University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2014-68
November 2014

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THE RELATIONSHIP BETWEEN OIL AND AGRICULTURAL COMMODITY PRICES IN SOUTH AFRICA: A QUANTILE CAUSALITY APPROACH

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Abstract

This paper investigates causality between oil prices and the prices of agricultural commodities in South Africa. We use daily data covering the period April 19, 2005 to July 31, 2014 for oil prices and the prices of soya beans, wheat, sunflower and corn. The test for Granger causality in conditional quantiles as proposed by Jeong et al., (2012) was employed. Our findings show that the effect of oil prices on agricultural commodity prices varies across the different quantiles of the conditional distribution. The impact on the tails is lower compared to the rest of the distribution. However, the highest impact is not necessarily at the mean. We show that due to nonlinear dependence between oil prices and agricultural commodity prices, regular Granger causality provides misleading results and also fails to characterize the relationship over the entire conditional joint distribution of the variables.

Keywords: Granger causality, South Africa, Nonparametric kernel, Quantile causality, Agricultural commodity prices.

JEL Codes: C32, Q02, Q43

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I. INTRODUCTION

What are the forces driving the upward trend of agricultural commodity prices (Corn, Wheat, Sunflower, and Soya beans) in recent years? The answer to this question is very important in order to decide appropriate policy options and to examine investment opportunities. According to Abbott et al. (2008), the main drivers of increasing agricultural commodity prices are the result of compound interactions among macroeconomic factors such as crude oil prices, exchange rate, growing demand for food and slowing growth in agricultural productivity, as well as the policy choices made by nations. Although these factors are mutually reinforcing, high oil prices are thought to be the major factor driving up the agricultural commodity prices (FAO, 2008, Mitchell, 2008 and OECD, 2008). This is based on the fact that agricultural markets and energy have become closely linked especially since the surge of bio fuel production in 2006.

Ethanol and biodiesel are substitutes for gasoline and diesel, thereby the recent surge in agricultural commodity prices are attributed to increasing usage of crops in production of bio fuels. It is thus very important to put a figure on price variability of agricultural products, as negative price shocks have an exacerbating impact on the economic growth of developing economies (Dehn, 2000). Moreover, the process of globalization has led economies around the world to be interconnected more than ever. Hence, a shock related to a change in any specific economic factor such as oil in one country gets carried over across the world instantly. This is more so the case when the economies where the shock originates from are major role players in shaping world economic activities. In other words, a specific country is not only likely to be affected by shocks which generated domestically, but also by external shocks.

A large body of empirical studies (Chenery, 1975; Hanson et al., 1993; Baffes, 2007; Kaltalioglu and Soytas, 2009) have tried to understand the relationship between oil prices and agricultural commodity prices but the results still remain ambiguous. For instance, empirical studies like Reboredo (2012) and Nazlioglu and Soytas (2011) found no evidence that oil prices lead agricultural commodity prices. Others such as Chen et al. (2010) showed that oil price rise significantly lead to increases in agricultural commodity prices. Some studies have gone as far as claiming that “food prices mirror oil prices” (Dancy, 2012). These results, however, rely on the methodology that was employed or the sampling period of the data. Furthermore, the most popular method used to investigate the energy-food nexus is based on conditional causality in the mean, developed by Granger (1969).

We start with the unit root tests, and then conduct the standard linear Granger causality test. We then check for non-linearity and structural breaks in the data, followed by the quantile causality test. The basic idea of the Granger causality is to describe causal relationships between two times series variables based on their conditional means. However, this method assumes a linear data generating process for the variables and constant parameters over time. In effect, the regular Granger causality test may be unable to pick up the existence of causality in the tails of the conditional distribution, as it assumes same estimates for the entire sample. Moreover, in the presence of structural breaks or non-linearity, the regular Granger causality test would provide incorrect results, as it fails to take these into account. We conducted the BDS independence tests and checked for the presence of structural breaks. Non-linearity and structural breaks would lead us to go beyond the conditional mean estimate and examine causality in the quantiles of the conditional distributions using non-parametric Granger causality tests. Our decision to use non-linear causality tests is thus based on the possibility of non-linear data generating processes for our macroeconomic variables (as we show), and the possible presence of structural breaks in the data.We ask the question "Do oil prices lead agricultural commodity prices in various conditional quantiles?"

To this end, we provide an understanding of the impact of oil prices across the different quantiles of agricultural commodity prices in South Africa using the quantile causality approach. Quantile regression was first introduced by Koenker and Bassett (1978) as a robust alternative to least-squares regression. Quantile regression offers a number of advantages over least-squares methods. For instance, it estimates quantiles of the conditional distribution rather than the mean and is more resistant to outliers than least-squares methods (Leider, 2012). Also, the method of quantile causality becomes more instructive in the case where the distributions of variables have fat tails.

We add to the limited existing literature on how local (specifically, South Africa) agricultural commodity prices respond to Brent crude oil price shocks. In this regard, we provide a holistic insight on how agricultural commodity prices in South Africa respond to oil prices. Also, we help the process of evidence-base policy making with respect to agricultural and energy policies. To the best of our knowledge, this is the first study to analyse causal relationship using quantile causality with South African data.

II. METHODOLOGY

II.1Linear Granger Causality Test

According to Granger (1969), causality between two stationary series x_t and y_t can be defined using the concept of predictability. x_t is said to "Granger" cause y_t if past realizations of x_t improve the prediction of y_t compared to predictions using historical values of x_t only.

Assuming that the stationary series x_t and y_t are of length n, a formal test for Granger causality between x_t and y_t requires estimating a p-order linear vector autoregressive model $VAR(p)$ of the form:

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{pmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} \phi_{11,p} & \phi_{12,p} \\ \phi_{21,p} & \phi_{22,p} \end{pmatrix} \begin{pmatrix} y_{t-p} \\ x_{t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{1}$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ represents a white noise process with zero mean and covariance matrix Σ. p is the optimal lag order of the process selected using a sequential likelihood ratio (LR) test. α_1 and α_2 are constants and $\phi's$ are parameters.

II.2 Non-parametric Granger Causality Test

Granger developed the primary method for deducing causality in financial applications .This method considers two time series and determines whether one predicts, or causes, the other. However, variables like financial returns tend to have fait tailed or nonelliptic distributions and this may render results of any analysis using conditional means uncertain. Moreover, causality relationships in the tails may be quite different from causality relationships at the center of the distribution (see Lee and Yang (2007)).

Previous research has shown that the correlations across financial variables depend on the market regime (Lin et al., 1994; Ang and Bekaert, 2002; Longin and Solnik, 2001; Ang and Chen, 2002). Extreme market conditions usually result in stronger financial co-movement across financial variables, and in contagion and volatility spillovers. Also, Granger causality in quantile is important for risk management and portfolio diversification (Hong et al. (2009)), as well as for the robustness properties of conditional quintile.

In instances where the causality only exists in certain regions of the conditional joint distribution of the variables, basing Granger causality tests on conditional means alone might be misleading. However, extending the linear Granger causality test to linear quintile regression could overcome this difficulty. Lee and Yang (2007) developed linear Granger tests in quintile that detect the existing causality relationships in the tails of the conditional distribution. However, the linear causality tests may still fail to detect non-linear causality relationships. Although Financial and economic variables usually are linear in the conditional mean, which is an overall summary of the conditional distribution, their behaviour tends to be extremely nonlinear in the tails of the distribution. To overcome the issues arising from the nonlinearity of the relationship between variables, several papers in the literature, such as Nishiyama et al. (2011), have proposed nonparametric Granger causality tests based on the kernel density estimation. Jeong et al. (2012) developed a nonparametric test of Granger causality in quantile based on the kernel density method. This paper fills the existing gap in the literature both in terms of the causality in the conditional and nonlinearity of the relationship. The authors defined the Granger causality in quantile as follows:

1. x_t does not cause y_t in the θ-quantile with respect to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if
$$Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}) \tag{2}$$
2. x_t is a prima facie cause y_t in the θ-quantile with respect to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if
$$Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) \neq Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}) \tag{3}$$

where $Q_\theta(y_t|\cdot)$ is the θth conditional quantile of y_t given $\cdot$, which depends on *t* and $0 < \theta < 1$.

Let consider $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $Z_{t-1} \equiv (y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p})$, $V_t = (X_t, Z_t)$, and $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ are the conditional distribution function y_t given Z_{t-1} and Y_{t-1}, respectively.

The conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all V_{t-1}. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have,

$$F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta \text{w.p.1}$$

Consequently, the hypothesis to be tested based on definitions (2) and (3) are

$$H_0 = P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \text{a.s.} \tag{4}$$

$$H_1 = P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \text{a.s.} \tag{5}$$

Building on Zheng (1998)'s work, Jeong et al. (2012) reduce the problem of testing quantile restriction by using as distance the measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\}$,where ε_t is the regression error term and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}.This allows for testing quantile restriction as specifically testing a particular type of mean restriction. The regression error ε_t arises from the fact that the null hypothesis in (3) can only be true if only if $E[\mathbf{1}\{y_t \le Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or equivalently $\mathbf{1}\{y_t \le Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Jeong et al. (2012) specify the distance function as

$$J = E\left[\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta\right\}^2 f_Z(Z_{t-1})\right] \tag{6}$$

Where $J \ge 0$ and the equality holds if and only if the null hypothesis H_0 in equation (4) is true, while $J > 0$ holds under the alternative H_1 in equation (5). From the result in Fan and Li (1999), a feasible test statistic based on the distance measure J in equation (6) has the leading term that follows a second order degenerate U-statistic. Jeong et al. (2012) show that under the β-mixing process, the asymptotic distribution of the statistic is asymptotically normal.

Additionally, Jeong et al. (2012) showed that the feasible kernel-based test statistic based on J has the following form:

$$\hat{J}_T = \frac{1}{T(1-1)h^{2p}} \sum_{t=1}^{T} \sum_{s\neq t}^{T} K\left(\frac{Z_{t-1}-Z_s}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{7}$$

where $K(\cdot)$ is the kernel function with bandwidth h and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated from

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \le \hat{Q}_\theta(Y_{t-1}) - \theta\} \tag{8}$$

where $\hat{Q}_\theta(Y_{t-1})$ is estimate of the θth conditional quantile of y_t given Y_{t-1}. $\hat{Q}_\theta(Y_{t-1})$ can be estimated by the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta|Y_{t-1}) \tag{9}$$

Here, $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ is the Nadarya-Watson kernel estimator and given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s\neq t} L\left(\frac{Y_{t-1}-Y_s}{h}\right)\mathbf{1}(Y_s \leq Y_{t-1})}{\sum_{s\neq t} L\left(\frac{Y_{t-1}-Y_s}{h}\right)} \tag{10}$$

with the kernel function $L(\cdot)$ and bandwidth h.

III. DATA ANALYSIS

1. DATA DESCRIPTION

We employ daily data spanning from April 19, 2005 to July31, 2014 for Brent crude oil prices, corn, wheat, sunflower and soya beans prices. The choice of the starting date was based on data availability. The agricultural commodity prices were obtained from the Johannesburg Stock Exchange, and the series of Brent crude oil prices from the U.S. Department of Energy. Note that, we retain the oil price in dollar terms and do not convert it into South African Indian Rand to avoid capturing the impact of the exchange rate on food prices along with the price of oil, as well as, to retain the oil price as purely exogenous.

Figure 1 shows a time series plot of Brent crude oil prices and agricultural commodity prices for the sampling period. Table 1shows the descriptive statistics for the variables. During the sampling period, soya beans had the highest average return while Brent crude oil returns were more volatile. All variables have a positive kurtosis. Also, the negative skewness over the sample period suggests return decreases.

Before testing for quantile causality, we investigate the order of integration of each series by means of Augmented Dickey Fuller (hereafter ADF) test (ADF, 1979),the Phillips and Perron (hereafter PP) test (Philips and Perron, 1988), and the Ng and Perron (hereafter NP) test (NP, 2001).Checking for stationarity of data series is an important prerequisite in most empirical time series analysis,as these methods require stationarity of the variables.Table 2presents empirical results of the unit root tests and indicate that the natural logarithms of the variables are all $I(1)$ processes at 5% significance level. The null of unit root can therefore be rejected for the first differences of all variables.

2. RESULTS

In this paper we use returns (first-differences of the data in its natural logarithmic form) of Brent crude oil and agricultural commodities (corn, wheat, sunflower, and soya beans) to test whether oil prices Granger cause agricultural commodity prices across the conditional quantiles of the agricultural commodities distribution. We do not consider the case of reverse causality between oil prices and agricultural commodity prices because of the relative size of the South African commodity market to that of the world market.

We begin by testing for stationarity of the data and find that the series are non-stationary. Testing for the simple Granger causality in the data, there is no evidence against the hypothesis that Brent crude oil prices granger-cause agricultural commodity prices in South Africa. Note that, to keep our results comparable with the quantile causality discussed below, we use a lag-length of one. Table 3 provides the test statistics and the p-values for this test. However, this test is only conducted at a mean level and does thus not provide an overall picture of the existing causality from oil prices to agricultural commodity prices.

We then performed the BDS test (Brock, Dechert, Scheinkman and Le Baron, 1987) for non-linearity in the residuals of the linear equation relating the returns on the agricultural commodity to oil, as well as the Bai-Perron (2003) test on the equation itself, to check for the existence of structural breaks, realizing the possibility of both regime changes and structural breaks in the relationships amongst high-frequency financial data. The results are reported in tables 4 and 5 respectively. From table 4, we reject the null hypothesis of residuals i.i.d (independent and identically distributed) for all the agricultural commodities and possible dimensions. This implies that, there are remaining dependence and the presence of omitted non-linear structure which was not captured by the linear specification, and hence there is non-linearity in the data. Further, the existence of structural breaks is also clearly established. Under the presence of structural breaks and non-linearity, the standard Granger causality test is no longer reliable.

We therefore test for causality between oil prices and agricultural commodity prices using the quantile Granger causality method proposed by Jeong et al., (2012). Through this test, we not only look at the causality beyond the mean estimates, but we also account for the structural breaks and non-linearity present in the data, as the quantile causality is based on a non-parametric kernel estimation. For all results, the standardized test statistic (solid line) is plotted against the different quantiles. Also, the dotted line represents the critical value 1.96. Figure 2 shows the testing of whether oil prices Granger cause corn prices. Since, the test statistic exceeds the critical value when $0.55 < \tau^{1} < 0.70$, we conclude that oil price changes do not lead corn price changes in $\tau < 0.60$ or $\tau > 0.65$. However, changes in oil prices lead corn prices in the $0.55 < \tau < 0.70$quantile. The causality between oil prices and soya beans is shown in figure 3. The result indicates that when $0.50 \leq \tau < 0.90$, oil prices cause soya beans prices. There is no causality from oil prices to soya prices when $\tau < 0.50$ or $\tau > 0.85$. The results for wheat and sunflower, as shown in figures 4 and 5 respectively, indicate that oil prices Granger cause these commodities across the entire conditional distribution. In the case of Corn and Soya beans, causality exists within a given range of the conditional distributions. On the other hand, oil prices Granger cause wheat and sunflower across the entire conditional distributions.

Overall, using the test for Granger causality in conditional quantile, the impact of oil prices on agricultural commodity prices is lower at the tails of the conditional distributions than in the middle range. However, the highest impact of oil prices on agricultural commodity prices does not necessarily occur at the median. This result resonates with other empirical findings (Elobeid and Tokgoz, 2008; Chen et al., 2010) that high oil prices have led to increased derived demand for agricultural commodities, giving rise to higher agricultural commodity prices. However, the regular Granger causality might not truly characterize the co-dependency between these variables as the impact varies along the entire conditional distribution. Furthermore, the results indicate that the impact of oil price changes on wheat, soya beans and sunflower are higher and occurs at a wider range along the conditional distributions compared with corn. This may be due to South Africa being a net importer of these commodities (wheat, soya beans and sunflower). Therefore, local prices of these commodities are more volatile to changes in Brent crude oil price.

IV. CONCLUSION

This study conducted an empirical investigation into the relationship between oil prices and agricultural commodity prices in South Africa. We made use of daily data over the period April 19, 2005 to July 31, 2014 for oil prices and the prices of soya beans, wheat, sunflower and corn. We employed the consistent test for Granger causality in conditional quantiles proposed by Jeong et al., (2012). This allowed us the benefit to access the

[1] τ represents the quantiles (considered quantiles 0.10 – 0.90 with 0.05 increments).

relationship between oil prices and agricultural commodity prices along the entire conditional distribution.

Based on the standard linear granger causality test, we find no evidence of oil affecting agricultural commodity prices. However, realizing that causal relationships can exist across specific quantiles, and the presence of nonlinearity and structural changes, which in turn, do exist in the relationships between oil and the agricultural commodities, we resorted to a quantile causality approach that is based on a non-parametric kernel. Our results show that the impact of oil price changes on agricultural commodity prices differs across the entire conditional distribution. The highest impact is in the middle part of the conditional distribution but not necessarily the median. The evidence of causality across the entire conditional distributions of wheat and sunflower suggest that their prices are likely to be more affected to changes in Brent crude oil prices, irrespective of whether these markets are in bear, normal or bull-type modes. This might be due to South Africa being a net importer of these commodities. Our results, highlight the importance of going beyond standard linear Granger causality tests, which are merely based on conditional means, and looking at causal relationships based on quantiles, which allows us to model the entire conditional joint distribution of the variables based on a nonparametric kernel to account for nonlinearity and structural breaks present in the data, and hence, pick up causality at certain quantiles i.e., at specific phases of the markets.

V. REFERENCES

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

Ang, A., and Chen, J. (2002). Asymmetric correlations of equity portfolios. *Journal of Financial Economics*, *63*(3), 443-494.

Ang, A., and Bekaert, G. (2002). International asset allocation with regime shifts. *Review of Financial studies*, *15*(4), 1137-1187.

Baffes, J. (2007). Oil spills on other commodities. *Resources Policy*, *32*(3), 126-134.

Bai, J., and Perron, P. (2003). Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics* 18 (1): 1–22.

Brock, W. A., W. Dechert, and J. Scheinkman (1987). A test for independence based on the correlation dimension. Working paper, University of Winconsin at Madison, University of Houston, and University of Chicago.

Chen, S. T., Kuo, H. I., and Chen, C. C. (2010). Modelling the relationship between the oil price and global food prices. *Applied Energy*, *87*(8), 2517-2525.

Chenery, H. B. (1975). The structuralist approach to development policy. *The American Economic Review*, 310-316.

Dancy, J. (2012). Food Prices Mirror Oil Prices: The Crude Oil-FAO Food Price Index Price Correlation. Financial sense, May 14.

Dehn, J. (2000). *Commodity price uncertainty in developing countries* (Vol. 2426).World Bank, Development Research Group, Rural Development.

Dickey, D. A., and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431.

Elobeid, A., and Tokgoz, S. (2008). Removing distortions in the US ethanol market: What does it imply for the United States and Brazil?. *American Journal of Agricultural Economics*, *90*(4), 918-932.

Fan, Y., and Li, Q. (1999). Central limit theorem for degenerate U-statistics of absolutely regular processes with applications to model specification testing. *Journal of Nonparametric Statistics*, *10*(3), 245-271.

FAO, 2008. Soaring food prices: facts, perspectives, impacts and actions required. In: Proceedings of the High-Level Conference on World Food Security, Rome, 3–5 June 2008.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438.

Hanson, K., Robinson, S., and Schluter, G. (1993). Sectoral effects of a world oil price shock: economywide linkages to the agricultural sector. *Journal of Agricultural and Resource Economics*, 96-116.

Hong, Y., Liu, Y., and Wang, S. (2009). Granger causality in risk and detection of extreme risk spillover between financial markets. *Journal of Econometrics*, *150*(2), 271-287.

Jeong, K., Härdle, W. K., and Song, S. (2012). A consistent nonparametric test for causality in quantile. *Econometric Theory*, *28*(04), 861-887.

Kaltalioglu, M., and Soytas, U. (2009). Price transmission between world food, agricultural raw material, and oil prices. In *GBATA International Conference Proceedings* (pp. 596-603).

Koenker, R., and Bassett Jr, G. (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society*, 33-50.

Lee, T. H., and Yang, W. (2006). *Money-income Granger-causality in quantiles*. Working paper, UC Riverside.

Leider, J. (2012). A Quantile Regression Study of Climate Change in Chicago, 1960-2010. *Department of Mathematics, Statistics and Computer Science, University of Illinois, Chicago*.

Lin, W. L., Engle, R. F., and Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies*, *7*(3), 507-538.

Longin, F., and Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990?. *Journal of international money and finance*, *14*(1), 3-26.

Mitchell, D. (2008). A Note on Rising Food Prices, Policy research Working Paper No. 4682, Washington D.C., World Bank

Nazlioglu, S., and Soytas, U. (2011). World oil prices and agricultural commodity prices: evidence from an emerging market. *Energy Economics*, *33*(3), 488-496.

Ng, S., and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*, *69*(6), 1519-1554.

Nishiyama, Y., Hitomi, K., Kawasaki, Y., and Jeong, K. (2011). A consistent nonparametric test for nonlinear causality—Specification in time series regression. *Journal of Econometrics*, *165*(1), 112-127.

OECD (2008). Rising Agricultural Prices: Causes, Consequences and Responses, OECD Policy Brief, August 2008.

Phillips, P. C., and Perron, P. (1988).Testing for a unit root in time series regression, *Biometrika*,75(2), 335-346.

Reboredo, J. C. (2012). Do food and oil prices co-move?. *Energy Policy*, *49*, 456-467.

Zheng, J. X. (1998). A consistent nonparametric test of parametric regression models under conditional quantile restrictions. *Econometric Theory*, *14*(01), 123-138.

APPENDIX

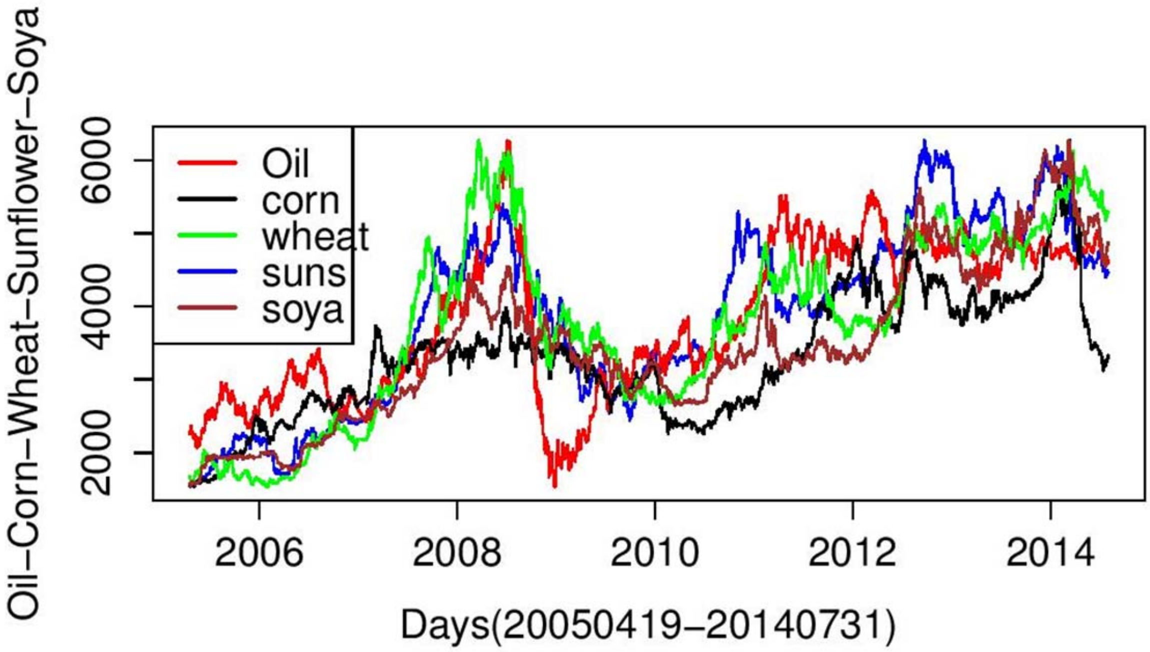

Figure 1. Plot of the Brent crude oil prices and agricultural commodity (corn, wheat, sunflower, soya) prices time series from April 19, 2005 to July 31, 2014.

Table 1: Descriptive Statistics

	Oil	Corn	Wheat	Sunflower	Soya

Mean	0.03	0.05	0.04	0.05	0.07
Standard deviation	2.11	2.00	1.28	1.31	1.39
Skewness	-0.01	-1.01	-0.40	-1.06	-0.21
Kurtosis	6.86	9.94	4.37	9.59	5.08
Min	-16.83	-22.08	-9.45	-12.86	-9.53
Max	18.13	9.57	8.20	7.93	11.08
Obs.	2251	2251	2251	2251	2251

NB: All variables are in returns.

Table 2: Unit Root Tests

		ADF		PP		NP	
Variable	Lag	Level	First Difference	Level	First Difference	Level	First Difference
Oil	1	-0.804	-21.795*	-1.418	-33.960*	-0.855	-996.689*
Corn	2	-1.354	-6.836*	-2.290	-36.225*	-0.644	-920.575*
Wheat	2	-0.413	-9.890*	-2.563	-32.767*	0.253	-600.168*
Sunflower	2	0.147	-10.333*	-1.188	-29.757*	-0.244	-828.522*
Soya	2	0.891	-9.088*	-1.400	-30.406*	0.483	-786.961*

NB: Lag lengths are selected using the Schwarz Bayesian information criterion.

* means that the null of unit root in the ADF, PP and NP tests are rejected at 5% level.

Table 3: Granger Causality Test

Dependent variable	Chi-sq	Prob.
Corn	4.7333	0.0938
Soya beans	2.8920	0.2355
Sunflowers	4.6363	0.0985
Wheat	1.0500	0.5916

NB: The results show the causality of oil returns on agricultural commodity returns.

Table 4: BDS Independence Test

	Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
Corn	2	0.0158	0.0017	9.5121	0.0000
	3	0.0306	0.0026	11.5811	0.0000
	4	0.0413	0.0031	13.1456	0.0000
	5	0.0466	0.0033	14.2734	0.0000
	6	0.0483	0.0031	15.3530	0.0000
	Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
Soya beans	2	0.0189	0.0017	11.3107	0.0000
	3	0.0349	0.00267	13.0912	0.0000
	4	0.0448	0.0032	14.1111	0.0000
	5	0.0489	0.0033	14.7788	0.0000
	6	0.0493	0.0032	15.4984	0.0000
	Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
Sunflowers	2	0.0248	0.0017	14.6704	0.0000
	3	0.0455	0.0027	16.9833	0.0000
	4	0.0571	0.0032	17.9631	0.0000
	5	0.0619	0.0033	18.7614	0.0000
	6	0.0623	0.0032	19.6348	0.0000
	Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
Wheat	2	0.0173	0.0018	9.79728	0.0000
	3	0.0325	0.0028	11.6164	0.0000
	4	0.0431	0.0033	12.9501	0.0000
	5	0.0484	0.0035	13.9653	0.0000
	6	0.0512	0.0033	15.3324	0.0000

Table 5: Date of Structural Breaks

Corn	2006/09/05	2008/09/30	2010/02/17	2011/08/05	2012/12/24
Soya beans	2006/09/11	2008/02/22	2009/07/16	2011/01/06	2012/06/08
Sunflowers	2006/08/29	2008/02/08	2009/06/30	2010/11/11	2012/04/05

Wheat	2006/09/11	2008/02/29	2009/07/21	2010/12/02	2012/07/09

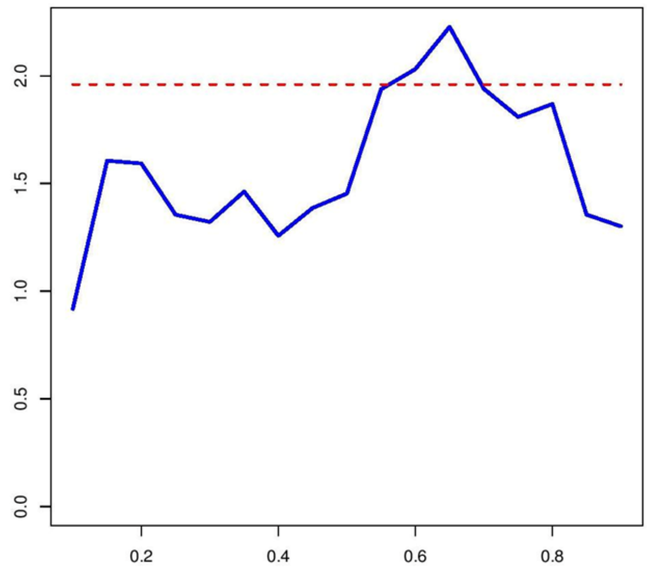

Figure 2: Test statistics with respect to different quantilefor oil-corn prices causality.

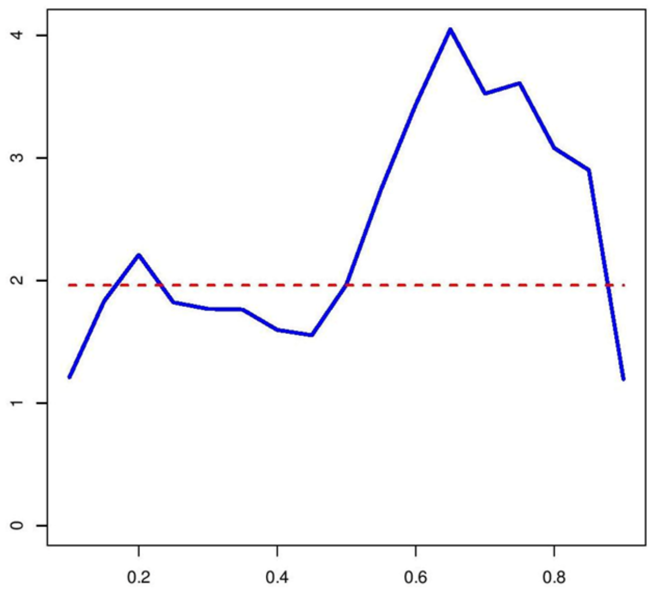

Figure 3: Test statistics with respect to different quantile for oil-soya beans prices causality.

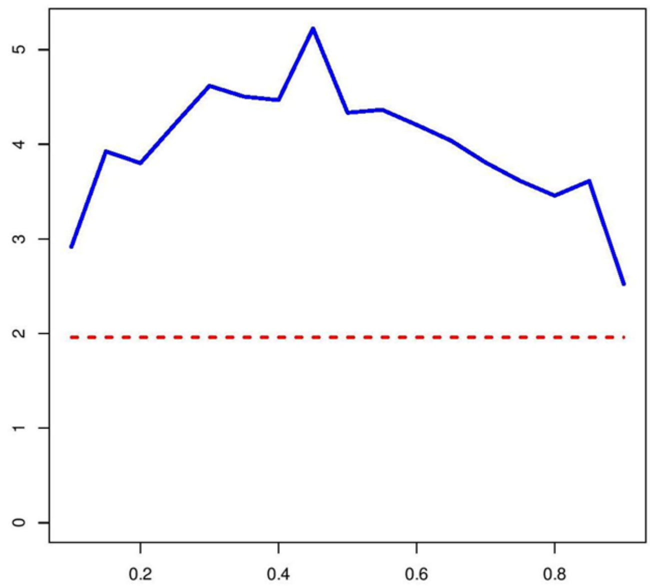

Figure 4: Test statistics with respect to different quantile for oil-wheat prices causality.

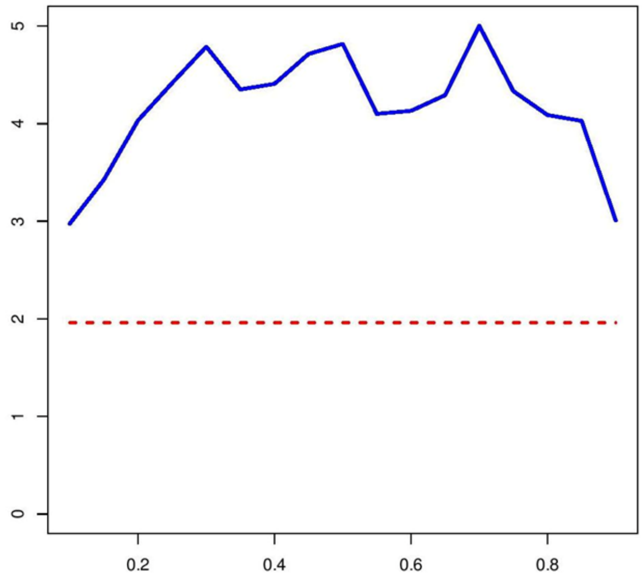

Figure 5: Test statistics with respect to different quantile for oil-sunflower prices causality.