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for Eurozone and Greece: How useful
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BANK OF GREECE
Economic Analysis and Research Department – Special Studies Division
21, E. Venizelos Avenue
GR-102 50 Athens
Tel: +30210-320 3610
Fax: +30210-320 2432

www.bankofgreece.gr

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FORECASTING MACROECONOMIC INDICATORS FOR EUROZONE AND GREECE: HOW USEFUL ARE THE OIL PRICE ASSUMPTIONS?

George Filis
University of Patras

Stavros Degiannakis
Bank of Greece

Zacharias Bragoudakis
Bank of Greece

Abstract

This study evaluates oil price forecasts based on their economic significance for macroeconomic predictions. More specifically, we first use the current state-of-the-art frameworks to forecast monthly oil prices and subsequently we use these forecasts, as oil price assumptions, to predict eurozone and Greek inflation rates and industrial production indices. The macroeconomic predictions are generated by means of regression-based models. We show that when we assess oil price forecasts, based on statistical loss functions, the MIDAS models, as well as the futures-based forecasts outperform those generated by the VAR and BVAR models. By contrast, in terms of their economic significance we show that none of the oil price forecasts are capable of providing predictive gains for the eurozone core inflation rate and the Greek industrial production index, whereas some gains are evident for the eurozone industrial production index and the Greek core inflation rate. However, in all cases the oil price forecasting models, including the random-walk, generate equal macroeconomic predictive accuracy. Thus, overall, we show that it is important to assess oil price forecasting frameworks based on the purpose that they are designed to serve, rather than based on their ability to predict oil prices *per se*.

Keywords: Oil price forecasts, MIDAS, conditional forecasts, core inflation, industrial production

JEL-classifications: C53, E27, E37, Q47

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Correspondence:

George Filis
University of Patras
Department of Economics
University Campus, 26504, Rio

1. Introduction

Over the last 15 years there is an increased interest in developing modelling frameworks for accurate oil price forecasts. Such interest stems from the fact that oil price forecasts are useful for numerous stakeholders, such as, industrial businesses, households, as well as, policy makers (Elder and Serletis, 2010; Baumeister *et al.*, 2014). For instance, the European Central Bank (ECB) uses the future path of oil prices in their macroeconomic projection exercises (ECB, 2016). They do so by using the futures oil prices, although they suggest that such an approach could lead to sizeable projection errors on macroeconomic variables (ECB, 2015). Even more, according to Baumeister and Kilian (2014a), the International Monetary Fund (IMF) uses oil price forecasts when assessing the economic outlook.

The fact that policy makers such as the ECB and IMF explicitly state that they rely on oil price forecasts for making informed decision, highlights the importance of assessing oil price forecasts based on their economic significance. Alquist et al. (2013) state that successful oil price forecasts are those that can improve macroeconomic forecasting. By contrast, we observe that the extant literature relies on developing accurate oil price forecasts, which are solely assessed based on statistical loss functions (see, for instance, Baumeister and Kilian 2012; 2014b; 2015; Baumeister *et al.*, 2015; Degiannakis and Filis, 2018). Hence, the current literature has neglected to assess whether accurate oil price forecasts are also economically useful when they are used for macroeconomic projections.

Given this important gap, the current report first generates oil price forecasts using the current state-of-the-art modelling frameworks and subsequently uses these forecasts to generate macroeconomic projections for two key indicators, namely, inflation and industrial production, for both the eurozone and Greece. Hence, we evaluate the quality of oil price forecasts based on their ability to generate accurate macroeconomic projections.

Assessing oil price forecasting frameworks based on their economic significance is of major importance for the eurozone and Greece. First, the eurozone and its member-countries are among the top global oil importers and thus their economic performance is impacted by oil price fluctuations. Second, such analysis could enable policy makers to make better assessments of the economic outlook.

The remainder of this report is structured as follows. Section 2 details the data that are used in the present study. Section 3 describes the oil price forecasting frameworks that are used in the study, primarily focusing on the MIDAS model, which is the more recently developed model. Section 4 explains the regression-based predictive models for the macroeconomic indicators and Section 5 analyses the empirical findings. Section 6 concludes the report.

2. Data description

2.1 Data for oil price forecasts

For our oil price forecasts we use both the fundamentals of the oil market, as well as an uncertainty measure of oil prices. The oil market fundamentals comprise monthly data for the global oil production (*Prod*), the global economic activity index (*GEA*), global oil stocks (*Stocks*) and the capacity utilisation (*Cap*). The data are obtained from the Federal Reserve Bank of St. Louis database, Lutz Kilian at the Federal Reserve Bank of Dallas, and the US Energy Information Administration.

However, given that recent efforts in the oil price forecasting literature employ the Mixed-Data Sampling (MIDAS) model (Degiannakis and Filis, 2018), we also use tick-by-tick data for the front-month Brent futures contracts, which we use to construct the daily Brent oil price volatility measures. These measures serve as our high-frequency data. The volatility measures are described in Section 2.1.1. The tick-by-tick data are obtained from TickData.

The study period is from 4th January 2010 until 30th August 2020 and it is dictated by the availability of the ultra-high-frequency data.

2.1.1. Brent intraday realized volatility measures

Degiannakis and Filis (2018) show that the use of the MIDAS framework, with the oil price volatility as the high-frequency predictor, can generate accurate oil price forecasts. Following their study, we construct seven oil price realized volatility measures, which are the most frequently used in the finance literature.

Let us denote as $r_{t,i} = (1 - L)\log(Oil_{t,i})$, the i^{th} intraday return at day t , with τ number of one-minute intervals within a trading day and as $Oil_{t,i}$ the i^{th} one-minute oil

price at day t . So, we estimate the realized volatility (RV_t) as $RV_t = \sum_{i=1}^{\tau} r_{t,i}^2$, the realized bipower variation ($RV_t^{(bpv)}$) as $RV_t^{(bpv)} = (2/\pi)^{-1} (\frac{\tau}{\tau-1}) \sum_{i=1}^{\tau-1} |r_{t,i}| |r_{t,i+1}|$, the median realized volatility ($RV_t^{(med)}$) as $RV_t^{(med)} = \frac{\pi}{6-4\sqrt{3}+\pi} (\frac{\tau}{\tau-2}) \sum_{i=2}^{\tau-1} \text{med}(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|)^2$, the minimum realized volatility ($RV_t^{(min)}$) as $RV_t^{(min)} = \frac{\pi}{\pi-2} (\frac{\tau}{\tau-1}) \sum_{i=1}^{\tau-1} \text{min}(|r_{t,i}|, |r_{t,i+1}|)^2$, the positive semi variance ($RV_t^{(pos)}$) as $RV_t^{(pos)} = \sum_{i=1}^{\tau} I\{r_{t,i} \geq 0\} r_{t,i}^2$ and the negative semi variance ($RV_t^{(neg)}$) as $RV_t^{(neg)} = \sum_{i=1}^{\tau} I\{r_{t,i} < 0\} r_{t,i}^2$, where $I\{\cdot\}$ is an indicator function that takes the value 1 if the argument is true. Moreover, we consider the difference between the positive and negative semi variance: $RV_t^{(sj)} = RV_t^{(+)} - RV_t^{(-)}$.

Detailed information for the statistical properties of the proposed measures can be found in Andersen and Bollerslev (1998), Barndorff-Nielsen and Shephard (2004), Andersen *et al.* (2012), and Barndorff-Nielsen *et al.* (2010). The RV_t has been applied in the majority of ultra-high frequency financial studies. The $RV_t^{(bpv)}$ is robust to the presence of jumps. The $RV_t^{(med)}$ is less sensitive to the existence of zero intraday returns. The $RV_t^{(pos)}$ and $RV_t^{(neg)}$ capture the variation solely from positive and negative returns.

The choice of using seven different volatility measures, rather than a single one, is that each of these measures can provide different information at different time periods. Hence, it is important to test whether there is a specific volatility measure that could provide the most accurate oil price forecasts and/or the most accurate macroeconomic forecasts.

2.2. Data for macroeconomic forecasts

For the macroeconomic forecasts we use the eurozone and Greek monthly core inflation rates and industrial production indices, for the period January 2010 to August 2020. We further use the eurozone and Greek monthly unemployment rates and quarterly non-accelerating inflation rate of unemployment (NAIRU) for the same period. The latter variables are used for the regression-based predictions of the core inflation rate. The data are obtained from Eurostat.

3. Forecasting modelling framework

3.1. Oil price forecasting models

As aforementioned in Section 1, we first use the current state-of-the-art modelling frameworks for oil price forecasting, which are (i) the Mixed-Data Sampling (MIDAS) model, which forecasts monthly oil prices using both low- and high-frequency data (Baumeister *et al.*, 2015; Degiannakis and Filis, 2018), (ii) the Vector Autoregressive (VAR) and Bayesian VAR models (BVAR) (e.g. Baumeister and Kilian 2012; 2014b; 2015; Baumeister *et al.*, 2015), which are based on oil market fundamentals, as well as, the futures-based forecasts (e.g. Alquist and Kilian, 2010). Table 1 reports some key studies in the oil price forecasting literature, along with the methods they use and the forecasting horizon.

[TABLE 1 HERE]

3.1.1. MIDAS framework

We model the monthly crude oil prices to be driven by the daily oil price volatility along with monthly oil price fundamentals based on the studies of Baumeister *et al.* (2015) and Degiannakis and Filis (2018). The daily oil price volatility information set includes the various realized volatility measures of oil price, which reflect the uncertainty in the oil market. 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 the oil futures price monthly returns as $y_t = (1 - L)\log(Oil_t)$. The vector $\mathbf{Z}_t = (Gea_t, (1 - L)\log(Prod_t), (1 - L)\log(Stocks_t), Cap_t)'$ includes the fundamental explanatory variables, which are available at a monthly frequency. The $\mathbf{UNC}_{(t)}^{(D)}$ defines the vector of realized volatilities, which are presented in Section 2.1.1. So, the MIDAS model estimates the non-linear relationship between monthly oil price returns, \mathbf{Z}_t and $\mathbf{UNC}_{(t)}^{(D)}$:

$$y_t = \mathbf{Z}'_{t-i}\boldsymbol{\beta} + \sum_{r=0}^{k-1} \mathbf{UNC}'_{(t-r-is)}^{(D)} \left(\sum_{j=0}^p r^j \boldsymbol{\theta}_j \right) + \varepsilon_t, \quad (1)$$

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

Eq. 1 shows that the present month's oil prices are related with the oil market fundamentals up to i lagged months and the uncertainty measures up to $is + r$ lagged days. For example, setting $i \geq 1$ and $is \geq 22$ we can predict the one-month ahead oil price and for $i \geq 3$ and $is \geq 66$ we can predict the three-months ahead oil price. More technical details regarding the estimation of MIDAS and technical details for k (the number of lagged days to be employed) and p (the dimension of the lag polynomial in the vector parameters $\boldsymbol{\theta}_j$) are available in Andreou *et al.* (2010, 2013) and Ghysels *et al.* (2006).

We estimate our oil price forecasts $Oil_{t+h|t}$, for the h -step ahead months, iteratively using only the available information at month t :

$$Oil_{t+h|t} = Oil_{t+h-1|t}^{(m)} e^{\left(\mathbf{F}'_{t-i+h} \boldsymbol{\beta}^{(t)} + \sum_{r=0}^{k-1} \mathbf{VOL}'_{(t-r-is)}^{(D)} \left(\sum_{j=0}^p r^j \boldsymbol{\theta}_j^{(t)} \right) \right)}. \quad (2)$$

3.1.2. VAR and BVAR models

Apart from the MIDAS framework, we further employ the standard VAR and BVAR models, which are developed by Kilian and Baumeister (Baumeister and Kilian, 2012, 2014a, 2015 for the technical details) and are based on the oil market fundamentals, namely, global oil production (*Prod*), global economic activity index (*GEA*), using 12 lags.

3.1.3 Futures-based forecasts

Motivated by Alquist and Kilian (2010) we use the most standard futures-based oil price forecasts, such as:

$$Oil_{t+h|t} = F_t^{(h)}, \quad (3)$$

where $F_t^{(h)}$ is the futures price of oil for $h = 1, 2, 3, \dots, 12$ months ahead.

Apart from the three aforementioned model classes (MIDAS, VAR and Futures-based), we also use the no-change forecast, based on a simple random-walk (RW) model.

3.2. Macroeconomic projections

Inspired by the relevant literature (e.g. Coibion and Gorodnichenko, 2015; and Gelos and Ustyugova, 2017), which assesses the in-sample impact of oil prices on inflation rates using an augmented Philips curve, we employ the same framework for our out-of-sample forecasts. In our case we use oil price forecasts, which are generated by the models of Section 3.1 to inform our inflation projections, such as that:

$$\begin{aligned} inf_{t+h}^{(m)} = & a + \sum_{i=1}^I \beta_i \left(inf_{t+h-i}^{(m)} \right) + \gamma(ungap_{t+h-1}) + \sum_{i=0}^I \delta_i \Delta(Oil_{t+h-i|t}^{(m)}) \\ & + e_{inf,t+h}, \end{aligned} \quad (4)$$

where, $inf_{t+h}^{(m)}$ denotes the h -step ahead forecast of the monthly change of the core inflation rate based on the different oil price forecasting models, m , for $h = 1, \dots, 12$ months. $Oil_{t+h-i|t}^{(m)}$ denotes the oil price forecasts from the different models, m , at month $t + h$. We should mention here that in order to avoid any forward-looking bias the $i \geq h$ condition must hold. The unemployment gap, $ungap$, is calculated as $ungap_{t+h-1} = un_{t+h-1} - nairu_{t+h-1}$ and $e_{inf,t+h}$ denotes the error term.

As far as the industrial production predictions are concerned, we use the following equation:

$$IndP_{t+h|t}^{(m)} = a + \sum_{i=1}^I \beta_i \left(IndP_{t+h-i}^{(m)} \right) + \sum_{i=0}^I \delta_i \Delta(Oil_{t+h-i|t}^{(m)}) + e_{IP,t+h}, \quad (5)$$

where, $IndP_{m,t+h}$ denotes the log of the industrial production index forecasts at month $t + h$, based on the different (m) oil price forecasting models ($Oil_{t+h|t}^{(m)}$) and $e_{IP,t+h}$ is the error term.

Eqs. (4) and (5) are estimated so as to assess whether oil price forecasts are economically useful for macroeconomic indicators predictions. Thus, in order to do so we also estimate the same equations without the oil price forecasting component

$(\sum_{i=0}^I \delta_i \Delta(Oil_{t+h-i|t}^{(m)}))$. The non-augmented models are named as non-oil models. Naturally, if oil price forecasts are economically useful, then the forecasts generated by eqs. (4) and (5) should be superior to these of the non-oil models.

3.3. Assessing the forecasting accuracy

Being in line with the forecasting literature we split our sample in halves and we use the first 1/2 of the available data for the initial in-sample estimation period, \tilde{T} (January 2010 - December 2014) and the remaining 1/2 of the observations for the out-of-sample evaluation period, \tilde{T} (January 2015 – August 2020).

We first assess the oil price forecasting performance of the competing models using the Mean Squared Predictive Error (MSPE), such as:

$$MSPE_{m,t} = \sum_{i=1}^{\tilde{T}} \frac{(Oil_{t+h|t}^{(m)} - Oil_{t+h})^2}{\tilde{T}}, \quad (6)$$

Subsequently we assess the forecasting performance of the macroeconomic predictive models, using again the MSPE, such as:

$$MSPE_{m,t} = \sum_{i=1}^{\tilde{T}} \frac{(Macro_{t+h|t}^{(m)} - Ind_{t+h})^2}{\tilde{T}}, \quad (7)$$

where $Macro_{t+h|t}^{(m)}$ is the prediction of each of the two macroeconomic indicators, based on each of the different (m) oil price forecasts.

4. Empirical analysis

4.1. Oil price forecasts evaluation based on a statistical loss function

We shall re-iterate that the aim of the report is to assess the economic significance of the oil price forecasts for macroeconomic projections. As we explained in Section 1, currently the empirical studies rely on the evaluation of oil price forecasts based on how close these are to the actual oil price at a future date. However, we posit that unless oil price forecasts are evaluated based on their economic significance, policy makers may make inappropriate decisions. Thus, oil price forecasts should be assessed based on their ability to improve macroeconomic forecasts.

In order to provide evidence on our hypothesis, we start the analysis from the evaluation of the oil price forecasts. Table 2 presents the results.

[TABLE 2 HERE]

From Table 2, which depicts a heat map with the MSPE of each competing model, we can identify that all models are able to outperform the random walk (RW) model, with some minor exceptions in the 9- and 12-months ahead horizons. Furthermore, it is evident that in the short-run horizons, i.e. from 2-months up to 6-months ahead, most of the MIDAS models are able to generate the smallest forecast errors, with the MIDAS-SJ being the model with the highest prediction accuracy in most cases. By contrast, in the 1-month ahead horizon, as well as, from the 7-months to 12-months ahead horizons, we observe that the futures-based forecast exhibits the lowest forecast error (with the exception being the 9-months ahead, when again the MIDAS-SJ reports the lowest forecast error). Nevertheless, in many cases the forecast errors of the MIDAS models are rather close to that of the futures-based model, for the longer-run horizons (7- to 12-months ahead) (see for instance, the MIDAS-RV and MIDAS-SJ). Interestingly enough, both the VAR and BVAR models are performing rather poorly in terms of their oil price forecasting accuracy.

Overall, these findings clearly suggest that by comparing oil price forecasting models in terms of their ability to generate accurate oil price forecasts, one can differentiate between the better and worse performing models. Based on these results, a policy maker should consider using either the MIDAS models (when interested in short-run macroeconomic predictions) or the futures-based forecasts (when interested in longer-run macroeconomic predictions). To assess whether such a claim can be valid, we turn to the next and most important part of this project, which evaluates the oil price forecasting frameworks based on their ability to generate accurate macroeconomic predictions, i.e., based on their economic usefulness.

4.2. Oil price forecasts evaluation based on their economic usefulness.

We continue the evaluation of the oil price forecasts, focusing on their economic significance. Our starting point is to assess which oil price forecasts could improve the

forecasts of core inflation rates for the eurozone and Greece¹. The results are shown in Table 3.

[TABLE 3 HERE]

Table 3 clearly shows two very important findings. First, the non-oil model for the eurozone outperforms all other models, which is suggestive of the fact that the augmented Philips curve, using the information extracted from the oil price forecasts, does not provide any predictive gains for the eurozone core inflation rate.

By contrast, the non-oil model for Greece is the worst performing model in all horizons. In fact, the incorporation of the oil price forecasts into the Philips curve model could improve the forecast of Greek core inflation rate from 1% up to 12%, relative to the non-oil model, depending on the forecasting horizon.

The fact that the forecasting improvement of the augmented Philips curve, relatively to the non-oil model, is evident for the Greek but not the eurozone's core inflation rate can be explained by the fact that the calculation of the latter may mask the effect of oil prices. In particular, the eurozone's inflation rate considers the price changes of consumer goods and services that are used by households across the whole euro area, hence it may smooth out the country-specific effects that oil prices exercise on price levels.

The second and most important finding is that the forecast errors of all forecasting models are extremely close, which suggests that the important predictive gains that the MIDAS and futures-based models demonstrated in Table 2, cannot be "translated" into predictive gains for the core inflation rate. Thus, if a policy maker considers the RW, the futures-based forecast or the MIDAS and VAR models for her core inflation prediction, the latter would be of the same quality.

Overall, the findings from the core inflation prediction suggests that unless the end-user of oil price forecasts, in this case the policy makers, assess oil price forecasts based on their economic usefulness, they cannot determine which is the best performing model.

¹ Please note that given our aim to evaluate oil price forecasts by means of conditional forecasting, we do not proceed with the direct forecast of the macroeconomic variables using MIDAS, VAR and BVAR models. We use these models to forecast oil prices that are subsequently used in our macroeconomic indicators' prediction models.

Next, we assess the economic significance of oil price forecasts for the prediction of the industrial production index. The results are shown in Table 4.

[TABLE 4 HERE]

Unlike the results for the core inflation rate, Table 4 shows that oil price forecasts can provide predictive gains for the eurozone's industrial production, which can be up to 16%, relatively to the non-oil model. Such a finding demonstrates the economic usefulness of oil price forecasts for the industrial production index. A close inspection, though, suggests that the MIDAS models offer very marginal predictive gains, relatively to the other competing oil price forecasting models, which once more suggests that the superior performance of the MIDAS framework on oil price forecasts (especially in the short-run horizons), does not convert into superior performance in the industrial production predictions, relatively to the other oil price forecasting models.

Turning our attention to the Greek industrial production predictions, we cannot report that any of the oil price forecasts are capable of improving the non-oil industrial production prediction model for Greece. This result could be the result of the specific out-of-sample period of the study, since Greece was recovering from the debt crisis. Hence, oil prices may have played the least role in the development of the country's industrial production index.

Despite the inability of the oil price forecasts to outperform the non-oil model for Greece's industrial production index, whereas they seem to add value for the eurozone's index, we can once more notice that all models exhibit similar performance. In particular, even in the case of the eurozone, none of the oil price forecasting models can provide superior industrial production predictions relatively to the no-change oil price forecast (i.e. the RW). Hence, even in the case of the industrial production index, we can confirm that oil price forecasting frameworks should be evaluated based on the purpose that they are designed to serve, rather than based on how close they can predict oil prices *per se*. Even more, we confirm that oil price forecasts can be economically useful, yet the current state-of-the-art forecasting frameworks are not capable of producing superior macroeconomic predictions relatively to the RW model.

5. Conclusion

The aim of the current report is to assess which oil price forecasting framework, based on the current state-of-the-art models, provides the most accurate forecasts for key macroeconomic indicators, such as inflation and industrial production. The predictive ability of these forecasting frameworks is assessed against the futures prices of crude oil, which are used as oil price assumptions by ECB.

To do so we initially estimate three model classes for oil price forecasts, namely, MIDAS, VAR-type and futures-based models. Subsequently, we use the oil price forecasts from the different frameworks to predict two key macroeconomic indicators for the eurozone and Greece, namely, the core inflation rate and the industrial production index. We use data from January 2010 to August 2020 and the out-of-sample forecasting period is January 2015 until August 2020.

We report two main findings from our results. First, we convincingly show that oil price forecasts should be assessed based on the purpose that they are designed to serve. Thus, although we report that the MIDAS and futures-based forecasts are superior in their oil price forecasting performance, compared to the RW and the VAR-type models, this is not translated into superior performance on the macroeconomic predictions. In fact, the RW model can provide equally predictive accuracy for both core inflation rates and industrial production index predictions with the other competing models. Second, we show that oil price forecasts can be economically useful, although this is not across both macroeconomic indicators and both regions. Thus, further evidence should be collected from additional European countries, as well as, macroeconomic indicators.

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TABLES

Table 1: Selected empirical studies on oil price forecasting			
Authors	Forecasting frequency	Forecasting models	Forecasting horizon
Alquist and Kilian (2010)	Monthly forecasts	Futures-based, survey-based, hotelling method	1-12 months ahead
Baumeister and Kilian (2012)	Monthly forecasts	VAR, Bayesia VAR, Futures-based	1-12 months ahead
Alquist <i>et al.</i> (2013)	Monthly forecasts	VAR, Futures-based	1-12 months ahead
Baumeister and Kilian (2014)	Quarterly forecasts	VAR, Bayesian VAR, Regression-based, time-varying parameter	4 quarters ahead
Baumeister <i>et al.</i> (2014)	Monthly and Quarterly forecasts	VAR, Futures-based, Regression-based	1-24 months ahead, 1-8 quarters ahead
Baumeister and Kilian (2015)	Monthly and Quarterly forecasts	VAR, Futures-based, Regression-based, time-varying parameter	1-24 months ahead, 1-8 quarters ahead
Baumeister <i>et al.</i> (2015)	Monthly forecasts	VAR, Regression-based, MIDAS, Mixed Frequency-VAR	1-24 months ahead
Naser (2016)	Monthly forecasts	FAVAR, VAR, Regression-based, Dynamic Model	1-12 months ahead
Degiannakis and Filis (2018)	Monthly forecasts	Averaging VAR, Bayesian VAR, MIDAS	1-12 months ahead

Table 2: Oil price forecast evaluation based on the MSPE. Evaluation period: 2015.01-2020.08.

<i>Model:</i>	Forecasting horizon											
	1-month	2-months	3-months	4-months	5-months	6-months	7-months	8-months	9-months	10-months	11-months	12-months
RW	1163.010	1153.848	1163.824	1161.461	1176.941	1189.749	1195.886	1189.964	1192.990	1225.478	1258.528	1261.132
MIDAS-RV	35.926	60.347	109.226	145.318	165.199	364.460	270.031	461.470	1032.539	318.311	282.067	1191.166
MIDAS-BPV	32.861	59.206	117.735	152.029	162.194	428.741	279.932	493.463	909.630	336.114	328.664	1060.190
MIDAS-MedRV	37.650	66.127	110.234	145.614	156.490	352.871	312.083	488.908	992.475	338.768	299.897	1056.093
MIDAS-MinRV	33.042	64.087	119.554	142.223	157.134	440.885	296.017	460.484	858.096	376.592	279.096	1173.595
MIDAS-RSV-	35.775	60.525	105.092	145.348	165.806	584.609	255.829	386.137	1335.717	302.655	307.418	658.454
MIDAS-RSV+	34.880	59.456	112.758	149.970	157.792	470.554	363.373	483.149	1810.153	315.803	331.540	2754.121
MIDAS-SJ	34.191	73.015	98.453	141.942	137.155	175.149	234.186	255.479	217.250	351.704	421.384	518.017
VAR(12)	728.121	799.686	886.773	964.122	1039.587	1103.207	1165.326	1201.524	1239.714	1269.181	1309.089	1294.173
BVAR(12)	828.789	825.666	841.179	843.371	865.004	884.579	899.441	897.867	903.227	929.380	956.336	955.611
Futures	18.269	68.582	117.609	150.516	167.297	184.810	202.702	219.660	237.042	255.257	275.467	292.722

Note: Moving from the green to the red colours, the results show the best to the worse forecasting accuracy.

Table 3: Oil price forecast evaluation based on the predictions of the CPI. Evaluation period: 2015.01-2020.08.

<i>Model:</i>	Forecasting horizon											
	1-month	2-months	3-months	4-months	5-months	6-months	7-months	8-months	9-months	10-months	11-months	12-months
Eurozone												
Non-oil	0.0110	0.0116	0.0177	0.0231	0.0290	0.0387	0.0466	0.0575	0.0717	0.0839	0.1007	0.1206
RW	1.0374	1.0527	1.0641	1.0678	1.0721	1.0608	1.0586	1.0585	1.0632	1.0694	1.0752	1.0745
MIDAS-RV	1.0374	1.0528	1.0640	1.0679	1.0721	1.0608	1.0587	1.0586	1.0632	1.0694	1.0752	1.0744
MIDAS-BPV	1.0374	1.0527	1.0641	1.0679	1.0721	1.0608	1.0587	1.0586	1.0632	1.0694	1.0752	1.0744
MIDAS-MedRV	1.0373	1.0527	1.0641	1.0679	1.0721	1.0608	1.0587	1.0586	1.0632	1.0694	1.0752	1.0744
MIDAS-MinRV	1.0373	1.0527	1.0641	1.0679	1.0721	1.0608	1.0587	1.0586	1.0632	1.0694	1.0752	1.0744
MIDAS-RSV-	1.0374	1.0527	1.0641	1.0679	1.0721	1.0608	1.0587	1.0586	1.0632	1.0694	1.0752	1.0744
MIDAS-RSV+	1.0374	1.0527	1.0640	1.0679	1.0721	1.0608	1.0587	1.0586	1.0631	1.0694	1.0752	1.0743
MIDAS-SJ	1.0375	1.0527	1.0641	1.0678	1.0721	1.0608	1.0587	1.0586	1.0632	1.0695	1.0753	1.0745
VAR(12)	1.0374	1.0525	1.0641	1.0676	1.0720	1.0604	1.0584	1.0583	1.0630	1.0692	1.0750	1.0742
BVAR(12)	1.0373	1.0526	1.0641	1.0678	1.0721	1.0608	1.0586	1.0585	1.0631	1.0694	1.0752	1.0744
Futures	1.0374	1.0527	1.0641	1.0678	1.0721	1.0608	1.0586	1.0585	1.0632	1.0694	1.0752	1.0744
Greece												
Non-oil	0.0537	0.1288	0.1953	0.2685	0.3608	0.4435	0.5141	0.5878	0.6684	0.7599	0.8618	0.9992
RW	0.9904	0.9457	0.8836	0.8608	0.8832	0.9080	0.9212	0.9317	0.9508	0.9552	0.9629	0.9699
MIDAS-RV	0.9899	0.9457	0.8839	0.8610	0.8834	0.9080	0.9214	0.9319	0.9506	0.9555	0.9632	0.9695
MIDAS-BPV	0.9902	0.9456	0.8837	0.8610	0.8834	0.9081	0.9214	0.9319	0.9506	0.9555	0.9631	0.9695
MIDAS-MedRV	0.9901	0.9456	0.8837	0.8610	0.8833	0.9080	0.9214	0.9319	0.9506	0.9555	0.9631	0.9695
MIDAS-MinRV	0.9903	0.9456	0.8837	0.8610	0.8833	0.9080	0.9214	0.9319	0.9506	0.9555	0.9631	0.9695

MIDAS-RSV-	0.9898	0.9458	0.8836	0.8610	0.8834	0.9080	0.9214	0.9319	0.9506	0.9555	0.9631	0.9697
MIDAS-RSV+	0.9901	0.9456	0.8841	0.8610	0.8833	0.9080	0.9214	0.9319	0.9506	0.9554	0.9631	0.9694
MIDAS-SJ	0.9911	0.9456	0.8839	0.8613	0.8833	0.9081	0.9214	0.9318	0.9507	0.9557	0.9631	0.9698
VAR(12)	0.9900	0.9452	0.8833	0.8606	0.8831	0.9077	0.9211	0.9314	0.9506	0.9552	0.9629	0.9694
BVAR(12)	0.9902	0.9456	0.8835	0.8608	0.8832	0.9080	0.9212	0.9316	0.9507	0.9552	0.9629	0.9698
Futures	0.9904	0.9456	0.8835	0.8607	0.8831	0.9080	0.9211	0.9316	0.9507	0.9552	0.9629	0.9698

Note: For the non-oil model we show the actual MSPE, whereas for the remaining models we show the MSPE ratios which have been normalised relatively to the non-oil model. Moving from the green to the red colours, the results show the best to the worse forecasting accuracy.

Table 4: Oil price forecast evaluation based on the predictions of the IndP index. Evaluation period: 2015.01-2020.08.

<i>Model:</i>	Forecasting horizon											
	1-month	2-months	3-months	4-months	5-months	6-months	7-months	8-months	9-months	10-months	11-months	12-months
Eurozone												
Non-oil	1.0468	1.9010	2.3060	3.0266	4.0071	4.9947	6.2339	7.1772	8.2153	12.6751	29.8088	37.9184
RW	0.9789	0.9225	0.8788	0.8873	0.8750	0.8592	0.8522	0.8577	0.8432	0.8915	0.9917	1.0254
MIDAS-RV	0.9789	0.9225	0.8788	0.8873	0.8749	0.8590	0.8523	0.8577	0.8425	0.8915	0.9918	1.0253
MIDAS-BPV	0.9789	0.9224	0.8788	0.8873	0.8750	0.8590	0.8522	0.8576	0.8424	0.8915	0.9918	1.0253
MIDAS-MedRV	0.9789	0.9224	0.8787	0.8873	0.8750	0.8590	0.8521	0.8576	0.8424	0.8915	0.9918	1.0253
MIDAS-MinRV	0.9789	0.9224	0.8788	0.8873	0.8750	0.8590	0.8521	0.8576	0.8424	0.8913	0.9918	1.0254
MIDAS-RSV-	0.9788	0.9225	0.8787	0.8873	0.8749	0.8589	0.8522	0.8577	0.8424	0.8916	0.9918	1.0254
MIDAS-RSV+	0.9789	0.9225	0.8788	0.8873	0.8751	0.8591	0.8521	0.8578	0.8426	0.8915	0.9917	1.0254
MIDAS-SJ	0.9789	0.9224	0.8788	0.8872	0.8750	0.8591	0.8520	0.8576	0.8428	0.8916	0.9915	1.0253
VAR(3,12)	0.9789	0.9227	0.8792	0.8876	0.8754	0.8595	0.8526	0.8582	0.8437	0.8917	0.9918	1.0256
BVAR(3,12)	0.9789	0.9225	0.8788	0.8873	0.8750	0.8592	0.8522	0.8577	0.8432	0.8915	0.9917	1.0254
Futures	0.9789	0.9225	0.8788	0.8874	0.8751	0.8593	0.8522	0.8578	0.8433	0.8916	0.9917	1.0255
Greece												
Non-oil	4.7891	7.2613	8.7269	9.9621	11.4030	12.8210	12.6832	13.5582	14.4269	15.4300	16.8941	18.0236
RW	1.0970	1.1933	1.3336	1.4311	1.5610	1.5764	1.5618	1.4998	1.5649	1.5999	1.6392	1.7065
MIDAS-RV	1.0970	1.1933	1.3342	1.4304	1.5617	1.5752	1.5624	1.4997	1.5636	1.6014	1.6414	1.7053
MIDAS-BPV	1.0969	1.1933	1.3343	1.4304	1.5617	1.5751	1.5624	1.4994	1.5635	1.6014	1.6413	1.7054
MIDAS-MedRV	1.0970	1.1933	1.3343	1.4304	1.5618	1.5752	1.5623	1.4995	1.5634	1.6014	1.6414	1.7054
MIDAS-MinRV	1.0970	1.1933	1.3343	1.4304	1.5620	1.5751	1.5623	1.4995	1.5635	1.6012	1.6412	1.7053

MIDAS-RSV-	1.0970	1.1934	1.3343	1.4306	1.5613	1.5756	1.5623	1.4999	1.5634	1.6016	1.6413	1.7058
MIDAS-RSV+	1.0970	1.1933	1.3341	1.4303	1.5619	1.5751	1.5619	1.4995	1.5636	1.6012	1.6412	1.7047
MIDAS-SJ	1.0970	1.1935	1.3347	1.4311	1.5615	1.5768	1.5620	1.5012	1.5641	1.6020	1.6407	1.7059
VAR(3,12)	1.0971	1.1935	1.3333	1.4302	1.5598	1.5753	1.5611	1.4991	1.5637	1.5986	1.6382	1.7051
BVAR(3,12)	1.0967	1.1928	1.3326	1.4297	1.5592	1.5745	1.5600	1.4981	1.5631	1.5980	1.6374	1.7046
Futures	1.0970	1.1933	1.3335	1.4308	1.5606	1.5759	1.5613	1.4993	1.5644	1.5993	1.6386	1.7059

Note: For the non-oil model we show the actual MSPE, whereas for the remaining models we show the MSPE ratios which have been normalised relatively to the non-oil model. Moving from the green to the red colours, the results show the best to the worse forecasting accuracy.

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