Working Paper Series 4/2021

The Rushin Index: A Weekly Indicator of Czech Economic Activity

Tomáš Adam, Ondřej Michálek, Aleš Michl, Eva Slezáková

Czech National Bank —— Working Paper Series —— 4/2021

CZECH NATIONAL BANK

www.cnb.cz

Reviewed by: Sercan Eraslan (Deutsche Bundesbank)
Róbert Ambriško (Czech National Bank)
Project Coordinator: Michal Franta

The Rushin Index: A Weekly Indicator of Czech Economic Activity

Tomáš Adam, Ondřej Michálek, Aleš Michl, and Eva Slezáková *

Abstract

We introduce the Rushin, a weekly index of Czech economic activity. The index is based on alternative, high-frequency indicators and standard, low-frequency macroeconomic data. Various information from the economy is aggregated to extract a signal about real-time dynamics in the real economy. Although the information on the GDP growth rate is not used directly in the construction of the index, the indicator fits GDP data well, particularly in turbulent times such as the global financial crisis and the COVID-19 crisis. Therefore, it can be used for the real-time monitoring of economic activity, nowcasting and identifying turning points in the economy. The name of the index alludes to the name of Czechoslovakia's first finance minister Alois Rašín and the timeliness (rush-) of the index (-in).

Abstrakt

Článek představuje týdenní index ekonomické aktivity Rushin. Index je založen jak na alternativních, vysokofrekvenčních ukazatelích, tak na standardních, nízkofrekvenčních makroekonomických datech. Informace z různých sektorů ekonomiky jsou agregovány tak, aby Rushin zachycoval signál o dynamice reálné ekonomiky v reálném čase. Přestože informace o tempu růstu HDP nevstupují přímo do konstrukce indexu, samotný index zachycuje údaje o HDP uspokojivým způsobem, a to zejména v turbulentních obdobích, jako byla globální finanční krize či krize COVID-19. Proto lze index využít pro monitorování ekonomické aktivity v reálném čase, hodnocení současného růstu HDP (nowcast) či pro identifikaci bodů zvratu v ekonomice. Název odkazuje na jméno prvního československého ministra financí Aloise Rašína a na včasnost (v angličtině spěch, rush-) indexu (-in).

JEL Codes: C32, C43, E01, E32.
Keywords: COVID-19 crisis, economic activity index, high-frequency indicators, nowcasting.

* Tomáš Adam, Czech National Bank, tomas.adam@cnb.cz
Ondřej Michálek, Czech National Bank, ondrej.michalek@cnb.cz
Aleš Michl, Czech National Bank, ales.michl@cnb.cz
Eva Slezáková, Czech National Bank, eva.slezakova@cnb.cz
This work was supported by Czech National Bank Research Project No. MP2/20. We would like to thank Sercan Eraslan and Robert Ambriško for valuable comments in their referee reports. We would also like to thank Kornelia Fabisik for her useful comments at the CES Biennial Conference and to Michal Franta and other seminar participants at the Czech National Bank for their valuable feedback and comments. The views expressed in the paper are those of the authors and do not necessarily represent those of the Czech National Bank. All errors and omission remain entirely the fault of the authors.

1. Introduction

The COVID-19 pandemic shock has given rise to several challenges for macroeconomic forecasters and policymakers. First, several countries imposed strict lockdowns to limit the spread of the virus, which led to abrupt and severe economic downturns. Time series and structural economic models calibrated to historical data were unable to reflect the depth of these downturns, since no similar episode had occurred in history, and the standard relationships between the variables used in the models broke down. Second, the lockdowns were not due to economic forces, and some sectors had to shut down completely; this reaction was highly non-linear and had not been assumed by the economic models. Finally, the explanatory power of the leading indicators used in nowcasting models diminished significantly; these indicators are typically constructed based on surveys where the participants are asked whether the situation will improve or worsen, but not by how much.

To estimate the scale of the downturns following the lockdowns, economists focused more on alternative, often high-frequency, indicators of economic activity. These indicators, such as electricity consumption, air pollution, toll collection on highways and Google searches, are not usually considered in economic modelling due to their noisiness or high volatility even in standard times ((INSEE, 2020), etc.). To extract meaningful signals from these noisy high-frequency indicators, several central banks have introduced indices of economic activity (the Fed, the Bundesbank, the Bank of Italy, the Austrian Central Bank and the Banco de Portugal).

We follow this strand of the literature and introduce the Rushin, an index of Czech economic activity. To this end, we aggregate four high-frequency indicators and six monthly macroeconomic indicators. The index is named in honor of Alois Rašín, a prominent economist and politician from the period of the establishment of the independent Czechoslovakia. His name is pronounced as rush-een in Czech; the modified term is an allusion to Mr Rašín and the timeliness (rush-) of the index (-in).

Although the information on the GDP growth rate is not used directly in the construction of the index, the index fits data on GDP growth well. This is the case particularly in turbulent times, such as during the Global Financial Crisis and the COVID-19 crisis. In quiet times, we show that the index has similar explanatory power to that of the standard macroeconomic indicators used routinely for nowcasting the GDP growth rate.

The paper is structured as follows. First, we review the relevant literature on economic activity indices built both in quiet and turbulent times. Next, we outline our approach to building the index. Subsequently, we describe the data used for the construction of the index. Finally, we present the index along with tests on how it fits the GDP growth rate, both at the time of the COVID-19 crisis and also in quiet times.

2. Literature Review

The capturing of aggregate economic conditions has long been heavily studied by both academics and practitioners. The sole idea of a business cycle rests on the assumption that there is a process that drives conditions and outcomes in the economy, which are subsequently reflected in economic indicators. Knowing the trajectory and position of such a process is attractive for policymakers, forecasters, businesses, households and journalists.

There is a consensus that economic conditions are not related to one particular indicator, such as GDP or the industrial production index (for example, (Lucas, 1995; Burns and Mitchell, 1946)). Instead, economic conditions are reflected in the comovement and interactions of many variables. Therefore, economic conditions are modelled as a latent variable which captures the common movement of many observed indicators. Economic activity indicators have subsequently been used primarily for nowcasting and forecasting exercises and also for visually capturing the current state of the economy.

The major task of building an economic conditions index is therefore to aggregate information from several indicators into a single index, which serves as a proxy to economic conditions. The early works considered indicators at a monthly frequency only (Stock and Watson, 1989, 2002). The next generation of indices utilized more advanced econometric techniques to combine indicators at mixed frequencies (see, for example, (Mariano and Murasawa, 2003; Aruoba et al., 2009; Giannone et al., 2008)).

Traditionally, the economic activity indices mentioned above employ standard macroeconomic indicators compiled by statistical offices or central banks. Alternative economic indicators are often used for developing countries or countries with a distrust of official statistics. For example, the Li Keqiang index in China, first compiled by the Economist[1] and available on Bloomberg, which is a weighted average of railway cargo volumes, electricity consumption and bank credit volumes (all in year-on-year terms). The advantage of such indicators is that they are often available at high frequency (usually weekly or even daily) and with a short publication lag. One drawback of alternative indices, such as electricity consumption volumes, is their volatility and relatively small correlation with economic series in quiet times (INSEE, 2020).

The onset of the COVID-19 crisis (March 2020) fueled (and rekindled) the interest in alternative indicators of economic activity, even in advanced countries. This was because the shock was unprecedented in that there was a rapid deterioration and considerable decline in economic activity. It could thus be argued that relying on models fitted to historical data would lead to suboptimal conclusions. In addition, standard economic indicators, subject to publication lags, could also be unreliable due to problems with data collection, since large segments of economies were put under strict lockdown. At the same time, central banks and governments needed timely information in order to calibrate policies effectively.

Early papers which monitor the effects of the pandemic on the economy focus on single high-frequency indicators. Chen et al. (2020) analyze data on mobility, electricity consumption and weekly claims for unemployment benefits to assess the effects of the early stage of the pandemic in the US and Europe. Gascon and Schmitz (2020) use proprietary data to monitor regional economic developments in the US. The effect of lockdown on the Czech economy is analyzed by Adam and Michl (2020, April 4) using electricity consumption adjusted for temperature effects. McWilliams and Zachmann (2020) conduct a similar analysis on most European countries. Google Trends search data are used by Woloszko et al. (2020) to track economic activity in OECD countries during the COVID-19 crisis.

To extract meaningful information from several noisy high-frequency indicators, the Fed and the Bundesbank introduced indices of economic activity in the months following the first lockdowns. Lewis et al. (2020) aggregate weekly indicators to construct a Weekly Economic Index for the United States. This index is unique in that it contains ten weekly indicators, spanning four differ-

[1] "Keqiang ker-ching: How China's next prime minister keeps tabs on its economy". The Economist. 2010-12-09.

ent areas: household consumption (proxies for retail sales), labor market (data on unemployment claims, hiring and tax collection), production sector (data related to steel production, fuel sales and traffic), and finally data on electric utility output. The index is constructed as the first principal component of year-on-year changes in each variable. Although data on GDP growth is not considered when building the index, it allows us to nowcast GDP growth accurately. The authors contrast the results with an index extracted by a dynamic factor model; the differences between the two indices are relatively small. The principal components method is also employed by Eraslan and Götz (2021), who construct a weekly activity index for Germany. They expand the information set of high-frequency data by standard macroeconomic data (industrial production and GDP) to create a proxy for the GDP growth rate. In addition to variables used in the US index, various novel indicators are considered (such as the pedestrian frequency in large German cities, data on air pollution, flights or the frequency of Google searches for terms related to the labor market).

Several other central banks have introduced indices of economic activity built on alternative high-frequency indicators in response to the COVID-19 crisis. Delle Monache et al. (2021) propose an Italian Weekly Economic Index, which takes into account daily, as well as monthly indicators. The index contains data on consumer expenditure (from POS terminals) and several leading indicators, such as PMI indices, in addition to the indicators already mentioned. Fenz and Stix (2021) construct an OeNB GDP indicator, which tracks the Austrian annual GDP growth rate in real-time. Simultaneously, the index is broken down into standard GDP components based on various data from the economy. The drawback of the index is that it spans only data obtained since the onset of the COVID-19 crisis in Europe (March 2020). Rua and Lourenço (2020) construct an economic activity index for Portugal which they use to track real developments at a daily frequency.

3. The Construction of the Index

The major challenge in constructing the Rushin index is the mixed-frequency (monthly and weekly) nature of the input indicators. To extract meaningful information from the whole dataset, we transform the data into the selected form and then use principal component analysis (PCA) to extract the index. We loosely follow the methodology by Eraslan and Götz (2021), who calculate the Weekly Activity Index for the German economy.

Before aggregating the mixed-frequency indicators into a common factor, we transform them and create a balanced dataset with weekly frequency. This dataset takes into account the relevance of some indicators by including their lagged values.[2] This step is necessary to align the dynamics of these indicators with current economic activity in the Czech Republic.

In the initial step, we transform the variables so that the final index reflects the quarter-on-quarter dynamics of Czech economic activity; this allows us to use the index as a proxy for the quarterly GDP growth rate. All indicators are therefore firstly transformed into moving averages that span one quarter. Then, the moving averages are converted into quarterly growth rates.

For the high frequency (weekly) indicators, one quarter consists of 13 weeks. Therefore, we calculate 13-week averages first, and then we compute 13-week growth rates from these averages:

[2] Leading indicators and stock prices, in particular, contain information on future economic developments.

$$\Delta^q w_t = \frac{\frac{1}{13}\sum_{i=0}^{12} w_{t-i} - \frac{1}{13}\sum_{i=13}^{25} w_{t-i}}{\frac{1}{13}\sum_{i=13}^{25} w_{t-i}} * 100 \tag{1}$$

Similarly, for the monthly indicators, quarterly growth rates are calculated by 1) averaging three subsequent months; 2) computing the growth rates of these averages:

$$\Delta^q m_t = \frac{\frac{1}{3}\sum_{i=0}^{2} m_{t-i} - \frac{1}{3}\sum_{i=3}^{5} m_{t-i}}{\frac{1}{3}\sum_{i=3}^{5} m_{t-i}} * 100 \tag{2}$$

Since $\Delta^q w_t$ and $\Delta^q m_t$ are moving quarterly growth rates, the resulting values at the end of a given quarter can be interpreted as a quarterly growth rate for that quarter.

To calculate the weekly index of economic activity, we align all the indicators, creating one weekly dataset. Since both weekly and monthly variables can be interpreted as moving quarterly growth rates, we put them into a dataset on a weekly frequency with missing observations. First, we convert monthly data into a weekly frequency by assigning it to the last week of a given month. The remaining weekly values are denoted as missing, regardless of the number of weeks in a particular month. If one week spans two months, it is assigned to a month depending on the date of the first weekday (Monday). Values of original monthly indicators, which are transformed into weekly time series, correspond to the 13-week growth rate of high-frequency weekly indicators and can then be combined into one dataset on a weekly frequency.

The resulting dataset includes two types of missing observations. One is due to the mixed frequency of the dataset – we observe only one weekly data point of monthly indicators (at the end of the month), while others are missing. The second type of missing value is due to the publication lag. For example, industrial production and retail sales are published usually six weeks after the end of a given month.

In the next step, missing observations are imputed using the Kalman filter. We assume a structural time series model with missing observations, where observed values are given by data described in the previous steps. The algorithm that we use selects the optimal order of the model and fits parameters using the maximum likelihood estimate. The missing variables are subsequently interpolated using the Kalman smoother.[3]

Having a full dataset X with no missing observations, we can now proceed with index construction. We apply the principal component analysis (PCA) on the dataset and extract the common factor.[4] Let us say $x_{i,t}$ is a single observation of variable i in week t and λ_i^1 is a loading of variable i in the first

[3] We use the na_kalman function from the imputeTS package in R.

[4] The results of the PCA on the selected dataset are presented in Appendix D.

vector of loadings which is given by the PCA. The resulting Rushin index is a linear combination – a weighted average – of n economic indicators, where each weight is given by the corresponding value of the first vector loading:

$$\text{Rushin}_t = \sum_{i=1}^{n} x_{i,t} \lambda_i^1 \tag{3}$$

Each variable's contribution to the index depends on how strongly it relates to the calculated factor from the PCA. Therefore, the resulting index is a standardized weighted average of all the variables in the dataset X. Since we want the index to relate to the quarterly GDP growth rate, in the last step, we scale it using the quarter-on-quarter GDP mean and the standard deviation[5] as:

$$\text{Rushin}_t^{sd} = \frac{\text{Rushin}_t}{sd^{\text{Rushin}}} * sd^{\text{GDP}} + mean^{\text{GDP}} \tag{4}$$

4. Data

The Rushin index aggregates comovement among several selected indicators. Of the candidate indicators, we considered both unconventional and traditional economic indicators. Some variables are available at high frequency (weekly, daily or even hourly); other indicators are available monthly. The drawback of monthly indicators is their publication lag, which can be up to several weeks.

We selected the variables based on three main criteria: a) economic relevance, b) the correlation with the quarterly GDP growth rate, and c) the association to the first principal component extracted from all selected variables. This section describes in detail the considered indicators and the process of selecting the indicators suitable for the index.

4.1 High-Frequency Indicators

The basic building blocks of the weekly economic activity index are relevant high-frequency indicators whose developments are very much related to specific sectors of the Czech economy. However, high-frequency data in the Czech Republic are not as easy to obtain as in larger economies, such as Germany or the USA, for which similar indices were constructed. Despite the scarcity of high-frequency indicators, we managed to collect six high-frequency data sets.[6] They were initially available at various frequencies and were transformed into weekly time series.

Electricity Consumption

Electricity consumption is a high-frequency indicator belonging to the group which serves as a proxy for industrial production. We made several adjustments to extract meaningful signals about

[5] The mean and the standard deviations of GDP growth used for scaling were computed on the same time period as the final index, i.e., since 2008 Q2.

[6] In addition to the time series described here, we considered including the data on VAT collection, which is available at the Czech National Bank. However, high-frequency data on tax collection are noisy and did not prove very informative for economic activity.

the economy from this indicator, including outdoor temperature adjustment and multiple seasonality adjustment.[7] The raw data on electricity consumption in the Czech Republic is obtained from the Czech transmission system operator CEPS.

NO2 Emissions

The atmospheric concentration of nitrogen dioxide can serve as an indicator of industrial production and traffic because the primary source of this gas is the combustion of fossil fuels in cars and industrial plants. Data on the hourly concentration in the atmosphere since 2013 is reported by the European Environment Agency. We filtered the raw data on air quality stations located in the most frequented areas, and then excluded public holidays, weekends and records outside of busy hours. Finally, we separated them into different regions and adjusted them for seasonality. Subsequently, we considered three time series for further use: the Prague region, the Central Bohemian region and the country average.

Google Trends

We selected three time series of the Google search frequency of the terms “unemployment”, “unemployment benefits” and “part-time work” for the Czech Republic.[8] These indicators reflect the labor market conditions. Google publishes them as relative normalized indices, and we collect them on a weekly frequency.

Indicators on German Economic Activity

The Czech economy is highly export-oriented, and consequently it is very much dependent on developments abroad. To capture changes in foreign demand, we considered the indicators of the German economy since Germany is our most important trading partner and our economies are strongly interconnected. Of the available indicators, we selected the truck toll mileage index published by the Bundesbank on a weekly frequency.

Currency in Circulation

We also considered and tested the data on real-time currency volume in circulation in the Czech Republic, which is available to us on a daily frequency. The average weekly value of this indicator, adjusted for seasonality, can serve as a coincident indicator and as a proxy for overall economic sentiment in a country.

Stock Market Index

The last indicator, which completes high-frequency variables, is the Prague Stock Exchange (PX) Index. For our index, we use a weekly average of daily closing prices of the index.

4.2 Monthly Indicators

Due to the availability constraints of high-frequency indicators and their high volatility, we have decided to include several conventional monthly indicators in our dataset. These variables should

[7] These adjustments are described in detail in Appendix A
[8] In Czech “nezamestnanost”, “podpora” and “brigáda”, respectively.

complete the set of information for each segment covered by high-frequency indicators and make the index more robust.

We collected 231 monthly indicators which can be divided into five main groups:

Group 1 (Production): The first group includes production indices from the main Czech industrial and construction sectors. All of the time series in this group are seasonally and calendar adjusted in constant prices (source: CZSO)[9].

Group 2 (Sentiment): The most prominent group covers developments of leading indicators in the domestic and in the German economy. Most of them are published by the CZSO; the rest comes from the OECD and the ifo[10].

Group 3 (New orders): Since Czech industrial production is closely connected to developments in the same sector in Germany, we also decided to test the value of seasonally and calendar adjusted new orders[11] in constant prices in German industry (total, domestic, foreign and foreign from the EU). The data was collected from the German statistical office (Destatis).

Group 4 (Sales): The group covers the performance of another crucial segment of the Czech economy – the tertiary sector (retail and market services). All indicators in this group are seasonally and calendar adjusted, and data is provided by the CZSO.

Group 5 (Other data): The last group contains the seasonally adjusted number of new car registrations in the Czech Republic and Germany (source: ECB). It also includes data on Czech exports and imports. Finally, this group includes truck tolls on the Czech highways (D1 and D5). The data are seasonally adjusted and provided by the Ministry of Transportation.

4.3 Data Selection Procedure

To test the time series suitability for the Rushin index described above, we performed Pearson's correlation test on the q-o-q growth of the indicators with the quarterly GDP growth rate. Since some of the variables, such as sentiment indicators, indicators of foreign demand or stock prices, may lead the development of GDP, we also identified the optimal lags of all the indicators as being up to ten weeks for high-frequency indicators and three months for monthly indicators. First, we calculated the average quarterly values of all the available variables and the q-o-q growth rates of these averages. Then the lags of these variables were created and added to the dataset.

Out of 110 high-frequency times series including their lags, 63 passed the test at a 5% significance level,[12] while out of 916 time series representing monthly variables and their lags, 514 passed the test[13]. This was the first threshold in the variable selection process. At the same time, it also provided us with information on the main characteristics of different indicators. Lagged variables were preferred only in cases where they significantly outperformed the unadjusted time series. Also, some variables were discarded based on a high number of lags since they would not fit our purpose of creating an almost real-time economic activity index. Later, we excluded additional indicators

[9] CZSO = Czech Statistical Office
[10] Leibniz Institute for Economic Research at the University of Munich
[11] Data on new industrial orders are also published for the Czech economy, but only in current prices.
[12] Correlation coefficients for all time series are presented in Appendix B
[13] Correlation coefficients for all time series are presented in Appendix C

due to the value of their correlation coefficient, which was not in line with standard economic theory and common sense.

Additionally, more variables were excluded in order not to over-represent specific sectors of the economy and keep the data sample well-balanced. Finally, since index creation is an iterative process, we altered the representation of different segments by replacing selected indicators with variables excluded in the previous step based on the properties of the first principal component. Therefore the optimal set of indicators was one, where all input variables were highly correlated with the common factor[14] and at the same time, the common factor was able to capture as much variability in the dataset as possible.

The final dataset consists of four weekly and six monthly indicators (Table 1). The weekly indicators include electricity consumption, Google searches of the term "unemployment benefits"[15], the German Truck Toll Mileage Index and the PX Index; the monthly indicators include sales in market services (NACE H, I, J, L, M and M), production in manufacturing, retail sales (NACE 45), the OECD Composite Leading Indicator for the Czech Republic, the ifo Business Climate Index for Germany and truck tolls on the D1 and D5 Czech highways.

Table 1: Data Used for Constructing the Rushin Index

variable	corr.	lag	description	source	unit	group	sample
Weekly Indicators							
electricity	0.77	0	Electricity consumption	CEPS, a.s.	Load (MW)	Production	08Q1:21Q4
toll_de	0.78	1	Truck toll mileage, DE	Bundesbank	Index	Foreign demand	08Q1:21Q4
px	0.53	4	Prague Stock Exchange Index	Prague Stock Exchange	Closing price	Other	08Q1:21Q4
gs_unem_benefits	-0.73	2	Google Searches "Unemployment benefits"	Google Trends	Normalized index	Labor market	08Q1:21Q4
Monthly Indicators							
toll	0.78	0	Truck toll D1 and D5, CZE	MoT	Truck toll collected on Czech highways (D1 and D5)	Other	10Q2:21Q1
ifo_bus_climate_de	0.72	0	Sentiment according to the ifo, Business climate, DE	IFO	Sentiment according to the ifo, Business climate, GER	Sentiment	05Q3:21Q1
oecd_cli	0.80	0	Composite leading indicator of OECD, CZE	OECD	Index, amplitude adjusted	Sentiment	96Q3:21Q1
retail	0.81	0	Sales, G45 - Wholesale and retail trade and repair of motor vehicles and motorcycles, CZE	CZSO	Index (average of 2015 = 100), SCA	Sales	00Q3:21Q1
services	0.90	0	Sales, H - Transport and storage, I - Accommodation and food service activities, J - Information and communication, L - Real estate activities, M - Professional, scientific and technical activities, N - Administrative and support service activities, CZE	CZSO	Index (average of 2015 = 100), SCA	Sales	05Q3:21Q1
industry_man	0.82	0	Production, Industry, C Manufacturing, CZE	CZSO	Index (average of 2015 = 100), SCA	Production	00Q3:21Q1

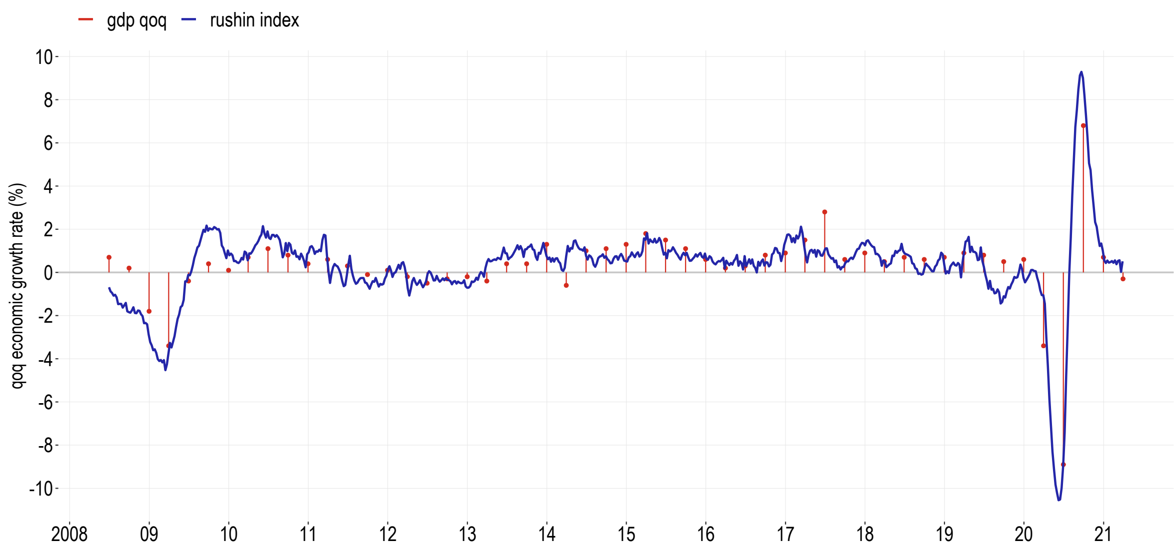
All selected monthly indicators have a positive correlation with the GDP growth rate. Although the correlation of the ifo BCI indicator with GDP growth is below 0.8 and is lower than for the other variables, the main advantage of this indicator is its timeliness. The ifo BCI for a given month is available even before the end of the month. Most of the high-frequency indicators are also closely related to GDP growth, although slightly less so than monthly indices.

[14] The first principal component should explain at least 20% of variability in each variable.
[15] "Podpora" in Czech.

5. Results

The Rushin index can be interpreted as a quarterly growth rate of Czech economic activity. This is because it is constructed as a common factor of quarterly dynamics of input indicators. To obtain a concrete indication of the explanatory power of the index, we can compare it to the quarterly GDP growth rate in Figure 1. It is worth repeating that the most relevant estimate related to developments in the current quarter is the last observation of the index. That is why the "lollipops" denoting GDP growth are assigned to the last day of the quarter. We can see that the Rushin index accurately captures the sharp decline in activity during the financial crisis (2008–2009) and the pandemic crisis (starting in 2020). Moreover, the index accurately identifies the slowdown in activity in 2011–2012 when the Czech economy was on the brink of a recession. The results also show that the index captures GDP dynamics very well, especially during periods of higher volatility, making it the ideal tool for tracking economic activity in the current rapidly-changing economic climate.

Figure 1: The Rushin Index and the Quarterly GDP Growth Rate

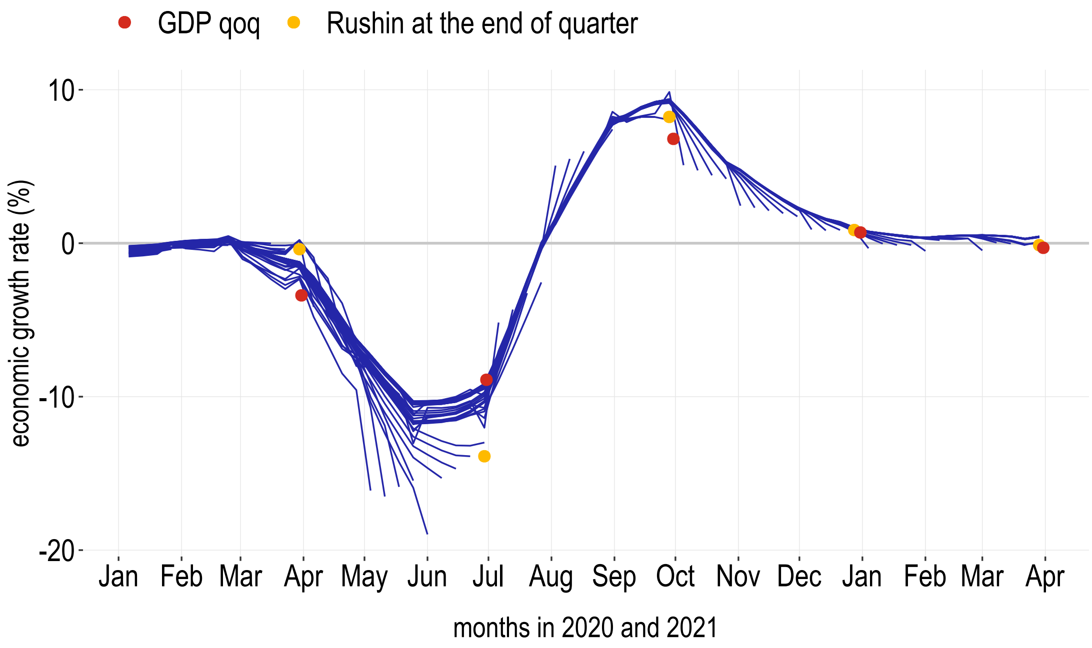


Note: The index measures quarterly change in economic activity on a weekly frequency; it is scaled to q-o-q GDP growth rate dynamics.

5.1 The Rushin in Pseudo-Real Time

The index presented so far was constructed using all the data that were available until the end of 2021 Q1. Therefore, one could argue that the loadings of the indicators are affected by the sharp decline in economic activity in the second quarter of 2020 followed by solid growth in the third quarter, which came with a significant delay. Figure 2 shows the real-time estimates of the index to give a sense of how the estimates of the index changed in 2020 and at the beginning of 2021. The index is recalculated for every week of the period; we only consider the data available on the Monday of a given week in our calculations. We therefore take into account the publication lag of the data. The vintages of the index show relatively substantial revisions of the downturn in 2020 Q2 (the value at the end of June); at the same time, the speed of the downturn in April was not subject to significant revisions. Also, the turning points in the economy were not revised. Overall, the revisions do not appear to be of any great concern in terms of the reliability of the index.

Figure 2: Pseudo-Real Time Estimates of the Rushin Index



Note: The chart shows weekly estimates of the Rushin index in pseudo-real time: in a given week, it uses only data available at that time (publication lag); however, final vintages are used in the estimate. The differences in the position of bullets on the horizontal axis are due to the different dating methods used for GDP and for Rushin.

5.2 Performance Test

Figure 1 illustrated a high correlation between the Rushin index and the quarterly growth rate of GDP. In this section, we conduct two sets of tests to assess the information content of the Rushin index. First, we test whether the index accurately captures the GDP growth rate on the whole sample. To this end, we run regressions of GDP growth rates on the values of the Rushin index (in the first, second or third month of a given quarter); additionally, we consider the GDP growth rate from the previous quarter as an explanatory variable. Next, we assess the nowcasting ability of the index in the pre-pandemic period (2016–2019) and during the pandemic (2020 and the beginning of 2021) and contrast it with the performance of standard monthly indicators in the set-up of bridge equation models. For this set of tests, we consider the pseudo-real-time estimates of the index presented in the previous section.

5.2.1 Rushin and GDP Growth

To test how well the Rushin index captures the quarterly dynamics of economic activity, we have run eight regressions, with the quarter-on-quarter GDP growth rate as a dependent variable. In each regression, exogenous variables include the value of the Rushin index at one or more different points in a given quarter. At the same time, half of these regressions also have an autoregressive term.

First, the nowcasting ability of the Rushin index is tested by the index value at the end of the quarter against the quarterly GDP growth rate via linear regression both without (Equation 5) and with (Equation 6) a lagged GDP growth rate:

$$\Delta^q GDP_q = \alpha + \beta Rushin_q + \varepsilon_q \tag{5}$$

and

$$\Delta^q GDP_q = \alpha + \beta Rushin_q + \gamma \Delta^q GDP_{\text{q-1}} + \varepsilon_q \tag{6}$$

where $\Delta^q GDP_{\text{q}}$ is q-o-q real GDP growth in quarter q, $\Delta^q GDP_{\text{q-1}}$ is q-o-q real GDP growth in quarter *q-1*, and $Rushin_q$ is the value of the index at the end of quarter q. The results are presented in columns 1 and 2 of Table 2. They show that the Rushin index is an important predictor of quarterly real GDP growth and can explain 85% of its variation. In contrast, given the additional information of lagged GDP growth, the explained variation in GDP increases to 87%.

In the next step, we test the nowcasting ability of the index as a flow of information. We regress the quarterly GDP growth rate on the values of the index at the end of the first month, at the end of both the first and second months and the end of all three months of a given quarter:

$$\Delta^q GDP_q = \alpha + \sum_{i=1}^{m} \beta_i Rushin_q^i + \varepsilon_q;\ m = 1,2,3 \tag{7}$$

and

$$\Delta^q GDP_q = \alpha + \sum_{i=1}^{m} \beta_i Rushin_q^i + \gamma \Delta^q GDP_{\text{q-1}} + \varepsilon_q;\ m = 1,2,3 \tag{8}$$

where $\Delta^q GDP_q$ again represents quarter-on-quarter real GDP growth in quarter q, $\Delta^q GDP_{\text{q-1}}$ is quarter-on-quarter real GDP growth in quarter *q-1* and $Rushin_q^i$ is the value of the index at the end of a given month m in quarter q. The results are reported in columns 3 to 8 of Table 2.

Although information from the first month of the quarter is a significant predictor of quarterly GDP changes, we do not consider it adequate to nowcast economic activity since it explains less than 40% of GDP variability. However, including the lagged GDP growth rate in the regression model increases the variability explained by the model to 64%. The flow of information up to the second month of a given quarter notably increases the ability to nowcast economic activity. At the same time, the index value from the end of the first month becomes an insignificant predictor. This model can explain 83% of the variability in quarterly GDP dynamics. Finally, the information from all three months of the quarter can explain 84% of GDP variability (for a model with a lagged GDP growth rate of 85%), while the only significant predictor in the model is the value of the Rushin index at the end of the last month of a given quarter, i.e. the value that directly captures quarter-on-quarter GDP growth.

Table 2: Test: Rushin and the GDP Growth Rate

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.08	0.01	0.08	0.15	0.07	0.04	0.05	−0.00
	(0.11)	(0.11)	(0.21)	(0.16)	(0.11)	(0.11)	(0.11)	(0.11)
$GDP_{q\text{-}1}$		0.11		-0.64^{***}		0.19		0.31^{*}
		(0.06)		(0.11)		(0.14)		(0.14)
$Rushin_{m=1}$			0.81^{***}	1.30^{***}	−0.15	−0.48	0.03	−0.44
			(0.14)	(0.14)	(0.11)	(0.26)	(0.15)	(0.25)
$Rushin_{m=2}$					0.93^{***}	1.11^{***}	0.24	0.26
					(0.08)	(0.15)	(0.36)	(0.34)
$Rushin_{m=3}$	0.83^{***}	0.85^{***}					0.59	0.83^{**}
	(0.05)	(0.05)					(0.30)	(0.31)
R^2	0.83	0.85	0.40	0.66	0.83	0.84	0.85	0.86
Adj. R^2	0.83	0.85	0.39	0.64	0.83	0.83	0.84	0.85
Num. obs.	52	51	51	51	51	51	51	51

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

5.2.2 The Rushin and the Monthly Indicators

To test whether the index outperforms traditional coincident and leading monthly indicators or their combination[16] in nowcasting GDP, we have carried out GDP nowcasts in pseudo-real time in each month of a given quarter. That is, we only use information available at the given time, both for monthly indicators and the Rushin index. The procedure was conducted using an expanding window OLS regression model and a bridge equation univariate model (e.g., (Adam and Novotný, 2018)). The estimation process is illustrated in Figure 3:

Let us assume that t represents the current month, $t+1$ the next month, etc. Q_t stands for the current quarter, Q_{t-1} for the previous quarter, etc. Three estimates are made in each quarter $Q_t$to nowcast GDP.

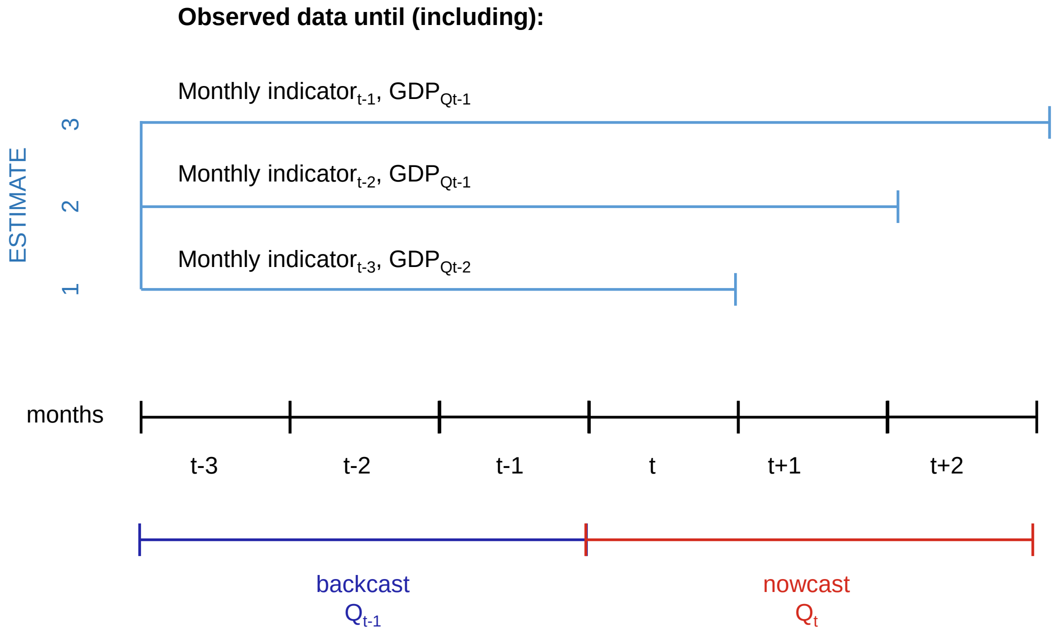
- Period t: The estimate is made at the end of period t, and it includes the observation of a given monthly indicator for period t-2. To obtain its values up to period $t+2$, we extrapolate the series using an ARMA model. In the case of the Rushin index, we only extrapolate the values for period $t+1$ and $t+2$. Due to the construction of the Rushin index (the change in the last 13 weeks relative to the preceding 13 weeks), only the value $t+2$ is comparable to the quarter-on-quarter GDP growth rate. The GDP figure is known only for period Q_{t-2}.

- Period $t+1$: The second estimate is conducted at the end of period $t+1$ and it includes the observation of a given monthly indicator for period t-1. The other values are again obtained using an ARMA model. The same holds for the Rushin index, although we need to predict its value for period $t+2$ only. A new observation of GDP for period Q_{t-1} is available and used.

- Period $t+2$: The third and final estimate is conducted in period $t+2$ when a monthly indicator for period t is observed. The remaining values are again obtained using an ARMA model. We do not need to extrapolate the Rushin index since we know its final value for quarter Q_t. Again, the observation of GDP for period Q_{t-1} is used.

[16] The comparison contains industrial production, retail sales and sales in services, sentiment (overall, business and consumer) and OECD indicators (CLI, BCI and CCI).

Figure 3: The Nowcasting Performance Test



- Since we use expanding window regression, all three steps are repeated until the end of the forecasting horizon.

Our final dataset includes observations from June 2008 (the first full month for which the Rushin index is available) until March 2021. We split the dataset into two samples and estimate the Rushin's nowcasting power separately for the period from 2016 to 2019 and for the sample since January 2020 using expanding window regressions. This allows us to assess the nowcasting ability of the Rushin Index independently for the pre-pandemic periods and for the period of higher volatility in economic activity during the pandemic. To evaluate its nowcasting performance, we calculated the root mean square error values for each estimate across both samples, grouped this depending on its order in a given quarter and compared it to the Rushin and some of the comparable monthly indicators or a combination thereof. The results are presented in Figure 4 and 5:

The black line represents the q-o-q GDP growth rate in a given quarter, and the dots are estimates of GDP based on the equation at the top of each subplot. The blue dots represent the first estimate of GDP growth for a given quarter; the red dots illustrate the second estimates, and the yellow ones show the last estimates. Each subplot also contains information about the size of RMSE in the pre-pandemic and pandemic period.

As the results of the estimates in the pre-pandemic period suggest, there is no significant difference in RMSE between the Rushin index and the selected indicators or their various combinations. Therefore, we can conclude that the index's ability to predict GDP in "normal" times is as good as that of any other selected predictor. One can, however, argue that the results of our weekly index are more robust since the Rushin index captures all the major sectors of the economy, whereas individual predictors provide only partial information about the economy.

Regarding the pandemic period, the Rushin index shows its true ability to capture sudden changes in GDP early and with a great deal of precision.[17] While the GDP nowcast based on the Rushin index started to indicate a sharp downturn in economic activity since April 2020, most of the other nowcasting equations implied growth or only a slight downturn in the same period. Moreover, the Rushin index's last estimates of GDP since 2020 Q2 were almost as precise as the final observed value, as confirmed by the lowest RMSE across selected equations. Although we can find lower RMSE for the first two estimates in the tested indicators, the difference is negligible, and one can apply the same argument about the robustness of the index as that cited in the previous paragraph.

The analysis confirms the robust GDP nowcasting performance of the Rushin index. This especially holds true during periods of significant change in economic activity. The index significantly outperforms most of the selected standard monthly economic indicators in various equation specifications. It therefore provides a timely indication of the development of GDP during the most uncertain of times, such as the ongoing COVID-19 pandemic and the related lockdowns of the Czech economy.

[17] One exception is the first estimate of GDP for 2020 Q4 (blue dot). However, the deviation from the observed value is due to the structure of nowcasting analysis, or more precisely, the extrapolation of the index by AR process. The steep downturn of the index in October led to its extrapolation into negative territory, even though the last observed value of the index was 4.4%).

Figure 4: GDP Nowcasting Performance: Rushin Index vs. Monthly Indicators

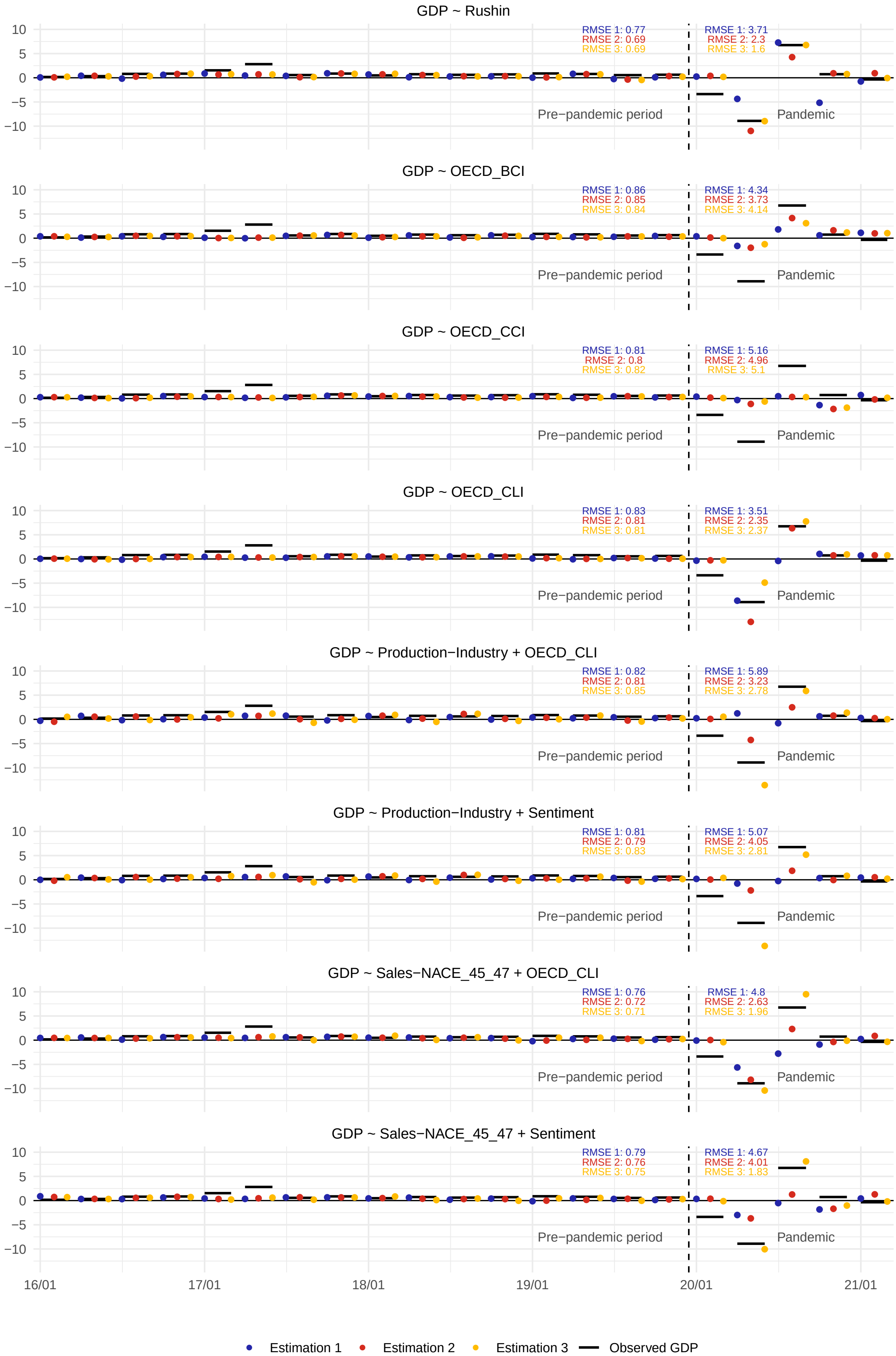
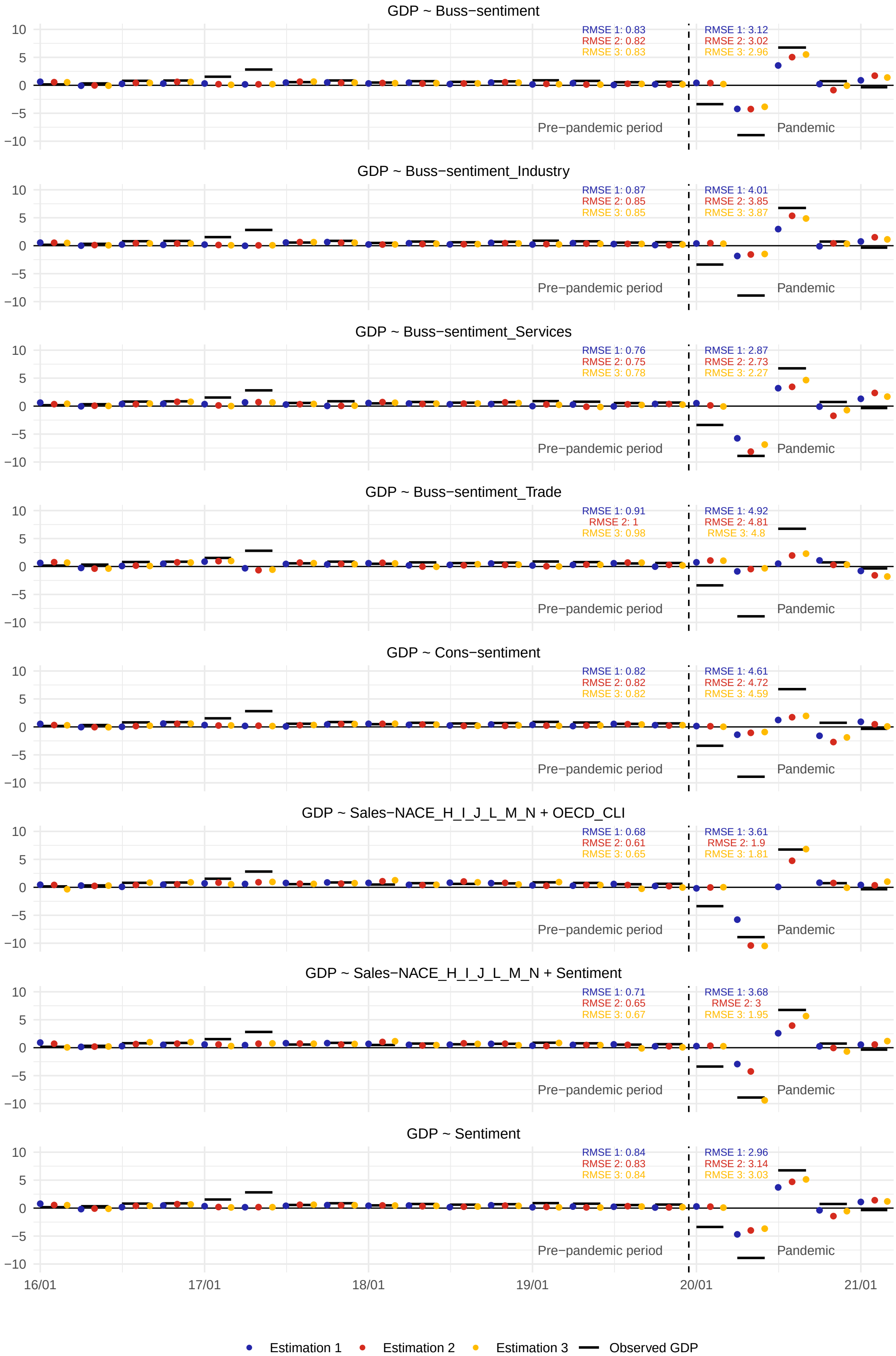


Figure 5: GDP Nowcasting Performance: Rushin Index vs. Monthly Indicators



6. Conclusion

In this paper we have introduced the Rushin, a weekly indicator of Czech economic activity. To the best of our knowledge, it is the first economic activity indicator that aggregates both the high-frequency and monthly indicators of Czech economic activity. We have shown that although the GDP growth rate does not directly enter the estimate of the index, the indicator is very much correlated with the GDP growth rate published with a significant lag. It performs well, particularly in turbulent times, such as during the COVID-19 pandemic and related lockdowns. Therefore, it could be used as an input for a nowcasting exercise, which is crucial to producing forecasts based on both time series and structural models.

The major challenge involved in constructing the index was the relatively limited availability of high-frequency data, particularly on household consumption. Although this data is regularly collected (for the purposes of tax collection or credit card transactions), they are not publicly available at a high frequency. We believe this drawback will slowly fade over time, as policymakers and business leaders realize that the optimal policy response to the COVID-19 pandemic is dependent on very granular and timely data availability.

References

ADAM, T. AND A. MICHL (2020, April 4): "První odhad dopadů pandemie COVID-19 na ekonomiku ČR." *čnBlog - oficiální blog České národní banky,* `https://www.cnb.cz/cs/o_cnb/cnblog/Prvni-odhad-dopadu-pandemie-COVID-19-na-ekonomiku-CR/`.

ADAM, T. AND F. NOVOTNÝ (2018): "Assessing the External Demand of the Czech Economy: Nowcasting Foreign GDP Using Bridge Equations." Working Papers 2018/18, Czech National Bank

ARUOBA, S. B., F. X. DIEBOLD, AND C. SCOTTI (2009): "Real-time Measurement Of Business Conditions." *Journal of Business & Economic Statistics,* 27(4):417–427.

BURNS, A. F. AND W. C. MITCHELL (1946): *Measuring Business Cycles.* New York: National Bureau of Economic Research.

CHEN, S., D. IGAN, N. PIERRI, A. F. PRESBITERO, ET AL. (2020): "Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States." *IMF Working Papers 2020/125.*

DELLE MONACHE, D., S. EMILIOZZI, AND A. NOBILI (2021): "Tracking Economic Growth During the COVID-19: A Weekly Indicator for Italy." *Note, January 2021, Banka d'Italia.*

ERASLAN, S. AND T. GÖTZ (2021): "An Unconventional Weekly Economic Activity Index For Germany." *Economics Letters,* 204:109881.

FENZ, G. AND H. STIX (2021): "Monitoring the Economy in Real Time with the Weekly OeNB GDP Indicator: Background, Experience and Outlook." *First View, Oesterreichische Nationalbank, February 2021.*

GASCON, C. S. AND A. SCHMITZ (2020): "Using High-Frequency Data to Track the Regional Economy." *The Regional Economist,* 28(3).

GIANNONE, D., L. REICHLIN, AND D. SMALL (2008): "Nowcasting: the Real-time Informational Content of Macroeconomic Data." *Journal of Monetary Economics,* 55(4):665–676.

INSEE (2020): "High-frequency Data are Especially Useful for Economic Forecasting in Periods of Devastating Crisis." *Economic Outlook, INSEE, 17 June 2020.*

LEWIS, D. J., K. MERTENS, J. H. STOCK, AND M. TRIVEDI (2020): "Measuring Real Activity Using a Weekly Economic Index." *Federal Reserve Bank of New York Staff Reports,* No. 920.

LUCAS, R. E. (1995): *Understanding Business Cycles.* In *Essential readings in economics,* pages 306–327. Springer.

MARIANO, R. S. AND Y. MURASAWA (2003): "A New Coincident Index of Business Cycles Based on Monthly and Quarterly Series." *Journal of Applied Econometrics,* 18(4):427–443.

MCWILLIAMS, B. AND G. ZACHMANN (2020): "Bruegel Electricity Tracker of COVID-19 Lockdown Effects." *Bruegel Datasets, Brussels.*

RUA, A. AND N. LOURENÇO (2020): "The DEI: Tracking Economic Activity Daily During the Lockdown." Working Papers 2/2020, Banco de Portugal, Economics and Research Department.

STOCK, J. H. AND M. W. WATSON (1989): "New Indexes of Coincident and Leading Economic Indicators." *NBER Macroeconomics Annual,* 4:351–394.

STOCK, J. H. AND M. W. WATSON (2002): "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business & Economic Statistics,* 20(2):147–162.

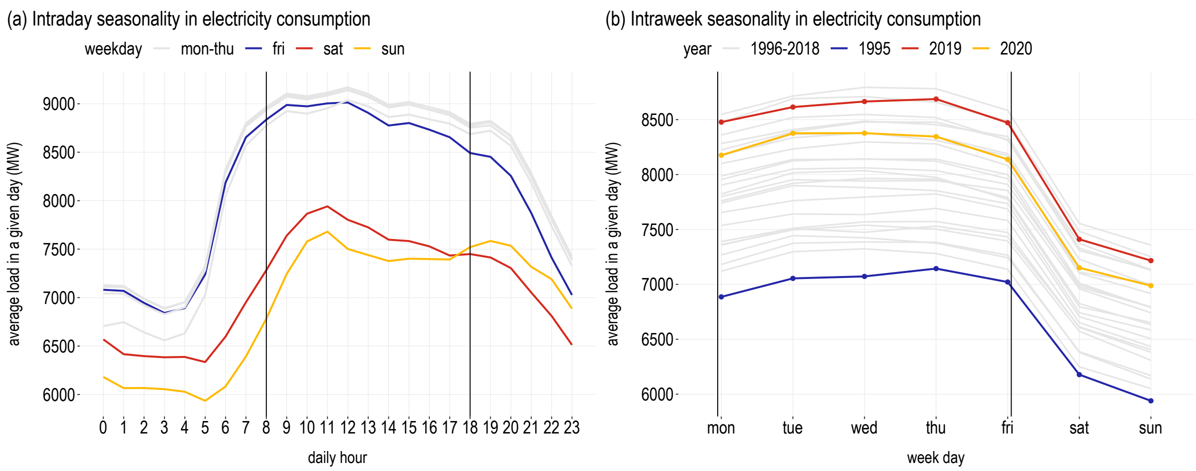
WOLOSZKO, N. ET AL. (2020): "Tracking Activity in Real Time with Google Trends." Technical report, OECD Publishing, No. 1634

Appendix A: Electricity Consumption Adjusted for Temperature

Data on electricity consumption (more precisely, the total load on the transmission grid) is available on up to an hourly frequency. The data has multiple seasonality: regular changes in consumption during the day, week and year. Also, electricity consumption drops significantly during public holidays. To extract economically-relevant signals from the data, several adjustments are needed.

Figure A1 (a) shows how electricity consumption varies across hours in a given day – it is low at night, goes up in the morning and then goes down, depending on the day of the week (see Figure A1 (b)). For our purposes, we consider the average consumption during working days (Mon-Fri) and peak hours (from 8 am to 6 pm), when electricity consumption is usually at its highest (and relatively stable) level.

Figure A1: Intraday and Intraweek Seasonality in Electricity Consumption Data



Note: The vertical lines denote the time spans we consider as economically meaningful for the estimate.
Source: ČEPS

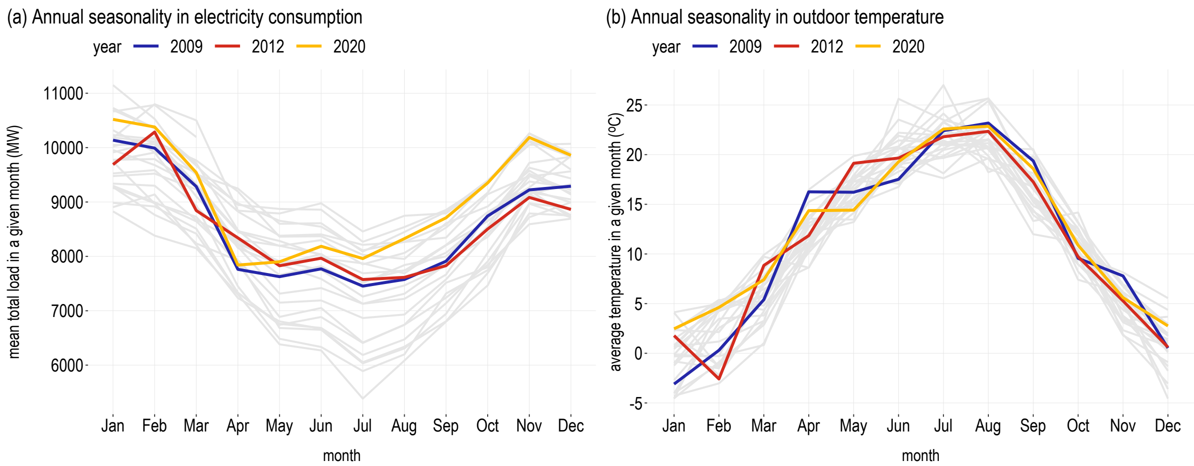
Next, annual seasonality is mainly related to fluctuations in outdoor temperatures (Figure A2). It usually peaks in January or February, when a significant amount of electricity is consumed for heating. Similarly, when the temperature rises in the summer, air conditioners consume a considerable amount of electricity.

To remove seasonality related to temperature fluctuations, we run a regression with a cubic term capturing the relationship between outdoor temperature and electricity consumption (Figure A3). Also, we add a dummy variable denoting 1) public holidays and 2) Christmas week, when electricity consumption generally drops. Next, we fit the regression for a given temperature and dummy variables (Table A1) and obtain deviations from normal levels of consumption. These deviations are then added to the mean consumption on those working days on which the temperature is zero.

This procedure removes a large proportion of seasonal fluctuations of electricity consumption over the year. To remove the residual seasonality, we run a multiple seasonality filter[18] (one seasonal pattern for daily data over a week, the second pattern for weekly data over the year). The resulting series (Figure A4) is then used in the construction of the Rushin index.

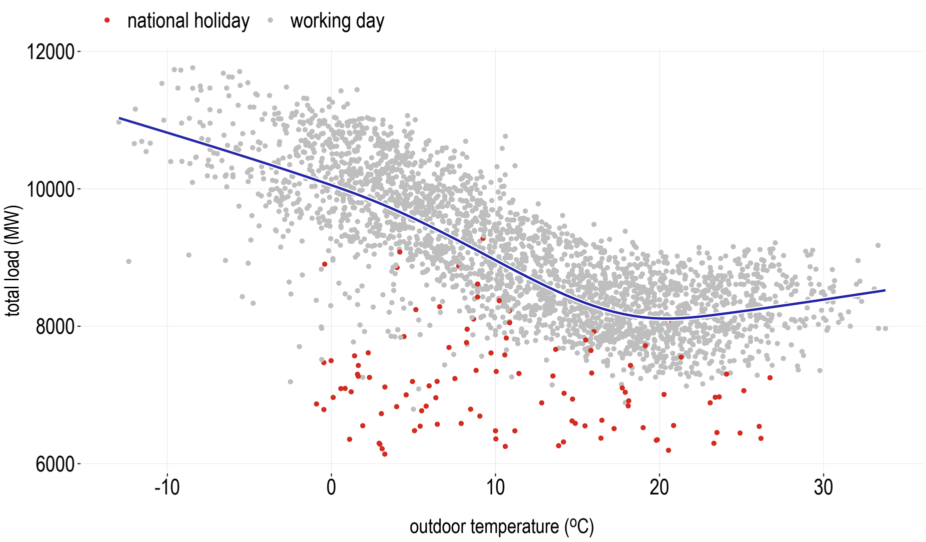
[18] We use *mtsdi* library in R.

Figure A2: Annual Seasonality in Electricity Consumption and Outdoor Temperature Data



Source: ČEPS, ASOS Network

Figure A3: The Relationship between Outdoor Temperature and Electricity Load



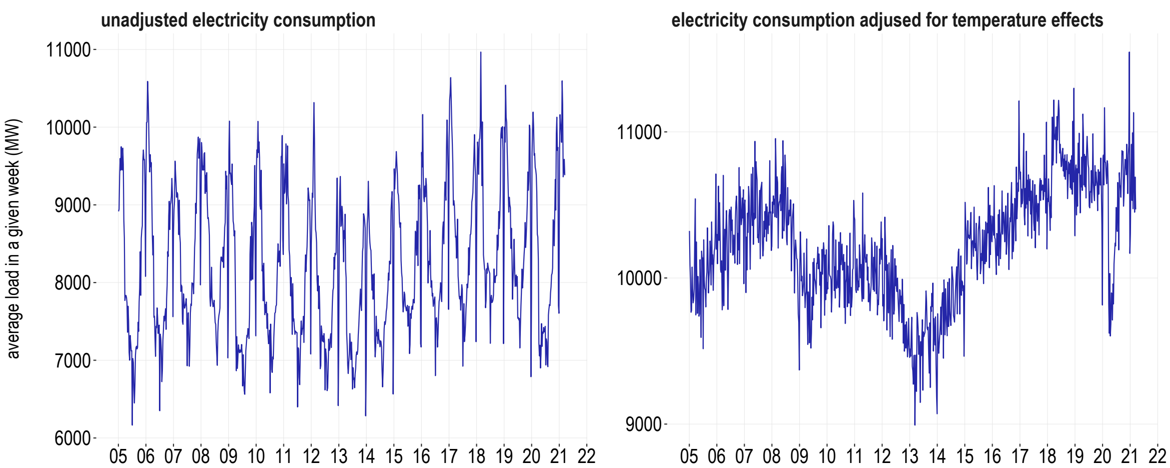
Source: ČEPS, ASOS Network

Table A1: Model Describing the Relationship Between Outdoor Temperature and Electricity Load

	daily data, 2016-2020
(Intercept)	10725.50 (23.97)***
temperature	-119.30 (4.95)***
temperature^2	-2.31 (0.48)***
temperature^3	0.14 (0.01)***
holiday	-2033.38 (65.56)***
xmas	-1501.93 (83.08)***
R^2	0.81
Adj. R^2	0.81
Num. obs.	1296
RMSE	448.82

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

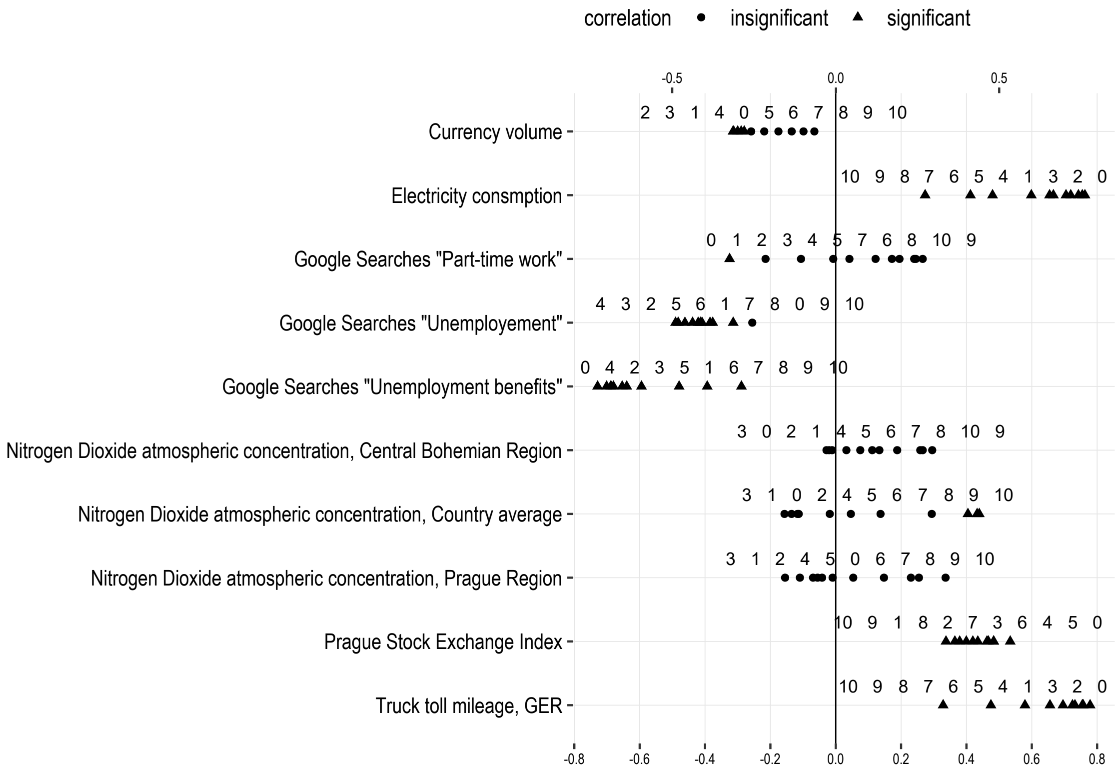
Figure A4: Developments in Electricity Consumption in the Czech Republic



Source: ČEPS, ASOS Network, Authors' Calculations

Appendix B: Tested Weekly Indicators

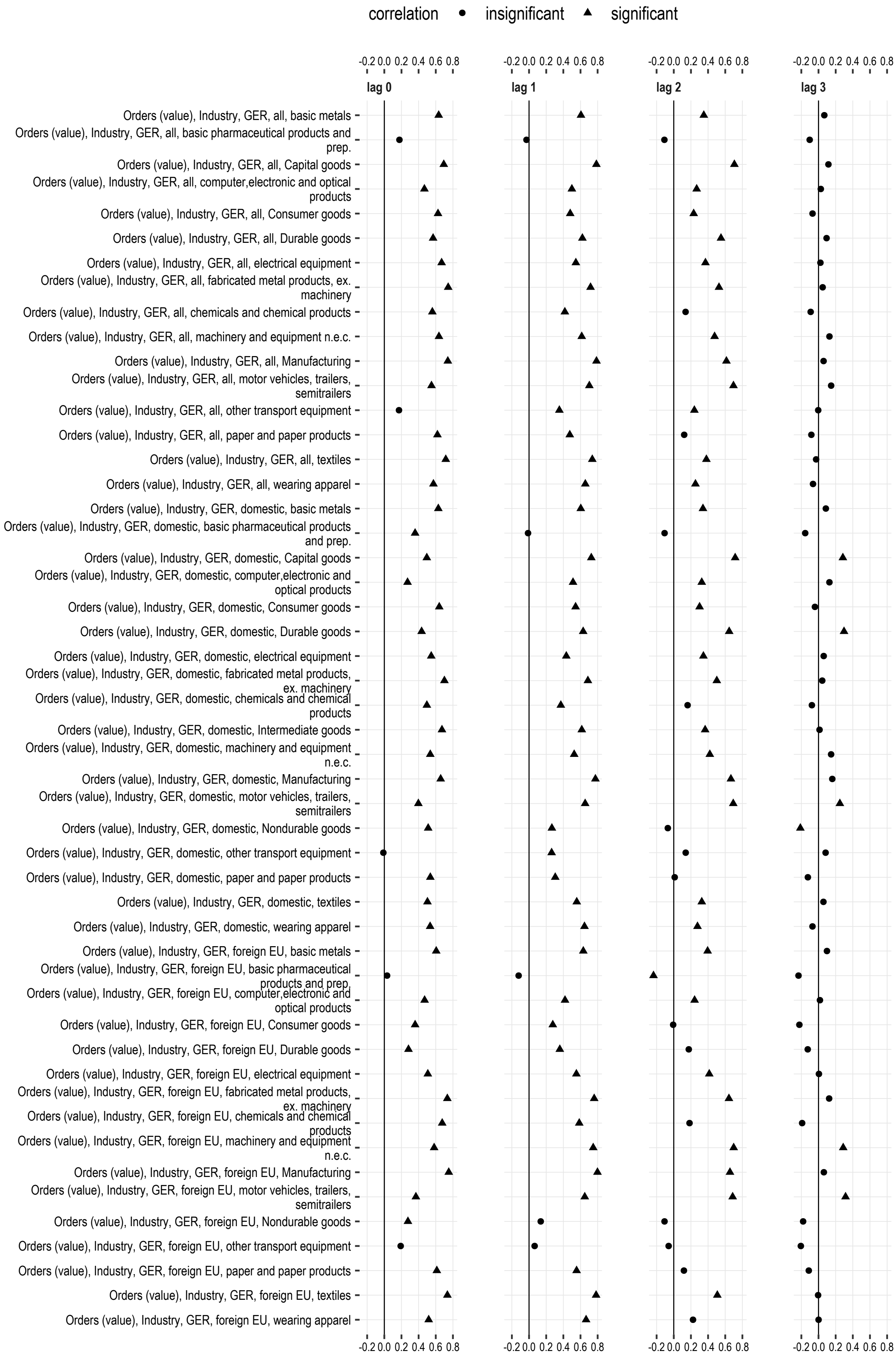
Figure B1: Tested Weekly Indicators



Note: Numbers denote the lag of a weekly indicator
Source: CNB, Google, CEPS, EEA, PSE, Bundesbank

Appendix C: Tested Monthly Indicators

Figure C1: Tested Monthly Indicators (1/5)



Source: Czech Statistical Office, Destatis, OECD

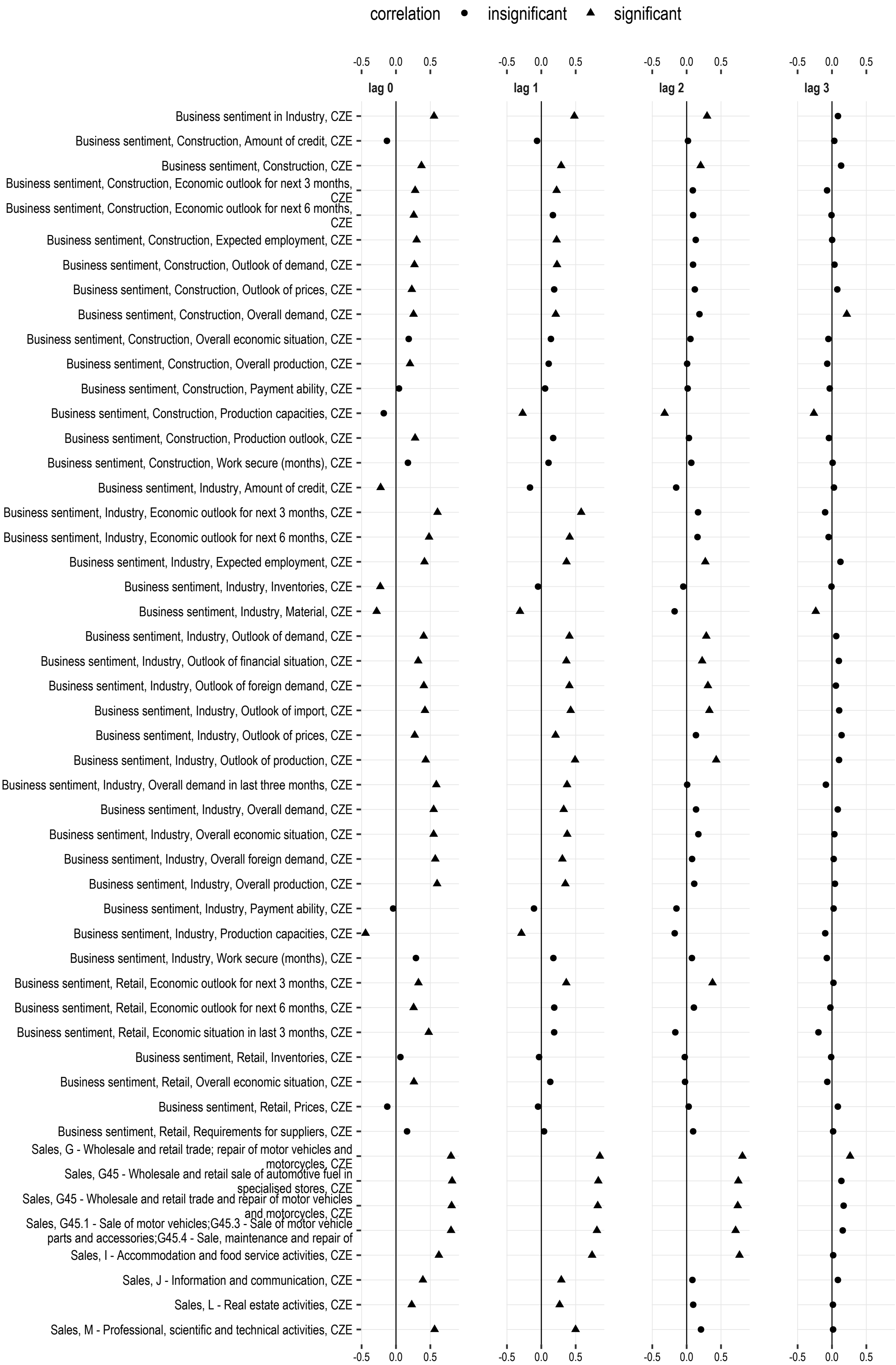
Figure C2: Tested Monthly Indicators (2/5)

Source: Czech Statistical Office, Destatis, OECD

Figure C3: Tested Monthly Indicators (3/5)

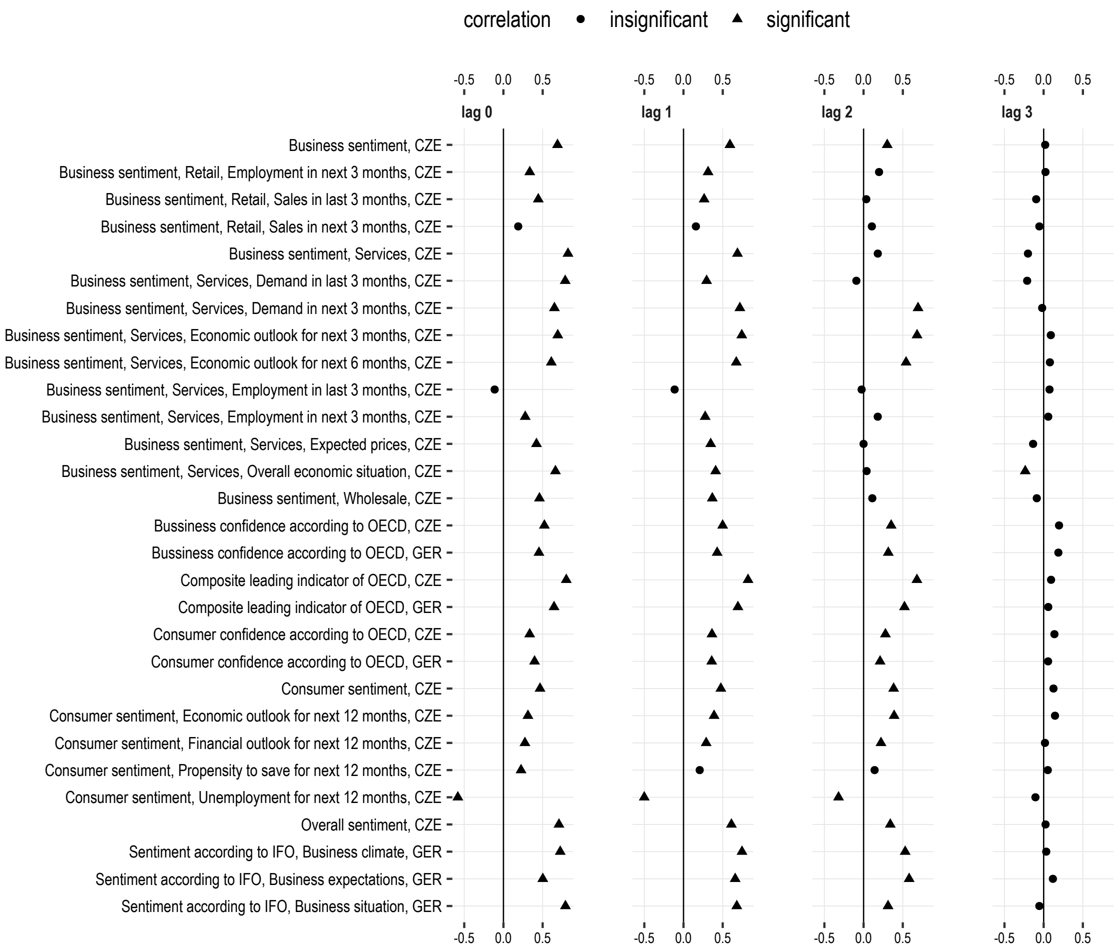
Source: Czech Statistical Office, Destatis, OECD

Figure C4: Tested Monthly Indicators (4/5)



Source: Czech Statistical Office, Destatis, OECD

Figure C5: Tested Monthly Indicators (5/5)



Source: Czech Statistical Office, Destatis, OECD

Appendix D: Principal Component Analysis: Diagnostics

The index is constructed as a first component extracted using the PCA on the final dataset X. The resulting eigenvectors of principal components, their standard deviations and proportion of variance explained by common factors can be found in the figures and tables that follow.

Since the standard deviation of the first principal component is equal to 2.6 while the standard deviations of the rest of the principal components are around one or lower, we can consider the dataset to be unidimensional and internally consistent, which allows us to construct a valid index. Furthermore, the first common factor of our model can explain 68 % of the variance of the dataset.

Figure D1: Principal Components Analysis: Summary

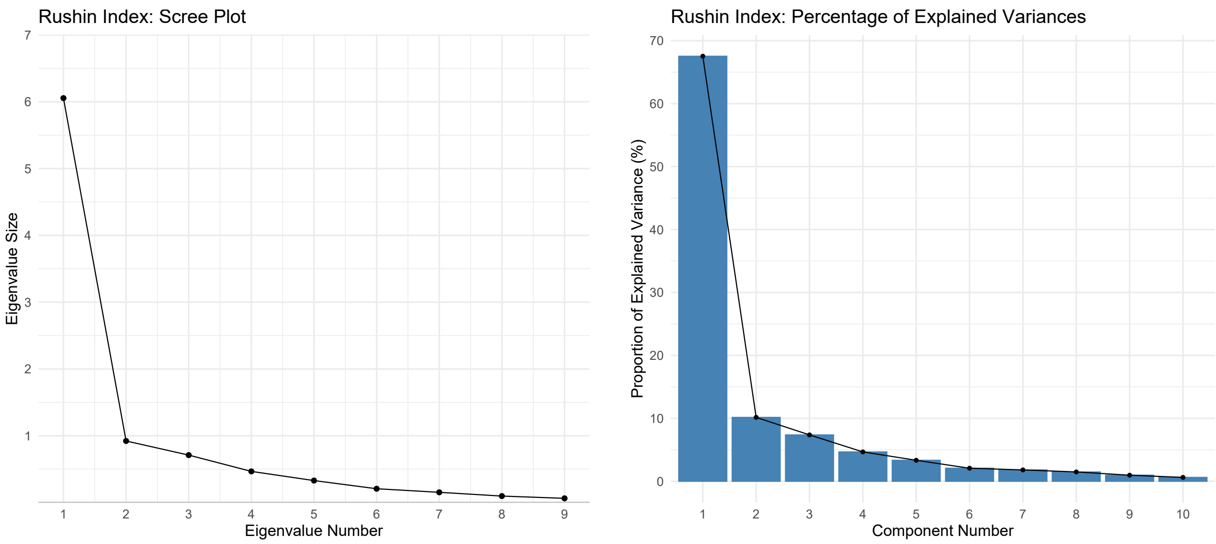


Table D1: Principal Components Analysis: Summary

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Standard deviation	2.60	1.01	0.86	0.68	0.58	0.46	0.42	0.39	0.31	0.25
Proportion of Variance	0.68	0.10	0.07	0.05	0.03	0.02	0.02	0.01	0.01	0.01
Cumulative Proportion	0.68	0.78	0.85	0.90	0.93	0.95	0.97	0.98	0.99	1.00

Table D2: The Rushin Index: Loadings of Variables (PCA)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
industry_man	0.37	0.06	0.15	-0.04	-0.19	-0.01	0.27	-0.18	0.04	-0.83
oecd_cli	0.36	-0.12	0.21	-0.17	-0.07	-0.19	0.12	0.01	-0.83	0.21
ifo_bus_climate_de	0.34	-0.28	0.21	-0.18	-0.17	-0.31	-0.08	-0.55	0.43	0.33
toll	0.33	0.33	0.17	0.03	-0.15	-0.15	-0.77	0.32	0.05	-0.08
services	0.33	0.20	-0.29	-0.26	0.34	0.60	-0.21	-0.40	-0.10	0.04
toll_de	0.33	-0.09	-0.00	0.52	-0.51	0.50	0.15	0.12	0.06	0.25
retail	0.32	0.35	0.10	-0.41	0.13	0.01	0.45	0.47	0.31	0.24
electricity_cz	0.31	0.06	0.12	0.63	0.65	-0.22	0.11	-0.05	0.04	0.03
px	0.21	-0.78	-0.07	-0.16	0.25	0.16	-0.15	0.41	0.10	-0.16
gs_unem_benefits	-0.25	-0.02	0.86	-0.05	0.15	0.40	-0.05	-0.05	0.02	-0.00

CNB Working Paper Series (since 2020)

WP 4/2021	Tomáš Adam Ondřej Michálek Aleš Michl Eva Slezáková	*The Rushin index: A weekly indicator of Czech economic activity*
WP 3/2021	Michal Franta Jan Libich	*Holding the economy by the tail: Analysis of short- and long-run macroeconomic risks*
WP 2/2021	Jakub Grossmann	*The effects of minimum wage increases in the Czech Republic*
WP 1/2021	Martin Časta	*Deriving equity risk premium using dividend futures*
WP 15/2020	Petr Polák Nikol Poláková Anna Tlustá	*How bad are trade wars? Evidence from tariffs*
WP 14/2020	Dominika Ehrenbergerová Josef Bajzík	*The effect of monetary policy on house prices – How strong is the transmission?*
WP 13/2020	Zuzana Rakovská	*Composite survey sentiment as a predictor of future market returns: Evidence for German equity indices*
WP 12/2020	Vojtěch Siuda	*A top-down stress-testing framework for the nonfinancial corporate sector*
WP 11/2020	Hana Hejlová Michal Hlaváček Blanka Vačkova	*Estimating commercial property price misalignment in the CEE countries*
WP 10/2020	Zuzana Rakovská Dominika Ehrenbergerová Martin Hodula	*The power of sentiment: Irrational beliefs of households and consumer loan dynamics*
WP 9/2020	Ivan Sutóris	*The intertemporal cost of living and dynamic inflation: The case of the Czech Republic*
WP 8/2020	Martin Hodula Jan Janků Martin Časta Adam Kučera	*On the determinants of life and non-life insurance premiums*
WP 7/2020	František Brázdik Tibor Hlédik Zuzana Humplová Iva Martonosi Karel Musil Jakub Ryšánek Tomáš Šestořád Jaromír Tonner Stanislav Tvrz Jan Žáček	*The g3+ model: An upgrade of the Czech National Bank's core forecasting framework*
WP 6/2020	Volha Audzei Jan Brůha	*A model of the Euro Area, China and the United States: Trade links and trade wars*

WP 5/2020	Dominika Ehrenbergerová Martin Hodula Zuzana Rakovská	*Does capital-based regulation affect bank pricing policy?*
WP 4/2020	Alexis Derviz	*Sovereign capital, external balance, and the investment-based Balassa-Samuelson effect in a global dynamic equilibrium*
WP 3/2020	Milan Szabo	*Growth-at-risk: Bayesian approach*
WP 2/2020	Martin Hodula Ngoc Anh Ngo	*Finance, growth and (macro)prudential policy: European evidence*
WP 1/2020	Michal Franta Ivan Sutóris	*Dynamics of Czech inflation: The role of the trend and the cycle*

CNB Research and Policy Notes (since 2020)

RPN 3/2020	Simona Malovaná Martin Hodula Zuzana Rakovská	*Researching the research: A central banking edition*
RPN 2/2020	Simona Malovaná Josef Bajzík Dominika Ehrenbergerová Jan Janků	*A prolonged period of low interest rates: Unintended consequences*
RPN 1/2020	Simona Malovaná	*How to organize research in central banks: The Czech National Bank's experience*

CZECH NATIONAL BANK
Na Příkopě 28
115 03 Praha 1
Czech Republic

ECONOMIC RESEARCH DIVISION
Tel.: +420 224 412 321
Fax: +420 224 412 329
http://www.cnb.cz
e-mail: research@cnb.cz

ISSN 1803-7070