Nowcasting industrial production using linear and non-linear models of electricity demand

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Overview

This study proposes different modelling approaches which exploit electricity market data to nowcast industrial production (IPI). Our models include linear, mixed-data sampling (MIDAS), Markov-Switching (MS) and MS-MIDAS regressions. Comparison against a commonly applied autoregressive approach shows that electricity market data significantly improves nowcasting performance especially during turbulent economic states characterised by high volatility and uncertainty, such as those generated by the recent COVID-19 pandemic. The most promising results are provided by MS models, which identify two regimes of different volatility. These results confirm that electricity market data provide timely and easy-to-access information for nowcasting macroeconomic variables, especially when it is most valuable, i.e. during times of crisis and uncertainty.

Methods

Our dataset spans from January 2006 to December 2021. We downloaded data on Industrial Production (IP) from Eurostat, electricity load data from ENTSO-E, and temperature data from the NOAA. In particular, as concerns temperature, we use the average Heating and Cooling Degree Days (HDD and CDD, respectively) for the cities of Rome and Milan.

Our benchmark model is represented by an AR(1) model, since our series is I(1), i.e. integrated of order one, and this model is commonly used as a benchmark to estimate IPI (Hassani et al., 2009; Heravi et al., 2004). We then estimate a linear model (LLM) in which we assume that industrial production is a function of short-term adjusted electricity load, that is, once seasonality and temperature effects are accounted for. In addition, we estimate a MS model built on the LLM, in which we let a latent variable identify up to two regimes, and a MIDAS model, in which four weekly load and temperature effects variables are used instead of monthly ones. Finally, we estimate a MS-MIDAS model, which results from the combination of the last two approaches. All previous models are also estimated under the assumption that temperature effects are symmetric, so that we use the sum of HDD and CDD (Total Degree Days, TDD) instead of the two temperature effects variables. All models are estimated over the 2006-2018 period, whereas the 2019-2021 constitutes our forecasting window. We further distinguish between a "calm" and a "turbulent" period within the forecasting window. The turbulent period ranges from Mar 2020 to Dec 2020, capturing the bulk of the economics shock induced by the COVID-19 pandemic. By contrast, the calm period covers from Jan 2019 to Feb 2020 and from Jan 2021 to Dec 2021.

We perform one-step ahead forecasts with a recurring forecasting window, i.e. the forecasting window increases by one month at each time step in the forecasting interval, so that we do not lose information. This means that the estimate for each month exploits all the information available at that time, including actual figures from previous months in the forecasting interval. We then evaluate the forecasting performance of the models by means of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), as is customary in the literature (Wang et al., 2022; Hassani et al., 2009). We test alternative specifications for the temperature and seasonlity effects as robustness checks. On a technical note, our analysis is performed on the statistical software R, using the MSwM package for the estimation of linear MS models (Perlin, 2015).

Results

We find that the AR(1) benchmark is not outperformed by any model during “calm” periods, whereas several models outperform the AR(1) during “turbulent” periods and when we consider the whole forecasting window. In addition, we find that the first vintage of IPI published by Eurostat does not outperform our best model (MS-TDD) during the “turbulent” period. On a side note, the MIDAS models, and especially their MS variants, are the ones with the lowest forecasting performance, likely due to overparametrisation issues.

Conclusions

Using the information provided by electricity load increases the accuracy when forecasting IPI with respect to the benchmark AR(1) model. This is in line with previous literature that shows the relevance of load to forecast other macroeconomic indicators such as GDP growth (Fezzi and Fanghella, 2021, 2020). In addition, distinguishing between different states of the economy is fundamental to deliver more accurate forecasts, as the MS variants of our linear models present lower MAE and RMSE. Indeed, we also discuss how the role of load and temperature and seasonality effects varies depending on whether the regime is a period of low or high volatility.

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