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Abstract

Despite the arguments that are put forward by the literature that oil price forecasts are economically useful, such claim has not been tested to date. In this study we evaluate the economic usefulness of oil price forecasts by means of conditional forecasting of three core macroeconomic indicators that policy makers are predicting, using assumptions about the future path of the oil prices. The chosen indicators are the core inflation rate, industrial production and purchasing price index. We further consider two more indicators, namely inflation expectation and monetary policy uncertainty. To do so, we initially forecast oil prices using a MIDAS framework and subsequently we use regression-based models for our conditional forecasts. Overall, there is diminishing importance of oil price forecasts for macroeconomic projections and policy formulation. An array of arguments is presented as to why this might be the case, which relate to the improved energy efficiency, the contemporary monetary policy tools and the financialisation of the oil market. Our findings remain robust to alternative oil price forecasting frameworks.

Keywords: Conditional forecasting, oil price forecasts, MIDAS, core inflation, inflation expectations.

JEL codes: C53, E27, E37, Q47.

1. Introduction

The aim of this paper is to extend the rather rich literature on oil price forecasting and the state-of-the-art forecasting approaches, concentrating for the first time on the economic usefulness of such forecasts, via conditional forecasting of macroeconomic indicators.

The extant literature supports that oil price forecasting is important for a number of stakeholders, including policy makers (such as central banks), firms and households (Elder and Serletis, 2010; Bauimeister *et al.*, 2014), given the role that oil prices play on several aspects of economic activity. More specifically, the literature suggests that oil price fluctuations (i) could exert a significant impact on growth paths, balance of payments and inflation, among others[1] and (ii) could also offer predictive power for the aforementioned economic variables, as well as, sentiment indicators[2].

For instance, Baumeister and Kilian (2014, p.869) maintain that "changes in the cost of imported crude oil are an important determinant of economic activity, which is why central banks worldwide and international organizations such as the International Monetary Fund (IMF) routinely rely on real-time forecasts of the price of oil in assessing the economic outlook" and that "central banks rely on forecasts of the real price of oil when making policy decisions. (p.886)". Even more, Baumeister *et al.* (2014, p.S33) further suggests that "accurate real-time forecasts of the price of oil are important to firms and consumers as well as state and national governments.", whereas, Baumeister *et al.* (2018, p.562) inform us that "users of oil price forecasts include international organizations, central banks, governments at the state and federal level as well as a range of industries including utilities and automobile manufacturers."

International institutions, central banks, as well as, global media also link the macroeconomic stability with oil price fluctuations. The IMF (2016), for example, supports that the deflationary pressures in the early part of the 2010s that was particularly observed in oil-importing countries, were caused by the significant drop in oil prices. Such deflationary pressures impose further constraints to central banks to support growth to fragile economies, due to the low interest rate environment. It is also indicatively that IMF (2016) further claims that prolong periods of low oil prices could also halt the economic growth of oil-exporting economies. Similarly, the ECB (2016a) provides evidence of the impact of the oil price slump on the fiscal policy stance of oil producers, since for many of them, oil prices are well below their fiscal breakeven prices.

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[1] See, *inter alia*, Backus and Crucini (2000), Aguiar-Conraria and Wen (2007), Hamilton (2008), Kilian *et al.* (2009), Bachmeier and Cha (2011), Natal (2012) and Jo (2014).

[2] See, for instance, Ravazzolo and Rothman (2013) and Güntner and Linsbauer (2018).

The global media, on the other hand, raise concerns as to how successful the ECB could be in raising inflation rates for 2016-2018 given the low oil prices (Barnato, 2016), whereas, Blas and Kennedy (2016) raise even more concerns maintaining that should energy prices continue to fall, then the world economy might enter into a tailspin.

Given the aforementioned indicative quotes and policy statements, which highlight the importance of oil price fluctuations and thus, oil price forecasts, it is rather interesting that the related literature has neglected to assess the economic usefulness of such forecasts. This is even more interesting when in fact Alquist *et al.* (2013) suggest that successful oil price forecasts have the potential to improve the forecasts for an array of macroeconomic variables, which could further lead to better policy responses; nevertheless, we observe that such claim has not been put into the test. More recently, Kilian and Vigfusson (2017) also opine that in order to provide an answer as to which model specification of oil price is more appropriate for policy making, this should be made based on model selection criteria rather than statistical testing. Thus, modelling frameworks for oil prices should be ranked according to their conditional performance relatively to a macroeconomic variable. At the same time, they highlight that the conditional performance of modelling frameworks in this line of research has been remained largely unexplored.

Despite the important points raised by Alquist *et al.* (2013) and Kilian and Vigfusson (2017), it is rather evident that existing studies concentrate on statistical loss functions in order to evaluate their oil price forecasts, ignoring their economic usefulness. Typically, the current practice is to use loss functions, such as the mean squared predictive error (MSPE) or the mean absolute predictive error (MAPE), irrespectively of the different forecasting frameworks that are used to forecast oil prices, i.e. futures-based forecasts (see, for instance, Alquist and Kilian 2010; Alquist *et al.*, 2013), forecasts based on oil price fundamentals (see, for example, Baumeister and Kilian 2012; 2014; 2015; Baumeister *et al.*, 2015; Degiannakis and Filis, 2018) or even based on financial data (see, Baumeister *et al*., 2015; Degiannakis and Filis, 2018). A recent review of the related literature can be found in Degiannakis *et al.* (2018a).

Thus, our paper fills this void by assessing oil price forecasts based on their ability to provide successful predictions for a wide range of macroeconomic indicators, which are at the core interest of policy makers, using conditional forecasting. Hence, for the first time in the bulk literature, we assess the economic usefulness of oil price forecasts.

It should be noted here that it is common practice for central banks to consider oil prices as an exogenous variable and thus, certain assumptions are made related to their future level, when it comes to macroeconomic projections (Coimbra and Esteves, 2004). ECB (2016b) clearly states that for all their projection exercises they proceed to certain macroeconomic assumptions, such as the future path of oil prices. A key issue, though, with the use of oil futures prices is that they tend to exhibit fairly large projection errors on macroeconomic variables (ECB, 2015).

Thus, in this paper we first forecast oil prices using the current state-of-the-art frameworks and subsequently we use these forecasts as assumptions of the future path of oil prices, so as to generate conditional forecasts for several macroeconomic indicators, including, inflation, industrial production and producers price index. We should highlight that the usefulness of conditional forecasting for macroeconomic variables has been well established, given that "prior knowledge, […], of the future evolution of some economic variables may contain information for the outlooks of other variables" (see, for instance, Bańbura *et al*., 2015, p. 740). Giannone *et al*. (2014, p.636) also maintains that conditional forecasts "allows for an […] outlook that is set within (and thus affected by) a clearly-described, albeit imperfectly known in advance, macroeconomic environment". Such macroeconomic environment could include the future path of oil prices.

As aforementioned, for the first step of our analysis we follow the current state-of-the-art modelling approaches for oil price forecasting, which maintain that the use of oil price volatility, based on high-frequency data, along with oil price fundamentals in lower frequency, can improve oil price forecasts (e.g. Degiannakis and Filis, 2018). Thus, motivated by these recent efforts, we employ a MIDAS framework to forecast the monthly WTI crude oil prices using the predictive information of various WTI realised volatility measures, as well as, the WTI implied volatility index (i.e. OVX index)[3]. The use of oil price volatility as potential predictor of oil prices is also motivated by ECB (2015), which suggests that the increased oil price volatility, over the last decade or so, has severe implications for oil price forecasting. For robustness purposes we also use the standard VAR and Bayesian VAR models, as these have been developed by Kilian and co-authors.

The remaining of the paper is structured as follows. Section 2 describes the data. Section 3 details the econometric approach employed in this paper and the conditional forecasting techniques. Section 4 provides a detailed analysis of the findings. Section 5 presents the results from additional monetary policy indicators and Section 6 includes the robustness check using alternative forecasting frameworks. Finally, Section 7 concludes the study.

[3] We should note here that previous research solely uses the typical realized volatility measure by Andersen and Bollerslev (1998), whereas the present study uses a wide range of realised and implied oil price volatilities, given that different volatility measures could provide different predictive information for oil prices.

2. Oil price forecasting framework

2.1 Data description

To perform our analysis, we use data at both ultra-high and low frequency. Starting from the former, we use tick-by-tick data for the front-month WTI futures contracts, which are transformed into intraday time-series (*ultra-high frequency*) so as to allow us the construction of the daily WTI volatility measures (*high frequency*). The specific volatility measures are presented in Section 2.2. Apart from the daily WTI realised volatility measures, we further use the daily prices of the OVX index, which is the WTI's implied volatility index. These volatility measures serve as our high-frequency predictors.

The *low-frequency* (i.e. monthly) predictors include the oil market fundamentals, namely, the global economic activity index (as proxy of the global business cycle), the global oil stocks (as proxies of oil inventories) and the global oil production. Motivated by Degiannakis and Filis (2018), we also use the capacity utilisation rate of the oil and gas industry, since it has been shown by Kaminska (2009) that there is a strong link between the capacity utilisation rate and oil prices.

As for the construction of our predicted variable, i.e. the monthly crude oil prices, we depart from the common practice of the literature, which is based on the average daily prices on any given month (see, for instance, Baumeister and Kilian, 2014, 2015; Naser, 2016; Zhang *et al.*, 2018), as these averages result in high first-order autocorrelation, which, artificially enhances the predictive ability of the modelling framework. Thus, by contrast, we construct our monthly crude oil prices from the tick-by-tick data. In particular, the monthly WTI oil price is considered to be the futures price of the last intraday observation of each month.

The period of the study spans from 4th January 2010 until 30th October 2017 and it is dictated by the availability of the ultra-high-frequency data (i.e. 1971 daily and 94 monthly observations). The tick-by-tick data are obtained from TickData, whereas the data for the OVX implied volatility index are retrieved from the CBOE.

2.2. WTI intraday realised volatility measures

Based on the literature, we have estimated seven variations of realized volatility, those with the greatest influence in financial modelling. Each proposed measure has each own advantages and disadvantages and, most importantly, the information they provide as explanatory variables diversifies. Let us denote as $r_{t,i} = log(P_{t,i}) - log(P_{t,i-1})$, the i^{th} intraday return (for i=1,…,τ) at day t, with τ number of intervals within a trading day. The $P_{t,i}$

is the i^{th} intraday asset price at day *t*. The seven intraday realized volatility measures IRV_t: $\left\{RV_t, RV_t^{(s)}, RV_t^{(b)}, RV_t^{(med)}, RV_t^{(min)}, RV_t^{(+)}, RV_t^{(-)}\right\}$ follow:

1. Andersen and Bollerslev's (1998) Realized Volatility (RV_t):

$$RV_t = \sum_{i=1}^{\tau} r_{t,i}^2 \,, \tag{1}$$

2. Hansen and Lunde's (2005) Scaled Realized Volatility ($RV_t^{(s)}$):

$$RV_t^{(s)} = \omega_1\left(logP_{t,1} - logP_{t-1,\tau}\right) + \omega_2 \sum_{i=1}^{\tau} r_{t,i}^2, \tag{2}$$

where the parameters ω_1 and ω_2 are estimated such as $\min\limits_{(\omega_1,\omega_2)} V\left(RV_t^{(s)}\right)$, because $\arg\min\limits_{(\omega_1,\omega_2)} E\left(RV_t^{(s)} - IV_t\right) = \arg\min\limits_{(\omega_1,\omega_2)} V\left(RV_t^{(s)}\right)$, and IV_t denotes the integrated volatility.

3. Barndorff-Nielsen and Shephard's (2004) Realized Bipower Variation ($RV_t^{(b)}$):

$$RV_t^{(b)} = (2/\pi)^{-1}\left(\frac{\tau}{\tau-1}\right) \sum_{i=1}^{\tau-1} \left|r_{t,i}\right| \left|r_{t,i+1}\right| \,, \tag{3}$$

4. Andersen's *et al.* (2012) Median Realized Volatility ($RV_t^{(med)}$):

$$RV_t^{(med)} = \frac{\pi}{6 - 4\sqrt{3} + \pi}\left(\frac{\tau}{\tau - 2}\right) \sum_{i=2}^{\tau-1} med\left(\left|r_{t,i-1}\right|, \left|r_{t,i}\right|, \left|r_{t,i+1}\right|\right)^2, \tag{4}$$

5. Andersen's *et al.* (2012) Minimum Realized Volatility ($RV_t^{(min)}$):

$$RV_t^{(min)} = \frac{\pi}{\pi-2}\left(\frac{\tau}{\tau-1}\right) \sum_{i=1}^{\tau-1} min\left(\left|r_{t,i}\right|, \left|r_{t,i+1}\right|\right)^2. \tag{5}$$

6. Barndorff-Nielsen *et al.* (2010) Positive Semi Variance ($RV_t^{(+)}$):

$$RV_t^{(+)} = \sum_{i=1}^{\tau} I\left\{r_{t,i} \geq 0\right\} r_{t,i}^2 \,, \tag{6}$$

where $I\{.\}$ is an indicator function taking the value 1 if the argument is true.

7. Barndorff-Nielsen *et al.* (2010) Negative Semi Variance ($RV_t^{(-)}$):

$$RV_t^{(-)} = \sum_{i=1}^{\tau} I\left\{r_{t,i} < 0\right\} r_{t,i}^2 \,. \tag{7}$$

The realized variance, RV_t, is the most known estimator of intraday realized volatility on a daily sampling frequency and it has been applied in all the financial studies that focus on volatility predictions.

The $RV_t^{(s)}$ has successfully introduced the combination of intraday volatility during the open-to-closed period with the closed-to-open inter-day volatility. Among the various modifications that have been suggested for the overnight adjustment of realized volatility, i.e. Blair *et al.* (2001), Martens (2002), Koopman *et al*. (2004), the $RV_t^{(s)}$ estimates the weight of overnight volatility based on the minimization of the expected distance between computed RV_t and latent (thus, unobservable) IV_t.

Barndorff-Nielsen and Shephard (2004 and 2006) showed that the $RV_t^{(b)}$ is an estimator of the integrated volatility IV_t in the presence of jumps. So, if we assume that the intraday asset price follows a jump-diffusion process, then the volatility includes a jump component and the quadratic variation QV_t equals to the integrated volatility plus the jump variation; or $QV_t = \int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1<s\le t} \kappa_s^2$. The bipower variation is robust to the presence of jumps and we can combine realized variance with bipower variation to estimate the jump variation components.

The $RV_t^{(med)}$ and $RV_t^{(min)}$, proposed by Andersen *et al.* (2012), also provide estimates for integrated variance in the presence of jumps. Both are more robust estimators than the $RV_t^{(b)}$ and its multipower variations due to the fact that large absolute returns associated with jumps tend to be eliminated from the calculation of the median and minimum operators; see also Theodosiou and Zikes (2009). When infrequent jumps are present the $RV_t^{(med)}$ is less sensitive to the existence of zero intraday returns and it has better efficiency properties than the tripower variation.

The $RV_t^{(+)}$ and $RV_t^{(-)}$ capture the variation solely from positive and negative returns. Patton and Sheppard (2015) provided evidence that for equity data, the downside realized semi-variance is much more important for forecasting future volatility than the positive realized semi-variance.

Apart from these realized volatility measures, we further consider the difference between the positive and negative semi variance ($RV_t^{(SJ)} = RV_t^{(+)} - RV_t^{(-)}$), the OVX index, as well as, the variance risk premiums (VRP_t) according to Bollerslev *et al.* (2009), as follows:

$$VRP_t = OVX_t - IRV_t, \tag{8}$$

where, OVX_t is the WTI implied volatility and IRV_t denotes each of the seven (7) different intraday realized volatility measures mentioned in this section, i.e. $IRV_t\colon \left\{RV_t, RV_t^{(s)}, RV_t^{(b)}, RV_t^{(med)}, RV_t^{(min)}, RV_t^{(+)}, RV_t^{(-)}\right\}$.

The motivation for using of the variance risk premiums (VRP_t), as additional predictors for oil price forecasts, stems from the fact that this relatively newly developed volatility measure has gained prominence in the finance literature in relation to its ability explaining asset price fluctuations (see, Carr and Wu, 2008; Bollerslev *et al*., 2009; Prokopczuk, 2017). Even more, the VRP_t is able to gauge investors' fear of a potential market crash (Tee and Ting, 2017). Thus, we maintain that the oil futures VRP_t could provide incremental predictive information for the future path of oil prices. In total we consider 16 volatility measures.

As the trading frequency increases substantially, i.e. $\tau \rightarrow \infty$, the market frictions impose additional noise in volatility estimates. Given the availability of the tick-by-tick data, we construct time series per 5-second intervals and we compute the intraday autocovariance, $Cov(r_{t,i}, r_{t,i-j}) = \sum_{j=1}^{\tau-1} \sum_{i=j+1}^{\tau} r_{t,i} r_{t,i-j}$, across sampling frequencies. Looking for the sampling frequency that minimizes the autocovariance bias, we find that the trade-off between accuracy and potential bias induced by microstructure frictions is achieved at 20-minutes for the WTI realized volatility.

An obvious question would be why we consider the different realised volatility measures to forecast oil prices. It would make sense only if they provide different information to oil prices. Figures 1 and 2 show the WTI oil prices along with selected measures of WTI price volatility. Figure 1 reveals that there are no material differences among either the volatility measures or the variance risk premiums. For instance, all the three chosen volatility measure seem to peak during 2011, given the economic turbulence in the Eurozone, as well as, during the oil price collapse of 2014-2016. A notable difference is only on the fact that the OVX seems to be less volatile compared to the intraday realised volatility measures, which is rather anticipated. Even more, the two chosen variance risk premiums also exhibit similar behaviour, with major troughs in the two aforementioned periods.

Nevertheless, to motivate our choice of using the different volatility measures we show Figure 2, which depicts the same volatility measures as in Figure 1, yet only for a randomly selected month. The visual inspection of Figure 2 clearly shows that the different volatility measures could incorporate different information, given that their behaviour is not necessarily similar.

[FIGURES 1 and 2 HERE]

2.3. The MIDAS framework for oil price forecasting

Motivated by Baumeister *et al.* (2015) and Degiannakis and Filis (2018), we model the future monthly crude oil prices to be driven by high-frequency data (oil price volatility in our case) along with low-frequency oil price fundamentals. The high-frequency oil volatility information set includes the various WTI realised volatility measures that we have computed; i.e. $\left\{RV_t, RV_t^{(s)}, RV_t^{(b)}, RV_t^{(med)}, RV_t^{(min)}, RV_t^{(+)}, RV_t^{(-)}\right\}$, the $RV_t^{(SJ)}$, the WTI implied volatility index; i.e. OVX_t, as well as, the variance risk premiums. The 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, at a monthly frequency.

Let us denote as $\Delta(Oil_t) = log(Oil_t/Oil_{t-1})$ the oil futures price monthly returns, as $\boldsymbol{F}_t = (Gea_t,\ \ log(Prod_t/Prod_{t-1}),\ \ log(Stocks_t/Stocks_{t-1}),\ \ Cap_t)'$, the vector of fundamental explanatory variables at a monthly frequency and as $\boldsymbol{VOL}_{(t)}^{(D)}$ the vector of realized volatilities, the $RV_t^{(SJ)}$, the OVX and variance risk premiums. The MIDAS model was built in order to regress the monthly dependent variable directly with the monthly explanatory variables, $\boldsymbol{F}_t$, and via the polynomial distributed lag weighting with the daily realized volatilities, $\boldsymbol{VOL}_{(t)}^{(D)}$:

$$\Delta(Oil_t) = \boldsymbol{F'}_{t-i}\boldsymbol{\beta} + \sum_{r=0}^{k-1} \boldsymbol{VOL'}_{(t-r-is)}^{(D)} \left(\sum_{j=0}^{p} r^j \boldsymbol{\theta}_j\right) + \varepsilon_t. \tag{9}$$

The error term is assumed to be normally distributed, $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, the $\boldsymbol{\beta}$, $\boldsymbol{\theta}_j$ are vectors of coefficients to be estimated, and the $s = 22$ denotes the number of daily observations at each month.

The current's month oil futures price is related with a) the oil price fundamentals up to i months before and b) the volatility measures up to $is + r$ trading days before. The variables have been constructed and their relationship with the dependent variable was established such as to avoid any possible looking ahead bias. Thus, we are able to estimate up to i months-ahead oil futures price forecasts without imposing the utilization of future actual information from explanatory variables. I.e., we set $i \geq 1$ (as well as $is \geq 22$) in order to predict the one-month ahead oil price. Additionally, we set $i \geq 6$ and $is \geq 132$, when we predict the six-months ahead oil price and so on.

Moreover, k, which is the number of lagged days to be employed, is estimated such as to minimize the in-sample sum of squared residuals. Additionally, the dimension of the lag polynomial in the vector parameters $\boldsymbol{\theta}_j$, denoted as p, has been investigated with a series of in-sample evaluation tests and was set equal to three. Henceforth, we avoid inducing a form of data mining bias, which would have been the case if we had estimated the *k* and p that minimize the sum of squared forecast errors in the out-of-sample period.

3. Evaluating oil price forecasts based on conditional forecasting

As aforementioned in Section 1, the aim of this study is to evaluate the economic usefulness of oil price forecasts by means of conditional forecasting. To do so, we focus on three core macroeconomic indicators that policy makers are forecasting, using assumptions about the future path of the oil prices. These indicators are the inflation rate, industrial production and purchasing price index. We shall reiterate that our oil price forecasts are used as assumptions in the following conditional forecasting framework.

3.1. Data description for conditional forecasting

To proceed with the conditional forecasts of core inflation, we use monthly data for the period January 2010 to October 2017 for the US core CPI and the US unemployment gap. The unemployment gap is measured as the difference between the US unemployment rate and the nonaccelerating inflation rate of unemployment (NAIRU). Furthermore, monthly data for the same period are obtain for the industrial production and purchasing price indices. All data are obtained from the Federal Reserve of St. Luis (Federal Reserve Economic Data).

3.2. Conditional forecasting framework for macroeconomic conditions

3.2.1. Inflation

Typically, the literature estimates an augmented Philips curve to assess the impact of oil prices on inflation, such as:

$$\pi_t = a + \sum_{i=1}^{I} \beta_i \pi_{t-i} + \gamma(un_{t-1} - nairu_{t-1}) + \sum_{i=0}^{I} \delta_i \Delta(Oil_{t-i}) + e_t, \qquad (10)$$

where, π_t denotes the core inflation rate at month t, un_t is the US unemployment rate, $nairu_t$ is the nonaccelerating inflation rate of unemployment, hence, $(un_t - nairu_t)$ refers to the unemployment gap and $\Delta(Oil_t)$ refers to the crude oil price monthly changes. Finally, $e_t \sim N(0, \sigma_e^2)$ is the error term.

Hooker (2002), for instance, uses the Philips curve to identify the oil price pass-through, whereas, Coibion and Gorodnichencko (2015), using the augmented Philips curve, reveal that inflation rate during the Global Financial Crisis (GFC) increased as a consequence of the increased oil prices at that period. More recently, Gelos and Ustyugova (2017) and Renou-Maissant (2019) also use the augmented Philips curve to identify the effects of oil price changes to inflation rates.

However, the aforementioned studies do not proceed to conditional forecasts of inflation, which reflect the actual needs of policy makers. Thus, we use a variant of eq.(10) so to accommodate the fact that oil price forecasts serve as macroeconomic assumptions for inflation projections, such as that:

$$\pi_{m,t+h} = a + \sum_{i=1}^{I} \beta_i \pi_{t+h-i} + \gamma(un_{t+h-1} - nairu_{t+h-1}) + \sum_{i=0}^{I} \delta_i \Delta(Oil_{m,t+h-i|t}) + e_{t+h}, \quad (11)$$

where, $\pi_{m,t+h}$ denotes the h-step ahead real conditional forecast of the core inflation based on the different oil price forecasting models, m, (for $h = 1, \dots 12$ months). $Oil_{m,t+h-i|t}$ denotes the prediction of oil price at month $t + h$, based on each of the 16 models, m (i.e. based on the 7 realized volatilities, the $RV_t^{(SJ)}$, the OVX and the 7 variance risk premiums), which has been estimated with the available information at month t. Note that $i \geq h$ should hold in order to avoid any looking-forward bias. Our oil price forecasts from month $t + 1$ up to month $t + h$ are estimated iterated based on the information set that is available on month t:

$$Oil_{m,t+h|t} = Oil_{m,t+h-1|t} e^{\left(\boldsymbol{F'}_{t-i+h}\boldsymbol{\beta}^{(t)} + \sum_{r=0}^{k-1} \boldsymbol{VOL}'^{(D)}_{(t-r-is)}\left(\sum_{j=0}^{p} r^j \boldsymbol{\theta}_j^{(t)}\right)\right)}, \quad (12)$$

for $h \geq 2$, whereas for $h = 1$ we predict oil as $Oil_{m,t+h|t} = Oil_t e^{\left(\boldsymbol{F'}_{t-i+1}\boldsymbol{\beta}^{(t)} + \sum_{r=0}^{k-1} \boldsymbol{VOL}'^{(D)}_{(t-r-is)}\left(\sum_{j=0}^{p} r^j \boldsymbol{\theta}_j^{(t)}\right) + \widehat{\sigma}_\varepsilon^2/2\right)}$. Eq.(11) allows us to evaluate which oil price forecast is performing best based on its ability to provide predictive gains for the core inflation.

We note that we estimate eq.(11) for π_t denoting (i) the log of the consumer price index (CPI_t), (ii) the *m-o-m* changes of CPI_t and (iii) the *y-o-y* change of CPI_t[4]. We do so since we are agnostic as to which transformation of the CPI series would provide accurate conditional forecasts of the CPI itself.

3.2.2. Industrial Production and Production Price indices

Similarly, to the inflation projection approach, we estimate the following equation to generate conditional forecasts for the industrial production and production price indices, respectively, based on oil price forecasts:

$$z_{m,t+h} = a + \sum_{i=1}^{I} \beta_i z_{t+h-i} + \sum_{i=0}^{I} \delta_i \Delta(Oil_{m,t+h-i|t}) + e_{t+h} \quad (13)$$

where, $z_{m,t+h}$ denotes either the log of industrial production (IP_t) or the purchasing price index (PPI_t) real conditional forecasts at month $t + h$, based on the different oil price forecasting models. $Oil_{m,t+h|t}$ denotes the oil price prediction at month $t + h$ given the information available at month t, and $e_t \sim N(0, \sigma_e^2)$ is the error term. For robustness purposes, we estimate

[4] The *m-o-m* denotes the month on month change, whereas the *y-o-y* denotes the year on year change.

eq.(13) for z_t denoting, apart from the log levels, the *m-o-m* and *y-o-y* changes of IP_t and PPI_t, as well.

We note that for economically useful comparisons we also generate conditional forecasts based on the *non-oil* models, which are the models from eqs. (11) and (13), excluding the information from the oil price forecasts (i.e. $\sum_{i=0}^{I} \delta_i \Delta(Oil_{m,t+h-i|t})$).

Thus, in total, for each macroeconomic indicator we estimate 16 MIDAS models, using each one of the WTI realised volatility measures, the $RV_t^{(SJ)}$, the OVX and the VRPs, at a time, as well as, the *non-oil* model.

3.2.3. Validate the Forecasting Accuracy

Being in line with forecasting literature (i.e. Degiannakis *et al*., 2018b and Marcellino *et al.*, 2003) and keeping in mind the high non-linearity of the MIDAS model, we use the 2/3 of the available data for the initial in-sample estimation period, $\breve{T}$ (January 2010 - November 2014) and the remaining 1/3 of the observations for the out-of-sample evaluation period, $\tilde{T}$ (December 2014 – October 2017). More technical details regarding the efficient estimation of MIDAS are available in Andreou *et al.* (2010, 2013) and Ghysels *et al.* (2006).

To establish the performance of the competing models to forecast Ind_t: $\{\pi_t, IP_t, PPI_t\}$, 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 predictive evaluation criterion[5]. We utilize the two most well-established statistical evaluation criteria, the Mean Squared Predictive Error (MSPE) and the Mean Absolute Predictive Error (MAPE). Let us denote the $\Psi_{m,t}^{(mspe)}$ and $\Psi_{m,t}^{(mape)}$ evaluation criteria:

$$\Psi_{m,t}^{(mspe)} = \left(Ind_{m,t+h|t} - Ind_{t+h}\right)^2, \tag{14}$$

and

$$\Psi_{m,t}^{(mape)} = \left|Ind_{m,t+h|t} - Ind_{t+h}\right|, \tag{15}$$

where $Ind_{m,t+h|t}$ denotes the prediction of each of the three macroeconomic indicators, based on each of the different oil price forecasts, from model m, at month $t+h$ which has been estimated with the information that is available at month t. The difference among the forecast error of any two models, m, m^*, at month t is defined as $d_{m,m^*,t} = \Psi_{m,t}^{(.)} - \Psi_{m^*,t}^{(.)}$, for any

[5] Relative methods of forecasting performance evaluation are the Clark and West's (2007), White's (2000) and Hansen's (2005) tests which compare the forecasting performance against a pre-selected benchmark model. However, we employ the MCS test because we do not want to *a priori* select a benchmark model.

$m, m^* \in M^0$, (M^0 is the set of all the competing models). The MCS test investigates the null hypothesis $H_{0,M}: E\left(d_{m,m^*,t}\right) = 0$, for $\vee\ m, m^* \in M$, $M \subset M^0$ against the alternative one $H_{1,M}: E\left(d_{m,m^*,t}\right) \neq 0$, for some $m, m^* \in M$. The MSPE and MAPE evaluation criteria for each model m are computed as the average performance across the out-of-sample period, $\Psi_m^{(.)} = \tilde{T}^{-1} \sum_{t=1}^{\tilde{T}} \Psi_{m,t}^{(.)}$.

4. Empirical analysis

Our analysis is based on the evaluation of the oil price forecasts in terms of their performance in conditional forecasting of key macroeconomic variables. Given that we use different transformations of the macroeconomic variables (i.e. level indices, *m-o-m* changes and *y-o-y* changes), the main section of the analysis presents these transformations that generate the smallest forecast errors. Nevertheless, all forecast evaluations are available in the online appendix.

We start with the conditional forecasts of CPI, based on the modelling of the *m-o-m* CPI changes, which are shown in Table 1. We can immediately understand there is no differentiation in terms of forecasting performance among the competing MIDAS models, which suggests that there is not a unique model specification that stands out. More importantly, though, we notice that the inclusion of the oil price forecasts (irrespectively of the oil price MIDAS model) as macroeconomic assumptions for core inflation prediction, does not provide any predictive gains since the non-oil model is constantly included in the set of the best models, according to the MCS test, across all forecasting horizons[6].

[TABLE 1 HERE]

Such findings do not offer support to the views expressed by Natal (2012) that price stability is influenced by oil price fluctuations, especially in the short-run. By contrast, they provide support to the findings reported by Hooker (2002), Blanchard and Gali (2009) and Bachmeier and Cha (2011) who maintain that there is diminishing importance of oil prices on inflation rates. We should note, though, that none of these studies have assessed the impact of oil prices on inflation rates in a framework similar to ours.

Such diminishing importance of oil prices on inflation rates could be explained by the efficient energy use that has improved over the last decades, suggesting that oil prices should not matter recently as they used to in the past. Another potential explanation is provided by

[6] We repeat our forecasts using the CPI (all items) and the results remain robust.

Blanchard and Gali (2007) who opine that the flexibility of the labour market, as well as, the improved tools that are at the disposal of the monetary authorities have contributed to the decreased importance of oil prices on inflation rates.

Next, we consider the conditional forecasts of the industrial production index. The results are shown in Table 2.

[TABLE 2 HERE]

Similarly, with the results from Table 1, we show that the oil price forecasts do not seem capable of generated prediction gains relatively to the non-oil model. The MCS test inform us that the non-oil model is included in the set of the best performing models for all horizon up to 9-months ahead. Nevertheless, the results for the 12-months ahead horizon suggest that the conditional forecasts of the industrial production index that incorporate the oil prices forecasts based on OVX and the VRP of the two semi-variances (i.e. $MIDAS - OVX$, $MIDAS - VRP - RV^{(-)}$, $MIDAS - VRP - RV^{(+)}$) are the only ones that belong to the set of the best predictive models. Despite the latter, we cannot support the view that oil price forecasts are particularly useful for industrial production predictions. Once again, our findings cannot offer support to Elder and Serletis (2010) who maintain that higher oil prices (and in particular the uncertainty surrounding them) have adverse impact on industrial production, especially after the mid-1970s.

The final macroeconomic indicator that we use is the purchasing price index, with the results being presented in Table 3.

[TABLE 3 HERE]

In the case of the PPI conditional forecasts, based on the modelling of the *m-o-m* PPI changes, the empirical findings from the conditional forecasts differ significantly relatively to the results already discussed for the core inflation and industrial production. More specifically, we observe that apart from the 1-month ahead horizon, the oil price forecasts generate significant forecasting gains (up to 48% relative to the *non-oil* model). Even more, we observe that the models that are constantly included in the set of the best performing models are primarily those with the VRP (and especially the $MIDAS - VRP - RV$, $MIDAS - VRP - RV^{(s)}$).

It is rather interesting, though, that despite the predictive power of oil prices on the purchasing price index, we cannot observe any such effects on the industrial production index or the inflation rate. At first, this may seem as a rather puzzling result; however, some plausible explanations are offered here. As far as the differentiating results between industrial production and PPI are concerned, these may be justified by the fact that the former measures output units, whereas the latter shows cost prices. Oil prices are anticipated to influence production costs (hence the PPI index) and not necessarily the level of output. Furthermore, the finding that oil price forecasts can provide predictive information to the PPI index but not the CPI could be also explained by the fact that there is a shift in the weight of services in the US CPI calculation. More specifically, we observed an increasing weight of services over the last decades, reducing the importance of production goods (where many of them are oil-users) in the CPI[7]. This latter argument further justifies the lack of predictive gains from oil price forecasts to core inflation predictions.

5. Additional monetary policy indicators

In Section 4 we established that oil price forecasts, as macroeconomic assumptions for inflation predictions, are not economically useful. Thus, for robustness purposes we use oil price forecasts to predict two additional monetary policy related instruments, namely, the 5-year break-even inflation rate ($BEIR_t$), as well as, the monetary policy uncertainty index (MPU_t). The choice of the former stems from the fact that it is one of the best indicators that captures inflation expectations (Ciccarelli and Garcia, 2009) and thus, its prediction is of major importance for policy makers. Inflation expectations are critical in evaluating (i) how effective the central bank communication is, and (ii) the predictions of real inflation. Thus, despite the fact the oil price forecasts may not be economically useful for inflation predictions, their importance may be manifested via their predictive power on inflation expectations.

As for the monetary policy uncertainty index, there is a recent literature that links oil prices with economic policy uncertainty (Antonakakis *et al.*, 2014; Kang *et al.*, 2017; Degiannakis and Filis, 2019), however, none of these papers assessed the economic usefulness of oil price forecasts on the predictability of the MPU index.

The monthly data for the US BEIR is obtained from the Federal Reserve of St. Luis (Federal Reserve Economic Data), whereas the data for the MPU is obtained from Baker *et al.* (2016).

Similarly to the frameworks we used in Section 4, we estimate the following equation to generate conditional forecasts for both $BEIR_t$ and MPU_t, based on oil price forecasts:

[7] Please see a report from the Federal Reserve Bank of St. Louis on this issue: fredblog.stlouisfed.org/2018/11/does-oil-drive-inflation/

$$w_{m,t+h} = a + \sum_{i=1}^{I} \beta_i w_{t+h-i} + \sum_{i=0}^{I} \delta_i \Delta(Oil_{m,t+h-i|t}) + e_{t+h} \tag{16}$$

where, $w_{m,t+h}$ denotes either the $BEIR_t$ or MPU_t forecast at month $t+h$, $Oil_{m,t+h|t}$ denotes the oil price prediction at month $t+h$ given the information available at month t, and $e_t \sim N(0, \sigma_e^2)$ is the error term. For robustness purposes, we estimate eq.(16) for w_t denoting the log level of the MPU_t index, as well as, its *m-o-m* and *y-o-y* changes[8].

The results for the BEIR and MPU conditional forecasts are shown in Table 4. Our findings for BEIR are both important and interesting, as they show that oil price forecasts are economically useful for BEIR predictions, especially in the medium- and long-term horizons (i.e. 6-month up to 12 months ahead horizons). More specifically, the MCS test suggests that the non-oil model is only included in the set of the best performing models for the first two horizons. By contrast, the models that constantly outperform all others are the ones based on the intraday realised volatility measures, rather than the ones with the variance risk premiums or the implied volatility index (with the only exception being the $MIDAS - RV^{(+)}$ and $MIDAS - VRP - RV^{(-)}$ models).

This might be another puzzling finding given that oil price forecasts do no provide gains for inflation predictions. Such finding may indicate that a monetary authority is not capable to offset oil price fluctuations in the medium-run (5 years ahead as we consider the 5-year BEIR), which could further suggest that inflation expectations are not well anchored to the long-run inflation target.

However, another plausible explanation here could be found to the alternative interpretation of the market-based measure of inflation expectations that is used in this paper, i.e. BEIR. Possibly what we observe here is that impact of oil price forecasts on the prediction of investors' required return premiums for inflation risk and liquidity to their investments. Such link may not be far from reality given that in the last two decades we observe the increased financialisation of the oil market (see, for instance, Tang and Xiong, 2013; Degiannakis and Filis, 2017; Le Pen and Sévi, 2018), and especially of the WTI crude. Hence, we further document that oil price forecasts may not be useful for monetary authorities.

The latter argument is further supported by the results we obtain from the MPU conditional forecasts. We note that there is not a single specification that generates superior

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[8] $BEIR_t$ is expressed in *y-o-y* changes only.

conditional forecasts for the MPU index. Even more, we note that none of the MIDAS models is capable of enhancing the predictive accuracy of the non-oil models.

[TABLE 4 HERE]

6. Alternative oil price forecasting frameworks

So far, we have convincingly shown that oil price forecasts could be economically useful for policy makers, although this depends on the macroeconomic variable and the most appropriate transformation of the predicted series. To provide further robustness of our results, related to the use of the MIDAS model this time, we repeat the same conditional forecasts for the five different macroeconomic indicators, using as oil price assumptions the forecasts that have been generated by Kilian's and co-authors VAR and Bayesian VAR (BVAR) models (see, for instance, Baumeister and Kilian, 2012, 2014, 2015 for the technical details). The results are shown in Table 5.

[TABLE 5 HERE]

In short, we observe that neither the VAR or the BVAR models can offer any improved predictive gains relatively to our MIDAS specifications. In fact, in many cases, the VAR and BVAR models are not included in the set of the best performing models, as assessed by the MCS test. These results strengthen our initial findings.

7. Conclusion

It is rather interesting that there is a vast literature supporting the view that oil price forecasts are important for a number of stakeholders, with the monetary authorities being among the key ones. Despite the improvements in oil price forecasting frameworks, the related literature has neglected to assess the economic usefulness of such forecasts. Such observation is even more striking since Alquist *et al.* (2013) and Kilian and Vigfusson (2017) put forward the arguments that oil price forecasts should have the potential to improve the forecasts for an array of macroeconomic variables and that modelling frameworks for oil prices should be ranked according to their conditional performance relatively to a macroeconomic variable.

Thus, adding to this important line of research, the aim of this study is to evaluate the economic usefulness of oil price forecasts by means of conditional forecasting of macroeconomic indicators. In particular, our main focus is on three core macroeconomic indicators that policy makers are forecasting, using assumptions about the future path of the oil prices. The chosen indicators are the core inflation rate, industrial production and purchasing price index. In our framework we consider the oil price forecasts as our oil price assumptions in the conditional forecasting framework.

To do so, we initially forecast oil prices using a MIDAS model, where we model the future monthly crude oil prices based on high-frequency information obtained by different measures of oil price volatility and low-frequency oil price fundamentals. Subsequently, we use regression-based models for our conditional forecasts which are augmented with the oil price forecasts. As our naïve model we consider a regression-based model that does not contain the information from the oil price forecasts, which we name as *non-oil* model.

Our findings show that there is not a specific model that provides the higher predictive accuracy for the conditional forecasts of core inflation and industrial production. Even more, the mixed frequency models cannot provide predictive gains for these two macroeconomic indicators relatively to the non-oil model. By contrast, oil price forecasts generate significant forecasting gains (up to 48% relative to the *non-oil* model) for the PPI, while the MIDAS models that generate this superior predictive performance are primarily those that consider the variance risk premiums as their high-frequency predictors.

We further proceed with conditional forecasts for the break-even inflation (which approximates inflation expectations) and for an index of monetary policy uncertainty. These results suggest that on one hand, there is not a single MIDAS model that stands out as the best oil price forecasting model and on the other hand, none of the oil price forecasts can provide predictive information that is useful for the monetary authorities. To test further the robustness of our findings, we proceed with the oil price forecasts using other state-of-the-art forecasting frameworks, namely, VAR and Bayesian VAR models. The results show that oil price forecasts based on VAR and Bayesian VAR models cannot provide better conditional forecasts compared to the MIDAS specifications.

Overall, these findings suggest that there is diminishing importance of oil price forecasts for macroeconomic projections and for policy formulation of the monetary authorities. We offer an array of arguments as to why this might be the case. First, the improved energy efficiency along with the contemporary monetary policy tools could explain the decoupling between inflation rates and oil price fluctuations. Even more, the fact that in the US we observe an increase in the weight of services in the CPI calculation could explain the relative unimportance of oil price forecasts. On the other hand, the lack of predictive power of oil price forecasts on industrial production conditional forecasts could be explained by the fact that the former may impact production costs (i.e. the overall price of production inputs) but not the level of production output.

By contrast, the fact that our MIDAS models offer significant predictive gains for the conditional forecasts of inflation expectations could suggest that latter are not well anchored to the long-run inflation target. Nevertheless, given the lack of predictive gains that our models have on core inflation rate, we subscribe to the belief that an alternative explanation could be in place. In particular BEIR could reflect investors' required return premiums for inflation risk and liquidity to their investments. Hence, the fact that oil price forecasts can improve the conditional forecasts for BEIR could constitute evidence of increased linkage between the bond and the oil market, which further suggests that the oil market is indeed financialised.

Overall, our findings do not argue against the usefulness of oil price forecasts. Rather, they tend to point out that such forecasts may not be useful for policy making purposes, whereas given the evidence provided by the recent literature, they may be more useful for investment purposes, possibly due to the market's increased financialisation process.

Given the interesting findings presented in this study, it is important to expand this approach for the evaluation of oil price forecasts based on their economic usefulness to other countries or regions, which could be separated between industrial and post-industrial, as well as, net oil-importers and net-oil exporters.

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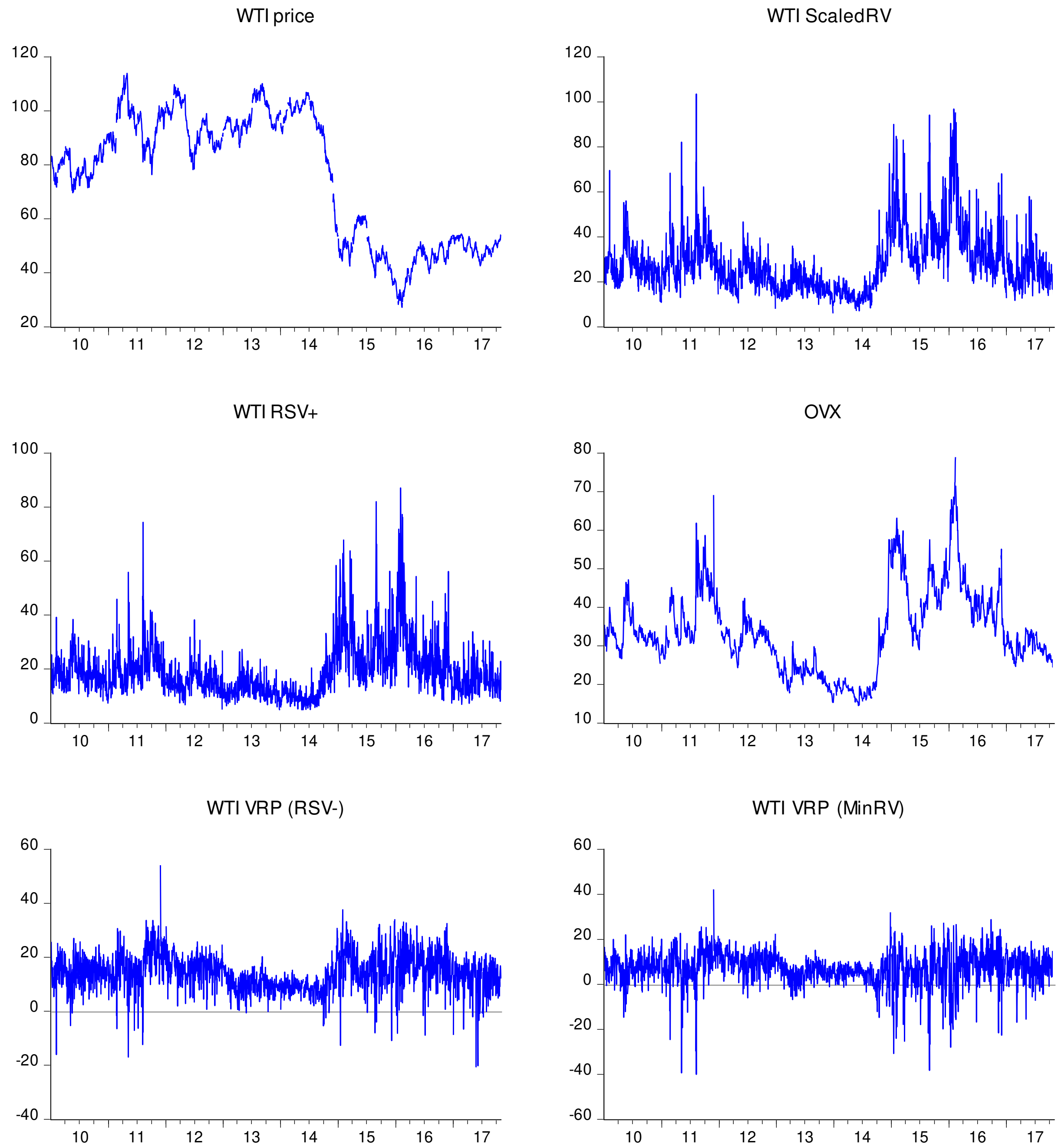
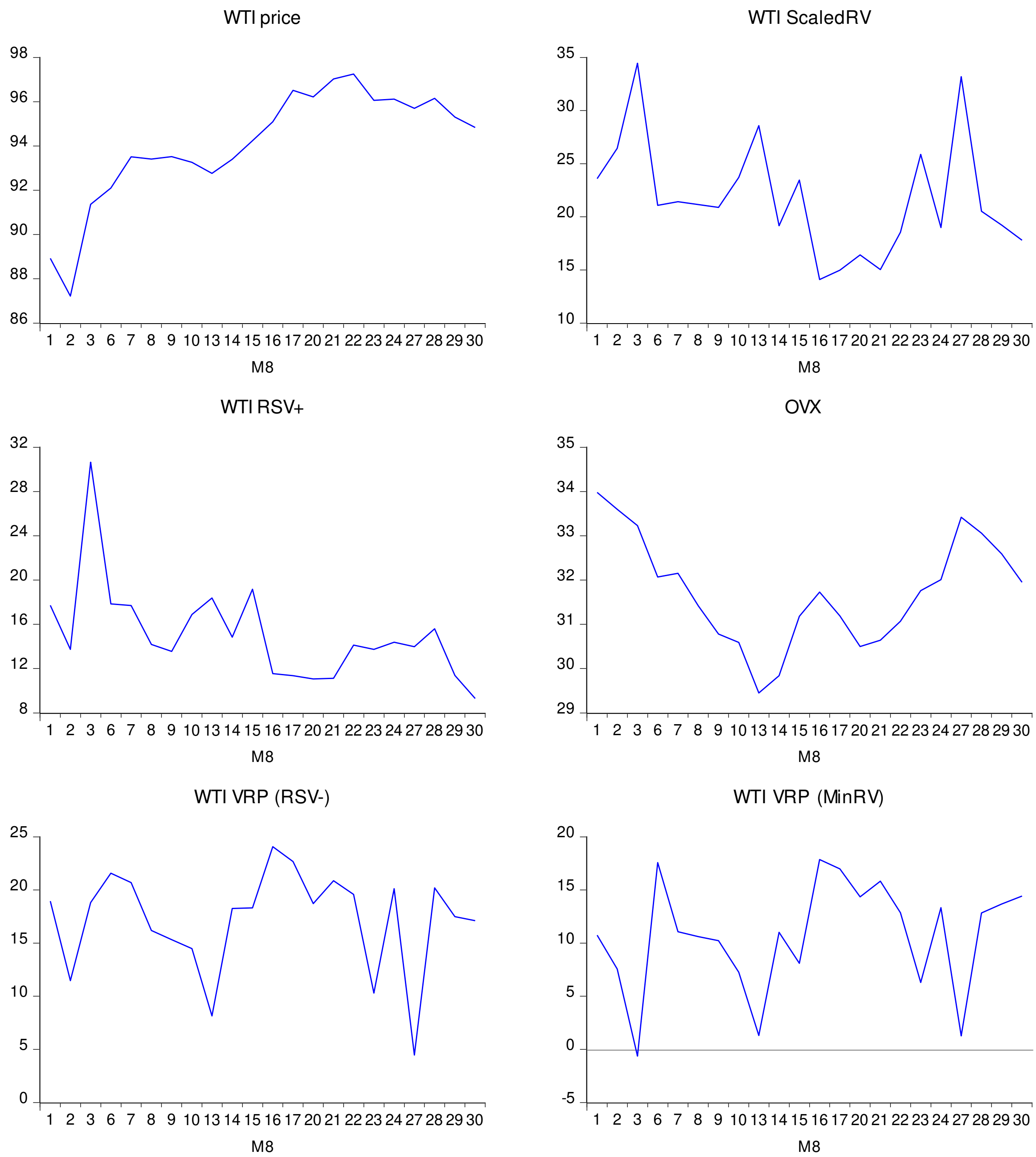
FIGURES

Figure 1. WTI oil prices, oil price volatility and variance risk premium



Note: For brevity, we show some indicative oil price volatility and variance risk premium measures.

Figure 2. WTI oil prices, oil price volatility and variance risk premium for a random month



Note: For brevity, we show some indicative oil price volatility and variance risk premium measures.

TABLES

Table 1: Oil price forecast evaluation based on conditional forecasts of core CPI based on *m-o-m* changes. Evaluation period: 2014.12-2017.10.

	MSPE				
	Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months
$Non-oil$	**0.0005**	**0.0009**	**0.0016**	**0.0024**	**0.0028**
$MIDAS-RV$	**0.0005**	**0.0009**	**0.0016**	0.0022	**0.0026**
$MIDAS-RV^{(s)}$	**0.0005**	0.0009	**0.0016**	**0.0022**	**0.0026**
$MIDAS-RV^{(b)}$	**0.0005**	0.0009	**0.0016**	**0.0022**	**0.0026**
$MIDAS-RV^{(med)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-RV^{(min)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-RV^{(-)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	0.0026
$MIDAS-RV^{(+)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-RV^{(sj)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-OVX$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-VRP-RV$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-VRP-RV^{(s)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-VRP-RV^{(b)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-VRP-RV^{(med)}$	0.0005	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-VRP-RV^{(min)}$	0.0005	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-VRP-RV^{(-)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**
$MIDAS-VRP-RV^{(+)}$	**0.0005**	**0.0009**	**0.0016**	**0.0022**	**0.0026**

Note: Bold face indicates that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test.

Table 2: Oil price forecast evaluation based on conditional forecasts of IP, based on the log-level data. Evaluation period: 2014.12-2017.10.

	MSPE				
	Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months
$Non-oil$	**0.2526**	**1.1190**	**2.7032**	**5.5700**	9.3322
$MIDAS-RV$	0.2472	**0.9284**	**2.2922**	**4.4508**	7.5352
$MIDAS-RV^{(s)}$	**0.2472**	**0.9284**	**2.2924**	4.4514	7.5353
$MIDAS-RV^{(b)}$	**0.2472**	**0.9284**	2.2922	**4.4510**	7.5344
$MIDAS-RV^{(med)}$	**0.2472**	**0.9284**	**2.2918**	**4.4507**	7.5357
$MIDAS-RV^{(min)}$	0.2472	**0.9284**	2.2922	**4.4508**	7.5348
$MIDAS-RV^{(-)}$	**0.2472**	**0.9284**	2.2928	**4.4502**	7.5380
$MIDAS-RV^{(+)}$	0.2473	**0.9283**	**2.2916**	4.4514	7.5332
$MIDAS-RV^{(sj)}$	0.2472	0.9286	**2.2926**	**4.4510**	7.5360
$MIDAS-OVX$	**0.2471**	**0.9283**	**2.2923**	**4.4502**	**7.5342**
$MIDAS-VRP-RV$	**0.2472**	**0.9286**	**2.2925**	**4.4498**	7.5337
$MIDAS-VRP-RV^{(s)}$	**0.2472**	**0.9286**	**2.2927**	**4.4504**	7.5341
$MIDAS-VRP-RV^{(b)}$	**0.2472**	**0.9286**	**2.2922**	**4.4501**	7.5327
$MIDAS-VRP-RV^{(med)}$	**0.2472**	**0.9285**	**2.2921**	**4.4499**	7.5353
$MIDAS-VRP-RV^{(min)}$	**0.2472**	0.9286	**2.2923**	**4.4504**	7.5347
$MIDAS-VRP-RV^{(-)}$	**0.2472**	**0.9286**	2.2932	**4.4503**	**7.5331**
$MIDAS-VRP-RV^{(+)}$	**0.2472**	**0.9287**	**2.2918**	**4.4500**	**7.5291**

Note: Bold face indicates that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test.

Table 3: Oil price forecast evaluation based on conditional forecasts of PPI, based on *m-o-m* changes. Evaluation period: 2014.12-2017.10.

	MSPE				
	Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months
$Non-oil$	**1.742**	10.970	32.926	46.500	58.963
$MIDAS-RV$	**1.555**	**6.284**	17.227	**27.463**	**31.209**
$MIDAS-RV^{(s)}$	**1.555**	**6.285**	17.227	**27.465**	**31.209**
$MIDAS-RV^{(b)}$	**1.556**	**6.284**	**17.223**	27.467	31.206
$MIDAS-RV^{(med)}$	**1.555**	**6.284**	**17.224**	27.468	**31.210**
$MIDAS-RV^{(min)}$	**1.555**	6.284	**17.223**	**27.467**	**31.213**
$MIDAS-RV^{(-)}$	**1.555**	**6.285**	17.228	**27.457**	31.219
$MIDAS-RV^{(+)}$	**1.555**	**6.285**	**17.220**	**27.463**	31.216
$MIDAS-RV^{(sj)}$	**1.554**	6.287	**17.223**	**27.437**	**31.217**
$MIDAS-OVX$	**1.554**	**6.284**	**17.223**	**27.455**	31.223
$MIDAS-VRP-RV$	**1.556**	**6.285**	**17.227**	**27.443**	**31.207**
$MIDAS-VRP-RV^{(s)}$	**1.556**	**6.285**	**17.226**	**27.443**	**31.207**
$MIDAS-VRP-RV^{(b)}$	**1.556**	**6.286**	**17.224**	27.444	**31.206**
$MIDAS-VRP-RV^{(med)}$	**1.556**	**6.286**	17.227	27.445	**31.209**
$MIDAS-VRP-RV^{(min)}$	**1.556**	6.286	**17.224**	27.445	**31.208**
$MIDAS-VRP-RV^{(-)}$	**1.555**	6.287	**17.226**	**27.445**	**31.216**
$MIDAS-VRP-RV^{(+)}$	**1.556**	**6.287**	**17.221**	**27.440**	31.214

Note: Bold face indicates that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test.

Table 4: Oil price forecast evaluation based on conditional forecasts of BEIR and MPU index level. Evaluation period: 2014.12-2017.10.

	MSPE - *BEIR*					MSPE - *MPU*				
	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
$Non-oil$	**0.0353**	**0.0704**	0.1512	0.2228	0.2835	**5376.13**	**6827.08**	**7389.51**	**7225.32**	**6382.65**
$MIDAS-RV$	**0.0328**	**0.0572**	**0.0553**	0.0505	0.1073	**5393.45**	7110.05	**6942.99**	**5525.10**	**6675.72**
$MIDAS-RV^{(s)}$	**0.0329**	**0.0569**	**0.0580**	**0.0488**	**0.1075**	**5393.57**	7109.94	**6942.74**	**5526.02**	**6675.78**
$MIDAS-RV^{(b)}$	**0.0330**	**0.0583**	**0.0482**	**0.0492**	**0.1078**	**5393.51**	7110.14	**6943.25**	5526.00	**6675.39**
$MIDAS-RV^{(med)}$	**0.0327**	**0.0575**	**0.0477**	**0.0487**	**0.1051**	**5393.46**	7110.22	**6943.59**	5525.98	**6676.13**
$MIDAS-RV^{(min)}$	**0.0322**	**0.0575**	**0.0489**	**0.0470**	**0.1028**	**5393.34**	7110.26	**6943.33**	5525.85	**6675.64**
$MIDAS-RV^{(-)}$	**0.0323**	**0.0559**	**0.0550**	**0.0595**	**0.0896**	**5393.30**	7109.72	**6943.29**	**5525.48**	**6677.45**
$MIDAS-RV^{(+)}$	**0.0318**	**0.0594**	0.0589	**0.0548**	**0.1113**	**5393.15**	7110.35	**6942.58**	**5524.83**	**6675.02**
$MIDAS-RV^{(sj)}$	**0.0311**	**0.0575**	0.0650	**0.0885**	**0.1110**	5393.64	7109.52	**6942.19**	**5523.34**	6677.50
$MIDAS-OVX$	**0.0315**	**0.0591**	**0.0591**	**0.0599**	**0.1082**	**5393.23**	7110.28	**6942.45**	**5525.49**	**6677.19**
$MIDAS-VRP-RV$	**0.0326**	0.0556	**0.0766**	0.0863	**0.1247**	**5393.35**	**7109.26**	**6942.13**	**5524.19**	**6676.16**
$MIDAS-VRP-RV^{(s)}$	**0.0326**	0.0557	**0.0781**	**0.0849**	**0.1253**	**5393.36**	**7109.11**	**6941.91**	**5524.39**	**6676.55**
$MIDAS-VRP-RV^{(b)}$	**0.0329**	0.0565	**0.0687**	**0.0848**	**0.1354**	**5393.50**	**7109.22**	**6942.23**	5524.81	**6675.77**
$MIDAS-VRP-RV^{(med)}$	**0.0335**	**0.0554**	0.0660	0.0845	**0.1231**	5393.71	**7109.17**	**6943.59**	5524.59	**6676.63**
$MIDAS-VRP-RV^{(min)}$	**0.0328**	0.0559	0.0698	**0.0830**	**0.1282**	**5393.46**	**7109.22**	**6942.76**	5525.00	**6676.99**
$MIDAS-VRP-RV^{(-)}$	**0.0314**	**0.0531**	**0.0616**	**0.0844**	**0.1114**	**5393.19**	**7109.01**	**6942.84**	**5524.99**	**6676.09**
$MIDAS-VRP-RV^{(+)}$	**0.0324**	**0.0525**	0.0701	0.0962	**0.1290**	**5393.50**	**7109.18**	**6942.43**	**5522.89**	**6674.50**

Note: Bold face indicates that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test.

Table 5: Oil price forecast evaluation based on conditional forecasts of the macroeconomic indicators. Evaluation period: 2014.12-2017.10.

	MSPE				
	Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months
	core CPI (based on m-o-m changes)				
VAR	**0.0005**	**0.0009**	**0.0016**	**0.0023**	**0.0027**
BVAR	**0.0005**	**0.0009**	**0.0016**	**0.0023**	**0.0027**
	IP (based on log-level data)				
VAR	**0.2472**	**0.9498**	*2.3239*	*4.6728*	**7.9451**
BVAR	**0.2472**	**0.9499**	*2.3234*	**4.6729**	7.9492
	PPI (based on m-o-m changes)				
VAR	**1.5524**	**6.1018**	**16.7525**	**26.4029**	*31.1108*
BVAR	**1.5581**	**6.1038**	*16.7374*	*26.403*	*31.0941*
	BEIR				
VAR	**0.0297**	**0.0376**	**0.0272**	**0.0535**	**0.0896**
BVAR	**0.0288**	**0.0387**	**0.0411**	**0.0519**	**0.0551**
	MPU (based on log-level data)				
VAR	**5.3919**	**6.9044**	**6.7622**	**5.4022**	**6.4605**
BVAR	*5.3927*	**6.9050**	**6.7636**	*5.4012*	**6.4630**

Note: Bold face indicate that the model has equal performance with the MIDAS models from Tables 1 – 4, according to the Model Confidence Set (MCS) test. *Italics* suggest that the model's performance is worse than the MIDAS models. MPU figures are multiplied by 10^{-3} so that they can fit to the table.

APPENDIX

Table A.1: Oil price forecast evaluation based on conditional forecasts of core CPI. Evaluation period: 2014.12-2017.10.

	MSPE – *Log-level data*					MSPE – *m-o-m change*					MSPE – *y-o-y changes*				
	Forecasting horizon in months					Forecasting horizon in months					Forecasting horizon in months				
Model:	1	3	6	9	12	1	3	6	9	12	1	3	6	9	12
$Non-oil$	0.0006	0.0014	0.0028	0.0045	0.0063	0.0005	0.0009	0.0016	0.0024	0.0028	0.0006	0.0012	0.0020	0.0032	0.0038
$MIDAS-RV$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-RV^{(s)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-RV^{(b)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-RV^{(med)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-RV^{(min)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-RV^{(-)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-RV^{(+)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-RV^{(sj)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-OVX$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-VRP-RV$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-VRP-RV^{(s)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-VRP-RV^{(b)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-VRP-RV^{(med)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-VRP-RV^{(min)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-VRP-RV^{(-)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054
$MIDAS-VRP-RV^{(+)}$	0.0006	0.0014	0.0029	0.0045	0.0064	0.0005	0.0009	0.0016	0.0022	0.0026	0.0008	0.0020	0.0035	0.0047	0.0054

Table A.2: Oil price forecast evaluation based on conditional forecasts of IP. Evaluation period: 2014.12-2017.10.

	MSPE – *Log-level data*					MSPE – *m-o-m changes*					MSPE – *y-o-y changes*				
	Forecasting horizon in months					Forecasting horizon in months					Forecasting horizon in months				
Model:	1	3	6	9	12	1	3	6	9	12	1	3	6	9	12
$Non-oil$	0.2526	1.1190	2.7032	5.5700	9.3322	0.3320	1.5364	3.8610	7.7126	12.1194	0.6828	3.3224	7.5673	12.3783	15.9679
$MIDAS-RV$	0.2472	0.9284	2.2922	4.4508	7.5352	0.3323	1.5370	4.4986	9.4594	15.8670	0.6449	2.6816	5.6680	9.4730	11.6711
$MIDAS-RV^{(s)}$	0.2472	0.9284	2.2924	4.4514	7.5353	0.3324	1.5369	4.4987	9.4590	15.8670	0.6448	2.6817	5.6664	9.4746	11.6709
$MIDAS-RV^{(b)}$	0.2472	0.9284	2.2922	4.4510	7.5344	0.3323	1.5370	4.4985	9.4590	15.8672	0.6449	2.6815	5.6680	9.4749	11.6700
$MIDAS-RV^{(med)}$	0.2472	0.9284	2.2918	4.4507	7.5357	0.3323	1.5370	4.4984	9.4591	15.8672	0.6448	2.6815	5.6680	9.4742	11.6722
$MIDAS-RV^{(min)}$	0.2472	0.9284	2.2922	4.4508	7.5348	0.3323	1.5370	4.4984	9.4591	15.8668	0.6448	2.6814	5.6674	9.4743	11.6732
$MIDAS-RV^{(-)}$	0.2472	0.9284	2.2928	4.4502	7.5380	0.3324	1.5370	4.4987	9.4594	15.8664	0.6447	2.6812	5.6684	9.4700	11.6784
$MIDAS-RV^{(+)}$	0.2473	0.9283	2.2916	4.4514	7.5332	0.3323	1.5372	4.4989	9.4597	15.8660	0.6450	2.6817	5.6656	9.4739	11.6739
$MIDAS-RV^{(sj)}$	0.2472	0.9286	2.2926	4.4510	7.5360	0.3323	1.5369	4.4992	9.4613	15.8662	0.6447	2.6818	5.6630	9.4546	11.6759
$MIDAS-OVX$	0.2471	0.9283	2.2923	4.4502	7.5342	0.3323	1.5369	4.4989	9.4597	15.8657	0.6447	2.6820	5.6647	9.4689	11.6824
$MIDAS-VRP-RV$	0.2472	0.9286	2.2925	4.4498	7.5337	0.3324	1.5371	4.4991	9.4609	15.8669	0.6446	2.6812	5.6614	9.4581	11.6712
$MIDAS-VRP-RV^{(s)}$	0.2472	0.9286	2.2927	4.4504	7.5341	0.3324	1.5371	4.4992	9.4610	15.8670	0.6446	2.6812	5.6611	9.4586	11.6711
$MIDAS-VRP-RV^{(b)}$	0.2472	0.9286	2.2922	4.4501	7.5327	0.3324	1.5372	4.4990	9.4608	15.8671	0.6446	2.6812	5.6630	9.4587	11.6701
$MIDAS-VRP-RV^{(med)}$	0.2472	0.9285	2.2921	4.4499	7.5353	0.3324	1.5370	4.4989	9.4608	15.8668	0.6447	2.6815	5.6638	9.4583	11.6732
$MIDAS-VRP-RV^{(min)}$	0.2472	0.9286	2.2923	4.4504	7.5347	0.3324	1.5371	4.4990	9.4608	15.8667	0.6447	2.6812	5.6632	9.4587	11.6743
$MIDAS-VRP-RV^{(-)}$	0.2472	0.9286	2.2932	4.4503	7.5331	0.3324	1.5369	4.4990	9.4606	15.8660	0.6447	2.6814	5.6642	9.4606	11.6788
$MIDAS-VRP-RV^{(+)}$	0.2472	0.9287	2.2918	4.4500	7.5291	0.3323	1.5368	4.4990	9.4612	15.8662	0.6448	2.6821	5.6616	9.4544	11.6752

Table A.3: Oil price forecast evaluation based on conditional forecasts of PPI. Evaluation period: 2014.12-2017.10.

	MSPE – *Log-level data*					MSPE – *m-o-m changes*					MSPE – *y-o-y changes*				
	Forecasting horizon in months					Forecasting horizon in months					Forecasting horizon in months				
Model:	1	3	6	9	12	1	3	6	9	12	1	3	6	9	12
$Non-oil$	3.017	13.928	32.142	52.682	71.244	1.742	10.970	32.926	46.500	58.963	4.897	22.385	50.700	98.954	161.828
$MIDAS-RV$	3.247	21.404	60.153	95.233	155.518	1.555	6.284	17.227	27.463	31.209	2.309	8.833	25.079	35.221	45.061
$MIDAS-RV^{(s)}$	3.247	21.403	60.178	95.224	155.525	1.555	6.285	17.227	27.465	31.209	2.309	8.833	25.106	35.206	45.064
$MIDAS-RV^{(b)}$	3.247	21.409	60.100	95.212	155.511	1.556	6.284	17.223	27.467	31.206	2.309	8.835	25.034	35.200	45.063
$MIDAS-RV^{(med)}$	3.247	21.405	60.079	95.207	155.510	1.555	6.284	17.224	27.468	31.210	2.309	8.834	25.024	35.200	45.051
$MIDAS-RV^{(min)}$	3.246	21.406	60.102	95.186	155.461	1.555	6.284	17.223	27.467	31.213	2.309	8.835	25.040	35.183	45.027
$MIDAS-RV^{(-)}$	3.247	21.403	60.171	95.301	155.442	1.555	6.285	17.228	27.457	31.219	2.310	8.837	25.081	35.308	44.984
$MIDAS-RV^{(+)}$	3.245	21.414	60.148	95.274	155.467	1.555	6.285	17.220	27.463	31.216	2.307	8.837	25.089	35.247	45.050
$MIDAS-RV^{(sj)}$	3.244	21.410	60.216	95.539	155.527	1.554	6.287	17.223	27.437	31.217	2.307	8.837	25.145	35.513	45.067
$MIDAS-OVX$	3.245	21.408	60.175	95.312	155.389	1.554	6.284	17.223	27.455	31.223	2.308	8.832	25.105	35.326	44.995
$MIDAS-VRP-RV$	3.246	21.404	60.270	95.477	155.568	1.556	6.285	17.227	27.443	31.207	2.310	8.835	25.195	35.481	45.114
$MIDAS-VRP-RV^{(s)}$	3.246	21.405	60.285	95.483	155.582	1.556	6.285	17.226	27.443	31.207	2.310	8.836	25.206	35.479	45.119
$MIDAS-VRP-RV^{(b)}$	3.247	21.406	60.227	95.472	155.613	1.556	6.286	17.224	27.444	31.206	2.311	8.836	25.155	35.472	45.155
$MIDAS-VRP-RV^{(med)}$	3.247	21.403	60.200	95.468	155.576	1.556	6.286	17.227	27.445	31.209	2.311	8.831	25.132	35.470	45.107
$MIDAS-VRP-RV^{(min)}$	3.247	21.405	60.231	95.475	155.584	1.556	6.286	17.224	27.445	31.208	2.311	8.835	25.155	35.466	45.120
$MIDAS-VRP-RV^{(-)}$	3.244	21.398	60.219	95.468	155.421	1.555	6.287	17.226	27.445	31.216	2.309	8.831	25.132	35.473	45.026
$MIDAS-VRP-RV^{(+)}$	3.246	21.383	60.210	95.541	155.433	1.556	6.287	17.221	27.440	31.214	2.309	8.818	25.152	35.531	45.070

Table A.4: Oil price forecast evaluation based on conditional forecasts of BEIR and MPU. Evaluation period: 2014.12-2017.10.

	MSPE – *Log-level data*					MSPE – *m-o-m changes*					MSPE – *y-o-y changes*				
	Forecasting horizon in months					Forecasting horizon in months					Forecasting horizon				
Model:	1	3	6	9	12	1	3	6	9	12	1	3	6	9	12
								BEIR							
$Non-oil$											0.035	0.070	0.151	0.223	0.284
$MIDAS-RV$											0.033	0.057	0.055	0.051	0.107
$MIDAS-RV^{(s)}$											0.033	0.057	0.058	0.049	0.108
$MIDAS-RV^{(b)}$											0.033	0.058	0.048	0.049	0.108
$MIDAS-RV^{(med)}$											0.033	0.058	0.048	0.049	0.105
$MIDAS-RV^{(min)}$											0.032	0.058	0.049	0.047	0.103
$MIDAS-RV^{(-)}$											0.032	0.056	0.055	0.060	0.090
$MIDAS-RV^{(+)}$											0.032	0.059	0.059	0.055	0.111
$MIDAS-RV^{(sj)}$											0.031	0.058	0.065	0.089	0.111
$MIDAS-OVX$											0.032	0.059	0.059	0.060	0.108
$MIDAS-VRP-RV$											0.033	0.056	0.077	0.086	0.125
$MIDAS-VRP-RV^{(s)}$											0.033	0.056	0.078	0.085	0.125
$MIDAS-VRP-RV^{(b)}$											0.033	0.057	0.069	0.085	0.135
$MIDAS-VRP-RV^{(med)}$											0.034	0.055	0.066	0.085	0.123
$MIDAS-VRP-RV^{(min)}$											0.033	0.056	0.070	0.083	0.128
$MIDAS-VRP-RV^{(-)}$											0.031	0.053	0.062	0.084	0.111
$MIDAS-VRP-RV^{(+)}$											0.032	0.053	0.070	0.096	0.129
								MPU							
$Non-oil$	5.376	6.827	7.390	7.225	6.383	7.478	11.873	12.687	12.650	18.407	13.665	17.075	18.656	18.214	18.621
$MIDAS-RV$	5.394	7.110	6.943	5.525	6.676	7.240	12.165	13.211	11.163	16.277	11.779	14.642	16.723	16.243	15.881
$MIDAS-RV^{(s)}$	5.394	7.110	6.943	5.526	6.676	7.240	12.165	13.210	11.164	16.277	11.779	14.643	16.722	16.246	15.881
$MIDAS-RV^{(b)}$	5.394	7.110	6.943	5.526	6.675	7.240	12.165	13.212	11.164	16.277	11.779	14.643	16.722	16.246	15.880
$MIDAS-RV^{(med)}$	5.394	7.110	6.944	5.526	6.676	7.240	12.165	13.213	11.164	16.278	11.779	14.643	16.722	16.246	15.882
$MIDAS-RV^{(min)}$	5.393	7.110	6.943	5.526	6.676	7.239	12.165	13.212	11.164	16.277	11.779	14.644	16.721	16.246	15.881

$MIDAS-RV^{(-)}$	5.393	7.110	6.943	5.526	6.678	7.239	12.166	13.213	11.162	16.276	11.779	14.641	16.724	16.242	15.888
$MIDAS-RV^{(+)}$	5.393	7.110	6.943	5.525	6.675	7.239	12.166	13.208	11.163	16.274	11.780	14.642	16.721	16.244	15.881
$MIDAS-RV^{(sj)}$	5.394	7.110	6.942	5.523	6.678	7.242	12.164	13.211	11.159	16.275	11.781	14.642	16.716	16.237	15.887
$MIDAS-OVX$	5.393	7.110	6.943	5.526	6.677	7.240	12.166	13.211	11.161	16.278	11.778	14.642	16.720	16.243	15.888
$MIDAS-VRP-RV$	5.393	7.109	6.942	5.524	6.676	7.240	12.166	13.208	11.159	16.275	11.779	14.640	16.722	16.239	15.882
$MIDAS-VRP-RV^{(s)}$	5.393	7.109	6.942	5.524	6.677	7.240	12.166	13.208	11.158	16.275	11.779	14.639	16.721	16.239	15.884
$MIDAS-VRP-RV^{(b)}$	5.394	7.109	6.942	5.525	6.676	7.240	12.166	13.209	11.159	16.275	11.779	14.640	16.722	16.241	15.880
$MIDAS-VRP-RV^{(med)}$	5.394	7.109	6.944	5.525	6.677	7.241	12.165	13.212	11.160	16.275	11.779	14.641	16.723	16.241	15.884
$MIDAS-VRP-RV^{(min)}$	5.394	7.109	6.943	5.525	6.677	7.240	12.166	13.210	11.160	16.275	11.779	14.641	16.722	16.242	15.885
$MIDAS-VRP-RV^{(-)}$	5.393	7.109	6.943	5.525	6.676	7.240	12.165	13.212	11.159	16.275	11.779	14.641	16.723	16.242	15.884
$MIDAS-VRP-RV^{(+)}$	5.394	7.109	6.942	5.523	6.675	7.241	12.166	13.208	11.159	16.275	11.780	14.643	16.720	16.236	15.881

Note: MPU figures are multiplied by 10^{-3} so that they can fit to the table.

Table A.5: Oil price forecast evaluation based on conditional forecasts of macroeconomic conditions – VAR and SVAR models. Evaluation period: 2014.12-2017.10.

	MSPE – *Level data*					MSPE – *m-o-m change*					MSPE – *y-o-y change*				
	Forecasting horizon in months					Forecasting horizon in months					Forecasting horizon in months				
<u>*Model:*</u>	1	3	6	9	12	1	3	6	9	12	1	3	6	9	12
	Core CPI														
VAR	0.001	0.001	0.003	0.004	0.006	0.001	0.001	0.002	0.002	0.003	0.001	0.002	0.003	0.005	0.005
BVAR	0.001	0.001	0.003	0.004	0.006	0.001	0.001	0.002	0.002	0.003	0.001	0.002	0.003	0.005	0.005
	IP														
VAR	0.247	0.949	2.323	4.673	7.945	0.332	1.503	4.351	9.168	15.330	0.644	2.629	5.502	9.247	11.328
BVAR	0.247	0.949	2.323	4.673	7.949	0.332	1.504	4.352	9.168	15.333	0.644	2.628	5.495	9.236	11.313
	PPI														
VAR	3.236	21.008	59.038	94.015	152.511	1.552	6.101	16.752	26.403	31.110	2.302	8.607	24.051	33.947	42.897
BVAR	3.239	21.053	59.167	94.061	152.614	1.558	6.103	16.737	26.403	31.094	2.306	8.652	24.182	33.988	42.895
	BEIR														
VAR											0.0297	0.037	0.027	0.053	0.089
BVAR											0.0288	0.038	0.041	0.052	0.055
	MPU														
VAR	5.392	6.904	6.762	5.402	6.461	7.237	11.832	12.762	10.938	15.568	11.776	14.187	16.150	15.636	15.183
BVAR	5.393	6.905	6.764	5.401	6.463	7.240	11.833	12.763	10.945	15.570	11.779	14.186	16.150	15.619	15.199

Note: MPU figures are multiplied by 10^{-3} so that they can fit to the table.