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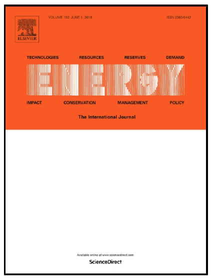

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ABSTRACT

Extraordinary oil price declines were observed from 2008 to 2009 and from 2014 to 2016. During these periods, international oil prices collapsed by more than one half. Several reasons have been suggested for these crashes by numerous industry experts and scholars. In this study, we propose a new approach to explain the causes of the extreme oil price plummets via the supply and demand factors of price determinants. The autoregressive models with exogenous variables reflecting real demand, speculative demand, and supply factors are proposed and applied for forecasting monthly global crude oil prices during their periods of decline. Using the forecasting results, we retrospectively try to discover the factor that is best able to improve forecasting performance. During the first period of oil price decline, real demand reduction seemed to play a more prominent role compared with the other factors. Meanwhile, some supply factors, measured by U.S. shale oil production, combined with real and speculative demand factors, played an important role during the period of second oil price drop.

Keywords: crude oil price, forecasting, OPEC production, U.S. shale oil, U.S. strategic petroleum reserve

1. Introduction

Oil prices experienced extraordinary plummets from 2008 to 2009 and 2014 to 2016. During these short periods, world oil prices crashed by more than one half. Many economic analysts ascribed the decline during the period 2008–2009 to the global financial crisis. They believed that the 2008 financial crisis resulted in a worldwide economic slump, which, in turn, undercut international oil prices. Later on, numerous industry experts and academics asserted that amassed supplies of oil resulted in tumbling prices during the period 2014–2016. In an attempt to designate the specific supply factors that are responsible for the decline, both U.S. shale oil development and increasing crude oil production of OPEC countries have been suggested. Moreover, there have been various other arguments used to explain the causes of unusual oil price declines. However, to the best of our knowledge, no study has conducted a thorough empirical investigation regarding these causes. Certainly, establishing the cause(s) of the recent collapses by rigorous evidence will provide meaningful information for both economic policymakers and scholars. Our research findings via a novel and rigorous approach suggested in this article may contribute to the work of professionals in both spheres.

This article proposes a new approach to verify the above views by examining the relation between demand and supply factors, and oil price dynamics, via some predictive models. In particular, the supply and demand factors of price determinants are examined to explain the causes of the plummets. We propose applying novel autoregressive models with exogenous variables reflecting real demand, speculative demand, and supply factors for forecasting monthly global crude oil prices during the periods of decline. Specifically, we build four different types of predictive models: (1) with only real demand factors, (2) with real and speculative demand factors, (3) with real demand and supply factors, and (4) with real and speculative demand and supply factors.

We evaluate these models and suggest which factors are the most important in explaining the oil price drops during the two aforementioned periods. First, we analyze the period of falling global oil prices (June 2008–February 2009). We then check whether the findings during the 2008 oil price fall were still observable during June 2014–February 2016, when prices collapsed again. Due to the backdrops of in-sample forecasting evaluation, such as sensitivity to outliers and model misspecifications (Inoue and Kilian, 2004; Panopoulou and Pantelidis, 2015), we utilize the out-of-sample forecasting approach in the evaluation of candidate models. The empirical forecasting results are retrospectively evaluated to identify the factors enabling improved forecasting performance.

Monthly crude oil spot prices for West Texas, Brent, and Dubai are utilized as response variables in the models. To represent real demand, the S&P 500 index, the OECD production industry index, the China stock index (SSE composite index), and the India stock index (S&P BSE SENSEX index) are alternately utilized in the forecasting model. U.S. crude oil in the strategic petroleum reserve is used to measure speculative demand. The OPEC crude oil supply and U.S. shale oil production are alternatively applied as supply factors in the predictive models. As will be shown later in the empirical result section, our approach explicitly demonstrates the causes of the recent collapses of global oil prices.

The rest of this paper is organized as follows. Numerous views on using certain macroeconomic variables as supply and demand factors in determining crude oil prices are reviewed in Section 2. Detailed characteristics of the data are analyzed, and patterns of oil prices are delineated using a time series plot in Section 3. In Section 4, oil price forecasting models are suggested and their predictive evaluation criteria are introduced. Forecasts are evaluated for three international oil markets during periods of falling oil prices in Section 5; the empirical results are then summarized and interpreted. Finally, concluding remarks are made in Section 6.

2. Literature on supply and demand factors

Numerous studies have attempted to explain the relation between economic activities and fluctuations in crude oil prices. One strand of literature focuses on oil price dynamics' impact on macroeconomic components (e.g., Hamilton, 1983, 2003; Kilian and Vigfusson, 2013; Mork, 1989; Ramos and Veiga, 2013; Zhang and Tu, 2016). They used oil prices as an input for forecasts of GDP growth, economic recessions, and stock markets. Another strand of literature examines the macroeconomic factors affecting crude oil price dynamics (e.g., Hamilton, 2009; Kilian, 2008a, 2009; Kilian and Hicks, 2013). Such studies investigated several macroeconomic variables affecting the demand and supply of oil and their impact on oil price changes. Kilian (2009) evidently argued that oil prices are driven by demand and supply factors. This paper focuses on that approach. In this section, we propose some macroeconomic variables as supply and demand factors for oil price determinants and suggest the rationale behind this claim via a literature review.

To measure global oil real demand, we suggest utilizing the S&P 500 index, the OECD production industry index, the China stock index (SSE composite index), and the India stock index (S&P BSE SENSEX index), alternately in the models. Recently, economies are increasingly becoming globally integrated. Hu (2010) studied daily returns from the S&P 500 index and the stock indices of several other countries, finding that the U.S. economy was significantly correlated with many other economies. Bhar and Malliaris (2011) also noted the positive influence of the S&P 500 index on oil prices. These analyses imply that the S&P 500 index could be considered as a predictor in our regression models: growth in the U.S. economy and/or the S&P 500 index could help the world economy to grow, which may increase the global demand for oil, driving up global oil prices. Meanwhile, China ranked first (USD116.2 billion, 17.3% of total crude oil imports) among crude oil importing countries in 2016 for the first time. Meanwhile, India ranked third (USD60.9 billion, 9.1%). These facts imply that two emerging Asian countries' economic conditions may influence the global oil prices as well. If they suffer recessions, their demand for oil may fall, possibly resulting in falling oil prices. To reflect the increasing economic impact of China and India on the real global demand for oil, we use their representative stock market indices. Lastly, the OECD production industry index was employed to represent global oil demand. The OECD is a group of leading economies (31 countries as of 2016). If their economic conditions turn downward, their global oil demand might decrease, perhaps resulting in a global oil price decline.

As a speculative demand factor, U.S.'s crude oil backup in the strategic petroleum reserve is employed in our model. Oil inventories or reserves have been recognized as contributing to speculative demand shocks in the literature. Kilian (2009), Hamilton (2009), Alquist and Kilian (2010), and Kilian and Murphy (2010), focusing on the role of oil inventories as an asset, observed that increased expectations of the future demand for crude oil increased demand for crude oil inventories, leading to a rise in oil prices. Since shifts in the demand for oil inventories are caused by forward looking behavior in this case, these demand shocks are referred to as "speculative demand shocks" (Kilian and Murphy, 2010). On the one hand, demand shocks emanating from exogenous events such as revolutions, invasions, or wars in the Middle East can increase demand for oil inventories, resulting in increased oil prices as well. On the other hand, Pirog (2005), Bamberger (2008), and Andrews and Pirog (2011) pointed out that the U.S. holds strategic oil inventory stocks as a buffer against any potential disruption in oil imports. The release of inventories may increase the market supply of oil, placing downward pressure on U.S. oil prices. Jiao et al. (2014) investigated the effect of China's strategic petroleum reserve on stabilizing domestic oil prices. Perhaps many nations maintain their own oil inventories, but U.S. oil inventory was larger than anyone else's during our research period. Thus, we used U.S. oil inventories as the speculative demand factor in our models.

Among supply factors, OPEC's crude oil supply and U.S. shale oil production are alternatively applied in the forecasting models. The apparent fluctuations in 2008 have received much attention in the literature (Kilian, 2008b; Irwin and Sanders, 2010; Singleton, 2014; Panopoulou and Pantelidis, 2015). Hamilton (2009) noted that the 2007 to 2008 increase in oil prices was caused by demand factors rather than by supply disruption. Kilian (2008a) concluded that reductions in oil supply accounted for only a small change in oil prices. Kilian (2009) also argued that oil price fluctuations are driven by demand factors rather than by supply factors. These studies commonly concluded that variations in oil supply did not strongly influence fluctuations in oil prices around 2008. However, the role of shale oil supply played in causing the 2014 decline is more persuasive (Kilian, 2016). Monge et al. (2017) also argued that the negative correlation between U.S. shale oil production and WTI (west Texas intermediate) prices during 2009 to 2014. Husain et al. (2015) claimed that both supply and demand factors contributed to the decline from 2014 and 2015, but supply factors played a more prominent role. They attributed the sharp drop to the prodigious supply of oil from U.S. shale oil development and greater than expected OPEC output. Ansari (2017) also claimed OPEC and shale oil revolution led to the oil price drop of 2014-2016.

3. Data

We collated monthly crude oil spot prices (USD/barrel) of West Texas, Brent, and Dubai from January 2005 to February 2016. The S&P 500 index, the OECD production industry index (2010 = 100), the China stock index (SSE composite index), and the India stock index (S&P BSE SENSEX index) were used to measure real demand on a monthly basis. U.S.'s final inventories of crude oil held at the strategic petroleum reserve for each month was utilized to measure speculative demand. The OPEC's crude oil supply (monthly sum of thousands of barrels) and shale' (tight) oil's total production for seven areas (thousands of barrels per day) were the factors of supply used in the forecasting models. The data were available from the U.S. Energy Information Administration (EIA) and Google finance.

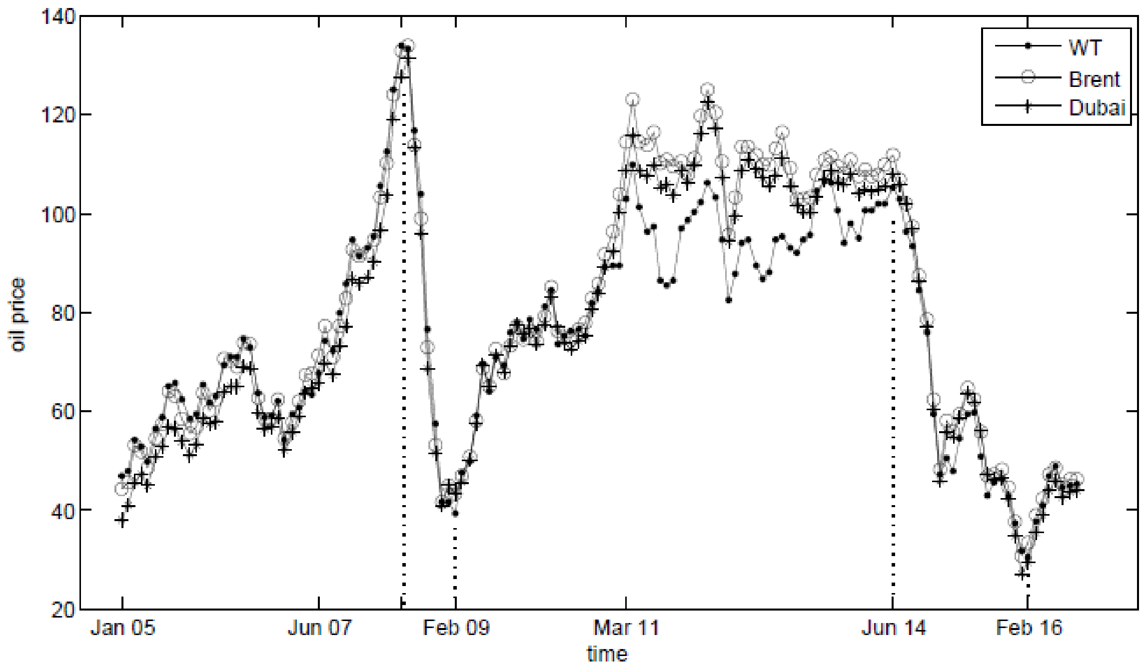

Fig. 1. Overlapping dynamics of crude oil prices for West Texas, Brent, and Dubai from January, 2005, to September, 2016. Here a couple of intervals with dotted lines from June, 2008, to February, 2009, and from June, 2014, to February, 2016, indicate the first and second periods of oil price decline, respectively.

The relation among the oil prices of West Texas, Brent, and Dubai may be observable in the overlapping time-series data depicted in Figure 1. Despite the slight deviations in the dynamics of each price, a determinant pattern of co-movement is evident. Though interrupted by mild fluctuations, oil prices registered a gradually increasing trend since early 2005, peaking in mid-2008, and then recorded a sharp fall until early 2009. At the 2008 peak, the three oil prices reached over 130 USD per barrel. Meanwhile, at the bottom during 2009, the same barrel fetched less than 44 USD. Prices plummeted more than 65% that year. We refer to this interval as the first period of oil price decline.

Subsequently, oil prices followed a gradually increasing pattern again through mid-2011, then continued to fluctuate, hovering around 100 USD per barrel. Suddenly, after June, 2014, prices collapsed again, spiraling down until February, 2016 from 105 USD to 30 USD per barrel. More than 70% of oil's price was shaved off within a couple of years. This interval corresponds to the second period of oil price decline.

Some important descriptive statistics regarding monthly crude oil prices for the three types of petroleum from March, 2007, to February, 2016, are summarized in Table 1. This table also reports summary statistics on the monthly observations over the same period of U.S.'s final inventories of crude oil in the strategic petroleum reserve (*SPR*), S&P 500 index (*S&P*), the OECD production industry index (*OECD*), the China stock index (*China*), the India stock index (*India*), shale oil production (*Shale*), and the OPEC crude oil supply (*OPEC*).

Table 1. Summary of descriptive statistics of several monthly-observed variables from March, 2007, to February, 2016.

	WT	Brent	Dubai	Shale	OPEC	OECD	S&P	China	India	SPR
mean	79.7	85.3	82.5	2853.7	958218.2	103.6	1503.7	2865.7	19529.7	703039.0
median	84.5	87.3	85.8	2326.5	959760.0	104.0	1416.2	2701.7	18619.7	695969.0
Min	30.4	30.8	27.0	1228.3	872610.0	90.5	735.1	1728.8	8891.6	688602.0
Max	133.9	133.9	131.2	5459.0	1025170.0	109.7	2173.6	5954.8	29220.1	726616.0
std dev	23.4	26.9	26.0	1547.1	31295.9	4.7	389.6	836.1	5045.6	13358.2
c.v.	0.29	0.32	0.32	0.54	0.03	0.04	0.26	0.29	0.26	0.02

4. Models and evaluation

Baumeister and Kilian (2012) suggested a forecasting method using backcasting and nowcasting techniques, empirically showing that an autoregressive model with global crude oil inventories outperforms other univariate time-series models in forecasting monthly oil prices. Exploiting their idea combining auto regression and exogenous predictors, we proposed using auto regression with exogenous variables (ARX) models, where the supply and demand factors of price determinants are utilized as exogenous components. In particular, four models with different sets of supply and/or demand factors were applied to forecast oil price dynamics during the two aforementioned periods. Using the out-of-sample based prediction result, we try to identify the factor that caused the oil price decline.

4.1. Suggested models

This study proposes ARX models for forecasting monthly global oil prices. The original observations are all natural log-transformed, and the first-order, time-lagged values are employed as both response and explanatory variables. For example, the initial ARX model is built as follows.

$$\ln(p_t) = \phi_0 + \phi_1 \ln(p_{t-1}) + \phi_2 \ln(D_{t-1}^r) + \varepsilon_t ,$$

where p_t and p_{t-1} are oil prices at time t and $t-1$. D_{t-1}^r is the real demand (an exogenous factor) at time t. Since $\ln(p_t)$ and $\ln(D_{t-1}^r)$ are non-stationary processes, the innovation term ε_t should be stationary to satisfy the co-integrated combination between series (Granger and Newbold, 1974; Engle and Granger, 1987). For appropriate estimation of this model, the first-order, time-lagged difference is necessarily applied to make the variables stationary (Mohammadi and Su, 2010; Bhar and Malliaris, 2011), where the intercept term ϕ_0 is removed from the model. Then we obtain:

$$\Delta \ln(p_t) = \phi_1 \Delta \ln(p_{t-1}) + \phi_2 \Delta \ln(D_{t-1}^r) + u_t ,$$

where Δ implies the first-order, time-lagged difference, e.g., $\Delta \ln(x_t) = \ln(x_t) - \ln(x_{t-1})$. Here u_t is the stochastic disturbance with $E(u_t) = 0$ and $V(u_t) = \sigma_u^2$. Coefficients of models are estimated using ordinary least squares. Using this scheme, we consider the following four models:

M1: $\Delta \ln(p_t) = \phi_1 \Delta \ln(p_{t-1}) + \phi_2 \Delta \ln(D_{t-1}^r) + u_t$,

M2: $\Delta \ln(p_t) = \phi_1 \Delta \ln(p_{t-1}) + \phi_2 \Delta \ln(D_{t-1}^r) + \phi_3 \Delta \ln(D_{t-1}^s) + u_t$,

M3: $\Delta \ln(p_t) = \phi_1 \Delta \ln(p_{t-1}) + \phi_2 \Delta \ln(D_{t-1}^r) + \phi_4 \Delta \ln(S_{t-1}) + u_t$,

M4: $\Delta \ln(p_t) = \phi_1 \Delta \ln(p_{t-1}) + \phi_2 \Delta \ln(D_{t-1}^r) + \phi_3 \Delta \ln(D_{t-1}^s) + \phi_4 \Delta \ln(S_{t-1}) + u_t$

The variables D_{t-1}^r, D_{t-1}^s, and S_{t-1} stand for real demand, speculative demand, and supply factors at time $t-1$, respectively. Four models M1–M4 include different sets of exogenous variables. M1 is a model with only real demand factor, M2 has real and speculative demand factors, M3 has real demand and supply factors, and M4 contains both real and speculative demand and supply factors.

For real demand, the S&P 500 index, the OECD industrial production index, the China stock index, and the India stock index were alternatively utilized in all forecasting models. OPEC crude oil and U.S. shale oil production are alternatively utilized as supply factors in the predictive models. Therefore, M3 and M4 are separated into M3-1, M3-2, M4-1, and M4-2. The OPEC supply is plugged into M3-1 and M4-1, whereas U.S. shale oil supply fits into M3-2 and M4-2. West Texas, Brent, and Dubai crude oil spot prices are utilized as p_t . In summary, we evaluate the forecasting performance of six models (M1, M2, M3-1, M3-2, M4-1, and M4-2) for the three global oil price datasets during both periods of decline.

Regarding the stochastic innovation u_t , we consider the following three different candidates.

1) $Corr(u_i, u_j) = 0$ for $i \neq j$

2) $u_t \sim$ AR(k)

3) $u_t \sim$ GARCH(p,q)

For example, $u_t \sim$ AR(1) implies $u_t = \theta_1 u_{t-1} + e_t$ and $u_t \sim$ GARCH(1,1) implies $u_t = \varepsilon_t \sigma_t = \varepsilon_t \sqrt{\alpha_0 + \alpha_1 u_{t-1}^2 + \beta_2 \sigma_{t-1}^2}$ with $\varepsilon_t \sim iid\ N(0, 1)$. Here, the first implication indicates the white noise assumption. The second one implies autocorrelation of innovation. The third one includes the GARCH mechanism. The GARCH type modeling was proposed to reflect persistent clustering patterns in the volatility of oil changes in the literature (Morana, 2001; Yang et al., 2002; Sadorsky, 2006; Agnolucci, 2009; Mohammadi and Su, 2010). Following them, we consider employing the GARCH approach on the error term. The adequacy of the innovative structure can be investigated using the residual.

4.2. *Out-of-sample prediction and evaluation*

We performed one-month-ahead forecasting. Its procedure was as follows. The proposed models were estimated using the initial in-sample data period and oil prices for one month ahead were predicted. Then, the window of the in-sample data period was moved forward by a month. Using the updated window, the models were estimated again. With the newly estimated model, an oil price prediction for one month was feasible. These procedures were repeated during the entire out-of-sample data period. Using the prediction results over the out-of-sample data period, we assess the forecasting performance of the models.

Regarding the first period, with in-sample data from March, 2007, to May, 2008, and out-of-sample data from June, 2008, to February, 2009. Using the initial-in-sample data, the predictive models were estimated and yielded a future oil price for June, 2008. After this, the initial in-sample data period was moved from April 2007 to June 2008. Using the updated in-sample data period, the models were newly estimated and a forecast for July, 2008, oil prices was provided. These procedures continued until the final forecast for February, 2009, was obtained. Using the forecasted monthly values from June, 2008, and February, 2009, the forecasting accuracy of the models was evaluated. In addition, we calculated a root mean square error (RMSE) and a mean absolute error (MAE), as follows.

$$RMSE = \left(\frac{1}{J} \sum_{j=1}^{J} (p_j - \hat{p}_j)^2 \right)^{1/2} \text{ and } MAE = \frac{1}{J} \sum_{j=1}^{J} | p_j - \hat{p}_j |$$

Here, $\hat{p}_j$ is predicted oil price at time j, and J is the total number of forecasted values.

For the second period, we utilized in-sample data from March, 2011, to May, 2014. The out-of-sample data covered June, 2014, through February, 2016. The predictive procedure was similar to that of the first period.

5. Empirical results

Prior to forecasting the oil prices using various models during the two periods, we looked for the existence of co-integration between log-transformed variables. First, we examined the existence of unit-root issues for all the log-transformed variables, using the Augmented Dickey–Fuller test (ADF) for March, 2007, to February, 2016. In fact, it existed. Hence, the Engle–Granger test was implemented to test whether there was co-integration over the same period. The test result indicated that there was significant co-integration, implying that our approach was appropriate. Although Engle and Granger's test is known to have a lower power than the Johansen's test (1992), test results showed that there is no unit root in the residuals of all models, thus rejecting the null hypothesis (no co-integration) even at the 1% significance level. This result indicates that the low power of Engle and Granger's method is not a problem in our case.

After that, we examined the residual-based innovation structure of first-order, time-lagged differenced models M1-4. We first test the stationarity of the residuals, and the results indicate that none of them have unit root. According to the partial autocorrelation function (PACF) plot and autocorrelation test results, any time-lagged term was not significant in models during the first period.

The same results were observed during the second period. Next, we investigated the adequacy of the GARCH approach. Engle's Lagrange multiplier (LM) test results for the ARCH effect were employed to select significant lag terms in the GARCH mechanism for each model, but there was no significant term for either period. These results imply that the white noise assumption on the error structure is recommended. Therefore, we estimated models using the OLS method under the white noise error assumption.

5.1. Results during the first period of falling oil prices during 2008–2009

According to the empirical test results on the innovative structure, we estimated the forecasting models with a white noise assumption on u_t. With this error structure, we predicted the oil price of models and evaluated the proposed models. Monthly-based, one-month-ahead forecasting procedures were applied to the data from June, 2008, to February, 2009. The RMSE and MAE results regarding the suggested models are summarized in Table 3, where "S&P," "India," "China," and "OECD" indicate real demand factors.

Table 3. Forecasting results for the period of falling oil prices from June, 2008, to February, 2009. The error in the model is assumed to be white noise.

1st fall	Texas				Brent				Dubai			
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
	M1		M2		M1		M2		M1		M2	
S&P	**8.623**	**6.709**	9.403	7.319	**9.382**	**7.395**	10.913	7.420	**9.744**	**7.729**	10.938	8.423
India	**9.876**	**7.257**	11.454	9.097	**10.761**	**7.773**	13.227	10.277	**10.476**	**7.911**	12.196	8.996
China	**9.703**	**7.184**	10.950	9.100	**10.519**	**7.702**	12.559	10.466	**10.148**	**7.648**	11.559	8.987
OECD	9.426	7.842	9.405	7.780	10.536	9.027	11.169	9.110	**9.671**	7.790	9.974	7.676
	M3-1		M3-2		M3-1		M3-2		M3-1		M3-2	
S&P	8.831	6.913	9.405	7.151	9.434	7.599	10.770	8.130	9.844	7.884	11.411	8.796
India	10.069	7.233	10.581	8.026	10.943	7.823	11.852	8.601	10.606	8.069	12.049	9.564
China	9.898	7.121	10.420	7.881	10.655	7.684	11.585	8.300	10.218	7.691	11.567	8.667
OECD	9.622	7.919	10.194	8.862	10.803	9.182	11.424	9.848	9.776	7.853	11.004	8.934
	M4-1		M4-2		M4-1		M4-2		M4-1		M4-2	
S&P	9.405	7.732	9.767	7.796	10.751	7.944	11.293	8.238	11.200	8.873	12.143	9.352
India	11.388	9.162	10.995	8.479	13.131	10.463	12.441	9.010	12.445	9.230	12.887	9.726
China	10.755	9.027	10.547	8.354	12.215	10.377	11.908	9.314	11.561	9.152	12.191	9.402
OECD	9.373	7.640	**8.660**	**7.189**	11.165	9.626	**10.146**	**7.225**	10.133	8.201	10.266	**7.322**

Regarding Texas (or WTI) oil prices, M1, along with S&P, provided the most accurate forecasting result; although, M4-2, along with OECD, showed exceptionally good predictive performance. In terms of RMSE, M1 tended to provide accurate predictive results, among others. M1 is a model with only real demand factors. This result implies that the economic recession caused by the 2008 financial crisis may have played a prominent role in declining oil prices during 2008–2009. In particular, real demand reduction measured by S&P seemed to be keenly significant in facilitating declining oil prices. Maybe the 2008 financial crisis generated by Lehman Brothers in the U.S. directly influenced the S&P, which in turn resulted in a persistent global economic recession. Regarding Brent and Dubai oil prices, similar results were observed. M1 tended to provide the most accurate forecasting results among other models.

5.2. Results during the second period of oil price decline, 2014–2016

The empirical test results on the innovative structure still suggested no correlation approach regarding the second period. Thus, the OLS method was applied to estimate the models. The forecasting results from June, 2014, to February, 2016 are summarized in Table 4.

Table 4. Forecasting results for the period of falling oil prices from June, 2014, to February, 2016. The error in the model is assumed to be white noise.

2nd fall	Texas				Brent				Dubai			
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
	M1		M2		M1		M2		M1		M2	
S&P	6.196	5.029	6.117	4.960	6.970	5.600	6.852	5.442	6.946	5.435	6.854	5.307
India	6.153	5.137	6.074	5.072	7.164	6.157	7.110	6.129	7.037	5.847	6.999	5.844
China	6.111	5.068	6.068	5.053	7.021	5.805	6.895	5.676	7.091	5.736	6.997	5.638
OECD	6.005	5.155	5.978	5.144	6.890	5.691	6.787	5.573	6.974	5.558	6.913	5.485
	M3-1		M3-2		M3-1		M3-2		M3-1		M3-2	
S&P	6.259	5.122	6.120	4.951	7.046	5.683	6.812	5.593	6.996	5.490	6.836	5.452
India	6.218	5.257	6.117	5.077	7.230	6.208	6.973	6.013	7.088	5.913	6.917	5.756
China	6.218	5.181	6.028	4.938	7.125	5.923	6.791	5.605	7.187	5.844	6.927	5.589
OECD	6.082	5.254	6.005	5.124	6.968	5.777	6.715	5.577	7.031	5.615	6.831	5.466
	M4-1		M4-2		M4-1		M4-2		M4-1		M4-2	
S&P	6.165	5.024	**5.947**	**4.794**	6.923	5.522	**6.531**	**5.264**	6.897	5.359	**6.603**	**5.158**
India	6.128	5.184	**5.940**	**4.910**	7.172	6.181	**6.730**	**5.773**	7.046	5.910	**6.713**	**5.550**
China	6.155	5.149	**5.918**	**4.867**	6.992	5.794	**6.513**	**5.308**	7.082	5.743	**6.702**	**5.333**
OECD	6.043	5.226	**5.905**	**5.040**	6.859	5.658	**6.448**	**5.286**	6.965	5.538	**6.634**	**5.237**

We would like to determine whether the findings concerning demand factors during the first period were still observable during the second. According to Table 4, regarding Texas, Brent, and Dubai oil prices, M4-2 tended to be the best forecasting model with the smallest RMSE and MAE. This implies that factors of real demand, speculative demand, and U.S. shale oil supply played important roles altogether in the oil price drop. The increasing oil supply facilitated by U.S. shale oil development might even lower the global oil prices amidst a world business depression. Furthermore, the U.S. government may not feel the necessity of increasing oil reserves when oil prices decline. M4-2 models tended to provide better forecasting results than M4-1 models, which include OPEC's supply instead of the U.S shale oil supply. This indicates that U.S. shale oil played a more important role than OPEC's production did in the either period of oil price plummet. Unlike the results summarized in Table 3, the predictive performance of M1 was inferior to that of M4-2, which indicated that real demand was not a unique, dominant factor in explaining the oil price decline.

5.3. The modified DM test results

Lastly, we applied the modified DM test (Harvey et al., 1997). For each demand factor (S&P, India, China, and OECD), forecasting accuracy of six models (M1, M2, M3-1, M3-2, M4-1, and M4-2) over three oil markets (WTI, Brent, and Dubai) were compared and evaluated. Regarding the first oil price falling period, M1 is compared with other models. Note that M1 tended to provide better forecasting accuracy than other models in many circumstances (see Table 3). Meanwhile, M4-2 is compared with other models for the second oil price falling period. According to Table 5, the DM test results showed that M4-2 tends to outperform other models significantly at the 10% level in most cases for the second oil price falling period. This outcome seems to confirm the result in Table 4. In contrast, the DM test did not provide the consistent superiority of M1 over other models for the first oil price falling period. M1 partly outperformed other models. We may attribute the inconsistent results for the first oil price falling period to a relatively small sample size to make a significant difference. The out-of-sample data for the first and second oil price falling period are 9 and 21 (months), respectively.

Table 5. The p-values of the modified DM test (one-side) for the 1st and 2nd oil price falling periods.

	Texas				Brent				Dubai			
1st fall	S&P	India	China	OECD	S&P	India	China	OECD	S&P	India	China	OECD
M1												
M2	0.281	**0.035**	**0.027**	0.483	0.493	**0.036**	**0.020**	0.320	0.246	0.143	0.115	0.446
M3-1	0.190	0.451	0.395	0.364	0.293	0.435	0.479	0.309	0.241	0.182	0.424	0.353
M3-2	0.189	0.115	**0.008**	**0.004**	0.126	0.117	0.166	0.033	0.292	**0.049**	**0.074**	**0.022**
M4-1	0.169	**0.032**	**0.044**	0.446	0.348	**0.030**	**0.027**	0.353	0.186	0.149	0.129	0.344

M4-2	0.140	0.179	0.186	0.315	0.281	0.222	0.152	0.166	0.117	**0.099**	**0.094**	0.355
2nd fall	S&P	India	China	OECD	S&P	India	China	OECD	S&P	India	China	OECD
M1	**0.020**	**0.048**	**0.053**	0.166	**0.069**	**0.040**	**0.011**	**0.018**	**0.087**	**0.064**	**0.017**	**0.028**
M2	**0.061**	**0.092**	**0.037**	0.166	0.202	**0.044**	**0.028**	**0.061**	0.222	**0.057**	**0.037**	**0.070**
M3-1	**0.008**	**0.018**	**0.027**	**0.050**	**0.037**	**0.037**	**0.004**	**0.007**	**0.064**	**0.050**	**0.009**	**0.019**
M3-2	**0.047**	**0.038**	0.223	0.146	**0.016**	**0.034**	**0.020**	**0.009**	**0.014**	**0.033**	**0.019**	**0.014**
M4-1	**0.026**	**0.032**	**0.019**	**0.064**	0.118	**0.037**	**0.009**	**0.025**	0.125	**0.045**	**0.016**	**0.046**
M4-2												

6. Conclusion

This study suggested a new forecasting model approach to find causes of recent extreme oil price declines. The proposed models include combinations of real demand, speculative demand, and supply factors. The models were used to forecast monthly crude oil prices in three global oil markets and their out-of-sample predictive performances were evaluated. Using the forecasting outcomes, we suggested the factors that are the most important in explaining the oil price declines.

Our empirical results showed that, around the 2008 oil price decline, the real demand reduction measured by stock indices was an important factor in explaining the decline. In terms of model performance, M1 tended to outperform other models, implying that the reduced demand factor owing to the occurrence of the global financial crisis mainly led the collapse of oil prices. In particular, the S&P 500 index measured real demand factors seemed to have significantly influenced the oil price drop among other things. The 2008 financial crisis starting in the U.S. may have directly impacted the U.S. economy, which in turn lowered global oil prices. In contrast, the causes of declining prices during 2014–2016 were different from those of the first period. In terms of model performance, M4-2 tended to provide a better prediction result than other models. Compared with M4-1, this result indicates that U.S. shale oil development was more significant than the increased oil supply by OPEC in dropping oil prices. In summary, real demand reduction was the most important factor in the first oil price drop. Whereas, increasing shale oil supply as well as reductions in real demand and speculative demand played important roles in the second decline.

This study represents an innovative approach toward empirically demonstrating the influence of supply and demand factors on the dynamics of oil prices during periods of declining prices. We may not be able to generalize the results and interpretation to other periods in crude oil market history because they were obtained for specific periods under unique conditions. However, the empirical results might help practitioners and researchers explain and interpret the dynamic relations between macroeconomic variables and oil prices. Furthermore, we expect that the suggested approaches will be utilized for interpreting other phenomena in oil markets at different points in history.

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"Impacts of supply and demand factors on declining oil prices"

Highlights

- Oil price drops are explained via supply and demand factors of price determinants.
- Demand reduction due to the global financial crisis led the 2008 oil price collapse.
- U.S.'s oil production was a more significant factor than OPEC's for the 2014 collapse.