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Keywords

VARMA models, Oil price shocks, Global oil market, Impulse responses, Forecasting.

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An analysis of the global oil market using SVARMA models

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March 8, 2019

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Abstract

The paper analyses the importance of supply versus demand shocks on the global oil market from 1974 to 2017, using a parsimonious structural vector autoregressive moving average (SVARMA) model. The superior out-of-sample forecasting performance of the reduced form VARMA compared to VAR alternatives advocates the suitability of this framework. We specifically account for the changes in the oil market over three distinctive sub-periods - pre moderation, great moderation and post moderation periods, to provide a means of identifying the changing nature of shock transmission mechanism across times. The findings shed some light on the effects of supply versus demand related oil shocks under different economic environment. Oil supply shocks explain large fraction of the movements in the global oil market in the pre and post moderation periods, i.e. during the slower economic growth periods. The importance of global activity shock on oil price movements is obvious during the 2003-2008 boom period. The oil specific shock has an interesting transmission path on the global economic activity, where the global activity responded positively and negatively during the global economic expansion and contraction respectively, emphasising the precautionary nature of the shock.

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1 Introduction

The movement of global oil prices since early 1970s could be attributed to the interaction of supply and demand for oil, much like other industrial commodity prices. Following the seminal paper by Kilian (2009), the vector autoregressive (VAR) models are largely used in the oil market analysis, to generate impulse response functions of oil prices to demand and supply driven shocks. Figure 1, highlights the relative importance and timing of the fluctuations in the global oil production and economic activity and their differing dynamic effects on the real price of oil. This could be broadly summarised as the disruption to crude oil production arising from political events in oil-producing countries, followed by changing demand for crude oil associated with the global business cycle, the discovery of new fields and improvements in the technology of extracting crude oil and the changing expectations about future shortfalls of supply relative to demand in the global oil market. This implies, the conventional VAR tools of impulse response analysis and forecast error variance decompositions can be misleading if constant parameters are assumed throughout the samples. Bataa et al. (2016) carried out various sub-sample analysis of the oil market and found the parameters of oil market variables are subject to change over different time periods.

The oil market variables, just like the economic and financial time series involve for example seasonal adjustment, de-trending, temporal and contemporaneous aggregation. Such time series include moving average dynamics even if one assumes its constituents being generated by a VAR. Applied researchers, tend to estimate a VAR model of order that is much higher than that selected by AIC or BIC, to describe the system adequately and to obtain reliable impulse responses.¹ For example, Kilian (2009) and the papers thereafter have used a VAR(24) to capture the dynamics in the oil market. The use of a long order VAR however, could be problematic for shorter sample period analyses due to limited number of observations. Bataa et al. (2016) overcome this issue by using a structural heterogeneous VAR model. In this paper, we propose the parsimonious structural vector autoregressive moving average (VARMA) model to examine the global oil market over different sub-periods.²

The objectives of this paper are to: (i) build a global oil market structural VARMA model and establish the necessary identification conditions to uncover the independent oil supply and demand shocks; (ii) assess whether a parsimonious SVARMA model is able to produce impulse responses that are consistent with the sign restrictions adopted by Kilian and Murphy (2012); (iii) carry out various sub-period analyses to examine changes in the transmission of supply and demand driven oil shocks across periods.

In our empirical modelling, we use a similar set of three variables as Kilian (2009); Lutkepohl and Netsunajev (2014); Bataa et al. (2016) who, among others have used global crude oil production, global economic activity index and global real oil price to analyse

¹In a simulation study, Kapetanios et al. (2007) show that a sample size of 30,000 observations and a VAR of order 50 are required to sufficiently capture the dynamic effects of some of the economic shocks.

²According to Fry and Pagan (2005), a subset of variables coming from a multivariate VAR process could be modelled using a vector autoregressive moving average (VARMA) model rather than a VAR.

the global oil market. However, in contrast to these papers, we have used the recently corrected and updated global economic activity index by Kilian (2018). Our period of study is longer, i.e. from January 1974 to December 2017 and we carry out sub-period analysis of the oil market using the parsimonious SVARMA model. These studies excludes the 2008 global financial crisis while in Bataa et al. (2016) the period covers from December 1972 to February 2014, which excludes the recent 2014 oil crisis. Though our period of study covers variety of events, it can be broadly categorised into three main periods - pre-moderation period which covers the mid-70s up to the mid-80s and it includes the great inflation period; this followed by the great moderation period which covers the tranquil period of the mid-80s to 2007, just before the global financial crisis (GFC) and the post-moderation period which begins from 2008, and it includes the GFC and the recent oil crisis. More on this are discussed under Section 2.

We apply the VARMA methodology of Athanasopoulos and Vahid (2008a) to capture the dynamics of a long lag structure to assess the effects of changes in the oil market. The impulse responses are derived by appealing to Wold's decomposition theorem and a finite order VARMA model would provide a better approximation to the Wold representation than a long finite order VAR model. Hence, VARMA models are expected to produce more reliable impulse responses than the VAR models. Athanasopoulos and Vahid (2008b) also show that VARMA models forecast macroeconomic variables more accurately than VARs and they demonstrate that the forecast superiority comes from the presence of moving average components. In this paper we provide further empirical evidence supporting these claims by comparing the two classes of models for modelling the oil market.

The use of the parsimonious SVARMA(2,1) enable us to carry out the analysis for shorter periods. As in Bataa et al. (2016), we infer parameters vary across these sub-periods but are constant within each period. This not only allow us to assess each sub-period separately but also enable us to construct confidence intervals for impulse response functions and forecast error variance decompositions for each sub-periods. To identify the contemporaneous structure of the model, we employ identification restrictions similar to Kilian (2009). Shocks to global crude oil production could be arising from political events, the discovery of new fields and improvements in the technology while shocks to the demand for crude oil depends on the changes to the global economic activity. Any shocks not associated with supply and demand, is defined as oil specific shock, reflecting shifts in expectations about future shortfalls of supply relative to demand in the global oil market.

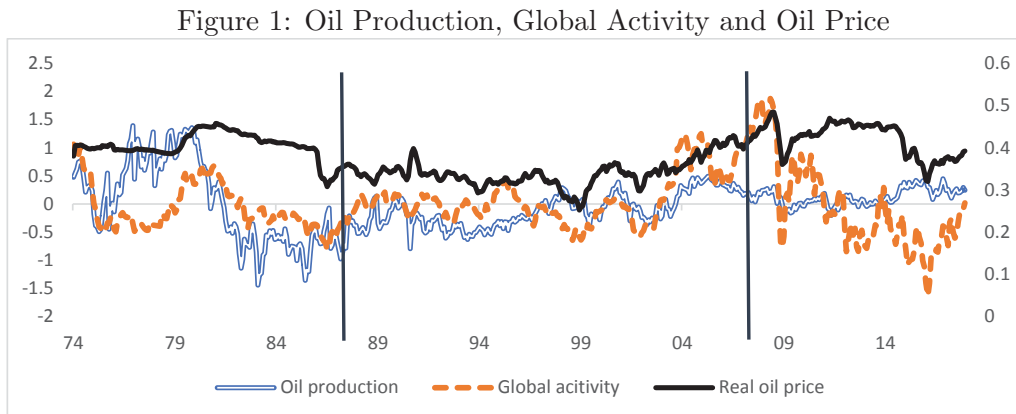
Relative to the responses by a SVAR, the responses generated by the SVARMA conform to the sign restrictions reported in Kilian and Murphy (2012). The superior out-of-sample forecasting performance of the reduced form VARMA compared to VAR alternatives further advocates the suitability of this framework for global oil market analysis. We document the evolution of the oil market over the three sub-periods and the empirical results provide some valuable insights into the transmissions of supply and demand driven oil shocks over time. Historical decomposition and variance decomposition allow contrast of shocks propagating under different sub-periods.

Broadly, the time path of the three shocks implied by our SVARMA model appear to be in line with that reported in Baumeister and Kilian (2016), who analysed the oil price fluctuations for the last forty years. Both global oil production and global economic activity are important sources of fluctuations for oil price, but their relative contribution varies across sub-periods. During the great moderation period, which includes the global economic boom period, the oil market is driven by demand related shocks originating from global activity and or oil-specific shocks. On the other hand, during the pre and post moderation periods, the market is mainly driven by oil supply related shocks. The pre-moderation supply shock could be associated with geopolitical tension while the post-moderation shock is associated with the discovery of new fields and improvements in the technology. The oil specific shock has an interesting transmission path to the global economic activity, where the global activity responded positively during the global economic expansion and negatively in the current sluggish economic environment. The different dynamic effects of supply and demand related shocks, highlight the changing nature of the shock transmissions in the global oil market. Therefore it is important for policymakers, financial analyst and economists alike to understand these changes and their implications on the global economy under different economic environment.

The paper is organized as follows: Section 2 briefly reviews the evolution of the global oil market. Section 3 describes the VARMA methodology and illustrates the identification of the oil market SVARMA model and the choice of variables. In Section 4, we compare the performance of SVARMA and SVAR models. In particular, we evaluate the impulse responses and out-of-sample forecasting performances. Section 5 reports and discusses the empirical findings for the three sub-periods and Section 6 concludes this paper.

2 The Global Oil Market

The movement of global oil prices since mid-1970s could be attributed to the interaction of various factors. Among them, the obvious two factors are global oil production and global economic activity. Figure 1, highlights the relative importance and timing of the fluctuations in these two variables and their differing dynamic effects on the real oil price.



Note: The sources of data are from US Energy Information website and Kilian, UM website. For more details refer to Table 8 in Appendix B.

As shown in Figure 1, between mid-70s to mid-80s, the real oil price is above trend. The period is characterized as a period that witnessed the oil price rises caused by the OPEC, growing geopolitical tensions in the middle-east, low spare capacity in oil production and easy monetary policies aimed to stimulate the economic growth (Baumeister and Kilian, 2016). In this period, high oil price volatility was leading to a period known as the great inflation period.

The period between mid-1980s to 2007 is described as tranquil period and the oil price is below trend. During this period, inflation was low and relatively stable, while the period contained the longest global economic expansion. This period also witnessed the 2003-2008 oil price boom. The most noticeable observation in Figure 1 is the rise in the real price of oil since early 2002, which is almost synonymous to the surge in global economic activity that started around 2001. Oil price increases are connected with strong global economic growth until 2008, mostly driven by surge in the demand for oil from emerging economies, particularly China and India (Hamilton, 2009; Kilian and Hicks, 2013). During these periods, there is no clear evidence to suggest that the increase in oil price was driven by any disruption in oil supply. In fact between the periods 2002 to 2005, the global oil production actually increased. The observation that the oil price movement is driven by business cycle fluctuations, is consistent with that reported in Hamilton (2009), Kilian (2009) and Kilian and Murphy (2014).

The period between 2008 and 2017 is commonly known as the post Global Financial crisis (GFC) period. In this period up to 2014, oil price appear to be above trend, In Figure 1 we can observe that from 2010 onwards, the oil price kept rising despite the weakening of global economic activities and with no disruption in global oil production. In fact, according to Kilian and Zhou (2018) the boom in global economic activity between 2003 to mid-2008 was largely transitory rather than permanent. This raises the question of what has been driving the oil price after 2010. Kilian and Murphy (2014) identifies a third factor, speculative demand associated with inventory building that could cause a hike in oil prices while others such as Ratti and Vespignani (2013), attributed the rise to expansion in global liquidity and Hesary and Yoshino (2014) attributed it to expansionary monetary policy. Since 2014, a sharp decline in oil price was observed and it is largely attributed to not only to the unexpected growth of US shale oil production, but also due to increased oil production in other countries including Canada and Russia and the slowing down of the global economy (see for example Baumeister and Kilian, 2016; Kilian and Zhou, 2018).

In view of the above discussion, the period under study is divided into three sub-periods as described in Table 1. The pre-moderation period is defined as a period with high oil price with weak global economy and contained oil production. The great moderation represents a calm period with continuous growth in global activity and the expansion of demand for oil. The post-moderation period represents a period with weak global economy and rising global oil production. The identified sub-periods overlaps with those reported in Sadorsky (1999), Peersman and Van Robays (2012) and Mohaddes and Pesaran (2017). Sadorsky (1999) and Peersman and Van Robays (2012) identified a change in the oil market around

early 1986 and Mohaddes and Pesaran (2017) around January 2008.³ The identified post-moderation period is also consistent with Kilian and Zhou (2018), who demonstrate the slowing down of the global economy since 2008. These three sub-periods are considered in this study primarily to assess the impact of the changes in the supply and demand driven oil shocks within each period. The responses of the oil market variables to supply shocks will be different compared to demand shocks and these responses are also expected to vary across time.

Table 1: Breakdown of the period of study

Description	Period
Full period	1974:1–2017:12
Pre-moderation period	1974:1–1985:12
Great moderation period	1986:1–2007:12
Post-moderation period	2008:1–2017:12

3 VARMA modeling

In this section, we discuss the VARMA methodology and its application to the global oil market analysis. In what follows, we first provide a brief discussion of the Athanasopoulos and Vahid (2008a) methodology for identifying and estimating a VARMA model. Then we discuss the identification of the SVARMA model for the oil market.

3.1 A VARMA methodology

Athanasopoulos and Vahid (2008a) proposed a complete methodology for identifying and estimating canonical VARMA models by extending the work of Tiao and Tsay (1989). They established necessary and sufficient conditions for exactly identifying a canonical VARMA model so that all parameters can be efficiently identified and estimated simultaneously using full information maximum likelihood (FIML). A detailed exposition of the methodology can be found in Appendix A and in what follows we provide a brief discussion of the methodology for identifying and estimating a parsimonious VARMA model.

A K dimensional VARMA(p, q) process can be written as

$$\mathbf{X}_t = \Phi_1 \mathbf{X}_{t-1} + \dots + \Phi_p \mathbf{X}_{t-p} + \mathbf{v}_t - \Theta_1 \mathbf{v}_{t-1} - \dots - \Theta_q \mathbf{v}_{t-q}, \quad (1)$$

where Φ_j represent the autoregressive coefficients while Θ_i represent the moving average (MA) coefficients. A non-zero linear combination $z_{i,t} = \beta_i' X_{i,t}$, follows a SCM(p_i, q_i) if β_i has the following properties:

$$\begin{aligned} \beta_i' \Phi_{p_i} &\neq \mathbf{0}^T \text{ where } 0 \leq p_i \leq p, \\ \beta_i' \Phi_l &= \mathbf{0}^T \text{ for } l = p_i + 1, \dots, p, \\ \beta_i' \Theta_{q_i} &\neq \mathbf{0}^T \text{ where } 0 \leq q_i \leq q, \\ \beta_i' \Theta_l &= \mathbf{0}^T \text{ for } l = q_i + 1, \dots, q. \end{aligned}$$

³Bataa et al. (2016) identified a break in the oil market around early 1988.

The scalar random variable $z_{i,t}$, depends only on lags 1 to p_i of all variables and lags 1 to q_i of all innovations in the system. To represent the K -dimensional VARMA(p, q) process in terms of K -SCMs, K linear transformation are preformed via the transformation matrix resulting in

$$\mathbf{z}_t = \mathbf{B}\mathbf{X}_t \quad (2)$$

where $\mathbf{B} = (\beta_1, \beta_2, \dots, \beta_k)'$ is a $(K \times K)$ invertible matrix while $\mathbf{z}_t = (z_{1,t}, z_{2,t}, \dots, z_{K,t})'$ is a transformed process associated with K -SCM(p_i, q_i) for $i = 1, 2, \dots, K$.

The identification of embedded scalar component models is done through a series of canonical correlation tests. Let the estimated squared canonical correlations between $\mathbf{Y}_{m,t} \equiv (\mathbf{X}'_t, \dots, \mathbf{X}'_{t-m})$ and $\mathbf{Y}_{h,t-1-j} \equiv (\mathbf{X}'_{t-1-j}, \dots, \mathbf{X}'_{t-1-j-h})'$ be $\hat{\lambda}_1 < \hat{\lambda}_2 < \dots < \hat{\lambda}_K$. Tiao and Tsay (1989) test sequentially for s zero canonical correlations. The test statistic for at least s SCM(p_i, q_i), i.e., s insignificant canonical correlations, against the alternative of less than s scalar components is

$$C(s) = -(n - h - j) \sum_{i=1}^s \ln \left\{ 1 - \frac{\hat{\lambda}_i}{d_i} \right\} \stackrel{a}{\sim} \chi_{s \times \{(h-m)K+s\}}^2 \quad (3)$$

where d_i is a correction factor that accounts for the fact that the canonical variate could be moving averages of order j and it is calculated as follows:

$$d_i = 1 + 2 \sum_{v=1}^j \hat{\rho}_v(\hat{\mathbf{r}}'_i \mathbf{Y}_{m,t}) \hat{\rho}_v(\hat{\mathbf{g}}'_i \mathbf{Y}_{h,t-1-j}) \quad (4)$$

where $\hat{\rho}_v(\cdot)$ is the v^{th} order autocorrelation of its argument and $\hat{\mathbf{r}}'_i \mathbf{Y}_{m,t}$ and $\hat{\mathbf{g}}'_i \mathbf{Y}_{h,t-1-j}$ are the canonical variate corresponding to the i^{th} canonical correlation between $\mathbf{Y}_{m,t}$ and $\mathbf{Y}_{h,t-1-j}$. Let, $\Gamma(m, h, j) = E(\mathbf{Y}_{h,t-1-j} \mathbf{Y}'_{m,t})$.

The identification of VARMA(p, q) process are carried out in three stages and they are described in more detail in Appendix A. First, by strategically choosing $\mathbf{Y}_{m,t}$ and $\mathbf{Y}_{h,t-1-j}$, we identify the overall tentative order of the VARMA(p, q). Conditional on the overall tentative order (p, q) we then repeat the search process but this time searching for individual components. The test results from identifying the overall tentative order and the individual SCMs are tabulated in what are referred to as *Criterion* and *Root* tables. We demonstrate the reading of these tables in Subsection (3.2).

3.2 Identifying an oil market VARMA model

In this study we use a similar set of three variables as Kilian (2009) for modelling the global oil market. These variables, as listed in Table 8 in Appendix B are monthly global oil production, global economic activity and the real oil price index. Herein, we have used the recently corrected and updated global economic activity index by Kilian (2018), and is expressed as percentage deviation from trend.⁴ The benefits of using the Kilian index as proxy for global economic activity, instead of the world GDP or the production index can be found in Kilian and Zhou (2018). To obtain the real oil price, the oil price variable

⁴Hamilton (2018) found the Kilian index developed by Kilian (2009) to be misleading. Hence, recently, the Kilian index has been corrected and the details can be found in Kilian (2018).

is deflated by US seasonally adjusted consumer price index (CPI). Both the real oil price and oil production are expressed in logarithms and detrended. The vector of variables is represented as

$$\mathbf{X}_t = [\text{OS}_t, \text{GA}_t, \text{OP}_t]' \quad (5)$$

The sample period of our study is from January 1974 to December 2017.⁵ We illustrate the application of the complete VARMA methodology outlined in Section (3.1) on the selected three variables of the global oil market as listed in 5.

In Stage 1 of the identification process, we identify the overall VARMA order and the orders of embedded scalar component models (SCMs). In Table 2, we report the results of all canonical correlations test statistics divided by their χ^2 critical for the full period. This table is known as the ‘‘Criterion Table’’. If the entry in the $(m, j)^{\text{th}}$ cell is less than one, it shows that there are three SCMs of order (m, j) or lower in this system.

Table 2: Stage I of the identification process of a VARMA model

PANEL A: Criterion Table						PANEL B: Root Table					
Full Period (Jan 1974–Dec 2017)											
m	j					m	j				
	0	1	2	3	4		0	1	2	3	4
0	273.33 ^a	33.19	17.69	11.88	8.88	0	0	0	0	1	
1	10.76	1.42	0.51	0.55	0.88	1	0	2	3	3	
2	1.41	0.78	0.67	0.83	0.79	2	2	3	5	6	
3	0.44	0.45	0.85	0.83	0.89	3	3	4	7	8	
4	0.71	0.93	0.58	1.04	0.89	4	3	6	7	9	

^aThe statistics are normalized by the corresponding 5% χ^2 critical values

From Panel A in Table 2, we infer that the overall order of the system is VARMA(2, 1). Conditional on this overall order, canonical correlation tests are performed to identify the individual orders of embedded SCMs. The number of insignificant canonical correlations found are tabulated in Panel B of Table 2. This is referred as the ‘‘Root Table’’. For example, the figures in bold in the Root Table show that two SCMs of order (1, 1) is initially identified in position $(m, j) = (1, 1)$. Then, there are three SCMs of order (2, 1) at position $(m, j) = (2, 1)$. From these, one is a new component of order (2, 1), as two are carried over from the SCM(1, 1). Hence, the identified VARMA(2, 1) consists of two SCM(1, 1) and one SCM(2, 1).

Among the variables, as defined in equation (5), OS and GA are found to be loading as SCM(1, 1), and OP loaded as SCM(2, 1). Implementing Stage II of the Athanasopoulos and Vahid (2008a) identification process described in Appendix A leads to additional zero restrictions on the matrix containing the contemporaneous relationships between the variables and the canonical SCM representation of the identified VARMA models.

The specified VARMA(2, 1) model is given by

⁵The period of study in Kilian (2009) was from January 1973 to December 2007, which excludes the 2008 global financial crisis while in Bataa et al. (2016) the period covers from December 1972 to February 2014, which excludes the 2014 oil crisis. These two studies have used the previously generated global economic activity index which Hamilton (2018) claimed to be misleading.

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{X}_t = \mathbf{c} + \begin{bmatrix} \phi_{11}^{(1)} & \phi_{12}^{(1)} & \phi_{13}^{(1)} \\ \phi_{21}^{(1)} & \phi_{22}^{(1)} & \phi_{23}^{(1)} \\ \phi_{31}^{(1)} & \phi_{32}^{(1)} & \phi_{33}^{(1)} \end{bmatrix} \mathbf{X}_{t-1} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ \phi_{31}^{(2)} & \phi_{32}^{(2)} & \phi_{33}^{(2)} \end{bmatrix} \mathbf{X}_{t-2} \\ + v_t - \begin{bmatrix} \theta_{11}^{(1)} & \theta_{12}^{(1)} & \theta_{13}^{(1)} \\ \theta_{21}^{(1)} & \theta_{22}^{(1)} & \theta_{23}^{(1)} \\ \theta_{31}^{(1)} & \theta_{32}^{(1)} & \theta_{33}^{(1)} \end{bmatrix} v_{t-1}.$$

3.3 Impulse response function, variance decomposition and historical decomposition

Impulse response functions, variance decomposition and historical decomposition are derived and estimated to assess the persistence and dynamic effects of various oil shocks on the oil market variables.

The VARMA(p, q) in (1) can be written as

$$\Phi(L)\mathbf{X}_t = \Theta(L)v_t, \quad (6)$$

where $\Phi(L) = \Phi_0 - \Phi_1 L - \Phi_2 L^2 - \dots - \Phi_p L^p$ and $\Theta(L) = \Theta_0 - \Theta_1 L - \Theta_2 L^2 - \dots - \Theta_q L^q$.

The effects of global oil market shocks are analysed from impulse response functions which are derived from pure vector moving average representations (VMA) of the model. The VMA representation of (6) is given by

$$\mathbf{X}_t = \Psi(L)v_t = v_t + \sum_{i=1}^{\infty} \Psi_i v_{t-i} \quad (7)$$

where

$$\Psi_i = \Theta_i + \sum_{j=1}^i \Phi_j \Psi_{i-j}$$

and $\Psi_0 = \mathbf{I}_k$, $\Phi_j = 0$ for $j > p$ and $\Theta_i = 0$ for $i > q$ while v_t is a $(K \times 1)$ multivariate white noise error process with the following properties of $E(v_t) = 0$ and $E(v_t v_t') = \Sigma_v$.

However, the VMA processes in (7) does not allow us to attribute the responses oil market variables to an economically interpretable shock.⁶ One way to circumvent this problem is to transform these exogenous shocks into a new set of orthogonal shocks, with each element independent of one another. As in Kilian (2009), the Choleski decomposition is applied where Σ_v is given by $\Sigma_v = \mathbf{S}\mathbf{S}'$. The reduced form errors v_t can be decomposed according to (8) where \mathbf{u}_t represents the standardised structural shocks.

$$v_t = \mathbf{S}\mathbf{u}_t \quad (8)$$

where

$$\mathbf{v}_t = \begin{bmatrix} v_{1,t} \\ v_{2,t} \\ v_{3,t} \end{bmatrix} = \begin{bmatrix} s_{11} & 0 & 0 \\ s_{21} & s_{22} & 0 \\ s_{31} & s_{32} & s_{33} \end{bmatrix} \begin{bmatrix} u_t^{os} \\ u_t^{ga} \\ u_{3,t}^{op} \end{bmatrix}$$

⁶This is because v_t is the combination of all fundamental oil market shocks rather than featuring a particular oil shock such as the oil supply shock or global activity shock.

The restrictions imposed are similar to those imposed by Kilian (2009). The global oil supply is assumed not to respond to global economic activity and global real oil price within the same month but do respond with a lag. These restrictions are realistic considering that the oil-producing countries will be slow to respond to any changes in oil price or global demand due to uncertainty associated with the state of the crude oil market and the time and costs needed for adjusting the oil production. The global economic activity is assumed to be contemporaneously affected by the global oil supply but not immediately by the oil price. This restriction is in line with the sluggish behavior of global economic activity after each of the major oil price movements (see Kilian, 2009). The oil price on the other hand is assumed to respond immediately to changes in oil supply and global economic activity.

The identified, three structural shocks, $\mathbf{u}_t = [u_t^{os}, u_t^{ga}, u_t^{op}]$ are oil supply shock, global activity shock and oil specific shock respectively. As in Kilian (2009), oil supply shock is defined as unpredictable innovations to global oil production, associated with geopolitical events, the discovery of new fields and improvements in the technology, while global activity shock is defined as shocks to the global demand for industrial commodities, associated with global business cycle movements. Oil specific shock is defined as reflecting shifts in expectations about future shortfalls of supply relative to demand in the global oil market, driven by uncertainty about future oil market and or financial conditions. This could include precautionary demand, speculative demand, global liquidity and or the effects of monetary policy.

Using (8) to substitute v_t in (7) gives

$$\mathbf{X}_t = \mathbf{S}\mathbf{u}_t + \sum_{i=1}^{\infty} \Psi_i \mathbf{S}\mathbf{u}_{t-i}. \quad (9)$$

The parameters on current and lagged \mathbf{u}_t represent one standard deviation orthogonalised impulse response functions.

The variance decomposition in terms of the separate contributions of the three shocks on the system to the h -step ahead is

$$\mathbf{V}\mathbf{D}_h = \sum_{i=0}^{h-1} \Psi_i S_1 S_1' \Psi_i + \sum_{i=0}^{h-1} \Psi_i S_2 S_2' \Psi_i + \sum_{i=0}^{h-1} \Psi_i S_3 S_3' \Psi_i, \quad h = 1, 2, \dots, \quad (10)$$

Historical decomposition of a variable utilizes a representation of any variable in terms of the product of its impulse responses with estimates of the structural shocks. It allows one to assess the contribution of each shock to the variable over time. The structural VMA representation of (9) is given by

$$\mathbf{X}_t = \sum_{i=0}^{\infty} \Xi_i \mathbf{u}_{t-i} \quad (11)$$

where $\Xi_i = \Psi_i \mathbf{S}$ and the historical decompositions can be derived by simply recognizing that the VARMA form allows for any variable to be written as a weighted sum of previous shocks plus the effects of an initial condition, that is

$$\mathbf{X}_t = \text{initial conditions} + \sum_{i=0}^t \Xi_i \mathbf{u}_{t-i} \quad (12)$$

and the contribution of the k th structural shock to the j th variable can be represented as

$$x_{jt}^{(k)} = \text{initial conditions} + \sum_{i=0}^t \xi_{jk,i} u_{k,t-i} \quad (13)$$

Ideally plotting the $x_{jt}^{(k)}$ for $k = 1, 2, \dots, K$, throughout the sample period, we could interpret and analyze the relative contributions of the different structural shocks to the j th variable.

4 SVARMA versus SVAR

In this section we compare the performance of the VARMA framework with its VAR counterpart in terms of forecasting ability and impulse responses. In Table 3, all three model selection criteria would select the VARMA model over any of the VAR alternatives. If we were only to choose a VAR model, VAR(2), VAR(3) and VAR(24) are selected by the SBIC, HQ and AIC respectively.

Table 3: Model selection criteria for the estimated VARMA and VAR models.

	AIC	HQ	BIC
VARMA(2,1)	-9.85	-9.63	-9.54
VAR(2)	-9.68	-9.61	-9.53
VAR(3)	-9.70	-9.61	-9.48
VAR(24)	-9.81	-9.13	-8.07

4.1 An out-of-sample forecast evaluation

Baumeister and Kilian (2012) demonstrate that the VAR model produce more accurate short-run forecast of the real oil price compared to the AR or ARMA models. In this section, we examine the forecast accuracy of VARMA compared to VAR models. In order to perform a robust out-of-sample forecast evaluation of the VARMA(2,1) we include as alternatives VAR(2), VAR(3) and VAR(24).⁷ We split our data into an in-sample period with 408 observations, covering January 1974 to December 2007 and an out-of-sample period with 120 observations, covering January 2008 to December 2017.⁸ We re-estimate all models using the in-sample period and forecast 1 to 12-steps-ahead. We then role all models forward and generate 1 to 12-steps-ahead forecasts until the end of the out-of-sample period. This generates 120 1-step-ahead forecasts, 119 2-steps ahead forecasts up to 109 12-steps-ahead forecasts, which are used for forecast evaluation.

In Table 4 we present the percentage gains (losses for negative entries) in RMSFE (Root Mean Squared Forecast Error) from forecasting with the VARMA(2,1) model compared to the alternative VARs. We present the results for the oil price (OP) as well as for all the three

⁷The forecasting exercise carried out in this section is not directly comparable to that reported in Baumeister and Kilian (2012), as the choice of variables and the estimation techniques applied are different.

⁸In-sample period represent closely to Kilian (2009) period of study and it also covers the first two sub-periods described in Table 1 while the hold-out period represents the third sub-period.

variables together. The results show that the VARMA(2,1) model forecasts the oil price considered in the multivariate system more accurately than the VAR counterparts. This is reflected by the gains in RMSFE from the VARMA model compared to the alternative VARs. The times that one of the VAR alternatives was more accurate were very few and the loss from using the VARMA(2,1) instead of the VAR alternative were very small in comparison to the gains. The averages across the series presented at the last row of each panel indicate that VARMA(2,1) outperforms the alternative VARs for all forecast horizons. In particular, the VARMA(2,1) forecast tend to have a percentage gain around 60% to 80% in RMSFE compared to VAR(24). These findings are consistent with those in previous studies such as Athanasopoulos and Vahid (2008b), Dufour and Pelletier (2011) and Raghavan et al. (2016) which also evaluate the forecasting accuracy of VARMA models versus VARs.

Table 4: Out-of-sample percentage gains in RMSFE from forecasting h -steps-ahead with a VARMA instead of the VAR alternatives. Negative entries correspond to a percentage loss.

	h						
	1	2	4	6	8	12	Average
VARMA(2,1) vs VAR(2)							
<i>OP</i>	-2.47	3.09	7.88	8.66	8.21	6.07	7.48
All variables	3.20	6.95	6.86	4.28	4.28	1.52	4.43
VARMA(2,1) vs VAR(3)							
<i>OP</i>	-0.53	3.06	5.91	5.93	5.39	4.58	5.27
All variables	3.63	4.86	3.10	1.81	1.51	1.05	1.27
VARMA(2,1) vs VAR(24)							
<i>OP</i>	59.17	58.83	70.75	81.98	84.41	79.09	78.55
All variables	58.93	52.53	69.84	83.76	91.90	89.88	83.31

4.2 SVARMA versus SVAR impulse responses

The main focus of this paper is to analyse the responses of oil market variables to various oil related shocks. Following Kilian (2009), many similar studies in the literature selected a VAR(24) for capturing all the dynamics in the data. In this section, therefore we compare the performance of our identified SVARMA(2,1) with the commonly used SVAR(24).

To assess the performance of each model, we refer to its ability to produce impulse responses that are consistent with the sign restrictions related studies in the oil market. Table 5 below shows Kilian and Murphy (2012) sign restrictions for impact responses in the oil market. The oil-supply shock, which represents the unexpected disruption of the global crude oil production is expected to raise the real oil price and lower global economic activity on impact. An unanticipated increase in global activity shock is expected to raise the real oil price and stimulate global oil production. The real oil price jumps, associated with oil-specific shock is expected to have a positive impact on global oil production. Although there is no direct effect of such a shock on global real activity within the month, it is

however expected to lower the global real activity indirectly.

Table 5: Sign restrictions for impact responses in the oil market

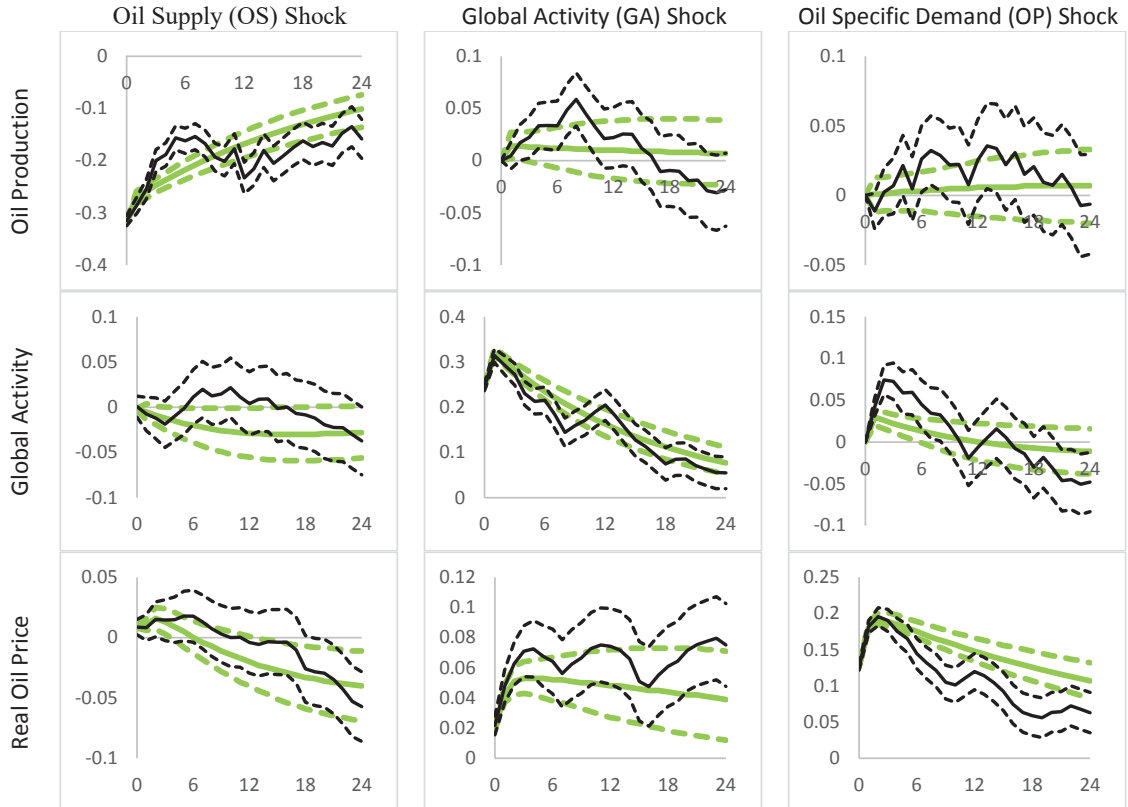
	Oil supply shock	Aggregate demand shock	Oil-market specific shock
OS	-	+	+
GA	-	+	-
OP	+	+	+

The sizes of the shocks, measured by one-standard deviation of the orthogonal errors of the SVARMA and SVAR models are presented in Table 6 and the sizes vary slightly between the two models. Therefore, to aid comparison, the impulse responses of the oil market variables across the two models are normalized by dividing them with the standard deviations estimated using SVARMA. We observe the behavior of these responses over a period of 24 months. 68% confidence bands are computed via bootstrapping 10000 samples, using the bootstrap-after-bootstrap method of Kilian (1998). SVARMA and SVAR impulse responses are shown in Figure 2 as unbroken green and black lines respectively with confidence bands shown as dashed lines.

Table 6: Magnitude of one standard deviation shocks from the VARMA and VAR models

Model	OS	GA	OP
SVARMA(2,1)	0.315	0.245	0.125
SVAR(24)	0.266	0.223	0.119

Figure 2: VARMA versus VAR responses



Note: VARMA and VAR impulse responses are shown as unbroken green and black lines respectively with confidence bands shown as dashed lines.

In many cases, SVARMA and SVAR models generate qualitatively similar impulse-response functions which are consistent with that reported in Kilian (2009).⁹ This indicates that the use of the newly corrected and updated global economic activity index by Kilian (2018) and the longer sample period have relatively little effect on the responses. Compared to SVAR, SVARMA are more consistent with the sign restrictions reported in Table 5, adopted from Kilian and Murphy (2012). In the SVAR model, the responses of global activity to OS and OP shocks appear to be problematic. The global activity is non-responsive to disruption to oil production and a similar result is also reported by Bataa et al. (2016), using a structural heterogeneous VAR. On the contrary, SVARMA model generated the expected negative response and is consistent with the results generated by Lutkepohl and Netsunajev (2014), who used a sign restrictions VAR with Markov switching mechanism. As shown via SVARMA model, the real oil price's response to oil supply disruption is positive but short lived, lasting for about six months. This implies an oil supply disruption shock may have a greater effect on the US price level than on the oil price, leading to an eventual fall in the real price of oil.¹⁰

Broadly speaking, a comparison of the results of the two alternative models indicates the benefits from using the SVARMA model over its SVAR counterpart. Compared to a SVAR model which requires long lag structure, a parsimonious SVARMA(2,1) model is able to capture the empirical dynamics of the data in order to produce plausible results that are consistent with expected sign restrictions and stylized facts. The confidence bands around the SVARMA responses appear to be narrower than those around the SVAR responses. This indicates that the parsimonious SVARMA model provides more precise impulse response functions compared to the SVAR model. Further, the benefit of applying the parsimonious SVARMA model is that it will enable us to analyse the oil market for various shorter sample periods.

5 The Changing Dynamics of Global Oil Market

As discussed in Section 2, the nature of the oil market has changed over the four decades following the oil price shocks of the mid-1970s. This section presents our main results, assessing the changing dynamics of the oil market for the three sub-periods identified in Table 1. First we generate the historical decomposition, derived using the SVARMA model for the full sample. Then we carry out the sub-period analysis by generating the impulse response functions and forecast error variance decomposition for each sub-period. Impulse responses and variance decomposition are estimated using the SVARMA model, under the assumption that there is no break within each sub-period.

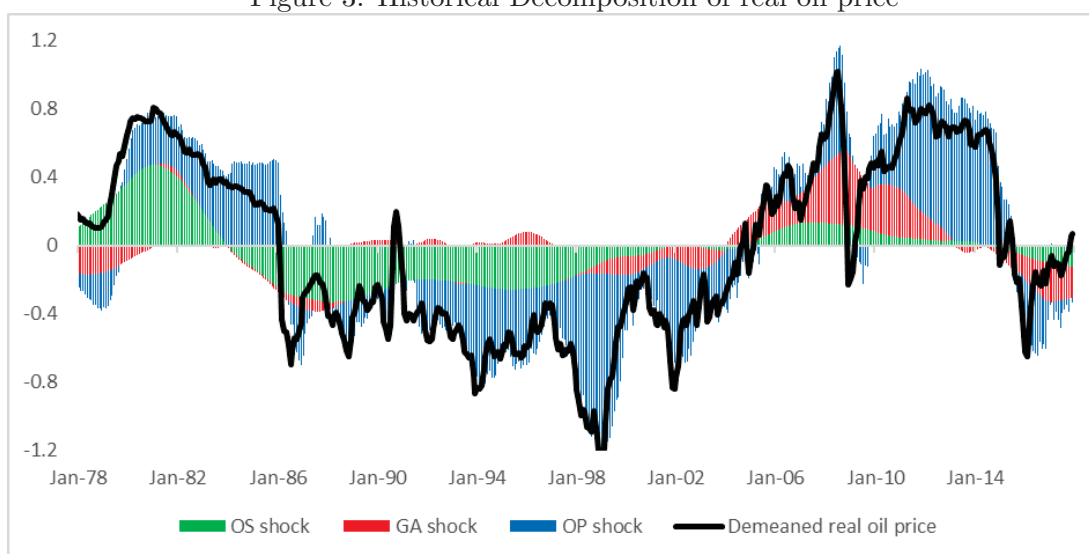
⁹Lutkepohl and Netsunajev (2014) and Bataa et al. (2016) also produce similar results where the former used a sign restrictions VAR with Markov switching mechanism while the latter used a structural heterogeneous VAR

¹⁰Lutkepohl and Netsunajev (2014) and Bataa et al. (2016) found oil price to be non-responsive to oil supply disruption.

5.1 Historical Decomposition

In this section we undertake a historical decomposition analysis of the relative contributions of the three oil related shocks to examine the evolution of the oil price over the sample from 1974 to 2017. The SVARMA model is used to decompose the real oil price into its component shocks. As shown in Figure 3, notable differences are observed in the way the various oil related shocks impact the global real oil price over time. The solid black line represents the demeaned real oil price over the sample period. The contribution of the oil-supply (OS) shock, global-demand shock (GA) and oil-specific (OP) shock are represented in green, red and blue bars respectively. The time path of the three shocks implied by the SVARMA(2,1) appear to be consistent with that reported in Baumeister and Kilian (2016).

Figure 3: Historical Decomposition of real oil price



During the pre-moderation period, the demeaned real oil price appears to be positive. Figure 3 shows the positive movement was largely contributed by OS and OP shocks. This is not surprising as the period covers the “official price” regime, when the oil price was set by Organization of the Petroleum Exporting Countries (OPEC).¹¹ However between 1978 to 1980, oil price declines, contributed by negative movements in GA and OP shocks. According to Baumeister and Kilian (2016), this could be attributed to Paul Volckers decision to raise US interest rates. The resulting move in the global monetary policy regimes towards contractionary policy, resulted in a global recession which lowered the demand for oil and hence the price of oil. In addition, the expected decline of future economic growth in conjunction with higher interest rates made it less attractive to hold stocks of oil, causing OP shocks to drive the oil price down. Our empirical oil market model confirms the OS shock, caused by the disruption in oil production played a role in increasing the oil price between early 1980s to mid-1980s. The cumulative price increase was also precipitated with increased OP shock. According to Baumeister and Kilian (2016), this can be associated with inventory demand in anticipation of future oil shortages, presumably

¹¹See Mabro (2006) for a detailed account of the oil market pricing regimes.

reflecting geopolitical tensions between the US and the middle-east. Kilian (2009) classifies any movements in oil price that are not accounted for by global oil production and economic activity as precautionary demand for oil, driven by fear of future oil supply shortfalls due to war or excessive demand.

During the great moderation period, the demeaned real oil price appear to be negative. According to Figure 3, between mid-1980s to early 1990s, the negative movement is mainly from OS shock. A sharp fall in the price of oil in 1986 could be caused by the resumption of Saudi Arabia oil production where the resulting losses of oil revenue forced Saudi to reverse its policy of restricting oil production (Kilian and Murphy, 2014). Between early 1990s to late 1990s, the decline appeared to be caused by a combination of OS and OP shocks. During this period, given the abundance of crude oil supplies in the world relative to oil demand, the price of oil weakened further. This reflects a reduction in inventory demand for oil, given that OPEC was unable to sustain a higher price of oil. By December 1998, the oil price reached an all time low associated with reduced demand for crude oil, caused by the Asian Financial Crisis of mid-1997. As observed in Figure 3, between 2003 to 2008, the recovery in the price reflected a combination of factors including higher demand for oil from a recovering global economy, some cuts in oil production, and increased inventory demand in anticipation of tightening oil markets. During this period, oil price increases are connected with strong global economic growth until 2008 mostly driven by surge in the demand for oil from emerging economies, particularly China and India (Hamilton, 2009; Baumeister and Peersman, 2013; Kilian and Hicks, 2013; Kilian and Murphy, 2014).

In the post-moderation period, the oil price kept rising despite the weakening of global economic activities and with no disruption in global oil production. This raises the question of what is actually driving the oil price after 2010. Figure 3 shows the positive contribution is coming from OP shocks. Kilian and Murphy (2014) classifies this as speculative demand driven by fear of future oil supply shortfalls due to excessive demand. This type of demand is typically associated with inventory building with the expectation of selling later at a profit. Ratti and Vespignani (2013) on the other hand highlights that the rise in oil price between 2009-2010 was caused by global liquidity, particularly due to the rise in China's real M2. Hesary and Yoshino (2014) argues that expansionary monetary policy stimulates oil demand through interest rate channels and this combined with a rigid global oil production, creates a surge in oil price. Since 2014, a sharp decline in oil price was observed. All three shocks are contributing to this decline. A negative contribution from OS shock can be attributed to unexpected growth in US shale production and the increased oil production from countries like Canada and Russia. A negative contribution from OP shock is associated with declined storage demand for oil while a negative contribution from GA shock is due to unexpected weakening of the global economy (Baumeister and Kilian, 2016).

The historical decomposition analysis allows us to have a clearer understanding of what was driving the changing dynamics of the global oil market over the last four decades. We observe the contribution of the three oil related shocks varied across the three sub-periods and this implies the parameters of oil market variables are subject to change under each

sub-period.

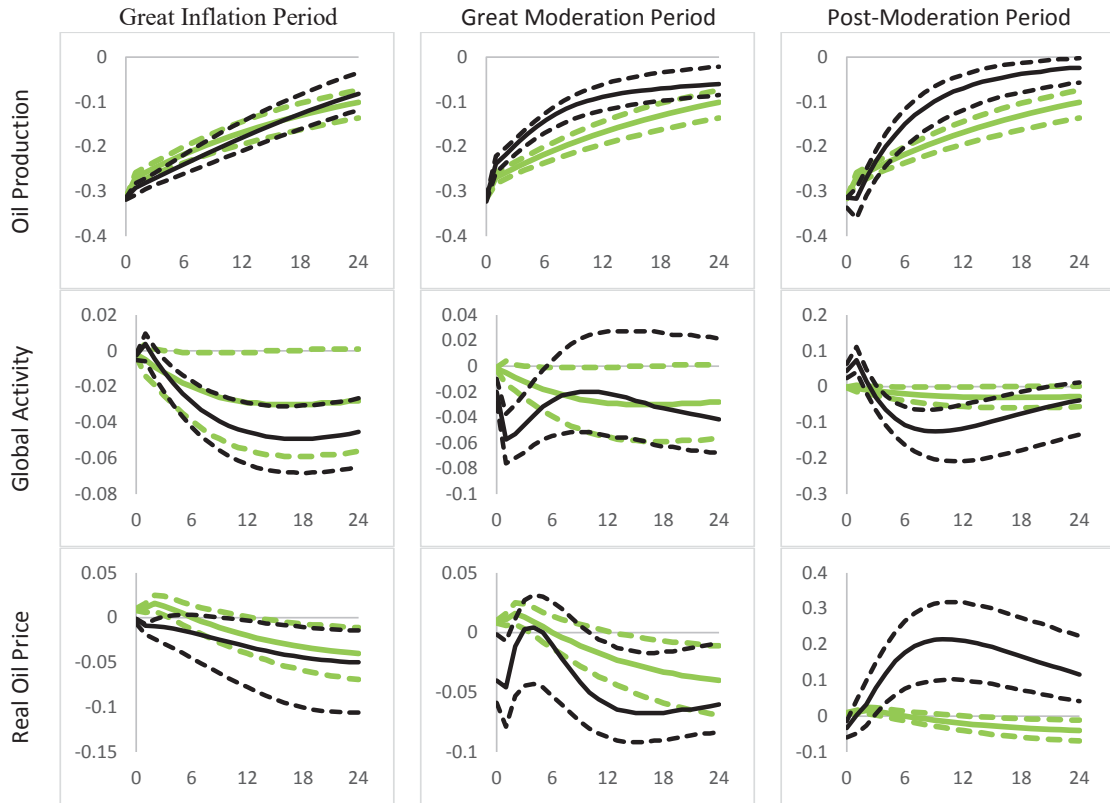
5.2 Impulse Responses

Impulse response functions estimated for each sub-period provide a quantitative comparison of time-variation in the responses of the oil market variables to the three oil related shocks. To aid comparisons, shocks of the same magnitude are applied across sub-periods, with these equal to one standard deviation of the corresponding shock estimated using the full sample, as reported in Table 6 for SVARMA(2,1). Each of the three columns in Figures 4 to 6 represents a sub-period. The unbroken black lines show estimated impulse responses associated with each of the sub-periods. The green lines provide impulse responses generated for the full period, similar as that shown in Figure 2. It should be noted that different vertical scales are employed across sub-periods.

Figure 4 traces the impact of oil supply shock (OS). The negative responses of oil production to one standard deviation OS shock across the three sub-periods appear to be similar and consistent with the full sample. In contrast to Bataa et al. (2016), we observe interesting differences in the responses of global activity. In the first and third sub-periods, the negative response of global activity after 12 months is respectively 2 and 4 times larger than that for the full sample. The OS shocks however have relatively little effect on global activity during the great moderation period. The responses of real oil price to an OS shock in the first sub-period is positive but short lived, lasting for less than three months. As stated in Lutkepohl and Netsunajev (2014), it could mean an oil supply disruption shock lead to greater rise in the US price level compare to the oil price, leading to a fall in the real price of oil. Real price of oil was also non-responsive to OS shock during the great moderation period. According to Bataa et al. (2016), due to excess capacity being at a record high, a production disruption can be quickly replaced and thus lead to minimal effects on oil price. In the post moderation period, a distinctive positive and persistent price responses compared to full period is observed. Given the sticky US price level, any effect on oil price is reflected directly on real oil price. Overall, OS shock plays an important role during the pre and post moderation periods.

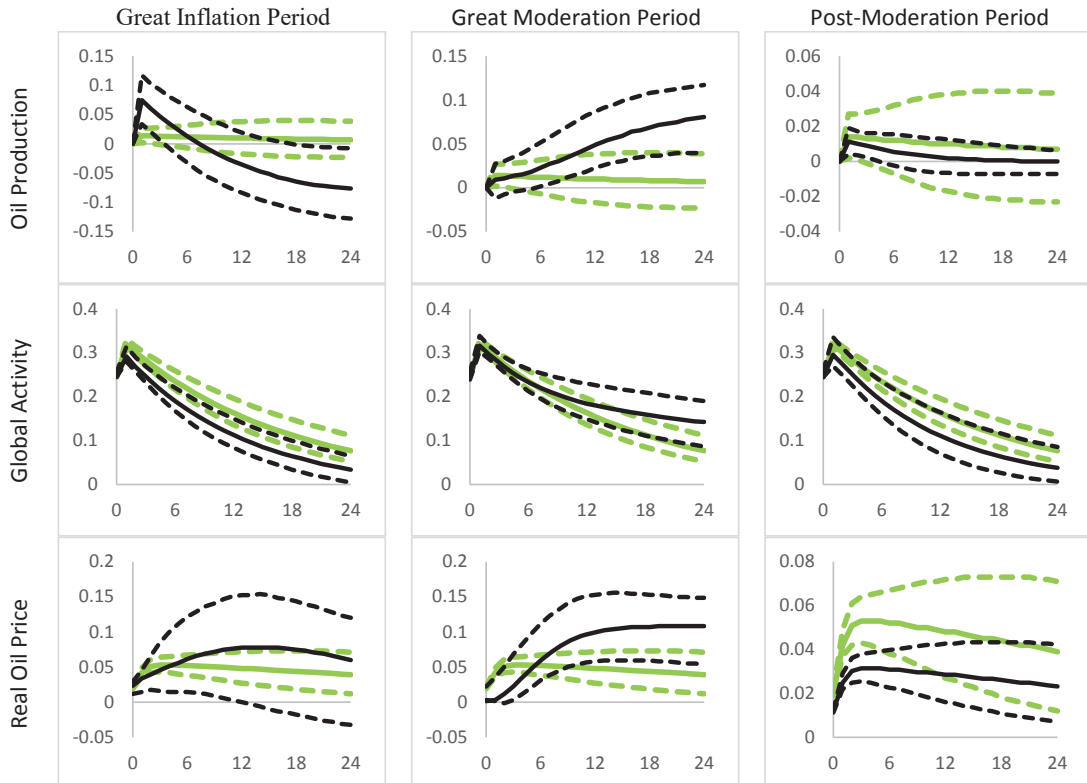
Figure 5 presents the responses to global activity (GA) shock over time. The responses of global economic activity to a GA shock is similar across time while the same cannot be said about the other two variables. In the great moderation period, oil production responded positively and persistently to a GA shock, indicating during this period oil production was based on market consideration. The responses however, appear to be more muted in the first and third sub-periods, implying that during these periods the production was set in the light of political and technological consideration respectively (Baumeister and Kilian, 2016). Though the GA shock appear to have positive and persistent effects on real price of oil, the intensity of the shock varies across all sub-periods. The largest effect was observed during the great moderation period, when the global economy was experiencing strong growth driven by surge in the demand for oil from emerging economies. In contrast to OS shock, GA shock appears to play an important role during the great moderation period.

Figure 4: Oil supply (OS) shock



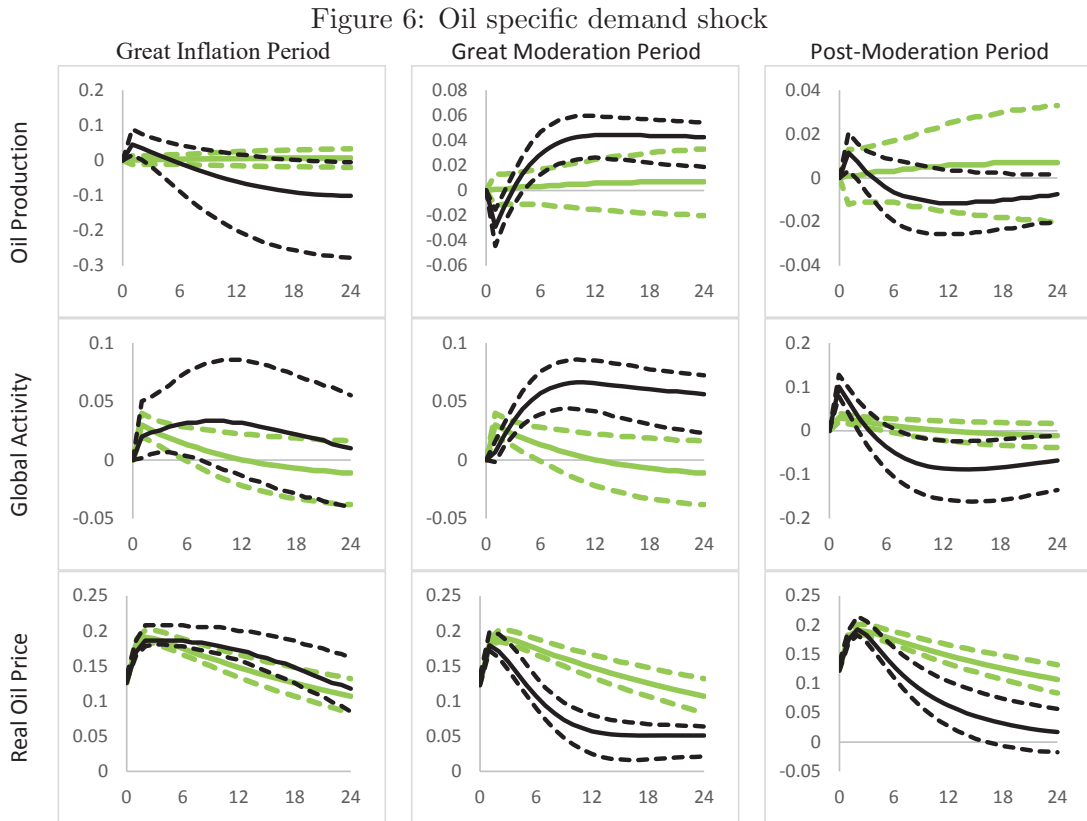
Note: Each of the three columns represents a sub-period. The green line provide impulse responses generated for the full period, similar as in Figure 2 while the black line provide the responses generated for each sub-period. The confidence bands shown as dashed lines.

Figure 5: Global activity shock



Note: See Figure 4.

Figure 6, shows the transmission mechanism for the effects of oil specific (OP) shocks. After having a short lived positive effect, the OP shock depresses the oil production in the first and third sub-periods. This can be associated with the rise in inventory capacity and weakening of global economic growth. In the second period, oil production responded positively, largely attributed to the increased inventory demand in anticipation of tightening oil markets due to strong global economic growth. The responses of global activity to an OP shock, varies over time. The global activity responded positively during the great moderation period and negatively during the post moderation period. In this regards the OP shock can be attributed as speculative shock, where during global economic expansion, this shock contributes positively to global activity while during weaker global environment it contributes negatively. The real oil price response positively across the three sub-period, however the responses are less persistent in the last two sub-periods.



Note: See Figure 4.

5.3 Variance Decomposition

In Table 7, the forecast error variance decomposition of the three oil market variables, for the pre moderation, great moderation and post moderation periods are presented. Results are reported for forecast horizons 6, 12, 24 and 60 months ahead. The results appear to have a varied path between the three sub-periods and illustrates how the dynamics of the oil market have altered between 1974 and 2017.

Focussing first on the pre-moderation period, the decompositions of the global activity and real oil price show that over a six months horizon, more than 90% of the variances are

Table 7: Forecast error variance decomposition of the oil market variables

Period	Pre-Moderation (1974:1–1985:12)			Great Moderation (1986:1–2007:12)			Post-Moderation (2008:1–2017:12)		
	OS	GA	OP	OS	GA	OP	OS	GA	OP
Horizon	Global Oil Production								
6	99.33 (0.99)	0.55 (0.77)	0.12 (0.22)	98.17 (0.38)	0.28 (0.76)	1.55 (0.39)	98.29 (1.85)	1.34 (1.68)	0.38 (0.17)
12	99.39 (0.88)	3.39 (0.29)	0.22 (1.18)	91.11 (5.56)	1.71 (2.56)	7.18 (3.00)	97.54 (0.57)	1.37 (2.13)	1.10 (2.71)
24	97.32 (8.16)	1.17 (1.31)	1.51 (6.85)	74.82 (11.36)	9.16 (6.31)	16.02 (5.05)	96.01 (5.47)	1.31 (1.85)	2.68 (7.31)
60	92.18 (18.37)	3.56 (3.93)	4.25 (14.44)	49.02 (16.98)	26.82 (10.88)	24.15 (6.10)	95.42 (9.08)	1.30 (1.16)	3.28 (10.24)
	Global Economic Activity								
6	1.47 (1.40)	97.88 (2.85)	0.65 (1.46)	2.44 (1.76)	93.72 (3.80)	3.85 (2.04)	1.84 (1.23)	96.07 (0.55)	2.09 (0.68)
12	8.52 (4.42)	90.20 (7.19)	1.28 (2.77)	1.80 (1.54)	87.09 (5.73)	11.11 (4.20)	6.42 (7.35)	89.82 (11.40)	3.76 (4.06)
24	24.22 (8.20)	74.21 (11.24)	1.57 (3.03)	2.16 (1.59)	80.17 (7.18)	17.67 (5.60)	9.21 (12.40)	81.91 (23.41)	8.88 (11.01)
60	34.94 (13.58)	63.30 (11.08)	1.77 (2.50)	4.98 (2.76)	71.47 (9.71)	23.49 (6.94)	9.07 (12.56)	79.27 (27.34)	11.66 (14.78)
	Real Oil Price								
6	1.62 (2.21)	5.41 (3.29)	92.97 (5.5)	1.00 (0.97)	1.01 (2.04)	97.99 (3.01)	3.08 (4.66)	17.56 (5.91)	79.36 (1.25)
12	4.58 (5.18)	8.90 (5.61)	86.52 (10.79)	2.30 (2.02)	7.36 (5.59)	90.33 (7.61)	12.70 (10.97)	18.32 (9.11)	68.98 (5.86)
24	16.53 (11.66)	12.93 (6.18)	70.55 (17.84)	7.73 (4.20)	20.24 (8.42)	72.03 (12.61)	22.48 (14.66)	17.82 (12.36)	59.70 (12.30)
60	36.18 (18.09)	11.46 (10.90)	52.37 (18.28)	10.46 (5.43)	34.87 (10.55)	54.67 (15.98)	24.90 (18.09)	17.67 (13.42)	57.43 (14.67)

Note: Standard errors are reported in the parentheses.

attributable to their own shocks. There is evidence that in the longer horizon of five years, OS shock is an important source of fluctuations for these two variables (i.e. its contribution is around 34.94% and 36.18% respectively). Interestingly, over the five year horizon, OP shock has relatively a minimal effect on global oil production and global activity while GA shock contributed around 11.46% of the variation in real oil price. According to our SVARMA model, oil supply shocks play a large role during this sub-period and a similar conclusion is also drawn by Bataa et al. (2016).

Different results are projected during the great moderation period. The decompositions of the oil market variables show that over a twelve months horizon, between 87.09% to 91.11% of the variances are attributable to their own shocks. Over a five horizon, the GA and OP shocks are important source of fluctuations. The contribution of GA and OP shocks to global oil production increases from 3.56% and 4.25% in the pre-moderation period to 26.82% and 24.15% in the great moderation period respectively. On the other hand the contribution of OS shock to global activity and oil price decline from 34.94% and 36.18% to 4.98% and 10.46%. This dramatic change is part of the narrative of recovery of the global economy and the discovery of new fields and improvements in the technology

The decomposition of global oil production in the post-moderation period is very similar to pre-moderation period, where over the five year horizon, more than 90% of the variation is dependent on its own shock. The contribution of demand driven shocks are minimal. Unlike the other periods, close to 80% of the variation in global activity is attributable to its own shock, while OS and OP contributed around 9% and 11% respectively. As for the real oil price the contribution of the OS (25%) has increased while GA (16.67%) has

decreased compared to the previous sub-period.

Across the three sub-periods, over the five year horizon, close to 50% of the oil price variation are attributable to the combination of OS and GA shocks. This reflects, both global oil production and global activity are important source of fluctuations for oil price. During the pre and post moderation period, OS shocks played an important role while during the great moderation period GA shock was important.

6 Conclusion

This paper builds a SVARMA model for investigating the evolution of the oil market for the last four decades. We observe over time, the fluctuations in the global oil production and economic activity have different dynamic effects on the real price of oil. To assess the impact of the changes in the supply and demand driven oil shocks, we document the evolution of the oil market over three distinctive sub-periods - pre-moderation, great moderation and post-moderation periods. This implies the parameters of oil market variables are subject to change under each sub-period and thus it can be misleading if constant parameters are assumed throughout the samples. Applied researchers tend to estimate a VAR model of order that is much higher than that selected by AIC or BIC; usually 24 lags to describe the oil market adequately and to obtain reliable impulse responses. The use of long order VAR however could be problematic for the sub-period analysis due to limited observations. In this regard, the use of a more parsimonious SVARMA model is deemed suitable.

To demonstrate the benefits of using a SVARMA model we compare the impulse responses generated by a SVARMA model with those generated by a SVAR. We find that the SVARMA model produces impulse responses that are consistent with the expected sign restrictions for impact responses in the oil market. SVARMA produce more accurate out-of-sample forecasts compared to the SVAR.

Historical decomposition, impulse responses and variance decomposition allow contrast of shocks propagating under different sub-periods. Both oil production and global activity are important source of fluctuations for oil price, but their relative contribution varies across sub-periods. During the great moderation period, the oil market is driven by demand related shocks originating from global activity and or oil-specific shocks. On the other hand, during the pre and post moderation periods, the market is mainly driven by oil supply related shocks. Broadly, the time path of the three shocks implied by our SVARMA model appear to be in line with that reported in Baumeister and Kilian (2016), who analysed the oil price fluctuations for the last forty years.

The empirical results based on the SVARMA methodology show notable differences in the supply and demand shock transmission under different sub-periods. Therefore, we concur with Bataa et al. (2016), that policymakers, financial analyst and economists who are interested in the movements of oil price and to understand the effects of various oil related shocks need to recognize that the nature of the world oil market has changed over the last four decades. The successful construction and implementation of the SVARMA model for oil market analysis, along with its promising impulse responses indicates the

suitability of this framework for studying the effects of oil market shocks on small open economies and transitional economies, especially for those economies that are not currently investigated due to limited data availability.

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Appendix

Appendix A: Identification and Estimation of a VARMA Model

We present the modelling of VARMA(p, q) process in three stages and they are briefly described in the following subsections.¹²

Stage I: Identification of the SCMs of the VARMA process

First, by strategically choosing $\mathbf{Y}_{m,t}$ and $\mathbf{Y}_{h,t-1-j}$, we identify the overall tentative order of the VARMA(p, q). The identification process, begins by searching for K SCMs of the most parsimonious possibility, i.e., SCM(0, 0), which is a white noise process by testing for the rank of $\mathbf{\Gamma}(0, 0, 0) = E(\mathbf{Y}_{0,t-1}\mathbf{Y}'_{0,t})$; where $\mathbf{Y}_{m,t} = \mathbf{Y}_{0,t}$ and $\mathbf{Y}_{h,t-1-j} = \mathbf{Y}_{0,t-1}$. If we do not find K linearly independent white noise scalar processes, we set $m = h$ and by incrementing m and j we search for the next set of K linearly independent scalar components.

Conditional on the overall tentative order (p, q) we then repeat the search process but this time searching for individual components. So starting again from the most parsimonious SCM(0,0), we sequentially search for K linearly independent vectors $(\alpha_1, \dots, \alpha_K)$ for $m = 0, \dots, p, j = 0, \dots, q$ and $h = m + (q - j)$ as for a tentative order of (p, q) each series is serially uncorrelated after lag q .

The test results from identifying the overall tentative order and the individual SCMs are tabulated in what are referred to as *Criterion* and *Root* tables. Reading from the Criterion table allows us to identify the overall tentative order of the model, while reading from the Root table allows us to identify the individual orders of the scalar components.

Suppose we have identified K linearly independent scalar components characterized by the transformation matrix $\mathbf{B} = (\beta_1, \beta_2, \dots, \beta_k)'$, the system in (1) can be rotated to obtain

$$\mathbf{z}_t - \mathbf{\Phi}_1^* \mathbf{z}_{t-1} - \dots - \mathbf{\Phi}_p^* \mathbf{z}_{t-p} = \mathbf{u}_t - \mathbf{\Theta}_1^* \mathbf{u}_{t-1} - \dots - \mathbf{\Theta}_q^* \mathbf{u}_{t-q}, \quad (14)$$

where $\mathbf{u}_t = \mathbf{B}v_t$, $\mathbf{\Phi}_j^* = \mathbf{B}\mathbf{\Phi}_j\mathbf{B}^{-1}$ and $\mathbf{\Theta}_j^* = \mathbf{B}\mathbf{\Theta}_j\mathbf{B}^{-1}$ for $j = 1$ to p (or q).

This rotated model incorporates whole rows of zero restrictions in the AR and MA parameter matrices on the RHS, as each row represents one identified SCM(p_i, q_i). However, note that obtaining the orders of SCMs does not necessarily lead to a uniquely identified system. For example, if two scalar components were identified such that $z_{r,t} = \text{SCM}(p_r, q_r)$ and $z_{s,t} = \text{SCM}(p_s, q_s)$, where $p_r > p_s$ and $q_r > q_s$, the system will not be identified as we need to set $\min\{p_r - p_s, q_r - q_s\}$ autoregressive or moving average parameters to zero. This process is known as the ‘‘general rule of elimination’’, and in order to identify a canonical VARMA model we set the moving average parameters to zero.

Stage II: Identification of the transformation matrix B

The space spanned by \mathbf{z}_{t-1} to \mathbf{z}_{t-p} is the same as the space spanned by \mathbf{X}_{t-1} to \mathbf{X}_{t-p} . So, for the transformed model (14), the right hand side of the equation can be written in terms of \mathbf{X}_{t-1} to \mathbf{X}_{t-p} instead of \mathbf{z}_{t-1} to \mathbf{z}_{t-p} without affecting the restrictions imposed by the scalar component rules.¹³ Hence, if we rotate the system by replacing $\mathbf{z}_{t-1}, \dots, \mathbf{z}_{t-p}$ with

¹²For further details, refer to Athanasopoulos and Vahid (2008a) and Tiao and Tsay (1989).

¹³A detailed explanation on this can be found in Athanasopoulos and Vahid (2008a).

$\mathbf{B}\mathbf{X}_{t-1}, \dots, \mathbf{B}\mathbf{X}_{t-p}$, the system can be represented in terms of the original series as follows:

$$\mathbf{B}\mathbf{X}_t = \mathbf{\Gamma}_1\mathbf{X}_{t-1} + \dots + \mathbf{\Gamma}_p\mathbf{X}_{t-p} + \mathbf{u}_t - \mathbf{\Theta}_1^*\mathbf{u}_{t-1} - \dots - \mathbf{\Theta}_q^*\mathbf{u}_{t-q}, \quad (15)$$

where $\mathbf{\Gamma}_i = \mathbf{\Phi}_i^*\mathbf{B}$ for $i = 1, \dots, p$ and with $\mathbf{\Gamma}_1, \dots, \mathbf{\Gamma}_p$ and $\mathbf{\Phi}_1^*, \dots, \mathbf{\Phi}_p^*$ satisfying the same restrictions as the right hand side of equation (14).

Some of the parameters in \mathbf{B} are redundant and can be eliminated. A brief description about the rules of placing restrictions on the redundant parameters are as follows:

1. Each row of the transformation matrix \mathbf{B} can be multiplied by a constant without changing the structure of the model; i.e, one parameter in each row can be normalized to one as long as this parameter is not zero. To make sure of this tests of predictability using subsets of variables are performed.
2. Any linear combination of a $\text{SCM}(p_1, q_1)$ and a $\text{SCM}(p_2, q_2)$ is a $\text{SCM}(\max\{p_1, p_2\}, \max\{q_1, q_2\})$. For all cases where there are two SCMs with weakly nested orders, i.e., $p_1 \geq p_2$ and $q_1 \geq q_2$, if the parameter in the i^{th} column of the row of \mathbf{B} corresponding to the $\text{SCM}(p_2, q_2)$ is normalized to one, the parameter in the same position in the row of \mathbf{B} corresponding to $\text{SCM}(p_1, q_1)$ should be restricted to zero.

Detailed explanations on these issues, together with examples, can be found in Athanassopoulos and Vahid (2008a).

Stage III: Estimation of the uniquely identified system

The identified model is estimated using FIML and is given by

$$\ln L(\mathbf{A}, \mathbf{\Sigma}) = -\frac{N-p}{2}(-\ln |\mathbf{B}| + \ln |\mathbf{\Sigma}_\varepsilon| - \ln |\mathbf{B}'|) - \frac{1}{2}\varepsilon_t' \mathbf{\Sigma}_\varepsilon^{-1} \varepsilon_t \quad (16)$$

thus

$$\ln L(\mathbf{A}, \mathbf{\Sigma}) \propto (N-p) \ln |\mathbf{B}| - \frac{N-p}{2} \ln |\mathbf{\Sigma}_\varepsilon| - \frac{1}{2}\varepsilon_t' \mathbf{\Sigma}_\varepsilon^{-1} \varepsilon_t \quad (17)$$

where $\mathbf{A} = [\mathbf{B} : \mathbf{\Phi}_1, \dots, \mathbf{\Phi}_p : \mathbf{\Theta}_1, \dots, \mathbf{\Theta}_q]$ and $\mathbf{\Sigma} = \text{var}(\mathbf{X}_t/\mathbf{X}_{t-1}, \dots, \mathbf{X}_1)$. As in Hannan and Rissanen (1982), a long VAR is used to obtain initial values of the parameters.

Appendix B: Oil Market Variables

Table 8: Data Descriptions and Sources

Variable	Description	Source
OS_t	Global Oil Production	Crude Oil Production (Thousand Barrels per day) (US Energy Information Website)
GA_t	Global Economic Activity	Real Bulk Dry Cargo Freight Rates (Kilian - UM Personal Website)
OP_t	World Oil Price Index	U.S. Crude Oil Imported Acquisition Cost by Refiners (Dollars per Barrel) (US Energy Information Website)