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Abstract

One characteristic of many macroeconomic and financial time series is their asymmetric behaviour during different phases of a business cycle. Oil price shocks have been amongst those economic variables that have been identified in theoretical and empirical literature to predict the phases of business cycles. However, the role of oil price shocks to determine business cycle fluctuations has received less attention in emerging and developing economies. The aim of this study is to investigate the role of oil price shocks in predicting the phases of the South African business cycle associated with higher and lower growth regimes. By adopting a regime dependent analysis, we investigate the impact of oil price shocks under two phases of the business cycle, namely high and low growth regimes. As a net importer of oil, South Africa is expected to be vulnerable to oil price shocks irrespective of the phase of the business cycle. Using a Bayesian Markov switching vector autoregressive (MS-VAR) model and data for the period 1960Q2 to 2013Q3, we found the oil price to have predictive content for real output growth under the low growth regime. The results also show the low growth state to be shorter-lived compared to the higher growth state.

Keywords: Macroeconomic fluctuations, oil price shocks, Bayesian Markov switching VAR

JEL Codes: C32, E32, Q43

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1. Introduction

The role of oil price shocks on macroeconomics variables emerged after the 1973 and 1979 oil price shocks that coincided with a period of high inflation, high unemployment and decelerating economic activities in a number of countries. Since then, macroeconomists have focused their attention on the macroeconomic consequences of oil price shocks. In economics, a number of transmission channels exist through which oil price affects output. From the supply side, an increase in the oil price will lead to higher input costs which will increase the cost of production of goods and services. The production volume may thus be affected, as firms may find it difficult in the short run to re-allocate resources in order to produce the same volume of goods and services. The magnitude of the impact of oil price shocks to the aggregate output will however depend on the energy intensity in the production process. On the demand side, an increase in the oil price will put pressure on the price level. In order to control the inflation, the central bank might increase the interest rate, which could lead to a reduction in investment, and hence a decline in output. Moreover, the increase in oil price affects the individual consumer as it will reduce the amount of goods and services that could be purchased with the consumer's existing level of income.

A number of studies have been conducted to investigate the linear relationship between oil price shocks and economic activities; using Sims' (1980) linear VAR model with the aid of impulse response analysis. In most instances, research findings reveal the existence of a negative relationship between oil prices shocks and economic activities; however the strength of the relationship in different countries are likely to depend on the energy intensity, structure of the economy and the sample period (Abeysinghe 2001; Nkomo 2006; and Tang, *et al.* 2010). Despite the evidence of an overall negative relationship between oil price and economic activity observed in a number of studies, when the oil price decreased significantly, by as much as 50 per cent in real terms, during the first half of 1986, for a number of countries it was found that the decline in oil price did not promote economic growth, giving rise to a renewed debate on oil price effects on economic activity. A number of studies consequently focused on the possibility of a nonlinear and asymmetric relationship between oil price and economic activity.

Mork (1989) in his study on the role of oil price shocks on economic activity, finds oil price increases to affect economic growth negatively while a decline in oil price does not have the opposite effect. Where the coefficients on oil price increases turn out to be negative and highly significant, the coefficients on price declines tend to be positive, but small and not statistically significant. Hamilton (1988) provides a theoretical framework to explain the source of asymmetry in the relationship between oil price and real output. The author observes that when the growth rate of oil price increases, durable consumption growth drops, as consumers choose to postpone their purchases. But when the growth rate of the price of oil slows down, durable consumption growth does not necessarily rise. Hooker (1996) reports an insignificant relationship between oil price shocks and US macroeconomic variables in the period following the 1973 oil price shock. Herrera, *et al.* (2011), investigate the presence of a linear relationship between an oil price shock and economic activity. Using industrial production as a measure of economic activity, the results fail to show any asymmetric relationship between oil price and industrial production at the aggregated level. Using data on industrial production at a disaggregated level however, the authors find strong evidence of a nonlinear and asymmetric relationship between oil price and output for industries that are energy intensive or produce goods that are energy intensive in use. Blanchard and Gali (2007) find that despite similar energy intensity levels for the four oil price shocks identified in their study, the effect of these shocks on growth and inflation has been different for different shocks. The 1970s shocks were characterised by higher inflation and lower growth while in the more recent period lower inflation and increasing growth are observed despite the on-going increase in energy consumption over time. The authors linked the recent dynamics of oil shocks on macroeconomic variables to a better monetary policy, a decrease in wage rigidities and a reduction of oil usage in production processes. Given the findings in a number of studies of a weakened relationship between oil shocks and economic activity observed for recent periods, and the fact that the effect of oil price increases seem to matter in a nonlinear setting, studies that use linear models may be incapable to capture the dynamics between oil prices shocks and economic activities accurately. Another interesting observation arises in the study by Kilian (2009), where the author argues that the impact of oil shocks on macroeconomic variables depends on the source of the oil shock. In his study, he considers oil supply shocks, global demand shocks and oil demand shocks. One of the conclusions of his analysis is that emphasis on oil supply shocks which is exogenous in explaining the impact of oil price shocks on macroeconomic variables might be misleading. In South Africa, a recent study by Chisadza, *et al.* (2013) investigates the impact of oil shocks on the South African economy using a sign restriction-based structural vector autoregressive (VAR) model. Considering oil supply shocks, oil demand shocks driven by global economic activity, and oil-specific demand shocks, the authors found output to be affected positively by both oil demand and oil-specific demand shocks, while oil supply shock has no significant effect on output. Aye et al., (2014) analyzes the impact of oil price uncertainty on manufacturing production of South Africa using a bivariate

GARCH-in-mean-VAR model, and shows oil price uncertainty to have a significant negative impact on manufacturing production. In addition, the paper also detects that the response of manufacturing production to positive and negative shocks are asymmetric.

Oil price shocks have also been identified in a number of studies as one of the contributing factors influencing the state of the business cycle. For the US economy, Hamilton (1983, 1996 and 2005), finds that an increase in the oil price has preceded almost all the recessions in the US, which finding has attracted a number of researchers to investigate the role of an oil price shock in predicting business cycle fluctuations. Raymond and Rich (1997) use a generalized Markov switching (MS) model, where net oil price increase is included in the model to examine its contribution to post-war US business cycle fluctuations. The authors confirm the oil price to be a contributing factor to phases of low output. However, the study finds oil prices not to predict the transition from the low growth to high growth phases of the business cycle. Moreover, the authors are of the opinion that the Hamilton (1983) study overstates the role of oil price shocks in predicting a recession. De Miguel, *et al.* (2003), employ a standard dynamic stochastic general equilibrium (DSGE) model for the small open Spanish economy, and include the oil price shock in the model as an exogenous technological shock and as the only source of fluctuation in economic activity. The study then analyses the effects of the shock on business cycle fluctuations and on welfare. Their model results are in line with the business cycle path of the Spanish economy; specifically, a negative impact of an increase in relative price of oil on welfare was identified. Schmidt and Zimmermann (2005) find the effect of an oil shock on German business cycle fluctuation to be limited and declining over time when the analysis is split into sub-periods of 1970-1986 and 1997-2002. The limited effect of oil price changes on the business cycle is also reported on in the study by Kim and Loungani (1992). Clements and Krolzig (2002) use a three-state Markov switching VAR (MS-VAR) to test whether oil prices can explain business cycle asymmetries. The authors find that oil prices movements cannot adequately explain business cycle asymmetries. Using a Markov switching analysis for the G-7 countries, Cologni and Manera (2006) investigate the asymmetric effect of an oil shock on different phases of the business cycle for each of the G-7 countries; and find regime dependent models to better capture the output growth process. Recently, Engemann, *et al.* (2010), using a Markov switching model, investigated whether oil price shocks significantly increase the probability of a recession in a number of countries and found oil price to affect the likelihood of moving into recession.

Despite significant evidence of the role of oil price shocks in explaining business cycle movement for the US and other developed countries, a limited number of studies have been conducted for developing countries to investigate the transmission of oil price shocks to economic activity. The effect of oil price shocks on macroeconomic variables in the case of developing economics also vary significantly across countries, due to the disparity in the degree of energy intensity of the economy, the size of the shock and economic structure of the country. South Africa as a net oil importer, consumes the second-largest amount of petroleum in Africa, behind Liberia; and 95 per cent of its crude oil needs are met through imports. South Africa imports crude oil mostly from OPEC countries in the Middle East and West Africa, with roughly half of imported oil coming from Saudi Arabia in 2013. Given the importance of oil in South African economy, the present paper investigates the impact of oil price shocks on South African business cycle fluctuation using a two-state Bayesian Markov switching VAR, the asymmetric response of oil shocks during high and low growth phases of the business cycle will be analysed through state-dependent impulse responses.

The Markov switching model used in this study has been widely used in empirical literature to capture nonlinearities and asymmetry among economic variables (Hamilton 1994; Krolzig 2001; and Krolzig and Clements 2002). First, the model allows us to classify regimes as depending on the parameter switches in the full sample and, therefore, it is possible to detect changes in dynamic interactions between the variables. Second, this model allows for many possible changes in the dynamic interactions between the variables at unknown periods. Third, it is possible to make probabilistic inference about the dates at which a change in regime occurred. To date, no study to our knowledge has been undertaken to investigate the effect of oil price shocks on South African business cycle fluctuations, using a MS-VAR model.[1]

The rest of the sections are outlined as follows: Section 2 discusses the methodology used in this study, Section 3 presents data, section 4 discusses the empirical findings, and Section 5 concludes.

2. Methodology

It is commonly accepted that one of the most important challenges facing macroeconometric time series models is structural change or regime shift (see Granger, 1996). Indeed, the survey papers by Hansen (2001) or Perron (2006) affirm that econometric applications should distinctly consider regime shifts.

Econometricians have recently introduced new models that can sufficiently deal with

[1] However, there does exist recent studies that have analyzed the (symmetric and asymmetric) impact of oil price shocks on inflation (Ajmi et al., 2014; Gupta and Kanda, 2014) and interest rates (Aye et al., forthcoming) for South Africa, in both time and frequency domains.

certain types of structural changes. One of the appealing methodologies that can deal with structural breaks is the Markov switching (MS) approach proposed by Hamilton (1990) and later extended to multivariate time series models by Krolzig (1997). The initial work by Hamilton (1990) studies univariate Markov switching autoregression (MS-AR) while a multivariate extension to Markov switching vector autoregression (MS-VAR) is introduced in Krolzig (1997). The MS models fall within the category of nonlinear time series models which is generated by nonlinear dynamic properties, such as high moment structures, time varying, asymmetric cycles, and jumps or breaks in a time series (Fan and Yao, 2003). The long time span of our data includes several influential events, such as the first and second OPEC oil price shocks in 1973 and 1979, respectively, the debt-standstill agreement and economic sanctions imposed against South Africa in 1985 as a consequence of its Apartheid regime, the relaxation of trade sanctions again and the transition to a democracy in 1994, the 1997/98 East Asian crisis, and more recently the global recession of 2008. The data also covers quite a number of influential business cycles. MS models are found to fit well to such time series data with business cycles features and regime shifts.

A number of studies successfully used MS models to analyse aggregate output and business cycles (e.g., Hamilton 1989; Diebold, *et al.* 1994; Durland and McCurdy 1994; Filardo 1994, Ghysels 1994; Kim and Yoo 1995; Filardo and Gordon 1998; and Krolzig and Clements 2002). Following these studies, we thus consider the MS-VAR model, which, with its rich structure, accommodates the features of oil price and output data we examine. The model choice unlike other traditional models not only efficiently captures the dynamics of the process, but also has a more appealing structural form and provides economically intuitive results.

The methodology we adopt is based on a vector autoregressive (VAR) model with time-varying parameters where, given our objectives, the parameter time-variation directly reflects regime switching. In this approach, changes in the regimes are treated as random events governed by an exogenous Markov process, leading to the MS-VAR model. The state of the economy is determined by a latent Markov process, with probability of the latent state process taking a certain value based on the sample information. In this model, inferences about the regimes can be made on the basis of the estimated probability, which is the probability of each observation in the sample coming from a particular regime. The MS-VAR model we use to analyse the time varying dynamic relationship between the quarterly real spot crude oil price and real GDP is an extension of the class of autoregressive models studied in Hamilton (1990) and Krishnamurthy and Rydén (1998). It also allows for asymmetric (regime dependent) inference for impulse response analysis. The structure of the MS-VAR model we use is based on the model studied in Krolzig (1997) and Krolzig and Clements (2002). Our estimation approach is based on the Bayesian Markov-chain Monte Carlo (MCMC) integration method of Gibbs sampling, which allows us to obtain confidence intervals for the impulse response functions of the MS-VAR model.

To be concrete, let P_t and Q_t denote the real crude oil price and real output[2], respectively. Define the time-series vector X_t up to and including period t as $X_t = [P_t, Q_t]'$ and let $\Im_t = \{X_\tau | \tau = t, t-1, ..., 1-p)$ $\Im_t = \{X_\tau | \tau = t, t-1, ..., 1-p)$, where p is a nonnegative integer. For the vector valued time series X_t of random variables, assume that a density (probability) function $f(X_t | \Im_{t-1}, \theta)$ exists for each $t \in \{1, 2,\ldots,T\}$. The parameters and the parameter space are denoted by θ and Θ, respectively. The true value of θ is denoted by $\theta_0 \in \Theta$. Let the stochastic variable $S_t \in \{1, 2, ..., q\}$ follow a Markov process (chain) with q states. In the MS-VAR model, the latent state variable S_t determines the probability of a given state in the economy at any point in time. Taking into account that the oil price and output series are not cointegrated and their dynamic interactions are likely to have time-varying parameters, our analysis is based on the following MS-VAR model:

$$\Delta X_t = \mu_{S_t} + \sum_{k=1}^{p-1} \Gamma_{S_t}^{(k)} \Delta X_{t-k} + \varepsilon_t, \qquad t = 1, 2, ..., T \tag{1}$$

where p is the order of the MS-VAR model, $[\varepsilon_t \mid S_t \sim N(0, \Omega_{st})]$, and Ω_{S_t} is a (2×2) positive definite covariance matrix. The random state or regime variable S_t, conditional on S_{t-1}, is unobserved, independent of past Xs, and assumed to follow a q-state Markov process. In other words, $\Pr[S_t = j | S_{t-1} = i, S_{t-2} = k_2, \ldots, \Im_{t-1}] = \Pr[S_t = j | S_{t-1} = i, \Im_{t-1}] = p_{ij}$, for all t and k_l, regimes i, j = 1, 2, ..., q, and $l \geq 2$. More precisely S_t follows a q state Markov process with transition probability matrix given by

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1q} \\ \vdots & \vdots & & \vdots \\ p_{q1} & p_{q2} & \cdots & p_{qq} \end{bmatrix}, \qquad \sum_{j=1}^{q} p_{ij} = 1. \tag{2}$$

Thus, p_{ij} is the probability of being in regime j at time t, given that the economy was in regime i at time (t-1), where i and j take possible values in $\{1, 2,\ldots, q\}$. The MS-VAR specified as above allows all parameters to depend on the latent regime or state variable S_t, that is all

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[2] The real crude oil price and real GDP series we analyse are both nonstationary time series as shown by the unit root tests reported on in Section 3. Moreover, the series also do not maintain a long-run relationship as they are not cointegrated, leading to a MS-VAR model in first differences.

parameters of the model including the variance matrix Ω_{S_t}.

In our particular application, the maintained hypothesis is that q=2, that is, two states or regimes for each variable are sufficient to describe the dynamic interactions between the oil price and output. This is consistent with crises-recovery (recession-expansion) cycles observed in many macroeconomic time series. A large number of studies showed that the two regime MS model is rich enough to capture the regime switching behaviour in macroeconomic time series (e.g., Hamilton 1989; Diebold, *et al.* 1994; Durland and McCurdy 1994; Filardo 1994, Ghysels 1994; Kim and Yoo 1995; Filardo and Gordon 1998; and Krolzig and Clements 2002).

The MS-VAR model in Equations (1)-(2) has some appealing properties for analysing the dynamic interactions of the variables. First, it allows us to classify regimes as depending on the parameter switches in the full sample and, therefore, it is possible to detect changes in dynamic interactions between the variables. Second, this model allows for many possible changes in the dynamic interactions between the variables at unknown periods. Third, it is possible to make probabilistic inference about the dates at which a change in regime occurred. We will be able to evaluate the extent of whether a change in the regime has actually occurred, and also identify the dates of the regime changes. Finally, this model also allows us to derive regime dependent impulse response functions to summarize whether the impact of the oil price on the GDP varies with regimes.

The empirical procedure for building a suitable MS-VAR models starts with identifying a possible set of models to consider. We determine the order p of the MS-VAR model using the Bayesian information Criterion (BIC) in a linear VAR(p) model. The MS-VAR model specifications may differ in terms of regime numbers (q) and the variance matrix specification. We only consider both regime-dependent (heteroscedastic) variance models, because both the oil price and output series span a number of periods where volatilities vary significantly. Once a specific MS-VAR model is identified, we next test for the presence of nonlinearities in the data. When testing the MS-VAR model against the linear VAR alternative, we follow Ang and Bekaert (2002) and use the likelihood-ratio statistic (LR), which is approximately $\chi^2(q)$ distributed, where q equals the number of restrictions plus the nuisance parameters (i.e., free transition probabilities) that are not identified under the null. We use p-values based on the conventional χ^2 distribution with q degrees of freedom and also for the approximate upper bound for the significance level of the LR statistic as derived by Davies (1987). Once we establish nonlinearity, we can choose the number of regimes and the type of the MS model based on both the likelihood-ratio statistic and the Akaike information Criterion (AIC).[3]

There are three commonly used methods used for estimating the parameters of MS models. Although the simplest method of estimation is maximum likelihood (ML), it may be computationally demanding and may have slow convergence.[4] The ML method faces two important practical difficulties. First, a global maximum of the likelihood may be difficult to locate. Second, the likelihood function for the important class of mixtures of normal distributions is not bounded and the ML estimator does not exist for the global maximum. Second, and more commonly used, the method of estimation for MS models is the expectation maximization (EM) algorithm (Dempster, *et al.* 1977; Lindgren 1978; Hamilton 1990, 1994). Assuming that the conditional distribution of X_t given $\{\Im_t, S_t, S_{t-1}, ..., S_0; \theta'\}$ is normal, the likelihood function is numerically approximated using the EM algorithm in two steps. In the first step, given the current parameter estimates and the data, the conditional expectation of log likelihood is computed (E-step), and in the second step parameters that maximize the complete-data log likelihood function computed (M-step). The EM algorithm may have slow convergence and also standard errors of the parameters cannot be directly obtained from the EM algorithm. A third method is the Bayesian MCMC parameter estimation based on Gibbs sampling. The ML and EM methods usually fail for certain types of models since it may not be possible to compute the full vector of likelihoods for each regime for each period. The MCMC works only with one sample path for the regimes rather than a weighted average of sample paths over all regimes, and therefore, avoids the problem faced by the ML and EM methods.

The MCMC indeed treats the regimes as a distinct set of parameters. Our MCMC implementation is based on the following steps[5]:

i. Draw the model parameters given the regimes. In our case, transition probabilities do not enter this step.
ii. Draw the regimes given the transition probabilities and model parameters.
iii. Draw the transition probabilities given the regimes. In our case, model parameters do not enter this step.

In the next step, we first draw Ω_{S_t} given regimes, *P*, and $\eta_{S_t} = (\beta, \mu_{S_t}, \alpha_{S_t}, \Gamma_{S_t})'$ using a hierarchical prior. Our implementation first draws a common covariance matrix from the Wishart distribution given the inverse of the regime specific covariances; and second we draw

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[3] Krolzig (1997) and Psaradakis and Spagnolo (2003) suggest selecting the number of regimes and the MS model using the AIC, and using a Monte Carlo experiment Psaradakis and Spagnolo (2003) show that the AIC generally yields better results in selecting the correct model.
[4] An excellent review of the ML estimation of the MS models is provided by Redner and Walker (1984).
[5] See Fruehwirth-Schnatter (2006) for the details of the MCMC estimation of the MS models.

the regime specific covariances from the inverse Wishart distribution given the common covariance. The degrees of freedom priors for Wishart and inverse Wishart distributions are both equal to 4. Second, we use a flat prior and draw $\eta_{S_t} = (\beta, \mu_{S_t}, \alpha_{S_t}, \Gamma_{S_t})'$ given regimes, *P*, and Ω_{S_t} from a multivariate Normal distribution with 0 mean. In the second step, we draw regimes S_t given $\eta_{S_t} = (\beta, \mu_{S_t}, \alpha_{S_t}, \Gamma_{S_t})'$, *P*, and Ω_{S_t}. This is obtained from the Bayes formula, where the relative probability of regime *i* at time *t* is given as the product of the unconditional regime probability times the likelihood of regime *i* at time *t*. Regimes are drawn as a random index from {1,…,*q*} given relative probability weights. Indeed, we use the Forward Filter-Backwards Sampling (FFBS) (also called Multi Move Sampling) algorithm described in Chib (1996) to draw the regimes. In the second step of the MCMC method we reject any draw, if less than 5% of the observations fall in any of the regimes. Finally, in the third step, unconditional probabilities *P* given the regimes are drawn from a Dirichlet distribution. We set the priors for the Dirichlet distribution as 80% probability of staying in the same regime and 20% probability of switching to the other regime. We perform the MCMC integration with 50,000 posterior draws with a 20,000 burn-in draws.

Since its first introduction in the influential work of Sims (1980), a natural tool to analyse the dynamic interaction between the oil price variable and output is the impulse response function (IRF). IRF analysis studies how a given magnitude of a shock in one of the variables propagates to all variables in the system over time, say for *h*=1,2,…, *H* steps after the shock hits the system. Computing multi-step IRFs from MS-VAR models as well as from all nonlinear time series models prove complicated because no ordinary method of computing the future path of the regime process exists. An ideal IRF analysis requires that we know the future path of the regime process, since the impulses depend on the regime of the system in every time period.

Ideally, the IRFs of the MS-VAR model should integrate the regime history into the propagation period, which is not easily resolved. Two approaches arose in the literature as a work-around to the history dependence of the IRS in the MS models. Ehrmann *et al.* (2003) suggested assuming that regimes do not switch beyond the shock horizon, leading to regime-dependent IRFs (RDIRFs). On the other hand, Krolzig (2006) acknowledges the history dependence and allows the regime process to influence the propagation of the shocks for the period of interest, *h*=1, 2, … *H*. In Krolzig's approach conditional probabilities of future regimes, S_{t+h}, are obtained given the regime S_t and the transition probabilities, *P*.

One major attraction of the RDIRF analysis is the possibility of determining the time variation in the responses of variables to a particular shock. The RDIRF traces the expected path of the endogenous variable at time *t+h* after a shock of given size to the *k-th* initial disturbance at time *t*, conditioned on regime *i*. The *k*-dimensional response vectors $\psi_{ki,1}, \ldots, \psi_{ki,h}$ represents a prediction of the response of the endogenous variables. (Ehrmann, *et al.* 2003). The RDIRFs[6] can be defined as follows:

$$\psi_{ki,h} = \left.\frac{\partial E_t X_{t+h}}{\partial u_{k,t}}\right|_{S_t = \cdots = S_{t+h} = i} \quad \text{for } h \geq 0 \tag{3}$$

where $u_{k,t}$ is the structural shock to the *k-th* variable. In general, the reduced form shocks ε_t will be correlated across the equations and $\varepsilon_{k,t}$ will not correspond to $u_{k,t}$. This leads to the famous identification problem for which several solutions exist. We assume that the structural shocks are identified as $\varepsilon_t = F_{S_t} u_t$. To make structural inferences from the data, the structural disturbances and hence F must be identified. In other words, sufficient restrictions are imposed on the parameter estimates in order to derive a separate structural form for each regime, from which RDIRFs are then computed. As in a standard VAR measuring the impact of the oil prices on output, we order the output last and use the recursive identification scheme, made popular by Sims (1980). The recursive identification scheme is based on the Cholesky decomposition of the covariance matrix as $\Omega_{S_t} = L_{S_t} L'_{S_t}$ and identifying structural shocks from $u_t = F_{S_t}^{-1} \varepsilon_t$ with $F_{S_t} = L_{S_t}$.

The RDIRF analysis, although significantly simplifies derivation and allows construction of confidence interval via bootstrap, it is not appropriate, if the regime switching is likely during propagation of shocks. The solution of Krolzig (2006) is appealing, but it leaves out the construction of the confidence intervals. In our study, we combine RDIRF analysis with MCMC integration. Given our interest is whether the dynamic response of the output to oil price shocks depends on the state of the economy, such as the recession or recovery periods, assuming a given regime – regime switching does not take place during the shock propagation periods – and studying the propagation of the oil price shock in the future is appropriate for our purpose. Building on the Bayesian impulse responses for the linear VAR models, which are well covered in Ni, *et al.* (2007), we drive the posterior density of the RDIRFs from the Gibbs sampling. The simulations of the posteriors of the parameters jointly with the identification of the structural shocks via the Gibbs sampler directly yield the posterior densities of the RDIRFs. The confidence bands are obtained by the MCMC integration with Gibbs sampling of 50,000 posterior draws with a burn-in of 20,000.

[6] Refer to Ehrmann, *et al.* (2003) for details on characteristics and computation of the regime-dependent impulse responses.

3. Data

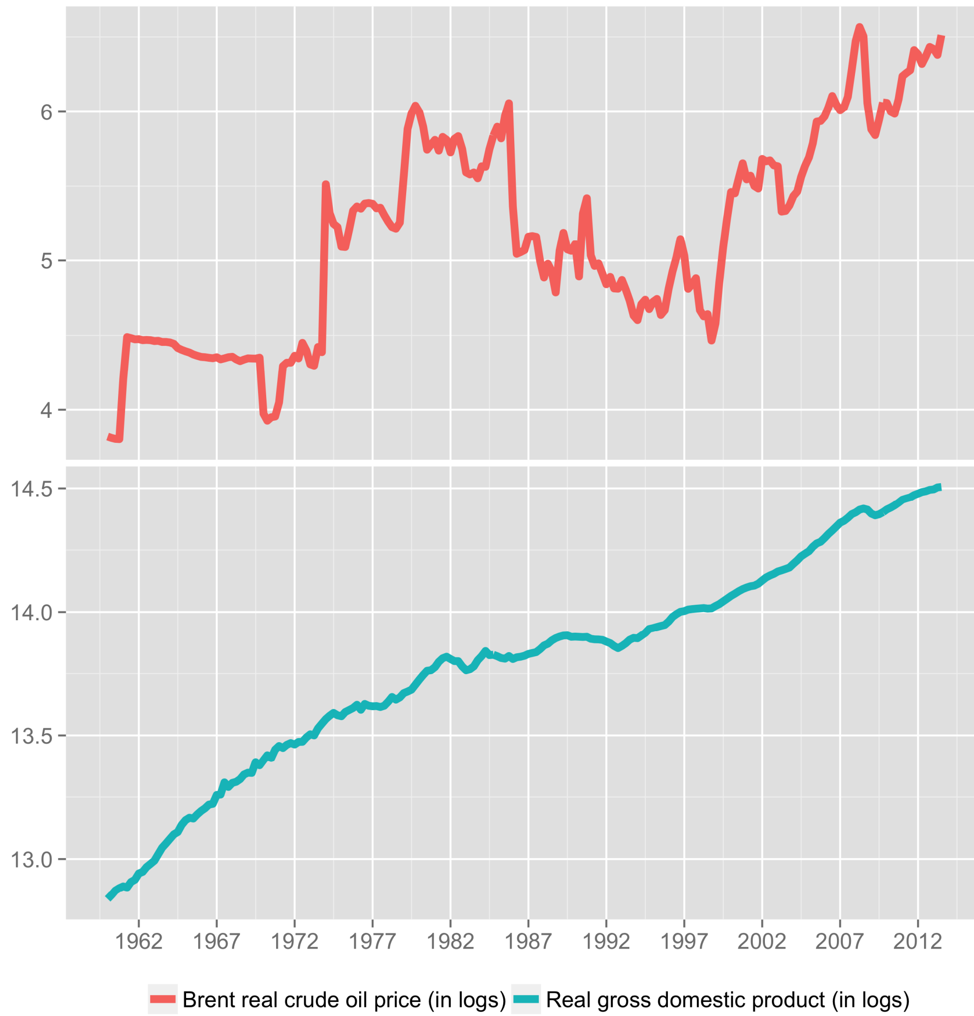
In this study, we employ quarterly data for the period 1960Q1-2013Q3 for real GDP and real oil price. We make use of real gross domestic product (GDP) at market prices from the South African Reserve Bank, and to obtain quarterly real oil price in South African currency, we use the nominal Brent crude oil spot price from the US Department of Energy as the main source (DCOILBRENTEU, 1987Q3-2013Q4) but supplement it further back with data from Global Financial Data (GFD) (BRT-D, 1970Q1-1987Q2). Since the spread between Brent crude and the WTI oil price in early years of the sample appears very small, we use WTI's oil price data to supplement for the 1960s. Nominal oil price data are seasonally adjusted using the X-12 procedure and converted into Rand values using the Rand/US$ exchange rate from GFD from 1960Q1-2012Q3. Lastly, nominal values are deflated using CPI from the International Financial Statistics (IFS) of the International Monetary Fund (IMF) to obtain the real oil price. Figure 1 shows the time series of the real Brent crude oil price in South African Rand, and the real gross domestic product. All values are expressed in natural logarithms. The sample period covers 1960Q1 – 2013Q3.

Different unit root tests were performed to investigate the univariate characteristics of both level variables. The set of formal unit root tests presented in Appendix A reveals that both variables are I(1), hence nonstationary in levels but stationary after first differencing. Given the nonstationarity of the log of real GDP and log of real oil price, in order to estimate the MS-VAR model, we make use of the growth of real GDP and growth of real oil price which are both stationary or I(0). The sample period used to estimate the MS-VAR is 1960Q2 to 2013Q3.

4. Empirical findings

Before we start estimating our models, we first contemplate some preliminary descriptive statistic on quarterly real Brent crude oil spot price in South African Rand (LROILP), and the quarterly real GDP of South Africa (LRGDP). The graphic representations and summary statistics on both variables are presented in Figure 1 and Table 1, respectively.

Figure 1. Time series plots of the real Brent crude oil price and the real GDP series



Both variables presented in Panel A are expressed in natural logarithm. Panel B gives the descriptive statistics for log-differences, or growth rates. The sample period covers 1960Q1-2013Q3 with n=215 observations. In addition to the mean, standard deviation (S.D.), minimum (min), maximum (max), skewness and kurtosis statistics, the table reports the Jarque-Bera normality test (JB) which show that both level data and growth data on both variables are normally distributed. The Ljung-Box first [Q(1)] and the fourth [Q(4)] autocorrelation tests show no sign of serial correlation with their respective lags for level and growth variables, and the first [ARCH(1)] and the fourth [ARCH(4)] order Lagrange multiplier (LM) tests for autoregressive conditional heteroskedasticity (ARCH) show the variance of the growth rate of real GDP to be time varying while the variance of growth rate of real oil price, as well as the variance of level data on real GDP and the variance of real oil price, are constant over time.

Table 1. Descriptive statistics

	LROILP	LRGDP
Panel A: log levels		
Mean	5.164	13.79
S.D.	0.685	0.424
Min	3.803	12.838
Max	6.566	14.506
Skewness	0.07	-0.333
Kurtosis	-1.014	-0.534
JB	9.053**	6.375**
$Q(1)$	200.598***	209.860***
$Q(4)$	702.204***	797.611***
ARCH(1)	187.031***	213.412***
ARCH(4)	184.044***	210.654***
Panel B: growth rates		
Mean	0.0126	0.0078
S.D.	0.1458	0.0106
Min	-0.693	-0.0214
Max	1.1244	0.0491
Skewness	1.4458	0.1374
Kurtosis	17.75	1.384
JB	2947.0640***	18.7960***
$Q(1)$	3.5380*	2.5189
$Q(4)$	10.4034**	28.1647***
ARCH(1)	0.3341	12.9154***
ARCH(4)	0.5079	14.7426***
N	215	215

***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Given that we found both variables to be I(1), we proceed to investigate if there exists any long-run relationship between the two variables under investigation. The results of the multivariate cointegration tests for the VAR(p) model of variables LROILP and LRGDP are presented in Appendix A. The VAR order is selected based on minimum BIC and is 1. Two tests of cointegration by Johansen (1988, 1991) report maximal eigenvalue (λ_{max}) and trace (λ_{trace}) cointegration test results. Non-rejection of r=0 for the Johansen tests implies no cointegration. Using both trace and maximum eigenvalue, both tests fail to detect any long-run relationship between the variables. Stock and Watson (1988) common trends testing confirms that the real oil prices and real GDP series are not cointegrated. Since Johansen cointegration tests fail to show any existence of a long-run relationship between real oil prices and real GDP, we then proceed our estimation using a Bayesian MS-VAR with 4 lags form 1960Q2 to 2013Q3 given that the growth rate of the series are stationary. Note that we opt for a two-state MS-VAR, and a linear VAR model is used as a benchmark for our analysis.

Table 2 reports estimation results and model selection criteria for the MS-VAR model given by Equations (1)-(2). The lag order selected by the BIC is 1 for both linear VAR and MS-VAR models. The MS-VAR model is estimated using the Bayesian Monte Carlo Markov Chain (MCMC) method where we utilize Gibbs sampling. The MCMC estimates are based on 20,000 burn-in and 50,000 posterior draws. All reported estimates in Table 2 for the MS-VAR model are obtained from the Bayesian estimation. The likelihood ratio (LR) statistics tests the linear VAR model under the null against the alternative MS-VAR model. The test statistic is computed as the likelihood ratio (LR) test. The LR test is nonstandard since there are unidentified parameters under the null. The χ^2 *p*-values (in square brackets) with degrees of freedom equal to the number of restrictions as well as the number of restrictions plus the numbers of parameters unidentified under the null are given. The LR test shows that the MS model is superior to the linear VAR model. The *p*-value of the Davies (1987) test is also given in square brackets and show strong rejection of linearity. Regime properties include ergodic probability of a regime (long-run average probabilities of the Markov process), where observations fall in a regime based on regime probabilities, and average duration of a regime. Specifically, in our multivariate model regime probability is a function of past values of real GDP growth, past values of oil price changes as well as shifts in conditional variances and covariances.

The results suggest two distinct regimes: *regime 1*, that appears to be associated with higher real economic growth rates in the South African economy, as well as less volatility in the oil market; and *regime 2*, marked by low and negative economic growth rates during periods of political and financial crisis as well as oil price shocks and higher oil price volatility. The probability of being in regime 1 at time *t,* given that the economy was in regime 1 at time (*t*-1) is 0.9397, while the probability of being in regime 2 at time *t*, given that the economy was in regime 2 at time (*t*-1) is 0.9160. These indicate that both regimes are persistent. Furthermore, the long-run average probabilities of regimes 1 and 2 equal 0.58 and 0.42, respectively. That is, for the observations in our sample, we expect regime 1 (high growth-low oil price volatility) to occur on 124 occasions, while we expect regime 2 (low and negative growth-higher oil price volatility) to occur on 89 occasions.

Linking the high growth (low oil price volatility) and low growth (high oil price volatility and oil price shocks) regimes to actual business cycle upswings and downswings, it may be expected that lower growth-higher volatility regimes will also be associated with downswings and recessions. It is generally acknowledged in the literature (Du Plessis 2006) that the probability of a state of lower growth or a contractionary phase should be smaller than the probability of a high growth state, or expansionary phase, since recessions tend to be shorter-lived than expansions. Therefore, we could also expect to find fewer periods of lower growth. Our results support this fact, namely suggesting an average duration of the high growth regime of 16.6 quarters compared to the low growth regime that lasts on average for 11.9 quarters.

Table 2. Estimation results for the MS-VAR model

Model selection criteria			
	MS(2)-VAR	Linear VAR(1)	
Log likelihood	880.5350	781.5413	
AIC criterion	-8.2348	-7.3927	
HQ criterion	-8.2658	-7.4067	
BIC criterion	-7.9149	-7.2488	
LR linearity test	Statistic	*p*-value	
	173.53916	$\chi^2(9)$ =[0.0000]***	
		$\chi^2(11)$=[0.0000]***	
		Davies=[0.0000]***	
Transition probability matrix			

$$P = \begin{bmatrix} 0.9397 & 0.0603 \\ 0.0840 & 0.9160 \end{bmatrix}$$

Regime properties			
	Probability	Observations	Duration (Quarters)
Regime 1	0.5823	124	16.5915
Regime 2	0.4177	89	11.8994

***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Figure 2. Smoothed probability estimates of low growth regime (regime 2)

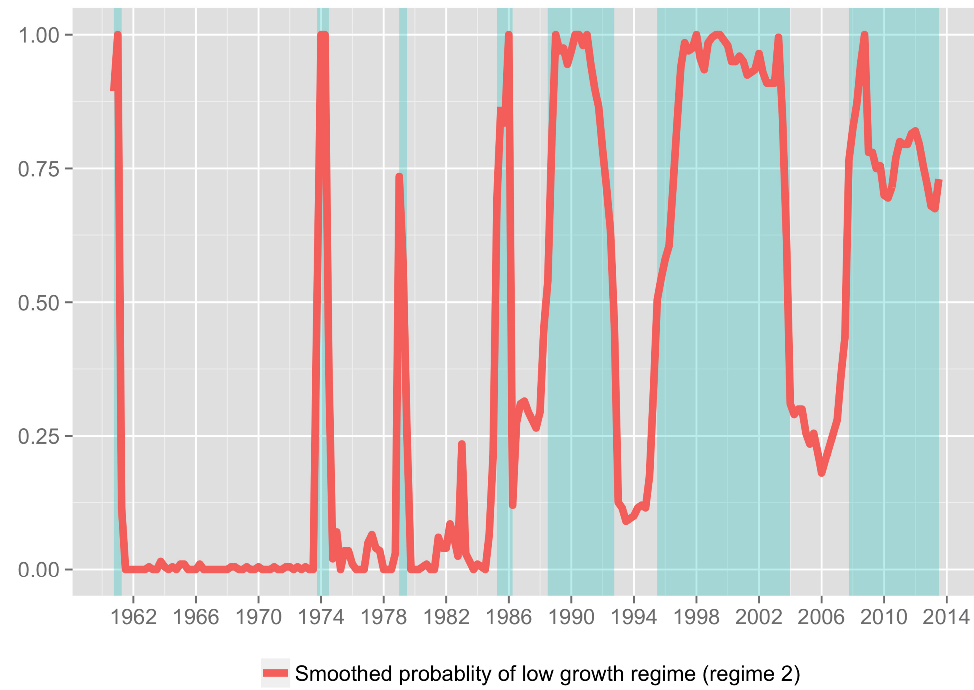


Figure 2 plots the estimates of the smoothed probabilities of a low growth regime (also associated with higher oil price volatility and oil price shocks) (labelled regime 2) of the MS-VAR model given in Equations (1)-(2). The lag order of the estimated MS-VAR model is 1 as selected by the BIC. The MS-VAR model is estimated using a Bayesian Monte Carlo Markov Chain (MCMC) method where we utilise Gibbs sampling. The MCMC estimates are based on 20,000 burn-in and 50,000 posterior draws. The MCMC method uses the Forward Filter-Backwards Sampling (FFBS) algorithm (Multi-move sampling) described in Chib (1996) to sample the regimes. The smoothed probabilities in Figure 2 are means of the 50,000 posterior draws for each time period based on the FFBS algorithm. Shaded (blue) regions in Figure 2 correspond to the periods where smoothed probability of the low growth regime is at the maximum.

We note that regime2 (low growth, high oil price volatility) occurs in the post 1973 and 1979 periods, both periods marked by significant oil price increases due to OPEC countries' oligopolistic approach to limit the extraction of oil and the Iranian revolution of 1979. The impact of the oil price shocks on South African output growth during these two periods appear to be short-lived however, and it could be argued that a rise in the gold price during the 1970s could be responsible for offsetting the impact of the oil price increases on output growth (Dagut, 1978). A low growth regime also coincides with the political crisis in the South Africa during and post 1985 with the debt standstill agreement and economic and trade sanctions imposed on the country. During this period of economic isolation, the economy entered a rather prolonged recession, with negative growth rates recorded for several periods. The sanctions were only gradually lifted during the first half of the 1990s, starting with the release of Nelson Mandela in 1990 and finally completely reversed with the transition to a democracy in 1994. The latter part of the 1980s and early 1990s were indeed marked by the longest downward phase in the South African business cycle, lasting 51 months, between March 1989 and May 1993, once again with persistent negative growth rates in real economic output. This period also include the 1990 Iraq war oil shock. It can be observed from Figure 2 that our analysis identifies this period as a low growth regime. The significant reduction in the oil price in 1986, namely by 50 per cent during March 1986, could potentially be responsible for the brief interruption in the low growth regime following the oil price decrease, despite the on-going political crisis. We enter another low growth regime during the late 1990s which lasts until the mid-2000s, a period characterised by increases in the global oil demand which led to increases in the oil price. Real economic growth rates recorded during this time are also lower than the preceding periods following the first few years of a democratic dispensation. This low growth period also include the East Asian crisis of 1998/99 and its evident impact on growth performance of developing economics world-wide. The final low growth regime suggested by our analysis commenced in 2008, coinciding with the global financial crisis, and lasts for the remainder of the sample period under consideration.

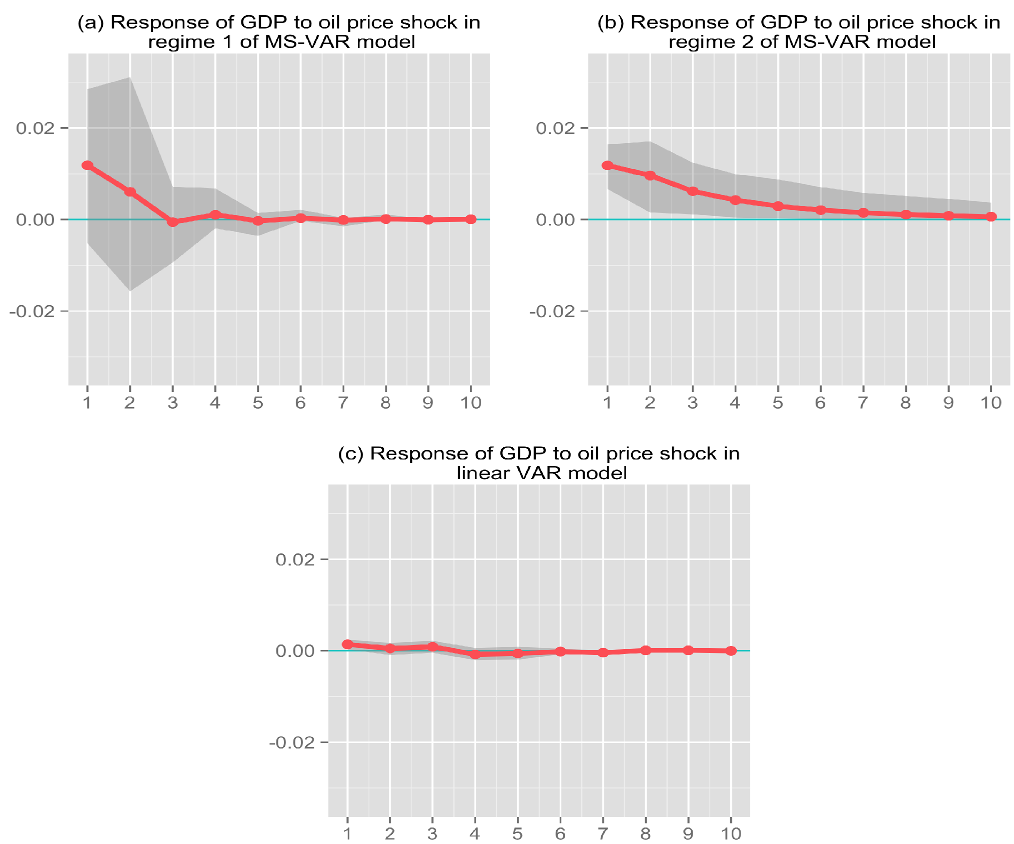
In Figures 4 and 5 in Appendix A, regime 2, is overlaid on real GDP growth rates and real oil price changes respectively. It is clear that our multivariate MS-VAR model identifies regime 2 based on either occurrences of oil price shocks and oil price volatility, or periods of low and negative growth rates, or both of these.

Figure 3 reports 1 to 20-step ahead impulse responses of real GDP growth to a 1 standard deviation shock in the real oil price growth. All impulses are based on Cholesky factor orthogonalization. Impulse responses are shown in solid and circle symbol lines. The dark grey regions around the impulse responses correspond to 95 percent confidence intervals. The confidence intervals for the linear VAR model are obtained from 1,000 bootstrap resampling. The MS-VAR impulse responses are computed using the regime dependent impulse response method suggested by Ehrmann, *et al.* (2003). The confidence intervals for the MS-VAR models are obtained from the 50,000 posterior draws for each step.

Figure 3(a) and (b) shows that the output growth response to an oil price shock in a high growth regime is short-lived and the output growth stabilizes to its equilibrium value after 3 quarters. The impact is however statistically insignificant. The impact of an oil shock on output growth during low growth regimes tends to be positive and significant. The impact is also more persistent with output growth stabilising to its equilibrium value after 8 quarters. The reason behind the persistence of an oil price shock during the low growth regime could be attributed to the reaction of monetary authorities. During low growth regimes, which typically also coincides with recessionary or downswings in the business cycle, the monetary authorities might adopt expansionary monetary policy, while during high growth regimes, coinciding with upswings in the business cycle, the monetary authority reacts to the increase in oil price by increasing the interest rate which will harm investment, hence delay the stabilisation of output to its equilibrium value.

In Figure 3(c), we observe no effect of oil price shocks on real output growth under the linear VAR model setting. These show the advantages of nonlinear regime switching models over the linear alternative, which does not distinguish between the different characteristics under each regime. The regime dependent IRF allows the asymmetries in terms of the magnitude and persistence of impact in each regime shown in Figure 3.

Figure 3. Impulse response of GDP to oil price in linear VAR and MS-VAR models



5. Conclusion

In this paper we have specified and estimated a Bayesian MS-VAR model with a linear VAR as benchmark, to investigate the role of oil price in different states, or regimes, namely a high growth–low oil price volatility regime, and a low growth–high oil price volatility regime during the period 1960Q2 to 2013Q3. Our findings can be summarised as follows: Firstly, the linear model is rejected in favour of a nonlinear alternative, implying that a regime switching model exists that characterises the South African business cycle. Secondly, the regime property of the model shows that the duration of the high growth regime on average is longer compared to that of low growth regime. Thirdly, we observe that oil price shocks increase the probability to be in a low growth regime. Using regime-dependent IRFs, we found that the oil price shock tends to be more persistent during low growth states compared to high growth states, and the impact on real output growth is also statistically significant. This might be attributed to the asymmetric reaction of monetary authorities to mitigate the inflationary effect of oil price shocks during low growth regimes. We furthermore observe that whereas the linear VAR, shows no impact of oil price shocks on real output growth, the regime-dependent IRFs are able to differentiate between responses of oil price shocks under each regime, and suggests a significant impact during periods of low growth.

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Appendix A

Table 3. Unit root tests

	LROILP	LRGDP
Panel A: Unit root tests in levels		
ADF	-0.7975 [5]	-2.1267 [7]
Z_α	-8.3953 [0]	-1.4807 [2]
MZ_α	-8.2175 [0]	-1.4167 [2]
MZ_t	-2.014 [0]	-0.79409 [2]
DF-GLS	-2.0575 [0]	-0.7799 [2]
KPSS	1.6308*** [0]	1.3030*** [2]
Zivot-Andrews	-4.2794 [5]	-3.5118 [7]
Panel B: Unit root test in first differences		
ADF	-8.4629*** [4]	-4.4396*** [6]
Z_α	-184.07*** [0]	-67.232*** [2]
MZ_α	-104.53*** [0]	-22.349*** [2]
MZ_t	-7.2153*** [0]	-3.3059*** [2]
DF-GLS	-12.7050*** [0]	-3.9420*** [2]
KPSS	0.0828 [9]	0.5493 [7]

Note: Panel A reports unit roots test results for the log levels of the series with a constant and a linear trend in the test equation. Panel B reports unit root test results for the first differences of the log series with only a constant in the test equation. ADF is the augmented Dickey-Fuller (Dickey and Fuller, 1979) test, Z_α is the Phillips-Perron Z_α unit root test (Phillips and Perron, 1988), MZ_α and MZ_t are the modified Phillips-Perron tests of Perron and Ng (1996), DF-GLS is the augmented Dickey Fuller test of Elliot, *et al.* (1996) with generalized least squares (GLS) detrending, KPSS is the Kwiatkowski, *et al.* (1992) stationarity test, and Zivot-Andres is the endogenous structural break unit root test of Zivot and Andres (1992) with breaks in both the intercept and linear trend. Z_α, MZ_α, and MZ_t tests are based on GLS detrending. For the ADF unit root statistic the lag order is selected by sequentially testing the significance of the last lag at 10% significance level. The bandwidth or the lag order for the MZ_α, MZ_t, DF-GLS, and KPSS tests are select using the modified Bayesian Information Criterion (BIC)-based data dependent method of Ng and Perron (2001). ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Multivariate cointegration tests

Panel A: VAR order selection criteria

Lag (p)	1	2	3	4	6	8	10
AIC	-13.0023	-13.0141	-13.0494	-13.0637	**-13.0714**	-13.0734	-13.0356
HQ	**-12.9630**	-12.9486	-12.9576	-12.9457	-12.9272	-12.9029	-12.8127
BIC	**-12.9051**	-12.8520	-12.8225	-12.7720	-12.7148	-12.6519	-12.4845

Panel B: Johansen cointegration tests

Eigenvalues	0.0420	0.0360

		Critical values			Cointegration vector	
H_0	λ_{max}	10%	5%	1%	LROILP	LRGDP
$r = 1$	7.8100	6.5000	8.1800	11.6500	1.0000	1.0000
$r = 0$	9.1400	12.9100	14.9000	19.1900	-6.5522	-1.0625

					Loadings	
H_0	λ_{trace}	10%	5%	1%	LROILP	LRGDP
$r \leq 1$	7.8100	6.5000	8.1800	11.6500	-0.0033	-0.0625
$r = 0$	16.9500*	15.6600	17.9500	23.5200	0.0009	-0.0017

Panel C: Stock-Watson cointegration test

H_0: $q(k,k\text{-}r)$	Statistic	Critical values for $q(4,3)$	
$q(2,0)$	-1.2029	1%	-30.3486
$q(2,1)$	-16.2054	5%	-22.8687
		10%	-19.2077

Note: Table reports selection criteria and multivariate cointegration tests for the VAR(p) model of variables LROILP and LRGDP. Panel A reports the AIC, BIC, and Hannan-Quinn (HQ) information criteria. The VAR order is selected based on minimum BIC and is 1. Panel B reports maximal eigenvalue (λ_{max}) and trace (λ_{trace}) cointegration order tests of Johansen (1988, 1991). Non-rejection of r=0 for the Johansen tests implies no cointegration. Panel C reports the multivariate cointegration test of Stock and Watson (1988). Under the null $q(k,k$-$r)$ of Stock-Watson cointegration test, k common stochastic trend is tested against k-r common stochastic trend (or r cointegration relationship). Rejection of $q(2,1)$ for the Stock-Watson test implies cointegration. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Figure 4. Real GDP growth rate

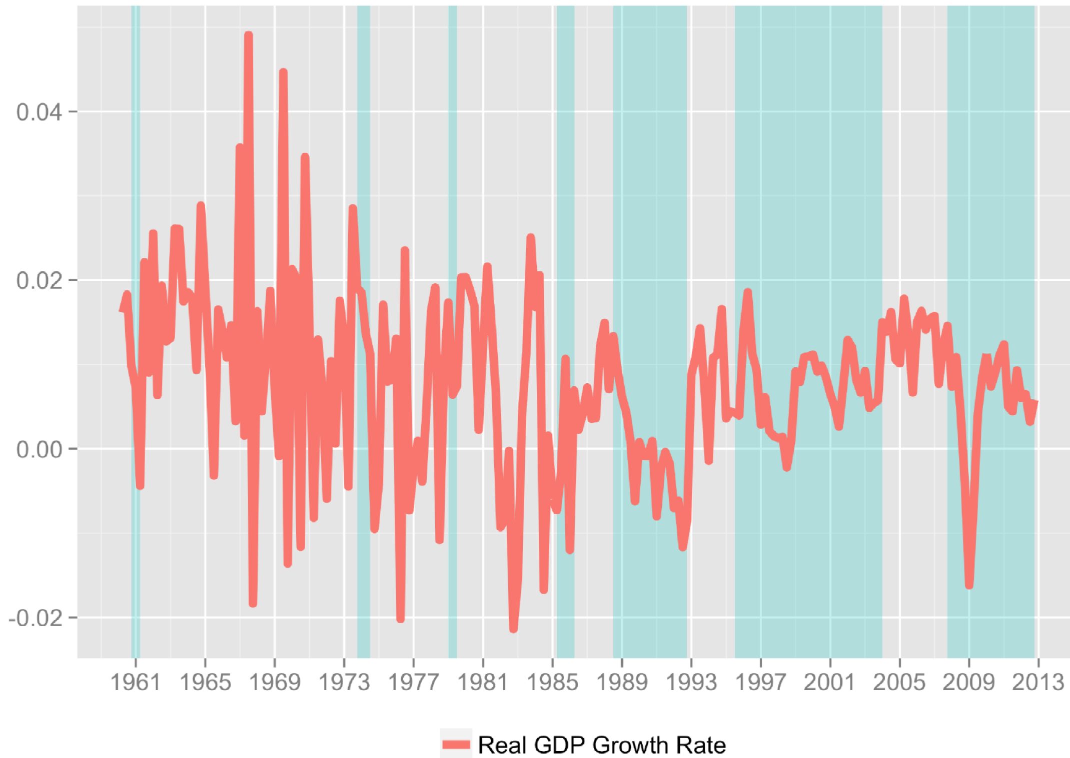

Figure 5. Real oil price change