LCERPA

Laurier Centre for Economic Research & Policy Analysis

LCERPA Working Paper No. 2021-4

May 2021

Futures Prices Are Useful Predictors of the Spot Price of Crude Oil

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Futures prices are useful predictors of the spot price of crude oil*

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May 14, 2021

Abstract: How well do futures prices forecast the spot price of crude oil? Contrary to the established view, futures prices significantly improve upon the accuracy of monthly no-change forecasts. This results from two innovations. First, we document that independent of the construction of futures-based forecasts, longer-horizon futures prices have become better predictors of crude oil spot prices since the mid-2000s. Second, we show that futures curves constructed using end-of-month prices instead of average prices can generate large accuracy-improvements for short-horizon forecasts of average prices. These findings are remarkably robust and apply to both WTI and Brent crude oil prices.

JEL classification: C1, C53, G13, G15, Q47
Keywords: Forecasting and Prediction Methods, Oil Price Forecast, Futures Market

*The views expressed in this paper are those of the authors; no responsibility for them should be attributed to the Bank of Canada.

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§We thank Lutz Kilian, Ron Alquist, Christiane Baumeister, Edouard Djeutem, Konrad Zmitrowicz, Pierre Siklos, Wing Chan and Willy Chetwin for detailed discussions, comments and suggestions.

1 Introduction

Given the importance of crude oil as a macroeconomic determinant used in models of central banks, in investment decisions, and in oil-intensive goods purchases, there is wide interest in accurately predicting the price of crude oil.[1] An early, frequently cited, result in this literature is that futures prices are not particularly useful to forecast the spot price of crude oil (Alquist and Kilian, 2010; Reeve and Vigfusson, 2011; Baumeister and Kilian, 2012; Alquist et al., 2013; Baumeister and Kilian, 2014). In this paper, we document that this result no longer holds. Futures-based forecasts are useful for forecasting the real and nominal average spot price of crude oil, and this occurs for two reasons.

First, the predictive content of crude oil futures prices at longer forecast horizons has improved since the mid-2000s. We show that whenever the end of the forecast evaluation period is extended beyond 2014, futures-based forecasts are found to be statistically significantly more accurate predictors of the spot price than the no-change forecast at horizons of one-year to five-years ahead. This result holds for forecasts of both nominal prices (as in Alquist and Kilian, 2010) and real prices (as in Baumeister and Kilian, 2012). It generalizes and corroborates recent evidence on the usefulness of future-based forecasts of real prices at some longer horizons.[2]

Second, we show that that futures curves constructed using end-of-month prices contain substantive predictive power of future average prices at short-run horizons. Incorporating end-of-period information improves the mean-squared prediction error (MSPE) and the directional accuracy of no-change forecast for average spot prices by 40 percent at the one-month horizon and remains statistically significant for forecasts up to the 12-month-ahead horizon. These improvements are remarkably robust and independent of the sample period.

A key insight from these exercises is that futures-based forecasts should always be constructed

[1] The literature on forecasting oil prices is vast and includes Ye et al. (2005); Baumeister and Kilian (2012); Alquist et al. (2013); Baumeister et al. (2014); Baumeister and Kilian (2014, 2015); Wang et al. (2015); Yin and Yang (2016); Snudden (2018); Zhang et al. (2018); Funk (2018); Garratt et al. (2019), among many others.

[2] For example, Baumeister and Kilian (2016) document statistically significant forecast-improvements for the real price of crude oil at the one-year horizon. Similar improvements for predicting real prices between the 9-month and two-year horizon have been document for quarterly by Manescu et al. (2016) and for monthly forecasts by Funk (2018).

using end-of-the-period prices rather than the average price that is standard in forecasts of the real price of oil (Baumeister and Kilian, 2012; Alquist et al., 2013). This seemingly innocuous difference yields substantial improvements for short-horizon forecasts. The use of closing prices is preferable because averaging changes the underlying data process (Rossana and Seater, 1995), which leads to a mechanical loss of information when forecasting persistent processes such as oil prices (Benmoussa et al., 2020). Futures curves constructed using end-of-month prices has precedent in Alquist and Kilian (2010) in the context of forecasting of the end-of-month nominal crude oil price. However, the model was never used to forecast average spot prices, which are standard for real prices.[3] While the distinction between end-of-period and average futures prices is crucial, the role of the deflator appears to be negligible for these results: using information from end-of-period futures prices work similarly well for forecasting average nominal and real prices.

The results contribute to a recurring debate on the role of futures prices in forecasting oil prices. Because of their simplicity and ease of implementation, futures-based forecast are popular among policy makers, investors and market participants. However, early results from the academic literature found little evidence that futures-based forecasts are helpful to forecast oil prices and recommended against their use (Alquist and Kilian, 2010; Baumeister and Kilian, 2012). Still, futures prices have remained a steady ingredient in the construction of forecast combinations (Baumeister and Kilian, 2015; Funk, 2018; Garratt et al., 2019); while other approaches focused on improving futures-based forecast by separating their expectations component from the risk premium (Baumeister and Kilian, 2016). Our results show that a decade's worth of additional data and as well as a simple modification to the originally proposed implimentation change the assessment of futures-based forecasts of the price of oil.

[3] The only exception in the literature seems to be Funk (2018), who documents gains in the accuracy of one-month-ahead forecasts from using closing prices. We show that when closing prices are applied to the futures spread, these gains are measurable and statistically significant for up to 1 year ahead.

2 Futures-Based Forecasts

Futures-based forecasts are constructed for monthly data using the percentage spread of the futures price with maturity h, $F_{t,x}^h$, over the spot price, $S_{t,x}$.[4] For nominal prices, the h-step-ahead forecast is

$$\hat{S}_{t+h,x|t} = S_{t,x}\left(1 + \ln F_{t,x}^h - \ln S_{t,x}\right), \tag{1}$$

where t denotes the current month, h denotes the forecast horizon, and x is an indicator for the price series that distinguishes between end-of-period observations ($x = n$) and monthly average observations ($x = a$). The monthly average price is the average of the n daily closing prices within the month, $S_{t,a} \equiv \frac{1}{n}\sum_{i=1}^{n} S_{t,i}$. In a similar fashion, futures-based forecasts for real prices are constructed via:

$$\hat{R}_{t+h,x|t} = R_{t,x}\left(1 + \ln F_{t,x}^h - \ln S_{t,x} - E_t\left(\pi_t^h\right)\right), \tag{2}$$

where $E_t\left(\pi_t^h\right)$ is the expected U.S. inflation rate over the next h periods, and $R_{t,x}$, $x \in \{a, n\}$, is the monthly measure of the real price of crude oil.

The distinction between average and end-of-period futures and spot prices clarifies the use of alternative futures-spreads and spot prices in the literature. For example, Alquist and Kilian (2010) forecast the end-of-month nominal spot price, $\hat{S}_{t+h,n|t}$ using end-of-month futures prices $F_{t,x}^h = F_{t,n}^h$.[5] By contrast, average prices are typically considered to be more economically relevant for the construction of macroeconomic variables and total pay-offs to oil investments. As such, the standard series for the real price of oil used in structural work and forecasting applications has always been the average monthly price, $R_{t,a}$ (see, e.g., Kilian, 2009; Alquist et al., 2013; Baumeister and Kilian, 2014, 2015).

In most applications, the futures-based forecast for real prices, $R_{t,a}$, has been constructed with

[4] The use of monthly data and log-percentage spreads is standard in the literature, see, e.g., Alquist and Kilian (2010); Baumeister and Kilian (2012); Alquist et al. (2013).

[5] Alquist and Kilian (2010) average over the last 3-5 trading days of the month. See also Pak (2018). However, we find that any averaging reduces forecast accuracy of future average prices. Thus, our analysis focuses on the closing price of the last trading day of the month.

average futures prices, $F^h_{t,a}$.[6] However, averaging oil prices can lead to a loss of information about price levels relative to end-of-period observations (Benmoussa et al., 2020). A key contribution of this study is to systematically compare the relative forecast performance of end-of-period futures prices, $F^h_{t,n}$, and average futures prices, $F^h_{t,a}$, for the real price of oil.

3 Application to Real-Time Forecasts

We construct monthly, recursive, real-time, and out-of-sample forecasts following Baumeister and Kilian (2012). For forecast horizons of up to one year, the sample starts in 1992M1. For longer-term contracts, the sample starts when the contract began to be traded at least once per day: 1995M5 for the 2-year-contract, 2006M3 for the 3-year contract, and 2007M8 for the 5-year contract.[7] For all forecasts, the sample period ends in 2018M12.

Daily and monthly spot prices of WTI crude oil were obtained from the Energy Information Administration (EIA). The end-of-the month prices for futures and spot prices are the closing prices on the last trading day of the month and are collected from Bloomberg. For the construction of real prices, monthly prices are deflated using real-time vintages of seasonally adjusted U.S. consumer price index obtained from the FRASER database of the Federal Reserve Bank of St. Louis and the Philadelphia Federal Reserve. Expected inflation is derived from the CPI price index which is projected using the historical average for CPI inflation from 1986M7.

Forecast evaluation is conducted using the mean-squared prediction error (MSPE) ratio and the success ratio for directional accuracy. Consistent with the literature, both measures are compared against the no-change constructed from the last available observation of the forecasted price series. Diebold-Mariano (Diebold and Mariano, 1995) tests are used for the MSPE ratios to test the null hypothesis of equal predictability, whereas Pesaran and Timmermann (2009) tests are used to test the null hypothesis of random directional accuracy.

[6] See, e.g., Alquist et al. (2013); Baumeister and Kilian (2014, 2015). The only exception to this rule seems to be Funk (2018), who used monthly average real spot prices, $R_{t,x} = R_{t,a}$ and $S_{t,x} = S_{t,a}$ but end-of-the month futures prices $F^h_{t,x} = F^h_{t,n}$ when documenting significant one-month-ahead forecasts of the real price of crude oil.

[7] An alternative approach to dealing with sparsely traded futures is to impute missing observations. However, while this approach extends the sample size, we found that it does not materially impact our results.

4 Forecast Results

Our main results focus on three different forecasting exercises, displayed in columns one to three in Table 1. The first column considers forecasts of the nominal end-of-month price of oil using end-of-the-month futures prices, as in Alquist and Kilian (2010). The futures-based forecasts exhibit lower MSPEs than the no-change forecasts at all forecast horizons. While the improvements are modest in magnitude and not statistically significant at short forecast horizons, they are large and significant for longer horizon. At the 1-year forecast horizon, the futures-based forecast reduces the MSPE of the no-change forecast by 13%, which is significant at the 5% significance level. Forecasts beyond one year are even better, with improvements close to 20% for the 2-year and 6-year horizon and more than 60% at the 3-year horizon. These improvements are statistically significant at the 1% significance level. A similar pattern emerges from the success ratios which compare the relative directional accuracy of the futures-based forecast with the no-change forecast. The futures-based forecast is slightly worse for short-term forecasts, but both economically and statistically significantly more accurate than the no-change forecasts for forecasts of 1-year ahead and longer. For these forecasts, the directional accuracy is over 60%, peaking at 90% at the 3-year horizon.

These results differ from Alquist and Kilian (2010), who focused on forecasts of up to 1-year, but found that futures prices typically performed worse than no-change forecasts in terms of the MSPE and only marginally better in terms of directional accuracy. We show that for a longer sample period that extend to 2018, futures prices are significantly (both economically and statistically) better predictors than the no-change forecast beginning at the 1-year horizon.

The results thus far apply to the full sample evaluations. To see how the forecast performance evolved, Figure 1 displays the evolution of the MSPE ratios and directional accuracy from recursively updated sample periods. Interestingly, the relative forecast performance at the one-year horizon started to improve considerably after 2007, just when the sample of Alquist and Kilian (2010) ended. By 2010, the gains were close to 10% and remained relatively stable, improving

Table 1. Futures-based forecasts of monthly prices of WTI crude oil

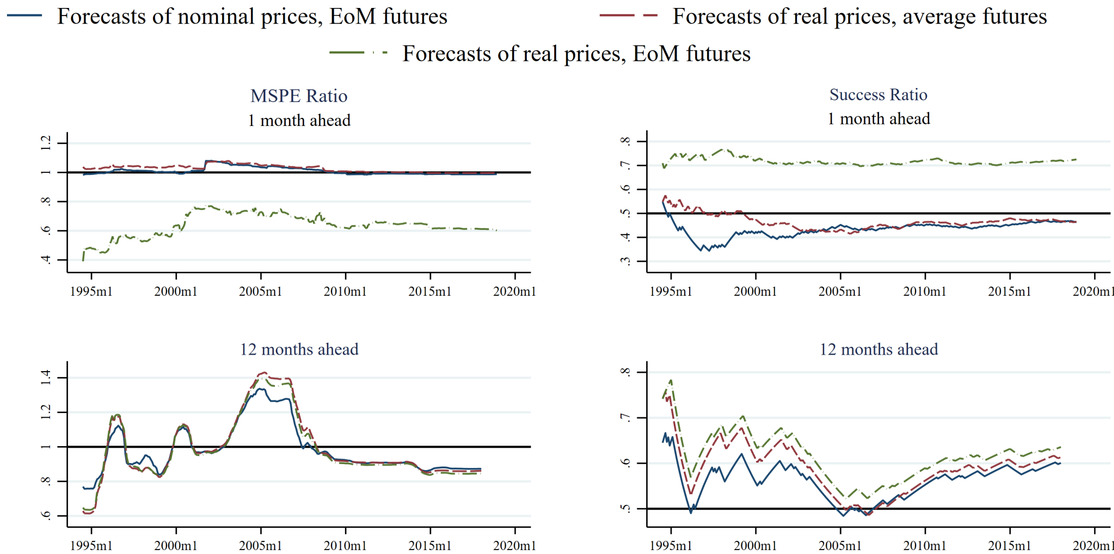
Forecasted Price	Nominal, EoM	Real, Average		Sample Start
Futures Model	EoM	Average	EoM	
Horizon		MSPE Ratio		
1	**0.99 (0.108)**	1.00 (0.333)	**0.60 (0.000)**	1992m1
3	**0.97 (0.137)**	**0.97 (0.145)**	**0.88 (0.036)**	1992m1
6	**0.97 (0.162)**	**0.96 (0.205)**	**0.93 (0.088)**	1992m1
12	**0.87 (0.019)**	**0.86 (0.039)**	**0.85 (0.025)**	1992m1
24	**0.81 (0.024)**	**0.83 (0.099)**	**0.82 (0.081)**	1995m5
36	**0.58 (0.000)**	**0.45 (0.000)**	**0.44 (0.000)**	2006m3
60	**0.82 (0.071)**	**0.51 (0.000)**	**0.51 (0.000)**	2007m8
		Success Ratio		
1	0.46 (0.357)	0.47 (0.512)	**0.73 (0.000)**	1992m1
3	0.49 (0.686)	**0.49 (0.535)**	**0.60 (0.002)**	1992m1
6	**0.53 (0.305)**	**0.53 (0.194)**	**0.55 (0.102)**	1992m1
12	**0.60 (0.014)**	**0.61 (0.002)**	**0.64 (0.000)**	1992m1
24	**0.66 (0.000)**	**0.61 (0.002)**	**0.62 (0.001)**	1995m5
36	**0.91 (0.000)**	**0.86 (0.000)**	**0.86 (0.000)**	2006m3
60	**0.64 (0.056)**	**0.83 (0.006)**	**0.84 (0.004)**	2007m8

Notes: Futures-based forecasts of the monthly price of WTI crude oil. *EoM* stands for end-of-the-month prices, *Average* for average prices. The start of sample is 1992m1 or the month when at least one contract at the respective maturity is traded per day; the end of the sample is 2018M12. Bold values indicate improvements over no-change forecast. The brackets show the p-values for serial-dependence-robust tests of Diebold and Mariano (1995) for the null hypothesis of equal MSPEs and of Pesaran and Timmermann (2009) for the null of no directional accuracy, both relative to the no-change forecast.

slightly until 2018. The p-values with the test for equal predictability associated with the recursively updated 1-year-ahead forecasts indicate that the null hypothesis of equal predictability can be rejected at the 5% confidence level for any estimation period that extends beyond December 2013. One possible explanation for these results is that volume of traded future contracts with longer maturities have gradually increased over the last decades, in particular during the 2000s (Alquist and Kilian, 2010). Much of this increase was associated with a rising participation of investors in futures markets, which caused broad-based concerns about potential market distortions. Contrary to these concerns, our results suggest that this influx could have provided additional liquidity and potentially even improved the informational efficiency of longer-term futures.

Qualitatively similar results are obtained for forecasts of the real price of oil when the forecasts are constructed with the average-futures price as in Baumeister and Kilian (2012). The results are displayed in column 2 of Table 1. Except for very short forecast horizons up to 6 months,

Figure 1. Recursive MSPEs and success ratios for futures-based forecasts of WTI crude oil prices



Notes: Evolution of recursively estimated forecast criteria for 1-month-ahead and 1-year-ahead forecasts of WTI oil prices. *EoM futures* stands for end-of-the-month futures prices, *average futures* for the monthly average futures price. The MSPEs are expressed as a ratio relative to the no-change forecast. The success ratios represent the fraction of times the forecast correctly predicts the direction of the change in the price of oil. The estimation period is 1992M1–2018M12, the first 30 months are not displayed to reduce starting-point effects.

the futures based-forecasts outperform the no-change forecast, both in terms of the MSPE ratio and the success ratio. These improvements are statistically significant at conventional levels for all horizons of one year and beyond. For the 3-year and 5-year horizon, the futures-based forecast reduce the MSPE by up to 50% and have a directional accuracy of more then 80%.

Figure 1 shows that similar to the forecasts for nominal end-of-the-month prices, the standard futures-based forecasts for the real price of oil improved considerably after the mid-2000s. Using a sample period until 2010, Baumeister and Kilian (2012) found that at forecast horizons up to one year, futures-based forecast were only marginally, and generally insignificantly, better than the no-change forecast. For larger sample periods, however, these forecasts are economically and statistically significant even at the one-year horizon. Our results show that the forecast performance of the standard futures-based forecast of the real price of oil steadily improved over the 2010 and became statistically significant for samples ending in June 2014, which explains more favorable results reported in more recent studies.[8]

[8] e.g., Baumeister and Kilian (2016); Manescu et al. (2016); Funk (2018); Garratt et al. (2019).

Finally, the 3rd column of Table 1 considers the forecasts of the real price of oil that are constructed using end-of-the-month futures. Contrary to the standard futures-based forecast, which are constructed with the average price, forecasts based on end-of-the-month futures significantly outperform the no-change forecast at all forecasting horizons. For the one-month-ahead forecast, the MSPE reduction is as large as 40%, and the directional accuracy larger than 70%. These gains in forecast accuracy exceed gains typically found in studies advocating for introducing new models, predictor variables, or forecast combination techniques (see, e.g. Baumeister and Kilian, 2015; Funk, 2018; Garratt et al., 2019).

The short-run forecast accuracy of end-of-the-month futures-based forecasts is exceptionally robust. Figure 1 shows that at the one-month ahead horizon, the forecasting gains according to both criteria are large throughout the sample period. The MSPE gains are statistically significant at the 5 percent level for 97.6 percent of the sample. This degree of robustness is impressive in a literature that is plagued with unstable forecast performances across different samples.[9]

At all horizons, the forecast based on end-of-the-month futures is at least as good as the average futures-based forecast. For the one-step ahead prediction, the improvements from introducing information from end-of-the-month prices are statistically significant at the 1% significance level for 93.7 percent of the sample, including the end of the sample. Likewise, for all forecast-horizons up to one year, the null hypothesis of equal forecast performance in terms of the MSPE and the success ratios can be rejected at the 10% significance level. Even though the improvements are somewhat weaker for longer-horizon forecasts, our results show that futures-based forecasts should always be constructed with end-of-month futures prices rather than average-price futures prices, which has been the common practice in forecasts of the real price of oil.[10]

The results are remarkably robust to alternative data assumptions.[11] First, very similar results are obtained for Brent oil prices and are on average, 6 percent more accurate for WTI at short

[9] The fact that the performance of oil-price forecasts is sensitive to the sample period is well-documented, e.g., in Baumeister et al. (2014); Baumeister and Kilian (2015); Snudden (2018); Funk (2018); Garratt et al. (2019).

[10] The only exception in the literature seems to be Funk (2018), see also Footnote 3.

[11] These results are not displayed for brevity, but are available upon request.

horizons. Second, our results are robust to alternative nowcasts of the real CPI index or the use of ex-post revised data instead of real-time data. More generally, the role of the price deflator is minimal, which is unsurprising given its low variability of US inflation compared to nominal oil prices. When average nominal prices are forecasted, end-of-the-month futures-based forecasts work similarly well as for real prices for forecasts up to fours years ahead.

The forecast performance is also robust to alternative futures-based model assumptions. Model extensions to include recursive estimates of the intercept and/or slope parameter fail to consistently improve forecasts for either nominal or real prices, which is consistent with the exercises presented in Alquist and Kilian (2010). The use of monthly average spot prices or monthly closing spot prices as the base in the futures spread model have almost no effect on the quantitative results. Similarly, using end-of-month futures prices directly instead of the futures-spread model has little quantitative effect.

The forecast performance is also robust to alternative forecast benchmarks and data frequencies. The futures-based forecasts outperform the historical average of the real spot price at all horizons. The end-of-month futures-based forecasts outperform the end-of-month no-change forecast at all horizons and result in statistically significant improvements at the five percent level at and beyond the one-year-horizon. Finally, the improvements in the one-step-ahead prediction are even larger for quarterly and annual data, which are of primary interest to policymakers (Baumeister and Kilian, 2014, 2015).

5 Conclusion

Contrary to established views, futures prices are useful predictors of the spot price of crude oil. Futures curves constructed with end-of-month prices generate robust one-step-ahead forecast accuracy improvements of over 40 percent for the average spot price. Moreover, the predictive content of longer horizon forecasts has improved considerably since the mid-2000s. Forecasts several years ahead perform particularly well, with reductions in the MSPE relative to the no-change forecast of over 55 percent at the 3-year horizons. A potential explanation for this result is that oil futures have become more effective predictors with the influx of investors over the 2000s and the associated decrease in the risk premium component of futures prices (Hamilton and Wu, 2014).

In the view of these results, previous recommendations against futures-based forecasts seem outdated. Futures-based forecast are easy to implement in real-time, offering policymakers, investors, and market participants straightforward forecasts of average crude oil prices that are significantly better than no-change forecasts. As such, they also provide a natural point of comparison to evaluate the usefulness of model-based forecasts of the price of crude oil, which have become increasingly popular over the last decade.

Our results also raise the question if similar improvements could be found for futures-based forecasts of other commodity prices. While historically, futures-based forecasts have proven to perform quite differently across different commodities (Chinn and Coibion, 2014), there is reason to believe that the insights of our paper apply more broadly. First, as suggested by Benmoussa et al. (2020), the gains from using end-of-period prices instead of average should apply to any persistent series, including the prices of other commodities. Second, the futures markets of non-oil commodities have experienced a similar process of financialization as the oil futures markets, which could, in principle, have contributed to similar changes in the predictive content of futures in these markets. Revisiting the predictive content of other commodity prices in the light of these findings opens a promising avenue for future research.

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