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Claudia Foroni, Francesco Ravazzolo, Luca Rossini

Forecasting daily electricity prices with monthly macroeconomic variables

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Abstract

We analyse the importance of macroeconomic information, such as industrial production index and oil price, for forecasting daily electricity prices in two of the main European markets, Germany and Italy. We do that by means of mixed-frequency models, introducing a Bayesian approach to reverse unrestricted MIDAS models (RU-MIDAS). We study the forecasting accuracy for different horizons (from 1 day ahead to 28 days ahead) and by considering different specifications of the models. We find gains around 20% at short horizons and around 10% at long horizons. Therefore, it turns out that the macroeconomic low frequency variables are more important for short horizons than for longer horizons. The benchmark is almost never included in the model confidence set.

JEL codes: C11, C53, Q43, Q47.

Keywords: Density Forecasting, Electricity Prices, Forecasting, Mixed-Frequency VAR models, MIDAS models.

Non-technical summary

Electricity markets have received increased attention in the literature since their deregulation in the late 90s. There are several reasons motivating such interest. First, electricity is not storable and therefore demand and supply must always match. To achieve this, sophisticated markets have been created, where the one day-ahead hourly spot market is the main market in terms of volume. In the day-ahead spot market hourly prices are set by matching demand and supply. This market offers large amount of data and requires forecasts of both demand and price. Second, power grids are one of the most critical infrastructures and have a major role in sustainable development and economic growth.

The literature on price forecasting has mainly focused only on the day-ahead spot market. Two possible reasons are that the predictive power of predictors for day-ahead spot prices is usually short lived, and longer future markets are subject to low liquidity and highly correlated to spot prices. In this paper, we try to fill this gap and introduces a new methodology to produce mid-term spot price forecasts, that is forecasts of day-ahead spot prices up to one month ahead. In order to accomplish this, we suggest applying lower frequency predictors based on macroeconomic variables containing more valuable information for mid-term horizons as opposed to the regressors usually applied in short term price forecasting. This develops a model that maps the discrepancy in frequency between the daily prices and the monthly macro variables.

In the empirical study, we analyse the importance of macroeconomic information, such as industrial production index and oil price, for forecasting daily electricity prices in two of the main European markets, Germany and Italy. We achieve this by means of mixed-frequency models and introducing a Bayesian approach to reverse unrestricted MIDAS models (RU-MIDAS). We study the forecasting accuracy for different horizons (from 1 day ahead to 28 days ahead) by considering the different specifications of the models. We find gains of around 20% at short horizons and around 10% at long horizons. We reach the conclusion that the macroeconomic low frequency variables are more important for short horizons than for longer horizons.

1 Introduction

Electricity markets have received increased attention in the literature since their deregulation in the late 90s. There are several reasons motivating such interest. First, electricity is not storable and therefore demand and supply must always match. To achieve this, sophisticated markets have been created, where the one day-ahead hourly spot market is the main market in terms of volume. In the day-ahead spot market hourly prices are set by matching demand and supply. This market offers large amount of data and requires forecasts of both demand and prices. Second, power grids are one of the most critical infrastructures and have a major role in sustainable development and economic growth. The recent innovation in energy production and, in particular, the large increase in renewable energy resources (RES) have added complexity to the management of the electricity system, see Gianfreda et al. (2018) for an application of RES to predict day-ahead prices. Moreover, smart grids are the future technologies in power grid development, management, and control, see Yu et al. (2011) and Yu and Xue (2016). They have revolutionized the regime of existing power grids, by employing advanced monitoring, communication and control technologies to provide secure and reliable energy supply. And new technologies have changed energy consumption, making it necessary to use effective energy management strategies based on electricity prices and electricity load forecasts. As a consequence, a growing literature has investigated these dynamics and built forecasting models for several markets all around the world (Europe, United States, Canada, and Australia).

The literature on load forecasting has focused on three horizons: short-term load forecasts (from one hour to one week); mid-term load forecasts (from one week to one month) and long-term load forecasts (from one month to years); see, for example, Alfares and Nazeeruddin (2002) and Suganthi and Samuel (2012) for definitions and models. By contrast, the literature on price forecasting has mainly focused only on the day-ahead spot market, see Weron (2014) for a recent and detailed review. Two possible reasons are that the predictive power of predictors for day-ahead spot prices is usually short lived, and longer future markets are subject to low liquidity and highly correlated to spot prices. This paper tries to fill this gap and introduces a new methodology to produce mid term spot price forecasts, that is forecasts of day-ahead spot prices up to one month ahead. In order to accomplish this, it suggests applying lower frequency predictors based on macroeconomic variables containing more valuable information for mid-term horizons as opposed to the regressors usually applied in short-term price forecasting. Further, it develops a model to match the mismatch in frequency between the daily prices and the monthly macro variables.

In the last years, there is a growing interest in models that account for data of different frequencies for forecasting purposes. The focus in the literature has mostly been on improving the forecast of low-frequency variables by means of high-frequency information. In particular, different models have been introduced for dealing with the different sampling frequencies at which macroeconomic and financial indicators are available. The most common choice is to reduce the model to state space form and use the Kalman filter for forecasting (e.g. see Aruoba et al. (2009); Giannone et al. (2008); Mariano and Murasawa (2002) and in a Bayesian context Eraker et al. (2015); Schorfheide and Song (2015)). As an alternative choice, Ghysels (2016) develops a class of mixed-frequency VAR model, where both low- and high-frequency variables are included in the vector of dependent variables (see Blasques et al., 2016, for an application in small-scale factor model). This class of model is estimated by OLS, but the number of regressors tends to increases due to the stacking structure of the model.

In an univariate context, Ghysels et al. (2006) introduce MIDAS, which links directly low- to high-frequency data (see Clements and Galvão, 2008, 2009, for macroeconomic forecasting), but it requires a form of NLS estimation, which improves the computational costs substantially in model with more than one high-frequency explanatory variables. Foroni et al. (2015a) develop unrestricted MIDAS (U-MIDAS) model, which can be estimated by OLS and thus handle high-frequency explanatory variables. However, the U-MIDAS models have problems when the frequency mismatch is high, thus leading to a Bayesian extension of the literature on MIDAS and U-MIDAS, see Foroni et al. (2015b) and Pettenuzzo et al. (2016), and a stochastic volatility estimation method for U-MIDAS in density nowcasting (Carriero et al., 2015).

Recently, new models have been proposed for forecasting high-frequency variables by means of low-frequency variables. An example is the paper of Dal Bianco et al. (2012), who analyse the forecasts of the euro-dollar exchange rate at weekly frequency by means of macroeconomic fundamentals in a state-space form à la Mariano and Murasawa (2009). Ghysels (2016) contributes by introducing a mixed-frequency VAR model, which address both the prediction of high-frequency variables using low-frequency variables and vice versa. Furthermore, Foroni et al. (2018) introduce Reverse Unrestricted MIDAS (RU-MIDAS) and Reverse MIDAS (R-MIDAS) model for linking high-frequency dependent variable with low-frequency explanatory variables in univariate context.

From a methodological innovation point of view, this paper proposes a Bayesian approach to RU-MIDAS of Foroni et al. (2018) in order to incorporate low frequency information into models for the prediction of high frequency variables. We assess the performance of the proposed approach by evaluating the relevance of macroeconomic variables that are available at monthly frequency for forecasting the daily electricity prices in two of the most important European countries, Germany and Italy. We predict the daily electricity price at different horizons and we introduce different low frequency explanatory variables, such as the industrial production index evaluated at different levels and the oil prices. In the last years, a large and growing body of literature deals with the forecasting of daily electricity prices (see Weron, 2014, for a review). However, the main focus of the literature is on the forecasting of electricity prices influenced by variables with the same frequency, such as renewable energy sources (Gianfreda et al., 2018) or weather forecasts (Huurman et al., 2012). This empirical application draws on the literature using macroeconomic variables to improve the forecasting performance of single frequency models, due to the fact that macroeconomic variables are of interested in the diagnostic of electricity prices.

The results show that there is a strong improvement in the forecasting if we add daily oil price and monthly macroeconomic variables, at almost all horizons for Italy and at the short horizons for Germany. We find gains around 20% at short horizons and around 10% at long horizons. The benchmark is almost never included in the model confidence set. The improvement is visible for point and density forecasts, but also in terms of sign predictability, which is often used as a criterion in terms of goodness of the forecasts for those variables for which investment strategies are important.

The paper is organized as follows. Section 2 summarizes the RU-MIDAS models and the Bayesian approach. Section 3 presents the data used in the paper. In Section 4, we present the forecasting of daily electricity prices by using monthly macroeconomic variables. Section 5 provides further robustness on our results. Section 6 concludes.

2 RU-MIDAS model

Foroni et al. (2018) show the derivation of the reverse unrestricted MIDAS (RU-MIDAS) regression approach from a general dynamic linear model and its estimation procedure. Here we sketch the derivation, adapting it to our case of monthly/daily observations. For the sake of simplicity, we assume the following two variables of interest. Let us observe at high-frequency (HF) the variable x for $t = 0, \frac{1}{k}, \dots, \frac{k-1}{k}, 1$, while the variable y can be observed at low frequency (LF) every k periods for $t = 0, 1, 2, \dots$.

In our case, the variable x follows an AR(p) process

$$c(L)x_t = d(L)y_t^* + e_{xt}, \tag{1}$$

where y^* is the exogenous regressor; $d(L) = d_1 L + \dots + d_p L^p$, $c(L) = I - c_1 L - \dots c_p L^p$ and the errors are white noise. Furthermore, we assume that the starting values $y^*_{-p/k}, \dots, y^*_{-1/k}$ and $x_{-p/k}, \dots, x_{-1/k}$ are all fixed and equal to zero.

It is possible to introduce the lag operator for the low and high-frequency variables. In particular, let us define Z, the LF lag operator such that $Z = L^k$ and $Z^j y_t = y_{t-j}$; and the polynomial in the HF lag operator, $\gamma_0(L)$ with $\gamma_0(L)d(L)$ containing only $L^k = Z$. If we multiple Eq. (1) by $\gamma_0(L)$ and $\omega(L)$, we have

$$\gamma_0(L)c(L)\omega(L)x_t = \gamma_0(L)d(L)\omega(L)y_t^* + \gamma_0(L)\omega(L)e_{xt}, \quad t = 0, 1, 2, \ldots \tag{2}$$

where $\omega(L) = \omega_0 + \omega_1 L + \ldots + \omega_{k-1}L^{k-1}$ represents the temporal aggregation scheme by means of a polynomial. Moreover, if Eq. (2) is represented as

$$\tilde{c}_0(L)x_t = g_0(Z)y_t + \tilde{\gamma}_0(L)e_{xt}, \quad t = 0, 1, 2, \ldots, \tag{3}$$

where $g_0(Z)$ is the product of $\gamma_0(L)$ and $d(L)$ and function only of Z, Eq. (3) is called an exact reverse unrestricted MIDAS model. In particular, in Eq. (3), the high-frequency variable is a function of its own lags, of the LF lags of the observable variable y and of the error terms. Thus, the HF period influences the model specification. For each $i = 0, \ldots, k-1$, a lag polynomial in the HF lag operator, $\gamma_i(L)$, can be defined and the product $g_i(L) = \gamma_i(L)d(L)$ is a function only of power of Z. As seen above, if we multiple Eq. (1) by $\gamma_i(L)$ and $d(L)$, we have

$$\tilde{c}_i(L)x_t = g_i(L^{k+i})y_t + \tilde{\gamma}_i(L)e_{xt}, \quad t = 0 + \frac{i}{k}, 1 + \frac{i}{k} \ldots, \quad i = 0, \ldots, k-1 \tag{4}$$

such that a period structure in the RU-MIDAS is introduced.

Since the parameters of Eq. (1) are unknown and also $\gamma_i(L)$ cannot predetermined exactly, it is possible to use an approximate reverse unrestricted MIDAS (RU-MIDAS) models based on linear lag polynomial

$$\tilde{a}_i(L)x_t = b_i(L^{k+i})y_t + \xi_{it}, \quad t = 0 + \frac{i}{k}, 1 + \frac{i}{k} \ldots, \quad i = 0, \ldots, k-1 \tag{5}$$

where the orders of $\tilde{a}_i(L)$ and $b_i(L^{k+i})$ are larger enough such that ξ_{it} is a white noise. Since the error terms ξ_{it} are correlated across i, one could estimate the RU-MIDAS equations for different values of i by using a system estimation method. In particular, Eq. (5) can be grouped in a single equation by adding a proper set of dummy variables. In our empirical application, we consider a daily dependent variable and monthly explanatory variables such that the single-equation version of Eq. (5) is

$$x_t = \alpha_1 \left(1 - \sum_{i=2}^{28} D_i\right) y_{t-\frac{1}{28}} + \alpha_2 D_2 y_{t-\frac{2}{28}} + \cdots + \alpha_{28} D_{28} y_{t-\frac{28}{28}} +$$

$$
\begin{aligned}
&+\beta_{1,1}\left(1-\sum_{i=2}^{28} D_i\right) x_{t-\frac{1}{28}}+\beta_{1,2} D_2 x_{t-\frac{1}{28}}+\cdots+\beta_{1,28} D_{28} x_{t-\frac{1}{28}}+ \\
&+\beta_{2,1}\left(1-\sum_{i=2}^{28} D_i\right) x_{t-\frac{2}{28}}+\beta_{2,2} D_2 x_{t-\frac{2}{28}}+\cdots+\beta_{2,30} D_{28} x_{t-\frac{2}{28}}+ \qquad (6) \\
&+\beta_{3,1}\left(1-\sum_{i=2}^{28} D_i\right) x_{t-\frac{7}{28}}+\beta_{3,2} D_2 x_{t-\frac{7}{28}}+\cdots+\beta_{3,28} D_{28} x_{t-\frac{7}{28}}+v_t \quad t=0, \frac{1}{28}, \frac{2}{28}, \ldots,
\end{aligned}
$$

where $D_2, \ldots, D_{28}$ are dummy variables taking value one in each last 28-th day, last 27-th day and first day of the month respectively. It is possible to estimate the model in Eq. (6) by GLS to allow the possible correlation and heteroskedasticity. However, it may be difficult to estimate the model by using a frequentist approach, thus we use a Bayesian approach to solve this issue.

2.1 Bayesian approach

Contrary to most of the MIDAS literature, which follows a classic approach, in this paper we estimate our models with Bayesian techniques. Few papers so far have focused on the Bayesian estimation of regular MIDAS models (see, for example, Pettenuzzo et al. (2016) and Foroni et al. (2015b)). However, the Bayesian method has not yet been applied to the RU-MIDAS approach, as described in the previous section. Differently than the classical estimation, our Bayesian approach allows for estimation of complex nonlinear models with many parameters, is useful for imposing parameter restrictions and, above all, allows to compute probabilistic statements without any further assumption.

In this paper, therefore, we focus on introducing the Bayesian estimation in the RU-MIDAS model. We define prior information on the vector of coefficients and on the variance, using the independent Normal-Wishart prior as in Koop and Korobilis (2010) adapted to univariate time series, thus a Normal-Gamma prior.

This section is devoted to the study of prior and posterior inference on the vector of coefficients of the autoregressive model and on the variance coefficient. In particular, we work with a prior which has AR coefficients and variance coefficients being independent each other, thus it is called independent Normal-Gamma prior.

The general prior for this kind of model, which does not involve the restrictions of the natural conjugate prior, is the independent Normal Gamma prior. Let us assume γ be the vector of the AR coefficients defined in equation (6) and made by $\alpha_1, \ldots, \alpha_{28}, \beta_{1,1}, \ldots, \beta_{1,28}, \beta_{3,1}, \ldots, \beta_{3,28}$ and σ^2 be the variance coefficients, thus the independent prior can be represented as $p(\gamma, \sigma^{-2}) = p(\gamma)p(\sigma^{-2})$. In this case, the prior for γ is a normal distribution:

$$\gamma \sim \mathcal{N}\left(\underline{\gamma}, \underline{V}_{\gamma}\right), \tag{7}$$

while the prior for the variance coefficients is a Gamma distribution

$$\sigma^{-2} \sim \mathcal{G}a(\underline{a}, \underline{b}) \tag{8}$$

By using these priors, the joint posterior $p(\gamma, \sigma^{-2}|x)$ has not a convenient form, but the conditional posterior distribution have a closed form. In particular, the posterior distribution for the vector of AR coefficients is:

$$\gamma|x, \sigma^{-2} \sim \mathcal{N}\left(\overline{\gamma}, \overline{V}_{\gamma}\right) \tag{9}$$

where the posterior mean and posterior variance are:

$$\begin{aligned}
\overline{V}_{\gamma} &= \left(\underline{V}_{\gamma}^{-1} + \frac{1}{\sigma^2}\sum_{t=1}^{T} z_t z_t\right)^{-1} \\
\overline{\gamma} &= \overline{V}_{\gamma}\left(\overline{V}_{\gamma}\underline{\gamma} + \frac{1}{\sigma^2}\sum_{t=1}^{T} z_t x_t\right),
\end{aligned}$$

where z_t is the vector containing the explanatory variables $y_{t-\frac{1}{28}}, \ldots, y_{t-\frac{28}{28}}$ and the lagged dependent variables $x_{t-\frac{1}{28}}, \ldots, x_{t-\frac{7}{28}}$.

Moreover, the posterior distribution for the variance coefficients is:

$$\sigma^{-2}|\gamma, x \sim \mathcal{G}a(\overline{a}, \overline{b}) \tag{10}$$

where the posterior hyperparameters are

$$\begin{aligned}
\overline{a} &= \frac{T + \underline{a}}{2} \\
\overline{b} &= \underline{b} + \sum_{t=1}^{T}(x_t - z_t\gamma)^2
\end{aligned}$$

We estimate the Bayesian model described above using the Bayesian Markov chain Monte Carlo (MCMC) methods. We have used the Gibbs sampling algorithm for both prior distributions and all our results are based on samples of 6.000 posterior draws, with a burn-in period of 1.000 iterations. Moreover, we choose the prior hyperparameters such that the prior are not informative.

Regarding the forecasting techniques adopted in the paper, we use the direct forecasting method (see, e.g. Marcellino et al., 2006) since the forecasting of the future values of the explanatory variable y are not required, although the model specification should change for each forecasting horizon considered.

3 Data Description

In this section we describe the two datasets analysed in the application. In particular, we consider two of the most important European countries from a macroeconomic and energy point of view, Germany and Italy, both parts of the G8 economies.

We use daily day-ahead prices (in levels) to estimate models for electricity traded/sold in Germany and Italy. Moreover, we employ different monthly macroeconomic variables, which either differ by country, such as industrial production index; or are equal for all the countries, such as the oil prices. The national electricity prices are obtained directly from the corresponding power exchanges. In particular, the German daily auction prices of the power spot market is collected from the *European Energy Exchange* EEX, whereas the daily single national prices PUN are collected from the Italian ISO.

In terms of macroeconomic variables, we consider the total industrial production index for Germany and Italy, and its main components: consumer goods (IPI-Cons, i.e. the consumer durable goods); electricity (IPI-Elec, i.e. the activity of providing electric power, natural gas, steam, hot water and the like through a permanent infrastructure (network) of lines, mains and pipes) and manufacturing (IPI-Manuf, i.e. the activities in the manufacturing section involve the transformation of materials into new products) . The data are taken from Eurostat and are seasonally and calendar adjusted.

The sample spans from 1 January 2006 to 31 December 2017 for both countries. We use the first six years as estimation sample and the last six years as forecast evaluation period. The historical dynamics of these series observed in Germany are reported in Fig. 1 (see Fig. 2 for Italy). Prices clearly show the new stylized fact of "downside" spikes together with mean-reversion. On the other hand, the oil prices shows two strong falls, the first around the end of 2008 and the beginning of 2009; the second around the end of 2014. Regarding the first fall, the drop in oil prices that started in 2008 takes place against the backdrop of the Global Financial Crisis (aka The Great Recession). In fact, the oil prices drop from historic highs of $141,06$\$ in July 2008 to 40.07\$ in March 2009. After an increase of the oil prices in the following years, the second fall appears in the fourth quarter of 2014 as robust global production exceeded demand, thus leading to a sharp decline.

Regarding the other macroeconomic variable of interest, the industrial production index (IPI), it shows a different behaviour between the two countries. In fact, in Germany, the industrial product index follows the first drop of the oil prices in 2008/2009, while it leads to a constant slow increase in the following years. On the other hand, the situation in Italy is completely different since after the fall in 2008, the situation remains the same or slightly decreases in the subsequent years, with a tiny increase at the end of 2017.

4 Empirical Results

In this section we present the results for the forecasting of daily electricity prices by means of different macroeconomic variables. In particular, the first estimation sample in the forecasting exercise extends from January 2006 to December 2011, and it is then extended recursively by keeping the size of the estimation window fixed to 6 years in such a way we perform a rolling window estimation. For each day of the evaluation sample, we compute forecasts from 1 to 28 days ahead, and we assess the goodness of our forecasts using different point and density metrics.

4.1 Forecasting framework

Regarding the accuracy of point forecasts, we use the root mean square errors (RMSEs) for each of the daily prices and for each horizons. Whereas, to evaluate density forecasts, we use both the average log predictive score, viewed as the broadest measure of density accuracy (see Geweke and Amisano, 2010) and the average continuous ranked probability score (CRPS). The latter measure does a better job of rewarding values from the predictive density that are close and not equal to the outcome, thus it is less sensitive to outlier outcome (see, e.g. Gneiting and Raftery, 2007; Gneiting and Ranjan, 2011).

As seen in Eq. (6), one can evaluate different RU-MIDAS model based on different lags order of the high-frequency variables and on the inclusion of different low-frequency variables. As suggested in Knittel and Roberts (2005), Weron and Misiorek (2008) and Raviv et al. (2015), we consider a RU-MIDAS model with lag order of the electricity prices equal to 7. In particular, this model includes only the first, second and the seventh lag of the daily electricity prices; with an abuse of notation we will set $p = 3$ and consequently AR(3). Moreover, due to the seasonal components of the daily electricity prices, we include seasonal dummies representing each season of the year: spring, summer, autumn and winter, respectively. In the benchmark models, called BAR(3), the estimation is provided by using a Normal-Gamma prior and the same prior as been used also for the Bayesian RU-MIDAS model, called B-RU-MIDAS.

In our analysis, we focus also on another benchmark model, the autoregressive model of order 1 (BAR(1)), where only one lag of the daily electricity prices is included. Also for this benchmark model, we include seasonal dummies in the analysis.[1]

The main interest of the paper is forecasting daily electricity prices by using macroeconomic variables. Thus, we consider different macroeconomic explanatory variables in the construction of the models. In each model and for each country, as explanatory variables, we include the daily oil prices[2] and then we add different monthly specification of the industrial production index (IPI). In particular, we consider IPI based on the manufacturing sector (IPI-Manuf), on the activity of providing electric power (IPI-Elec) and on Main Industrial Groupings (MIG) for consumer goods (IPI-Cons). We analyse models where we include either all the IPI, only one of the index, or combinations of two indices (IPI-Cons-Elec, IPI-Cons-Manuf, IPI-Elect-Manuf).

As a robustness check, we consider models where different specification of the oil and macroeconomic variables are considered. In particular, we include an autoregressive model with the daily oil price and the same macroeconomic variables for all the days of the month, as explanatory variables. In this case, the tables provide BAR models with different lags of the electricity prices and only one lag of the daily oil price and of the interpolated IPI macroeconomic variables.

As further robustness, we look at Bayesian RU-MIDAS with Normal-Gamma prior where the low frequency variables are the monthly oil price and the monthly macroeconomic variables.[3]

In detail, in our tables we report the RMSE, average log predictive score and average CRPS for the benchmark BAR(3) and BAR(1) with seasonal dummies and with a Normal-Gamma prior. For the other Bayesian RUMIDAS models with Normal-Gamma prior (B-RU-MIDAS), we report: the ratios of each model's RMSE to the baseline BAR model, such that entries smaller than 1 indicate that the given model yields forecasts more accurate than those from the baseline; differences in score relative to BAR baseline, such that a positive number indicates a model beats the baseline; and ratios of each model's average CRPS relative to the baseline BAR model, such that entries smaller than 1 indicate that the given model performs better.

To test the predictive accuracy, we apply Diebold and Mariano (1995) t-tests for equality of the average loss (with loss defined as squared error, log score or CRPS).[4] The asterisks

[1]We have also run the forecasting exercise without including the seasonal dummies in both the benchmark models, but we do not find any interesting results. The tables representing these results are not presented in the paper due to lack of space and are available in the Supplementary Material, available upon request to the authors.

[2]The daily oil price has been interpolated over the weekends in order to have a full sample size.

[3]For both the robustness analyses, we have also run the model with only one lag of the electricity prices and the results are available upon request to the authors.

[4]Regarding density forecasts, we use equal weights and not adopt weighting scheme as in Amisano and Giacomini (2007)

denote if the differences in accuracy are statistically different from zero, with one, two or three asterisks corresponding to significance level 10%, 5% and 1% respectively. We use p-values based on one-sided test, where the benchmark models are the null hypothesis and the other models are the alternatives. We also employ the Model Confidence Set procedure of Hansen et al. (2011) to jointly compare the predictive power of all models. We use the R package MCS detailed in Bernardi and Catania (2016) and differences are tested separately for each class of models (meaning for each panel in the tables and for each horizon).

At the end of the section, we provide also an economic evaluation of our forecasts by studying the directional predictability of the daily electricity returns. As explained in Christoffersen and Diebold (2006), sign predictability may exist even in the absence of mean predictability and it provides useful indication in addition to density forecasting in terms of creating profitable investment strategies. The success rate (SR) is computed as the percentage of times a model correctly predicts the sign of future returns. In practice, if the success rate is equal to 1, then the model predicts the correct sign for all the forecasts, while if it is equal to zero, the model never predicts the correct sign.

4.2 Forecasting Results

Point forecasts

We start by evaluating the point forecast of the different models and in the first panel of Table 1 and 2, we present the RMSEs for different mixed frequency models relative to the benchmark model, the so called Bayesian AR(3) with seasonal dummies and Normal-Gamma prior.

Focusing first on Germany, in Table 1 we observe that the RMSE remains broadly constant over the horizons. Since we are predicting daily electricity prices, there is a strong improvement in the forecasting if we add daily oil price and monthly macroeconomic variables. In particular, the improvement is large in the first horizons, and in general for short-term forecasts, while at longer horizons, such that 21 and 28, the content of daily or macro information is less relevant and we even see a decrease in the forecasting performance, even if gains are still 10% relative to the benchmark. It is in general hard to rank the models with different macroeconomic indicators, where the performance of the different model specifications in terms of point forecasting is rather similar. However, what we find, is a strong evidence of statistically superior predictability by the alternative models to the benchmark at several horizons. The B-RU-MIDAS model with all the IPI variables and daily oil price gives the best statistic at one day ahead with a 23% reduction in RMSE, but also other versions of B-RU-MIDAS with Electricity IPI provide economically sizeable gains at those horizons. Moreover, B-RU-MIDAS with IPI variables provide also statistically gains at longer horizons, such that $h = 21$, 28.

For the case of Italy, results are shown in Table 2. Contrary to the case of Germany, for the case of Italy there is a strong movement of the RMSEs from the first horizon to the 28 horizon, moving from 8.54 to 10.73. Moreover, the models that consider all the industrial production indexes analysed in the paper or only the IPI for the consumer goods and the electricity sector tend to dominate in terms of forecasting performance. In particular, the B-RU-MIDAS with all the IPI macroeconomic variables leads to a reduction around 20% of the RMSE with respect to the benchmark model at the first horizons. On the other hand, when the horizon size increases, the B-RU-MIDAS models gain somewhat less, but still the reduction is 9% or 10% from the benchmark. Differently from Germany, in Italy there is less evidence of statistically superior predictability in terms of Model Confidence Set, but yes in terms of Diebold-Mariano tests, at longer horizons ($h = 14, 21$ and 28).

In particular, we notice that in both countries if we include IPI-Elec, that is the Industrial Production Index related to Electricity, gas, steam and air conditioning supply, the point forecast accuracy of the models increases with respect to model with only Industrial production of consumer good or manufacturing or both of them. The inclusion of Electricity IPI leads to better forecasting at first horizons, but also at long horizons with higher gains. These results are also confirmed by the Model Confidence set, since the models that include Electricity IPI have statistically superior predictability during all the horizon length with respect to the others. As an example, in Germany, the inclusion of Electricity IPI leads to statistically superior predictability of models that were including Manufacturing, while models with Manufacturing included and not electricity have no gains in term of predictability.

All in all, we can conclude that in terms of point forecasting, the inclusion of macroeconomic variables, such as the industrial production index, is very helpful in predicting electricity prices in Germany and Italy.

Density forecasts

We now focus on two different metrics for the density forecasts: the log predictive score and the CRPS, the second and third panel of Table 1 and 2, for Germany and Italy respectively. In general, the accuracy of density forecasts improves in the models with macroeconomic variables, where we observe substantial low CRPS across the models and horizons. As before, we observe generally higher CRPS values when the horizon increases from 1 to 28. In particular as in the point forecast analysis, the B-RU-MIDAS with all the monthly IPI variables and daily oil price gives the best statistics at one day ahead with a 26% reduction in average CRPS in Germany and with a 20% reduction in Italy. At longer horizons, as in the point forecast analysis, the inclusion of daily or macro information leads to lower gains, but still significant and around 10% better relative to the benchmark models. Differently from the point forecast, the B-RU-MIDAS in all the different models provide statistically gains at all the horizons and also at longer horizons for both countries.

Regarding the average log predictive score (see the third panel in Table 1 and 2), the results change with respect to the average CRPS. In particular, for Germany, the average log predictive likelihood shows higher increases at all horizons except for the last. The gains in term of log predictive score is higher in the models that include the Electricity IPI moving from a 16% at the first horizons to a 8% at the last horizons. In this case, there are no evidences of superior predictability of a models over the others, except that the models that include macroeconomic variables leads to gains with respect to the benchmark models. These analysis are less evident if we are looking at the Diebold-Mariano tests.

Also for Italy, the analysis confirms the previous results, but it is harder to find a model prevailing over the others. In this case, the gains of using macroeconomic variables is more stable over the horizons. Hence, the inclusion of macroeconomic variables leads to an increase of the 20% of forecasting accuracy at the first horizon and of 10% at longer horizons. Moreover, differently from Germany, the models that includes the exogenous variables leads to evidence in terms of Diebold-Mariano test over all the horizons. As previously described in Germany, also in Italy the inclusion of IPI Electricity leads to an improvement in the forecasting with respect to models that do not include it.

The statistically superior predictability of the models relative to the benchmark is stronger in the first seven horizon for Germany and at all the horizons for Italy.

Sign Predictability

While most of the studies in macroeconomic forecasting focus on the point and density forecasting, in our study we are also interested in the directional predictability of our models. In other words, we are interested in understanding whether (and how often) our models are able to predict correctly an increase (or decrease) of the price. In the last panel of Table 1 and 2 we report the success rate, i.e. the percentage of time that the model into question predicts the correct sign.

In the case of Germany, the B-RU-MIDAS model with different macroeconomic variables included does well with success rate higher than 70% at first horizons (till the third day horizon), and statistics above 60% in all the other cases and horizons. On the other side, the benchmark models is never above the 65% with a peak at the third day horizon. As stated before, the inclusion of the Industrial production index related to the electricity production

(IPI-Elec) in the models leads to better success rate in the models with respect to benchmark and models that are not analysing this IPI index. As an example, at horizon 28, the gains of adding Electricity IPI is 64%, while if we not consider it, the gains decreases at around 62%.

In the case of Italy, the benchmark model never exceeds the 65%, while the B-RU-MIDAS model with macroeconomic variables included have a success rate of 75% at third day horizon and never below 62% over all the horizons. The nature of IPI index is less relevant in the Italian case, in fact we can see that the inclusion of Electricity IPI leads to lower success rate with respect to the model that including all the IPI indexes. Thus moving the success rate at the 7-days horizon from 62% to 64%. However, this gain is more relevant with respect to the benchmark models.

5 Robustness

In this section we present a series of robustness checks, in order to further strengthen the evidence shown in Section 4.2.

First, we consider a simpler technique to deal with frequency mismatch, that is interpolation. In this case, we do not need a RU-MIDAS framework, but we simply run OLS regressions, where the monthly variable is transformed into a daily series by keeping the monthly value constant over the days of the month. Results are presented in Tables 3 and 4 in Appendix B.

Second, we instead consider RU-MIDAS models with monthly macroeconomic variables and monthly oil price. Results are shown in Tables 5 and 6) in Appendix B.

Third, we consider the same two robustness exercises just explained, but we consider a different benchmark, meaning including only one lag of daily information. Results are shown in Tables 9 and 11 for Germany and in Tables 10 and 12 for Italy.

Regarding the use of simple interpolation instead that RU-MIDAS techniques, Table 3 and 4 show that in terms of RMSE with interpolation we obtain only 5% gain with respect to the benchmark, while with RU-MIDAS we have found up to 25% gains. As an example, at the one-day horizon, the ratio relative to the benchmark of the model which includes daily IPI variables increases from 0.771 in the RU-MIDAS case to 0.958 in the case of interpolation for Germany, and from 0.810 to 0.955 for Italy. Looking at the metrics to evaluate density forecasts, we obtain a similar picture when we consider the CRPS, while results have a weak interpretation when looking at the predictive likelihood. A better performance of the RU-MIDAS model is visible also in terms of success rate.

The use of monthly oil price rather than daily, the results in terms of RMSE still deteriorates relative to the main results shown in 4.2, but not dramatically. For example, the ratio at the one-day horizon deteriorates of roughly one percent both for Germany and for Italy (see results in Tables 5 and 6). In terms of density forecasts, the use of monthly oil prices is surprisingly more relevant at longer horizons when looking at the CRPS. Possibly, the monthly interpolation of oil prices mitigates oil volatility and this is preferred at longer horizons. In terms of predictive likelihood, results are again similar to the main ones. The same for the success rate. These results, therefore, highlight that the RUMDAS models are performing better than the benchmark in terms of forecasting electricity prices.

Finally, regarding the different benchmark model, if we include only one lag of the daily electricity price, the interpretation of the results for point and density forecasts does not change and leads to the same interpretation as in the main exercise (see second panel in Table 7 and 8). In general though, results are more supportive of the inclusion of the three lags, and not only of the first (both the RMSE and the CRPS are smaller in absolute value for both the benchmark and alternative models when three lags are included).

6 Conclusions

This paper analyses for the first time to the best of our knowledge the forecasting performances of mixed frequency models for electricity prices. In particular, we use monthly macroeconomic variables for predicting daily electricity prices in two of the most important European countries, Germany and Italy. The paper studies how to incorporate low-frequency information from industrial production index and oil prices into models that forecasts high frequency variables, the daily electricity prices.

Our analysis of point and density forecasting performances covers different horizons (from one day to one month ahead) on the sample spanning from 2012 to 2017. Our results clearly indicate that the RU-MIDAS specifications with macroeconomic variables at different frequency (daily and monthly) dominate AR models, both in terms of point and density forecasting over all the horizons. Moreover, we find gains around 20% at short horizons and around 10% at long horizons, thus it turns out that the macroeconomic low frequency variables are more important for short horizons than for longer horizons. Moreover, the benchmark model is almost never included in the model confidence set. Another interesting results is related to the directional predictability gain of the models that includes macroeconomic variables. In fact, the success rate or sign predictability is stronger in the model that includes monthly industrial production index and daily oil price over all the horizons.

We conclude that from an energy forecasting perspective these mixed frequency models

Table 1: RMSE (first panel), average CRPS (second), average Predictive Likelihood (third) and Success rate (forth) for Germany for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with daily oil index and monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(3)	11.226	12.410	12.664	11.052	11.505	12.001	11.933
B-RU-MIDAS (All-IPI)	0.771***	0.742***	0.750***	0.903***	0.921***	0.916***	0.936***
B-RU-MIDAS (IPI-Cons)	0.771***	0.743***	0.751***	0.903***	0.922***	0.917***	0.937***
B-RU-MIDAS (IPI-Elec)	0.768***	0.740***	0.747***	0.898***	0.916***	0.909***	0.930***
B-RU-MIDAS (IPI-Manuf)	0.776***	0.749***	0.758***	0.912***	0.933***	0.928***	0.950**
B-RU-MIDAS (IPI-Cons-Elec)	0.770***	0.741***	0.748***	0.901***	0.919***	0.914***	0.935***
B-RU-MIDAS (IPI-Cons-Manuf)	0.773***	0.746***	0.754***	0.906***	0.926***	0.920***	0.939***
B-RU-MIDAS (IPI-Elec-Manuf)	0.770***	0.741***	0.749***	0.901***	0.920***	0.915***	0.936***
Average CRPS							
BAR(3)	5.995	6.702	6.812	5.689	5.930	6.184	6.227
B-RU-MIDAS (All-IPI)	0.737***	0.705***	0.716***	0.898***	0.917***	0.914***	0.930***
B-RU-MIDAS (IPI-Cons)	0.736***	0.705***	0.716***	0.897***	0.918***	0.915***	0.932***
B-RU-MIDAS (IPI-Elec)	0.733***	0.701***	0.712***	0.892***	0.911***	0.907***	0.924***
B-RU-MIDAS (IPI-Manuf)	0.742***	0.711***	0.724***	0.908***	0.930***	0.928***	0.946***
B-RU-MIDAS (IPI-Cons-Elec)	0.735***	0.702***	0.713***	0.895***	0.915***	0.912***	0.929***
B-RU-MIDAS (IPI-Cons-Manuf)	0.739***	0.709***	0.720***	0.901***	0.923***	0.919***	0.934***
B-RU-MIDAS (IPI-Elec-Manuf)	0.736***	0.704***	0.715***	0.897***	0.917***	0.913***	0.930***
Average predictive likelihood							
BAR(3)	-3.953	-4.055	-4.084	-4.032	-4.170	-4.221	-4.141
B-RU-MIDAS (All-IPI)	0.162***	0.147**	0.145**	0.124**	0.173**	0.136*	0.050
B-RU-MIDAS (IPI-Cons)	0.144**	0.137*	0.137*	0.103*	0.147*	0.097	0.076**
B-RU-MIDAS (IPI-Elec)	0.144**	0.166**	0.121*	0.124*	0.099	0.111	0.080**
B-RU-MIDAS (IPI-Manuf)	0.119*	0.159**	0.128*	0.118**	0.142*	0.064	0.057*
B-RU-MIDAS (IPI-Cons-Elec)	0.142**	0.155**	0.131*	0.125**	0.176**	0.116	0.084**
B-RU-MIDAS (IPI-Cons-Manuf)	0.140**	0.154**	0.127*	0.083	0.121*	0.112	0.085**
B-RU-MIDAS (IPI-Elec-Manuf)	0.137**	0.126*	0.138*	0.137**	0.142*	0.102	0.049
Success Rate							
BAR(3)	0.581	0.657	0.673	0.616	0.642	0.613	0.629
B-RU-MIDAS (All-IPI)	0.733	0.796	0.802	0.644	0.660	0.648	0.635
B-RU-MIDAS (IPI-Cons)	0.737	0.796	0.797	0.648	0.659	0.644	0.633
B-RU-MIDAS (IPI-Elec)	0.739	0.801	0.800	0.645	0.666	0.648	0.638
B-RU-MIDAS (IPI-Manuf)	0.734	0.797	0.798	0.644	0.656	0.639	0.625
B-RU-MIDAS (IPI-Cons-Elec)	0.731	0.798	0.800	0.648	0.661	0.649	0.636
B-RU-MIDAS (IPI-Cons-Manuf)	0.735	0.796	0.799	0.643	0.660	0.641	0.630
B-RU-MIDAS (IPI-Elec-Manuf)	0.734	0.796	0.800	0.646	0.658	0.647	0.637

Notes:

[1] The benchmark model is a Bayesian AR model with 3 lags and seasonal dummies.

[2] Please refer to Section 2 for details on model formulations. The B-RU-MIDAS indicates Bayesian RU-MIDAS with Normal-Gamma prior including 3 lags and seasonal dummies and with different exogenous variables. The B-RU-MIDAS includes daily Oil index and different monthly IPI variables. All forecasts are produced with recursive estimation of the models.

[3] For the BAR baseline models, the table reports the RMSEs, the average CRPSs and the average values of log predictive density scores (first row of each panel); for all other B-RU-MIDAS models, the table reports the ratios/differences between the current model and the benchmark.

[4] ***, ** and * indicate that the RMSE and CRPS ratios or score differences are significantly different from 1 at the significance levels of 1%, 5% and 10%, according to the Diebold-Mariano t-statistic test for equal RMSEs, CRPSs and scores.

[5] Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

Table 2: RMSE (first panel), average CRPS (second), average Predictive Likelihood (third) and Success rate (forth) for Italy for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with daily oil index and monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(3)	8.544	9.184	9.339	8.530	9.500	10.181	10.736
B-RU-MIDAS (All-IPI)	0.810***	0.792***	0.802***	0.916***	0.918***	0.917***	0.920***
B-RU-MIDAS (IPI-Cons)	0.823***	0.807***	0.817***	0.934***	0.935**	0.927***	0.929**
B-RU-MIDAS (IPI-Elec)	0.815***	0.797***	0.806***	0.921***	0.919***	0.912***	0.916***
B-RU-MIDAS (IPI-Manuf)	0.822***	0.806***	0.815***	0.933***	0.932**	0.923***	0.925**
B-RU-MIDAS (IPI-Cons-Elec)	0.814***	0.796***	0.805***	0.917***	0.921***	0.918***	0.921***
B-RU-MIDAS (IPI-Cons-Manuf)	0.819***	0.802***	0.813***	0.933***	0.931***	0.922***	0.923***
B-RU-MIDAS (IPI-Elec-Manuf)	0.814***	0.796***	0.806***	0.918***	0.920***	0.918***	0.922***
Average CRPS							
BAR(3)	4.601	4.944	5.023	4.627	5.114	5.439	5.778
B-RU-MIDAS (All-IPI)	0.803***	0.783***	0.792***	0.915***	0.926***	0.927***	0.931***
B-RU-MIDAS (IPI-Cons)	0.815***	0.798***	0.807***	0.934***	0.943***	0.937***	0.940***
B-RU-MIDAS (IPI-Elec)	0.808***	0.790***	0.799***	0.922***	0.928***	0.922***	0.925***
B-RU-MIDAS (IPI-Manuf)	0.815***	0.797***	0.806***	0.934***	0.941***	0.935***	0.937***
B-RU-MIDAS (IPI-Cons-Elec)	0.807***	0.789***	0.797***	0.917***	0.928***	0.928***	0.931***
B-RU-MIDAS (IPI-Cons-Manuf)	0.811***	0.792***	0.802***	0.933***	0.939***	0.934***	0.935***
B-RU-MIDAS (IPI-Elec-Manuf)	0.806***	0.786***	0.795***	0.918***	0.929***	0.930***	0.933***
Average predictive likelihood							
BAR(3)	-3.602	-3.743	-3.760	-3.679	-3.773	-3.890	-3.933
B-RU-MIDAS (All-IPI)	0.138***	0.202***	0.208***	0.071***	0.074**	0.103***	0.109***
B-RU-MIDAS (IPI-Cons)	0.102**	0.165***	0.187***	0.062***	0.030	0.097***	0.107***
B-RU-MIDAS (IPI-Elec)	0.128***	0.203***	0.200***	0.066***	0.083***	0.096***	0.082**
B-RU-MIDAS (IPI-Manuf)	0.111**	0.174***	0.164***	0.078***	0.074***	0.087***	0.084**
B-RU-MIDAS (IPI-Cons-Elec)	0.150***	0.206***	0.190***	0.093***	0.083***	0.100***	0.097***
B-RU-MIDAS (IPI-Cons-Manuf)	0.116**	0.190***	0.163***	0.057***	0.071***	0.075**	0.063*
B-RU-MIDAS (IPI-Elec-Manuf)	0.134***	0.199***	0.165***	0.080***	0.058*	0.108***	0.092***
Success Rate							
BAR(3)	0.584	0.639	0.646	0.600	0.593	0.593	0.608
B-RU-MIDAS (All-IPI)	0.670	0.749	0.749	0.642	0.639	0.626	0.641
B-RU-MIDAS (IPI-Cons)	0.680	0.751	0.738	0.626	0.626	0.624	0.638
B-RU-MIDAS (IPI-Elec)	0.684	0.746	0.738	0.629	0.636	0.630	0.644
B-RU-MIDAS (IPI-Manuf)	0.676	0.747	0.736	0.625	0.631	0.623	0.638
B-RU-MIDAS (IPI-Cons-Elec)	0.675	0.752	0.741	0.638	0.635	0.630	0.641
B-RU-MIDAS (IPI-Cons-Manuf)	0.678	0.751	0.739	0.631	0.637	0.623	0.640
B-RU-MIDAS (IPI-Elec-Manuf)	0.677	0.754	0.747	0.636	0.631	0.623	0.640

Notes: See the notes to Table 1

seem to have interesting and important advantages over simpler models. Going forward, it would be interesting to study the possible extension of these models to hourly data in order to include other variables of interest, such as renewable energy sources, which are currently taking lead in the electricity generation.

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A Graphical Representation of the Data

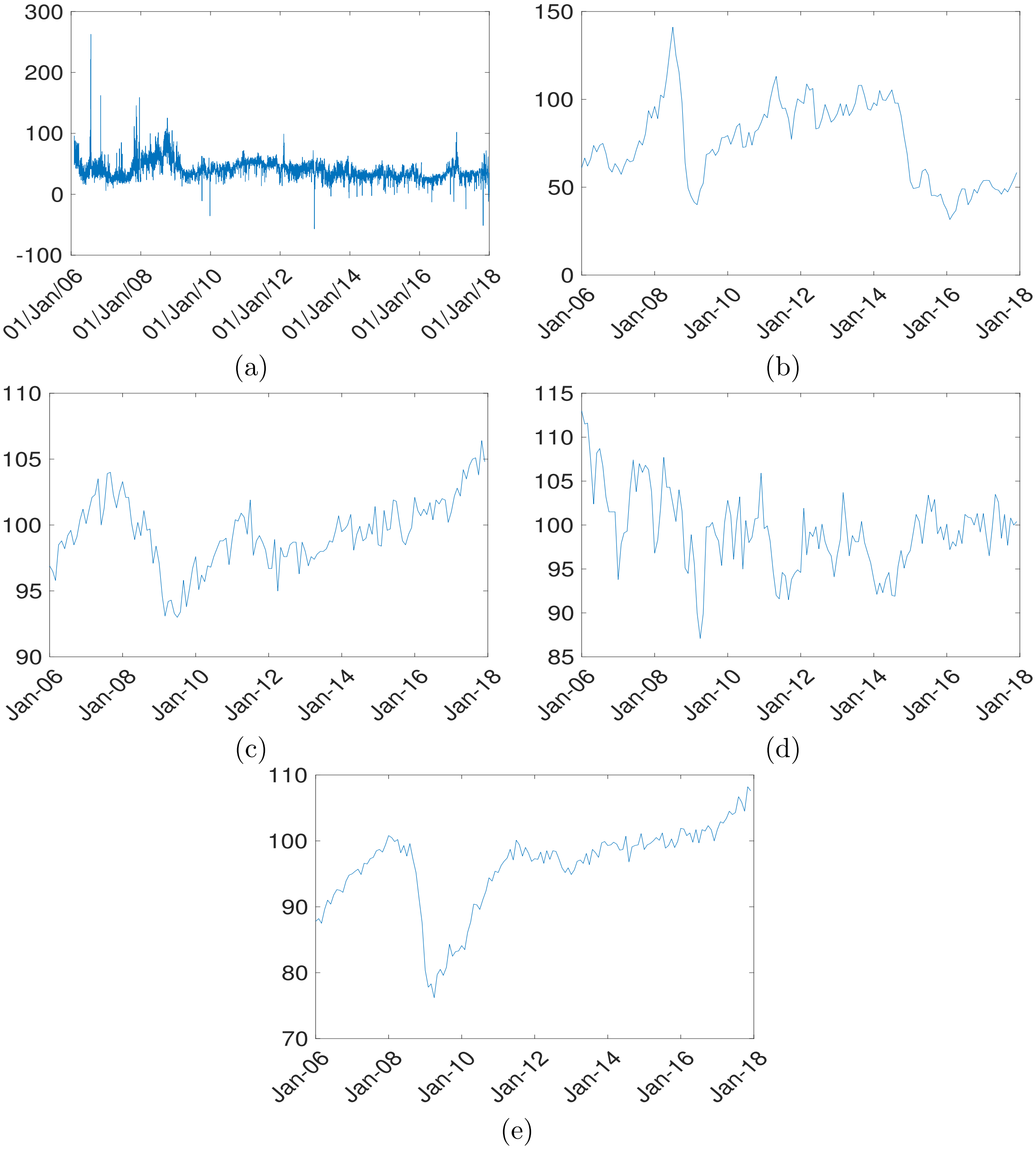

Figure 1: Daily Electricity Prices for Germany (panel (a)); Monthly Oil Prices (b); Monthly Industrial Production index (IPI) for Consumer Goods (c); Monthly IPI for Electricity Prices (d) and Monthly IPI for Manufacturing (e) from January 2006 to December 2017.

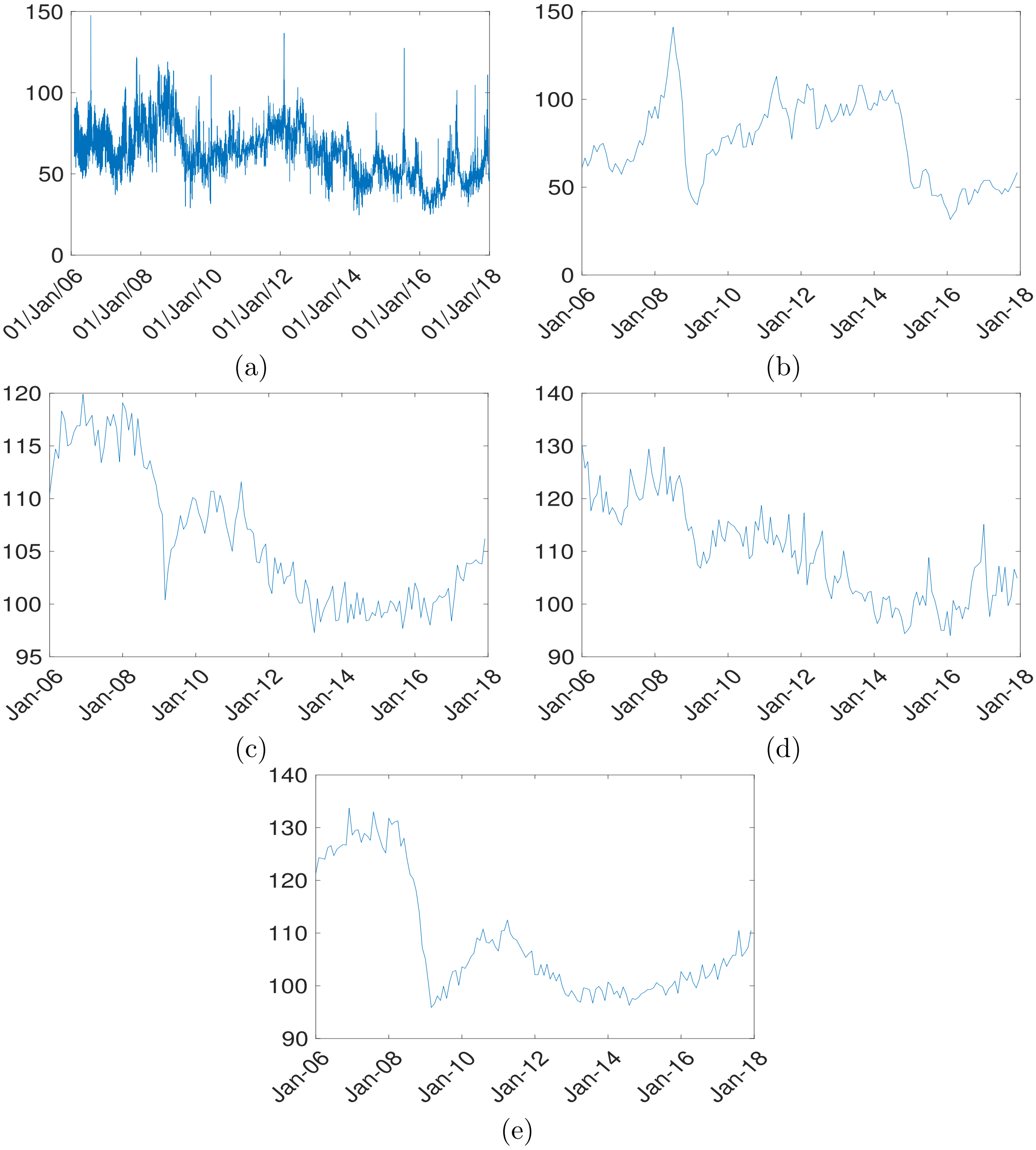

Figure 2: Daily Electricity Prices for Italy (panel (a)); Monthly Oil Prices (b); Monthly Industrial Production index (IPI) for Consumer Goods (c); Monthly IPI for Electricity Prices (d) and Monthly IPI for Manufacturing (e) from January 2006 to December 2017.

B Robustness Check

Different macroeconomic variables analysed

Table 3: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Germany for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with daily oil index and interpolated monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(3)	11.226	12.410	12.664	11.052	11.505	12.001	11.933
BARX(3) (All-IPI)	0.958***	0.934***	0.926***	0.966**	0.973**	0.967**	0.972*
BARX(3) (IPI-Cons)	0.961***	0.937***	0.930***	0.967***	0.972**	0.963**	0.970*
BARX(3) (IPI-Elec)	0.956***	0.932***	0.923***	0.963***	0.967***	0.957***	0.965**
BARX(3) (IPI-Manuf)	0.967***	0.948***	0.940***	0.973**	0.981*	0.973	0.981
BARX(3) (IPI-Cons-Elec)	0.956***	0.931***	0.922***	0.963***	0.968***	0.962**	0.969*
BARX(3) (IPI-Cons-Manuf)	0.962***	0.940***	0.931***	0.969**	0.976**	0.968*	0.972*
BARX(3) (IPI-Elec-Manuf)	0.957***	0.933***	0.924***	0.964***	0.970**	0.964**	0.970*
Average CRPS							
BAR(3)	5.995	6.702	6.812	5.689	5.930	6.184	6.227
BARX(3) (All-IPI)	0.946***	0.912***	0.904***	0.961***	0.965***	0.964***	0.967***
BARX(3) (IPI-Cons)	0.949***	0.916***	0.908***	0.960***	0.964***	0.962***	0.967***
BARX(3) (IPI-Elec)	0.945***	0.909***	0.901***	0.957***	0.959***	0.955***	0.961***
BARX(3) (IPI-Manuf)	0.956***	0.926***	0.918***	0.967***	0.973**	0.973**	0.978*
BARX(3) (IPI-Cons-Elec)	0.945***	0.909***	0.901***	0.957***	0.960***	0.959***	0.965***
BARX(3) (IPI-Cons-Manuf)	0.950***	0.918***	0.909***	0.964***	0.968***	0.965***	0.967***
BARX(3) (IPI-Elec-Manuf)	0.945***	0.911***	0.903***	0.958***	0.962***	0.961***	0.965***
Average predictive likelihood							
BAR(3)	-3.953	-4.055	-4.084	-4.032	-4.170	-4.221	-4.141
BARX(3) (All-IPI)	0.019	0.029	0.044	0.085*	0.017	0.095*	0.090***
BARX(3) (IPI-Cons)	0.005	0.007	0.051*	0.089**	0.034	0.074	0.077**
BARX(3) (IPI-Elec)	0.017	0.032	0.028	0.077*	0.028	0.091*	0.056**
BARX(3) (IPI-Manuf)	-0.000	0.011	0.027	0.068*	0.028	0.059	0.039
BARX(3) (IPI-Cons-Elec)	0.006	0.026	0.045	0.094**	0.079	0.099*	0.080***
BARX(3) (IPI-Cons-Manuf)	0.025	-0.005	0.043	0.082*	0.048	0.103*	0.074**
BARX(3) (IPI-Elec-Manuf)	0.024	0.019	0.032	0.065	0.044	0.100*	0.067**
Success Rate							
BAR(3)	0.581	0.657	0.673	0.616	0.642	0.613	0.629
BARX(3) (All-IPI)	0.566	0.664	0.678	0.628	0.650	0.639	0.648
BARX(3) (IPI-Cons)	0.556	0.657	0.681	0.627	0.653	0.634	0.638
BARX(3) (IPI-Elec)	0.555	0.661	0.676	0.631	0.652	0.643	0.643
BARX(3) (IPI-Manuf)	0.554	0.650	0.673	0.615	0.655	0.628	0.635
BARX(3) (IPI-Cons-Elec)	0.563	0.667	0.679	0.632	0.656	0.640	0.641
BARX(3) (IPI-Cons-Manuf)	0.559	0.662	0.677	0.620	0.646	0.634	0.644
BARX(3) (IPI-Elec-Manuf)	0.567	0.666	0.680	0.628	0.650	0.637	0.644

Notes:

[1] The benchmark model is a Bayesian AR model with 3 lags and seasonal dummies.

[2] Please refer to Section 2 for details on model formulations. The BARX indicates Bayesian AR with Normal-Gamma prior including 3 lags and seasonal dummies and with different exogenous variables. The BARX includes daily Oil index and different interpolated monthly IPI variables. All forecasts are produced with recursive estimation of the models.

[3] For the BAR baseline models, the table reports the RMSEs, the average CRPSs and the average values of log predictive density scores (first row of each panel); for all other BARX models, the table reports the ratios/differences between the current model and the benchmark.

[4] ***, ** and * indicate that the RMSE and CRPS ratios or score differences are significantly different from 1 at the significance levels of 1%, 5% and 10%, according to the Diebold-Mariano t-statistic test for equal RMSEs, CRPSs and scores.

[5] Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

Table 4: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Italy for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with daily oil index and interpolated monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(3)	8.544	9.184	9.339	8.530	9.500	10.181	10.736
BARX(3) (All-IPI)	0.955***	0.940***	0.936***	0.955***	0.951**	0.952	0.952
BARX(3) (IPI-Cons)	0.974***	0.965***	0.963***	0.976*	0.968	0.961	0.957
BARX(3) (IPI-Elec)	0.965***	0.952***	0.948***	0.964***	0.953**	0.946**	0.944**
BARX(3) (IPI-Manuf)	0.974***	0.965***	0.962***	0.975*	0.966	0.958	0.953
BARX(3) (IPI-Cons-Elec)	0.954***	0.938***	0.934***	0.952***	0.947***	0.947**	0.947*
BARX(3) (IPI-Cons-Manuf)	0.974***	0.967***	0.965***	0.978	0.969	0.962	0.957
BARX(3) (IPI-Elec-Manuf)	0.959***	0.947***	0.943***	0.959***	0.956*	0.955	0.955
Average CRPS							
BAR(3)	4.601	4.944	5.023	4.627	5.114	5.439	5.778
BARX(3) (All-IPI)	0.952***	0.938***	0.934***	0.959***	0.959***	0.963***	0.964***
BARX(3) (IPI-Cons)	0.968***	0.958***	0.956***	0.975***	0.971***	0.968***	0.966***
BARX(3) (IPI-Elec)	0.961***	0.948***	0.944***	0.965***	0.958***	0.955***	0.952***
BARX(3) (IPI-Manuf)	0.969***	0.959***	0.956***	0.976***	0.971***	0.967***	0.964***
BARX(3) (IPI-Cons-Elec)	0.951***	0.936***	0.932***	0.954***	0.953***	0.956***	0.956***
BARX(3) (IPI-Cons-Manuf)	0.970***	0.961***	0.959***	0.981***	0.976***	0.973***	0.972***
BARX(3) (IPI-Elec-Manuf)	0.955***	0.941***	0.938***	0.960***	0.962***	0.964***	0.966***
Average predictive likelihood							
BAR(3)	-3.602	-3.743	-3.760	-3.679	-3.773	-3.890	-3.933
BARX(3) (All-IPI)	0.002	0.080**	0.065***	0.039***	0.043*	0.063***	0.076***
BARX(3) (IPI-Cons)	-0.024	0.017	0.025**	0.024**	0.037*	0.052*	0.074**
BARX(3) (IPI-Elec)	-0.012	0.026	0.053***	0.031**	0.036*	0.066***	0.091***
BARX(3) (IPI-Manuf)	-0.000	0.020	0.020	0.033**	0.016	0.044	0.081***
BARX(3) (IPI-Cons-Elec)	0.007	0.077***	0.067***	0.043***	0.046*	0.082***	0.087***
BARX(3) (IPI-Cons-Manuf)	-0.003	0.039	0.034**	0.032**	0.024	0.055**	0.057**
BARX(3) (IPI-Elec-Manuf)	-0.018	0.028	0.050**	0.048***	0.052**	0.061***	0.050*
Success Rate							
BAR(3)	0.584	0.639	0.646	0.600	0.593	0.593	0.608
BARX(3) (All-IPI)	0.594	0.653	0.660	0.620	0.631	0.615	0.626
BARX(3) (IPI-Cons)	0.575	0.636	0.642	0.618	0.616	0.614	0.622
BARX(3) (IPI-Elec)	0.578	0.644	0.645	0.620	0.631	0.622	0.635
BARX(3) (IPI-Manuf)	0.573	0.638	0.642	0.614	0.623	0.611	0.626
BARX(3) (IPI-Cons-Elec)	0.597	0.662	0.659	0.620	0.632	0.624	0.631
BARX(3) (IPI-Cons-Manuf)	0.565	0.634	0.640	0.611	0.619	0.609	0.625
BARX(3) (IPI-Elec-Manuf)	0.592	0.653	0.659	0.618	0.625	0.618	0.626

Notes: See the notes to Table 3

Table 5: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Germany for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with monthly oil index and monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(3)	11.226	12.410	12.664	11.052	11.505	12.001	11.933
B-RU-MIDAS (All-IPI)	0.782***	0.753***	0.763***	0.919***	0.937***	0.934**	0.962
B-RU-MIDAS (IPI-Cons)	0.784***	0.757***	0.766***	0.921***	0.942**	0.939*	0.967
B-RU-MIDAS (IPI-Elec)	0.780***	0.753***	0.762***	0.916***	0.936**	0.932**	0.959
B-RU-MIDAS (IPI-Manuf)	0.788***	0.761***	0.771***	0.928***	0.949*	0.947	0.975
B-RU-MIDAS (IPI-Cons-Elec)	0.782***	0.753***	0.762***	0.919***	0.939**	0.937*	0.964
B-RU-MIDAS (IPI-Cons-Manuf)	0.785***	0.757***	0.767***	0.923***	0.942**	0.938*	0.965
B-RU-MIDAS (IPI-Elec-Manuf)	0.781***	0.752***	0.762***	0.917***	0.936***	0.932**	0.960
Average CRPS							
BAR(3)	5.995	6.702	6.812	5.689	5.930	6.184	6.227
B-RU-MIDAS (All-IPI)	0.745***	0.712***	0.725***	0.915***	0.939***	0.939***	0.960***
B-RU-MIDAS (IPI-Cons)	0.747***	0.715***	0.728***	0.918***	0.944***	0.944***	0.965**
B-RU-MIDAS (IPI-Elec)	0.743***	0.711***	0.723***	0.913***	0.937***	0.936***	0.956***
B-RU-MIDAS (IPI-Manuf)	0.751***	0.720***	0.734***	0.926***	0.952***	0.954***	0.974*
B-RU-MIDAS (IPI-Cons-Elec)	0.744***	0.711***	0.724***	0.914***	0.940***	0.941***	0.963**
B-RU-MIDAS (IPI-Cons-Manuf)	0.748***	0.717***	0.729***	0.921***	0.945***	0.943***	0.964**
B-RU-MIDAS (IPI-Elec-Manuf)	0.744***	0.711***	0.724***	0.914***	0.938***	0.936***	0.957***
Average predictive likelihood							
BAR(3)	-3.953	-4.055	-4.084	-4.032	-4.170	-4.221	-4.141
B-RU-MIDAS (All-IPI)	0.129**	0.150**	0.128*	0.147**	0.140*	0.132*	0.061*
B-RU-MIDAS (IPI-Cons)	0.119*	0.152**	0.143**	0.068	0.137*	0.139*	0.051
B-RU-MIDAS (IPI-Elec)	0.159***	0.152**	0.186***	0.104*	0.136	0.087	0.039
B-RU-MIDAS (IPI-Manuf)	0.162***	0.134**	0.127*	0.085	0.153*	0.094	0.016
B-RU-MIDAS (IPI-Cons-Elec)	0.150**	0.159**	0.138**	0.096	0.167*	0.118	0.068**
B-RU-MIDAS (IPI-Cons-Manuf)	0.148**	0.133*	0.126*	0.080	0.147*	0.118	0.032
B-RU-MIDAS (IPI-Elec-Manuf)	0.111*	0.160**	0.111	0.119**	0.160**	0.125	0.065**
Success Rate							
BAR(3)	0.581	0.657	0.673	0.616	0.642	0.613	0.629
B-RU-MIDAS (All-IPI)	0.731	0.794	0.785	0.630	0.651	0.637	0.629
B-RU-MIDAS (IPI-Cons)	0.729	0.791	0.786	0.633	0.644	0.636	0.623
B-RU-MIDAS (IPI-Elec)	0.729	0.792	0.787	0.635	0.651	0.638	0.632
B-RU-MIDAS (IPI-Manuf)	0.729	0.794	0.785	0.628	0.643	0.630	0.619
B-RU-MIDAS (IPI-Cons-Elec)	0.729	0.794	0.789	0.632	0.647	0.636	0.630
B-RU-MIDAS (IPI-Cons-Manuf)	0.725	0.795	0.783	0.628	0.648	0.637	0.626
B-RU-MIDAS (IPI-Elec-Manuf)	0.729	0.793	0.786	0.628	0.650	0.637	0.628

Notes:
[1] The benchmark model is a Bayesian AR model with 3 lags and seasonal dummies.
[2] Please refer to Section 2 for details on model formulations. The B-RU-MIDAS indicates Bayesian AR with Normal-Gamma prior including 3 lags and seasonal dummies and with different exogenous variables. The B-RU-MIDAS includes monthly Oil index and different monthly IPI variables. All forecasts are produced with recursive estimation of the models.
[3] For the BAR baseline models, the table reports the RMSEs, the average CRPSs and the average values of log predictive density scores (first row of each panel); for all other B-RU-MIDAS models, the table reports the ratios/differences between the current model and the benchmark.
[4] ***, ** and * indicate that the RMSE and CRPS ratios or score differences are significantly different from 1 at the significance levels of 1%, 5% and 10%, according to the Diebold-Mariano t-statistic test for equal RMSEs, CRPSs and scores.
[5] Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

Table 6: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Italy for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with monthly oil index and monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(3)	8.544	9.184	9.339	8.530	9.500	10.181	10.736
B-RU-MIDAS (All-IPI)	0.824***	0.806***	0.817***	0.937***	0.939*	0.936*	0.937*
B-RU-MIDAS (IPI-Cons)	0.837***	0.822***	0.832***	0.955**	0.956	0.948	0.948
B-RU-MIDAS (IPI-Elec)	0.829***	0.811***	0.821***	0.943***	0.942	0.933**	0.934*
B-RU-MIDAS (IPI-Manuf)	0.836***	0.819***	0.830***	0.953**	0.952	0.943	0.942
B-RU-MIDAS (IPI-Cons-Elec)	0.825***	0.807***	0.817***	0.936***	0.942*	0.937*	0.940
B-RU-MIDAS (IPI-Cons-Manuf)	0.835***	0.818***	0.829***	0.954***	0.952	0.943	0.942
B-RU-MIDAS (IPI-Elec-Manuf)	0.829***	0.811***	0.822***	0.940***	0.941*	0.937*	0.939
Average CRPS							
BAR(3)	4.601	4.944	5.023	4.627	5.114	5.439	5.778
B-RU-MIDAS (All-IPI)	0.818***	0.798***	0.808***	0.937***	0.949***	0.948***	0.948***
B-RU-MIDAS (IPI-Cons)	0.830***	0.814***	0.825***	0.957***	0.967***	0.960***	0.960***
B-RU-MIDAS (IPI-Elec)	0.823***	0.806***	0.816***	0.946***	0.953***	0.945***	0.945***
B-RU-MIDAS (IPI-Manuf)	0.829***	0.811***	0.822***	0.955***	0.964***	0.956***	0.954***
B-RU-MIDAS (IPI-Cons-Elec)	0.819***	0.801***	0.810***	0.937***	0.951***	0.948***	0.950***
B-RU-MIDAS (IPI-Cons-Manuf)	0.827***	0.809***	0.820***	0.956***	0.963***	0.955***	0.954***
B-RU-MIDAS (IPI-Elec-Manuf)	0.822***	0.801***	0.812***	0.940***	0.951***	0.950***	0.951***
Average predictive likelihood							
BAR(3)	-3.602	-3.743	-3.760	-3.679	-3.773	-3.890	-3.933
B-RU-MIDAS (All-IPI)	0.117***	0.182***	0.161***	0.083**	0.043*	0.097***	0.116***
B-RU-MIDAS (IPI-Cons)	0.108***	0.196***	0.130***	0.027	0.046**	0.068**	0.053*
B-RU-MIDAS (IPI-Elec)	0.131***	0.188***	0.162***	0.053**	0.048*	0.098***	0.073**
B-RU-MIDAS (IPI-Manuf)	0.095**	0.185***	0.152***	0.053***	0.046*	0.075***	0.087**
B-RU-MIDAS (IPI-Cons-Elec)	0.099**	0.191***	0.189***	0.072***	0.055**	0.120***	0.078**
B-RU-MIDAS (IPI-Cons-Manuf)	0.111**	0.166***	0.121***	0.084***	0.044*	0.071***	0.083**
B-RU-MIDAS (IPI-Elec-Manuf)	0.112**	0.170***	0.147***	0.062***	0.045*	0.096***	0.077**
Success Rate							
BAR(3)	0.584	0.639	0.646	0.600	0.593	0.593	0.608
B-RU-MIDAS (All-IPI)	0.670	0.748	0.742	0.635	0.633	0.618	0.626
B-RU-MIDAS (IPI-Cons)	0.673	0.747	0.733	0.627	0.625	0.615	0.628
B-RU-MIDAS (IPI-Elec)	0.675	0.754	0.738	0.631	0.631	0.621	0.635
B-RU-MIDAS (IPI-Manuf)	0.677	0.746	0.733	0.627	0.623	0.612	0.623
B-RU-MIDAS (IPI-Cons-Elec)	0.669	0.749	0.738	0.635	0.631	0.624	0.630
B-RU-MIDAS (IPI-Cons-Manuf)	0.674	0.746	0.730	0.626	0.623	0.611	0.625
B-RU-MIDAS (IPI-Elec-Manuf)	0.673	0.751	0.740	0.633	0.631	0.618	0.632

Notes: See the notes to Table 5

Different benchmark models

Table 7: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Germany for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with daily oil index and monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(1)	12.811	13.743	14.074	12.867	13.601	13.955	14.414
B-RU-MIDAS (All-IPI)	0.697***	0.696***	0.702***	0.796***	0.802***	0.813***	0.807***
B-RU-MIDAS (IPI-Cons)	0.699***	0.698***	0.704***	0.798***	0.805***	0.815***	0.809***
B-RU-MIDAS (IPI-Elec)	0.694***	0.692***	0.698***	0.791***	0.796***	0.806***	0.801***
B-RU-MIDAS (IPI-Manuf)	0.707***	0.708***	0.714***	0.809***	0.819***	0.830***	0.824***
B-RU-MIDAS (IPI-Cons-Elec)	0.695***	0.694***	0.700***	0.794***	0.800***	0.811***	0.805***
B-RU-MIDAS (IPI-Cons-Manuf)	0.701***	0.701***	0.707***	0.801***	0.809***	0.819***	0.813***
B-RU-MIDAS (IPI-Elec-Manuf)	0.696***	0.695***	0.701***	0.794***	0.801***	0.812***	0.806***
Average CRPS							
BAR(1)	6.871	7.390	7.590	6.719	7.161	7.312	7.515
B-RU-MIDAS (All-IPI)	0.667***	0.666***	0.673***	0.785***	0.790***	0.802***	0.801***
B-RU-MIDAS (IPI-Cons)	0.669***	0.667***	0.675***	0.787***	0.793***	0.805***	0.805***
B-RU-MIDAS (IPI-Elec)	0.664***	0.661***	0.668***	0.779***	0.783***	0.794***	0.795***
B-RU-MIDAS (IPI-Manuf)	0.678***	0.678***	0.686***	0.799***	0.808***	0.822***	0.822***
B-RU-MIDAS (IPI-Cons-Elec)	0.665***	0.663***	0.670***	0.781***	0.787***	0.800***	0.800***
B-RU-MIDAS (IPI-Cons-Manuf)	0.672***	0.671***	0.679***	0.791***	0.797***	0.809***	0.808***
B-RU-MIDAS (IPI-Elec-Manuf)	0.666***	0.665***	0.672***	0.784***	0.789***	0.802***	0.800***
Average predictive likelihood							
BAR(1)	-4.076	-4.146	-4.201	-4.198	-4.259	-4.308	-4.433
B-RU-MIDAS (All-IPI)	0.213**	0.211**	0.231**	0.257***	0.244**	0.145	0.310***
B-RU-MIDAS (IPI-Cons)	0.219**	0.211**	0.247***	0.224**	0.245**	0.169*	0.320***
B-RU-MIDAS (IPI-Elec)	0.211**	0.199**	0.267***	0.275***	0.254**	0.178*	0.306***
B-RU-MIDAS (IPI-Manuf)	0.190**	0.202**	0.219***	0.250***	0.241**	0.166*	0.280***
B-RU-MIDAS (IPI-Cons-Elec)	0.235**	0.227***	0.253***	0.252***	0.239**	0.168*	0.294***
B-RU-MIDAS (IPI-Cons-Manuf)	0.207**	0.179**	0.226**	0.256***	0.237**	0.162*	0.269***
B-RU-MIDAS (IPI-Elec-Manuf)	0.215**	0.201**	0.258***	0.266***	0.265**	0.152	0.324***
Success Rate							
BAR(1)	0.547	0.662	0.664	0.581	0.577	0.567	0.574
B-RU-MIDAS (All-IPI)	0.715	0.785	0.786	0.629	0.648	0.635	0.622
B-RU-MIDAS (IPI-Cons)	0.715	0.784	0.785	0.630	0.648	0.624	0.620
B-RU-MIDAS (IPI-Elec)	0.713	0.786	0.789	0.633	0.649	0.638	0.630
B-RU-MIDAS (IPI-Manuf)	0.710	0.783	0.782	0.625	0.644	0.620	0.611
B-RU-MIDAS (IPI-Cons-Elec)	0.710	0.787	0.787	0.630	0.647	0.635	0.622
B-RU-MIDAS (IPI-Cons-Manuf)	0.715	0.783	0.789	0.632	0.653	0.625	0.622
B-RU-MIDAS (IPI-Elec-Manuf)	0.711	0.784	0.788	0.630	0.646	0.634	0.625

Notes:

[1] The benchmark model is a Bayesian AR model with 1 lag and seasonal dummies.

[2] Please refer to Section 2 for details on model formulations. The B-RU-MIDAS indicates Bayesian RU-MIDAS with Normal-Gamma prior including 1 lag and seasonal dummies and with different exogenous variables. The B-RU-MIDAS includes daily Oil index and different monthly IPI variables. All forecasts are produced with recursive estimation of the models.

[3] For the BAR baseline models, the table reports the RMSEs, the average CRPSs and the average values of log predictive density scores (first row of each panel); for all other B-RU-MIDAS models, the table reports the ratios/differences between the current model and the benchmark.

[4] ***, ** and * indicate that the RMSE and CRPS ratios or score differences are significantly different from 1 at the significance levels of 1%, 5% and 10%, according to the Diebold-Mariano t-statistic test for equal RMSEs, CRPSs and scores.

[5] Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

Table 8: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Italy for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with daily oil index and monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(1)	9.698	10.245	10.499	10.003	10.866	11.474	12.173
B-RU-MIDAS (All-IPI)	0.752***	0.744***	0.752***	0.815***	0.824***	0.829***	0.829***
B-RU-MIDAS (IPI-Cons)	0.768***	0.765***	0.772***	0.838***	0.847***	0.844***	0.843***
B-RU-MIDAS (IPI-Elec)	0.754***	0.748***	0.756***	0.819***	0.825***	0.825***	0.824***
B-RU-MIDAS (IPI-Manuf)	0.767***	0.763***	0.771***	0.838***	0.844***	0.840***	0.838***
B-RU-MIDAS (IPI-Cons-Elec)	0.753***	0.747***	0.754***	0.816***	0.824***	0.829***	0.829***
B-RU-MIDAS (IPI-Cons-Manuf)	0.766***	0.760***	0.769***	0.836***	0.843***	0.840***	0.837***
B-RU-MIDAS (IPI-Elec-Manuf)	0.756***	0.750***	0.756***	0.818***	0.826***	0.830***	0.832***
Average CRPS							
BAR(1)	5.227	5.517	5.636	5.373	5.899	6.156	6.530
B-RU-MIDAS (All-IPI)	0.750***	0.743***	0.750***	0.826***	0.831***	0.841***	0.844***
B-RU-MIDAS (IPI-Cons)	0.765***	0.761***	0.769***	0.848***	0.854***	0.856***	0.857***
B-RU-MIDAS (IPI-Elec)	0.752***	0.747***	0.755***	0.831***	0.833***	0.836***	0.837***
B-RU-MIDAS (IPI-Manuf)	0.765***	0.760***	0.769***	0.849***	0.852***	0.853***	0.854***
B-RU-MIDAS (IPI-Cons-Elec)	0.752***	0.747***	0.754***	0.826***	0.831***	0.841***	0.843***
B-RU-MIDAS (IPI-Cons-Manuf)	0.764***	0.756***	0.765***	0.847***	0.850***	0.852***	0.852***
B-RU-MIDAS (IPI-Elec-Manuf)	0.753***	0.746***	0.753***	0.829***	0.833***	0.843***	0.847***
Average predictive likelihood							
BAR(1)	-3.786	-3.850	-3.895	-3.820	-3.868	-3.981	-4.075
B-RU-MIDAS (All-IPI)	0.271***	0.282***	0.282***	0.185***	0.159***	0.203***	0.209***
B-RU-MIDAS (IPI-Cons)	0.258***	0.233***	0.250***	0.147***	0.127**	0.181***	0.196***
B-RU-MIDAS (IPI-Elec)	0.267***	0.262***	0.286***	0.192***	0.156***	0.210***	0.227***
B-RU-MIDAS (IPI-Manuf)	0.249***	0.261***	0.274***	0.151***	0.150***	0.185***	0.212***
B-RU-MIDAS (IPI-Cons-Elec)	0.252***	0.314***	0.298***	0.181***	0.159***	0.190***	0.233***
B-RU-MIDAS (IPI-Cons-Manuf)	0.252***	0.272***	0.223***	0.173***	0.161***	0.168***	0.192***
B-RU-MIDAS (IPI-Elec-Manuf)	0.273***	0.271***	0.284***	0.187***	0.160***	0.203***	0.221***
Success Rate							
BAR(1)	0.548	0.608	0.629	0.577	0.566	0.567	0.573
B-RU-MIDAS (All-IPI)	0.650	0.741	0.729	0.630	0.642	0.615	0.639
B-RU-MIDAS (IPI-Cons)	0.654	0.731	0.720	0.620	0.622	0.608	0.630
B-RU-MIDAS (IPI-Elec)	0.659	0.743	0.725	0.625	0.631	0.622	0.641
B-RU-MIDAS (IPI-Manuf)	0.651	0.735	0.719	0.617	0.618	0.610	0.629
B-RU-MIDAS (IPI-Cons-Elec)	0.654	0.743	0.728	0.621	0.637	0.622	0.638
B-RU-MIDAS (IPI-Cons-Manuf)	0.647	0.733	0.719	0.619	0.622	0.607	0.631
B-RU-MIDAS (IPI-Elec-Manuf)	0.651	0.738	0.730	0.630	0.634	0.614	0.639

Notes: See the notes to Table 7

Table 9: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Germany for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with daily oil index and interpolated monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(1)	12.811	13.743	14.074	12.867	13.601	13.955	14.414
BARX(1) (All-IPI)	0.886***	0.868***	0.861***	0.891***	0.891***	0.896***	0.885***
BARX(1) (IPI-Cons)	0.890***	0.872***	0.865***	0.894***	0.892***	0.894***	0.886***
BARX(1) (IPI-Elec)	0.882***	0.862***	0.856***	0.886***	0.882***	0.884***	0.876***
BARX(1) (IPI-Manuf)	0.903***	0.887***	0.881***	0.905***	0.907***	0.910***	0.901***
BARX(1) (IPI-Cons-Elec)	0.882***	0.863***	0.856***	0.886***	0.884***	0.890***	0.881***
BARX(1) (IPI-Cons-Manuf)	0.893***	0.875***	0.868***	0.897***	0.897***	0.899***	0.886***
BARX(1) (IPI-Elec-Manuf)	0.885***	0.866***	0.859***	0.888***	0.888***	0.893***	0.883***
Average CRPS							
BAR(1)	6.871	7.390	7.590	6.719	7.161	7.312	7.515
BARX(1) (All-IPI)	0.877***	0.852***	0.842***	0.895***	0.887***	0.896***	0.889***
BARX(1) (IPI-Cons)	0.882***	0.857***	0.846***	0.898***	0.890***	0.896***	0.892***
BARX(1) (IPI-Elec)	0.873***	0.847***	0.836***	0.890***	0.879***	0.885***	0.880***
BARX(1) (IPI-Manuf)	0.895***	0.872***	0.862***	0.912***	0.906***	0.914***	0.910***
BARX(1) (IPI-Cons-Elec)	0.873***	0.847***	0.837***	0.890***	0.881***	0.890***	0.887***
BARX(1) (IPI-Cons-Manuf)	0.884***	0.860***	0.849***	0.901***	0.895***	0.899***	0.891***
BARX(1) (IPI-Elec-Manuf)	0.876***	0.850***	0.839***	0.892***	0.885***	0.893***	0.887***
Average predictive likelihood							
BAR(1)	-4.076	-4.146	-4.201	-4.198	-4.259	-4.308	-4.433
BARX(1) (All-IPI)	0.061	0.106**	0.128**	0.214***	0.191**	0.158*	0.289***
BARX(1) (IPI-Cons)	0.041	0.113**	0.166***	0.199***	0.198**	0.155*	0.234***
BARX(1) (IPI-Elec)	0.059	0.107**	0.155***	0.225***	0.213**	0.167*	0.283***
BARX(1) (IPI-Manuf)	0.057	0.090*	0.100*	0.197***	0.189**	0.122	0.232***
BARX(1) (IPI-Cons-Elec)	0.056	0.089	0.128**	0.221***	0.209**	0.158*	0.280***
BARX(1) (IPI-Cons-Manuf)	0.053	0.075	0.138**	0.209***	0.195**	0.167*	0.279***
BARX(1) (IPI-Elec-Manuf)	0.082	0.082	0.150***	0.217***	0.213**	0.153*	0.281***
Success Rate							
BAR(1)	0.547	0.662	0.664	0.581	0.577	0.567	0.574
BARX(1) (All-IPI)	0.542	0.653	0.654	0.612	0.632	0.630	0.627
BARX(1) (IPI-Cons)	0.526	0.640	0.651	0.613	0.630	0.632	0.620
BARX(1) (IPI-Elec)	0.531	0.642	0.654	0.612	0.634	0.632	0.629
BARX(1) (IPI-Manuf)	0.525	0.631	0.642	0.608	0.626	0.622	0.609
BARX(1) (IPI-Cons-Elec)	0.538	0.649	0.657	0.610	0.639	0.631	0.625
BARX(1) (IPI-Cons-Manuf)	0.534	0.650	0.653	0.610	0.630	0.630	0.624
BARX(1) (IPI-Elec-Manuf)	0.541	0.651	0.660	0.608	0.632	0.629	0.626

Notes:
[1] The benchmark model is a Bayesian AR model with 1 lag and seasonal dummies.
[2] Please refer to Section 2 for details on model formulations. The BARX indicates Bayesian AR with Normal-Gamma prior including 1 lag and seasonal dummies and with different exogenous variables. The BARX includes daily Oil index and different interpolated monthly IPI variables. All forecasts are produced with recursive estimation of the models.
[3] For the BAR baseline models, the table reports the RMSEs, the average CRPSs and the average values of log predictive density scores (first row of each panel); for all other BARX models, the table reports the ratios/differences between the current model and the benchmark.
[4] ***, ** and * indicate that the RMSE and CRPS ratios or score differences are significantly different from 1 at the significance levels of 1%, 5% and 10%, according to the Diebold-Mariano t-statistic test for equal RMSEs, CRPSs and scores.
[5] Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

Table 10: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Italy for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with daily oil index and interpolated monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(1)	9.698	10.245	10.499	10.003	10.866	11.474	12.173
BARX(1) (All-IPI)	0.883***	0.873***	0.866***	0.876***	0.873***	0.877***	0.876***
BARX(1) (IPI-Cons)	0.918***	0.911***	0.906***	0.910***	0.904***	0.898***	0.891***
BARX(1) (IPI-Elec)	0.899***	0.888***	0.883***	0.890***	0.881***	0.876***	0.871***
BARX(1) (IPI-Manuf)	0.918***	0.911***	0.906***	0.910***	0.903***	0.894***	0.887***
BARX(1) (IPI-Cons-Elec)	0.883***	0.871***	0.864***	0.874***	0.869***	0.872***	0.872***
BARX(1) (IPI-Cons-Manuf)	0.918***	0.911***	0.907***	0.912***	0.904***	0.898***	0.890***
BARX(1) (IPI-Elec-Manuf)	0.895***	0.884***	0.877***	0.885***	0.884***	0.885***	0.882***
Average CRPS							
BAR(1)	5.227	5.517	5.636	5.373	5.899	6.156	6.530
BARX(1) (All-IPI)	0.890***	0.878***	0.873***	0.890***	0.883***	0.892***	0.893***
BARX(1) (IPI-Cons)	0.921***	0.910***	0.908***	0.921***	0.910***	0.910***	0.905***
BARX(1) (IPI-Elec)	0.904***	0.892***	0.888***	0.902***	0.888***	0.889***	0.884***
BARX(1) (IPI-Manuf)	0.921***	0.911***	0.909***	0.922***	0.910***	0.908***	0.904***
BARX(1) (IPI-Cons-Elec)	0.890***	0.876***	0.870***	0.886***	0.877***	0.886***	0.884***
BARX(1) (IPI-Cons-Manuf)	0.923***	0.913***	0.910***	0.925***	0.914***	0.914***	0.910***
BARX(1) (IPI-Elec-Manuf)	0.899***	0.886***	0.881***	0.897***	0.891***	0.898***	0.897***
Average predictive likelihood							
BAR(1)	-3.786	-3.850	-3.895	-3.820	-3.868	-3.981	-4.075
BARX(1) (All-IPI)	0.161***	0.135***	0.164***	0.148***	0.117**	0.178***	0.176***
BARX(1) (IPI-Cons)	0.110**	0.097**	0.092*	0.098**	0.110**	0.141**	0.164***
BARX(1) (IPI-Elec)	0.141***	0.115***	0.139***	0.139***	0.096*	0.146**	0.211***
BARX(1) (IPI-Manuf)	0.122**	0.089**	0.119**	0.130***	0.109**	0.153***	0.159***
BARX(1) (IPI-Cons-Elec)	0.142**	0.155***	0.170***	0.134***	0.140***	0.179***	0.198***
BARX(1) (IPI-Cons-Manuf)	0.133**	0.095**	0.121***	0.098**	0.099*	0.129**	0.172***
BARX(1) (IPI-Elec-Manuf)	0.140***	0.133***	0.141***	0.123**	0.107**	0.154***	0.187***
Success Rate							
BAR(1)	0.548	0.608	0.629	0.577	0.566	0.567	0.573
BARX(1) (All-IPI)	0.575	0.642	0.647	0.612	0.631	0.615	0.627
BARX(1) (IPI-Cons)	0.553	0.626	0.628	0.604	0.609	0.593	0.619
BARX(1) (IPI-Elec)	0.562	0.634	0.634	0.612	0.617	0.613	0.626
BARX(1) (IPI-Manuf)	0.560	0.628	0.623	0.611	0.615	0.602	0.620
BARX(1) (IPI-Cons-Elec)	0.583	0.646	0.646	0.609	0.627	0.613	0.628
BARX(1) (IPI-Cons-Manuf)	0.553	0.622	0.622	0.608	0.609	0.598	0.621
BARX(1) (IPI-Elec-Manuf)	0.575	0.643	0.649	0.615	0.623	0.614	0.630

Notes: See the notes to Table 9

Table 11: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Germany for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with monthly oil index and monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(1)	12.811	13.743	14.074	12.867	13.601	13.955	14.414
B-RU-MIDAS (All-IPI)	0.712***	0.712***	0.718***	0.815***	0.823***	0.832***	0.829***
B-RU-MIDAS (IPI-Cons)	0.717***	0.717***	0.724***	0.821***	0.831***	0.839***	0.836***
B-RU-MIDAS (IPI-Elec)	0.711***	0.711***	0.717***	0.814***	0.822***	0.831***	0.827***
B-RU-MIDAS (IPI-Manuf)	0.724***	0.725***	0.732***	0.831***	0.841***	0.850***	0.847***
B-RU-MIDAS (IPI-Cons-Elec)	0.713***	0.712***	0.719***	0.816***	0.826***	0.835***	0.833***
B-RU-MIDAS (IPI-Cons-Manuf)	0.717***	0.718***	0.725***	0.822***	0.830***	0.838***	0.835***
B-RU-MIDAS (IPI-Elec-Manuf)	0.711***	0.710***	0.718***	0.813***	0.822***	0.830***	0.829***
Average CRPS							
BAR(1)	6.871	7.390	7.590	6.719	7.161	7.312	7.515
B-RU-MIDAS (All-IPI)	0.680***	0.679***	0.688***	0.806***	0.814***	0.828***	0.829***
B-RU-MIDAS (IPI-Cons)	0.685***	0.685***	0.693***	0.813***	0.824***	0.835***	0.838***
B-RU-MIDAS (IPI-Elec)	0.679***	0.679***	0.686***	0.804***	0.814***	0.826***	0.827***
B-RU-MIDAS (IPI-Manuf)	0.693***	0.694***	0.702***	0.823***	0.835***	0.848***	0.851***
B-RU-MIDAS (IPI-Cons-Elec)	0.680***	0.679***	0.687***	0.807***	0.818***	0.831***	0.834***
B-RU-MIDAS (IPI-Cons-Manuf)	0.686***	0.686***	0.695***	0.813***	0.823***	0.835***	0.837***
B-RU-MIDAS (IPI-Elec-Manuf)	0.679***	0.678***	0.687***	0.804***	0.814***	0.825***	0.828***
Average predictive likelihood							
BAR(1)	-4.076	-4.146	-4.201	-4.198	-4.259	-4.308	-4.433
B-RU-MIDAS (All-IPI)	0.217**	0.187**	0.252***	0.249***	0.229**	0.202**	0.274***
B-RU-MIDAS (IPI-Cons)	0.196**	0.195**	0.233***	0.244***	0.219**	0.142	0.260***
B-RU-MIDAS (IPI-Elec)	0.190**	0.233***	0.216**	0.280***	0.245**	0.151	0.302***
B-RU-MIDAS (IPI-Manuf)	0.184**	0.184**	0.213***	0.222***	0.253***	0.136	0.265***
B-RU-MIDAS (IPI-Cons-Elec)	0.168*	0.204**	0.236***	0.249***	0.238**	0.210**	0.320***
B-RU-MIDAS (IPI-Cons-Manuf)	0.172*	0.175**	0.230***	0.239***	0.250**	0.149	0.289***
B-RU-MIDAS (IPI-Elec-Manuf)	0.223**	0.198**	0.247***	0.257***	0.274***	0.169	0.299***
Success Rate							
BAR(1)	0.547	0.662	0.664	0.581	0.577	0.567	0.574
B-RU-MIDAS (All-IPI)	0.699	0.774	0.773	0.626	0.634	0.625	0.613
B-RU-MIDAS (IPI-Cons)	0.701	0.773	0.777	0.624	0.628	0.629	0.608
B-RU-MIDAS (IPI-Elec)	0.703	0.775	0.779	0.627	0.631	0.629	0.612
B-RU-MIDAS (IPI-Manuf)	0.702	0.773	0.776	0.622	0.630	0.622	0.607
B-RU-MIDAS (IPI-Cons-Elec)	0.699	0.775	0.778	0.624	0.629	0.625	0.611
B-RU-MIDAS (IPI-Cons-Manuf)	0.700	0.771	0.775	0.625	0.630	0.622	0.610
B-RU-MIDAS (IPI-Elec-Manuf)	0.702	0.773	0.775	0.618	0.635	0.625	0.609

Notes:
[1] The benchmark model is a Bayesian AR model with 1 lag and seasonal dummies.
[2] Please refer to Section 2 for details on model formulations. The B-RU-MIDAS indicates Bayesian AR with Normal-Gamma prior including 1 lag and seasonal dummies and with different exogenous variables. The B-RU-MIDAS includes monthly Oil index and different monthly IPI variables. All forecasts are produced with recursive estimation of the models.
[3] For the BAR baseline models, the table reports the RMSEs, the average CRPSs and the average values of log predictive density scores (first row of each panel); for all other B-RU-MIDAS models, the table reports the ratios/differences between the current model and the benchmark.
[4] ***, ** and * indicate that the RMSE and CRPS ratios or score differences are significantly different from 1 at the significance levels of 1%, 5% and 10%, according to the Diebold-Mariano t-statistic test for equal RMSEs, CRPSs and scores.
[5] Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

Table 12: RMSE (first panel), average CRPS (second), average Predictive Likelihood score (third) and Success rate (forth) for Italy for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28. Models with monthly oil index and monthly IPI variables.

horizon	1	2	3	7	14	21	28
RMSE							
BAR(1)	9.698	10.245	10.499	10.003	10.866	11.474	12.173
B-RU-MIDAS (All-IPI)	0.769***	0.761***	0.769***	0.836***	0.849***	0.853***	0.852***
B-RU-MIDAS (IPI-Cons)	0.788***	0.784***	0.792***	0.861***	0.875***	0.872***	0.869***
B-RU-MIDAS (IPI-Elec)	0.773***	0.767***	0.775***	0.843***	0.853***	0.852***	0.849***
B-RU-MIDAS (IPI-Manuf)	0.787***	0.781***	0.789***	0.859***	0.870***	0.866***	0.861***
B-RU-MIDAS (IPI-Cons-Elec)	0.768***	0.762***	0.769***	0.836***	0.851***	0.854***	0.854***
B-RU-MIDAS (IPI-Cons-Manuf)	0.787***	0.780***	0.789***	0.861***	0.871***	0.866***	0.862***
B-RU-MIDAS (IPI-Elec-Manuf)	0.775***	0.767***	0.774***	0.841***	0.853***	0.855***	0.854***
Average CRPS							
BAR(1)	5.227	5.517	5.636	5.373	5.899	6.156	6.530
B-RU-MIDAS (All-IPI)	0.769***	0.759***	0.769***	0.848***	0.859***	0.866***	0.868***
B-RU-MIDAS (IPI-Cons)	0.787***	0.782***	0.791***	0.874***	0.886***	0.887***	0.886***
B-RU-MIDAS (IPI-Elec)	0.774***	0.767***	0.776***	0.857***	0.864***	0.865***	0.863***
B-RU-MIDAS (IPI-Manuf)	0.787***	0.779***	0.788***	0.873***	0.881***	0.880***	0.879***
B-RU-MIDAS (IPI-Cons-Elec)	0.769***	0.762***	0.771***	0.848***	0.861***	0.867***	0.869***
B-RU-MIDAS (IPI-Cons-Manuf)	0.786***	0.778***	0.788***	0.874***	0.882***	0.880***	0.879***
B-RU-MIDAS (IPI-Elec-Manuf)	0.773***	0.764***	0.773***	0.852***	0.863***	0.869***	0.870***
Average predictive likelihood							
BAR(1)	-3.786	-3.850	-3.895	-3.820	-3.868	-3.981	-4.075
B-RU-MIDAS (All-IPI)	0.256***	0.249***	0.265***	0.191***	0.145**	0.175***	0.212***
B-RU-MIDAS (IPI-Cons)	0.235***	0.224***	0.203***	0.134***	0.122**	0.165***	0.177***
B-RU-MIDAS (IPI-Elec)	0.240***	0.251***	0.273***	0.169***	0.143***	0.180***	0.236***
B-RU-MIDAS (IPI-Manuf)	0.246***	0.222***	0.198***	0.158***	0.136***	0.180**	0.211***
B-RU-MIDAS (IPI-Cons-Elec)	0.278***	0.237***	0.291***	0.185***	0.136**	0.174***	0.206***
B-RU-MIDAS (IPI-Cons-Manuf)	0.208***	0.228***	0.231***	0.132***	0.138**	0.163***	0.190***
B-RU-MIDAS (IPI-Elec-Manuf)	0.273***	0.289***	0.243***	0.188***	0.131**	0.171***	0.219***
Success Rate							
BAR(1)	0.548	0.608	0.629	0.577	0.566	0.567	0.573
B-RU-MIDAS (All-IPI)	0.636	0.733	0.723	0.626	0.626	0.612	0.626
B-RU-MIDAS (IPI-Cons)	0.639	0.731	0.717	0.622	0.603	0.599	0.622
B-RU-MIDAS (IPI-Elec)	0.638	0.735	0.727	0.625	0.617	0.610	0.628
B-RU-MIDAS (IPI-Manuf)	0.637	0.733	0.718	0.623	0.610	0.601	0.615
B-RU-MIDAS (IPI-Cons-Elec)	0.636	0.738	0.723	0.629	0.622	0.612	0.629
B-RU-MIDAS (IPI-Cons-Manuf)	0.639	0.730	0.719	0.620	0.608	0.602	0.615
B-RU-MIDAS (IPI-Elec-Manuf)	0.638	0.735	0.728	0.629	0.622	0.613	0.625

Notes: See the notes to Table 11

Online Appendix for: "Forecasting daily electricity prices with monthly macroeconomic variables"

A Table Results - Daily Data for Oil for Germany

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	11.226	12.410	12.664	11.052	11.505	12.001	11.933
B-RUMIDAS (All-IPI)	0.771***	0.742***	0.750***	0.903***	0.921***	0.916***	0.936***
B-RUMIDAS (IPI-Cons)	0.771***	0.743***	0.751***	0.903***	0.922***	0.917***	0.937***
B-RUMIDAS (IPI-Elec)	0.768***	0.740***	0.747***	0.898***	0.916***	0.909***	0.930***
B-RUMIDAS (IPI-Manuf)	0.776***	0.749***	0.758***	0.912***	0.933***	0.928***	0.950**
B-RUMIDAS (IPI-Cons-Elec)	0.770***	0.741***	0.748***	0.901***	0.919***	0.914***	0.935***
B-RUMIDAS (IPI-Cons-Manuf)	0.773***	0.746***	0.754***	0.906***	0.926***	0.920***	0.939***
B-RUMIDAS (IPI-Elec-Manuf)	0.770***	0.741***	0.749***	0.901***	0.920***	0.915***	0.936***
benchmark 3 lags							
BAR(3)	11.257	12.437	12.700	11.090	11.557	12.068	12.005
B-RUMIDAS (All-IPI)	0.771***	0.742***	0.750***	0.901***	0.918***	0.913***	0.932***
B-RUMIDAS (IPI-Cons)	0.770***	0.743***	0.750***	0.902***	0.919***	0.913***	0.932***
B-RUMIDAS (IPI-Elec)	0.767***	0.739***	0.746***	0.897***	0.913***	0.907***	0.926***
B-RUMIDAS (IPI-Manuf)	0.776***	0.749***	0.757***	0.909***	0.930***	0.925***	0.944**
B-RUMIDAS (IPI-Cons-Elec)	0.769***	0.741***	0.748***	0.900***	0.916***	0.911***	0.930***
B-RUMIDAS (IPI-Cons-Manuf)	0.772***	0.746***	0.754***	0.906***	0.923***	0.917***	0.935***
B-RUMIDAS (IPI-Elec-Manuf)	0.769***	0.741***	0.748***	0.901***	0.917***	0.912***	0.932***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	12.811	13.743	14.074	12.867	13.601	13.955	14.414
B-RUMIDAS (All-IPI)	0.697***	0.696***	0.702***	0.796***	0.802***	0.813***	0.807***
B-RUMIDAS (IPI-Cons)	0.699***	0.698***	0.704***	0.798***	0.805***	0.815***	0.809***
B-RUMIDAS (IPI-Elec)	0.694***	0.692***	0.698***	0.791***	0.796***	0.806***	0.801***
B-RUMIDAS (IPI-Manuf)	0.707***	0.708***	0.714***	0.809***	0.819***	0.830***	0.824***
B-RUMIDAS (IPI-Cons-Elec)	0.695***	0.694***	0.700***	0.794***	0.800***	0.811***	0.805***
B-RUMIDAS (IPI-Cons-Manuf)	0.701***	0.701***	0.707***	0.801***	0.809***	0.819***	0.813***
B-RUMIDAS (IPI-Elec-Manuf)	0.696***	0.695***	0.701***	0.794***	0.801***	0.812***	0.806***
benchmark 1 lag							
BAR(1)	12.900	13.839	14.182	12.977	13.710	14.080	14.536
B-RUMIDAS (All-IPI)	0.695***	0.693***	0.699***	0.792***	0.798***	0.807***	0.800***
B-RUMIDAS (IPI-Cons)	0.696***	0.696***	0.701***	0.794***	0.800***	0.809***	0.803***
B-RUMIDAS (IPI-Elec)	0.691***	0.690***	0.696***	0.787***	0.792***	0.801***	0.795***
B-RUMIDAS (IPI-Manuf)	0.704***	0.704***	0.711***	0.805***	0.814***	0.824***	0.818***
B-RUMIDAS (IPI-Cons-Elec)	0.693***	0.691***	0.697***	0.790***	0.795***	0.806***	0.800***
B-RUMIDAS (IPI-Cons-Manuf)	0.699***	0.699***	0.704***	0.797***	0.804***	0.813***	0.806***
B-RUMIDAS (IPI-Elec-Manuf)	0.694***	0.692***	0.698***	0.790***	0.797***	0.807***	0.801***

Table 13: RMSE for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	5.995	6.702	6.812	5.689	5.930	6.184	6.227
B-RUMIDAS (All-IPI)	0.737***	0.705***	0.716***	0.898***	0.917***	0.914***	0.930***
B-RUMIDAS (IPI-Cons)	0.736***	0.705***	0.716***	0.897***	0.918***	0.915***	0.932***
B-RUMIDAS (IPI-Elec)	0.733***	0.701***	0.712***	0.892***	0.911***	0.907***	0.924***
B-RUMIDAS (IPI-Manuf)	0.742***	0.711***	0.724***	0.908***	0.930***	0.928***	0.946***
B-RUMIDAS (IPI-Cons-Elec)	0.735***	0.702***	0.713***	0.895***	0.915***	0.912***	0.929***
B-RUMIDAS (IPI-Cons-Manuf)	0.739***	0.709***	0.720***	0.901***	0.923***	0.919***	0.934***
B-RUMIDAS (IPI-Elec-Manuf)	0.736***	0.704***	0.715***	0.897***	0.917***	0.913***	0.930***
benchmark 3 lags							
BAR(3)	6.014	6.726	6.833	5.707	5.958	6.218	6.266
B-RUMIDAS (All-IPI)	0.737***	0.704***	0.716***	0.897***	0.914***	0.910***	0.924***
B-RUMIDAS (IPI-Cons)	0.735***	0.704***	0.716***	0.897***	0.915***	0.911***	0.926***
B-RUMIDAS (IPI-Elec)	0.732***	0.700***	0.711***	0.891***	0.908***	0.904***	0.918***
B-RUMIDAS (IPI-Manuf)	0.741***	0.710***	0.723***	0.906***	0.927***	0.924***	0.939***
B-RUMIDAS (IPI-Cons-Elec)	0.734***	0.701***	0.713***	0.895***	0.912***	0.908***	0.923***
B-RUMIDAS (IPI-Cons-Manuf)	0.738***	0.708***	0.720***	0.902***	0.919***	0.915***	0.928***
B-RUMIDAS (IPI-Elec-Manuf)	0.735***	0.703***	0.715***	0.896***	0.913***	0.909***	0.924***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	6.871	7.390	7.590	6.719	7.161	7.312	7.515
B-RUMIDAS (All-IPI)	0.667***	0.666***	0.673***	0.785***	0.790***	0.802***	0.801***
B-RUMIDAS (IPI-Cons)	0.669***	0.667***	0.675***	0.787***	0.793***	0.805***	0.805***
B-RUMIDAS (IPI-Elec)	0.664***	0.661***	0.668***	0.779***	0.783***	0.794***	0.795***
B-RUMIDAS (IPI-Manuf)	0.678***	0.678***	0.686***	0.799***	0.808***	0.822***	0.822***
B-RUMIDAS (IPI-Cons-Elec)	0.665***	0.663***	0.670***	0.781***	0.787***	0.800***	0.800***
B-RUMIDAS (IPI-Cons-Manuf)	0.672***	0.671***	0.679***	0.791***	0.797***	0.809***	0.808***
B-RUMIDAS (IPI-Elec-Manuf)	0.666***	0.665***	0.672***	0.784***	0.789***	0.802***	0.800***
benchmark 1 lag							
BAR(1)	6.920	7.444	7.651	6.780	7.215	7.374	7.577
B-RUMIDAS (All-IPI)	0.665***	0.664***	0.670***	0.781***	0.786***	0.797***	0.794***
B-RUMIDAS (IPI-Cons)	0.667***	0.665***	0.672***	0.783***	0.789***	0.800***	0.799***
B-RUMIDAS (IPI-Elec)	0.661***	0.660***	0.666***	0.775***	0.780***	0.790***	0.789***
B-RUMIDAS (IPI-Manuf)	0.676***	0.676***	0.683***	0.795***	0.804***	0.817***	0.816***
B-RUMIDAS (IPI-Cons-Elec)	0.663***	0.661***	0.668***	0.778***	0.783***	0.795***	0.794***
B-RUMIDAS (IPI-Cons-Manuf)	0.670***	0.669***	0.676***	0.787***	0.794***	0.803***	0.801***
B-RUMIDAS (IPI-Elec-Manuf)	0.664***	0.663***	0.670***	0.780***	0.786***	0.796***	0.795***

Table 14: Average CRPS for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	-3.953	-4.055	-4.084	-4.032	-4.170	-4.221	-4.141
B-RUMIDAS (All-IPI)	0.162***	0.147**	0.145**	0.124**	0.173**	0.136*	0.050
B-RUMIDAS (IPI-Cons)	0.144**	0.137*	0.137*	0.103*	0.147*	0.097	0.076**
B-RUMIDAS (IPI-Elec)	0.144**	0.166**	0.121*	0.124*	0.099	0.111	0.080**
B-RUMIDAS (IPI-Manuf)	0.119*	0.159**	0.128*	0.118**	0.142*	0.064	0.057*
B-RUMIDAS (IPI-Cons-Elec)	0.142**	0.155**	0.131*	0.125**	0.176**	0.116	0.084**
B-RUMIDAS (IPI-Cons-Manuf)	0.140**	0.154**	0.127*	0.083	0.121*	0.112	0.085**
B-RUMIDAS (IPI-Elec-Manuf)	0.137**	0.126*	0.138*	0.137**	0.142*	0.102	0.049
benchmark 3 lags							
BAR(3)	-3.989	-4.068	-4.088	-4.019	-4.181	-4.220	-4.123
B-RUMIDAS (All-IPI)	0.198***	0.166**	0.165**	0.084	0.161*	0.110	0.047
B-RUMIDAS (IPI-Cons)	0.188***	0.179**	0.159**	0.098*	0.115	0.106	0.052
B-RUMIDAS (IPI-Elec)	0.189***	0.143**	0.165**	0.091	0.188**	0.146*	0.042
B-RUMIDAS (IPI-Manuf)	0.177***	0.168**	0.119*	0.081	0.124*	0.131*	0.001
B-RUMIDAS (IPI-Cons-Elec)	0.188***	0.170**	0.130*	0.105*	0.157*	0.162**	0.044
B-RUMIDAS (IPI-Cons-Manuf)	0.188***	0.159**	0.130*	0.059	0.145*	0.126*	0.029
B-RUMIDAS (IPI-Elec-Manuf)	0.191***	0.171**	0.128*	0.071	0.154*	0.138*	0.023
benchmark 1 lag + Seasonal Dummies							
BAR(1)	-4.076	-4.146	-4.201	-4.198	-4.259	-4.308	-4.433
B-RUMIDAS (All-IPI)	0.213**	0.211**	0.231**	0.257***	0.244**	0.145	0.310***
B-RUMIDAS (IPI-Cons)	0.219**	0.211**	0.247***	0.224**	0.245**	0.169*	0.320***
B-RUMIDAS (IPI-Elec)	0.211**	0.199**	0.267***	0.275***	0.254**	0.178*	0.306***
B-RUMIDAS (IPI-Manuf)	0.190**	0.202**	0.219***	0.250***	0.241**	0.166*	0.280***
B-RUMIDAS (IPI-Cons-Elec)	0.235**	0.227***	0.253***	0.252***	0.239**	0.168*	0.294***
B-RUMIDAS (IPI-Cons-Manuf)	0.207**	0.179**	0.226**	0.256***	0.237**	0.162*	0.269***
B-RUMIDAS (IPI-Elec-Manuf)	0.215**	0.201**	0.258***	0.266***	0.265**	0.152	0.324***
benchmark 1 lag							
BAR(1)	-4.145	-4.174	-4.172	-4.227	-4.286	-4.337	-4.392
B-RUMIDAS (All-IPI)	0.292***	0.224**	0.191*	0.289***	0.262**	0.215**	0.265***
B-RUMIDAS (IPI-Cons)	0.296***	0.210**	0.209**	0.279***	0.269**	0.202**	0.247***
B-RUMIDAS (IPI-Elec)	0.302***	0.197**	0.209**	0.316***	0.254**	0.198**	0.226***
B-RUMIDAS (IPI-Manuf)	0.248***	0.201**	0.184*	0.238***	0.276***	0.180*	0.220***
B-RUMIDAS (IPI-Cons-Elec)	0.281***	0.255***	0.193*	0.278***	0.268**	0.188**	0.277***
B-RUMIDAS (IPI-Cons-Manuf)	0.272***	0.242**	0.178*	0.273***	0.273***	0.164*	0.252***
B-RUMIDAS (IPI-Elec-Manuf)	0.290***	0.214**	0.201**	0.267***	0.277***	0.186*	0.291***

Table 15: Average Predictive Likelihood score for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	0.581	0.657	0.673	0.616	0.642	0.613	0.629
B-RUMIDAS (All-IPI)	0.733	0.796	0.802	0.644	0.660	0.648	0.635
B-RUMIDAS (IPI-Cons)	0.737	0.796	0.797	0.648	0.659	0.644	0.633
B-RUMIDAS (IPI-Elec)	0.739	0.801	0.800	0.645	0.666	0.648	0.638
B-RUMIDAS (IPI-Manuf)	0.734	0.797	0.798	0.644	0.656	0.639	0.625
B-RUMIDAS (IPI-Cons-Elec)	0.731	0.798	0.800	0.648	0.661	0.649	0.636
B-RUMIDAS (IPI-Cons-Manuf)	0.735	0.796	0.799	0.643	0.660	0.641	0.630
B-RUMIDAS (IPI-Elec-Manuf)	0.734	0.796	0.800	0.646	0.658	0.647	0.637
benchmark 3 lags							
BAR(3)	0.575	0.655	0.673	0.617	0.633	0.608	0.627
B-RUMIDAS (All-IPI)	0.734	0.795	0.799	0.644	0.657	0.647	0.638
B-RUMIDAS (IPI-Cons)	0.738	0.794	0.798	0.646	0.658	0.646	0.634
B-RUMIDAS (IPI-Elec)	0.737	0.798	0.801	0.651	0.662	0.647	0.640
B-RUMIDAS (IPI-Manuf)	0.736	0.794	0.801	0.641	0.653	0.640	0.631
B-RUMIDAS (IPI-Cons-Elec)	0.736	0.799	0.801	0.649	0.662	0.646	0.635
B-RUMIDAS (IPI-Cons-Manuf)	0.734	0.793	0.799	0.639	0.654	0.642	0.631
B-RUMIDAS (IPI-Elec-Manuf)	0.735	0.794	0.801	0.640	0.660	0.646	0.638
benchmark 1 lag + Seasonal Dummies							
BAR(1)	0.547	0.662	0.664	0.581	0.577	0.567	0.574
B-RUMIDAS (All-IPI)	0.715	0.785	0.786	0.629	0.648	0.635	0.622
B-RUMIDAS (IPI-Cons)	0.715	0.784	0.785	0.630	0.648	0.624	0.620
B-RUMIDAS (IPI-Elec)	0.713	0.786	0.789	0.633	0.649	0.638	0.630
B-RUMIDAS (IPI-Manuf)	0.710	0.783	0.782	0.625	0.644	0.620	0.611
B-RUMIDAS (IPI-Cons-Elec)	0.710	0.787	0.787	0.630	0.647	0.635	0.622
B-RUMIDAS (IPI-Cons-Manuf)	0.715	0.783	0.789	0.632	0.653	0.625	0.622
B-RUMIDAS (IPI-Elec-Manuf)	0.711	0.784	0.788	0.630	0.646	0.634	0.625
benchmark 1 lag							
BAR(1)	0.543	0.663	0.662	0.580	0.578	0.565	0.569
B-RUMIDAS (All-IPI)	0.716	0.784	0.786	0.627	0.641	0.634	0.622
B-RUMIDAS (IPI-Cons)	0.714	0.783	0.785	0.628	0.646	0.628	0.617
B-RUMIDAS (IPI-Elec)	0.714	0.782	0.791	0.630	0.645	0.636	0.626
B-RUMIDAS (IPI-Manuf)	0.715	0.784	0.788	0.622	0.641	0.617	0.612
B-RUMIDAS (IPI-Cons-Elec)	0.715	0.783	0.787	0.630	0.643	0.634	0.624
B-RUMIDAS (IPI-Cons-Manuf)	0.718	0.782	0.790	0.626	0.644	0.623	0.619
B-RUMIDAS (IPI-Elec-Manuf)	0.712	0.782	0.787	0.626	0.641	0.634	0.618

Table 16: Success Rate (SR) for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

B Table Results - Daily Data for Oil for Italy

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	8.544	9.184	9.339	8.530	9.500	10.181	10.736
B-RUMIDAS (All-IPI)	0.810***	0.792***	0.802***	0.916***	0.918***	0.917***	0.920***
B-RUMIDAS (IPI-Cons)	0.823***	0.807***	0.817***	0.934***	0.935**	0.927***	0.929**
B-RUMIDAS (IPI-Elec)	0.815***	0.797***	0.806***	0.921***	0.919***	0.912***	0.916***
B-RUMIDAS (IPI-Manuf)	0.822***	0.806***	0.815***	0.933***	0.932**	0.923***	0.925**
B-RUMIDAS (IPI-Cons-Elec)	0.814***	0.796***	0.805***	0.917***	0.921***	0.918***	0.921***
B-RUMIDAS (IPI-Cons-Manuf)	0.819***	0.802***	0.813***	0.933***	0.931***	0.922***	0.923***
B-RUMIDAS (IPI-Elec-Manuf)	0.814***	0.796***	0.806***	0.918***	0.920***	0.918***	0.922***
benchmark 3 lags							
BAR(3)	8.547	9.194	9.341	8.536	9.518	10.225	10.831
B-RUMIDAS (All-IPI)	0.813***	0.796***	0.807***	0.922***	0.923***	0.918***	0.920***
B-RUMIDAS (IPI-Cons)	0.825***	0.808***	0.819***	0.937***	0.936**	0.926***	0.927***
B-RUMIDAS (IPI-Elec)	0.818***	0.800***	0.810***	0.926***	0.922***	0.913***	0.916***
B-RUMIDAS (IPI-Manuf)	0.824***	0.807***	0.818***	0.936***	0.934**	0.923***	0.922***
B-RUMIDAS (IPI-Cons-Elec)	0.818***	0.800***	0.810***	0.924***	0.925***	0.919***	0.921***
B-RUMIDAS (IPI-Cons-Manuf)	0.821***	0.804***	0.816***	0.936***	0.933**	0.922***	0.921***
B-RUMIDAS (IPI-Elec-Manuf)	0.817***	0.799***	0.810***	0.923***	0.924***	0.919***	0.921***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	9.698	10.245	10.499	10.003	10.866	11.474	12.173
B-RUMIDAS (All-IPI)	0.752***	0.744***	0.752***	0.815***	0.824***	0.829***	0.829***
B-RUMIDAS (IPI-Cons)	0.768***	0.765***	0.772***	0.838***	0.847***	0.844***	0.843***
B-RUMIDAS (IPI-Elec)	0.754***	0.748***	0.756***	0.819***	0.825***	0.825***	0.824***
B-RUMIDAS (IPI-Manuf)	0.767***	0.763***	0.771***	0.838***	0.844***	0.840***	0.838***
B-RUMIDAS (IPI-Cons-Elec)	0.753***	0.747***	0.754***	0.816***	0.824***	0.829***	0.829***
B-RUMIDAS (IPI-Cons-Manuf)	0.766***	0.760***	0.769***	0.836***	0.843***	0.840***	0.837***
B-RUMIDAS (IPI-Elec-Manuf)	0.756***	0.750***	0.756***	0.818***	0.826***	0.830***	0.832***
benchmark 1 lag							
BAR(1)	9.732	10.270	10.535	10.032	10.897	11.515	12.256
B-RUMIDAS (All-IPI)	0.756***	0.750***	0.758***	0.822***	0.829***	0.831***	0.830***
B-RUMIDAS (IPI-Cons)	0.770***	0.767***	0.775***	0.843***	0.848***	0.845***	0.843***
B-RUMIDAS (IPI-Elec)	0.757***	0.754***	0.760***	0.825***	0.829***	0.828***	0.826***
B-RUMIDAS (IPI-Manuf)	0.770***	0.767***	0.774***	0.842***	0.846***	0.841***	0.838***
B-RUMIDAS (IPI-Cons-Elec)	0.757***	0.753***	0.759***	0.823***	0.830***	0.832***	0.832***
B-RUMIDAS (IPI-Cons-Manuf)	0.768***	0.763***	0.772***	0.840***	0.845***	0.840***	0.837***
B-RUMIDAS (IPI-Elec-Manuf)	0.759***	0.754***	0.761***	0.825***	0.832***	0.833***	0.832***

Table 17: RMSE for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	4.601	4.944	5.023	4.627	5.114	5.439	5.778
B-RUMIDAS (All-IPI)	0.803***	0.783***	0.792***	0.915***	0.926***	0.927***	0.931***
B-RUMIDAS (IPI-Cons)	0.815***	0.798***	0.807***	0.934***	0.943***	0.937***	0.940***
B-RUMIDAS (IPI-Elec)	0.808***	0.790***	0.799***	0.922***	0.928***	0.922***	0.925***
B-RUMIDAS (IPI-Manuf)	0.815***	0.797***	0.806***	0.934***	0.941***	0.935***	0.937***
B-RUMIDAS (IPI-Cons-Elec)	0.807***	0.789***	0.797***	0.917***	0.928***	0.928***	0.931***
B-RUMIDAS (IPI-Cons-Manuf)	0.811***	0.792***	0.802***	0.933***	0.939***	0.934***	0.935***
B-RUMIDAS (IPI-Elec-Manuf)	0.806***	0.786***	0.795***	0.918***	0.929***	0.930***	0.933***
benchmark 3 lags							
BAR(3)	4.603	4.948	5.026	4.629	5.128	5.463	5.836
B-RUMIDAS (All-IPI)	0.806***	0.787***	0.796***	0.921***	0.929***	0.929***	0.930***
B-RUMIDAS (IPI-Cons)	0.816***	0.799***	0.809***	0.938***	0.943***	0.936***	0.937***
B-RUMIDAS (IPI-Elec)	0.811***	0.793***	0.802***	0.928***	0.930***	0.924***	0.924***
B-RUMIDAS (IPI-Manuf)	0.815***	0.799***	0.808***	0.937***	0.941***	0.935***	0.933***
B-RUMIDAS (IPI-Cons-Elec)	0.811***	0.792***	0.801***	0.923***	0.931***	0.929***	0.931***
B-RUMIDAS (IPI-Cons-Manuf)	0.813***	0.794***	0.804***	0.936***	0.940***	0.933***	0.932***
B-RUMIDAS (IPI-Elec-Manuf)	0.809***	0.789***	0.799***	0.923***	0.931***	0.930***	0.931***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	5.227	5.517	5.636	5.373	5.899	6.156	6.530
B-RUMIDAS (All-IPI)	0.750***	0.743***	0.750***	0.826***	0.831***	0.841***	0.844***
B-RUMIDAS (IPI-Cons)	0.765***	0.761***	0.769***	0.848***	0.854***	0.856***	0.857***
B-RUMIDAS (IPI-Elec)	0.752***	0.747***	0.755***	0.831***	0.833***	0.836***	0.837***
B-RUMIDAS (IPI-Manuf)	0.765***	0.760***	0.769***	0.849***	0.852***	0.853***	0.854***
B-RUMIDAS (IPI-Cons-Elec)	0.752***	0.747***	0.754***	0.826***	0.831***	0.841***	0.843***
B-RUMIDAS (IPI-Cons-Manuf)	0.764***	0.756***	0.765***	0.847***	0.850***	0.852***	0.852***
B-RUMIDAS (IPI-Elec-Manuf)	0.753***	0.746***	0.753***	0.829***	0.833***	0.843***	0.847***
benchmark 1 lag							
BAR(1)	5.247	5.530	5.656	5.389	5.919	6.182	6.576
B-RUMIDAS (All-IPI)	0.754***	0.748***	0.755***	0.832***	0.836***	0.843***	0.845***
B-RUMIDAS (IPI-Cons)	0.767***	0.764***	0.771***	0.853***	0.854***	0.857***	0.857***
B-RUMIDAS (IPI-Elec)	0.755***	0.753***	0.759***	0.836***	0.837***	0.839***	0.838***
B-RUMIDAS (IPI-Manuf)	0.767***	0.764***	0.771***	0.853***	0.853***	0.854***	0.854***
B-RUMIDAS (IPI-Cons-Elec)	0.755***	0.752***	0.759***	0.833***	0.837***	0.843***	0.846***
B-RUMIDAS (IPI-Cons-Manuf)	0.765***	0.759***	0.768***	0.851***	0.852***	0.853***	0.853***
B-RUMIDAS (IPI-Elec-Manuf)	0.756***	0.751***	0.758***	0.836***	0.839***	0.845***	0.847***

Table 18: Average CRPS for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	-3.602	-3.743	-3.760	-3.679	-3.773	-3.890	-3.933
B-RUMIDAS (All-IPI)	0.138***	0.202***	0.208***	0.071***	0.074**	0.103***	0.109***
B-RUMIDAS (IPI-Cons)	0.102**	0.165***	0.187***	0.062***	0.030	0.097***	0.107***
B-RUMIDAS (IPI-Elec)	0.128***	0.203***	0.200***	0.066***	0.083***	0.096***	0.082**
B-RUMIDAS (IPI-Manuf)	0.111**	0.174***	0.164***	0.078***	0.074***	0.087***	0.084**
B-RUMIDAS (IPI-Cons-Elec)	0.150***	0.206***	0.190***	0.093***	0.083***	0.100***	0.097***
B-RUMIDAS (IPI-Cons-Manuf)	0.116**	0.190***	0.163***	0.057***	0.071***	0.075**	0.063*
B-RUMIDAS (IPI-Elec-Manuf)	0.134***	0.199***	0.165***	0.080***	0.058*	0.108***	0.092***
benchmark 3 lags							
BAR(3)	-3.656	-3.767	-3.759	-3.654	-3.776	-3.916	-3.919
B-RUMIDAS (All-IPI)	0.193***	0.221***	0.183***	0.039	0.052*	0.148***	0.064**
B-RUMIDAS (IPI-Cons)	0.202***	0.193***	0.148***	0.040	0.070***	0.134***	0.046
B-RUMIDAS (IPI-Elec)	0.186***	0.229***	0.188***	0.065*	0.070***	0.132***	0.099***
B-RUMIDAS (IPI-Manuf)	0.169***	0.209***	0.178***	0.041	0.065***	0.124***	0.069**
B-RUMIDAS (IPI-Cons-Elec)	0.183***	0.226***	0.188***	0.068***	0.053*	0.156***	0.072**
B-RUMIDAS (IPI-Cons-Manuf)	0.183***	0.204***	0.167***	0.033	0.062***	0.133***	0.076**
B-RUMIDAS (IPI-Elec-Manuf)	0.180***	0.210***	0.162***	0.046*	0.063**	0.132***	0.078***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	-3.786	-3.850	-3.895	-3.820	-3.868	-3.981	-4.075
B-RUMIDAS (All-IPI)	0.271***	0.282***	0.282***	0.185***	0.159***	0.203***	0.209***
B-RUMIDAS (IPI-Cons)	0.258***	0.233***	0.250***	0.147***	0.127**	0.181***	0.196***
B-RUMIDAS (IPI-Elec)	0.267***	0.262***	0.286***	0.192***	0.156***	0.210***	0.227***
B-RUMIDAS (IPI-Manuf)	0.249***	0.261***	0.274***	0.151***	0.150***	0.185***	0.212***
B-RUMIDAS (IPI-Cons-Elec)	0.252***	0.314***	0.298***	0.181***	0.159***	0.190***	0.233***
B-RUMIDAS (IPI-Cons-Manuf)	0.252***	0.272***	0.223***	0.173***	0.161***	0.168***	0.192***
B-RUMIDAS (IPI-Elec-Manuf)	0.273***	0.271***	0.284***	0.187***	0.160***	0.203***	0.221***
benchmark 1 lag							
BAR(1)	-3.774	-3.852	-3.893	-3.853	-3.876	-3.974	-4.074
B-RUMIDAS (All-IPI)	0.273***	0.265***	0.285***	0.191***	0.181***	0.179***	0.218***
B-RUMIDAS (IPI-Cons)	0.239***	0.240***	0.258***	0.180***	0.153***	0.176***	0.208***
B-RUMIDAS (IPI-Elec)	0.236***	0.257***	0.273***	0.206***	0.148***	0.222***	0.238***
B-RUMIDAS (IPI-Manuf)	0.243***	0.243***	0.219***	0.195***	0.141***	0.144***	0.212***
B-RUMIDAS (IPI-Cons-Elec)	0.232***	0.277***	0.283***	0.202***	0.161***	0.193***	0.213***
B-RUMIDAS (IPI-Cons-Manuf)	0.248***	0.269***	0.220***	0.186***	0.166***	0.166***	0.217***
B-RUMIDAS (IPI-Elec-Manuf)	0.246***	0.287***	0.255***	0.223***	0.142***	0.193***	0.233***

Table 19: Average Predictive Likelihood score for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	0.584	0.639	0.646	0.600	0.593	0.593	0.608
B-RUMIDAS (All-IPI)	0.670	0.749	0.749	0.642	0.639	0.626	0.641
B-RUMIDAS (IPI-Cons)	0.680	0.751	0.738	0.626	0.626	0.624	0.638
B-RUMIDAS (IPI-Elec)	0.684	0.746	0.738	0.629	0.636	0.630	0.644
B-RUMIDAS (IPI-Manuf)	0.676	0.747	0.736	0.625	0.631	0.623	0.638
B-RUMIDAS (IPI-Cons-Elec)	0.675	0.752	0.741	0.638	0.635	0.630	0.641
B-RUMIDAS (IPI-Cons-Manuf)	0.678	0.751	0.739	0.631	0.637	0.623	0.640
B-RUMIDAS (IPI-Elec-Manuf)	0.677	0.754	0.747	0.636	0.631	0.623	0.640
benchmark 3 lags							
BAR(3)	0.582	0.636	0.644	0.599	0.589	0.595	0.596
B-RUMIDAS (All-IPI)	0.675	0.747	0.747	0.633	0.630	0.623	0.635
B-RUMIDAS (IPI-Cons)	0.680	0.749	0.736	0.619	0.623	0.621	0.635
B-RUMIDAS (IPI-Elec)	0.680	0.746	0.737	0.628	0.626	0.629	0.634
B-RUMIDAS (IPI-Manuf)	0.684	0.746	0.738	0.620	0.628	0.620	0.635
B-RUMIDAS (IPI-Cons-Elec)	0.676	0.746	0.739	0.631	0.631	0.628	0.636
B-RUMIDAS (IPI-Cons-Manuf)	0.678	0.746	0.739	0.622	0.627	0.623	0.630
B-RUMIDAS (IPI-Elec-Manuf)	0.680	0.752	0.745	0.628	0.625	0.625	0.634
benchmark 1 lag + Seasonal Dummies							
BAR(1)	0.548	0.608	0.629	0.577	0.566	0.567	0.573
B-RUMIDAS (All-IPI)	0.650	0.741	0.729	0.630	0.642	0.615	0.639
B-RUMIDAS (IPI-Cons)	0.654	0.731	0.720	0.620	0.622	0.608	0.630
B-RUMIDAS (IPI-Elec)	0.659	0.743	0.725	0.625	0.631	0.622	0.641
B-RUMIDAS (IPI-Manuf)	0.651	0.735	0.719	0.617	0.618	0.610	0.629
B-RUMIDAS (IPI-Cons-Elec)	0.654	0.743	0.728	0.621	0.637	0.622	0.638
B-RUMIDAS (IPI-Cons-Manuf)	0.647	0.733	0.719	0.619	0.622	0.607	0.631
B-RUMIDAS (IPI-Elec-Manuf)	0.651	0.738	0.730	0.630	0.634	0.614	0.639
benchmark 1 lag							
BAR(1)	0.550	0.607	0.625	0.579	0.564	0.567	0.566
B-RUMIDAS (All-IPI)	0.647	0.741	0.732	0.626	0.629	0.612	0.636
B-RUMIDAS (IPI-Cons)	0.650	0.733	0.722	0.609	0.615	0.605	0.630
B-RUMIDAS (IPI-Elec)	0.653	0.738	0.729	0.620	0.623	0.616	0.635
B-RUMIDAS (IPI-Manuf)	0.649	0.730	0.721	0.609	0.619	0.599	0.627
B-RUMIDAS (IPI-Cons-Elec)	0.652	0.740	0.731	0.617	0.627	0.613	0.632
B-RUMIDAS (IPI-Cons-Manuf)	0.646	0.731	0.723	0.611	0.615	0.601	0.630
B-RUMIDAS (IPI-Elec-Manuf)	0.651	0.739	0.730	0.627	0.624	0.610	0.639

Table 20: Success Rate (SR) for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

C Table Results - Interpolated Data (only macroeconomic variables) for Germany

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	11.226	12.410	12.664	11.052	11.505	12.001	11.933
BARX(3) (All-IPI)	0.958***	0.934***	0.926***	0.966**	0.973**	0.967**	0.972*
BARX(3) (IPI-Cons)	0.961***	0.937***	0.930***	0.967***	0.972**	0.963**	0.970*
BARX(3) (IPI-Elec)	0.956***	0.932***	0.923***	0.963***	0.967***	0.957***	0.965**
BARX(3) (IPI-Manuf)	0.967***	0.948***	0.940***	0.973**	0.981*	0.973	0.981
BARX(3) (IPI-Cons-Elec)	0.956***	0.931***	0.922***	0.963***	0.968***	0.962**	0.969*
BARX(3) (IPI-Cons-Manuf)	0.962***	0.940***	0.931***	0.969**	0.976**	0.968*	0.972*
BARX(3) (IPI-Elec-Manuf)	0.957***	0.933***	0.924***	0.964***	0.970**	0.964**	0.970*
benchmark 3 lags							
BAR(3)	11.257	12.437	12.700	11.090	11.557	12.068	12.005
BARX(3) (All-IPI)	0.958***	0.936***	0.926***	0.965***	0.970**	0.963**	0.967**
BARX(3) (IPI-Cons)	0.959***	0.938***	0.929***	0.965***	0.968***	0.959**	0.965**
BARX(3) (IPI-Elec)	0.956***	0.932***	0.922***	0.961***	0.963***	0.954***	0.960***
BARX(3) (IPI-Manuf)	0.965***	0.948***	0.940***	0.971**	0.977*	0.969*	0.976
BARX(3) (IPI-Cons-Elec)	0.956***	0.932***	0.922***	0.961***	0.964***	0.957***	0.963**
BARX(3) (IPI-Cons-Manuf)	0.961***	0.940***	0.931***	0.967**	0.973**	0.963**	0.967**
BARX(3) (IPI-Elec-Manuf)	0.956***	0.934***	0.924***	0.961***	0.966***	0.960***	0.963**
benchmark 1 lag + Seasonal Dummies							
BAR(1)	12.811	13.743	14.074	12.867	13.601	13.955	14.414
BARX(1) (All-IPI)	0.886***	0.868***	0.861***	0.891***	0.891***	0.896***	0.885***
BARX(1) (IPI-Cons)	0.890***	0.872***	0.865***	0.894***	0.892***	0.894***	0.886***
BARX(1) (IPI-Elec)	0.882***	0.862***	0.856***	0.886***	0.882***	0.884***	0.876***
BARX(1) (IPI-Manuf)	0.903***	0.887***	0.881***	0.905***	0.907***	0.910***	0.901***
BARX(1) (IPI-Cons-Elec)	0.882***	0.863***	0.856***	0.886***	0.884***	0.890***	0.881***
BARX(1) (IPI-Cons-Manuf)	0.893***	0.875***	0.868***	0.897***	0.897***	0.899***	0.886***
BARX(1) (IPI-Elec-Manuf)	0.885***	0.866***	0.859***	0.888***	0.888***	0.893***	0.883***
benchmark 1 lag							
BAR(1)	12.900	13.839	14.182	12.977	13.710	14.080	14.536
BARX(1) (All-IPI)	0.883***	0.865***	0.858***	0.886***	0.885***	0.889***	0.877***
BARX(1) (IPI-Cons)	0.887***	0.869***	0.861***	0.888***	0.885***	0.887***	0.878***
BARX(1) (IPI-Elec)	0.879***	0.860***	0.852***	0.881***	0.877***	0.878***	0.870***
BARX(1) (IPI-Manuf)	0.899***	0.884***	0.876***	0.899***	0.900***	0.903***	0.894***
BARX(1) (IPI-Cons-Elec)	0.878***	0.860***	0.852***	0.881***	0.878***	0.882***	0.875***
BARX(1) (IPI-Cons-Manuf)	0.889***	0.873***	0.865***	0.891***	0.891***	0.891***	0.879***
BARX(1) (IPI-Elec-Manuf)	0.882***	0.864***	0.855***	0.883***	0.882***	0.886***	0.874***

Table 21: RMSE for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and we interpolate the monthly IPI macroeconomic variables in order to have daily data. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	5.995	6.702	6.812	5.689	5.930	6.184	6.227
BARX(3) (All-IPI)	0.946***	0.912***	0.904***	0.961***	0.965***	0.964***	0.967***
BARX(3) (IPI-Cons)	0.949***	0.916***	0.908***	0.960***	0.964***	0.962***	0.967***
BARX(3) (IPI-Elec)	0.945***	0.909***	0.901***	0.957***	0.959***	0.955***	0.961***
BARX(3) (IPI-Manuf)	0.956***	0.926***	0.918***	0.967***	0.973**	0.973**	0.978*
BARX(3) (IPI-Cons-Elec)	0.945***	0.909***	0.901***	0.957***	0.960***	0.959***	0.965***
BARX(3) (IPI-Cons-Manuf)	0.950***	0.918***	0.909***	0.964***	0.968***	0.965***	0.967***
BARX(3) (IPI-Elec-Manuf)	0.945***	0.911***	0.903***	0.958***	0.962***	0.961***	0.965***
benchmark 3 lags							
BAR(3)	6.014	6.726	6.833	5.707	5.958	6.218	6.266
BARX(3) (All-IPI)	0.947***	0.913***	0.905***	0.959***	0.961***	0.959***	0.961***
BARX(3) (IPI-Cons)	0.948***	0.916***	0.908***	0.960***	0.960***	0.957***	0.960***
BARX(3) (IPI-Elec)	0.944***	0.909***	0.901***	0.955***	0.954***	0.951***	0.954***
BARX(3) (IPI-Manuf)	0.954***	0.925***	0.919***	0.965***	0.969***	0.968**	0.972**
BARX(3) (IPI-Cons-Elec)	0.944***	0.909***	0.901***	0.955***	0.955***	0.953***	0.958***
BARX(3) (IPI-Cons-Manuf)	0.950***	0.917***	0.909***	0.962***	0.964***	0.960***	0.961***
BARX(3) (IPI-Elec-Manuf)	0.945***	0.911***	0.903***	0.955***	0.957***	0.956***	0.958***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	6.871	7.390	7.590	6.719	7.161	7.312	7.515
BARX(1) (All-IPI)	0.877***	0.852***	0.842***	0.895***	0.887***	0.896***	0.889***
BARX(1) (IPI-Cons)	0.882***	0.857***	0.846***	0.898***	0.890***	0.896***	0.892***
BARX(1) (IPI-Elec)	0.873***	0.847***	0.836***	0.890***	0.879***	0.885***	0.880***
BARX(1) (IPI-Manuf)	0.895***	0.872***	0.862***	0.912***	0.906***	0.914***	0.910***
BARX(1) (IPI-Cons-Elec)	0.873***	0.847***	0.837***	0.890***	0.881***	0.890***	0.887***
BARX(1) (IPI-Cons-Manuf)	0.884***	0.860***	0.849***	0.901***	0.895***	0.899***	0.891***
BARX(1) (IPI-Elec-Manuf)	0.876***	0.850***	0.839***	0.892***	0.885***	0.893***	0.887***
benchmark 1 lag							
BAR(1)	6.920	7.444	7.651	6.780	7.215	7.374	7.577
BARX(1) (All-IPI)	0.875***	0.851***	0.839***	0.890***	0.882***	0.889***	0.881***
BARX(1) (IPI-Cons)	0.879***	0.854***	0.844***	0.894***	0.884***	0.889***	0.885***
BARX(1) (IPI-Elec)	0.871***	0.846***	0.833***	0.886***	0.875***	0.879***	0.875***
BARX(1) (IPI-Manuf)	0.892***	0.870***	0.858***	0.906***	0.900***	0.907***	0.903***
BARX(1) (IPI-Cons-Elec)	0.870***	0.845***	0.833***	0.884***	0.876***	0.884***	0.880***
BARX(1) (IPI-Cons-Manuf)	0.881***	0.858***	0.847***	0.896***	0.889***	0.893***	0.884***
BARX(1) (IPI-Elec-Manuf)	0.874***	0.849***	0.836***	0.887***	0.879***	0.886***	0.879***

Table 22: Average CRPS for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and we interpolate the monthly IPI macroeconomic variables in order to have daily data. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	-3.953	-4.055	-4.084	-4.032	-4.170	-4.221	-4.141
BARX(3) (All-IPI)	0.019	0.029	0.044	0.085*	0.017	0.095*	0.090***
BARX(3) (IPI-Cons)	0.005	0.007	0.051*	0.089**	0.034	0.074	0.077**
BARX(3) (IPI-Elec)	0.017	0.032	0.028	0.077*	0.028	0.091*	0.056**
BARX(3) (IPI-Manuf)	-0.000	0.011	0.027	0.068*	0.028	0.059	0.039
BARX(3) (IPI-Cons-Elec)	0.006	0.026	0.045	0.094**	0.079	0.099*	0.080***
BARX(3) (IPI-Cons-Manuf)	0.025	-0.005	0.043	0.082*	0.048	0.103*	0.074**
BARX(3) (IPI-Elec-Manuf)	0.024	0.019	0.032	0.065	0.044	0.100*	0.067**
benchmark 3 lags							
BAR(3)	-3.989	-4.068	-4.088	-4.019	-4.181	-4.220	-4.123
BARX(3) (All-IPI)	0.045**	0.031	0.048*	0.077*	0.047	0.063	0.051**
BARX(3) (IPI-Cons)	0.042**	0.041	0.051*	0.038	0.046	0.090*	0.057*
BARX(3) (IPI-Elec)	0.052***	0.033	0.046	0.086**	0.071	0.092**	0.030
BARX(3) (IPI-Manuf)	0.034*	0.036*	0.007	0.060	0.047	0.070	0.031
BARX(3) (IPI-Cons-Elec)	0.025	-0.002	0.080***	0.060	0.057	0.073*	0.051**
BARX(3) (IPI-Cons-Manuf)	0.030	0.029	0.039	0.058	0.062	0.099*	0.057*
BARX(3) (IPI-Elec-Manuf)	0.060***	0.032	0.048*	0.091**	0.040	0.085	0.041
benchmark 1 lag + Seasonal Dummies							
BAR(1)	-4.076	-4.146	-4.201	-4.198	-4.259	-4.308	-4.433
BARX(1) (All-IPI)	0.061	0.106**	0.128**	0.214***	0.191**	0.158*	0.289***
BARX(1) (IPI-Cons)	0.041	0.113**	0.166***	0.199***	0.198**	0.155*	0.234***
BARX(1) (IPI-Elec)	0.059	0.107**	0.155***	0.225***	0.213**	0.167*	0.283***
BARX(1) (IPI-Manuf)	0.057	0.090*	0.100*	0.197***	0.189**	0.122	0.232***
BARX(1) (IPI-Cons-Elec)	0.056	0.089	0.128**	0.221***	0.209**	0.158*	0.280***
BARX(1) (IPI-Cons-Manuf)	0.053	0.075	0.138**	0.209***	0.195**	0.167*	0.279***
BARX(1) (IPI-Elec-Manuf)	0.082	0.082	0.150***	0.217***	0.213**	0.153*	0.281***
benchmark 1 lag							
BAR(1)	-4.145	-4.174	-4.172	-4.227	-4.286	-4.337	-4.392
BARX(1) (All-IPI)	0.113	0.134**	0.127*	0.221***	0.233**	0.191**	0.237***
BARX(1) (IPI-Cons)	0.134*	0.109*	0.096	0.231***	0.232***	0.201**	0.209**
BARX(1) (IPI-Elec)	0.118*	0.123**	0.137**	0.244***	0.247***	0.193**	0.247***
BARX(1) (IPI-Manuf)	0.086	0.065	0.094	0.197***	0.187**	0.163*	0.200**
BARX(1) (IPI-Cons-Elec)	0.163**	0.121*	0.100	0.256***	0.222**	0.187**	0.225**
BARX(1) (IPI-Cons-Manuf)	0.140**	0.104*	0.065	0.235***	0.208**	0.158*	0.205**
BARX(1) (IPI-Elec-Manuf)	0.118*	0.101	0.094	0.241***	0.220**	0.178**	0.210**

Table 23: Average Predictive Likelihood score for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and we interpolate the monthly IPI macroeconomic variables in order to have daily data. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	0.581	0.657	0.673	0.616	0.642	0.613	0.629
BARX(3) (All-IPI)	0.566	0.664	0.678	0.628	0.650	0.639	0.648
BARX(3) (IPI-Cons)	0.556	0.657	0.681	0.627	0.653	0.634	0.638
BARX(3) (IPI-Elec)	0.555	0.661	0.676	0.631	0.652	0.643	0.643
BARX(3) (IPI-Manuf)	0.554	0.650	0.673	0.615	0.655	0.628	0.635
BARX(3) (IPI-Cons-Elec)	0.563	0.667	0.679	0.632	0.656	0.640	0.641
BARX(3) (IPI-Cons-Manuf)	0.559	0.662	0.677	0.620	0.646	0.634	0.644
BARX(3) (IPI-Elec-Manuf)	0.567	0.666	0.680	0.628	0.650	0.637	0.644
benchmark 3 lags							
BAR(3)	0.575	0.655	0.673	0.617	0.633	0.608	0.627
BARX(3) (All-IPI)	0.561	0.659	0.677	0.627	0.653	0.635	0.647
BARX(3) (IPI-Cons)	0.552	0.657	0.674	0.629	0.650	0.629	0.638
BARX(3) (IPI-Elec)	0.554	0.656	0.675	0.627	0.655	0.638	0.646
BARX(3) (IPI-Manuf)	0.554	0.649	0.670	0.617	0.649	0.627	0.634
BARX(3) (IPI-Cons-Elec)	0.564	0.661	0.677	0.631	0.660	0.638	0.643
BARX(3) (IPI-Cons-Manuf)	0.559	0.657	0.677	0.623	0.649	0.631	0.647
BARX(3) (IPI-Elec-Manuf)	0.563	0.661	0.677	0.630	0.648	0.635	0.647
benchmark 1 lag + Seasonal Dummies							
BAR(1)	0.547	0.662	0.664	0.581	0.577	0.567	0.574
BARX(1) (All-IPI)	0.542	0.653	0.654	0.612	0.632	0.630	0.627
BARX(1) (IPI-Cons)	0.526	0.640	0.651	0.613	0.630	0.632	0.620
BARX(1) (IPI-Elec)	0.531	0.642	0.654	0.612	0.634	0.632	0.629
BARX(1) (IPI-Manuf)	0.525	0.631	0.642	0.608	0.626	0.622	0.609
BARX(1) (IPI-Cons-Elec)	0.538	0.649	0.657	0.610	0.639	0.631	0.625
BARX(1) (IPI-Cons-Manuf)	0.534	0.650	0.653	0.610	0.630	0.630	0.624
BARX(1) (IPI-Elec-Manuf)	0.541	0.651	0.660	0.608	0.632	0.629	0.626
benchmark 1 lag							
BAR(1)	0.543	0.663	0.662	0.580	0.578	0.565	0.569
BARX(1) (All-IPI)	0.544	0.651	0.656	0.609	0.635	0.628	0.628
BARX(1) (IPI-Cons)	0.529	0.637	0.648	0.611	0.628	0.623	0.622
BARX(1) (IPI-Elec)	0.531	0.636	0.654	0.610	0.636	0.630	0.629
BARX(1) (IPI-Manuf)	0.527	0.628	0.643	0.612	0.627	0.622	0.608
BARX(1) (IPI-Cons-Elec)	0.538	0.643	0.652	0.610	0.633	0.633	0.628
BARX(1) (IPI-Cons-Manuf)	0.536	0.640	0.652	0.611	0.631	0.632	0.627
BARX(1) (IPI-Elec-Manuf)	0.543	0.650	0.656	0.607	0.631	0.630	0.627

Table 24: Success Rate (SR) for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and we interpolate the monthly IPI macroeconomic variables in order to have daily data. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

D Table Results - Interpolated Data (only IPI) for Italy

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	8.544	9.184	9.339	8.530	9.500	10.181	10.736
BARX(3) (All-IPI)	0.955***	0.940***	0.936***	0.955***	0.951**	0.952	0.952
BARX(3) (IPI-Cons)	0.974***	0.965***	0.963***	0.976*	0.968	0.961	0.957
BARX(3) (IPI-Elec)	0.965***	0.952***	0.948***	0.964***	0.953**	0.946**	0.944**
BARX(3) (IPI-Manuf)	0.974***	0.965***	0.962***	0.975*	0.966	0.958	0.953
BARX(3) (IPI-Cons-Elec)	0.954***	0.938***	0.934***	0.952***	0.947***	0.947**	0.947*
BARX(3) (IPI-Cons-Manuf)	0.974***	0.967***	0.965***	0.978	0.969	0.962	0.957
BARX(3) (IPI-Elec-Manuf)	0.959***	0.947***	0.943***	0.959***	0.956*	0.955	0.955
benchmark 3 lags							
BAR(3)	8.547	9.194	9.341	8.536	9.518	10.225	10.831
BARX(3) (All-IPI)	0.961***	0.947***	0.944***	0.962***	0.955*	0.954	0.952
BARX(3) (IPI-Cons)	0.977***	0.968***	0.966***	0.978*	0.970	0.959	0.954
BARX(3) (IPI-Elec)	0.968***	0.955***	0.953***	0.968**	0.956**	0.947**	0.943**
BARX(3) (IPI-Manuf)	0.976***	0.967***	0.967***	0.978	0.967	0.957	0.951
BARX(3) (IPI-Cons-Elec)	0.959***	0.945***	0.941***	0.959***	0.952**	0.949**	0.947**
BARX(3) (IPI-Cons-Manuf)	0.978***	0.968***	0.968***	0.980	0.970	0.961	0.955
BARX(3) (IPI-Elec-Manuf)	0.965***	0.952***	0.950***	0.965***	0.960	0.956	0.954
benchmark 1 lag + Seasonal Dummies							
BAR(1)	9.698	10.245	10.499	10.003	10.866	11.474	12.173
BARX(1) (All-IPI)	0.883***	0.873***	0.866***	0.876***	0.873***	0.877***	0.876***
BARX(1) (IPI-Cons)	0.918***	0.911***	0.906***	0.910***	0.904***	0.898***	0.891***
BARX(1) (IPI-Elec)	0.899***	0.888***	0.883***	0.890***	0.881***	0.876***	0.871***
BARX(1) (IPI-Manuf)	0.918***	0.911***	0.906***	0.910***	0.903***	0.894***	0.887***
BARX(1) (IPI-Cons-Elec)	0.883***	0.871***	0.864***	0.874***	0.869***	0.872***	0.872***
BARX(1) (IPI-Cons-Manuf)	0.918***	0.911***	0.907***	0.912***	0.904***	0.898***	0.890***
BARX(1) (IPI-Elec-Manuf)	0.895***	0.884***	0.877***	0.885***	0.884***	0.885***	0.882***
benchmark 1 lag							
BAR(1)	9.732	10.270	10.535	10.032	10.897	11.515	12.256
BARX(1) (All-IPI)	0.892***	0.882***	0.876***	0.885***	0.881***	0.882***	0.878***
BARX(1) (IPI-Cons)	0.921***	0.914***	0.910***	0.914***	0.906***	0.898***	0.889***
BARX(1) (IPI-Elec)	0.904***	0.895***	0.889***	0.895***	0.886***	0.879***	0.873***
BARX(1) (IPI-Manuf)	0.920***	0.915***	0.910***	0.913***	0.905***	0.895***	0.886***
BARX(1) (IPI-Cons-Elec)	0.891***	0.880***	0.873***	0.882***	0.876***	0.877***	0.874***
BARX(1) (IPI-Cons-Manuf)	0.921***	0.915***	0.911***	0.915***	0.907***	0.899***	0.890***
BARX(1) (IPI-Elec-Manuf)	0.900***	0.891***	0.885***	0.892***	0.889***	0.888***	0.884***

Table 25: RMSE for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and we interpolate the monthly IPI macroeconomic variables in order to have daily data. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	4.601	4.944	5.023	4.627	5.114	5.439	5.778
BARX(3) (All-IPI)	0.952***	0.938***	0.934***	0.959***	0.959***	0.963***	0.964***
BARX(3) (IPI-Cons)	0.968***	0.958***	0.956***	0.975***	0.971***	0.968***	0.966***
BARX(3) (IPI-Elec)	0.961***	0.948***	0.944***	0.965***	0.958***	0.955***	0.952***
BARX(3) (IPI-Manuf)	0.969***	0.959***	0.956***	0.976***	0.971***	0.967***	0.964***
BARX(3) (IPI-Cons-Elec)	0.951***	0.936***	0.932***	0.954***	0.953***	0.956***	0.956***
BARX(3) (IPI-Cons-Manuf)	0.970***	0.961***	0.959***	0.981***	0.976***	0.973***	0.972***
BARX(3) (IPI-Elec-Manuf)	0.955***	0.941***	0.938***	0.960***	0.962***	0.964***	0.966***
benchmark 3 lags							
BAR(3)	4.603	4.948	5.026	4.629	5.128	5.463	5.836
BARX(3) (All-IPI)	0.958***	0.945***	0.942***	0.966***	0.961***	0.965***	0.963***
BARX(3) (IPI-Cons)	0.971***	0.961***	0.959***	0.978***	0.972***	0.967***	0.963***
BARX(3) (IPI-Elec)	0.964***	0.951***	0.949***	0.969***	0.960***	0.956***	0.950***
BARX(3) (IPI-Manuf)	0.971***	0.961***	0.960***	0.978***	0.971***	0.967***	0.961***
BARX(3) (IPI-Cons-Elec)	0.957***	0.943***	0.939***	0.961***	0.957***	0.957***	0.955***
BARX(3) (IPI-Cons-Manuf)	0.973***	0.963***	0.962***	0.982**	0.976***	0.973***	0.968***
BARX(3) (IPI-Elec-Manuf)	0.960***	0.947***	0.944***	0.966***	0.964***	0.965***	0.964***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	5.227	5.517	5.636	5.373	5.899	6.156	6.530
BARX(1) (All-IPI)	0.890***	0.878***	0.873***	0.890***	0.883***	0.892***	0.893***
BARX(1) (IPI-Cons)	0.921***	0.910***	0.908***	0.921***	0.910***	0.910***	0.905***
BARX(1) (IPI-Elec)	0.904***	0.892***	0.888***	0.902***	0.888***	0.889***	0.884***
BARX(1) (IPI-Manuf)	0.921***	0.911***	0.909***	0.922***	0.910***	0.908***	0.904***
BARX(1) (IPI-Cons-Elec)	0.890***	0.876***	0.870***	0.886***	0.877***	0.886***	0.884***
BARX(1) (IPI-Cons-Manuf)	0.923***	0.913***	0.910***	0.925***	0.914***	0.914***	0.910***
BARX(1) (IPI-Elec-Manuf)	0.899***	0.886***	0.881***	0.897***	0.891***	0.898***	0.897***
benchmark 1 lag							
BAR(1)	5.247	5.530	5.656	5.389	5.919	6.182	6.576
BARX(1) (All-IPI)	0.898***	0.887***	0.882***	0.898***	0.890***	0.897***	0.895***
BARX(1) (IPI-Cons)	0.923***	0.914***	0.911***	0.925***	0.911***	0.909***	0.903***
BARX(1) (IPI-Elec)	0.909***	0.898***	0.894***	0.908***	0.893***	0.890***	0.885***
BARX(1) (IPI-Manuf)	0.925***	0.916***	0.913***	0.926***	0.912***	0.909***	0.903***
BARX(1) (IPI-Cons-Elec)	0.897***	0.885***	0.879***	0.895***	0.884***	0.890***	0.886***
BARX(1) (IPI-Cons-Manuf)	0.925***	0.916***	0.914***	0.929***	0.916***	0.915***	0.909***
BARX(1) (IPI-Elec-Manuf)	0.904***	0.893***	0.888***	0.905***	0.896***	0.901***	0.898***

Table 26: Average CRPS for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and we interpolate the monthly IPI macroeconomic variables in order to have daily data. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	-3.602	-3.743	-3.760	-3.679	-3.773	-3.890	-3.933
BARX(3) (All-IPI)	0.002	0.080**	0.065***	0.039***	0.043*	0.063***	0.076***
BARX(3) (IPI-Cons)	-0.024	0.017	0.025**	0.024**	0.037*	0.052*	0.074**
BARX(3) (IPI-Elec)	-0.012	0.026	0.053***	0.031**	0.036*	0.066***	0.091***
BARX(3) (IPI-Manuf)	-0.000	0.020	0.020	0.033**	0.016	0.044	0.081***
BARX(3) (IPI-Cons-Elec)	0.007	0.077***	0.067***	0.043***	0.046*	0.082***	0.087***
BARX(3) (IPI-Cons-Manuf)	-0.003	0.039	0.034**	0.032**	0.024	0.055**	0.057**
BARX(3) (IPI-Elec-Manuf)	-0.018	0.028	0.050**	0.048***	0.052**	0.061***	0.050*
benchmark 3 lags							
BAR(3)	-3.656	-3.767	-3.759	-3.654	-3.776	-3.916	-3.919
BARX(3) (All-IPI)	0.044	0.052**	0.042***	0.010	0.034	0.086**	0.051*
BARX(3) (IPI-Cons)	0.039	0.046*	0.013	-0.005	0.017	0.071**	0.057*
BARX(3) (IPI-Elec)	0.050	0.073**	0.039**	0.003	0.034*	0.103**	0.046
BARX(3) (IPI-Manuf)	0.051*	0.023	-0.004	0.007	0.010	0.060*	0.059**
BARX(3) (IPI-Cons-Elec)	0.042	0.078**	0.043**	0.019	0.057***	0.110***	0.059*
BARX(3) (IPI-Cons-Manuf)	0.060*	0.044	0.033***	-0.003	0.027	0.086**	0.063**
BARX(3) (IPI-Elec-Manuf)	0.045	0.058*	0.039**	0.000	0.027	0.090**	0.042*
benchmark 1 lag + Seasonal Dummies							
BAR(1)	-3.786	-3.850	-3.895	-3.820	-3.868	-3.981	-4.075
BARX(1) (All-IPI)	0.161***	0.135***	0.164***	0.148***	0.117**	0.178***	0.176***
BARX(1) (IPI-Cons)	0.110**	0.097**	0.092*	0.098**	0.110**	0.141**	0.164***
BARX(1) (IPI-Elec)	0.141***	0.115***	0.139***	0.139***	0.096*	0.146**	0.211***
BARX(1) (IPI-Manuf)	0.122**	0.089**	0.119**	0.130***	0.109**	0.153***	0.159***
BARX(1) (IPI-Cons-Elec)	0.142**	0.155***	0.170***	0.134***	0.140***	0.179***	0.198***
BARX(1) (IPI-Cons-Manuf)	0.133**	0.095**	0.121***	0.098**	0.099*	0.129**	0.172***
BARX(1) (IPI-Elec-Manuf)	0.140***	0.133***	0.141***	0.123**	0.107**	0.154***	0.187***
benchmark 1 lag							
BAR(1)	-3.774	-3.852	-3.893	-3.853	-3.876	-3.974	-4.074
BARX(1) (All-IPI)	0.120**	0.136***	0.158***	0.160**	0.117**	0.153***	0.192***
BARX(1) (IPI-Cons)	0.116**	0.093**	0.124**	0.136**	0.085**	0.090*	0.168***
BARX(1) (IPI-Elec)	0.109**	0.157***	0.154***	0.175***	0.113***	0.168***	0.196***
BARX(1) (IPI-Manuf)	0.104**	0.113**	0.100*	0.145***	0.103**	0.139***	0.173***
BARX(1) (IPI-Cons-Elec)	0.134***	0.153***	0.155***	0.152**	0.108**	0.150***	0.190***
BARX(1) (IPI-Cons-Manuf)	0.091**	0.090**	0.124**	0.130**	0.091**	0.122**	0.176***
BARX(1) (IPI-Elec-Manuf)	0.132**	0.130**	0.137**	0.138**	0.118***	0.138***	0.173***

Table 27: Average Predictive Likelihood score for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and we interpolate the monthly IPI macroeconomic variables in order to have daily data. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	0.584	0.639	0.646	0.600	0.593	0.593	0.608
BARX(3) (All-IPI)	0.594	0.653	0.660	0.620	0.631	0.615	0.626
BARX(3) (IPI-Cons)	0.575	0.636	0.642	0.618	0.616	0.614	0.622
BARX(3) (IPI-Elec)	0.578	0.644	0.645	0.620	0.631	0.622	0.635
BARX(3) (IPI-Manuf)	0.573	0.638	0.642	0.614	0.623	0.611	0.626
BARX(3) (IPI-Cons-Elec)	0.597	0.662	0.659	0.620	0.632	0.624	0.631
BARX(3) (IPI-Cons-Manuf)	0.565	0.634	0.640	0.611	0.619	0.609	0.625
BARX(3) (IPI-Elec-Manuf)	0.592	0.653	0.659	0.618	0.625	0.618	0.626
benchmark 3 lags							
BAR(3)	0.582	0.636	0.644	0.599	0.589	0.595	0.596
BARX(3) (All-IPI)	0.592	0.654	0.661	0.619	0.626	0.615	0.624
BARX(3) (IPI-Cons)	0.574	0.640	0.648	0.618	0.615	0.605	0.620
BARX(3) (IPI-Elec)	0.581	0.650	0.656	0.618	0.626	0.614	0.627
BARX(3) (IPI-Manuf)	0.569	0.642	0.647	0.614	0.622	0.606	0.627
BARX(3) (IPI-Cons-Elec)	0.597	0.662	0.658	0.614	0.626	0.615	0.626
BARX(3) (IPI-Cons-Manuf)	0.568	0.637	0.648	0.614	0.619	0.604	0.625
BARX(3) (IPI-Elec-Manuf)	0.592	0.656	0.661	0.620	0.625	0.609	0.624
benchmark 1 lag + Seasonal Dummies							
BAR(3)	0.548	0.608	0.629	0.577	0.566	0.567	0.573
BARX(3) (All-IPI)	0.575	0.642	0.647	0.612	0.631	0.615	0.627
BARX(3) (IPI-Cons)	0.553	0.626	0.628	0.604	0.609	0.593	0.619
BARX(3) (IPI-Elec)	0.562	0.634	0.634	0.612	0.617	0.613	0.626
BARX(3) (IPI-Manuf)	0.560	0.628	0.623	0.611	0.615	0.602	0.620
BARX(3) (IPI-Cons-Elec)	0.583	0.646	0.646	0.609	0.627	0.613	0.628
BARX(3) (IPI-Cons-Manuf)	0.553	0.622	0.622	0.608	0.609	0.598	0.621
BARX(3) (IPI-Elec-Manuf)	0.575	0.643	0.649	0.615	0.623	0.614	0.630
benchmark 1 lag							
BAR(3)	0.550	0.607	0.625	0.579	0.564	0.567	0.566
BARX(3) (All-IPI)	0.578	0.643	0.644	0.609	0.627	0.612	0.626
BARX(3) (IPI-Cons)	0.550	0.624	0.624	0.605	0.604	0.593	0.617
BARX(3) (IPI-Elec)	0.561	0.640	0.634	0.606	0.622	0.608	0.624
BARX(3) (IPI-Manuf)	0.554	0.622	0.618	0.603	0.609	0.598	0.620
BARX(3) (IPI-Cons-Elec)	0.573	0.642	0.644	0.603	0.624	0.615	0.624
BARX(3) (IPI-Cons-Manuf)	0.551	0.622	0.617	0.604	0.606	0.591	0.617
BARX(3) (IPI-Elec-Manuf)	0.565	0.646	0.644	0.613	0.615	0.613	0.620

Table 28: Success Rate (SR) for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and we interpolate the monthly IPI macroeconomic variables in order to have daily data. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

E Table Results - Monthly Data for Germany

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	11.226	12.410	12.664	11.052	11.505	12.001	11.933
B-RUMIDAS (All-IPI)	0.782***	0.753***	0.763***	0.919***	0.937***	0.934**	0.962
B-RUMIDAS (IPI-Cons)	0.784***	0.757***	0.766***	0.921***	0.942**	0.939*	0.967
B-RUMIDAS (IPI-Elec)	0.780***	0.753***	0.762***	0.916***	0.936**	0.932**	0.959
B-RUMIDAS (IPI-Manuf)	0.788***	0.761***	0.771***	0.928***	0.949*	0.947	0.975
B-RUMIDAS (IPI-Cons-Elec)	0.782***	0.753***	0.762***	0.919***	0.939**	0.937*	0.964
B-RUMIDAS (IPI-Cons-Manuf)	0.785***	0.757***	0.767***	0.923***	0.942**	0.938*	0.965
B-RUMIDAS (IPI-Elec-Manuf)	0.781***	0.752***	0.762***	0.917***	0.936***	0.932**	0.960
benchmark 3 lags							
BAR(3)	11.257	12.437	12.700	11.090	11.557	12.068	12.005
B-RUMIDAS (All-IPI)	0.781***	0.753***	0.762***	0.917***	0.934***	0.930**	0.955*
B-RUMIDAS (IPI-Cons)	0.783***	0.755***	0.765***	0.919***	0.938**	0.935*	0.960
B-RUMIDAS (IPI-Elec)	0.779***	0.752***	0.760***	0.915***	0.933***	0.928**	0.953*
B-RUMIDAS (IPI-Manuf)	0.787***	0.761***	0.770***	0.927***	0.945**	0.942	0.968
B-RUMIDAS (IPI-Cons-Elec)	0.781***	0.753***	0.761***	0.917***	0.936***	0.932**	0.958
B-RUMIDAS (IPI-Cons-Manuf)	0.783***	0.757***	0.766***	0.921***	0.939**	0.935**	0.959
B-RUMIDAS (IPI-Elec-Manuf)	0.780***	0.752***	0.761***	0.916***	0.933***	0.929**	0.954*
benchmark 1 lag + Seasonal Dummies							
BAR(1)	12.811	13.743	14.074	12.867	13.601	13.955	14.414
B-RUMIDAS (All-IPI)	0.712***	0.712***	0.718***	0.815***	0.823***	0.832***	0.829***
B-RUMIDAS (IPI-Cons)	0.717***	0.717***	0.724***	0.821***	0.831***	0.839***	0.836***
B-RUMIDAS (IPI-Elec)	0.711***	0.711***	0.717***	0.814***	0.822***	0.831***	0.827***
B-RUMIDAS (IPI-Manuf)	0.724***	0.725***	0.732***	0.831***	0.841***	0.850***	0.847***
B-RUMIDAS (IPI-Cons-Elec)	0.713***	0.712***	0.719***	0.816***	0.826***	0.835***	0.833***
B-RUMIDAS (IPI-Cons-Manuf)	0.717***	0.718***	0.725***	0.822***	0.830***	0.838***	0.835***
B-RUMIDAS (IPI-Elec-Manuf)	0.711***	0.710***	0.718***	0.813***	0.822***	0.830***	0.829***
benchmark 1 lag							
BAR(1)	12.900	13.839	14.182	12.977	13.710	14.080	14.536
B-RUMIDAS (All-IPI)	0.710***	0.708***	0.715***	0.811***	0.818***	0.825***	0.822***
B-RUMIDAS (IPI-Cons)	0.714***	0.714***	0.720***	0.816***	0.825***	0.832***	0.829***
B-RUMIDAS (IPI-Elec)	0.709***	0.708***	0.714***	0.809***	0.817***	0.823***	0.820***
B-RUMIDAS (IPI-Manuf)	0.720***	0.722***	0.728***	0.826***	0.835***	0.843***	0.839***
B-RUMIDAS (IPI-Cons-Elec)	0.710***	0.709***	0.715***	0.812***	0.821***	0.829***	0.825***
B-RUMIDAS (IPI-Cons-Manuf)	0.714***	0.714***	0.721***	0.817***	0.825***	0.831***	0.828***
B-RUMIDAS (IPI-Elec-Manuf)	0.708***	0.707***	0.714***	0.809***	0.817***	0.823***	0.821***

Table 29: RMSE for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and IPI and we have different benchmark models. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	5.995	6.702	6.812	5.689	5.930	6.184	6.227
B-RUMIDAS (All-IPI)	0.745***	0.712***	0.725***	0.915***	0.939***	0.939***	0.960***
B-RUMIDAS (IPI-Cons)	0.747***	0.715***	0.728***	0.918***	0.944***	0.944***	0.965**
B-RUMIDAS (IPI-Elec)	0.743***	0.711***	0.723***	0.913***	0.937***	0.936***	0.956***
B-RUMIDAS (IPI-Manuf)	0.751***	0.720***	0.734***	0.926***	0.952***	0.954***	0.974*
B-RUMIDAS (IPI-Cons-Elec)	0.744***	0.711***	0.724***	0.914***	0.940***	0.941***	0.963**
B-RUMIDAS (IPI-Cons-Manuf)	0.748***	0.717***	0.729***	0.921***	0.945***	0.943***	0.964**
B-RUMIDAS (IPI-Elec-Manuf)	0.744***	0.711***	0.724***	0.914***	0.938***	0.936***	0.957***
benchmark 3 lags							
BAR(3)	6.014	6.726	6.833	5.707	5.958	6.218	6.266
B-RUMIDAS (All-IPI)	0.744***	0.712***	0.724***	0.914***	0.936***	0.933***	0.951***
B-RUMIDAS (IPI-Cons)	0.745***	0.713***	0.727***	0.916***	0.940***	0.939***	0.957***
B-RUMIDAS (IPI-Elec)	0.741***	0.710***	0.722***	0.912***	0.933***	0.932***	0.949***
B-RUMIDAS (IPI-Manuf)	0.750***	0.719***	0.732***	0.925***	0.947***	0.948***	0.966**
B-RUMIDAS (IPI-Cons-Elec)	0.742***	0.710***	0.722***	0.913***	0.937***	0.936***	0.954***
B-RUMIDAS (IPI-Cons-Manuf)	0.747***	0.716***	0.729***	0.919***	0.940***	0.939***	0.956***
B-RUMIDAS (IPI-Elec-Manuf)	0.743***	0.710***	0.723***	0.913***	0.933***	0.932***	0.949***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	6.871	7.390	7.590	6.719	7.161	7.312	7.515
B-RUMIDAS (All-IPI)	0.680***	0.679***	0.688***	0.806***	0.814***	0.828***	0.829***
B-RUMIDAS (IPI-Cons)	0.685***	0.685***	0.693***	0.813***	0.824***	0.835***	0.838***
B-RUMIDAS (IPI-Elec)	0.679***	0.679***	0.686***	0.804***	0.814***	0.826***	0.827***
B-RUMIDAS (IPI-Manuf)	0.693***	0.694***	0.702***	0.823***	0.835***	0.848***	0.851***
B-RUMIDAS (IPI-Cons-Elec)	0.680***	0.679***	0.687***	0.807***	0.818***	0.831***	0.834***
B-RUMIDAS (IPI-Cons-Manuf)	0.686***	0.686***	0.695***	0.813***	0.823***	0.835***	0.837***
B-RUMIDAS (IPI-Elec-Manuf)	0.679***	0.678***	0.687***	0.804***	0.814***	0.825***	0.828***
benchmark 1 lag							
BAR(1)	6.920	7.444	7.651	6.780	7.215	7.374	7.577
B-RUMIDAS (All-IPI)	0.678***	0.677***	0.685***	0.801***	0.811***	0.820***	0.822***
B-RUMIDAS (IPI-Cons)	0.683***	0.682***	0.690***	0.808***	0.819***	0.829***	0.831***
B-RUMIDAS (IPI-Elec)	0.677***	0.677***	0.684***	0.800***	0.810***	0.819***	0.819***
B-RUMIDAS (IPI-Manuf)	0.690***	0.691***	0.699***	0.819***	0.830***	0.841***	0.842***
B-RUMIDAS (IPI-Cons-Elec)	0.677***	0.677***	0.685***	0.802***	0.814***	0.825***	0.825***
B-RUMIDAS (IPI-Cons-Manuf)	0.683***	0.683***	0.692***	0.809***	0.819***	0.828***	0.829***
B-RUMIDAS (IPI-Elec-Manuf)	0.676***	0.675***	0.684***	0.800***	0.809***	0.819***	0.820***

Table 30: Average CRPS for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and IPI and we have different benchmark models. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	-3.953	-4.055	-4.084	-4.032	-4.170	-4.221	-4.141
B-RUMIDAS (All-IPI)	0.129**	0.150**	0.128*	0.147**	0.140*	0.132*	0.061*
B-RUMIDAS (IPI-Cons)	0.119*	0.152**	0.143**	0.068	0.137*	0.139*	0.051
B-RUMIDAS (IPI-Elec)	0.159***	0.152**	0.186***	0.104*	0.136	0.087	0.039
B-RUMIDAS (IPI-Manuf)	0.162***	0.134**	0.127*	0.085	0.153*	0.094	0.016
B-RUMIDAS (IPI-Cons-Elec)	0.150**	0.159**	0.138**	0.096	0.167*	0.118	0.068**
B-RUMIDAS (IPI-Cons-Manuf)	0.148**	0.133*	0.126*	0.080	0.147*	0.118	0.032
B-RUMIDAS (IPI-Elec-Manuf)	0.111*	0.160**	0.111	0.119**	0.160**	0.125	0.065**
benchmark 3 lags							
BAR(3)	-3.989	-4.068	-4.088	-4.019	-4.181	-4.220	-4.123
B-RUMIDAS (All-IPI)	0.180***	0.152**	0.134*	0.091*	0.154*	0.101	0.049
B-RUMIDAS (IPI-Cons)	0.160**	0.128*	0.125*	0.073	0.130	0.094	0.030
B-RUMIDAS (IPI-Elec)	0.161**	0.163**	0.127*	0.072	0.155*	0.124	0.046
B-RUMIDAS (IPI-Manuf)	0.177***	0.151**	0.120*	0.062	0.116	0.112	-0.002
B-RUMIDAS (IPI-Cons-Elec)	0.178***	0.165**	0.116*	0.120**	0.159*	0.105	0.032
B-RUMIDAS (IPI-Cons-Manuf)	0.160**	0.137**	0.143**	0.067	0.169*	0.134*	0.018
B-RUMIDAS (IPI-Elec-Manuf)	0.167***	0.189***	0.116	0.081	0.180**	0.111	0.036
benchmark 1 lag + Seasonal Dummies							
BAR(1)	-4.076	-4.146	-4.201	-4.198	-4.259	-4.308	-4.433
B-RUMIDAS (All-IPI)	0.217**	0.187**	0.252***	0.249***	0.229**	0.202**	0.274***
B-RUMIDAS (IPI-Cons)	0.196**	0.195**	0.233***	0.244***	0.219**	0.142	0.260***
B-RUMIDAS (IPI-Elec)	0.190**	0.233***	0.216**	0.280***	0.245**	0.151	0.302***
B-RUMIDAS (IPI-Manuf)	0.184**	0.184**	0.213***	0.222***	0.253***	0.136	0.265***
B-RUMIDAS (IPI-Cons-Elec)	0.168*	0.204**	0.236***	0.249***	0.238**	0.210**	0.320***
B-RUMIDAS (IPI-Cons-Manuf)	0.172*	0.175**	0.230***	0.239***	0.250**	0.149	0.289***
B-RUMIDAS (IPI-Elec-Manuf)	0.223**	0.198**	0.247***	0.257***	0.274***	0.169	0.299***
benchmark 1 lag							
BAR(1)	-4.145	-4.174	-4.172	-4.227	-4.286	-4.337	-4.392
B-RUMIDAS (All-IPI)	0.260***	0.226**	0.211**	0.281***	0.253**	0.166*	0.255***
B-RUMIDAS (IPI-Cons)	0.262***	0.221**	0.223**	0.256***	0.246**	0.161*	0.228**
B-RUMIDAS (IPI-Elec)	0.268***	0.241**	0.215**	0.284***	0.243**	0.183*	0.277***
B-RUMIDAS (IPI-Manuf)	0.242***	0.192**	0.173*	0.251***	0.245**	0.165*	0.236***
B-RUMIDAS (IPI-Cons-Elec)	0.244***	0.223**	0.173*	0.279***	0.262**	0.196**	0.230***
B-RUMIDAS (IPI-Cons-Manuf)	0.245***	0.203**	0.178*	0.263***	0.233**	0.183*	0.249***
B-RUMIDAS (IPI-Elec-Manuf)	0.249***	0.221**	0.208**	0.262***	0.270***	0.217**	0.247***

Table 31: Average Predictive Likelihood score for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and IPI and we have different benchmark models. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	0.581	0.657	0.673	0.616	0.642	0.613	0.629
B-RUMIDAS (All-IPI)	0.731	0.794	0.785	0.630	0.651	0.637	0.629
B-RUMIDAS (IPI-Cons)	0.729	0.791	0.786	0.633	0.644	0.636	0.623
B-RUMIDAS (IPI-Elec)	0.729	0.792	0.787	0.635	0.651	0.638	0.632
B-RUMIDAS (IPI-Manuf)	0.729	0.794	0.785	0.628	0.643	0.630	0.619
B-RUMIDAS (IPI-Cons-Elec)	0.729	0.794	0.789	0.632	0.647	0.636	0.630
B-RUMIDAS (IPI-Cons-Manuf)	0.725	0.795	0.783	0.628	0.648	0.637	0.626
B-RUMIDAS (IPI-Elec-Manuf)	0.729	0.793	0.786	0.628	0.650	0.637	0.628
benchmark 3 lags							
BAR(3)	0.575	0.655	0.673	0.617	0.633	0.608	0.627
B-RUMIDAS (All-IPI)	0.727	0.792	0.782	0.631	0.657	0.641	0.632
B-RUMIDAS (IPI-Cons)	0.725	0.791	0.783	0.634	0.645	0.641	0.631
B-RUMIDAS (IPI-Elec)	0.730	0.790	0.785	0.632	0.651	0.640	0.638
B-RUMIDAS (IPI-Manuf)	0.724	0.788	0.783	0.628	0.645	0.632	0.620
B-RUMIDAS (IPI-Cons-Elec)	0.726	0.789	0.785	0.635	0.648	0.639	0.636
B-RUMIDAS (IPI-Cons-Manuf)	0.725	0.790	0.784	0.627	0.645	0.639	0.630
B-RUMIDAS (IPI-Elec-Manuf)	0.727	0.792	0.784	0.627	0.651	0.637	0.631
benchmark 1 lag + Seasonal Dummies							
BAR(1)	0.547	0.662	0.664	0.581	0.577	0.567	0.574
B-RUMIDAS (All-IPI)	0.699	0.774	0.773	0.626	0.634	0.625	0.613
B-RUMIDAS (IPI-Cons)	0.701	0.773	0.777	0.624	0.628	0.629	0.608
B-RUMIDAS (IPI-Elec)	0.703	0.775	0.779	0.627	0.631	0.629	0.612
B-RUMIDAS (IPI-Manuf)	0.702	0.773	0.776	0.622	0.630	0.622	0.607
B-RUMIDAS (IPI-Cons-Elec)	0.699	0.775	0.778	0.624	0.629	0.625	0.611
B-RUMIDAS (IPI-Cons-Manuf)	0.700	0.771	0.775	0.625	0.630	0.622	0.610
B-RUMIDAS (IPI-Elec-Manuf)	0.702	0.773	0.775	0.618	0.635	0.625	0.609
benchmark 1 lag							
BAR(1)	0.543	0.663	0.662	0.580	0.578	0.565	0.569
B-RUMIDAS (All-IPI)	0.699	0.773	0.773	0.620	0.638	0.622	0.615
B-RUMIDAS (IPI-Cons)	0.700	0.772	0.772	0.624	0.631	0.622	0.611
B-RUMIDAS (IPI-Elec)	0.703	0.776	0.774	0.628	0.637	0.631	0.616
B-RUMIDAS (IPI-Manuf)	0.704	0.772	0.772	0.617	0.632	0.622	0.604
B-RUMIDAS (IPI-Cons-Elec)	0.699	0.772	0.774	0.622	0.632	0.629	0.610
B-RUMIDAS (IPI-Cons-Manuf)	0.700	0.770	0.771	0.624	0.636	0.623	0.612
B-RUMIDAS (IPI-Elec-Manuf)	0.701	0.770	0.771	0.619	0.639	0.626	0.613

Table 32: Success Rate (SR) for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

F Table Results - Monthly Data for Italy

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	8.544	9.184	9.339	8.530	9.500	10.181	10.736
B-RUMIDAS (All-IPI)	0.824***	0.806***	0.817***	0.937***	0.939*	0.936*	0.937*
B-RUMIDAS (IPI-Cons)	0.837***	0.822***	0.832***	0.955**	0.956	0.948	0.948
B-RUMIDAS (IPI-Elec)	0.829***	0.811***	0.821***	0.943***	0.942	0.933**	0.934*
B-RUMIDAS (IPI-Manuf)	0.836***	0.819***	0.830***	0.953**	0.952	0.943	0.942
B-RUMIDAS (IPI-Cons-Elec)	0.825***	0.807***	0.817***	0.936***	0.942*	0.937*	0.940
B-RUMIDAS (IPI-Cons-Manuf)	0.835***	0.818***	0.829***	0.954***	0.952	0.943	0.942
B-RUMIDAS (IPI-Elec-Manuf)	0.829***	0.811***	0.822***	0.940***	0.941*	0.937*	0.939
benchmark 3 lags							
BAR(3)	8.547	9.194	9.341	8.536	9.518	10.225	10.831
B-RUMIDAS (All-IPI)	0.827***	0.809***	0.821***	0.942***	0.942*	0.936**	0.935**
B-RUMIDAS (IPI-Cons)	0.839***	0.822***	0.834***	0.957**	0.957	0.945	0.943
B-RUMIDAS (IPI-Elec)	0.831***	0.813***	0.825***	0.947***	0.944	0.932**	0.931**
B-RUMIDAS (IPI-Manuf)	0.837***	0.820***	0.832***	0.956**	0.953	0.940	0.938*
B-RUMIDAS (IPI-Cons-Elec)	0.829***	0.811***	0.822***	0.942***	0.944*	0.937*	0.936**
B-RUMIDAS (IPI-Cons-Manuf)	0.837***	0.819***	0.832***	0.957**	0.953	0.940	0.937*
B-RUMIDAS (IPI-Elec-Manuf)	0.832***	0.813***	0.826***	0.945***	0.944*	0.937*	0.936*
benchmark 1 lag + Seasonal Dummies							
BAR(1)	9.698	10.245	10.499	10.003	10.866	11.474	12.173
B-RUMIDAS (All-IPI)	0.769***	0.761***	0.769***	0.836***	0.849***	0.853***	0.852***
B-RUMIDAS (IPI-Cons)	0.788***	0.784***	0.792***	0.861***	0.875***	0.872***	0.869***
B-RUMIDAS (IPI-Elec)	0.773***	0.767***	0.775***	0.843***	0.853***	0.852***	0.849***
B-RUMIDAS (IPI-Manuf)	0.787***	0.781***	0.789***	0.859***	0.870***	0.866***	0.861***
B-RUMIDAS (IPI-Cons-Elec)	0.768***	0.762***	0.769***	0.836***	0.851***	0.854***	0.854***
B-RUMIDAS (IPI-Cons-Manuf)	0.787***	0.780***	0.789***	0.861***	0.871***	0.866***	0.862***
B-RUMIDAS (IPI-Elec-Manuf)	0.775***	0.767***	0.774***	0.841***	0.853***	0.855***	0.854***
benchmark 1 lag							
BAR(1)	9.732	10.270	10.535	10.032	10.897	11.515	12.256
B-RUMIDAS (All-IPI)	0.774***	0.766***	0.774***	0.843***	0.854***	0.854***	0.851***
B-RUMIDAS (IPI-Cons)	0.789***	0.785***	0.795***	0.864***	0.876***	0.870***	0.865***
B-RUMIDAS (IPI-Elec)	0.776***	0.771***	0.778***	0.848***	0.856***	0.852***	0.847***
B-RUMIDAS (IPI-Manuf)	0.788***	0.783***	0.791***	0.863***	0.870***	0.864***	0.859***
B-RUMIDAS (IPI-Cons-Elec)	0.772***	0.766***	0.775***	0.842***	0.855***	0.856***	0.852***
B-RUMIDAS (IPI-Cons-Manuf)	0.789***	0.782***	0.791***	0.863***	0.872***	0.865***	0.859***
B-RUMIDAS (IPI-Elec-Manuf)	0.778***	0.771***	0.779***	0.847***	0.857***	0.856***	0.853***

Table 33: RMSE for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and IPI and we have different benchmark models. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	4.601	4.944	5.023	4.627	5.114	5.439	5.778
B-RUMIDAS (All-IPI)	0.818***	0.798***	0.808***	0.937***	0.949***	0.948***	0.948***
B-RUMIDAS (IPI-Cons)	0.830***	0.814***	0.825***	0.957***	0.967***	0.960***	0.960***
B-RUMIDAS (IPI-Elec)	0.823***	0.806***	0.816***	0.946***	0.953***	0.945***	0.945***
B-RUMIDAS (IPI-Manuf)	0.829***	0.811***	0.822***	0.955***	0.964***	0.956***	0.954***
B-RUMIDAS (IPI-Cons-Elec)	0.819***	0.801***	0.810***	0.937***	0.951***	0.948***	0.950***
B-RUMIDAS (IPI-Cons-Manuf)	0.827***	0.809***	0.820***	0.956***	0.963***	0.955***	0.954***
B-RUMIDAS (IPI-Elec-Manuf)	0.822***	0.801***	0.812***	0.940***	0.951***	0.950***	0.951***
benchmark 3 lags							
BAR(3)	4.603	4.948	5.026	4.629	5.128	5.463	5.836
B-RUMIDAS (All-IPI)	0.821***	0.800***	0.811***	0.942***	0.949***	0.947***	0.944***
B-RUMIDAS (IPI-Cons)	0.831***	0.814***	0.826***	0.959***	0.967***	0.957***	0.955***
B-RUMIDAS (IPI-Elec)	0.825***	0.807***	0.819***	0.950***	0.954***	0.943***	0.940***
B-RUMIDAS (IPI-Manuf)	0.830***	0.811***	0.823***	0.958***	0.962***	0.953***	0.949***
B-RUMIDAS (IPI-Cons-Elec)	0.823***	0.804***	0.815***	0.942***	0.952***	0.947***	0.945***
B-RUMIDAS (IPI-Cons-Manuf)	0.829***	0.809***	0.822***	0.958***	0.962***	0.953***	0.948***
B-RUMIDAS (IPI-Elec-Manuf)	0.824***	0.804***	0.815***	0.945***	0.952***	0.949***	0.946***
benchmark 1 lag + Seasonal Dummies							
BAR(1)	5.227	5.517	5.636	5.373	5.899	6.156	6.530
B-RUMIDAS (All-IPI)	0.769***	0.759***	0.769***	0.848***	0.859***	0.866***	0.868***
B-RUMIDAS (IPI-Cons)	0.787***	0.782***	0.791***	0.874***	0.886***	0.887***	0.886***
B-RUMIDAS (IPI-Elec)	0.774***	0.767***	0.776***	0.857***	0.864***	0.865***	0.863***
B-RUMIDAS (IPI-Manuf)	0.787***	0.779***	0.788***	0.873***	0.881***	0.880***	0.879***
B-RUMIDAS (IPI-Cons-Elec)	0.769***	0.762***	0.771***	0.848***	0.861***	0.867***	0.869***
B-RUMIDAS (IPI-Cons-Manuf)	0.786***	0.778***	0.788***	0.874***	0.882***	0.880***	0.879***
B-RUMIDAS (IPI-Elec-Manuf)	0.773***	0.764***	0.773***	0.852***	0.863***	0.869***	0.870***
benchmark 1 lag							
BAR(1)	5.247	5.530	5.656	5.389	5.919	6.182	6.576
B-RUMIDAS (All-IPI)	0.773***	0.765***	0.773***	0.855***	0.863***	0.866***	0.866***
B-RUMIDAS (IPI-Cons)	0.787***	0.783***	0.793***	0.876***	0.885***	0.883***	0.880***
B-RUMIDAS (IPI-Elec)	0.775***	0.771***	0.780***	0.861***	0.867***	0.864***	0.861***
B-RUMIDAS (IPI-Manuf)	0.787***	0.781***	0.789***	0.875***	0.881***	0.878***	0.876***
B-RUMIDAS (IPI-Cons-Elec)	0.772***	0.766***	0.775***	0.854***	0.864***	0.867***	0.867***
B-RUMIDAS (IPI-Cons-Manuf)	0.787***	0.780***	0.789***	0.876***	0.882***	0.879***	0.875***
B-RUMIDAS (IPI-Elec-Manuf)	0.776***	0.768***	0.776***	0.858***	0.865***	0.868***	0.869***

Table 34: Average CRPS for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and IPI and we have different benchmark models. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	-3.602	-3.743	-3.760	-3.679	-3.773	-3.890	-3.933
B-RUMIDAS (All-IPI)	0.117***	0.182***	0.161***	0.083**	0.043*	0.097***	0.116***
B-RUMIDAS (IPI-Cons)	0.108***	0.196***	0.130***	0.027	0.046**	0.068**	0.053*
B-RUMIDAS (IPI-Elec)	0.131***	0.188***	0.162***	0.053**	0.048*	0.098***	0.073**
B-RUMIDAS (IPI-Manuf)	0.095**	0.185***	0.152***	0.053***	0.046*	0.075***	0.087**
B-RUMIDAS (IPI-Cons-Elec)	0.099**	0.191***	0.189***	0.072***	0.055**	0.120***	0.078**
B-RUMIDAS (IPI-Cons-Manuf)	0.111**	0.166***	0.121***	0.084***	0.044*	0.071***	0.083**
B-RUMIDAS (IPI-Elec-Manuf)	0.112**	0.170***	0.147***	0.062***	0.045*	0.096***	0.077**
benchmark 3 lags							
BAR(3)	-3.656	-3.767	-3.759	-3.654	-3.776	-3.916	-3.919
B-RUMIDAS (All-IPI)	0.160***	0.198***	0.155***	0.037*	0.035	0.107***	0.065***
B-RUMIDAS (IPI-Cons)	0.142***	0.174***	0.151***	0.014	0.032	0.098**	0.056*
B-RUMIDAS (IPI-Elec)	0.164***	0.187***	0.165***	0.045**	0.063***	0.122***	0.072***
B-RUMIDAS (IPI-Manuf)	0.154***	0.170***	0.141***	0.022	0.060***	0.108**	0.080***
B-RUMIDAS (IPI-Cons-Elec)	0.167***	0.206***	0.177***	0.037	0.042*	0.118***	0.053*
B-RUMIDAS (IPI-Cons-Manuf)	0.158***	0.171***	0.111**	0.005	0.021	0.122***	0.087***
B-RUMIDAS (IPI-Elec-Manuf)	0.149***	0.175***	0.125***	0.039	0.035	0.122***	0.068**
benchmark 1 lag + Seasonal Dummies							
BAR(1)	-3.786	-3.850	-3.895	-3.820	-3.868	-3.981	-4.075
B-RUMIDAS (All-IPI)	0.256***	0.249***	0.265***	0.191***	0.145**	0.175***	0.212***
B-RUMIDAS (IPI-Cons)	0.235***	0.224***	0.203***	0.134***	0.122**	0.165***	0.177***
B-RUMIDAS (IPI-Elec)	0.240***	0.251***	0.273***	0.169***	0.143***	0.180***	0.236***
B-RUMIDAS (IPI-Manuf)	0.246***	0.222***	0.198***	0.158***	0.136***	0.180**	0.211***
B-RUMIDAS (IPI-Cons-Elec)	0.278***	0.237***	0.291***	0.185***	0.136**	0.174***	0.206***
B-RUMIDAS (IPI-Cons-Manuf)	0.208***	0.228***	0.231***	0.132***	0.138**	0.163***	0.190***
B-RUMIDAS (IPI-Elec-Manuf)	0.273***	0.289***	0.243***	0.188***	0.131**	0.171***	0.219***
benchmark 1 lag							
BAR(1)	-3.774	-3.852	-3.893	-3.853	-3.876	-3.974	-4.074
B-RUMIDAS (All-IPI)	0.225***	0.233***	0.253***	0.199***	0.133***	0.173***	0.196***
B-RUMIDAS (IPI-Cons)	0.206***	0.237***	0.207***	0.146**	0.134***	0.144***	0.181***
B-RUMIDAS (IPI-Elec)	0.236***	0.236***	0.255***	0.196***	0.149***	0.160***	0.214***
B-RUMIDAS (IPI-Manuf)	0.195***	0.223***	0.208***	0.157***	0.126***	0.140***	0.194***
B-RUMIDAS (IPI-Cons-Elec)	0.217***	0.257***	0.258***	0.217***	0.119**	0.171***	0.209***
B-RUMIDAS (IPI-Cons-Manuf)	0.224***	0.210***	0.195***	0.181***	0.128***	0.166***	0.194***
B-RUMIDAS (IPI-Elec-Manuf)	0.225***	0.256***	0.207***	0.190***	0.117**	0.198***	0.216***

Table 35: Average Predictive Likelihood score for Italy with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Wishart prior. The X includes the Oil Prices and IPI and we have different benchmark models. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

horizon	1	2	3	7	14	21	28
benchmark 3 lags + Seasonal Dummies							
BAR(3)	0.584	0.639	0.646	0.600	0.593	0.593	0.608
B-RUMIDAS (All-IPI)	0.670	0.748	0.742	0.635	0.633	0.618	0.626
B-RUMIDAS (IPI-Cons)	0.673	0.747	0.733	0.627	0.625	0.615	0.628
B-RUMIDAS (IPI-Elec)	0.675	0.754	0.738	0.631	0.631	0.621	0.635
B-RUMIDAS (IPI-Manuf)	0.677	0.746	0.733	0.627	0.623	0.612	0.623
B-RUMIDAS (IPI-Cons-Elec)	0.669	0.749	0.738	0.635	0.631	0.624	0.630
B-RUMIDAS (IPI-Cons-Manuf)	0.674	0.746	0.730	0.626	0.623	0.611	0.625
B-RUMIDAS (IPI-Elec-Manuf)	0.673	0.751	0.740	0.633	0.631	0.618	0.632
benchmark 3 lags							
BAR(3)	0.582	0.636	0.644	0.599	0.589	0.595	0.596
B-RUMIDAS (All-IPI)	0.672	0.751	0.736	0.630	0.628	0.615	0.628
B-RUMIDAS (IPI-Cons)	0.674	0.750	0.735	0.630	0.622	0.605	0.625
B-RUMIDAS (IPI-Elec)	0.682	0.749	0.737	0.626	0.626	0.612	0.632
B-RUMIDAS (IPI-Manuf)	0.676	0.747	0.736	0.627	0.619	0.605	0.624
B-RUMIDAS (IPI-Cons-Elec)	0.672	0.746	0.739	0.634	0.630	0.610	0.629
B-RUMIDAS (IPI-Cons-Manuf)	0.675	0.747	0.730	0.626	0.622	0.605	0.628
B-RUMIDAS (IPI-Elec-Manuf)	0.676	0.749	0.741	0.629	0.624	0.612	0.628
benchmark 1 lag + Seasonal Dummies							
BAR(1)	0.548	0.608	0.629	0.577	0.566	0.567	0.573
B-RUMIDAS (All-IPI)	0.636	0.733	0.723	0.626	0.626	0.612	0.626
B-RUMIDAS (IPI-Cons)	0.639	0.731	0.717	0.622	0.603	0.599	0.622
B-RUMIDAS (IPI-Elec)	0.638	0.735	0.727	0.625	0.617	0.610	0.628
B-RUMIDAS (IPI-Manuf)	0.637	0.733	0.718	0.623	0.610	0.601	0.615
B-RUMIDAS (IPI-Cons-Elec)	0.636	0.738	0.723	0.629	0.622	0.612	0.629
B-RUMIDAS (IPI-Cons-Manuf)	0.639	0.730	0.719	0.620	0.608	0.602	0.615
B-RUMIDAS (IPI-Elec-Manuf)	0.638	0.735	0.728	0.629	0.622	0.613	0.625
benchmark 1 lag							
BAR(1)	0.550	0.607	0.625	0.579	0.564	0.567	0.566
B-RUMIDAS (All-IPI)	0.632	0.733	0.723	0.617	0.620	0.610	0.623
B-RUMIDAS (IPI-Cons)	0.635	0.727	0.717	0.619	0.603	0.593	0.615
B-RUMIDAS (IPI-Elec)	0.638	0.730	0.725	0.622	0.613	0.606	0.624
B-RUMIDAS (IPI-Manuf)	0.629	0.729	0.719	0.618	0.608	0.600	0.609
B-RUMIDAS (IPI-Cons-Elec)	0.638	0.731	0.725	0.619	0.621	0.609	0.623
B-RUMIDAS (IPI-Cons-Manuf)	0.631	0.729	0.715	0.616	0.607	0.597	0.610
B-RUMIDAS (IPI-Elec-Manuf)	0.640	0.731	0.727	0.622	0.618	0.609	0.623

Table 36: Success Rate (SR) for Germany with a rolling window for different horizons $h = 1, 2, 3, 7, 14, 21$ and 28 in a Bayesian framework with Normal-Gamma prior. The X includes the Daily Oil Prices and monthly IPI. Different benchmark models have been considered with one lag or three lags of the daily electricity prices. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure at confidence level 10%.

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Claudia Foroni
European Central Bank, Frankfurt am Main, Germany; email: claudia.foroni@ecb.europa.eu

Francesco Ravazzolo
Free University of Bozen-Bolzano, Bolzano, Italy; CAMP, BI Norwegian Business School; email: francesco.ravazzolo@unibz.it

Luca Rossini
Vrije Universiteit Amsterdam, Amsterdam, The Netherlands; email: l.rossini@vu.nl

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