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Assessing the External Demand of the Czech Economy: Nowcasting Foreign GDP Using Bridge Equations

Tomáš Adam and Filip Novotný *

Abstract

We propose an approach to nowcasting foreign GDP growth rates for the Czech economy. For presentational purposes, we focus on three major trading partners: Germany, Slovakia and France. We opt for a simple method which is very general and which has proved successful in the literature: the method based on bridge equation models. A battery of models is evaluated based on a pseudo-real-time forecasting exercise. The results for Germany and France suggest that the models are more successful at backcasting, nowcasting and forecasting than the naive random walk benchmark model. At the same time, the various models considered are more or less successful depending on the forecast horizon. On the other hand, the results for Slovakia are less convincing, possibly due to the stability of the GDP growth rate over the evaluation period and the weak relationship between GDP growth rates and monthly indicators in the training sample.

Abstrakt

Článek představuje přístup k nowcastingu růstu zahraničního HDP pro českou ekonomiku. Z důvodu stručnosti prezentace výsledků se zaměřuje na tři nejvýznamnější obchodní partnery ČR: Německo, Slovensko a Francii. Využívá jednoduchou metodu, která je velmi obecná a úspěšná v odborné literatuře: regresi, která „přemosťuje" informace z měsíčních na čtvrtletní data (bridge equations). Článek hodnotí výsledky mnoha modelů na základě predikčního cvičení v pseudoreálném čase. Výsledky pro Německo a Francii ukazují, že navrhované modely jsou pro odhad růstu HDP v předchozím, současném a příštím čtvrtletí úspěšnější než benchmarkový naivní model založený na náhodné procházce. Pro úspěšnost jednotlivých modelů hraje navíc roli horizont předpovědi. Na druhou stranu výsledky pro Slovensko jsou méně přesvědčivé, což může být způsobeno stabilitou tempa růstu HDP v testovacím období a dále nízkou korelací mezi růstem HDP a měsíčními ukazateli na cvičném vzorku dat.

JEL Codes: C53, E37.
Keywords: Bayesian model averaging, bridge equations, nowcasting, short-term forecasting.

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Nontechnical Summary

Reasonable assumptions about the external economic environment are essential for meaningful forecasting of a small open economy. At the Czech National Bank, the primary source of these assumptions is Consensus Forecasts, supplemented by the Economist Intelligence Unit database (The Economist) and prices and rates implied by financial and commodity derivatives. Although Consensus Forecasts are published monthly, they provide outlooks for core economic variables (GDP growth, inflation etc.) only on an annual basis. Therefore, they need to be disaggregated into quarterly frequency, as required by the CNB's core model (g3). Currently, a mechanistic procedure which does not take into account timely data on the state of the economy is used for the decomposition.

The main aim of this paper is to improve the procedure for disaggregating yearly forecasts into quarterly figures. To this end, it introduces a framework which can be used to evaluate past, current and one-quarter-ahead GDP growth, the variable which is used as a proxy for external demand in the g3 model. Although the current state of the Czech economy is assessed on a regular basis, no method for routinely nowcasting foreign GDP growth has been proposed yet. Besides fixing several points in the disaggregation procedure, the GDP growth estimates provided by the suggested techniques can serve as a basis for making expert judgments on the Consensus Forecasts, which sometimes only slowly incorporate new information. Finally, the outcomes of the models can serve as a tool for enhancing the monitoring of major trading partners of the Czech economy.

Currently, the "effective" euro area GDP indicator is used as a proxy for external demand. The indicator is based on a weighted average of the GDP growth rates of 17 euro area member states (i.e. all countries except Luxembourg and Malta), where the weights are the shares of each euro area country in Czech exports. Nowcasting all 17 countries puts enormous demands on data processing, which is naturally prone to mistakes. To reduce the computational burden of nowcasting the full aggregate, we focus only on the three most critical euro area trading partners (as measured by their shares in Czech exports): Germany, Slovakia and France. These three countries cover more than 70% of total Czech exports to the euro area; one could argue that including more countries is not necessary from the economic point of view, since the GDP growth rates of most of the remaining euro area countries are highly correlated with the German one. Furthermore, focusing on a few countries allows an economic analyst to gain deeper expert knowledge of each country and thus get a better understanding of the dynamics of the overall effective indicator.

The method based on bridge equation (BEQ) models is employed to backcast, nowcast and one-quarter-ahead forecast (for simplicity nowcast hereafter) GDP growth for Germany, Slovakia and France. BEQ models "bridge" information from timely monthly indicators (e.g. industrial production) into quarterly ones (GDP growth in our case) by means of a simple linear regression model. The estimated linear relationship is subsequently used for nowcasting. The missing observations of monthly indicators in a given quarter are extrapolated by a simple AR process. Three types of modes are then used: univariate models, which are averaged into five categories, then more complex multivariate models, and finally models based on common components.

The evaluation exercise takes into account 58 publicly available time series. The sample starts in January 1999, i.e. at the inception of the euro area and the date since when most of the time series have been published. The variables considered include several indicators for the United States to capture the external demand of the euro area countries, and particular attention is given to the automotive industry, which is relevant for the German economy.

The calculated nowcasts are compared on an evaluation period starting in the first quarter of 2012. The models are re-estimated every quarter on currently available data, and the pseudo-real-time forecasting exercise takes into account the publication lags of the monthly indicators.

The forecasting performance of the various competing BEQ models is not constant and varies based on the forecasting horizon considered (i.e. backcast, nowcast and one-quarter-ahead forecast). In line with intuition, the forecasting ability of the models containing leading indicators is strongest at longer horizons, but diminishes for nowcasting and backcasting. At the same time, the power of the models containing industrial production is higher in the case of nowcasting and backcasting (compared to forecasting), especially in the third month, when the industrial production index is published for the first month of the current quarter.

The ability of industrial production to explain GDP growth is highest in the case of Germany and France and lower in the case of Slovakia, where the correlation between the growth rates of industrial production and GDP is considerably lower. Finally, the forecasting performance of most of the BEQ models compared to a naive benchmark is highest for backcasting, followed by nowcasting and forecasting. The relatively poor performance of the BEQ models for forecasting stems from the extrapolation of monthly indicators, which sometimes involves producing more than ten monthly forecasts using simple AR models.

1. Introduction

GDP growth nowcasting has long been a topic of interest to both economic practitioners and academics. For forecasters, assessing the current state of the economy is of utmost importance, since the most recent observations are what drives forecasts to a significant extent, especially at the short ends of forecast horizons. Unfortunately, estimates of GDP growth are available with substantial lags, so estimates of the current (or even the last) GDP growth rates have to be produced. On a theoretical level, nowcasting has been of particular interest, since the techniques used face the challenge of extracting meaningful signals from a multitude of variables representing different parts of the economy. At the same time, these indicators are available with various lags and can be subject to significant measurement errors.

Forecasters of a small open economy face a challenge in that a successful forecast needs to take into account developments abroad. Very often, effective aggregates of foreign GDP growth, inflation rates and interest rates are constructed and assumptions are made about their future paths to produce forecasts for the domestic economy. In the case of the Czech Republic, the core forecasting model of the Czech National Bank assumes the paths of "effective" euro area aggregates of GDP and PPI inflation rates, which are constructed as trade-weighted averages[1] of variables of the 17 most important euro area trading partners of the Czech Republic. These assumptions are taken from Consensus Forecasts (produced by Consensus Economics), which are published at monthly frequency. However, the forecasts are produced for yearly data and have to be disaggregated into quarterly frequency. Currently, the temporal disaggregation is based on a simple mechanistic approach which does not take into account timely data from the economy and available leading indicators.

This paper introduces an approach to producing nowcasts, backcasts and one-quarter-ahead forecasts of foreign GDP for the Czech economy, which drives foreign demand in the Czech National Bank's core forecasting model. The main aim of producing these estimates is to improve the current mechanistic approach to disaggregating the forecasted annual growth rates of GDP produced by external institutions which operate in the economies of interest. In addition, producing backcasts, nowcasts and one-quarter-ahead forecasts can provide a basis for making expert adjustments to the Consensus Forecast projections, which tend to reflect new information slowly.

Since we face the challenge that many (17) countries enter the forecasting process at the Czech National Bank, we opt for one of the simplest, but also most successful, nowcasting methods, based on bridge equations. This approach "bridges" information from timely monthly indicators to quarterly GDP growth rates. For the sake of brevity, the paper presents the results for the three most important trading partners of the Czech Republic, Germany, Slovakia and France, which cover about 70% of exports to the euro area. The results are presented for a battery of models, starting with simple univariate bridge equation models, followed by more complex multivariate models and finishing with models containing principal components, which capture the co-movement among all relevant variables.

The results suggest that in the case of Germany and France, even most of the simplest models beat the naive forecasts at all horizons (i.e. when we consider backcasting, nowcasting and forecasting performance). The models containing leading indicators perform best at the one-quarter-ahead forecasting horizon in the case of Germany and to a smaller extent in the case of France. For shorter horizons (nowcasting and backcasting), the power of the models containing coincident indicators increases, especially in the third month of the quarter, when the industrial production index

[1] The share of exports to the euro area in overall Czech exports is about 65%.

is published for the first month of the quarter. Finally, the model containing common components performs well at all horizons, especially in the case of nowcasting the current GDP growth rate. On the other hand, the results for Slovakia are not as successful. This stems primarily from low correlations of monthly indicators with GDP growth rates. In addition, GDP growth exhibited very low volatility over our evaluation period, so the naive forecast performs best.

2. Literature Review

Short-term forecasting tools are used widely by policy institutions, since appropriate policy measures need to take into account timely information on macroeconomic developments. Specifically, data on GDP growth, which is published with a substantial time lag (typically 6 to 8 weeks), are observed closely by policymakers. Nowcasting of quarterly GDP growth has thus become very common at central banks. Traditional nowcasting methods used by central banks include bridge equation (BEQ) models and dynamic factor models (DFMs). These two groups of models are supplemented by other related models, e.g. OLS models with more explanatory variables, ARMAX models, mixed frequency VARs and MIDAS equations.

Feldkircher et al. (2015) apply both BEQ models and DFMs to Central and Eastern European countries. The models are estimated for the period from the first quarter of 2000 to the second quarter of 2008. Their evaluation period then ranges to the third quarter of 2014, covering the period since the Great Recession. They follow the standard practice when evaluating out-of-sample forecasting accuracy, which is measured by the root mean squared error (RMSE) with the latest available GDP growth figures (quasi out-of-sample forecasts). Their small-scale nowcasting models outperform a simple AR(1) model, but the model performance varies strongly across countries. Additionally, Huček et al. (2015) show that BEQ models and DFMs outperform ARMA models in the case of the Slovak economy. Moreover, BEQ models may offer an advantage over DFMs, since they are simple to construct and easy to understand.

Similarly, Antipa et al. (2012) forecast German GDP growth rates for the current quarter using factor and bridge models. They show that changing the bridge model equations by including newly available monthly information generally provides more precise forecasts and is preferable to maintaining the same equation over the horizon of the exercise. Importantly, the forecast errors of the BEQ models are smaller than those of the DFMs. Furthermore, the BEQ models not only provide very accurate forecasts, but are also straightforward to interpret. Indicators that appear to be unrelated or only loosely linked to the target variable can be neglected. The datasets are therefore relatively small and thus not costly to update. Second, BEQ model predictions allow for a better description of the forecast based on the evolution of the explanatory indicators. The ability to identify and interpret the drivers of forecasts is a useful feature, especially in periods characterized by significant or changing volatility.

This paper focuses on BEQ models due to their above-mentioned advantages over other types of models, particularly DFMs. BEQ models were introduced by Klein and Sojo (1989) as a regression-based system for GDP growth forecasting. BEQ models are essentially regressions relating quarterly GDP growth to one or a few monthly variables (such as industrial production or various survey indicators, especially leading ones) aggregated to quarterly frequency. The forecasting accuracy of bridge equations seems to rely on selecting the "right" higher frequency indicators conditional on the forecast horizon (Trehan, 1992). Since only partial monthly information is usually available for the target quarter, the monthly variables are forecasted using auxiliary models such as ARIMA models (Banbura et al., 2013). In order to exploit the information content from several monthly predictors, bridge equations are sometimes pooled (see, for example, (Kitchen and Monaco)). Since BEQ models are designed to be used on a monthly basis, the industrial production index is probably the most relevant and widely analysed high-frequency indicator.

The underlying structure of BEQ models is different from standard macroeconomic models, which are built around behavioural and causal relations between the variables. The gains of forecasts based on BEQ models relative to naive constant growth models are substantial, especially at very short horizons, and most of all for the current quarter, according to Baffigi et al. (2004). The high accuracy of forecasts at shorter horizons implies that these models should be used primarily to forecast growth in the current and previous quarters. In addition, it is straightforward to incorporate new data as soon as it is released. Early in the quarter, soft indicators have been found to be extremely important, especially since hard data (e.g. industrial production) is not yet available.

Furthermore, Giannone et al. (2008) propose a method which consists of bridging quarterly GDP with monthly data via regressing GDP growth rates on factors extracted from a large panel of monthly series with different publication lags. Angelini et al. (2011) show on euro area data that bridging via factors produces more accurate estimates than traditional bridge models. The factor model thus improves the pool of bridge equation models. They also show that survey data and other "soft" information are valuable for nowcasting. BEQ models for France, Germany, Italy and the euro area over the period from 1980 to 1999 are estimated by Baffigi et al. (2004). They conclude that BEQ models are far better than selected ARIMA and VAR models and a structural model. Moreover, over a forecasting horizon one- to two-steps ahead, the aggregation of forecasts by country performs better in forecasting euro area GDP and also offers information on the state of the single economies.

ECB staff use a set of bridge equations in their regular monitoring of economic activity in the euro area (Diron, 2008; Rünstler and Sédillot, 2003). In Germany, the higher volatility of GDP growth rates probably stems from the country's reliance on the industrial sector and exports, which are sensitive to the global business cycle. Deutsche Bundesbank operates factor models and bridge equations for GDP growth forecasts. It updates its forecasts twice a month and concentrates on nowcasting the current quarter or backcasting the last quarter using all the available indicator-based information. In addition, one-quarter-ahead prediction (forecasting) is conducted (Bundesbank, 2013; Götz and Knetsch, 2019). Recently, Pinkwart (2018) argues that the forecast performance of BEQ models can be substantially improved in the case of Germany by combining the production side and the demand side projections. Mogliani et al. (2017) use a model which relies exclusively on business survey data in industry and services conducted directly by the Banque de France. Some soft indicators are even used by the French national statistics institute (INSEE) to compile its GDP figures. The National Bank of Slovakia regularly publishes its nowcast of the real economy in its monthly bulletin. To this end, it uses several approaches, including BEQ models. Incomplete monthly series of economic indicators are forecasted by ARMA models and then bridge equations are estimated by OLS for each explanatory variable. Finally, the average of the individual BEQ models is weighted by the AIC Huček et al. (2015); Tvrz (2016).

This paper concentrates on techniques for nowcasting foreign economic variables (specifically the GDP growth of the Czech Republic's main trading partners). The variety of BEQ models used ranges from simple univariate BEQ models to models based on common components. The main motivation is that a small open economy is substantially influenced by external developments.

On the other hand, the research into short-term forecasting at the Czech National Bank has so far focused exclusively on the Czech economy. Benda and Růžička (2007) evaluate nowcasts of Czech

GDP growth using principal component analysis (PCA) and seemingly unrelated regression estimation (SURE) with monthly and quarterly explanatory variables. They show that these methods provide relatively accurate nowcasts and near-term forecasts of GDP fluctuations. Similarly, Arnoštová et al. (2011) forecast the quarterly GDP growth of the Czech economy up to three quarters ahead using six competing simple econometric models. Furthermore, Rusnák (2016) employs a dynamic factor model (DFM) to nowcast Czech GDP growth. Havránek et al. (2010) evaluate to what extent financial variables improve the forecasts of Czech GDP growth and inflation. More recently, the impact of financial variables on Czech macroeconomic developments is investigated by Adam and Plašil (2014) and Franta et al. (2016), who use various mixed-frequency data models to forecast Czech GDP growth. Babecká and Brůha (2016) present nowcast models for Czech external trade. This is a novel approach, since no nowcast model for trade has been described previously in the literature. They apply four empirical models: principal component regression, elastic net regression, the dynamic factor model and partial least squares.

3. Methodology and the Design of the Nowcasting and Forecasting Exercises

This paper employs the method based on bridge models (Rünstler and Sédillot, 2003; Baffigi et al., 2004; Diron, 2008). This method is one of the most straightforward, but also most general and successful, techniques used for nowcasting and, as a result, it is widely used in practice. Models from this class "bridge" information from timely monthly indicators into quarterly frequency. The method used to extract the information on the dynamics of a quarterly variable from monthly indicators is simple linear regression. This section describes the approach taken by the paper to forecasting[2] GDP growth in a given quarter using one model. It subsequently describes the strategy used for the selection, aggregation and evaluation of several competing models.

3.1 The Case of One Model

Bridge models exploit statistical relations between monthly and quarterly indicators. For example, the coefficients of correlation between changes in GDP growth rates and quarterly averages of changes in several indicators exceed 0.7 in the case of Germany and France (Figures C1, C2 and C3). This relation is intuitive and reflected in the nature of the business cycle, which exhibits co-movements among many economic indicators (Burns and Mitchell, 1947).

Formally, in line with Antipa et al. (2012), let Y_t denote the quarter-on-quarter GDP growth rate and X_t denote the quarterly averages[3] of q monthly explanatory variables (also referred to as indicators). The bridge model can be specified as:

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i Y_{t-1} + \sum_{j}^{q} \sum_{i}^{k} \delta_{j,i} X_{j,t-i} + \varepsilon_t, \tag{1}$$

[2] Throughout the paper, the term forecast can have two meanings – either a proper forecast of future GDP growth or a fitted value from a model, which could also denote a nowcast of GDP growth in the current quarter or even a backcast of GDP growth in the last quarter.

[3] In line with Mariano and Murasawa (2003), quarterly growth rates are constructed by taking moving averages of monthly growth rates.

where m is the number of autoregressive parameters and k is the number of lags for the explanatory variables. In all specifications, we opt for $m = 0$. This choice is common in the literature (Diron, 2008; Arnoštová et al., 2011) and is aimed at reducing the persistence of forecasts (and thus improving forecasting power when fundamentals change abruptly). In addition, the lagged GDP growth rate is not observed in the first two months of a given quarter and its extrapolation would add additional noise to the forecasts. Finally, one can argue that the lagged series is highly collinear with the monthly indicators, which leads to larger forecast sampling errors. Regarding the number of lags of each explanatory variable, parameters k were set based on an automatic selection procedure where the Akaike information criterion was minimized on the training sample (1999Q1–2011Q4).

Equation 1 is estimated using a simple ordinary least squares estimator. The estimated relationship can subsequently be used for the nowcasting and forecasting of a given quarter provided that the variables on the right-hand side (X_t) are known. This is rarely the case (with the exception of backcasting) and one hence needs to extrapolate observations of monthly indicators so that all observations are known in a given quarter. The literature uses simple AR, ARMA or VAR models for this task. For the sake of computational simplicity, we opt for AR models.[4]

One can infer various sources of forecast errors. First, even if all the monthly indicators are known precisely (i.e. without any measurement errors), the GDP figures may not be estimated accurately (using bridge equations, or by other approaches). Next, since the models are estimated using simple OLS regressions, the choice of indicators matters and it is not clear what variables explain GDP growth rates best. In addition, the coefficients in Equation 1 are only estimated and are subject to statistical uncertainty. Finally, not all the monthly indicators are known in a given quarter and the missing figures are extrapolated, which very likely leads to further errors.

3.2 The Evaluation of Nowcasts and Forecasts

In order to compare the performance of various competing models, we perform a pseudo-real-time out-of-sample forecasting exercise. For each month in a given quarter (denoted as M1, M2 and M3 in the paper), forecasts for three horizons are considered: (i) a backcast (estimating GDP growth in the last quarter when the figure has not yet been published), (ii) a nowcast (estimating GDP growth in the given quarter), (iii) a forecast of GDP growth in the next quarter. It is assumed that the forecasts are made at the end of the month, so that all indicators which are published during the given month are known.

The models are estimated since the first quarter of 1999 (provided the data is available) and the evaluation period starts in the first quarter of 2012. For each month since January 2012, we take the following steps:

1. Missing observations are introduced at the tail of the sample according to the publication lag, in order to simulate "pseudo" real-time data vintages.[5]
2. Observations from complete quarters are used in order to estimate the parameters in Equation 1.

[4] Preliminary estimates suggested that the forecasting performance gain from using ARMA models compared to AR models is negligible. At the same time, the computational cost of selecting the optimal lag structure of AR and MA parameters was large.

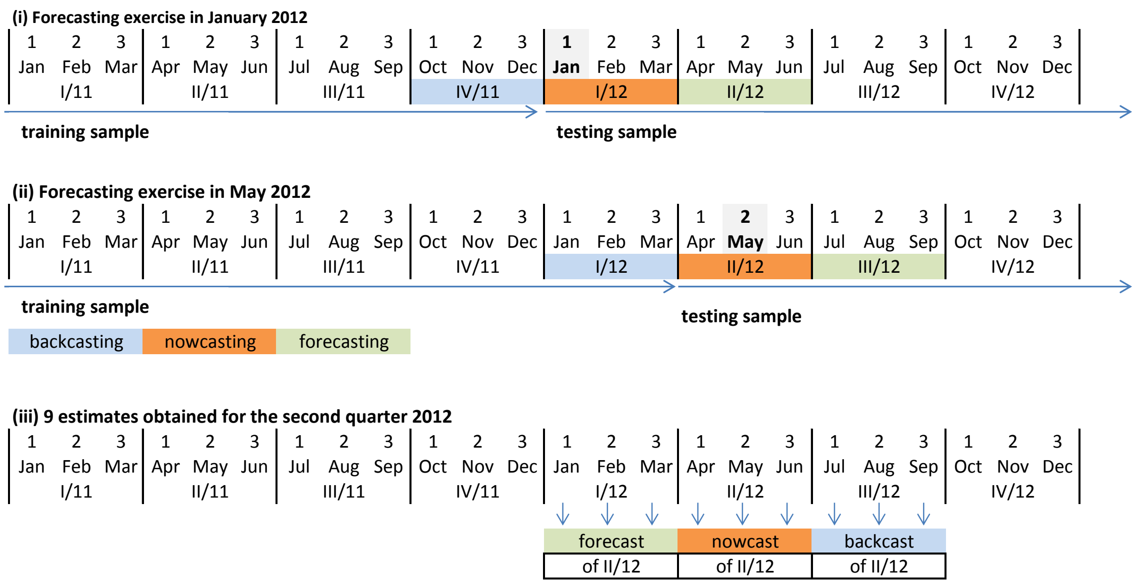
[5] All publication lags are described in Table A1 in the Appendix. The lags are denoted in months, i.e. 0 means that the data are available at the end of the given month at the latest; 1 means that the data are published by the end of the following month at the latest.

3. The missing observations of monthly indicators are subsequently extrapolated using the AR models[6] described in the previous subsection and aggregated to quarterly frequency. One should note that we extrapolate not only the missing observations due to the procedure described in the first step, but also the observations of the remaining months in the given and next quarters.

4. The estimated model is fitted in order to obtain a backcast, a nowcast and a forecast and the estimates are saved.

In other words, the forecast evaluation is performed recursively and the model is re-estimated every quarter. For each of the months considered, we obtain three sets of forecasts (a backcast, a nowcast and a forecast; panels (i) and (ii) in Figure 1) and for each quarter, we obtain nine sets of forecasts depending on the forecasting horizon (panel (iii) in Figure 1). For presentation purposes, we drop one of the horizons – the backcast in the third month, since the GDP figure for the last quarter is already published by then.

Figure 1: Timing Scheme of the Forecasting Exercise



The models are compared based on the root mean square error for each forecast horizon. This is because one could expect the forecasting performance of each model to vary across the forecasting horizon and the month of the forecast. In the first month of a given quarter, when only leading indicators are available, one could expect these models to perform best for nowcasting. On the other hand, in the third month of a given quarter, when hard data from industry are available for the first month, models with industrial production may perform better.

In the presentation of the results, the benchmark model is a naive model based on a random walk forecast. This model assumes that GDP growth in the last, current and next quarters remains the same as the last published GDP growth figure.

[6] The order of the AR models is selected automatically based on the Akaike information criterion for each variable separately.

3.3 Three Types of Models

The next section describes the variables considered in the forecasting exercise. In total, we have amassed 58 variables. In order to obtain results which are relatively easy to compare and present, we consider the following three groups of models for each country:

Univariate Bridge Equation Models

In these models, only one variable is used as an indicator in the bridge equation (we also consider its lags, as described in Section 3.1). At the same time, we average the outcomes of these models (in line with Arnoštová et al. (2011), for example) and group them into the following categories:

1. BMA
2. correlations
3. leading indicators
4. financial variables
5. foreign variables

The BMA category includes indicators selected based on Bayesian model averaging,[7] which accounts for the model uncertainty. Specifically, priors on regression parameters are set as non-informative and priors on probabilities are set as uniform. The posterior probabilities of the models are approximated using the simple Bayesian Information Criterion. The BMA category considers all variables whose posterior probabilities of inclusion exceed 0.1%.

Similarly, the correlations category contains 15 variables, which were selected based on their correlations with GDP growth rates. The probability threshold and the number of variables in the correlations category were chosen arbitrarily. However, this led to approximately the same number of indicators in each category, and variables from each important category (hard, soft, foreign indicators) were also selected.

Multivariate Models

Multivariate models include multiple variables selected on the basis of economic intuition and also of their correlations with GDP growth. For each country, we consider (i) two models containing only a combination of two leading indicators; (ii) four models containing various coincident indicators (usually a combination of the industrial production index, the retail sales index and a measure of unemployment); (iii) two models containing both leading and coincident indicators. The precise model specifications are described in Appendix D.

Models Based on Common Components

The last model we consider is based on common components which capture the comovement among all the indicators relevant to a particular country. Since some of the observations are missing, especially at the start of the training sample, a method based on the EM algorithm (described by (Josse and Husson, 2012)) is used to extract the common components, estimate the loadings and impute the missing observations on the training sample.[8] The iterative PCA algorithm starts by

[7] The R library by Raftery et al. (2018) was used for the computations.
[8] The package by Josse and Husson (2016) was used for the estimation.

replacing missing observations with the initial values (such as the mean of the variable). It is followed by PCA of this provisional dataset and by imputing initially missing observations using the extracted common components and loadings. The process is then iterated until convergence is achieved.

The nowcasting procedure described above is modified slightly. First, the loadings of the principal components are obtained on the training sample using the method cited in the previous paragraph. Then, missing values are then imposed for each of the variables (based on their publication lags), which are then extrapolated using an AR process. Finally, the principal components are fitted based on the loadings estimated on the training sample, and the GDP growth forecast is subsequently obtained.

4. Data

4.1 The Choice of Countries

Seventeen euro area countries[9] are currently used in the CNB's forecasting process (only Luxembourg and Malta are excluded from the total aggregate). GDP growth rates and measures of the inflation of these countries are weighted in order to generate "effective" euro area aggregates. The weights used for the aggregation are based on the trade weights of Czech exports. Nowcasting all 17 countries puts enormous demands on data processing, which is naturally prone to mistakes. In addition, when choosing the number of countries to include in the forecasting process, one faces a trade-off between covering a higher export share on the one hand and the ability to make expert judgments on the forecasts. This is partly because with 17 countries, the time-consuming process can lead to poor monitoring of individual countries. This is one of the advantages of BEQ models.

To reduce the computational burden of nowcasting the full aggregate, and in order to make the presentation of the results concise, we focus only on the three most important euro area countries weighted by their shares in Czech exports: Germany, France and Slovakia. We argue that, firstly, these three countries cover more than 70% of total Czech exports to the euro area (Figure B2). This share increases to more than 83% when we include another two countries (Austria and Italy). Nevertheless, one could argue that including more countries is not necessary from the economic point of view, since the GDP growth rates of both Austria and Italy are highly correlated with German GDP growth (Figure B3).

4.2 Data Used for the Analysis

The dataset used in the nowcasting and forecasting exercises was obtained at the beginning of October 2018. In the terminology of the previous section, the exercise is performed in the third month (M3) of the third quarter of 2018. The data set starts in January 1999, i.e. at the inception of the euro area and the date when most of the time series start to be available. As stated in the previous section, the training sample spans 1999Q1–2011Q4 and the evaluation period is 2012Q1–2018Q3.

The downloaded variables represent various sectors of the economy and can be grouped into the following categories: (i) production and turnover in industry and construction, (ii) labour market variables, (iii) consumer and business surveys, (iv) external trade data, (iv) financial variables. In addition, since the economies studied in the paper are linked closely to the car industry, we use a variable on new passenger car registrations. Finally, as these economies are also very open, we

[9] The weight of Czech exports to the euro area in all Czech exports is about 65%.

use several indicators for the United States, which capture the global business cycle and foreign demand.[10]

In total, 58 variables were downloaded from publicly available sources. Some of these variables are country-specific but the definitions are the same across countries (such as the industrial production index); some variables are country-specific and unique to a given country (such as the ZEW index indicator in the case of Germany). There are also some indicators which are shared by models in every country (such as US leading or financial indicators). The complete list of variables (along with their precise definitions) can be found in Table A1 in the Appendix. The data are downloaded in an automatic way using the APIs of the data providers (in the case of Eurostat, the ECB, Deutsche Bundesbank, Federal Reserve Economic Data (FRED) and Yahoo Finance) or directly from the ZEW and CESifo websites and can be routinely updated.

All the data, with the exception of financial variables, were seasonally adjusted by the publishing institutions. The nowcasting and forecasting exercises rely on stationary variables, i.e. we used log-differences or differences of variables that were non-stationary (I(1)).

Unfortunately, we were not able to obtain historical data vintages. As a result, the analysis is performed not in real time, but on the most recently available data. Nevertheless, as stated in the previous section, the analysis is performed on pseudo-real-time vintages, which take into account the publication lag of each time series (the lags are described in Table A1 in the Appendix).

5. Results

This section summarizes the results of the forecast evaluation exercise. All computations were performed in R,[11] primarily using libraries in the Tidyverse collection.[12] Charts were generated using the ggplot2 library[13].

The text uses various names for the forecast horizon: longer horizons denote proper forecasting of next-quarter GDP growth, while shorter horizons denote nowcasts and backcasts. The figures in this section summarize the root mean square errors of the forecasts at each horizon graphically. The precise figures can be found in Section E in the Appendix. It is worth noting that the numbers on the horizontal axes of the figures denote the months in the quarters when the forecast is performed. As a result, the information sets (or data) available to the forecaster are the same for each month.

5.1 Germany

In the case of Germany (Figure 2), all the models considered based on bridge equations perform better than the naive random walk benchmark model. Regarding univariate models, the models based on leading indicators perform best at the long forecast horizon. However, their forecasting ability declines as the horizon of the forecast gets shorter both in absolute terms (slightly) and compared to some of the other competing models (considerably). The models based on BMA perform moderately well at longer horizons but improve when the horizon is shorter. The same holds

[10] In the case of Slovakia, the case for including US variables is weaker, since the country trades mostly with other euro area member states. To address this feature of the Slovak economy, we included a German leading indicator in one of the multivariate models to capture the foreign demand channel (Model 2).
[11] R Core Team (2018)
[12] Wickham (2017)
[13] Wickham (2016)

for the models based on variables selected based on the correlation coefficients and for the models containing industrial production indicators, especially in the case of backcasting. On the other hand, foreign variables do not necessarily improve nowcasting much compared to the benchmark model, but such models still perform better than those containing financial variables.

The evaluation exercise based on multivariate and common component models provide similar results to the univariate models. First, the models based on leading indicators perform best at the long end of the forecasting horizon, but their performance worsens for nowcasting and backcasting. Compared to the models based on leading indicators, those based on coincident and mixed indicators perform moderately worse at the longer end of the horizon, but their performance improves in the case of nowcasting and backcasting. The model based on common components performs relatively poorly at the longer end of the forecasting horizon, but its forecasting ability still beats that of the benchmark model. The performance of the common components model improves in the case of nowcasting and backcasting and is comparable to the best models from the other two groups.

5.2 Slovakia

The performance of the bridge models is considerably worse in the case of Slovakia (Figure 3). None of the models considered outperforms the random walk benchmark model, and the root mean square errors are more dispersed than in the case of Germany. The poor performance of the models for Slovakia can be explained by several factors. First, the volatility of GDP growth is very low in the case of Slovakia (Figure B1), which leads to very high performance of the benchmark model. Interestingly, the performance of the AR(2) model is worse than that of the random walk model, due to the stability of GDP growth rates. In addition, looking at the correlations between GDP growth rates and industrial production, the coefficient is significantly lower for Slovakia than for Germany and France (Figure B4, Table B5). Strikingly, the correlation coefficients between the two variables were even negative before the financial crisis (B1). They subsequently turned positive, but were still lower than in the other two countries analysed. This signals issues with the measurement of GDP before the financial crisis.[14]

Still, one can identify several features shared with the results for Germany. The models containing the industrial production index perform moderately well. Interestingly, however, the root mean square errors of the two multivariate models based on coincident indicators (coincident indicators 2 and 3) perform worse for nowcasting in the third month compared to the previous two months. As in the case of Germany, financial and foreign variables also do not add much information to the forecasts. The performance of the model based on common components can be assessed as consistently satisfactory.

5.3 France

In the case of France, almost all the models considered outperform the benchmark random walk model based on the random walk forecast. One major exception is the model containing financial variables, which performs worse in the case of the nowcast (in months 1 and 2) and the forecast (in month 3). This feature is similar to the cases of the two countries discussed previously.

The performance of all the other models considered is very similar at the long end of the forecasts. Looking at nowcasting, the performance of the models based on correlations and BMA improves,

[14] We tried to eliminate the extreme GDP growth rates observed before the crisis, but this did not improve the performance of the models significantly.

Figure 2: Germany

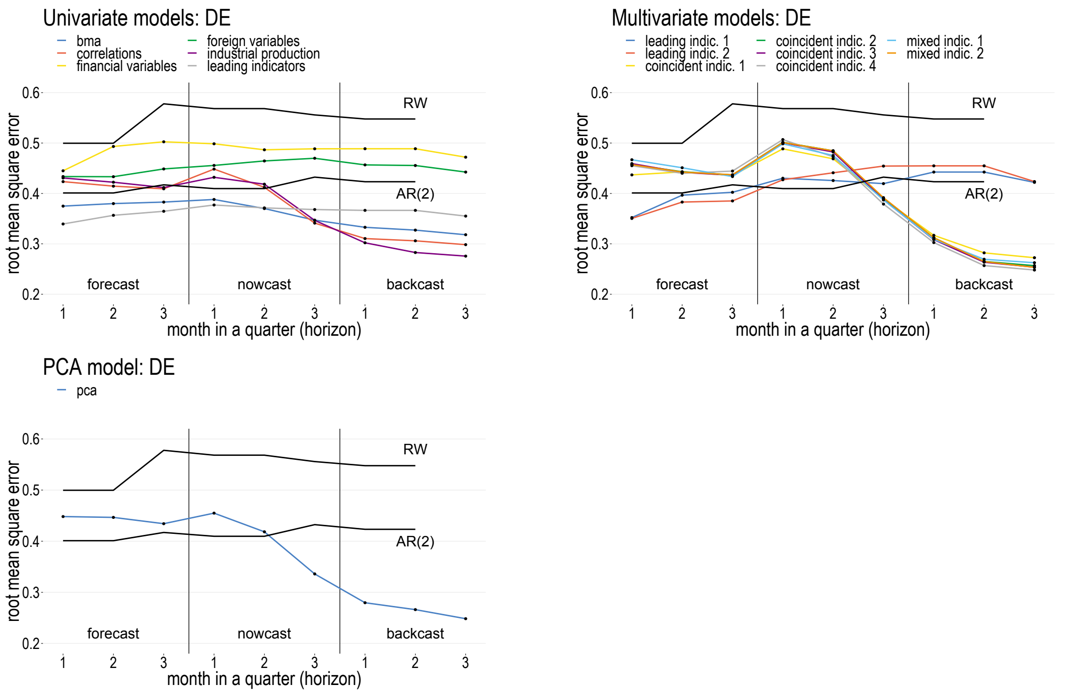
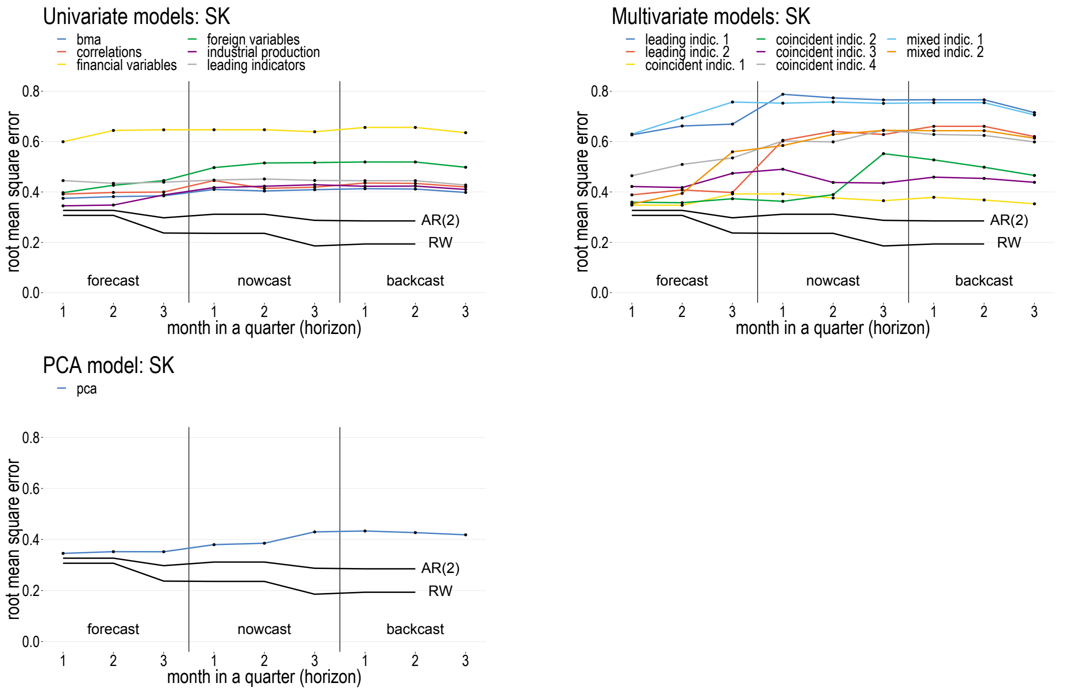
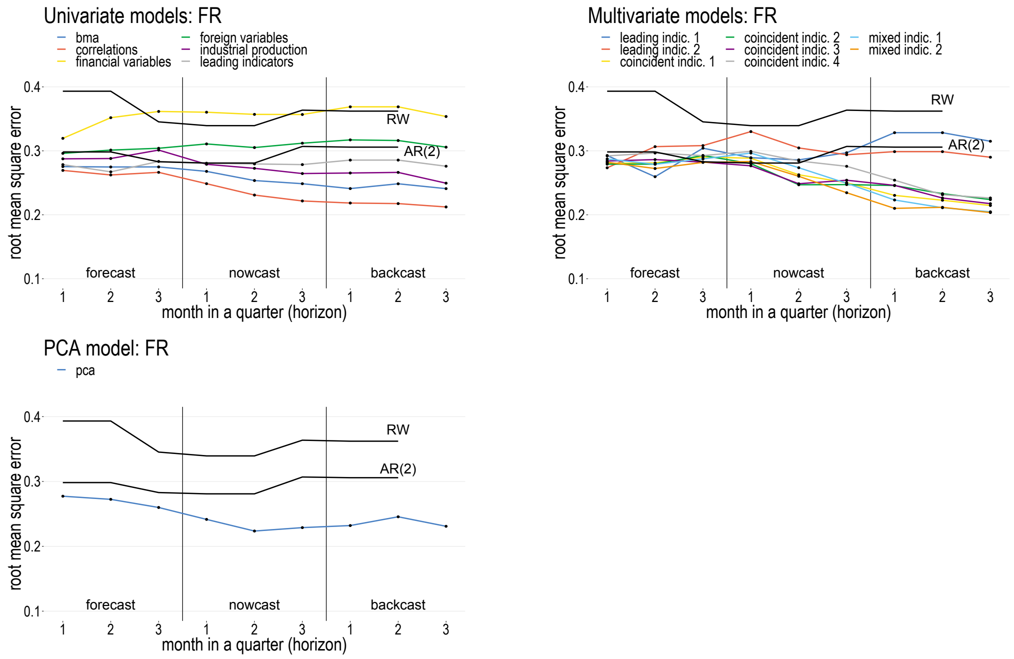


Figure 3: Slovakia



as does that of the multivariate models based on coincident and mixed indicators. The two models with mixed indicators perform best at the nowcasting horizon, both in absolute terms and compared to other models. Finally, the forecasts based on common components yield consistently satisfactory results.

Figure 4: France



5.4 Discussion of the Results

To sum up, the forecasting performance of the various competing models is not constant and varies based on the forecasting horizon considered. In line with intuition, the forecasting ability of the models containing leading indicators is strongest at longer horizons, but diminishes for nowcasting and backcasting. At the same time, the power of the models containing industrial production is increasing in the case of nowcasting and backcasting (compared to forecasting), especially in the third month, when the industrial production index is published for the first month of the current quarter. The ability of the industrial production index to explain GDP growth is highest in the case of Germany and France and lower in the case of Slovakia. This finding is not surprising in the case of Germany, as German economic output relies largely on industry (especially manufacturing) and the industrial production index is one of the sources used to compute the GDP figures.

The models for Slovakia perform very poorly even when they are contrasted with the naive random walk model. This is due to the low volatility of GDP growth observed in recent years, especially after 2012, and the relatively high volatility of the monthly indicators. At the same time, the contemporaneous correlations between industrial production and GDP growth are small relative to the cases of Germany and France (Figure C2).

Overall, the forecasting performance of most of the models is highest for backcasting, followed by nowcasting and forecasting. This result is in line with the size of the information set available at the time of the forecast. The relatively poor performance of bridge models for forecasting stems from the extrapolation of monthly indicators, which sometimes involves producing more than ten monthly observations using simple AR models (the forecast horizon is nine months, plus the publication lag is up to two months). As a result, alternative models such as VAR or structural models might be useful for short-term forecasting.

On the other hand, bridge models exploit a significant amount of information from monthly indicators to produce nowcasts and backcasts. However, even these estimates are crucial for forecasting GDP growth many quarters ahead, since assessing the current state of the economy is critical in order to produce meaningful forecasts.

6. Conclusion

This paper introduced a new approach to nowcasting foreign GDP growth for the Czech economy. Although the current state of the Czech economy is assessed on a regular basis, no method for routinely nowcasting the foreign GDP growth of several countries has been proposed yet. To this end, the paper employed a relatively simple, but general and successful technique based on bridge models. These models extract information from timely monthly indicators to infer GDP growth rates in the past, current and even next quarters.

The method of bridge equations was employed to perform backcasts, nowcasts and short-term forecasts of GDP growth rates in three major trading partners of the Czech Republic: Germany, Slovakia and France. A pseudo-real-time forecasting exercise was performed for the three horizons for each of the three months in a given quarter for the whole evaluation period. The estimates were subsequently evaluated based on the root mean square errors for each forecast horizon.

The results for Germany and France confirmed economic intuition and the findings in the literature, in that the various models are more or less successful depending on the forecast horizon. Overall, most of the models considered in the paper outperform the benchmark model based on random walk forecasts. The models with industrial production indices are most successful for nowcasting and backcasting, notably when the industrial production index has already been published for a given quarter. On the other hand, the models containing leading indicators are more successful at the longer ends of forecasts, especially in the case of Germany, for which many soft indicators are constructed. In addition, the model containing common components capturing the overall dynamics shared by the monthly indicators performs well at all horizons, particularly in the case of nowcasting the current GDP growth rate.

On the other hand, the performance of the models for Slovakia is not as successful. Their poor performance stems from two major factors. The first is the very low volatility of GDP over the evaluation period, which is reflected in the highest performance of the random walk benchmark model. Second, the correlation coefficient between the industrial production index and GDP growth rates was negative before the crisis, signalling issues with the measurement of GDP in the first half of the sample.

The models based on bridge equations perform best for the nowcasting and backcasting horizons, but they can also be valuable for assessing the direction of GDP growth in the coming quarter. In addition, having accurate estimates of the last and current GDP growth rates enables one to impose more precise initial conditions in more complex models. As a result, the techniques in this paper can be considered the first step for future research into time series forecasting of external economic developments for the Czech economy.

References

ADAM, T. AND M. PLAŠIL (2014): "The impact of financial variables on Czech macroeconomic developments." CNB Working Paper No. 11/2014.

ANGELINI, E., G. CAMBA-MENDEZ, D. GIANNONE, L. REICHLIN, AND G. RÜNSTLER (2011): "Short-term forecasts of euro area GDP growth." *The Econometrics Journal,* 14(1):C25–C44.

ANTIPA, P., K. BARHOUMI, V. BRUNHES-LESAGE, AND O. DARNÉ (2012): "Nowcasting German GDP: A comparison of bridge and factor models." *Journal of Policy Modeling,* 34(6):864–878.

ARNOŠTOVÁ, K., D. HAVRLANT, L. RŮŽIČKA, AND P. TÓTH (2011): "Short-term forecasting of Czech quarterly GDP using monthly indicators." *Finance a Úvěr,* 61(6):566.

BABECKÁ, K. O. AND J. BRŮHA (2016): "Nowcasting the Czech Trade Balance." CNB Working Paper No. 11/2016

BAFFIGI, A., R. GOLINELLI, AND G. PARIGI (2004): "Bridge models to forecast the euro area GDP." *International Journal of Forecasting,* 20(3):447–460.

BANBURA, M., D. GIANNONE, M. MODUGNO, AND L. REICHLIN (2013): "Now-casting and the real-time data flow." *Handbook of Economic Forecasting,* 2(Part A):195–237.

BENDA, V. AND L. RŮŽIČKA (2007): "Short-term forecasting methods based on the LEI approach: the case of the Czech Republic." CNB Research and Policy Notes 1/2007.

BUNDESBANK, D. (2013): "Forecasting models in short-term business cycle analysis." *Monthly Report,* 65(9):69–84.

BURNS, A. F. AND W. C. MITCHELL (1947): *Measuring business cycles.* National Bureau of Economic Research.

DIRON, M. (2008): "Short-term forecasts of euro area real GDP growth: an assessment of real-time performance based on vintage data." *Journal of Forecasting,* 27(5):371–390.

FELDKIRCHER, M., F. HUBER, J. SCHREINER, J. WÖRZ, M. TIRPÁK, AND P. TÓTH (2015): "Small-scale nowcasting models of GDP for selected CESEE countries." NBS Working Paper No. 4/2015.

FRANTA, M., D. HAVRLANT, AND M. RUSNÁK (2016): "Forecasting Czech GDP using mixed-frequency data models." *Journal of Business Cycle Research,* 12(2):165–185.

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.

GÖTZ, T. B. AND T. A. KNETSCH (2019): "Google data in bridge equation models for German GDP." *International Journal of Forecasting,* 35(1):45–66.

HAVRÁNEK, T., R. HORVÁTH, AND J. MATĚJŮ (2010): "Do financial variables help predict macroeconomic environment?" CNB Working Paper No. 6/2010.

HUČEK, J., A. KARŠAY, AND M. VÁVRA (2015): "Short-term forecasting of real GDP using monthly data." NBS Occasional Paper No. 1/2015.

JOSSE, J. AND F. HUSSON (2012): "Handling missing values in exploratory multivariate data analysis methods." *Journal de la Société Française de Statistique,* 153(2):79–99.

JOSSE, J. AND F. HUSSON (2016): “missMDA: A package for handling missing values in multivariate data analysis.” *Journal of Statistical Software,* 70(1):1–31.

KITCHEN, J. AND R. MONACO: “Real-time forecasting in practice: The US Treasury staff’s real-time GDP forecast system.” *Business Economics,* 38(4):10–19.

KLEIN, L. AND E. SOJO (1989): *Combinations of high and low frequency data in macroeconometric models.* In *Economics in theory and practice: An eclectic approach,* pages 3–16. 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.

MOGLIANI, M., O. DARNÉ, AND B. PLUYAUD (2017): “The new MIBA model: Real-time nowcasting of French GDP using the Banque de France’s monthly business survey.” *Economic Modelling,* 64:26–39.

PINKWART, N. (2018): “Short-term forecasting economic activity in Germany: A supply and demand side system of bridge equations.” Technical report, Bundesbank Discussion Paper No. 36/2018

R CORE TEAM (2018): *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria.

RAFTERY, A., J. HOETING, C. VOLINSKY, I. PAINTER, AND K. Y. YEUNG (2018): *BMA: Bayesian Model Averaging.* R package version 3.18.8

RÜNSTLER, G. AND F. SÉDILLOT (2003): “Short-term estimates of euro area real GDP by means of monthly data.” ECB Working Paper No. 276

RUSNÁK, M. (2016): “Nowcasting Czech GDP in real time.” *Economic Modelling,* 54:26–39.

TREHAN, B. (1992): “Predicting contemporaneous output.” Federal Reserve Bank of San Francisco Economic Review 2/1992, pp. 3-11.

TVRZ, S. (2016): “Modelové prístupy k odhadu krátkodobého výhľadu ekonomickej aktivity (Nowcasting HDP).” Analytický komentář č. 29, január 2016.

WICKHAM, H. (2016): *ggplot2: Elegant Graphics for Data Analysis.* Springer-Verlag New York.

WICKHAM, H. (2017): *tidyverse: Easily Install and Load the ’Tidyverse’.* R package version 1.2.1

Appendix A: Data Used For the Analysis

Table A1: Data Used For the Analysis

	ticker	keys	lags	DE	SK	FR	EA19	US
Eurostat								
GDP growth								
GDP qoq growth SCA	gdp_qoq	namq_10_gdp: Q.CLV_PCH_PRE.SCA.B1GQ.	5	x		x		
GDP qoq growth SA	gdp_qoq	namq_10_gdp: Q.CLV_PCH_PRE.SA.B1GQ.	5		x			
production in industry								
industry total	ip_total	sts_inpr_m: M.PROD.B-D.SCA.PCH_PRE.	2	x	x	x		
manufacturing	ip_manufacturing	sts_inpr_m: M.PROD.C.SCA.PCH_PRE.	2	x	x	x		
electricity, gas, steam and air conditioning supply	ip_energy	sts_inpr_m: M.PROD.D.SCA.PCH_PRE.	2	x	x	x		
mining and quarrying	ip_mining_quarrying	sts_inpr_m: M.PROD.B.SCA.PCH_PRE.	2	x	x	x		
intermediate goods industry	ip_intermediate	sts_inpr_m: M.PROD.MIG_ING.SCA.PCH_PRE.	2	x	x	x		
capital goods industry	ip_capital_goods	sts_inpr_m: M.PROD.MIG_CAG.SCA.PCH_PRE.	2	x	x	x		
durable consumer goods industry	ip_durables	sts_inpr_m: M.PROD.MIG_DCOG.SCA.PCH_PRE.	2	x	x	x		
non-durable consumer goods industry	ip_nondurables	sts_inpr_m: M.PROD.MIG_NDCOG.SCA.PCH_PRE.	2	x	x	x		
production in construction								
production in construction	construction	sts_copr_m: M.PROD.F.SCA.PCH_PRE.	2	x	x	x		
deflated turnover in retail trade								
retail trade, except of motor vehicles and motorcycles	retail_excl_vehicles	sts_trtu_m: M.TOVV.G47.SCA.PCH_PRE.	2	x	x	x		
retail trade of non-food products (except fuel)	retail_nonfood	sts_trtu_m: M.TOVV.G47_NFOOD_X_G473.SCA.PCH_PRE.	2	x	x	x		
turnover in industry								
mining and quarrying	it_mining_quarrying	sts_intv_m: M.TOVT.B.SCA.PCH_PRE.	2	x	x	x		
manufacturing	it_manufacturing	sts_intv_m: M.TOVT.C.SCA.PCH_PRE.	2	x	x	x		
turnover in industry; domestic market								
mining and quarrying	it_dom_mining_quarrying	sts_intvd_m: M.TOVD.B.SCA.PCH_PRE.	2	x	x	x		
manufacturing	it_dom_manufacturing	sts_intvd_m: M.TOVD.C.SCA.PCH_PRE.	2	x	x	x		

	ticker	keys	lags	DE	SK	FR	EA19	US
turnover in industry; non-domestic market								
mining and quarrying	it_nondom_mining_quarrying	sts_intvnd_m: M.TOVE.B.SCA.PCH_PRE.	2	x	x	x		
manufacturing	it_nondom_manufacturing	sts_intvnd_m: M.TOVE.C.SCA.PCH_PRE.	2	x	x	x		
labour market								
unemployment rate total	unrate_total	une_rt_m: M.SA.TOTAL.PC_ACT.T.	1	x	x	x		
unemployment rate, 25 years and over	unrate_25over	une_rt_m: M.SA.Y25-74.PC_ACT.T.	1	x	x	x		
unemployment rate, under 25 years	unrate_25under	une_rt_m: M.SA.Y_LT25.PC_ACT.T.	1	x	x	x		
consumer and business surveys								
consumer confidence indicator	ecs_consumer_confidence	ei_bsco_m: M.BS-CSMCI.SA.BAL.	0	x	x	x		
consumer unemployment expectations	ecs_consumer_exp_unem	ei_bsco_m: M.BS-UE-NY.SA.BAL.	0	x	x	x		
industry confidence indicator	ecs_industry_confidence	ei_bsin_m_r2: M.BS-ICI.SA.BAL.	0	x	x	x		
industry employment expecations	ecs_industry_exp_employment	ei_bsin_m_r2: M.BS-IEME.SA.BAL.	0	x	x	x		
services confidence indicator	ecs_services_confidence	ei_bsse_m_r2: M.BS-SCI.SA.BAL.	0	x	x	x		
services employment expectations	ecs_services_exp_employment	ei_bsse_m_r2: M.BS-SEEM.SA.BAL.	0	x	x	x		
retail confidence indicator	ecs_retail_confidence	ei_bsrt_m_r2: M.BS-RCI.SA.BAL.	0	x	x	x		
retail employment expectations	ecs_retail_exp_employment	ei_bsrt_m_r2: M.BS-REM.SA.BAL.	0	x	x	x		
construction confidence indicator	ecs_construction_confidence	ei_bsbu_m_r2: M.BS-CCI-BAL.SA.	0	x	x	x		
construction employment expectations	ecs_construction_exp_empl	ei_bsbu_m_r2: M.BS-CEME-BAL.SA.	0	x	x	x		
external trade								
exports outside of the EU, current value	exports_ex_eu	ext_st_28msbec: M.EXP.TRD_VAL_SCA.EXT_EU28.TOTAL.	2	x	x	x		
exports, current value	exports_world	ext_st_28msbec: M.EXP.TRD_VAL_SCA.WORLD.TOTAL.	2	x	x	x		
ECB								
car registrations								
new passenger car registration mom, sa	car_registrations	STS.M.I8.Y.CREG.PC0000.3.PER	2				x	
Buba								
orders received								
industry, constant prices	orders_industry	BBDE1.M.DE.Y.AEA1.A2P300000.F.C.I15.A	2	x				
intermediate goods, constant prices	orders_intermediates	BBDE1.M.DE.Y.AEA1.A2P310000.F.C.I15.A	2	x				
capital goods, constant prices	orders_capital_goods	BBDE1.M.DE.Y.AEA1.A2P320000.F.C.I15.A	2	x				

	ticker	keys	lags	DE	SK	FR	EA19	US
consumer goods, constant prices	orders_consumer_goods	BBDE1.M.DE.Y.AEA1.A2P350000.F.C.I15.A	2	x				
Fred								
foreign variables								
Industrial production: manufacturing	us_manufacturing	IPMAN	1					x
Industrial production index	us_ip_total	INDPRO	1					x
University of Michigan: consumer sentiment	us_umcsent	UMCSENT	0					x
Motor vehicle retail sales: domestic autos	us_dom_cars	DAUTOSA	1					x
Retail sales	us_retail	RETAILSMSA	2					x
OECD consumer confidence indicator for the US	us_oecd_consop	CSCICP03USM665S	2					x
OECD business confidence indicator for the US	us_oecd_business_surveys	BSCICP03USM665S	2					x
Other								
leading indicators - Germany								
ifo business climate, industry and trade	ifo_industry_climate		0	x				
ifo business situation, industry and trade	ifo_industry_situation		0	x				
ifo business expectations, industry and trade	ifo_industry_expectations		0	x				
ifo business climate, manufacturing	ifo_manufacturing_climate		0	x				
ifo business situation, manufacturing	ifo_manufacturing_situation		0	x				
ifo business expectations, manufacturing	ifo_manufacturing_expectations		0	x				
ZEW indicator of economic sentiment, Germany	zew_sentiment		0	x				
ZEW indicator of economic situation, Germany	zew_situation		0	x				
financial variables								
DAX performance index	dax	yahoo: ^GDAXI	0	x				
CAC 40	cac40	yahoo: ^FCHI	0			x		
Euro Stoxx 50	stoxx50	yahoo: ^STOXX50E	0				x	
S&P 500 Index	sp500	yahoo: ^GSPC	0					x

Note:

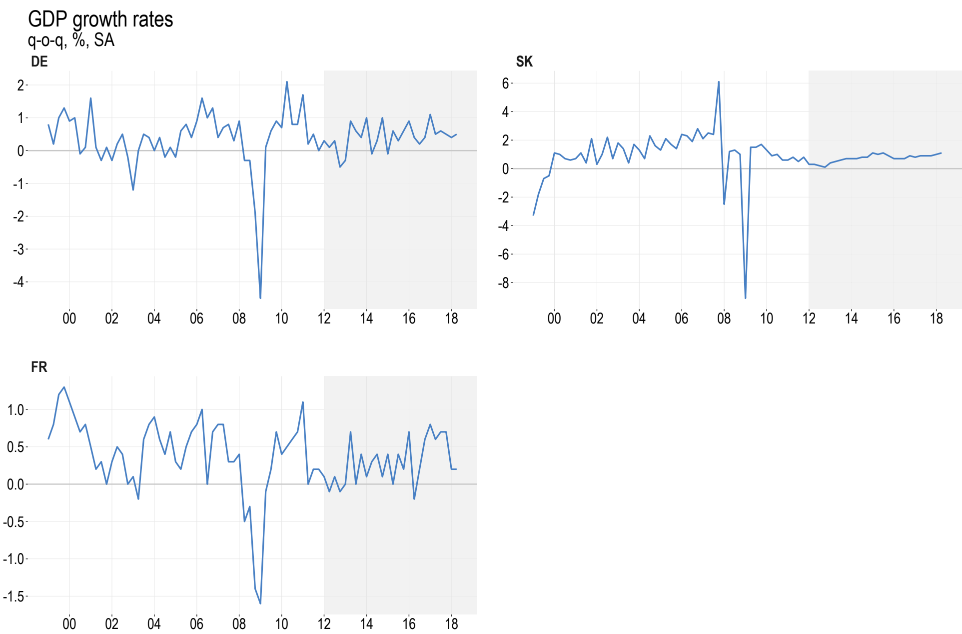
Data sources are printed in bold. Keys column denotes the name of the database (in the case of Eurostat) and other identification dimensions / tickers.

Column lags denotes the publication lag in weeks (i.e., zero indicates that the variable is published by the end of a given month).

Variables in the Other category were downloaded from the websites of publishing institutions (CESifo or Center for European Economic Research, ZEW) or from Yahoo Finance (financial variables).

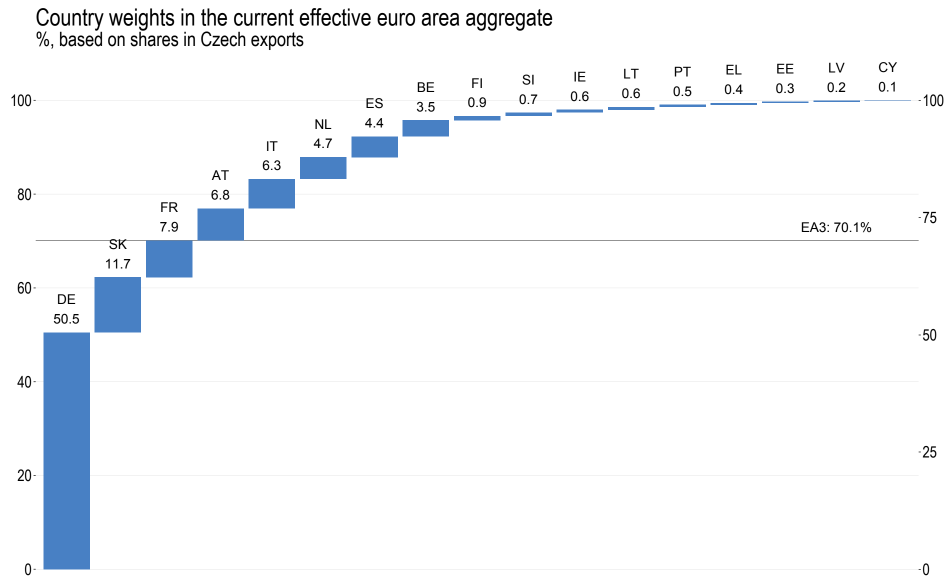
Appendix B: Major Trading Partners of the Czech Republic: Stylized Facts

Figure B1: GDP Growth Rates in the Considered Countries



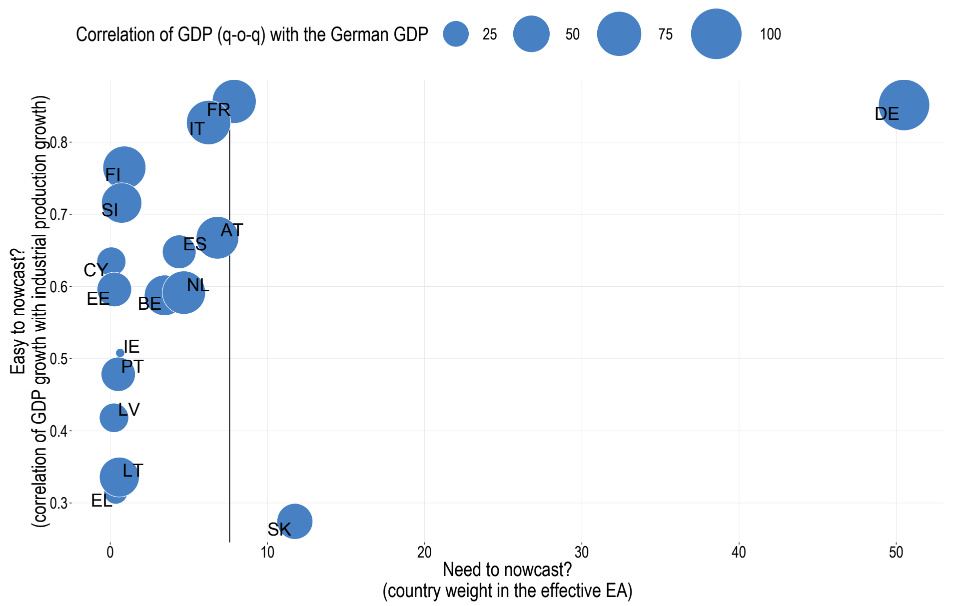
Source: Eurostat

Figure B2: EA Country Weights Based on the Czech Export Shares (2018 Q1)



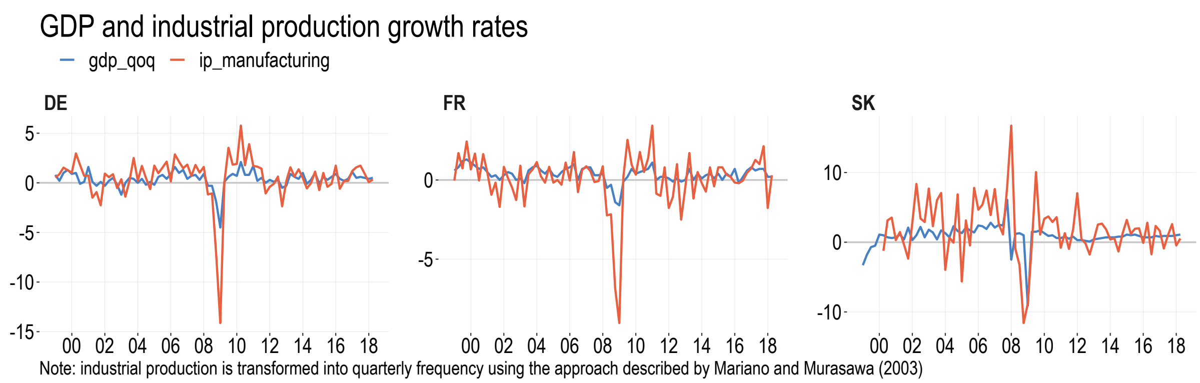
Source: Eurostat, CZSO

Figure B3: EA Country Weights Based on the Czech Export Shares, Correlations of GDP Growth Rates With Industrial Production Growth



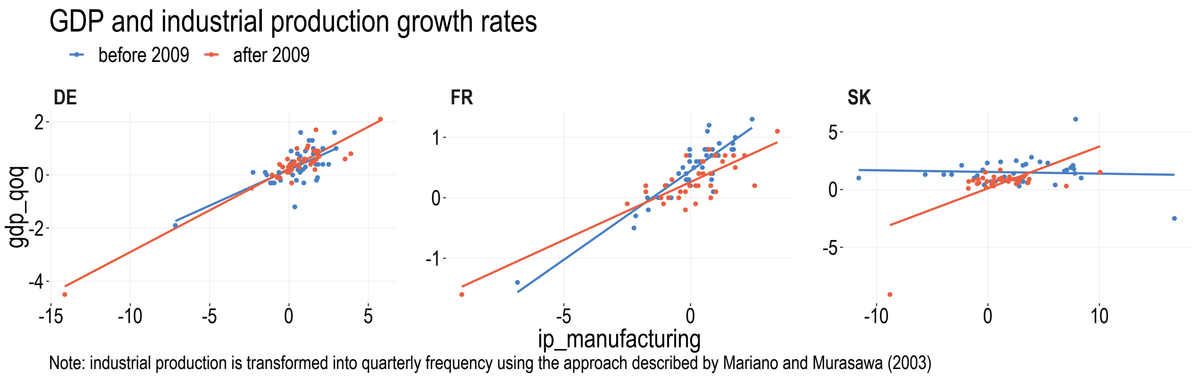
Source: Eurostat

Figure B4: GDP and Industrial Production Growth Rates



Source: Eurostat

Figure B5: GDP and Industrial Production Growth Rates



Source: Eurostat

Table B1: Correlation Coefficients Between GDP Growth Rates and Industral Production Growth Rates

	before 2009	after 2009
DE	0.68	0.94
FR	0.90	0.85
SK	-0.06	0.62

Source: Eurostat

Appendix C: Monthly Indicators in Univariate Models (BMA, Correlations)

Figure C1: Variables Selected Based on BMA and Correlations: Germany

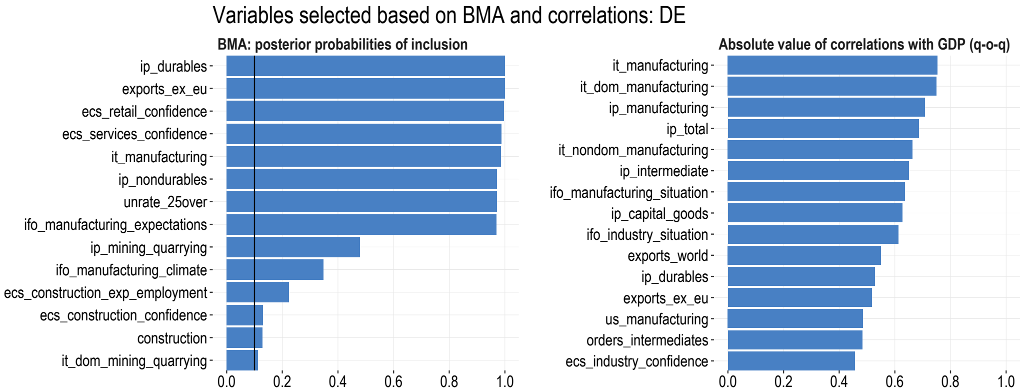


Figure C2: Variables Selected Based on BMA and Correlations: Slovakia

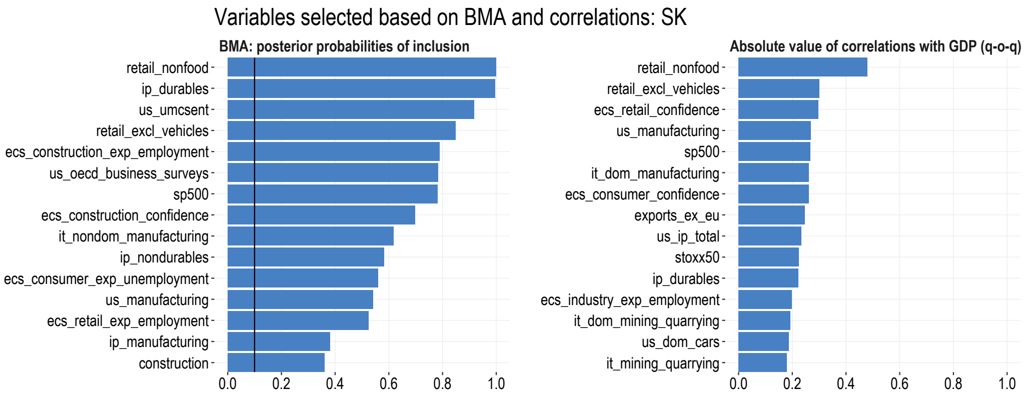
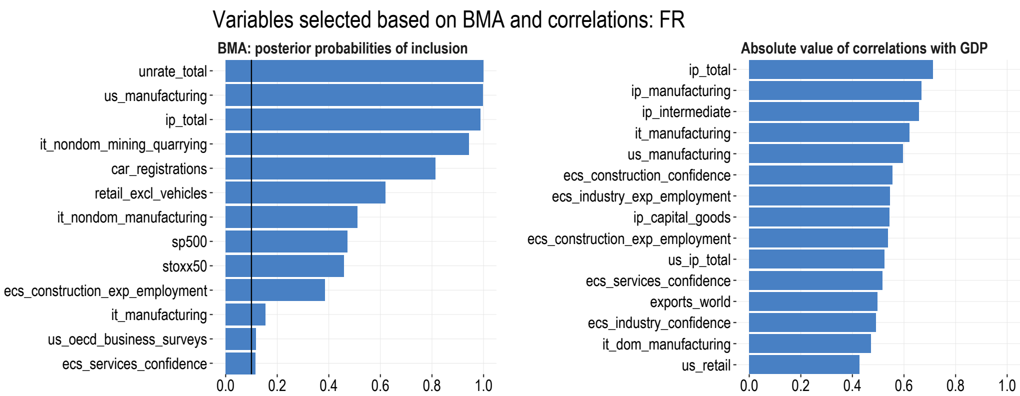


Figure C3: Variables Selected Based on BMA and Correlations: France



Appendix D: Multivariate Model Equations

D.1 Germany

Models with leading indicators:

- Model 1: $gdp\_qoq \sim ecs\_industry\_exp\_employment + ecs\_industry\_exp\_employment\_lag + ifo\_manufacturing\_expectations\_lag$
- Model 2: $gdp\_qoq \sim ifo\_manufacturing\_expectations + ifo\_manufacturing\_expectations\_lag + zew\_sentiment$

Models with coincident indicators:

- Model 3: $gdp\_qoq \sim ip\_total + retail\_nonfood$
- Model 4: $gdp\_qoq \sim ip\_manufacturing + retail\_nonfood$
- Model 5: $gdp\_qoq \sim ip\_manufacturing + orders\_industry\_lag + retail\_nonfood$
- Model 6: $gdp\_qoq \sim ip\_manufacturing + retail\_nonfood + unrate\_25over$

Models with leading and coincident indicators:

- Model 7: $gdp\_qoq \sim ifo\_manufacturing\_expectations + ip\_manufacturing$
- Model 8: $gdp\_qoq \sim ifo\_manufacturing\_expectations + ip\_manufacturing + retail\_nonfood$

D.2 Slovakia

Models with leading indicators:

- Model 1: $gdp\_qoq \sim ecs\_consumer\_exp\_unemployment + ecs\_consumer\_exp\_unemployment\_lag + ecs\_construction\_exp\_employment$
- Model 2: $gdp\_qoq \sim ecs\_consumer\_exp\_unemployment + ifo\_manufacturing\_expectations$

Models with coincident indicators:

- Model 3: $gdp\_qoq \sim ip\_manufacturing + ip\_manufacturing\_lag + retail\_excl\_vehicles$
- Model 4: $gdp\_qoq \sim ip\_durables + ip\_durables\_lag + retail\_nonfood$
- Model 5: $gdp\_qoq \sim ip\_manufacturing\_lag + retail\_excl\_vehicles + unrate\_total + unrate\_total\_lag$
- Model 6: $gdp\_qoq \sim ip\_total + ip\_total\_lag + retail\_excl\_vehicles + us\_manufacturing$

Models with leading and coincident indicators:

- Model 7: $gdp\_qoq \sim ip\_total\_lag + retail\_excl\_vehicles\_lag + ecs\_consumer\_exp\_unemployment\_lag$
- Model 8: $gdp\_qoq \sim ip\_total\_lag + retail\_excl\_vehicles\_lag + ecs\_construction\_exp\_employment$

D.3 France

Models with leading indicators:

- Model 1: $gdp\_qoq\ ecs\_industry\_exp\_employment + ecs\_construction\_exp\_employment$
- Model 2: $gdp\_qoq\ ecs\_industry\_confidence + ecs\_services\_confidence$

Models with coincident indicators:

- Model 3: $gdp\_qoq\ ip\_total + ip\_total\_lag + retail\_excl\_vehicles$
- Model 4: $gdp\_qoq\ ip\_manufacturing + ip\_manufacturing\_lag + retail\_excl\_vehicles$
- Model 5: $gdp\_qoq\ ip\_manufacturing + ip\_manufacturing\_lag + unrate\_total$
- Model 6: $gdp\_qoq\ ip\_total + us\_manufacturing\_lag$

Models with leading and coincident indicators:

- Model 7: $gdp\_qoq\ ip\_total + ip\_total\_lag + ecs\_industry\_exp\_employment$
- Model 8: $gdp\_qoq\ ip\_total + ip\_total\_lag + retail\_nonfood + ecs\_industry\_exp\_employment$

Appendix E: Root Mean Square Errors

Table E1: Root Mean Square Errors: Germany

	Backcast			Nowcast			Forecast		
model	M1	M2	M3	M1	M2	M3	M1	M2	M3
benchmark models									
AR(2)	0.423	0.423	NA	0.401	0.401	0.417	0.410	0.410	0.432
random walk	0.548	0.548	NA	0.500	0.500	0.578	0.568	0.568	0.556
common component model									
pca	0.280	0.266	0.248	0.448	0.447	0.434	0.455	0.418	0.336
economic models									
coincident indicators 1	0.317	0.282	0.272	0.437	0.443	0.436	0.488	0.469	0.389
coincident indicators 2	0.312	0.265	0.257	0.457	0.443	0.437	0.501	0.485	0.391
coincident indicators 3	0.308	0.264	0.254	0.459	0.442	0.436	0.501	0.482	0.387
coincident indicators 4	0.303	0.257	0.248	0.455	0.440	0.444	0.507	0.473	0.379
leading indicators 1	0.442	0.442	0.422	0.352	0.397	0.402	0.430	0.426	0.419
leading indicators 2	0.455	0.455	0.424	0.350	0.383	0.385	0.427	0.441	0.454
mixed indicators 1	0.309	0.269	0.263	0.467	0.451	0.433	0.498	0.475	0.387
mixed indicators 2	0.312	0.265	0.253	0.457	0.442	0.437	0.501	0.485	0.392
pairwise models									
bma	0.333	0.327	0.318	0.375	0.380	0.383	0.388	0.370	0.347
correlations	0.310	0.306	0.298	0.423	0.414	0.409	0.448	0.412	0.341
financial variables	0.489	0.489	0.472	0.445	0.493	0.502	0.499	0.487	0.489
foreign variables	0.457	0.455	0.442	0.433	0.433	0.449	0.456	0.464	0.470
industrial production	0.302	0.283	0.276	0.431	0.422	0.412	0.432	0.418	0.347
leading indicators	0.366	0.366	0.355	0.339	0.357	0.365	0.377	0.371	0.368

Table E2: Root Mean Square Errors: Slovakia

	Backcast			Nowcast			Forecast		
model	M1	M2	M3	M1	M2	M3	M1	M2	M3
benchmark models									
AR(2)	0.285	0.285	NA	0.327	0.327	0.297	0.312	0.312	0.287
random walk	0.193	0.193	NA	0.307	0.307	0.237	0.236	0.236	0.186
common component model									
pca	0.433	0.427	0.418	0.346	0.352	0.352	0.380	0.385	0.430
economic models									
coincident indicators 1	0.379	0.368	0.353	0.348	0.347	0.392	0.392	0.376	0.365
coincident indicators 2	0.527	0.498	0.466	0.359	0.357	0.373	0.363	0.389	0.552
coincident indicators 3	0.459	0.454	0.438	0.422	0.417	0.474	0.490	0.438	0.435
coincident indicators 4	0.628	0.625	0.599	0.464	0.509	0.535	0.602	0.599	0.645
leading indicators 1	0.766	0.766	0.715	0.627	0.662	0.669	0.788	0.774	0.766
leading indicators 2	0.661	0.661	0.620	0.389	0.408	0.398	0.605	0.641	0.628
mixed indicators 1	0.755	0.755	0.706	0.630	0.694	0.757	0.753	0.757	0.752
mixed indicators 2	0.643	0.643	0.614	0.352	0.394	0.559	0.584	0.628	0.645
pairwise models									
bma	0.413	0.412	0.398	0.375	0.381	0.385	0.410	0.404	0.409
correlations	0.435	0.434	0.420	0.391	0.398	0.400	0.445	0.414	0.419
financial variables	0.656	0.656	0.635	0.599	0.644	0.647	0.647	0.647	0.639
foreign variables	0.519	0.519	0.498	0.397	0.427	0.445	0.497	0.515	0.517
industrial production	0.422	0.423	0.410	0.345	0.348	0.388	0.417	0.423	0.429
leading indicators	0.445	0.445	0.427	0.445	0.434	0.439	0.447	0.451	0.446

Table E3: Root Mean Square Errors: France

	Backcast			Nowcast			Forecast		
model	M1	M2	M3	M1	M2	M3	M1	M2	M3
benchmark models									
AR(2)	0.306	0.306	NA	0.298	0.298	0.283	0.281	0.281	0.307
random walk	0.362	0.362	NA	0.393	0.393	0.345	0.339	0.339	0.364
common component model									
pca	0.232	0.246	0.231	0.277	0.272	0.260	0.242	0.224	0.229
economic models									
coincident indicators 1	0.230	0.223	0.215	0.280	0.281	0.290	0.288	0.263	0.250
coincident indicators 2	0.246	0.233	0.224	0.279	0.279	0.293	0.280	0.247	0.247
coincident indicators 3	0.246	0.226	0.217	0.284	0.286	0.282	0.277	0.249	0.254
coincident indicators 4	0.254	0.231	0.226	0.292	0.297	0.293	0.299	0.284	0.276
leading indicators 1	0.328	0.328	0.315	0.293	0.260	0.304	0.289	0.286	0.297
leading indicators 2	0.299	0.299	0.290	0.273	0.307	0.308	0.330	0.305	0.294
mixed indicators 1	0.223	0.211	0.205	0.287	0.279	0.287	0.297	0.274	0.249
mixed indicators 2	0.210	0.212	0.203	0.282	0.272	0.282	0.283	0.260	0.235
pairwise models									
bma	0.241	0.248	0.241	0.275	0.275	0.275	0.268	0.254	0.249
correlations	0.218	0.218	0.212	0.269	0.262	0.266	0.249	0.231	0.222
financial variables	0.369	0.369	0.354	0.320	0.352	0.362	0.360	0.357	0.357
foreign variables	0.317	0.316	0.306	0.296	0.301	0.304	0.311	0.305	0.312
industrial production	0.265	0.266	0.249	0.287	0.288	0.301	0.279	0.273	0.264
leading indicators	0.286	0.286	0.276	0.278	0.267	0.283	0.281	0.280	0.278

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