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World oil and agricultural commodity prices: Evidence from nonlinear causality

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ABSTRACT

The increasing co-movements between the world oil and agricultural commodity prices have renewed interest in determining price transmission from oil prices to those of agricultural commodities. This study extends the literature on the oil–agricultural commodity prices nexus, which particularly concentrates on nonlinear causal relationships between the world oil and three key agricultural commodity prices (corn, soybeans, and wheat). To this end, the linear causality approach of Toda–Yamamoto and the nonparametric causality method of Diks–Panchenko are applied to the weekly data spanning from 1994 to 2010. The linear causality analysis indicates that the oil prices and the agricultural commodity prices do not influence each other, which supports evidence on the neutrality hypothesis. In contrast, the nonlinear causality analysis shows that: (i) there are nonlinear feedbacks between the oil and the agricultural prices, and (ii) there is a persistent unidirectional nonlinear causality running from the oil prices to the corn and to the soybeans prices. The findings from the nonlinear causality analysis therefore provide clues for better understanding the recent dynamics of the agricultural commodity prices and some policy implications for policy makers, farmers, and global investors. This study also suggests the directions for future studies.

1. Introduction

World agricultural commodity prices have considerably increased from the beginning of 2006 to the mid of 2008. The prices of key agricultural commodities—corn, soybeans, and wheat-reached at their record levels in the mid of 2008 at which the peak level of oil prices was observed and they turned back to their early 2007 levels by the end of 2008 (Fig. 1). The recent surge in agricultural commodity prices has attracted interest in determining what drive agricultural commodity prices. In this respect, many factors are considered as the driving factors[1] . Although the factors are mutually reinforcing and complex (Zhang et al., 2010), high oil prices are thought to be major factor driving up the agricultural commodity prices (Abbott et al., 2008; FAO, 2008; Mitchell, 2008; OECD, 2008). Indeed, as depicted in Fig. 1, the recent dynamics of the agricultural commodity prices have matched with those of oil prices.

The observed linkages between energy and agricultural markets during the recent years have renewed interest in determining price transmission from energy prices to agricultural prices. The traditional oil price transmission to agricultural commodity prices implies that a rise in oil prices results in higher agricultural commodity prices by increasing costs of production through its impacts on fertilizer, chemicals, transportation costs, and other inputs. However, the debate on energy–agriculture linkage has now been concentrating on the second transmission mechanism that the recent increase in oil prices results in the growth of corn- and soybean-based biofuels production that drives up demand for these agricultural commodities and thereby boosts the agricultural commodity prices (Chen et al., 2010).

One of the recent tendencies in agricultural price determination is therefore to investigate causal linkages from oil prices to agricultural commodity prices. On the one hand, it is found that the agricultural commodity prices and oil prices do not cause each other, supporting the neutrality hypothesis (for instance, Yu et al., 2006; Zhang and Reed, 2008; Kaltalioglu and Soytas, 2009; Gilbert, 2010; Lombardi et al., 2010; Mutuc et al., 2010, Nazlioglu and Soytas, in press). On the other hand, a small number of studies find unidirectional causality from oil prices to agricultural commodity prices (for example, Hameed and Arshad, 2008; Cooke and Robles, 2009). In a more recent study, Zhang et al. (2010) show that sugar prices have a positive influence on oil prices. As this literature review indicates, the oil–agricultural commodity prices nexus is not clear-cut and there is a further need to handle the issue within the context of different approaches.

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[1] The causes of soaring agricultural commodity prices are well documented in Abbott et al. (2008), FAO (2008), Mitchell (2008), OECD (2008), Trostle (2008), von Braun (2008), McCalla (2009), and Gilbert (2010).

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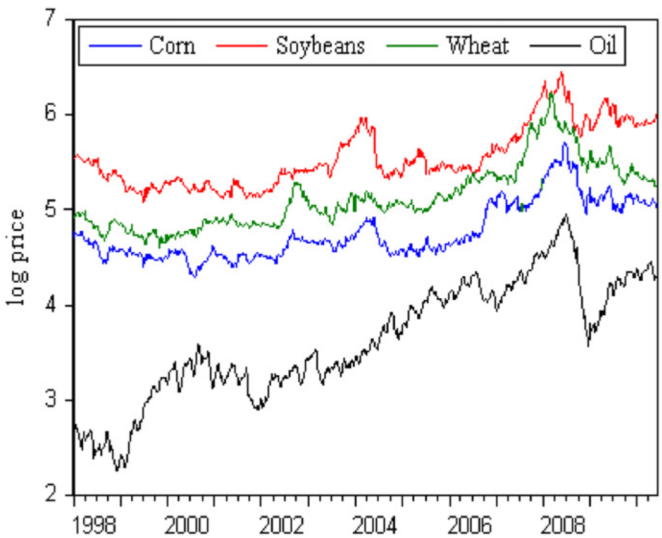

Fig. 1. The weekly agricultural commodity and the oil prices (1998–2010).

In addition to above econometric studies, the second line of the empirical modeling has relied upon partial and computable general equilibrium (CGE) models (for instance, Hanson et al., 1993; Tokgoz et al., 2008; Gohin and Chantret, 2010). However, partial and the CGE models suffer from arbitrarily determined or calibrated price elasticities that are used in stimulating long-run sensitivity of agricultural commodity prices to oil price shocks. Furthermore, they are not able to capture short-run dynamics between oil prices to agricultural commodity prices.

This study extends the literature on causal dynamics between the world oil and the global agricultural commodity prices. The causal linkages are determined employing weekly data for the key agricultural commodity prices (corn, soybeans, and wheat) by means of both the linear and nonlinear Granger causality methods. To best of our knowledge, this is the first study to employ the linear causality approach developed by Toda and Yamamoto (1995, hereafter TY) and the nonlinear causality test of Diks and Panchenko (2006, hereafter DP). The results from empirical analysis show that even though the linear causality analysis supports the neutrality hypothesis as most of the previous studies, the nonlinear causality test detects nonlinear feedbacks between the oil and the agricultural prices. Furthermore, this study shows that there is strong unidirectional nonlinear causality running from the oil prices to the corn and to the soybeans prices. Thereby, the findings support the hypothesis that the recent increase in the oil prices stimulates the agricultural commodity prices by increasing demand for corn-based ethanol production and soybean-based biodiesel production.

Unlike the previous studies, this study particularly focuses on investigating nonlinear causal linkages between the oil and the agricultural commodity prices. The oil and agricultural commodity prices seem to be higher than their historical levels (OECD, 2008), which means that the agricultural commodities may have new price regimes and the prices are characterized by nonlinear behavior. There are some sources of potential nonlinearity in commodity prices. As emphasized by Myers (1994, p. 171), while large fluctuations in agricultural prices tend to be followed by other large changes, small price changes tend to be followed by other small fluctuations. Therefore, the volatility of agricultural commodity prices varies over time, which results in nonlinear behavior of commodity prices. The rational expectation competitive storage theory asserts that commodity stocks, expected prices, and carriage costs are the forces driving commodity prices and that the equilibrium prices are formed by competitive speculators who hold stock due to price expectations and costs of carry. The inability of competitive speculators to hold negative inventories leads to the asymmetry in storage behavior, which results in turn the nonlinear price processes (Ahti, 2009). Furthermore, the impossibility of negative storage in storable commodities raises nonlinearity in prices of those commodities (Deaton and Laroque, 1995). In addition to the sources of nonlinearity in commodity prices, there are sources of asymmetric response of one price to another, implying the nonlinear price adjustment. In this respect, policy changes in commodity markets, inventory holding behaviors of farmers and governments, and different reactions to increase/decrease in input costs are thought to be the sources of nonlinear price adjustments (Rapsomanikis et al., 2003).

The change in policies may be the basic factor for expecting a nonlinear price linkage between the oil and the agricultural commodity prices. During the recent years, the energy policies tend to be towards environment-friendly and focusing on renewable and cheaper energy sources. In this respect, one of the recent developments in the energy policies is to support the production of biofuels and alternative energy sources. This tendency in energy policies, on the one hand, leads farmers to reallocate arable lands for producing cereals and oilseeds used in the production of biofuels. On the other hand, it leads the governments to encourage the production of those commodities. Nevertheless, it is argued that the volatile agricultural price dynamics during the recent years compared with the past are attributed to the instability of the energy prices (Saghaian, 2010). In order to cope with the negative effects of soaring/volatile agricultural prices on the agricultural markets, the governments take different measures such as price controls and trade barriers. However, the common view is that the interventions to domestic agricultural markets further spur the rise in and volatility of the global prices of agricultural commodities. Therefore, while the agricultural commodity prices may be gradually adjusted to the oil prices in the past, an increase in the oil prices may be rapidly transmitted to the agricultural commodity prices during the recent years, implying an asymmetric price linkage between energy and agricultural markets.

In the presence of regime shifts and structural breaks in variables, the forecasting performance of nonlinear approach is better than that of linear models (Baek and Brock, 1992; Chiou-Wei et al., 2008). Some more recent studies in the energy literature show that linear and nonlinear causality methods may produce different findings (for instance, Bekiros and Diks, 2008; Cheng-Lang et al., 2010; Kim et al., 2010). This recent empirical literature and the above discussion on the nonlinear price transmission call attention to investigate the nonlinear causal linkages between the oil and the agricultural commodity prices.

The rest of the paper is organized as follows. The next section is devoted to outline the econometric methods followed by description of the data. Section 4 presents the empirical findings. Sections 5 and 6 respectively provide the discussion and the concluding remarks.

2. Econometric methods

2.1. Toda–Yamamoto linear Granger causality test

In a standard Granger causality analysis, zero restrictions based on the Wald principle are imposed on the lagged coefficients obtained from the estimation of Vector Autoregressive (VAR) model. However, the Wald statistic may lead to nonstandard limiting distributions depending upon the cointegration properties of the VAR system that these nonstandard asymptotic properties stem from the singularity of the asymptotic distributions of the estimators

(Lütkepohl, 2004, p. 148). The TY procedure overcomes this singularity problem by augmenting VAR model with the maximum integration degree of the variables. In addition to this advantage, the TY approach does not require testing for cointegration relationships and estimating the vector error correction model and is robust to the unit root and cointegration properties of the series.

The standard Granger causality analysis requires estimating a VAR (p) model in which p is the optimal lag length(s). In the TY procedure, the following VAR ($p+d$) model is estimated where d is the maximum integration degree of the variables.

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \cdots + A_{p+d} y_{t-(p+d)} + \mu_t. \quad (1)$$

where y_t is vector of k variables, v is a vector of intercepts, μ_t is a vector of error terms and A is the matrix of parameters. The null hypothesis of no-Granger causality against the alternative hypothesis of Granger causality is tested by imposing zero restriction on the first p parameters. The so-called modified Wald (MWALD) statistic has asymptotic chi-square distribution with p degrees of freedom irrespective of the number of unit roots and of the cointegration relations.

2.2. Diks–Panchenko nonlinear granger causality test

The linear Granger causality test does not account for nonlinear causal relationships among the variables. In order to test for nonlinear Granger causality, various nonparametric methods are developed. In an early study, Baek and Brock (1992) propose a nonparametric statistical method for detecting nonlinear Granger causality by using correlation integral between time series. In Baek and Brock's test, the time series are assumed to be mutually and individually independent and identically distributed. By relaxing this strict assumption, Hiemstra and Jones (1994) develop a modified test statistic for the nonlinear causality, which allows each series to display short-term temporal dependence. However, Diks and Panchenko (2005) show that the test advocated by Hiemstra and Jones (1994) may over reject the null hypothesis of non-causality in the case of increasing sample size since it ignores the possible variations in conditional distributions. In a recent study, Diks and Panchenko (2006, hereafter DP) develop a new nonparametric test for Granger causality that overcomes the over-rejection problem in the Hiemstra and Jones test. In what follows, following Diks and Panchenko (2006) and Bekiros and Diks (2008) I outline the details of the DP nonparametric causality test.

Testing granger causality from one time series (X) to another (Y) is based on the null hypothesis that X does not contain additional information about Y_{t+1}, which is specified as

$$H_0 : Y_{t+1} \left| (X_t^{\ell_X}; Y_t^{\ell_Y}) \sim Y_{t+1} \right| Y_t^{\ell_Y} \quad (2)$$

where lx and ly respectively denote the past observations (i.e., lag length) of X and of Y. By assuming $Z_t = Y_{t+1}$ and by dropping time index and lags in Eq. (2), the conditional distribution of Z given $(X,Y)=(x,y)$ is the same as that of Z given $Y=y$ under the null hypothesis. Hence, Eq. (2) can be restated in terms of joint distributions that the joint probability density function $f_{X,Y,Z}(x,y,z)$ and its marginals must satisfy the following condition, which explicitly states that X and Z are independent conditionally on $Y=y$ for each fixed value of y.

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_y(y)} \quad (3)$$

Diks and Panchenko (2006) then re-specify the null hypothesis of no nonlinear Granger causality as follows:

$$q \equiv E\left[f_{X,Y,Z}(X,Y,Z) f_Y(Y) - f_{X,Y}(X,Y) f_{Y,Z}(Y,Z)\right] = 0 \quad (4)$$

where $\hat{f}_W(W_i)$ is a local density estimator of a d_W—variate random vector W at W_i defined by $\hat{f}w(W_i) = (2\varepsilon_n)^{-d_W}(n-1)^{-1}\sum_{jj \neq i} \mathrm{I}_{ij}^W$ that $\mathrm{I}_{ij}^W = \mathrm{I}(\left|\left|W_i - W_j\right|\right| < \varepsilon_n)$ with the indicator function $I(.)$ and the bandwidth ε_n, depending on the sample size n. Given this estimator, the test statistic, which is a scaled sample version of q in Eq. (4), is developed as

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_i (\hat{f}_{X,Z,Y}(X_i,Z_i,Y_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)) \quad (5)$$

If $\varepsilon_n = Cn^{-\beta}(C > 0,(1/4) < \beta < (1/3))$ for one lag $(\ell_X = \ell_Y = 1)$, the test statistic in Eq. (5) satisfies:

$$\sqrt{n}\frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{D} N(0,1)$$

where $\xrightarrow{D}$ denotes convergence in distribution and S_n is an estimator of the asymptotic variance of $T_n(.)$. Accordingly, the DP test statistic in Eq. (5) for nonlinear causality is asymptotically distributed as standard normal and diverges to positive infinity under the alternative hypothesis. Thereby, the statistic greater than 1.28 rejects the null hypothesis at 10% level of significance and supports evidence in favor of a nonlinear Granger causality.

3. Data

Data frequency plays an important role in determining price transmission from oil prices to agricultural prices. Monthly observations do not capture the dynamic causal linkages between the oil and the agricultural commodity prices well enough (Zhang and Reed, 2008). This study therefore employs weekly observations spanning from 1st week in 1994 to 29th week in 2010 for three agricultural commodity prices—corn, soybeans, and wheat. Corn and soybeans are the main crops used as an input in production of biofuels. Wheat is more energy-intensive and the key agricultural commodity for food in the world. Furthermore, corn, soybeans, and wheat are products competing with each other for crop rotation. The starting and ending date of the period were restricted to availability of price series of the agricultural commodities. Accordingly, the period starts from 1st week in 1998 for wheat. The agricultural commodity prices were compiled from the FAO International Commodity Price Database. Europe Brent spot price obtained from U.S Energy Information Administration was used as a proxy for the world oil prices. All the price series are measured in US dollars and expressed in natural logarithms.

Table 1 presents the correlation coefficients among the price series. The high correlation coefficients between the agricultural commodity prices are consistent with the high degree of integration among agricultural markets, signaling that a shock to an agricultural commodity price may affect prices of other agricultural commodities. The agricultural and the oil prices seem to have positive linear correlations, which support the observed co-movements between the oil and the agricultural prices displayed in Fig. 1. However, it is important to note that high linear correlation coefficient between two variables does not necessarily imply causal flows. Therefore, one needs to employ advanced econometric tools instead of simple descriptive and graphical

Table 1
Correlation coefficients.

	Corn	Soybeans	Wheat	Oil
Corn	1.000			
Soybeans	0.902	1.000		
Wheat	0.906	0.861	1.000	
Oil	0.725	0.689	0.812	1.000

Notes: The correlation matrix is for the period from 1998 to 2010 which is adjusted based on the starting date for wheat price.

analyses in determining causal linkage between the oil and the agricultural commodity prices.

4. Empirical findings

The TY and the DP causality analyses require investigating unit root properties of the variables. To this end, the unit root tests developed by Dickey and Fuller (1979, henceforth ADF), Phillips and Perron (1988, henceforth PP), and Kwiatkowski et al. (1992, henceforth KPSS) are applied to the series and results are illustrated in Table 2. The ADF and PP tests do not reject the null of a unit root for the levels of the corn, the soybeans, and the oil prices and imply uniform inference on stationarity of the level of the wheat prices. The KPSS test, in which the null hypothesis is stationarity instead of non-stationary, indicates that the null hypothesis is clearly rejected for the level forms of all series. When the tests are applied to the first-differences of the variables, the results strongly implies that all variables are stationary.

The ADF, PP, and KPSS tests do not take into account possible structural break(s) in series. In the case of structural breaks, unit root tests without structural breaks may result in misleading inferences. In addition to the ADF, PP, and KPSS test, I also employ minimum Lagrange Multiplier (LM) t-statistic unit root test of Lee and Strazicich (2003, hereafter LS)[2] in which the rejection of the null hypothesis of a unit root with two structural breaks unambiguously implies a trend stationary data. In the LS approach, the break dates are endogenously determined by minimizing LM statistic with a grid search. LS specified two models in order to investigate the unit root properties of the series around two structural breaks. The so-called Model A allows for two structural shifts in intercept and Model C allows for structural breaks in intercept and trend.

Minimum LM t-statistics for the levels of the variables presented in Table 3 show that the results are similar to those of the unit root tests without structural breaks and thereby the unit root properties of the variables under study are not affected by the structural breaks. Accordingly, all series have a unit root in their levels. Even though wheat prices seem to be stationary in Model C, this is not supported by Model A. The breakpoints in model A are slightly different for the oil and the agricultural commodity prices. Although model C at first glance indicates that the first break in the oil and the corn prices were occurred in the early 1998, it is not possible to draw uniform conclusion for the second break dates.

The unit root analysis implies that the variables are integrated of order one. Accordingly, the maximum integration order (d) of the variables will be equal to one in the TY procedure and the series in first difference (i.e., stationary series) will be used in the DP test. The information from the unit root tests also signals that the linear combinations of the variables may produce a stationary process, which implies the long-run cointegration relationship. Furthermore, as shown in Fig. 1, the increasing co-movements between the oil and the agricultural commodity prices during the recent years necessitate assessing the cointegration relations among the variables of interest. To test for the cointegration between the oil and the agricultural commodity prices, I utilize the multivariate cointegration approach based on maximum likelihood principle in a vector error correction modeling framework advocated by Johansen (1988). In order to identify the number of cointegration vectors, Johansen (1988) proposes the trace and maximum eigenvalue statistics. While the trace statistic is designed for testing the null hypothesis of r cointegration vector against the alternative hypothesis of k cointegrating relation where k is the number of endogenous variables, the maximum eigenvalue statistic tests for the null hypothesis of r cointegration vector against the alternative of $r+1$.

Table 2
Unit root tests without structural break.

Levels		ADF	PP	KPSS
Constant	Corn	−1.72	−1.70	1.12 ***
	Soybeans	−1.84	−1.76	1.33 ***
	Wheat	−1.57	−2.07	2.33 ***
	Oil	−1.21	−1.13	3.19 ***
Constant+trend	Corn	−2.17	−2.15	0.57 ***
	Soybeans	−2.54	−2.48	0.55 ***
	Wheat	−2.76	−4.30 **	0.17 **
	Oil	−2.87	−2.56	0.30 ***
First differences				
Constant	Corn	−30.94 ***	−30.91 ***	0.09
	Soybeans	−34.16 ***	−35.07 ***	0.10
	Wheat	−20.18 ***	−38.45 ***	0.05
	Oil	−23.78 ***	−23.64 ***	0.03
Constant+trend	Corn	−30.95 ***	−30.91 ***	0.04
	Soybeans	−34.15 ***	−35.12 ***	0.03
	Wheat	−20.16 ***	−38.42 ***	0.05
	Oil	−23.76 ***	−23.62 ***	0.03

Notes: The statistics are the pseudo-t ratios for ADF and PP tests and the LM statistics for KPSS test. The optimal lags for ADF test were selected by Schwarz information criterion; the bandwidth for PP and KPSS tests was selected with Newey-West using Bartlett kernel. *** and ** denote statistical significance at 1% and 5% level of significance, respectively.

Table 3
Unit root test with structural break.

	Model A: breaks in intercept			Model C: breaks in intercept and trend		
	Statistic	1st break	2nd break	Statistic	1st break	2nd break
Corn	−2.60	1996w28	2006w41	−3.79	1998w11	2007w02
Soybeans	−2.76	1997w36	2005w29	−3.87	1998w23	2007w41
Wheat	−2.78	2007w30	2007w41	−6.88***	2007w28	2007w52
Oil	−2.90	1998w13	2004w38	−4.07	1998w13	2008w38

Notes: The critical values of Model A: −4.55, −3.84, and −3.51 for 1%, 5%, and 10% levels of significance, respectively. Critical values of Model C: −6.16, −5.59, and −5.28 for $\lambda=(0.2, 0.4)$; −6.40, −5.74, and −5.32 for $\lambda=(0.2, 0.6)$; −6.33, −5.71, and −5.33 for $\lambda=(0.2, 0.8)$; −6.46, −5.67, and −5.31 for $\lambda=(0.4, 0.6)$; −6.42, −5.4, and −5.43 for $\lambda=(0.4, 0.8)$; −6.32, −5.73, and −5.32 for $\lambda=(0.6, 0.8)$. λ denotes the location of breaks.

*** Statistical significance at 1% level of significance.

Before turning to the results from the cointegration test, it is important to note that the Johansen cointegration method is not good enough to capture the impact of the structural break(s) in the series, and thereby the results from the cointegration test on the full sample may suffer from neglecting the effect of structural changes in both the oil and the agricultural commodity prices. In addition to testing the cointegration on the full sample, I examine the existence of cointegration in four sub-periods (1994w1–1998w12, 1998w13–2004w37, 2004w38–2008w37, and 2008w38–2010w29) for corn and soybeans. Since the data on wheat prices covers the period from 1998 to 2010, it is divided into three sub-periods: 1998w1–2004w37, 2004w38–2008w37, and 2008w38–2010w29.

The results from the cointegration analysis based on the trace statistic are illustrated in Table 4. The results clearly indicate that there are similar cointegration relations for corn-oil and soybeans-oil prices. The trace statistics, on the one hand, show that the corn

[2] In order to save space, the details of the LS unit root test are not explained here. An interested reader is referred to Lee and Strazicich (2003).

Table 4
Cointegration test without structural break.

	1994w1–2010w29	1994w1–1998w12	1998w13–2004w37	2004w38–2008w37	2008w38–2010w29
Corn-oil					
H_0:$r=0$	8.11 [0.4535]	6.03 [0.6913]	10.21 [0.2648]	9.45 [0.3246]	18.07 [0.0200]
H_0:$r=1$	1.07 [0.2996]	1.32 [0.2502]	1.76 [0.1834]	0.05 [0.8111]	1.16 [0.2810]
Soybeans-oil					
H_0:$r=0$	9.52 [0.3193]	7.01 [0.5762]	7.65 [0.5028]	12.67 [0.1274]	18.69 [0.0159]
H_0:$r=1$	0.85 [0.3558]	0.95 [0.3290]	2.07 [0.1495]	1.76 [0.1846]	2.79 [0.1159]
Wheat-oil	1998w1–2010w29	1998w1–2004w37	2004w38–2008w37	2008w38–2010w29	
H_0:$r=0$	15.55 [0.0489]	10.40 [0.2512]	18.47 [0.0173]	14.95 [0.0602]	
H_0:$r=1$	1.54 [0.2154]	1.65 [0.1988]	1.12 [0.2884]	0.34 [0.5571]	

Notes: The numbers in brackets are MacKinnon-Haug-Michelis (1999) p-values. The Schwarz information criterion was used to determine the optimal lag lengths in VAR(p) models to conduct the cointegration test.

and the soybeans prices do not have any cointegration relation over the full sample as well as first three sub-periods (i.e., 1994w1–1998w12, 1998w13–2004w37, and 2004w38–2008w37). On the other hand, the null hypothesis of no cointegration relation is rejected for the fourth sub-sample, supporting evidence on that the corn and the soybeans prices are cointegrated with the oil prices during the period 2008–2010. This finding is in fact consistent with increasing importance of corn and soybeans as a consequence of the significant expansion of biofuels in the last years. The story for wheat–oil prices is slightly different than those of corn and soybeans. According to the trace statistics, the null of no cointegration between the wheat and the oil prices is rejected for all periods with the exception of the sub-period 1998–2004. Indeed, this result is expected since wheat requires an energy-intensive production process.

The cointegration relationship between the oil and the agricultural prices, particularly during the period 2008–2010, enables us to continue with testing for weak exogeneity in order to determine which price series are not sensible to perturbations in the long-run cointegration relationship. Testing for weak exogeneity requires imposing zero restriction on the adjustment coefficients in the vector error correction model. The result from the weak exogeneity tests are given in Table 5. The likelihood ratio test, which is asymptotically distributed as chi-square indicates that the null hypothesis of weak exogeneity is rejected for the oil and the agricultural prices. Accordingly, the prices respond to perturbations in the long-run equilibrium vectors, implying that the oil and the agricultural commodity prices are not solely the driving forces for each other.

As mentioned above, I divided the full sample into the sub-groups in order to avoid misleading inferences in Johansen cointegration method that are possible to arise from the structural change. However, the results from the Johansen method may still overlook the impacts of structural shifts since the structural break dates were determined exogenously instead of finding them endogenously in the cointegration model. Thereby, I further investigate the cointegration relationship between the oil and agricultural commodity prices by utilizing the residual-based cointegration test with the structural shift proposed by Gregory and Hansen(1996)[3] . Gregory and Hansen(1996) develop ADF*, Z_t^* and Z_α^* statistics to test for the null hypothesis of no cointegration against the alternative of cointegration in the presence of a structural change that could occur in intercept (level shift), in intercept with trend (level shift with trend), or in cointegration

Table 5
Weak exogeneity test.

	Corn-oil		Soybeans-oil		Wheat-oil	
	Corn	Oil	Soybeans	Oil	Wheat	Oil
LR-test	15.37	3.67	3.10	4.66	13.90	5.94
p-value	0.0000	0.0553	0.0781	0.0308	0.0001	0.0147

vector (regime shift). The point of the structural change (i.e., break date) is endogenously determined by the smallest value of the test statistic.

The results from the cointegration tests with the structural change are presented in Table 6. For the case of corn and oil prices, ADF* test statistics do not reject the null of no cointegration. However, $Z_t^*$and Z_α^* tests show that while the null hypothesis of no cointegration with the level shift (model C and C/T) is not rejected, the null hypothesis is rejected in the regime shift model (model C/S). According to Gregory and Hansen (1996), the regime shift model is the most general specification since it allows shift in both intercept and slope coefficient. The break date in the corn-oil case is found at the mid of April 2002, which implies that the corn and the oil prices are tend to move together during the recent years as depicted in Fig. 1. For the long-run relationship between the soybeans and the oil prices, the tests do not support evidence on the existence of a cointegration relationship. For the wheat and the oil prices, although ADF* test does not indicate a cointegration relationship, $Z_t^*$and Z_α^*tests provide strong evidence on the existence of the cointegration. The break date is found at the mid of July 2007, which is consistent with the increasing co-movements between the wheat and the oil prices since beginning of 2007.

After determining the cointegration relationships between the oil and the agricultural commodity prices, I now proceed to investigating the existence of price transmission mechanism among the variables of interest by means of the TY causality approach. It is worthwhile noting that the TY procedure likewise the Johansen cointegration method may be misleading when there are structural breaks in the variables. Thereby, the TY causality test is applied to both the full sample and the sub-periods in order to avoid misleading inferences.

The results for the linear Granger causality tests along with the diagnostic tests are presented in Table 7. The Breusch–Godfrey serial correlation test implies that the residuals of the estimated models are free from autocorrelation problem. The Ramsey model miss-specification test clearly shows that the functional forms of the models are appropriately specified. However, White's heteroscedasticity and Engel's autoregressive conditional heteroscedasticity

[3] To conserve space, the details of Gregory and Hansen's (1996) cointegration method are not outlined here. An interested reader is referred to Gregory and Hansen (1996).

Table 6
Cointegration test with structural break.

	Corn-oil		Soybeans-oil		Wheat-oil	
	Statistic	Break date	Statistic	Break date	Statistic	Break date
ADF[*] test						
Model C	−3.77	1999w25	−4.00	1999w16	−3.93	2007w21
Model C/T	−4.19	2007w04	−4.31	1999w08	−3.88	2007w21
Model C/S	−4.59	2002w49	−3.98	1999w16	−4.04	2000w01
Z_t^* test						
Model C	−3.64	1999w25	−3.83	1999w16	−5.32***	2007w28
Model C/T	−3.78	2006w47	−4.51	1999w08	−5.26**	2007w28
Model C/S	−5.85***	2002w15	−4.08	2007w21	−5.44**	2007w28
Z_α^* test						
Model C	−26.06	1999w25	−31.25	1999w16	−52.76***	2007w28
Model C/T	−28.22	2006w47	−38.54	1999w08	−51.59**	2007w28
Model C/S	−54.64**	2002w15	−32.22	2007w21	−55.26**	2007w28

Notes: Model C: Level shift; Model C/T: Level shift with trend; Model C/S: Regime shift. The critical values for ADF[*] and Z_t^* tests are −5.13 at 1%, −4.61 at 5%, and −4.34 at 10% in Model C; −5.45 at 1%, −4.99 at 5%, and −4.72 at 10% in Model C/T; −5.47 at 1%, −4.95 at 5%, and −4.68 at 10% in Model C/S. The critical values for tests Z_α^*test are −50.07 at 1%, −40.48 at 5%, and −39.19 at 10% in Model C; −57.28 at 1%, −47.96 at 5%, and −43.42 at 10% in Model C/T; −57.17 at 1%, −47.04 at 5%, and −41.85 at 10% in Model C/S. The lag length is for ADF[*] test was selected on the basis of a *t*-test. *** and ** denote statistical significance at 1% and 5% level of significance, respectively.

Table 7
Linear Granger causality test.

	1994w1–2010w29	1994w1–1998w12	1998w13–2004w37	2004w38–2008w37	2008w38–2010w29
Oil ≠ > corn	2.854 [0.2400]	2.335 [0.1264]	0.185 [0.6667]	1.101 [0.2938]	1.164 [0.2806]
Corn ≠ > oil	0.063 [0.9687]	1.365 [0.2425]	0.206 [0.6496]	0.000 [0.9870]	0.047 [0.8276]
BG	1.759 [0.1534]	0.441 [0.7788]	0.800 [0.5258]	1.085 [0.3650]	1.532 [0.1997]
White	5.090 [0.0000]	3.919 [0.0000]	0.990 [0.4627]	1.808 [0.0396]	2.914 [0.0013]
ARCH	11.141 [0.000]	3.771 [0.0055]	1.243 [0.2923]	1.925 [0.1076]	2.353 [0.0601]
RESET	0.580 [0.4439]	0.321 [0.5715]	0.300 [0.5837]	1.700 [0.1937]	2.036 [0.1365]
Oil ≠ > soybeans	0.316 [0.8535]	1.892 [0.3882]	0.014 [0.9926]	1.079 [0.2989]	0.821 [0.3648]
Soybeans ≠ > oil	1.291 [0.5241]	2.217 [0.3299]	0.601 [0.7403]	0.127 [0.7210]	0.791 [0.3736]
BG	1.663 [0.1268]	0.656 [0.6229]	0.957 [0.4310]	1.268 [0.2837]	0.193 [0.9413]
White	3.271 [0.0000]	2.474 [0.0002]	11.143 [0.0000]	0.748 [0.7237]	2.967 [0.0012]
ARCH	8.656 [0.0000]	8.445 [0.0000]	32.418 [0.0000]	1.215 [0.3054]	3.599 [0.0094]
RESET	0.000 [0.9975]	2.487 [0.1163]	1.199 [0.2741]	0.058 [0.8092]	0.072 [0.7888]
	1998w1–2010w29	1998w1–2004w37	2004w38–2008w37	2008w38–2010w29	
Oil ≠ > wheat	0.492 [0.7819]	0.278 [0.8699]	0.325 [0.8497]	2.614 [0.1059]	
Wheat ≠ > oil	1.580 [0.4537]	2.541 [0.2806]	0.667 [0.7162]	0.002 [0.9461]	
BG	1.653 [0.1922]	1.175 [0.3212]	1.238 [0.2960]	0.957 [0.4350]	
White	4.633 [0.0000]	6.721 [0.0000]	1.079 [0.3681]	0.990 [0.4705]	
ARCH	18.915 [0.0000]	9.467 [0.0000]	4.139 [0.0030]	0.858 [0.4923]	
RESET	0.062 [0.8022]	2.627 [0.1059]	1.149 [0.2850]	0.282 [0.5963]	

Notes: ≠ > denotes non-Granger causality hypothesis. BG: The Breusch-Godfrey's serial correlation test. White: White's heteroscedasticity test. ARCH: Engle's autoregressive conditional heteroscedasticity test. RESET: Ramsey's functional misspecification test. The SBC was used to determine the optimal lag lengths for VAR(*p*) models. Numbers in brackets are *p*-values.

(ARCH) tests indicate the violation of homoscedasticity assumption in most of the estimated models. The models in which heteroscedasticity was detected were estimated by using the Newey–West method to obtain heteroscedasticity corrected standard errors and covariance.

The linear causality analysis for the full sample and the subperiods shows that there is no causal linkage from the oil prices (the agricultural commodity prices) to the agricultural commodity prices (the oil prices). Thereby, the linear Granger causality analysis strongly supports the neutrality hypothesis, which is consistent with the findings obtained by Yu et al. (2006), Zhang and Reed (2008), Gilbert (2010), Kaltalioglu and Soytas (2009), Lombardi et al. (2010), and Mutuc et al. (2010).

Although the linear causality methods can safely capture linear causal dynamics, they may overlook nonlinear relations. Therefore, I continue the empirical analysis with examining the nonlinear causal linkages between the oil and agricultural commodity prices. Following Bekiros and Diks (2008), the nonlinear Granger causality analysis is carried out in two steps. The DP test is first applied to the stationary series to detect nonlinear interrelationships. In the second step, the DP test is reapplied to the filtered VAR residuals to see whether there is a strict nonlinear causality in nature. After removing linear causality with a VAR model, any causal linkage from one residual series of the VAR model to another can be considered as nonlinear predictive power (Hiemstra and Jones, 1994, p. 1648). In the DP test, the value of the bandwidth plays an important role in making a decision on existence of nonlinear causality. Since the bandwidth value smaller (larger) than one generally results in larger (smaller) *p*-value (Bekiros and Diks, 2008. p. 1646), the bandwidth value is set to one.

Table 8 shows the results from the nonlinear causality test up to four lags. For the causality between the corn and oil prices, the results for raw data indicate one-way nonlinear causality from

Table 8
Nonlinear Granger causality test.

	Oil $\neq>$ corn		Corn $\neq>$ oil	
Lag	Raw data[a]	Residuals[b]	Raw data[a]	Residuals[b]
1	2.067 [0.0193]	1.319 [0.0934]	0.466 [0.3205]	0.661 [0.2540]
2	2.020 [0.0136]	0.878 [0.1987]	0.319 [0.3746]	−0.277 [0.6094]
3	1.988 [0.0233]	1.471 [0.0706]	0.057 [0.4769]	−0.065 [0.5259]
4	2.001 [0.0226]	1.410 [0.0792]	0.199 [0.4207]	0.3083 [0.3789]
	Oil $\neq>$ soybeans		Soybeans $\neq>$ oil	
Lag	Raw data[a]	VAR residuals[b]	Raw data[a]	Residuals[b]
1	2.738 [0.0030]	1.362 [0.0864]	1.296 [0.0973]	0.960 [0.1684]
2	3.350 [0.0004]	1.427 [0.0766]	1.722 [0.0424]	0.182 [0.4276]
3	3.529 [0.0002]	0.861 [0.1944]	1.687 [0.0457]	0.336 [0.3681]
4	3.539 [0.0002]	1.257 [0.1042]	2.007 [0.0223]	0.920 [0.1787]
	Oil $\neq>$ wheat		Wheat $\neq>$ oil	
Lag	Raw data[a]	Residuals[b]	Raw data[a]	Residuals[b]
1	4.222 [0.0000]	0.060 [0.4758]	2.128 [0.0166]	−0.900 [0.8161]
2	3.859 [0.0000]	0.029 [0.4882]	1.792 [0.0365]	−0.746 [0.7724]
3	3.590 [0.0001]	0.505 [0.3068]	1.541 [0.0616]	−0.413 [0.6602]
4	3.435 [0.0002]	0.160 [0.4364]	1.528 [0.0631]	−0.633 [0.7366]

[a] The series in first differences.
[b] The residuals of the VAR($p+d$) models. Numbers in brackets are p-values.

the oil to the corn prices. In order to determine whether this causal linkage is strictly nonlinear, I concentrate on the results from the residuals that are fitted from the VAR model estimation. The nonlinear causality on the residuals supports the existence of nonlinear causality from the oil to the corn prices, implying a strict nonlinear price transmission.

For the price transmission between the oil and the soybeans prices, the nonlinear causality test on raw data supports a feedback relationship. Further investigation of nonlinear causality with the VAR residuals indicates unidirectional causality from the oil to the soybeans prices at lag one and two, which implies the strict nonlinear causal effect of the oil prices on the soybeans prices does not persist over the long-term.

With respect to the nonlinear causal linkages between the oil and the wheat prices, the results for raw data indicate two-way causal linkages. However, the nonlinear causality test on the residuals does not support the existence of nonlinear causality. We can accordingly infer that even though there may be an asymmetric price transmission between the oil and the wheat prices, this relationship does not seem to be persistent.

The results from the causality analysis in sum imply that the findings from the linear causality methods are subject to neglecting possible nonlinear dependence between the oil and the agricultural commodity prices. The results from the nonlinear causality test on the VAR residuals show that the price transmission between the oil and the wheat prices is not strictly nonlinear. However, the nonlinear causality on the VAR residuals finds out the strict nonlinear causality from the oil prices to the corn and to the soybeans prices.

5. Discussion

The findings obtained from the linear and the nonlinear causality analyses provide different policy implications. The linear causality analysis does not show any feedback from the oil to the agricultural prices, which implies that the movements in the oil prices do not play a role on the fluctuations of agricultural commodity prices. On the other hand, the nonlinear causality analysis indicates that the changes in the oil prices have predictive power in determining the future dynamics of the agricultural commodity prices. Thereby, the nonlinear analysis provides clues to better understand the recent dynamics of the agricultural commodity prices.

The linkage between energy and agricultural markets becomes stronger as demand for biofuels production increases due to rising oil prices. The feedback from energy to agricultural markets leads to a closer link from oil prices to corn and to soybeans prices due to the fact that corn and soybeans are the main crops used in the production of ethanol and biofuels. Accordingly, the recent dynamics of corn and soybeans prices can be attributed to developments in energy markets. Surging corn and soybeans prices have led farmers to increase production of these commodities at the expense of wheat production which in turn likely to boost wheat prices. Furthermore, by taking into account the growing demand for biofuels that arises from not only higher energy prices but also environmental concerns, we can expect that the linkage between energy and agricultural markets will become stronger and agricultural commodity prices will be more related to the changes in energy prices in the future.

As biofuels sector expands, agricultural commodity producers will be faced to choose producing for people or fuel and this decision will be due to the profitability of choices (Zhang et al., 2010). The growing importance of biofuels – as a renewable energy and as an alternative to fuels – has motivated farmers to produce for fuels. No doubt that the agricultural price spikes harm the poor more than others because the poor have to spend a large share of their incomes on food products. As international institutions – such as FAO, World Bank, and FAPRI – strongly emphasized, agriculture has a crucial role in alleviating world hunger and poverty. Therefore, the food versus fuel trade-off, which moves in favor of fuel during the recent years, calls attention to invest more in agriculture in the long-run. Besides, food subsidies may be a short-run strategy to decrease the negative effects of the surging agricultural prices on the poor.

The changes in agricultural commodity prices affect the large portion of population in both the least developed and developing countries since the agriculture is still the mainstay of economy in those countries. Therefore, the agricultural support and price polices are one of the key concerns. In addition to growing international demand for agricultural commodities that stems from the income increases in the BRIC countries (Brazil, Russia, India, and China), high oil prices and ongoing support policies toward biofuel production– particularly in USA and European Union – imply that agricultural commodity prices are expected to remain high in the future. Even though the linear causality analysis does not attribute a role to energy markets in designing the agricultural policies, the nonlinear causality analysis supports that the agricultural policies should be designed within the context of the tendencies and structural shifts in energy policies.

The linear and nonlinear causality analyses have also different policy implications for global investors. The linear causality analysis supports the neutrality between the oil and agricultural commodity prices. Accordingly, the investors cannot determine the future prices of these assets by following the spot prices. The neutrality also implies that the investors are able to hedge risks by portfolio diversification policies. However, the causal linkages obtained from the nonlinear analysis indicate that the investors may benefit from information about the oil prices to invest in agricultural commodities. The nonlinear causality shows that the dynamics of the oil prices can help investors to forecast of the future values of the agricultural commodity prices, which provide information to the investors for investment strategies. If the investors expect an increase or decrease in the oil prices, they can gain revenues by investing or speculating in the agricultural commodity markets. The nonlinear causality analysis therefore supports the finding of Cooke and Robles (2009) that financial activity in futures markets and speculation plays an important role in the recent agricultural price booms.

6. Conclusion

This paper assesses the price transmission from the world oil prices to the key agricultural commodity prices (corn, soybeans, and wheat) by employing weekly data from 1994 to 2010. In order to determine the causal linkages among the variables in question, we employ both the linear and nonlinear Granger causality methods. The empirical analysis presents three key findings: (i) the linear Granger causality analysis supports the neutrality hypothesis, which means that the oil and the agricultural commodity prices do not cause each other, (ii) the nonlinear Granger causality test shows that there are nonlinear causal linkages between the oil and the agricultural commodity prices, and finally (iii) the nonlinear causality from the oil prices to corn and soybeans prices seems to be strict.

The findings from the nonlinear causality analysis imply that the recent surge in the agricultural commodity prices can be attributed the changes in the oil prices. The findings also provide some policy implications. First of all, the governments/policy makers should design the agricultural policies within the context of tendencies in energy markets and policies. Second, since the rising agricultural prices hits the poor, food subsidy programs should be implemented in the short-run and investments in agricultural sector should be increased in the long-run. Finally, the findings imply that global investors can predict the prices of the agricultural commodities by following the fluctuations in the oil prices.

In some studies, it is found out that the local agricultural commodity prices do not respond to the world oil prices (for example, Zhang and Reed, 2008; Mutuc et al., 2010, Nazlioglu and Soytas, in press). Even though the local prices are not sensitive to the world oil prices, there may be price transmissions from the global agricultural commodity prices to the local prices. The causal linkages from the world oil prices to global commodity prices provide room to examine whether the changes in the world agricultural commodity prices last into the local agricultural commodity prices. Therefore, future studies can focus on this issue within the context of linear and nonlinear econometric methods.

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