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**Article**

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# Oil Price Dynamics Forecasting: An Indicator-Pivoted Paradigm

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**ABSTRACT**

Changes in the price of crude oil have significant impacts on a company's production cost. Therefore, research on forecasting the movement of oil prices is imperative to obtain a profound yet forward-looking idea regarding their future direction. Contributing to this effort, this paper endeavours to design and build an oil price indicator that incorporates the ability to determine lead time and has great predictive power and directional accuracy. Applying the indicator construction approach, the present study successfully constructed an OPI with an average leading time of 3.6 months, moving ahead of West Texas Intermediate, a main crude oil benchmark used across the globe. The results revealed that OPI achieves as high as 75.0% accuracy. The main goal of this paper is to determine whether the indicator approach can be applied in predicting global oil prices. Upcoming research endeavours can extend the current model to out-of-sample forecasting of oil prices.

**Keywords:** Oil Price, Forecasting, Indicator Approach
**JEL Classifications:** C14, E32, Q47

## 1. INTRODUCTION

The year 2017 had a good start for global crude oil when the Organisation of the Petroleum Exporting Countries (OPEC) finally agreed to trim production by 1.2 million barrels per day (hereafter b/d); this announcement came in November 2016 and marked the first drop in production since the subprime mortgage crisis in 2008. Russia also expressed support by cutting 300 thousand b/d. Such a sound compromise again renews hope among oil producers and investors to pick up the pieces of oil price recovery. The recent oil price slump after June 2014 had some Wall Street oil experts pointing to shale oil producers as the culprits because they produce an enormous amount for the crude oil market. Publicly known as shale oil, or tight oil as the US Energy Information Administration (EIA) calls it, it is produced only in certain US states and has emerged since the early 2000s. This synthetic crude oil is mainly used as heating oil, marine fuel and as a chemical for railroad wood preservative, which may offer an alternative for producers in these fields, who have traditionally relied solely on conventional crude oil. The sudden emergence of the very low-permeability oil is mainly due to technological advancements that can reduce the costs of drilling activity as well as improve the drilling efficiency. However, its feverish production, especially from 2010 onwards, has started to worry Saudi Arabia and Russia as they have always led in global crude oil production. Their worries have finally matched with the Reference Case in the Annual Energy Outlook 2016 as released by the US EIA (2016), which indicates that US tight oil production is expected to reach 7.1 million b/d in 2040. The report even estimates that the world tight oil production will double between 2015 and 2040, growing from 4.98 million b/d to 10.36 million b/d, with most of the projection anticipated to come from the US.

Another possible reason for the oil price remaining low is the mighty return of Iran to the crude oil market. When the economic sanctions on Iran were lifted in the first quarter of 2016, Iran picked up the pace in producing crude oil. Iran ran wild in crude oil production right after that because it was attempting to regain its market share in the crude oil market, as well as increase its economic revenue because the economic sanctions had actually hit the country hard in an economic and financial sense. However, it was bad timing to have Iran come back aggressively into the global oil market when the oil price was plummeting. OPEC's attempts to secure and stabilize global oil prices appear to have encountered a bottleneck for the past 2 years. OPEC did provide a few constructive opinions regarding cuts in oil production after the oil price slump in mid-2014, which were ideally perceived to support oil prices. Nevertheless, the vaulting ambition among the lead producers, especially Saudi Arabia and Russia, to retain their market shares resulted in no mutual cooperation being achieved; consequently, oil prices have remained low for the last 2 years. To a certain extent, the 13-member OPEC (including Saudi Arabia) seems to have become an off-putting factor in efforts to cope with the oil price shocks, most likely because of the geopolitical conflict among Russia, Saudi Arabia, and the US. This circumstance reveals the clash of vision between Russia and Saudi Arabia when the cartel has not been able to get them to cooperate and cut oil production together over the past 2 years. Certainly, the crude oil glut was even worse than anticipated and thus weakened any hope for an oil price rebound.

In fact, many companies fell victim to the events surrounding oil shocks every single time, and the impacts this had are widespread and worldwide. Thus, research on oil prices has taken on new importance because everyone in the field wants to benefit from it and avoid any bad times in the oil market. This renaissance in crude oil price studies, especially on forecasting and volatility, has again brought the area to fame as many are eager to develop profound yet forward-looking ideas about the future direction of the oil prices. From the statistical and econometric perspectives, oil prices are usually presumed to exhibit nonlinearity and nonstationarity attributes, which makes predictions rather perplexing and challenging. However, researchers have gotten a good start by applying artificial intelligence (AI) in oil price forecasting studies. Those studies include Kulkarni and Haidar (2009), Pan et al. (2009), Gabralla and Abraham (2013), Barunik and Malinska (2016), Mostafa and El-Masry (2016) and Wang and Wang (2016). Most of these studies have agreed that AI-based models of oil price forecasting show superior findings to the traditional techniques.

However, the emerging AI tool involves rather complicated algorithm-based assumptions which make such computational analysis and interpretation incur relatively high cost, especially in time constraints. In contrast, the indicator method as asserted in this paper is rather simple to use for cyclical analysis. Despite the fact that oil price studies rarely apply the indicator approach, it is particularly successful in business cycle analysis [Gallegati (2014), Abu Mansor et al. (2015), Pestova (2015), Tkacova and Sinicakova (2015) and Puah et al. (2016b)], and also in other fields; for example, Babecky et al. (2013) worked on a crisis incidence indicator, Vasicek et al. (2015) were interested in developing a financial stress index and Puah et al. (2016a) assessed the property cycle. More to the point, this study did not locate a plethora of comprehensive studies on oil price forecasting based on the indicator approach, even though the energy sector has been growing rapidly. In this sense, the present study intends to bridge the gap by applying an indicator-pivoted model to forecast oil price dynamics with the retrieval cyclical constituent. In tandem, OPI, which has leading ability, great predictive power and directional accuracy set into one, centers the present study. Recognising the success in business cycle analysis, using the indicator to predict the global crude oil price is projected to capture the cyclical component of oil prices and determine the turning points in the crude oil market.

It is empirically appealing to model oil price dynamics using the indicator approach and, thus, the constructed OPI constitutes a novel discovery, which can indicate the movements in the global oil market where the turning points of any phenomenon can be foreseen. Hence, the OPI is expected to provide remarkable signalling ability and serve as a tool for indicating the oil market, which could assist oil market players and policymakers to nurture timely yet precautionary countermeasures to the volatile oil market, especially when the oil market is being pressured towards oil hikes or an oil crisis. The early signal carried in OPI can thus enhance policy making and stabilize markets if it is applied to forward decision-making as well as policy establishment in those oil-producing nations. Last, but not least, the asserted OPI would be extremely attractive to oil-producing companies in their oil-related explorations, such as drilling and refinery activities, as well as business planning. Ultimately, this study can improve the position of policymakers and oil market players through being well-informed and diligent.

## 2. INDICATOR APPROACH

This paper employs monthly series data from January 2001 through June 2016. An indicator study must have reference series and component series, whereby the former refers to the benchmark with representative power in the field of research and the latter is a set of variables for selection to construct an indicator. West Texas Intermediate (WTI) crude is chosen as the reference series in this study (both the global crude oil benchmarks, Brent and WTI, are empirically tested to produce almost similar cyclical movements and turning points; thus, either one could have been chosen as the reference series in this paper), while the component series is made up of OPEC and non-OPEC crude oil production change, world crude oil consumption change, world crude oil stock change, WTI futures contract price, open interest (number of contract) (sourced from US EIA) and US business confidence index (taken from Organisation for Economic Co-operation and Development [OECD] data). The Chicago Board Options Exchange crude oil volatility index (OVXCLS) is currently available in the shares market as one investor reference for investment in the crude oil market. This data series is specially adopted in this study as the competitive model for assessing the performance of the constructed OPI's predictive power as well as its forecasting accuracy. Note the data available on OVXCLS start from June 2007; thus, the comparative analysis of directional accuracy and binomial testing between the constructed OPI and OVXCLS will be conducted for the period from June 2007 through June 2016. This paper constructs the OPI as well as the index compilation following procedures from the Conference Board (2000). Once the appropriate constituents (i.e., the seven elements mentioned earlier) are selected into the component series, they will be aggregated into composite form and rebasing procedures will be conducted on the composite index by taking 2010 as the base year. The following procedures define the detailed instructions of index aggregation:

1. Compute the month-to-month changes ($m_{p,t}$), where p=1,…, n for each component series ($x_{p,t}$) based on the symmetric percentage change formula below:

$$m_{p,t} = \frac{X_{p,t} - X_{p,t-1}}{X_{p,t} + X_{p,t-1}} * 200 \quad (1)$$

Variable(s) in percentage form within the component series will be differenced on simple arithmetic (i.e., OPEC and non-OPEC crude oil production change, world crude oil consumption change and world crude oil stock change).

2. Measure the monthly input for each component series ($c_{p,t}$) by multiplying the month-to-month changes ($m_{p,t}$) with a standardization factor ($f_p$). The standardization factor can be derived by inversing the standard deviation of the month-to-month changes for each component series ($m_{p,t}$).
3. Total up the adjusted symmetric changes across the component series to obtain the total contribution across all component series for a particular month.

$$S_t = \sum_{p=1}^{n} c_{p,t} \quad (2)$$

4. Set the first value of the index to 100 and derive the preliminary index of OPI recursively with the formula, as follows:

$$I_2 = \frac{200+S_2}{200-S_2} * I_1 \quad (3)$$

5. Rebase the preliminary index of OPI into the base year of 2010.

Next, both the WTI and OPI will be seasonally adjusted using the Census X-12 method and will be tested in tandem to ease the observation of the cyclical movements in the series. Then, the raw index of the constructed OPI and the WTI price are transformed into a growth cycle, in which the cyclical attributes are extracted through the filter technique (Christiano and Fitzgerald, 2003) that can generate an alternative reference cycle on the basis of the band-pass filtering method. The turning points in the cycles (i.e., the local minimum and local maximum values of both OPI and WTI) are then dated through the Bry and Boschan (1971) dating algorithm. After this, the cyclical trend of OPI will be interpreted and evaluated together with that of the reference series in graphical form.

Apart from the aforementioned details of indicator construction, it is also important to examine the accuracy of the desired indicator's predictive power after it is constructed. Even when the constructed OPI is empirically proven to have great predictive power and lead the WTI, the accuracy of its leading power is still unknown. To examine this, directional accuracy is one of the forecast evaluations used to assess such performance on the indicator. This study incorporates the constructed OPI into a series of directional accuracy tests, as the name implies, to determine the accuracy of the OPI's directions in predicting the WTI. There are three classes of forecast states, i.e., large predicted increase, no significant changes and large predicted decrease. This study chooses a boundary of 5% significance level (similar to Greer, 2003) to differentiate small from large changes. In the directional accuracy test, this study also allows the OPI to go through the incorporated binomial test, serving as a robustness test, to determine whether the predictive power of OPI is computed by chance or not. The null hypothesis states that the probability of correctly predicting the direction of change in the forecasting model is 50.0%. The null hypothesis could possibly be rejected (1) if the model's accuracy rate is more than 50.0%, it statistically outperforms the chances of a mere guess or, in other words, the indicator genuinely has predictive and accurate power; (2) if it is <50.0%, it is statistically verified that the predictive power in the model is merely formed on a wild guess. In particular, comparative analysis will be conducted on both the OPI and OVXCLS to determine and compare their accuracy in predicting WTI.

## 3. FINDINGS AND DISCUSSIONS

In overview, Figure 1 shows that the cyclical movement of OPI always coherently moves ahead of WTI across the period of 2001 to mid-2016. In particular, the shaded areas reveal five episodes of oil price shocks whereby the WTI goes from peaks to troughs (recessions). The detected peaks and troughs of WTI are consistent with the historical

**Figure 1:** Cyclical Movements of OPI versus West Texas Intermediate, 2001M01-2016M06

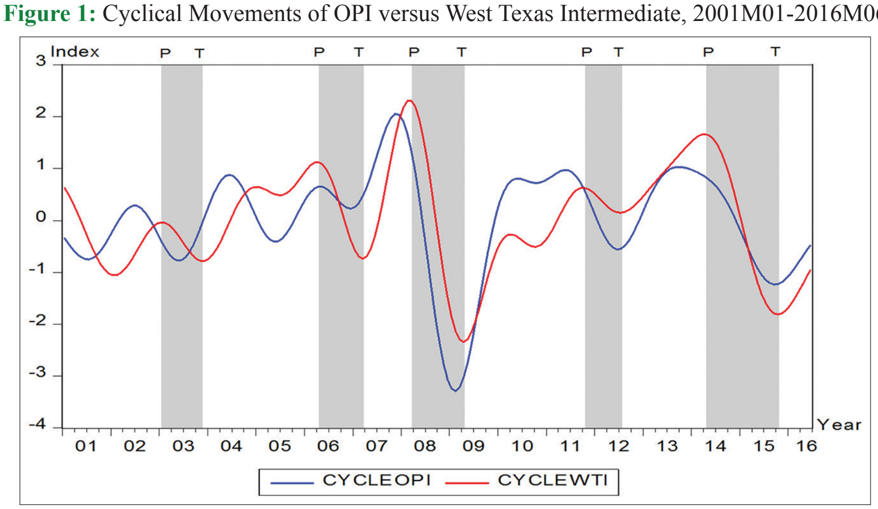

**Table 1: Turning points analysis results of OPI and WTI**

| Cycle condition | WTI | OPI | Amount of early signals | Significant events |
|---|---|---|---|---|
| Peak | 2003M01 | 2002M06 | 7 | Venezuelan political instability and second Persian gulf war |
| Trough | 2003M11 | 2003M05 | 6 | |
| Peak | 2006M04 | 2006M04 | 0 | Aftermath of low oil spare capacity |
| Trough | 2007M03 | 2006M12 | 3 | |
| Peak | 2008M03 | 2007M11 | 4 | Subprime mortgage crisis |
| Trough | 2009M04 | 2009M02 | 2 | |
| Peak | 2011M10 | 2011M05 | 5 | Libyan civil war |
| Trough | 2012M07 | 2012M06 | 1 | |
| Peak | 2014M04 | 2013M09 | 7 | Concurrence of production oversupply and stagnant demand |
| Trough | 2015M10 | 2015M09 | 1 | |
| Average | | | 3.6 months | |

WTI: West Texas Intermediate

**Table 2: Comparative analysis of directional accuracy and binomial testing**

| Lag (month) | Directional accuracy (%) | | P (binomial) | |
|---|---|---|---|---|
| | OPI | OVXCLS | OPI | OVXCLS |
| 1 | 71.3 | 33.3 | 0.000 | 0.000 |
| 2 | 73.8 | 31.8 | 0.000 | 0.000 |
| 3 | 74.5 | 30.2 | 0.000 | 0.000 |
| 4 | 75.2 | 29.5 | 0.000 | 0.000 |
| 5 | 67.3 | 34.6 | 0.000 | 0.001 |
| 6 | 67.0 | 35.0 | 0.000 | 0.001 |

oil price shocks during the empirical sample period. The constructed OPI successfully dated 10 turning points of WTI, where each turning point leads for varied months (Table 1). The average lead time of 3.6 months shows that the OPI can provide forward-manner signaling to the WTI cycle, and it fulfils the goal of the present study.

Table 2, on the other hand, reveals that the constructed OPI can predict as high as 75.2% accuracy on the WTI, whereas the competing model OVXCLS hits an accuracy of only up to 35.0%. Shown together, the results of a binomial test, which uncovers the decision to reject the null hypothesis at a significance level of 1% for both OPI and OVXCLS, indicate that the OPI statistically outperforms chance or mere guessing. Subsequently, the findings suggest that the sources of the constructed OPI's correct prediction lie in its strong predictive power.

## 4. CONCLUSION

When global organizations such as the OECD, Eurostat and Bureau of Economic Analysis apply the indicator approach to construct business cycles, it shows the usefulness, efficiency, effectiveness and trustworthiness of this approach. International accreditation notwithstanding, research using the indicator approach to predict short-term crude oil price fluctuations is seldom found. Inspired by the success of the indicator approach in constructing business cycles, when oil price movement is believed to exhibit cyclical attributes, predicting the movement using the indicator approach is feasible, as proposed in this paper, for constructing an oil price indicator. Comparing a global-based oil price cycle and a country-based business cycle, constructing the indicator for the former might be rather difficult because the factors affecting the crude oil price are dynamic and worldwide.

This paper allows the exclusion of unpredictable geopolitical variability and weather uncertainty in the selection of component series, despite their momentous role in affecting oil prices. The main highlight of this paper is the usefulness of the indicator approach to predict global crude oil prices; it is cost-efficient and simple to apply as compared to the evolutionary AI-based techniques in predicting short-term oil price. In this sense, the current in-sample forecasting of oil prices has shown that the constructed OPI can lead the WTI price by 3.6 months on average throughout the study period. Upcoming research endeavours can extend the current study of the indicator-based model to out-of-sample forecasting of oil prices.

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