Alternative Investment Analyst Review

WHAT A CAIA MEMBER SHOULD KNOW
Understanding Drawdowns
Galen Burkhardt, Ryan Duncan, and Lianyan Liu

CAIA SUBMISSION
Liquid Real Assets
Anton Loukine, CAIA

RESEARCH REVIEW
Crude Oil Price Forecasting Techniques: a Comprehensive Review of Literature
Niaz Bashiri Behmiri and Jose Ramos Pires Manso

TRADING STRATEGIES
Alternative Inflation Hedging Portfolio Strategies: Going Forward Under Immoderate Macroeconomics
Nicolas Fulli-Lemaire

CAIA MEMBER PERSPECTIVE
The Next Wave of Futurization
Kathryn M. Kaminski, CAIA

Q4 2013, Volume 2, Issue 3 Chartered Alternative Investment Analyst Association®

Crude Oil Price Forecasting Techniques: a Comprehensive Review of Literature

Niaz Bashiri Behmiri
and José R. Pires Manso

1. Introduction

In light of the importance of crude oil to the world's economy, it is not surprising that economists have devoted great efforts towards developing methods to forecast price and volatility levels. While the most popular forecasting approaches are based on traditional econometrics, computational approaches such as artificial neural networks and fuzzy expert systems have gained popularity in financial markets because of their flexibility and accuracy. However, there is still no general consensus on which methods are more reliable.

In this study, we categorize the extant oil price forecasting literature into two main categories: (1) quantitative and (2) qualitative methods. Section 3.1 of the paper focuses on quantitative methods including econometric and computational approaches, while Section 3.2 covers qualitative methods including computational and technological approaches. Appendix A provides a premier on time series models including ARCH and GARCH modeling.

2. Crude Oil Price Forecasting Techniques

Quantitative methods, which utilize numerical variables that impact oil prices, can be further segmented into two categories: (1) econometric methods and (2) non-standard methods. Econometric models are further sorted into the three classes of models: (1) time-series models, (2) financial models, and (3) structural models. The non-standard methods that are most frequently applied to oil price forecasting are artificial neural networks and support vector machines. Qualitative methods estimate the impact of infrequent events such as wars and natural disasters on oil prices. These approaches have recently grown in popularity in the oil price forecasting literature. While there are many qualitative forecasting methods, few have been applied to forecast oil prices, such as the Delphi method, belief

---

Exhibit 1 Standard Specifications for Select Quantitative Models

1. ARIMA (p, d, q) model: Auto-Regressive Integrating Moving Average, where

- p = number of autoregressive terms
- d = number of nonseasonal differences
- q = number of lagged forecast errors

Examples: ARIMA (0, 1, 0) – Random Walk model with a drift

$$y_{t+1} = \alpha + y_t + \varepsilon_{t+1}$$

ARIMA (1, 1, 1) – Mixed Autoregressive and Moving Average model with constant

$$y_{t+1} = a_0 + a_1 y_t + a_2 \varepsilon_{t+1} + a_3 \varepsilon_t$$

2. Markov Switching Model of Conditional Mean.

$$y_{t+1} = \begin{cases} a_0 + \beta y_t + \varepsilon_{t+1} & \text{if } s_t = 0 \\ a_0 + a_1 + \beta y_t + \varepsilon_{t+1} & \text{if } s_t = 1 \end{cases}$$

Here s_t represents the regime (e.g., $s_t = 0$ may represent high interest rate environment, while $s_t = 1$ may represent low interest rate environment).

3. ARCH/GARCH models

$$y_t = a_0 + a_1 y_{t-1} + \sqrt{h_t} \times \varepsilon_t$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 \qquad \text{ARCH(q)}$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \ldots + \beta_p h_{t-p} \qquad \text{GARCH(p,q)}$$

networks, fuzzy logic and expert systems, and web text mining.

3. Review of the Literature

3.1. Quantitative Models

Quantitative methods are based on quantitative historical data and mathematical models and focus on short- and medium-term predictions. We divide quantitative methods into two broad categories: (1) econometric models and (2) non-standard models.

3.1.1. Econometric Models

Econometric models are the most frequently used methods in oil price forecasting. In this study, we further classify econometric methods into three categories: (1) time-series, (2) financial, and (3) structural models.

3.1.1.1. Time-Series Models

Time-series models predict future oil prices based on historical oil price data. These models are most often employed when (1) the data exhibit a systematic pattern, such as autocorrelation, (2) the number of possible explanatory variables is large, and their interactions suggest an exceedingly complex structural model, or (3) forecasting the dependent variable requires the prediction of the explanatory variables, which may be even more involved than forecasting the dependent variable itself. All of these conditions appear to apply to oil prices.

Time-series models include three main categories: (1) naïve models, (2) exponential smoothing models, and (3) autoregressive models such as ARIMA[1] and the ARCH [2]/GARCH[3] family of models. In this context, Pindyck (1999) examines long-run behavior of crude oil, coal, and natural gas prices from 1887-1996. He incorporates unobservable state variables such as marginal costs, the resource reserve base, and demand parameters into the model and estimates the model with a Kalman filter. The author examines the forecasting ability of the model, adding mean reversion to a deterministic linear trend. The results suggest that the inclusion of a deterministic linear trend produces more accurate forecasts. Radchenko (2005) extends the Pindyck study. He applies a shifting trend model with an autoregressive process in error terms rather than Pindyck's white noise process. The results confirm Pindyck's conclusions. The author states that the shortcoming of the model is an inability to consider the impact of OPEC's behavior. For this reason, he combines the model with autoregressive and random walk models and concludes that the combined model outperforms the original model.

Lanza et al. (2005) estimate the relationship between 10 heavy crude oil price series and 14 petroleum product price series in Europe and United States. The study covers the period from 1994-2002, and the authors apply cointegration and error correction (ECT) tests to determine the relationships among the variables and forecast crude oil prices. The empirical results provide evidence that product prices are related to heavy oil prices in the short- and long-term. Furthermore, in the United States neither the error correction model (ECM) or the naïve model dominates, whereas in Europe the ECM marginally outperforms the naïve model. Wang et al. (2005) apply ARIMA to model the linear component of monthly WTI crude oil data from January 1970 to December 2003. The out-of-sample forecasts indicate that the linear ARIMA model exhibits poor forecasting power when compared to the nonlinear artificial neural network and the nonlinear integrated fuzzy expert system approaches. Xie et al. (2006) forecast WTI crude oil prices by applying the ARIMA method to WTI spot prices from January 1970 to December 2003. They compare the results with those of support vector machine and artificial neural networks methods. Once again, the out-of-sample forecasts indicate that the ARIMA model provides the poorest forecasting performance among the methods considered. Fernandez (2010) performs an out-of-sample forecast for short- and long-term horizons employing daily natural gas and Dubai crude oil prices from 1994-2005 using an ARIMA model. The results indicate that for very short-horizon forecasts, the ARIMA model outperforms the artificial neural networks and the support vector machine approaches, however, for long-horizon forecasts, the ARIMA model underperforms the other approach. The ARIMA model is a linear model so it is not surprising that there is a general consensus in the literature that this model is not able to describe the nonlinear components of oil price time-series.

Furthermore, a wide range of studies analyze the volatility of crude oil markets through the ARCH/GARCH class of models. For instance, Cheong (2009) compares the volatility forecasting ability of GARCH-type models. The author uses daily WTI and Brent crude oil spot prices for the period from January 4, 1993 to December 31, 2008. The out-of-sample forecasting accuracy is estimated for 5-, 20-, 60-, and 100-day horizons. The results indicate that in the case of Brent crude oil prices, the standard short memory GARCH normal and student-t models outperform for the 5- and 20-day horizon forecasts and GARCH models that account to asymmetric reaction of oil volatility to price changes perform better at longer horizons. Thus a single model is not uniformly superior to predicting changes in oil price volatility.

Kang et al. (2009) compare the volatility prediction ability of the various types of GARCH models. They use daily spot prices of Brent, WTI, and Dubai crude oil during the period of January 6, 1992 to December 29, 2006. The out-of-sample forecasts consider 1-, 5-, and 20-day horizons. The results indicate that in the case of Brent and Dubai crude oil for all three forecasting horizons, the fractionally integrated GARCH model outperforms the other models and in the case of WTI crude oil the component GARCH model outperforms the other models. Wei et al. (2010) extend the work of Kang et al. (2009), applying nine linear and nonlinear GARCH-type models. They consider 1-, 5- and 20-day out-of-sample volatility forecasts based on daily Brent and WTI crude oil spot prices covering the period from January 6, 1992 to December 31, 2009. The out-of-sample forecasts show that across all six loss functions there is no evidence that a single GARCH model outperforms the other models for both Brent and WTI. The only differentiation between models is that the linear GARCH-type models seem to fit better for short -run (one day) volatility forecasts and the nonlinear GARCH-type models seem to fit better for long-run (5- and 20-day) volatility forecasts.

Vo (2009) compares the forecasting ability of four different models: (1) a Markov switching stochastic volatility (MSSV) model with constant variance, which is the combination of regime switching with a stochastic volatility model, (2) a stochastic volatility (SV) model, (3) a GARCH model, and (4) a Markov switching (MS) model. The author uses WTI weekly spot prices for the period from January 3, 1986 to January 4, 2008. The author finds that the in-sample forecast accuracy depends on the evaluation criteria and despite mixed results the simple MS model seems to perform better than the others. In terms of the out-of -sample forecasts, the MSSV outperforms the other models under all three of the evaluation criteria. Mohammadi and Su (2010) compare the out-of-sample forecasting ability of various GARCH, exponential GARCH models. They apply the models to weekly data on 11 different crude oil (FOB) spot price time-series in international markets during the period of January 3, 1997 to February 13, 2009. The results indicate that the forecasting accuracy of a nonlinear GARCH model outperforms the other models.

Silva et al. (2010) investigate the performance of hidden Markov model (HMM) to forecast the medium term future crude oil price movements. This approach is a nonlinear time-series model which uses historical time-series data to forecast future prices. They use daily WTI spot prices and apply wavelets to omit the high frequency movements of the time-series, and then perform HMM to forecast oil prices. The HMM model forecasts the probability distribution of accumulated returns over the following days. From this distribution, they explore future price trends. The results suggest that HMM model provides good forecasting performance.

The results of these studies show that (a) time-series model are adequate for forecasting oil prices in the short run, but they have limited forecasting ability in the medium and long-term, (b) time-series models proved accurate forecasts of oil price volatility, but a single model cannot be used in every case, (c) oil prices and their volatility display significant nonlinearity, which indicates that small shocks to the economy could have large and unpredictable implications for oil prices and their volatility.

3.1.1.2. Financial Models

In oil price forecasting, financial models estimate the relationship between spot and futures prices, and investigate whether futures contract prices are unbiased predictors of future spot prices, and whether they are efficient based on the efficient market hypothesis (EMH). Toward this goal, Bopp and Lady (1991) examined the impact of lagged futures and lagged spot oil prices on future spot prices. They use monthly heating oil prices traded on NYMEX[4] covering the period from December 1980 to October 1988. The authors apply an autoregressive model and conclude that the predictive power of each data series depends on the type of data.

When deseasonalized data is applied then the predictive performance of spot and futures prices are the same, but when actual prices are used, the forecasting ability of futures prices is superior to that of spot prices. The forecasting performance of the autoregressive financial model is compared with the random walk model and the results suggest that both models exhibit similar forecasting ability.

Serletis (1991) investigates futures market efficiency and unbiasedness. The author uses daily spot and futures prices on heating oil and crude oil traded on NYMEX from July 1, 1983 to August 31, 1988, and daily spot and future prices on unleaded gasoline covering the period of March 14, 1985 to August 31, 1988. The author applies a cointegration test to determine the relationships among the variables and uses Fama's variance decomposition method to test the joint measurement of variation in the premium and expected future spot prices, and concludes that variation in the premium reduces the forecasting ability of futures prices. Green and Mork (1991) examined efficiency and unbiasedness among official oil prices and ex-post spot prices. For this purpose they use a generalized method of moments (GMM) estimation approach using Middle East light and African light/North sea monthly crude oil prices covering the period from 1978-1985. They conclude that ex-post spot prices are not efficient or unbiased in the sub-period of 1981-1985, but there is evidence of improvement in efficiency during the period.

Sami (1992) examined WTI crude oil futures prices (3- and 6-month futures) as a function of WTI spot prices and interest rates (i.e., he uses the cost of carry model). The author employs daily data from September 20, 1991 to July 15, 1992, and monthly data from January 1984 to June 1992. The results suggest that interest rates do not have a clear influence on prices. On the other hand, spot and future prices are highly correlated but the direction of the causal relationship between them is not identified.

Day and Lewis (1993) and Agnolucci (2009) compare volatility forecasting accuracy of different GARCH models. The authors compare the prediction ability of these models with that of the implied volatility (IV) model. Using daily WTI crude oil future prices traded on the NYMEX during the period of December 31, 1991 to May 2, 2005. The results indicate that the GARCH- type models outperform the IV model. Furthermore, among the GARCH-type models, those with asymmetric effects provide the best accuracy forecasts. Moosa and Aloughani (1994) also investigate the efficiency and unbiasedness in crude oil futures markets. They use monthly WTI crude oil spot and futures prices traded on the NYMEX covering the period from January 1986 to July 1990. The results of cointegration and error correction model (ECM) tests indicate that futures prices (3- and 6-month futures) are neither unbiased nor efficient forecasts of spot prices.

Zeng and Swanson (1998) examine the forecasting ability of futures prices on spot prices. For this purpose, several models are applied, including random walk with drift, random walk without drift, VAR model, and VECM models. They apply the models to daily futures prices on four commodities including: (1) crude oil traded on the NYMEX, (2) gold traded on the New York Commodity Exchange, (3) treasury bonds traded on the Chicago Board of Trade, and (4) the S&P 500 index traded on the Chicago Mercantile Exchange for the period of April 1, 1990 to October 31, 1995. The results indicate that the ECM model outperforms the other models.

Gulen (1998) estimates efficiency and forecasting power of posted oil prices. For this purpose, he incorporates both posted and futures oil prices as explanatory variables in the model. The author uses monthly WTI crude oil spot prices, and 1-, 3-, and 6-month futures prices traded on the NYMEX covering the period from March 1983 to October 1995. The results of a cointegration test suggest that futures prices are efficient predictors of future spot prices, with better predictive ability than posted prices. However, posted prices show predictive power for very short horizons. Schwartz and Smith (2000) introduce a two factor model of commodity prices which reflects two effects: (1) mean reversion in short-term prices and (2) uncertainty in the equilibrium level to which the prices mean revert. They model long-term prices with a geometric Brownian motion process, and the short-term deviation of spot prices from equilibrium prices is expected to revert to zero according to an Ornstein-Uhlenbeck process.

Morana (2001) applies a semi-parametric approach suggested by Barone-Adesi et al. (1998) to forecast the volatility of Brent crude oil price, which is based on the relationship between spot and futures prices. The GARCH property of oil price volatility is applied to forecast short-term prices based on 1-month forward prices. The author uses Brent crude oil daily prices during the period of January 4, 1982 to January 21, 1999. The results indicate that Brent forward prices seem to be biased predictors of future spot prices. Furthermore, he compares the financial model with a time-series random walk model and concludes that for short-time horizons both specifications are unbiased.

Cortazar and and Schwartz (2002) examine the relationship between spot and futures oil prices, extending the two-factor model of Schwartz (1997) to a three-factor model. They use daily prices of all futures contracts traded on the NYMEX for the period from 1991-2001. In their three-factor model, the long term spot price return is allowed to be stochastic and to mean revert to a long term average. The in-sample and out-of-sample forecasts indicate that the three-factor model performs better than the two-factor model and fits the data quite well. Furthermore, the authors suggest a Kalman filter approach which provides more reliable results.

Fong and See (2002) apply a Markov regime switching (MRS) model to explain the volatility of oil prices. The model is based on the standard ARCH/GARCH approach, allowing jumps in the conditional variance between regimes. They use WTI crude oil daily prices for the nearest futures contracts covering the period from January 2, 1992 to December 31, 1997. The results suggest that the regime switching model with the ARCH effects (RSARCH) outperforms the constant variance and the standard GARCH model for the all three out-of-sample forecasts.

Chernenko et al. (2004) examine the efficiency and unbiasedness of broad sort of forward and futures contracts including crude oil and natural gas futures. They use monthly 3-, 6-, and 12-month WTI crude oil futures prices traded on the NYMEX from April 1989 to December 2003. The authors find in most cases, forward and futures prices are not efficient or unbiased predictors of future spot prices. The results for crude oil and natural gas are mixed and they find little evidence of risk premiums. They compare their financial model to a time-series random walk specification and conclude that a random walk process predicts future spot prices better than futures prices do. Abosedra and Baghestani (2004) estimate the unbiasedness of 1-, 3-, 6-, 9-, and 12-month crude oil futures prices, and use a naïve forecasting model as a benchmark. They use monthly WTI spot and futures prices traded on the NYMEX from January 1991 to December 2002. The empirical results suggest that future prices and naïve forecasts are unbiased in all time horizons, however, the 1- and 12-month futures price based forecasts outperform the naïve forecasts. Abosedra (2005) employs a simple univariate model to examine unbiasedness and efficiency of crude oil spot and futures prices. The author uses monthly WTI crude oil spot and futures prices from January 1991 to December 2001. In this study, the goal is to forecast the 1-month futures price of crude oil for each trading day using the previous trading day's spot price and concludes that 1-month futures prices seems to be an unbiased and semi-strongly efficient predictor. Chin et al. (2005) examine the ability of energy futures prices to accurately forecast future spot prices. The authors use monthly prices for WTI, gasoline, heating oil, and natural gas spot and 3-, 6-, and 12-month futures prices from January 1999 to October 2004, and assume that spot prices follow a random walk process with drift and rational expectations. The results suggest that future prices are unbiased predictors of spot prices with the exception of 3-month natural gas futures. They outperform time-series models.

Yousefi et al. (2005) apply a wavelet methodology in providing out-of-sample forecasts for oil prices in 1-, 2-, 3-, and 4-month forecast time horizons. They use average monthly WTI spot prices and WTI futures prices, covering the period from January 2, 1986 to January 31, 2003. They conclude that the wavelet procedure exhibits greater predictive power than futures prices and this superiority does not decrease with increasing time horizons. Furthermore, their results suggest that futures markets are not efficiently priced.

Sadorsky (2006) compares different types of forecasting models, including the random walk, historical mean, moving average, exponential smoothing, linear regression models, autoregressive models, and various GARCH models to forecast petroleum prices. Sadorsky uses WTI daily futures prices of crude oil, heating oil #2, and unleaded gasoline covering the period from February 5, 1988 to January 31, 2003 (natural gas data covers the period of April 3, 1990 to January 31, 2003).

The results indicate that for heating oil and natural gas the TGARCH model fits best, while the GARCH model fits best for crude oil and unleaded gasoline, therefore, GARCH-type models outperform the other techniques.

Coppola (2008) investigates the long-run relationship between spot and futures oil prices using weekly WTI spot and futures prices traded on the NYMEX from January 1986 to September 2006. The author performs cointegration tests and VECM to examine short- and long-run relationships between spot and futures prices. The in-sample forecasting results indicate that futures prices seem to explain spot price movements and the out-of-sample forecast results suggest that the VECM outperforms the random walk model.

Alizade et al. (2008) are the first to apply the Markov regime switching approach to estimate the time varying minimum variance hedge ratio (Hung et al. 2011) by introducing a Markov regime switching error correction model with a GARCH error structure. They apply the model to weekly spot and futures prices for WTI, unleaded gasoline and heating oil traded on the NYMEX from January 23, 1991 to December 27, 2006. The in- and out-of-sample forecasting results specify that the dependent hedge ratios are able to provide significant reduction in portfolio risk (Alizadeh et al. 2008).

Murat and Tokat (2009) examine the relationship between crude oil and crack spread prices, where the crack spread is the difference between crude oil prices and crude oil product (heating oil and gasoline) prices. The authors use weekly WTI spot prices and weekly prices of NYMEX future contracts from January 2000 to February 2009. They apply a Johansen cointegration test and VECM approach to analyze the Granger causality relationship between the two variables and to forecast WTI oil prices. Furthermore, they apply a time-series random walk model as a benchmark and conclude that the random walk model displays the poorest forecasting accuracy, while the VECM approach works well with crack spread futures and the ECM is effective with crude oil futures.

Nomikos et al. (2011) consider the volatility forecasting ability and VaR performance of various volatility regime switching models including the MIX (distribution) GARCH and two regime MRS-GARCH models based on the mixed conditional heteroscedasticity models proposed by Haas et al. (2004a) and Alexander and Lazar (2006) and the Markov model of Haas et al. (2004b). They append the squared lagged basis of futures prices in the specification of the conditional variance GARCH-X models proposed by Lee (1994) and Ng and Pirrong, (1996), then, extend this framework by adding conditional extreme value theory (EVT). They apply the models to daily WTI crude oil and heating oil futures prices traded on the NYMEX from January 23, 1991 to December 31, 2008, and Brent crude oil and gas traded on ICE[5] from April 19, 1991 to December 31, 2008. The authors find evidence that the MIX-GARCH and the MRS-GARCH models outperform the other models and the MIX-GARCH-X model provides the best performance in terms of out-of-sample volatility forecasting across all the markets considered. Furthermore, the results of VaR performance indicate that the augmented GARCH-X model is the most reliable model.

These results show that while the cost of carry model and the close relationship between current spot and futures are robust and hold strongly, the relationship between futures prices and future spot prices is time-varying cannot be explained accurately by existing models. Even though financial models predict the presence of a risk premium in futures prices in comparison to expected future spot prices, the existing models cannot accurately estimate the premium and its dynamics through time.

3.1.1.3. Structural Models

In structural models, oil price movements are modeled as a function of a collection of fundamental variables. The explanatory variables that are commonly used to explain oil price behavior are OPEC behavior, oil inventory level, oil consumption and production, and some non-oil variables such as economic activity, interest rates, exchange rates, and other commodity prices. In this context, there are many studies that investigate oil price movements based on fundamental variables and some of them explain the price movement fairly well. However, this does not necessarily imply that they provide good forecasting performance, as future values of the explanatory variables may be required to forecast commodity prices. Due to the data limitations and the complexities of structural models, few studies have used structural analyses to forecast oil prices. We categorize the structural models that are used to forecast oil prices into five categories: (1) OPEC behavior models, (2) inventory models, (3) a combination of inventory and OPEC behavior models, (4) supply and demand models, and (5) non-oil models.

3.1.1.3.1. OPEC Behavior Models

According to Huntington (1994), structural forecasting models based on supply and demand were not successful in predicting oil prices in the 1990s due to two major errors. The first error was inaccurate forecasts of GDP, especially for developing countries, and the second was an incorrect prediction of the increase in the supply of oil by non-OPEC countries. In addition to these errors, Tang and Hammoudeh (2002) state that another source of error was the omission of market participants' expectations of OPEC's interventions.

Tang and Hammoudeh (2002) perform an empirical investigation of OPEC attempts to control prices within a target zone during the period of 1988-1999. They employ the basic target zone model proposed by Krugman (1991) which had been applied to oil markets by Hammoudeh and Madan (1995). They use the average basket price of seven types of crude oil products of OPEC members. During the period of study OPEC was not officially following a target zone policy, as the first price band was not announced by OPEC until March 2000. However, the authors state that there is evidence that OPEC supported target zone models during the period. The authors explain that OPEC is strongly motivated to support a lower limit for prices as oil is the major source of income for almost all OPEC member nations. Furthermore, OPEC is motivated to maintain an upper limit on prices since excessively high oil prices encourage investment by non-OPEC nations thereby reducing OPEC's market share. In keeping with these motivations, the authors establish an oil price model based on production quotas, inventory levels and expectations of future market prices determined by the currently available information.

The out-of-sample forecasting results suggest that the basic target zone model offers good forecasting ability. While the model performs well when the price is approaching the upper or lower bound without price jumps, it exhibits large forecasting errors when the price is well within the bounds or outside of the band. The model performs poorly if oil prices experience jumps.

3.1.1.3.2. Inventory Models

Ye et al. (2002) provide a description of OPEC in the 1990s that contradicts Tang and Hammoudeh (2002). The authors state that from 1991-2001, OPEC did little to adjust production in response to changes in demand. When OPEC did take action, it was not sufficient to constrain prices, therefore, price volatility was high in this period. In this study the authors focus on OECD petroleum inventory levels (crude oil and oil products) to forecast oil prices. They perform a short-run forecast of nominal WTI monthly spot prices. In this model, WTI spot price is a function of three factors: (1) OECD relative petroleum inventory level, which is the deviation of actual inventories from the normal inventory level (they calculate normal inventory level by de-seasonalizing and de-trending historical data), (2) lower than normal OECD inventory levels, which capture the asymmetric price changes in response to changes in inventories when the inventory level is below the normal level versus price changes when inventory levels are above normal, and (3) the annual differences in monthly inventories. They use data from January 1992 to February 2001. The in-sample forecasts indicate that the model exhibits good forecasting performance. Ye et al. (2005) modify the study of Ye et al. (2002). They predict the short-term 1-month ahead nominal WTI crude oil spot price by assessing the impact of relative inventory levels.

In this model, the only explanatory variable is OECD industrial relative petroleum inventory levels. In addition, the September 11, 2001 terrorist attack and the OPEC quota tightening of 1999 are used as dummy variables in the model. The authors exclude the lower than normal OECD inventory level variable from their new model as this variable increases the out-of-sample forecast error. They use monthly data from January 1992 to April 2003. They compare the results from the previously mentioned inventory-based model to two benchmark forecasting models: (1) a naïve autoregressive forecasting model and (2) a modified alternative model. The in and out-of-sample evaluation criteria indicate that the relative inventory model provides the best forecasting performance and the naïve model provides the worst. Ye et al. (2006) extend the work of Ye et al. (2005) suggesting a nonlinear model to forecast monthly nominal WTI crude oil spot prices. They argue that short-run crude oil prices are expected to behave differently when inventory levels near their lower bound than when they vary around the mid-range, because inventory has a zero lower bound or some minimum required operating level. In this model, price is a function of relative OECD industrial crude oil inventory levels and nonlinear low and high inventory variables. The September 11, 2001 terrorist attack and the OPEC quota tightening of 1999 are used as dummy variables in the model. They use monthly data from January 1992 to October 2003 and find that the low inventory level variables are more significant than the high inventory level variables. This result is expected because of the psychological effect of low inventories, which leads to an asymmetric response. Prices are more sensitive at low inventory levels than at high inventory levels. The results indicate that the forecasting power of the new nonlinear model is stronger than the previous simple linear model of Ye et al. (2005), both in and-out-of sample, especially when inventory levels are very low or very high.

Merino and Ortiz (2005) extend the inventory model proposed by Ye et al. (2005) with a three-step methodology. Using monthly data from January 1992 to June 2004 in the first step, the authors forecast oil prices with the initial inventory model proposed by Ye et al. (2005) and obtain the price premium of this model, which is the deviation of the estimated price from the actual price. For this step, relative OECD petroleum industrial inventory level is the only explanatory variable of the model. In the next step, the authors attempt to explain the price premium by testing the Granger causality between a group of variables and the price premium and investigate the systematic information that each new variable can add to the original inventory model.

These new variables include oil market variables as well as financial and commodity prices. The oil market variables include backwardation (the difference between spot prices and futures prices), speculation, OPEC spare capacity, the U.S. gasoline relative inventory level, open interest, and U.S. refinery capacity. For non-oil variables, they choose U.S. interest rates, the U.S. dollar/Euro exchange rate, commodity spreads, and non-energy commodity prices. They perform the Granger causality test with each of the mentioned variables versus the price premium for three time periods: (1) 1992-2004, (2) 1996-2004, and (3)1999-2004. The results indicate changes in the price premium are Granger caused by speculation, OPEC spare capacity, and the U.S. gasoline relative inventory level. However, they find no Granger causality for any of the non-oil variables. Consequently, in the final step they estimate three extended models to forecast crude oil prices.

In model A, relative OECD petroleum industrial inventory levels and speculation are explanatory variables. In model B, relative OECD petroleum industrial inventory levels and OPEC spare capacity are explanatory variables. In model C, relative OECD petroleum industrial inventory levels and the U.S. gasoline relative inventory levels are explanatory variables of crude oil price. They find that only speculation and oil prices are cointegrated or there is a long-run relationship between them, therefore, the only variable that adds systematic information to the model is speculation. As the result, they forecast oil prices using model A and compare its forecasting power with the initial inventory model of Ye et al. (2005). The results indicate that the various models generate similar forecasts in the 1992-2001 period, however, for the 2001-04 period the extended model generates better forecasts. The only exception is the 2000-01 period, in which the basic model provides better forecasts than the extended model.

3.1.1.3.3. Combination of Inventory and OPEC Behavior Models

Kaufmann (1995) proposes a Project Link model to describe the world oil market for the period of 1954-1989. He investigates the effects of economic, geological, and political events on oil prices. In this model, world oil price is function of market conditions and the strategic behavior of OPEC. The key factors are OPEC and non-OPEC capacity utilization, OPEC capacity, the OPEC share of world oil production, and the OECD inventory level. The OPEC quota and the 1974 oil shock are included as dummy variables. The results indicate that the model has good power to describe the world oil market.

Kaufmann et al. (2004) investigate the impact of OPEC behavior on real oil prices. The authors examine Granger causality between OPEC capacity utilization, OPEC quotas, OPEC members cheating on quotas, and the days of forward consumption of OECD crude oil stocks, calculated by dividing OECD crude oil stocks by OECD crude oil demand. Furthermore, they incorporate the

Persian Gulf War and seasonal dummies into the model. They use quarterly data from 1986-2000, and perform cointegration tests between variables that confirm the existence of a long-run relationship between real oil prices and the variables of the model. The Granger causality test by a vector error correction model finds evidence of Granger casualty from OPEC behavior variables to real oil prices but not vice versa.

Dees et al. (2007) examine the forecasting ability of the Kaufmann et al. (2004) model. The static and dynamic forecasting results from 1995-2000 display that forecasting performance of the model is fairly strong, although it is sensitive to the choice of time period and volatility in real oil prices caused by exogenous shocks. The model performs well for in-sample forecasting, however, it shows weak performance in out-of-sample forecasting (2004-2006). This suggests that the model's performance suffers from omitting the variables that were responsible for the increase in oil prices in the period of 2004-2006.

In order to further develop this model and solve the problem of omitted variables, Kaufmann et al. (2008) extend the work of Dees et al. (2007) by including the U.S. refinery utilization rate, the non-linearity in supply conditions, and expectations about supply and demand misbalances. However, they eliminate OPEC quotas from the model and incorporate cheating on OPEC quotas into the capacity utilization variable. They use the near-month and 4-month futures prices for WTI from 1986-2006. The results indicate that OECD stocks, OPEC capacity utilization rates, U.S. refinery utilization rates and price expectations Granger cause changes in real oil prices. The one step ahead out-of-sample forecast results show that the model has strong forecasting power and is able to account for much of the $27 rise in crude oil prices from 2004-2006. Finally the authors compare their results with those of a random walk model and a future contract benchmark model and find that the structural econometric model produces more accurate forecasts.

Chevillon and Christine (2009) assess the impact of the physical oil market on the clearing price. In this study, the authors investigate determinant factors of the real Brent crude oil spot price. They use quarterly data from 1988-2005. They model price as a function of six explanatory variables, including OECD and non-OECD demand, OPEC quotas, OECD and non-OECD stocks, and the OPEC implicit target for real price. They also include the first and second Iraq Wars, the terrorist attack of September 11, 2001 and the Afghan War as dummy variables. To the best of our knowledge, this study is the first to incorporate non-OECD inventory levels into a price forecasting model. They perform a VAR analysis and conclude that concerns external to the physical market caused the increase in oil prices.

3.1.1.3.4. Supply and Demand Models

Yang et al. (2002) introduce a model to describe the determinants of U.S. oil prices. Their model primarily focuses on OPEC production, real U.S. GDP, and the price and income elasticity of demand for oil in the U.S. They use monthly data from January 1975 to September 2000. They use a GARCH model to describe the volatility of oil prices. They perform a cointegration test and use an ECM model to investigate the short- and long-run relationships between oil demand and oil prices, real GDP, and natural gas and coal prices in order to determine the price and income elasticity of demand. They then carry out a simulation of potential oil prices under different scenarios of reductions in OPEC production. They conclude that OPEC production reductions will result in increases in oil prices, but the magnitude and duration of the increase depends on the size of the OPEC reduction and the increase of domestic production by the U.S. or other non-OPEC producers.
Mirmirani and Li (2004) perform a structural analysis using VAR and artificial neural network (ANN) models to predict crude oil prices. They use monthly light sweet crude oil futures prices traded on the NYMEX (lagged oil prices), oil supply, petroleum consumption and money supply as explanatory variables, covering the period from January 1980 to December 2002. The results indicate that the ANN model outperforms the VAR model.

3.1.1.3.5. Non-Oil Variables Models

Lalonde et al. (2003) investigate the effects of the non-oil variables on real WTI crude oil spot prices. They use quarterly data from 1974-2001. In their model, real WTI crude oil spot price is function of the world output gap[6] and the real U.S. dollar effective exchange rate gap[7]. In addition, three dummy variables are included in the model, including the 1979 Iranian revolution, the Iran-Iraq war of 1980,the mid-1980s collapse of OPEC discipline, and the oil price collapse of 1986. They exclude the real U.S. dollar effective exchange rate gap from the model since it is not found to be a significant variable, although they do include petroleum inventory levels. The out-of-sample forecasting results indicate that this model outperforms the random walk model and the autoregressive model benchmarks. However, when inventory levels are excluded from the model, the forecasting ability is inferior to that of the two benchmarks.

3.1.2. Non-Standard Methods

Non-standard or computational methods are nonlinear approaches to forecasting that recently gained popularity. The proponents of non-standard methods consider traditional approaches of forecasting such as time-series methods inappropriate for strongly nonlinear and chaotic time-series such as oil prices since traditional methods assume that the time-series are generated by linear processes.

The main computational tool in oil price forecasting is Artificial Neural Networks (ANNs). Recent studies on ANNs show that ANNs have strong pattern classification and pattern recognition capabilities. ANNs are inspired by human brain biology and have the ability to learn and generalize experiences. Currently, ANNs are being used for a wide variety of tasks in a range different fields in business, industry and science (Widrow et al., 1994, Zhang et al., 1998).

Very recently support vector machine (SVM) has gained a great deal of attention as a forecasting tool. SVM is a novel neural network technique, which has gained ground in classification, forecasting, and regression analysis (Venables and Riplay (2002), Chang and Lin (2005), Dong, Cao, and Lee (2005), and Fernandez (2010). One major application of ANNs is forecasting (Sharda, 1994, Zhang et al., 1998).

In the case of oil price forecasting, Kaboudan (2001) uses two compumetric forecasting methods including Genetic Programming (GP) and ANN to perform short-term oil price forecasts and compares the forecasts with those of a naïve random walk model. His analysis is based on monthly crude oil prices from January 1993 to December 1998. The results suggest that GP forecasting performance is superior to that of the other techniques and the ANN forecasts exhibit the poorest accuracy.

Yu et al. (2007, 2008) apply a Multi Scale Neural Network (EMD-FNN-ALNN) model instead of a Single Scale Neural Network, which is based on an Empirical Mode Decomposition (EMD) approach to forecast WTI and Brent crude oil prices. In this method, the original price series is decomposed into the various intrinsic modes with different scales, then using three layer Feed Forward Neural Networks (FNN) the internal correlation structures of different components are extracted, and finally some important subseries are selected as inputs into an Adaptive Linear Neural Network (ALNN) for prediction. The authors use daily WTI crude oil price data from January 1, 1986 to September 30, 2006. The results indicate that multi-scale neural network performance is superior to that of the single scale neural network, therefore, this method improves the prediction ability of a single scale neural network.

Shambora and Rossiter (2007) use a financial model to predict crude oil prices. For this purpose, they apply an ANN model and use crude oil price futures contracts traded on the NYMEX from April 16, 1991 to December 1, 1997. Furthermore, they compare the results with a buy-and-hold strategy, the simple moving average crossover model, and the random walk model. The Sharpe ratio of each model indicates that the ANN model performance is superior to that of the other models. However, the ANN results suggest that oil futures prices are not efficient predictors of spot prices.

Kulkarni and Haidar (2009) use a multilayer Feed Forward Neural Network (FNN) model to perform short-term crude oil price tendency forecasting and investigate the efficiency of futures prices on spot price. They use daily WTI crude oil spot prices from 1996-2007 and prices for 1-, 2-, 3-, and 4-month WTI futures contracts. They conclude that futures prices provide new information about spot prices especially in the case of 1- and 2-month futures contracts.

Xie et al. (2006) apply a Support Vector Machine (SVM) method to predict crude oil prices. They use monthly WTI spot prices from January 1970 to December 2003. The authors compare the results with the ARIMA and BPNN methods. The results indicate that the SVM method does not necessarily perform better than the ARIMA and BPNN methods in all sub periods. Fernandez (2010) forecasts crude oil and natural gas spot prices, based on the SVM and ANN techniques and applies the ARIMA model as a benchmark. He uses daily data from 1994-2005. The out-of-sample forecasts show in short-time horizons the ARIMA model outperforms the ANN and SVM methods, but in long-run horizons, the ANN and SVM outperform the ARIMA, therefore, time horizon is an important element of forecasting ability. Furthermore, the linear combination of the ANN and SVM methods produces more accurate forecast than either of the single methods.

3.2. Qualitative Models

In addition to fundamental economic variables such as OPEC behavior, inventory level, and oil production and consumption, many qualitative factors impact oil prices, including military and political factors, natural disasters, and speculation. Knowledge-based approaches are used to model the infrequent and irregular events that can impact oil markets. There are very few studies that employ qualitative approaches to forecasting oil prices. For example, Abramson and Finniza (1991) apply belief networks based on Monte Carlo analyses to predict OPEC and WTI crude oil prices. Belief networks is a qualitative knowledge-based technique under the classification of artificial intelligence. Abramson and Finniza (1995) extend the work by Abramson and Finniza (1991) and suggest a probabilistic belief network model based on Monte Carlo analysis to produce probabilistic forecasts of average annual oil prices. This method combines qualitative variables with algebraic formulas, conditional probabilities, and econometric relationships.

Wang et al. (2004) proposed a new hybrid system to predict oil prices, integrating an ANN approach which has a Back Propagation Neural Network (BPNN) structure, and Rule-Based Expert Systems (RES), with Web-Based Text Mining (WTM) techniques (BPNN-WTM-RES), using monthly WTI crude oil spot prices from January 1970 to December 2002. A comparison of simple BPNN and new hybrid methods indicates that in out-of-sample forecasting, the hybrid method outperforms the individual BPNN methods in all sub periods. Wang et al. (2005) extend the work by Wang et al. (2004) by introducing a novel nonlinear integrated approach called TEI@I to predict WTI crude oil prices. In the first step they use an ARIMA model, and in the second step they integrate the ARIMA with a BPNN approach to model linearities and nonlinearities of the time-series. They investigate the effects of irregular and infrequent events on oil prices by applying the Web-based Text Mining (WTM) and the Rule-based Expert Systems (RES) techniques, and integrate the ARIMA-BPNN methodology with the WTM-RES technique and create the ARIMA-BPNN-WTM-RES technique. The results indicate that the out-of-sample forecasting performance of the TEI@I methodology is superior to that of the individual ARIMA and the ARIMA-BPNN approaches.

Yu et al. (2005) propose a rough set Refined Text Mining (RSTM) approach as a new knowledge-based forecasting system for crude oil price tendency forecasting. This system is a combination of two modules; the first one applies the text mining technique to produce rough knowledge and the second one applies the rough set theory as a knowledge refiner for the rough knowledge. They use monthly crude oil data from January 1970 to October 2004. The authors compare the out-of-sample forecasting ability of the RSTM approach to the random walk, the linear regression model, the ARIMA model, and the Back Propagation Neural Network (BPNN) model. The hit ratio of each model indicates that the performance of the new RSTM approach is better than the other models, and the random walk model has the poorest performance.

Gori et al. (2007) analyze the evolution of oil price and consumption over the last 30 years to construct a relationship between them. They forecast future trends under three scenarios: (1) parabolic, (2) linear, and (3) chaotic behavior. In the first scenario, oil price prediction is based on a parabolic curve, in the second scenario oil price prediction is based on a linear curve, and in the third scenario fuzzy logic is used to predict oil prices. Gaffari and Zare (2009) propose a method based on Adaptive Neuro Fuzzy Inference Systems (ANFIS) to predict daily WTI crude oil spot prices. This method is a combination of ANN and fuzzy logic. The results indicate that this technique predicts the sign of daily oil price movements correctly more than 66% of the time, in contrast to 46.67% by Morana (2001), 45.76% by Gori et al. (2007), and 54.54% by Fan et al. (2006).

4. Conclusions

In this study we review the extant literature on crude oil price forecasting. We group forecasting methods into the two main categories of quantitative and qualitative techniques.

Quantitative methods are further divided into econometric methods (including time-series models, financial models, structural models, and non-standard or computational approach). These quantitative methods are used to model the numerical determinants of oil prices. On other hand, qualitative methods include knowledge-based techniques such as the Delphi method, the web-based text mining method, fuzzy logic and fuzzy expert systems, and belief networks which investigate the impact of irregular and infrequent events on oil prices.

A wide range of studies forecast crude oil prices with the aforementioned methods. To the best of our knowledge, this literature review covers virtually every study that performs crude oil price forecasting and is available in a peer reviewed journal. The most frequently used techniques are time-series econometrics. The second most frequently used is the financial method, and the third most frequently used techniques are based on structural models and non-standard computational models. Finally, the least used technique is the qualitative knowledge-based method.

Appendix A
A Brief Primer on Time Series Econometrics

Time series econometrics are used to estimate the relationship between a variable, its own lagged values, time (trend and seasonality), and other variables. The simplest version of such a model would be the random walk model without a trend, where the changes in the variable are independent and identically distributed with a zero mean. Such a process might be described by the following equation:

$$y_{t+1} = y_t + \varepsilon_{t+1}$$

where ε_{t+1} represents a white-noise term with a mean of zero, constant variance and zero auto-correlation. We can see that changes in y t are independent from each other. If we were to include a deterministic trend in the random walk model, the process would become:

$$y_{t+1} = a + y_t + \varepsilon_{t+1}$$

where α represents the trend.

Raw variables are often non-stationary, the distribution of the variable is not constant over time due to a trend, seasonality or changing variance. In order to facilitate time series modeling, we often difference our variable by modeling the change in our variable rather its level. In this case, we would model Δ_y t where

$$\Delta y_t = y_t - y_{t+1}$$

Furthermore, the data is often seasonally differenced prior to analysis to eliminate seasonal non-stationarity. To account for changing variance, the ARCH/GARCH family of models is often used.

A starting point for time series modeling is often autoregressive (AR) or moving-average models (MA). In AR models, the value of the random variable of interest, in this case y t, depends on its previous values plus a white-noise component. Such a model would be represented by an equation such as:

$$y_{t+1} = a_0 + y_t + \varepsilon_{t+1}$$

In a moving average model, the current value of the variable will be a linear function of previous values of another variable (e.g., εt). For example, the following is a moving average processes:

$$y_t = a_0 + \beta_0\varepsilon_t + \beta_1\varepsilon_{t-1} + \beta_2\varepsilon_{t-2}$$

More generally, we can combine AR and MA models into an autoregressive moving-average (ARMA) model. An ARMA (p, q) model can be written as:

$$y_t = a_0 + \sum_{i=1}^{p} a_i\, y_{t-i} + \sum_{i=0}^{q} \beta_i\, \varepsilon_{t-i}$$

where p is the number of autoregressive lags and q is the number of moving average lags. Such models can be very effective in forecasting future levels of stationary time series.

While most econometric models assume homoscedasticity (constant variance), it is clear that the volatilities of economic time series tend to vary significantly over time. In other words, the next period's volatility of a time series will depend on the current state of the model (conditional variance). Further, many time series display persistence in volatility, which means periods of high volatility tend to continue for several periods (volatility clustering).

A simple method of forecasting conditional volatilities is the exponential weighted moving average (EWMA) approach. In the EWMA approach, conditional volatility is simply modeled as a function of previously observed volatilities, with more recent observations receiving higher weights. More specifically, current volatility is modeled as:

$$y_{t+1} = a_0 + y_t + \sigma_{t+1}\varepsilon_{t+1}$$

$$\sigma_{t+1}^2 = \lambda\sigma_t^2 + (1-\lambda)\varepsilon_t^2$$

In this type of a model, ε_{t+1} represents unexpected changes or news.

In this case the value of λ is selected by the user. For example, Risk Metrics suggests λ=0.94 for certain applications. Rather selecting the value of the parameter in an ad hoc manner, Engel (1982) provides an autoregressive conditional heteroscedastic (ARCH) model in which the mean and variance can be simultaneously modeled and forecasted. Also, the values of the parameters are selected to provide the best fit. ARCH models model variance as a function of lagged squared errors. So in an ARCH (q) model, the variance can be described as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_q\varepsilon_{t-q}^2$$

Therefore, the ARCH (q) model using an AR (p) model for y_t is:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_t$$

where

$$\varepsilon_t \sim N(0, \sigma_t^2)$$

and

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_q\varepsilon_{t-q}^2$$

Similar to the way that the AR(p) model may be extended to an ARMA (p, q) model, the generalized autoregressive conditional heteroscedastic (GARCH (p, q)) model proposed by Bollerslev (1986) extends ARCH(q) by modeling the conditional variance as a function of lagged squared errors as well as its own lagged values.

Therefore, the GARCH (p, q) model using an AR (r) model for y_t is:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_t$$

where

$$\varepsilon_t \sim N(0, \sigma_t^2)$$

and

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_q\varepsilon_{t-q}^2 + \beta_1\sigma_{t-1}^2 + \ldots + \beta_p\sigma_{t-p}^2$$

In addition to the basic ARCH and GARCH models, a wide variety of models based on ARCH/GARCH are available. These include the exponential general autoregressive conditional heteroscedastic (EGARCH) model of Nelson (1991). EGARCH allows asymmetric changes in volatility due to news events and leverage effects. EGARCH allows a model to incorporate the stylized fact that negative news (i.e., $\varepsilon_{t+1} < 0$) tends to have a larger impact on volatility than positive news and significant reductions in firm value (and stock price) increase the financial leverage of firms, thereby increasing their risk and volatility.

Another example of an ARCH/GARCH extension is the integrated general autoregressive conditional heteroscedastic (IGARCH) model of Engel and Bollerslev (1986) in which shocks to volatility persist, impacting forecasts for all time horizons. Thus volatility has a very long memory in IGARCH. While these are two of the more popular variations on the ARCH/GARCH approach, many more exist.

A number of software programs are available for estimation of time series models. The simplest versions can be estimated using Microsoft Excel, while the more complex versions require specialized software. Matlab, and the free version, Octave, are powerful programs for estimating various time series models. R-project, a free software, provides a comprehensive library of programs in this area. Other popular programs are Stata, SAS, and EViews.

Appendix References

Bollerslev, T. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics*. April 1996, Vol. 31, No.3, pp. 307-27.

Engel, R. F. "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica*, 1982, Vol. 50, No.4, pp. 987-1007.

Engle, R. F. and T. Bollerslev. "Modeling the Persistence of Conditional Variances." *Econometric Reviews*, 1986, Vol. 5, pp. 1-50.
Nelson, D. B. "Conditional Heteroskedasticity in Asset

Returns: A New Approach." *Econometrica*, 1991, Vol. 59, No.2, pp. 347-70.

Software Programs:
Eviews, http://www.eviews.com
Matlab, http://www.mathworks.com
Octave, http://www.gnu.org/software/octave/
R-Project, http://www.r-project.org/
SAS, http://www.sas.com/
STATA, http://www.stata.com/

References

Abosedra, S. and H. Baghestani. (2004). "On the Predictive Accuracy of Crude Oil Futures Prices." *Energy Policy,* Vol. 32, pp. 1389–1393.

Abosedra, S. (2005). "Futures Versus Univariate Forecast of Crude Oil Prices." OPEC Review, Vol. 29, pp.231–241.

Abramson, B. and A. Finizza. (1991). "Using Belief Networks to Forecast Oil Prices." *International Journal of Forecasting*, Vol. 7, pp.299–315.

Abramson, B. and A. Finizza. (1995). "Probabilistic Forecasts From Probabilistic Models: a Case Study in the Oil Market." I*nternational Journal of Forecasting*, Vol. 11, pp.63–72.

Agnolucci, P. (2009). "Volatility in Crude Oil Futures: a Comparison of the Predictive Ability of GARCH and Implied Volatility Models." *Energy Economics*, Vol. 31, pp.316–321.

Alexander, C. and E. Lazar. (2006). "Normal Mixture GARCH (1, 1): Applications to Exchange Rate Modelling." *Journal of Applied Econometrics*, Vol. 21, pp.307–336.

Alizadeh, A.H., N.K. Nomikos, and P.K. Pouliasis. (2008). "A Markov Regime Switching Approach for Hedging Energy Commodities." *Journal of Banking and Finance*, Vol. 32, pp.1970–1983.

Aloui, C. and S. Mabrouk. (2010). "Value-at-risk Estimations of Energy Commodities via Longmemory, Asymmetry and Fat-tailed GARCH Models." *Energy Policy,* Vol. 38, pp.2326–2339.

Baillie, R.T., T. Bollerslev, and H.O. Mikkelsen. "Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics*, 1996, Vol. 74, pp.3–30.

Barone-Adesi, G. and F. Bourgoin, K. Giannopoulos. (1998). "Don't Look Back." *Risk*, Vol. 11, pp.100–104.

Bollerslev, T. (1986). "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics,* Vol. 31, pp.307–327.

Bopp, A.E. and G.M. Lady. (1991). "A Comparison of Petroleum Futures Versus Spot Prices as Predictors of Prices in the Future." *Energy Economics*, Vol. 13, pp.274–282.

Cabedo, J.D. and I. Moya. (2003). "Estimating Oil Price 'Value at Risk' Using the Historical Simulation Approach." *Energy Economics*, Vol. 25, pp.239–253.

Cai, J. (1994). "A Markov Model of Switching-regime ARCH." *Journal of Business and Economic Statistics*, Vol. 12, pp.309–316.

Chang, C.C. and C.J. Lin. (2005). "LIBSVM: a Library for Support Vector Machines." http://www.csie.ntu.edu.tw/~cjlin.

Cheong, C.W. (2009). "Modeling and Forecasting Crude Oil Markets Using ARCH-type Models." *Energy Policy,* Vol. 37, pp.2346–2355.

Chernenko, S., K. Schwarz, and J.H. Wright. (2004). "The Information Content of Forward and Futures Prices: Market Expectations and the Price of Risk." FRB International Finance Discussion Paper 808.

Chevillon, G. and C. Rifflart. (2009). "Physical Market Determinants of the Price of Crude Oil and the Market premium." *Energy Economics*, Vol. 31. pp.537–549.

Chin, M.D., M. Leblanch, Coibion, O. (2005). "The Predictive Content of Energy Futures: An Update on Petroluem, Natural Gas, Heating Oil and Gasoline." NBER Working Paper 11033.

Coppola, A. (2008) "Forecasting Oil Price Movements: Exploiting the Information in the Futures Market." *Journal of Futures Market*, Vol. 28, pp.34–56.

Cortazar, G. and E.S. Schwartz. (2005). "Implementing a Stochastic Model for Oil Futures Prices." *Energy Economics*, Vol. 25, pp.215–238.

Costello, A., and E. Asem, and E. Gardner. (2008). "Comparison of Historically Simulated VaR: Evidence From Oil Prices." *Energy Economics,* Vol. 30, pp.2154–2166.

Darbellay, G. A. and M. Slama. (2000). "Forecasting the Short-term Demand for Electricity: Do Neural Networks Stand a Better Chance?" *International Journal of Forecasting,* Vol. 16, pp.71– 83.

Davidson, J. (2004). "Moment and Memory Properties of Linear Conditional Heteroscedasticity Models, and a New Model." *Journal of Business and Economic Statistics,* Vol. 22, pp.16–29.

Day, T.E. and C.M. Lewis. (1993). "Forecasting Futures Market Volatility." *The Journal of Derivatives,* Vol. 1, pp.33–50.

Dees, S., and P. Karadeloglou, R.K. Kaufmann, and M. Sanchez. (2007). "Modelling the World Oil Market: Assessment of a Quarterly Econometric Model." *Energy Policy,* Vol. 35, pp.178–191.

Diebold, F.X. and R.S. Mariano. (1995). "Comparing predictive Accuracy." *Journal of Business and Economic Statistics,* Vol. 13, pp.253–263.

Ding, Z., C.W. J. Granger, and R.F. Engle. (1993). "A Long Memory Property of Stock Market Returns and a New Model." *Journal of Empirical Finance,* Vol. 1, pp.83–106.

Dong, B., C. Cao, and S.E. Lee. (2005). "Applying Support Vector Machines to Predict Building energy consumption in tropical region." *Energy and Buildings,* Vol. 37, pp.545-553.

Edmundo G., F.L.L. Luiz, and A. Edmundo. (2010). "Forecasting Oil Price Trends Using Wavelets and Hidden Markov Models." *Energy Economics,* Vol. 32. pp.1507–1519.

Fan, Y., Y-J. Zhang, H.T. Tsai, and Y.M. Wei. (2008). "Estimating Value at risk of crude oil price and its spillover effect using the GED-GARCH approach." *Energy Economics,* Vol. 30, pp.3156-3171.

Fong, W.M. and K.H. See. (2002). "A Markov switching model of the conditional volatility of crude oil prices." *Energy Economics,* Vol. 24, pp.71–95.

Frey, G., M. Manera, A. Markanday, and A. Scarpa. (2009). "Econometric models for oil price forecasting: A critical survey." CESifo Forum, No.1.

Gaffari, A. and S. Zare. (2009). "A novel algorithm for Prediction of Crude Oil Price Variation Based on Soft Computing." *Energy Economics,* Vol. 31, pp.531–536.

Giot P., and S. Laurent. (2003). "Market Risk in Commodity Markets: a VaR Approach." *Energy Economics,* Vol. 25, pp.435-457.

Gori, F., D. Ludovisi, and P.F. Cerritelli. (2007). "Forecast of Oil Price and Consumption in the Short-term Under Three Scenarios: Parabolic, Linear and Chaotic behavior." *Energy Economics,* Vol. 32, pp.1291–1296.

Green, S. L. and K.M. Mork. (1991). "Towards Efficiency in the Crude Oil Market." *Journal of Applied Econometrics,* Vol. 6, pp.45–66.

Gulen, S. G. (1998). "Efficiency in the Crude Oil Futures Markets." *Journal of Energy Finance and Development,* Vol. 3, pp.13–21.

Haas, M., S. Mittnik, and M.S. Paollela. (2004a). "Mixed Normal Conditional Heteroscedasticity." *Journal of Financial Econometrics,* Vol. 2, pp.211–250.

Haas, M., S. Mittnik, and M.S. Paollela. (2004b). "A New Approach to Markov-switching GARCH Models." *Journal of Financial Econometrics,* Vol. 2, pp.493–530.

Hamilton, J.D. and R. Susmel. (1994). "Autoregressive Conditional Heteroskedasticity and Changes in Regime." *Journal of Econometrics*, Vol. 64, pp.307-333.

Hammoudeh, S. and V. Madan. (1995). "Expectations, target Zones and Oil Price Dynamics." *Journal of Policy Modeling,* Vol. 17, pp.597–613.

Hansen, P.R. (2005). "A Test for Superior Predictive

Ability." *Journal of Business and Economic Statistics,* Vol. 23, pp.365–380.

Huang, D., B. Yu, J. Frank, F. Fabozzi, and M. Fukushima. (2009). "CAViaR-based Forecast for Oil Price Risk." *Energy Economics,* Vo. 31, pp.511–518.

Hung, J.C., and M.C. Lee, and H.C. Liu. (2008). "Estimation of Value-at-Risk for Energy Commodities via Fat-tailed GARCH Models." *Energy Economics,* Vol. 30, pp.1173–1191.

Hung, J.C., Y.H. Wang, M.C. Chang, K.H. Shih, and H.H. Kao. (2011). "Minimum Variance Hedging with Bivariate Regime-switching Model for WTI Crude Oil." *Energy,* Vol. 36, pp.3050–3057.

Huntington, H. (1994). "Oil Price Forecasting in the 1980s: What Went Wrong?" *Energy Journal,* Vol. 15, pp.1–22.

Kaboudan, M.A. (2001). "Compumetric Forecasting of Crude Oil Prices." The Proceedings of IEEE Congress on Evolutionary Computation, pp. 283–287.

Kang, S.H., S.M. Kang, and S.M. Yoon. (2009). "Forecasting Volatility of Crude Oil Markets." *Energy Economics,* Vol. 31, pp. 119–125.

Kaufmann, R.K. (1995). "A Model of the World Oil Market for Project LINK: Integrating Economics, Geology, and Politics." *Economic Modelling,* Vol. 12, pp. 165–178.

Kaufmann, R.K. (2004). "Does OPEC Matter? An Econometric Analysis of Oil Prices." *The Energy Journal,* Vol. 25, pp. 67–91.

Kaufmann, R.K., S. Dees, A. Gasteuil, and M. Mann. (2008). "Oil Prices: The Role of Refinery Utilization, Futures Markets and Non-linearities." *Energy Economics,* Vol. 30, pp. 2609–2622.

Krugman, P. (1991). "Target Zones and Exchange Rate Dynamics." *The Quarterly Journal of Economics,* Vol. 106, pp. 669–682.

Lalonde, R., Z. Zhu, and F. Demers,. (2003). "Forecasting and Analyzing World Commodity Prices." Bank of Canada, Working Paper, pp. 2003–2024.

Lamoureux, C.G. and W.D. Lastrapes. (1990). "Persistence in Variance, Structural Change, and the GARCH Model." *Journal of Business and Economic Statistics*, Vol. 8, pp. 225–234.

Lanza, A., M. Manera, and M. Giovannini. (2005). "Modeling and Forecasting Cointegrated Relationships Among Heavy Oil and Product Prices." *Energy,* Vol. 27, pp. 831-848.

Lee, T. (1994). "Spread and Volatility in Spot and Forward Exchange Rates." *Journal of International Money and Finance,* Vol. 13, pp. 375–383.

Merino, A. and A. Ortiz. (2005). "Explaining the So-called 'Price Premium' in Oil Markets." *OPEC Review,* Vol. 29, pp. 133–152.

Mirmirani, S. and H.C. Li. (2004). "A Comparison of VAR and Neural Networks with Genetic Algorithm in Forecasting Price of Oil." *Advances in Econometrics,* Vol. 19, pp. 203–223.

Mohammadi, H. and L. Su. (2010). "International Evidence on Crude Oil Price Dynamics: Applications of ARIMA–GARCH Models." *Energy Economics,* Vol. 32, pp. 1001–1008.

Moosa, I. A. and N.E. Al-Loughani. (1994). "Unbiasedness and Time Varying Risk Premia in the Crude Oil Futures Market." *Energy Economics,* Vol. 16, pp. 99–105.

Morana, C. (2001). "A Semiparametric Approach to Short-term Oil Price Forecasting." *Energy Economics,* Vol. 23, pp. 325–338.

Moshiri, S. and F. Foroutan. (2005). "Forecasting Nonlinear Crude Oil Futures Prices." *The Energy Journal,* Vol. 27, pp. 81-95.

Murat, A. and E. Tokat. (2009). "Forecasting Oil Price Movements with Crack Spread Futures." *Energy Economics,* Vol. 31, pp. 85–90.

Naseri, M.R. and E.A. Gharacheh. (2007). "A Hybrid Artificial Intelligence Approach to Monthly Forecasting of Crude Oil Price Time-series." The Proceedings of the 10th International Conference on Engineering Applications of Neural Networks, CEUR-WS284, pp. 160–167.

Nelson, Y., S. Stoner, G. Gemis, and H.D. Nix. "Results of Delphi VIII Survey of Oil Price Forecasts." Energy report, California Energy Commission, 1994.

Nomikos, N.K. and P.K. Pouliasis. (2011). "Forecasting petroleum futures markets volatility: The role of regimes and market conditions." *Energy Economics,* Vol. 33, pp. 321–337.

Pindyck, R.S. (1999). "The Long-run Evolution of Energy Prices." *The Energy Journal,* Vol. 20, pp.1–27.

Radchenko, S. (2005). "The Long-run Forecasting of Energy Prices Using the Model of Shifting Trend." University of North Carolina at Charlotte, Working Paper.

Sadeghi, M. and S. Shavvalpour. (2006). "Energy Risk Management and Value at Risk Modeling." *Energy Policy,* Vol. 34, pp. 3367-3373.

Sadorsky, P. (2006). "Modeling and Forecasting Petroleum Futures Volatility." *Energy Economics,* Vol. 28, pp. 467–488.

Samii, M.V. (1992). "Oil Futures and Spot Markets. *OPEC Review,* Vol. 4, pp. 409–417.

Schwartz, E. and J.E. Smith. (2000). "Short-term Variations and Long-term Dynamics in Commodity Prices." *Management Science,* Vol. 46, pp. 893–911.

Serletis, A. (1991). "Rational Expectations, Risk and Efficiency in Energy Futures Markets." *Energy Economics,* Vol. 13, pp. 111–115.

Shambora, W. and R. Rossiter. (2007). "Are There Exploitable Inefficiencies in the Futures Market for Oil?" *Energy Economics*, Vol. 29, pp.18–27.

Sharda, R. (1994). "Neural Networks for the MS/OR Analyst: An Application Bibliography." *Interfaces,* Vol. 24, pp. 116–130.

Stock, J.H. and M.W. Watson. (1993). "A simple estimator of cointegrating vectors in higher order integrated systems." *Econometrica,* Vol. 61, pp. 783–820.

Tang, L. and S. Hammoudeh. (2002). "An Empirical Exploration of the World Oil Price Under the Target Zone model." *Energy Economics,* Vol. 24, pp. 577–596.

Venables, W. and B. Ripley. (2002). "Modern Applied Statistics with S." Forth edition. Springer-Verlag New York, Inc.

Vo, M.T. (2009). "Regime-switching Stochastic Volatility: Evidence From the Crude Oil Market." *Energy Economics,* Vol. 31, pp. 779–788.

Wang, S.Y., L. Yu, and K.K. Lai. (2004). "A Novel Hybrid AI System Framework for Crude Oil Price Forecasting." *Lecture Notes in Computer Science,* Vol. 3327, pp. 233–242.

Wei, Y., Y. Wang, and D. Huang. (2010). "Forecasting Crude Oil Market Volatility: Further Evidence Using GARCH-class Models." *Energy Economics,* Vol. 32, pp. 1477–1484.

B. Widrow, D.E. Rumelhart, and M.A. Lehr. (1994). "Neural networks: Applications in Industry, Business and Science." Communications of the ACM, Vol. 37, pp. 93–105.

Xie, W., L. Yu, S. Xu, and S. Wang. (2006). "A new method for Crude Oil Price Forecasting Based on Support Vector Machines." International Conference on Computational Science (Part IV), pp. 444–451.

Yang, C.W., and M.J. Hwang, and B.N. Huang. 2002. "An Analysis of Factors Affecting Price Volatility of the U.S. Oil Market." *Energy Economics,* Vol. 24, pp. 107–119.

Ye, M., Zyren, J., Shore, J. (2002). "Forecasting Crude Oil Spot Price Using OECD Petroleum Inventory Levels." *International Advances in Economic Research*, Vol. 8, pp. 324–334.

Ye, M., J. Zyren, and J. Shore. (2005), "A Monthly Crude Oil Spot Price Forecasting Model Using Relative Inventories." *International Journal of Forecasting,* Vol. 21, pp. 491–501.

Ye, M., J. Zyren, and J. Shore (2006). "Forecasting Short-run Crude Oil Price Using High and Low Inventory Variables." *Energy Policy,* Vol. 34, pp. 2736–2743.

Yousefi, S., and I. Weinreich, and D. Reinarz. (2005)."Wavelet-based Prediction of Oil Prices." *Chaos, Solitons and Fractals,* Vol. 25, pp. 265–275.

Yu, L., S.Y. Wang, and K.K. Lai. (2005). "A Rough-set-refined Text Mining Approach for Crude Oil Market Tendency Forecasting." *International Journal of Knowledge and Systems Sciences*, Vol. 2, pp. 33–46.

Yu, L., K.K. Lai, S.Y. Wang, and K.J. He. (2007). "Oil Price Forecasting with an EMD-based Multiscale Neural Network Learning Paradigm." *Lecture Notes in Computer Science,* Vol. 4489, pp. 925–932.

Yu, L., S.Y. Wang, and K.K. Lai. (2008). "Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm." *Energy Economics,* Vol. 30, pp. 2623–2635.

Zeng, T. and N.R. Swanson. (1998). "Predective Evaluation of Econometric Forecasting Models in Commodity Future Markets." *Studies in Nonlinear Dynamics and Econometrics,* Vol. 2, pp. 159–177.

Endnotes

1. Autoregressive integrated moving average
2. Autoregressive conditional heteroskedastisity
3. Generalized autoregressive conditional heteroskedastisity
4. New York Mercantile Exchange
5. IntercontinentalExchange
6. Difference between the world actual output and output at full capacity
7. Difference between the actual exchange rate and its equilibrium level

Authors' Bios

Niaz Bashiri Behmiri is a PhD candidate in Energy Economics in University of Beira Interior-Portugal.

Co-author **José R. Pires Manso** is a Full professor of Economics in University of Beira Interior-Portugal.