Causality between Oil Price and South Africa's Food Price: Time Varying Approach

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Abstract

This paper examines the dynamic causal relationship between global oil price and South Africa's food price using both full sample and time varying Granger causality tests. Monthly data from 2000:1 to 2014:6 is used. Result from the linear full sample Granger causality result shows no evidence of significant causality between oil price and food price. However, various stability tests show that the relevant VAR is unstable, thus invalidating conclusions from the full sample linear Granger causality tests. Based on this the causality analysis is performed using a time varying approach. Result from the latter shows that oil price Granger causes South Africa's food price at different sub-periods: 2002-2003, 2006 and 2010. This challenges the assumption that the causal relationship between the two variables is constant over time. Therefore, these results highlight the importance of using methods that account for structural breaks and nonlinearities in the dynamic causal relationship between global oil price and South Africa's food price.

JEL Classification: C32, Q11, Q40

Keywords: Oil price; food price; causality; time varying

Introduction

There has been an increasing trend in the price of food globally. FAO (2014) report shows that global food prices increased by 38.2% from early 2006 to mid-2008. This led to a global food crisis, political and economic unrest in both developed and emerging economies. South Africa as an emerging economy is not shielded from the rising food prices. Over the last two decades there has been a remarkable increase in the contribution of food prices to headline inflation in South Africa. Food-product's contribution to headline inflation was proportional to its weight in the consumer price index (CPI) in the 1980s. However, the contribution of food-products to headline inflation rose to approximately 1.4 times its weight in the consumption basket between 2000 and 2008 (Rangasamy, 2011). Rangasamy (2011) noted that the rate of food inflation in South Africa suggests that food inflation may be more persistent than that of other commodities and may thus be an important source of underlying inflationary pressures in the economy. This scenario has not changed. The year-on-year inflation rate for all food items rose from 1.2% in September 2010 to 10.3% in January, 2012 and as well above the general inflation level. According to Statistics South Africa (2014), the year 2014 started with acceleration in the general inflation rate to 5.8% from the 5.4% recorded in December 2013. Petrol and food inflation were considered as the major driving forces to the rise in the general inflation. For instance, food prices rose by 1.6% between December 2013 and January 2014.

Further, the South African agricultural and food economy has some unique features that motivate the understanding of the dynamics of food prices in South Africa. According to Kirsten (2012), the economy on the one hand has a large productive agricultural and agribusiness sector ensuring national food security. On the other hand, 52% of households experienced hunger in South Africa while almost 14 million, or about 35%, of the South African population are generally considered to be food insecure and categorized as poor in 2005. Clearly the issue of food availability and affordability has been a concern in South Africa. Therefore, it is important to understand the drivers of food price. A number of factors might be at play and mutually reinforcing. However, this paper focuses particularly on oil price as one of the possible drivers (FAO, 2008; OECD, 2008; Harri et al., 2009). This is because the worldwide surge in food crop prices and of course in South Africa between 2007 and 2010 occurred at about the same time as a similar surge in the price of crude oil, raising the suspicion that oil and food crop prices have become more closely linked in recent years (Tyner 2010).

Many experts believe that oil prices may affect food prices in a number of ways (Westhoff, 2012). In the words of Dancy (2012), "food prices mirror oil prices". The relationship between food and energy price can be viewed from the interdependence of resources-how demand for one resource can drive demand for another, and similarly, how the cost of one resource can determine the efficiency of production of the other. For example, food production demands energy; energy is an important input in fertilizers, irrigation, raising of livestock and accessing marine food resources as well as throughout the value chain in processing, packaging, distributing, storing, preparing, serving and disposal of food and water extraction (Gulati et al., 2013). This is reaffirmed by Baumeister and Kilian (2014) who noted that the potential price pressures from rising oil prices are not limited to the production stage of food and that higher energy costs may also raise the cost of food processing, food packaging and distribution. Baumeister and Kilian (2014) also gave an interesting analogy on how corn as one example of food crop used for producing ethanol can be directly linked to the price of crude oil and hence put upward pressure on the price of food in general by affecting meat and dairy prices as well as other agricultural commodities that compete with corn for fertilizer, scarce water and land resources. Moreover, other experts have suggested that the use of food crops for biofuel production may suggest some links between the energy and food markets (Mallory et al. 2012; Timilsina et al. 2012; High Level Panel of Experts (HLPE), 2013 cited in Brent, 2014). In this regard, Wakeford (2006) noted that although biofuels, seems at first glance to have particular merit in mitigating future oil shocks in South Africa, the use of agricultural products for fuel will increasingly compete with food production at global and national levels, and contribute to spiralling food costs. However, Ajanovic (2011) is of the view that food price increases would be due to increased volatility coupled with, for example, crude-oil price increases and not necessarily an increase in biofuel production.

A number of empirical studies (Hanson et al., 1993; Yu et al., 2006; Baffes, 2007; Zhang and Reed, 2008; Harri et al., 2009; Campiche et al., 2007; Chen et al., 2010; Nazlioglu and Soytas, 2011, 2012; Reboredo 2012 and Baumeister and Kilian, 2014 among others) have attempted to examine the relationship between oil prices and agricultural and/or food commodity prices but the results are so far mixed. This study is aimed at providing empirical evidence on the causal relationship between oil price and food price in South Africa. As far as South Africa is concerned, there is a dearth of studies linking crude oil price and food or agricultural prices. Recently, Balcilar et al., (2014) investigate the causality between oil prices and the prices of four agricultural commodities (soya beans, wheat, sunflower and corn) in South Africa using daily data from April 19, 2005 to July 31, 2014. Employing the Granger causality test in conditional quantiles as proposed by Jeong et al. (2012), they show that the effect of oil prices on agricultural commodity prices varies across the different quantiles of the conditional distribution with the impact on the tails being lower compared to the rest of the distribution. They also find that the standard Granger causality test provides misleading results and also fails to find any relationship over the entire conditional joint distribution of the variables due to nonlinearities. Ajmi et al. (2014) investigate the causal relationship between seven agricultural prices (white maize, yellow maize, wheat, sunflower seed, soya, corn and sorghum) in South Africa and global oil prices. Using a nonlinear Granger causality test based on moment conditions, introduced by Nishiyama et al. (2011), they find that a causal relationship between global oil prices and some agricultural commodity prices in South African. Particularly, the mean price of wheat, sunflower and soya are Granger caused by oil price while the volatility of wheat, sunflower seed and sorghum prices are also caused by oil price. The rest of the crops were not Granger caused by oil prices. Also Gulati et al. (2013) and Brent (2014) provide some conceptual link between energy, water and food in South Africa.

The mixed results in the literature could be as a result of the methodology employed as well as the sampling period of the data. The causal connection between oil price and food price has generally been investigated with standard linear Granger causality tests (Granger, 1969) that ignores structural shifts or instability in an economy. The assumption is that the causal relationship between oil price and food price applies to every point in the whole sample. It is possible that the experience of any particular country could support a causality during some periods, while providing no casualty in yet further sub samples, i.e. the relationship could be time-varying. The motivation for this paper is to address this particular shortcoming in the literature by examining the causal link between oil price and aggregate food price in South Africa with a bootstrap subsample rolling window estimation approaches. To ensure robustness against sample size, stationarity and integration-cointegration properties of the data, the bootstrap causality test is used. This time varying bootstrap rolling approach will not only account for any nonlinear behaviour and structural breaks in the series, but also has the capacity to indicate at which specific period or sub-periods causality exists between oil price and South Africa's food price. Also the result from the bootstrap full sample approach will be presented for comparison.

Data and Econometric Model

Monthly time-series data on oil price and food price are used. These covers from 2000:1 to 2014:6. The starting and ending dates for the sample is determined by food price data availability. The oil price is the Brent crude oil price obtained from the US Energy Information Administration (EIA). For food price, the South Africa's consumer price index for food is used.[1] This was obtained from Food and Agriculture Organisation (FAO). Both variables are transformed into natural logarithms. As a robustness check both nominal and real values are used. The real price of oil is obtained by taking the ratio of nominal oil price and US CPI. The US CPI was obtained from International Financial Statistics (IFS). The general CPI for South Africa also from FAO is used to obtain real food price.[2] In order to capture the exogenous impact of global oil shocks on South African food prices, the oil price is retained in US dollars. This also avoids feeding in the impact of exchange rate changes into the domestic food prices. The plots of the two series in nominal and real terms are shown in Figure 1 and Figure 2. The co-movement between the two series does not seem quite strong throughout the entire period. Instead it is observed that the two series move together at some periods and differently at other periods. However, this will be verified using the relevant tests as described below. Prior to investigating Granger causality, the stationarity of the data is tested using the Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979), the Phillips and Perron (PP) test (Philips and Perron, 1988), and the Ng and Perron (NP) test (Ng and Perron, 2001). Also the series are examined for possible cointegration using the Johansen cointegration test.

[1] Consumer price index is used instead of prices of individual agricultural commodities because of the advantage that idiosyncratic factors affecting individual commodities have far less influence on an index capturing a basket of different commodities (Belke et al., 2013; Klotz et al., 2014).

[2] It would have been preferable to use the South Africa's consumer food price excluding food consistent with Baumeister and Kilian (2014). However, this data is discontinued since 2008. The alternative definition, CPI excluding food and alcoholic beverages only dates back to 2008. Hence, the best available is the general CPI. Moreover, the nominal prices serve as a robustness check.

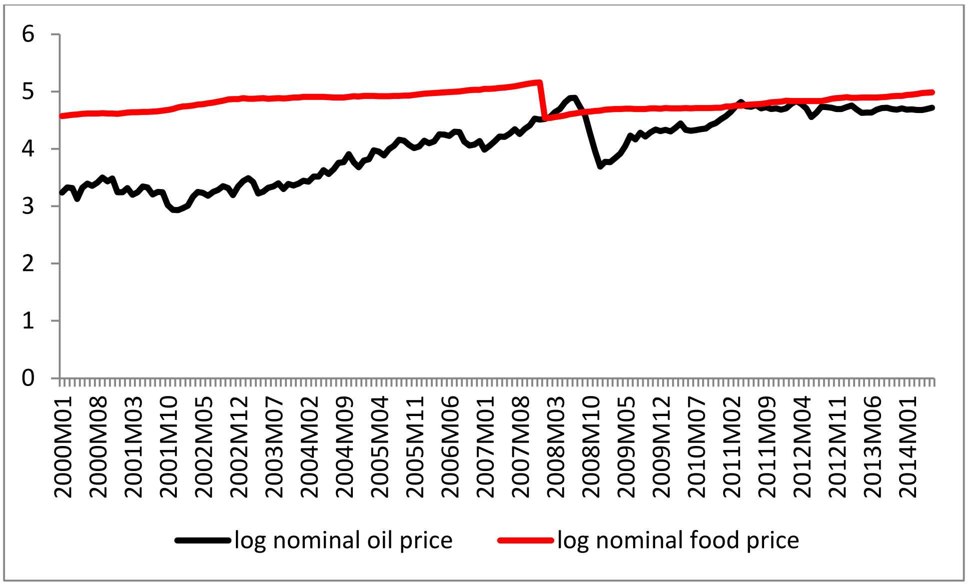

Figure 1: Log nominal oil and food prices

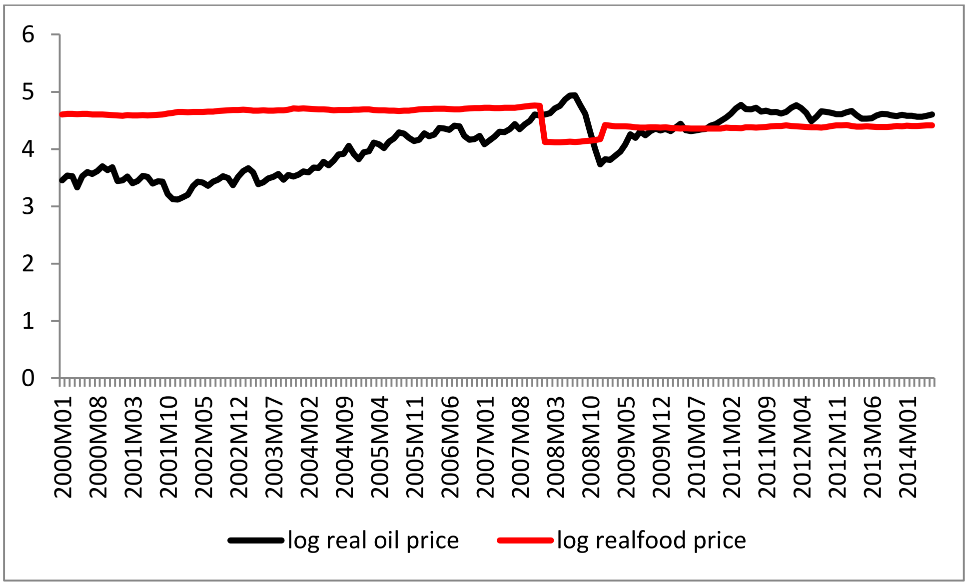

Figure 2: Log real oil and food prices

The null hypothesis is Granger non-causality between oil price and food price. Granger non-causality occurs when the information set on the first variable (e.g., oil price) does not improve the prediction of the second variable (e.g., food price) over and above the predictive capacity of the information in the food price time series. From a statistical perspective the Granger non-causality test is performed by examining the joint significance of lagged values for the first variable in a predictive model for the second variable that is usually embedded in a two-equation VAR model. In such a VAR framework the joint parameter restriction associated with the Granger non-causality test can be conducted with the Wald, Likelihood ratio (*LR*) and Lagrange multiplier (*LM*) statistics. But these test statistics are based on the assumption that the underlying data is stationary. With non-stationary data, as is typical in macroeconomic studies, these tests may not have standard asymptotic distributions.

To address the problems of non-stationary underlying data, Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) proposed a modification to the standard Granger causality test. Starting with a VAR(*p*), where *p* is the lag order, and the data is integrated of the first order, the proposed method based on estimating a VAR(*p*+1) in the levels and they derived standard asymptotic distributions for the Granger causality test regardless of the integration-cointegration properties of the data. The method entails estimating a VAR(*p*+1) with the Granger non-causality test carried out on the first *p* lags. Thus, one coefficient matrix, which relates to the $(p+1)^{\text{th}}$ lag, remains unrestricted under the null, giving the test a standard asymptotic distribution.

This paper builds on the Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) modified test, but with an extension to use a residual based bootstrap (*RB*) test developed by Balcilar et al. (2010) rather than standard asymptotic tests. The study also accounts for the fact that global crude oil price has no in-sample predictability for South African food price, which understandably is a valid assumption given the size of South Africa’s food market relative to that of the global market. It is the outstanding performance (in terms of power and size) of the residual *RB* method, irrespective of cointegration, that justifies this step (Hacker and Hatemi-J, 2006). In line with Balcilar et al. (2010), Balcilar and Ozdemir (2013) and Aye et al. (2014), this method is used to examine the causal relationship between oil price and food price. To illustrate the bootstrap modified-*LR* Granger causality test, consider the following bivariate VAR(*p*) process:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + ... + \Phi_p y_{t-p} + \varepsilon_t,\ t = 1,2...,T, \qquad (1)$$

where $e_t = (e_{1t}, e_{2t})'$ is a white noise process with zero mean and covariance matrix Σ and *p* is the lag order of the process. In the empirical section, the Akaike Information Criterion (*AIC*) is used to select the optimal lag order *p*. To simplify the representation, y_1 is partitioned into two sub-vectors, oil price (y_1) and food price (y_2). Hence, rewrite equation (1) as follows:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & 0 \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}, \tag{2}$$

where $\phi_{ij}(L) = \sum_{k=1}^{p+1} \phi_{ij,k} L^k$, $i, j = 1,2$ and L is the lag operator such that $L^k y_{it} = y_{it-k}$, $i = 1,2$.

The restriction $\phi_{12}(L) = 0$ in equation (2) is due to the assumption of exogeneity of the South Africa's food price in the global oil price equation as explained earlier. More so, this is consistent with Baumeister and Kilian (2014) who postulate that global crude oil prices are predetermined with respect to U.S. agricultural and food prices, which allows them to study the response of the latter prices to oil price shocks using semi-structural vector autoregressions. According to them the assumption of predetermined oil prices means that unpredictable changes in the real price of oil affect agricultural and food prices within the current month, but are not themselves subject to instantaneous feedback from agricultural and food prices (Baumeister and Kilian, 2014). The null hypothesis that oil price does not Granger cause food price can be tested by imposing zero restrictions $\phi_{21,i} = 0$ for $i = 1,2,..., p$. In other words, oil price does not contain predictive content, or is not causal for food price if the joint zero restrictions under the null hypothesis:

$$H_0 : \phi_{21,1} = \phi_{21,2} = ... = \phi_{21,p} = 0 . \tag{3}$$

are not rejected. If the hypothesis in equation (3) is rejected, then oil price Granger causes food price. The hypothesis can be tested using a number of testing techniques. However, this study uses the bootstrap approach which uses critical or *p* values generated from the empirical distribution derived for the particular test using the sample data. In this case, the bootstrap approach is employed to test for Granger non-causality.

Granger non-causality tests assume that parameters of the VAR model used in testing are constant over time. This assumption is often violated because of structural changes and as pointed out by Granger (1996), parameter non-constancy is one of the most challenging issues confronting empirical studies. Structural changes shift the parameters and the pattern of the causal relationship may change over time. Although the presence of structural changes can be detected beforehand and the estimations can be modified to address this issue using several approaches, such as including dummy variables and sample splitting, such an approach introduces pre-test bias. Therefore, this study adopts rolling bootstrap estimation in order to overcome the parameter non-constancy and avoid pre-test bias. In addition to full sample estimation, this study applies the bootstrap causality test to rolling window subsamples for $t = \tau - l + 1, \tau - l, ..., \tau, t = l, l + 1, ..., T$, where l is the size of the rolling window.

The full sample VAR will be tested for parameter inconsistency. However, if the parameters prove to be unstable, the Granger causality tests and the cointegration tests to the full sample are proven invalid. Overall, parameter instability can occur in many ways. Given the difficulty in test selection, this study uses several tests, namely, *Sup-F*, *Exp-F* and *Mean-F* (Andrews 1993; Andrews and Ploberger 1994) based on their optimality properties (Balcilar et al., 2010). These tests are computed from the sequence of *LR* statistics that tests constant parameters against the alternative of a one-time structural change at each possible point of time in the full sample. Andrews (1993) and Andrews and Ploberger (1994) report the critical values for the non-standard asymptotic distributions of these tests. To avoid the use of asymptotic distributions, the critical values and *p*-values are obtained using the parametric bootstrap procedure. Specifically, the *p*-values are obtained from a bootstrap approximation to the null distribution of the test statistics, constructed by means of Monte Carlo simulation using 2000 samples generated from a VAR model with constant parameters. The *Sup-F*, *Exp-F*, and *Mean-F* tests need to be trimmed at the ends of the sample. Following Andrews (1993) trimming is done at 15 per cent from both ends and these tests are calculated for the fraction of the sample in [0.15, 0.85].

Results

Results of the unit root tests are presented in Table 1. All tests show that the null hypothesis of unit root cannot be rejected for all the series in levels. This implies that the series are non-stationary. However, these tests show that the first differences of all the series are stationary, hence are integrated of order one, I(1). Further, the series are subjected to Johansen cointegration test. The results are presented in Table 2. Both the trace and maximum eigenvalue tests show that the null hypothesis of no cointegration cannot be rejected, meaning that these series are not cointegrated and therefore do not have a long run relationship.

Table 1: Unit Root Tests

Nominal oil and food prices						
Variable	Level			First Differences		
	ADF	PP	NP	ADF	PP	NP
Food price	-2.396	-2.428	-2.646	-12.930***	-12.936***	-85.988***
Oil price	-1.249	-1.270	-0.331	-10.792***	-10.820***	-69.714***
Real oil and food prices						
	Level			First Differences		
	ADF	PP	NP	ADF	PP	NP
Food price	-1.935	-1.995	-6.379	-12.824***	-12.823***	-85.873***
Oil price	-1.492	-1.500	-1.105	-10.858***	-10.885***	-70.273***

*** indicates significance at 1% level.

Table 2: Johansen Cointegration Test

Cointegration test between nominal oil and food prices							
Trace test				Maximum eigenvalue test			
H_o	H_1	Statistic	5% CV	H_o	H_1	Statistic	5% CV
$r = 0$	$r \geq 1$	10.063	15.495	$r = 0$	$r = 1$	7.764	14.265
$r \leq 1$	$r \geq 2$	2.299	3.842	$r = 1$	$r = 2$	2.299	3.842
Cointegration test between real oil and food prices							
Trace test				Maximum eigenvalue test			
H_o	H_1	Statistic	5% CV	H_o	H_1	Statistic	5% CV
$r = 0$	$r \geq 1$	15.114	15.495	$r = 0$	$r = 1$	11.952	14.265
$r \leq 1$	$r \geq 2$	3.162	3.841	$r = 1$	$r = 2$	3.162	3.841

The lack of cointegration should not influence the exercise. This is because the variables might exhibit Granger temporal causality (Balcilar et al., 2010). Therefore, the study proceeds with the examination of Granger causality. As noted earlier, both the bootstrap LR full sample and rolling window Granger causality are performed. The results from the bootstrap *LR* full sample causality test performed on a VAR model of order 1, as selected by AIC is reported in Table 3. The test fails to reject the null hypothesis of Granger non-causality, thus implying that there are no causal links between oil price and food price for the full sample. The result is robust to both nominal and real values.

Table 3: Full Sample Granger Causality Test between Oil Price and Food Price

	H_0: Nominal oil price does not Granger cause food price		H_0: Real oil price does not Granger cause food price	
	Statistics	P-value	Statistics	P-value
Bootstrap LR test	0.025	0.862	1.596	0.184

To investigate whether this result is reinforced by parameter constancy, the short run temporal stability of the VAR is tested using the *Sup-F*, *Exp-F* and *Mean-F* tests. The Sup-F statistic tests parameter constancy against a one-time sharp shift in parameters, while the Ave-F and Exp-F, are appropriate if the regime shift is gradual and assume the parameters follow a martingale process. The results are presented in Table 4. For both nominal and real oil price and food price equations, there is evidence of parameter non-constancy as indicated by the small p-values of the respective tests though at varying degrees. Both *Mean-F* and *Exp-F* statistics test for the overall constancy of the parameters (Andrews and Ploberger, 1994). These findings imply that there is instability in the short-run parameters of the VAR model, with evidence of both a one-time shift and gradual shifting of the parameters. The stability tests show the presence of structural change in the dynamic relationship between oil price and food price. Therefore, the Granger causality test based on the full sample VAR model is not reliable.

Table 4: Parameter Stability Tests in VAR (1) Model

	Nominal Food price equation		Nominal Oil price equation	
	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value
Sup-F	9.442*	0.101	7.253***	0.005
Exp-F	0.990	0.216	1.656***	0.014
Mean-F	0.815	0.657	2.795*	0.023
	Real Food price equation		Real Oil price equation	
	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value
Sup-F	17.410**	0.044	12.852***	0.001
Exp-F	4.059**	0.053	2.631***	0.006
Mean-F	1.620	0.221	2.615*	0.100

***, ** and * indicates significance at 1%, 5% and 10% level respectively.

On this basis the study proceeds to examine the causal relationship between oil price and food price using the bootstrap rolling window approach. This technique, also known as fixed-window estimators, is based on a changing subsample of fixed length that moves sequentially from the beginning to the end of sample by adding one observation at the end of the sample while dropping one at the start. With window size l and full series length T, this provides a sequence of $T-l$ causality tests. An important choice parameter in rolling estimations is the window size l as the precision and representativeness of the subsample estimates are controlled by the window size. There is usually a trade-off between precision of estimates and representativeness. On one hand, precision may be improved by using large window size, however, in the presence of heterogeneity, the representativeness may be compromised. On the other hand, heterogeneity can be reduced while at the same time increasing the representativeness of the parameters, but this may increase the standard errors thereby reducing precision (Balcilar and Ozdemir, 2013). Pesaran and Timmerman (2005) show through a Monte Carlo simulation that the bias in autoregressive (AR) parameters can be minimised by a window size as low as 10 to 20 when there are frequent breaks present. This paper uses a rolling window of small size of 24 (this excludes the observations required for lags and hence is the actual number of observations in the VAR) to guard against heterogeneity. The choice of small window size may lead to imprecise estimates. Therefore, the bootstrap technique is applied to each subsample estimation so as to improve the accuracy of the parameter estimates and raise the power of inferential tests.

The residual based *p*-values (bootstrap *p*-value) of the modified *LR*-statistics that tests the absence of Granger causality from oil price to food price are computed based on 2000 replications. These are computed from the VAR defined in equation (2) fitted to a rolling window of 24 observations. The null hypothesis is that the oil price does not Granger cause food price. The reverse causality is not considered given the relative size of South Africa's food market compared to that of the global market as stated earlier. The non-causality hypothesis is tested at the 10 % level of significance. The plots of the bootstrap *p*-values of the rolling test statistics are given in Figures 3 and 4, for nominal and real prices respectively with the horizontal axes showing the final observation in each of the 24 month rolling windows. Figure 3 shows the bootstrap p-values of the rolling test statistics, testing the null hypothesis that nominal oil price does not Granger-cause nominal food price. This null hypothesis is rejected at 10% significance level in the sub periods 2002:2-2002:9 and 2010:5-2010:12. Figure 4 shows the bootstrap p-values of the rolling test statistics, testing the null hypothesis that real oil price does not Granger-cause real food price. Again this null hypothesis is rejected at 10% significance level in the sub periods 2002:2- 2002:6, 2003:1-2003:10, 2006:12 and 2010:1-2010:12. In general results based on nominal and real values reinforce each other rejecting the null hypothesis that oil price does not Granger cause food price over time. These results highlight the importance of accounting for structural breaks and nonlinearities when examining the relationship between oil and food prices given the sharp contrast between the full sample and the rolling window Granger causality tests results. As can be seen, time varying approach is an appealing methodology given its ability to show the periods in which oil price has causal effect on food price.

The causal effect between 2000 and 2006 is also not surprising. This can be explained by the fact that after the 1998 Asian crisis, the world oil price increased in 1999 due to the growing Asian oil demand which signify recovery from crisis and also the shrinking of non-OPEC production (Nkomo, 2006). Prices continued to rise in 2000 and then plummeted in November 2001 following successive quota increases, a weakening US economy and increases in non-OPEC production. Soon afterwards, prices rose to the US$25 range, and hovered above US$40 per barrel in 2004 as a result of the continued fall of the US dollar, the political tension in the Middle East, the high demand for crude oil by China, and uncertainly about the future of Yukos, the Russian producer. Also the 2003 invasion of Iraq marked a significant event for oil markets as Iraq contains a large amount of global oil reserves leading to increased oil prices. Bacon and Mattar (2005) show that the price of Brent crude oil rose by 72% (from US$28.8 to US$ 49.5) from 2003 to mid-2005 and increased above US$ 55 after mid-2005. It is shown that South Africa imported on average about 95% of its crude oil requirement between 1998 and 2003 (Nkomo, 2006). Given its heavy dependence on imported crude oil both as input in the production of food crops and other economic activities, it is not surprising that food prices is significantly Granger caused by oil prices during these periods. More so, the 2006:12 causal effect might be a signal to the potential global financial and economic recession that eventually occurred between 2007 and 2010. Although, the results here do not precisely show significant evidence of oil price on food price during the 2007-2008 global financial crisis, it is able to pick the 2010 European financial crisis that affected economic activities worldwide, including South Africa. It can be argued that the initial concern over how European countries would reduce their budget deficits could have affected demand leading to fall in oil prices. For instance Brent oil price dropped from about US $85/barrel in April 2010 to US $76.barrel in May 2010. However, prices rose back to US $91/barrel in December 2010. Overall oil price shocks have been shown to Granger cause food price in South Africa at different times.

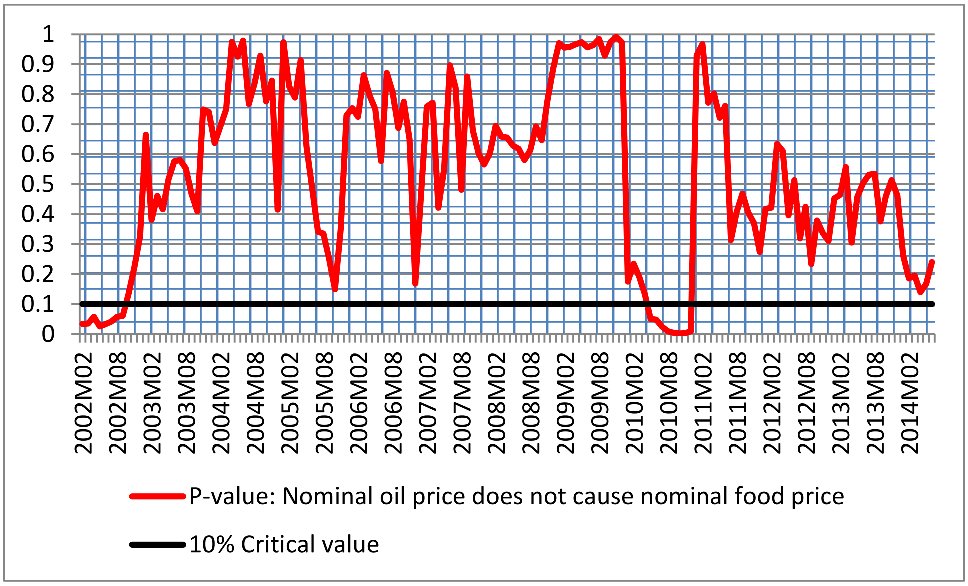

Figure 3: Rolling Window Bootstrap p-Value: Nominal Oil Price Does Not Granger Cause Nominal Food Price

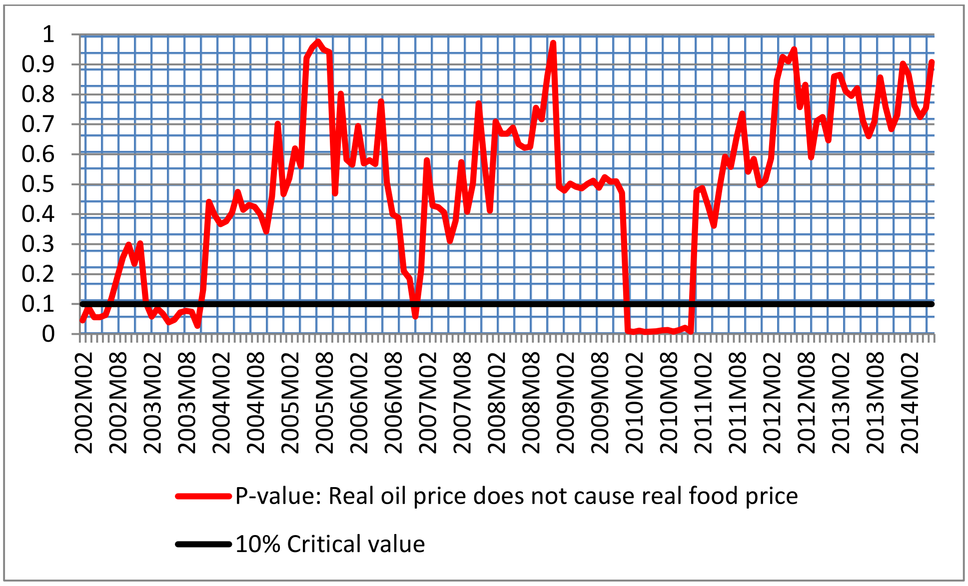

Figure 4: Rolling Window Bootstrap p-Value: Real Oil Price Does Not Granger Cause Real Food Price

Conclusion

This paper contributes to the growing literature on the oil price and food price relationship by examining the dynamic causal relationship between global oil price and South Africa's food price. Monthly data on Brent crude oil price and South Africa's consumer food price index from 2000:1 to 2014:6 is used. As opposed to previous studies on the dynamic causal relationship between oil price and food price, this study use both full sample bootstrap Granger causality tests and bootstrap rolling window tests (a time varying causality test) with fixed sample size, which allows inference without considering whether the series are integrated-cointegrated. Based on the results of full sample bootstrap Granger causality tests, oil price has no predictive power for food price. In other words, oil price does not Granger cause food price. This applies to the case where nominal oil and food prices are used as well as where their real values are used. However, using parameter stability tests on the full sample VAR, results show that both oil price and food price equations are unstable, undermining the inference drawn from full-sample Granger causality tests. Using the bootstrap rolling window estimation, it is shown that at 10 per cent level of significance, oil price has predictive power for food price during the 2002:2- 2002:6, 2003:1-2003:10, 2006:12 and 2010:1-2010:12 sub-periods.

These findings have some important implications. From econometric perspective, these results indicate that the causal relationship between oil price and food price is episodic, nonlinear and time varying. Therefore, these properties need to be taken into account in any analysis relating to these series to avoid misleading policy conclusions. From economic and policy perspective, it has been shown by previous studies that changes in the price of corn alone can cause significant changes in the food market. Therefore any changes in policy actions with respect to biofuel production in general and ethanol in particular needs to consider the effect of these on food prices. This is because a serious competition between ethanol and crude oil in producing refined products such as gasoline and diesel, may lead to higher corn prices hence food prices in general. Moreover, there need is for both the government and private partners to develop policy options and interventions that will encourage cost-effective agricultural production, processing and production efficiencies. This may include improved economic, social and ecological infrastructures as well as increased investment in research and development among others. Also there is need for more research on the appropriate strategies that will be used for managing production and price risk in the food subsector in order to cushion the effects of unanticipated oil price shocks.

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