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Abstract

Accurate and economically useful oil price forecasts have gained significant importance over the last decade. The majority of the studies use information from the oil market fundamentals to generate oil price forecasts. Nevertheless, the extant literature has convincingly shown that oil prices are nowadays interconnected with the financial and commodities markets. Despite this, there is scarce evidence as to whether information from these markets could improve the forecasting accuracy of oil prices. Even more, there is limited knowledge whether high frequency data, given their rich information, could improve monthly oil prices. In this study we fill this void, employing a Mixed Data-Sampling (MIDAS) method using both oil market fundamentals and high frequency data from 15 financial and commodities assets. Our findings show that either the daily realized volatilities or daily returns of these assets significantly improve oil price forecasts relatively to the no-change forecast, as well as, relatively to the well-established models of the literature. These results hold true even when we consider tranquil and turbulent oil market conditions.

Keywords: Oil price forecasting, Brent crude oil, intra-day data, MIDAS.

JEL: C53, G14, G15, Q43, Q47

1. Introduction

The importance of oil price forecasting has been long established in the extant literature, as well as, in the economic press and policy documents. For instance, the IMF (2016) maintains that the recent falling oil prices create significant deflationary pressures (especially for the oil-importing economies), imposing further constraints to central banks to support growth, given that many countries currently operate in a low interest rate environment. Even more, at the same report the IMF (2016) concludes that "A protracted period of low oil prices could further destabilize the outlook for oil-exporting countries" (p. XVI). ECB (2016), on the other hand, maintains that "the fiscal situation has become increasingly more challenging in several major oil producers, particularly those with currency pegs to the US dollar…" (p. 2), given that "crude oil prices falling well below fiscal breakeven prices…" (p. 2).

The media also provide anecdotal evidence on the macroeconomic effects of the recent oil price fluctuations. Barnato (2016), for example, links oil price fluctuations with the quantitative easing in EMU, arguing that "Given the recent oil price rise, a key question is to what extent the ECB will raise its inflation projections for 2016-2018 and what this might signal for its QE (quantitative easing) policy after March 2017." Similarly, Blas and Kennedy (2016) highlight the concern that the declining energy prices might push the world economy "into a tailspin".

Overall, the importance of oil price forecasting stems from the fact that these forecasts are essential for stakeholders, such as oil-intensive industries, investors, financial corporations and risk managers, but also for regulators and central banks, in order to measure financial and economic stability (Elder and Serletis, 2010). Thus, accurate and economically useful oil price forecasts have gained significant importance over the last decade.

Nevertheless, the literature maintains that oil price forecasting could be a difficult exercise, due to the fact that oil prices exhibit heterogeneous patterns over time as at different times they are influenced by different (fundamental) factors (i.e. demand or supply of oil, oil inventories, etc.).

For instance, according to Hamilton (2009a,b) there are period when the oil prices are pushed to higher levels due to major oil production disruptions (e.g. during the Yom Kippur War in 1973, the Iranian revolution in 1978 or the Arab Spring in 2010), which were not accommodated by a similar reduction in oil demand. On the other hand, Kilian (2009) maintains that increased precautionary oil demand due to uncertainty for the future availability of oil leads to higher oil prices. According to Kilian (2009), the aforementioned uncertainty increases when geopolitical uncertainty (particularly in the Middle-East region) is high.

Even more, the remarkable growth of several emerging economies, and more prominently this of the Chinese economy, from 2004 to 2007 significantly increased the oil demand from these countries, while the oil supply did not follow suit, driving oil prices at unprecedented levels (Hamilton, 2009a,b, Kilian, 2009). Equivalently, the global economic recession during the Global Financial Crisis of 2007-09 led to the collapse of the oil prices, as the dramatic reduction of oil demand was not accompanied by a reduction in the supply of oil.

Other authors also maintain that most of the largest oil price fluctuations since the early 70s, reflect changes in oil demand (see, for instance, see, e.g., Barsky and Kilian 2004; Kilian and Murphy 2012, 2014; Lippi and Nobili 2012; Baumeister and Peersman 2013; Kilian and Hicks 2013; Kilian and Lee 2014).

Despite the fact that oil market fundamentals have triggered oil price swings, a recent strand in the literature maintains that the crude oil market has experienced an increased financialisation since the early 2000 (see, for instance, Büyüksahin and Robe, 2014; Silvennoinen and Thorp, 2013; Fattouh et al., 2013; Tang and Xiong, 2012), which has created tighter links between the financial and the oil markets. In particular, Fattouh et al. (2013) argue that the financialisation of the oil market, as this is documented by the increased participation of hedge funds, pension funds and insurance companies in the market, has led to its increased comovements with the financial markets, as well as, other energy-related and non-energy related commodities. Akram (2009) also maintains that the financialisation of the oil market is evident due to the increased correlation between oil and foreign exchange returns. Thus, apart from the fundamentals that could drive oil prices, financial and commodity markets are expected to impact oil price fluctuations and thus provide useful information for oil price forecasts.

As we explain in Section 2, typical efforts to forecast the price of oil include time-series and structural models, as well as, the no-change forecasts (which are used as the main benchmark). Furthermore, the vast majority of the existing literature uses low frequency data (monthly or quarterly) to forecast monthly or quarterly oil prices, based on oil market fundamentals.

Against this backdrop the aim of this study is twofold. First, we develop a forecasting framework that takes into consideration the different channels that provide predictable information to oil prices (i.e. fundamentals, financials, commodities, etc.). Second, we utilise ultra-high frequency data (tick-by-tick) to forecast monthly oil prices.

To do so, we employ a MIDAS framework, using tick-by-tick financial and commodities data, which complement the set of the established oil market fundamental variables. Several studies have provided evidence that the MIDAS framework has the ability to improve the forecasting accuracy for low-frequency data, using information from higher-frequency predictors (see, for instance, Andreou et al., 2013; Clements and Galvao, 2008, 2009; Ghysels and Wright, 2009; Hamilton, 2008). Needless to mention that in order to allow for meaningful comparisons, we also consider the existing state-of-the-art forecasting models. Even more, the forecasting literature has shown that single model predictive accuracy is time-dependent and thus there might not be a single model that outperforms all others at all times. Hence, our paper also compares the forecasts from the MIDAS framework against combined forecasts, in a time-varying environment.

The rest of the paper is structured as follows. Section 2 briefly reviews the literature. Section 3 provides a detailed description of the data. Section 4 describes the econometric approach employed in this paper and the forecasting evaluation techniques. Section 5 analyses the findings of the study and Section 6 includes the robustness checks. Section 7 concludes the study.

2. Brief review of the literature

The aim of this section is not to provide an extensive review of the existing literature but rather to highlight the current state-of-the-art and motivate our approach. Table 1 provides a summary of the key econometric models that have been used in the literature, along with their findings.

[TABLE 1 HERE]

One of the early studies in this line of research was conducted by Knetsch (2007), who uses a random walk and futures-based forecasts as benchmarks and investigates whether convenience yield forecasting models exhibit a superior predictive ability. The author considers several definitions for the convenience yield and finds that the convenience yield forecasting models provide superior forecasts for 1 up to 11 months ahead, as well as, superior prediction of the direction of change, compared to the two benchmark models.

Coppola (2008) employs Vector Error Correction Models (VECM) using monthly spot oil prices and a set of futures prices, whereas Murat and Tokat (2009) employ the same methodology for monthly spot oil prices and crack spread futures. Both studies show that the VECM model based on the information extracted from the futures market provide improved forecasts compared to the random walk.

Alquist and Kilian (2010) also focus on the information extracted by the futures market and forecast monthly oil prices using several specifications of futures-based models. For robustness, they compare these forecasts against the random walk, the Hotelling method, as well as, survey-based models. Alquist and Kilian (2010) cannot offer support to the findings of Coppola (2008) and Murat and Tokat (2009), as their findings suggest that the futures-based forecasts are inferior to the random walk forecasts.

Furthermore, Baumeister et al. (2013) investigate the usefulness of the product spot and futures spreads of gasoline and heating oil prices against crude oil prices. Using several robustness tests, the authors provide evidence that the futures spreads offer important predictive information of the spot crude oil prices.

Many of the subsequent studies focus on the superior predictive ability of the VAR-based models. For instance, Baumeister and Kilian (2012) show that recursive VAR-based forecasts[1] based on oil market fundamentals (oil production, oil inventories, global real economic activity) generate lower predictive errors (particularly at short horizons until 6 months ahead) compared to futures-based forecasts, as well as, time-series models (AR and ARMA models), and the no-change forecast. More specifically, the authors use unrestricted VAR, Bayesian VAR (BVAR) and structural VAR (SVAR) with 12 and 24 lags and their findings suggest that the BVAR generate both superior forecasts and higher directional accuracy. Alquist et al. (2013) also suggest that VAR-based forecasts have superior predictive ability, at least in the short-run, corroborating the results by Baumeister and Kilian (2012).

[1] The authors use unrestricted VAR, Bayesian VAR and structural VAR (developed by Kilian and Murphy, 2010) with 12 and 24 lags.

Furthermore, Baumeister and Kilian (2014) assess the forecasting ability of a Time-Varying Parameter (TVP) VAR model, as well as, forecast averaging. Their findings show that the TVP-VAR is not able to provide better forecasts compared to the established VAR-based forecasts. Nevertheless, they report that forecast averaging is capable of improving the VAR-based forecasts, although only for the longer horizons.

Another study that also provides support to the findings that the VAR-based models provide superior oil price forecasts is this by Baumeister and Kilian (2016) who use these models to show the main factors that contributed to the decline in oil prices from June 2014 until the end of 2014.

Baumeister and Kilian (2015) and Baumeister et al. (2014) extend further this line of research by examining the advantages of forecast combinations based on a set of forecasting models, including the no-change and VAR-based forecasts, as well as, forecasts based on futures oil prices, the price of non-oil industrial raw materials (as per Baumeister and Kilian, 2012), the oil inventories and the spread between the crude oil and gasoline prices. Baumeister and Kilian (2015) also consider a time-varying regression model using price spreads between crude oil and gasoline prices, as well as, between crude oil and heating oil prices. Their results show that equally weighted combinations generate superior predictions and direction of change for all horizons form 1 to 18 months. These findings remain robust to quarterly forecasts for up to 6 quarters ahead. Baumeister et al. (2014) further report that higher predictive accuracy is obtained when forecast combinations are allowed to vary across the different forecast horizons.

Manescu and Van Robays (2014) further assess the effectiveness of forecast combinations, although focusing on the Brent crude oil prices, rather than WTI. More specifically, the authors employ the established oil forecasting frameworks (i.e variants of VAR, BVAR, future-based and random walk), as well as, a DSGE framework. The authors provide evidence similar to Baumeister et al. (2014), showing that none of the competing models is able to outperform all others at all times and only the forecast combinations are able to constantly generate the most accurate forecasts for up to 11 months ahead.

More recently, Naser (2016) employs a number of competing models (such as Autoregressive (AR), VAR, TVP-VAR and FAVAR) models) to forecast the monthly WTI crude oil prices, using data from several macroeconomic, financial and geographical variables (such as, CPI, oil futures prices, gold prices, OPEC and non-OPEC oil supply, among others) and compares their predictive accuracy against the Dynamic Model Averaging (DMA) and Dynamic Model Selection (DMS) approaches. Naser (2016) finds that the latter approaches exhibit a significantly higher predictive accuracy.

A slightly different approach is adopted by Yin and Yang (2016), who assess the ability of technical indicators to successfully forecast the monthly WTI prices. In particular, they use three well-established technical strategies, namely, the moving average (MA), the momentum (MOM) and on-balance volume averages (VOL), which are then compared against a series of bivariate predictive regressions. For the latter regressions the authors use eighteen different macro-financial indicators (such as, CPI, term spread, dividend yield of the S&P500 index, industrial production, etc.). Their findings suggest that technical strategies are shown to have superior predictive ability compared to the well-established macro-financial indicators.

Thus far, we have documented that the models which seem to exhibit the highest predictive accuracy both in terms of minimising the forecasting error, as well as, of generating the highest success ratios are the VAR-based models. Even more, there is evidence that forecast combinations can increase further the forecasting accuracy of the VAR-based models, given that the literature has shown that no single model can outperform all others over a long time period.

Nevertheless, all aforementioned studies primarily use monthly data not only for the crude oil prices and the oil market fundamentals but also for all other macro-financial variables. Baumeister et al. (2015) is the only study to use higher frequency financial data (weekly[2]) to forecast the monthly crude oil prices. To do so, they authors employ a Mixed-Data Sampling (MIDAS) framework and compare its forecasting performance against the well-established benchmarks of the no-change and VAR-based forecasts. Interestingly enough, the authors claim that even though the MIDAS framework works well, it does not always perform better than the other competing models and there are cases where it produces forecasts which are inferior

[2] Their high-frequency variables include: (i) the spread between the spot prices of gasoline and crude oil; (ii) the spread between the oil futures price and the spot price of crude oil; (iii) cumulative percentage changes in the Commodity Research Bureau index of the price of industrial raw materials, (iv) the US crude oil inventories, (v) the Baltic Dry Index (BDI), (vi) returns and excess returns on oil company stocks, (vii) cumulative changes in the US nominal interest rates, and (viii) cumulative percentage changes in the US trade-weighted nominal exchange rate. Weekly series are constructed from daily data.

to the no-change model. Thus, they maintain that "…not much is lost by ignoring high- frequency financial data in forecasting the monthly real price of oil." (p. 239).

Contrary to Baumeister et al. (2015) we maintain that the usefulness of high-frequency financial data in the forecast of oil prices is by no means conclusive. We make such claim given the compelling evidence that financial markets and the oil market have shown to exhibit increased comovements over the last decade, as also aforementioned in Section 1. Furthermore, there is scope to examine further the benefits of high-frequency financial data in forecasting oil prices, given that Baumeister et al. (2015) have not used an exhaustive list of high-frequency financial and commodities data, which we consider in this study.

Even more, the bulk literature has concentrated its attention in the forecast of WTI or the refiner`s acquisition cost of imported crude oil prices, ignoring the importance of the Brent crude oil price forecasts. Thus, in this paper we focus on the latter, which is one of the main global oil benchmark, given that a number of institutions, such as the European Central Bank, the IMF and the Bank of England are primarily interested in Brent oil price forecasts, rather than WTI (Manescu and Van Robays, 2014).

3. Data Description

In this study we use both ultra-high and low frequency data. We employ monthly data for the main oil market fundamentals, as these have been identified by the literature. In particular, we use the global economic activity index and Baltic Dry Index (as proxies of the global business cycle), the global oil production, the global oil stocks (as a proxy of oil inventories), as well as, the capacity utilisation rate of the oil and gas industry. The latter is used as an additional measure of oil demand in relation to economic activity. For instance, Kaminska (2009) highlights the link between lower oil prices and the substantial decrease in oil and refinery capacity utilisation during the global financial crisis period. Global oil production and global oil stocks are converted into their log-returns.

The ultra-high frequency data comprise tick-by-tick data of the front-month futures contracts for the Brent crude oil, three major exchange rates (GBP/USD, CAD/USD, EUR/USD), four stock market indices (FTSE100, S&P500, Hang Seng, Euro Stoxx 50), five main commodities (Gold, Copper, Natural Gas, Palladium, Silver) and the US 10yr T-bills. We also use daily data for the Economic Policy

Uncertainty (EPU) index, which is used as a proxy of the US macroeconomic volatility[3].

The period of our study spans from August 2003 to August 2015 and it is dictated by the availability of intraday data for the Brent Crude oil futures contracts. Table 2 summarizes the data and the sources from which they have been obtained.

[TABLE 2 HERE]

The choice of variables is justified by the fact that there is a growing literature that confirms the cross-market transmission effects between the oil, the commodities and the financial markets[4], as well as, the findings related to the financialisation of the oil market, as discussed in Section 1[5].

Using the tick-by-tick data we construct the daily returns and the daily volatilities of all aforementioned assets. In total we consider 29 high-frequency series.

4. Forecasting models

4.1. MIDAS regression model

We define the log-returns of oil price at a monthly frequency as $y_t = log(OP_t/OP_{t-1})$, and the vector of explanatory variables at a monthly frequency as $\boldsymbol{X}_t = \left(Gea_t{}^6 \quad log(Prod_t/Prod_{t-1}) \quad log(Stocks_t/Stocks_{t-1}) \quad Cap_t\right)'$, where Gea_t, $Prod_t$, $Stocks_t$, and Cap_t denote the, global economic activity, changes in the global oil production, changes in global oil stocks and capacity utilisation rate, respectively. The vector of explanatory variables at a daily frequency is denoted as $\boldsymbol{X}^{(D)}_{(t)/s}$, where $s = 22$ is the number of daily observations at each month. The MIDAS

[3] The index is constructed by Baker *et al.* (2016). EPU index is constructed based on three types of underlying components. The first component quantifies newspaper coverage of policy-related economic uncertainty. The second component reflects the number of federal tax code provisions set to expire in future years. The third component uses disagreement among economic forecasters as a proxy for uncertainty. For more information the reader is directed to http://www.policyuncertainty.com/.

[4] See, *inter alia*, Aloui and Jammazi (2009), Sari *et al.* (2010), Arouri *et al.* (2011), Souček and Todorova (2013, 2014), Mensi *et al.* (2014), Antonakakis *et al.* (2014), Sadorsky (2014), Phan *et al.* (2015), IEA (2015).

[5] For a justification of the specific asset prices, which are included in our sample, please refer to Degiannakis and Filis (2016). However, we should also add that the use of exchange rates is also justified by the claim that when forecasting oil prices for countries other than the United States, the inclusion of the exchange rates in the forecasting models is necessary (Baumeister and Kilian, 2014). Finally, the specific series are among the most tradable futures contracts globally.

[6] We replace GEA with the Baltic Dry Index for robustness. Results are qualitative similar.

model with polynomial distributed lag weighting, first proposed by Almon (1965), is expressed as:

$$y_t = \boldsymbol{X'}_{t-i}\boldsymbol{\beta} + \sum_{\tau=0}^{k-1} \boldsymbol{X}'^{(D)}_{(t-\tau-is)/s} \left(\sum_{j=0}^{p} \tau^j \boldsymbol{\theta}_j\right) + \varepsilon_t, \tag{1}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, and $\boldsymbol{\beta}$, $\boldsymbol{\theta}_j$ are vectors of coefficients to be estimated. The p is the dimension of the lag polynomial in the vector parameters $\boldsymbol{\theta}_j$. The k is the number of lagged days to use, which can be less than or greater than s.

The proposed MIDAS model relates the current's month oil price with the low-frequency explanatory variables i months before and the high-frequency explanatory variables $s + \tau$ trading days before. Hence, such a model is able to provide i months-ahead oil price forecasts. For example, if we intend to predict the one-month ahead oil price then the MIDAS model is estimated for $i \geq 1$, thus $is \geq 22$. In the case we intend to predict the three-month ahead oil price then the MIDAS model is estimated for $i \geq 3$, thus $is \geq 66$.

The number of lagged days k is defined for the minimum sum of squared residuals. Thus, at each model estimation the optimum k varies. In order to investigate the adequate number of polynomial order, we run a series of model estimations for various values of p. We conclude that the appropriate dimension of the lag polynomial is $p = 3$.

Denoting the constructed variable based on the lag polynomial as $\widetilde{\boldsymbol{X}}_{j,t} = \sum_{\tau=0}^{k-1} \tau^j \boldsymbol{X}'^{(D)}_{(t-\tau-is)/s}$, the MIDAS model is written as:

$$y_t = \boldsymbol{X'}_{t-i}\boldsymbol{\beta} + \sum_{j=0}^{p} \widetilde{\boldsymbol{X}}_{j,t}\boldsymbol{\theta}_j + \varepsilon_t, \tag{2}$$

Thus, the number of vector coefficients to be estimated $\boldsymbol{\theta}_j$ depends on p and not on the number of daily lags k.

Technical information for MIDAS model is available in Andreou et al. (2010, 2013). Ghysels et al. (2006, 2007) proposed the weighting scheme to be given by the exponential Almon lag polynomial or the Beta weighting. Foroni et al. (2015) proposed the unrestricted MIDAS polynomial. Those polynomial specifications work adequately for small values of s.

In total we estimate 29 MIDAS models, which correspond to the 29 high-frequency returns and volatility series in our sample.

MIDAS forecasts are compared with the models that have been suggested by the literature. In particular, we use a random-walk model (as the no-change forecast), AR(12), AR(24), AR(p) and ARMA(p,q) models (where p and q are dictated by the Akaike Information Criterion), as well as, VAR-based models. For the latter we use unrestricted VAR models and BVAR models, with three and four endogenous variables. The trivariate VAR models include the changes in the global oil production, the global economic activity index and the Brent crude oil prices, whereas for the four variable VAR models we add the global oil stocks. We should emphasize here that we estimate the VAR models using both the level oil prices (with 12 and 24 lags), as well as, oil price returns (where the lags are dictated by the Akaike Information Criterion). The choice of the aforementioned models is motivated by Baumeister et al. (2015), Kilian and Murphy (2014), Baumeister and Kilian (2012), among others.

4.2. Forecast prediction and evaluation

Our forecasts are estimated recursively using an initial sample period of 100 months. The MIDAS predictions are estimated as in eq. 3:

$$OP_{t+h|t} = OP_t \times exp\left(\boldsymbol{X'}_{t-i+h}\boldsymbol{\beta}^{(t)} + \sum_{\tau=0}^{k-1} \boldsymbol{X}'^{(D)}_{\frac{(t-\tau-hs)}{s}} \left(\sum_{j=0}^{p} \tau^j \boldsymbol{\theta}_j^{(t)}\right) + {}^1\!/_2\, \hat{\sigma}_\varepsilon^2\right) \qquad (3)$$

For a description of the remaining models' predictions, please refer to Baumeister et al. (2015), Kilian and Murphy (2014) and Baumeister and Kilian (2012).

Initially, the monthly forecasting ability of our models is gauged using both the Mean Squared Predicted Error (MSPE) and the Mean Absolute Percentage Predicted Error (MAPPE), relative to the same loss functions of the monthly no-change forecast. All evaluations are taking place based on the level oil prices. A ratio above one would suggest that a forecasting model is not able to perform better than the no-change forecast, whereas the reverse holds true for ratios below 1.

To establish further the forecasting performance of the competing models, we employ the Model Confidence Set (MCS) (Hansen *et al.*, 2011), which identifies the set of the best models, according to a loss function. The benefit of the MCS test, relative to other approaches (such as the Diebold Mariano test) is that there is no need for an *a priori* choice of a benchmark model. The MCS test is estimated using two loss functions, namely, the MSPE and MAPE (Mean Absolute Predictive Error).

Finally, we also assess the directional accuracy of our models, using the success ratio, which depicts the number of times a forecasting model is able to predict correctly whether the oil price will increase or decrease. A ratio below 0.5 denotes no directional accuracy, whereas any values above 0.5 suggest an improvement relatively to the no-change forecast. We use the Pesaran and Timmermann (2009) test to assess the significance of the directional accuracy improvements of any model relative to the no-change forecast.

5. Empirical results

5.1. MAPPE and MSPE

We start our analysis with the two loss functions reported in Table 3.

[TABLE 3 HERE]

It is evident from Table 3 that all MIDAS models exhibit important gains in forecasting accuracy relatively to the no-change forecast, especially the MIDAS(v) models, suggesting that the financial assets' volatilities have significant predictive information for the oil prices. Even more, these gains seem to become quite substantial as the forecasting horizon increases. The fact that as the forecasting horizon increase so do the forecasting gains relatively to the no-change forecast is also observed in Baumeister et al. (2015). Furthermore, comparatively to Baumeister et al. (2015) who report gains of forecasting accuracy at the level of 30% using a MIDAS model based on crude oil inventories, we report gains at the level of 75% with our MIDAS(v) model, based on the MPSE.

Comparing the MIDAS models performance against all other benchmarks we are able to deduct the conclusion that the former are clearly outperforming. Even more, we observe that in many cases, the benchmark models do not seem to be able to provide any gains in forecasting accuracy relatively to the no-change forecasts.

Furthermore, our MIDAS models achieve success ratios with extremely significant gains in directional accuracy, which are though evident in the shorter horizons (until 6-months ahead forecasts). By contrasts, the four-variable BVAR model, based on oil price returns, exhibits a success ratio above 50% in the 9-months ahead forecasts. Interestingly enough, none of the models is able to generate significant gains in directional accuracy when we consider the 12-months ahead forecasts.

5.2. Model Confidence Set (MCS) procedure

Next, we need to establish whether the gains in the forecasting accuracy that were observed in Table 3 for the MIDAS models are significantly higher compared to all other models. To do so, we perform an MCS test, which assesses the models that can be included among the set of the best performing models, based on two loss functions. The results are reported in Table 4.

[TABLE 4 HERE]

From Table 4 we can clearly notice that only the MIDAS models can be included in the set of the best performing models, based on both loss functions. In particular, the MIDAS(v) model is included in the set of the best performing models in all forecasting horizons (except the 6-months ahead), whereas in the shorter horizons the MIDAS(r) model is also among the best performing models. These findings strengthen our findings from Table 3, verifying that MIDAS can indeed offer superior forecasting ability not only relatively to the no-change forecast but also to all other benchmark models.

6. Further tests

6.1 Predictive accuracy during high and low oil prices

So far we have shown quite convincingly that MIDAS models can provide significant gains on both the forecasting and directional accuracy. This is a rather important finding, which highlights the importance of the information extracted from the high-frequency financial and commodities data in forecasting the monthly oil prices.

Nevertheless, our out-of-sample forecasting period include the period that Brent crude oil sharply lost more than 50% of its price during the period 2014-2015. Baumeister and Kilian (2016) provide a very good overview of the main consequences of this oil price collapse and the factors that might have contributed to this fall.

Motivated by this extreme movement in oil prices during 2014-2015, our next step in assessing the forecasting accuracy of our models is to split our out-of-sample forecasting period between December 2011 – May 2014 (denoted as the calm period) and June 2014 – August 2015 (denoted as the oil collapse period). The results for both periods are shown in Tables 5 and 6.

[TABLE 5 HERE]

[TABLE 6 HERE]

The results from Table 5 are rather interesting, as they clearly show that during tranquil times for the oil market, none of the benchmark models can systematically generate significant gains in forecasting accuracy relative to the no-change forecast. By contrasts, the MIDAS models are once again performing significantly better than the no-change forecast, with gains in forecasting accuracy that range between 27% and 53% (depending on the MIDAS specification and the forecasting horizon).

Turning to the success ratios, we observe that MIDAS models are among the models with the most significant gains in directional accuracy, although the BVAR models also show to perform equally well in this case.

Most importantly, though, is to investigate the performance of our competing models during the oil collapse period. Oil market stakeholders are primarily interested in successful oil price predictions during the volatile period, given that these are the periods that call for actions to mitigate the adverse effects of sharp oil price changes.

The results reported in Table 6 corroborate those from Table 3. In particular, the findings show that the MIDAS(v) model generates forecasts with the highest predictive accuracy, relative to the no-change forecast, in all forecasting horizons. Importantly, we should highlight the fact that during turbulent period the MIDAS(v) model can achieve forecasting gains at the rate of more than 80%. We should not lose sight of the fact, though, that the MIDAS(r) also provides significant forecasting gains relative to the no-change forecast.

Nevertheless, the evidence shows that the superior forecasting performance of the MIDAS models is not translated into an equal performance in terms of directional accuracy. The only exception is the impressive directional accuracy of the MIDAS(v) model in the 1-month ahead forecasting horizon. It is reasonable, though to argue that during turbulent times it is rather difficult to achieve high directional accuracy.

7. Conclusion

The aim of this study is to forecasting monthly oil prices using information for high frequency data of financial and commodities assets. We do so using a MIDAS model and by constructing daily realized volatility and daily returns from the high frequency data. Our data span from August 2003 until August 2015. The out-of-sample period runs from December 2011 until August 2015.

We compare the forecasts generated by our MIDAS model against the no-change forecast, as well as, the current state-of-the art forecasting models. The findings of the study show that MIDAS models using either daily asset price volatility or asset price returns exhibit significantly higher predictive ability and directional accuracy. Based on the MIDAS model with the daily realized volatilities we report predictive gains relatively to the no-change forecast at the level of 75% at the 12-month ahead forecasting horizon. Even more, our MIDAS models also exhibit a very high directional accuracy, especially up to 6-months ahead.

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References

Akram, Q. F. (2009). Commodity prices, interest rates and the dollar. *Energy Economics*, 31(6), 838-851.

Aloui, C., & Jammazi, R. (2009). The effects of crude oil shocks on stock market shifts behaviour: A regime switching approach. *Energy Economics*, *31*(5), 789-799.

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

Alquist, R., Kilian, L., & Vigfusson, R. J. (2013). Forecasting the price of oil. *Handbook of economic forecasting*, *2*, 427-507.

Almon, S. (1965). The distributed lag between capital appropriations and expenditures. *Econometrica: Journal of the Econometric Society*, 178-196.

Andreou, E., Ghysels, E., & Kourtellos, A. (2010). Regression models with mixed sampling frequencies. *Journal of Econometrics*, *158*(2), 246-261.

Andreou, E., Ghysels, E., & Kourtellos, A. (2013). Should macroeconomic forecasters use daily financial data and how?. *Journal of Business & Economic Statistics*, *31*(2), 240-251.

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Economics*, *44*, 433-447.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: implications for portfolio management. *Journal of International Money and Finance*, *30*(7), 1387-1405.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593-1636.

Barnato, K. (2016). Here's the key challenge Draghi will face at this week's ECB meeting, CNBC, 30th May, http://www.cnbc.com/2016/05/30/heres-the-key-challenge-draghi-will-face-at-this-weeks-ecb-meeting.html

Barsky, R. B., & Kilian, L. (2004). Oil and the Macroeconomy since the 1970s. *The Journal of Economic Perspectives*, *18*(4), 115-134.

Baumeister, C., & Kilian, L. (2012). Real-time forecasts of the real price of oil. *Journal of Business & Economic Statistics*, 30(2), 326-336.

Baumeister, C., Kilian, L., & Zhou, X. (2013). Are product spreads useful for forecasting? An empirical evaluation of the Verleger hypothesis (No. 2013-25). Bank of Canada Working Paper.

Baumeister, C., & Kilian, L. (2014). What central bankers need to know about forecasting oil prices. *International Economic Review*, *55*(3), 869-889.

Baumeister, C., & Kilian, L. (2015). Forecasting the real price of oil in a changing world: a forecast combination approach. *Journal of Business & Economic Statistics*, *33*(3), 338-351.

Baumeister, C., & Kilian, L. (2016). Understanding the Decline in the Price of Oil since June 2014. *Journal of the Association of Environmental and Resource Economists*, *3*(1), 131-158.

Baumeister, C., Kilian, L., & Lee, T. K. (2014). Are there gains from pooling real-time oil price forecasts?. *Energy Economics*, *46*, S33-S43.

Baumeister, C., Guérin, P., & Kilian, L. (2015). Do high-frequency financial data help forecast oil prices? The MIDAS touch at work. *International Journal of Forecasting*, *31*(2), 238-252.

Baumeister, C., & Peersman, G. (2013). Time-varying effects of oil supply shocks on the US economy. *American Economic Journal: Macroeconomics*, *5*(4), 1-28.

Blas, J., & Kennedy, S. (2016). For Once, Low Oil Prices May Be a Problem for World's Economy, Bloomberg, 2nd February, https://www.bloomberg.com/news/articles/2016-02-02/for-once-low-oil-prices-may-be-a-problem-for-world-s-economy.

Büyükşahin, B., & Robe, M. A. (2014). Speculators, commodities and cross-market linkages. *Journal of International Money and Finance*, *42*, 38-70.

Clements, M. P., & Galvão, A. B. (2008). Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the United States. *Journal of Business & Economic Statistics*, *26*(4), 546-554.

Clements, M. P., & Galvão, A. B. (2009). Forecasting US output growth using leading indicators: An appraisal using MIDAS models. *Journal of Applied Econometrics*, *24*(7), 1187-1206.

Coppola, A. (2008). Forecasting oil price movements: Exploiting the information in the futures market. *Journal of Futures Markets*, 28(1), 34-56.

ECB (2016). Economic Bulletin, Issue 4, European Central Bank. https://www.ecb.europa.eu/pub/pdf/other/eb201604_focus01.en.pdf?48284774d83e30563e8f5c9a50cd0ea2.

Elder, J., & Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, *42*(6), 1137-1159.

Fattouh, B., Kilian, L., & Mahadeva, L. (2013). The Role of Speculation in Oil Markets: What Have We Learned So Far?. *The Energy Journal*, *34*(3), 7.

Foroni, C., Marcellino, M., & Schumacher, C. (2015). Unrestricted mixed data sampling (MIDAS): MIDAS regressions with unrestricted lag polynomials. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *178*(1), 57-82.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, *131*(1), 59-95.

Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews*, *26*(1), 53-90.

Ghysels, E., & Wright, J. H. (2009). Forecasting professional forecasters. *Journal of Business & Economic Statistics*, *27*(4), 504-516.

Hamilton, J. D. (2008). Daily Monetary Policy Shocks and the Delayed Response of New Home Sales, *Journal of Monetary Economics*, 55, 1171-1190.

Hamilton, J. D. (2009a). Causes and Consequences of the Oil Shock of 2007–08. *Brookings Papers on Economic Activity*.

Hamilton, J. D. (2009). Understanding Crude Oil Prices. *The Energy Journal*, 30(2), 179-206.

Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The model confidence set. *Econometrica*, 79(2), 453-497.

IEA (2015). What drives crude oil prices? US International Energy Administration, July 07. https://www.eia.gov/finance/markets/spot_prices.cfm

IMF (2016). World Economic Outlook – Too slow for too long, International Monetary Fund: Washington DC. https://www.imf.org/external/pubs/ft/weo/2016/01/pdf/text.pdf.

Kaminska, I. (2009). Just how big a problem is falling capacity utilisation?, Financial Times, 27th April, https://ftalphaville.ft.com/2009/04/27/55161/just-how-big-a-problem-is-falling-capacity-utilisation/

Kilian, L. (2009). Not All Oil Price Shocks are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market? *American Economic Review*, 99 (3), 1053-1069.

Kilian, L., & Hicks, B. (2013). Did unexpectedly strong economic growth cause the oil price shock of 2003–2008?. *Journal of Forecasting*, *32*(5), 385-394.

Kilian, L., & Lee, T. K. (2014). Quantifying the speculative component in the real price of oil: The role of global oil inventories. *Journal of International Money and Finance*, *42*, 71-87.

Kilian, L., & Murphy, D. (2010). Why Agnostic Sign Restrictions Are Not Enough: Understanding the Dynamics of Oil Market VAR Models. http://www-personal.umich.edu/~lkilian/km042810.pdf.

Kilian, L., & Murphy, D. (2012). Why agnostic sign restrictions are not enough: understanding the dynamics of oil market VAR models. *Journal of the European Economic Association*, *10*(5), 1166-1188.

Kilian, L., & Murphy, D. (2014). The Role of Inventories and Speculative Trading in the Global Market for Crude Oil, *Journal of Applied Econometrics*, 29, 454–78.

Knetsch, T. A. (2007). Forecasting the price of crude oil via convenience yield predictions. *Journal of Forecasting*, *26*(7), 527-549.
Lippi, F., & Nobili, A. (2012). Oil and the macroeconomy: a quantitative structural analysis. *Journal of the European Economic Association*, *10*(5), 1059-1083.
Manescu, C., & Van Robays, I. (2014). *Forecasting the Brent oil price: addressing time-variation in forecast performance* (No. 1735). European Central Bank.
Mensi, W., Hammoudeh, S., Nguyen, D. K., & Yoon, S. M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Economics*, *43*, 225-243.
Murat, A., & Tokat, E. (2009). Forecasting oil price movements with crack spread futures. *Energy Economics*, *31*(1), 85-90.
Naser, H. (2016). Estimating and forecasting the real prices of crude oil: A data rich model using a dynamic model averaging (DMA) approach. *Energy Economics*, 56, 75-87.
Phan, D. H. B., Sharma, S. S., & Narayan, P. K. (2015). Oil price and stock returns of consumers and producers of crude oil. *Journal of International Financial Markets, Institutions and Money*, *34*, 245-262.
Sadorsky, P. (2014). Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. *Energy Economics*, *43*, 72-81.
Sari, R., Hammoudeh, S., & Soytas, U. (2010). Dynamics of oil price, precious metal prices, and exchange rate. *Energy Economics*, *32*(2), 351-362.
Silvennoinen, A., & Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money*, *24*, 42-65.
Souček, M., & Todorova, N. (2013). Realized volatility transmission between crude oil and equity futures markets: A multivariate HAR approach. *Energy Economics*, *40*, 586-597.
Souček, M., & Todorova, N. (2014). Realized volatility transmission: The role of jumps and leverage effects. *Economics Letters*, *122*(2), 111-115.
Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal*, *68*(5), 54-74.
Yin, L., & Yang, Q. (2016). Predicting the oil prices: Do technical indicators help?. *Energy Economics*, 56, 338-350.

TABLES

Table 1: Summary of the empirical findings

Authors	Forecasting frequency	Forecasting models	Forecasting horizon	Best performing model(s)
Knetsch (2007)	Monthly forecasts	RBF with CY, NCF, FBF, CF	1-11 months ahead	CY-based forecasts
Coppola (2008)	Monthly forecasts	NCF, VECM, FBF	1 month ahead	VECM
Murat and Tokat (2009)	Weekly forecasts	NCF, VECM	1 month ahead	VECM
Alquist and Kilian (2010)	Monthly forecasts	NCF, FBF, HF, SBF	1-12 months ahead	NCF
Baumeister and Kilian (2012)	Monthly forecasts	NCF, VAR, BVAR, FBF, AR, ARMA	1-12 months ahead	BVAR
Alquist et al (2013)	Monthly forecasts	NCF, AR, ARMA, VAR, FBF	1-12 months ahead	VAR but also AR and ARMA (in short run), NCF (in long run)
Baumeister and Kilian (2014)	Quarterly forecasts	NCF, FBF, VAR, BVAR, TVP, RBF, CF	4 quarters ahead	VAR in the short run
Baumeister et al. (2014)	Monthly and Quarterly forecasts	NCF, VAR, FBF, RBF, CF	1-24 months ahead, 1-8 quarters ahead	CF
Manescu and Van Robays (2014)	Monthly forecasts	NCF, FBF, RBM, VAR, BVAR, DSGE, RW, CF	1-11 quarters	CF
Baumeister and Kilian (2015)	Monthly and Quarterly forecasts	NCF, VAR, FBF, RBF, TV-RBF, CF	1-24 months ahead, 1-8 quarters ahead	CF
Baumeister et al (2015)	Monthly forecasts	NCF, VAR, PSF, RBF, MIDAS, MF-VAR	1-24 months ahead	RBF with oil inventories
Naser (2016)	Monthly forecasts	FAVAR, VAR, RBF with factors, DMA, DMS	1-12 months ahead	DMA and DMS

Yin and Yang (2016)	Monthly forecasts	RBF with technical indicators, VAR, BVAR, TVPVAR, CF	1 month ahead	RBF with technical indicators
Baumeister et al. (2017)	Monthly forecasts	NCF, FBF, PSF, CF	1-24 months ahead	PSF

Notes: BVAR=Bayesian VAR models, CY=Convenience yield, DMA=Dynamic model averaging, DMS=Dynamic model selection, FBF=Futures-based forecasts, HF=Hotelling method, MF-VAR=Mixed-frequency VAR, MIDAS=Mixed Data Sampling, NCF, No=change forecasts, PSF=Product spreads forecasts, RBF=Regression-based forecasts, SBF=Survey-based forecasts, TV-RBF=Time-varying regression-based forecasts, VAR=Vector Autoregressive models.

Table 2: Variable description and sources			
Name	Acronym	Description	Source
Global Economic Activity Index	GEA	Proxy for global business cycle	Lutz Kilian website (http://www-personal.umich.edu/~lkilian/)
Baltic Dry Index	BDI	Proxy for global business cycle	Datasteam
Global Oil Production	PROD	Proxy for oil supply	Energy Information Administation
Global Oil Stocks	STOCKS	Proxy for global oil inventories	Energy Information Administation
Capacity Utilisation Rate	CAP	Proxy for oil demand in relation to economic activity	Federal Reserve Economic Data
Brent Crude Oil	OP	Tick-by-tick data of the front-month futures prices	TickData
GBP/USD exchange rate	BP	Tick-by-tick data of the front-month futures prices	TickData
CAD/USD exchange rate	CD	Tick-by-tick data of the front-month futures prices	TickData
EUR/USD exchange rate	EC	Tick-by-tick data of the front-month futures prices	TickData
FTSE100 index	FT	Tick-by-tick data of the front-month futures prices	TickData
S&P500 index	SP	Tick-by-tick data of the front-month futures prices	TickData
Hang Seng index	HI	Tick-by-tick data of the front-month futures prices	TickData
Euro Stoxx 50 index	XX	Tick-by-tick data of the front-month futures prices	TickData
Gold	GC	Tick-by-tick data of the front-month futures prices	TickData
Copper	HG	Tick-by-tick data of the front-month futures prices	TickData
Natural Gas	NG	Tick-by-tick data of the front-month futures prices	TickData
Palladium	PA	Tick-by-tick data of the front-month futures prices	TickData
Silver	SV	Tick-by-tick data of the front-month futures prices	TickData
US 10yr T-bills	TY	Tick-by-tick data of the front-month futures prices	TickData
Economic Policy Uncertainty Index	EPU	Proxy for the US macroeconomic volatility	Baker et al. (2016)

Table 3: Forecasting monthly oil prices. Evaluation period: 2011.12-2015.8.

Forecasting Horizon	AR(1)	ARMA(1,1)	AR(12)	AR(24)	3-VAR_R	3-VAR(12)	3-VAR(24)	4-VAR_R	4-VAR(12)
	MAPPE ratio								
1	0.9730	0.9739	1.1614	1.0013	0.9811	1.4458	1.0047	1.0587	1.6411
3	1.0324	1.0446	1.1941	1.0016	1.0953	1.6384	1.0315	1.0453	1.8344
6	0.9927	0.9996	1.1718	1.0015	1.0209	1.5506	1.0291	0.8724	1.8115
9	0.9797	0.9776	1.1778	1.0008	0.7614	1.2795	1.0501	0.7404	1.3476
12	0.9783	0.9741	1.1228	0.9991	0.7403	1.2132	1.1144	0.7350	1.1081
	MSPE ratio								
1	0.9500	0.9627	1.3273	1.0066	1.2178	2.4064	1.0060	1.2290	3.2684
3	0.9957	1.0145	1.2820	1.0040	1.3471	2.7991	1.0044	1.2067	3.9489
6	0.9652	0.9657	1.2792	1.0026	0.9795	3.1503	1.0205	0.8128	4.4444
9	0.9737	0.9692	1.2907	1.0006	0.7345	2.0165	1.0855	0.6687	2.2675
12	0.9729	0.9681	1.1887	0.9968	0.6007	1.5690	1.1942	0.5771	1.3006
	Success ratio								
1	0.5581	0.5814*	0.3721	0.3953	0.6047**	0.4884	0.5116	0.4884	0.5116
3	0.3902	0.4146	0.4878	0.4634	0.4878	0.4146	0.4146	0.4634	0.3415
6	0.4737	0.4737	0.4474	0.4737	0.6053**	0.5000	0.4737	0.5789*	0.5000
9	0.4286	0.4286	0.3714	0.3714	0.5429	0.4571	0.3714	0.4857	0.4286
12	0.3438	0.3125	0.3438	0.3438	0.4375	0.3438	0.3438	0.4688	0.3750

Table 3 (continued): Forecasting monthly oil prices. Evaluation period: 2011.12-2015.8.

Forecasting Horizon	4-VAR(24)	3-BVAR_R	3-BVAR(12)	3-BVAR(24)	4-BVAR_R	4-BVAR(12)	4-BVAR(24)	MIDAS(v)	MIDAS(r)
					MAPPE ratio				
1	1.0440	0.8873	0.9105	0.9668	0.9070	0.9208	0.9667	**0.8002**	0.8558
3	1.0776	0.9941	1.0060	0.9477	1.0039	0.9983	0.9477	**0.7885**	0.7937
6	1.0831	0.8390	0.7889	0.8813	0.8535	0.7748	0.8814	0.7568	**0.6829**
9	0.9317	0.7019	0.7003	0.8293	0.7145	0.6935	0.8292	**0.5253**	0.7886
12	0.8841	0.7136	0.7070	0.7991	0.7282	0.7096	0.7989	**0.4825**	0.6605
					MSPE ratio				
1	1.1068	0.9342	0.9303	0.9553	0.9690	0.9344	0.9552	**0.6450**	0.7623
3	1.1337	0.9818	0.9965	0.9051	1.0342	0.9922	0.9051	0.6048	**0.5921**
6	1.0191	0.7143	0.7117	0.8048	0.7350	0.6836	0.8047	0.5044	**0.4771**
9	0.8898	0.5599	0.5737	0.7477	0.5861	0.5631	0.7475	**0.2963**	0.6302
12	0.8937	0.5129	0.5394	0.6972	0.5300	0.5343	0.6970	**0.2438**	0.4674
					Success ratio				
1	0.4884	0.6279**	0.5349	0.4651	0.6047**	0.5116	0.4651	**0.6977****	0.6744**
3	0.4878	0.5122	0.5122	0.5122	0.5366	0.4878	0.5122	0.4878	**0.5610***
6	0.4474	**0.6316****	**0.6316****	0.4474	**0.6316****	**0.6316****	0.4474	0.5000	**0.6316****
9	0.4857	0.5429	0.4571	0.4286	**0.5714***	0.4571	0.4286	0.5143	0.4286
12	0.2813	0.4063	0.4063	0.2500	0.4063	0.4063	0.2500	0.3750	0.2500

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. VAR and BVAR models with (r) denote that they are estimated based on oil price log-returns. MIDAS(v) and MIDAS(r) denote the best MIDAS model based on the volatilities and returns of the high-frequency series, respectively. Boldface indicates the best performing forecasting model. The statistical significance of the success ratios is tested based on the Pesaran and Timmermann (2009) under the null hypothesis of no directional accuracy. ** and * denote significance at 5% and 10% level, respectively.

Table 4: MCS p-values for 1-month to 12-months ahead. Evaluation period: 2011.12-2015.8

Loss function: MAPPE	Forecasting Horizon				
	1-month	3-months	6-months	9-months	12-months
	p-values are reported				
RW	0.1375	0.2944	0.0280	0.0178	0.0000
AR(1)	0.1666	0.0842	0.0098	0.0185	0.0000
ARMA(1,1)	0.1666	0.0316	0.0037	0.0180	0.0000
AR(12)	0.0726	0.1204	0.0134	0.0012	0.0000
AR(24)	0.1375	0.2944	0.0280	0.0178	0.0000
3-VAR_R	0.1666	0.0842	0.0022	0.0185	0.0053
3-VAR(12)	0.0008	0.0000	0.0012	0.0002	0.0659
3-VAR(24)	0.0000	0.0033	0.0029	0.0386	0.0502
4-VAR_R	0.0569	0.1013	0.0348	0.0386	0.0160
4-VAR(12)	0.0000	0.0005	0.0029	0.0024	0.0127
4-VAR(24)	0.0000	0.0033	0.0025	0.0386	0.0502
3-BVAR_R	0.4008	0.0842	0.0348	0.0386	0.0160
3-BVAR(12)	0.0424	0.2944	0.0338	0.0028	0.0160
3-BVAR(24)	0.0000	0.0000	0.0000	0.0002	0.0127
4-BVAR_R	0.1666	0.0885	0.0338	0.0386	0.0051
4-BVAR(12)	0.0449	0.2944	0.0338	0.0025	0.0160
4-BVAR(24)	0.0000	0.0000	0.0000	0.0002	0.0127
MIDAS(v)	**1.0000**	**0.8816**	0.1174	**1.0000**	**1.0000**
MIDAS(r)	**0.7113**	**1.0000**	**1.0000**	0.0386	0.1059

Table 4 (continued): MCS p-values for 1-month to 12-months ahead.
Evaluation period: 2011.12-2015.8.

Loss function: MSE	Forecasting Horizon				
	1-month	3-months	6-months	9-months	12-months
	p-values are reported				
RW	0.0881	0.1910	0.1051	0.0400	0.0096
AR(1)	0.1435	0.1445	0.1051	0.0400	0.0096
ARMA(1,1)	0.1435	0.1202	0.1000	0.0400	0.0096
AR(12)	0.0537	0.1075	0.1051	0.0002	0.0000
AR(24)	0.0881	0.1910	0.1051	0.0400	0.0096
3-VAR_R	0.1435	0.1445	0.0467	0.0351	0.0035
3-VAR(12)	0.0090	0.0305	0.0118	0.0015	0.0468
3-VAR(24)	0.0128	0.0469	0.0363	0.0400	0.0468
4-VAR_R	0.1435	0.1373	0.1051	0.0351	0.0079
4-VAR(12)	0.0128	0.0670	0.1051	0.0400	0.0096
4-VAR(24)	0.0128	0.0458	0.0354	0.0400	0.0468
3-BVAR_R	0.2031	0.1061	0.1051	0.0354	0.0139
3-BVAR(12)	0.0881	0.1910	0.1000	0.0108	0.0205
3-BVAR(24)	0.0000	0.0000	0.0002	0.0006	0.0118
4-BVAR_R	0.1435	0.1075	0.1051	0.0231	0.0045
4-BVAR(12)	0.0881	0.1910	0.1000	0.0106	0.0205
4-BVAR(24)	0.0000	0.0000	0.0002	0.0006	0.0118
MIDAS(v)	**1.0000**	**0.8976**	**0.7326**	**1.0000**	**1.0000**
MIDAS(r)	0.281	**1.0000**	**1.0000**	0.0400	0.0468

Table 5: Forecasting monthly oil prices during the calm period. Evaluation period: 2011.12-2014.5

Forecasting Horizon	AR(1)	ARMA(1,1)	AR(12)	AR(24)	3-VAR_R	3-VAR(12)	3-VAR(24)	4-VAR_R	4-VAR(12)
	MAPPE ratio								
1	0.9793	0.9972	1.2330	1.0034	1.2551	1.8482	1.0772	1.2767	2.2706
3	1.0715	1.1011	1.2950	1.0054	1.5397	2.4080	1.1312	1.4066	2.8753
6	1.0162	1.0389	1.3639	1.0053	1.6181	2.9804	1.1566	1.2388	3.9909
9	0.9956	1.0156	1.4201	1.0043	1.7172	2.8580	1.3264	1.3662	3.2626
12	0.9484	0.9407	1.3437	0.9987	1.4167	2.1219	1.4398	1.2380	1.8739
	MSPE ratio								
1	0.9501	0.9919	1.4994	1.0141	1.7165	3.3570	1.0818	1.6227	5.1231
3	1.1067	1.1788	1.5234	1.0101	2.6504	5.3469	1.1363	2.2060	8.3724
6	1.0257	1.0700	1.7250	1.0121	2.7896	11.3969	1.3361	1.9666	18.2918
9	1.0520	1.0959	1.7584	1.0061	3.1375	8.7205	1.8122	2.2603	10.6713
12	0.9567	0.9584	1.5599	0.9893	1.9956	4.5771	1.9920	1.6542	3.6063
	Success ratio								
1	0.5517	0.5862*	0.4483	0.4828	0.5517	0.5517	0.4828	0.5172	0.5862*
3	0.4815	0.5185	0.5556	0.5556	0.5185	0.5185	0.4815	0.5556	0.4074
6	0.5417	0.5417	0.5000	0.5417	0.5833*	0.5000	0.5417	0.5833*	0.5000
9	0.5714*	0.5714*	0.4762	0.4762	0.6190	0.5238	0.4762	0.5714	0.5238
12	0.4444	0.3889	0.4444	0.4444	0.5556	0.4444	0.4444	**0.6111****	0.5000

Table 5 (continued): Forecasting monthly oil prices during the calm period. Evaluation period: 2011.12-2014.5

Forecasting Horizon	4-VAR(24)	3-BVAR_R	3-BVAR(12)	3-BVAR(24)	4-BVAR_R	4-BVAR(12)	4-BVAR(24)	MIDAS(v)	MIDAS(r)
					MAPPE ratio				
1	1.2565	1.0445	1.0211	0.9677	1.0783	1.0398	0.9678	0.8665	**0.8330**
3	1.3602	1.2612	1.2333	0.9401	1.3049	1.2565	0.9405	0.9346	**0.8657**
6	1.4295	1.0198	0.7381	0.7816	1.1206	0.7492	0.7821	1.0506	**0.6444**
9	0.9353	1.1146	0.8049	0.6355	1.2286	0.7865	**0.6350**	0.7831	0.9827
12	**0.5147**	0.9106	0.5493	0.5764	1.0709	0.5857	0.5754	0.6637	0.6100
					MSPE ratio				
1	1.3846	1.1722	1.1194	0.9618	1.2404	1.1400	0.9620	**0.6736**	0.7234
3	1.6224	1.6072	1.5315	0.9005	1.7566	1.5723	0.9009	0.8438	**0.7299**
6	1.7358	1.2518	0.7828	0.6051	1.4866	0.8105	0.6055	1.0058	**0.4813**
9	0.9602	1.4396	0.8524	0.4622	1.7407	0.8469	**0.4614**	0.6516	0.9951
12	0.3536	0.8632	**0.3430**	0.3956	1.1573	0.3845	0.3944	0.4772	0.4711
					Success ratio				
1	0.4483	0.5517	0.5517	0.4828	0.5517	0.5172	0.4828	**0.6552****	**0.6552****
3	0.4815	0.5926*	0.5926*	0.5926	0.5926*	0.5556	0.5926*	0.5556	**0.6296****
6	0.5000	**0.6667****	**0.6667****	0.5000	**0.6667****	**0.6667****	0.5000	0.4583	**0.6667****
9	**0.6667****	**0.6667****	0.5714	0.5714*	**0.6667****	0.5714*	0.5714*	0.5714*	0.5714*
12	0.3889	0.5556	0.5556	0.3333	0.5556	0.5556	0.3333	0.5000	0.3333

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. VAR and BVAR models with (r) denote that they are estimated based on oil price log-returns. MIDAS(v) and MIDAS(r) denote the best MIDAS model based on the volatilities and returns of the high-frequency series, respectively. Boldface indicates the best performing forecasting model. The statistical significance of the success ratios is tested based on the Pesaran and Timmermann (2009) under the null hypothesis of no directional accuracy. ** and * denote significance at 5% and 10% level, respectively.

Table 6: Forecasting monthly oil prices during the oil collapse period. Evaluation period: 2014.6-2015.8

Forecasting Horizon	AR(1)	ARMA(1,1)	AR(12)	AR(24)	3-VAR_R	3-VAR(12)	3-VAR(24)	4-VAR_R	4-VAR(12)
					MAPPE ratio				
1	0.9684	0.9569	1.1089	0.9998	0.7803	1.1507	0.9516	0.8989	1.1796
3	1.0071	1.0079	1.1287	0.9992	0.8075	1.1400	0.9669	0.8113	1.1603
6	0.9826	0.9827	1.0891	0.9998	0.7636	0.9347	0.9742	0.7145	0.8727
9	0.9749	0.9660	1.1040	0.9998	0.4703	0.7986	0.9659	0.5498	0.7643
12	0.9872	0.9840	1.0571	0.9992	0.5394	0.9432	1.0177	0.5856	0.8806
					MSPE ratio				
1	0.9500	0.9369	1.1752	0.9999	0.7767	1.5658	0.9389	0.8808	1.6283
3	0.9279	0.9143	1.1348	1.0003	0.5518	1.2443	0.9238	0.5968	1.2493
6	0.9496	0.9387	1.1639	1.0002	0.5118	1.0194	0.9390	0.5147	0.8665
9	0.9589	0.9451	1.2019	0.9996	0.2778	0.7110	0.9474	0.3662	0.6704
12	0.9762	0.9700	1.1135	0.9983	0.3180	0.9594	1.0325	0.3588	0.8333
					Success ratio				
1	0.5714*	0.5714*	0.2143	0.2143	0.7143	0.3571	0.5714	0.4286	0.3571
3	0.2143	0.2143	0.3571	0.2857	0.4286	0.2143	0.2857	0.2857	0.2143
6	0.3571	0.3571	0.3571	0.3571	**0.6429****	0.5000	0.3571	0.5714*	0.5000
9	0.2143	0.2143	0.2143	0.2143	0.4286	0.3571	0.2143	0.3571	0.2857
12	0.2143	0.2143	0.2143	0.2143	0.2857	0.2143	0.2143	0.2857	0.2143

Table 6 (continued): Forecasting monthly oil prices during the oil collapse period. Evaluation period: 2014.6-2015.8

Forecasting Horizon	4-VAR(24)	3-BVAR_R	3-BVAR(12)	3-BVAR(24)	4-BVAR_R	4-BVAR(12)	4-BVAR(24)	MIDAS(v)	MIDAS(r)
					MAPPE ratio				
1	0.8882	0.7720	0.8294	0.9661	0.7813	0.8335	0.9660	**0.7515**	0.8726
3	0.8946	0.8212	0.8588	0.9525	0.8091	0.8310	0.9524	**0.6939**	0.7471
6	0.9338	0.7611	0.8107	0.9242	0.7384	0.7858	0.9242	**0.6302**	0.6995
9	0.9307	0.5762	0.6684	0.8884	0.5579	0.6652	0.8884	**0.4468**	0.7295
12	0.9939	0.6551	0.7539	0.8653	0.6265	0.7464	0.8653	**0.4286**	0.6756
					MSPE ratio				
1	0.8611	0.7237	0.7630	0.9495	0.7290	0.7526	0.9492	**0.6197**	0.7967
3	0.8355	0.6002	0.6699	0.9079	0.5933	0.6382	0.9077	**0.4589**	0.5080
6	0.8339	0.5754	0.6933	0.8564	0.5408	0.6508	0.8562	**0.3748**	0.4760
9	0.8764	0.3927	0.5208	0.8020	0.3667	0.5092	0.8019	**0.2288**	0.5608
12	1.0032	0.4419	0.5792	0.7583	0.4029	0.5647	0.7583	**0.1964**	0.4666
					Success ratio				
1	0.5714*	0.7857**	0.5000	0.4286	0.7143**	0.5000	0.4286	**0.7857****	0.7143
3	0.5000	0.3571	0.3571	0.3571	0.4286	0.3571	0.3571	0.3571	0.4286
6	0.3571	0.5714*	0.5714*	0.3571	0.5714*	0.5714*	0.3571	0.5714*	0.5714*
9	0.2143	0.3571	0.2857	0.2143	0.4286	0.2857	0.2143	0.4286	0.2143
12	0.1429	0.2143	0.2143	0.1429	0.2143	0.2143	0.1429	0.2143	0.1429

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. VAR and BVAR models with (r) denote that they are estimated based on oil price log-returns. MIDAS(v) and MIDAS(r) denote the best MIDAS model based on the volatilities and returns of the high-frequency series, respectively. Boldface indicates the best performing forecasting model. The statistical significance of the success ratios is tested based on the Pesaran and Timmermann (2009) under the null hypothesis of no directional accuracy. ** and * denote significance at 5% and 10% level, respectively.