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Nowcasting real GDP growth with business tendency surveys data: A cross country analysis

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Abstract

We use nowcasting methodology to forecast the dynamics of the real GDP growth in real time based on the business tendency surveys data. Nowcasting is important because key macroeconomic variables on the current state of the economy are available only with a certain lag. This is particularly true for those variables that are collected on a quarterly basis. To conduct out-of-sample forecast evaluation we use business tendency surveys data for 22 European countries. Based on the different dataset and using out-of-sample recursive regression scheme we conclude that nowcasting model outperforms several alternative short-term forecasting statistical models, even when the volatility of the real GDP growth is increasing both in time and across different countries. Based on the Diebold-Mariano test statistics, we conclude that nowcasting strongly outperforms BVAR and BFAVAR models, but comparison with AR, FAAR and FAVAR does not produce sufficient evidence to prefer one over another.

JEL-Classification: *E52, C33, C38, C52, C53, E37*

Keywords: Nowcasting, short-term forecasting, dynamic and static principal components, Bayesian VAR, Factor Augmented VAR, real GDP growth, European OECD countries

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1. Introduction

Effective economic policy conduct is conditioned by availability of the timely and accurate economic data and their forecasts (Giannone et al., 2008; Jansen et al., 2016).[1] However, often (i) the data are not available in required time or are incomplete, and (ii) resulting accuracy of forecasts is potentially plagued by volatility present in input data. We employ less explored type of data based on business tendency surveys and compare the forecast accuracy of nowcasting and forecasting algorithms that use the real economy data originating from 22 European countries that can be characterized by different volatility regimes. Our goal is to show which type of algorithm delivers the most accurate short-term forecasts of the real GDP growth.

The key macroeconomic indicator of the state of economy is the growth rate of the real GDP, which is available around two months after the end of a reference quarter. On the other hand, a substantial amount of various (higher frequency) economic indicators is available between the start of the quarter and the publication of the official real GDP figure. This information includes data on industrial production, prices and exchange rates, external sector indices, financial variables, money aggregates, business climate and confidence indicators. Thus, various high frequency data could be quite useful to predict and understand the dynamics of the real GDP (Giannone et al., 2008; Jansen et al., 2016). For this type of data, nowcasting represents a suitable tool whose basic principle is to use early published information in order to obtain an early estimate of the real GDP growth before the official figure becomes available (Gianonne et al., 2008).

The forecasting literature has recently developed different algorithms for extracting useful information from large datasets in order to improve the assessment of the real GDP growth in a current quarter (Camacho et al., 2013). These include: dynamic factor model, mixed-data sampling model (MIDAS), and mixed-frequency vector-autoregressive (MFVAR) model. The main idea underlying these models is to provide a framework for the integration of a large number of economic series with different frequencies and publication lags to exploit all useful information to forecast the real GDP growth in a current quarter.

In most of the empirical work, nowcasting procedure is considered only for a single country and for a limited number of models (Aastveit et al., 2012; D'Agostino et al., 2012; Kuzin et al., 2013; Yiu et al., 2010). In contrast, in this paper we consider nowcasting method for a large set of countries: 22

[1] Typical case is represented by central banks where policy makers, as a rule, have to make decisions in real time with incomplete information on current economic conditions.

European countries that are members of the OECD. Furthermore, we undertake a comparison between nowcasting algorithms and several alternative short-term forecasting models, namely the traditional AR, Unrestricted VAR, small-scale Bayesian VAR, Unrestricted Factor Augmented VAR and Bayesian Factor Augmented VAR (hereafter AR, VAR, BVAR, FAAR, FAVAR and BFAVAR). For all models with additional factors we use static and dynamic approaches to extract unobserved components (factors). Finally, we investigate how the nowcasting and forecasting results change when the volatility of the real GDP growth changes. For that our sample includes the volatile episodes of the 2008 financial crisis and its aftermath. In order to obtain comparable and robust results we include a large set of countries utilizing the same set of information across counties.

We design and conduct an out-of-sample forecast evaluation. For all countries we use the same unified dataset which includes 25 variables on business tendency surveys. These data are available, as a rule, at the end of the reference month; the source of the data is OECD. Intentionally, we do not use other high frequency macroeconomic variables, such as variables from real or external sectors of economy. The reason is that macroeconomic variables on real and external sectors of economy in a number of OECD countries are released with at least 1.5 months of delay compared to the reference month. For example, data referring to January become available only by mid of March (Gayer, Girardi and Reuter, 2014). This means that these data are not timely. Hence, business tendency surveys data which are published earlier than the real GDP growth rates are more timely than other macroeconomic variables and have direct relation with the current situation in the real sector of economy. Therefore, these data could contain useful information for nowcasting real growth of GDP and could improve our assessment of the current economic conditions.

In this paper, we contribute to the existing research in two ways. First, we provide a comprehensive comparison of the nowcasting and forecasting methods on a wide range of countries over a pre-crisis and post-crisis time span. Specifically, based on the business tendency surveys data for various countries with different volatility of the real GDP growth, we estimate the nowcasting model and then compare obtained results with those from a large range of the short-term forecasting models. Second, we show that the nowcasting based on the business tendency surveys data is a useful tool for a current quarter forecasting when the real GDP growth volatility is increasing both in time and across various countries.

The remainder of the paper is organized as follows. In section 2 we briefly review the literature related to the researched topic. In section 3 we present the computational details of the nowcasting model proposed by Gianonne et al. (2008) and in Section 4 we briefly present the main methodological aspects of the short-term forecasting models (AR, VAR, BVAR, FAAR, FAVAR and BFAVAR). In section 5 we present the dynamics of the real GDP growth and some important descriptive statistics for selected countries. In this section we also give short description of additional explanatory variables that serve as initial variables for extracting the dynamics of unobservable factors. In section 6 we present a recursive regression scheme for our experimental design. In section 7 we present the out-of-sample evaluation results. Section 8 concludes.

2. Literature Review

Policy makers very often have to make decisions in real time with incomplete information on current economic conditions. From the other side a large amount of data series are available on time, that is between the start of the quarter and the date of official publication of the real GDP growth. Thus, the question arises of whether this earlier available information can be effectively used to improve the forecasted values of the real GDP in real time. According to a number of empirical papers, the nowcasting model can be used to improve the real GDP forecasts as new information becomes available. In other words, the nowcasting model allows to incorporate a new available information progressively after its release making it possible to increase our understanding of the drivers of GDP growth. The literature offers several approaches in terms of the nowcasting models: bridge equation models, mixed data sampling (MIDAS) regressions and dynamic factor models.

Forecasting with bridge equation is performed in two steps: in the first step we forecast each high-frequency indicator (for example using ARIMA) to deal with ragged ends; in the next step monthly indicators are averaged (with equal weights) to quarterly frequency and used to forecast GDP growth or its subcomponents via simple bivariate regression. The MIDAS regression represents more modern benchmark model (Ghysels et al., 2007). MIDAS deals with mixed frequencies by employing a polynomial weighting function to link high-frequency and low-frequency data. The main difference between MIDAS and bridge model is that the MIDAS regression is a direct forecasting tool, while in bridge regression we should model the dynamics of each indicators separately and then to use expanded indicators to nowcast real GDP growth. The dynamic factor models approach to nowcasting was proposed by Gianonne at al. (2008) and we present its details in the next section. The methodology has been adopted by a number of central banks and it has served to nowcast GDP in specific countries. For example, real GDP growth was nowcasted via dynamic factor models for Norway (Aastveit et al., 2012) Switzerland (Siliverstovs et al., 2012), Ireland (D'Agostino et al., 2012), France (Barhoumi et al., 2010), New Zealand (Matheson, 2010), or China (Yiu et al., 2011; Gianonne et al., 2013).

Hence, the dynamic factor models approach has become a popular and effective tool for both nowcasting and short-term forecasting. In particular, three factor models became frequently used in applied research during the last decades: (i), the static principal component approach (Stock and Watson, 2002), (ii) the dynamic principal components estimated in the frequency domain (Forni et al., 2005), and (iii) the dynamic principal components estimated in the time domain (Doz et al., 2011, 2012). The Stock and Watson (2002) approach uses eigenvalues and eigenvectors of the covariance (correlation) matrix of the initial variables to extract the unobservable components; it is similar to a regression on extracted principal components. Forni et al. (2005) use time series spectral analysis methodology, while Doz et al., (2011, 2012) approach use Kalman filtering and state-space modelling methodology. All three approaches represent the same purpose: given a large number of initial variables the purpose is to extract only a small number of factors that summarize most of the information contained in the whole dataset.

In our paper we compare the performance of nowcasting versus short-term forecasting models based on the Doz et al. (2011) approach that has been very recently successfully applied. For example, Porshakov et al. (2016) show the performance of dynamic factor models in predicting Russian GDP growth compared with other alternative specifications, such as random walk model and bridge equations. Kabundi et al. (2016) use the South African data and show that the nowcasting model outperforms all other benchmark models (AR, VAR, Large BVAR) by a significant margin. Chernis et al. (2017) estimate the dynamic factor model to nowcast Canadian GDP growth. Based on the out-of-sample forecast evaluation, they conclude that the dynamic factor model outperforms all other alternative models, such as bridge regression and mixed data sampling (MIDAS) model. Liu et al. (2012) evaluate nowcasts and forecasts of real GDP growth using five alternative models for ten Latin American countries. Based on the out-of-sample evaluation they show that dynamic factor model produces more accurate nowcasts and forecasts relative to other model specifications. Jansen et al. (2016) estimate dynamic factor models for the Euro area and its five largest countries over the periods 1996-2011. Based on the out-of-sample forecast evaluation they show that dynamic and static factor model outperform other models (bridge equation, VAR, MIDAS) especially during the crisis period.

Despite of the recent employment of the dynamic factor model approach, the pieces of the literature are focused on a single or a few countries, employ only a handful of models, differ in the size of the information set, and cover relatively short spans where the variability of the GDP does not represent a significant issue. In this respect, the existing literature does not bring a comparative point of view.

In our paper we account for the limitations mentioned above and extend the literature on nowcasting and short-term forecasting methodology in the following ways. First, we conduct a comparison of a broad range of linear statistical models. Second, we assess nowcasting and short-term forecasting models when the variability of the GDP for each country is increasing over the time; our sample includes the volatile part of the 2008 financial crisis. Further, we also assess whether the nowcasting outperforms all other models under increasing amplitude of volatility in the GDP growth. For that instead of generating artificial GDP growth data, we use the actual GDP growth data for a broad range of countries with different amplitudes in the GDP growth variability. In this way we provide an assessment of the nowcasting under conditions of the varying uncertainty in an economy.

3. The nowcasting model

One of the major advantages of the nowcasting is its ability to use high-frequency data to estimate quarterly macroeconomic variables, particularly real growth of GDP in real time. We now present the methodology for extraction of the dynamic factors via an algorithm proposed by Doz et al., (2011). Then, we show how these extracted factors can be used for nowcasting purposes. According to the Doz et al., (2011) the dynamic factor model in the state-space form can be presented as:

$$y_t = \Lambda f_t + \varepsilon_t \qquad \varepsilon_t \sim N(0,R)$$

$$f_t = A_1 f_{t-1} + A_2 f_{t-2} + ... + A_p f_{t-p} + u_t \qquad u_t \sim N(0,Q)$$

In the above model $f_t(r \times 1)$ is the vector of extracted factors (principal components), $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{nt}]$ is the idiosyncratic component uncorrelated with f_t at all lags and leads (Banbura and Madugno, 2014), Λ is $(n \times r)$ matrix of factor loadings, and $A_1, A_2, ..., A_p$ are $(r \times r)$ matrices of autoregressive coefficients.

According to the Doz et al. (2011), in order to estimate the dynamics of factors, we first need to estimate eigenvalues (λ) and eigenvectors (F) of the initial set of variables with the use of the static principal component approach (Stock and Watson, 2002). Then, we obtain A and Q matrices by estimating the unrestricted VAR model on $\hat{F}$ obtained in the previous step. The elements of matrix R

are estimated as $y_t - \hat{\Lambda}\hat{f}_t = \hat{\varepsilon}_t$. Then, to estimate the remaining elements of f_t we use the two-step Kalman filtering algorithm that involves the following computational steps.[2]

In the first step, the Kalman filter is defined as:

$$\begin{aligned}
&L = \left(\Lambda_t P_{t|t-1} \Lambda_t^{'} + R_t\right)^{-1} \\
&f_{t|t} = f_{t|t-1} + P_{t|t-1} \Lambda^{'} L \left(y_t - \Lambda f_{t|t-1}\right) \\
&P_{t|t} = P_{t|t-1} - P_{t|t-1} \Lambda^{'} L \Lambda P_{t|t-1} \\
&K_t = A P_{t|t} \Lambda^{'} L \\
&f_{t+1|t} = A f_{t|t} + K_t \left(y_t - \Lambda f_{t|t}\right) \\
&P_{t+1|t} = A P_{t|t} A^{'} + Q
\end{aligned}$$

In the second step, smoothing is performed as:

$$f_{t|T} = f_{t|t} + P_{t|t} A^{'} P_{t+1|t}^{-1} \left(f_{t|t+1} - f_{t+1|t}\right)$$

$$P_{t|T} = P_{t|t} + P_{t|t} A^{'} P_{t+1|t}^{-1} \left(P_{t|T+1} - P_{t+1|t}\right) \left(P_{t|t} A^{'} P_{t+1|t}^{-1}\right)^{'}$$

Having estimated dynamic factors by the two-step Kalman filtering approach we can estimate the real growth of GDP in real time ($y_{t|\theta_j}$) by using the following bridge equation (Kabundi et al., 2016):

$$y_{t|\theta_j} = \mu + \Lambda F_t + \varepsilon_{t|\theta_j}\,.$$

In the equation above, μ is a constant, Λ is $(n \times r)$ coefficient matrix, $\varepsilon_{t|\theta_j}$ is a white noise error, and F_t contains the estimated factors using two-step Kalman filter algorithm.

4. Alternative short-term forecasting models

As an alternative to the nowcasting we also aim to assess the performance of nine widely used short-term forecasting models. Unlike the nowcasting model that exploits data in a mixed frequency domain, the alternative models use only quarterly variables. In the current paper we use both univariate and multivariate models. As a univariate model, we use the well known AR(p) model. Adding unobservable factors to the AR(p) process we obtain a so called Factor Augmented AR(p) model. In a multivariate setting, we use a traditional unrestricted VAR(p) model as well as non-traditional and more advanced models like Bayesian VAR, Factor Augmented VAR and Bayesian Factor Augmented VAR. We now briefly present the main idea and computational characteristics of those models.

[2] The MATLAB codes for nowcasting can be accessed at https://www.newyorkfed.org/research/economists/giannone/pub, where the computational steps of the nowcasting algorithms are presented in detail.

We begin with an unrestricted VAR model that can be presented as follows:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + \nu_t, \quad t = 1,...,T$$

In the above mode, y_t is a $(n \times 1)$ vector of variables to be forecasted, A_0 is a $(n \times 1)$ vector of constant terms, $A_1, A_2, ..., A_p$ is a $(n \times n)$ matrix of estimated parameters for different lag length $(l = 1,2,..., \ p)$, and ν_t is $(n \times 1)$ vector of error terms. We assume that $\nu_t \sim N(0, \sigma^2 I_{(n \times n)})$, where $I_{n \times n}$ is $(n \times n)$ identity matrix. The parameters of the unrestricted VAR models can be consistently estimated by using an OLS algorithm as described in Hamilton (1994; pp. 293-294). On the other hand, since in the VAR model we often need to estimate many parameters, such over-parametrization could cause inefficient estimates and large out-of-sample forecast errors. To overcome this over-parametrization problem Bayesian estimation approach presents itself as a viable alternative (Gupta and Kabundi, 2011b).

In this paper we use a standard Bayesian VAR model with well-known Minnesota-style priors. According to these priors, the restrictions are imposed by specifying normal prior distributions with zero mean and small standard deviation decreasing as the number of lags increases. The exception to this is that the coefficient on the first own lag of a variable has a mean of unity. Thus, according to the Minnesota-type priors, the prior mean and standard deviation can be set as follows:

5. The parameters of the first lag of the dependent variables follow an AR(1) process while parameters for other lags equal to zero.
6. The variance of the priors can be specified as follows:

$$\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 \quad \text{if } i = j, \quad \left(\frac{\sigma_i \lambda_1 \lambda_2}{\sigma_j l^{\lambda_3}}\right)^2 \quad \text{if } i \neq j, \quad (\sigma_1 \lambda_4)^2 \quad \text{for the constant term}.$$

In the above, i refers to the dependent variable in the *i*-th equation and j to the independent variable in that equation, σ_i and σ_j are standard errors from the AR regressions estimated via OLS. The ratio of σ_i and σ_j controls for the possibility that variable i and j may have different scales (l is the lag length). The parameters $\lambda's$ are set by a researcher to control the tightness of the prior. In practice, the following parametrization is frequently used: $\lambda_1 = 0.2, \ \lambda_2 = 0.5, \ \lambda_3 = 1 \text{ or } 2, \lambda_4 = 10^5$ (for details see Canova, 2008). After setting the values of the priors we can calculate the posterior parameters using Bayesian approach. For that we can use the following analytical formulas:

$$\beta^* = \left(H^{-1} + \Sigma^{-1} \otimes X_t^{'} X_t\right)^{-1} \left(H^{-1} \tilde{b}_0 + \Sigma^{-1} \otimes X_t^{'} X_t \hat{b}\right),$$

$$\text{var}(\beta^*) = \left(H^{-1} + \Sigma^{-1} \otimes X_t^{'} X_t\right)^{-1}$$

where β^{*} is the vector of the posterior parameters, $\tilde{b}_0$ is the vector of the prior parameters, H is the diagonal matrix with the prior variance on the diagonal, X_t is the $(T \times k)$ matrix of the initial time series $(t = 1,..., T)$, and Σ is the $(k \times k)$ identity matrix.

Given that the nowcasting model comprises of 25 variables, it is reasonable to compare the nowcasting performance with other large-scale models. It is well known that a traditional VAR model cannot accommodate large number of variables as these could cause serious problems with forecasting accuracy of the model. Thus, in addition to small-scale unrestricted VAR and Bayesian VAR models we also use Factor Augmented VAR (FAVAR) and Bayesian Factor Augmented VAR (BFAVAR) models. Following Bernanke et al. (2005), the FAVAR and BFAVAR model can be presented as follows:

$$\begin{vmatrix} Y_t \\ F_t \end{vmatrix} = A_1 \begin{vmatrix} Y_{t-1} \\ F_{t-1} \end{vmatrix} + A_2 \begin{vmatrix} Y_{t-2} \\ F_{t-2} \end{vmatrix} + ... + A_p \begin{vmatrix} Y_{t-p} \\ F_{t-p} \end{vmatrix} + \begin{vmatrix} v_t \\ u_t \end{vmatrix}.$$

In the above model, Y_t is the vector of observable variables, F_t is the vector of unobservable variables estimated via a two-step Kalman filter algorithm, $A_1, A_2,..., A_p$ are $(r \times r)$ matrices of estimated parameters, and v_t and u_t are the error terms with zero mean and diagonal variance-covariance matrices, $Q \text{ and } V$. In the presented model, the parameters can be estimated either by the OLS or via the Bayesian estimation approach. In the FAVAR and BFAVAR models, the first imperative is to estimate the dynamics of the unobservable (or principal) components.

As a rule, FAVAR and BFAVAR models can be estimated in two steps: in the first step we estimate the dynamics of principal components and in the second step we estimate the model parameters and conduct forecasts. As mentioned in the previous section, the principal components can be estimated via three popular approaches. In this paper we follow the approach suggested by Doz et al., (2011): we use a dynamic factor model developed in the time domain where factors can be estimated in a similar manner presented in the section 3. After estimating the dynamics of factors, the FAVAR and BFAVAR models can be estimated in a traditional manner. In other words, we use a small scale VAR model containing variables of interest augmented by extracted factors.

5. Data and descriptive statistics

For nowcasting and short-term forecasting purposes we use the dataset containing 25 monthly variables on business tendency surveys. In Table 1 we present a complete list of variables used for nowcasting and short-term forecasting for selected countries. Gianonne, et al. (2008) and Alvarez et al., (2016) show that medium-sized data sets (i.e., with 10-30 variables) perform equally well as models with larger data sets with over 100 variables. With these considerations in mind, we select 25 variables from the business tendency surveys that satisfy three conditions (Chernis and Sekkel, 2017): they must be (i) timely, (ii) updated frequently (e.g., monthly), and (iii) helpful to predict a real GDP growth.

In Table 1 we list in detail all 25 variables. The source is the OECD database. The monthly data are available on a seasonally adjusted basis from the source. All business tendency surveys variables were standardized by subtracting the mean and dividing by the standard deviation. The variables based on the business tendency surveys satisfy all three conditions. First, they are timely as they are usually available within or at the end of the reference month (Gayer et al., 2014). Second, they are updated on a monthly basis. This is in contrast to the regularly used data on production and sales, and some of the monetary and financial indicators that are not timely. Specifically, for our set of countries the industrial production and retail trade indices are available around 4-7 weeks after the end of the current month (for example data referring to January is available by the mid or end of March). Similar lags are present also for monetary aggregates (about 5 weeks), imports and exports indices (3-5 weeks). Thus, from the timeliness perspective the business tendency surveys data are truly timely when compared with the real, external and monetary sector data.

Third, to verify whether business tendency surveys data are helpful to predict real GDP growth we calculated correlation coefficients (not reported, but available upon request) for all countries included in our data set. If there exists a strong or moderate linear relationship between the real GDP growth and business tendency surveys data, then a particular variable is considered to be helpful to predict real GDP growth in real time. We considered the following three extents of correlation: (i) the values between 0 and 0.3 (0 and -0.3) indicate a weak positive (negative) linear relationship, (ii) values between 0.3 and 0.7 (-0.3 and -0.7) indicate a moderate positive (negative) linear relationship and (iii) values between 0.7 and 1.0 (-0.7 and -1.0) indicate a strong positive (negative) linear relationship. For all 25 variables we identify either a moderate or strong relationship with the real GDP.

Based on the above, we conclude that the selected business tendency surveys data meet all three conditions and are good candidates for nowcasting and short-term forecasting experiments. Additional feature of the business tendency and consumer surveys data is their high degree of stability, since they are usually subject to no or only minor revisions (Gayer, Girardi and Reuter, 2014).

The second set of data we use are the yearly real GDP growth rates for 22 Europe an countries listed in Table 2; the countries are members of the OECD. We do not use the full OECD set due to the inconsistencies in data availability for the rest of the countries). Further, we have computed the coefficient of variability (C_v ; in percent) defined as:

$$C_v = \sigma_y \times 100 / \overline{y},$$

where $\overline{y}$ is an average value of the GDP growth, and the variability of the GDP growth (σ_y) is defined as:

$$\sigma_y = \sqrt{\sum_{t=1}^{T} \left(y_t - \hat{y}_t \right) / (n-p)},$$

where, y_t is the GDP growth at time *t*, $\hat{y}_t$ is a fitted value of the GDP growth at time *t* calculated by trend line equation, and *p* is the number of parameters in the trend line equation (*p*=2).

In order to understand how the variability of the real GDP growth changes, we divide the whole period into two sub-periods: before and after the global financial crisis (GFC). Then, we compute actual values of the coefficient of variability for two sub-periods: 2000Q1 - 2007Q4 and 2008Q1 - 2017Q4 (see Table 2).

From Table 2 we can see that the coefficient of variability increased during the post-crisis period for 19 countries. We assume that increase in the coefficient of variability might be caused mainly by the world financial crisis in the end of 2008. Further, we can compare minimum and maximum values of the coefficient of variability for various countries and two sub-periods separately. For example, the minimum value of the coefficient of variability in pre-crisis period is observed for the United Kingdom (0.41 %), while the maximum value is observed for Luxembourg (2.95%). Hence the amplitude of variability during the pre-crisis period is 2.54 percentage points (2.95-0.41). During the post-crisis period, the minimum value of the coefficient of variability is observed for Switzerland (1.07 %), while the maximum value is observed for Latvia (6.34 %). Hence the amplitude of variability during the post-crisis period is 5.27 percentage points (6.34 –1.07). Thus, we conclude that during the post-crisis period the amplitude of the coefficient of variability among countries substantially increased.

We aim to assess whether the nowcasting algorithm is able to outperform short-term forecasting algorithms when the coefficient of variability of the real GDP growth is steadily increasing both in time and across of countries, as we evidenced earlier. The empirical assessment is grounded in the use of the actual data on real GDP growth and our conclusions are based on the real data rather than artificial generated data.[3]

7. Experiment design

We employ recursive regression scheme to analyze the relative performances of nowcasting versus short-term forecasting models (AR, VAR, BVAR, FAAR, FAVAR and BFAVAR) when the coefficient of variability of the real GDP is changing (increasing and decreasing) both in time and across various countries. Following Gayer, Girardi and Reuter (2014) we implement a recursive rather than a rolling regression scheme. Based on the out-of-sample RMSFE criterion we assess performances of the nowcasting versus alternative short-term forecasting models.

For out-of-sample experiment we divide the whole data sample into the in-sample and out-of-sample parts. In order to conduct out-of-sample experiments we transform all our monthly data to quarterly data by averaging three months of the balance data. This is because the real GDP growth data in our set are in quarterly frequency. Then, taking into account the length of the real GDP quarterly data for each country we choose the appropriate length of the in-sample and out of sample size: in-sample size is 70% of observations while remaining 30% is the out of sample size. In Table 3 we report the details specific to each country.

For out-of-sample forecast comparison we use recursive regression scheme. A forecasting model with a recursive window assumes that initial estimation period is fixed and additional observations are added one at a time to the estimation period. For nowcasting model the recursive simulation experiment is designed as follows. We use Austria (the first country in Table 3) as an example to explain the steps of the experiments; of course, the steps of the experiments remain the same for all other countries included in our analysis. The available time span for Austria ranges from 1997Q1 to 2017Q4. Hence, according to the 70/30 rule we have 59 observations for in-sample period and 25 observations for out-of-sample period. Having in-sample period, first we estimate the dynamic factors for the period of 1997Q1-2011Q4. Our purpose is to forecast the real GDP growth for the 2011Q4, because we assume that for this quarter we do not have yet the actual value of real GDP growth. Therefore we can include the fourth quarter of 2011Q4 in the sample, because we assume that, with exception of the real GDP growth, all other additional variables are known at that time. After estimating the factor dynamics we skip 2011Q4 quarter and estimate bivariate regression model for the period 19971-2011Q3 (which

[3] An alternative approach would be based on some distributional assumptions to generate artificial real GDP data and use of the Monte-Carlo simulations.

coincides with the in-sample period 59 observations), where the dependent variable is real GDP growth, and the independent variables are extracted factors. Then, having estimated coefficients for the bivariate regression model along with the actual value of the extracted factors for the 2011Q4 we can compute the value of the real GDP for the fourth quarter of 2011. After that, we increase our sample by one observation (that is 1997Q1 – 2012Q1) and then again we re-estimate the dynamic factors. Then again we skip the most recent quarter (2012Q1) and estimate the bivariate regression model for the period of 1997Q1-2011Q4 (which coincides with the in-sample period with 60 observations, because we have added one additional observation). After obtaining actual values of the dynamic factors for 2012Q1 we calculate the value of real GDP growth for 2012Q1. Continuing in this manner we obtain 25 points of one-step-ahead forecasts for the Austrian real GDP growth rate. In the same manner we can conduct out of sample nowcasting experiments for the other countries included in our analysis.

A slightly different design is used for the short-term forecasting models (VAR, BVAR, FAVAR and BFAVAR). For these models the out-of-sample recursive experiments proceeds as follows. Let's again consider the case of Austria (the same steps apply for other countries). First we estimate the factors for 1997Q1-2011Q4 (59 observations), because in this case we assume that the actual values of the additional variables are not known. Using regression model, we estimate the unknown parameters and generate one-step-ahead forecast. Then, we increase the sample size by one (60 observations) and generate again one-step-ahead forecast. We continue increasing the sample size until we have 84 observations in the sample, in which case we compute the last forecast for 2017Q4. In this manner we obtain 25 points for one-step-ahead forecasts.

The main differences in the experiment design is that for the nowcasting model we take into account all information available in the current quarter, while for the short-term forecasting model we ignore the information available in the current quarter, as it would not be available in reality. The main task is to describe whether the information available in the current quarter helps to improve the accuracy of the forecast for the target variable. Thus, after obtaining all forecasts points for all available models we can compare nowcasting and different short-term forecasting models to find the best choice. To do that, we use the out-of-sample nowcasts and short-term forecasts from recursive regression scheme to check the forecast accuracy produced by different models for different countries. We assess the forecast accuracy with the standard Root Mean Squared Forecast Error (RMSE) measure that is defined as:

$$RMSFE_{gdp}^{i} = \sqrt{\frac{1}{T^{*}-1}\sum_{t=1}^{T^{*}-1}\left(\hat{y}_{t}-y_{t}\right)^{2}}$$

where $RMSFE_{gdp}^{i}$ is the calculated Root Mean Squared Forecast Error for i-th country, y_t is the actual value of the GDP growth rate, $\hat{y}_t$ is the estimated value of the GDP growth rate, and T^* denotes the out-of-sample period, which is different among of countries.

8. Empirical results

In this section we present estimation results for 10 models; namely one nowcasting model and 9 alternative models for short-term forecasting. In order to use available information in a current quarter, we use a nowcasting model based on extraction of factors that was proposed by Gianonne et al. (2008). In contrast, the short-term forecasting models generate forecasts based on the past information set. At the same time we also want to check the behavior of nowcasting model versus short-term forecasting models when the coefficient of variability of real GDP is changing (increasing or decreasing) both in time and across countries.

We use different lag lengths to estimate parameters for short-term forecasting models, particularly from one lag up to four lags. The maximum number of lags in forecasting models is 4, because real GDP data is quarterly. In addition all additional variables also were transformed from monthly to quarterly frequency. Further, we estimate short-term forecasting models separately for one, two, three and four lags. Finally, we compare estimated models to each other and select only the model that provides a minimum value of the RMSFE.

In order to determine the number of common factors we use a simple approach: we retain the factors with eigenvalues more than 1. In this way we are able to determine the appropriate number of static factors.[4] For example, Table 3 presents the number of additional explanatory variables (column 5), the number of extracted static factors (column 6) and the total variance explained by the extracted factors (column 7). The numbers presented in Table 3 can be explained through an example of the Austrian data. For Austria the number of additional variables that were used to extract the static factors is 25 (column 5). Using these 25 additional variables on business tendency surveys, we extracted 3 static factors which have eigenvalues more than 1 (column 6). These 3 static factors explain 82.95% of the variance of the initial variables (column 7). Hence, this simple procedure allows extracting the maximum number of static factors. In the same manner we have extracted the number of static factors for all remaining countries.

[4] An alternative would be to use formal statistical tests. For example to determine the number of common factors the Bai and Ng (2002) information criterion can be used. Also it is possible to implement recently proposed criterion by Alessi et al. (2010).

Thus, we select the appropriate number of dynamic factors that cannot exceed the number of static factors (D'Agostino and Gianonne, 2012). Therefore, we can restrict the number of dynamic factors by the maximum number of static factors. For example, we have 3 static factors for Austria. Therefore, the maximum number of dynamic factors can be less or equal to 3. Following D'Agostino and Gianonne (2012) we chose different combinations of dynamic and static factors to obtain the maximum number of all possible combinations.[5] In case of our example country (Austria) the maximum equals to 6. The best of all possible combinations of static and dynamic factors is chosen based on the RMSFE criterion.[6]

In Tables 4 we present results on the forecasting performance of the 9 statistical short-term forecasting models for 22 European countries. In Tables 4 we report forecasting performance results for one-period-ahead forecasts as we are interested in one period forecast for the current quarter.

In Table 4 for the AR model, we report the chosen lag length and RMSFE indices. In order to select the appropriate lag length, we run the AR model separately for 1, 2, 3 and 4 lags and select those that exhibit smaller values of the RMSFE. We proceed in the same way for the unrestricted VAR, but in contrast to AR model, we run model for 4 key macroeconomic variables, namely GDP growth rate, inflation, nominal short-term interest rate and harmonized unemployment rate (see Pirshel and Wolters, 2014). Again as in the case of AR, we run VAR models separately for 1, 2, 3 and 4 lags and we choose those lags based on the smallest value of the RMSFE.

In order to run a small scale Bayesian VAR we go through the same steps as in the case of VAR. The difference is that in case of Bayesian VAR, we must also use two additional parameters, particularly overall tightness and lag decay. Following Gupta and Kabundi (2011b) overall tightness is set to range from 0.1-0.3 with increments of 0.1. The decay factor takes values of 1 and 2. Thus we run a grid search over all possible combinations of hyper parameters and lag lengths. In our case, the lag length equals to 1,2,3 and 4, overall tightness is 0.1, 0.2 and 0.3, and lag decay takes values of 1 and 2. Thus all possible combinations of hyper parameters (overall tightness and lag decay) and lag length yield 24 BVAR models (for 22 countries it yields 24 times 22 = 528 models). As in the case of AR and VAR the out-of-sample forecast accuracy is measured in terms of RMSFE. We select the hyperparameters and lag length by

[5] Thus, we can conduct experiments for different combinations of dynamic and static factors: for example, one dynamic and one static factors. Then if we choose 2 static factors, then we can have one dynamic and two static or two dynamic and two static factors. Then if we select 3 static factors then the possible combinations can be, one dynamic three static, two dynamic and three static, three dynamic and three static factors.

[6] We should mention that all necessary procedures for nowcasting and short-term-forecasting were performed with software specially created for this purpose. This software is written with two powerful object-oriented programming languages C#.NET and VBA (Visual Basic for Application). This software is working directly in MS Excel 2010, 2013 spreadsheets. The software can be provided upon request.

inspecting the pseudo out-of-sample forecast performances; the model with the minimum RMSFE is selected as the best model and its results are reported in Table 4.

To estimate the Factor augmented AR (FAAR) model, we repeat the same steps as in the case of AR model. But the main difference is that here we use additional factors. In Table 4 we report results for two FAAR models, particularly FAAR model with static factors and FAAR model with dynamic factors. To select the appropriate combination of dynamic and static factors as well as the lag lengths, we go through all possible combinations for the dynamic and static factors.[7] After that we select the appropriate number of static and dynamic factors and lag length by assessing the out-of-sample forecast performances: the FAAR model with the minimum RMSFE is selected as the best model and the corresponding number of static and dynamic factors and lag length we report in Table 4. In a similar manner we select an appropriate model for the Factor augmented VAR and Factor augmented BVAR. The only difference is that here we use four target variables, GDP growth rate, inflation, nominal short-term interest rate and unemployment rate (see Pirshel and Wolters, 2014).

In order to check whether the obtained results for RMSFE are significantly different among models, we also perform across-model tests between nowcasting and 9 short-term forecasting models, namely AR, FAAR, FAVAR and BFAVAR. The across-model test is based on a statistic proposed by Diebold and Mariano (1995). Let ε_t^{nc} denote the forecast errors from the nowcasting model and ε_t^{i} denote the forecast errors from the alternative short-term forecasting models (i = AR, VAR, BVAR, FAAR, FAVAR and BFAVAR). Then the Diebold-Mariano test statistics is defined as:

$$s = l / \sigma_l ,$$

where l is the sample mean of the loss $l_t = \left(\varepsilon_t^{nc}\right)^2 - \left(\varepsilon_t^{i}\right)^2$, and σ_l is the standard error of l. The Diebold-Mariano statistic is asymptotically distributed as a standard normal random variable and it can be estimated under the null hypothesis of equal forecast accuracy; H_0: $l = 0$. If $s < 0$, then nowcasting outperforms the alternative short-term forecasting models and vice versa. The results of Diebold-Mariano statistics are presented in Table 5 and we conclude that nowcasting significantly outperforms BVAR and BFAVAR_SW and BFAVAR_TS models for most countries. In contrast, when we compare the nowcasting results with the AR, FAAR_SW, FAAR_TS and FAVAR_SW, FAVAR_TS models then we see that the there is no strong evidence to prefer one over the others.

[7] We illustrate it on an example. In case of Austria we have extracted 3 static factors and therefore we have 6 combinations in total. Taking into account that we run models for 4 different lag lengths, we have 24 scenarios in total (6 times 4). Then we recursively estimate each model and construct one-step-ahead forecast.

Table 6 presents the models' performances in terms of rank in ascending order based on the RMSFE values; all ranks presented in Table 6 have been derived from RMSFE indices presented in Tables 4 .[8] These are absolute results that we also translate into relative terms. Based on the data in Table 6, we can directly observe the distribution of ranks among all algorithms. For all countries under research, nowcasting algorithm exhibits the lowest RMSFE in about 50.0%. This means that nowcasting algorithm, in general, outperforms all competing short-term forecasting algorithms and exhibits an advantage over all alternative models for forecasting real GDP in real time. The result also means that all additional information that we have in real time are useful for improving the real GDP forecast. From Table 6 we can observe that nowcasting algorithm is followed in terms of accuracy by the Factor based AR models, specifically FAAR_TS (13.6%), FAAR_SW (9.1%) and FAVAR_SW (9.1%) models. This result again shows that models with additional explanatory variables are able to provide more accurate forecasts than traditional small scale benchmark models like VAR or small-scale BVAR. From Table 6 we can also observe that Bayesian VAR and Factor Augmented BVAR are last place. The result is not surprising because these models are better suited for forecasting more than one period ahead.

Based on the results provided in Tables 6 we conclude that for one-step-ahead real GDP forecast it is optimal to use nowcasting technique with the help of additional business tendency surveys information. The nowcasting model in general outperforms all alternative short-term forecasting models including the large scale models that are known to do well given their advantage in accommodating many variables. Further, short-term forecasting models are not able to absorb monthly real time information and produce forecasts based only on the past information set. Monthly statistical information contain valuable information that can be extracted by using the nowcasting algorithm and therefore this method could provide the largest gain in accuracy for one period forecasts. Thus, the relative benefit from using nowcasting algorithm is the improvement of the assessment of the current state of economy. By using actual data for various countries we see that nowcasting algorithm outperforms all competing short term forecasting models, even when the coefficient of variability of the real GDP is changing over time. We also conclude that early available information is able to substantially improve the forecast accuracy even when the uncertainty becomes relatively large.

[8] In Tables 4 we present the values of the RMSFE: the lowest value of RMSFE means that this particular algorithm outperforms all other alternative algorithms. For example, let's consider again the case of Austria (the way of assessment is same for all other countries): from Table 4 we see that for Austria the minimum value of RMSFE is observed for nowcatsing algorithm – hence, this method receives the first rank. The second lowest value of RMSFE is observed for FAAR_TS – hence, this method receives the second rank. FAAR_SW algorithm receives the third rank, and so on.

9. Conclusions

We deliver two contributions to the empirical literature on forecasting real GDP in the short run. The first contribution is a comparison of ten statistical models for 22 European countries, utilizing the same information set across countries. In essence, we compare nowcasting performance with alternative forecasting models when the volatility is changing over time. Our sample span allows us to compare the forecasting abilities of different models for the period after the financial crisis which is much more volatile than the pre-crisis period. The second contribution concerns the potential usefulness of nowcasting algorithm for one period real GDP forecast when the real GDP dynamics varies across countries. Based on 22 countries dataset we show that the nowcasting algorithm is quite useful even when the coefficient of variability amplitude is changing both over time and across countries.

We summarize our findings as follows. First, monthly business tendency surveys data contain valuable information that can be extracted by nowcasting procedure. Based on our analysis we show that monthly information is very useful for nowcasting: using real time information for nowcasting algorithm it is possible to increase accuracy for the current quarter real GDP foreacast. Traditional statistical forecasting models do not take into account monthly information that is available in time. Hence, based on the nowcasting algorithm it is possible to improve the assessment of the current state of the economy. Based on calculated RMSFE indices we conclude that nowcasting algorithm outperforms all competing short-term forecasting models when the variability is changing over time. Thus, monthly information that is available earlier is able to substantially improve forecast accuracy, even when the variability of dependent variables during the time is changing.

Second, the nowcasting model which is based on the dynamic factor model approach displays the best forecasting capabilities for a prevailing part of countries under our consideration. The results show that the nowcasting algorithm performs better than all competing short-term forecasting models, even when the amplitude of variability of the real GDP is changing among the countries. When we apply Diebold-Mariano test statistics we see that nowcasting significantly outperforms BVAR and BFAVAR models, but comparing with AR, FAAR and FAVAR we conclude that there is not sufficient evidence to prefer one over another.

The results of our comparative analysis may be useful to policy makers, financial analyst and economic agents. They can use nowcasting algorithm for improving assessment of the current state of economy even in time of uncertainty. Thus, the nowcasting algorithm based on dynamic factor model is the obvious candidate model for generating one period accurate forecast for real GDP growth.

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Table 1: Dataset of business tendency surveys data

No	Variable
1	Manufacturing production tendency, balance, percentage
2	Manufacturing production future tendency, balance, percentage
3	Manufacturing finished goods stocks level, balance, percentage
4	Manufacturing order books level, balance, percentage
5	Manufacturing export order books (or demand) level, balance, percentage
6	Manufacturing selling prices future tendency, balance, percentage
7	Manufacturing employment future tendency, balance, percentage
8	Manufacturing confidence indicators, balance, percentage
9	Construction business situation, tendency, balance, percentage
10	Construction confidence indicators, balance, percentage
11	Construction order books level, balance, percentage
12	Construction employment future tendency, balance, percentage
13	Construction selling prices future tendency, balance, percentage
14	Retail trade business situation tendency, balance, percentage
15	Retail trade business situation future tendency, balance, percentage
16	Retail trade confidence indicators, balance, percentage
17	Retail trade volume of stocks, balance, percentage
18	Retail trade employment future tendency, balance, percentage
19	Retail trade order intentions (or demand) future tendency, balance, percentage
20	Service (excl. retail trade) business situation tendency, balance, percentage
21	Service (excl. retail trade) confidence indicators, balance, percentage
22	Service (excl. retail trade) demand evolution tendency, balance, percentage
23	Service (excl. retail trade) demand evolution future tendency, balance, percentage
24	Service (excl. retail trade) employment tendency, balance, percentage
25	Service (excl. retail trade) employment future tendency, balance, percentage

Note: We perform no differencing or log-differencing data transformation, Data are seasonally adjusted. All series are standardized by subtracting the mean and dividing by the standard deviation. Source of the data is the OECD – Organization for economic co-operation and development: Source http://stats.oecd.org/.

Table 2. Real GDP growth rate and coefficient of variability (in %)

	2000	2005	2010	2015	2016	2017	Coefficient of variability 2000-2007 %	Coefficient of variability 2008-2017, %
Austria	3.37	2.14	1.93	1.09	1.45	2.93	1.11	1.48
Belgium	3.63	2.09	2.74	1.40	1.47	1.69	0.90	1.11
Czech Republic	4.27	6.53	2.27	5.31	2.59	4.29	0.69	3.16
Denmark	3.75	2.34	1.87	1.61	1.96	2.11	1.32	1.92
Estonia	10.57	9.37	2.26	1.67	2.06	4.85	1.53	5.05
Finland	5.63	2.78	2.99	0.14	2.14	2.75	1.35	2.64
France	3.88	1.61	1.97	1.07	1.19	1.82	1.34	1.19
Germany	2.96	0.71	4.09	1.75	1.94	2.23	1.41	1.91
Greece	3.92	0.60	-5.48	-0.29	-0.24	1.35	1.26	5.46
Hungary	4.21	4.39	0.68	3.37	2.21	3.99	1.04	3.51
Italy	3.71	0.95	1.69	0.95	0.86	1.47	1.01	2.08
Latvia	5.41	10.70	-3.94	2.97	2.21	4.55	2.34	6.34
Luxembourg	8.24	3.17	4.87	2.86	3.08	2.30	2.95	3.41
Netherlands	4.24	2.16	1.40	2.26	2.21	3.11	1.93	2.20
Poland	4.26	3.49	3.61	3.84	2.86	4.55	2.14	1.28
Portugal	3.79	0.77	1.90	1.82	1.62	2.67	1.95	2.68
Slovak Republic	1.21	6.75	5.04	3.85	3.32	3.40	2.20	2.40
Slovenia	4.16	4.00	1.24	2.26	3.15	5.00	1.59	3.89
Spain	5.29	3.72	0.01	3.43	3.27	3.05	0.54	3.73
Sweden	4.74	2.82	5.99	4.52	3.23	2.40	1.03	2.55
Switzerland	3.94	3.12	3.00	1.23	1.38	1.05	1.79	1.07
United Kingdom	3.66	3.10	1.69	2.35	1.94	1.74	0.41	2.16

Note: This table presents the average annual real GDP growth rate (calculated by geomean formula). The last two columns contain the values of the coefficient of variability. The coefficients of variability are calculated for two sub-periods, particularly before crisis and after the crisis. The coefficient of variability is always positive; if its values are larger then we conclude that during the post-crisis sub-period the variability of the real GDP growth was higher than before the crisis. As we can see for most of the countries (19 countries) the coefficient of variability during the second sub-period increased, while for three countries (France, Poland and Switzerland) decreased.

Table 3. The appropriate number of static factors

Country	Time spans	The number of observations for in-sample period	The number of observations for out-of-sample period	Number of additional explanatory variables	Number of extracted factors with eigenvalues more than 1	Total variance explained, %
1	2	3	4	5	6	7
Austria	1997Q1 – 2017Q4	59	25	25	3	82.95
Belgium	1995Q1 – 2017Q4	65	27	25	4	88.56
Czech Republic	2003Q1 – 2017Q4	41	18	25	4	84.59
Denmark	2000Q1 – 2017Q4	50	21	25	4	87.83
Estonia	2003Q1 – 2017Q4	41	18	22	2	87.62
Finland	1997Q1 – 2017Q4	58	25	25	4	82.94
France	1991Q1 – 2017Q4	76	32	25	3	83.99
Germany	1995Q1 – 2017Q4	64	27	24	4	90.86
Greece	1997Q1 – 2017Q4	58	25	25	4	86.13
Hungary	2002Q1 – 2017Q4	44	19	25	3	89.77
Italy	1998Q1 – 2017Q4	56	24	25	4	86.87
Latvia	2002Q1 – 2017Q4	44	19	25	2	90.03
Luxembourg	1991Q1 – 2017Q4	75	32	13	2	78.01
Netherlands	1996Q1 – 2017Q4	62	26	25	3	83.87
Poland	1998Q1 – 2017Q4	56	24	19	3	87.22
Portugal	1997Q1 – 2017Q4	59	25	25	4	89.31
Slovak Republic	2002Q1 – 2017Q4	45	19	25	5	86.71
Slovenia	2002Q1 – 2017Q4	44	19	24	3	85.64
Spain	1997Q1 – 2017Q4	59	25	25	4	90.95
Sweden	1996Q1 – 2017Q4	61	26	25	4	86.16
Switzerland	1999Q1 – 2017Q4	53	23	14	3	86.25
United Kingdom	1997Q1 – 2017Q4	59	25	25	4	89.62

Note: In this table we present some important characteristics to select the appropriate number of factors. In column 2 we present the time spans which have been used for unobservable factor extraction. Columns 3 and 4 present the number of observations for in-sample and out of sample periods for each countries separately. Then, in the column 5 we present the number of available additional explanatory variables (for each country separately). In column 6, we present the number of extracted factors which have eigenvalues more than 1. The total variance explained is shown incolumn 7. Austria can serve as an illustrative example: we have 25 additional explanatory data on business tendency surveys. Using these additional dataset we have extracted 3 unobservable factors, which explain 82.95 % of variation of the initial variables. In the same manner we can explain the data presented for other countries.

Table 4. Out of sample RMSFE indices for real GDP growth (Panel A)

Country	Nowcasting				AR		VAR		Small BVAR				FAAR_SW			FAAR_TS			
	r	q	p	RMSFE	p	RMSFE	p	RMSFE	p	w	d	RMSFE	r	p	RMSFE	r	q	p	RMSFE
Austria	3	1	1	***0.364***	3	*0.432*	2	*0.452*	1	0.3	1	*0.525*	1	3	*0.427*	3	1	1	*0.411*
Belgium	1	1	1	*0.268*	1	*0.275*	1	*0.257*	2	0.3	1	*0.298*	4	1	*0.270*	4	4	1	*0.273*
Czech Republic	2	1	4	***0.659***	1	*0.767*	1	*0.838*	2	0.3	1	*0.826*	1	2	*0.717*	1	1	2	*0.707*
Denmark	4	4	1	*0.511*	1	*0.511*	1	*0.513*	1	0.3	1	*0.608*	4	1	***0.502***	4	4	1	*0.509*
Estonia	1	1	1	*0.740*	4	***0.648***	2	*1.420*	3	0.3	1	*0.924*	1	1	*0.738*	1	1	1	*0.716*
Finland	2	2	3	*0.550*	3	*0.656*	2	*0.584*	4	0.3	1	*0.656*	4	1	*0.600*	4	1	1	*0.597*
France	1	1	4	*0.287*	2	*0.313*	2	*0.332*	1	0.3	1	*0.374*	2	3	***0.277***	1	1	3	*0.286*
Germany	2	1	2	***0.371***	1	*0.458*	1	*0.527*	1	0.3	1	*0.533*	1	3	*0.422*	2	1	4	*0.38*
Greece	3	1	4	*0.995*	4	***0.929***	3	*1.169*	3	0.3	1	*1.292*	4	1	*1.072*	4	4	1	*1.104*
Hungary	3	1	1	*0.569*	2	*0.603*	1	*0.617*	1	0.3	1	*0.670*	2	4	*0.525*	1	1	4	***0.518***
Italy	4	1	1	***0.257***	1	*0.274*	1	*0.276*	4	0.3	1	*0.272*	1	1	*0.282*	1	1	1	*0.281*
Latvia	1	1	1	***0.587***	2	*0.712*	2	*0.890*	2	0.3	1	*0.824*	2	3	*0.699*	1	1	1	*0.702*
Luxembourg	2	1	4	*1.700*	1	*1.626*	2	***1.615***	2	0.3	1	*1.792*	1	2	*1.629*	1	1	2	*1.619*
Netherlands	3	2	4	*0.380*	3	*0.503*	1	*0.493*	1	0.3	1	*0.584*	2	2	*0.367*	2	2	2	***0.349***
Poland	2	1	2	***0.503***	3	*0.564*	4	*0.570*	1	0.3	1	*0.584*	1	3	*0.562*	2	1	1	*0.537*
Portugal	4	1	4	***0.538***	2	*0.637*	2	*0.665*	1	0.3	1	*0.700*	4	2	*0.554*	4	3	3	*0.559*
Slovak Republic	2	1	4	*0.211*	4	*0.174*	1	*0.389*	3	0.1	1	*0.133*	1	1	*0.238*	2	1	1	*0.137*
Slovenia	3	1	4	***0.457***	1	*0.475*	1	*0.536*	2	0.3	1	*0.512*	1	2	*0.461*	3	1	3	*0.468*
Spain	4	2	4	*0.232*	4	*0.219*	1	*0.234*	2	0.3	1	*0.243*	4	1	*0.237*	4	1	1	***0.210***
Sweden	3	3	1	***0.544***	4	*0.682*	3	*0.723*	1	0.3	1	*0.862*	3	3	*0.612*	2	2	3	*0.578*
Switzerland	1	1	1	***0.283***	2	*0.348*	1	*0.347*	1	0.3	1	*0.423*	1	2	*0.333*	3	3	2	*0.321*
United Kingdom	2	1	1	***0.332***	3	*0.429*	1	*0.445*	1	0.3	1	*0.489*	1	3	*0.424*	2	2	3	*0.408*

Note: In this table we present nowcasting and short-term forecasting results for 22 European countries. We put nowcasting results in competition with 9 alternative short-term forecasting results (AR, VAR, small BVAR, FAAR, FAVAR and BFAVAR). For model comparison we use RMSFE measure-root mean squared forecast error. r-is the number of static factors, q-is the number of dynamic factors, p – number of lags, w- overall tightness for Bayesian model, d – is the decay parameter for Bayesian model. For example let's explain results for the first country in the tables, that is Austria. For nowcasting we have extracted the optimal combinations of static and dynamic factors, which is r = 3 static and q = 1 dynamic factors. The optimal number of lags is p = 1. The calculated value of RMSFE = 0.364. All other models can be explained in a similar manner, with exception of Bayesian method where in addition we have overall tightness (w) and lag decay (d).

Table 4. Out of sample RMSFE indices for real GDP growth (Panel B)

Country	FAVAR_SW			FAVAR_TS				BFAVAR_SW					BFAVAR_TS					
	r	p	RMSFE	r	q	p	RMSFE	r	p	w	d	RMSFE	r	q	p	w	d	RMSFE
Austria	1	2	*0.455*	3	1	1	*0.429*	1	2	0.3	2	*0.527*	3	1	1	0.3	1	*0.528*
Belgium	4	1	***0.246***	4	4	1	*0.249*	4	1	0.3	1	*0.295*	4	4	1	0.3	1	*0.295*
Czech Republic	1	2	*0.808*	1	1	2	*0.808*	1	2	0.3	1	*0.828*	1	1	2	0.3	1	*0.828*
Denmark	1	1	*0.504*	2	1	1	*0.504*	1	1	0.3	1	*0.608*	2	1	1	0.3	1	*0.609*
Estonia	1	1	*0.934*	2	1	1	*0.903*	1	1	0.3	1	*0.893*	2	1	1	0.3	1	*0.897*
Finland	1	2	***0.512***	2	1	2	*0.558*	1	2	0.3	1	*0.658*	2	1	2	0.3	1	*0.677*
France	3	2	*0.318*	3	3	2	*0.311*	3	2	0.3	1	*0.38*	3	3	2	0.3	1	*0.381*
Germany	1	2	*0.495*	1	1	2	*0.466*	1	2	0.3	2	*0.546*	1	1	2	0.3	2	*0.547*
Greece	1	1	*1.204*	4	2	1	*1.187*	1	1	0.3	1	*1.319*	4	2	1	0.3	1	*1.318*
Hungary	3	1	*0.602*	3	3	1	*0.599*	3	1	0.3	1	*0.686*	3	3	1	0.3	1	*0.687*
Italy	3	1	*0.273*	2	1	1	*0.27*	3	1	0.3	1	*0.273*	2	1	1	0.3	1	*0.273*
Latvia	1	2	*1.091*	2	1	2	*1.043*	1	2	0.3	1	*0.82*	2	1	2	0.3	1	*0.81*
Luxembourg	1	2	*1.617*	2	1	2	*1.624*	1	2	0.3	1	*1.788*	2	1	2	0.3	1	*1.79*
Netherlands	2	2	*0.435*	2	2	3	*0.418*	2	2	0.3	2	*0.589*	2	2	3	0.3	2	*0.591*
Poland	1	4	*0.542*	3	1	4	*0.512*	1	4	0.3	1	*0.592*	3	1	4	0.3	1	*0.594*
Portugal	1	1	*0.657*	2	2	1	*0.656*	1	1	0.3	1	*0.708*	2	2	1	0.3	1	*0.712*
Slovak Republic	4	1	*0.443*	2	1	1	*0.285*	4	1	0.1	1	*0.181*	2	1	1	0.3	1	***0.121***
Slovenia	1	1	*0.531*	2	1	1	*0.524*	1	1	0.3	1	*0.515*	2	1	1	0.3	1	*0.534*
Spain	2	1	*0.235*	4	1	1	*0.213*	2	1	0.3	1	*0.244*	4	1	1	0.3	1	*0.239*
Sweden	1	3	*0.683*	2	2	3	*0.674*	1	3	0.3	1	*0.871*	2	2	3	0.3	1	*0.886*
Switzerland	1	1	*0.376*	2	1	2	*0.363*	1	1	0.3	1	*0.425*	2	1	2	0.3	1	*0.429*
United Kingdom	2	1	*0.446*	4	3	1	*0.432*	2	1	0.3	1	*0.492*	4	3	1	0.3	1	*0.492*

Note: In this table we present nowcasting and short-term forecasting results for 22 European countries. We put nowcasting results in competition with 9 alternative short-term forecasting results (AR, VAR, small BVAR, FAAR, FAVAR and BFAVAR). For model comparison we use RMSFE measure-root mean squared forecast error. r-is the number of static factors, q-is the number of dynamic factors, p – number of lags, w- overall tightness for Bayesian model, d – is the decay parameter for Bayesian model. For example let's explain results for the first country in the tables, that is Austria. For nowcasting we have extracted the optimal combinations of static and dynamic factors, which is r = 3 static and q = 1 dynamic factors. The optimal number of lags is p = 1. The calculated value of RMSFE = 0.364. All other models can be explained in a similar manner, with exception of Bayesian method where in addition we have overall tightness (w) and lag decay (d).

Table 5: Diebold-Mariano test (nowcasting vs. short-term forecasting models)

	NOWCASTING VS.								
	AR	VAR	BVAR	FAAR_SW	FAAR_TS	FAVAR_SW	FAVAR_TS	BFAVAR_SW	BFAVAR_TS
Austria	-1.56	-2.02**	-2.04**	-1.63	-1.49	-2.02**	-1.67*	-2.07**	-2.07**
Belgium	-0.35	0.44	-0.77	-0.08	-0.17	0.92	0.76	-0.72	-0.73
Czech Republic	-0.85	-1.25	-1.00	-0.58	-0.50	-1.49	-1.43	-1.00	-1.00
Denmark	0.02	-0.04	-1.66*	0.21	0.08	0.29	0.32	-1.67*	-1.70*
Estonia	0.61	-1.93*	-0.62	0.08	0.21	-0.74	-0.67	-0.55	-0.58
Finland	-1.62	-0.30	-2.05**	-0.78	-0.84	0.45	-0.05	-2.13**	-2.24**
France	-1.05	-1.62	-2.10**	0.41	0.02	-1.05	-0.94	-2.24**	-2.25**
Germany	-1.49	-2.25**	-2.42**	-0.73	-0.14	-1.45	-1.16	-2.71**	-2.72**
Greece	0.80	-1.24	-3.15***	-0.78	-0.98	-2.28**	-2.16**	-3.29***	-3.30***
Hungary	-0.45	-0.74	-1.08	0.60	1.01	-0.68	-0.61	-1.18	-1.18
Italy	-0.52	-0.47	-0.36	-0.72	-0.68	-0.42	-0.39	-0.40	-0.43
Latvia	-1.43	-1.68*	-1.75*	-1.94*	-1.44	-2.24**	-2.12**	-1.74*	-1.68*
Luxembourg	1.80*	0.67	-0.96	0.59	0.65	0.54	0.50	-0.87	-0.93
Netherlands	-3.05***	-2.78**	-3.99***	0.39	1.00	-0.81	-0.69	-4.30***	-4.49***
Poland	-1.94*	-1.49	-1.74*	-1.71*	-1.61	-0.92	-0.10	-2.06**	-2.15**
Portugal	-1.25	-1.64	-1.85*	-0.23	-0.40	-1.49	-1.19	-1.89*	-1.86*
Slovak Republic	0.89	-2.92**	1.88*	-0.67	2.36	-2.16	-1.29	0.63	2.33**
Slovenia	-0.29	-1.36	-0.66	-0.05	-0.10	-0.91	-0.91	-0.63	-0.90
Spain	0.31	-0.05	-0.18	-0.12	0.57	-0.08	0.50	-0.20	-0.11
Sweden	-1.21	-1.88*	-1.95*	-0.80	-0.50	-1.36	-1.25	-2.34**	-2.51**
Switzerland	-1.05	-1.39	-1.48	-1.23	-1.48	-1.72*	-2.01**	-1.47	-1.50
United Kingdom	-1.42	-1.63	-2.04**	-1.40	-1.26	-1.84*	-2.45**	-2.06**	-2.07**

Note: ***, **, * indicates 1%, 5% and 10 % level of significance. We compare results of the nowcasting algorithm versus alternative short-term forecasting algorithms. We assess whether the nowcasting results are significantly different from the short-term forecasting models. When we compare nowcasting with the BVAR and BFAVAR, we see that for most part of countries the nowcasting results significantly outperform the alternative models. When we compare nowcasting results with the AR, FAAR and FAVAR models, we conclude that the differences are not significant.

Table 6: Model performances based on RMSFE

Country	Nowcasting	AR	VAR	BVAR	FAAR_SW	FAAR_TS	FAVAR_SW	FAVAR_TS	BFAVAR_SW	BFAVAR_TS
Austria	1	5	6	8	3	2	7	4	9	10
Belgium	4	7	3	10	5	6	1	2	8	9
Czech Republic	1	4	10	7	3	2	5	6	8	9
Denmark	5	6	7	8	1	4	2	3	9	10
Estonia	4	1	10	8	3	2	9	7	5	6
Finland	2	7	4	8	6	5	1	3	9	10
France	3	5	7	8	1	2	6	4	9	10
Germany	1	4	7	8	3	2	6	5	9	10
Greece	2	1	5	8	3	4	7	6	10	9
Hungary	3	6	7	8	2	1	5	4	9	10
Italy	1	7	8	3	10	9	4	2	5	6
Latvia	1	4	8	7	2	3	10	9	6	5
Luxembourg	7	5	1	10	6	3	2	4	8	9
Netherlands	3	7	6	8	2	1	5	4	9	10
Poland	1	5	7	8	5	3	4	2	9	10
Portugal	1	4	7	8	2	3	6	5	9	10
Slovak Republic	6	4	9	2	7	3	8	10	5	1
Slovenia	1	4	10	5	2	3	8	7	6	9
Spain	4	3	5	9	7	1	6	2	10	8
Sweden	1	5	7	8	3	2	6	4	9	10
Switzerland	1	5	4	8	3	2	7	6	9	10
United Kingdom	1	4	6	8	3	2	7	5	9	10

Note: The performances of the nowcasting and short-term forecasting algorithms are ranked from 1 to 10. For most countries the nowcasting records the lowest value of RMSFE and outperforms all other competing short-term forecasting models. The FAAR_TS algorithm comes at the second place because it has the RMSFE value larger than nowcasting RMSFE but lower than the RMSFE for all other competing algorithms. The FAAR_SW stands at the third place because it has RMSFE value more than the corresponding values for nowcasting and FAAR_TS but lower than the corresponding values for all another competing models.