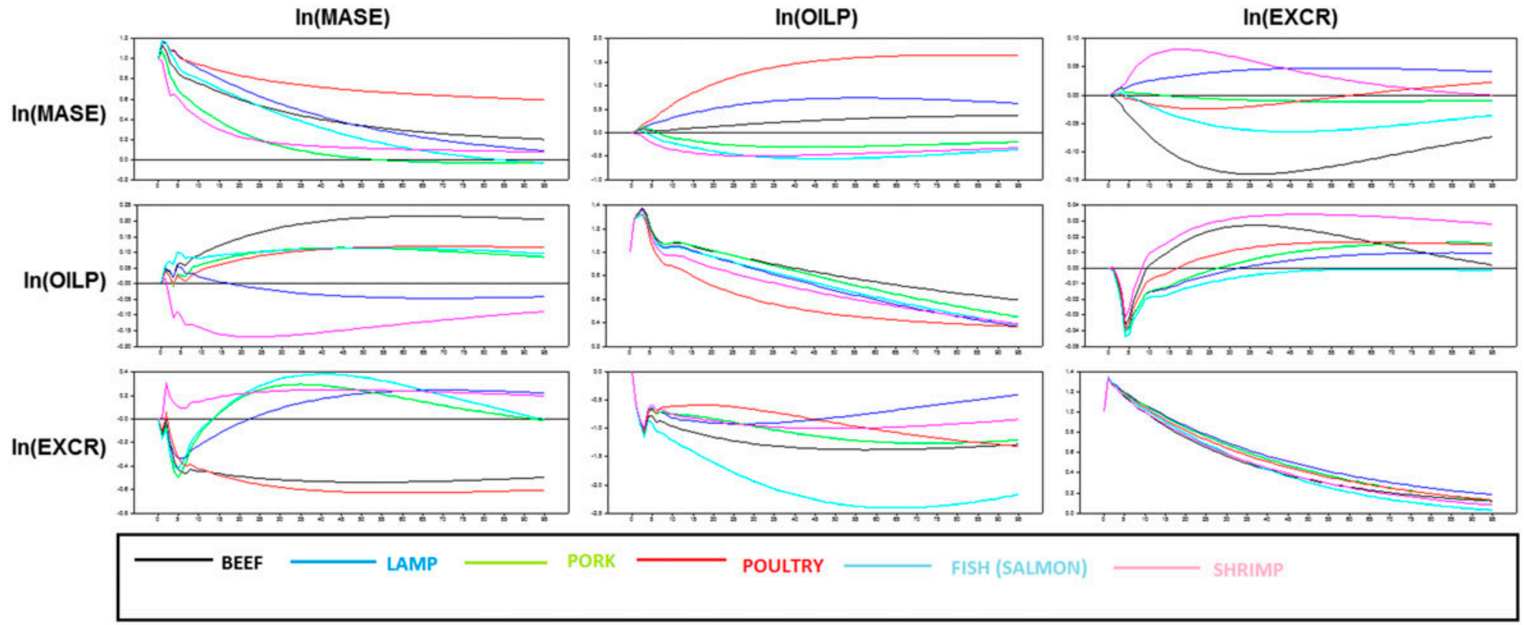

Figure 11. Full VAR-IRF comparison in the *MASE* commodity group.

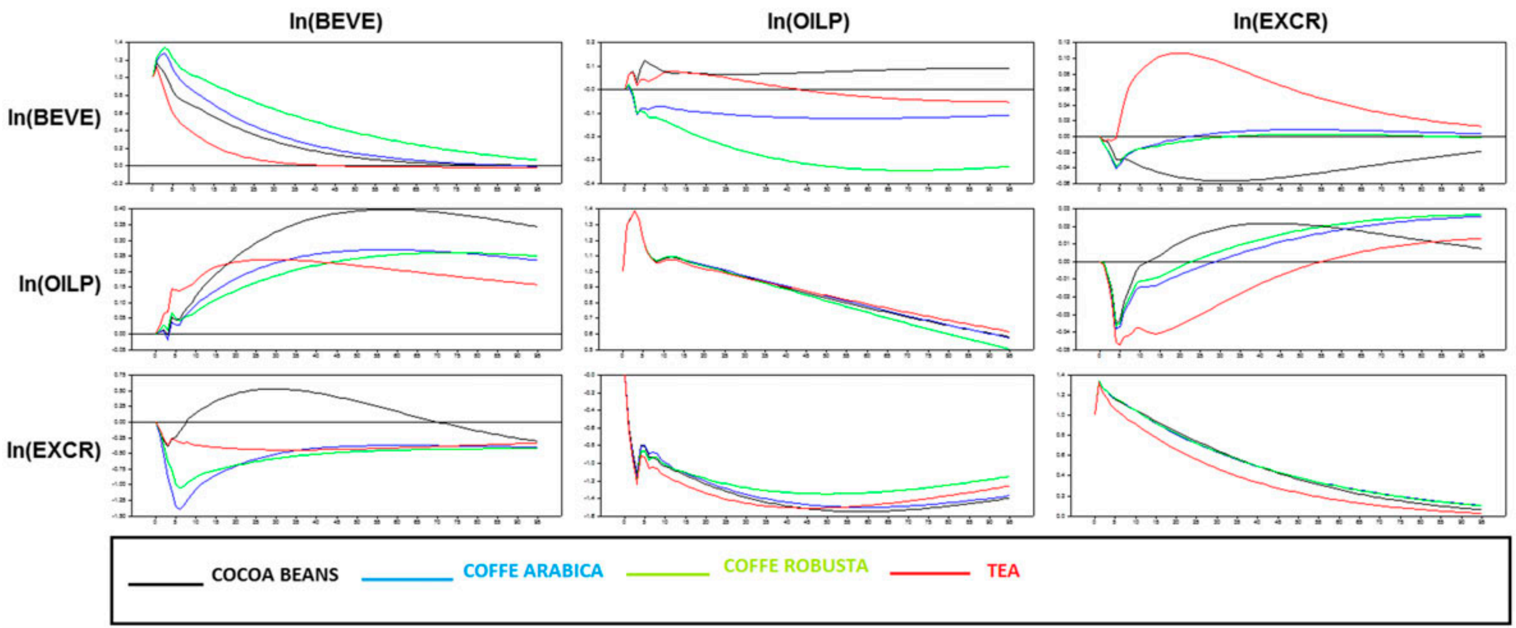

Figure 12. Full VAR-IRF comparison in the *BEVE* commodity group.

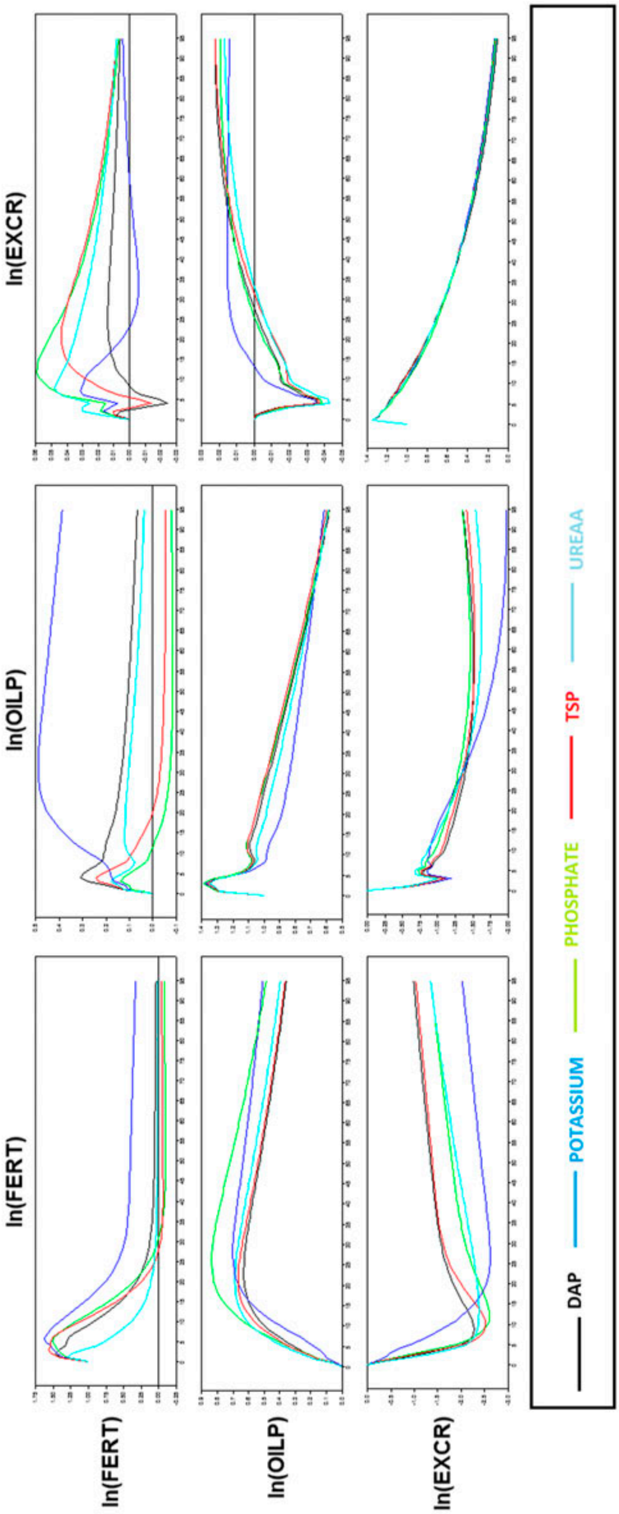

Figure 13. Full VAR-IRF comparison in the *FERT* commodity group.

Table 3. Panel and individual Granger causality test results (F-statistics and p-values) between agricultural commodities, crude oil and exchange rate.

	Crude oil (*OILP*) price	Exchange rate (*EXCR*)	Crude oil (*OILP*) price	Exchange rate (*EXCR*)
Agricultural Commodity Price(*AGCP*)	Null hypothesis:OILP does not cause AGCP $\nleftarrow$	Null hypothesis:EXCR does not cause AGCP $\nleftarrow$	Null hypothesis:AGCP does not cause OILP $\nrightarrow$	Null hypothesis:AGCP does not cause EXCR $\nrightarrow$
Cereals (*CERL*)	92.094^{***}[0.0000] $\leftarrow$	64.616^{***}[0.00237] $\leftarrow$	59.187^{***}[0.00878] $\rightarrow$	44.29[0.16158] $\nrightarrow$
Barley (*BARL*)	11.599^{*}[0.07154] $\leftarrow$	11.4^{*}[0.07678] $\leftarrow$	7.093[0.31234] $\nrightarrow$	11.685^{*}[0.06937] $\rightarrow$
Corn (*CORN*)	14.931^{**}[0.0208] $\leftarrow$	10.013[0.12412] $\nleftarrow$	8.308[0.21641] $\nrightarrow$	5.993[0.424] $\nrightarrow$
Rice (*RICE*)	11.892^{*}[0.06441] $\leftarrow$	12.897^{**}[0.0447] $\leftarrow$	10.232[0.1152] $\nrightarrow$	9.412[0.15168] $\nrightarrow$
Sorghum (*SORG*)	13.866^{**}[0.03117] $\leftarrow$	11.717^{**}[0.06859] $\leftarrow$	6.606[0.35886] $\nrightarrow$	5.597[0.46985] $\nrightarrow$
Wheat (*WHEH*)	19.97^{***}[0.0028] $\leftarrow$	10.888^{*}[0.09188] $\leftarrow$	11.893^{*}[0.0644] $\rightarrow$	6.874[0.33266] $\nrightarrow$
Soft Red Winter Wheat (*WHES*)	19.836^{***}[0.00296] $\leftarrow$	7.701[0.26082] $\nleftarrow$	15.056^{**}[0.01983] $\rightarrow$	4.729[0.57898] $\nrightarrow$
Vegetable Oils and Protein Meals (*VOPM*)	162.188^{***}[0.0000] $\leftarrow$	104.308^{***}[0.00034] $\leftarrow$	53.342[0.71579] $\nrightarrow$	67.804[0.22846] $\nrightarrow$
Coconut Oil (*COCO*)	13.3^{**}[0.03851] $\leftarrow$	5.691[0.45864] $\nleftarrow$	5.236[0.51397] $\nrightarrow$	10.864^{*}[0.09269] $\rightarrow$
Fishmeal (*FISM*)	19.974^{***}[0.0028] $\leftarrow$	10.788^{*}[0.09515] $\leftarrow$	6.267[0.39395] $\nrightarrow$	3.876[0.69346] $\nrightarrow$
Groundnuts (*GRON*)	24.647^{***}[0.0004] $\leftarrow$	14.525^{**}[0.02429] $\leftarrow$	9.207[0.16228] $\nrightarrow$	7.345[0.29011] $\nrightarrow$
Olive Oil (*OLIO*)	5.116[0.529] $\nleftarrow$	8.492[0.20423] $\nleftarrow$	5.161[0.52329] $\nrightarrow$	6.162[0.40526] $\nrightarrow$
Palm Oil (*PALO*)	12.883^{*}[0.04493] $\leftarrow$	5.223[0.51548] $\nleftarrow$	7.937[0.24277] $\nrightarrow$	7.328[0.29159] $\nrightarrow$

(Continued)

Table 3. (*Continued*).

	Crude oil (*OILP*) price	Exchange rate (*EXCR*)	Crude oil (*OILP*) price	Exchange rate (*EXCR*)
Peanut Oil (*PEAO*)	15.058**[0.01981] $\leftarrow$	18.825***[0.00447] $\leftarrow$	0.453[0.99836] $\nrightarrow$	6.315[0.38883] $\nrightarrow$
Soybean Meal (*SOYM*)	17.899***[0.00649] $\leftarrow$	13.315**[0.03829] $\leftarrow$	3.27[0.77432] $\nrightarrow$	10.906*[0.09134] $\rightarrow$
Soybean Oil (*SOYO*)	15.95**[0.01402] $\leftarrow$	5.4[0.49359] $\nleftarrow$	6.853[0.33467] $\nrightarrow$	3.075[0.79942] $\nrightarrow$
Soybeans (*SOYB*)	16.305**[0.01221] $\leftarrow$	10.4*[0.1088] $\leftarrow$	6.74[0.34557] $\nrightarrow$	7.701[0.26084] $\nrightarrow$
Sunflower (*SUNF*)	21.055***[0.00179] $\leftarrow$	11.647*[0.07032] $\leftarrow$	2.219[0.89853] $\nrightarrow$	4.233[0.6452] $\nrightarrow$
CBOS	75.682***[0.0000] $\leftarrow$	57.035***[0.00017] $\leftarrow$	25.816[0.36259] $\nrightarrow$	47.785***[0.00268] $\rightarrow$
Cotton (*COTT*)	5.961[0.42763] $\nleftarrow$	15.192**[0.01881] $\leftarrow$	8.538[0.2013] $\nrightarrow$	19.389***[0.00355] $\rightarrow$
Bananas (*BANA*)	36.669***[0.0000] $\leftarrow$	15.649**[0.01577] $\leftarrow$	7.82[0.25159] $\nrightarrow$	6.069[0.41551] $\nrightarrow$
Oranges (*ORAN*)	17.584***[0.00736] $\leftarrow$	8.923[0.17793] $\nleftarrow$	6.601[0.35936] $\nrightarrow$	13.588**[0.03459] $\rightarrow$
Sugar (*SUGA*)	15.469**[0.0169] $\leftarrow$	17.27***[0.00834] $\leftarrow$	2.857[0.82653] $\nrightarrow$	8.739[0.18881] $\nrightarrow$
Meat & Seafood (*MASE*)	65.655***[0.00183] $\leftarrow$	40.785[0.26809] $\nleftarrow$	52.618**[0.03634] $\rightarrow$	35.755[0.48016] $\nrightarrow$
Beef (*BEEF*)	6.443[0.37543] $\nleftarrow$	3.525[0.74064] $\nleftarrow$	7.073[0.31417] $\nrightarrow$	7.171[0.30532] $\nrightarrow$
Lamb (*LAMB*)	11.503*[0.07401] $\leftarrow$	7.75[0.25702] $\nleftarrow$	4.692[0.58385] $\nrightarrow$	5.823[0.4433] $\nrightarrow$
Pork (PORK)	8.367[0.21246] $\nleftarrow$	9.614[0.14189] $\nleftarrow$	10.902*[0.09146] $\rightarrow$	5.69[0.45876] $\nrightarrow$

(*Continued*)

Table 3. (*Continued*).

	Crude oil (*OILP*) price	Exchange rate (*EXCR*)	Crude oil (*OILP*) price	Exchange rate (*EXCR*)
Poultry (*POUL*)	14.045** [0.02914] $\longleftarrow$	6.076[0.41474] $\not\longleftarrow$	19.663*** [0.00318] $\longrightarrow$	2.207[0.89967] $\not\longrightarrow$
Fish (salmon) (*SALM*)	13.75** [0.03255] $\longleftarrow$	10.025[0.1236] $\not\longleftarrow$	6.242[0.39665] $\not\longrightarrow$	4.956[0.54943] $\not\longrightarrow$
Shrimp (*SHRI*)	11.547* [0.07288] $\longleftarrow$	3.796[0.70425] $\not\longleftarrow$	4.046[0.67047] $\not\longrightarrow$	9.907[0.12863] $\not\longrightarrow$
Beverages (*BEVE*)	33.189* [0.10016] $\longleftarrow$	25.678[0.3697] $\not\longleftarrow$	23.308[0.50168] $\not\longrightarrow$	38.907** [0.02793] $\longrightarrow$
Cocoa Beans (*COCB*)	8.746[0.18835] $\not\longleftarrow$	7.25[0.29834] $\not\longleftarrow$	7.936[0.24286] $\not\longrightarrow$	5.542[0.47644] $\not\longrightarrow$
Coffee Arabica (*COFA*)	9.805[0.13309] $\not\longleftarrow$	6.388[0.38117] $\not\longleftarrow$	3.352[0.76349] $\not\longrightarrow$	3.894[0.69105] $\not\longrightarrow$
Coffee Robusta (*COFR*)	5.443[0.4884] $\not\longleftarrow$	6.364[0.3837] $\not\longleftarrow$	5.388[0.49514] $\not\longrightarrow$	4.427[0.61906] $\not\longrightarrow$
Tea (*TEA*)	9.194[0.16296] $\not\longleftarrow$	5.676[0.46041] $\not\longleftarrow$	6.633[0.35617] $\not\longrightarrow$	25.044*** [0.00034] $\not\longrightarrow$

Numbers are F-statistics while those in brackets are *p*-values. ***, **, * show statistical significance at 1%, 5% and 10% level of significance, respectively. The symbols $\longrightarrow$ and $\longleftarrow$ indicates the presence of Granger causality, while $\not\longrightarrow$ and $\not\longleftarrow$ indicate that Granger causality does not exist.

Table 4. Panel and individual Granger causality test results (F-statistics and p-values) between fertilizers, crude oil and exchange rate.

	Crude oil (OILP) price	Exchange rate (EXCR)	Crude oil (OILP) price	Exchange rate (EXCR)
Fertilizer (*FERT*)	Null Hypothesis:OILP does not cause FERT $\nleftarrow$	Null Hypothesis:EXCR does not cause FERT $\nleftarrow$	Null Hypothesis: $\nrightarrow$FERT does not cause OILP	Null Hypothesis:FERT does not cause EXCR $\nrightarrow$
Fertilizer (*FERT*)	127.127^{***}[0.00000] $\longleftarrow$	74.534^{***}[0.00001] $\longleftarrow$	34.493 [0.26155] $\nrightarrow$	29.864 [0.47262] $\nrightarrow$
DAP (diammonium phosphate)	26.722^{***}[0.00016] $\longleftarrow$	12.265^{*}[0.05632] $\longleftarrow$	6.065[0.41600] $\nrightarrow$	4.538 [0.60425] $\nrightarrow$
Potassium chloride (*POTA*)	33.960^{***}[0.00001] $\longleftarrow$	16.746^{**}[0.01026] $\longleftarrow$	2.596 [0.85762] $\nrightarrow$	5.663 [0.46198] $\nrightarrow$
Phosphate rock (*PHOS*)	21.680^{***}[0.00138] $\longleftarrow$	11.374^{*}[0.07748] $\longleftarrow$	6.216 [0.39947] $\nrightarrow$	5.496 [0.48192] $\nrightarrow$
TSP (triple superphosphate)	20.042^{***}[0.00272] $\longleftarrow$	16.940^{***}[0.00951] $\longleftarrow$	9.397 [0.15246] $\nrightarrow$	6.770 [0.34267] $\nrightarrow$
Urea (*UREA*)	24.724^{***}[0.00038] $\longleftarrow$	17.209^{***}[0.00855] $\longleftarrow$	10.220 [0.11567] $\nrightarrow$	7.397 [0.28567] $\nrightarrow$

Numbers are F-statistics while those in brackets are p-values. ***, **, * show statistical significance at 1%, 5% and 10% level of significance, respectively. The symbols $\longrightarrow$ and $\longleftarrow$ indicate the presence of Granger causality, while $\nrightarrow$ and $\nleftarrow$ indicate that Granger causality does not exist.

Table 5. Overall panel Granger causality test results (F-statistics and *p*-values) between, agricultural commodity, crude oil and exchange rate.

Null hypothesis	F-statistics [*p*-values]
OILP does not cause AGCP $\nrightarrow$	428.808^{***}[0.0000] $\longrightarrow$
EXCR does not cause AGCP $\nrightarrow$	292.422^{***}[0.0000] $\longrightarrow$
AGCP does not cause OILP $\nrightarrow$	214.271^{**}[0.04115] $\longrightarrow$
AGCP does not cause EXCR $\nrightarrow$	234.541^{***}[0.00389] $\longrightarrow$
OILP does not cause EXCR $\nrightarrow$	233.736^{***} [0.00433] $\longrightarrow$
EXCR does not cause OILP $\nrightarrow$	415.181^{***}[0.00000] $\longrightarrow$

Numbers are F-statistics while those in brackets are *p*-values. ***, ** show statistical significance at 1% and 5% level of significance, respectively. The symbol $\longrightarrow$ indicates the presence of Granger causality, while $\nrightarrow$ indicates that Granger causality does not exist.

IRFs of commodity prices due to one unit shock in EXCR. In a similar manner, the *IRFs* for the commodity prices (*CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*) due to one unit shock in *EXCR* (exchange rates) indicate a negative response for most of the commodities in each commodity group, at least during the first few months following the initial shock. More specifically, Figures 8–13 indicate that the highest response is shown by *BARLEY* (barley), *FISM* (fishmeal), *ORAN* (oranges), *BEEF* (beef), *COCB* (cocoa beans) and *DAP* for the commodity groups *CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*, respectively. The negative responses of the commodity prices to the *EXCR* (exchange rates) are also supported by the corresponding negative cumulative effects $\left(\sum_{l=1}^{6} \beta_{13l}\right)$ presented in Table 2, except in the case of *MASE* (meat and seafood), which is positive but statistically insignificant at the 5% level of significance.

IRFs of OILP due to one unit shock in commodity prices and EXCR. With regard to the responses of *OILP* (oil prices) to the one unit shock in commodity prices (*CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*) and *EXCR* (exchange rates), the *IRFs* presented in Figures 8–13 indicate a positive response to the former and a negative response to the latter. These results are also supported by the corresponding cumulative effects presented in Table 2. In particular, the response of the oil prices to the commodity prices $\left(\sum_{l=1}^{6} \beta_{21l}\right)$ is positive except in the cases of *MASE* (meat and seafood) and *BEVE* (beverages), in which it is negative but statistically insignificant, while the response of the oil prices to the exchange rates $\left(\sum_{l=1}^{6} \beta_{23l}\right)$ is negative and statistically significant.

IRFs of EXCR due to one unit shock in commodity prices and OILP. Finally, Figures 8–13 indicate that the responses of *EXCR* (exchange rates) to one unit shock in commodity prices (*CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*) and *OILP* (oil prices) are mostly negative during the first few months after the initial shock and then show a positive trend. Most of the corresponding cumulative effects corresponding to the commodity prices $\left(\sum_{l=1}^{6} \beta_{31l}\right)$ and to the oil prices $\left(\sum_{l=1}^{6} \beta_{32l}\right)$ that are shown in Table 2 highlight the positive trend of the *EXCR* (exchange rates) response, although the estimated effects are very close to zero, indicating a very weak cumulative effect.

4.2.2. Panel and individual Granger causality tests

Table 3 presents five panel Granger causality tests, each of which corresponds to each of the five agricultural commodity groups (*CERL, VOPM*, *CBOS*, *MASE* and *BEVE*), while Table 4 presents panel Granger tests for the fertilizer group. Furthermore, Tables 3 and 4 present individual Granger causality tests corresponding to each of the individual agricultural and fertilizer commodities, respectively. This is because rejection of the null hypothesis of non-causality indicates that causality is present in at least some of the individual members of the panel; thus, it is necessary to display the results of the joint (panel) Granger causality test as well as the individual Granger causality tests. Note that it is possible for all the individual Granger causality tests to be statistically insignificant while the joint Granger causality test is statistically significant. This is because the joint test gives more and better information, since it is based on the whole sample, than the individual tests, which are based on the individual samples. Finally, Table 5 provides panel Granger causality tests for the whole group of agricultural commodities, which contains the five aforementioned agricultural commodity subgroups, i.e. *CERL, VOPM*, *CBOS*, *MASE* and *BEVE*.

Table 3 indicates that in the case of *CERL* (*cereals*), the panel Granger causality tests show that crude oil prices Granger cause cereal prices; exchange rates Granger cause cereal prices; cereal prices Granger cause crude oil prices; and cereal prices do not Granger cause exchange rates. On the other hand, the Granger causality tests for the individual cereal commodities (i.e. *BARL*, *CORN*, *RICE*, *SORG*, *WHEH* and *WHES*) indicate that crude oil prices Grange cause all the individual cereal commodity prices; exchange rates Granger cause all the individual cereal commodity prices except *CORN* (corn price) and *WHES* (soft red winter wheat price); and among the cereal commodity prices only *WHEH* (wheat price) and *WHES* (soft red winter wheat price) Granger cause oil prices and only *BARL* (barley price) Granger causes exchange rates.

In the case of *VOPM* (*vegetable oils and protein meals*), the panel (joint) Granger causality tests show that crude oil prices Granger cause *VOPM* prices; exchange rates Granger cause *VOPM* prices; *VOPM* prices do not Granger cause crude oil prices; and *VOPM* prices do not Granger cause exchange rates. The individual Granger causality tests indicate that crude oil prices Granger cause all the individual *VOPM* commodity prices except *OLIO* (olive oil); exchange rates Granger cause all the individual *VOPM* commodity prices except *COCO* (coconut oil), *OLIO* (olive oil), *PALO* (palm oil) and *SOYB* (soybean oil); the prices of any individual *VOPM* commodity do not Granger cause crude oil prices; and among the individual *VOPM* commodity prices only the prices of *COCO* (coconut oil) and *SOYM* (soybean meal) Granger cause exchange rates.

The panel Granger causality tests for the *CBOS* (*cotton*, *bananas*, *oranges* and *sugar*) commodity group indicate that crude oil prices Granger cause *CBOS* prices; exchange rates Granger cause *CBOS* prices; *CBOS* prices do not Granger cause crude oil prices; and *CBOS* prices Granger cause exchange rates. The individual Granger causality tests indicate that crude oil prices Granger cause all the individual *CBOS* commodity prices except *COTT* (cotton); exchange rates Granger cause all the individual *CBOS* commodity prices except *ORAN* (oranges); the prices of any individual *CBOS* commodity do not Granger cause crude oil prices; and among the individual *CBOS* commodity prices the prices of *COTT* (cotton) and *ORAN* (oranges) Granger cause exchange rates while the prices of *BANA* (bananas) and *SUGA* (sugar) do not Granger cause exchange rates.

Moving on to the *MASE* (*meat and seafood*) commodity group, the panel Granger causality tests indicate that crude oil prices Granger cause *MASE* prices; exchange rates do not Granger cause *MASE* prices; *MASE* prices Granger cause crude oil prices; and *MASE* prices do not Granger cause exchange rates. The individual Granger causality tests show that crude oil prices Granger cause all the individual *MASE* commodity prices except *BEEF* (beef) and *PORK* (pork); exchange rates do not Granger cause any of the individual *MASE* commodity prices; among the individual *MASE* commodity prices only the prices of *PORK* (pork) and *POUL* (poultry) Granger cause oil prices and the prices of any individual *MASE* commodity do not Granger cause exchange rates.

The Granger causality tests presented at the bottom of Table 3 refer to *BEVE* (beverages). In particular, the panel Granger causality test indicates that crude oil prices Granger cause *BEVE* prices but the individual Granger causality tests indicate that crude oil prices do not cause any of the individual *BEVE* commodity prices. The joint (panel) and the individual Granger causality tests indicate that the exchange rates do not Granger cause the *BEVE* prices as a group as well as any individual *BEVE* commodity prices. Furthermore, the panel and the individual Granger causality tests indicate that *BEVE* prices as a group (as well as any individual *BEVE* commodity prices) do not Granger cause crude oil prices. Finally, the panel Granger causality test indicates that the *BEVE* prices as a group Granger cause exchange rates but the individual Granger causality tests indicate that among the individual *BEVE* commodity prices only the price of *TEA* (tea) Granger causes exchange rates.

Table 4 presents the panel and individual Granger causality tests for the *FERT* (fertilizer) commodity group. The panel and the individual Granger causality tests indicate that crude oil prices (exchange rates) Granger cause *FERT* prices as a group as well as individual *FERT* commodity prices. Furthermore, the joint and the individual Granger causality tests indicate that *FERT* prices as a group as well as any individual *FERT* commodity price do not Granger cause crude oil prices (exchange rates).

Table 5 presents the overall panel Granger causality tests, which are calculated based on the whole sample of 30 agricultural commodity prices (*AGCP*), which belong to the five agricultural commodity group categories considered in the present study (i.e. *CERL*, *VOPM*, *CBOS*, *MASE* and *BEVE*). The overall panel Granger test results indicate that crude oil prices (exchange rates) Granger cause *AGCP* and *AGCP* Granger causes oil prices (exchange rates). Finally, oil prices (exchange rates) Granger cause exchange rates (oil prices).

5. Conclusions

This study examines the relationship between crude oil prices, US dollar exchange rates and the prices of 30 selected international agricultural commodities (and five international fertilizer commodities) as well as five sub-groups of those commodities. The present study may be the first in the international literature to investigate the dynamic relationship between the aforementioned variables using panel VAR methods. In particular, this paper uses panel VAR models to obtain univariate impulse response functions, full VAR impulse response functions (i.e. multivariate impulse responses), the cumulative effects of the right-hand lagged variables of the VAR model and panel as well as individual Granger causality tests between the variables under consideration.

The univariate impulse response functions provide information about the response and persistence of commodity prices due to unit shocks to the mean estimates of each commodity group under consideration (i.e. *CERL*, *VOPM*, *CBOS*, *MASE*, *BEVE* and *FERT*). The multivariate impulse responses are obtained by creating unit shocks to all the variables under consideration (i.e. commodity prices, crude oil prices and US exchange rates). In general, the empirical results of the multivariate impulse responses as well as the cumulative effects indicate that: (i) the greatest response of each variable is attributed to itself,; (ii) the responses of commodity prices to changes in oil prices are positive, while those to changes in the US dollar exchange rates are negative; (iii) the responses of crude oil prices to changes in commodity prices are positive, while those to changes in the US dollar exchange rates are negative; and (iv) the impulse responses of the US dollar exchange rates due to one unit shock of commodity prices and crude oil prices are negative during the first few months after the shock and then show a positive trend, while the corresponding cumulative effects are positive but close to zero, indicating a weak cumulative positive response of the US dollar exchange rate to commodity and crude oil price changes.

The panel Granger causality test results show: (i) bidirectional causality between crude oil prices and *cereal* commodity group prices but unidirectional causality running from exchange rates to *cereal* group prices; (ii) unidirectional causalities running from crude oil prices and exchange rates to the *vegetable oils and protein meals* commodity group prices; (iii) unidirectional causality running from crude oil prices to the *cotton, bananas, oranges and sugar* commodity group prices but bidirectional causality between the aforementioned commodity group prices and exchange rates; (iv) bidirectional causality between crude oil prices and the *meat and seafood* commodity group prices but no causality between the aforementioned commodity group prices and exchange rates; (v) unidirectional causality from the crude oil prices to the *beverages* group prices as well as unidirectional causality from the *beverages* group prices to exchange rates; and (vi) unidirectional causalities running from crude oil prices and exchange rates to the *fertilizer* commodity group prices. Finally, the overall panel Granger causality tests, which are estimated based on the whole sample of 30 agricultural commodity prices, indicate bidirectional causality between: (i) crude oil prices and agricultural commodity group prices; (ii) exchange rates and agricultural commodity group prices; and (iii) crude oil prices and exchange rates.

The findings of the present study support the results of the study by Nazlioglu and Soytas (2012), which indicate that world oil prices as well as US dollar exchange rates affect agricultural commodity prices. Furthermore, contrary to the finding of several studies in the literature, the present study supports bidirectional panel causality with empirical evidence between world oil prices and international agricultural prices as well as between US exchange rates and international agricultural prices. These findings might be attributed to the use of panel data rather than time series data. As the studies by Doan (2013) and Nazlioglu and Soytas (2012) indicate, panel data sets provide increased power information than simple time series data sets since the latter derive information only from the time dimension of the sample while the former use both the time and the cross-sectional dimension.

References

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

Abbott, P. C., C. Hurt, and W. E. Tyner. 2011. "What's Driving Food Prices?" Issue Report, Farm Foundation, 2009-3.

Akram, Q. F. 2009. "Commodity Prices, Interest Rates and the Dollar." *Energy Economics* 31: 838–851.

Alquist, R., and O. Coibion. 2014. "Commodity Price Co-movement and Global Economic Activity." Bank of Canada Working Paper, August 2014-32.

Arshad, F. M., and A. A. A. Hameed. 2009. "The Long Run Relationship between Petroleum and Cereals Prices." *Global Economy & Finance Journal* 2 (2): 91–100.

Canova, F., and M. Ciccarelli. 2009. "Estimating Multi-country VAR Models." *International Economic Review* 50: 929–961.

Canova, F., and M. Ciccarelli. 2013. "Panel Vector Autoregressive Models: A Survey." Working Paper Series, European Central Bank, January No. 1507.

Canova, F., M. Ciccarelli, and E. Ortega. 2007. "Similarities and Convergence in G-7 Cycles." *Journal of Monetary Economics* 54: 850–878.

Chen, S.-T., H.-I. Kuo, and C.-C. Chen. 2010. "Modeling the Relationship between the Oil Price and Global Food Prices." *Applied Energy* 87: 2517–2525.

Ciaian, P., and d'A. Kancs. 2011. "Interdependences in the Energy-Bioenergy-Food Price Systems: A Cointegration Analysis." *Resource and Energy Economics* 33: 326–348.

Cooke, B., and M. Robles. 2009. *Recent Food Prices Movements: A Time Series Analysis*. Washington DC, USA: International Food Policy Research Institute.

Doan, T. A. 2012. *RATS Handbook for Panel and Grouped Data*. Draft Version, Estima.

Du, X., and L. L. McPhail. 2012. "Inside the Black Box: The Price Linkage and Transmission between Energy and Agricultural Markets." *The Energy Journal* 33: 171–194.

Enders, W. 2010. *Applied Econometric Time Series*. 3rd Edition, Hoboken, NJ: John Wiley & Sons.

Frank, J., and P. Garcia. 2010. "How Strong are the Linkages among Agricultural, Oil, and Exchange Rate Markets?" *Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, St. Louis, Mo.

Gilbert, C. L. 2010. "How to Understand High Food Prices." *Journal of Agricultural Economics* 61: 398–425.

Hameed, A. A. A., and F. M. Arshad. 2009. "The Impact of Petroleum Prices on Vegetable Oils Prices: Evidence from Co-integration Tests." *Oil Palm Industry Economic Journal* 9 (2): 31–40.

Harri, A., L. Nalley, and D. Hudson. 2009. "The Relationship between Oil, Exchange Rates, and Commodity Prices." *Journal of Agricultural and Applied Economics* 41: 501–510.

Headey, D., and S. Fan. 2008. "Anatomy of a Crisis: The Causes and Consequences of Surging Food Prices." *Agricultural Economics* 39 (1): 375–391.

Mitchell, D. 2008. "A Note on Rising Food Prices." Policy Research Working Paper 4682, Development Prospects Group, World Bank, Washington, DC, USA.

Nazlioglu, S., and U. Soytas. 2012. "Oil Price, Agricultural Commodity Prices, and the Dollar: A Panel Cointegration and Causality Analysis." *Energy Economics* 34: 1098–1104.

Pala, A. 2013. "Structural Breaks, Cointegration, and Causality by VECM Analysis of Crude Oil and Food Price." *International Journal of Energy and Policy* 3: 238–246.

Rezitis, A. N., and M. Sassi. 2013. “Commodity Food Prices: Review and Empirics.” *Economics Research International* 2013, Article ID 694507, 15 pages.

Robles, M., M. Torero, and J. von Braun. 2009. *When Speculation Matters*. International Food Policy Research Institute, Washington DC, USA.

Saghaian, S. H. 2010. “The Impact of the Oil Sector on Commodity Prices: Correlation or Causation?” *Journal of Agricultural and Applied Economics* 42: 477–485.

Schnepf, R. 2008. *High Agricultural Commodity Prices: What Are the Issues?* Hauppauge, NY, USA: Nova Science Publisher.

Sims, C. 1980. “Macroeconomics and Reality.” *Econometrica* 48: 1–49.

Sims, C., J. Stock, and M. W. Watson. 1990. “Inference in Linear Time Series Models with some Unit Roots.” *Econometrica* 58: 113–144.

Stock, J., and M. Watson. 1993. “A Simple Estimator of Cointegrating Vector in Higher Order Integrating Systems.” *Econometrica* 61: 783–820.

Timmer, C. P. 2009. “Did Speculation Affect World Rice Prices?” ESA Working Paper 09-07, FAO Agricultural Development Economics Division.

Trostle, R. 2008. “Fluctuating Food Commodity Prices. A Complex Issue with No Easy Answers.” *Amberwaves* 6: 10–17.

Wright, B. D. 2009. “International Grain Reserves and other Instruments to Address Volatility in Grain Markets.” Policy Research Working Paper 5028, The World Bank, Washington DC, USA.

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

Zhang, Z., L. Lohr, C. Escalante, and M. Wetzstein. 2010. “Food Versus Fuel: What Do Prices Tell Us?” *Energy Policy* 38: 445–451.