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The Dynamic Relationship between Oil and Wheat Markets

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Abstract

The aim of this paper is to analyze the cross-market interactions between crude oil prices and wheat prices. We investigate the dynamic relationship between world oil market and wheat market in assumption that the increase of volatility in wheat price is caused by the exogenous crude oil price. To this end, Granger Causality test and kernel Granger Causality test are applied to daily crude oil and wheat prices from January 2000 to June 2013. The linear causality analysis indicates that the oil prices and the wheat prices do not influence each other; this result supports the neutrality hypothesis of Granger causality. In Contrast, the non linear causality analysis proves the existence of non linear feedbacks between oil and wheat markets. These findings provide information for better understanding the recent dynamics of wheat market. Thus, the interdependence between wheat and oil markets is mainly explained by production cost, transportation cost, Biofuel markets and speculation.

Keywords: wheat market, oil market, Granger Causality, Kernel Granger Causality.

JEL Classification codes : C12, C13, G15.

1. Introduction

In recent years, the agricultural markets have been going through difficult phases. The 2007-2008 agricultural price spikes pushed a further 200 million people worldwide into hunger. High and volatile agricultural commodity prices are likely to persist and constitute a cause for concern among governments, traders, producers and consumers. The wheat market is therefore a perfect illustration of the specificities of agricultural markets. In this respect, the World Development Movement states that the rising price of wheat caused the price of other agricultural to subsequently rise as well. Moreover, the FAO[i] (2009) notes that 'in early 2008 the volatility in price of wheat was twice the level seen in 2007 and it is never reached its previous record. Climate change could have a drastic and harmful effect on agriculture but the movements of wheat prices are expected to be influenced by many other factors. Indeed, growth in world population, incomes and food consumption in emerging countries with rising demand of staples from China and India due to rapid change in their consumption habits contribute to the excess of wheat demand (Heady and Fan 2008). However, The high volatility in wheat prices is mainly linked to the decline in stock levels in the five main exporting countries; there is a radical decline in world wheat stock levels since 2000 (-50%), which by dropping below the critical threshold of 17% of world consumption cannot accomplish the stabilization of wheat prices, adding the stock replenishment rates and their consequent effects on international trade expectations and decisions (Trostle, 2008). Furthermore, the strengthening of the euro versus the US dollar negatively impacts the wheat prices expressed in dollar (Agritel[ii]). Additionally, growing speculation in financial markets increases price volatility and leading to unreasonable price fluctuations (Robles *et* al., 2009). Furthermore, the fluctuations in wheat market are also linked to the non-food use of wheat, particularly biofuels, in reason of the necessity to diversify sources of energy supplies (Moschini and Hennessy 2001).

The globalization and growing integration of financial and energy markets with agricultural commodity markets, has created complex interactions between oil and wheat markets and has increased difficulties to understanding the wheat price movements. The increasing trend in wheat prices raised some question. One such question is whether the fluctuations in oil market lead to similar behavior in wheat market, and if so, what is the structure of this link? The answer to this question is important whereas high in wheat market increases uncertainty, which complicates decision-making for farmers, processors, traders and end-consumers.

A considerable body of research has been devoted to investigating the mechanism of transmission of volatility between the oil and agricultural markets. For example, Chang and Su (2010) have shown that fluctuations in oil futures contracts had an influence on the future prices of corn and soybeans; they provided evidence of volatility spillover from crude oil to corn and soybeans and showed a positively economic substitution effect during the higher crude oil price period. . Chen et al. (2010) studied the relationship between oil prices and soybeans prices and demonstrated that recent increase in oil prices results in growth of agricultural biofuels production that drives up demand for the agricultural commodities. Campiche *et* al. (2007) studied the co-movement between oil and agricultural markets (corn, sorghum, sugar and soy) over the period 2003-2007; they found co-integration effect between markets only during crisis period. Kanamura (2009) examined the relationship between energy market and futures contracts of sugar, wheat and corn and he showed that the correlation between these markets has increased following the creation of Biofuels markets in 2004. Mitchell (2008) focused on the U.S and European biofuels production as a decisive factor in the increased of the cost of production of agricultural and food products. Yang et al. (2008) showed that the increase in the international corn and wheat prices during the food crisis can be attributed to biofuels markets. Harri *et* al. (2009) found that there is volatility spillover from oil futures prices to corn futures prices after the food price crisis. Abbott *et* al. (2008) and Baffes (2007) explained that the speculation on agricultural markets can be considered as an alternative for investors to speculate in case of major fluctuations in oil markets.

In contrast, some researches indicate that there is no direct relationship between oil and agricultural commodity prices. For example, Zhang and Reed (2008) argued that oil price volatility do not have direct impacts on agricultural commodity prices. Pindyck and Rotemberg (1990) examined the co-movement of wheat, cotton, copper, gold, crude oil, lumber and cocoa prices and found that the cross-price elasticity of demand and supply are zero. Yu *et* al (2006) and Gilbert (2010) stated that there is no direct causal relationship between oil and agricultural markets and linked high volatility agricultural prices to demand growth, monetary and financial developments. Zhang *et* al. (2010) analyze both short and long-run relationship between prices of fuel and agricultural commodities. Their results show that there is no direct long-run price relation between fuel and agricultural commodity prices and there is only limited, if any, direct short-run relationships.

Apparently there is a rapidly emerging literature on the dynamics of price transmissions between energy and agricultural commodity markets. One of the recent tendencies in agricultural price determination is therefore to investigate causal linkages from oil prices to agricultural commodity prices. The conclusion appears to be mixed. Furthermore, although there is some evidence on the financialization of commodity markets, there aren't many studies that consider risk transmission across oil and wheat markets, which can be considered as the most volatile of commodity markets in response to changing economic circumstances.

Some more recent studies exist on the linkages between crude oil and agricultural commodity price show that linear and nonlinear causality methods may produce different findings (Bekiros and Diks 2008 and Kim *et* al. 2010. Our study differs from other studies by employing a newly developed causality model, kernel Granger Causality.

Various non-parametric causality tests have been proposed in the literature. Baek and Brock (1992) argued that parametric linear Granger causality tests have low power against certain nonlinear alternatives. Hiemstra and Jones (1994) modified the version of Baek and Brock (1992) and detected the nonlinear granger-causal relationship between variables by testing whether the past values influence present and future values. Diks and Panchenko (2006) developed a non-parametric causality test in order to avoid spurious rejections of the null hypothesis of Granger causality by applying Hiemstra and Jones test. However, Melhem and Terraza (2010) used a Mackey-Glass model and demonstrated that the relationship tested by Hiemstra and Jones test is not generally compatible with conditional heteroscedasticity error terms, leading to the possibility of spurious estimation. As an alternative, Marinazzo et al. (2008) developed a new approach of Granger causality by using the theory of reproducing kernel Hilbert spaces in order to cope with the problem of overfitting. Hence, exploiting the geometry of reproducing kernel Hilbert spaces, they have introduced a filtered index which is able to measure cause-effect relationships with an arbitrary amount of nonlinearity and is not affected by overfitting.

In the following section, we describe the kernel Granger Causality model. Section 3 represents our data, while Section 4 presents the empirical results. Concluding remarks are presented in Section 5.

2. Kernel Granger Causality Method

Kernel Granger Causality test is defined as a non-parametric test able to detect the linear and non linear causality between time series. To understand KGC as a generalization of the linear case, we review the linear case. The temporal dynamics of a stationary time series $\{x(t)\}_{t=1,\dots,N+m}$ can be explained using an autoregressive model based on the past values of the time series:

$$x_n = \sum_{j=1}^{m} a_j x_{n-j} + e_n \tag{1}$$

In order to include information from a simultaneously recorded time series $\{y(t)\}_{t=1,\dots,N+m}$, causality tests are typically implemented through bivariate regressions:

$$x_n = \sum_{j=1}^{m} a'_j x_{n-j} + \sum_{j=1}^{m} b_j y_{n-j} + e'_n \tag{2}$$

Where the matrices a' and b are called the autoregression coefficients and the e' is the white noise[iii]. *m* is the order of the autoregressive model chosen according to Baysian criterion (BIC) or other order selection criteria (Akaike information criterion, Schwartz criterion and Hannan-Quinn criterion).

The causality between two time series is explained by the difference of the variance of innovations, if the variance of *e'* is significantly smaller than the variance of innovations of *e* then the coefficients of b are different from zero and y cause x (same reasoning to evaluate the causality in the opposite direction x → y). An index measuring the strength of the causal interaction is defined as :

$$\delta = 1 - \frac{\langle e'^2 \rangle}{\langle e^2 \rangle} \tag{3}$$

Where $\langle \cdot \rangle$ denotes averaging over n (note that $\langle e \rangle = \langle e' \rangle = 0$). The test considers $X_i = (x_i, \dots, x_{i+m-1})^T$ and $Y_i = (y_i, \dots, y_{i+m-1})^T$ as *N* realization of stochastic variables of *X* and *Y*. Let **X** be an *m x N* matrix having vectors X_i as columns, and **Z** be a *2m x N* matrix having vectors $Z_i = (X_i^T Y_i^T)^T$ as columns. The values of α are organized in a vector $\alpha = (x_{1+m}, \dots, x_{N+m})^T$. Each component of X and Y has zero mean, and the vector α has zero mean and is normalized ($\alpha^T . \alpha = 1$).

Then, for each $i = 1, \dots, N$ the vectors $\tilde{x} = (\tilde{x}_1, \dots, \tilde{x}_N)^T$ and $\tilde{x}' = (\tilde{x}'_1, \dots, \tilde{x}'_N)^T$ are the estimated values by linear regression in two cases. $\tilde{x}$ *and* $\tilde{x}'$ have the following geometrical interpretation. Let $H \subseteq \Re^N$ be the range of the *N x N* matrix $K = X^T X$. Then $\tilde{x}$ is the projection of α on *H*. In other words, calling *P* The projector on the space *H*, then $\tilde{x} = P\alpha$ and $u = \alpha - P\alpha$. Analogously, $\tilde{x}' = P'\alpha$ and *P'* being the projector on the 2m-dimensional space $H' \subseteq \Re^N$, equal to the range of the matrix $K' = Z^T Z$. Note that $H \subseteq H'$ and *H'* is decomposed as follows: $H' = H \oplus H^\perp$, where $H^\perp$ is the space of all vectors of *H'* orthogonal to all vectors of *H*. $H^\perp$ corresponds to the additional features due to inclusion of variables. Calling $P^\perp$ the projector on H, the index of causality can be written:

$$\delta = \frac{\|P^\perp u\|^2}{1 - \tilde{x}^T \tilde{x}} \tag{4}$$

Note that *H* is the range of the matrix and $\tilde{K} = K' - K'P - P(K' - K'P) = K' - PK' - K'P + PK'P$. It follows that $H^\perp$ is spanned by the set of eigenvectors with no vanishing eigenvalues, of $\tilde{K}$. calling $t_1, \dots, t_m$ these eigenvectors, the index of causality becomes:

$$\delta = \sum_{i=1}^{m} r_i^2 \tag{5}$$

Where r_i is the Pearson correlation coefficient of u *and* t_i. In order to avoid false causalities and compensate the threshold of significance for multiple comparison, the false discovery rate (FDR) correction is used to select eigenvectors t_i, correlating to *y*, with the expected fraction of false positives equal to 0.05 and the new causality index is obtained by summing only the $\{r_{i'}\}$ that pass the FDR test:

$$\delta_F(y \to x) = \sum_{i'} r_i^2 \tag{6}$$

By exchanging the roles of the two time series, we may evaluate the causality index $\delta_F(x \to y)$. The nonlinear Granger causality derived from the linear case has been described completely in Marinazzo et al. article and is based on the theory of reproducing kernel Hilbert spaces[iv]. Given a kernel function K, with spectral representation:

$$K(X, X') = \sum_a \lambda_a \phi_a(X) \phi_a(X') \tag{7}$$

With *H* range of the *N x N* Gram matrix, there is K with elements $K_{ij} = k(X_i, X_j)$. While using both X and Y to predict x, the Gram matrix K' is evaluated with elements $K'_{ij} = k(Z_i, Z_j)$. The regression values form the vectors $\tilde{x}'$ equal to the projection of *x* on *H'*, the range of *K'*. Hence, there are two choices for the kernel: the inhomogeneous polynomial (IP) of integer order *p* and the Gaussian kernel.

Inhomogeneous polynomial kernel: The IP kernel of integer order *p* is:

$$K_p(X,X') = (1 + X^T X')^P \quad (8)$$

Along the same lines as described for the linear case, the kernel Granger causality is taking into account only the eigenvectors of $\widetilde{K}$ that pass the FDR test, the index of causality is:

$$\delta_F^K = \sum_{i'} r_{i'}^2 \quad (9)$$

Gaussian Kernel: The Gaussian kernel is defined as:

$$K_\sigma(X,X') = \exp\left(-\frac{(X-X')^T(X-X')}{2\sigma^2}\right) \quad (10)$$

It depends on the width σ, which controls the complexity of the model: the dimension of the range of the Gram matrix decreases as σ increases. Thereby, L is considered as $m_1 - dimensional$ span of the eigenvectors of K whose eigenvalue is not smaller than λ_{max}, where λ_{max} is the largest eigenvalue of K and μ is a small number (10^{-6}) and $x = P\alpha$ with P the projector on L, by evaluating the Gram matrix K', the following matrix is considered :

$$K^* = \sum_{i=1}^{m2} \rho_i w_i w_i^T \quad (11)$$

Where $\{w\}$ are the eigenvectors of K', and the sum is over the eigenvalues $\{\rho_i\}$ not smaller than μ times the largest eigenvalue of K'. Thereby $\widetilde{K} = K^* - PK^* - K^*P + PK^*P$ and $P^{\perp}$ is the projector onto the $m_3 - dimensional$ range of $\widetilde{K}$. Note that the condition $m_2 = m_1 + m_3$ may not be strictly satisfied in this case. The Kernel Granger causality index for the Gaussian kernel is then constructed as in the previous case, see equation (9).

3. Data

This section carries out a descriptive analysis of the wheat spot prices and the oil crude spot prices. The study covers the period starting on January 2000 and ending on June 2013 for a total of 3520 observations. Data frequency plays an important role in determining price transmission from oil market to wheat market. We use daily observations; monthly observations do not capture the dynamic causal linkages between time series (Zhang and Reed, 2008). Wheat data are downloaded from “MGEX- Minneapolis Grain Exchange” and Oil crude data are compiled from “NYMEX-New York Mercantile Exchange”. The data are analyzed using the R: a language and environment for statistical computing and the Matlab for Windows.

To facilitate the analysis of volatility spillover between crude oil and wheat market, we apply the structural change test algorithm proposed in Hansen (2000) to test for possible structural change of wheat prices over the sample period. The test results are presented in Fig.1 with the structural change points indicated by the vertical line, it indicates that the wheat prices have a structural change in the first of November 2006. The timing of the structural change in wheat prices is consistent with the findings of Irwin and Good (2009), who examined changes in the agricultural commodity prices and showed that recent commodity price changes have higher averages and wider variations than previous price changes. For comparison, the sample is dividing into two subsamples and the causality tests are applied to quantify possible interactions between wheat and oil markets. Thereby, the data cover two sample periods which spans from January 3, 2000 to November 1, 2006 expressed by PI with 1783 observations and from November 3, 2006 to June 30, 2013 expressed by PII with 1737 observations.

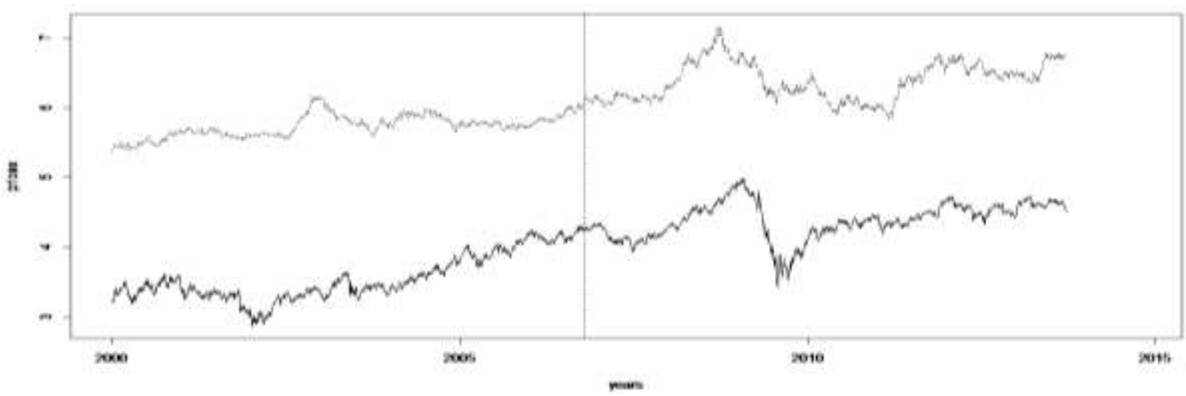

Figure 1. The evolution of oil and wheat log-prices with market structural change from January 2000 to June 2013.Crude Oil Price ($/barrel) Wheat Price ($/bushel)

4. Empirical Results

The empirical methodology comprises three steps. In first, we apply the unit root test in order to examine the stationarity of the oil and wheat time series in each period PI and PII. Then, we explore the linear dynamic linkage between the two markets by applying Granger causality test. Finally, we investigate the hypothesis of non-linear causality using kernel Granger causality test.

On the one hand, we estimate the correlation between oil and wheat prices. Table 1 illustrates the Pearson and Spearman correlation matrix among the log-prices for series in question. It seems that the wheat prices are more positively correlated with oil prices in PII. This is reasonable due to both the direct and indirect effects through which oil prices influence wheat market. It should be noted that Spearman coefficients for PI (0.671) and PII (0.797) are higher than Pearson coefficients (0.581 and 0.658), these findings explain the possibility of existence of non-linear relationship between the two markets.

Table 1. Pearson and Spearman Correlation Matrix

Period	PI		PII	
Pearson's Correlation	Oil	Wheat	Oil	Wheat
Oil	1		1	
Wheat	0.581	1	0.658	1
Spearman's Correlation				
Oil	1		1	
Wheat	0.671	1	0.797	1

However, the simple correlation coefficients do not imply causality. In order to assess the existence and direction of causality we have to employ more advanced techniques than simple correlation analysis.

4.1 Unit Root tests and Descriptive Statistics

In order to detect time series stationarity, we test the existence of unit root of oil and wheat prices for PI and PII by applying the augmented test of Dickey and Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS*)* tests. The results of unit root tests are reported in the corresponding panels of Tables 2. To overcome the difficulty of presenting large tables, the corresponding p-values are denoted by "*". As shown in table 2, the unit root analysis implies that the log-price of oil and wheat series are integrated of order one. Thus, the unit root tests reject the stationary hypothesis of all series in log-levels at customary 5% significance levels while all the variables appear to be stationary in returns.

Table 2. Results for Unit Root Tests

Market	Period		PI		PII	
	Unit Root Test		Log price	returns	Log price	returns
Oil	ADF	Intercept	-1.35	-44.07*	-2.26	-22.28*
		Trend & Intercept	-2.78	-44.06*	-2.36	-22.28*
	PP	Intercept	-1.16	-44.48*	-2.23	-41.59*
		Trend & Intercept	-2.52	-44.47*	-2.33	-41.58*
	KPSS	Intercept	4.37*	0.06	0.92*	0.06
		Trend & Intercept	1.84*	0.04	0.22*	0.06
Wheat	ADF	Intercept	-1.79	-39.60*	-2.08	-41.59*
		Trend & Intercept	-2.75	-39.59*	-1.98	-41.54*
	PP	Intercept	-1.82	-39.52*	-2.13	-41.55*
		Trend & Intercept	-2.68	-39.51*	-2.04	-41.55*
	KPSS	Intercept	3.05*	0.05	0.74*	0.10
		Trend & Intercept	1.28*	0.04	0.43*	0.08

* indicates the rejection of the null hypothesis at the 5% level.

Based on this analysis, we use the returns as stationary variables in order to investigate the relationship mechanism between oil and wheat markets. The returns of the two markets over the two subsample periods are displayed in fig.2. Specifically, the returns are defined as $r_t = \ln(P_t) - \ln(P_{t-1})$ where P_t is the closing price on day *t*.

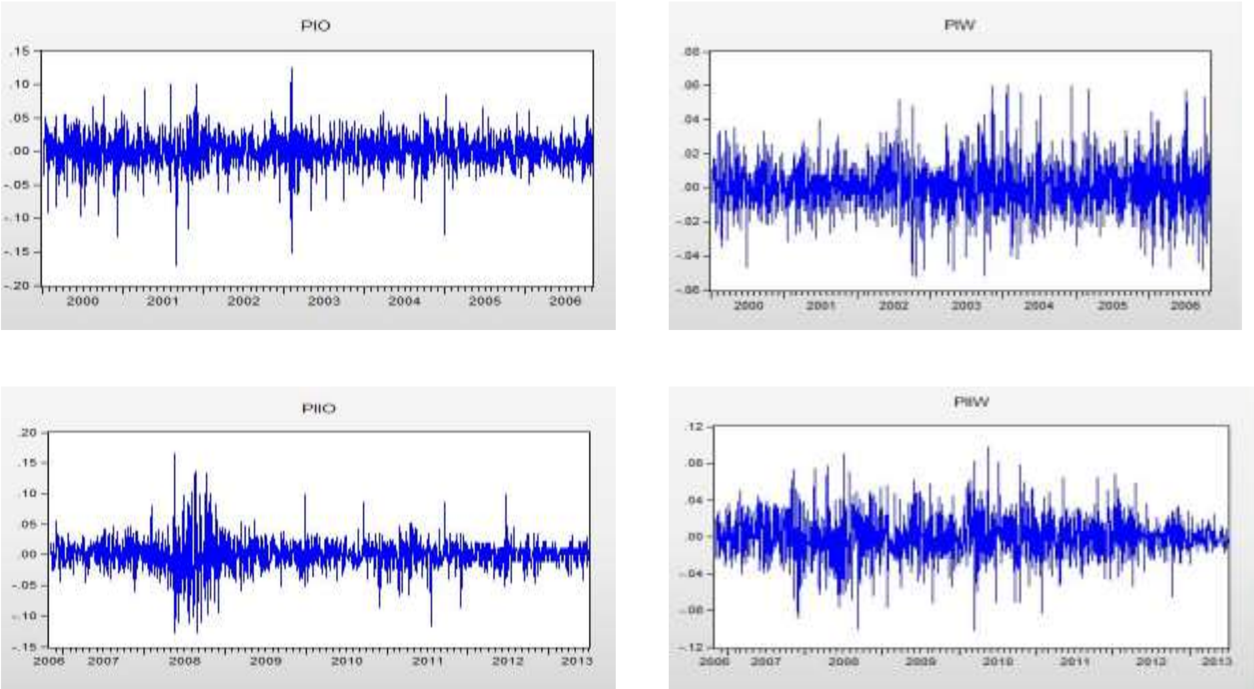

Figure 2. Oil and Wheat returns for PI and PII

The descriptive statistics of oil and wheat returns for the sub-periods are summarized in Table 3. It seems that data characteristics of the return series are different in PI and PII. The standard deviation is changed from 0.020 for PI to 0.026 for PII in oil market and from 0.014 to 0.022 in wheat market. The normality of the series based on Jarque Bera is rejected for the two markets. The ARCH effect for oil and wheat returns identifies a time-varying conditional volatility and may explain the presence of excess kurtosis. The descriptive analysis indicates that the oil and wheat prices are likely to be determined by new price regimes during the recent years.

Table 3. Descriptive statistics of Oil and Wheat returns

Period	Market	ARCH(5)	Mean	Std.Dev	Skweness	Kurtosis	Jarque-Bera
PI	Oil	76.322	0.000463	0.020	-1.5682	6.9164	1234.788
	Wheat	21.478	0.000405	0.018	-0.6194	5.2233	119.651
PII	Oil	307.556	0.000355	0.026	0.0916	8.4212	2127.246
	Wheat	74.545	0.000186	0.032	-0.6349	6.5096	165.294

PI: 01 January 2000 – 31 October 2006, PII: 01 November 2006 – 30 June 2013

The different data characteristics in PI and PII raise the question of whether the relationship between the world oil and wheat market. In this respect, we investigate the dynamic relationship between world oil market and wheat oil market by applying Granger Causality test and kernel Granger Causality test.

4.2 Linear Granger Causality test

The linear Granger causality test introduced by Clive Granger in 1969 is usually constructed in the context of a reduced-form vector autoregression VAR. Let x_n and y_n two stationary time series with *m* number of lags. Then the bivariate VAR (*m*) model is given as follows:

$$x_n = \sum_{j=1}^{m} a'_j x_{n-j} + \sum_{j=1}^{m} b_j y_{n-j} + e'_n \qquad (12)$$

If in a regression of x_n on lagged values of x_n and y_n, the coefficients of the y_n values are zero then the series y_n fails to Granger-cause x_n. The error terms e' are separate i.i.d processes with zero mean and constant variance. The lag lengths of the VAR specification were selected using the Akaike information criterion (AIC), then in what follows we discuss results for lags $m=5$. Table.4 presents the estimated results of the linear Granger causality test for PI and PII.

Table 4. Granger Causality test

Null hypothesis	PI	PII
Oil does not Granger cause Wheat	0.659 (0.654)	0.580 (0.714)
Wheat does not Granger cause Oil	0.268 (0.930)	1.513 (0.182)

p-value in parentheses corresponds to 95% confidence level.

The results from the Granger causality method clearly show that the null hypothesis of no causality from oil market to wheat market and from wheat market to oil market is accepted for two sub-periods PI and PII. The F-test results indicate no causal relationship between oil and wheat returns. In short, these results show no links between oil and wheat markets, rejecting the assumption that instability in each market causes instability in the other. A similar result was reported in Yu et al. (2006), Zhang and Reed (2008), Gilbert (2010) and Nazlioglu (2011).

4.3 Kernel Granger Causality Test

After determining the results of linear Granger causality between oil and wheat markets, we now concentrate on investigating whether there is a non linear dynamic interactions between the two markets. It should be noted that linear causality tests have high power in identifying linear causal relations, but their power against nonlinear causal links might be low, as pointed out by Hiemstra and Jones (1994). To this end, we adopt the KGC test with its two forms. We use the Inhomogeneous polynomial kernel with various values of p and the Gaussian kernel with various values of σ to show how the two parameters affect the causality index. Then, we evaluate the bivariate causality for variables within 100 times simulation. The optimal order of the model *m* is chosen by the AIC criterion (*m*=5). Based on the results of the simulation study, we then select values of p and σ from 2 to 5. Table 5 presents the estimated results using the KGC method with the different values of p and σ. To compare the validity of detecting causality, the results of the p=1 and σ=1 (which corresponds to linear Granger causality) are also evaluated. Thereby, for linear estimation we have: *Inhomogeneous polynomial kernel:*

$$K(X,X') = (1 + X^T X') \text{ and Gaussian Kernel: } K_1(X,X') = \exp\left(-\frac{(x-x')^T(x-x')}{2.1^2}\right)$$

Table 5. Causality Index of KGC between Oil and Wheat markets in PI and PII

p & σ		1	2	3	4	5
Causality index (*Inhomogeneous polynomial kernel with various values of p*)						
PI	Oil->Wheat	0	0.26	0.25	0.23	0.19
	Wheat->Oil	0	0.12	0.11	0.08	0.07
PII	Oil->Wheat	0	0.65	0.52	0.50	0.49
	Wheat->Oil	0	0.14	0.11	0.11	0.09
Causality Index (*Gaussian kernel with various values of* σ)						
PI	Oil->Wheat	0	0.35	0.31	0.31	0.30
	Wheat->Oil	0	0.11	0.09	0.09	0.08
PII	Oil->Wheat	0	0.53	0.50	0.51	0.47
	Wheat->Oil	0	0.13	0.10	0.09	0.09

Notes: *p* integer order of inhomogeneous polynomial kernel and *σ* scale parameter of Gaussian kernel change from 1 to 5, the optimal order of the model *m=5* chosen by the AIC criterion.

The IP kernel Granger causality method exhibits a causality index equal zero between oil and wheat returns with p=1. When p varies from 2 to 5 the values of causality index reveal the presence of nonlinear causal link between oil and wheat and explain that changes in oil prices can have an influence on the wheat dynamic prices. Note that the causality index is maximum with p=2 (up to 0.26 in PI and 0.65 in PII). Further, by estimating the transmission of information from wheat to oil market, we find that the causality index is also significant and records a maximum value with p=2 (0.12 in PI and 0.14 in PII).

For Gaussian kernel Granger causality method, the hypothesis of non causal relationship between oil and wheat markets is accepted with σ = 1. On the other hand, when σ varies from 2 to 5 the causality index is considerable and detects a nonlinear causal relationship from oil to wheat (up to 0.35 in PI and 0.53 in PII with σ=2) and from wheat to oil (up to 0.11 in PI and 0.13 in PII with σ=2).

Thereby, it seems that when p = 1 and σ = 1 (which corresponds to linear Granger causality) there is no information transfer between markets, the causality index equal zero. This finding is consistent with the linear Granger causality test. Otherwise, when p and σ ≥ 2 , the KGC method evaluates the Granger causality for nonlinear relationship between time series and reveals a no linear causal link between series. The causality index of KGC method is non zero and maximal at p=2 and σ=2, the interaction being quadratic. These results confirm the strongly non linear nature of the interaction dynamic between oil and wheat markets.

Thus, it seems that when we employ KGC mode with various values of p and σ, the results change dramatically. There is a bidirectional non linear causality between oil and wheat markets. It seems that causality in nonlinear dynamics between the two markets exists before and after structural change in 2006. Our analysis reveals that the information transfer mechanism between oil and wheat is essentially non linear, as depicted in figure 3.

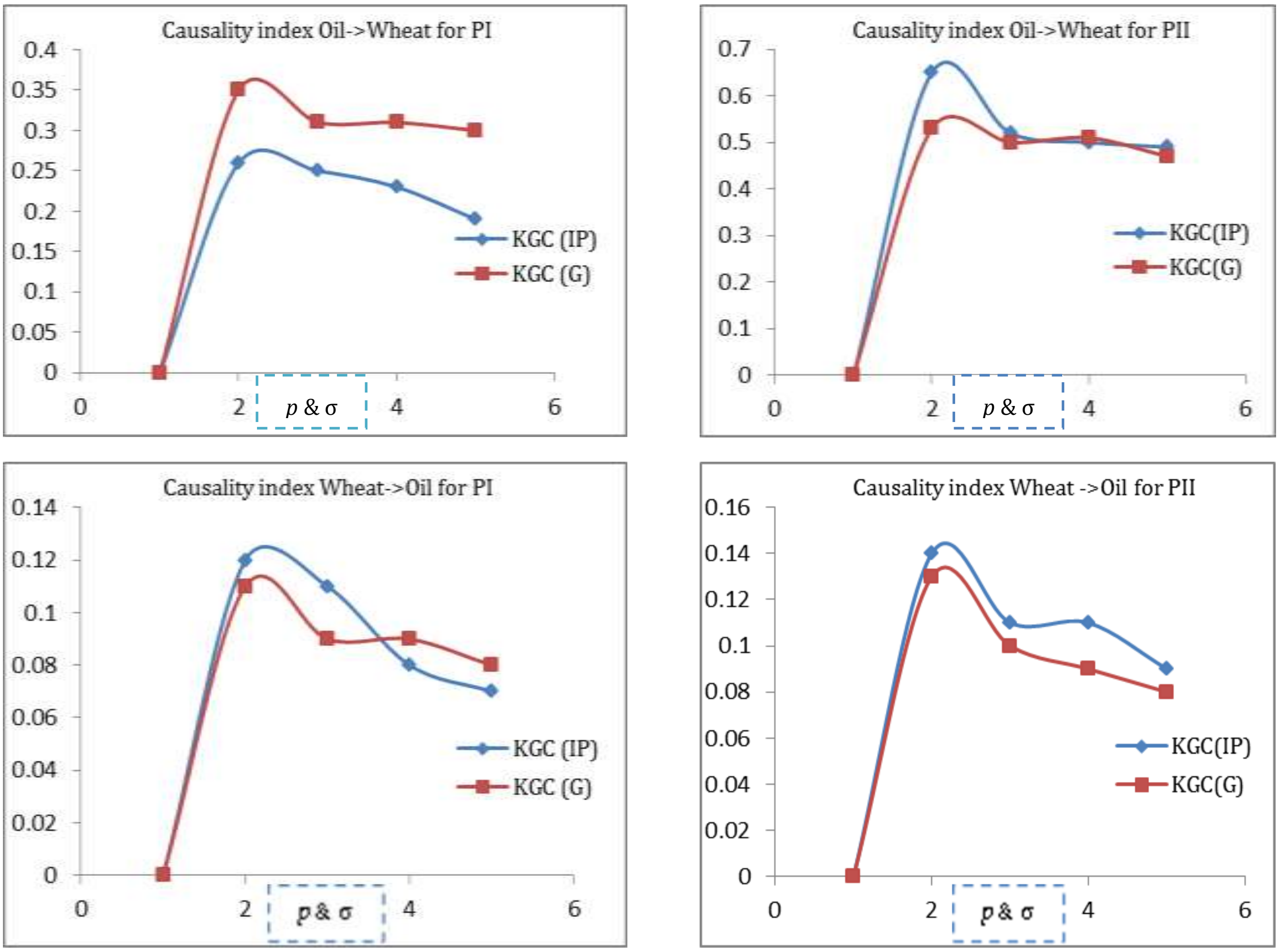

Figure 3. Causality Index between Oil and Wheat markets with various values of p & σ

Therefore, these findings illustrate the dynamic relationship between oil and wheat markets and clarify the effect of volatility transmission between the two markets which can be explained by changing in production and transportation costs as well as biofuels production. This effect is extending in crisis period 2006-2008 and till today still aggravated by growing integration of financial markets and speculation.

5. Conclusion

This paper investigates the dynamic relationship between oil crude and wheat markets characterized by high volatility in order to find out how risk transmission mechanism works between oil and wheat financial and commodity markets. The daily data spanning from January 2000 to June 2013 are divided into two sub-periods as January 01, 2000 to October 30, 2006 and November 01, 2006 to June 30, 2013 according to structural change in wheat market in 2006. In order to detect the dynamic relationship between the two markets we apply Granger causality test proposed by Clive Granger in 1969 and Kernel Granger causality test developed by Marinazzo et al. in 2008. Using a relatively new test for causality, a non-parametric test based on the theory of reproducing kernel Hilbert spaces, in the interest to evaluate the existence of nonlinear causal linkages between series.

The results of the linear Granger causality analysis accept the neutrality hypothesis and do not show any interaction assessment between markets. The F-test results indicate no causal relationship which implies that there is no information flow and no risk transfer between oil and wheat prices in PI and PII.

The KGC method is consistent with the GC test when values of p and σ equal 1. However, when p and σ varies from 2 to 5, KGC method exhibits a significant causality index (maximal at p=2 and σ=2) and provides an evidence nonlinear relationship between oil and wheat markets for PI and PII. These findings indicate that changes in each market have a strongly impact in determining the dynamic prices in the other. The information flow between oil and wheat markets supports a clear evidence of transmission volatility between the two markets.

The findings realized from linear and nonlinear causality analysis revealed different policy implications. It is marked that there are many key linkages between oil and wheat prices, oil as a production cost, transportation cost, biofuels and co-movement with wheat commodity due to investment fund activity. On the one hand, the traditional oil price transmission to wheat commodity prices implies that a rise in oil prices results higher wheat commodity prices by increasing costs of production through its impacts on fertilizer, chemicals, transportation costs and other inputs. However, OECD[v] shows that 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 agricultural biofuels production. The linkage between energy and agricultural markets becomes stronger as demand for biofuels production increases due to rising oil prices. Furthermore, by taking into account the growing demand for biofuels that arises from not only higher energy prices but also environmental concerns, the growing importance of biofuels as a renewable energy and as an alternative to fuels has motivated farmers to produce for fuels. Thereby, the link between oil and agricultural market in terms of biofuels was also examined by Serra (2011) and Serra et al. (2011), Serra analyzed the volatility spillover between crude oil, ethanol and sugar prices in Brazil and found a strong relationship between crude oil and sugar markets which can be explained by the high volatility in the ethanol prices. Further Serra et al investigated the fluctuations in US ethanol market and found the existence of long-run relationship among ethanol corn oil, and gasoline as well as strong links between energy and food prices.

On the other hand, it is well established that oil markets have always attracted global investors. The causal linkages between oil and wheat markets indicate that the investors may benefit from information about the oil prices to invest in wheat markets and reveal that the dynamics of the oil prices can help investors to forecast of the future values of wheat commodity prices. Thus, the fact that significant risk transmissions are observed from oil to wheat market suggests that investors have played a crucial role in the agricultural markets fluctuations during crisis period. Moreover, Du et al. (2011) investigated the role of speculation in driving crude oil price variation and they attempted to quantify the extent to which volatility in the crude oil market pass through into agricultural commodity markets (corn and wheat) in the US through speculative activities .They found evidence of volatility spillover among crude oil, corn and wheat markets after the fall in 2006. Thus, after the Subprime crisis it is remarkable that the investors are looking to diversify their portfolios and minimize their risk by choosing agricultural financial markets as an alternative.

Furthermore, the non linear causality from wheat prices to oil crude prices can be explained by the variation in wheat world market which can indirectly affect oil market. Thus, the demand and supply variation of wheat market would lead to increase or to lower demand in oil market which can affect oil price mechanism through the key linkages between the two markets. Thereby, investors interested in commodity markets should realize that risk in one commodity market may not be independent of risk in other commodity markets and they should design the agricultural policies within the context of the tendencies in energy policies.

Finally, it should be noted that changes in agricultural commodity prices affect a large portion of population in both the least developed and developing countries since the agriculture still the mainstay of economy in those countries which also are more vulnerable to food price fluctuations. Moreover, high oil prices and ongoing support policies toward biofuels production particularly in USA and European Union imply that agricultural commodity prices are expected to remain high in the future. It will be possible to have new episodes of high agricultural volatility and soaring prices, therefore further negative repercussion on food security; it remains very important to appropriate policy implications by understanding energy and agricultural interdependency and risk transmission in order to avoid increasing an already difficult situation.

After determining the dynamic interaction between oil and wheat markets by using kernel Granger causality method, a non-linear autoregressive model using kernel machines will be our interest for future research to realize a new approach of nonlinear model of financial time series and derive a new nonlinear prediction scheme.

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[i] Food and Agriculture Organization of the United Nations established on 16 October 1945.

[ii] Agritel is a society dealing with price risk management for agricultural commodities. Paris, France. www.agritel.fr

[iii] The coefficients of the models are estimated using a standard least squares optimization.

[iv] See Marinazzo et al. (2008). Kernel method for nonlinear Granger Causality.

[v] The Organization for Economic Co-operation and Development. Paris, France. www.oecd.org