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

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ABSTRACT

The increase in agricultural commodity prices in the recent past has renewed interest in ascertaining the factors that drive agricultural commodity prices. Though a number of factors are possible, higher oil prices are thought to be the major factor driving up agricultural commodity prices, especially as the demand for biofuels production increases. However, empirical evidence of this relationship remain ambiguous and largely depends on the method used. For this reason, there is a need to examine the relationship in the context of different methodologies. Furthermore, information on how South African commodity prices respond to world oil price shocks is less certain. A good understanding of the factors that drive local commodity prices will assist in making sound agricultural policies. In this paper, the Granger causality test is applied to the mean to investigate the causality between oil prices and agricultural (soya beans, wheat, sunflower and corn) commodity prices in South Africa. Daily data spanning from 19 April 2005 to 31 July 2014 is used for Brent crude oil, corn, wheat, sunflower and soya beans prices. 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. Results from the linear causality test indicate that oil prices do not influence agricultural commodity prices. However, owing to structural breaks and nonlinear dependence between the variables of study, these results are misleading. As an alternative, the nonparametric test of Granger causality in quantiles, as proposed by Jeong, Härdle and Song (2012) is used. Through this test, we not only look at causality beyond the mean estimates but also accounts for the structural breaks and nonlinear dependence present in the data. Additionally, the method becomes more instructive in the case where the distribution of variables has fat tails. The findings show that the effect of changes in oil prices on agricultural commodity prices vary across the different quantiles of the conditional distribution. The highest impact is not at the median, and the impact on the tails is lower compared to the rest of the distribution. The analysis shows that the relationship between oil prices and agricultural commodity prices depends on specific phases of the market, and therefore contradicts the neutrality hypothesis that oil prices do not cause agricultural commodity prices in South Africa. This implies that policies to stabilize domestic agricultural commodity prices must consider developments in the world oil markets.

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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 on appropriate policy options and to examine investment opportunities. According to Abbott, Hurt and Tyner (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, Zhang et al., 2010). This is due to the strong linkage between energy and agricultural markets, especially as the demand for biofuels production increases. 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 biofuels (Nazlioglu & Soytas, 2010). It is therefore 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, Robinson, & Schluter, 1993; Baffes, 2007; Kaltalioglu & Soytas, 2009; Nazlioglu, 2011) 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 (2010) found no evidence that oil prices lead agricultural commodity prices. Others such as Chen, Kuo and Chen (2010) showed that a rise in oil price significantly increases 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. Also, the most popular method used to investigate the energy-food nexus is based on conditional causality in the mean, developed by Granger (1969). This method assumes a linear data generating process for the variables and constant parameters over time. However, evidence in the energy literature shows that results from linear and nonlinear causality methods are different (Bekiros and Diks, 2008; Kim et al., 2010). For this reason, there is need to examine the oil-food relationship in the context of different methods. Furthermore, information on how South African commodity prices respond to world oil price shocks is less certain. A good understanding of the factors that drive local commodity prices will assist in making sound agricultural policies.

South Africa is a net importer of crude oil, which is an important input to various sectors. Any fluctuation in world oil prices would therefore have important consequences for domestic agricultural prices. Industry data shows that coke and refined petroleum accounted for about 10% of intermediate input costs into agriculture, forestry and fishing in 2013 (Quantec, 2014). According to the department of agriculture, forestry and fishing (2014), South Africa is a net importer of wheat, sunflower and soya beans, but is self-sufficient in maize production. This means that domestic prices for wheat, sunflower and soya beans will be strongly impacted by dynamics on the international market. It is important to note that the government does not intervene in the grains market, but only sets the policy.

In this paper, we investigate the causal relationship between world oil prices and agricultural commodity prices in South Africa using a nonparametric test of Granger causality in quantiles. We start with the unit root tests, and then conduct the standard linear Granger causality test. Also, we conduct the BDS independence test and check for the presence of structural breaks. In the presence of nonlinear dependence, structural breaks and regime shifts, the standard linear Granger causality test will provide unreliable and biased results. Therefore, our decision to use nonlinear causality test is based on the possibility of nonlinear data generating process for our variables of study and the possible presence of structural breaks in the data. In addition, the nonparametric test of Granger causality in quantiles is able to pick up causality in the tails of the conditional distribution. This becomes more instructive in the case where the distribution of variables have fat tails. We ask the question "Do oil prices lead agricultural commodity prices in various conditional quantiles?". In this regard, we provide a holistic insight on how agricultural commodity prices in South Africa respond to oil prices. Furthermore, we help the process of evidence-based policy making with respect to agricultural and energy policies. To the best of our knowledge, this is the first study to analyse the energy-food relationship using quantile causality with South African data.

The rest of the paper is organised as follows: Section 2 presents the methodology employed in this study, Section 3 discusses the data and empirical results, and finally, Section 4 concludes our study.

METHODOLOGY

Linear 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 y_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:

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

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.

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 fat 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, Engle, and Ito, 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, Liu and Wang (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, Härdle and Song (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
$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \quad (2)$$
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

$$Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\right) \neq Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}\right) \quad (3)$$

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

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

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

Building on Zheng (1998)'s work, Jeong, Härdle and Song (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$\varepsilon_t$ 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 $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or equivalently $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Jeong, Härdle and Song (2012) specify the distance function as

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

Where $J \geq 0$ 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, Härdle and Song (2012) show that under the β-mixing process, the asymptotic distribution of the statistic is asymptotically normal.

Additionally, Jeong, Härdle and Song (2012) showed that the feasible kernel-based test statistic based on J has the following form:

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

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

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

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.

DATA ANALYSIS

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 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 1 shows 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.

FIGURE 1. PLOT OF THE BRENT CRUDE OIL PRICES AND AGRICULTURAL COMMODITY (CORN, WHEAT, SUNFLOWER, SOYA) PRICES TIME SEIRES FROM APRIL 19, 2005 TO JULY 31, 2014

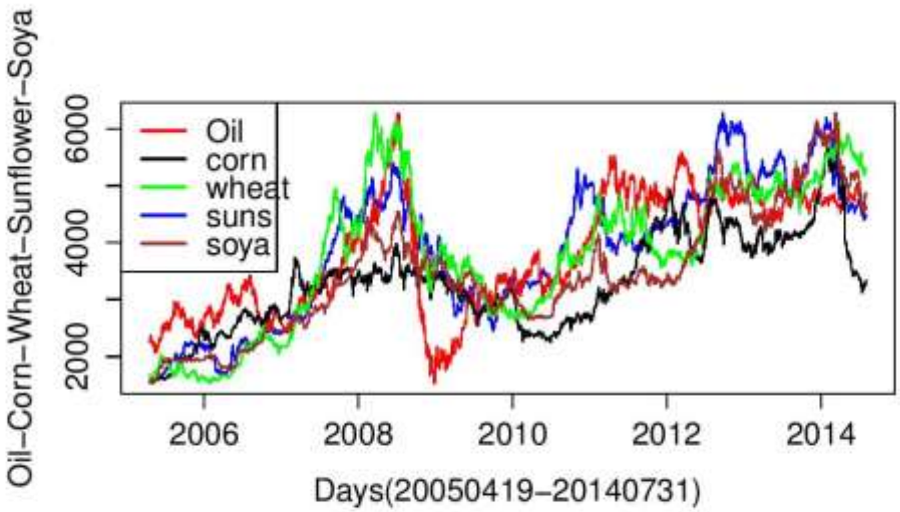


TABLE 1. DESCRIPTIVE STATISTICS

	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

Note: All variables are in returns.

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 2 presents 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 difference of all variables.

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*

Note: 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.*

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 commodity 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 linear Granger causality in the data, there is no evidence against the null hypothesis that Brent crude oil prices does not 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. The findings corroborate with those obtained by Kaltalioglu and Soytas (2009), Gilbert (2010) and Lombardi,Osbat and Schnatz (2010). These findings support the neutrality hypothesis of agricultural commodity markets to oil price fluctuations. However, linear causality is only conducted at the mean level and does not provide an overall picture of the existing causality from oil prices to agricultural commodity prices. Also, it fails to account for nonlinear feedback that may exist between variables.

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

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

We performed the BDS test (Broock et al. 1996) for nonlinearity in the residuals of the linear equation relating the returns of 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 is remaining dependence and omitted nonlinear structure which was not captured by the linear specification, and hence there is nonlinearity in the data. Furthermore, the existence of structural breaks is also clearly established. Under the presence of structural breaks and nonlinearity, the standard linear Granger causality test is no longer reliable.

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

Therefore, we test for causality between oil prices and agricultural commodity prices using the nonparametric test of Granger causality in quantiles proposed by Jeong, Härdle and Song (2012). Through this test, we not only look at the causality beyond the mean estimates, but we also account for the structural breaks and nonlinearity present in our data, as the quantile causality is based on a nonparametric 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 beans 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.

FIGURE 2. TEST STATISTICS WITH RESPECT TO DIFFERENT QUANTILE FOR OIL-CORN PRICES CAUSALITY

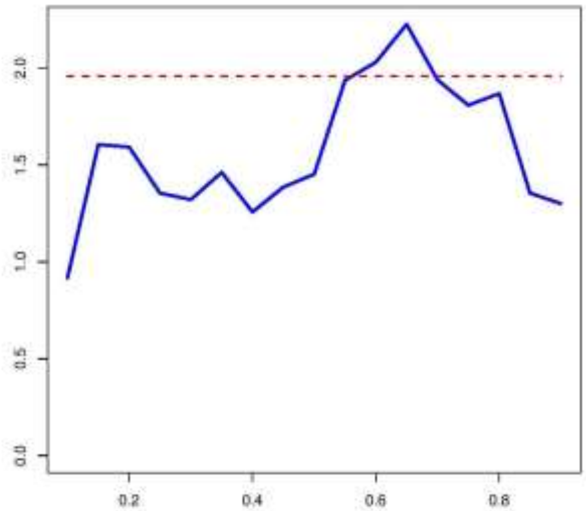


FIGURE 3. TEST STATISTICS WITH RESPECT TO DIFFERENT QUANTILE FOR OIL-SOYA PRICES CAUSALITY

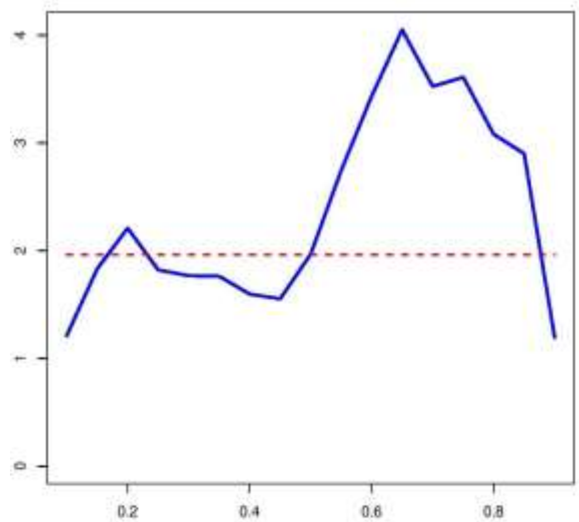


FIGURE 4. TEST STATISTICS WITH RESPECT TO DIFFERENT QUANTILE FOR OIL-WHEAT PRICES CAUSALITY

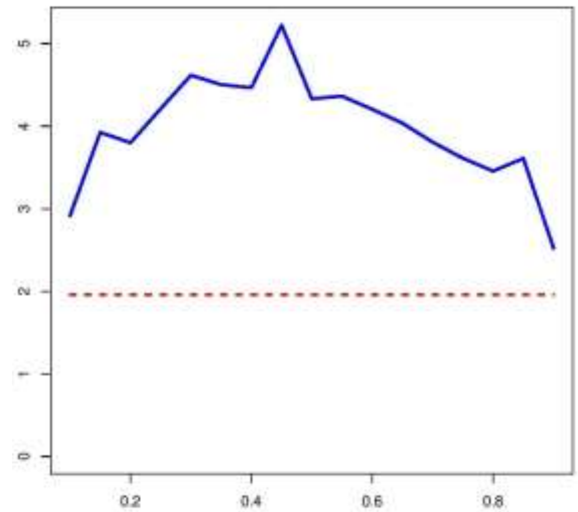
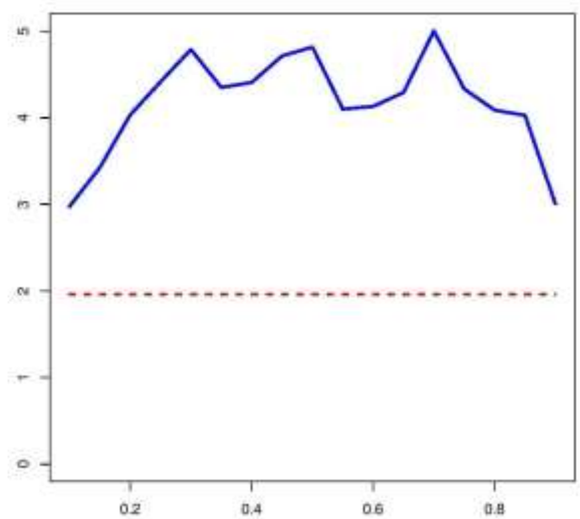


FIGURE 5. TEST STATISTICS WITH RESPECT TO DIFFERENT QUANTILE FOR OIL-SUNFLOWER PRICES CAUSALITY



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 & Tokgoz, 2008; Chen, Kuo & Chen.,

2010) that high oil prices have led to increased derived demand for agricultural commodities, giving rise to higher agricultural commodity prices. 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 is due to the fact that South Africa is a net importer of these commodities (wheat, soya beans and sunflower). As a result, fluctuations in world oil prices have predictive power for the prices of these commodities. Investors can therefore, profit from the information about Brent crude oil prices to invest in wheat, soya beans and sunflower.

CONCLUSIONS

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 test for Granger causality in conditional quantile as proposed by Jeong, Härdle and Song (2012). This allowed us to capture the 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 nonparametric 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 range of the conditional distribution but not necessarily the median. The evidence of causality across the entire conditional distributions of wheat and sunflower suggests that their prices are likely to be more affected by 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 agrees with Harri et al. (2009) and Nazlioglu (2011) for soya beans, but contradict their results for corn and wheat. We 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, as they allow us to model the entire conditional joint distribution of the variables based on a nonparametric kernel. This accounts 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. Our findings imply that policies to stabilize agricultural prices in South Africa must consider developments in the world oil markets.

ENDNOTES

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

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