Crude Oil Prediction:

AI Model For Predicting The Crude Prices

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Abstract

This project's main aim is to forecast the future price of crude oil. Investors can benefit from our project by being able to predict the future price of crude oil. In order to predict crude oil prices in the near future, this project includes several factors that may affect them. It is possible to estimate the price of a barrel of crude oil (158 liters or 42 gallons) using this project. As crude oil's volatility is high, we estimate the price of crude oil in a certain range. External and internal factors can be calculated by this AI model to make precise oil price projections.

Everybody can use this service to plan, invest, and forecast oil prices using this platform. This AI model is integrated with a web application that allows users to extract data. We also provide oil price charts as a forecast. Oil is becoming a common resource for all nations in the world. Europe is experiencing a catastrophic oil crisis. Inflation is really high. Additionally, the price of oil surpassed $100. The cost of commodities is significantly influenced by the price of oil.

Review of Literature

The Measurement of oil price volatility

The literature has revealed a growing interest in modeling and forecasting oil price volatility in recent years (Wang et al., 2012; Rahman and Serletis, 2012, p. 1). Several approaches have been proposed to detect oil price bubbles in recent years. Oil price volatility has been widely analyzed using GARCH-type models in the literature (Alizadeh et al., 2008; Fan et al., 2008; Agnolucci, 2009a; Kang et al., 2009; Cheong, 2009; Mohammadi and Su, 2010; Wei et al., 2010; Nomikos and Pouliasis, 2011, p. 1). Zhang and Wang (2015) discovered that oil price bubbles existed between 2003 and 2012 using the regime-switching procedure of the WTI crude oil fundamental prices and market trading prices. Lammerding et al. (2013) used the state-space model together with a Markov regime-switching model to study bubbles in oil prices and found strong evidence for their existence. Zhang and Yao (2016) used the state-space model to measure oil price bubbles, and found strong evidence for the presence of bubbles. In light of the multiscaling, long memory, and structural breaks observed in oil price volatility, Lux et al. (2016) use the Markov-switching multifractal (MSM) model and a battery of generalized autoregressive conditional heteroscedasticity (GARCH)-based models to describe and forecast oil prices. Wang and Wang (2016) introduce a new forecasting algorithm, ST-ERNN, to forecast crude oil prices as well as oil stock prices.

Measurement of oil price risk

Within the oil industry, employing statistical theory to measure risk is an important issue. Despite the significant need and interest in measuring risk in the oil industry, very few studies have examined risk predictions. Despite the few studies researching risk in the energy market, Krehbiel and Adkins (2005) investigated risk in NYMEX's energy market by employing an extreme value theory approach. From the existing literature, there are a few studies that concentrate on conventional risk management approaches to estimating risk (Cabedo and Moya, 2003; Costello et al., 2008; Huang et al., 2008; Fan et al., 2008; Zhao and Xi, 2009). VaR quantity is estimated for both short and long oil trading positions by combining unconditional and conditional EVT models in order to forecast value and risk, as proposed by Marimoutou et al. (2009). Huang et al. (2009), employing CAViaR, forecasted oil price risk. Additionally, in the market for crude oil and gasoline, Youssef (2015) adopted long memory processes heteroscedasticity, asymmetry, and fat tails. Their findings demonstrate that factoring in those circumstances aids in the prediction of VaR in the extremely unpredictable energy market.

In July 2008 the nominal price of oil reached USD 133.40 a barrel, a five-fold (500%) increase from 2002. In September 2008 Lehman Brothers declared bankruptcy, marking the abrupt beginning of a global economic crisis from which advanced economies have not fully recovered. Prominent ecological economists such as Herman Daly, Robert Goodland and Joan Martinez-Alier suggest a direct causal link from peak oil to high oil prices to low growth and economic crisis. In contradistinction to neoclassical resource or environmental economics, a core thesis of ecological economics is that “increased energy use is the main or only cause of economic growth” (Stern, 2011, 30) and that abundant and cheap energy has been historically a major driver of economic growth (Ayres and Warr, 2009, Cleveland et al, 1984). Peak oil and declining energy returns on energy investment for oil and other primary energy resources (Murphy and Hall, 2010) are then likely to limit economic growth and cause recession (Martinez-Alier, 2016, Tverberg, 2012). Mainstream economics is more optimistic about the capacity of advanced economies to overcome resource limits given technological change and the possibilities of substitution. Ecological economists instead argue that fossil fuels had remarkably high EROIs and substitute energy sources will not be able to sustain contemporary levels of economic output. There are limits also to the substitution of energy by other factors of production (e.g. capital or knowledge); such substitutes require substantial amounts of energy too. Technological change does not alter these limits, since it is just another name for substitution (see review in Stern, 2011). The end of cheap oil, ecological economists argue, therefore will bring the end of the era of dramatic, continuous economic growth. Ecological economists may be right that limits in oil supply will limit economic growth in the future, but is this sufficient proof that the 2008 crisis resulted from increasing oil scarcity, as Daly, Goodland and Martinez-Alier suggest? The 1970s oil crisis gave birth to the "limits to growth" movement, and to the community of ecological economics. By now we know that that crisis had less to do with depletion or 'running out of oil' (though domestic peak oil in the US may have arguably contributed to a massive global economic change); the primary causes of the economic dislocation of the 70s were geopolitical and economic (Mitchell, 2011). Today oil prices remain low while the global economy grows: is this proof that ecological economists were again too quick to presume that physical oil scarcity was an enduring reality, producing perpetually high oil prices, which in turn caused financial and economic crisis? Beyond predicting ultimate limits to growth, ecological economics has less to say about the interdependent factors that connect oil and the economy in the short-term, and the role of political and monetary forces. Ecological economics for example is mute on how monetary policy, interest rates, or capital flows affect resource markets and resource use, treating them as epiphenomena, a "virtual economy" top resting upon the base of the "real-real" economy of biophysical stocks and flows (Daly, 2014, Martinez-Alier, 2016). We believe, however, in the spirit of Keynes, that the financial economy is integral to the understanding of the physical economy; we find it useful, however difficult, to try to understand and explain the complex interrelationships between resource and money flows, and the role of (geo)politics and power in governing them. Toward this end, this article offers a systematic review of the literature in oil economics, macroeconomics (international and financial economics) and political economy, complementing and complicating the way ecological economics understands the links between oil and the economy. An oil price shock preceded all but one of the eleven U.S. recessions since World War II (Hamilton, 2012). Figure 1 illustrates the direct correspondence between high oil prices (indicated here relative to gold prices to distinguish between oil and general price increases) and US recessions. One might deduce from this that a rise in the price of oil causes an economic downturn. Yet oil prices are endogenous to macroeconomic conditions (Kilian, 2008), making it hard to infer directionality. In other words, the causation may be inverse: it could be that an economic expansion increases the demand for oil and its price and an economic downturn reduces it. Or it might be the case that both oil prices and economic output respond to some third variable, such as interest rates, capital flows, or a structural or policy change. Interest rates and capital flows—or oil investment, extraction, and trade—are not pure market outcomes; they are influenced, if not determined, by politics and geo-political relations.

Method

There are three types of oil price forecasts: long-term, intermediate-term, and short-term The long-term forecast is used to make macroeconomic policies by central banks and governments. As a consequence, individuals have difficulty implementing it and government agencies are increasingly doing so. To forecast various energy-related factors related to U.S. energy, such as production, consumption, pricing, etc., the Energy Information Administration (EIA) of the Department of Energy (DOE) has developed a tool called the national energy model system (NEMS). Using this tool, you can forecast the energy market at the national level in the future. A comprehensive list of energy-related factors has been predicted by this model since 1993 in DOE's annual energy outlook. It includes many inputs and assumptions and is based on macroeconomic and financial models. It is composed of several integrated modules that interact to calculate equilibrium.

Models that forecast oil prices over the medium-term focus on a few-year time horizon. Macroeconomic decisions are made by central banks based on medium-term oil price forecasts. The most popular model to predict the medium-term oil price is the Vector Autoregressive (VAR) model. VAR models generally have higher accuracy and lower mean-square prediction error than random walks for forecast horizons up to two years. In the working paper published by the International Monterey Fund (IMF), nominal oil prices were forecast instead of real oil prices using VAR models. Real-time VAR models have been used to predict real oil prices over one year recently. Real price forecasts are more accurate than future price forecasts by Baumeister and Kilian. Forecast estimates are based on quarterly vector autoregressive models. Quarterly forecasts can be approached in different ways.

In one method, monthly real oil prices are forecast and then converted to quarterly averages based on Baumeister and Kilian (2014). A short-term forecast of future oil prices, specifically WTI crude oil, is the focus of this project. It remains one of the main challenges for econometricians to predict such unpredictable economic series. To forecast and predict short-term oil prices, several different models have been proposed in the literature. Linear structural models have historically not performed well at forecasting oil prices, and nonlinear time series models have performed much better. An overview of time series analysis by F Bosler was presented in LAM (2013), which included linear and nonlinear time series analysis, as well as structural models. According to him, the linear ARIMA model performs better and follows oil price volatility better than the neural network autoregressive model for nonlinear time series analysis.

The Box-Jenkins methodology was also used by D Lam to model oil prices using univariate time series. According to Bosler (2010), ARIMA was selected based on ACF, PACF, and GARCH residuals. In addition to his nonlinear model, he also built a regression model. As a comparison to his nonlinear model, he also built a regression model. He used eight explanatory variables for the regression model: production, consumption, net imports, ending stocks, refinery utilization rate, U.S. interest rates, NYMEX oil futures contract 4, and S&P 500 index. GARCH and APARCH, however, performed the best in the study.

A further nonlinear model for forecasting daily crude oil futures prices was presented by Moshiri. To forecast the series, they used an artificial neural network (ANN) model that was nonlinear and flexible. According to this research, linear models can lead to large forecast errors if data generation processes are nonlinear. Model specification, however, can be time-consuming and very case-dependent in nonlinear modeling.

It has been proposed by Shabri that an even more complex forecasting model is based on the integration of wavelet transforms with artificial neural networks (WANN). Each wavelet component is decomposed and an ANN model is applied separately to each of them. It was concluded that WANN models provide a better prediction of crude oil spot prices at lead times of one day for West Texas Intermediate (WTI) and Brent crude oil.

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