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Abstract

Sudden changes in oil prices have been a major concern for countries – oil producing and non-oil producing countries alike. Due to this, we assessed the effects of such an uncertainty on the real output of Nigeria, an oil producing country, during the period 1980:1 to 2014:4. We achieved this objective by using a bivariate GARCH-in-mean VAR model that allows for an uncertainty measure. We then quantified the responses of real output to positive and negative real oil price shocks. Using the conditional standard deviation of the forecast revision of the growth in the composite refiners' acquisition cost of crude oil deflated by US GDP deflator as our measure of oil price uncertainty, we found that uncertainty about oil prices exerted negative and significant impact on the real output of Nigeria. In addition, real output responded to positive and negative shocks to real oil prices symmetrically.

Keywords: Oil Price Uncertainty, Real Output, GARH-in-mean VAR, Nigeria
JEL Codes: C32; E23; E32

1. Introduction

Unexpected changes in oil prices have introduce another source of concern for all countries around the globe, even so because such changes have become pronounced in recent years (see Ayadi, 2005; Chuku *et al.*, 2011). Oil and hydroelectric power are the main sources of energy, and thus count among the core drivers of the real economy. Hence, volatility in oil prices is a major issue that the policymaker has to deal with. In their paper, Elder and Serletis (2010) elaborate the theoretical transmission channels of real oil price shocks to the rest of the economy. They noted that real oil price shocks transmit directly unto real balances and monetary policy. They explained that an increase in oil prices leads to a rise in the overall price level then to a fall in real money balances held by households and firms, which in turn depresses aggregate demand. They explained, in addition, that changes in oil prices generate income transfer. For example, if there is an increase in oil prices, incomes are transferred from oil importing countries to oil exporting countries, and vice versa (see Elder and Serletis, 2010).

Nigeria is an oil producing country whose economic activities are largely driven by oil revenues (see Ayadi, 2005). The economy depends largely on oil, so that shocks to oil prices could have extensive ramifications to its fundamentals. For example, oil accounts for over 90% of Nigeria's export revenues and over 90% of its foreign exchange earnings. In addition, over 80% of government revenue comes from this source (see Ayadi, 2005). Since the country exports oil, increases in oil prices should generate savings to ensure high investment levels and sustainable growth (see Chuku *et al.*, 2011; Iwayemi and Fowowe, 2011). Iwayemi and Fowowe (2011) argued that because Nigeria exports oil, positive shocks to oil prices should directly translate into higher economic growth. But this is not the entire story. As Chuku *et al.* (2011) observed, Nigeria doubles as an oil exporter and importer. Hence, the appropriate effect of oil price shocks could lie somewhere in-between. Nigeria imports most of its technology oriented goods such as home appliances, television, cars, and computers among others. These goods are mostly produced using oil-intensive plants, and therefore should be expensive as oil prices increase. The implication is that positive oil price shocks will lead to imported inflation, and depletion in external reserves due to currency depreciation – indicators which are not favourable for real output growth. Positive oil price shocks have the potential of generating a boom in the oil sector, and a potential Dutch disease problem, thereby shrinking productivity in the rest of the economy.

Prior to the 1970s, oil prices have been quite stable. In the 1970s, conversely, oil prices have experienced rapid increase, rising from their previous levels of about $40 per barrel to slightly above $100 per barrel. At the turn of the 1980s, these prices dropped to nearly $20 per barrel and persisted at this level till somewhere around 2001 (see Aye *et al.*, 2014). Oil prices started rising faster towards the peak of the recent housing market bubble in the US (i.e. somewhere around 2006), and reached an all-time high of $145 per barrel during the peak of the recent financial crises (see Hamilton, 2009; Aye *et al.*, 2014). The volatility and sharp rises in oil prices have reignited the literature on the role of oil prices in the real economy. The literature dates far back to seminal papers such as Hamilton (1988), Mork (1989), Lee *et al.* (1995), and Hooker (1996). These studies have generally found an inverse relationship between oil price shocks and the real economy, and thus shed comprehensive policy insights.

Recently, these findings have been corroborated in studies such as Hooker (2002), who found positive oil price shocks to drive up the U.S. core inflation, and to depress productivity before 1981, and Barsky and Kilian (2002, 2004), as well as Edelstein and Kilian (2007a, 2007b) who found similar evidence to hold. In particular, the latter studies found oil price shocks to significantly affect the real economy, through a supply channel by increasing the cost of production, which then reduces production. Later, Hamilton (2009) found this to be the case. He found oil price shocks to exert negative and significant impact on the US economy.

Other studies found that apart from oil price changes, oil price volatility does not bode well with the real economy. For example, in their paper, Elder and Serletis (2010) found oil price uncertainty to affect the US economy negatively and significantly. This study analyzed the real options and investment model, by looking at consumption patterns under the uncertainty of future returns, and found oil price volatility to reduce some components of aggregate investment. Their finding is generally consistent with the real option theory which argues that firms may delay or even abandon their investments in an environment whereby future returns are uncertain as the degree of uncertainty amplifies. This is a view shared by older studies such as Bernanke (1983) and Pindyck (1991), and in a recent study by Lee *et al.* (2011) who assessed the effects of oil price shocks on firms' investment decisions in the U.S. manufacturing sector. Lee *et al.* (2011) found firms' stock price volatility alongside future oil price uncertainty to negatively affect firms' investment decisions for at least the first and second year of the initial shock (see, also, Aye *et al.*, 2014, for this discussion).

There are a number of studies that have investigated the effects of oil price shocks on various macroeconomic variables in the case of Nigeria. For example, Ayadi *et al.* (2000) examined the impact of the energy (or oil) sector on the functioning of the Nigerian economy, including the financial markets using a standard VAR and found the energy sector to exert significant influence on the economy. Also, Ayadi (2005) analyzed the relationship between oil price changes and economic development via industrial production with a standard VAR and found that an increase in oil prices does not lead to an increase in industrial production in Nigeria. Recent studies have revisited the issue. For example, Chuku *et al.* (2011) assessed the relationship between oil price shocks and current account dynamics in Nigeria using a standard VAR and found oil price shocks to have a significant short-run effect on current account balances. Moreover, Iwayemi and Fowowe (2011) found oil price shocks to have weak impact on most macroeconomic variables in Nigeria. The major limitation of these studies is that they failed to account for the observed volatility in oil prices, and therefore left out an important transmission channel. Our paper can be seen as an important improvement upon these studies. In particular, our paper is an extension of the studies on oil price shocks and the real economy. The paper is closely related to those of Elder and Serletis (2010), and Aye *et al.* (2014) who studied the role of oil price uncertainty in the real economy for the US and South Africa, respectively. Unlike these studies, we consider an oil producing economy which also doubles as an importer, and by classification is a developing country with various structural and institutional problems. Specifically, we analyzed the effect of oil price uncertainty on the real output. Then we considered whether the real output responded asymmetrically to oil price shocks.

Majority of the existing studies have tended to examine the effects of oil price shocks on the real economy within single-equation based models or standard VAR models. These models are limited because they are unable to capture oil price volatility (or any kind of volatility, for that matter) which is said to have amplified after the early 1970s. Historical events suggest that particular time series such as oil prices have exhibited different volatilities and, more frequent than not, time varying volatilities (see Fama, 1965; Orhan and Köksal, 2012). Failure to account for such volatilities in most of these existing studies has the potential that their suggested impact of oil price changes on the real economy may have been underestimated. The suitable models for handling volatilities of this kind are those advanced in Bollerslev (1986a, 1986b) and their extensions thereof. Our mission is to avoid this stand out limitation of the existing studies by using a model that accounts for reverse causality as well as volatility in oil prices. This is the structural VAR augmented with GARCH-in-mean errors developed in Engle and Kroner (1995) and Elder (1995, 2004). The model's key property is that it allows for homoscedasticity as a special case, meaning that the true data generating process is shown in the estimates (see Elder, 2003, 2004). It also allows the conditional variance of one or more variables in a simultaneous equation system to affect the conditional mean of one or more other variables, and therefore offers an improvement upon the standard VAR which assumes that the conditional variance is homoscedastic over time (see Elder, 2003, 2004). This improvement is particularly useful to the policymaker because the typical standard VAR simulates the response of the real economy to oil price shocks – positive or negative – by permitting conditional means of the variables in the model to interact, thereby excluding other transmission channels. The GARCH-in-mean VAR model, in contrast, offers the policymaker the standard VAR transmission channels and an additional channel to assess the response of the real economy to oil price shocks, namely the volatility channel as indexed by the GARCH term (see, also, Elder and Serletis, 2010).

The rest of the paper is organized as follows. In the next section, we present the empirical methodology. Then, in section 3, we present the data and the results. Section 4 concludes the paper.

2. The Empirical Methodology

There is a vast VAR literature that offers extensive insight into the modelling of oil prices and the real economy. Among the popular ones are Hamilton (1983), Mork (1989), Lee *et al.* (1995), Hooker (1996), Bernanke *et al.* (1997), Hamilton and Herrera (2004), Edelstein and Kilian (2007a, 2009), and Kilian (2009a, 2009b). These studies have varied their empirical specifications, regarding the measures of real output, number of variables, and the frequency of the series. However, studies such as Kilian (2009a), and Elder and Serletis (2010) argued in support of bivariate models with quarterly data. Following Elder and Serletis (2010), we used a bivariate GARCH-in-mean VAR with quarterly data on real price of oil growth and real GDP growth. This GARCH-in-mean VAR, originally developed by Elder (1995, 2004), is a structural VAR with modifications for conditional heteroskedasticity in the parametric form of multivariate GARCH-in-mean.

The GARCH-in-mean VAR is basically a model in which the dynamics of the structural system is a linear function of the variables of interest augmented by a term related to the conditional variance. The model can be specified as follows:

$$By_t = C + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \cdots + \Gamma_p y_{t-p} + \Lambda(L) H_t^{1/2} + \varepsilon_t, \qquad (1)$$

where y_t is a vector of real oil price growth, and real output growth, $dim(B) = dim(\Gamma_i) = (N \times N)$, $\varepsilon_t|\psi_{t-1} \sim iidN(0, H_t)$, $H_t^{1/2}$ is a diagonal, $\Lambda(L)$ is a matrix polynomial in the lag operator, and ψ_{t-1} is the information set at $t-1$, which includes variables dated $t-1$ and earlier. The system is identified by assuming that the structural disturbances ε_t are conditionally and contemporaneously uncorrelated and by imposing a sufficient number of exclusion restrictions on the matrix B.

Eq. (1) permits the matrix of conditional standard deviations ($H_t^{1/2}$) to influence the conditional mean. This condition permits the researcher to assess the effect of oil price uncertainty on the real economy, via an appropriate element of Λ (Elder and Serletis, 2010). This means that should oil price uncertainty affect the real economy negatively, the conditional standard deviation of oil price growth in the real output growth equation should be negative and statistically significant.

The conditional variance H_t is modelled as a bivariate generalized GARCH of Bollerslev (1986a, 1986b) and Engle and Kroner (1995) in the following form:

$$h_t = C_v + \sum_{j=1}^{J} F_j vec(\varepsilon_{t-j}\varepsilon'_{t-j}) + \sum_{i=1}^{I} G_i h_{t-i}, \qquad (2)$$

$$z_t \sim iidN(0, I);\ \varepsilon_t = H_t^{1/2} z_t,$$

where C_v is $N^2 \times 1$, F and G are $N^2 \times N^2$, and $h_t = vec(H_t)$. H_t may not be positive definite.

This issue can be surmounted by imposing a common identifying restriction on the structural disturbances. That is, we must impose a zero contemporaneous correlation of structural disturbances such that the conditional matrix H_t becomes a diagonal. This reduces the required number of variance function parameters substantially (see Elder, 2004). A suitable re-dimensioning of the variance function parameter matrices C_v, F and G, reduces the variance function to one of the form:

$$diag(H_t) = C_v + \sum_{j=1}^{J} F_j diag(\varepsilon_{t-j}\varepsilon'_{t-j}) + \sum_{i=1}^{I} G_i diag(H_{t-i}), \qquad (3)$$

where $diag$ is an operator which extracts the diagonal from a square matrix. If we assume that the conditional variance of $y_{i,t}$ depends only on its past squared errors and its past conditional variances, the parameter matrices F_j and G_i will also be diagonal (see Elder, 2004).

Eqs. (1) and (3) represent the bivariate GARCH-in-mean VAR model. This model is estimated using the method of full information maximum likelihood (FIML). This approach surmounts the Pagan's (1984) generated regressor problems when estimating the variance function parameters separately from the conditional mean parameters (see Elder, 2004; Elder and Serletis, 2010). The FIML approach entails that we maximize the log likelihood $\sum_{t=1}^{T} l_t$ with respect to the structural parameters of the GARCH-in-mean (i.e. B, C, $\Gamma_1, \Gamma_2, .., \Gamma_p$, Λ, F, and G). l_t is defined as follows:

$$l_t = -(N/2)\ln(2\pi) + 1/2 \ln|B|^2 - 1/2 \ln|H_t| - 1/2\,(\varepsilon_t' H_t^{-1} \varepsilon_t). \tag{4}$$

We closely followed Elder and Serletis (2010) and set the pre-sample values of the conditional variance matrix H_0 to their unconditional expectations and condition on the pre-sample values $y_0, y_{t-1}, \dots, y_{t-p+1}$. Then, we restrict H_t to be positive definite and ε_t to be covariance stationary by imposing the restrictions that: C_v is element-wise positive, F and G are element-wise nonnegative, and the modulus of the eigenvalues of $(F + G)$ is less than unity. By imposing the standard regularity conditions, the FIML estimates are asymptotically normal and efficient, with the asymptotic covariance matrix defined as the inverse of the Fisher's information matrix (see Elder, 2004).

The next step is to generate the impulse responses, which is perhaps the most important part of VAR analysis. In the current case, we closely followed Elder (2003) and specified the following infinite order moving average representation of a reduced form VAR:

$$y_{t+k} = \theta(L) \cdot (C_0 + \Pi_0 H_{t+k} + B^{-1}\varepsilon_{t+k}), \tag{5}$$

where $C_0 = B^{-1}C$, $\Pi_0 = B^{-1}\Lambda$, $\theta(L)$ is a matrix polynomial in the lag operator. The impulse response function associated with a k-step ahead forecast revision of $y_{j,t}$ due to an innovation in the structural disturbance $\varepsilon_{j,t}$ is defined as:

$$\frac{\partial E(y_{j,t+k}|\varepsilon_{i,t}, \Psi_{t-1})}{\partial \varepsilon_{i,t}} = \sum_{\tau=0}^{k-1} \frac{\partial[\theta_\tau B^{-1}\Lambda(F+G)^{k-\tau-1}F \cdot E(\varepsilon_t \varepsilon_t' | \varepsilon_{i,t}, \Psi_{t-1})]}{\partial \varepsilon_{i,t}} + \frac{\partial E(\theta_k B^{-1}\varepsilon_t)}{\partial \varepsilon_{i,t}}. \tag{6}$$

This representation [i.e. *Eq.* (6)] is analogous to the impulse response function of an orthogonalized VAR (see Elder, 2003). Ψ_t is the information set at period t. The first term on the *RHS* of *Eq.* (6) captures the effect on the conditional forecast of $y_{j,t+k}$ through the forecasted effect on the conditional variance. The second term on the *RHS* of *Eq.* (6) captures the direct effect of a shock $\varepsilon_{j,t}$ on the conditional forecast of $y_{j,t+k}$. It is similar to the impulse response in the conventional homoscedastic VAR.

The standard practice in the literature is to shock the system by a given standard deviation (the common being one standard deviation), and generate the implied responses (see Elder, 2004). We constructed the confidence bands for the corresponding impulse responses using the Monte Carlo method, as elaborated in Hamilton (1994, p.337). This entails that we simulate the impulse responses from the maximum likelihood estimates of the parameters of the model. Following Elder and Serletis (2010), we generated the confidence intervals by simulating 1000 impulse responses derived from parameter values which are drawn randomly from the sampling distribution of the maximum likelihood estimates. The associated covariance matrix of the maximum likelihood estimates is obtained from an estimate of the Fisher's information matrix.

Finally, to identify the shocks, we closely followed Edelstein and Kilian (2007a), Elder and Serletis (2010), and Kilian and Vega (2011) and imposed the usual VAR identifying restrictions, which permits the policymaker to estimate $N(N-1)/2$ free parameters in B, subject to a rank condition. Since our model is bivariate, it means that we can only estimate one free parameter in B. Following these studies, we allowed the real output growth to respond contemporaneously to innovations in the real oil price growth. In the next section, we describe the data and report the results.

3. Data and Empirical Results

Following previous studies (see for example, Elder and Serletis, 2010), we measured the price of oil as the composite refiners' acquisition cost (RAC) of crude oil, which is compiled by the US Department of Energy. This is calculated as a weighted average of domestic and imported crude oil costs, including transportation and other fees paid by refiners. This price index therefore measures the price of crude oil as an input to production. Since this price index takes into account the cost of imported oil, it measures oil prices more broadly than domestic price measures, such as the West Texas Intermediate (WTI) crude oil price at Chicago, which is the price paid to domestic producers in the United States (see Elder and Serletis, 2010).

We arrived at our final measure of the real oil price by deflating the RAC of crude oil by the US GDP deflator which we obtained from the website of the Federal Reserve Bank of St Louis. Again, following the previous studies, we measured real output by real GDP. We obtained the data on real GDP from the Central Bank of Nigeria. The original data is in the local currency (i.e. naira). We converted this figures from naira to dollars by multiplying the real GDP (in naira) by the dollar-naira exchange rate, obtained from the Central Bank of Nigeria. Note that real oil price and real output are in natural logarithms.

Our pre-sample begins in the second quarter of 1980 and end in the last quarter of 2014 (i.e. 1980:2 – 2014:4). Consistent with existing studies (see, for example, Elder, 2004; Elder and Serletis, 2010); we measured oil price uncertainty as the conditional standard deviation of the one-step-ahead forecast revision of the change in the real price of oil.

It is not uncommon in the VAR literature to proceed with the analysis by differencing the variables without testing for their stationary properties. However, we followed an alternative course by testing for the stationary properties of real oil prices and real output using two known tests: the Phillips-Perron (PP) and the Dickey-Fuller GLS (DF-GLS) tests. The tests show that both variables are stationary at first difference (see Table 1).[2] Hence, we proceed to use the first difference of the variables, which are by definition, the real oil price growth and real output growth. Fig. 1 shows a plot of the variables in their first differences.

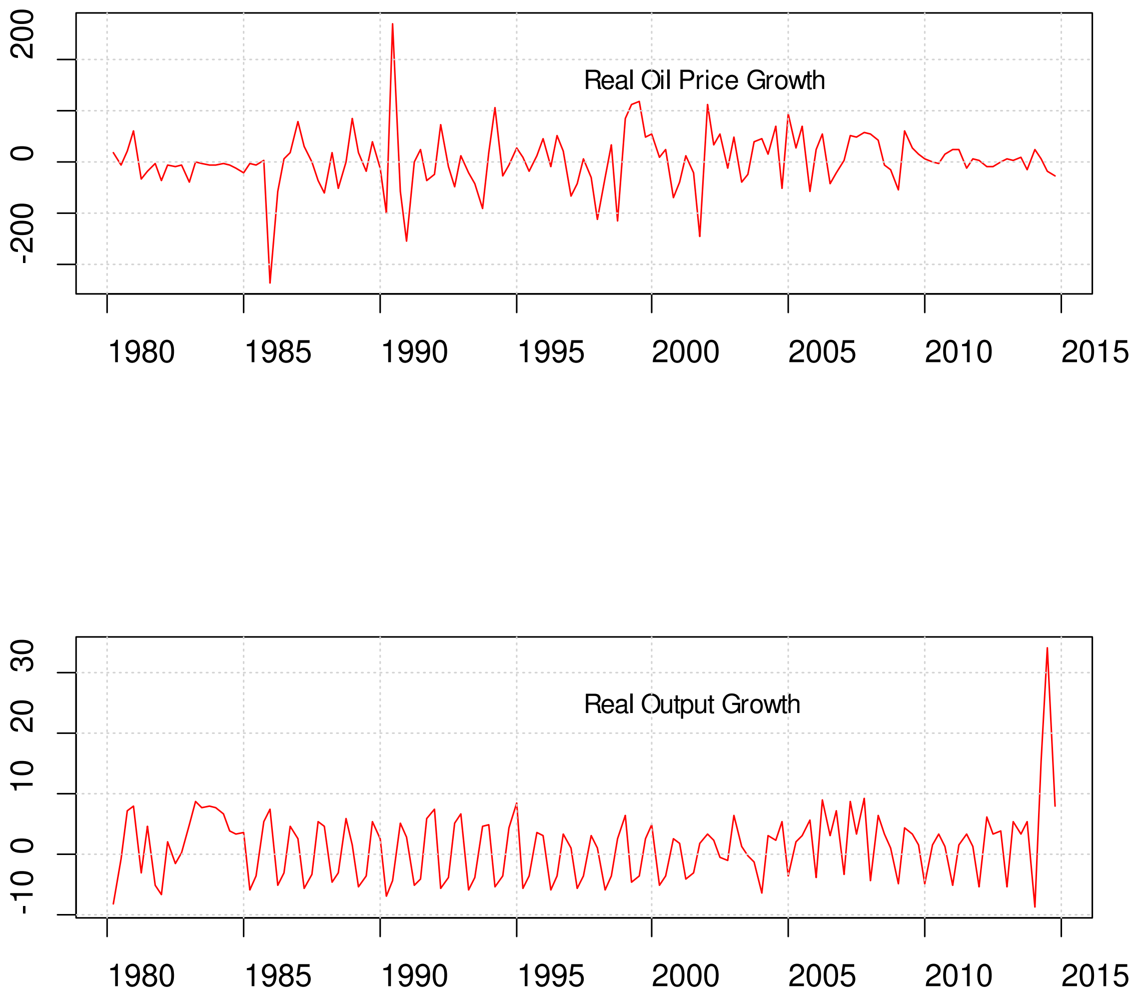
Table 1: Tests for Stationarity.

Variable	Level			
	Intercept			Intercept and Trend
	PP	DF-GLS	PP	DF-GLS
Real Oil Price	-1.355	-1.276	-2.891	-1.803
Real Output	-1.270	1.208	-1.984	-2.463
	First difference			
	Intercept			Intercept and Trend
	PP	DF-GLS	PP	DF-GLS
Real Oil Price	-8.575***	-9.546***	-8.573***	-8.814***
Real Output	-6.904***	-5.218***	-7.058***	-6.073***

Note: *** denotes significance at 1% level.

[2] All computations and plots, except Fig. 1 (which is plotted using R software), are carried out in RATS software. The scripts and data are available upon request.

Fig. 1: Real Oil Price Growth and Real Output Growth.



We restricted the number of lags in the bivariate model to 4. This is standard in the VAR literature on quarterly data (see also Elder and Serletis, 2010). We adjudged the performance of our bivariate GARCH-in-mean VAR as against the conventional bivariate homoscedastic VAR using the Schwarz information criteria (SIC). The SIC penalizes any additional parameters necessary for estimating the GARCH-in-mean VAR. The estimated SICs indicate that our bivariate GARCH-in-mean VAR improves upon the conventional bivariate homoscedastic VAR (see Table 2). This is because the SIC of the conventional bivariate homoscedastic VAR is higher than the SIC of the bivariate GARCH-in-mean VAR (see Table 2).

Table 2: Model Specification Test.

Equation	Bivariate VAR	Bivariate GARCH-in-mean VAR
Real Oil Price, Real Output 1980:2 – 2014:4	2357.594	2283.267

Table 3 reports the point estimates of parameters of the variance function in the bivariate GARCH-in-mean VAR. The real oil price and real output equations exhibit, respectively, the evidence of ARCH and GARCH effects. Volatility in the real oil price is less persistent, since only the coefficient on the lagged squared errors is significant at quarterly frequency (see Table 3).

Table 3: Coefficient estimates for the variance function of the bivariate GARCH-in-mean VAR.

	Conditional variance	Constant	$\varepsilon_t(t-1)^2$	$H_{i,i}(t-1)$
Real Oil Price	$H_{1,1}(t)$	1508.009*** (4.187)	0.710*** (2.795)	0.000
Real Output	$H_{2,2}(t)$	0.601** (1.973)	0.375*** (3.118)	0.684*** (11.519)

Note: ** and *** denote, respectively, 5% and 1% significance levels.

Recall that the conditional standard deviation, which is given by an appropriate element of $H_t^{1/2}$, captures the uncertainty of interest – in the current case, the effects of real oil price uncertainty on real output. In our present empirical exercise, we find this coefficient to be negative and statistically significant (i.e. coefficient of -0.041 and t-statistic of 2.724). This shows that higher oil price uncertainty leads to decrease in real output.

We then examined the effect of incorporating oil price uncertainty on the dynamic response of real GDP to an oil price shock by plotting the associated impulse responses in Fig. 2. This is simulated from the MLEs of the model's parameters as described in the methodology section. These impulse responses are based on an oil price shock equal to the annualized unconditional standard deviation of the change in the real price of oil. The magnitude of the shock is chosen such that the associated impulses are comparable to those of the standard homoscedastic VAR. In particular, we analyzed the response of real output to positive and negative real oil price shocks in order to see whether they are symmetric. The error bands are constrained to one standard error bands.

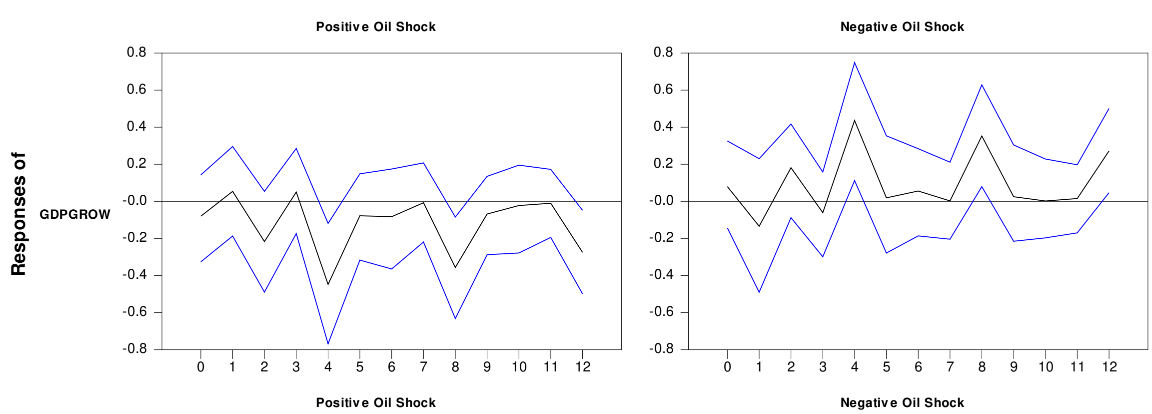
A positive oil price shock has no significant impact on real output on impact. The real economy begins to feel the impact beyond the first quarter after the positive real oil price shock, as real output falls by 0.2% from its baseline by the second quarter. Real output climbs back to its baseline during the third quarter but soon drops by 0.4% during the fourth quarter. From the fourth quarter onwards, real output has hovered between its baseline and -0.2% (see Fig. 2). The impulse response of real output does not appear to stabilize twelve quarters following the positive oil price shock.

A negative oil price shock leads to a downward response by real output during the first quarter, where real output falls by 0.1% from its baseline on impact. The real output then returns to and above its baseline during the second quarter, rising by 0.2%. It then falls to its baseline during the third quarter, then rises strongly by 0.4% during the fourth quarter. From the fourth quarter onwards, real output hovered between its baseline and 0.2%. As with the positive shock, the response of real output does not stabilize after twelve quarters, following the negative real oil price shock.

Generally speaking, since the response of real output to a positive oil price shock is a mirror image of a negative oil price shock; we can firmly conclude that the shocks are symmetric. We carried out a robustness check of our results by converting the series into the domestic currency, the naira. The results – not shown here to conserve space but are available upon request – are qualitatively similar to the ones presented here. Specifically, we found the volatility process for the real oil price to be less persistent; real oil price uncertainty to exert negative influence on real output, and the positive and negative real oil price shocks to be symmetric.

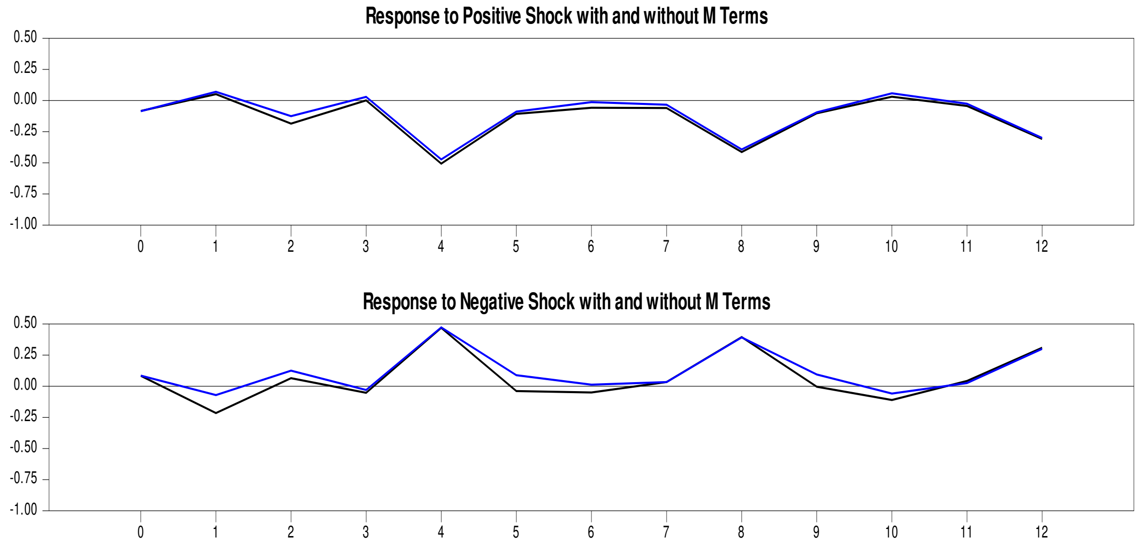
The final results entail the impulse responses to positive and negative real oil price shocks, of real output with and without M terms. These are shown in Fig. 3. The black and blue lines denote, respectively, the responses with and without the M terms. Though not very pronounced, we find the M terms to amplify the responses of real output to positive and negative real oil price shocks, further buttressing the other results.

Figure 2: Impulse Responses for Bivariate GARCH-in-mean VAR.



Note: The black lines represent the impulse responses, while the blue lines represent the one standard deviation error bands.

Figure 3: Impulse Responses with and without M terms.



Note: The black and blue lines represent, respectively, the impulse responses with and without the M terms.

4. Conclusion

In this paper, we assessed the effects of oil price uncertainty on the real output in Nigeria during the period 1980:1 – 2014:4. The theory posits a negative response of the real economy to oil price uncertainty. The existing studies have often narrowed the empirics to non-oil producing countries. This is why we pursued the issue by considering an oil producing country, Nigeria. We attained this objective by employing an augmented VAR model that allows for an uncertainty measure. This is the bivariate GARCH-in-mean VAR proposed in Elder (1995, 2004) and utilized to pursue the same objective in Elder and Serletis (2010). In this model, oil price uncertainty is captured by the conditional standard deviation of the one period ahead forecast error of the change in the price of oil. Four key results emerged from our empirical analysis. First, using the Schwarz information criteria, we found the bivariate GARCH-in-mean VAR to capture the true data generating process of oil price growth and real output growth, as compared with a homoskedastic VAR. Second, uncertainty about oil prices has negative effects on real output in Nigeria. Third, real output tends to respond negatively to positive real oil price shocks, and positively to negative real oil price shocks. Fourth, the responses of real output following positive and negative real oil price shocks are symmetric. Our results remained robust to denominating the series in the local currency, and are consistent with the study conducted by Elder and Serletis (2010) for the US. Our empirical results on oil price uncertainty quite reflect in the two main characteristics noted in the relationship between real output and oil prices. In the mid-1980s, the sharp decline in oil prices failed to generate the rapid output growth predicted by the theory. Likewise, the episode of sharp increases in oil prices from 2002 to 2008 failed to generate the recession expected in many countries (see also Elder and Serletis, 2010).

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