The Effect of Oil Price Uncertainty on Food Price in South Africa

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Abstract—This paper examines the effect of the volatility of oil prices on food price in South Africa using monthly data covering the period 2002:01 to 2014:09. Food price is measured by the South African consumer price index for food while oil price is proxied by the Brent crude oil. The study employs the GARCH-in-mean VAR model, which allows the investigation of the effect of a negative and positive shock in oil price volatility on food price. The model also allows the oil price uncertainty to be measured as the conditional standard deviation of a one-step-ahead forecast error of the change in oil price. The results show that oil price uncertainty has a positive and significant effect on food price in South Africa. The responses of food price to a positive and negative oil price shocks is asymmetric.

Keywords—Oil price volatility, Food price, Bivariate GARCH-in-mean VAR, Asymmetric.

I. INTRODUCTION

THIS paper investigates the effect of oil price uncertainty on food price in South Africa. In recent times, there has been an increasing trend and spikes in the price of agricultural commodities in general and food prices in particular. The nominal prices of almost all food commodities increased by more than 50% between 2007 and 2008, and three years after the global crisis food prices surged again in 2010-2011 [1]. This has been and continues to be a cause for concern among all stakeholders- governments, traders, producers, and consumers- in both advanced and developing countries. This is particularly crucial given the implication of this on low income groups who are likely to be the most vulnerable to higher inflation rates as they spend greater share of their income on staple foods. The interest in commodity prices is not a recent phenomenon. However, there is a renewed interest since the global financial crisis and large fluctuations in commodity prices. Apart from the 2007-2008 crisis when food prices globally rose significantly, South Africa is still witnessing rising food prices. According to [2], 2014 started with increase in inflation rate of which energy and food prices were prime contributors. Food prices rose by 1.6% between December 2013 and January 2014. Meat prices, which fell during much of 2013, started rising again in September 2013, shot up by a further 2% between December 2013 and January 2014. Beef prices increased by 3.1% and frozen chicken portions by 1.5% in January 2014. Maize meal prices rose by 3.3% in the month. Vegetables increased by 6.3%, potatoes (15.6%), pumpkins (12.3%) and carrots (10.5%).

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Given increasing food prices in South Africa and many countries in the world, it is important to understand food price dynamics. A number of complex and mutually reinforcing factors were highlighted by [3] as the potential causes of the food price trend and spikes. These include droughts in key grain-producing regions, low stocks for cereals and oilseeds, increased feedstock use in the production of biofuels, rapidly rising oil prices and a continuing devaluation of the US dollar [3]. Also [4], [5] noted that in addition to weather shocks, energy shocks, increased biofuel usage and high world liquidity, weak dollar, fiscal and monetary expansion are other explanations. However, this study focuses on the link between crude oil price and food price. This is due to the simultaneous upward trend in world food prices and oil prices in the 2000s which has triggered an increased interest in the information transmission dynamics between the two markets [6]. Of particular interest is the effect of oil price uncertainty. Crude oil prices have been exhibiting large fluctuations (volatility) since the 2000s. For instance, the spot price of Brent crude oil increased from $19.42 per barrel in January 2002 to $132.72 in July 2008. Then following a downward trend it declined down to as low as $39.95 per barrel by the end of December 2008, before resuming another upward trend and reaching $125.45 per barrel in March, 2012. Since then, it has been up and down until it started falling consistently from July 2014 when it stood at $111.3 and as at September 2014 (the last month in the study sample) it stood at $97.09 per barrel. Similar trend is observed in other crude oil prices like the West Texas Intermediate (WTI) [7].

An oil price increase can be viewed as an inflationary shock. As a consequence, an oil price increase leads to a rise in the consumer price index, depending upon the share of oil products in the consumption basket [8]. One argument about the recent rise in food prices is that rising energy prices drive the food prices up [9]. This argument is due to the fact that energy is an important input in agricultural activities. Two possible transmission mechanisms among energy and food commodity prices have been explained by researchers. According to [10], the first linkage is based on the direct effects from oil prices to agricultural commodity prices which is based on the argument that soaring oil prices result in higher agricultural commodity prices through cost-push effects by increasing cost of production and through higher demand for the agricultural commodities used in biofuel production by increasing the demand for biofuels. This is because a substantial amount of diverse fuels (e.g. crude oil, coal, gas and biofuels) are required for agricultural activities such as: planting, the application of fertilizer, harvesting, storage and

transportation. Thus increases in oil price may be disruptive to agricultural commodity prices. In support of this, [7] noted that due to the increasing portion of corn dedicated to the production of alternative energy sources (biofuel: ethanol and diesel), crude oil prices may have contributed to the increase in prices of agricultural crops by not only increasing input costs but also boosting demand especially given relatively fixed land resources and competition between corn and other crops. The second link is the indirect effect of energy prices on food commodity prices through the exchange rate. According to [11], a rise in oil prices leads to exchange rate effects by increasing current account deficit which depreciates the local currency. There is yet another channel, which is the co-movement of oil price with agricultural commodities due to investment fund activity [12].

On the one hand, it is now well established at least in the theoretical literature that oil price shocks exert adverse impacts on food prices through raising production, processing, packaging, and distribution costs. Large empirical studies have attempted to examine these links. These include [9], [13]-[17] and the cited literatures in these papers. Overall, results in the empirical literature are mixed.

On the other hand, large oil price changes-either increases or decreases, i.e. volatility- may affect food prices adversely because they delay business investment by raising uncertainty or by inducing costly sectoral resource reallocation [18]. The theoretical explanation of the uncertainty channel is explained by [19]. He demonstrates that when firms experience increased uncertainty about the future price of oil then it is optimal for them to postpone irreversible investment expenditures. As the level of oil price volatility increases, the option value associated with waiting to invest rises and the incentive to investment declines [20]. The downward trend in investment incentives ultimately transmits to different sectors of the economy including agriculture. The sectoral resource allocation channel is discussed in [21]. A number of empirical studies have examined this for economic activities and some specific sectors of various countries. However, empirical evidence on the risk transfer between oil and agricultural commodity prices is scarce. The few known ones will be reviewed in depth since they are closely related to the objectives of the current study.

Evidence of volatility spillover from world oil futures prices to world corn futures prices after the food price crisis is found by [14]. Consistent with this finding, [22] find evidence of volatility spillover from crude oil to corn. They also indicate that soybean prices are positive and significant during higher crude oil price period, implying an economic substitution effect during higher crude oil price period. The joint impact of oil price and food price uncertainties and their correlation on the food price for a small oil producing country, Trinidad and Tobago is examined by [23]. Assuming the country to be a price taker and the market to be competitive and using the concept of indirect expected utility function, a statistical model for examining the interaction between the series is developed and the results from the model show that a higher oil price increases food price and higher oil price volatility

yields a higher food price. Using Bayesian Markov Chain Monte Carlo methods and weekly crude oil, corn, and wheat futures prices from November 1998 to January 2009, [7] find evidence of volatility spillover among crude oil, corn, and wheat markets after the fall of 2006. According to [6], variation in oil prices does not Granger cause the variance in food and agricultural raw material prices using the Cheung-Ng procedure. They conclude that the absence of volatility spillover from oil markets to food and agricultural raw material markets, implies that investors can benefit from risk diversification. Based on results from [24], there are strong volatility relationships between oil, ethanol and sugar prices in Brazil and that crude oil and sugar market shocks cause an increase in the volatility of the ethanol price thus proving the existence of a dynamic link between biofuel, fuel, and agricultural markets.

The investigation of volatility spillover from the world oil prices to food prices for the selected Asia and Pacific countries is done by [25] and they find that food price volatility is positively correlated with world oil price volatility. However, the results vary across countries and sub-periods. The effect is stronger for the more recent sub-period implying increasing interdependence between world oil and Asia Pacific agricultural markets. In a study by [26], both constant and time-varying copula-based models are used and results show that there is relatively weak symmetric tail dependence between crude oil and agricultural commodity prices in all pairs. The volatility transmission between world oil and selected agricultural commodity prices (wheat, corn, soybeans, and sugar) using causality in variance test and impulse response functions is examined by [12]. Employing daily data from 01 January 1986 to 21 March 2011 which is sub-divided into pre-crisis period (01 January 1986 to 31 December 2005) and post- food crisis period (01 January 2006–21 March 2011), they find no evidence of risk transmission between oil and agricultural commodity markets in the pre-crisis period, but oil market volatility spills on the agricultural markets-with the exception of sugar-in the post-crisis period.

From the foregoing, the effect of oil price uncertainty or volatility on either aggregate food price or individual food prices is not adequately studied. The dearth of studies is even worse for emerging markets and developing countries. The conclusions from the existing ones are also mixed warranting further studies. Moreover, the issue of asymmetric effect is not yet understood with respect to oil price uncertainty and food prices despite a lot of research on this in other sectors since the pioneering work of [27] who proposes filtering the oil price signal into positive and negative components to restore the causal relationship identified by [28]. According to [8], the possible explanations for this asymmetry rely on monetary policy [29], adjustment costs [21], adverse effects of uncertainty on the investment environment [30] and asymmetry in petroleum product prices [31], [32]. Giving these research gaps in relation to agricultural market, the main objective of this study is to examine the dynamics of the risk transmission from oil price to food price using South Africa as

a case. In addition, the study examines the asymmetric effects of oil price uncertainty on food price. The study also provides the generalized impulse responses of food price to oil price volatility, a feature which is rare in most related studies. This will help to track the responses of food price to oil price uncertainty over time and to understand how quickly or otherwise the effect dies off.

II. METHODOLOGY

The study use monthly time-series data on oil price and food price. These covers from 2002:1 to 2014:9. The oil price is the Brent crude oil price obtained from the US Energy Information Administration (EIA). The South Africa's consumer price index for food is used as a proxy for food price. This was obtained from Statistics South Africa. Both variables are transformed into natural logarithms. Fig. 1 presents the plots of the two series in logs. A preliminary analysis is conducted to examine the unit root properties of the oil price and food price using the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and the Ng-Perron (NP) test.
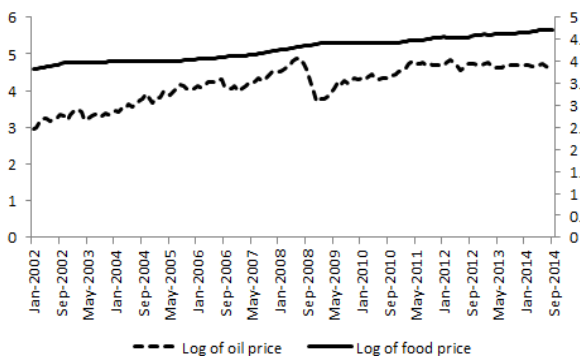

Fig. 1 Natural log of oil and food prices

Various volatility measures, both parametric and non-parametric (such as historical volatility, stochastic volatility, implied volatility, realized volatility, and conditional volatility) have been suggested in the literature [18]. The measure of oil price uncertainty in this study is defined as the conditional standard deviation of a one-step-ahead forecast error of the change in oil price. The study use the GARCH-in-mean VAR model initially developed by [33], [34] and used in [35] to examine the effect of oil price uncertainty on food price. The assumption is that the dynamics of the structural system can be summarized by a linear function of the variables of interest, and a term related to the conditional variance which is given as:

$$\mathbf{B}y_t = \mathbf{C} + \mathbf{\Gamma}_1\mathbf{y}_{t-1} + \mathbf{\Gamma}_2\mathbf{y}_{t-2} + \ldots + \mathbf{\Gamma}_p\mathbf{y}_{t-p} + \mathbf{\Lambda}(\mathbf{L})\sqrt{\mathbf{H}_t} + \varepsilon_t \quad (1)$$

where dim $(\mathbf{B})$ = Dim (Γ_i) are p × p matrices, $\sqrt{\mathbf{H}_t}$ is a diagonal matrix of conditional standard deviations and $\mathbf{\Lambda}(\mathbf{L})$ is a matrix polynomial in the lag operator. $\mathbf{y}_t$ is a vector containing oil price and food price growth rates, $\varepsilon_t \parallel \Pi_{t-1} \sim iid\,(\mathbf{0}, \mathbf{H}_t)$

represents uncorrelated structural disturbances in the system where Π_{t-1} is the available information set at time t-1.

To test whether oil price uncertainty affects food price, a test of restrictions on the elements of $\mathbf{\Lambda}(\mathbf{L})$ that relate the conditional standard deviation of oil price, given by the appropriate element of $\sqrt{\mathbf{H}_t}$, to the conditional mean of $\mathbf{y}_t$ is performed. If oil price volatility has adversely affected food price, then one would expect to find a positive (positive because a rise in food price is not desirable) and statistically significant coefficient on the conditional standard deviation of oil price in the food price equation.

The conditional variance $\mathbf{H}_t$ is modelled as bivariate GARCH. After re-dimensioning the variance function parameter matrices, one obtains the following variance function:

$$diag(\mathbf{H}_t) = \mathbf{C}_v + \sum_{j=1}^{J} \mathbf{F}_j diag(\varepsilon_{t-j}\varepsilon'_{t-j}) + \sum_{i=1}^{I} \mathbf{G}_i diag(\mathbf{H}_{t-i}) \quad (2)$$

$$\varepsilon_t \sim \sqrt{\mathbf{H}_t}\mathbf{z}_t; \, \mathbf{z}_t \sim iidN(0, \mathbf{I}),$$

where $\mathbf{C}_v$ is $N^2 \times 1$ matrix, $\mathbf{F}$ and $\mathbf{G}$ are $N^2 \times N^2$ matrices. *diag* is the operator that extracts the diagonal from a square matrix. The second and third terms on the RHS of (2) represents the ARCH and GARCH terms respectively. Imposing an additional restriction that the conditional variance of $y_{i,t}$ depends only on its own past squared errors and its own conditional variances, the parameter matrices $\mathbf{F}_j$ and $\mathbf{G}_i$ are also diagonal. The bivariate GARCH-in-mean VAR model given by (1) and (2) are simultaneously estimated by full information maximum likelihood (FIML), to avoid generated regressor problem related to estimating the variance function parameters separately from the conditional mean parameters. More technical details on this model can be found in [35].

III. RESULTS

The unit root tests results are presented in Table I. The test results in levels are presented in the first panel while the second panel shows the results based on the variables first differences. All the three unit root tests show that all the variables are non-stationary in levels but stationary in their first differences. The result present here is based on intercept only. However, the assumption of intercept and trend yield a similar result. Hence the analysis proceeds with the first log differences of the variables to avoid spurious regression. This is also consistent with [35].

One important step that needs to be taken before proceeding with the rest of the analysis is to show suitability of the GARCH (1,1)-in-mean VAR specification over the conventional homoscedastic VAR. This is done using the Schwarz Information Criterion (SIC) statistic from both models. The SIC includes a substantive penalty for the additional parameters required to estimate GARCH models, and so an improvement in the Schwarz criterion suggests

strong evidence in favour of the bivariate GARCH-in-mean VAR specification [35]. From Table II, it is clear that the GARCH (1,1)-in-mean VAR specification is capable of capturing the features of the data better than the standard homoscedastic VAR since the SIC value for the former is smaller than the value for the latter.

TABLE I
UNIT ROOT TESTS

Level			
Variable	ADF	PP	NP
Food price	-0.272	-0.427	-1.559
Oil price	-2.238	-2.240	-0.177
First Difference			
	ADF	PP	NP
Food price	-5.394***	-9.408***	-38.478***
Oil price	-9.262***	-9.260***	-68.021***

*** indicates significance at 1% level.

TABLE II
MODEL SPECIFICATION TEST

Bivariate VAR model	Schwarz Criterion Value	
	VAR	GARCH-in-mean VAR
Oil price and food price	1435.12	1421.24

Additional support of the GARCH-in-mean VAR specification is provided by the point estimates of the variance parameters, which are reported in Table III. The results in Table III support the rejection of the null hypothesis of no ARCH (F=0) and no GARCH-M (F = G = Λ =0) terms. Specifically, there is evidence of GARCH in food price and evidence of ARCH in oil price.

Oil price uncertainty is captured by the conditional standard deviation of oil price changes $\sqrt{H_t}$. It is the coefficient on this conditional standard deviation in the food price that provides the evidence of the effect of oil price uncertainty on food price. The result shows that the effect of oil price uncertainty is positive (0.02) and significant at 1%.

TABLE III
COEFFICIENT ESTIMATES FOR THE VARIANCE FUNCTION OF THE GARCH-IN-MEAN VAR

	Conditional variance	Constant	$\varepsilon_i(t-1)^2$	$H_{i,i}(t-1)$
Oilprice equation	$H_{1,1}(t)$	35.270*** (6.705)	0.428*** (3.609)	0.0
Food price equation	$H_{2,2}(t)$	0.742*** (24.511)	0.192*** (11.957)	0.869 (17.908)

Note: These are the constants and parameter estimates of *F* and *G* from the model given by (1) and (2) with $\varepsilon_t \parallel \Pi_{t-1} \sim iid\ (0, H_t)$. Asymptotic t-statistics are in parentheses. *** indicates significance at 1% level.

The effect of oil price uncertainty on the dynamic response of food price is assessed using impulse responses, which are simulated from the maximum likelihood estimates of the parameters of the model. To make the impulses comparable to those of a homoscedastic VAR, the magnitude of the impulse responses used to simulate the impulse response functions is based on an oil price shock that is equal to the unconditional standard deviation of the change in the price of oil. To examine whether the responses to positive and negative

shocks are symmetric or asymmetric, the response of food price to positive and negative oil price shock are simulated. The impulse responses (solid lines) and the one-standard deviation error bands (dashed lines) are presented in Fig. 2. The impulse response indicates that accounting for the effects of oil price uncertainty, a positive oil price shock increases food price, inducing an upward revision in food price by about 17% after the third month. Thereafter the impact declines but remained positive and persistent. The response is significant throughout the 12 month horizon. With respect to the dynamic response of food price to a negative oil price shock, food price immediately declined, became positive half way into the second month, return to the negative trend in the second month and remained negative before the effect died off after 8 months. The response was significant between the first one and half month and the third month where food price declined to a maximum of about 12%. Clearly, the effects of positive and negative oil price shocks are not same. The positive oil price shock has a larger effect on food price than the negative oil price shock of equal size. Moreover, the image of a positive oil price shock is not perfectly a mirror of that of the negative price shock. Therefore, this study concludes that the responses are asymmetric.
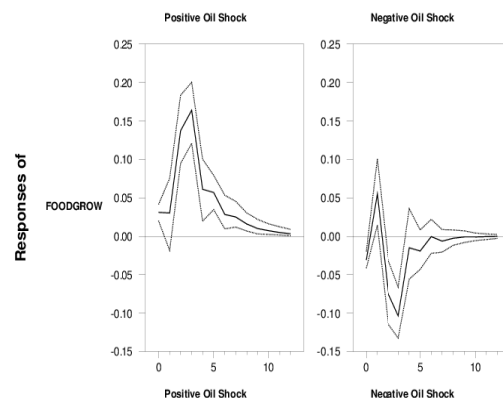

Fig. 2 Response of food price to positive and negative oil price shocks

This study also compares the responses of food price to positive and negative oil price shocks with and without the M terms as shown in Fig. 3 where the error bands have been suppressed for clarity. A model that includes the M terms accounts for the effect of oil price uncertainty while the coefficients of oil price uncertainty is constrained to zero in the model without the M terms. In Fig. 3, the solid lines represent the response of food price following an oil price shock after allowing oil price uncertainty into the food price equation. The dashed lines represent the response of food price following an oil price shock without allowing the oil price uncertainty into the food price equation. Fig. 3 shows that the inclusion of the M terms magnifies the responses of food price to a positive oil price shock while it diminishes its response to a negative oil price shock. This result further confirms that oil price uncertainty do indeed play a role in food price in South Africa.
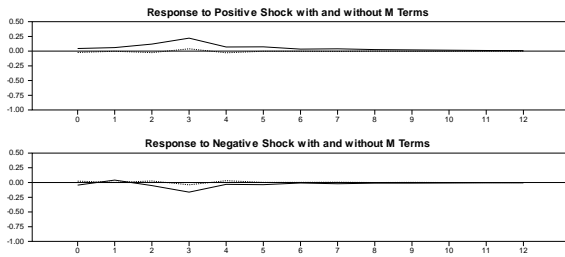
Fig. 3 Response of food price to oil price shock with and without M terms

IV. CONCLUSION

The paper examines the effect of oil price uncertainty on food price in South Africa using monthly data from 2002:1 to 2014:9. The measure of oil price uncertainty in this study is defined as the conditional standard deviation of a one-step-ahead forecast error of the change in oil price. The empirical analysis is based on a bivariate GARCH-in-mean VAR model. The results show that high oil price uncertainty leads to increases in food price and this effect is statistically significant at 1%. To examine the effect of incorporating oil price uncertainty on the dynamic response of food price to an oil price shock, the impulse responses, which are simulated from the maximum likelihood estimates of the parameters of the model is used. Results from the impulse responses show that food price responds positively to a shock in oil price and the response is persistent and significant throughout. Food price response to a negative oil price shock is negative most of the periods. The effect is of a negative oil price shock is quantitatively smaller than that of the positive oil price, thus supporting an asymmetric effect. The study also finds that accounting for oil price uncertainty tend to amplify the dynamic response of food price to a positive oil price shock, while dampening the response to a negative oil price shock. Overall, the study provides evidence in support of an increasing effect of oil price uncertainty on food price. The findings have important implications for policy makers, producers, traders and consumers. The results could be used to optimise and stabilize the markets and to make strategic portfolio investment decisions. The government of South Africa can help to reduce the effect of oil price uncertainty through strategic oil reserves or stocks, improved energy efficiency, energy portfolio diversification and price smoothing. However, caution needs to be taken in the case of price smoothing especially if the country is not yet in position of effective risk coping instruments.

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