

Use of Electricity Market Data in Nowcasting

Subjects: Economics

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Traditional forecasting methods usually rely on historical macroeconomic indicators with significant delays. To address this problem, new opportunities for economic modeling and forecasting are emerging by using real-time data and making nowcasting of economic activity.

Keywords: economic activity ; electricity market data ; MIDAS ; nowcasting

1. Introduction

During various economic shocks, such as the COVID-19 pandemic, energy, and financial crises, when the economic situation and working conditions change very quickly, the need for reliable economic predictions has grown radically. Traditional forecasting methods mostly rely on historical macroeconomic indicators with relatively significant delays, which diminishes the accuracy of economic forecasts and makes it difficult to predict business turning points or economic shocks with only a limited set of macroeconomic indicators.

To address this problem, new opportunities for economic modeling and forecasting are emerging by using real-time data and making the nowcasting of economic activity. Nowcasting is usually defined as the prediction of the present, the very near future, and the very recent past ([Bańbura et al. 2013](#)) and has been recently introduced in economics research. Nowcasting is particularly relevant for those key macroeconomic variables that are collected at low frequency, typically every quarter, and released with a substantial delay. To obtain 'early estimates' of these key economic indicators, researchers use information from data that are related to the target variable, but are collected more frequently, typically monthly, and released in a more timely manner. These early estimates can be updated sequentially when new information becomes available ([Blanco et al. 2017](#)).

Understanding economic activity in the different phases of the business cycle does not differ significantly and is primarily related to changes in GDP or industrial production ([Cooper and Priestley 2013](#); [Baumeister and Hamilton 2019](#); [Kilian 2019](#); [Herrera and Rangaraju 2020](#)). More broadly, all activities that are performed in exchange for money or things of value are economic activities. However, the concept of economic activity in the context of the COVID-19 pandemic or other economic shocks was expanded and treated much more broadly, as a larger and more diverse set of indicators or factors was included ([Sampi and Charl 2020](#); [Diaz and Perez-Quiros 2021](#); [Angelov and Waldenström 2021](#)).

There are studies that try to nowcast economic activity using data from alternative sources, such as social media information, business data, traffic data, sectorial data, and survey indicators ([Cavallo 2015](#); [Mellander et al. 2015](#); [Kapetanios and Papailias 2018](#); [Fenz and Stix 2021](#)). The obvious transformation of the activities (economic, social, etc.), conducted by economic entities towards the digital space, generates a huge amount of data that can be employed for nowcasting economic activity. The so-called nowcasts allow one to assess the economic activity in real time or with a minimum possible delay.

Mostly studies of the use of electricity market data in nowcasting refer to large countries, such as the US ([Bennedsen et al. 2021](#)), Germany ([Eraslan and Götz 2021](#)), and Portugal ([Lourenço and Rua 2021](#)), or higher-developed countries of Europe ([Fezzi and Fanghella 2021](#)). However, there is a lack of research on nowcasting economic activity using electricity market data in small open economies of Eastern Europe. According to [Chen et al. \(2018\)](#), small open economies possess the following characteristics: (1) their business cycle volatility is usually comparable in size to that seen in large wealthy economies, (2) their consumption is less volatile than output, and (3) their interest rates are procyclical (an increase in economic activity is usually associated with an increase in interest rates today and in the near future). It can be argued that for small economies to thrive, they need to focus on open trade. The development of an economic activity index following the example of a small open economy country would be an interesting example and would complement the weekly or even daily.

2. Nowcasting Economic Activity under Uncertain Time

The main idea of economic activity indicators is to represent reality without much delay (almost in “real time”), and according to [Fenz and Stix \(2021\)](#), they are not prone to behavioral changes and are not biased by fiscal or monetary policy measures or other measures taken to contain the crisis. That is why traditional forecasting methods became outdated, and their performance under circumstances of economic shocks rapidly deteriorated. The macroeconomic forecasting itself during crises is a challenging task, much more complex than in normal times ([Ferrara and Sheng 2022](#)). The economic shock represents an unexpected and unprecedented reaction of the economy to the changes, and no past observations could provide a relevant signal about its potential economic impact ([Barbaglia et al. 2022](#)). Furthermore, the uncertainty around government restrictions and policy support made it very difficult to assess their impact on national economies ([Ferrara and Sheng 2022](#)).

Nowcasting is usually defined as the prediction of the present, the very near future, and the very recent past ([Bańbura et al. 2013](#)). Nowcasting is particularly relevant for those key macroeconomic variables that are collected at low frequency, typically every quarter, and released with a substantial delay. To obtain ‘early estimates’ of such key economic indicators, researchers use data that are related to the target variable but collected at a higher frequency, typically monthly, and released more quickly. These early estimations can be updated sequentially, when new information becomes available ([Blanco et al. 2017](#)). The so-called nowcasts allow assessing the conditions and factors of economic activity in real time or with a minimum possible lag.

Many challenges remain for nowcasting during uncertain times ([Barbaglia et al. 2022](#); [Huber et al. 2023](#)); however, they can be divided into two broad categories: (a) the new massive and high-frequency alternative datasets and (b) associated models for forecasting. Usually, the nowcasting challenges with and without uncertain times aspect are similar, however, in a different scale. In the special context of the pandemic, the selection of fast-moving indicators goes hand in hand with the use of modelling methodologies that account for both the quick changes in big data variables and the structural relations among standard macroeconomic time series ([Barbaglia et al. 2022](#)). More models and more sophisticated econometric techniques are used to verify the nowcasting, as under uncertain times, it is more difficult to capture an abrupt change in economic activity ([Huber et al. 2023](#)).

The digitalization of economic activities generates a huge amount of data that can be used to nowcast economic activity. To capture the turning points of economic activity ([Eckert et al. 2020](#)) or accurately estimate the intensity of the recession ([Carriero et al. 2020](#)), the alternative or less directly related indicators of economic activity started to be used in nowcasting. The latest studies have provided evidence of the usefulness of fast-moving measurements extracted from big data sources to complement the information of classical economic variables ([Barbaglia et al. 2022](#)). The various data from such alternative sources as social media information (Google Trends data, search keywords, tone and polarity in the text, etc.), business data (real estate and consumer goods prices available in online portals, transaction volumes, etc.), traffic data (data of fixed and mobile sensors, satellite data, etc.), sectorial data (energy prices, production and consumption, pollution data, etc.), and survey indicators (consumer and business confidence, retail and construction sector activity, etc.) have proved to be useful to track economic activity in real time ([Cavallo 2015](#); [Mellander et al. 2015](#); [Kapetanios and Papailias 2018](#); [Fenz and Stix 2021](#)). The increasing use of alternative indicators among researchers indicates that this type of indicator will play an increasingly important role in economic monitoring in the future. According to [Lourenço and Rua \(2021\)](#), they are very sensitive to the business cycle.

However, the use of alternative indicators also has some drawbacks. Following [Eckert et al. \(2020\)](#), some of the indicators may be loosely related to economic activity as measured by statistical offices or cover only very specific aspects of economic activity. Additionally, series often fluctuate strongly and are affected by factors not related to the business cycle. Furthermore, most of them have only a short history and are subject to irregular patterns of missing observations and publication lags.

Timely big data signals reveal to be decisive during the pandemic ([Barbaglia et al. 2022](#)); however, there is still a need for a deeper understanding of the use of various alternative indicators to nowcast economic activity in uncertain times, as they must still be interpreted with caution ([Blonz and Williams 2020](#)).

3. The Use of Electricity Market Data in Nowcasting

Electricity data are unique in their ability to provide high-frequency data with a relatively full coverage of economic activity ([Blonz and Williams 2020](#)) at different geographic and sectoral scales. There is a strong correlation between growth rates in the real gross domestic product and electricity use ([Vipin and Lieskovsky 2014](#)). [Fezzi and Fanghella \(2021\)](#) also found

a close relationship between GDP growth and electricity consumption during the first wave of COVID-19; however, there is not yet an agreement on the methodology that should be used to correctly estimate such causal impacts.

Despite the advantages of electricity market data, there is still academic discussion about the usefulness of electricity market data in nowcasting. Usually, three types of electricity market data are used, that is, electricity consumption, electricity (including solar) production, and electricity prices. [Blonz and Williams \(2020\)](#) declared that the use of electricity data should be justified and the results interpreted with caution. [Lehmann and Sascha \(2022\)](#) found that electricity consumption is the best-performing indicator in the nowcasting setup and has higher accuracy than other conventional indicators, based on a monthly forecasting experiment. In addition, electricity consumption by subgroups of customers can be particularly informative about economic activity in specific sectors, such as manufacturing. [Wegmüller et al. \(2023\)](#) dropped electricity production from the initial list of data for the weekly economic activity index for Switzerland, as electricity production is not related to business cycle dynamics and is primarily driven by particular movements in the energy market and weather conditions. The authors used only electricity consumption. [Knotek and Zaman \(2017\)](#) identified that high-frequency energy price data play a key role in improving nowcasting accuracy. [Blonz and Williams \(2020\)](#) stated that the relationship between electricity usage and economic output can shift in unknown ways during a severe shock, making it challenging to directly translate changes in electricity demand to economic activity. Given this challenge, electricity high-frequency indicators are best used to determine when economic activity began to decline, when the recovery starts and progresses, and when demand has returned to preshock levels. According to [Fezzi and Fanghella \(2021\)](#), it is impossible to evaluate whether forecasting models successfully encompass the many long- (e.g., technological change) and short- (e.g., temperature, weekly seasonality) run drivers of electricity demand, thereby deriving unbiased causal effects.

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