Forecasting oil prices: High-frequency financial data are indeed useful

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Abstract

The paper examines the importance of combining high frequency financial information, along with the oil market fundamentals, in order to gain incremental forecasting accuracy for oil prices. Inspired by French *et al.* (1986) and Bollerslev *et al.* (1988), who maintain that future asset returns are also influenced by past volatility, we use daily volatilities and returns from financial and commodity markets to generate real out-of-sample forecasts for the monthly oil futures prices. Our results convincingly show that although the oil market fundamentals are useful for long-run forecasting horizons, the combination of the latter with high-frequency financial data significantly improve oil price forecasts, by reducing the RMSE of the no-change forecast by approximately 68%. Results are even more impressive during the oil price collapse period of 2014-15. These findings suggest that we cannot ignore the information extracted from the financial markets when forecasting oil prices. Our results are both statistically and economically significant, as suggested by several robustness tests.

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

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[1]. The media also provide anecdotal evidence on the macroeconomic effects of the recent oil price fluctuations[2]. Overall, the importance of oil price forecasts stems from the fact that they 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). Even more, it has been long established in the literature that oil price changes significantly impact growth conditions, external balances and price levels (see, *inter alia*, Jo, 2014; Natal, 2012; Bachmeier and Cha, 2011; Kilian *et al.*, 2009; Aguiar-Conraria and Wen, 2007; Hamilton, 2008a; Backus and Crucini, 2000) and it can also provide predictive information for economic variables (see, for instance, Ravazzolo and Rothman, 2013).

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 periods when the oil prices are pushed to higher levels due to major oil production disruptions, which were not accommodated by a similar reduction in oil demand (e.g. during the Yom Kippur War in 1973, the Iranian revolution in 1978 or the Arab Spring in 2010). 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 is high (particularly in the Middle-East region).

[1] For instance, the IMF (2016) maintains that the recent fall of 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…", given that "crude oil prices falling well below fiscal breakeven prices…" (p. 2).

[2] 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".

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 since the early 70s oil price fluctuations primarily reflect changes in oil demand. See, for instance, papers by Barsky and Kilian (2004), Kilian and Murphy (2012, 2014), Lippi and Nobili (2012), Baumeister and Peersman (2013), Kilian and Hicks (2013), and 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; Tang and Xiong, 2012), which was created by the increased participation of hedge funds, pension funds and insurance companies in this market and created tighter links between the financial, energy and non-energy 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.

Nevertheless, the vast majority of the existing literature uses low sampling frequency data (monthly or quarterly) to forecast monthly or quarterly oil prices, based solely on oil market fundamentals. 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.

We further maintain, though, that since oil market fundamentals are available on a monthly frequency, they cannot capture instant developments in the commodities and financial markets, as well as, in economic conditions at a higher sampling frequency (e.g. on a daily basis). Hence, forecasting models relying solely on oil market fundamentals are not incorporating this daily information in their oil price forecasts, rendering important the combination of high frequency information, along with the market fundamentals, in order to gain significant incremental forecasting ability.

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, financial markets, commodities, macroeconomic factors, etc.). Second, we utilise both low sampling frequency data on oil price fundamentals and ultra-high frequency financial and commodities data (tick-by-tick) to forecast monthly oil prices. We maintain that we generate real out-of-sample forecasts in the sense that at the point that each forecast is generated, we do not use any unavailable or future information, which would be impossible for the forecaster to have at her disposal.

To do so, we employ a Mixed-Data Sampling (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 at a low-frequency, using information from higher-frequency predictors (see, for instance, Andreou *et al.*, 2013; Clements and Galvao, 2008, 2009; Ghysels and Wright, 2009; Hamilton, 2008b). 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.

Our findings show that oil market fundamentals are useful in forecasting oil futures prices in the long-run horizons. Nevertheless, we report, for the first time, that the combination of oil market fundamentals with ultra-high frequency data from financial, commodity and macroeconomic assets provide significant incremental predictive gains in monthly oil price forecasts. In particular, the daily realized volatilities from the aforementioned assets reduce the Mean Squared Predicted Error (MSPE) by almost 38% in 6-months ahead forecasting horizon, relatively to the no-change forecast, whereas a 68% of predictive gains are achieved in 12-months ahead horizon. We further show that at least in the short-run (up-to 3-month horizon), the use of ultra-high frequency data provides gains in directional accuracy. The results remain robust to several tests, including comparison with combined forecasts and U.S.

Energy Information Administration (EIA) official forecasts, as well as, forecasting performance during turbulent oil market periods. The results are also economically important, as evident by the results of a trading game.

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. Section 6 includes the robustness checks, along with the comparison of the results from the forecasting framework against the EIA official forecasts and Section 7 reports the results from the trading game. Finally, Section 8 concludes the study.

2. 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[3] 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 (Autoregressive (AR) and Autoregressive Moving Average (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).

Furthermore, Baumeister and Kilian (2014) assess the forecasting ability of a Time-Varying Parameter (TVP) VAR model, as well as, forecast averaging techniques. 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

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

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 West Texas Intermediate (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 Dynamic Stochastic General Equilibrium (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 AR, VAR, TVP-VAR and Factor-augmented Vector Autoregressive (FAVAR) models) to forecast the monthly WTI crude oil prices, using data from several macroeconomic, financial and geographical variables (such as, consumer price index (CPI), oil futures prices, gold prices, OPEC and non-OPEC oil supply) and compares their predictive accuracy against the Dynamic Model Averaging and Dynamic Model Selection 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, the momentum and on-balance volume averages, 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 VAR-based models seem to exhibit the highest predictive accuracy both in terms of minimising the forecast error, as well as, of generating the highest directional accuracy. Even more, there is evidence that forecast combinations can increase further the predictive 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[4]) to forecast the monthly crude oil prices. To do so, authors employ a 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 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, the use of weekly data may still mask important daily information which is instrumental to oil price forecasting. We should not lose sight of the fact that oil prices have exhibited over the last ten years significant daily variability and so daily data could provide incremental predictive information. In addition, Baumeister *et al.* (2015) have not used an exhaustive list of high-frequency data from financial and commodity markets. Therefore, we maintain

[4] 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.

that there is still scope to examine further the benefits of high-frequency financial data in forecasting oil prices.

Finally, 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. In this paper we focus on the latter, which is one of the main global oil benchmarks, given that a number of institutions, such as the European Central Bank (ECB), the International Monetary Fund (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 and the global oil stocks (as proxies of oil inventories). We also use the capacity utilisation rate of the oil and gas industry, as an additional measure of oil demand in relation to economic activity. 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. The Baltic Dry index, the global oil production and global oil stocks are converted into their log-returns.

The ultra-high frequency data comprise tick-by-tick prices of the front-month futures contracts for three major exchange rates (GBP/USD, CAD/USD, EUR/USD), four stock market indices (FTSE100, S&P500, Hang Seng, Euro Stoxx 50), six commodities (Brent crude oil, Gold, Copper, Natural Gas, Palladium, Silver) and the US 10yr T-bills. The tick-by-tick data are used to construct the realized volatilities of all aforementioned assets[5], as well as, their daily log-returns. We also employ the daily US Economic Policy Uncertainty (EPU) index, which, along with the US 10yr

[5] The realized volatility is estimated as the sum of squared intra-day returns and it is adjusted with the close-to-open volatility according to Hansen and Lunde (2005); i.e. minimising the variance of the realized volatility. The intra-day sampling frequency is defined as the highest frequency that minimises the autocovariance bias. More specifically, the intraday sampling frequencies of GBP/USD, CAD/USD and EUR/USD, are 30, 25 and 16 minutes, respectively. The sampling frequencies of FTSE100, S&P500, Hang Seng, Euro Stoxx 50 and US 10y T-bill are 1, 6, 60, 3 and 15 minutes, respectively. Finally, for the commodities, the sampling frequencies of Brent Crude Oil, Gold, Copper, Natural Gas, Palladium and Silver are 23, 15, 20, 10, 90, 28 minutes, respectively.

T-bills, are proxies of the global macroeconomic volatility[6]. In total we consider 29 high frequency time-series (15 volatility series and 14 returns series), which belong to four different asset classes, namely, *Forex*, *Stocks*, *Commodities* and *Macro*.

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 commodity and the financial markets[7], as well as, the findings related to the financialisation of the oil market, as discussed in Section 1. For a justification of the specific asset prices, which are included in our sample, please refer to Degiannakis and Filis (2017). 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). The specific series, used in this paper, are also among the most tradable futures contracts globally. Furthermore, the aforementioned assets reflect market conditions in Europe, as well as, globally.

Tick-by-tick data are considered given that we seek to obtain the most accurate daily information. For instance, Andersen *et al.* (2006) maintain that ultra-high frequency data provide the most accurate volatility estimate.

The use of asset returns is motivated by the extant literature which documents spillover effects between oil, commodities and financial assets' returns, as discussed in Sections 1 and 2. On the other hand, the use of realized volatilities as predictors of oil prices is related to the arguments put forward by French *et al.* (1986), Engle *et al.* (1987), Bollerslev *et al.* (1988), among others, that expectations related to future asset returns are also influenced by its own current and past variance. Hence, motivated by this argument, we extend it further to assess whether future oil prices are not only influenced by its own current and past variance, but also by the current and past variances of other assets.

[6] 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.

[7] See, *inter alia*, Aloui and Jammazi (2009), Kilian and Park (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).

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]

4. Forecasting models

4.1. MIDAS regression model

We define the oil futures price returns at a monthly frequency as $y_t = log(OP_t/OP_{t-1})$, and the vector of explanatory variables at a monthly frequency as $\boldsymbol{X}_t = (Gea_t,\ \ log(Prod_t/Prod_{t-1}),\ \ log(Stocks_t/Stocks_{t-1}),\ \ Cap_t)'$, where GEA_t, $Prod_t$, $Stocks_t$ and Cap_t denote the global economic activity, the global oil production, the global oil stocks and the capacity utilisation rate, respectively. The vector of daily returns or realized volatilities is denoted as $\boldsymbol{X}_{(t)}^{(D)}$. The MIDAS model with polynomial distributed lag weighting, first proposed by Almon (1965), is expressed as:

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

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, $s = 22$ is the number of daily observations at each month, 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 futures price with the low-frequency explanatory variables i months before and the ultra-high frequency explanatory variables $s + \tau$ trading days before. Hence, such a model is able to provide i months-ahead oil futures 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 $i \geq 3$, so $is \geq 66$.

The number of lagged days k is defined for the minimum sum of squared residuals, so that at each model's estimation the optimum k varies[8]. 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 $\widetilde{\boldsymbol{X}}_{j,t} = \sum_{\tau=0}^{k-1} \tau^j \boldsymbol{X}'^{(D)}_{(t-\tau-is)}$, the MIDAS model is written as:

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

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, using one asset's volatility or return at a time[9]. We denote MIDAS-RV and MIDAS-RET the MIDAS models based on realized volatilities and returns, respectively. We should also highlight here that we have experimented using the daily squared returns as an additional measure of daily volatility, yet in such case the MIDAS-RV models did not perform satisfactorily. Hence, our analysis is based on the ultra-high frequency data[10].

MIDAS forecasts are compared with the models that have been suggested by the literature (denoted as the standard models). In particular, we use a random-walk model (as the no-change forecast), AR(1), AR(12), AR(24) and ARMA(1,1) models, 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

[8] We select the k that minimizes the sum of squared residuals in the estimation period. If we had selected the k that minimizes the sum of squared forecast errors in the out-of-sample period, then we would have induced a form of data mining bias.

[9] Even though we have 15 assets, EPU is considered as a proxy of macroeconomic volatility and thus it is only included in the set of asset volatilities.

[10] Thus, we claim that it is not just the MIDAS model but also the use of tick-by-tick data that are required to produce superior forecasts.

changes in global oil stocks[11]. We should emphasize here that we estimate the VAR models using the level oil prices with 12 and 24 lags. The choice of the aforementioned models is motivated by Baumeister *et al.* (2015), Kilian and Murphy (2014) and Baumeister and Kilian (2012), among others.

4.2. Forecast prediction and evaluation

Our forecasts are estimated recursively (i.e. using an increasing window to re-estimate the forecasts) based on an initial sample period of 100 months[12]. The MIDAS predictions are estimated as in eq. 3:

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

For a description of the competing 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 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 suggests 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) of Hansen *et al.* (2011), which identifies the set of the best models which have equal predictive accuracy, 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[13]. The MCS test is estimated based on the two aforementioned loss functions.

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[11] All VAR and BVAR models are stationary. For brevity we do not show the test results here, but they are available upon request.

[12] The estimation of the MIDAS models requires a large sample size due to its non-linearity. Thus, following the forecasting literature, we decide to use the 2/3 of the available data for the initial in-sample estimation period and the remaining 1/3 of the observations for the out-of-sample evaluation period. In any case, it is common in the literature to use approximately *1*/3 of the total observations for the out-of-sample forecasts (see for instance, Silva and Hassani, 2015; Marcellino *et al.*, 2003). We should of course highlight that initial in-sample estimation periods of 90 and 80 months were also considered and the results were qualitatively similar.

[13] Several studies compare different competing forecasting models against a pre-selected benchmark, using tests, such as the Diebold-Mariano (Diebold and Mariano, 1995), the Equal Predictive Accuracy

For M^0 denoting the initial set of forecasting models, let $\Psi_{n,t}$ be the evaluation function of any model n at month t. We denote the evaluation differential as $d_{n,n^*,t} = \Psi_{n,t} - \Psi_{n^*,t}$, for $n, n^* \in M^0$. The $\Psi_{n,t}$ is the evaluation function under consideration; e.g. for the MSPE, we have $\Psi_{n,t} \equiv \left(OP_{t+s|t} - OP_{t+s}\right)^2$, where $OP_{t+s|t}$ is the s-months-ahead oil price forecast. The null hypothesis $H_{0,M}: E\left(d_{n,n^*,t}\right) = 0$, for $\vee$ $n, n^* \in M$, $M \subset M^0$ is tested against the $H_{1,M}: E\left(d_{n,n^*,t}\right) \neq 0$, for some $n, n^* \in M$.

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. MIDAS-RV models

We start our analysis with the MIDAS-RV and the results are reported in Table 3. It is evident from Table 3 that almost all MIDAS-RV models exhibit important gains in forecasting accuracy relatively to the no-change forecast, suggesting that the financial assets' volatilities have significant predictive information for the monthly oil prices. Even more, these gains seem to become quite substantial as the forecasting horizon increases, although this does not hold for all assets. The fact that the forecasting gains, relatively to the no-change forecast, increase as the forecasting horizons extends further out is also observed in Baumeister *et al.* (2015). Specifically, we report gains up to about 68% with the MIDAS-RV model, based on the MPSE in the 12-months-ahead horizon, whereas in the short- and medium-run horizons of 1- and 6-months ahead, the predictive gains are between 15% and 40%, approximately.

[TABLE 3 HERE]

(Clark and West, 2007), the Reality Check for Data Snooping (White, 2000) or the Superior Predictive Ability (Hansen, 2005). By contrast, our aim is to simultaneously evaluate the forecasting performance of the competing models, without using a benchmark model.

Comparing the MIDAS-RV models performance against all other benchmarks we are able to deduct the conclusion that the former are clearly outperforming. The only exception is the 9-months ahead forecasting horizon where the trivariate BVAR model with 12 lags (3-BVAR(12)) outperforms all others, with predictive gains relatively to the no-change forecast of 38%. We should not lose sight of the fact though, that even in the 9-month horizon, the MIDAS-RV models generate substantial predictive gains which reach the level of 20%.

Nevertheless, we observe that at least in the short- and medium-run (up to 6-months horizon), the standard models do not seem to provide any gains in forecasting accuracy relatively to the no-change forecasts, as opposed to the models that incorporate the ultra-high frequency based realized volatilities.

It is also important to highlight the fact that, as we move further out to the forecasting horizon, it is a different asset class that provides the highest forecast accuracy. More specifically, in the short-run (1-month ahead) the stock market volatility, and in particular the Eurostoxx 50 volatility, provides the highest predictive gains. In the medium-run (3- and 6-months ahead) the information obtained from the foreign exchange market (GBP/USD volatility) enhances the forecasting accuracy of oil prices, whereas in the long-run we observe that the commodities are assuming the role of the best performing model (PA volatility). This is a very important finding, which has not been previous reported in the literature, and suggests that different assets provide different predictive information for oil prices at the different forecasting horizons.

Given that Brent crude oil is the benchmark used in the European market, the fact that the assets which provide the most valuable predictive information are the Eurostoxx 50 and the GBP/USD volatilities, suggests it is the European rather than the global financial conditions that incorporate important information for the future path of oil prices. Even more, we would anticipate that stock market and foreign exchange volatility would transmit predictive information for oil prices in the short- and medium-run respectively, given that these markets are more short-run oriented. By contrast, the longer run predictive information that is contained in palladium volatility is possibly explained by the fact that this particular commodity is heavily used by the automobile industry. The latter is an industry tightly linked with information related to longer run economic prospects.

Next, we need to establish whether the gains in the forecasting accuracy that were achieved using the MIDAS-RV models are statistically significantly higher compared to all other models. To do so, we perform the MCS test, which assesses the models that can be included among the set of the best performing models with equal predictive accuracy. The models that are included in the set of the best performing models are shown in Table 3 with an asterisk.

The MCS test clearly shows that the best performing models in all forecasting horizons (apart from the 9-month ahead) are the MIDAS-RV models and particularly the MIDAS-RV-XX, MIDAS-RV-BP and MIDAS-RV-PA. This finding is rather important as it reinforces our argument that ultra-high frequency data are capable of providing superior predictive accuracy not only relatively to the no-change forecast, but also to the current state-of-the-art models.

Furthermore, we report the success ratios of the competing models (see Table 4). Our findings suggest that the MIDAS-RV models exhibit high directional accuracy, which is particularly evident in the shorter horizons (up to 6-months horizon). The directional accuracy ranges between 55% and 68%, depending on the horizon and the MIDAS-RV model. Even more, we show that the MIDAS-RV models with the exchange rate (i.e. MIDAS-RV-BP and MIDAS-RV-CD) are particularly those with the highest directional accuracy up to 3-months ahead forecasting horizon, along with the MIDAS-RV-HG. Nevertheless, in the longer term periods we notice that the VAR and BVAR models exhibit higher success ratios compared to the MIDAS-RV models. The only exception is the MIDAS-RV-PA, which demonstrates significant success ratio in the 12-months ahead horizon.

[TABLE 4 HERE]

5.2. MIDAS-RET models

We proceed further with the examination of whether we can achieve even higher predictive accuracy using asset returns, as opposed to asset volatilities, based on the high frequency data. The results are shown in Table 5.

[TABLE 5 HERE]

Overall, the results suggest that most MIDAS-RET models are not able to outperform the no-change forecast constantly, as in most cases the ratios of the loss functions are above 1. Even more, in the cases where MIDAS-RET models provide predictive gains, these are not material. Furthermore, the MIDAS-RET models do not seem to provide any incremental predictive gains compared to the MIDAS-RV models, suggesting that the main predictive information is transmitted to oil prices via the uncertainty that exists in the financial, commodities and macroeconomic assets. The only exception is the MIDAS-RET-CD, which provides important predictive gains in two horizons (3- and 12-months ahead), classifying it among the set of the best performing models (based on the MCS test).

Turning our attention to the directional accuracy of the MIDAS-RET models, we show that even though they improve the directional accuracy of the no-change forecast, they are able to do so only in the short- to medium-run (i.e. up to the 3-month horizon), as reported in Table 6. Nevertheless, this improvement is not higher compared to the MIDAS-RV models, providing further evidence of the superior performance of the latter models compared to MIDAS-RET.

[TABLE 6 HERE]

Section 5 provides convincing empirical evidence that the realized volatility measures, based on the ultra-high frequency data, provide the more accurate predictive information for oil prices.

5.3. Predictive accuracy during the oil price collapse of 2014-2015

So far we have shown that MIDAS-RV models can provide significant gains on both the forecasting and directional accuracy, not only compared to the no-change forecast but also compared to the current state-of-the-art, as well as the MIDAS-RET models. This is a rather important finding, which highlights the value of the information that can be extracted from the ultra-high frequency financial and commodities data in forecasting monthly oil prices.

Nevertheless, our out-of-sample forecasting period includes the 2014-15 period that Brent crude oil sharply lost more than 50% of its price. 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. Oil market stakeholders are primarily interested in successful oil price predictions during oil market volatile periods, given that these are the periods that call for actions to mitigate the adverse effects of sharp oil price changes.

Therefore, motivated by this extreme movement in oil prices between June 2014 and August 2015, coupled with the fact that forecasting instability is a common problem in forecasting, our next step is to assess the forecasting accuracy of our

MIDAS-RV and MIDAS-RET models, relatively to the standard models in the literature, during this oil collapse period. The results are shown in Table 7.

[TABLE 7 HERE]

The results from Table 7 are rather interesting, as they clearly show that the several MIDAS-RV and MIDAS-RET models generate forecasts with the highest predictive accuracy, relative to the no-change forecast. Importantly, we should highlight the fact that during this turbulent period, MIDAS-RV models achieve forecasting gains at the 6-month horizon, which exceed the 60% level (based on the MSPE). Furthermore, MIDAS-RV models can also provide significant predictive gains even for the longer run forecasting horizons (9- and 12-months ahead) that exceed the level of 73% (see MSPE of the MIDAS-PA in the 12-months ahead), although these gains are relatively lower compared to the predictive gains of the trivariate and four-variable BVAR(24) models that exceed the level of 81% in the 12-months ahead. The MIDAS-RET models perform better compared to the full out-of-sample period, nevertheless, they do not outperform the MIDAS-RV models.

In terms of the models that belong to the set with the best performing models (based on the MCS test), these are clearly the MIDAS-RV models until the 6-month horizon, although the MIDAS-RET models with the commodities are also included in the best performing models at the 1-month horizon.

Overall, we maintain that MIDAS models using ultra-high frequency data are useful alternatives (especially for the short- to medium-run forecasting horizons) to the standard models that are currently employed in the literature, although this primarily holds for the use of realized volatilities rather than the returns.

We should of course highlight here that the findings for the oil collapse period should be treated as indicative due to the small number of the out-of-sample observations.

6. Robustness

6.1. MIDAS models based on asset classes' returns and volatilities.

Next, we investigate whether combined information, either from single asset classes or from all assets together can increase further the forecasting accuracy of oil prices.

In order to avoid imposing selection and look-ahead bias, we employ the Principal Component Analysis (PCA) that captures the combined asset class volatility (return); see for more information Degiannakis and Filis (2017) and Giannone *et al.* (2008). For g denoting the number of asset volatilities (returns) within an asset class, the PCA volatility (returns) components are computed as:

$$\boldsymbol{X}_{(t)}^{(D)} = \boldsymbol{\Lambda}^{(g)} \boldsymbol{X}_{(t)}^{(PCA)} + \boldsymbol{e}_t^{(g)}, \tag{4}$$

where $\boldsymbol{\Lambda}^{(g)}$ is the matrix of factor loadings, $\boldsymbol{X}_{(t)}^{(PCA)}$ is the vector with the common factors, and $\boldsymbol{e}_t^{(g)}$ is the vector of the idiosyncratic component. E.g. for the *Stocks* asset class, we use the volatilities of the g=4 stock market indices to estimate the PCA volatility (return) components; $\boldsymbol{X}_{(t)}^{(PCA)} \equiv \begin{bmatrix} RV_{(PCA),X_{(1)},t} \\ \vdots \\ RV_{(PCA),X_{(g)},t} \end{bmatrix}$, where $X_{(g)}$ denotes the daily common factors that are incorporated in the MIDAS-RV-Stocks (or MIDAS-RET-Stocks) models[14]. We apply the same procedure for the remaining three asset classes. Finally, based on PCA we extract the common factors of all assets' returns or volatilities together, denoted as MIDAS-RV-Combined and MIDAS-RET-Combined. The results are presented in Tables 8 and 9 for the full out-of-sample period and the oil collapse period, respectively.

[TABLE 8 HERE]

[TABLE 9 HERE]

Tables 8 and 9 reveal that even though some of the combined asset classes' volatilities (e.g. the MIDAS-RV-Forex and MIDAS-RV-Stocks) provide predictive gains relatively to the no-change forecast in almost forecast horizons, they cannot outperform the forecasting accuracy of the MIDAS-RV models with single asset volatility, as shown in Tables 3 and 7. This also holds true for the MIDAS-RET models. These results also apply for the MIDAS-RV-Combined and MIDAS-RET-Combined, suggesting that we cannot improve further the forecasting accuracy of oil prices by combining all assets' volatilities or returns together.

Similar conclusions can be drawn for the directional accuracy of the MIDAS models based on the four asset classes (see Table 10).

[TABLE 10 HERE]

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[14] For the returns of the stock market indices, we estimate the PCA return components, $\boldsymbol{X}_{(t)}^{(PCA)} \equiv \begin{bmatrix} x_{(PCA),X_{(1)},t} \\ \vdots \\ x_{(PCA),X_{(g)},t} \end{bmatrix}$.

6.2. Forecast combinations

Finally, we examine whether forecast combinations are able to outperform the MIDAS-RV models, which are the best performing models thus far. To do so, we construct three simple average models, namely, the average of all standard models suggested by the literature (denoted as FC-Standard), the average of all MIDAS-RV and MIDAS-RET models, separately (denoted as FC-MIDAS-RV and FC-MIDAS-RET), and finally the average of all competing models (denoted as FC-All)[15]. The results are reported in Table 11, whereas, Table 12 exhibits the directional accuracy of the forecast combinations.

[TABLE 11 HERE]

[TABLE 12 HERE]

It is evident from Table 11 that forecast combinations, either in the full out-of-sample period or in the oil collapse period, are able to perform better than the no-change forecast, nevertheless they cannot provide incremental gains relatively to the best MIDAS-RV models that were identified in Tables 3 and 7. In terms of directional accuracy, we show that forecast combinations do not demonstrate improved directional accuracy.

Overall, the robustness tests confirm our earlier evidence that asset volatilities, which are constructed using ultra-high frequency data, provide significantly superior predictive accuracy, as well as, directional accuracy for the monthly oil prices, which is particularly evident in the short- and medium-run horizons.

6.3. Comparing MIDAS-RV forecasts against EIA official forecasts

Next, we proceed with a direct comparison between the forecasts from our MIDAS-RV models and the EIA's official forecasts[16]. The comparisons for the full out-of-sample period and the oil price collapse period are shown in Tables 13 and 14, respectively.

[TABLE 13 HERE]

[TABLE 14 HERE]

[15] The construction of other forecast combinations suggested in the literature, i.e. the ordinary least-squares estimate for the forecasts combination weights, the performance-based weights or the trimming approach which discards the worst performing model, usually suffer from forward looking bias, as the weights are estimated based on the out-of-sample forecasting performance of the competing models.

[16] The following link (https://www.eia.gov/outlooks/steo/outlook.cfm) provides the EIA official forecasts for the Brent crude oil prices.

It is evident that the MIDAS-RV models are able to outperform the EIA's forecasts in many instances. More importantly, we should highlight that the predictive gains of the MIDAS-RV models relatively to the EIA's forecasts can reach up to the levels of 24% and 42% during the full out-of-sample and oil price collapse period, respectively (these figures refer to the 12-months ahead horizon, based on the MSPE loss function).

Furthermore, we evaluate the incremental directional accuracy of our MIDAS-RV models relatively to directional accuracy of the EIA's forecasts (see Table 15).

[TABLE 15 HERE]

Even in this case, the MIDAS-RV models seem to be capable of performing better that the EIA's success ratio, particularly in the short run horizons and for the MIDAS-RV models with the exchange rates (i.e. MIDAS-RV-BP and MIDAS-RV-CD). Overall, these results highlight further the previous conclusions, i.e. that asset volatilities provide important superior predictive ability even relatively to the EIA.

7. Forecast evaluation based on a trading strategy

In this section we compare the trading performance of the standard models of the literature against the MIDAS-RV models. We proceed to the evaluation of our forecasts based on a simple trading game so to demonstrate the economic importance of the forecasting gains from the MIDAS-RV models.

Our trading strategy is as follows. A trader assumes a long (short) position in the oil futures prices when the $t+h$ forecasted oil price is higher (lower) compared to the actual price at month t. Cumulative portfolio returns are then calculated as the aggregate returns over the investment horizon, which equals our out-of-sample forecasting period, i.e. December, 2011 up to August, 2015. We also calculate the cumulative returns in dollar terms. Given that the MIDAS-RV models provide predictive gains and high directional accuracy particularly in the short run horizons, we present the trading gains/losses for the 1- and 3-months ahead horizons. The results of the trading strategy are reported in Table 16. The trading game provides evidence that the MIDAS-RV models constantly generate positive returns, which is not the case for the standard models. In addition, for the 1-month ahead horizon, the MIDAS-RV-CD provides the higher positive returns, whereas for the 3-month ahead, we observe that the 3-BVAR(12) and 4-BVAR(12) models exhibit the highest returns.

Overall, the findings from the trading game confirm the superiority of the MIDAS-RV models in the short run horizons.

[TABLE 16 HERE]

8. Conclusion

The aim of this study is to forecast the monthly oil futures prices using information for ultra-high frequency data of financial, commodities and macroeconomic assets. We do so using a MIDAS model and by constructing daily realized volatilities from the ultra-high frequency data, as well as, daily log-returns. Our data span from August 2003 to August 2015. The out-of-sample period runs from December 2011 to August 2015. In our study, real out-of-sample forecasts are generated, i.e. we do not use any future information, which would be impossible for the forecaster to have at her disposal at the time of the forecast.

We compare the forecasts generated by our MIDAS-RV and MIDAS-RET models against the no-change forecast, as well as, the current state-of-the-art forecasting models. The findings of the study show that for longer term forecasts the BVAR models tend to exhibit higher predictive accuracy, given that these models are based on oil market fundamentals, capturing the long term equilibrium relationship among the global business cycle, global oil production and global oil stocks. Nevertheless, we show that MIDAS models which combine oil market fundamentals along with the information flows from the financial markets at a higher sampling frequency provide superior predictive ability, particularly for forecasting horizons up to 6-months. In particular, the MIDAS models' predictive gains, relatively to the no-change forecast, exceed the level of 38% at the 6-month ahead forecasting horizon. These results hold true even when we only consider the predictive accuracy of our models during the oil price collapse period of 2014-2015.

For robustness purposes we estimate MIDAS models based on asset classes' volatilities and returns. The findings confirm that the aggregated information from the asset classes cannot provide incremental superior predictive accuracy relatively to the MIDAS-RV models. These results remain robust even when forecast averaging is employed and when our forecasts are compared against the EIA's official forecasts. The results from the trading game also demonstrate that the forecasting gains from using ultra-high frequency data are economically important.

Hence, we maintain that the use of ultra-high frequency data is able to significantly enhance the predictive accuracy of the monthly oil prices. These findings suggest that there is still scope to extend further this line of research. For instance, future research could further investigate the usefulness of ultra-high frequency data in forecasting oil prices using financial instruments that approximate aggregated asset classes, such as the US equity index futures, USD index futures and the Standard & Poor's - Goldman Sachs Commodity Index (S&P-GSCI) futures. Future studies should assess how to use the incremental predictive accuracy of the ultra-high frequency information, which is particularly obtained in the short run horizons, so to obtain higher forecasting accuracy in longer forecasting horizons. Finally, interesting avenues for further research comprise the use of asymmetric loss functions which would take into account the potentially complex links between oil prices and macroeconomic and financial dynamics, as well as, the investigation of density and interval oil price forecasts, utilising the predictive information extracted by the financial markets, which are particularly important to policy makers.

Acknowledgements

The authors would like to thank one of the editors, Prof. Perry Sadorsky, and the anonymous reviewers for their helpful comments on a previous version of this paper. The authors acknowledge the support of the European Union's Horizon 2020 research and innovation programme, which has funded them under the Marie Sklodowska-Curie grant agreement No 658494. We also thank Lutz Kilian, Vipin Arora and David Broadstock for their valuable comments on an earlier version of the paper. Finally, we would also like to thank the participants of the ISEFI 2017 conference, as well as, the participants of the research seminars at the Hong Kong Polytechnic University.

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TABLES

Table 1: Summary of findings from selected empirical studies

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, CF=combined forecasts, 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: Description of variables and data sources.

Name	Acronym	Description/Frequency	Source
Global Economic Activity Index	GEA	Proxy for global business cycle. Monthly data.	Lutz Kilian website (http://www-personal.umich.edu/~lkilian/)
Baltic Dry Index	BDI	Proxy for global business cycle. Monthly data.	Datasteam
Global Oil Production	PROD	Proxy for oil supply. Monthly data.	Energy Information Administation
Global Oil Stocks	STOCKS	Proxy for global oil inventories. Monthly data	Energy Information Administation
Capacity Utilisation Rate	CAP	Proxy for oil demand in relation to economic activity. Monthly data	Federal Reserve Economic Data
Brent Crude Oil	CO	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. Daily data.	Baker *et al.* (2016)

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

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
AR(1)	**0.9730**	1.0297	1.0073	**0.9735**	**0.9777**	**0.9500**	**0.9948**	**0.9771**	**0.9679**	**0.9705**
ARMA(1,1)	**0.9739**	1.0436	1.0143	**0.9685**	**0.9728**	**0.9627**	1.0156	**0.9779**	**0.9611**	**0.9641**
AR(12)	1.0327	1.0455	1.0323	1.0477	1.0545	1.0878	1.0776	1.0467	1.0813	1.0903
AR(24)	1.0013	1.0011	1.0014	1.0008	**0.9992**	1.0066	1.0034	1.0026	1.0006	**0.9972**
3-VAR(12)	1.4614	1.6930	1.4154	**0.8932**	**0.6942**	2.4851	2.8562	2.1953	**0.8567**	**0.4953**
3-VAR(24)	3.6851	2.0039	1.3245	**0.9587**	**0.7714**	11.8383	3.1099	1.4655	**0.9154**	**0.6344**
4-VAR(12)	1.7398	1.9557	1.9424	1.1202	**0.7991**	3.6381	4.5889	5.2078	1.7593	**0.6783**
4-VAR(24)	3.7139	2.0161	1.3283	**0.9626**	**0.7735**	11.9459	3.1386	1.4709	**0.9190**	**0.6369**
3-BVAR(12)	1.1128	1.0249	**0.8877**	**0.8025***	**0.6737**	1.2625	1.1292	**0.7579**	**0.6215***	**0.4520**
3-BVAR(24)	4.1202	2.1044	1.3075	**0.8944**	**0.6733**	14.3190	3.3762	1.3834	**0.7950**	**0.4863**
4-BVAR(12)	1.1160	1.0266	**0.8905**	**0.8038**	**0.6743**	1.2664	1.1279	**0.7599**	**0.6230**	**0.4524**
4-BVAR(24)	4.1203	2.1045	1.3075	**0.8944**	**0.6733**	14.3191	3.3763	1.3834	**0.7950**	**0.4863**
MIDAS-RV-CO	**0.9369**	**0.9998**	**0.8210**	**0.8717**	1.0319	**0.9474**	1.1376	**0.7028**	**0.8341**	1.2504
MIDAS-RV-FT	**0.9312**	1.0453	**0.8696**	1.0328	**0.9697**	**0.9632**	1.1292	**0.7796**	1.1950	1.0275
MIDAS-RV-SP	**0.9303**	**0.9151**	**0.9099**	1.2465	**0.9852**	**0.9718**	**0.8819**	**0.8561**	1.7304	1.0549
MIDAS-RV-XX	**0.8999***	**0.8981**	**0.9343**	1.0126	**0.8146**	**0.8440***	**0.8089**	**0.9102**	1.1815	**0.7569**
MIDAS-RV-HI	**0.9452**	**0.9817**	**0.9618**	1.5920	1.2453	**0.9582**	**0.9612**	1.0639	3.0822	1.7642
MIDAS-RV-BP	**0.9526**	**0.8384***	**0.7554***	**0.8960**	**0.8668**	1.0122	**0.6956***	**0.6280***	**0.8820**	**0.8038**
MIDAS-RV-CD	**0.9032**	**0.8968**	**0.8560**	**0.9710**	1.4640	**0.9351**	**0.8193**	**0.7947**	1.0245	2.2432
MIDAS-RV-EC	**0.9587**	**0.8938**	**0.8162**	**0.9369**	**0.7599**	1.0637	**0.7770**	**0.6730**	**0.9218**	**0.6321**
MIDAS-RV-GC	1.0266	1.1385	1.0410	1.2246	**0.7948**	1.0438	1.2770	1.2712	1.8171	**0.7056**
MIDAS-RV-HG	**0.9598**	**0.9680**	**0.8452**	**0.9426**	**0.8688**	**0.9917**	**0.9665**	**0.7554**	**0.9488**	**0.9026**

MIDAS-RV-NG	**0.9965**	1.0834	**0.9216**	1.0423	**0.9911**	1.0749	1.3582	**0.9609**	1.3522	1.1247
MIDAS-RV-PA	**0.9545**	1.0699	1.1328	**0.8561**	**0.5271***	**0.9677**	1.2014	1.2771	**0.7946**	**0.3233***
MIDAS-RV-SV	**0.9953**	1.1354	1.0397	1.1034	**0.8678**	1.0355	1.3437	1.3126	1.4175	**0.8092**
MIDAS-RV-TY	**0.9425**	**0.9430**	1.1409	1.3810	**0.7070**	**0.9405**	**0.9811**	1.3195	2.3787	**0.5442**
MIDAS-RV-EPU	**0.9475**	1.0344	**0.9240**	1.5993	**0.9640**	**0.9779**	1.1650	**0.8967**	2.8471	1.0115

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test.

3-VAR(12): Trivariate VAR with 12 lags, 3-VAR(24): Trivariate VAR with 24 lags, 4-VAR(12): Four-variable VAR with 12 lags, 4-VAR(24): Four-variable VAR with 24 lags, 3-BVAR(12): Trivariate Bayesian VAR with 12 lags, 3-BVAR(24): Trivariate Bayesian VAR with 24 lags, 4-VAR(12): Four-variable Bayesian VAR with 12 lags, 4-VAR(24): Four-variable Bayesian VAR with 24 lags, MIDAS-RV-CO: MIDAS model based on Brent Crude Oil Realized Volatility, MIDAS-RV-FT: MIDAS model based on FTSE100 index Realized Volatility, MIDAS-RV-SP: MIDAS model based on S&P500 index Realized Volatility, MIDAS-RV-XX: MIDAS model based on Euro Stoxx 50 index Realized Volatility, MIDAS-RV-HI: MIDAS model based on Hang Seng index Realized Volatility, MIDAS-RV-BP: MIDAS model based on GBP/USD exchange rate Realized Volatility, MIDAS-RV-CD: MIDAS model based on CAD/USD exchange rate Realized Volatility, MIDAS-RV-EC: MIDAS model based on EUR/USD exchange rate Realized Volatility, MIDAS-RV-GC: MIDAS model based on Gold Realized Volatility, MIDAS-RV-HG: MIDAS model based on Copper Realized Volatility, MIDAS-RV-NG: MIDAS model based on Natural Gas Realized Volatility, MIDAS-RV-PA: MIDAS model based on Palladium Realized Volatility, MIDAS-RV-SV: MIDAS model based on Silver Realized Volatility, MIDAS-RV-TY: MIDAS model based on US 10yr T-bills Realized Volatility, MIDAS-RV-EPU: MIDAS model based on Economic Policy Uncertainty Index.

Table 4: Success ratios of competing models. Evaluation period: 2011.12-2015.8

	Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months
AR(1)	**0.5455**	0.4286	0.2821	0.3056	0.2727
ARMA(1,1)	**0.5682**	0.4524	0.3077	0.3056	0.2727
AR(12)	0.3636	0.4524	0.3077	0.3056	0.2727
AR(24)	0.3864	0.4524	0.3077	0.3056	0.2727
3-VAR(12)	**0.5909**	**0.5476**	0.4615	**0.6944****	**0.6667***
3-VAR(24)	0.4091	0.5000	**0.5128**	0.4444	0.4545
4-VAR(12)	0.5000	**0.5238**	0.4103	**0.6389****	**0.6364***
4-VAR(24)	0.4091	0.5000	**0.5128**	0.4444	0.4242
3-BVAR(12)	0.5000	**0.6190**	**0.7179***	**0.6667**	**0.7273****
3-BVAR(24)	0.5000	**0.5238**	**0.6923**	**0.6667**	**0.7273****
4-BVAR(12)	**0.5455**	**0.6190**	**0.7179***	**0.6667**	**0.7273****
4-BVAR(24)	0.5000	**0.5238**	**0.6923**	**0.6667**	**0.7273****
MIDAS-RV-CO	**0.5227**	0.4286	0.4103	0.3333	0.3030
MIDAS-RV-FT	**0.5455**	0.4762	0.4359	0.3611	0.2727
MIDAS-RV-SP	0.5000	**0.5714**	0.4872	0.3333	0.3030
MIDAS-RV-XX	**0.5455**	**0.5476**	0.4615	0.3889	0.3333
MIDAS-RV-HI	**0.5455**	0.4762	0.4615	0.3056	0.2121
MIDAS-RV-BP	**0.6136***	**0.6429***	**0.5641**	0.3889	0.2121
MIDAS-RV-CD	**0.6818****	**0.6667****	**0.5641**	0.3333	0.2727
MIDAS-RV-EC	**0.5682**	**0.5952**	0.4872	0.3056	0.4545
MIDAS-RV-GC	0.4773	0.3810	0.3846	0.2778	**0.5152**
MIDAS-RV-HG	**0.6136****	0.4048	0.4872	0.3056	0.4545
MIDAS-RV-NG	0.5000	0.5000	**0.5385**	0.3889	0.3030
MIDAS-RV-PA	**0.5682**	0.4524	0.3333	0.2778	**0.6667***
MIDAS-RV-SV	0.5000	0.3810	0.3590	0.3056	0.3333
MIDAS-RV-TY	**0.5227**	0.5000	0.3846	0.3333	0.2727
MIDAS-RV-EPU	**0.5909**	0.4762	**0.5128**	0.3056	0.3030

Note: 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. Bold face denotes improvement of the directional accuracy relatively to the no-change forecast.

Table 5: Forecasting monthly oil prices – MIDAS-RET models. Evaluation period: 2011.12-2015.8

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
MIDAS-RET-CO	**0.9281**	1.0909	**0.9970**	1.2859	1.3799	**0.9192**	1.1015	1.0095	1.8187	2.2511
MIDAS-RET-FT	1.0374	1.0437	1.3488	1.4559	1.0807	1.0597	**0.9747**	2.1940	2.3881	1.3293
MIDAS-RET-SP	**0.9603**	**0.9055**	1.0967	1.3611	1.8250	**0.8756**	**0.8934**	1.1954	2.2493	3.4728
MIDAS-RET-XX	1.1158	1.0365	1.1272	2.2701	**0.9355**	1.1097	1.0236	1.9332	6.6529	1.0420
MIDAS-RET-HI	**0.9743**	**0.9101**	1.1955	1.7927	1.0475	**0.9478**	**0.7933**	1.6618	3.9176	1.2709
MIDAS-RET-BP	1.0988	1.2602	1.2588	1.5200	1.0968	1.1592	1.8422	1.9347	2.4557	1.2962
MIDAS-RET-CD	1.1024	**0.7625***	1.0667	1.6392	**0.5380***	1.1323	**0.7111***	1.2580	3.3350	**0.3645***
MIDAS-RET-EC	1.0386	1.1835	1.0672	2.2144	1.4114	1.0623	1.6374	1.3344	5.3958	2.1255
MIDAS-RET-GC	1.0785	1.2083	1.2841	1.5201	1.1308	1.0704	1.4603	1.7321	2.2984	1.3456
MIDAS-RET-HG	1.0729	1.0278	1.4565	1.2768	**0.8927**	1.1475	1.2863	2.7099	1.8640	**0.9867**
MIDAS-RET-NG	1.0942	1.1516	1.4696	1.4382	**0.9755**	1.1578	1.4379	2.3460	2.3790	1.0522
MIDAS-RET-PA	1.0406	1.4164	1.2049	1.1283	1.7149	1.0477	2.2970	1.8342	1.4566	2.9151
MIDAS-RET-SV	1.0758	1.2160	1.2808	1.0123	1.6872	1.2265	1.8575	2.0911	1.1178	3.0539
MIDAS-RET-TY	**0.9723**	1.0370	1.3589	2.6200	1.7797	**0.9580**	**0.9348**	2.0311	8.3700	3.8064

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test, along with the best models from Table 3.

MIDAS-RET-CO: MIDAS model based on Brent Crude Oil Realized Volatility, MIDAS-RET-FT: MIDAS model based on FTSE100 index Realized Volatility, MIDAS-RET-SP: MIDAS model based on S&P500 index Realized Volatility, MIDAS-RET-XX: MIDAS model based on Euro Stoxx 50 index Realized Volatility, MIDAS-RET-HI: MIDAS model based on Hang Seng index Realized Volatility, MIDAS-RET-BP: MIDAS model based on GBP/USD exchange rate Realized Volatility, MIDAS-RET-CD: MIDAS model based on CAD/USD exchange rate Realized Volatility, MIDAS-RET-EC: MIDAS model based on EUR/USD exchange rate Realized Volatility, MIDAS-RET-GC: MIDAS model based on Gold Realized Volatility, MIDAS-RET-HG: MIDAS model based on Copper Realized Volatility, MIDAS-RET-NG: MIDAS model based on Natural Gas Realized Volatility, MIDAS-RET-PA: MIDAS model based on Palladium Realized Volatility, MIDAS-RET-SV: MIDAS model based on Silver Realized Volatility, MIDAS-RET-TY: MIDAS model based on US 10yr T-bills Realized Volatility.

Table 6: Success ratios of MIDAS-RET models. Evaluation period: 2011.12-2015.8

	Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months
MIDAS-RET-CO	**0.5909***	0.4048	0.3590	0.3333	0.2424
MIDAS-RET-FT	0.5000	**0.5952**	0.4103	0.3333	0.2424
MIDAS-RET-SP	**0.5227**	**0.6190**	0.3590	0.3889	0.2121
MIDAS-RET-XX	**0.5227**	**0.5476**	0.4359	0.3611	0.2727
MIDAS-RET-HI	**0.5455**	**0.5714**	0.3846	0.3611	0.1818
MIDAS-RET-BP	0.5000	**0.5476**	0.2308	0.2222	0.3030
MIDAS-RET-CD	0.5000	**0.6190***	0.3590	0.2500	0.2121
MIDAS-RET-EC	0.4091	**0.5238**	0.3333	0.3889	0.4242
MIDAS-RET-GC	0.5000	0.4524	0.4359	0.3333	0.2424
MIDAS-RET-HG	0.4773	**0.5476**	0.4359	0.3056	0.2727
MIDAS-RET-NG	**0.5682**	**0.5476**	0.4359	0.2778	0.2727
MIDAS-RET-PA	**0.5227**	0.5000	0.3590	0.2778	0.2424
MIDAS-RET-SV	0.5000	**0.5476**	0.3846	0.5000	0.1818
MIDAS-RET-TY	0.5000	**0.5476**	0.3333	0.3333	0.4242

Note: 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. Bold face denotes improvement of the directional accuracy relatively to the no-change forecast.

Table 7: Forecasting monthly oil prices during the oil collapse period. Evaluation period: 2014.6-2015.8.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
AR(1)	**0.9684**	1.0071	**0.9826**	**0.9749**	**0.9872**	**0.9500**	**0.9279**	**0.9496**	**0.9589**	**0.9762**
ARMA(1,1)	**0.9569**	1.0079	**0.9827**	**0.9660**	**0.9840**	**0.9369**	**0.9143**	**0.9387**	**0.9451**	**0.9700**
AR(12)	1.0085	1.0055	1.0121	1.0209	1.0290	1.0146	1.0113	1.0200	1.0382	1.0563
AR(24)	**0.9998**	**0.9992**	**0.9998**	**0.9998**	**0.9992**	**0.9999**	1.0003	1.0002	**0.9996**	**0.9983**
3-VAR(12)	1.1564	1.1208	**0.8408**	**0.6800**	**0.6099**	1.5728	1.1959	**0.8409**	**0.5193**	**0.3951**
3-VAR(24)	4.2741	2.2743	1.3756	**0.9432**	**0.8213**	15.1141	3.5331	1.4639	**0.8857**	**0.6876**
4-VAR(12)	1.1779	1.1566	**0.8841**	**0.6841**	**0.6226**	1.6030	1.2727	**0.8487**	**0.5299**	**0.4059**
4-VAR(24)	4.2953	2.2840	1.3737	**0.9426**	**0.8211**	15.2499	3.5552	1.4619	**0.8850**	**0.6879**
3-BVAR(12)	**0.9769**	**0.8379**	**0.7240**	**0.6332**	**0.5355**	**0.9187**	**0.7315**	**0.5679**	**0.4235**	**0.3100**
3-BVAR(24)	2.6136	1.3260	**0.7588**	**0.4984***	**0.4140***	5.7729	1.2227	**0.4583**	**0.2570***	**0.1825***
4-BVAR(12)	**0.9895**	**0.8445**	**0.7283**	**0.6337**	**0.5358**	**0.9283**	**0.7297**	**0.5686**	**0.4239**	**0.3105**
4-BVAR(24)	2.6136	1.3260	**0.7588**	**0.4984**	**0.4140**	5.7731	1.2228	**0.4583**	**0.2570***	**0.1825***
MIDAS-RV-CO	**0.8607***	**0.9241**	**0.7675**	**0.8575**	**0.8012**	**0.8249**	**0.7046**	**0.5818**	**0.7685**	**0.6528**
MIDAS-RV-FT	**0.8629***	**0.9855**	**0.7873**	**0.9455**	**0.9577**	**0.9162**	**0.8571**	**0.6113**	**0.8971**	**0.9166**
MIDAS-RV-SP	**0.8689***	**0.8642**	**0.8260**	1.0564	**0.9086**	**0.8727**	**0.6574**	**0.6655**	1.1240	**0.8299**
MIDAS-RV-XX	**0.8515***	**0.8712**	**0.8220**	**0.9639**	**0.8266**	**0.8136**	**0.7143**	**0.6650**	**0.9496**	**0.6966**
MIDAS-RV-HI	**0.8729**	**0.9626**	**0.8223**	1.0979	1.3997	**0.8474**	**0.8483**	**0.6842**	1.2476	1.9717
MIDAS-RV-BP	**0.9052**	**0.8769**	**0.6884**	**0.8608**	**0.8164**	**0.9419**	**0.6489**	**0.4759**	**0.7810**	**0.6803**
MIDAS-RV-CD	**0.7827***	**0.8387***	**0.7271**	**0.8919**	1.3627	**0.7210***	**0.6104***	**0.5313**	**0.8056**	1.8671
MIDAS-RV-EC	**0.8843**	**0.7946***	**0.6375***	**0.7880**	**0.7071**	**0.9275**	**0.5739***	**0.3916***	**0.6443**	**0.5093**
MIDAS-RV-GC	**0.9343**	1.0477	**0.8275**	**0.9964**	**0.7434**	**0.9012**	**0.9691**	**0.6951**	1.0130	**0.5815**

MIDAS-RV-HG	**0.8881**	**0.9298**	**0.7261**	**0.8990**	**0.7182**	**0.8580**	**0.7548**	**0.5304**	**0.8168**	**0.5371**
MIDAS-RV-NG	**0.8978**	1.0298	**0.7437**	**0.8311**	1.0543	**0.8239**	1.0335	**0.5925**	**0.7432**	1.1184
MIDAS-RV-PA	**0.9063**	**0.9758**	**0.9556**	**0.8519**	**0.4963**	**0.8647**	**0.8456**	**0.8853**	**0.7558**	**0.2635**
MIDAS-RV-SV	**0.9316**	1.0090	**0.8466**	**0.9921**	**0.8839**	**0.9306**	**0.9175**	**0.7087**	1.0337	**0.8017**
MIDAS-RV-TY	**0.8958**	**0.8758**	**0.9062**	1.0258	**0.7545**	**0.8894**	**0.7035**	**0.7866**	1.1111	**0.5796**
MIDAS-RV-EPU	**0.8916**	**0.7906***	**0.8020**	1.3886	**0.9869**	**0.8565**	**0.5861***	**0.6404**	1.8961	**0.9922**
MIDAS-RET-CO	**0.9121**	**0.9850**	**0.8789**	**0.8534**	**0.8656**	1.0201	**0.8639**	**0.7434**	**0.7482**	**0.7611**
MIDAS-RET-FT	**0.9028**	**0.9819**	**0.8307**	**0.9972**	**0.8614**	**0.8959**	**0.8307**	**0.6793**	1.0086	**0.7469**
MIDAS-RET-SP	**0.9269**	**0.8771**	**0.8692**	**0.8983**	**0.9415**	**0.9391**	**0.7184**	**0.7520**	**0.8201**	**0.9033**
MIDAS-RET-XX	**0.8198***	**0.9267**	**0.8140**	1.0237	**0.8463**	**0.7552***	**0.7467**	**0.6577**	1.0603	**0.7227**
MIDAS-RET-HI	**0.8776**	**0.8737**	**0.8663**	**0.9931**	**0.8609**	**0.8233**	**0.6857**	**0.7239**	1.0045	**0.7626**
MIDAS-RET-BP	**0.9120**	**0.8756**	**0.9321**	**0.9525**	**0.7956**	**0.8821**	**0.6983**	**0.8591**	**0.9445**	**0.6426**
MIDAS-RET-CD	**0.9301**	**0.9068**	**0.8265**	**0.9031**	**0.8504**	**0.8518**	**0.7507**	**0.6437**	**0.8308**	**0.7307**
MIDAS-RET-EC	**0.9214**	**0.9464**	**0.8689**	**0.8372**	**0.7697**	**0.8489**	**0.8438**	**0.7406**	**0.7064**	**0.5973**
MIDAS-RET-GC	**0.8697***	**0.9821**	**0.7784**	1.0612	1.0692	**0.8018**	**0.8831**	**0.6112**	1.1465	1.1627
MIDAS-RET-HG	**0.9091**	**0.9004**	**0.7768**	**0.8652**	**0.9503**	**0.9054**	**0.7398**	**0.5873**	**0.7761**	**0.9018**
MIDAS-RET-NG	**0.8504***	**0.9911**	**0.7763**	1.0247	**0.8975**	**0.7665***	**0.8738**	**0.6102**	1.0668	**0.8182**
MIDAS-RET-PA	**0.9072**	**0.8550**	**0.8160**	**0.8780**	**0.9300**	**0.8753**	**0.6768**	**0.6637**	**0.7898**	**0.8782**
MIDAS-RET-SV	**0.8688***	**0.9029**	**0.7783**	**0.7332**	**0.8832**	**0.7963**	**0.8020**	**0.5912**	**0.5455**	**0.8025**
MIDAS-RET-TY	**0.8532***	**0.9308**	**0.8587**	**0.9684**	**0.7828**	**0.7975**	**0.8596**	**0.7127**	**0.9561**	**0.6252**

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test.

Table 8: Forecasting monthly oil prices – MIDAS-RV and MIDAS-RET models based on PCA. Evaluation period: 2011.12-2015.8.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
	Asset volatilities									
MIDAS-RV-Stocks	**0.9019**	**0.9838**	**0.8850**	1.2023	1.0245	**0.8870**	**0.9800**	**0.8126**	1.6851	1.1628
MIDAS-RV-Forex	**0.8933***	**0.8308***	**0.8025**	**0.9195**	**0.8725**	**0.9430**	**0.6981***	**0.6949**	**0.8685**	**0.8323**
MIDAS-RV-Commodities	**0.9882**	1.0569	**0.9296**	1.0305	**0.7984**	1.0535	1.1653	**0.8909**	1.1750	**0.7102**
MIDAS-RV-Macro	1.0008	**0.9710**	1.1893	1.6623	**0.8926**	1.0434	**0.9476**	1.4539	3.2236	**0.8897**
MIDAS-RV-Combined	1.0124	**0.9682**	**0.8642**	1.1662	1.0264	1.1074	**0.8954**	**0.7451**	1.5273	1.1943
	Asset Returns									
MIDAS-RET-Stocks	1.1426	**0.9908**	1.2565	1.9910	**0.7456**	1.1930	**0.9823**	1.6626	4.8951	**0.6620**
MIDAS-RET-Forex	1.0280	**0.9470**	1.0365	2.0187	1.1739	1.1019	1.0921	1.1087	4.6586	1.7703
MIDAS-RET-Commodities	1.0321	1.1226	1.3112	1.0867	1.4684	1.0703	1.3262	2.2308	1.3348	2.1872
MIDAS-RET-Macro	**0.9723**	1.0370	1.3589	2.6200	1.7797	**0.9580**	**0.9348**	2.0311	8.3700	3.8064
MIDAS-RET-Combined	1.0623	**0.9771**	1.2775	1.5718	1.5068	1.1837	**0.9796**	2.1063	3.0625	2.7465

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models, according to the Model Confidence Set (MCS) test, along with the best models from Tables 3 & 5.

Table 9: Forecasting monthly oil prices during the oil collapse period – MIDAS-RV and MIDAS-RET models based on PCA. Evaluation period: 2014.6-2015.8.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
	Asset volatilities									
MIDAS-RV-Stocks	**0.8224***	**0.9533**	**0.7992**	1.0162	1.0248	**0.8000**	**0.8077**	**0.6338**	1.0443	1.0635
MIDAS-RV-Forex	**0.8234***	**0.7986***	**0.7036**	**0.8652**	**0.7966**	**0.8087**	**0.5736***	**0.4924**	**0.7638**	**0.6386**
MIDAS-RV-Commodities	**0.8857**	**0.9782**	**0.7378**	1.0114	**0.7289**	**0.8587**	**0.8438**	**0.5389**	1.0625	**0.5462**
MIDAS-RV-Macro	**0.9445**	**0.8625**	**0.8635**	1.1601	**0.9450**	**0.9413**	**0.6795**	**0.7255**	1.3427	**0.9261**
MIDAS-RV-Combined	**0.9108**	**0.8952**	**0.7790**	**0.9596**	**0.8600**	**0.9492**	**0.6841**	**0.5798**	**0.9693**	**0.7419**
	Asset Returns									
MIDAS-RET-Stocks	**0.9293**	**0.9025**	**0.8526**	1.0328	**0.8715**	**0.9503**	**0.7251**	**0.7118**	1.0879	**0.7676**
MIDAS-RET-Forex	**0.9116**	**0.9322**	**0.8663**	**0.9098**	**0.9527**	**0.8004**	**0.8297**	**0.7607**	**0.8574**	**0.9317**
MIDAS-RET-Commodities	**0.8947**	**0.9491**	**0.7809**	**0.8062**	**0.9433**	**0.8509**	**0.8337**	**0.6016**	**0.6570**	**0.9104**
MIDAS-RET-Macro	**0.8532***	**0.9308**	**0.8587**	**0.9684**	**0.7828**	**0.7975**	**0.8596**	**0.7127**	**0.9561**	**0.6252**
MIDAS-RET-Combined	**0.9037**	**0.8824**	**0.7827**	**0.8429**	**0.9443**	**0.8801**	**0.7297**	**0.6069**	**0.7533**	**0.9013**

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models, along with these in Table 7, according to the Model Confidence Set (MCS) test.

Table 10: Success ratios of the MIDAS-RV and MIDAS-RET models based on PCA. Evaluation period: 2011.12-2015.8.

Model:	Forecasting horizon				
	1-month	3-months	6-months	9-months	12-months
Asset volatilities					
MIDAS-RV-Stocks	**0.5455**	0.4762	0.4359	0.3056	0.2727
MIDAS-RV-Forex	**0.6136***	**0.5476**	0.4872	0.2500	0.3333
MIDAS-RV-Commodities	0.5000	0.4286	0.3846	0.2778	0.4848
MIDAS-RV-Macro	0.4545	**0.5714**	0.3846	0.3056	0.3939
MIDAS-RV-Combined	0.5000	**0.5238**	0.4359	0.2778	0.3333
Asset returns					
MIDAS-RET-Stocks	0.4186	**0.6190**	0.4359	0.3889	0.1515
MIDAS-RET-Forex	0.4651	0.5000	0.3590	0.2500	0.2727
MIDAS-RET-Commodities	0.4651	**0.5238**	0.4359	0.4167	0.2121
MIDAS-RET-Macro	0.4884	**0.5476**	0.3333	0.3333	0.4242
MIDAS-RET-Combined	**0.5116**	**0.5476**	0.4359	0.4167	0.2727

Note: 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. Bold face denotes improvement relatively to the no-change forecast.

Table 11: Forecasting monthly oil prices - forecast combinations.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
Model:	Full out-of-sample period									
FC-Standard	1.4151	1.0052	**0.8013**	**0.6709***	**0.5866**	1.9760	**0.9832**	**0.7363**	**0.5558***	**0.4287**
FC-MIDAS-RV	**0.9160**	**0.9285**	**0.8951**	1.0633	**0.8825**	**0.9183**	**0.9063**	**0.8547**	1.2883	**0.8408**
FC-MIDAS-RET	**0.9132**	**0.9141**	**0.9050**	1.0265	**0.8958**	**0.8786**	**0.8943**	**0.8496**	1.1341	**0.8547**
FC-All	1.0485	**0.8701**	**0.7901**	**0.8631**	**0.7314**	1.0318	**0.8127**	**0.7109**	**0.8405**	**0.6025**
	Oil collapse period									
FC-Standard	1.4416	1.0914	**0.8714**	**0.7608**	**0.7117**	2.0312	1.0177	**0.7498**	**0.6071**	**0.5207**
FC-MIDAS-RV	**0.8743**	**0.9177**	**0.7878**	**0.9616**	**0.8923**	**0.8425**	**0.7423**	**0.6179**	**0.9442**	**0.7998**
FC-MIDAS-RET	**0.8901**	**0.9236**	**0.8275**	**0.9278**	**0.8789**	**0.8339**	**0.7701**	**0.6721**	**0.8697**	**0.7785**
FC-All	1.1034	**0.8800**	**0.7731**	**0.8722**	**0.8121**	1.0811	**0.7714**	**0.6496**	**0.7819**	**0.6647**

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. FC stands for Forecast Combination. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test, along with the best models from Tables 3, 4 and 7.

FC-Standard: Forecast combination of all standard models suggested by the literature, FC-MIDAS-RV: Forecast combination of all MIDAS-RV models, FC-MIDAS-RET: Forecast combination of all MIDAS-RET models, FC-All: Forecast combination of all competing models.

Table 12: Success ratios of the forecast combinations. Evaluation period: 2011.12-2015.8

	Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months
FC-Standard	0.4545	**0.5238**	**0.6410**	**0.7500****	**0.5758**
FC-MIDAS-RV	**0.5909**	**0.5238**	0.4103	0.3056	0.3030
FC-MIDAS-RET	0.4884	0.4762	0.4359	0.3333	0.2727
FC-All	0.5000	**0.5714**	**0.5641**	0.3889	0.3333

Note: FC stands for Forecast Combination. 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. Bold face denotes improvement relatively to the no-change forecast.

Table 13: Forecasting monthly oil prices – comparing MIDAS vs EIA forecasts. Evaluation period: 2011.12-2015.8.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
MIDAS-RV-CO	1.1124	1.0580	1.0337	1.2653	1.6618	1.2793	**0.9418**	**0.9026**	1.4843	2.7662
MIDAS-RV-FT	1.0512	1.1390	1.0674	1.5984	1.7071	1.2113	1.1631	**0.9311**	2.3024	2.6023
MIDAS-RV-SP	1.1354	1.0645	1.1098	1.9374	1.6824	1.3790	1.0479	1.0063	3.3389	2.5686
MIDAS-RV-XX	1.0434	1.0595	1.1481	1.5602	1.4648	1.1076	1.0058	1.0904	2.2687	1.9635
MIDAS-RV-HI	1.1192	1.0840	1.1026	2.2217	2.2640	1.2978	1.0538	1.0279	5.3071	4.6739
MIDAS-RV-BP	1.1068	**0.9689**	**0.9405**	1.3681	1.4240	1.3399	**0.8540**	**0.7796**	1.6696	1.8061
MIDAS-RV-CD	1.0367	1.0479	1.0165	1.4706	2.5150	1.2053	1.0159	**0.8641**	1.9260	5.5621
MIDAS-RV-EC	1.1217	1.0075	**0.9474**	1.2796	1.2990	1.3712	**0.8877**	**0.6644**	1.4413	1.5302
MIDAS-RV-GC	1.2177	1.2891	1.1500	1.8470	1.3008	1.4067	1.3799	1.0640	3.4440	1.5290
MIDAS-RV-HG	1.1169	1.0678	1.0023	1.4329	1.3066	1.2722	1.0125	**0.8324**	1.8015	1.6549
MIDAS-RV-NG	1.1815	1.1744	1.0510	1.5608	1.6508	1.3651	1.2688	**0.9096**	2.5299	2.5943
MIDAS-RV-PA	1.1222	1.1791	1.4132	1.3028	**0.8888**	1.2707	1.1807	1.5532	1.5158	**0.7627**
MIDAS-RV-SV	1.1676	1.2181	1.1530	1.7135	1.4713	1.3309	1.2571	1.0658	2.7290	1.9705
MIDAS-RV-TY	1.1140	1.0466	1.3343	2.0139	1.2556	1.2615	**0.9769**	1.3260	4.3610	1.4061
MIDAS-RV-EPU	1.0904	1.1705	1.1096	2.4817	1.7237	1.2418	1.3792	0.9844	5.4846	2.6390

Note: All MAPPE and MSPE ratios have been normalized relative to EIA official forecasts. Bold face indicates predictive gains relatively to the EIA official forecasts.

Table 14: Forecasting monthly oil prices – comparing MIDAS vs EIA forecasts during the oil collapse period. Evaluation period: 2014.6-2015.8.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
MIDAS-RV-CO	1.0440	1.0096	0.9445	1.1487	1.2343	1.0733	**0.7825**	**0.7801**	1.3116	1.4424
MIDAS-RV-FT	1.0467	1.0767	0.9688	1.2665	1.4753	1.1921	**0.9519**	**0.8197**	1.5310	2.0252
MIDAS-RV-SP	1.0540	**0.9442**	1.0165	1.4152	1.3997	1.1354	**0.7301**	**0.8924**	1.9182	1.8338
MIDAS-RV-XX	1.0329	**0.9518**	1.0115	1.2912	1.2735	1.0586	**0.7933**	**0.8918**	1.6206	1.5391
MIDAS-RV-HI	1.0588	1.0517	1.0119	1.4707	2.1563	1.1026	**0.9421**	**0.9175**	2.1292	4.3564
MIDAS-RV-BP	1.0980	**0.9580**	**0.8471**	1.1532	1.2576	1.2255	**0.7207**	**0.6381**	1.3329	1.5031
MIDAS-RV-CD	**0.9495**	**0.9163**	**0.8947**	1.1948	2.0993	**0.9381**	**0.6779**	**0.7125**	1.3748	4.1254
MIDAS-RV-EC	1.0726	**0.8682**	**0.7845**	1.0556	1.0893	1.2068	**0.6374**	**0.5251**	1.0996	1.1253
MIDAS-RV-GC	1.1333	1.1447	1.0182	1.3347	1.1452	1.1725	1.0763	**0.9321**	1.7287	1.2848
MIDAS-RV-HG	1.0773	1.0159	0.8935	1.2043	1.1064	1.1163	**0.8382**	**0.7113**	1.3939	1.1868
MIDAS-RV-NG	1.0891	1.1251	0.9152	1.1133	1.6242	1.0720	1.1478	**0.7945**	1.2683	2.4711
MIDAS-RV-PA	1.0993	1.0661	1.1759	1.1412	**0.7646**	1.1250	**0.9392**	1.1871	1.2899	**0.5822**
MIDAS-RV-SV	1.1301	1.1024	1.0418	1.3290	1.3616	1.2108	1.0190	**0.9503**	1.7641	1.7714
MIDAS-RV-TY	1.0866	**0.9569**	1.1150	1.3742	1.1624	1.1572	**0.7813**	1.0548	1.8962	1.2807
MIDAS-RV-EPU	1.0815	**0.8638**	**0.9868**	1.8602	1.5203	1.1144	**0.6509**	**0.8587**	3.2359	2.1923

Note: All MAPPE and MSPE ratios have been normalized relative to EIA official forecasts. Bold face indicates predictive gains relatively to the EIA official forecasts.

Table 15: Success ratios – comparing MIDAS vs EIA forecasts. Evaluation period: 2011.12-2015.8.

	Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months
MIDAS-RV-CO	**0.9444**	1.5000	1.6000	2.6250	2.5000
MIDAS-RV-FT	**0.8095**	1.0500	1.4118	2.6250	2.8571
MIDAS-RV-SP	1.0000	1.0500	1.2632	2.6250	2.5000
MIDAS-RV-XX	**0.8947**	1.2353	1.3333	2.6250	2.2222
MIDAS-RV-HI	**0.8947**	1.2353	1.4118	2.6250	4.0000
MIDAS-RV-BP	**0.7727**	**0.9545**	1.2000	2.3333	4.0000
MIDAS-RV-CD	**0.6800**	**0.9545**	1.1429	2.6250	2.8571
MIDAS-RV-EC	**0.8095**	1.0000	1.3333	2.3333	1.5385
MIDAS-RV-GC	1.0000	1.7500	1.6000	3.0000	1.3333
MIDAS-RV-HG	**0.7727**	1.5000	1.2632	3.0000	1.5385
MIDAS-RV-NG	**0.9444**	1.2353	1.2000	2.1000	2.8571
MIDAS-RV-PA	**0.8500**	1.4000	2.0000	3.5000	1.0000
MIDAS-RV-SV	**0.9444**	1.6154	1.8462	2.6250	2.5000
MIDAS-RV-TY	**0.9444**	1.1667	1.7143	2.3333	2.5000
MIDAS-RV-EPU	**0.8095**	1.1667	1.2632	2.6250	2.8571

Note: All success ratios have been normalized relative to EIA official forecasts. Bold face denotes improvement relatively to the EIA official forecasts.

Table 16: Cumulative trading returns of competing models. Evaluation period: 2011.12-2015.8

	Forecasting horizon			
	Percentage returns	Dollar returns	Percentage returns	Dollar returns
Model:	1-month	1-months	3-months	3-months
RW	-0.5552	-57.93	-1.3221	-152.81
AR(1)	**0.1137**	**20.49**	-1.6108	-156.87
ARMA(1,1)	**0.2415**	**34.35**	-0.7785	-78.07
AR(12)	-0.8197	-85.97	-1.3221	-152.81
AR(24)	-0.5552	-57.93	-1.3221	-152.81
3-VAR(12)	**0.2794**	**38.63**	**0.3388**	**28.61**
3-VAR(24)	-0.6125	-55.97	-0.6940	-68.19
4-VAR(12)	**0.1321**	**22.43**	-0.1464	-19.65
4-VAR(24)	-0.6125	-55.97	-0.6940	-68.19
3-BVAR(12)	-0.0831	-9.49	**2.3239***	**218.77***
3-BVAR(24)	-0.1055	-3.83	**0.7608**	**83.67**
4-BVAR(12)	**0.2146**	**34.69**	**2.3239***	**218.77***
4-BVAR(24)	-0.1055	-3.83	**0.7608**	**83.67**
MIDAS-RV-CO	**0.1653**	**31.13**	**0.8988**	**121.07**
MIDAS-RV-FT	**0.3662**	**48.61**	**0.9377**	**125.27**
MIDAS-RV-SP	**0.3383**	**28.59**	**0.8988**	**121.07**
MIDAS-RV-XX	**0.5606**	**64.95**	**1.4473**	**165.53**
MIDAS-RV-HI	**0.5413**	**47.33**	**0.9900**	**131.59**
MIDAS-RV-BP	**0.4719**	**50.61**	**1.3129**	**162.87**
MIDAS-RV-CD	**1.7900***	**131.93***	**0.8988**	**121.07**
MIDAS-RV-EC	**0.7291**	**47.45**	**1.6440**	**185.91**
MIDAS-RV-GC	**0.1633**	**3.51**	**0.9362**	**109.57**
MIDAS-RV-HG	**1.1243**	**96.29**	**1.1961**	**139.77**
MIDAS-RV-NG	**0.3487**	**28.81**	**1.0927**	**123.83**
MIDAS-RV-PA	**1.0473**	**87.99**	**0.8988**	**121.07**
MIDAS-RV-SV	**0.1949**	**14.47**	**0.9055**	**121.79**
MIDAS-RV-TY	**0.7111**	**55.77**	**1.5722**	**176.09**
MIDAS-RV-EPU	**0.8243**	**80.57**	**0.7595**	**89.29**

Note: Bold face denotes positive cumulative returns. * denotes highest positive cumulative returns.