[*LINEAR AND FACTOR OIL PRICE FORECASTS*]

[Dr. Abdullah Al Shammre, King Faisal University, Saudi Arabia, 0966555938238, ashammre@kfu.edu.sa]
[Dr. Benaissa Chidmi, Texas Tech University, Lubbock, United States, 018606340512, benaissachidmi@gmail.com]

Overview

This study deals with presenting and estimating different oil price forecasting models. We consider some traditional time series models, such as random walk, autoregressive (AR), moving average (MA), and autoregressiove integrated moving average (ARIMA) to forecast oil prices. The previous models are augmented by including factors or components resulting from the data reduction process and summarizing the information contained in 128 variables of the Federal Reserve Economic Data. To this end, we employ two data reduction techniques: principal component analysis and partial least squares analysis. In the former, we extract the most critical components without using the oil price variable. In partial least squares, we extract the components factors using the 128 economic indicators and the oil price.

Methods

We present the different models that describe the process of oil price forecasting. First, I describe the linear time series models, including the random walk, autoregressive (AR), moving average (MA), and autoregressive integrated moving average (ARIMA) to forecast oil prices. The study considers using principal component analysis (PCA) and partial least squares (PLS) to extract factors to be used in addition to the ARIMA process (ARIMAX).

Results

The results in table 4.9 indicate that the coefficient for MA(1) and factor 5 and 6 labeled as employment and exchange rates are statistically significant at 1% level, while MA(2) and factor 7, labeled as inflation factor are statistically significant at 5% level of significance. Employment and inflation factors have a positive and statistically significant impact on oil price. However, the exchange rates factor has a negative and statistically significant impact on oil price. Factors 1, 4, 8, and 10 have a negative and statistically insignificant impact on oil price. Compare to RW, AR(2), MA(1), ARIMA(0,1,1), partial least squares provide the lowest volatility value of 1.78, the lowest AIC 1884.14, and the highest log likelihood of -929.07 among all previous models that we estimated except PCA, where PCA provide the same volatility value of 1.7 and the highest log likelihood of -928.5. Regarding to the magnitude of coefficients, the MA(1) has greater impact on oil price compared to all PLS factors.
Our sample period is from March 1959 to November 2019, while the out-of-sample assessment period starts from December 2004. table 4.12 compares the forecasting performance for all the forecasting models, the lower error indicates a more accurate prediction. Forecasts based on Arima with PLS and PCA factors can be considered more accurate than the forecast based on the benchmark model as well as plain Arima. However, PLS model with 10 factors provide significantly better predictions and outperforming the PCA regression with 11 factors. Therefore, PLS can select the effective predic tors from a large set of indicators and demonstrate strong out-of-sample predictive power relative to PCA.

Table 4.11. Forecast performance

Metrics	RW	AR	MA	ARIMA	ARIMA(PCA)	ARIMA(PLS)
RMSE	1.00	1.50	3.49	0.97	1.38	1.35
MAPE	1.00	1.39	3.53	0.98	3405.27	1932.02
MAE	1.00	1.29	3.39	1.00	-	-

Note: This table reports the ratio of the out-of-sample RMSE of the random walk (RW) model various forecasting models for the oil price, the autoregressive (AR) model, the moving average (MA), the autoregressive integrated moving average(ARIMA), the principal components analysis and partial least squares (PLS). Values below one favor the random walk (RW) model.

Conclusions

In this study, we construct different oil prices forecasting models and estimate them with 128 monthly indicators that tell a complex macroeconomic story of the US economy from 1959 to 2020. This study deals with presenting and estimating different oil price forecasting models. The study divides the forecasting models into linear and factor models.

References

Abdel-Aal, R. E., & Al-Garni, A. Z. (1997). Forecasting monthly electric energy consumption in eastern Saudi Arabia using univariate time-series analysis. Energy, 22(11), 1059-1069.

Agnolucci, P. (2009). Volatility in crude oil futures: a comparison of the predictive ability of GARCH and implied volatility models. Energy Economics, 31(2),316-321.

Alexander, S. S. (1964). Price Movements in Speculative Markets–Trends or Random Walks, Number 2. IMR; Industrial Management Review (pre-1986), 5(2),25.

Aloui, C., & Mabrouk, S. (2010). Value–at–risk estimations of energy commodities via long–memory, asymmetry and fat–tailed GARCH models. EnergyPolicy, 38(5), 2326–2339.

Alquist, R., & Kilian, L. (2010). What do we learn from the price of crude oil futures?. Journal of Applied econometrics, 25(4), 539–573.

Álvarez-Díaz, M. (2019). Is it possible to accurately forecast the evolution of Brent crude oil prices? An answer based on parametric and nonparametric forecasting methods. Empirical Economics, 1-21.

Bacon, R. (1991). Modelling the price of oil. Oxford review of economic policy, 7(2), 17-34.

Bai, J. (2003). Inferential theory for factor models of large dimensions. Econometrica, 71(1), 135-171.

Bai, J., Ng, S. (2002). Determining the number of factors in approximate factor models. Econometrica, 70(1), 191-221.

Binder, K. E., Pourahmadi, M., Mjelde, J. W. (2020). The role of temporal dependence in factor selection and forecasting oil prices. Empirical Economics, 58(3), 1185-1223.

Blanchard, M., & Desrochers, G. (1984). Generation of autocorrelated wind speeds for wind energy conversion system studies. Solar Energy, 33(6), 571-579.

Boivin, J., & Ng, S. (2006). Are more data always better for factor analysis?. Journal of Econometrics, 132(1), 169-194.

Box, G. E. P., & Jenkins, G. M., & Reinsel, G. C. (1994). Time Series analysis forecasting and control (3rd ed.). Englewood Cliffs, N. J. Prentice Hall Press.

Box, G. E., & Jenkins, G. M. (1976). Time Series of Analysis, Forecasting and Control, San Fransisco, Helden-Day. California. USA.

Brockwell, P.J., Davis, R.A.: Introduction to Time Series and Forecasting, 2nd edn, p. 449. Springer, New York (2002).

Brown, B. G., Katz, R. W., & Murphy, A. H. (1984). Time series models to simulate and forecast wind speed and wind power. Journal of climate and applied meteorology, 23(8), 1184-1195.

Brunetti, C., & Gilbert, C. L. (2000). Bivariate FIGARCH and fractional cointegration. Journal of Empirical Finance, 7(5), 509-530.

Campbell, B., & Dufour, J. M. (1997). Exact nonparametric tests of orthogonality and random walk in the presence of a drift parameter. International Economic Review, 151–173. Chamberlain, G., & Rothschild, M. (1982). Arbitrage, factor structure, and mean-variance analysis on large asset markets.