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ARTICLE INFO	Goodness C. Aye (2015). Does oil price uncertainty matter for stock returns in South Africa?. *Investment Management and Financial Innovations*, *12*(1-1), 179-188
RELEASED ON	Tuesday, 07 April 2015
JOURNAL	"Investment Management and Financial Innovations"
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

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Does oil price uncertainty matter for stock returns in South Africa?

Abstract

This paper examines the impact of oil price uncertainty on South Africa's stock returns using weekly data that cover the period 1995:07:01 to 2014:08:30. The measure of oil price uncertainty is the conditional standard deviation of the one-step-ahead forecast error for the change in the price of oil. A bivariate GARCH-in-mean vector autoregressive model was used for analysis. The results with oil price in US Dollars show that oil price uncertainty had negative but marginally significant effect on stock returns. However, when oil price is converted to Rands, the effect is still negative effect but significant at 5%. The study also finds that accounting for oil price uncertainty in an oil price-stock returns equation tends to amplify the negative dynamic response of stock returns to a positive oil shock, while diminishing the response of stock returns to a negative oil price shock compared to a model which excludes oil price uncertainty from entering the oil price-stock returns equation. Furthermore, the response of stock returns to negative and positive oil price uncertainty shocks is asymmetric.

Keywords: real oil price, real stock returns, volatility, asymmetry, GARCH-in-mean VAR, emerging market.
JEL Classification: C32, G10, G15, Q43.

Introduction

In recent times, the world energy prices have shown great instability. Başkaya et al. (2013) show that there have been periods in which the volatility of oil prices increased even when the level is controlled for. Volatility is an inherent feature of oil price in general because of its extensive use as input in the production process and as a final consumption good (Swanepoel, 2006). Hence, oil price volatility may exert great influence on the global economy. This volatile nature has raised concern by policy makers, international institutions, politicians and investors about the possibility of detrimental impact on the macro economy. Consequently, researchers have become increasingly interested in understanding the nature of the linkage between oil price volatility and macroeconomic performance. While a number of researches have been conducted with respect to real economic activities such as consumption, investment, and growth, the recent global financial crisis has also heightened attention to the stock market. This current study intends to contribute to the body of literature examining the volatility spillovers from oil price to the stock market using South Africa as a case. There is no doubt that South Africa being an oil-importing country is exposed to the developments in the crude oil market. Whether the impact on its stock market is detrimental or beneficial and to what extent is subject to further investigation.

Theoretically, asset prices should be determined by their expected discounted cash flows (Fisher, 1930; Williams, 1938). Therefore, factors that can alter the expected discounted cash flows are expected to have a significant effect on these asset prices. Accordingly, any oil price increase would result to increased costs, restraining profits and in greater extent, would cause a decrease in shareholders' value. Hence, any oil price increase should be accompanied by a decrease in the stock prices (Filis et al., 2011). According to Bjornland (2009) and Jimenez-Rodriguez and Sanchez (2005), an oil price increase is expected to have a positive effect in an oil exporting country, since this has the potential of increasing the country's income. As income increases, expenditure and investment are expected to increase, this in turn creates greater productivity and lower unemployment. Under this situation, stock markets will tend to respond positively.

However, for an oil-importing country, an oil price increase will tend to have a negative effect (LeBlanc and Chinn, 2004; Hooker, 2002). This is because oil price increase will result in higher production costs, since oil is one of the most important factors of production (Filis et al., 2011; Arouri and Nguyen, 2010; Backus and Crucini, 2000; Kim and Loungani, 1992). The increase costs will be transferred to the consumers in a form of higher consumer prices, leading to lower demand and thus reduced consumer spending (Bernanke, 2006; Hamilton, 1988). Lower consumption could lead to lower production and thus increased unemployment (Lardic and Mignon, 2006; Brown and Yücel, 2002; Davis and Haltiwanger, 2001). In this case stock markets would react negatively (Sadorsky, 1999; Jones and Kaul, 1996).

Ross (1989) suggests that volatility of price changes may be an accurate measure of the rate of information flow in financial markets. Consequently, oil price volatility shocks may have impacts on real stock returns. Filis et al. (2011) also noted that oil price shocks could affect stock markets due to the uncertainty that the former create to the financial world, depending on whether the shock is from the demand side or supply-side. In this case stock markets could respond positively to an oil price shock, which originates from the demand side, and negatively if the shock originates from the supply side (Filis et al., 2011).

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Another interesting issue that researchers struggle to understand is whether the effect of oil price shock is asymmetric, that is whether the impact of oil price increases and oil price decreases are not the same. Two possible explanations for the asymmetric impact of positive and negative oil price shocks on the economy are provided by Sadorsdy (1999). The first relates to the literature on sectorial shocks, which suggests that it is the magnitude of relative price changes that matter. The second relates to the literature on irreversible investment under uncertainty, which stresses there is an option value associated with waiting to invest. Using a multi-sector model of an economy, Hamilton (1988) shows that it is costly to shift labor and capital inputs between sectors due to labor mobility and training costs. Under this condition relative price shocks can reduce aggregate employment by inducing workers in adversely affected sectors to remain unemployed while they wait for labour conditions to improve in their sector rather than moving to a sector which is not adversely affected.

Pindyck (1991) shows that under an assumption of irreversible investment, a firm may be faced with the choice of adding energy-efficient capital or energy-inefficient capital. Increased energy price uncertainty due to higher volatility in energy prices raises the option value associated with waiting to invest. Decreases in energy prices can also be offset by increases in uncertainty. It is also noted that sharp increases and decreases in oil prices increase volatility and increased volatility leads to a decline in investment and economic activity, such sharp changes in oil prices can yield asymmetric responses (Guo and Kliesen, 1995; Elder and Serletis, 2010; Başkaya et al., 2013).

Although there is vast literature that investigates the effects of oil prices on the real economy, there are relatively few studies that investigate the effect of uncertainty about oil prices on the stock markets. The dearth of such studies is more pronounced for emerging economies in general and Africa in particular as would be evidenced in the literature review section. This study intends to contribute to the existing body of literature in this regard by quantifying the effect of oil price uncertainty on South Africa's stock returns. Unlike most studies in this area, this current study also performs impulse response analysis to investigate how quickly stock returns move to its expected value following an oil price volatility shock. Moreover, it examines whether the effect of oil price uncertainty on stock returns is asymmetric. The study employs a bivariate framework where the structural vector autoregression is modified to accommodate bivariate GARCH-in-mean errors. In this framework all the parameters are simultaneously estimated by the full information maximum likelihood to avoid the generated regressor problem discussed in Pagan (1984). The measure of uncertainty in this study is the conditional (i.e. conditional on the contemporaneous information set) standard deviation of the one-step-ahead forecast error for the change in the price of oil.

1. Literature review

This section concentrates on papers that examine volatility transmission between oil prices and the stock market. Most of the research has focused on the developed countries. Ågren (2006) investigates volatility spillover from oil prices to stock markets within an asymmetric BEKK model. Using weekly data covering the first week of 1989 through week seventeen of 2005 on the aggregate stock markets of Japan, Norway, Sweden, the U.K., and the U.S., he finds strong evidence of volatility spillover for all stock markets except the Swedish one, where only weak evidence is found. News impact surfaces show that, although statistically significant, the volatility spillovers are quantitatively small. Basher and Sadorsky (2006) use an international multi-factor model that allows for both unconditional and conditional risk factors to investigate the relationship between oil price risk and 21 emerging stock market returns. Using daily data from December 31, 1992 to October 31, 2005, the study finds in general strong evidence that oil price risk positively impacts stock price returns in emerging markets.

Malik and Ewing (2009) use weekly data during 1992 to 2008 to examine volatility transmission between oil prices and three equity sector returns in the US (namely technology, healthcare and consumer services). Results from bivariate GARCH models indicate the existence of negative and significant relationship between the sector index returns and volatility of oil prices. Arouri et al. (2011) using a generalized vector autoregressive-generalized autoregressive conditional heteroskedastic (VAR-GARCH) approach examine volatility transmission between oil and stock markets in Europe and the United States at the sector level. Evidence from weekly data shows a widespread direct spillover of volatility between oil and stock sector returns. Furthermore, the volatility cross effects run only from oil to stock sectors in Europe while bilateral spillover effects are observed in the United States. Lee and Chiou (2011) applied a univariate regime switching GARCH model to examine the relationship between West Texas Intermediate (WTI) oil prices and S&P500 returns. They concluded that when there are significant fluctuations in oil prices, the resultant unexpected asymmetric price changes lead to negative impacts on S&P500 returns, but the result does not hold in a regime of lower oil price fluctuations.

Choi and Hammoudeh (2010) applied a symmetric DCC-GARCH model and find increasing correlations among Brent oil, WTI oil, copper, gold and silver but decreasing correlations with the S&P500 index. Filis et al. (2011) investigate the time-varying correlation between stock market prices and oil prices for oil-importing and oil-exporting countries considering the origin of oil price shocks (i.e. aggregate demand-side, precautionary demand or supply-side). The analysis is based on monthly data (from 1987 to 2009) on stock and oil prices from three oil-exporting countries (Canada, Mexico and Brazil) and three oil-importing countries (US, Germany and Netherlands). The contemporaneous correlation results show that although time-varying correlation does not differ for oil-importing and oil-exporting economies, the correlation increases positively (negatively) in respond to important aggregate demand-side (precautionary demand) oil price shocks, arising from global business cycle's fluctuations or world turmoil (i.e. wars). However, supply-side oil price shocks do not influence the relationship of the two markets. The lagged correlation results show that oil prices have a negative effect in all stock markets, notwithstanding the origin of the oil price shock. Masih et al. (2011) find a negative impact of oil price volatility on real stock returns in South Korea. Jouini (2013) employs the VAR-GARCH procedure to investigate the link between world oil price and stock sectors in Saudi Arabia using weekly data during 2007 to 2011 and finds volatility transmission between oil price and stock sectors.

Chang et al. (2009) use various multivariate GARCH (1,1) models to study volatility spillovers between WTI crude-oil futures returns and stock returns of ten worldwide oil companies. The empirical findings show no volatility spillover effects in any pairs of return series. Arouri et al. (2012) investigate the volatility spillovers between oil and stock markets in Europe at both the aggregate and sector levels. Results from VAR-GARCH approach and weekly data covering from January 01, 1998 to December 31, 2009 show significant volatility spillovers between oil price and sector stock returns. It is however noted that the observed spillover effects come entirely from spillovers of shocks, and that spillovers of volatilities are all insignificant. Jiranyakul (2014) investigates the impact of oil price uncertainty on the Stock Exchange of Thailand using monthly data from May 1987 to December 2013. A two-stage procedure is applied whereby in the first step, a bivariate generalized autoregressive conditional heteroskedastic (GARCH) model is estimated to obtain the volatility series of stock market index and oil price. In the second step, the pairwise Granger causality tests are performed to determine the direction of volatility transmission between oil to stock markets. Results show that movement in real oil price does not adversely affect real stock market return, but stock price volatility does affect real stock return. Further, there exists a positive one-directional volatility transmission running from oil to stock market.

Olson et al. (2014) examine the relationship between the energy and equity markets by estimating volatility impulse response functions from a multivariate BEKK model of the Goldman Sach's Energy Index and the US S&P500. Using weekly data covering from January 1st 1985 to April 24th 2013, they show that low S&P500 returns cause substantial increases in the volatility of the energy index; however, they find only a weak response from S&P500 volatility to energy price shocks. Lin et al. (2014) examine the dynamic volatility and volatility transmission between oil and Ghanaian stock market returns in a multivariate setting using the VAR-GARCH, VAR-AGARCH and DCC-GARCH frameworks. Their findings point to the existence of positive and significant volatility spillover and interdependence between oil and the two stock market returns.

From the foregoing, it is clear that empirical evidence on the link between oil price volatility and stock returns is mixed. Therefore, this study contributes by studying the link between oil price volatility and South Africa's stock market. This study is also an attempt to add to the scarce literature on developing countries and emerging markets especially in the context of Africa. Only a few studies have examined the relationship between oil price and stock returns in South Africa (Gupta and Modise, 2013; Swanepoel, 2006). However, these studies considered oil price level rather than volatility. The only closely related paper is that of Basher and Sadorsky (2006) who investigated the impact of oil price changes on a large set of 21 emerging stock market returns including South Africa using pooled regression. However, the response of South Africa's stock returns may be concealed in such a panel setting. Moreover, this current study uses a more updated data (1995:07:1 to 2014:08:30) that cover the most recent global financial crisis and also differs in the methodological approach. Further, barring Olson et al. (2014) volatility impulse response functions have not examined by prior literature examining energy – equity returns linkages; therefore it is not known how quickly stock returns move to its expected value following an oil price volatility shock. Moreover, the asymmetric effect of oil price volatility on stock returns has not been adequately captured in the literature and where there are, results are mixed. Therefore, this study uses a general bivariate framework in which a vector autoregression is modified to accommodate GARCH-in-mean errors, thus avoiding the generated regressor problem, by simultaneously estimating all the parameters by the full information maximum likelihood following Elder (1995, 2004) and Elder and Serletis (2010). The model also offers a way to address the asymmetric volatility (Engle and Ng, 1993) puzzle which refers to the fact that the stock returns respond differently to increases and decreases in oil prices.

2. Empirical model

The empirical model used in this study was initially developed by Elder (1995, 2004) and used in Elder and Serletis (2010). It is a bivariate monthly model in stock price growth (i.e. stock returns) and the price of oil growth. The model is based on a structural VAR with modifications for conditional heteroskedasticity in the parametric form of the bivariate GARCH-in-mean. The operational 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:

$$\begin{aligned} \mathrm{B}y_t &= \mathrm{C} + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + ... \\ &+ \Gamma_p y_{t-p} + \Lambda(L)\sqrt{\mathrm{H}_t} + \varepsilon_t, \end{aligned} \tag{1}$$

where dim (B) = Dim (Γ_i) are $p \times p$ matrices, $\sqrt{\mathrm{H}_t}$ is a diagonal and $\Lambda(L)$ is a matrix polynomial in the lag operator. y_t is a vector containing real oil price and real stock price growth rates (returns), $\varepsilon_t || \Pi_{t-1} \sim iid(0, \mathrm{H}_t)$ represents uncorrelated structural disturbances in the system where Π_{t-1} is the available information set at time t-1.

The above specification allows the matrix of conditional standard deviations ($\sqrt{\mathrm{H}_t}$) to affect the conditional mean. To test whether oil price volatility affects stock returns, a test of restrictions on the elements of $\Lambda(L)$ that relate the conditional standard deviation of stock returns, given by the appropriate element of $\sqrt{\mathrm{H}_t}$, to the conditional mean of y_t is performed. If oil price volatility has adversely affected stock returns, then one would expect to find a negative and statistically significant coefficient on the conditional standard deviation of oil in the stock returns equation.

The conditional variance H_t is modelled as bivariate GARCH of which a general version is represented in Engle and Kroner (1995) as:

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

$\varepsilon_t \sim \sqrt{H_t} z_t;\ z_t \sim iidN(0,\mathrm{I})$, where C_v is $N^2 \times 1$ matrix, F and G are $N^2 \times N^2$ matrices and $h_t = vec(H_t)$. This specification does not however guarantee that H_t is positive definite.

Imposing a common identifying assumption in structural VARs simply substantially simplifies the variance function written in terms of the structural disturbances (Elder, 2004). In other words, given a zero contemporaneous correlation of structural disturbances, the conditional variance matrix H_t is then diagonal, reducing the requisite number of variance function parameters substantially. By re-dimensioning the variance function parameter matrices C_vF and G, the variance function reduces to:

$$\begin{aligned} diag(H_t) &= C_v + \sum_{j=1}^{J} F_i diag(\varepsilon_{t-j}\varepsilon'_{t-j}) + \\ &+ \sum_{i=1}^{I} G_i diag(H_{t-i}), \end{aligned} \tag{3}$$

where *diag* is the operator that extracts the diagonal from a square matrix. The second and third terms on the RHS of equation (3) 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 F_j and G_i are also diagonal. The variance function given by equation (3) is estimated with $J = I = 1$, which is the specification for a GARCH (1,1)-in-mean VAR model.

The bivariate GARCH-in-mean VAR model is therefore given by equations (1) and (3) which are simultaneously estimated by full information maximum likelihood (FIML), a procedure which avoids Pagan's (1984) generated regressor problem related to estimating the variance function parameters separately from the conditional mean parameters. The procedure is to maximize the log likelihood with respect to the structural parameters $B, C, \Gamma_1, \Gamma_2, ..., \Gamma_p, \Lambda, F$ and G, where:

$$\begin{aligned} l_t &= -(N/2)\ln(2\pi) + 1/2\ln|B|^2 - \\ &-1/2\ln|H|_t - 1/2(\varepsilon_t' H_t^{-1}\varepsilon_t). \end{aligned} \tag{4}$$

Consistent with Elder and Serletis (2010), the pre-sample values of the conditional variances matrix H_0 are set to their unconditional expectation and condition on the pre-sample values $y_0, y_{t-1}, \ldots, y_{t-p+1}$. The following restrictions are imposed to ensure a positive definite and covariance stationary H_t and ε_t respectively: C_v is element wise-positive, F are element-wise non-negative, and the eigen-values of $(F + G)$ are less than one in modulus. Under the assumption that the standard regularity conditions hold, FIML produces asymptotically normal and efficient estimates, with the asymptotic covariance given by the inverse of the Fisher's information matrix. By imposing the usual identifying procedure in VARs, one can estimate free parameters in B subject to a rank condition. This means that in a bivariate VAR, one can estimate one free parameter in B. To do so, this study follows Edelstein and Kilian (2007) and Elder and Serletis (2010) and allow the stock returns to respond to contemporaneous innovations in the change in the oil price.

An important tool in VAR analysis is the impulse response function which simulates the effects of a shock to one variable in the system on the conditional forecast of another variable. The impulse responses for the GARCH-in-mean VAR are calculated following Elder (2003). The confidence (error) bands are constructed using the Monte Carlo method described in Hamilton (1994, p. 337). This implies that the impulse responses are simulated from the maximum likelihood estimates (MLEs) of the parameters of the model. Then based on parameter values drawn randomly from the sampling distribution of the MLEs, confidence intervals are generated by simulating 1000 impulse responses. It should be noted that the Fisher's information matrix is used to obtain the covariance matrix of the MLEs.

3. Data and empirical results

The measure of the price of oil is the closing value for the West Texas Intermediate (WTI) spot price. It is sourced from the Energy and Information Administration. The measure of uncertainty about oil price is standard deviation of the one-step-ahead forecast error, conditional on the contemporaneous information set. This is consistent with Elder and Serletis (2010). Stock price on the other hand is measured as the FTSE/JSE All Share Index. Stock price data is obtained from INET BFA, Africa's leading provider of financial data feeds. A battery of unit root tests was conducted to determine the order of integration of both series. These include the Augmented Dickey-Fuller (ADF), The Phillip-Perron (PP), the Ng-Perron (NP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The tests indicate that both oil and stock price series are non-stationary (Panel A of Table 1). However, the logarithmic first differences are stationary (Panel B of Table 1). Therefore, both series are used in their logarithmic first differences (returns). Weekly data covering the period 1995:07:01 to 2014:08:30 are used. The starting date is determined by the availability of the stock price. The plots of both series are presented in Figure 1. Oil price is denoted as (*OILP*) while stock returns is denoted as (*SR*). Note that, oil price is expressed in US Dollars instead of South African Rand to avoid capturing the effect of the exchange rate on stock returns along with oil price, and also to keep the oil price purely exogenous[1]. Figure 1 shows that both series exhibit high volatility with spikes at different points in time.

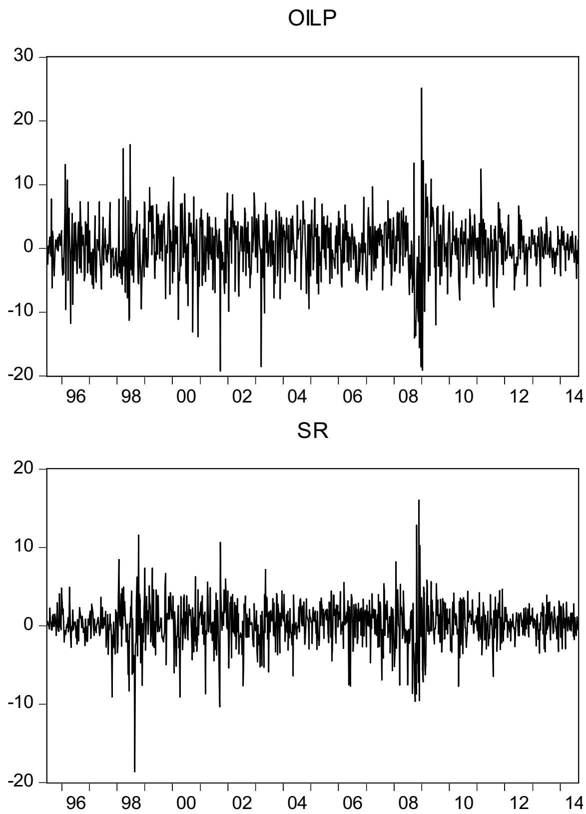


Fig. 1. Oil price and stock price in first log differences

[1] However as suggested by one of the reviewers, the analysis is also conducted using oil price in South African Rand for robustness check.

Table 1. Unit root tests

	ADF		PP		NP		KPSS	
	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
OILP	-1.28	-3.01	-1.17	-2.91	0.15	-17.49**	3.75***	0.22***
SR	-0.33	-2.57	-0.35	-2.69	1.41	-11.69	3.99***	0.24***
ΔOILP	-16.86***	-16.85***	-27.96***	-27.95***	-22.40***	-47.73***	0.04	0.04
ΔSR	-31.78***	-31.76***	-31.79***	-31.77***	-499.49***	-499.50***	0.04	0.04

Note: *** and ** indicate significance at 1% and 5% level, respectively.

The weekly effect of oil price uncertainty on stock returns is analyzed by including 8 lags as suggested by the Akaike Information criterion (AIC). The suitability of the GARCH (1,1)-in-mean VAR model specification on capturing the features of the data is tested against that of traditionally parsimonious homoscedastic VAR through the use of the Schwarz Information Criterion (SIC) statistics. 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 favor of the bivariate GARCH (1,1)-in-mean VAR specification (Elder and Serletis, 2010). From Table 2, it is clear that the GARCH (1,1)-in-mean VAR model suits the research data better than the standard homoscedastic VAR since the SIC value for the former is smaller than the value for the latter.

Table 2. Model specification test

Bivariate VAR model	Schwarz criterion value	
	VAR	GARCH-in-mean VAR
Oil price and stock returns	10676.69	10455.15

The GARCH-in-mean VAR specification is also supported by the point estimates of the variance parameters, which are reported in Table 3. The results in Table 3 are plausible and support the rejection of the null hypothesis of no ARCH ($F = 0$) and GARCH-M ($F = G = \Lambda = 0$) terms. Specifically, there is evidence of GARCH in stock returns and evidence of ARCH in the oil price. At a weekly frequency, the volatility process for the price of oil is quite persistent. 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 stock return equation that provides the evidence of the effect of oil price uncertainty on stock returns. The result shows that an increase in oil price uncertainty leads to negative impact (-0.20) on South African stock returns with a *t*-statistic of -1.57 and a *p*-value of 0.11. The significance of this coefficient is only very marginal. A robustness check with the Brent crude oil price produced similar results and hence is not reported here.

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

	Conditional Variance	Constant	$\varepsilon_i(t-1)^2$	$H_{i,i}(t-1)$
OILP equation	$H_{1,1}(t)$	13.46*** (19.31)	0.20*** (5.04)	0.0
SR equation	$H_{2,2}(t)$	0.21** (2.43)	0.11*** (4.77)	0.86*** (26.88)

Note: These are the constants and parameter estimates of *F* and *G* from the model given by equations (1) and (3) with $\varepsilon_t \|\Pi_{t-1} \sim iid(0, \mathrm{H}_t)$. Asymptotic t-statistics are in parentheses. *** and ** indicates significance at 1% and 5% level, respectively.

The effect of oil price uncertainty on the dynamic response of stock returns 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 stock returns to positive and negative oil price shock are simulated. The impulse responses (solid lines) and the one-standard deviation error bands (dotted lines) are presented in Figure 2. The impulse responses indicate that a positive oil price shock tends to immediately and significantly reduce stock returns, inducing a downward revision in the stock returns from about 50% at the moment of impact to negative 20% after 1 week. The dynamic effect of the positive oil price shock is also relatively persistent with the effect dying off only after 10 weeks.

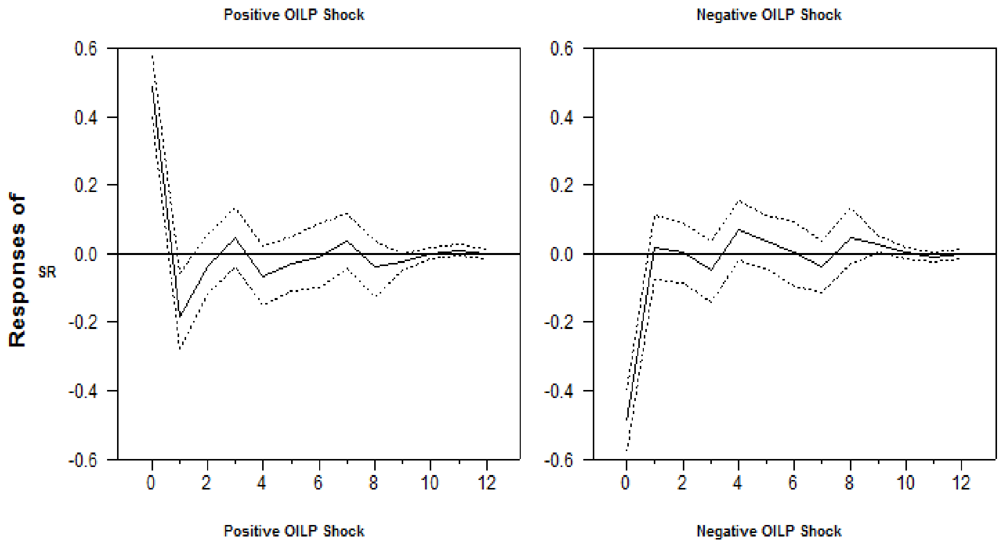
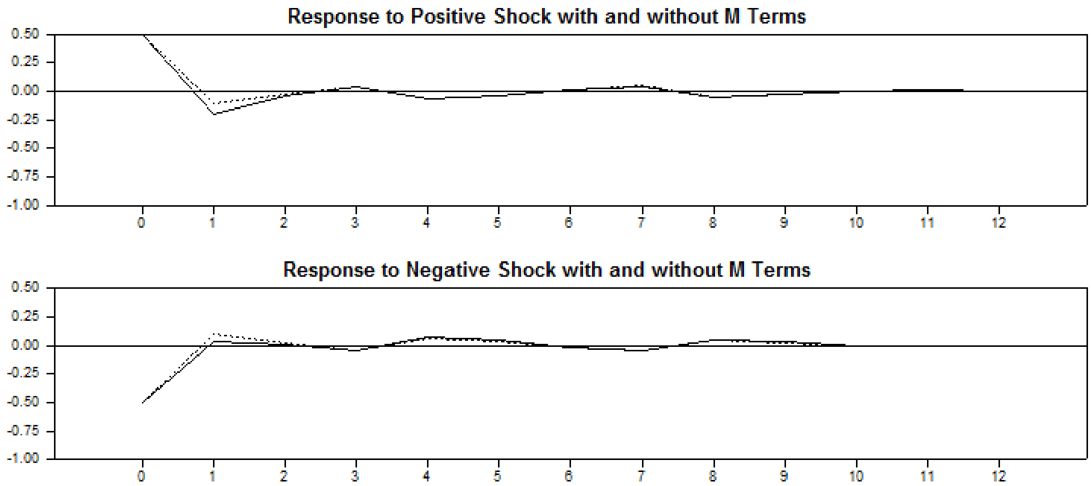


Fig. 2. Response of stock returns to positive and negative oil price shocks



Note: The solid lines represent the response of stock returns following an oil price shock after allowing the oil price uncertainty into the stock returns equation. The dotted lines represent the response of stock returns following an oil price shock without allowing the oil price uncertainty into the stock returns equation.

Fig. 3. Response of stock returns to oil price shock with and without M terms

On the other hand the dynamic response of stock returns to a negative oil price shock also immediately caused stock return to rise and the effect also died off after 10 weeks. The impact is also significant at least for the first week. It is noted that stock returns witnessed periods of decline and rise in the case of both positive and negative shocks. Judging from the quantitative effects of positive and negative oil price shocks, this study concludes that the responses are asymmetric since the responses are not equal in absolute terms. The positive oil price shock appears to have a larger effect than the negative oil price shock of equal size.

Finally, this study compares the responses of stock returns to positive and negative oil price shocks with and without the M terms as shown in Figure 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 Figure 3, the solid lines represent the response of stock returns following an oil price shock after allowing the oil price uncertainty into the stock returns equation. The dotted lines represent the response of stock returns following an oil price shock without allowing the oil price uncertainty into the stock returns equation. It can be observed that the inclusion of the M terms amplifies the responses of stock returns to positive oil price shock while it dampens its response to a negative oil price shock at least for the first two horizons. This result further confirms that oil price uncertainty matter for stock returns in South Africa.

To ensure that the effect of exchange rate is not ignored, the entire analyses were performed again using oil price converted from US Dollars to South African Rand. It is observed that the coefficient of oil price uncertainty in the stock returns equation is -0.236 with a *t*-statistics of -1.98 and *p*-value of 0.04. This implies that the effect of oil price uncertainty on stock return is negative and significant at 5%. The results for the specification test, estimates for the variance function of the GARCH-in-mean VAR and the impulse responses are presented in the appendix. The major conclusions remain the same irrespective of whether oil price is expressed in Dollars or in Rand. That is, oil price uncertainty has a negative effect on South Africa's stock returns, the response of stock returns to positive and negative oil price uncertainty is asymmetric and the response is more pronounced for a positive oil price shock and dampened for a negative oil price shock when oil price uncertainty is included in the stock return equation than when it is excluded. What differ is the magnitude of the effect and responses and the fact that the effect is significant at 5% when oil price is expressed in Rand while it is only marginally significant when oil price is expressed in Dollars.

Conclusion

This paper investigates the effect of oil price uncertainty on South African stock returns using a bivariate GARCH-in-mean VAR and weekly data covering the period 1995:07:08 to 2014:08:30. Oil price is the logarithmic first difference of the West Texas Intermediate (WTI) expressed in US Dollars while the stock returns is logarithmic first difference of the FTSE/JSE All Share Index expressed in South African Rand. The measure of oil price uncertainty is the conditional standard deviation of the one-step-ahead forecast error of the change in oil price. Based on the Schwartz Information Criterion, the results show that the dynamic bivariate GARCH-in-mean VAR describes the features of the research data better than the conventional homoscedastic VAR. The study finds a negative but marginally statistically significant coefficient capturing oil price uncertainty, suggesting that uncertainty about oil price has negative impacts on South African stock returns. Evidence from the impulse response functions indicate that a positive oil price shock immediately reduces the stock returns significantly from a high of 50% to a low of negative 20%. Negative oil price shocks tend to increase stock returns after an initial negative response but the impact is quantitatively smaller than that of a positive shock of equal size. This implies that the response of stock returns to positive and negative oil price shocks of equal magnitude is asymmetric. Evidence also shows that accounting for oil price uncertainty tends to amplify the negative dynamic response of stock returns to a positive oil shock, while diminishing the response of stock returns to a negative oil price shock. Expressing the oil price in South African Rand produced essentially similar result as when oil price is expressed in US Dollars except that the coefficient is significant at 5% and slightly larger in the former case. The nature of the impulse responses is also similar with slight variation in the magnitudes.

The results from this study have some important policy implications. Lower oil prices will reduce production costs which will benefit consumers by ensuring good product prices and hence increased consumer demand and spending. Producers also enjoy increasing profits and dividends which are the main drivers of stock prices. Improved cash flow will lead to further increased investment, production, employment and subsequently improvement in stock prices and overall economic growth. However, the asymmetric effect in the results shows that reducing oil prices may not automatically translate to increased production, since any sharp increases in the volatility of oil prices may offset the positive effect of any reduction in prices. Overall, policies that will reduce oil price volatility will be of benefit to the South African stock market. This is because such policies will favour lower import bills and expansion in exports through the exchange rate channel. Hence, the need to maintain stable oil prices cannot be overstressed.

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Appendix. Robustness check using oil price in rand

Table 4. Model specification test

Bivariate VAR model	Schwarz criterion value	
	VAR	GARCH-in-mean VAR
Oil price and stock returns	10729.03	10501.39

Table 5. Coefficient estimates for the variance function of the GARCH-in-mean VAR

	Conditional variance	Constant	$\varepsilon_i(t-1)^2$	$H_{i,i}(t-1)$
OILP equation	$H_{1,1}(t)$	13.65*** (18.45)	0.22*** (4.70)	0.0
SR equation	$H_{2,2}(t)$	0.21*** (2.61)	0.11*** (5.21)	0.86*** (32.80)

Note: These are the constants and parameter estimates of *F* and *G* from the model given by equations (1) and (3) with $\varepsilon_t \| \Pi_{t-1} \sim iid(0,\mathrm{H}_t)$. Asymptotic *t*-statistics are in parentheses. *** indicates significance at 1%.

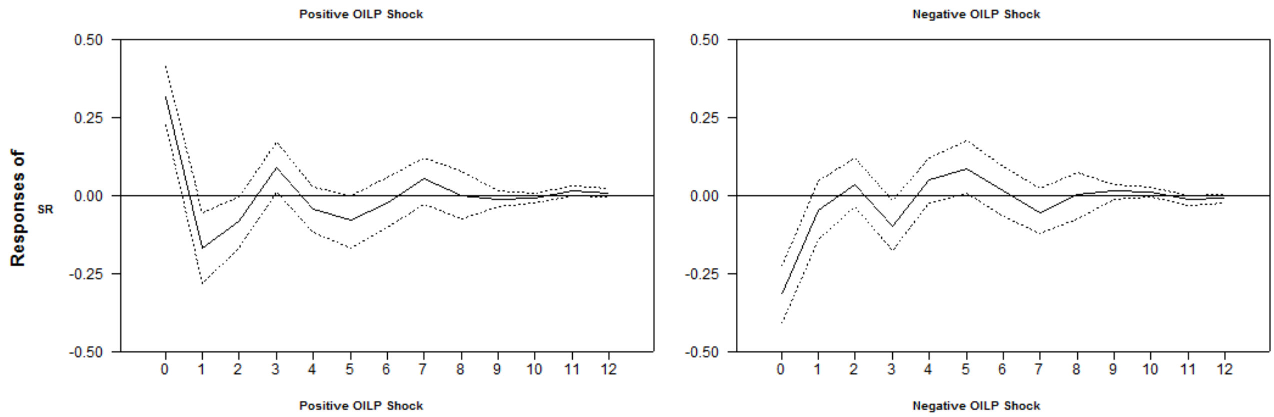
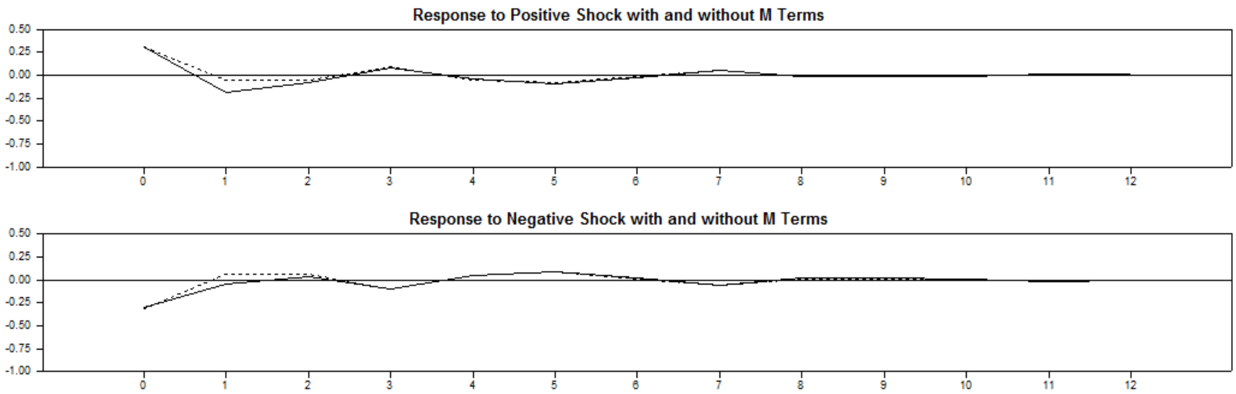


Fig. 4. Response of stock returns to positive and negative oil price shocks



Note: The solid lines represent the response of stock returns following an oil price shock after allowing the oil price uncertainty into the stock returns equation. The dotted lines represent the response of stock returns following an oil price shock without allowing the oil price uncertainty into the stock returns equation.

Fig. 5. Response of stock returns to oil price shock with and without M terms