Theoretical and Applied Economics
Volume XXIV (2017), No. 2(611), Summer, pp. 197-212

An enquiry into the dynamics of real oil prices: A state space approach

Jaweriah HAZRANA
ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi, India
exuberantme2@gmail.com
Aisha NAZRANA
M.A. Economics, Jamia Millia Islamia, New Delhi, India
anikki85@gmail.com

Abstract. *This paper empirically investigates the nature of the underlying stochastic processes characterizing real oil prices using a Structural Time Series Model for the period 1960 to 2016. Based on the state space framework the STM decomposes the data into separate stochastic components by the maximum likelihood via the Kalman Filter. In contrast to the extant literature, this approach obviates the need to attain stationarity. Instead, it explicitly represents the non-stationarity properties of real oil prices through time varying structures and incorporation of structural breaks.*

The results establish that real oil prices are a composite of a long term trend, effect of shocks and short term fluctuations. The trend exhibits stochastic evolution and is punctuated by distinctive breaks triggered by unpredictable and significant events. Short term fluctuations are driven by transitory market influence and result in mean reverting patterns. Overall, the model captures, in a nonstructural framework, oil price movements and allows generation of forecasts based on the concrete implications of data characteristics.

Keywords: cycle, oil resources, real prices, structural time series model, trend.

JEL Classification: Q30, Q32, C51.

1. Introduction

Oil is widely recognized to be one of the most significant energy resources worldwide and is known for frequent price swings in times of shortage or oversupply. It has substantial influence on global economic activities. An increase in oil prices results in rising inflation and is detrimental for oil-importing countries while a decrease can lead to economic recession and political instability in oil-exporting countries due to curtailment of economic development. Besides absolute price levels oil price volatility can also translate into severe economic losses.

There have been abundant theoretical and empirical attempts to analysis and forecast crude oil price.(1) Empirical approaches can broadly be segregated into structure models and data-driven methods (Zhang et al., 2008). The former aim to define and analyze oil price movements in terms of a supply and demand framework (e.g. Huntington, 1994 and Yang et al., 2002). This approach is useful in highlighting and quantifying the mechanisms of price determination. However, it integrates a high degree of complexity and is constrained due to the scanty availability of related data. Moreover, in spite of using a fully specified model, irrespective of the number of explanatory variables included, the variability of the series will only be partly accounted for. Data based methods popularly utilize linear approaches where price is assumed to follow some kind of autoregressive specification (such as Autoregressive Moving Average and Autoregressive Conditional Heteroscedasticity). Under this framework the primary issue of contention is to test for the presence of unit roots to determine whether oil prices demonstrate trend or difference stationarity.(2) In the context of unit root testing Perron (1988) pointed out that it is crucial to select an appropriate specification for the trend function. If the data contain a unit root than application of the least squares method will result in severe size distortions. Similarly, if the data are generated by a trend stationary process but modeled as difference stationary the tests will be inefficient and lack power relative to the trend stationary process (Perron and Yabu, 2009). Another major complication arises if the series is impacted by structural breaks. The exclusion of breaks in a trend stationary process can lead to the spurious confirmation of unit root (Perron, 1989) and in a difference stationary process it can incorrectly confirm stationarity (Leybourne et al., 1998). Though several recent studies incorporate structural breaks in standard unit root tests these tests provide negligible information concerning the existence and number of breaks. Testing whether a series is characterized by a trend break is further complicated as the nature of persistence in the errors is generally unidentified. Notably results of existing studies are agnostic on this specific issue and display a perceptible lack of conformity. Implicitly assuming trend stationarity, Slade (1982) concludes that the evolution of eleven resource prices, including oil, follow a U-shaped time path. Slade (1988) shows that the data are non-stationary and proposes that the series are characterized by uncertainty not captured by deterministic models. Berck and Roberts (1996) update the same data to 1990 and apply the Lagrange-Multiplier and Dickey-Fuller tests to find that resource prices are non-stationary. Still with the same series, Ahrens and Sharma (1997) use multiple unit root tests to conclude that five series are non-stationary while six are trend stationary. Lee et al. (2006) incorporate two endogenously determined structural breaks and contradict non-stationarity and support trend stationarity. In contrast to unit root tests, an innovative dimension to understanding price movements was provided by Pindyck (1999). Firstly, the study went beyond unit root testing and applied a state space approach and the Kalman Filter to establish that the prices of energy products (oil, gas and coal) fluctuate around a stochastic long-term trend over the period 1870 to 1996. Secondly, the study explicitly related its empirical findings to standard resource economic framework and showed that they are consistent with a basic model of exhaustible resource production.

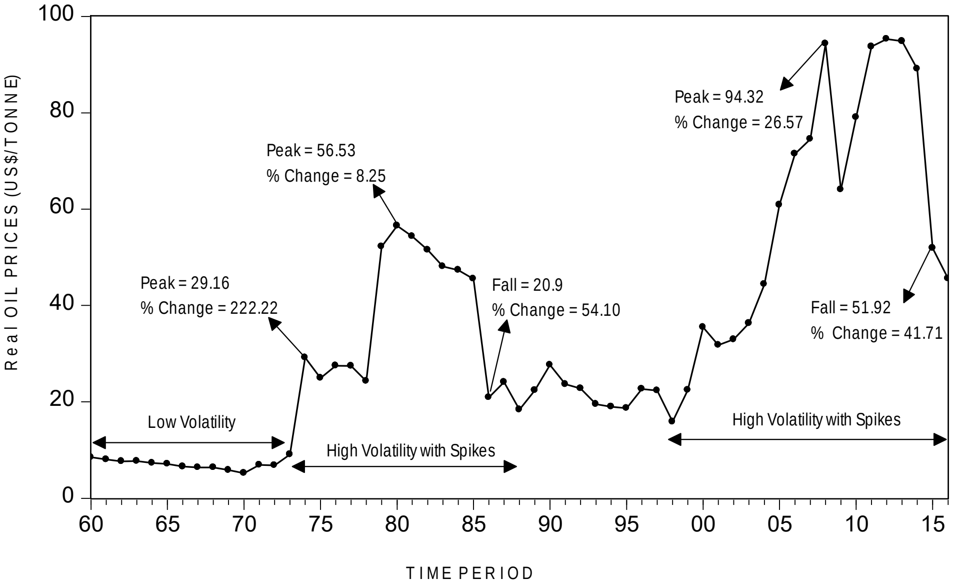
Motivated by the above mentioned considerations the present study seeks to complement the existing literature by using a state space approach to obtain a comprehensive derivation of oil price movements. To this end, it applies the Structural Time Series Model (STM) to categorize the separate stochastic components defining oil prices over the period 1960 to 2016. Additionally it allows integration of structural breaks and additive outliers in the form of intervention analysis and generates forecasts. Based on the state space framework and estimated using the Kalman Filter, this class of model has been successfully applied to metals (Alagidede, 2009) and agricultural commodity (Rezitis et al., 2015) price movements. However, their utilization in the context of energy modelling is somewhat limited. Furthermore understanding the characteristics of the data is mandatory to determine the admissibility of related theoretical frameworks. For example, though it is not explicit most studies on resource prices are based on Hotelling's (1931) principal which states that the net price of an exhaustible resource will increase in accordance to the interest rate in competitive market equilibrium yielding a rising price trajectory over the long term. Modifications of the basic Hotelling model propose that the price could initially decline, as reserve accumulation or technical advancement cause the marginal extraction cost to fall, but over the long term the depletion effect will offset the impact of technological change causing price to rise. Building on these Hotelling style deterministic models several tests establish increasing or U-shaped price paths to highlight the depletion effect of resource use (Krautkraemer, 1998) while others settle to conduct unit root tests. However when analyzing whether a resource is growing increasingly scarce, based on trend evaluation, it is necessary to select the correct specification for the trend function. If the data surface in stochastic patterns (for example due to demand shifts or reserves growth) then the standard Hotelling framework and its implication will not be applicable. The situation is further complicated due to the possibility of unaccounted structural breaks, arising in response to market disruptions (for example the oil price shock of the 1970s). On the other hand, if the data demonstrate a tendency for short run deviation testing for long term growth will be inefficient and will lack power to explain high price runs. In this context, the STM analyzes the data generation process without the mandate of unit root pretesting and its empirical results facilitate easy economic interpretation. Several key results surface from the present research. Estimates from the STM indicate that the long term trend is best captured by a stochastic rather than deterministic specification. The trend is rather characterized by two breaks. These are both statistically significant and are of economic importance for explaining price behaviour. The findings also document the frequency and duration of oil price cycles. This result can be utilized for formulating policies to regularize trade shocks and its resultant macroeconomic effects arising due to price disruptions as well as to design counter cyclical policies to manage price fluctuations. Finally the model performs well in forecasts. Section 2 commences with a descriptive analysis of the data and discusses the methodology applied in the present research. Section 3 outlines the empirical results derived from estimating the Structural Time Series Model. Section 4 provides a discussion of the results and concludes.

2. Data and modeling approach

The data set utilized in the present study consists of annual average spot price of Brent, Dubai and West Texas Intermediate which are assigned equal weights for the duration of 1960 to 2016. It is measured in US dollars per barrel ($/bbl) and obtained from the World Bank. Following the literature the series is deflated using the Wholesale Price Index for all commodities and is expressed in 2010 constant terms. Notably, while several studies utilize long period data sets the present analysis is limited to six and a half decades of data mainly because a stochastic modelling approach increases the likelihood of data snooping, i.e. for a long duration time series a single or more structural changes will be detected that might not have any empirical significance and explanation to its occurrence.

The logarithm of real oil prices over the complete sample period is exhibited in Figure 1. The graph clearly manifests that the series is characterized by several specific features. First, a visual examination is adequate to indicate that the data does not demonstrate a deterministic trend. Prices were generally declining until 1970, after which there is no clear trend. Another wave of falling prices was observed post the mid-1980s and was succeeded by a rising trend. Prices declined in 2008-2009 and then more recently in 2014, representing one of the most dramatic fall in oil prices over the sample period. Second, there is a strong suggestion of changes in the trend line in the early 1970s (around the time of the first oil shock) and mid-1980s (around the time of the oil glut) and the occurrence of occasional spikes indicates the possibility of outliers. Third, the data displays a high degree of fluctuations with possible trend reversions.

Figure 1. *Evolution of Real Oil Prices, 1960-2016*



2.1. The structural time series model

The Structural Time Series Model is a rich and flexible class of models which is popularly utilized to decompose a dependent variable into separate latent components of trend, seasonal, cyclical and irregular terms. These terms are defined through stochastic evolution over time and their segregation allows direct economic interpretation (Harvey and Shepard, 1993). The formulating rationale behind the STM is that the unobserved level component is the true value which is subject to a disturbance captured by a noise component resulting in the observed value. So, the different terms represent the true values that can be examined conditional to the addition of noise. The STM is highly suitable for data that integrate stochastic structures that frequently appear in observed series as the underlying data-generating processes (Harvey, 1989). Its application to real oil prices can serve to shed light on both long and short term movements. Being a special case of state space models STM is estimated by the maximum likelihood via the Kalman Filter and specified as follows:

$$y_t = \mu_t + \gamma_t + \psi_t + \sum_{j=1}^{i} \lambda_j d_{j,t} + \varepsilon_t \qquad \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2) \quad t = 1, 2, \ldots, T \qquad (1)$$

Where y_t is the real oil price, μ_t is the trend, γ_t and ψ_t are the cyclical terms, $d_{j,t}$ is the dummy variable and ε_t is the irregular component. The trend represents the long-term growth of the response series and can include level and/or slope. A level denotes the definite value while the slope captures the integral tendencies of the data. The latter is included if the data demonstrates a constant growth pattern. The trend can be modelled as a Random Walk Model (RWM) or Local Level Trend (LLT) model. The former is suitable for flat and slow turning series and is specified as follows:

$$\mu_t = \mu_{t-1} + \eta_t \qquad \text{where } \eta_t \sim NIID\left(0, \sigma_\eta^2\right) \tag{2}$$

Inclusion of the slope in the RWM yields the LLT consisting of a stochastic level and slope.

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad \eta_t \sim NIID\left(0, \sigma_\eta^2\right) \tag{3}$$

$$\beta_t = \beta_{t-1} + \xi_t \qquad \xi_t \sim NIID\left(0, \sigma_\xi^2\right) \tag{4}$$

Restrictions can be imposed on equations 3 and 4 to derive specific cases. If $\sigma_\eta^2 = 0$ the trend is smooth and the model converts to a Smooth Trend Model (SMTM), if $\sigma_\xi^2 = 0$ the trend displays a fixed slope and if $\sigma_\eta^2 = \sigma_\xi^2 = 0$ it becomes deterministic. A cycle component captures the short term movements in the data series which can be modelled to arrest complex periodic patterns of varying periods and amplitudes. Each cycle is characterized by a combination of sine and cosine waves.

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} cos\lambda & sin\lambda \\ -sin\lambda & cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} v_t \\ v_t^* \end{bmatrix} \tag{5}$$

Where $v_t \; and \; v_t^*$ are independently distributed as $N(0, \sigma_v^2)$ and the damping factor $(0 < \rho < 1)$ is included to display the pace at which fluctuations dampen. The fourth term in equation 1 is the irregular component. It reflects unexplained variation in the data and is assumed to be Gaussian white noise.

2.2. Intervention tests

Considering the potential presence of intertemporal changes in the characteristics of the data, structural breaks (SB) and additive outliers (AO) are identified and included in the analysis. The former occur in response to a permanent shift (upwards or downward) in the series while the latter represent an abnormal value in real oil prices. The de Jong and Penzer (1998) approach is applied to identify both SB and AO. Once identified these are included using dummy variables in the specified STM.

According to the de Jong and Penzer (1998) approach the fitted model is considered to be the null and any value and structural breaks that are not adequately accounted for by it are recognized as outliers. To appropriately represent the data generation process it is specified as follows:

$$y = (y_1^{'}, \dots, y_n^{'})' \tag{6}$$

Equation 6 specifies the null model and states that y has mean **0** and covariance matrix $\sigma^2\sum$**.** The objective is to test for the existence of deviations from the null model by the inclusion of an intervention variable given as follows:

$$D = (D_1^{'}, \dots, D_n^{'})' \tag{7}$$

The alternative hypothesis is specified as

$$y \sim (D\delta, \sigma^2\sum) \tag{8}$$

Equation 8 reduces to the null hypothesis in the situation where $\delta = 0$. Notably in the case of a univariate series (like the present study) with δ, $\mathbf{D}$ specifies a column vector called the intervention signature. The intervention can be a measurement intervention that captures a single outlying data point (modelled through impulse intervention), a structural break that causes the level of the series to shift over the long term (modelled through step intervention) or a switch intervention which represents the presence of extreme values on either side of the current level of the series (modelled through step intervention). Notably the graph in Figure 1 is highly suggestive of both outliers and structural breaks.

Given $\boldsymbol{D}$ and $\sum$ the Generalized Least Squares is utilized to approximate the intervention parameter δ.

$$\hat{\delta} = S^{-1}s, cov(\hat{\delta}) = \sigma^2 S^{-1}, \tag{9}$$

Where $s = \boldsymbol{D}'\sum^{-1}\boldsymbol{y}$, $\quad S = \boldsymbol{D}'\sum^{-1}\boldsymbol{D}$, (10)

Where s is the intervention contrast. The test of the hypothesis of no shock i.e. $\delta = 0$ is founded on the following.

$$\hat{\delta}'\{cov(\hat{\delta})\}^{-1}\hat{\delta} = \sigma^{-2}s'S^{-1}s \tag{11}$$

σ^2 can also be replaced by normal based maximum likelihood estimate where

$$\hat{\sigma}^2 = (y'\sum^{-1}\boldsymbol{y})/n, \tag{12}$$

Equation 12 yields the test statistic

$$\tau^2 = \hat{\sigma}^{-2}s'S^{-1}s \tag{13}$$

The estimate σ^2 can be modified to include the intervention as follows

$$\hat{\sigma}^2 = n^{-1}(\boldsymbol{y}'\sum^{-1}\boldsymbol{y} - \boldsymbol{s}'\boldsymbol{S}^{-1}\boldsymbol{s}) \tag{14}$$

The statistic τ^2 has an approximately χ^2_p distribution, where p denotes the rank of $\boldsymbol{S}$**.** Dividing each component of $\hat{\delta}$ by its estimated standard error provides τ the analog of the usual regression *t* statistic. Finally neither D nor $\sum$ is known. In general $\sum$ **i**s a function of hyperparameters estimated under the null. The presence of shocks may distort these estimates and thus affect the test statistics.

The above method provides an efficient way to judge the abnormality of a data point in the tested series by computing SB and AO regression coefficients and their standard errors. Table 1 presents the results of the de Jong and Penzer (1998) intervention test for real oil prices.

Table 1. *Structural breaks and additive outliers in real oil prices*

S. No.	Date	Break type	Estimate	Chi-square
1	1974	Structural break	0.96839*	15.83
2	1986	Structural break	-0.69258*	11.271
3	1978	Additive Outlier	-0.42599*	8.651

*Significant at the 5% level.

3. Results

In this section the results of the Structural Time Series model are presented. This methodology comprises of interpretable components, such as trends, cycles, irregular and intervention terms, which are specified as stochastic progressions dependent on normally distributed disturbances. The output parameters of the STM consist of variances of the disturbance terms, damping coefficients and cycle frequencies. Estimation of equations 1 to 5 is carried out in a step wise procedure where first the variance hyperparameters are attained and then the trend and cyclical terms are extracted based on the smoothing algorithm contained in Koopman et al. (2009).

The parameters are provided in Table 2. Summing up the variances of all the components allows to derive variation in real oil prices (σ_y^2). The level is deterministic while the variance of the slope is different from zero. This result somewhat contradicts the findings obtained by several earlier studies which establish a deterministic trend (overall rising or U-shaped) for oil prices (e.g. Slade 1982). With reference to the cyclical components, the short cycle (Cycle-1) has a variance of 0.01722 while the longer cycle (Cycle-2) displays an insignificant variance. Clearly Cycle-1 is stochastic while Cycle-2 evolves in a deterministic pattern. Interpretively, the cycles in oil prices arise due to a multitude of demand and supply influences, geopolitical events, technological advances, and changes in market structure. These incidences involve a high measure of arbitrariness causing the timing, periodicity and amplitude of the cycles to exhibit stochastic properties. Cycle-1 lasts for the duration of 9.44 years while Cycle-2 displays a period of 25.87 years. The duration of Cycle-1 corresponds with the length of a typical business cycle. The interval of Cycle-2 is quite long but can be attributed to capital intensity, long gestation period, and uncertainties prevailing in upstream oil investment projects. In addition, both cycles are persistent, with a damping factor of around 0.58 for Cycle-1 and 1 for Cycle-2. For validation, full sample estimates are provided in the right column and are reasonably similar.

The q-ratios are calculated and reported in Table 2. They are defined as the ratio of each variance to the largest and are effective is estimating the relative contribution of separate components to the data. Results show that majority of the variation in oil prices is attributable to Cycle-1 followed by the slope. The q-ratio of the irregular component is close to zero confirming that the other included components account for all the movement in the data.

The regression estimates of the trend parameters and intervention variables are displayed in the last panel of Table 3. The long term trend is punctuated by two structural breaks and a single outlier (see results in Table 1). All three interventions are statistically significant as evaluated by the reported statistics and capture major economic events. Break-1974 arrests the Arab oil embargo by the Organization of Petroleum Exporting Countries (OPEC) and was accompanied by the stock market crash. This episode represents the most striking rise in real oil price of modern history where the nominal price rose fourfold over the course of half a year. Post 1974 oil prices remained relatively low and when adjusted for inflation they present a moderate decline. Outlier-1978 reflects this decline when many economists considered that oil prices were unsustainably low (Gately. 1986) prior to the Iranian revolution. Finally, Level-1986 captures the popular oil glut. Post 1980 there was global decline in demand for oil due to overproduction resulting in global surplus. Oil price continuously declined for a period of six years culminating in a 46 percent price drop in 1986 (Gately, 1986) and almost equaling its level prior to 1973.

Table 2. *Estimation results for real oil prices*

Hyperparameters	In sample period (1960-2009)	Full sample period (1960-2016)
Level (σ_η^2)	0 (0)	0 (0)
Slope (σ_ξ^2)	0.00000613* (0.00036)	0.00002056* (0.001408)
Cycle (σ_γ^2)	0.01722* (1)	0.01430* (1)
Cycle (σ_ψ^2)	1.957648E-7 (1.14E-05)	1.44E-07 (9.99E-06)
Irregular (σ_ε^2)	1.03727E-10 (6.02E-09)	1.259804E-8 (8.81E-07)
Cycle-1		
Duration ($2\pi/\lambda$)	9.40794*	6.77887*
Damping Factor (ρ)	0.58144*	0.59991*
Frequency (λ_C)	0.66786	0.92688
Variance (σ_ψ^2)	0.02602	0.02234
Cycle-2		
Duration ($2\pi/\lambda$)	25.87982*	25.66335*
Damping Factor (ρ)	1.00000*	0.99357
Frequency (λ_C)	0.24278	0.24483
Variance (σ_ψ^2)	0.06324	0.11202
Coefficients of final state		
Level (μ_t)	3.690881*	3.976540*
Slope (β_t)	0.042684	0.038561
Level-1974	1.00431*	0.96780*
Level-1986	-0.77938*	-0.77981*
Outlier-1978	-0.43265*	-0.43202*

Notes: q-ratios are reported in parentheses.
*Significant at the 5% level.

Figure 2 shows the decomposition of real oil price. The first graph in the upper panel illustrates that the long-run slope component of the trend is stochastic with a small growth rate. The second graph shows the long-run trend along with the intervention effects. For clarity, the actual data points are also included. It is evident that Level-1974 led to a dramatic upward shift in the trend and Level-1986 caused it to move downwards. The smoothed cyclical components are displayed in the lower panel. Cycle-2 displays a large amplitude causing the data to deviate from its long-run trend.

Considering a cycle to be composed of a period from peak to trough and trough to peak there is evidence of one complete and 2 half cycles. The amplitude of Cycle-1 remains within the range of -0.25 to 0.25 but rises towards the end of the sample period. This result is consistent with the literature which proposes that price volatility increased in the mid-2000s. Oil prices surged in mid-2000 reaching a record high in 2008 fuelled by high demand relative to supply. A decline occurred in 2009 with the onset of the global financial crises but a strong recovery in global oil demand combined with slower supply growth soon revived oil prices. From 2011 to mid-2014 oil prices remained stable but then declined to reflect one of the most dramatic falls till date. Notably this period was characterized by the influence of market specific factors such as positive oil supply shocks, increased production in non-OPEC countries, sustained production levels by OPEC and declining demand. This recent price decline is broadly comparable to the magnitude of price fall in 1986 (when OPEC reversed production cuts) and 2008-2009 (due to the global financial crisis). The former was primarily supply driven and the latter was mostly influenced by breakdown in demand. In contrast, the recent fall in oil price appears to be a mix of the two. These observations combine to cast a doubt on whether the data would have demonstrated an increasing trend, since the mid-1970s, in the absence of the included intervention variables and cyclical movements.

Figure 2. *Decomposition of oil prices*

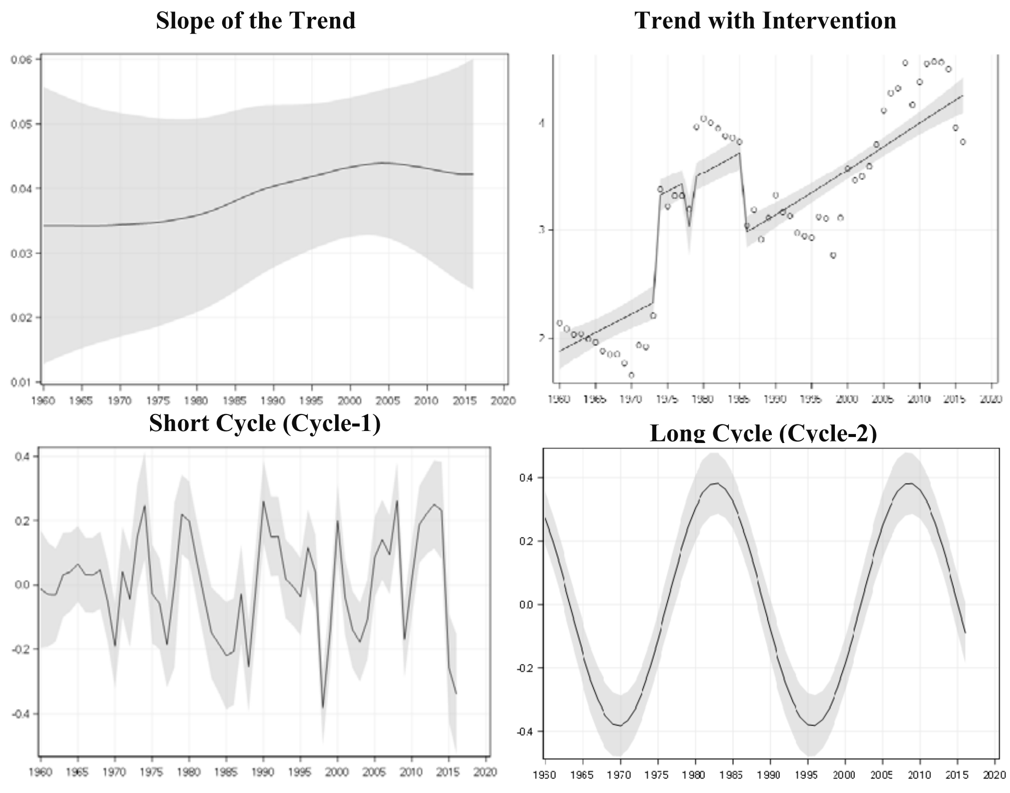


Table 3 presents the diagnostics and goodness-of-fit statistics for the estimated model. These include the mean squared error, the root mean squared error, the mean absolute percentage error, the maximum percentage error, the adjusted R^2 and R^2. The adjusted R^2 and R^2 show a reasonable fit and the statistics presented in Table 3 do not indicate any deficiencies in the estimated model.

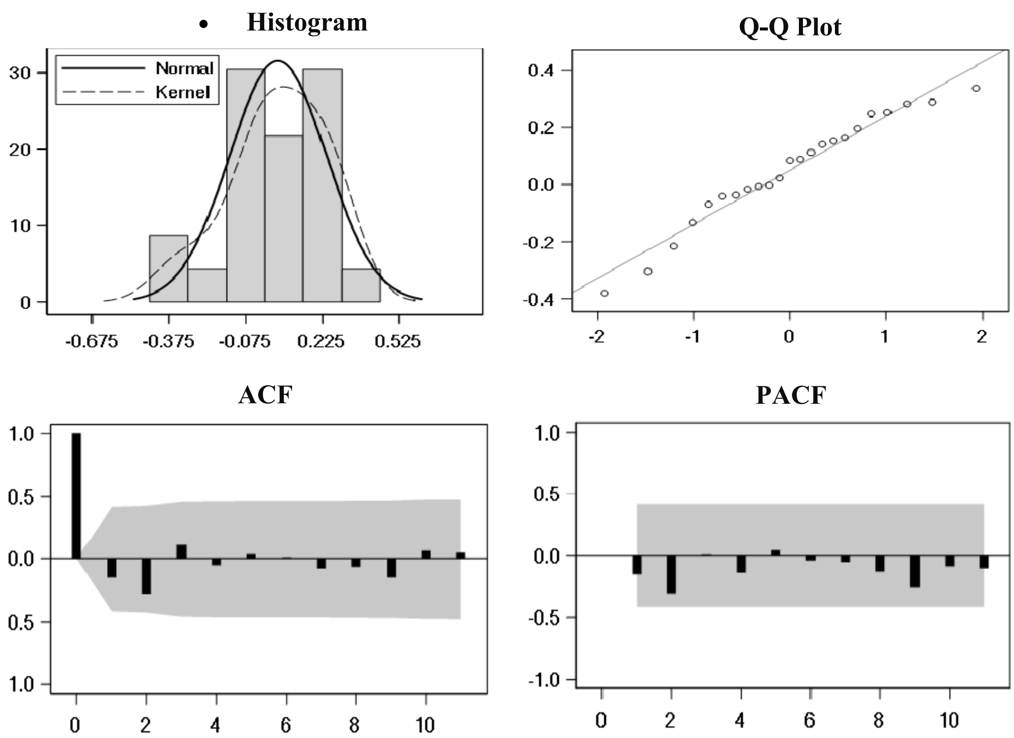
Table 3. *Fit statistics based on residuals for real oil prices*

Statistics	In sample period (1960-2009)	Full sample period (1960-2016)
Mean Squared Error	0.03674	0.03894
Root Mean Squared Error	0.19168	0.19733
Mean Absolute Percentage Error	4.52741	4.67147
Maximum Percentage Error	9.43231	9.24999
Adjusted R^2	0.79189	0.85696
R^2	0.85811	0.89149

Note: Number of non-missing residuals used for computing the fit statistics = 23.

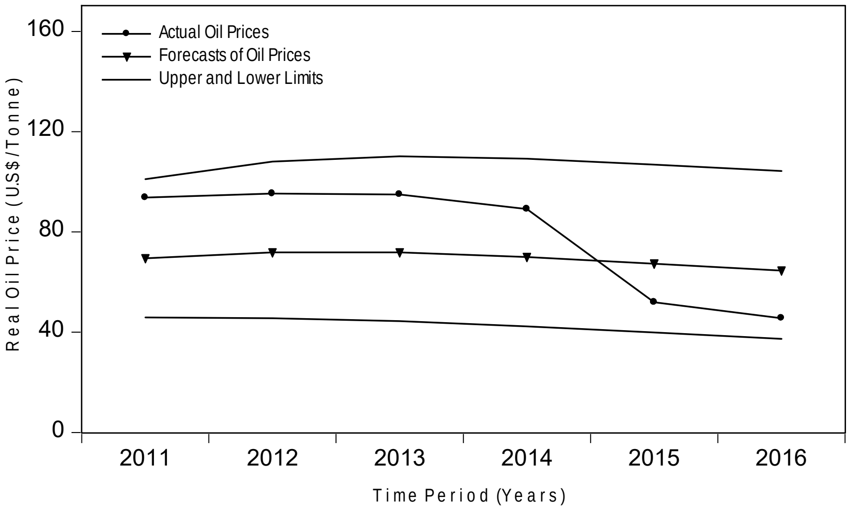
Figure 3 displays the residuals based on the standardized one-step-ahead prediction errors as defined in Koopman et al. (2009). For an accurately specified model these are normally and independently distributed. The histogram and Q-Q plot displayed in the top panel do not exhibit any violation of normality. The lower panel confirms that the autocorrelation and partial autocorrelation functions do not violate the assumption of whiteness. The statistics (Table 3) and graphs (Figure 3) are the means of checking the validity of the model and suggest that it is robust.

Figure 3. *Residual diagnostics*



Generation of forecasts is an important part of modeling time series patterns and gauging its statistical adequacy as it provides the means of projecting the past into the future by attaching suitable weights to the past and current observations. STMs are formulated directly in terms of unobserved components and are effective not only for capturing the salient features of the data but also for forecasting. The model in the present section is estimated with the first 50 data points and the last six years are reserved for out-of-sample forecasts. The actual values, forecasts and 95% confidence bands are illustrated in Figure 4. The forecast seem to be generally satisfactory and do not deviate more than two standard errors, even in the case of recent price descent, from the observed value establishing that the estimated model is accurate. This result validates that for oil prices a stochastic trend model with cycles and structural breaks provides an adequate and flexible account of the data. Notably identifying the stochastic process is instrumental in determining reasonable forecasts which play an important role in macro economy policy making and are important for investment decisions. Moreover, the trend specification of the estimated STM is close in spirit to the model proposed and estimated by Pindyck (1999) which also utilized annual data but for a longer time span.

Figure 4. *Real oil price forecasts (2009 to 2014)*



4. Discussion and conclusions

Oil is a classic case of an exhaustible resource and its price has significant theoretical implications which govern its utilization. Trends in oil prices have always been an important research area for economists, not only because of its non-renewability but also due to its significant impact on the world economy. An important task for researchers is to relate findings of empirical tests to the existing theory. As emphasized in Section 1, multiple research works focus on the behavior of oil price but don't facilitate drawing theoretical inferences from their results. Specifically the popularly applied autoregressive model based tests are unequipped in this regard. The present study seeks to contribute in this direction by accounting for separate structural components inherent in real oil prices and shedding light on its theoretical implications.

One of the most widely cited and referred work is Hotelling's (1931) theoretical model of exhaustible resources. In its basic form it states that the net price of an exhaustible resource, which is an economic measure of resource scarcity, should grow at the rate of interest. This prediction is referred to as the Hotelling rule (Krautkraemer, 1998). Under a perfectly competitive market the rule implies that the market price minus marginal costs will grow at the rate of interest therefore the natural resource price should be increasing over time. Extensions to the model also establish a U-shaped long-run price trajectory (e.g. Pindyck, 1978 and Slade, 1982). Based on this fundamental rationale of a long term deterministic growth several studies analyze price trends of natural resources, such as oil, assuming trend stationarity or conduct unit root tests. Both these approaches are less informative about the underlying data generation process and rely on mechanical procedures with the possibility of spurious results. Furthermore, though Hotelling's theory and its extensions are elegant, observed oil price data over the past decades suggests that is evolves in patterns more complex than either deterministic trends or unit root processes. For example real oil prices exhibit a steady declining trend in the beginning of the 1960s and sharp fall between 1982 and 1986 while a rising trend prevailed during 1970s and post 2000. These periods also exhibited the impact of high fluctuations and multiple spikes.

The key innovation in this paper is the use of structural time series model to overcome the problems inherent in extant studies. It builds on the conception that oil prices are characterized by complex behavioral patterns that can be represented appropriately within a state space framework. The STM is set up to consist of a stochastic trend, cycle and irregular components which are extracted by the state-space smoothing algorithm. This approach yields several interesting facts about real oil prices. Firstly, oil prices have not shown a persistent increase over the past decades rather the long term trend is stochastic and impacted by three significant interventions. By modeling the trend with interventions it was observed that oil price is sensitive to market disruptions resulting in trend shifts. These disruptions occur due to some unusual and significant events in oil markets such as political issues or decisions of oil exporting countries. This result for the long term trend contradicts some of the earlier studies which establish deterministic price paths (for example Slade 1982) but is largely in agreement with Pindyck's (1999) who suggested that over the long term price trajectory will be time varying to reflect the impact of demand shifts, reserves growth and technical change. Moreover, the discovery of breaks corroborates the findings derived by Lee et al. (2006). Notably omission to discover structural breaks can lead to erroneous and inaccurate interpretation of trends resulting in unwarranted policies that may raise issues associated with oil price fluctuations. Secondly, the analysis presents substantiation of persistent cyclical movements and documents their frequency and duration. The first cycle spans a duration of 9.4 years while the second one is for 25.8 years. The speed with which oil price cycles rise and fall are quite persistent and estimated to average 0.79 for both cycles. This cyclical behaviour is an aspect that is not reflected in the Hotelling's theory and unaccounted for in most empirical tests which tend to focus primarily on the trend component of oil prices. However, oil prices present high volatility implying a lack of steadiness that cannot be explained by trend analysis. For example, oil prices post mid-1970s and mid-2000s present periods of high volatility that are effectively explained by the existence and persistence of cycles. Moreover the validation of cyclical behaviour holds major significance for related policies concerning stabilization, consumption and income of both producer and consumer economics. The above results cast a doubt on Hotelling style deterministic trends in oil prices. A general conclusion of this study is that oil price developments tend to be more complex than captured by the assumption of exponentially increasing prices. While several tests in the literature propose that prices increase in the long run yet the more superior fit of oil prices is the one that accounts for the underlying stochastic processes in oil prices. This approach captures the multiple influence of long term variables (such as demand shifts, technological change, reserves growth and site development) and small fluctuations in the short term (primarily due to supply-demand disequilibrium) and structural breaks (significant market disruptions) which Hotelling, and associated tests, do not account for. The STM class of model also provides a favorable vehicle for forecasting.

In conclusion the promise of the above applied approach derives largely from the fact that it captures in a nonstructural framework what basic theory tells us should be driving price movements. The framework presented here can effectively be extended to other nonrenewable resources while accounting for market specific interventions.

Notes

(1) While the literature on oil prices is extensive (see Hamilton, 2008) the present study focuses on the strand that seeks to test Hotelling theory of exhaustible resources utilizing real prices.

(2) A series is defined to be strictly stationary when its joint probability distribution does not vary over time periods. Weak stationarity is defined when its mean and variance are constant and the autocovariance depends only on the length of the lag (Hamilton, 1994).

References

Ahrens, W.A. and Sharma, V.R., 1997. Trends in natural resource commodity prices: deterministic or stochastic?. *Journal of Environmental Economics and Management,* 33(1), pp. 59-74.

Alagidede, P., 2009. Trends, cycles and seasonal components in primary commodities: State Space Modelling and the Kalman Filter. In: *15th Annual Conference on Econometric Modelling for Africa.* Cairo, Egypt, 7-8 July 2010.

Berk, P. and Roberts, M., 1996. Natural resource prices: will they ever turn up?. *Journal of Environmental Economics and Management,* 31(1), pp. 65-78.

De Jong, P. and Penzer, J., 1998. Diagnosing shocks in time series. *Journal of the American Statistical Association,* 93(442), pp. 796-806.

Gately, D., 1986. Lessons from the 1986 oil price collapse. *Brookings Papers on Economic Activity,* 2, pp. 237-284.

Hamilton, J.D., 2009. Understanding crude oil prices, *Energy Journal,* 30(2), pp. 179-206.

Hamilton, J.D., 1994. *Time Series Analysis*. Princeton: Princeton University Press.

Harvey, A.C. and Shephard. N. 1993. Structural Time Series Models. In: C.R. Rao and H.D. Vinod, ed. *Handbook of Statistics*, Amsterdam: North Holland. pp. 261-302.

Harvey, A.C., 1989. *Forecasting, Structural Time Series Models and the Kalman Filter*. London: Cambridge University Press.

Hotelling, H., 1931. The Economics of exhaustible resources. *Journal of Political Economy,* 39(2), pp. 137-175.

Huntington, H.G., 1994. Oil price forecasting in the 1980s: what went wrong?. *The Energy Journal*, 15 (2), pp. 1-22.

Koopman, S.J., Harvey, A.C., Doomik, J.A. and Shephard, N., 2009. *Structural Time Series Analyser, Modeller and Predictor,* London: Timberlake Consultants.

Krautkraemer, J.A., 1998. Nonrenewable resource scarcity. *Journal of Economic Literature,* 36(4), pp. 2065-2107.

Lee, J., List, J. and Strazicich, M.C., 2006. Non-renewable resource prices: Deterministic or stochastic Trends?, *Journal of Environmental Economics and Management,* 51(3), pp. 354-370.

Leybourne, S.J., Mills, T.C. and Newbold, P., 1998. Spurious rejections by Dickey-Fuller Tests in the presence of a break under the null. *Journal of Econometrics,* 87(1), pp. 191-203.

Perron, P. and Yabu, T. 2009. Estimating deterministic trends with an integrated or stationary noise component. *Journal of Econometrics*, 151(1), pp. 56-69.

Perron, P., 1988. Trends and Random Walks in Macroeconomic Time Series: Further Evidence from a New Approach. *Journal of Economic Dynamics and Control,* 12(2-3), 297-332

Perron, P., 1989. The great crash, oil price shocks and the unit root hypothesis. *Econometrica*, 57 (6), pp. 1361-1491.

Pindyck, R.S., 1999. The long-run evolution of oil prices. *The Energy Journal,* 20(2), pp. 1-26.

Rezitis, A.N., Ntinou, A.G. and Pachis, D.N., 2015. Investigating the international prices of wheat and rice. *Agricultural and Food Economics,* 23(4), pp. 3-16.

Slade, M.E., 1982. Trends in natural-resource commodity prices: An analysis of the time domain. *Journal of Environmental Economics and Management,* 9(2), pp. 122-137.

Slade, M.E., 1988. Grade selection under uncertainty: Least cost last and other anomalies. *Journal of Environmental Economics and Management,* 15(2), pp. 189-205.

Yang, C.W., Hwang, M.J. and Huang, B.N., 2002. An analysis of factors affecting price volatility of the US oil market. *Energy Economics*, 24(2), pp. 107-119.

Zhang, X., Lai, K.K. and Wang, S., 2008. A new approach for crude oil price analysis based on Empirical Model Decomposition. *Energy Economics*, 30(3), pp. 905-918.