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## Abstract

In this paper, we study the predictive power of electricity consumption data for regional economic activity. Using unique weekly and monthly electricity consumption data for the second-largest German state, the Free State of Bavaria, we conduct a pseudo out-of-sample forecasting experiment for the monthly growth rate of Bavarian industrial production. We find that electricity consumption is the best performing indicator in the nowcasting setup and has higher accuracy than other conventional indicators in a monthly forecasting experiment. Exploiting the high-frequency nature of the data, we find that the weekly electricity consumption indicator also provides good predictions about industrial activity in the current month even with only one week of information. Overall, our results indicate that regional electricity consumption offers a promising avenue to measure and forecast regional economic activity.

JEL-Codes: E170, E270, R110.

Keywords: electricity consumption, real-time indicators, forecasting, nowcasting.

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# 1. Introduction

In recent years, high-frequency indicators from unconventional data sources have attracted the interest of academic and applied economic forecasters. In periods of rapid disruption of economic activity, as in the recent Corona crisis, especially policymakers and firms require readily available information about the state of the economy. However, conventional economic indicators from official statistics are usually published with considerable delay, are heavily revised or can only be analyzed with insufficient frequency (for example, on a quarterly basis). Moreover, while high-frequency indicators have recently been established at the national level for many countries, such indicators are often missing at the regional level. Therefore, when an economic shock has heterogeneous effects on different regions of a country, it is nearly impossible for agents to assess the current state of the regional economy.

In this paper, we evaluate a new indicator based on electricity consumption data as a potential predictor of regional economic activity. We do so for the second largest and highly industrialized German state, the Free State of Bavaria, as we have exclusive access to electricity consumption data from the Bavarian Transmission System Operators, which cover the complete consumption of large, electricity-intensive customers in Bavaria. We conduct a pseudo out-of-sample forecast experiment for Bavarian industrial production and compare the forecast accuracy of electricity consumption to other readily available indicators. We choose industrial production as the target series as it is available at monthly frequency, accounts for most of the regional business cycle fluctuations, and has a large overlap with electricity consumption in terms of economic activities covered by both aggregates.

We take a two-step approach to our forecasting experiment. First, we aggregate the electricity consumption data to the monthly frequency in order to evaluate its forecasting power relative to other indicators that are only available at the monthly level. Second, we exploit the high-frequency nature of the data in various ways to test its performance at the weekly level. We do so by either simulating different information sets within one month or by applying Mixed-data sampling (MIDAS) methods. Our results indicate that electricity consumption is the best indicator for predicting the current month's development (nowcast). However, all indicators, including electricity consumption, lose power when predicting industrial production growth in the next month (forecast) compared to a benchmark model. Moreover, exploiting the high-frequency nature of the data, we show that weekly electricity information is a good predictor for monthly industrial production development. More specifically, the electricity indicator provides valuable signals about the monthly growth rate of the target series after only one week of information, making it a powerful tool for applied forecasters, policymakers, and even (industrial) firms.

Our paper is related to three, partially overlapping strands of the literature: (i) economic forecasting with high-frequency data, (ii) regional economic forecasting, and (iii) (regional) business cycle measurement at higher frequency. As new data sources have become available in recent years, forecasters have used these alternative indicators to forecast current economic conditions at a higher frequency than previously possible based on more traditional indicators (monthly or quarterly). Various high-frequency indicators have been tested, such as transport data (Fornaro, 2020), financial transaction data (Aastveit *et al.*, 2020), internet search queries (Götz and Knetsch, 2019), newspaper articles (Thorsrud, 2020), or even several series at the same time (Jardet and Meunier, 2022). In addition to these unconventional indicators, the literature has also explored the properties of high-frequency electricity consumption data by considering it as one of the key inputs to nowcast an economic target series such as GDP, employment, or industrial production. The studies refer to the US (Lewis *et al.*, 2020), Germany (Eraslan and Götz, 2021), Portugal (Lourenço and Rua, 2021), and other countries. Moreover, Fezzi and Fanghella (2021) use electricity consumption data to nowcast the decline in economic activity during the first wave of COVID-19 across several European countries and find a close relation with GDP growth. Similar to the aforementioned papers, our study illustrates that indicators with a high temporal resolution provide valuable signals about current economic developments. In addition, we show that electricity consumption by subgroups of customers can be particularly informative about economic activity in specific sectors such as manufacturing.

The literature on regional economic forecasting has developed rapidly in recent years; Lehmann and Wohlrabe (2014) provide an overview of studies conducted up to the mid 2010s. More recent articles apply more sophisticated econometric techniques such as factor models (Chernis *et al.*, 2020; Gil *et al.*, 2019) or some form of vectorautoregressions (Bokun *et al.*, 2022; Koop *et al.*, 2020a,b). In particular, we contribute to the regional forecasting literature for Germany. Previous attempts applied standard panel techniques to annual data (Kholodilin *et al.*, 2008) or bridge equations (Henzel *et al.*, 2015; Lehmann and Wohlrabe, 2015). More recent articles make use of boosting (Lehmann and Wohlrabe, 2017), Mixed-data sampling (Claudio *et al.*, 2020), or factor models (Kuck and Schweikert, 2021). While some international studies have employed electricity consumption data as a real-time indicator of regional COVID-19 effects, they have implicitly assumed that there is a close relationship between changes in electricity consumption and economic activity at the regional level (see, for example, Janzen and Radulescu, 2020; Prol and Sungmin, 2020). Baumeister *et al.* (2022) go one step further and use electricity consumption along with other indicators to track regional economic activity on a weekly basis. To the best of our knowledge, this paper is the first to assess the predictive power of electricity consumption for regional economic forecasting. Overall, our results suggest that the availability of regional electricity consumption data is a promising avenue for measuring and forecasting regional economic activity.

The paper is organized as follows. Section 2 describes the underlying data as well as the new electricity consumption indicator and the forecasting approach. Section 3 presents the results and addresses further issues. Section 4 concludes.

# 2. Data and Forecasting Experiment

This section describes the regional target series to be forecasted, the new indicator based on the electricity consumption data, and other ready-to-use indicators that ensure a realistic forecasting competition. Moreover, we explain our forecasting approach based on either monthly or weekly information, as well as the data preparations required in advance.

## 2.1. Target Series

As in many other developed countries, measuring regional economic activity in Germany is a difficult task given the limited availability of official statistics at the federal state level. For instance, macroeconomic indicators at the state level such as gross domestic product (GDP) are only available at annual frequency and with a significant time lag.[1] We therefore evaluate the forecasting performance for monthly price-adjusted industrial production in Bavaria, which covers output in manufacturing and mining and quarrying.[2]

Using monthly industrial production as the target series has several advantages, but also some disadvantages. One main advantage is its importance for the quarterly GDP flash estimate in Germany, that is published around 30 days after the end of the quarter. The Federal Statistical Office uses industrial production as one of the main monthly economic indicators for this first estimate. Moreover, there is a large overlap between industrial production and our new electricity consumption data: both aggregates contain mainly industrial firms with an electricity-intensive production structure. One disadvantage of the target series is the exclusive focus on industrial activities. However, the share of Bavaria's manufacturing industry in nominal gross value added (GVA) was 25% in 2019, which is rather high compared to Germany as a whole (22%) and the European average (EU-27: 16%). Given its importance, manufacturing is responsible for a large share of variation in the Bavarian business cycle, as can be seen from the close connection between industrial production and GDP growth. Measured on an annual basis, the correlation is 0.89 for the years 2008 to 2020.[3]

As is the case with all other official business cycle indicators, there are fairly long publication delays of data for Bavarian industrial production. These delays currently amount, on average, to one and a half months. In this respect, electricity consumption data provide significant added value, as—in addition to the high-frequency measurement—it is available without significant time lag. Due to a change in accounting and methodological standards, a long(er) series for Bavarian industrial production is only available as of January 2005.

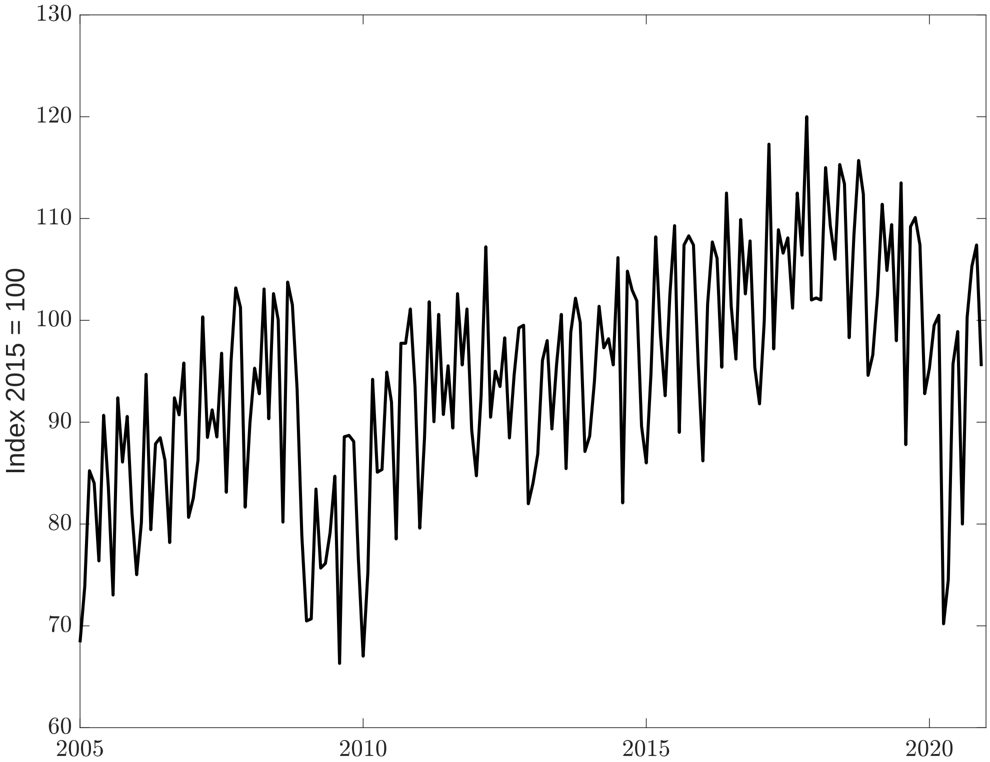
[1] The paper by Lehmann and Wikman (2022) presents quarterly GDP estimates for all 16 German states. Due to the close relationship between electricity consumption data and industrial production, we focus on monthly production values rather than GDP.

[2] The Bavarian data can be accessed here: `https://www.statistik.bayern.de/statistik/wirtschaft_handel/verarbeitendes_gewerbe`.

[3] For Germany, manufacturing output shows the strongest connection with GDP. The correlation coefficient between the quarterly change in GDP and industrial production is 0.78 for the period from 1994 to 2019, which is higher than for other economic indicators (production in construction: 0.38; retail sales: 0.49).

Figure 1 presents Bavarian industrial production in the period from 2008 to 2020, clearly showing the two severe recessions of the past 15 years. The economic and financial crisis led to a sharp slump in Bavarian industrial production at the turn of 2008/2009, followed by a rather sluggish recovery. Around 2010, the upswing set in, followed by a trend increase in industrial production until 2018, after which Bavarian manufacturing fell into a downturn and, with the first Corona lockdown in spring 2020, into a severe recession. Afterwards, Bavarian industrial production recovered quite quickly, but was still below pre-Corona levels as of December 2020.

**Figure 1:** Price-adjusted Bavarian Industrial Production




*Source:* Bavarian Statistical Office.

## 2.2. Electricity Consumption Data

Compared to conventional indicators, electricity consumption data can generally be a valuable data source for two reasons. First, it is collected at a high frequency and allows for weekly or even daily analyses. Second, there is no significant publication lag in the electricity series. In this paper, we explore another dimension of electricity data: regional disaggregation. As the availability of regional data in Germany is generally unsatisfactory, our results could provide the impetus for further efforts to improve this by examining electricity consumption data for all German states. To the best of our knowledge, these data are currently not publicly available.

The electricity consumption data set was obtained from four Bavarian transmission system operators (TSOs).[4] The TSOs distinguish customers according to their annual consumption. Customers with a so-called "standard load profile" (in German: "Standardlastprofil", SLP) are private households and small businesses, while customers with an annual consumption of 100.000 kilowatt-hours (kWh) or more are covered by the so-called "recorded power measurement" (in German: "Registrierende Leistungsmessung", RPM). Our data includes only the latter customers, who report their electricity consumption to the TSOs every 15 minutes. This feature is particularly interesting for a forecasting experiment. Additionally, according to the TSOs, the data mainly covers medium-sized to large manufacturing companies, which implies that the electricity data cover similar economic activities as industrial production. However, this comes at a price, as less electricity-intensive customers such as small businesses and households are neglected.

Figure 2 shows the monthly electricity consumption of RPM customers in Bavaria. As the length of the available time series varies among the four TSOs, the longer time series, covering January 2007 to December 2020, comprises the information from the two TSOs N-ERGIE and SWM. These two TSOs covered about 60% of the market share in the Bavarian electricity market in 2020. The shorter times series that covers all four TSOs is only available as of January 2015.[5]

The figure reveals three salient features of Bavarian electricity consumption. First, the time series exhibit seasonal and calendar effects that must be accounted for in the forecasting experiment and which we discuss in Section 2.4. Second, aggregate electricity consumption is downward trending, indicating adjustments towards more energy-efficient production processes. Third, we can identify business cycles with booms and recessions in the data. For instance, electricity consumption decreased significantly during the 2008/09 global financial crisis as well as during the first COVID-19 lockdown in 2020. On the other hand, it increased during the manufacturing boom in 2018.

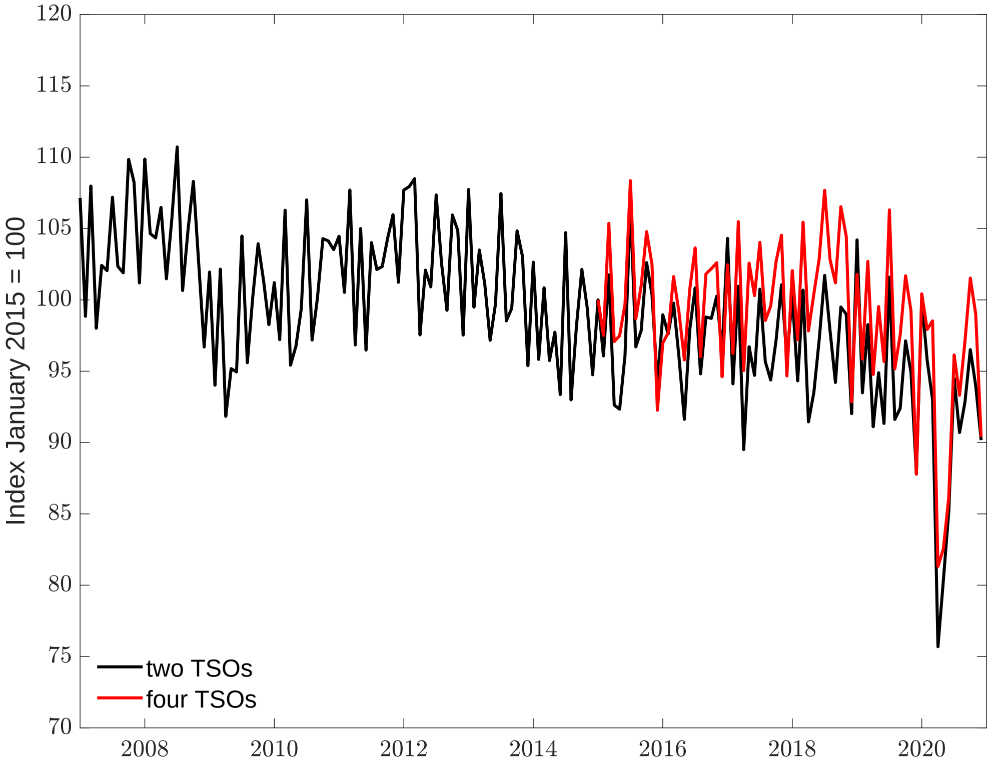
## 2.3. Other Indicators

In order to evaluate the predictive power of the novel electricity consumption data, we compare their performance with other ready-to-use indicators that are available in the Bavarian context. This ensures a fair forecasting experiment. A monthly measurement of price-adjusted new orders is one official indicator that signals industrial production in advance. These orders include incoming domestic and foreign orders of manufacturing firms operating in Bavaria. As long as cancellations—which the index does not take into account—are quantitatively irrelevant, new orders should enter manufacturing production with a certain

[4]The four Bavarian TSOs are: Bayernwerk Netz GmbH (Bayernwerk), LEW Verteilnetz GmbH (LVN), N-ERGIE Netz GmbH (N-ERGIE) and SWM Infrastruktur GmbH & Co. KG (SWM).

[5]For our baseline forecasting experiment, we only use the information from the two TSOs that provide longer time series. However, we discuss the robustness of our results based on the shorter time series.

**Figure 2:** Electricity Consumption Data




*Note:* The black line shows the longer electricity consumption series based on two TSOs (N-ERGIE and SWM). The red line comprises the electricity information from all four TSOs. *Source:* Bavarian TSOs.

delay. Nevertheless, new orders have the same drawback as industrial production: they are subject to the same publication lags, which limits their use as a timely measure of current developments in manufacturing.

Leading indicators for manufacturing that are available without delay are mainly derived from qualitative surveys. In Germany, the ifo Institute publishes regional evaluations of its business survey indicators for selected German states including Bavaria (Lehmann *et al.*, 2019). In a wide-ranging survey article, Lehmann (2020) shows that the ifo indicators have high predictive power for various economic aggregates, including regional ones. We employ five indicators from the ifo business survey for the Bavarian manufacturing sector: (i) the ifo Business Situation, (ii) the ifo Business Expectations for the next six months, (iii) the ifo Business Climate as the geometric mean of the first two indicators, (iv) the ifo Production Realization compared to the previous month, and (v) the ifo Production Expectations for the next three months. While the first three indicators tend to focus on general business activity, the last two are likely to better reflect developments in industrial production, as they are specifically targeted at firms' production. We also expect the indicators to have different leading properties. While two indicators focus on current assessments, the remaining three reflect expectations for future economic developments.

Finally, we also evaluate the forecasting performance of three rather unconventional indicators: Germany's total electricity consumption and the truck toll mileage index both for Germany and Bavaria. Total German electricity consumption is reported by the Federal Network Agency for Electricity, Gas, Telecommunications, Post and Railway (in German: "Bundesnetzagentur", BNetzA) since 2015.[6] The BNetzA obtains this data directly from the European Network of Transmission System Operators for Electricity (ENTSO-E), the European umbrella organisation of TSOs. We combine the historical data from ENTSO-E for the years 2006 to 2015 with the electricity consumption data from BNetzA to obtain a long time series for Germany. For both data sources, there is one year of overlap to check whether this merging is valid. It can be seen that the electricity consumption data for the year 2015 match perfectly, with a correlation coefficient of 1.00. The key difference between the Bavarian electricity consumption data and the ones at the national level is that the latter includes all consumers of net electricity consumption, i.e. also private households and small enterprises. The truck toll mileage index published as experimental data by the Federal Statistical Office captures a large portion of the mileage of trucks subject to tolls on German federal motorways.[7] We use the index at both the national and the state level. While the truck toll index at the national level is available at both a monthly and daily frequency since 2005, the state level index is only been published at a monthly basis since 2008.

## 2.4. Forecasting Approach

**Data preparation.** Before we can use the target series and the indicators in our forecasting experiments, we have to eliminate seasonal and calendar effects. Unfortunately, the statistical offices of the German states do not publish seasonally- and calendar-adjusted series, so that we have to make the adjustments ourselves. However, we closely follow the recommendations of the Federal Statistical Office for adjusting monthly business cycle indicators for Germany such as industrial production (Linz *et al.*, 2018). The adjustment of Bavarian industrial production and new orders is carried out using the X13 JDemetra+ method, in which we explicitly incorporate a calendar adjustment based on Bavarian working days.[8]

The adjustment of regional electricity consumption data is much more difficult, since there are essentially no examples available from official statistics. Therefore, we must base our adjustment strategy on our own experience and plausibility checks. In the following, we elaborate on the adjustment procedure for the monthly electricity consumption data used in the forecasting experiment; we discuss the procedure for weekly data in the corresponding paragraph and will again return to this issue in the discussion section. The Bavarian electricity data, which are available on a 15-minute basis, were converted to monthly values

[6]The German electricity consumption data can be accessed via SMARD: `https://www.smard.de/en`.

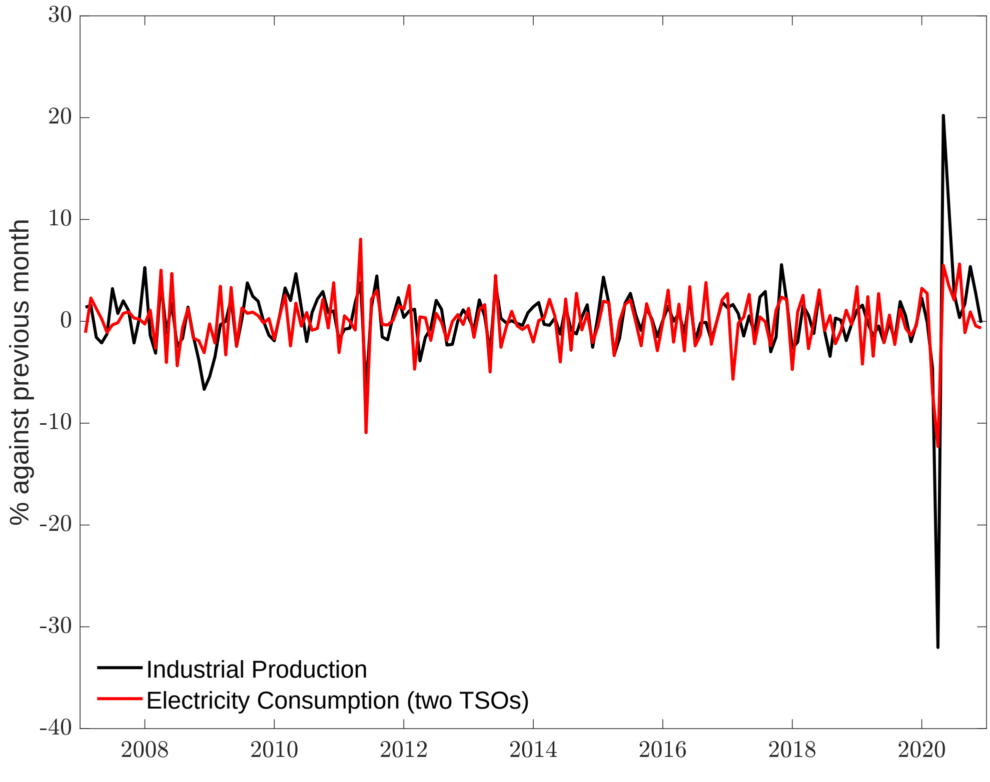
[7]More details on the truck toll mileage index can be found at `https://www.destatis.de/EN/Service/EXDAT/Datensaetze/truck-toll-mileage.html` or in Cox *et al.* (2020).

[8]Please note that holidays differ quite considerably across the individual German states.

by summing up the daily information. These monthly values are then adjusted according to the rules we applied to Bavarian industrial production and we let the adjustment procedure automatically decide which specification fits best.

To provide a visual impression of the connection between Bavarian electricity consumption and industrial production, Figure 3 shows the monthly changes in seasonally- and calendar-adjusted data for the period from 2007 to 2020; the electricity data are based on two TSOs. Overall, Bavarian electricity consumption is less volatile than industrial production, but both growth rates are closely correlated (correlation coefficient: 0.62). If we instead use the electricity consumption data from all four Bavarian TSOs in the period from 2015 and 2020, the correlation increases to 0.73. If we exclude the year 2020 and thus the Corona crisis, the correlations are around 0.50. This first graphical inspection suggests a high predictive power of the electricity consumption data for Bavarian industrial production.

**Figure 3:** Industrial Production and Electricity Consumption Growth




*Note:* The electricity consumption data are based on two TSOs. *Source:* Bavarian TSOs and Bavarian Statistical Office.

In vein of the Bavarian data, we apply the same adjustment procedure to electricity consumption for Germany. In contrast, the ifo indicators and the truck toll index are already available in seasonally- and calendar-adjusted form. Especially the latter indicators also show a high correlation with Bavarian industrial production and could also be valuable leading indicators. In the following, we present our forecasting experiment based on monthly data.

**Monthly forecasting experiment.** The forecasting exercise at the monthly level is motivated by the fact that—with the exceptions of electricity data and the truck toll index—all remaining indicators and the target series are only available at this frequency. Therefore, we aggregate the 15-minute frequency electricity consumption data to the monthly frequency in order to be able to use conventional forecasting models such as bridge equations. To test the indicators' predictive power for Bavarian industrial production, we follow Lehmann and Reif (2021) and apply the following three autoregressive indicator models, AR-X($p, q$), where $p$ and $q$ indicate either the lag length of the target series or the respective indicator:

1. **Indicator model 1**: AR-X(0,0) model with a constant and the contemporaneous value of an indicator, but without lags of the target series.
2. **Indicator model 2**: AR-X(0,q) model with a constant and up to $q$ lags of the indicator. We select the optimal lag length based on the Akaike Information Criterion (AIC). Again, no lag of the target series is added.
3. **Benchmark model**: AR(1) model with a constant and one lag of the target series.

We formulate predictions for two forecast horizons, $h \in \{0, 1\}$, in which $h = 0$ denotes the nowcast and $h = 1$ the forecast. Accordingly, we test the indicators' performance only for forecasts of at most one month ahead. Our pseudo out-of-sample forecasting experiment covers the period from January 2008 to December 2019; we discuss the impact of the Corona crisis in a separate chapter. The first estimation of the models is based on the first 48 months, so that the first nowcast and forecast are produced for January 2012 and February 2012, respectively. After computing these two predictions, the sample is expanded by one month of observations, then the models are re-estimated, and new nowcasts and forecasts are calculated. In each iteration step, we assume that the respective forecaster formulates the predictions at the end of each month; we use an alternative assumption in our weekly forecasting experiment. The procedure is repeated until the end of our observation period. Overall, the number of nowcasts to be evaluated is 96 and the number of forecasts equals 95. For the first-best forecast experiment, we would have liked to use real-time data of Bavarian industrial production. Unfortunately, to the best of our knowledge, there is no official source with different vintages. We therefore evaluate the forecasting properties in a pseudo real-time setting by at least accounting for the different publication lags. While the electricity consumption data, the ifo indicators and the truck toll indices are available at the end of a given month, the data on new orders and industrial production for Bavaria are subject to a publication delay of one and a half months. These circumstances are explicitly taken into account in the forecasting experiment, and only the information set available to the forecaster at that point in time is used. Technically, the three forecasting models introduced are adjusted by indicator-specific publication lags. The ifo indicators enter the models in first differences, and all remaining indicators enter as monthly growth rates.

**Weekly forecasting experiment.** One major advantage of the electricity consumption data is their high-frequency nature. In order to use this dimension for our forecasting experiment, we first need to make some further adjustments. Daily and monthly data differ greatly in terms of seasonal and calendar patterns. However, seasonal and calendar adjustment of high-frequency data is still a controversial topic, and statistical offices in Germany and Europe generally do not yet agree on an appropriate methodology. We follow the methods used by the Federal Statistical Office for the truck toll mileage index (Hauf *et al.*, 2020) as well as Ollech (2022) and proceed in three steps. First, the raw electricity data provided by the TSOs are aggregated to the daily frequency, which should eliminate much of the day-night variation. Second, we apply the LOESS-based decomposition procedure STL as proposed by Cleveland *et al.* (1990).[9] Third, we aggregate the adjusted daily data to a weekly frequency by assuming a seven-day week. As weeks have a rolling character, we compute the average daily electricity consumption rather than its sum.

Our forecasting experiment at the weekly frequency is designed twofold. In the first approach, we simulate three different weekly information sets within a month, together with an experiment based on full information. Essentially, we take the information set after one, two or three weeks, treat the electricity consumption data up to this point as representative of the given month, and apply the same bridge equations as in the monthly forecasting experiment. In the second approach, we use standard Mixed-data sampling (MIDAS) models which allow us to explicitly model different time frequencies (in our case: monthly and weekly). We use the third-order Almon-Lag-Polynomial as the weighting function, which fits our data best and is commonly used in the literature (see, for example, Marcellino and Schumacher, 2010, for forecasting German GDP). The maximum number of lags is set to ten, and the optimal number is selected using the Bayesian Information Criterion (BIC). As MIDAS models require a constant ratio between the weekly and monthly frequencies, we assume that one month always consists of four weeks.

The weekly data availability differs from the monthly experiment. While the monthly time series spans from 2008 to 2020 and comprises two TSOs, we can access weekly data for three TSOs (LVN, N-ERGIE, and SWM) the period from 2012 to 2020. Consequently, the availability of an additional TSO comes at the expense of the length of the data series. However, we argue that a better representation of Bavarian manufacturing outweighs the brevity of the series. Again, we use the first 48 months for the initial model estimation.

[9] In this method, a time series is decomposed into its seasonal and trend components while simultaneously taking all other influences into account. The procedure allows the modelling of recurring fluctuations with different periodicity. For the Bavarian electricity consumption data, fluctuations within one day as well as within one week were modelled, and the original data were adjusted for these influences.

**Forecast evaluation.** The indicators' forecast performance is evaluated using the root mean squared forecast error (RMSFE). In order to assess the relative forecasting performance of the indicators, we plot their RMSFEs relative to that of the benchmark model. If this ratio is less than one, the indicator performs better than the benchmark on average. If the ratio is greater than one, the respective indicator provides no additional information compared to the last known value of the target series.

# 3. Results

This section first presents the baseline results from our monthly and weekly forecasting experiment. Second, we briefly discuss some issues related to the baseline procedure: the influence of the Corona crisis, the forecasting performance over time, and the usage of electricity data for all four Bavarian TSOs.

## 3.1. Baseline Performance

Table 1 shows the relative RMSFE of the monthly forecasting experiment for the period from 2008 to 2019 and the two models outlined in the former section. The upper part of the table presents the nowcast and the lower part shows the forecast. Overall, Bavarian electricity consumption is the best performing indicator in the nowcasting setup with relative RMSFEs of 0.85 and 0.84. These figures correspond to an improvement of 15% and 16% compared to the benchmark model.

In addition, the results reveal that for model 1 the forecast errors of all ifo indicators (for example, ifo Production Expectations Manufacturing Bavaria with a relative RMSFE of 0.92) are smaller than one. The Bavarian manufacturing new orders indicator performs rather poorly, which may relate to the fact that it is subject to the same publication delays as the target series. Both truck toll mileage indices display almost identical forecast performances, but do not perform as well as the Bavarian electricity data. The same holds true for total German electricity consumption. In most cases, the indicator performance decreases when model 2 is applied.

When forecasting the following month's development ($h = 1$), all indicators lose accuracy and do not perform better than the benchmark model.[10] The relative forecast errors of the electricity consumption data are 1.01 and 1.02 in models 1 and 2, respectively. Overall, the results illustrate that monthly Bavarian electricity consumption has a high nowcasting accuracy, but its leading properties are rather weak.

[10] One exception are new orders of the Bavarian manufacturing industry (relative RMSFEs: 0.99 and 0.97).

**Table 1:** Monthly Forecasting Performance of the Indicators 2008 to 2019

| **Indicator** | **Model 1** | **Model 2** |
|---|---|---|
| | *Nowcast* | |
| Electricity Consumption Bavaria | 0.85 | 0.84 |
| New Orders Manufacturing Bavaria | 1.13 | 1.16 |
| ifo Business Situation Manufacturing Bavaria | 0.95 | 0.94 |
| ifo Business Climate Manufacturing Bavaria | 0.95 | 0.99 |
| ifo Business Expectations Manufacturing Bavaria | 0.93 | 0.99 |
| ifo Production Realization Manufacturing Bavaria | 0.94 | 1.01 |
| ifo Production Expectations Manufacturing Bavaria | 0.92 | 0.95 |
| Electricity Consumption Germany | 0.95 | 0.95 |
| Truck Toll Mileage Index Germany | 0.95 | 0.98 |
| Truck Toll Mileage Index Bavaria | 0.95 | 0.99 |
| | *Forecast* | |
| Electricity Consumption Bavaria | 1.01 | 1.02 |
| New Orders Manufacturing Bavaria | 0.99 | 0.97 |
| ifo Business Situation Manufacturing Bavaria | 1.01 | 1.02 |
| ifo Business Climate Manufacturing Bavaria | 1.07 | 1.08 |
| ifo Business Expectations Manufacturing Bavaria | 1.05 | 1.08 |
| ifo Production Realization Manufacturing Bavaria | 1.07 | 1.07 |
| ifo Production Expectations Manufacturing Bavaria | 1.04 | 1.06 |
| Electricity Consumption Germany | 1.02 | 1.04 |
| Truck Toll Mileage Index Germany | 1.05 | 1.05 |
| Truck Toll Mileage Index Bavaria | 1.06 | 1.07 |

*Notes:* The forecast errors of the indicators are expressed relative to the performance of the benchmark model (RMSFE Nowcast: 1.9 percentage points; RMSFE Forecast: 1.8 percentage points). The monthly forecasting period runs from January 2012 to December 2019. Bavarian electricity consumption is based on the information of two TSOs. The two models are described in Section 2.4.

In the following, we focus on the weekly level to test the high-frequency prediction performance of Bavarian electricity consumption data. Table 2 presents the results of our forecasting experiment based on data from 2012 to 2019 using different information sets within a month for the standard indicator models (second and third column) and the MIDAS approach (column four). Overall, the nowcast accuracy increases with the available information within a month. At the end of week 1, the electricity consumption data are already as precise as the benchmark model. With information including the first two weeks, the relative RMSFEs of Bavarian electricity consumption for both models are already 0.93; the relative forecasting performance does not change with information at the end of week 3 (relative RMSFEs: 0.93). The new indicator therefore yields reliable forecasting signals for Bavarian industrial production at a very early point in a given month. The best relative performance is achieved with full information at the end of the month.

The forecast accuracy for the next month varies only slightly within the month, but reaches RMSFEs equivalent to the benchmark model when complete information is available. In general, the MIDAS approach performs slightly worse than the indicator models in both the nowcasting and the forecasting setup. One potential explanation for this might be the high volatility of the weekly data.

Overall, the nowcasting and forecasting results at the weekly level confirm our findings from the monthly experiment: the Bavarian electricity consumption data have a high predictive power for Bavarian industrial production. Moreover, the immediate and high-frequency availability of the data is a major advantage, as the information set at the end of the second week is already sufficient to formulate reliable nowcasts for the target series at hand. In the following, we discuss how the Corona crisis affects the overall forecasting performance, how the forecast errors evolve over time, and how results change with data from all four TSOs.

**Table 2:** Weekly Forecasting Performance of Electricity Consumption 2012 to 2019

| Information Set | Model 1 | Model 2 | MIDAS |
|---|---|---|---|
| *Nowcast* | | | |
| End of week 1 | 1.00 | 1.00 | 1.01 |
| End of week 2 | 0.93 | 0.93 | 1.01 |
| End of week 3 | 0.93 | 0.93 | 1.01 |
| End of the month | 0.90 | 0.89 | 1.00 |
| *Forecast* | | | |
| End of week 1 | 1.07 | 1.10 | 1.10 |
| End of week 2 | 1.06 | 1.09 | 1.10 |
| End of week 3 | 1.08 | 1.11 | 1.09 |
| End of the month | 0.99 | 1.00 | 1.04 |

*Notes:* The forecast errors of the indicators are expressed relative to the performance of the benchmark model (RMSFE Nowcast: 1.8 percentage points; RMSFE Forecast: 1.9 percentage points). The weekly forecasting period runs from January 2016 to December 2019. Different information sets reflect different forecasting situations, for which Bavarian electricity consumption data are either available for the total month, the first one, two, or three weeks within the month. Bavarian electricity consumption is based on the information of three TSOs. The models are described in Section 2.4.

## 3.2. Discussion

**Impact of the Corona crisis.** The long publication delays in important business cycle indicators and the resulting lack of information on the economic development during the Corona crisis requires alternative, high-frequency indicators. We therefore want to determine how the overall forecast accuracy of Bavarian electricity consumption data changes when we include its development in 2020. Based on the monthly forecasting experiment, Table 3 shows the nowcasting performance for the period from 2012 to 2020.[11]

[11] The performance of the forecasts for the next month does not change as much as in the nowcasting setup. Therefore, we do not discuss them in detail. However, especially forward-looking indicators such as the

The nowcasting performance of Bavarian electricity consumption data increases significantly when the year 2020 is included. The relative RMSFEs are 0.73 and 0.76, which corresponds to an improvement of 27% and 24%, respectively. Only one indicator can achieve similar or even better results: the Bavarian truck toll mileage index. Its relative RMSFEs are 0.67 and 0.73. However, these results do not detract from the performance of the electricity data when considering the potential driving force behind this outcome: returning to Figure 3, we hypothesize that the seasonal and calendar adjustment might trigger these results. Whereas the truck toll mileage index is seasonally- and calendar-adjusted by official institutions, we do this on our own for the electricity consumption data. As Figure 3 demonstrates, our adjustment can capture the sharp declines in production in March and April 2020, but not the subsequent sharp increases in May and June 2020. However, the seasonally- and calendar-adjusted Bavarian truck toll mileage index adequately captures both movements. As a detailed analysis is beyond the scope of this paper, we only test what happens if we eliminate the forecast errors for May and June 2020 from the calculation of the RMSFEs. In this case, the Bavarian electricity data is again the best performing indicator. We therefore conclude that the good results for the new indicator might only represent a lower bound of forecasting performance and that accuracy increases with a more fine-tuned seasonal and calendar adjustment procedure.[12]

**Table 3:** Monthly Nowcasting Performance of the Indicators Including 2020

| **Indicator** | **Model 1** | **Model 2** |
|---|---|---|
| Electricity Consumption Bavaria | 0.73 | 0.76 |
| New Orders Manufacturing Bavaria | 1.00 | 1.10 |
| ifo Business Situation Manufacturing Bavaria | 0.87 | 0.92 |
| ifo Business Climate Manufacturing Bavaria | 0.78 | 0.84 |
| ifo Business Expectations Manufacturing Bavaria | 0.78 | 0.83 |
| ifo Production Realization Manufacturing Bavaria | 0.88 | 0.94 |
| ifo Production Expectations Manufacturing Bavaria | 0.78 | 0.83 |
| Electricity Consumption Germany | 0.85 | 0.86 |
| Truck Toll Mileage Index Germany | 0.75 | 0.83 |
| Truck Toll Mileage Index Bavaria | 0.67 | 0.73 |

*Notes:* The forecast errors of the indicators are expressed relative to the performance of the benchmark model (RMSFE: 4.8 percentage points). The monthly nowcasting period runs from January 2012 to December 2020. Bavarian electricity consumption is based on the information of two TSOs. The two models are described in Section 2.4.

ifo Business Expectations for the manufacturing sector in Bavaria are able to outperform the benchmark model. The detailed results for $h = 1$ can be found in Appendix A.

[12] For a discussion on daily and weekly seasonal and calendar adjustment see Ollech (2022).

We also extended the weekly forecasting experiment to include the performance for the year 2020. Table 4 shows the corresponding relative RMSFEs for both the indicator models and the MIDAS approach in the nowcasting setup.[13] The relative performance of the electricity indicator at the end of week 1 ranges from 0.73 to 0.85, representing a 27% and 15% improvement over the benchmark, respectively. Using the data up to the end of week 2, the relative nowcast error varies between 0.72 and 0.85; including week 3, the range spans from 0.75 and 0.85. These findings highlight the need to analyze the high-frequency electricity data: timely business cycle analyses and nowcasting can be significantly improved and extreme economic fluctuations can be detected quickly.

**Table 4:** Weekly Nowcasting Performance of Electricity Consumption Including 2020

| **Information Set** | **Model 1** | **Model 2** | **MIDAS** |
|---|---|---|---|
| End of week 1 | 0.73 | 0.79 | 0.85 |
| End of week 2 | 0.72 | 0.79 | 0.85 |
| End of week 3 | 0.75 | 0.83 | 0.85 |
| End of the month | 0.64 | 0.72 | 0.84 |

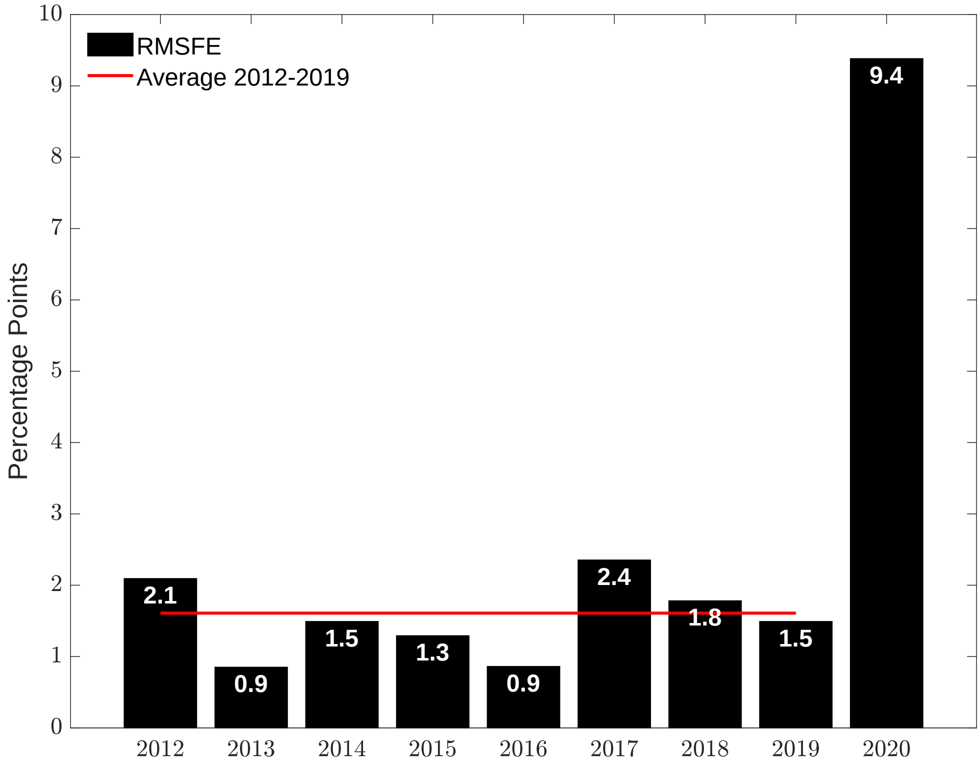
*Notes:* The forecast errors of the indicators are expressed relative to the performance of the benchmark model (RMSFE: 6.2 percentage points). The weekly nowcasting period runs from January 2016 to December 2020. Different information sets reflect different forecasting situations, for which Bavarian electricity consumption data are either available for the total month, the first one, two, or three weeks within the month. Bavarian electricity consumption is based on the information of three TSOs. The models are described in Section 2.4.

**Forecast errors over time.** All previous results represented average forecast errors over the entire forecast period (either up to 2019 or up to 2020). To shed light on the performance over time, Figure 4 reports the nowcasting RMSFEs of the monthly experiment in each year.[14] Between 2012 to 2019, the average RMSFE is 1.6 percentage points and varies between 0.9 and 2.4 percentage points. In 2020, however, the RMSFE of the nowcast increases sharply to 9.4 percentage points due to the Corona crisis. While the Bavarian electricity consumption data indicate the collapse of production in April 2020 and the rebound in May 2020 (the nowcast in April 2020 was -6.2% and the forecast for May 2020 was 4.3%), the fluctuations in industrial production during these months were much larger and unique in historical comparison (April 2020: -32.0%, May 2020: 20.2%). As many other indicators, Bavarian electricity consumption fails to predict such a large volatility during the pandemic. This might again indicate an improvement in the seasonal and calendar adjustment procedure. Moreover, future research might combine electricity consumption data with new ideas for economic forecasting that model heavy outliers (see, for example, Carriero *et al.*, 2022; Lenza and Primiceri, 2022). Nevertheless, Bavarian electricity consumption is one of the best performing indicators in the nowcasting setup.

[13] The weekly results for the forecasting exercise ($h = 1$) can be found in Appendix A. It can be seen that the Bavarian electricity consumption indicator performs slightly better than the benchmark. Thus, deep recessions can be identified quickly.

[14] The corresponding figure for the forecasting accuracy can be found in Appendix B.

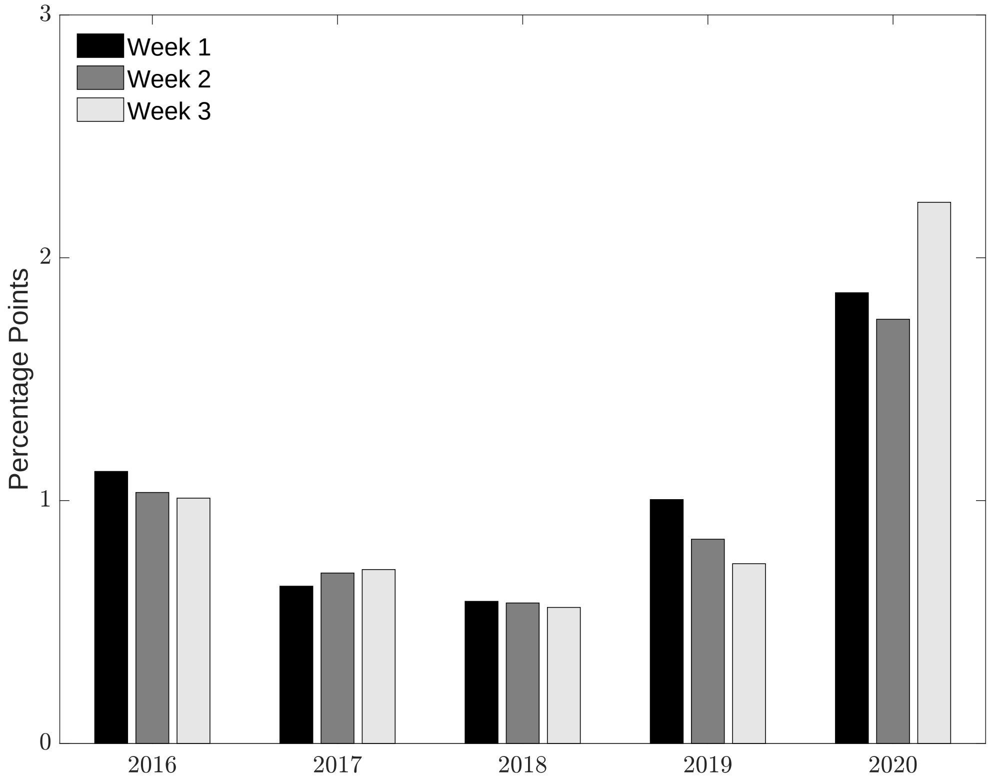
**Figure 4:** Nowcast Accuracy 2012 to 2020




*Note:* The red line indicates the average root mean squared forecast error (RMSFE) for the years 2012 to 2019 (1.6 percentage points). The electricity consumption data are based on two TSOs.

We also examine the evolution of the nowcast errors within a month and over the years. To this end, we first calculate the absolute deviations (DEV) of the nowcast errors (NE) of the different information sets from the forecast errors in the experiment based on data from the end of a given month (M). For an exemplary error from a nowcast at the end of week 1 (W1), this deviation looks as follows: $\text{DEV}_t^{W1} = |\text{NE}_t^{W1} - \text{NE}_t^{M}|$. We choose absolute values to avoid the netting of positive and negative deviations, so that we can assess the deviation's magnitude. Second, we average the monthly deviations for each year. Figure 5 plots these deviations of the nowcast errors for the years 2016 to 2020. In general, we can confirm the average results shown in Table 2 and Table 4: the errors become smaller as more information are available. However, the years 2017 and 2020 are an exception. Whereas the deviations across weeks are quite similar for the year 2017, we can observe a significant deterioration in forecast accuracy from week 2 to week 3 for the year 2020. The main reason is that some monthly nowcasts for 2020 produce larger errors when data from week 3 is included than when only information from up to the end of week 2 is utilized. Again, we hypothesize that the seasonal and calendar adjustment, together with the simplifying assumption that a month consists of four standard weeks, are the main causes for this result.

**Figure 5:** Absolute Deviation of the Nowcast Errors Within a Month 2016 to 2020




*Note:* Absolute average deviations of the weekly nowcast errors from the errors based on full information.

The deviations of the forecast errors show similar trends as for the nowcast; the corresponding figure can be found in Appendix B. For the years 2016 and 2018, the average forecast errors decrease steadily with more information. For the remaining years, the errors increase from week 2 to week 3. However, these increases are overall small. Again, we hypothesize that the adjustment procedure might be the main reason for this result. A smoother course of Bavarian electricity consumption after adjustment might further improve the very good nowcasting and forecasting properties.

**Data from all four TSOs.** In our baseline analysis, we rely on data from only two of the Bavarian TSOs in order to exploit a longer time series. As a robustness check, we repeat our monthly forecasting experiment using data from all four TSOs, which cover the entire territory of the Free State of Bavaria. However, the extension to four TSOs restricts the analysis to the time period between 2015 and 2020, which implies that the prediction power of the electricity consumption data can only be evaluated for a very short time period. Consequently, we shorten the initial estimation period to 36 months (January 2015 to December 2017), resulting in 36 nowcasts and 35 forecasts for the period from 2018 to 2020. This should be taken into account when interpreting the following results, since they are strongly influenced by the Corona crisis.

Our baseline results remain essentially unchanged when using the short time series. The Bavarian electricity consumption data continue to perform well in the nowcasting setup and provide a significant gain in accuracy compared to the benchmark (see Table 5 for the results of model 2).[15] Both excluding and including the Corona crisis, the Bavarian electricity data is the best performing indicator. It can also outperform the benchmark in forecasting Bavarian industrial production ($h = 1$). However, other indicators perform slightly better. Future research could examine whether our results based on four TSOs can be generalized for longer time periods.

**Table 5:** Monthly Forecasting Performance Including all TSOs, Model 2

| **Indicator** | **excl. Corona** | **incl. Corona** |
|---|---|---|
| *Nowcast* | | |
| Electricity Consumption Bavaria | 0.89 | 0.68 |
| New Orders Manufacturing Bavaria | 1.03 | 0.94 |
| ifo Business Situation Manufacturing Bavaria | 1.09 | 0.74 |
| ifo Business Climate Manufacturing Bavaria | 1.05 | 0.70 |
| ifo Business Expectations Manufacturing Bavaria | 1.10 | 0.72 |
| ifo Production Realization Manufacturing Bavaria | 1.07 | 0.86 |
| ifo Production Expectations Manufacturing Bavaria | 1.04 | 0.72 |
| Electricity Consumption Germany | 1.03 | 0.69 |
| Truck Toll Mileage Index Germany | 1.03 | 0.74 |
| Truck Toll Mileage Index Bavaria | 1.05 | 0.69 |
| *Forecast* | | |
| Electricity Consumption Bavaria | 0.93 | 0.98 |
| New Orders Manufacturing Bavaria | 0.95 | 1.09 |
| ifo Business Situation Manufacturing Bavaria | 0.89 | 1.03 |
| ifo Business Climate Manufacturing Bavaria | 0.93 | 0.90 |
| ifo Business Expectations Manufacturing Bavaria | 1.00 | 0.91 |
| ifo Production Realization Manufacturing Bavaria | 1.16 | 1.02 |
| ifo Production Expectations Manufacturing Bavaria | 1.01 | 0.97 |
| Electricity Consumption Germany | 0.87 | 0.91 |
| Truck Toll Mileage Index Germany | 0.90 | 0.83 |
| Truck Toll Mileage Index Bavaria | 0.94 | 1.00 |

*Notes:* The forecast errors of the indicators are expressed relative to the performance of the benchmark (RMSFE Nowcast excl. Corona: 1.7 percentage points; RMSFE Nowcast incl. Corona: 9.6 percentage points; RMSFE Forecast excl. Corona: 1.9 percentage points RMSFE Forecast incl. Corona: 8.0 percentage points) and are based on indicator model 2. The monthly forecasting period either runs from January 2018 to December 2019 (excl. Corona) or up to December 2020 (incl. Corona). Bavarian electricity consumption is based on the information of all four TSOs. The model is described in Section 2.4.

[15] The results for model 1 are essentially identical and are shown in Appendix A.

# 4. Conclusion

High-frequency indicators from unconventional sources have become widely accepted in academic and applied economic forecasting in recent years. In this paper, we test the forecasting performance of unique electricity consumption data for regional industrial production. We do so for the second-largest German state for the period from January 2008 to December 2020. Our results clearly indicate that electricity consumption is the best indicator for nowcasting, outperforming other, more conventional indicators. Additionally, we find that the high-frequency nature of the data is beneficial: with only one week of information, the electricity consumption indicator delivers good predictions for the current month's industrial production growth.

In case of Germany, our results indicate that an unconventional data source can offer advantages for regional economic forecasts, pointing to promising avenues for future research. It is certainly desirable to explore whether data of other German Transmission System Operators could be made available to the public. If this is the case, our study could be extended to all 16 German states and other countries. Furthermore, our methodology could even be transferred to smaller regional units, such as the county level, to create indicators at a regional level at which data availability is currently particularly restricted. In addition to benefits for regional policymakers who could, for example, detect turning points earlier, these indicators can improve our understanding of regional business cycle movements.

Moreover, it can be inferred from our study that the electricity consumption of certain customer groups, such as large manufacturing firms, might be particularly useful for tracking and predicting industrial developments at the regional level. This would give us a more nuanced understanding of how industries evolve over time and across space.

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# A. Additional Forecasting Results

**Table A1:** Monthly Forecasting Performance of the Indicators Including 2020

| Indicator | Model 1 | Model 2 |
|---|---|---|
| Electricity Consumption Bavaria | 0.98 | 0.98 |
| New Orders Manufacturing Bavaria | 1.01 | 1.07 |
| ifo Business Situation Manufacturing Bavaria | 1.05 | 1.06 |
| ifo Business Climate Manufacturing Bavaria | 0.98 | 1.01 |
| ifo Business Expectations Manufacturing Bavaria | 0.95 | 0.99 |
| ifo Production Realization Manufacturing Bavaria | 1.02 | 1.05 |
| ifo Production Expectations Manufacturing Bavaria | 0.99 | 1.03 |
| Electricity Consumption Germany | 0.99 | 1.00 |
| Truck Toll Mileage Index Germany | 0.98 | 1.02 |
| Truck Toll Mileage Index Bavaria | 0.97 | 1.01 |

*Notes:* The forecast errors of the indicators are expressed relative to the performance of the benchmark model (RMSFE: 4.3 percentage points). The monthly forecasting period runs from February 2012 to December 2020. Bavarian electricity consumption is based on the information of two TSOs. The two models are described in Section 2.4.

**Table A2:** Weekly Forecasting Performance of Electricity Consumption Including 2020

| Information Set | Model 1 | Model 2 | MIDAS |
|---|---|---|---|
| End of week 1 | 0.95 | 0.97 | 1.11 |
| End of week 2 | 0.95 | 0.98 | 1.03 |
| End of week 3 | 0.96 | 0.99 | 1.03 |
| End of the month | 0.95 | 0.95 | 1.03 |

*Notes:* The forecast errors of the indicators are expressed relative to the performance of the benchmark model (RMSFE: 5.6 percentage points). The weekly forecasting period runs from February 2016 to December 2020. Different information sets reflect different forecasting situations, for which Bavarian electricity consumption data are either available for the total month, the first one, two, or three weeks within the month. Bavarian electricity consumption is based on the information of three TSOs. The models are described in Section 2.4.

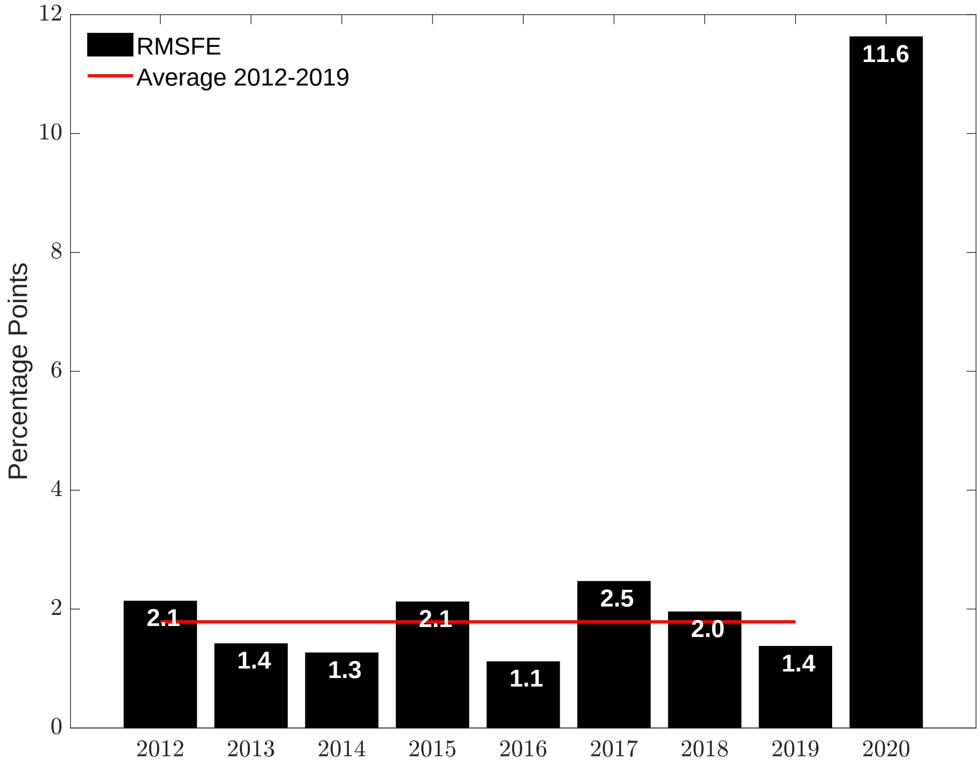
**Table A3:** Monthly Forecasting Performance Including all TSOs, Model 1

| **Indicator** | **excl. Corona** | **incl. Corona** |
|---|---|---|
| | *Nowcast* | |
| Electricity Consumption Bavaria | 0.91 | 0.61 |
| New Orders Manufacturing Bavaria | 1.02 | 0.84 |
| ifo Business Situation Manufacturing Bavaria | 1.08 | 0.76 |
| ifo Business Climate Manufacturing Bavaria | 1.03 | 0.61 |
| ifo Business Expectations Manufacturing Bavaria | 1.02 | 0.60 |
| ifo Production Realization Manufacturing Bavaria | 1.05 | 0.73 |
| ifo Production Expectations Manufacturing Bavaria | 1.03 | 0.63 |
| Electricity Consumption Germany | 1.06 | 0.66 |
| Truck Toll Mileage Index Germany | 1.03 | 0.58 |
| Truck Toll Mileage Index Bavaria | 1.01 | 0.53 |
| | *Forecast* | |
| Electricity Consumption Bavaria | 0.90 | 0.89 |
| New Orders Manufacturing Bavaria | 0.90 | 0.97 |
| ifo Business Situation Manufacturing Bavaria | 0.91 | 0.94 |
| ifo Business Climate Manufacturing Bavaria | 0.89 | 0.85 |
| ifo Business Expectations Manufacturing Bavaria | 0.88 | 0.78 |
| ifo Production Realization Manufacturing Bavaria | 0.97 | 0.95 |
| ifo Production Expectations Manufacturing Bavaria | 0.89 | 0.82 |
| Electricity Consumption Germany | 0.87 | 0.87 |
| Truck Toll Mileage Index Germany | 0.87 | 0.78 |
| Truck Toll Mileage Index Bavaria | 0.88 | 0.82 |

*Notes:* The forecast errors of the indicators are expressed relative to the performance of the benchmark (RMSFE Nowcast excl. Corona: 1.7 percentage points; RMSFE Nowcast incl. Corona: 9.6 percentage points; RMSFE Forecast excl. Corona: 1.9 percentage points RMSFE Forecast incl. Corona: 8.0 percentage points) and are based on indicator model 1. The monthly forecasting period either runs from January 2018 to December 2019 (excl. Corona) or up to December 2020 (incl. Corona). Bavarian electricity consumption is based on the information of all four TSOs. The model is described in Section 2.4.

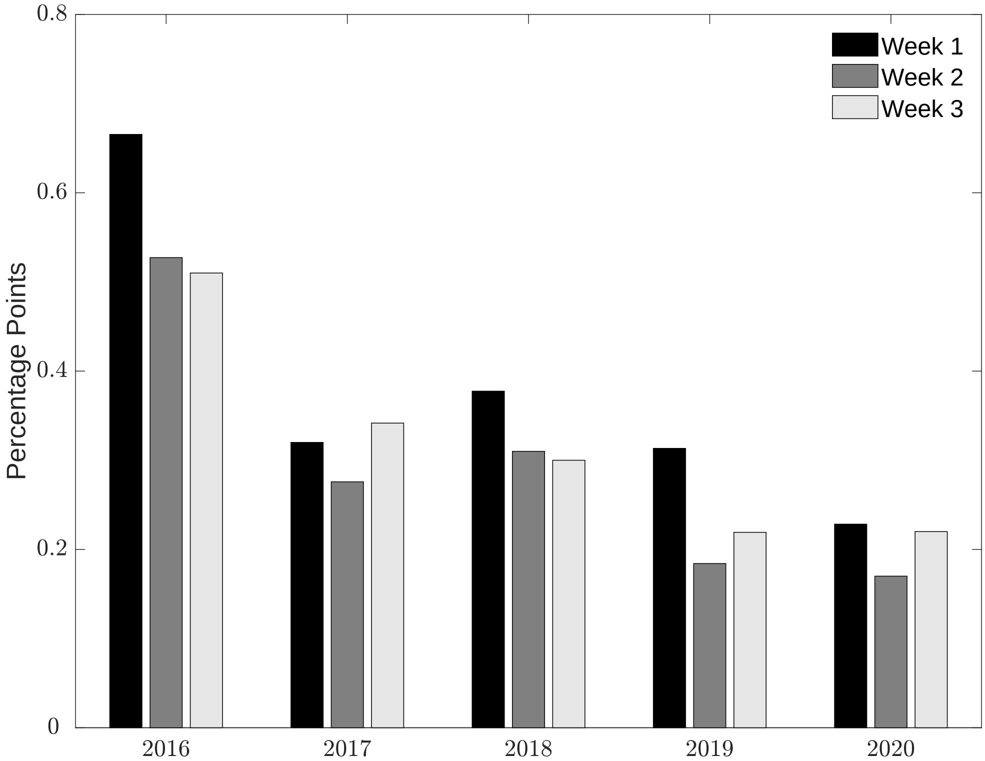
# B. Additional Figures

**Figure B1:** Forecast Accuracy 2012 to 2020




*Note:* The red line indicates the average root mean squared forecast error (RMSFE) for the years 2012 to 2019 (1.8 percentage points). The electricity consumption data are based on two TSOs.

**Figure B2:** Absolute Deviation of the Forecast Errors Within a Month 2016 to 2020




*Note:* Absolute average deviations of the weekly forecast errors from the errors based on full information.