International Journal of Economics and Finance; Vol. 14, No. 7; 2022
ISSN 1916-971X E-ISSN 1916-9728
Published by Canadian Center of Science and Education

Forecasting Oil Prices: A Comparative Study

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Received: June 3, 2022 Accepted: June 29, 2022 Online Published: June 30, 2022

doi:10.5539/ijef.v14n7p55 URL: https://doi.org/10.5539/ijef.v14n7p55

Abstract

Oil prices have been a major concern for many policy makers, businesses and individuals throughout the years. The spillover of inflation, which is at its highest level since several decades, due to the supply chain problems and spike in energy prices, following the war between Russia and Ukraine pushed oil and gas under the spotlight recognizing its crucial role. In turn, this has imposed many challenges on numerous countries across regions building up feelings of fear and anxiety amid serious concerns about energy and food security. Forecasting oil prices is still a major challenge as it is stimulated by various influencers. With the availability of numerous techniques to forecast oil prices, this study aims to use multiple linear regressions which include the Vector Autoregression (VAR), Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models in order to attempt coming out with decent models that can help in forecasting oil prices and estimating their volatility.

Keywords: forecasting, regression, oil, energy, volatility, economics

1. Introduction

Crude oil has been a main strategic resource influencing geopolitics for many decades. Crude oil price change has been shown to have a significant impact on the global economy on various levels, as the oil and gas drilling sector is estimated to contribute up to three percent to the global gross domestic product (GDP) (Miao et al., 2017). In turn, the fluctuation in oil prices would then have a significant impact on each nation's economy, either positively or negatively, depending on how it was affected.

It is important to predict how oil prices will change in the future because not only will it impact many economic factors, but also the political scene. Many experts have been interested in forecasting oil prices for a long time because they want to understand how prices vary over time. Predicting the price of crude oil is thought to be a crucial undertaking because economies of many countries depend directly on oil output and its price (An et al., 2019). As crude oil continues to be the primary energy source in the globe, adopting accurate price forecasts is still an important duty because it would help many decision-makers around the world adapt to the always changing circumstances and corporations and learn how to hedge against the fluctuation in prices of this commodity.

A variety of techniques has been continuously tested with the purpose of understanding the changes in oil prices due to the complicated characteristics that crude oil frequently exhibits, such as its nonlinearity and volatility. However, because the modeling technique employed in terms of data, methodology, and sample period has an impact on forecasting crude oil prices, it might be difficult to choose which forecasting model to use in order to get the most significantly appealing results (Zhang et al., 2015). It is worthwhile to note that based on previous literature, earlier models showed diverse signals in forecasting oil prices where their accuracy was questioned numerously, specifically that oil prices are assumed to obey a random walk (Fama, 1995). As a result, many academics and decision-makers around the world are constantly interested in testing and implementing new models to estimate crude oil prices.

Energy price shocks have been a major concern over the years. With various events taking place during certain periods, oil prices have been subjected to different shocks. As per the World Bank (2022), the Russian-Ukrainian war could result in a food and energy crisis that could last for years. They state that commodity markets have been subjected to a huge shock. Such a shock may eventually change global patterns of trade, production and consumption in the upcoming years due to the sudden surge in inflation.

2. Literature Review

Oil price predictions are made using a variety of methods. These methods are utilized in various applications and vary from one another in terms of how they are implemented. The various methods used to forecast oil prices and estimate their volatility and how they differ from one another have been the subject of extensive research (Zhao et al., 2017).

In this research, three different methods for forecasting oil prices and estimating their volatility will be tackled which include the Vector Autoregression (VAR) technique, Autoregressive Conditional Heteroskedasticity (ARCH) technique and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) technique.

2.1 Vector Autoregression (VAR) Technique

The vector autoregression (VAR) model is one of the most widely used and straightforward methods for the analysis of time-series data. VARs are a form of flexible time-series model that can be used to describe complex relationships among multiple macroeconomic variables (Giannone et al., 2015). The first step in creating a VAR model is to determine the precise amount of lag lengths in order to describe the model (Rautava, 2004). Additionally, by selecting the proper lag length, serial correlation problems for each of the model's variables can be eliminated. The impulse response function (IRF) is used to analyze the effects of a one percent increase in any of the independent variables on the dependent variable under study after the appropriate VAR model has been set up (Zhang et al., 2008). The price of oil is one of key global macroeconomic indicators, thus in a study by Baumeister and Kilian (2012), they produced real-time projections for it. They accomplished this by putting into practice a number of regression techniques, among which is the VAR approach. Their findings demonstrated that the VAR model gave the most precise short-term predictions for oil prices, whether for the West Texas Intermediate (WTI) price or the cost of crude oil procurement for U.S. refiners. In a similar vein, Sadorsky (1999) forecasted oil prices and assessed how such variations may affect a nation's economic activity. He did so by using a VAR model. He emphasized how oil price shocks eventually have a negative impact on real stock returns while demonstrating how oil prices fluctuate over time.

2.2 Autoregressive Conditional Heteroskedasticity (ARCH) Technique

ARCH models can be employed in predicting applications because they distinguish between conditional and unconditional variances (Bollerslev et al., 1994). Additionally, they are especially utilized when the conditional variance varies over time. The ARCH model, despite being a straightforward regression model, is crucial for volatility forecasting. Cheong (2009) employed an ARCH model to predict the volatility in prices of both the WTI and Europe Brent in terms of predicting oil prices. The findings demonstrated that the ARCH model is capable of accurately predicting both forms of crude oil prices, but that Europe Brent prices are more significant. Similar to this, Salisu and Fasanya (2013) used an ARCH model to predict how WTI and Brent oil markets will behave. Their findings indicated the necessity for an alternative modeling approach to study oil prices while simultaneously taking structural breaks, as the ARCH model produces statistically negligible effects.

2.3 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Technique

The GARCH model is one addition to the ARCH model. Moreover, the GARCH model is employed in a number of financial applications. GARCH models can be expanded to forecast over larger time horizons because they can be used to make volatility predictions for the next period (Ederington & Guan, 2010). GARCH models are frequently used in financial applications, particularly those that deal with risk and volatility forecasts over extended time periods (Bollerslev, 1986). The GARCH model can be used to forecast oil prices as well as to describe how their prices change over time. In order to predict the value at risk related to oil prices, Costello et al. (2008) used a variety of modeling strategies, some of which included the GARCH. Their findings demonstrated the importance of the GARCH model in capturing volatility changes, further demonstrating its value in predicting oil prices. Similar to this, Wang and Wu (2012) employed GARCH models to account for market volatility in the energy sector. They were able to forecast different energy costs by using GARCH models, which gives investors a clearer idea of what to invest in.

3. Data

Data used for the following research constitutes of 29 distinct variables that were selected after an overview of the literature, which are used to forecast oil prices. Yet, those 29 variables were selected after having accounted for serial correlation with other predictors. These variables demonstrated to be reliable predictors for oil prices. The variables include:

- The closing price of the European Brent oil and the closing price of the WTI crude oil, where Friday was taken as the last day of the week.
- Delta 1 and 4 of the WTI and Brent closing price where they refer to their first and fourth lags, respectively.
- Implied volatility which refers to the range of possible uncertainty around how much oil prices might fluctuate.
- Oil curve, which reflects the difference in price between the 1st and 13th month delivery.
- Oil over equity, which compares the movement of the US oil companies to that of the entire equity market (S&P 500).
- Delta 1 and 4 of the oil over equity, where they refer to their first and fourth lags, respectively as mentioned previously.
- Exchange rate of the Norwegian, Mexican, Brazilian, Colombian, Canadian and Russian currencies against the dollar, where those countries were chosen as they are among the major producers and exporters of oil.
- Delta 1 and 4 of those listed currencies.
- Oil crack spread, which is the difference between the price of crude oil and its resulting refined products.
- US dollar index, which represents the dollar value relative to the following currencies: Euro, Japanese yen, Pound sterling, Canadian dollar, Swedish krona and Swiss franc.
- Inflation and GDP of US, EU, UK, China, Japan, France and Germany as oil prices are interdependent with inflation and economic growth of those countries which are considered to be among the largest economies.
- Demand and supply, which are considered to be among the main driving factors of oil prices.
- Imbalance between demand and supply, which may represent the seasonal changes within oil prices (Ye et al., 2002).
- Total speculators buyers and sellers of oil, which are those who choose to flow with the risk associated with oil prices.
- Imbalance of speculators, which represents the percentage of the position of net speculators.
- Total hedgers buyers and sellers of oil, which are those who choose to hedge against the risk associated with oil prices.
- Imbalance of hedgers, which represents the percentage of the position of net hedgers.
- The month and the week of month to track whether there is a calendar effect on the crude oil market.

The following variables were chosen after having accounted for the presence of any issue of serial correlation. In order to ensure that there was not any issue of serial correlation, a multicollinearity test was implemented with the aim of checking whether any of the independent variables used for the study are correlated.

After having ensured that all the 29 variables did not witness any serial correlation, unit root tests were implemented to determine whether the variables were stationary or not, where the Augmented Dickey-Fuller (ADF) was implemented. The results showed all the variables to be stationary without the need to take any log difference.

4. Methodology

In order to forecast oil prices and estimate their volatility, three different models were implemented with the use of the 29 variables. The models included the VAR, ARCH and GARCH models. With reference to Baumeister and Kilian (2012), a VAR model is given by:

$$y_t^W = v + B_1 y_{t-1}^{\ W} + \ldots + B_p y_p^{\ W} + u_t$$

where y_t^W denotes an nx1 vector of variables under study which include the aforementioned variables in the data section, v refers to the vector of intercepts, B_p denotes an nxn matrix of coefficients and u_t refers to the shocks.

Before carrying out the VAR model, the alternative information criteria were implemented in order to determine the optimal lag length where the Akaike Information Criterion showed to be minimized at five lags, suggesting that five lags is the optimal number of lags required to be integrated in the analysis.

5. Results

5.1 VAR Model

Starting off with VAR model for all the 29 variables and their impact on WTI crude oil price, the Granger causality test showed some variables to have a significant effect on the WTI price. In terms of significance, the variables MONTH, WEEK OF MONTH USINFLATION and DSIMBALANCE i.e. the imbalance between demand and supply showed to significantly Granger cause WTI crude oil prices, where at 5% level of significance, the variables recorded 0.006, 0.002, 0.033 and 0.004, respectively (see Table 1). A one percent increase in each of those variables would cause a decrease in WTI crude oil prices by 0.0027927, 0.0050789 and 0.030548 percent, respectively, except for DSIMBALANCE which caused an increase in WTI crude oil prices by 0.18344 percent. As for the remaining variables, the results were insignificant. In terms of effect on the Brent crude oil price, the variables MONTH, IMPLIEDVOL which is the implied volatility, DSIMBALANCE and UKGDP showed to significantly Granger cause Brent crude oil prices. A one percent increase in each of those variables would cause a decrease in Brent crude oil prices by 0.0022322, 0.0012359 and 0.1686795 percent, respectively, except for UKGDP which caused an increase in Brent crude oil prices by 0.142384 percent.

5.2 ARCH and GARCH Models

In terms of ARCH model, the null hypothesis of having no ARCH effects was rejected for some variables while it was failed to be rejected for others. On one hand, the results of the ARCH model showed that the variables D1EQUITY which is the delta 1 of the oil over equity, D1NOK which is the delta 1 of the Norwegian currency and DELTA1 which is delta 1 of the WTI crude oil price did not witness any ARCH effects while all other variables did. In other words, for those variables, the null hypothesis of having no ARCH effects was failed to be rejected. As for those who witnessed ARCH effects, OCS which is the oil crack spread, IMPLIEDVOLATILITY, D1MXN which is delta 1 of the Mexican currency, D1RUB which is the delta 1 of the Russian currency and EUINFLATION witnessed significant ARCH effects. On the other hand, the results of the GARCH model showed that the variables DELTA1 which is delta 1 of the WTI crude oil price, D1MALPORT which is delta 1 of the price of oil in Kertih in Malaysia, D1NOK which is delta 1 of the Norwegian currency, D1RUB, D1COP which is delta 1 of the Colombian peso, D4COP which is delta 4 of the Colombian peso, UKINFLATION and DSIMBALANCE did not witness any GARCH effects. As for those who witnessed GARCH effects, the variables MONTH, WEEKOFMONTH, DELTA4 which is delta 4 of the WTI crude oil price, D1 EQUITY, D4 EQUITY which is the delta 4 of the oil over equity, D4NOK which is the delta 4 of the Norwegian currency, D4MXN which is the delta 4 of the Mexican currency, D4RUB which is the delta 4 of the Russian currency, DOLLARINDEX, USINFLATION, JAPANINFLATION, CHINAINFLATION, UKGDP, JAPANGDP and USGDP showed to have insignificant GARCH effects. Alternatively, the variables OCS, IMPLIEDVOLATILITY, D1MXN and EUINFLATION witnessed significant GARCH effects.

Such outcomes showed alternating results where some variables witnessed significant effects, others witnessed insignificant effects and others did not witness any ARCH effects. The significant ARCH effects showed that the previous observations of the variables OCS, IMPLIEDVOLATILITY, D1MXN, D1RUB and EUINFLATION affect the volatility of oil prices. As for the significant GARCH effects, they showed that the previous volatilities of the OCS, IMPLIEDVOLATILITY, D1MXN and EUINFLATION variables affect the volatility of oil prices.

The presence of ARCH effects refers to the presence of a mean reverting volatility phenomenon in which the volatility of the series under study reverts to its mean, where this is due to the fact that ARCH models are utilized to explain the time-varying volatility of a time series (Engle, 1982). Nevertheless, the presence of ARCH effects solely does not imply the presence of a long-run variance effect in the time series, as such a phenomenon would require performing additional tests such as an ARIMA model or the Engle-Bollerslev test to assert it (Engle, 1982; Bollerslev, 1986). The long-run variance effect states that the variance of a time series verges to return to a long-run mean progressively, regardless of any variations on the short-term (Engle, 1982).

6. Discussion

The paper was constructed to forecast the prices of Brent and WTI oil prices and assess their volatility while using three different techniques. The results showed that all three models were promising tools for forecasting oil prices and estimating their volatility, yet other methods should be considered for comparison purposes. The use of an ARCH model is an important step to assess the time-varying volatility of a time-series, where obtaining significant ARCH effects reflects the presence of time-varying conditional volatility which was the case for some of our used variables. Furthermore, GARCH models rely on past observations to capture present ones and are widely used to describe volatility changes in financial markets (Bollerslev, 1986), thus, obtaining significant GARCH effects would be useful. Accordingly, the obtained significant GARCH effects in our study asserted that the previous volatilities of the variables contributed in influencing the volatility of oil prices. In addition, in cases where the value of the GARCH coefficient is greater than that of the ARCH coefficient, volatility clustering is present (Miles, 2008), which was the case for the DELTA1, D1EQUITY, D1NOK, D1RUB and D1COP variables. It is also worthwhile to mention that the necessary parameters of the ARCH and GARCH models should be estimated and the stability of those models should be tested. Otherwise, different models could be considered in order to obtain further enhanced results.

The results of the VAR model showed that certain variables negatively affected oil prices. Such a result is in line with that of Baumeister and Kilian (2012), who stated that the VAR approach gives precise short-term predictions for the WTI crude oil. Moreover, compared to the study by Baumeister and Kilian (2012), this paper forecasted the prices of Brent crude oil rather than that of the cost of crude oil procurement for U.S. refiners which further gave a more detailed picture on the different categories of crude oil. Nevertheless, in our study, as the variables MONTH, WEEK OF MONTH showed to have a significant impact on forecasting oil prices, it can be stated that oil prices often exhibit a calendar effect where it witnesses escalations or diminutions during different times of the year.

As for the ARCH model, the results showed that various variables did not witness any ARCH effects, where it can be stated that the ARCH model is not significant enough in terms of estimating the volatility of oil. This is in line with the study conducted by Salisu and Fasanya (2013), who stated that the ARCH model only produced statistically negligible effects calling the need for an alternative approach. In turn, the ARCH model may not be a suitable option to estimate the volatility of oil prices as more developed models may further enhance the forecasting results.

In terms of the GARCH model, similar to the ARCH model, several variables had insignificant GARCH effects. Such a finding is in contrast with the study by Costello et al. (2008) who stated that the GARCH model possesses a significant value in terms of determining oil prices.

This paper offers a number of contributions to the existing literature. First, in addition to previous research using the following models to forecast oil prices, this paper uses a set of variables which have not been utilized previously all combined. Furthermore, along with the results obtained by exploiting such a framework, the call for alternative models to be implemented may be done in order to check if other methods can outperform the obtained results.

Table 1. VAR Granger Causality results

	(1) WTI	(2) Brent
MONTH	0.006	0.003
WEEKOFMONTH	0.002	0.252
DELTA1	0.748	0.361
DELTA4	0.767	0.907
IMPLIED VOLATILITY	0.066	0.001
D1EQUITY	0.233	0.462
D4EQUITY	0.547	0.812
D1NOK	0.953	0.966
D4NOK	0.535	0.883
D1MXN	0.646	0.379
D4MXN	0.837	0.715
D1RUB	0.183	0.237
D4RUB	0.075	0.135
D1COP	0.756	0.509
D4COP	0.644	0.177
OCS	0.286	0.886
DOLLARINDEX	0.985	0.965
USINFLATION	0.033	0.309
EUINFLATION	0.474	0.445
UKINFLATION	0.066	0.536
JAPANINFLATION	0.520	0.450

CHINAINFLATION	0.551	0.542
UKGDP	0.057	0.036
JAPANGDP	1.000	0.828
USGDP	0.277	0.590
DSIMBALANCE	0.004	0.001

Table 2. ARCH and GARCH results.

Coefficient	
MONTH	
ARCH	1.026023
GARCH	0.0056789
WEEKOFMONTH	
ARCH	0.2436622
GARCH	0.0033916
DELTA1	
ARCH	-.0039539
GARCH	0.7854395
DELTA4	
ARCH	0.6144644
GARCH	-0.0051139
IMPLIED VOLATILITY	
ARCH	0.834632
GARCH	0.1909056
D1EQUITY	
ARCH	0.0165795
GARCH	0.8373328
D4EQUITY	
ARCH	0.5988534
GARCH	-0.0690996
D1NOK	
ARCH	0.0251025
GARCH	0.8032236
D4NOK	
ARCH	0.6514877
GARCH	-0.0786625
D1MXN	
ARCH	0.0757954
GARCH	0.711563
D4MXN	
ARCH	0.5387192
GARCH	-0.0701631
D1RUB	
ARCH	0.1505308
GARCH	0.5542933
D4RUB	
ARCH	0.6171407
GARCH	-0.0103427
D1COP	
ARCH	
GARCH	0.106783
D4COP	0.4821532
ARCH	
GARCH	0.6577871
OCS	0.227415
ARCH	
GARCH	0.8268829
DOLLARINDEX	0.1756924
ARCH	
GARCH	0.4875967
USINFLATION	0.1119437

ARCH	
GARCH	1.003571
EUINFLATION	0.2057727
ARCH	
GARCH	0.897299
UKINFLATION	-0.0264307
ARCH	
GARCH	1.13261
JAPANINFLATION	-0.0025041
ARCH	
GARCH	1.030946
CHINAINFLATION	-.0226404
ARCH	
GARCH	0.9721803
UKGDP	0.0394877
ARCH	1.26225
GARCH	0.0015935
JAPANGDP	
ARCH	1.029103
GARCH	-0.0113924
USGDP	
ARCH	1.124059
GARCH	0.1178564
DSIMBALANCE	
ARCH	1.004624
GARCH	0.0000559

7. Conclusion

During the present time and for the years ahead, crude oil is still seen as a major factor that influences economic growth and energy security, where it is still a significant element affecting industries and the worldwide economy. Yet, fluctuations in oil prices impose obstacles on many nations and policy makers as it may be subjected to unforeseen events. As a result, with the continuous changes in oil prices over time, forecasting oil prices remains an issue for many researchers and policy makers.

The following study has presented three different standard methods used for forecasting oil prices and estimating their volatility while using 29 different variables. As a result, it would be intriguing for other researchers to employ other techniques and factors to compare them with the obtained results. Also, with the continuous developments and technological advancements, new models might outperform the classical methods for forecasting oil prices.

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