Is it possible to successfully forecast the real price of crude oil at short horizons?

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Abstract

The aim of the paper is to investigate the possibilities of forecasting the real price of crude oil Brent. The analysis follows a recursive scheme. Forecasting models are developed for monthly data from the period between January 1995 and October 2014, and forecasts are generated for the period between January 2005 and October 2014. A wide range of variables describing real economy, financial processes and energy prices is used in our analysis, which makes it particularly valuable. These variables are used to estimate the ARDL models Forecast accuracy generated by these models is compared with two benchmark models: the naïve forecast and the AR(1) model. The results obtained indicate that, at short horizons, certain models generate more accurate forecasts than the benchmark models.

Keywords: *accurate forecasts, crude oil prices, real economy, financial market*

JEL Classification: C53, Q47

1. Introduction

The price of crude oil is one of the key variables in forecasting macroeconomic indicators, including real GDP or inflation. That is why forecasting crude oil prices is of great interest to researchers and analysis of economists, analysts and decision-makers (see Alquist et al., 2013; Baumeister and Kilian, 2014).

Literature offers two views on the possibility of forecasting the price of crude oil at short horizons. According to the first one, represented by, for example, Hamilton (2009), generating accurate forecasts of crude oil prices is impossible due to the fact that the real price of crude oil seems to follow the random walk without drift (Hamilton, 2009), which leaves a no-change forecast (a naïve forecast) as the best option, as it guarantees minimizing the root mean square error RMSE. Other researcher, for example Baumeister and Kilian, (2014), are of a different opinion and demonstrate effective forecasting models.

The aim of the paper aims is to investigate which variables describing energy prices, real economy and financial processes can be used as effective predictors of the real price of crude oil. The autoregressive distributed lag (ARDL) models are used to verify the accuracy of forecasting this price at short horizons. The study is conducted using monthly data from the period between January 1995 and October 2014 for which 1-month ahead forecasts are

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generated. Our models follow a recursive scheme, which means that the number of observations used to evaluate the parameters of the model increases by one observation for each consecutive model estimated. The verification period covers observations from January 2005 to October 2014. Forecast accuracy is compared with forecasts generated by two benchmark models: the random walk without drift (the naïve forecast) and the autoregression (AR) benchmark model. Similar analytical framework is adopted in the paper by Śmiech (2015).

The root mean square error (RMSE) and the mean absolute percentage error (MAPE) are used to compare the accuracy of forecasts generated by ARDL models with the the accuracy of forecasts generated by the naïve forecast and the autoregression model, while Diebold-Mariano test(1995) and Clark-West test (2007) are used to compare the statistical significance of the forecast errors.

2. Methodology

The possibility of forecasting real crude oil prices at short horizons is verified with the use of the autoregressive distributed lag (ARDL) models.

Let $\Delta y_{t+1|t} = y_{t+1} - y_t$, where y_t is the logarithm of the index of the real crude oil Brent price (that is $y_t = \ln p_t$, p_t is the index of the real crude oil Brent price and $x_{i,t}$ is one of the predictors $(i = 1,\ldots,n)$. Then, the ARDL(*p, q*) model takes the following form:

$$\Delta y_{t+1|t} = \alpha_0 + \sum_{j=0}^{p-1} \beta_j \Delta y_{t-j|t-j-1} + \sum_{j=0}^{q-1} \gamma_j x_{i,t-j} + \varepsilon_{t+1|t}, \ \boldsymbol{t = 1,..,T} \qquad (1)$$

where $\Delta y_{t-j|t-j-1} = y_{t-j} - y_{t-j-1}$ $(j = 1,\ldots q_1 - 1)$ and $\varepsilon_{t+1|t}$ is an error term.

Following the convention adopted in literature, the predictive accuracy of the ARDL(*p,q*) model is compared with two benchmark models: (Chen et al., 2010; Groen and Pesenti, 2011; Baumeister and Kilian, 2012, 2014; Gargano and Timmermann, 2014): the random walk without drift (the naïve forecast, no-change model) ($\Delta y_{t+1|t} = 0 + \varepsilon_{t+1|t}$, $t = 1,\ldots,T$,) and the autoregresion (AR) benchmark model: ($\Delta y_{t+1|t} = \beta_0 + \beta_1 \Delta y_{t|t-1} + \varepsilon_{t+1|t}$, $t = 1,\ldots,T$).

The analysis of the predictive accuracy of the models to generate forecasts of the real price of crude oil Brent at short horizons is conducted on monthly data from the period between January 1995 and October 2014, which means that the whole sample period covers 238 monthly observations.

This analysis follows a recursive scheme (Inoue and Kilian, 2005; Alquist et al., 2013 and Baumeister and Kilian, 2014). The recursive scheme applied in our study means that the number of observations used to evaluate the parameters of the model increases by one observation for each consecutive model estimated. We assume that, during the first step, the estimation period will cover observations $y_1, \ldots, y_{120}$, that is between January 1995 and December 2004, and the forecast is generated for one period ahead $(T+1)$, that is $\hat{y}_{121}$ (January 2005). During the second step, the parameters are estimated on the basis of observations $y_1, \ldots, y_{121}$, and the forecast is generated for the period $\hat{y}_{122}$, etc. During the last step the parameters of the model are estimated on the basis of observations $y_1, \ldots, y_{237}$ (that is between January 1995 and September 2014), and the forecast is generated for the period $\hat{y}_{238}$ (October 2014).

The application of this forecasting scheme makes it possible to develop a time series $\{\hat{y}_t\}_{t=121}^{238}$, with forecast values generated by consecutively estimated models. The values of this series will be further used to evaluate forecast accuracy. This means that the out-of-sample period used to evaluate forecast performance contains 118 observations (from January 2005 till October 2014).

Forecast accuracy is evaluated by means of several methods. At first, the following measures are used to compute forecast accuracy: the root mean square error (RMSE) and the mean absolute percentage error (MAPE). Next, depending on whether the forecasts obtained are compared with the naïve forecast or forecasts generated by the AR model, we use either measure out-of-sample R_{OS}^2 proposed by Campbell and Thompson (2008) or its adjusted version $\left(R_{OS}^2\right)^{adj}$ for nested models suggested by Groen and Pesenti (2011).

Measure R_{OS}^2 is computed in the following way:

$$R_{OS}^2 = 1 - \frac{MSFE_M}{MSFE_B} \tag{2}$$

where $MSFE_M = \frac{1}{T}\sum_{t=1}^{T}\left(y_t - \hat{y}_{M,t}\right)^2$ be the mean squared forecast error $\hat{y}_{M,t}$ from the M model and $MSFE_B = \frac{1}{T}\sum_{t=1}^{T}\left(y_t - \hat{y}_{B,t}\right)^2$ denote the mean squared forecast error $\hat{y}_{B,t}$ from the benchmark model.

Measure $\left(R_{OS}^2\right)^{adj}$ is computed in the following way:

$$\left(R_{OS}^2\right)^{adj} = 1 - \frac{MSFE_M - adj}{MSFE_B} \tag{3}$$

where $MSFE_M$ and $MSFE_B$ are defined as above, and $adj = \frac{1}{T}\sum_{t=1}^{T}\left(\hat{y}_{B,t} - \hat{y}_{M,t}\right)^2$ is a coefficient correcting the mean squared forecast error generated by nested models, where the benchmark model is the model nested relative to the M model.

A positive (negative) value of R_{OS}^2 or $\left(R_{OS}^2\right)^{adj}$ indicates by how many percent forecast errors of the M model are more (less) accurate than forecasts generated by the benchmark model.

During the last stage of evaluating forecast accuracy, we investigate the statistical significance between forecast errors for the M model and the benchmark model. We use Diebold and Mariano test (1995) (DM) when forecast accuracy is evaluated relative to the naïve forecast, and we use the CW-statistic (Clark and West, 2007) when forecasts generated by the M model are evaluated relative to forecasts generated by the AR model (that is, forecasts generated by two different models, one of which is nested in the other).

3. Data

The Brent spot price of crude oil is chosen for the verification of the possibility of forecasting prices of fossil fuels. This price, together with WTI, is considered the world benchmark (see, e.g. Baumeister and Kilian, 2014). The International Monetary Fund serves as a source of data. Crude oil spot price is expressed as real, in constant prices in 2010. The consumer price index in the USA CPI_{US} is used as the GDP deflator. The analysis is based on monthly data from the period between January 1995 and October 2014. This means that the whole sample period contains 238 monthly observations.

Following the recommendations offered in literature, for our models we selected three sets of predictor variables describing the impact of macroeconomic and financial factors on crude oil prices. They describe: a) real economy b) financial processes and c) the energy price. Each set includes variables describing economy of the U.S. and the EU, since they are the largest world economies. Several variables describe global economy.

a) Macroeconomic variables describing real economy

Variables describing real economy include two variables referring to the global industrial production index (*IP_W*) and in the euro area (*IP_EA*) (e.g. Akram, 2009; Anzuini et al., 2013; Arora and Tanner, 2013) and variables referring to future information on the economic activity (see Kilian and Hicks, 2013; Groen and Pesenti, 2011), such as: the ISM manufacturing index in the U.S. (*ISM_US*), and the German Ifo index (*IFO*) for the business climate among entrepreneurs in trade and industry published by the Ifo Institute. Other variables include the Baltic Dry Index (*BDI*), as a key indicator of future global economic growth (see Baumeister and Kilian, 2012; Groen and Pesenti, 2011) and the global real economic activity index (*IK*) proposed by Kilian (2009). The remaining variables refer to the global oil market: the global crude oil production (*PR_OIL*) (see Ratti and Vespignani 2013; Kilian, 2009 and Kilian and Murphy, 2014) and the world crude oil inventories (*INV*) (Kilian and Murphy, 2014).

b) Variables describing financial processes

Variables in the second set describe financial factors which might improve accuracy of the forecast of crude oil prices. They include the ones connected with the financial market, such as, the real short-term interest rates in the U.S. (*IR_US*) and in the euro area (*IR_EA*), and the real money supply M1 in the U.S. (*M1_US*) and in the euro area (*M1_EA*) (see, e.g. Anzuini et al., 2013; Ratti and Vespignani, 2013; Welch and Goyal, 2008; Groen and Pesenti, 2011 and Gargano and Timmermann, 2014). Another two variables are the real effective exchange rates deflated by the consumer price index (narrow index) (2010 = 100) (*RN_US*) published by the Bank of International Settlements, and the US dollar-euro exchange rate (*REX*) (see Chen et al., 2010). The last subset includes variables connected with the stock market, such as: the Standard and Poor's 500 (SP500) stock price index, the German stock index – DAX (DAX) (Bastourre et al., 2010), and the Chicago Board Options Exchange Market Volatility Index (*VIX*) (Issler et al., 2014).

c) Energy prices

The third group of variables contains the following energy prices: WTI crude oil spot price (*WTI*), steam coal price in Australian ports (*NEWC*), steam coal price in Richards Bay port (the Republic of South Africa) (*RB*), Russian natural gas border price in Germany (*NG_RUS*) and natural gas spot price in the U.S. (*NG_US*). The data are taken from the International Monetary Fund (IMF). All prices are expressed as real, in constant prices in 2010. The consumer price index in the USA CPI_{US} is used as a deflator.

4. Empirical results

The regressive ARDL models are considered with the following variables modified following Groen and Pesenti (2011) suggestions. Variables *IP_W, IP_EA, PR_OIL, IFO, INV, BDI, SP500, DAX, REX, RN_US, NEWC, RB, WTI, NG_RUS, NG_US* are expressed in their logarithmic forms, and their differences are used in the analyses. Variables *IR_US*, *IR_EA* are transformed according to the formula: $X_t = Y_t - Y_{t-1}$, and variables *M1_US*, *M1_EA* are transformed according to the formula: $X_t = \ln(Y_t / Y_{t-12}) - \ln(Y_{t-1} / Y_{t-13})$. The variables *ISM_US*, *VIX* and *IK* are not transformed.

To evaluate forecast accuracy, first the parameters of the ARDL models are assessed for each of 22 variables describing real economy, financial processes and the energy prices. In further stages of the analysis the names of the ARDL models selected on the basis of the independent variables are used, for example, *IP_W* model denotes the autoregressive distributed lag model of the variable 'changes in global industrial production', etc. This means that 22 time series $\left\{\Delta\hat{y}_{t+1|t}^{ARDL_i}\right\}_{t=120}^{237}$ are generated, and each of them contains forecasts of the rates of return of the Brent crude oil price in their logarithmic form. The parameters of the ARDL(p,q) models are estimated for each subsample according to a selected forecast pattern, and the Schwarz Information criterion (BIC) is used to select the lag order p and q. Additionally, it is assumed that the lag order equals 1 for p and q, so it is possible to compare forecast accuracy with the random walk without drift model forecasts generated by the AR benchmark model and it is possible to include i–th predicator in the model.

Next, forecasts of the return rates of the Brent crude oil prices in their logarithmic forms are transformed into forecasts of real crude oil prices.

The assessment of forecast accuracy of the ARLD models relative to two benchmark models (the random walk without drift model and the AR model) is conducted with the use of the root mean square error (RMSE) and the mean absolute percentage error (MAPE). The R_{OS}^2 measure is obtained from Eq. (2) when the ARDL model is compared with the random walk without drift model, while the $\left(R_{OS}^2\right)^{adj}$ measure is obtained from Eq. (3) when the ARDL model is compared with the AR benchmark model. Diebold-Mariano test (1995) (DM) is used to verify the statistical significance of the differences found between forecasts generated by the ARDL models and the random walk without drift model. Clark and West (2007) test (CW) is used to verify the significance of the differences found between forecasts generated by the ARDL models and the AR benchmark model as an example of a nested model.

Table 1 presents the RSME, the MAPE, the R_{OS}^2 and the $\left(R_{OS}^2\right)^{adj}$ for two benchmark models and for the ARDL models used in the study. The results indicate that the RMSE and the MAPE for the AR benchmark model are lower than for the no-change model.

Additionally, the results of the DM test (at 10% significance level) lead to the conclusion that the AR benchmark model is more accurate than the no-change model.

The comparison of the RMSE for the benchmark models and the ARDL models indicates that many of latter have lower RMSE than the no-change model. However, the results of the DM test or the CW test lead to the conclusion that only several ARDL models generate significantly more accurate forecast than the benchmark model.

The CW test presented in Table 1 indicates that more accurate forecasts relative to the AR models can be generated by using the following models: *INV*, *RN_US*, *REX*, *NEWC*. This means that variables such as the world crude oil inventories, the real effective exchange rates of dollar, the US dollar-euro exchange rate and steam coal prices are variables which have a significant influence on the improvement of forecast accuracy of the real crude oil price.

However, when we compare the naïve forecast with forecasts generated by the autoregressive models which contain the following variables: the global oil production (*PR_OIL*), the global oil inventories (*INV*), the German stock index - DAX (*DAX*), coal prices in Australian ports (*NEWC*) as well as the real effective exchange rates deflated by the consumer price index (narrow index) (2010=100) (*RN_US*) and the US dollar-euro exchange rate (*REX),* it can be concluded that (at 0.1 and 0.05 significance levels respectively), forecasts generated by the ARDL models are more accurate than the naïve forecast.

Taking into consideration the CW test and 10% significance level, it can be seen that only the autoregressive model with the difference of the real interest rate in the euro area generates less accurate forecasts than the benchmark models.

Conclusion

The main aim of the paper is to asses forecast accuracy of the real price of Brent crude oil at short horizons. ARDL models are used to verify which variables describing energy prices, real economy and financial processes improve the forecast accuracy of this price in comparison with forecasts generated by benchmark models, that is the naïve forecast and the AR model in the period between January 2005 and October 2014.

Model	**RMSE**	**MAPE [%]**	R_{OS}^2	$\left(R_{OS}^2\right)^{adj}$
IP_W	7.729	5.759	**0.076**	**0.077**
IP_EA	7.902	5.944	**0.034**	**0.010**
ISM_US	7.960	6.003	**0.020**	**0.002**

IFO	7.662	5.867	**0.092**	**0.156**
BDI	8.247	6.192	-0.052	-0.026
IK	7.962	5.977	**0.019**	-0.008
PR_OIL	7.893	5.932	**0.036***	**0.008**
INV	7.828	5.892	**0.052***	**0.025***
SP500	7.800	5.918	**0.059**	**0.049**
DAX	7.847	5.935	**0.047***	**0.027**
VIX	7.942	6.054	**0.024**	**0.034**
IR_US	8.199	6.133	-0.040	-0.035
IR_EA	8.041	6.072	**0.000**	-0.024*
M1_US	7.944	6.074	**0.024**	**0.057**
M1_EA	7.970	6.013	**0.017**	**0.001**
RN_US	7.790	5.886	**0.061****	**0.046****
REX	7.892	5.904	**0.036****	**0.012***
WTI	7.920	6.008	**0.029**	**0.017**
NEWC	7.822	5.961	**0.054***	**0.038***
RB	7.885	5.946	**0.038**	**0.030**
NG_RUS	8.079	6.057	-0.010	-0.031
NG_US	7.838	6.001	**0.050**	**0.030**
Naïve model	8.040	6.029	X	-0.034*
AR model	**7.905**	**5.964**	**0.033***	X

Note: *, **, *** denote respectively p-value 0.10, 0.05 and 0.01 in the DM test for the naïve model and in the CW test for the AR model.

Table 1. The evaluation of forecast accuracy with the use of the RMSE, the MAPE, the R_{OS}^2 and the $\left(R_{OS}^2\right)^{adj}$ measures for the ARDL models in the out-of-sample period between January 2005 and October 2014.

The results of our analysis indicate that greater forecast accuracy of the real crude oil price is generated by several ADRL models than by the naïve forecast. It is obtained using the following variables: the global crude oil inventories, the real effective exchange rates, the steam coal price, the global production of crude oil and the German stock index DAX. Additionally, the first four variables also improve forecast accuracy generated by the AR benchmark model. The AR model also generates more accurate forecasts than the random walk without drift model.

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