International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2015, 5(3), 851-868.

Empirical Analysis of Agricultural Commodity Prices, Crude Oil Prices and US Dollar Exchange Rates using Panel Data Econometric Methods

Anthony N. Rezitis*

Department of Economics and Management, University of Helsinki, P.O. Box 27, Latokartanokaari 9, FI-00014, Finland.
*Email: antonios.rezitis@helsinki.fi

ABSTRACT

This study examines the long-run relationship between crude oil prices, *US* dollar exchange rates *(EXCR*) and the prices of 30 selected international agricultural prices and five international fertilizer prices using panel econometric methods with and without unobserved heterogeneous effects on data sets of the period from June 1983 to June 2013. The empirical results indicate that in the long-run the impact of crude oil price changes on agricultural prices is positive and statistically significant, while the impact of US dollar *EXCR* changes is negative and statistically significant. Furthermore, the effect of US dollar *EXCR* changes on commodity prices is stronger than that of crude oil price changes. The present study estimates the speed of adjustment of agricultural commodity prices (*AGCP*) towards the long-run equilibrium and the empirical results indicate that *AGCP* adjust slowly towards the long-run equilibrium. Furthermore, the results of this study indicate that when unobserved heterogeneous effects with common factors are considered, the effects of oil prices and US dollar *EXCR*s on *AGCP* are much weaker than in the case in which such effects are not considered. Finally, the persistent movements of agricultural prices are mostly attributed to the first common factor, which is closely related to the US dollar *EXCR*, while the short-lived deviations of *AGCP* away from their long-run equilibrium level might be due to the remaining four stationary common factors, which are capturing factors affecting the world supply and demand conditions of the international agricultural prices.

Keywords: Agricultural Commodity Prices, Oil Prices, Exchange Rates, Panel Cointegration, Panel Error Correction, Unobserved Heterogeneity, Common Factors
JEL Classifications: O13, C01, C32

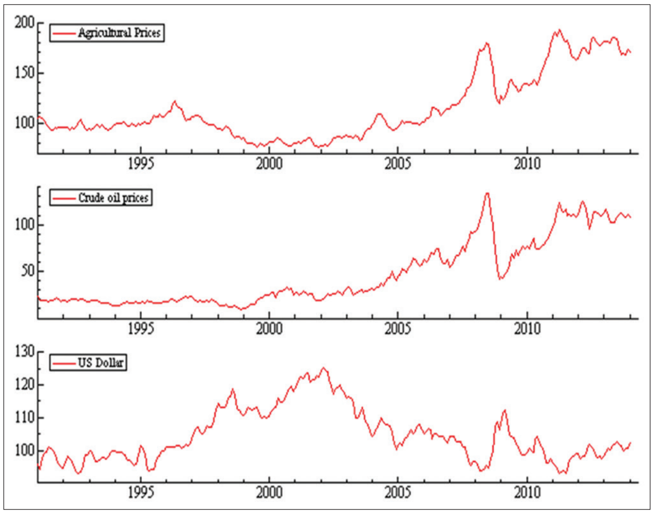
1. INTRODUCTION

Since the middle of 2000s, the world witnessed a remarkable increase of agricultural and fertilizer prices which has been coincided with an increase in world oil prices and a decline in the value of the US dollar (Figure 1). In particular, crude oil affects agricultural commodity (*AGCP*) production and thus *AGCP* through input prices (i.e. cost-push effects), since their production may depend in the use of crude oil. Furthermore, more increasingly recently, crude oil prices potentially affect at least some agricultural commodities (e.g. grains, sugar and vegetable oils) through competition in output markets for bio-fuel production. In other words, high crude oil prices make bio-fuel production more profitable and this causes increases in the prices of agricultural commodities used in bio-fuel production.

Since many agricultural commodities are priced in US dollars in international markets, a weaker dollar may increase the demand for agricultural commodities of foreign consumers and thus the prices of agricultural commodities. Note, that the price impact of the demand shift of agricultural commodities may be particularly large since it is believed that the demand and supply of these commodities are price inelastic. Another reason of the inverse relationship between *AGCP* and the US dollar exchange rate (*EXCR*) may be inflation. Investors and speculators invest in agricultural commodity futures when the US dollar depreciates because they are concerned about high inflation rates, thus driving up agricultural commodity and food prices (Rezitis and Sassi, 2013).

The purpose of this study is to examine the long-run relationship between crude oil prices, US dollar *EXCR* and the prices of

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



30 selected world agricultural commodities (and five fertilizer commodities). In order to analyze the relation between crude oil prices, US *EXCR*, and *AGCP* (as well as fertilizer prices), panel data econometric methods are employed on commodity price data sets based on monthly observations from June 1983 to June 2013. In particular, seven price data sets which are presented in Table 1 are used in the present study, of which the fist is consisted of 30 *AGCP*, the second of six cereal prices (*CERL*), the third of 10 vegetable oil and protein meals prices (*VOPM*), the forth of cotton, bananas oranges and sugar prices (*CBOS*), the fifth of six meat and seafood prices (*MASE*), the sixth of four beverage prices (*BEVE*) and the seventh of five fertilizer prices (*FERT*).

The panel econometric methods used in the present study attempt to capture the long-run dynamics between the series under consideration as well as the speed of adjustment towards the long-run equilibrium of *AGCP* in the case that these prices are found to be away from the long-run equilibrium. In particular, the present study uses panel econometric methods with and without unobserved cross-sectional dependence due to common factors (Baltagi, Ch. 12, 2008; Banerjee and Wagner, 2009; Verbeek, Ch. 10, 2012) to estimate the long-run equilibrium relationship between *AGCP*, crude oil prices and US dollar *EXCR*. The classical non-stationary panel data methods consider unobserved cross-sectional dependence with the use of dummy variables or with certain assumptions about the error term.[1] Moreover, unobserved heterogeneity across cross-sectional units is assumed to remain constant through time within each cross-sectional unit. More recent panel methods consider unobserved heterogeneity across cross-sectional units with the use of common factors and, thus, unobserved heterogeneity is allowed to have heterogeneous time trends across cross-sectional units. It has been shown that neglecting such effects may lead to serious biases in parameter estimates and wrong inference.

1 In this paper, the terminology "classical non-stationary panel data methods" refers to the "first-generation panel methods" (Verbeek, Ch. 10, p. 412, 2012)

The empirical results indicate that significant price dynamics exist in the long-run between the series under consideration and that *AGCP* adjust slowly towards the long-run equilibrium. An interesting finding of the present study is that the effects of crude oil prices and dollar *EXCR* on international agricultural prices become weaker when the unobserved heterogeneity across cross-sectional units with the use of common factors is taken into consideration.

This study contributes to the related literature in several ways. First, it is the first study to use panel econometric methods with and without unobserved heterogeneous effects, which are modeled by the factor structure to examine the long-run price dynamics between 30 *AGCP* (and five fertilizer prices) as well as subgroups of these commodities, crude oil prices and US dollar *EXCR*. Thus, the present study is able to compare and contrast the results provided by the two aforementioned panel econometric approaches. Among the previous literature, only two studies (i.e., Chen et al., 2010; Nazlioglou and Soytas, 2012) use similar methods to examine international commodity price dynamics. More specifically, the study by Nazlioglou and Soytas (2012) uses only classical non-stationary panel methods (i.e., without a factor structure) to examine the relationship between 24 *AGCP*, world oil prices and the US dollar, while the study by Chen et al. (2010) uses only panel econometric methods with common factors to examine the price dynamics of 51 tradable commodities. Second, among the classical non-stationary panel techniques used by the present study, the approach of Pesaran et al. (1997; 1999) is used to estimate the error correction structure of the international agricultural prices, crude oil prices and US dollar *EXCR*, while the study by Nazlioglou and Soytas (2012) uses the traditional Engle and Granger (1987) approach modified in a panel framework. More specifically, this approach falls into the category of traditional pool estimators (e.g., random-effects and fixed-effects estimators), in which the intercepts are allowed to differ across units while all the other estimated coefficients and error variances are constrained to be the same across units. On the other hand, the panel error correction model used in the present study allows the short-run coefficients and error variances to change among units (i.e., *AGCP*), thus allowing the dynamic specification to differ across units. Third, the panel error correction approach used in the present study (Pesaran et al., 1997; 1999) is a one-step estimation approach that is based on the estimation of an autoregressive distributed lag (ARDL) equation in which the short- and long-run coefficients are estimated simultaneously. Fourth, the present paper not only captures cross-sectional dependence across the individual commodity prices with the use of common factors by using the approaches of Bai (2009) and Kneip et al. (2012), but it also estimates the direct effects of crude oil prices and US *EXCR* on commodity prices. On the other hand, the study by Chen et al. (2010), while considering cross-sectional dependence and the factor structure by using the methodology of Bai and Ng (2004), does not estimate the direct effects of oil prices and US *EXCR* on commodity prices. Finally, the panel data econometric approaches used in the present study provide more and better information than the simple time series methods because the former derives information from both time and cross-sectional dimensions, but the latter only from the time dimension.

Table 1: Data description: Agricultural commodity, fertilizer, petroleum prices and *EXCR*

No.	Commodity	Description	Unit
1-30: 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% 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: VOPM			
7	Coconut oil (COCO)	Coconut oil (Philippines/Indonesia), bulk, CIF 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% FFA	US dollars per metric ton
12	Peanut oil (PEAO)	Any origin, CIF Rotterdam	US dollars per metric ton
13	Soybean meal (SOYM)	Chicago soybean meal futures (first contract forward) minimum 48% 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, CSCE contract No. 11 nearest future position	US cents per pound
21-26: Meat and 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	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	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. *EXCR*			
	EXCR	Real effective US dollar *EXCR*	Narrow index (2010=100)

Source: Items No. 1-No. 36 are obtained from: http://www.indexmundi.com/commodities/, Item No. 37 is obtained from http://www.bis.org/statistics/eer/. CSCE: Coffee sugar and cocoa exchange, DAP: Diammonium phosphate, TSP: Triple superphosphate, EXCR: Exchange rates, CBOS: Cotton, bananas oranges and sugar prices, VOPM: Vegetable oil and protein meals prices, AGCP: Agricultural commodity prices

The remainder of this paper is organized as follows. Section 2 presents and discusses the literature on the linkages of *AGCP*, oil prices and US dollar *EXCR*, focusing mainly on the long-run relationships between the aforementioned series. Section 3 presents the empirical model and the data, while Section 4 provides the econometric methods and the empirical results. Conclusions are drawn in Section 5.

2. LITERATURE REVIEW

The paper by Rezitis and Sassi (2013) reviews several studies analyzing factors influencing food prices. Among these factors are energy and fertilizer prices (Abbott et al., 2008; Mitchell, 2008; Trostle, 2008); neglected investment in R and D and infrastructure

(Abbott et al., 2008); high oil prices (Abbott et al., 2008); shocks in production (Schnepf, 2008); emerging economics and structural change in global demand (Headey and Fan, 2008); depreciation of the US dollar (Mitchell, 2008; Trostle, 2008; Abbott et al., 2011); inelastic markets (Abbott et al., 2011); import policies (Wright, 2009; Abbott et al., 2011); low level of global inventories (Wright, 2009; 2011); global bio-fuels production (Mitchell, 2008; Abbott et al., 2008; Wright, 2009; Headey and Fan, 2008; Abbott et al., 2011); and export policies (Trostle, 2008). Moreover, the paper discusses related literature (e.g. Robles et al., 2009; Cooke and Robles, 2009; Gilbert, 2010; Timmer, 2009) on the role of bio-fuels and speculation on food and agricultural commodity markets. The empirical part of the paper uses a structural time series approach to examine the behavior of the monthly commodity food prices for the period from January 1992 to October 2012. The results support that commodity food prices show cyclicality and seasonality and that US real effective *EXCR* has a negative effect on commodity food prices while crude oil price has a positive effect. Furthermore, the impact (in absolute value) of crude oil price on commodity food prices is smaller (i.e. 0.0399) than the impact of the US *EXCR* (i.e. −0.7868).

The paper by Nazlioglou and Soytas (2012) examines the dynamic relationship between oil price, US dollar *EXCR* and 24 world agricultural commodities in a panel framework using classical panel cointegration and causality analysis for the period from January 1980 to February 2010. The empirical results on panel cointegration indicate that the impact of an increase in the oil prices is positively significant in all individual agricultural commodities except in the case of cotton and coffee. Furthermore, the impact of a decline in the value of the US dollar is positive in all individual *AGCP* except in the case of coconut oil, cacao, and coffee. With regard to the panel coefficients, *AGCP* are positively correlated with the oil prices with an estimated coefficient of 0.25, and are negatively correlated with the US dollar *EXCR* with an estimated coefficient between −0.71 and −0.72.

The paper by Pala (2013) investigates the linkage between food price index and crude oil price index, using Johansen cointegration test, and Granger causality in a vector error correction model (VECM) framework 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. Cointegration regression coefficient between the crude oil and food price variables is negative at the full sample and at the period from January 1990 to August 2008 while positive at the period from November 2008 to August 2011.

The study by Ghaith and Awad (2011) uses cointegration analysis to investigate long-run relationships between the prices of crude oil and several food commodities (e.g. maize, wheat, sorghum, soybean, barley, linseed oil, soybean oil, and palm oil) for the period from January 1980 to December 2009. The results indicate that there is strong evidence of long-run relationship between crude oil and food commodity prices.

The work by Ciaian and Kancs (2011) investigates the interdependences between the energy, bio-energy and food prices. The paper uses a time series cointegration mechanism to nine major *AGCP* such as corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum and tea, along with one average crude oil price for the period January 1994-December 2008. The empirical findings show that the prices of all nine aforementioned agricultural commodities are cointegrated with crude oil price especially during the sub-period January 2004-December 2008. Furthermore, the results show that an increase in oil price by 1 $/barrel increases the *AGCP* between 0.10 $/barrel and 1.80 $/barrel.

The paper by Saghaian (2010) presents empirical results using a VEC system to investigate the long-run relationships between oil, ethanol, corn, soybeans, and wheat price. The empirical results from the VEC system supports five cointegrating equations and that the speed of adjustment coefficients show overshooting of each commodity price series indicating that the price system quickly adjusts to its long-run equilibrium.

The study by Zhang et al. (2010) uses price data on fuels (i.e. ethanol, gasoline and oil), and agricultural commodities (i.e. 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 fuels and agricultural prices and limited short-run relationship between fuels and agricultural prices.

The study by Chen et al. (2010) analyzes the relationship between the prices of corn, soybeans and wheat, and the crude oil price. The empirical results show that the change in each one of the aforementioned grain prices is significantly influenced by the change in the crude oil price as well as by the change of other grain prices.

The paper by Frank and Garcia (2010) using weekly data from 1998 to 2008 investigates the linkages between several *AGCP* (i.e. wheat, corn, cattle and hogs), *EXCR*, and oil prices by employing value at risk (VAR) and VECM methods. The paper identifies a break point which divides the sample period into two sub-periods (i.e. 1998-2006 and 2006-2009). The empirical results of this study show that for the first sub-period the crude oil price and the *EXCR* have limited effect on *AGCP*, while for the second sub-period the effects of the crude oil prices and the *EXCR* on agricultural prices are much stronger.

The paper by Chen et al. (2010) performs common factor analysis on a panel of 51 international commodity prices from January 1980 to December 2009. The study uses the Panel Analysis of Non-stationarity in Idiosyncratic and Common Components procedure developed by Bai and Ng (2004) and identifies two common factors for commodity prices. The results indicate that the first common factor is non-stationary, while the second common factor is stationary. The graphical evidence shows that the first common factor is a mirror image of the US *EXCR*. Thus, the study concludes that the highly persistent movements of commodity prices are mainly attributed to the first common component, which is closely related to the US *EXCR*, while the stationarity of the second common factor implies short-lived deviations from equilibrium price dynamics reflecting changes in the world demand

and supply conditions in accordance with prices theories (Kellard and Wohar, 2006; Wang and Tomek, 2007).

The study by Harri et al. (2009) examines the relationship between *AGCP* (i.e. corn, soybeans, soybean oil, cotton and wheat), *EXCR* and oil prices using cointegration analysis for the period from January 2000 to September 2008. The empirical results indicate that corn, cotton, and soybean prices are related to oil prices but wheat prices are not. *EXCR* are related to all aforementioned commodity prices.

The study by Arshad and Hameed (2009) examines the relationship between crude oil prices and cereal prices (i.e. maize, rice and wheat) using data of the period from January 1980 to March 2008. This paper uses the Engle–Granger two-stage estimation approach and Granger causality tests. The empirical results support the presence of a unidirectional long-run causality from crude oil prices to the three cereal prices. The study by Hameed and Arshad (2009) investigates potential linkages 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 direction relationship from crude oil price to the prices of each of the four vegetable oils. The reverse is not true, i.e. crude oil price is not influenced by the price of any of the vegetable oils under consideration. Furthermore, the speed of adjustment of palm oil, rapeseed oil, soybean oil, and sunflower oil prices to their long-run levels equaled 0.017, 0.032, 0.032 and 0.034, respectively, indicating a very slow adjustment of each one of the aforementioned commodities towards the long-run equilibrium.

3. MODEL AND DATA

Based on the aforementioned discussions *AGCP* can be modeled as a function of oil prices and *EXCR*. The empirical model in the log-log form is presented as follows:

$$\ln AGCP_{\mathrm{it}} = \alpha_{\mathrm{i}} + \delta_{\mathrm{i}} t + \beta_{1\mathrm{i}} \ln OILP_{\mathrm{t}} + \beta_{2\mathrm{i}} \ln EXCR_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \tag{1}$$

For $i = 1,\ldots,N$; t = 1983:06-2013:06

Where $AGCP_{\mathrm{it}}$ is referred to the price of the agricultural commodity i ($i = 1,\ldots,30$ Table 1) at time t (t = 1983:06-2013:06), *OILP* is the world crude oil price, and *EXCR* is the real effective US dollar *EXCR*. The parameter α_{i} is a fixed-effect parameter while $\beta_{1\mathrm{t}}$ and $\beta_{2\mathrm{t}}$ are the slope parameters and the term $\delta_{\mathrm{t}} t$ indicates deterministic time trends which are specific to individual units (members or cross-sections) of the panel. Notice that a similar empirical model can be applied for analyzing fertilizer prices (*FERT*) and any one of the five subgroups of agricultural prices as they are presented in Table 1, i.e., cereals (*CERL*), *VOPM*, *CBOS*, meat and seafood (*MASE*) and beverages (*BEVE*).

The data used in this study consists of monthly observations of the period from June 1983 to June 2013 of 30 *AGCP*, five fertilizer prices, the world crude oil prices and the real effective US dollar *EXCR*. Table 1 provides a detailed description of the data. It is worth stating that agricultural commodity and fertilizer price data have been converted into the same unit of measurement, i.e. dollar per metric ton, in order to avoid data potential inconsistency generated for measuring prices in different units.

4. EMPIRICAL METHODS AND RESULTS

The empirical methods used in the present study include, first, panel unit root tests (i.e. Harris and Tzavalis, 1999; Im et al., 2003; Levin et al., 2002) to provide information about the stationarity properties of the variables under consideration. Second, panel cointegration tests (i.e. Pedroni, 1997; 1999) are performed to ascertain the presence of cointegration and then the estimation of long-run cointegration parameters is carried out based on the studies by Pedroni (2001; 2007). Third, panel error correction estimation is performed based on the study by Pesaran et al. (1999), which presents three alternative pooled estimates, i.e. mean group (MG), pooled MG (PMG) and dynamic fixed-effects (DFE) estimators. Finally, a panel data analysis with unobservable heterogeneous effects based on the studies by Bai (2009) and Kneip et al. (2012) is conducted to deal with the potential problem of the unobserved heterogeneity. Note that the panel unit root tests, the panel cointegration tests and the panel error correction estimation utilize the Regression Analysis of Time Series procedures found in Doan (2012), while the unobserved heterogeneity estimation uses the R-package procedures developed by Bada and Liebl (2014).

It is worth stating that even though the data set used in the present study is not purely panel in nature, since the crude oil prices and *EXCR* do not change across the different types of agricultural commodities, this study uses panel data econometric techniques to analyze the long-run relationship between international *AGCP*, crude oil prices and *EXCR*. This is because the panel data econometric approaches used in the present paper derive information from both the time and the cross-sectional dimension of the *AGCP* and combine them with the time dimension of the crude oil prices and the *EXCR*. Since, however, the data set used in the present paper is not purely panel in nature, the information content is rather limited. For this reason, the present study, in addition to the classical non-stationary panel methods (i.e., panel unit roots, panel cointegration and error correction models), uses panel data approaches with unobservable heterogeneous effects and a factor structure.

4.1. Panel Unit Root Analysis

Panel unit root tests provide information about the order of integration of the variables under consideration which is crucial in empirical analysis since applying the ordinary least square estimator in non-stationary variables results in spurious regressions. The present study employs three different panel unit root tests in order to test the order of integration of the variables. The first test is the one developed by Levin et al. (2002, henceforth LLC), the second is the Harris and Tzavalis (1999, henceforth, HT), and the third is the Im et al. (2003, henceforth IPS). Most of the panel unit root tests use the following general structure:

$$\Delta y_{it} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \theta_{i,L} \Delta y_{i,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{it} \tag{2}$$

$m = 1,2,3$

Where, Δ is the first difference operator, p is the lag length, d_{mt} is a vector of deterministic variables and α_{mt} the corresponding vector of coefficients for models $m = 1, 2$, and 3 where $d_{1t} = \{\text{empty set}\}$, $d_{2t} = \{1\}$ and $d_{3t} = \{1, t\}$, correspondingly. $\rho_i = 0$ indicates that the y process has a unit root for individual i, while $\rho_i < 0$ indicates a stationary process. According to LLC (2002), since ρ_i is fixed across i the alternative hypothesis is that the ρ_t are identical and negative. A similar but simpler test is derived for (2) by HT (1999) when the time dimension of the panel is relatively short, with a null hypothesis of a unit root and an alternative with a single stationary value. Unlike the two aforementioned tests, the IPS (2003) test allows the ρ_i to vary and in fact the null hypothesis implies that all series have a unit root, i.e. $\rho_i = 0$ for all i, while the alternative hypothesis indicates that some of the series are stationary, i.e., $\rho_i < 0$ for some i.

The panel unit root test results are presented in Tables 2 and 3. Most of the panel unit root results show a tendency of failing to reject the null hypothesis of panel unit root for the levels of the variables.[2] On the contrary, most of the results indicate rejection of the null of panel unit root of the first-differences of the variables in support of the alternative of stationary first-differences of the variables. Thus, from the panel unit root analysis, it could be concluded that the variables are integrated of order one, suggesting a possible long-run cointegrating relation among each one of the *AGCP* such as ln*AGCP*, ln*CERL*, ln*VOPM*, ln*CBOS*, ln*MASE*, ln*BEVE*, and ln*FERT* with the oil price, ln*OILP*, and the *EXCR*, ln*EXCR*, variables. Thus, the next step of the empirical analysis investigates the presence of cointegration between *AGCP* and oil price and *EXCR*.

Table 2: Results of panel unit root LLC test (1983:06-2013:06)

Variables	None	Constant	Constant and trend
Variables in levels			
ln*AGCP*	2.25 [0.985]	1.94 [0.974]	3.66 [0.999]
ln*CERL*	1.06 [0.848]	1.56 [0.941]	1.45 [0.92]
ln*VOPM*	1.05 [0.854]	1.01 [0.843]	1.55 [0.940]
ln*CBOS*	0.52 [0.701]	0.89 [0.814]	2.07 [0.981]
ln*MASE*	1.88 [0.970]	1.13 [0.871]	3.21 [0.999]
ln*BEVE*	−0.36 [0.357]	0.30 [0.621]	1.44 [0.926]
ln*FERT*	1.09 [0.862]	1.31 [0.905]	2.06 [0.981]
ln*OILP*	3.68 [0.999]	6.29 [1.00]	2.45 [0.992]
ln*EXCR*	−4.36 [0.00]	−2.85 [0.002]	1.71 [0.957]
Variables in differences			
Δln*AGCP*	−23.5 [0.00]	−54.7 [0.00]	−14.8 [0.00]
Δln*CERL*	−26.5 [0.00]	−14.5 [0.00]	−10.0 [0.00]
Δln*VOPM*	−35.1 [0.00]	−21.7 [0.00]	−17.5 [0.00]
Δln*CBOS*	−18.9 [0.00]	−5.91 [0.00]	−2.09 [0.018]
Δln*MASE*	−22.3 [0.00]	−3.93 [0.00]	1.23 [0.892]
Δln*BEVE*	−15.8 [0.00]	−1.42 [0.077]	2.42 [0.999]
Δln*FERT*	−16.0 [0.00]	−1.14 [0.125]	2.84 [0.998]
Δln*OILP*	−50.5 [0.00]	−6.01 [0.00]	6.03 [1.00]
Δln*EXCR*	−67.8 [0.00]	−45.6 [0.00]	−35.5 [0.00]

LLC: Levin, Lin and Chu (Levin et al., 2002) panel unit root test. Δ is the difference operator. Numbers in brackets are *P* values, VOPM: Vegetable oil and protein meals prices, AGCP: Agricultural commodity prices, EXCR: Exchange rates, CBOS: Cotton, bananas oranges and sugar prices

4.2. Panel Cointegration Analysis

In this section, a number of studies by Pedroni (1997; 1999; 2001; 2007) are used in order to test and estimate panel cointegration among the variables in question. These studies allow not only differing short-run dynamics but also differing cointegrating vectors. The panel cointegration test developed by Pedroni (1997; 1999) is used to test the existence of the long-run equilibrium relationship among the variables. In particular, the testing procedure specifies a null hypothesis indicating that the series are not cointegrated, that is, that the residuals from (1) are still I(1). More specifically, if the alternative is that the series are cointegrated and have a common cointegrating vector, then the null is that the series are not cointegrated or they are cointegrated but do not have a common cointegrating vector. Table 4 presents the results of the seven different statistics developed by Pedroni (1997; 1999). Of these seven statistics, four are based on pooling along the within-dimension (panel cointegration statistics) and the remaining three are based on pooling along the between-dimension (group mean panel cointegration statistics). The panel cointegration statistics are based on estimators that pool the autoregressive coefficient across different units for the unit root tests on the estimated residuals, while the group mean panel cointegration statistics are based on estimators that average the individually estimated coefficients for each unit *i*. With regard to the first set of statistics, three of the four statistics (panel *v*-statistic, panel ρ-statistic, and panel Phillips and Perron [PP] - statistic) use non-parametric corrections analogous to the work of Phillips and Perron (1988), while the fourth (panel augmented Dickey-Fuller [ADF] - statistic) is a parametric ADF *t*-statistic. In the second set of statistics, two of the three statistics (group ρ-statistic, and group *PP*-statistic) are based on non-parametric corrections while the third (group ADF - statistic) is an ADF based test statistic. Let's denote by γ_t the autoregressive coefficient of the residuals in the i^{th} unit then the null and alternative hypothesis of the panel statistics are specified as follows:

H_0: $\gamma_i = 1$, for all i,

$$H_A: \gamma_i = \gamma < 1, \text{ for all } i \tag{3}$$

By contrast the hypothesis of the group statistics are described as:

H_0: $\gamma_i = 1$, for all i,

$$H_A: \gamma_i < 1, \text{ for all } i \tag{4}$$

Note that the alternative hypothesis of the within-dimension (panel) statistics presumes a common value for $\gamma_i = \gamma$, while the

2 Note that the paper by Rezitis (2014) used a panel VAR approach (in levels) rather than a panel error correction model for investigating the relationship between oil prices, US exchange rates and agricultural commodity prices. This was done because some of the panel unit root tests rejected the null of unit root for the levels of the variables.

Table 3: Results of panel unit root HT and IPS tests (1983:06-2013:06)

Variables	HT test			IPS test	
	None	Constant	Constant and trend	Constant	Constant and trend
Variables in levels					
ln*AGCP*	0.23 [0.594]	−7.59 [0.00]	−5.36 [0.00]	−1.42 [0.076]	−3.60 [0.00]
ln*CERL*	0.23 [0.594]	−0.61 [0.267]	−1.21 [0.111]	−0.10 [0.456]	−0.96 [0.166]
ln*VOPM*	0.26 [0.602]	−1.33 [0.091]	−0.60 [0.272]	−1.22 [0.111]	−2.78 [0.002]
ln*CBOS*	0.03 [0.513]	−9.43 [0.00]	−9.62 [0.00]	−1.03 [0.151]	−1.61 [0.053]
ln*MASE*	0.04 [0.518]	−6.43 [0.00]	−4.14 [0.00]	−1.04 [0.148]	−0.48 [0.314]
ln*BEVE*	−0.01 [0.494]	−2.39 [0.008]	0.07 [0.526]	−1.66 [0.048]	−1.21 [0.112]
ln*FERT*	0.37 [0.646]	1.10 [0.866]	0.70 [0.759]	−0.003 [0.49]	−2.23 [0.013]
ln*OILP*	1.14 [0.874]	2.96 [0.998]	−1.95 [0.025]	6.00 [1.00]	−2.63 [0.004]
ln*EXCR*	−0.20 [0.418]	−4.12 [0.00]	2.32 [0.990]	−4.96 [0.00]	−0.13 [0.445]
Variables in differences					
Δln*AGCP*	−1159.9 [0.00]	−511.8 [0.00]	−318.9 [0.00]	−31.1 [0.00]	−30.5 [0.00]
Δln*CERL*	−480.7 [0.00]	−212.2 [0.00]	−132.1 [0.000]	−20.7 [0.00]	−13.2 [0.00]
Δln*VOPM*	−564.7 [0.00]	−248.9 [0.00]	−154.6 [0.00]	−16.2 [0.00]	−29.9 [0.00]
Δln*CBOS*	−486.3 [0.00]	−214.7 [0.00]	−134.0 [0.00]	−14.6 [0.00]	−14.6 [0.00]
Δln*MASE*	−553.6 [0.00]	−244.3 [0.00]	−152.4 [0.00]	−20.3 [0.00]	−14.5 [0.00]
Δln*BEVE*	−398.2 [0.00]	−175.4 [0.00]	−109.2 [0.00]	−10.3 [0.00]	−9.98 [0.00]
Δln*FERT*	−346.4 [0.00]	−152.8 [0.00]	−94.6 [0.00]	−12.9 [0.00]	−12.5 [0.00]
Δln*OILP*	−1050.4 [0.00]	−463.7 [0.00]	−288.3 [0.00]	−42.2 [0.00]	−42.9 [0.00]
Δln*EXCR*	−1007.4 [0.00]	−443.8 [0.00]	−275.6 [0.00]	−55.3 [0.00]	−24.3 [0.00]

HT indicates the Harris and Tzavalis (1999) panel unit root test while IPS indicates the Im, Pesarant and Shin (Im et al., 2003) panel unit root test. Δ is the difference operator. Numbers in brackets are *P* values. VOPM: Vegetable oil and protein meals prices, AGCP: Agricultural commodity prices, EXCR: Exchange rates, CBOS: CBOS: Cotton, bananas oranges and sugar prices

Table 4: Panel cointegration test (1983:06-2013:06)

Variables	Panel				Group		
	v-statistic	*ρ*-statistic	*PP*-statistic	*ADF*-statistic	*ρ*-statistic	*PP*-statistic	*ADF*-statistic
Cointegration test-with time dummies							
ln *AGCP*, ln*OILP*, ln*EXCR*	8.42***	−3.98***	−3.30***	−3.54***	−7.15***	−5.24***	−6.08***
ln*CERL*, ln*OILP*, ln*EXCR*	8.66***	−7.72***	−5.55***	−5.97***	−7.27***	−5.76***	−6.40***
ln*VOPM*, ln*OILP*, ln*EXCR*	7.67***	−4.10***	−3.10***	−3.63***	−5.07***	−4.07***	−4.88***
ln*CBOS*, ln*OILP*, ln*EXCR*	8.11***	−6.52***	−4.30***	−4.48***	−9.57***	−5.92***	−6.69***
ln*MASE*, ln*OILP*, ln*EXCR*	1.10	0.07	−0.14	−0.07	0.63	0.24	0.12
ln*BEVE*, ln*OILP*, ln*EXCR*	2.64***	−1.18	−1.10	−1.36	−1.15	−1.22	−1.59
ln*FERT*, ln*OILP*, ln*EXCR*	6.02***	−3.33***	−2.40**	−2.53**	−2.51**	−2.25**	−2.63***
Cointegration test-without time dummies							
ln*AGCP*, ln*OILP*, ln*EXCR*	9.92***	−7.35***	−5.64***	−6.62***	−10.5***	−7.56***	−9.56***
ln*CERL*, ln*OILP*, ln*EXCR*	4.15***	−4.08***	−3.11***	−4.03***	−3.22***	−2.84***	−3.95***
ln*VOPM*, ln*OILP*, ln*EXCR*	5.98***	−3.67***	−2.75***	−3.31***	−3.90***	−3.20***	−3.98***
ln*CBOS*, ln*OILP*, ln*EXCR*	9.27***	−8.94***	−5.58***	−6.52***	−12.2***	−7.34***	−9.33***
ln*MASE*, ln*OILP*, ln*EXCR*	2.57**	−2.29**	−1.90**	−1.87*	−2.48**	−2.00**	−2.09**
ln*BEVE*, ln*OILP*, ln*EXCR*	1.90*	−0.92	−0.85	−1.34	−1.65*	−1.29	−2.10**
ln*FERT*, ln*OILP*, ln*EXCR*	4.42***	−4.51***	−3.16***	−4.13***	−4.22***	−3.42***	−4.67***

***,**,*Indicate statistical significance at 1%, 5% and 10% level of significance, respectively. The statistics are standard normally distributed asymptotically. VOPM: Vegetable oil and protein meals prices, AGCP: Agricultural commodity prices, EXCR: Exchange rates, CBOS: Cotton, bananas oranges and sugar prices

between-dimension (group) statistics do not presume a common value for $\gamma_i = \gamma$ and allow an additional source of potential heterogeneity across individual units of the panel.

The results of panel cointegration tests presented in Table 4 are obtained with and without the inclusion of time dummies. All the test statistics reject the null hypothesis of no cointegration between *AGCP* (fertilizers), oil prices and *EXCR*. Furthermore, the panel cointegration tests reject the null hypothesis of no cointegration for all subgroups of *AGCP* except in the cases of *MASE* (meat and seafood) and *BEVE* (beverages). In the case of *MASE* the test results obtained with the inclusion of time dummies fail to reject the null of no cointegration while the test results obtained without the inclusion of time dummies support the presence of cointegration. With regards to *BEVE* one of the test results (panel *v*-statistic) obtained with the inclusion of time dummies support the presence of cointegration, while three out of seven of the test results (panel *v*-statistic, group ρ- statistic, and group *ADF*-statistic) obtained without the inclusion of dummy dummies support the presence of cointegration. In general, the panel cointegration test results support the presence of cointegration among the variables under consideration which implies that prices converge to their long-run equilibrium by correcting any deviation from the long-run equilibrium in the short-run.

Since the panel cointegration tests indicate the presence of cointegration relationships among the variables under consideration then the next step is the estimation of the long-run parameters. Based on Pedroni (2001; 2007) two estimators are used for estimating the long-run parameters of the cointegration relationships given by Equation (1). These estimators are the fully-modified least squares (*FMLS*) which was firstly developed by Phillips and Hansen (1990) and Hansen (1992) and the dynamic ordinary least squares (*DOLS*) which was also proposed independently by Stock and Watson (1993). Note that the least squares estimated parameters in Equation (1) suffer from simultaneity bias due to the correlation between the left-hand side variable ($\ln AGCP_{it}$) and the error term (ε_{it}) and from dynamic endogeneity due to serial correlation of the error term (ε_{it}). The *FMLS* estimator used in estimating (1) corrects for the bias of the estimated parameters, while the *DOLS* estimator deals with the endogeneity by adding the current, lags and leads of the first difference of the right-hand variables (ln*OILP*, ln*EXCR*) to the regression of Equation (1).[3]

Tables 5-7 present the results of the panel fully modified ordinary least squares (*FMOLS*) and *DOLS* estimators. In particular, Table 5 presents panel cointegration coefficients for the *AGCP* as a group as well as for each specific agricultural commodity (components) price *i* (*i* = 1,…,30 Table 1). In an analogous manner, Table 6 presents the results for each *AGCP* sub-group while Table 7 shows the results corresponding to the fertilizer group as well as to each specific fertilizer price component. Furthermore, all the aforementioned tables are accompanied by heterogeneity tests (χ^2-tests) for the estimated coefficients $\left(\hat{\alpha}_i,\ \hat{\delta}_i,\ \hat{\beta}_{1i},\ \hat{\beta}_{2i}\right)$ corresponding to the variables under consideration (intercept, time, $\ln OILP_i$, $\ln ECXP_i$). The null hypothesis of the heterogeneity test is that each individual coefficient is equal to the average of the group.

An inspection of the empirical results presented in Tables 5-7 indicates that *FMOLS* and *DOLS* estimators produce very similar results in terms of the magnitude and statistical significance of the parameter estimates for both the average group price and the individual price components.

4.2.1. Agricultural commodities (AGCP)

The third row of Table 5 presents the estimated parameters of the cointegration vector corresponding to the panel, i.e. whole group of *AGCP*. These estimates indicate that in the long-run the average *AGCP* responds positively (about 0.32) to the crude oil price (*OILP*) and negatively (about −0.74) to the U.S. *EXCR* at conventional levels of significance. Note that *AGCP* shows a higher response to the *EXCR* changes rather than to the *OILP* changes. The same Table 5 indicates that all individual price components respond positively (except *OLIO*, *LAMB*, *POUL*, and *SHRI*) to the crude oil price changes and negatively (except *SHRI*, *COCB* and *TEA*) to the U.S. *EXCR* at conventional levels of significance. Notice that although each of the *COCO*, *FISM*, *PALO*,

3 For the *DOLS*, one lag and one lead are used. A number of different lags and leads were tried but it was found that the estimates are not sensitive to the selection of the lag and lead length. Note also that both the Akaike information criterion and the Schwarz Bayesian criterion support the aforementioned lag and lead length.

Table 5: Panel cointegration coefficients (1983:06-2013:06): *AGCP* prices, oil price and US *EXCR*

Variables	Panel *FMOLS*				Panel *DOLS*			
	Intercept	Trend	ln*OILP*	ln*EXCR*	Intercept	Trend	ln*OILP*	ln*EXCR*
ln*AGCP*	8.8136***	−0.0003***	0.3104***	−0.7119***	8.9315***	−0.0004***	0.3193***	−0.7414***
	(0.1913)	(0.0001)	(0.0090)	(0.0406)	(0.1934)	(0.0001)	(0.0094)	(0.0411)
ln*BARL*	6.3188***	0.0016***	0.2980***	−0.6496***	6.2885***	0.0015***	0.3006***	−0.6435***
	(0.8334)	(0.0003)	(0.0394)	(0.1766)	(0.8444)	(0.0003)	(0.0410)	(0.1794)
ln*CORN*	7.0916***	−0.0005*	0.4488***	−0.7922***	7.3385***	−0.0006**	0.4624***	−0.8516***
	(1.0325)	(0.0003)	(0.0488)	(0.2188)	(1.0243)	(0.0003)	(0.0498)	(0.2176)
ln*RICE*	11.5539***	−0.0003	0.3744***	−1.5135***	11.8586***	−0.0005*	0.3927***	−1.5878***
	(1.0288)	(0.0003)	(0.0486)	(0.2180)	(1.0252)	(0.0003)	(0.0498)	(0.2178)
ln*SORG*	6.9754***	−0.0002	0.3969***	−0.7520***	7.1749***	−0.0003	0.4078***	−0.8000***
	(0.9282)	(0.0003)	(0.0439)	(0.1967)	(0.9250)	(0.0003)	(0.0450)	(0.1965)
ln*WHEH*	8.3720***	−0.0002	0.3723***	−0.9628***	8.5291***	−0.0003	0.3871***	−1.0035***
	(0.8371)	(0.0003)	(0.0396)	(0.1774)	(0.8430)	(0.0003)	(0.0410)	(0.1791)
ln*WHES*	9.3143***	−0.0006**	0.3901***	−1.1790 ***	9.5281***	−0.0007**	0.4098***	−1.2346***
	(0.8791)	(0.0003)	(0.0415)	(0.1863)	(0.8764)	(0.0003)	(0.0426)	(0.1862)
ln*COCO*	7.3150***	−0.0008	0.4779***	−0.5049	7.3035***	−0.0009*	0.4859***	−0.5058
	(1.5049)	(0.0005)	(0.0711)	(0.3189)	(1.5126)	(0.0005)	(0.0735)	(0.3213)
ln*FISM*	5.6575***	−0.0002	0.5530***	−0.1967	5.9346***	−0.0003	0.5698***	−0.2653
	(1.0561)	(0.0003)	(0.0499)	(0.2238)	(1.0441)	(0.0003)	(0.0507)	(0.2218)
ln*GRON*	8.7990***	−0.0005*	0.3820***	−0.6799***	8.8799***	−0.0006**	0.3818***	−0.6959***
	(0.9832)	(0.0003)	(0.0465)	(0.2084)	(0.9935)	(0.0003)	(0.0483)	(0.2110)
ln*OLIO*	12.8388***	0.0021***	−0.1488***	−0.9920***	12.6666***	0.0022***	−0.1607***	−0.9486***
	(1.0241)	(0.0003)	(0.0484)	(0.2171)	(1.0441)	(0.0003)	(0.0507)	(0.2218)
ln*PALO*	6.3950***	0.0004	0.3962***	−0.3731	6.3725***	0.0003	0.4054***	−0.3724
	(1.4877)	(0.0005)	(0.0703)	(0.3153)	(1.5331)	(0.0005)	(0.0745)	(0.3257)
ln*PEAO*	7.5486***	0.0005*	0.3860 ***	−0.4431**	7.6308***	0.0004	0.3980***	−0.4660**
	(1.0193)	(0.0003)	(0.0482)	(0.2160)	(1.0423)	(0.0003)	(0.0507)	(0.2214)
ln*SOYM*	9.6910***	0.00001	0.2807***	−1.1171***	9.8888***	−0.00003	0.2822***	−1.1596
	(0.9042)	(0.0003)	(0.0427)	(0.1916)	(0.9111)	(0.0003)	(0.0443)	(0.1935)

Condt...

Table 5: *(Continued)*

Variables	Panel *FMOLS*				Panel *DOLS*			
	Intercept	**Trend**	**ln*OILP***	**ln*EXCR***	**Intercept**	**Trend**	**ln*OILP***	**ln*EXCR***
ln*SOYO*	8.8506***	−0.0006**	0.4588***	−0.8473***	8.9844***	−0.0008***	0.4756***	−0.8839***
	(1.0171)	(0.0003)	(0.0481)	(0.2156)	(1.0315)	(0.0003)	(0.0501)	(0.2191)
ln*SOYB*	8.9482***	−0.0006**	0.3890***	−0.9902***	9.1189***	−0.0006**	0.3982***	−1.0307***
	(0.9300)	(0.0003)	(0.0440)	(0.1971)	(0.9341)	(0.0003)	(0.0454)	(0.1984)
ln*SUNF*	9.6869***	−0.0001	0.4303***	−0.9852***	9.7912***	−0.0001	0.4477***	−1.0157***
	(1.0523)	(0.0003)	(0.0497)	(0.2230)	(1.0658)	(0.0003)	(0.0518)	(0.2264)
ln*COTT*	12.4737***	−0.0015***	0.2665***	−1.2385***	12.6637***	−0.0015***	0.2670***	−1.2790***
	(1.0401)	(0.0003)	(0.0492)	(0.2204)	(1.0647)	(0.0003)	(0.0517)	(0.2262)
ln*BANA*	8.9948***	0.0006**	0.2654***	−0.8011***	9.2716***	0.0005*	0.2858***	−0.8716***
	(0.8937)	(0.0003)	(0.0422)	(0.1894)	(0.8795)	(0.0003)	(0.0427)	(0.1868)
ln*ORAN*	8.3603***	0.0014***	0.2555***	−0.6724***	8.4873***	0.0013***	0.2673***	−0.7049***
	(0.8596)	(0.0003)	(0.0406)	(0.1822)	(0.8816)	(0.0003)	(0.0428)	(0.1873)
ln*SUGA*	16.8693***	0.0005	0.2183***	−2.6311***	17.4375***	0.0005	0.2144***	−2.7529***
	(1.2187)	(0.0004)	(0.0576)	(0.2583)	(1.2194)	(0.0004)	(0.0593)	(0.2590)
ln*BEEF*	10.8946***	−0.0010***	0.3336***	−0.8689***	11.1236***	−0.0011***	0.3467***	−0.9242***
	(0.6090)	(0.0002)	(0.0288)	(0.1291)	(0.5981)	(0.0002)	(0.0291)	(0.1271)
ln*LAMB*	9.5923***	0.0017***	−0.0859***	−0.3612**	9.4446***	0.0017***	−0.0913***	−0.3280**
	(0.6869)	(0.0002)	(0.0325)	(0.1456)	(0.6900)	(0.0002)	(0.0335)	(0.1466)
ln*PORK*	6.9498***	−0.0035***	0.4558***	−0.1083	7.1037***	−0.0037***	0.4751***	−0.1497
	(0.9963)	(0.0003)	(0.0471)	(0.2112)	(1.0083)	(0.0003)	(0.0490)	(0.2142)
ln*POUL*	7.8000***	0.0025***	−0.0141	−0.2174***	7.8204***	0.0025***	−0.0137	−0.2212***
	(0.2635)	(0.0001)	(0.0125)	(0.0559)	(0.2649)	(0.0001)	(0.0129)	(0.0563)
ln*SALM*	14.6938***	−0.0033***	0.3800***	−1.4811***	14.7812***	−0.0034***	0.3883***	−1.5031***
	(0.7593)	(0.0002)	(0.0359)	(0.1609)	(0.7432)	(0.0002)	(0.0361)	(0.1579)
ln*SHRI*	4.9683***	0.0004**	−0.2958***	0.3263**	4.9150***	0.0005**	−0.3182***	0.3501**
	(0.7136)	(0.0002)	(0.0337)	(0.1512)	(0.7048)	(0.0002)	(0.0343)	(0.1497)
ln*COCB*	3.4497***	−0.0009**	0.4472***	0.5616**	3.5362***	−0.0010**	0.4607***	0.5344**
	(1.1384)	(0.0004)	(0.0538)	(0.2413)	(1.1399)	(0.0004)	(0.0554)	(0.2422)
ln*COFA*	9.1578***	−0.0016***	0.3973***	−0.5075	9.2619***	−0.0017***	0.4186***	−0.5409
	(1.6538)	(0.0005)	(0.0782)	(0.3505)	(1.6996)	(0.0006)	(0.0826)	(0.3610)
ln*COFR*	9.8579***	−0.0038***	0.5336***	−0.7689**	10.0293***	−0.0039***	0.5537***	−0.8153**
	(1.8875)	(0.0006)	(0.0892)	(0.4000)	(1.9370)	(0.0006)	(0.0941)	(0.4115)
ln*TEA*	4.9905 ***	−0.0001	0.2685***	0.3890**	4.7806***	−0.0002	0.2813***	0.4281**
	(0.8002)	(0.0003)	(0.0378)	(0.1696)	(0.8056)	(0.0003)	(0.0391)	(0.1711)
Heterogeneity test (χ^2_{29} -test) for the estimated coefficients								
Intercept	273.28				291.37			
	[0.000]				[0.000]			
Trend	1320.56				1308.00			
	[0.000]				[0.000]			
ln*OILP*	1058.09				1066.51			
	[0.000]				[0.000]			
ln*EXCR*	311.00				334.62			
	[0.000]				[0.000]			

Numbers in parenthesis are standard errors while those in brackets are *P* values. ***,**,*indicate statistical significance at 1%, 5% and 10% level of significance, respectively.
VOPM: Vegetable oil and protein meals prices, AGCP: Agricultural commodity prices, EXCR: Exchange rates, FMOLS: Fully modified ordinary least squares, DOLS: Dynamic ordinary least squares

PORK and *COFA* prices show a negative response to the *EXCR* changes, however, these responses are statistically insignificant at any conventional level of significance. The heterogeneity tests for the estimated coefficients presented in the five last rows of Table 5 reject the hypothesis of equality of the individual estimated coefficient to the corresponding average panel (group) coefficient presented in the third row of the Table 5.

4.2.2. Cereals (CERL)

Table 6 presents panel cointegration coefficients referred to the responses of the whole group of cereal prices with respect to the crude oil price and to the U.S. *EXCR*. The results indicate that the average cereal price (*CERL*) responds positively (about 0.39) to the *OILP* and negatively (about −1.0) to the *EXCR* at conventional levels of significance. Table 5 supports that all individual cereal prices respond positively to the *OILP* changes at conventional levels of significance. The heterogeneity test of Table 6, however, indicates that individual cereal price responses to *OILP* changes are not statistically significantly different than the average cereal price at any conventional level of significance. Furthermore, all individual cereal prices (Table 5) respond negatively to the *EXCR* at conventional levels of significance. With regards to the

Table 6: Panel cointegration coefficients and heterogeneity tests by specific commodity subgroup (1983:06-2013:06): *CERL, VOPM, CBOS, MASE, BEVE*

Variables	Panel *FMOLS*				Panel *DOLS*			
	Intercept	Trend	ln*OILP*	ln*EXCR*	Intercept	Trend	ln*OILP*	ln*EXCR*
Panel cointegration coefficients								
ln*CERL*	8.2709***	−0.00005	0.3801***	−0.9748***	8.4530***	−0.0001	0.3934***	−1.0202***
	(0.3784)	(0.0001)	(0.0178)	(0.0801)	(0.3782)	(0.0001)	(0.0184)	(0.0803)
ln*VOPM*	8.5730***	0.00003	0.3605***	−0.7129***	8.6571***	−0.00003	0.3683***	−0.7343***
	(0.3531)	(0.00011)	(0.0167)	(0.0749)	(0.3577)	(0.0001)	(0.0173)	(0.0759)
ln*CBOS*	11.6745***	0.0003	0.2514***	−1.3358***	11.9650***	0.0002	0.2586***	−1.4021***
	(0.5065)	(0.0002)	(0.0239)	(0.1073)	(0.5106)	(0.0002)	(0.0248)	(0.1085)
ln*MASE*	9.1498***	−0.0005***	0.1289***	−0.4518***	9.1981***	−0.0006***	0.1311***	−0.4627***
	(0.2882)	(0.0001)	(0.0136)	(0.0611)	(0.2872)	(0.0001)	(0.0140)	(0.0610)
ln*BEVE*	6.8640***	−0.0016***	0.4117***	−0.0815	6.9020***	−0.0017***	0.4286***	−0.0984
	(0.7174)	(0.0002)	(0.0339)	(0.1520)	(0.7327)	(0.0002)	(0.0356)	(0.1556)
Heterogeneity tests (χ^2_5 -test) for the estimated coefficients								
ln*CERL*	20.24	43.37	6.49	12.61	22.10	43.46	7.24	14.32
	[0.001]	[0.000]	[0.260]	[0.027]	[0.000]	[0.000]	[0.203]	[0.013]
ln*VOPM*	31.20	58.66	138.59	17.94	28.33	59.51	138.47	17.16
	[0.000]	[0.000]	[0.000]	[0.035]	[0.000]	[0.000]	[0.000]	[0.046]
ln*CBOS*	39.52	45.52	0.52	43.31	42.26	40.02	0.96	46.12
	[0.000]	[0.000]	[0.913]	[0.000]	[0.000]	[0.000]	[0.808]	[0.000]
ln*MASE*	118.45	945.26	404.72	92.51	126.66	942.98	424.94	101.73
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln*BEVE*	13.85	34.63	12.47	13.41	14.12	32.67	11.97	13.93
	[0.003]	[0.000]	[0.005]	[0.003]	[0.002]	[0.000]	[0.007]	[0.002]

Numbers in parenthesis are standard errors while those in brackets are *P* values. ***,**,*indicate statistical significance at 1%, 5% and 10% level of significance, respectively. VOPM: Vegetable oil and protein meals prices, CBOS: Cotton, bananas oranges and sugar prices, FMOLS: Fully modified ordinary least squares, DOLS: Dynamic ordinary least squares

Table 7: Panel cointegration coefficients and heterogeneity tests (1983:06-2013:06): Fertilizer *(FERT)* prices, oil price and US *EXCR*

Variables	Panel *FMOLS*				Panel *DOLS*			
	Intercept	Trend	ln*OILP*	ln*EXCR*	Intercept	Trend	ln*OILP*	ln*EXCR*
Panel cointegration coefficients								
ln*FERT*	7.9124***	0.0007***	0.5863***	−1.0949***	7.9124***	0.0007***	0.5863***	−1.0949***
	(0.5380)	(0.0002)	(0.0254)	(0.1140)	(0.5380)	(0.0002)	(0.0254)	(0.1140)
ln*DAP*	8.1293***	0.0001	0.5899***	−1.0093***	8.2916***	−0.0001	0.6144***	−1.0563***
	(1.0900)	(0.0003)	(0.0515)	(0.2310)	(1.1044)	(0.0004)	(0.0537)	(0.2346)
ln*POTA*	7.2824***	0.0025***	0.4320***	−0.9069***	7.5917***	0.0023***	0.4604***	−0.9875***
	(1.2188)	(0.0004)	(0.0576)	(0.2583)	(1.2040)	(0.0004)	(0.0585)	(0.2558)
ln*PHOS*	6.1097***	0.0008*	0.6246***	−0.9476***	6.3559***	0.0006	0.6524***	−1.0137***
	(1.5150)	(0.0005)	(0.0716)	(0.3211)	(1.5134)	(0.0005)	(0.0735)	(0.3215)
ln*TSP*	8.2544***	0.0007*	0.5311***	−1.0620***	8.4056***	0.0006	0.5489***	−1.1033***
	(1.1108)	(0.0004)	(0.0525)	(0.2354)	(1.1273)	(0.0004)	(0.0548)	(0.2395)
ln*UREA*	9.7862***	−0.0006**	0.7539***	−1.5487***	9.9007***	−0.0008***	0.7834***	−1.5874***
	(1.0169)	(0.0003)	(0.0481)	(0.2155)	(1.0104)	(0.0003)	(0.0491)	(0.2146)
Heterogeneity test (χ^2_5 -test) for the estimated coefficients								
Intercept	4.91				4.48			
	[0.296]				[0.343]			
Trend	39.19				38.54			
	[0.000]				[0.000]			
ln*OILP*	20.60				20.40			
	[0.000]				[0.000]			
ln*EXCR*	5.19				4.81			
	[0.268]				[0.307]			

Numbers in parenthesis are standard errors while those in brackets are *P* values. ***,**,* indicate statistical significance at 1%, 5% and 10% level of significance, respectively. DAP: Diammonium phosphate, TSP: Triple superphosphate, EXCR: Exchange rates coefficients of *EXCR*, heterogeneity test (Table 6) indicates that individual cereal price responses are statistically significantly different than the average cereal price response at the 5% level of significance. In particular as indicated in Table 5, the highest response (in absolute value) presents *RICE* (about −1.58) followed by *WHES* (about −1.2).

4.2.3. VOPM

Table 6 shows panel cointegration results related to the whole group of vegetable oils and protein meal. The cointegration parameters for the whole group of the aforementioned category indicate that the average price of *VOPM* responds positively (about 0.36) to the *OILP* and negatively (about −0.73) to the *EXCR* at conventional levels of significance. As indicated in Table 5, all individual *VOPM* prices (except *OLIO*) respond positively to the *OILP* changes at conventional levels of significance with *FISM* showing the highest response (about 0.56). Furthermore, the heterogeneity test (Table 6) indicates that individual vegetable oils and protein meal price responses to *OILP* changes are statistically significantly different than the average vegetable oils and protein meal prices at any conventional level of significance. All individual *VOPM* prices (Table 5) respond negatively to the *EXCR* at conventional levels of significance, except for the cases of *COCO*, *FISM*, and *PALO* prices which do not show any statistical significant response to *EXCR* changes at any conventional level of significance. The heterogeneity test (Table 6) indicates that individual vegetable oils and protein meal price responses to the *EXCR* changes are statistically significantly different than the average vegetable oils and protein meal prices at the 5% level of significance.

4.2.4. CBOS

Table 6 presents coefficients referred to the responses of the whole group of *CBOS* prices with respect to the crude oil price and to the U.S. *EXCR*. The average *CBOS* price shows a positive response (about 0.25) to the *OILP* and negative (about −1.4) to the *EXCR* at conventional levels of significance. As indicated in Table 5, all individual prices respond positively to the *OILP* changes at conventional levels of significance. The heterogeneity test (Table 6), however, indicates that individual *CBOS* price responses to *OILP* changes are not statistically significantly different than the average *CBOS* price at any conventional level of significance. Moreover, all individual *CBOS* prices (Table 5) respond negatively to the *EXCR* at conventional levels of significance, with *SUGA* showing the highest (in absolute value) response (about −2.7) following by *COTT* (about −1.2). The heterogeneity test (Table 6) indicates that individual *CBOS* price responses to the *EXCR* changes are statistically significantly different than the average *CBOS* prices at the 5% level of significance.

4.2.5. Meat and seafood (MASE)

Table 6 presents panel cointegration coefficients for the group of meat and seafood prices. In particular, the average *MASE* price presents a positive response (about 0.13) to the *OILP* and negative (about −0.46) to the *EXCR* at conventional levels of significance. As indicated in Table 5, among individual prices *BEEF*, *PORK* and *SALM* respond positively and statistically significant at conventional levels of significance to the *OILP*, while although *LAMB*, *SHRI* and *POUL* show negative responses only the first two are statistically significant at conventional levels of significance. All individual prices (Table 5) respond negatively (except *SHRI*) and statistically significant at conventional level of significance (except *PORK*) to the *EXCR* changes. The heterogeneity tests (Table 6) indicate that individual *MASE* price responses to the *OILP* and *EXCR* changes are statistically significantly different than the average *MASE* prices at any statistical level of significance.

4.2.6. Beverages (BEVE)

Table 6 shows panel cointegration coefficients for the group of beverage prices. The average *BEVE* price presents a positive and statistical significant response (about 0.42) to the *OILP* and a negative (about −0.09) but statistical insignificant effect to the *EXCR*. All individual prices (Table 5) show a positive and statistical significant response to *OILP* at conventional levels of significance. Among individual prices *COFA* and *COFR* show negative responses to *EXCR* changes with only the response of *COFR* to be statistically significant at the 5% level. Furthermore, the prices of *COCH* and *TEA* present a positive and statistically significant response to *EXCR* changes at conventional levels of significance. The heterogeneity tests (Table 6) indicate that individual *BEVE* price responses to the *OILP* and *EXCR* changes are statistically significantly different than the average *BEVE* price changes at any statistical level of significance.

4.2.7. Fertilizers (FERT)

Finally, Table 7 presents panel cointegration results for the whole group of fertilizers as well as for individual fertilizer prices. The average *FERT* price shows a positive response (about 0.58) to the *OILP* and a negative (about −1.09) to the *EXCR* at any conventional levels of significance. All individual prices (Table 7) show a positive response to *OILP* and a negative response to *EXCR* at any conventional level of significance. Furthermore, the heterogeneity test (Table 7) indicates that the individual *FERT* price responses to the *OILP* changes are statistically significantly different than the average *FERT* price response at any statistical level of significance. The heterogeneity test (Table 7), however, indicates that the individual *FERT* price responses to *EXCR* changes are statistically insignificantly different than the average *FERT* price response at any statistical level of significance.

4.3. Panel Error Correction Analysis

The usual practice of generating panel error estimates is either to estimate separate regressions for each individual unit of the panel and calculate the coefficient means, which is called the MG estimator, or to pool the data and assume that the slope coefficients and error variances are identical. The studies by Pesaran et al. (1997; 1999), however, proposed an intermediate procedure, the PMG estimator, which constraints long-run coefficients to be identical across individual units of the panel but allows short-run coefficients and error variances to change among units. There are several reasons to assume the long-run equilibrium relationships between variables to be similar across individual units of the panel, due to arbitrage conditions, common weather and technologies affecting all units in a similar way. The present study computes and presents MG, PMG and DFE estimators for the variables under consideration. Note that the DFE estimator constraints all of the slope coefficients and the error variances to be the same across all individual units of the panel.

Let's assume that the long-run relationship between *AGCP*, crude oil price and *EXCR* is similar to Equation (1). Then the following ARDL(1,1,1) equation is used:

$$\ln AGCP_{\mathrm{it}} = \mu_{\mathrm{i}} + \delta_{10i} \ln OILP_{\mathrm{t}} + \delta_{11\mathrm{i}} \ln OILP_{\mathrm{t-1}}$$
$$\delta_{20\mathrm{i}} \ln EXCR_{\mathrm{t}} + \delta_{21,\mathrm{i-1}} \ln EXCR_{\mathrm{t-1}} + \lambda_{\mathrm{i}} \ln AGCP_{\mathrm{i,t-1}} + u_{\mathrm{it}} \tag{5}$$

And the error correction equation becomes:

$$\Delta \ln AGCP_{\mathrm{it}} = \phi\left(\ln AGCP_{\mathrm{i,t-1}} - \theta_{0\mathrm{i}} - \theta_{1\mathrm{i}} \ln OILP_{\mathrm{t}} - \theta_{2\mathrm{i}} \ln EXCR_{\mathrm{t}}\right)$$
$$-\delta_{11\mathrm{i}} \Delta \ln OILP_{\mathrm{t}} - \delta_{21\mathrm{i}} \Delta \ln EXCR_{\mathrm{t}} + u_{\mathrm{it}} \tag{6}$$

Where,

$$\theta_{0i} = \frac{\mu_i}{1-\lambda_i}, \quad \theta_{1i} = \frac{\delta_{10i}+\delta_{11i}}{1-\lambda_i}, \quad \theta_{2i} = \frac{\delta_{20i}+\delta_{21i}}{1-\lambda_i}, \quad \phi_i = -\left(1-\lambda_i\right)$$

Note that the error correction Equation (6) is written in terms of current, rather than lagged levels of exogenous variables. The DFE approach can be applied in estimating Equation (5) and the long-run estimated coefficients are provided in Equation (6).

The MG estimator assumes that all the coefficients of Equation (6) are heterogeneous and they are estimated by least squares for each individual unit of the panel. Then the coefficients of the individual regressions are pooled by averaging, which provides the MG estimates. Note that, the estimated model given by Equation (6) is linear in the variables but non-linear in the parameters. In the MG estimation approach, model (6) is estimated in the linear form and then the non-linear coefficients are derived. In particular, the linear form of Equation (6) is given as:

$$\Delta \ln AGCP_{\mathrm{it}} = \phi \ln AGCP_{\mathrm{i,t-1}} - \theta_{0\mathrm{i}}^{'} - \theta_{1\mathrm{i}}^{'} \ln OILP_{\mathrm{t}} - \theta_{2\mathrm{i}}^{'} \ln EXCR_{\mathrm{t}} -$$
$$\delta_{11\mathrm{i}} \Delta \ln OILP_{\mathrm{t}} - \delta_{21\mathrm{i}} \Delta \ln EXCR_{\mathrm{t}} + u_{\mathrm{it}} \tag{7}$$

Then θ_{0i}, θ_{1i} and θ_{2i} are obtained as follows:

$$\theta_{0\mathrm{i}} = \frac{\theta_{0\mathrm{i}}^{'}}{\phi}, \quad \theta_{1\mathrm{i}} = \frac{\theta_{1\mathrm{i}}^{'}}{\phi}, \quad \theta_{2\mathrm{i}} = \frac{\theta_{2\mathrm{i}}^{'}}{\phi}. \tag{8}$$

Finally the PMG estimator is more complicated relative to the MG estimator. It fixes the long-run coefficients (θ_{0i}, θ_{1i} and θ_{2i}) and allows the short-run coefficients (δ_{11i} and δ_{21i}) to vary across the individual units of the panel. It uses an iterative procedure which solves the first order conditions for the two sets of parameters (homogeneous vs. heterogeneous) given the other.

Table 8 presents the three aforementioned pooled estimates.[4] More specifically, the MG estimate which does not impose any restrictions, the PMG estimate which imposes common long-run coefficients and the DFG estimate which imposes common slope coefficients and error variances across the individual units of the panel. The results of Table 8 indicate that the long-run coefficients as well as the speed of adjustment coefficient have the expected signs and they are statistically significant at conventional levels of significance for the three alternative pooled estimation approaches (MG, PMG and DFE). Furthermore, the response of *AGCP* is higher to *EXCR* change rather than to the *OILP* change. In particular, these estimates indicate that in the long-run *AGCP* responds positively (between 0.327 and 0.405) to the *OILP* and negatively (between −1.132 and −1.380) to the *EXCR* at conventional levels of significance. Comparing the present results to those discussed in the previous subsection and particularly to those presented in the third row of Table 5 it can be seen that they are close with respect to the response of *AGCP* to the *OILP* changes but the present results show higher response of *AGCP* to *EXCR* changes.

On the contrary to the empirical model of the previous subsection (Pedroni, 2001; 2007) the empirical models of the present subsection (MG, PMG and DFE) provide estimates of the speed of adjustment coefficients because they estimate error correction models. Note, that the MG estimator suggests faster adjustment (about −0.055) than the PMG or DFE estimators (−0.046 and −0.037 respectively). The reason is that imposing homogeneity restrictions causes an upwards bias in the coefficient of the lagged dependent variable, and thus the MG estimator shows a higher

4 The models were estimated with a longer lag order but the estimates were not sensitive to the inclusion of additional lags. This is also supported by Pesaran et al. (1999), who indicate that the coefficients are robust to the lag order, especially in the case of large *T* (time). It should also be noted that when additional lags were included they were found to be insignificant. Furthermore, diagnostic tests of the residuals of the estimated models indicate that there is no evidence of autocorrelation and heteroskedasticity. Furthermore, the inclusion of seasonal dummies did not show any evidence of seasonality. Finally, to check the robustness, the models were re-estimated with shorter time spans, i.e. the first 5 years of the data and/or the last 5 years were omitted, and the empirical results showed a high degree of robustness.

Table 8: Alternative pooled estimates for *ARDL* (1,1,1) *AGCP* prices (1983:06-2013:06): MG, PMG and DFE

Variables	MG	PMG	DFE
ln*OILP*	0.327***	0.405***	0.341***
	(7.227e-159)	(0.021)	(0.030)
ln*EXCR*	−1.132***	−1.380***	−1.332***
	(4.425e-158)	(0.139)	(0.204)
Speed of	−0.055***	−0.046**	−0.037***
adjustment (ϕ)	(9.793e-160)	(0.021)	(0.003)
Log likelihood	14484.95	14444.50	12741.99
Number of estimated parameters	210	152	36

The error correction term does not include an intercept because the intercept is allowed to vary, while the slopes of the error correction parameters are constrained to be fixed (Doan, 2012). Numbers in parenthesis are standard errors. ***,**indicate statistical significance at 1%, and 5% level of significance, respectively. MG: Mean group, PMG: Pooled mean group, DFE: Dynamic fixed-effects, AGCP: Agricultural commodity prices adjustment than the PMG or DFE estimators (Pesaran et al., 1999). Overall the results of Table 8 indicate that the average adjustment coefficient seems to be about −0.046 indicating that it will take about 21.74 months for the *AGCP* to close the gap between the actual price level and the long-run equilibrium price level.

Table 9 provides DFE estimates for each component of the *AGCP* group (*CERL*, *VOMP*, *CBOS*, *MASE* and *BEVE*) as well as for the group of fertilizer (*FERT*) prices. All estimated coefficients have the expected sign and they are statistically significant at all conventional levels of significance (except the coefficients of *EXCR* in the *BEVE* and *MASE* price components). The results indicate that the response of each one of the agricultural price components and fertilizer price, presented in Table 9, is higher to the *EXCR* change rather than to the *OILP* change. Furthermore, among the agricultural price components *CERL* and *VOMP* show the highest responses (about 0.435 each one of them) to the *OILP* and *MASE* shows the lowest response (about 0.131). Moreover, *CERL* shows the highest response (about −1.809) to the *EXCR*, followed by *VOMP* and *CBOS* (of about −1.798 and −1.607 respectively) while *MASE* and *BEVE* do not show any statistical significant response. With regards to the speed of adjustment coefficients, *CBOS* shows the highest adjustment (about −0.101) while *BEVE* shows the lowest (about −0.024). Finally, comparing the long-run estimated coefficients of Table 9 to those discussed in the previous subsection and specifically to those presented in Tables 6 and 7 it can be seen that the coefficients corresponding to the *OILP* are close, while the coefficients of the present subsection corresponding to the *EXCR* are much higher than those of the previous subsection, except in the case of *MASE* where it is statistically insignificant.

4.4. Panel Data Analysis with Unobserved Heterogeneous Effects

This subsection examines the relationship between crude oil prices, US dollar *EXCR* and international agricultural prices by considering unobserved heterogeneity, in a panel framework, which is modeled by a factor structure. Classical panel data models incorporate unobserved heterogeneity with the use of dummy variables or with structural assumptions regarding the error term. Furthermore, the unobserved heterogeneity is assumed to remain constant though time within each cross-sectional unit. In recent studies on panel data analysis, such as Ahn et al. (2013); Bai (2009); Kneip et al. (2012) and Pesaran (2006), unobserved individual effects are allowed to have heterogeneous (i.e., individual-specific) time trends that can be approximated by a factor structure. Based on the studies by Bai (2009) and Kneip et al. (2012), Model (1) becomes:

$$\ln AGCP_{\mathrm{it}} = \mu + \alpha_{\mathrm{i}} + \beta_1 \ln OILP_{\mathrm{t}} + \beta_2 \ln EXCR_{\mathrm{t}} + v_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{9}$$

For $i = 1,\ldots,N$; t = 1983:06-2013:06

Where, μ is the intercept, α_i are time-constant individual effects of individual commodity i ($i = 1,\ldots,30$ Table 1) and v_{it} are time-varying individual effects of individual commodity i ($i = 1,\ldots,30$ Table 1) for time period t (t = 1983:06-2013:06), which are assumed to be generated by d common time-varying factors. Two specifications of the time-varying individual effects are used in the present study. The first is the specification proposed by Kneip et al. (2012) and is given by:

$$v_{\mathrm{i}}(t) = \sum_{\mathrm{l=1}}^{\mathrm{d}} \lambda_{\mathrm{il}} f_{\mathrm{l}}(t) \tag{10}$$

The second specification is proposed by Bai (2009) and is given by:

$$v_{\mathrm{it}} = \sum_{\mathrm{l=1}}^{\mathrm{d}} \lambda_{\mathrm{il}} f_{\mathrm{lt}} \tag{11}$$

Note that $f_l(t)$ and f_{lt} are the unobserved common factors for the models of Kneip et al. (2012) and Bai (2009), respectively, while λ_{il} are unobserved individual loading parameters and d is the unknown factor dimension.

The approach of Kneip et al. (2012) consists of a two-step estimation procedure. First, the common slope parameters (β_1 and β_2), the intercept (μ), the time-constant individual effects (α_i) and the time-varying individual effects ($v_i(t)$) are obtained semi-parametrically. Second, the functional principal component approach is employed to estimate the common factors $f_1(t),\ldots,f_d(t)$ and to re-estimate the time-varying individual effects ($v_i(t)$) more efficiently. This approach considers the case in which the common factors $f_l(t)$ show relatively smooth patterns through time. It includes positively auto-correlated stationary as well as non-stationary factors. Furthermore, the time-varying individual effects, $v_i(t)$, are approximated by smooth non-parametric functions and Equation (9) becomes a semi-parametric model that is estimated using the aforementioned two-step estimation procedure. It also should be noted that since the vector of explanatory variables in

Table 9: DFE estimates for *ARDL* (1,1,1) *AGCP* components and fertilizers (1983:06-2013:06)

Variables	*CERL*	*VOMP*	*CBOS*	*MASE*	*BEVE*	*FERT*
ln*OILP*	0.435***	0.435***	0.283***	0.131***	0.384***	0.773***
	(0.042)	(0.052)	(0.047)	(0.064)	(0.125)	(0.048)
ln*EXCR*	−1.809***	−1.798***	−1.607***	−0.385	−0.138	−2.332***
	(0.289)	(0.364)	(0.311)	(0.418)	(0.791)	(0.331)
Speed of adjustment (ϕ)	−0.051***	−0.033***	−0.101***	−0.034***	−0.024***	−0.049***
	(0.006)	(0.004)	(0.011)	(0.006)	(0.005)	(0.005)
Log likelihood	2951.58	4757.26	1054.19	2856.12	1765.45	2422.91
Number of estimated parameters	12	16	10	12	10	11

Numbers in parenthesis are standard errors. ***indicates statistical significance at the 1%, level of significance. AGCP: Agricultural commodity prices, CBOS: Cotton, bananas oranges and sugar prices, EXCR: Exchange rates model (9) is allowed to contain an intercept (μ), the time-varying individual effects ($v_i(t)$) are centered around a common intercept term for each specific time point and are not centered around zero.

Kneip et al. (2012) propose a sequential testing procedure based on the KSS.C test statistic to estimate the factor dimension d. The null hypothesis (H_0) of the KSS.C test statistic is that $d = 0$, while the alternative hypothesis (H_1) is $d = 1,2,3,\ldots$ until H_0 cannot be rejected. The estimated dimension is given by the smallest dimension d, which rejects H_0. The dimensionality KSS.C test statistic of Kneip et al. (2012) can be used for non-stationary as well as stationary factors, but it ignores factors that are weakly auto-correlated and thus the number of factors can be underestimated. To overcome this problem, Bai and Ng (2002) propose four directionality tests (i.e. PC1, PC2, PC3 and BIC3). The BIC3 test seems to perform well when the errors are cross-correlated. It has been shown that the aforementioned four tests might underestimate the true variance and for this reason Bai and Ng (2002) propose three additional directionality criteria (i.e. IC1, IC2 and IC3). In order to improve the finite sample properties of the IC1 and IC2 tests, Alessi et al. (2010) propose two refined directionality criteria, i.e., ABC.IC1 and ABC.IC2. Furthermore, Ahn and Horenstein (2013) suggest two additional selection criteria, i.e. the eigenvalue ratio and growth ratio, while Bai (2004) propose three panel criteria, i.e. IPC1, IPC2 and IPC3, to estimate the number of unit root factors. Finally, Onatski (2010) introduces a threshold approach, which can be used for both stationary and non-stationary factors and is called the criterion of eigenvalue differences.

The panel model proposed by Bai (2009), i.e., Equations (9) and (11), is estimated with the use of the entirely updated estimators (Eup) proposed by Bada and Kneip (2014). More specifically, this approach allows for dependency and weak forms of heteroskedasticity in both time and cross-section dimensions and uses an iterated least-squares approach to estimate (9) for non-stationary deterministic trends or stationary time-varying individual effects, v_{it}, such as autoregressive moving average model processes. However, this approach excludes a large class of non-stationary processes, such as stochastic processes with integration. Furthermore, Bai (2009) assumes that factor dimension d is a known parameter, which is not always the case. However, this study uses an algorithm proposed by Bada and Kneip (2014), i.e., Eup, which is a refinement of Bai's method, in order to estimate the number of unobserved common factors d jointly with the remaining parameters of the model.

Table 10 presents the empirical results of three different panel models. In particular, the second column of Table 10 presents the empirical results of a panel model with only time-constant individual-specific effects. The next two columns present the empirical results of two panel models including time-constant individual effects as well as time-varying individual unobservable effects. More specifically, the third column of Table 10 presents empirical results based on the Kneip et al. (2012) estimation approach, while the fourth column presents empirical results based on the Bai (2009) estimation method. The same Table 10 presents the results of the Kneip et al. (2012) test, which tests the

Table 10: Estimation results of panel models with time-constant additive and time-varying unobserved individual effects (1983:06-2013:06)

Variables	ln*AGCP*[a]	ln*AGCP*[b]	ln*AGCP*[c]
Intercept	8.5100***	8.3400***	8.4800***
	(0.3140)	(0.4740)	(0.0027)
ln*OILP*	0.2740***	0.0348*	0.0677***
	(0.0042)	(0.0181)	(0.0087)
ln*EXCR*	−0.6320***	−0.4220***	−0.4750***
	(0.0277)	(0.0979)	(0.0413)
Test-statistic of Kneip et al. (2012) test[d]: 143.15 [0.00]			
Factor dimensions (*d*) selection criteria			
PC1	-	5	5
PC2	-	5	5
PC3	-	5	5
BIC3	-	2	2
IC1	-	5	5
IC2	-	5	5
IC3	-	5	5
IPC1	-	0	0
IPC2	-	0	0
IPC3	-	0	0
ABC.IC1	-	2	-
ABC.IC2	-	2	-
KSS.C	-	23	-
ED	-	2	-
ER	-	2	-
GR	-	23	-

[a]The model presented in this column includes only time-constant additive effects (α_i); [b]The model presented in this column includes time-constant additive (α_i) and time-varying unobserved individual effects ($v_i(t)$), and uses the Kneip et al. (2012) estimation method; [c]The model presented in this column includes time-constant additive (α_i) and time-varying unobserved individual effects (v_{it}) and uses the Bai (2009) estimation method; [d]The test of Kneip et al. (2012) is testing the presence of time-varying interactive effects; PC1-PC3, BIC3, and IC1-IC3 are the selection criteria of Bai and Ng (2009); IPC1-IPC3 are from Bai (2004) while ABC.IC1 and ABC.IC2 are from Alessi et al. (2010); KKS.C is the selection criterion of Kneip et al. (2012); ED is the eigenvalue differences criterion of Onatski (2010); ER and GR are the eigenvalue ratio and growth ratio criteria of Ahn and Horenstein (2013), respectively; Numbers in parenthesis are standard errors while those in brackets *P* values. ***,*indicate statistical significance at 1%, and 10% level of significance, respectively. EXCR: Exchange rates

presence of unobservable common factors beyond the presence of the individual time-constant effects.[5] The test results indicate that the common factors should be included in the model.

Among the 16-factor dimensionality (d) criteria, which are presented in Table 10, a significant number support the presence of five unobserved common factors. The empirical results presented in Table 10 are obtained by selecting five unobservable common factors in the estimation process. Note, however, that the empirical results are robust to the selection of the number of common factors. The results indicate that the effect of crude oil prices on world *AGCP* is positive and statistically significant at the 10% level of significance in the Kneip et al. (2012) model and at the 1% level of significance in the Bai (2009) model, while the effect of *EXCR* is negative and statistically significant at the 1% level in both models. Furthermore, in the case of the Bai (2009) and Kneip et al. (2012) models, the effect of the crude oil is much smaller in absolute values (i.e. 0.0348 and 0.0677) than the effect of *EXCR* (−0.4220 and −0.4750). It should be stated that the estimated

5 This test is based on the dimensionality criterion proposed by Kneip et al. (2012) to test the following hypothesis: H_0: $d = 0$ versus H_1: $d > 0$.

slope coefficients of crude oil prices and *EXCR* obtained by the panel data models with unobservable heterogeneous effects and common factors are smaller, in absolute values, than those obtained by the static panel model with only additive time-constant fixed effects (Table 10). Furthermore, these estimated slope coefficients are smaller (in absolute values) than those obtained by the dynamic panel models without common factors presented in the previous subsections of the present study as well as those obtained by the study of Nazlioglou and Soytas (2012). Table 11 presents the results of the *ADF* test and the panel unit root tests (*LLC* and *IPC*) of the residuals of Kneip et al.'s (2012) estimated model, i.e., Equations (9) and (10). The test results of Table 11 support the stationarity of the error term of the estimated model.[6]

The left panel of Figure 2 shows that the 30 different agricultural commodities have considerably different time-constant levels (i.e., $\hat{\alpha}_i$ where $i = 1,\ldots,30$) of prices. The middle panel of Figure 2 shows the five estimated common factors (i.e. $\hat{f}_l(t)$, where $l = 1,\ldots,5$), while the right panel of Figure 2 presents the time-varying individual effects. For better visualization, each one of the five estimated common factors is also presented alone in Figure 3.

6 Furthermore, diagnostic tests of the residuals indicate that there is no evidence of autocorrelation and heteroskedasticity. It should also be noted that similar stationarity and diagnostic tests were performed on the residuals of the Bai (2009) model, i.e. Equations (9) and (11): The test results supported stationarity and no evidence of autocorrelation and heteroskedasticity was found.

Table 11: ADF and panel unit root tests (1983:06-2013:06): Estimated residuals

ADF tests					
No.	*ADF*	No.	*ADF*	No.	*ADF*
1	−5.2514***	11	−3.2730***	21	−4.4636***
2	−4.0762***	12	−6.0074***	22	−5.4968***
3	−5.8448***	13	−5.1881***	23	−4.5432***
4	−4.5437***	14	−4.6202***	24	−4.0866***
5	−4.8458***	15	−5.4018***	25	−5.1955***
6	−4.8921***	16	−4.8494***	26	−3.9122***
7	−5.1702***	17	−5.0498***	27	−3.8218***
8	−5.3097***	18	−4.6116***	28	−4.4794***
9	−5.1272***	19	−4.0907***	29	−4.3232***
10	−5.5002***	20	−6.1531***	30	−4.7548***

Panel unit tests			
LLC		IPS	
Constant	Constant and trend	Constant	Constant and trend
−14.26 [0.00]	−9.39 [0.00]	−17.82 [0.00]	−16.11 [0.00]

ADF indicates the augmented Dickey-Fuller *t*-statistic with the null of nonstationarity. LLC indicates the Levin, Lin and Chu (Levin et al., 2002) panel unit root test while IPS indicates the Im, Pesarant and Shin (Im et al., 2003) panel unit root test. ***refers to the case when the null hypothesis is rejected at the 1% level of significance. Numbers in brackets are *P* values

It is calculated that the first two common factors explain most of the total variance (about 68.87%) of the time-varying individual effects (i.e., $\hat{v}_i(t)$, where $I = 1,\ldots,30$). More specifically, 35.63% is explained by the first common factor and 33.24% is explained by the second one. Furthermore, the third common factor explains 12.96%, while the fourth and fifth explain about 10.13% and 8.04%, respectively.

As Figure 3 indicates, the first estimated common factor, $\hat{f}_1(t)$, resembles the US *EXCR*. Based on Chen et al. (2010), it could be appropriate to infer that the first common factor and the *EXCR* share information content. In other words, factors that have a predictable effect on *EXCR* will have a predicable effect on *AGCP*. The *ADF* test results presented in Table 12 indicate that the first common factor is non-stationary while the remaining four are stationary. Thus, it could be inferred that the non-stationarity (i.e. persistent movements) of the *AGCP* could be attributed to the first common factor, which is related to the *EXCR*, or to factors having a predictable effect on the *EXCR*. The remaining four factors may reflect the stationary behavior (i.e. temporal movements) of the *AGCP* around their long-run equilibrium level. Note that the temporal deviations of prices from their long-run equilibrium might be attributed to factors affecting the world supply and demand conditions of international agricultural commodities (Kellard and Wohar, 2006; Rezitis and Sassi, 2013; Wang and Tomek, 2007).

A comparison of the findings of the present paper with those obtained by Chen et al. (2010) indicates that in the paper by Chen et al. (2010) the non-stationary factor explains the largest proportion of the variation in the panel of prices, while in the present paper the non-stationary factor explains only about 35.63%. Note, however, that in the present paper the *ADF* test indicates that the second factor, which explains about 33.24% of the variation, is non-stationary at the 5% level of significance. Thus, in this case (i.e. the 5% significant level), the non-stationary factors explain about 68.87% of the variation in prices and thus the results of the present study come closer to those of the study by Chen et al. (2010).

5. CONCLUSIONS

This study examines the long-run relationship between crude oil prices, US dollar *EXCR* and the prices of 30 selected world agricultural commodities (and five fertilizer commodities) using panel methods on *AGCP* data based on monthly observations from June 1983 to June 2013. The present study uses classical non-stationary panel econometric methods (such as panel cointegration and error correction models), which do not assume unobservable cross-sectional dependence, as well as panel methods, which

Table 12: ADF test (1983:06-2013:06): Estimated common factors

Estimated factors	$\hat{f}_1(t)$	$\hat{f}_2(t)$	$\hat{f}_3(t)$	$\hat{f}_4(t)$	$\hat{f}_5(t)$
ADF	−0.9865	−1.8280*	−2.3208**	−2.5729***	−3.3130***

ADF indicates the augmented Dickey-Fuller *t*-statistic with the null of non-stationarity. ***,**,*refers to the case when the null hypothesis is rejected at the 1%, 5% and 10% level of significance, respectively

Figure 2: Left panel: Estimated time-constant individual specific effects (i.e., $\hat{\alpha}_i$ where $i = 1,\ldots,30$). Middle panel: Estimated common factors (i.e., $\hat{f}_l(t)$ where $l = 1,\ldots,5$). Right panel: Estimating time-varying individual effects (i.e., $\hat{v}_i(t)$ where $i = 1,\ldots,30$)

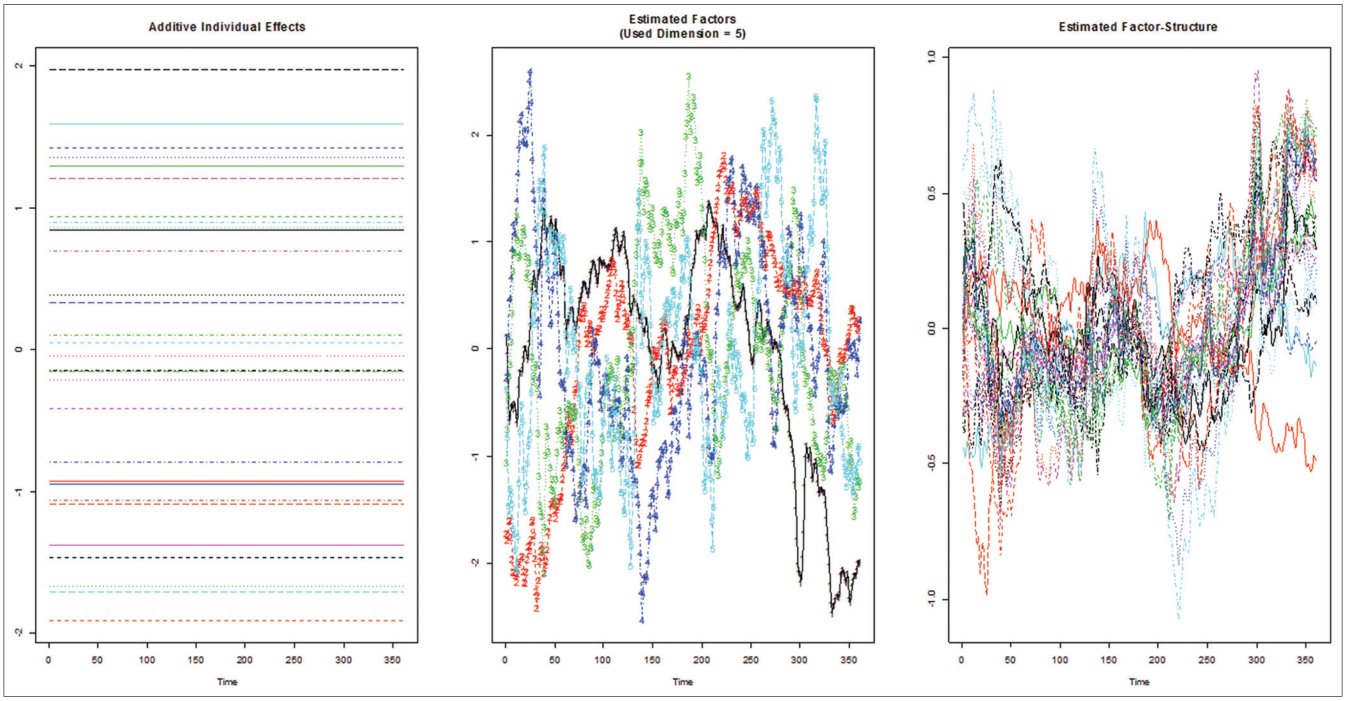
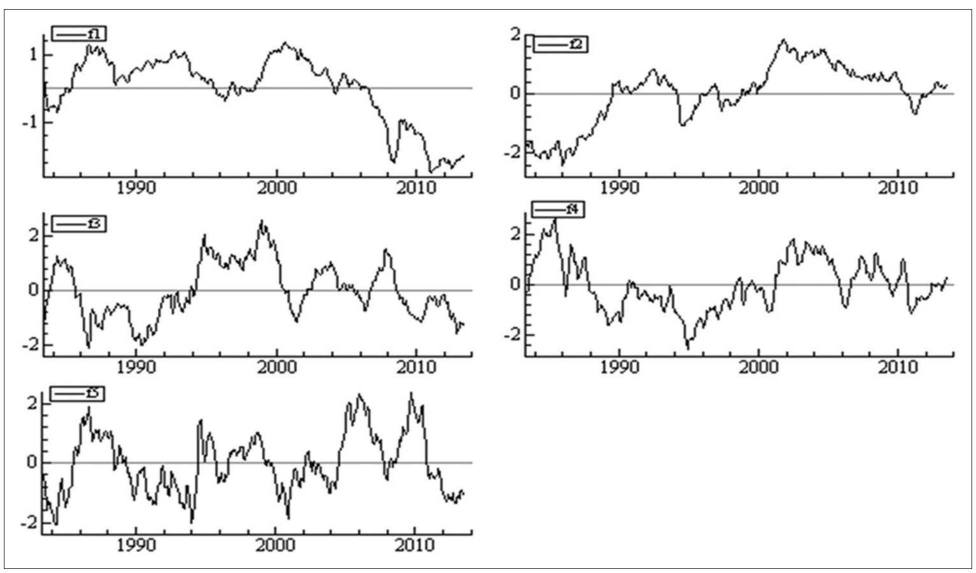


Figure 3: Estimated factors: $\hat{f}_1(t)$, $\hat{f}_2(t)$, $\hat{f}_3(t)$, $\hat{f}_4(t)$ and $\hat{f}_5(t)$



assume cross-sectional dependence due to common factors, to estimate the long-run dynamics between the series under consideration. It has been shown that neglecting unobserved heterogeneity may lead to biased parameter estimates.

The empirical results of the classical panel cointegration estimation with regard to the whole panel of the 30 *AGCP* indicate significant price dynamics. In particular, *AGCP* responds positively (0.32) to the crude oil price and negatively (−0.74) to the US *EXCR*. Similar results hold for the five agricultural commodity subgroups (i.e. *CERL*, *VOPM*, *CBOS*, *MASE* and *BEVE*) and for fertilizer prices. The empirical results of the classical panel error correction model reinforce the results of the panel cointegration model, supporting the significant price dynamics in the long-run between the series under consideration. The speed of adjustment coefficients estimated by the error correction model indicates a low but statistically significant speed of adjustment of *AGCP*. More specifically, the speed of adjustment is between −0.037 and −0.055, indicating that only between 3.7% and 5.5% of the disequilibrium in *AGCP* is corrected every month, which is a relatively low rate.

Among the *AGCP* subgroups, the highest speed of adjustment is shown by the *CBOS* price subgroup, which is about −0.101, while the lowest is given by the beverages price subgroup (*BEVE*) with about −0.024.

The empirical results of the panel data method with unobserved heterogeneous effects and a factor structure indicate statistically significant price dynamics among the variables under consideration but the effects are much smaller (in absolute values) than in the case of panel models without heterogeneous effects and common factors. In particular, the effect of crude oil prices on *AGCP* is positive and between 0.0348 and 0.0677, while the effect of *EXCR* is negative and between −0.4220 and −0.4750. Furthermore, the common factor analysis indicates the presence of five common factors. Among these common factors, a graphical representation shows that the first one has a close relation to the US *EXCR*. This indicates that factors that have a predicable effect on *EXCR* will have a predicable effect on *AGCP*. The *ADF* test shows that this factor is non-stationary and thus it is inferred that the persistent movements of *AGCP* could mainly be attributed to the first common factor (i.e. US *EXCR* or factors predicting the US *EXCR*). The short-run deviations of agricultural prices away from their long-run equilibrium level can be attributed to the stationary common factors that represent changes in the world agricultural commodity supply and demand conditions.

The findings of the present study support the results of previous studies, which indicate that the *AGCP* are positively correlated with the oil prices and are negatively correlated with the US dollar *EXCR*. The results of this study, however, indicate that when unobserved heterogeneous effects with common factors are considered, the effects of oil prices and *EXCR* on *AGCP* are much weaker than in the case in which such effects are not considered.

REFERENCES

Abbott, P.C., Hurt, C., Tyner, W.E. (2008), What's driving food prices? Farm Foundation.

Abbott, P.C., Hurt, C., Tyner, W.E. (2011), What's driving food prices in 2011? Farm Foundation.

Ahn, S.C., Horenstein, A.R. (2013), Eigenvalue ratio test for the number of factors. Econometrica, 81(3), 1203-1227.

Ahn, S.C., Lee, Y.H., Schmidt, P. (2013), Panel data models with multiple time-varying individual effects. Journal of Econometrics, 174(1), 1-14.

Alessi, L., Barigozzi, M., Capasso, M. (2010), Improved penalization for determining the number of factors in approximate factor models. Statistics and Probability Letters, 80(23-24), 1806-1813.

Arshad, F.M., Hameed, A.A.A. (2009), The long run relationship between petroleum and cereals prices. Global Economy and Finance Journal, 2(2), 91-100.

Bada, O., Kneip, A. (2014), Parameter cascading for panel models with unknown number of unobserved factors: An application to the credit spread puzzle. Computational Statistics and Data Analysis, 76, 95-115.

Bada, O., Liebl, D. (2014), Panel data analysis with heterogeneous time trends. R package version 3.1.1. Available from: http://www.cran.r-project.org/web/packages/phtt/index.html.

Bai, J. (2004), Estimating cross-section common stochastic trends in nonstationary panel data. Journal of Econometrics, 122(1), 137-183.

Bai, J. (2009), Panel data models with interactive fixed effects. Econometrica, 77(4), 1229-1279.

Bai, J., Ng, S. (2002), Determining the number of factors in approximate factor models. Econometrica, 70(1), 191-221.

Bai, J., Ng, S. (2004), A PANIC attact on unit roots and cointegration. Econometrica, 72(4), 1127-1177.

Baltagi, B.H. (2008), Econometric Analysis of Panel Data. 4th ed., Ch. 12. Chichester, UK: John Wiley and Sons.

Banerjee, A., Wagner, M. (2009), Panel methods to test for unit roots and cointegration. In: Mills, T.C., Patterson, K., editors. Palgrave Handbook of Econometrics. 1st ed., Vol. 2., Ch. 13. New York: Applied Econometrics. Springer. p632-726.

Chen, S.L., Jackson, J.D., Kim, H., Resiandini, P. (2010), What drives commodity prices. Auburn University Department of Economics Working Paper Series, AUWP, 2010-05.

Chen, S.T., Kuo, H.I., Chen, C.C. (2010), Modeling the relationship between the oil price and global food prices. Applied Energy, 87, 2517-2525.

Ciaian, P., Kancs, A. (2011), Interdependences in the energy-bioenergy-food price systems: A cointegration analysis. Resource and Energy Economics, 33, 326-348.

Cooke, B., Robles, M. (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. Evanston, IL: Estima.

Engle, R.F., Granger, C.W.J. (1987), Co-Integration and error correction: Representation, estimation and testing. Econometrica, 55, 251-276.

Frank, J., Garcia, P. (2010), How strong are the linkages among agricultural, oil, and exchange rate markets? Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis. St. Louis, MO: Forecasting, and Market Risk Management.

Ghaith, Z., Awad, I.M. (2011), Examining the long term relationship between crude oil and food commodity prices: Co-integration and causality. International Journal of Economics and Management Sciences, 5(1), 62-72.

Gilbert, C.L. (2010), How to understand high food prices. Journal of Agricultural Economics, 61(2), 398-425.

Hameed, A.A.A., Arshad, F.M. (2009), The impact of petroleum prices on vegetable oils prices: evidence from co-integration tests. Oil Palm Industry Economic Journal, 9(2), 31-40.

Hansen, B.E. (1992), Efficient estimation and testing of cointegrating vectors in the presence of deterministic trends. Journal of Econometrics, 53(1), 87-121.

Harri, A., Nalley, L., Hudson, D. (2009), The relationship between oil, exchange rates, and commodity prices. Journal of Agricultural and Applied Economics, 41(2), 501-510.

Harris, R.D.F., Tzavalis, E. (1999), Inference for unit roots in dynamic panels where the time dimensions is fixed. Journal of Econometrics, 91(2), 201-226.

Headey, D., Fan, S. (2008), Anatomy of a crisis: the causes and consequences of surging food prices. Agricultural Economics, 39(1), 375-391.

Im, K., Pesarant, M.H., Shin, Y. (2003), Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115, 29-52.

Kellard, N., Wohar, M.E. (2006), On the prevalence of trend in primary commodity prices. Journal of Development Economics, 79(1), 146-167.

Kneip, A., Sickles, R.C., Song, W. (2012), A new panel data treatment for heterogeneity in time trends. Econometric Theory, 28(3), 590-628.

Levin, A., Lin, C.F., Chu, S.S. (2002), Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108, 1-24.

Mitchell, D. (2008), A note on rising food prices. Policy Research Working Paper 4682, Development Prospects Group, World Bank, Washington, DC, USA.

Nazlioglou, S., Soytas, U. (2012), Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. Energy Economics, 34(2012), 1098-1104.

Onatski, A. (2010), Determaning the number of factors from empirical distribution of eigenvalues. The Review of Economics and Statistics, 92(4), 1004-1015.

Pala, A. (2013), Structural breaks, cointegration, and causality by VECM analysis of crude oil and food price. International Journal of Energy Economics and Policy, 3(3), 238-246.

Pedroni, P. (1997), Panel cointegration; Asymptotic and finite sample properties of pooled time series tests, with an application to the PPP hypothesis: New results. Working Paper, Indiana University, April.

Pedroni, P. (1999), Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and Statistics, 61, 653-669.

Pedroni, P. (2001), Purchasing power parity tests in cointegrated panels. Review of Economics and Statistics, 83(4), 727-731.

Pedroni, P. (2007), Social capital, barriers to production and capital shares: Implications for the importance of parameter heterogeneity from a nonstationary panel approach. Journal of Applied Econometrics, 22(2), 429-451.

Pesaran, H.M. (2006), Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), 967-1016.

Pesaran, M.H., Shin, Y., Smith, R.P. (1997), Pooled estimation of long-run relationships in dynamic heterogeneous panels. DAE Working Papers Amalgamated Series No 9721, University of Cambridge.

Pesaran, M.H., Shin, Y., Smith, R.P. (1999), Pooled mean group estimation of dynamic heterogeneous panels. Journal of American Statistical Association, 94(446), 621-634.

Phillips, P.C.B., Hansen, B. (1990), Statistical inference in instrumental variables regression with I(1) processes. Review of Economic Studies, 57(1), 99-125.

Phillips, P.C.B., Perron, P. (1988), Testing for a unit root in time series regressions. Biometrika, 75, 335-346.

Rezitis, A.N. (2014), The relationship between agricultural commodity prices, crude oil prices, and the US dollar exchange rates: A panel VAR approach and causality analysis. Working Paper, Department of Business Administration of Food and Agricultural Enterprises, University of Patras, Greece.

Rezitis, A.N., Sassi, M. (2013), Commodity food prices: Review and empirics. Economics Research International, 2013, Article ID: 694507, 15.

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

Saghaian, S.H. (2010), The impact of the oil sector on commodity prices: Correlation or causation? Journal of Agricultural and Applied Economics, 42(3), 477-485.

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

Stock, J.H., Watson, M.W. (1993), A simple estimator of cointegrating vectors in higher order integrated systems. Econometrica, 61(4), 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(5), 10-17.

Verbeek, M. (2012), A Guide to Modern Econometrics. 4th ed., Ch. 10. West Sussex, UK: John Wiley and Sons.

Wang, D., Tomek, W.G. (2007), Commodity prices and unit root tests. American Journal of Agricultural Economics Association, 89(4), 873-889.

Wright, B.D. (2009), International grain reserves and other instruments to address volatility in grain markets. Policy Research Working Paper 5028. Washington, DC, USA: TheWorld Bank.

Wright, B.D. (2011), The economics of grain price volatility. Applied Economic Perspectives and Policy, 33(1), 32-58.

Zhang, Z., Lohr, L., Escalante, C., Wetzstein, M. (2010), Food versus fuel: What do prices tell us? Energy Policy, 38, 445-451.