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Nowcasting Bosnia and Herzegovina GDP in Real Time

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Abstract

The aim of this paper is to evaluate current quarterly nowcasts of the gross domestic product in Bosnia and Herzegovina based on the flow of available monthly economic indicators that are available during the same quarter. The nowcasting performance indicates that it is worthwhile to include a broad group of forecasting models based on the different methodologies. In addition to the models, the choice of the variables and measurement of the loss function in evaluating nowcasting performance are the core of nowcasting. In a time marked by pandemic of corona virus and war in Ukraine, nowcasting models have more profound role than more structural models. The high variance of the specific nowcasting model influences the use of the results of combinations of many models. Using a comprehensive method for preselection of variables and by using the other combination methods, the forecasting errors are lower, even in times of high uncertainty.

Keywords: Nowcasting, short-term forecasting, uncertainty, pandemic.

JEL: E17, E66, C52, C55, O11

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1. Introduction

Nowcasting is a specific forecasting process in which a particular variable is estimated in the current quarter or month based on available indicators at a higher or the same frequency before the official release of that variable. Generally, nowcasting and forecasting are one of the crucial goals of empirical analysis. Moreover, nowcast models are supposed to outperform traditional time series models.

The corona virus pandemic caused an enormous uncertainty shock; therefore, the forecasting is extremely challenging during pandemic. The impact of the pandemic on the economy is still uncertain and there is the possibility of the emergence and spread of new variants of viruses. Moreover, the new uncertainty shock caused by the war in Ukraine influenced slowing economic activity and rising prices. Therefore, nowcasting models have more profound role, compared to the structural forecasting models used for longer-term horizon.

The first step in nowcasting is to identify a selection of economic variables that might be a strong predictor of real economic activity. This guarantees that the resulting factors will correlate with the target variable and supposedly improve nowcasting performance.

One approach to compare the accuracy of the nowcasts with univariate time-series models is by using the Root Mean Square Error. A nowcasting model with a good in-sample fit does not necessarily imply that it will have good out-of-sample performance. Therefore, pseudo out-of-sample forecasts are used in this study, which evaluates the relative forecast performance. The average results of many models frequently leads to more accurate nowcasts than those obtained based on specific individual models.

In this study, the improvement of nowcasting performance is achieved by using the preselection of variables and by using the additional evaluation methods with optimal combining weights. The updating of the nowcasting model is continuous work, especially in times of high uncertainty.

The paper is organized as follows: Section 2 contains a literature review. Section 3 presents an overview of nowcasting dynamics in Bosnia and Herzegovina and its developments. Moreover, it explains the methodology, the model development and the forecasting performance. Section 4 presents improvement in the nowcasting model by using new accuracy measures and variable preselection. The last section offers some concluding remarks and future recommendations.

2. The literature

Most empirical studies on the nowcasting of GDP focus on the applying different models based with the high frequency indicators. Therefore, the literature reviews is been focused on influential paper concerning the nowcasting of GDP.

The results in the literature have showed that gains of nowcasting relative to the naive constant growth model are substantial at very short horizons and in particular for the current quarter. The bridge models, which are rather naive and traditional nowcasting tool, have their role as benchmark models at central banks to obtain early estimates of GDP (Kitchen and Monaco (2003) and Baffigi, Golinelli, and Parigi (2004)). However, partial models such as the traditional bridge equations capture only a limited aspect of the nowcasting process.

In the 1980s, Robert Litterman and Christopher Sims developed important macroeconomic forecasting models based on vector auto regressions (VAR models), which become very popular in the area of time series modelling. Giannone, Reichlin, and Small (2008) have proposed nowcasting GDP from a large set of monthly indicators, including VAR models. The papers that have used Bayesian shrinkage (BVAR models) to handle large information sets in the context of nowcasting are Bloor and Matheson (2011) and Carriero, Clark, and Marcellino (2012).

In the literature, there is an increasing number of papers on forecasting with factor models, starting with Stock and Watson (2002b) for the USA and Marcellino, Stock and Watson (2003) for the euro area. Stock and Watson (2002a), Schumacher and Breitung (2008) impute missing values with the Expectation Maximization algorithm, where the factors are estimated based on principal component analysis (PCA). This results in the representation of factors for different groups of monthly variables (e.g. for domestic or foreign variables), which ensures higher flexibility in modelling and may serve in the interpretation of results.

Alvarez-Aranda, Camacho and Perez-Quiros (2009) examine the empirical pros and cons of forecasting with large versus small factor models. Their main result is that the larger models might bias the results of the estimated common factor. In later research, Camacho and Perez-Quiros (2009) proposed a small-scale factor model to compute short-term forecasts of Spanish GDP growth rate in real time.

Starting with Evans (2005) and Giannone, Reichlin, and Small (2008), the literature has provided a statistical framework to implant the nowcasting process through a model with a state space representation, which allows the use of the Kalman filter to obtain projections for both the observed and the state variables. Although most applications are based on the dynamic factor model, there is increasing trend in using mixed frequency VARs (MFVAR) (Kuzin, Marcellino, and Schumacher (2011)).

In times of high uncertainty, the forecasts of real economic activity are even more challenging; therefore, several authors examine nowcasting performance in the pandemic period. For the time being, the economic effects of the war in Ukraine are still not considered, since the start of the Russian invasion occurred in the last days of February 2022; this issue will likely lead to a new evaluation of the process to project macroeconomic variables, mainly GDP and inflation. Huber et al. (2020) indicate that, with the arrival of the COVID-19 pandemic, the MFVAR models suitable for nowcasting have become even more important. Moreover, Schorfheide and Song (2020) use a MFVAR to produce real-time macroeconomic forecasts for the U.S. during the COVID-19 pandemic; they found that forecasts based on a pre-crisis estimate, using data up until the end of 2019, appear to be more stable and realistic than forecasts that include the most recent observations.

Siliverstovs (2021) investigates models' forecasting performance of real GDP during the pandemic for the euro area, where he shows that ignoring asymmetries in forecasting performance across the business cycle typically leads to a biased judgment of the models' predictive ability in each phase. Due to the high variability of GDP growth rates across a wide range of countries during the pandemic, the forecast errors of the models for these quarters are highly likely to be extraordinary large. Therefore, recursive measures, which divide the models' forecasting performance observation by observation, provide detailed insights into the core causes of a specific model's domination over the others.

Ankargren and Lindholm (2021) nowcast Swedish GDP using different types of the short-term forecasting models. Their results shows a clear divide between pre-pandemic performance and the usefulness of nowcasting during the pandemic. By decomposing the dynamic factor model nowcast into contributions, they found that updated parameters caused large revisions. The re-estimated models' nowcasts are more reasonable and accurate compared with models that are not re-estimated to take into account the pandemic.

3. Overview of the nowcasting in the Bosnia and Herzegovina

Nowcasting of macroeconomic variables began at the CBBH in the early 2021 with the support of the Graduate Institute of Geneva's Bilateral Assistance and Cooperation with the Central Banks (BCC) program. The aim of this program was to assess the state of the total economic activity in real time based on available high-frequency indicators. The result of the mission are nowcasting models for gross domestic product (GDP), exports and imports of goods and services, consumer price index (CPI), non-performing loans and real estate prices. However, the purpose of this paper is to improve GDP nowcasting performance by selecting additional explanatory variables and by including new accuracy measures.

The Agency for Statistics of Bosnia and Herzegovina (BHAS) publishes certain indicators with a significant time lag, such as quarterly data on the GDP, which according to the release calendar is usually published more than three months after the end of the quarter (Table 1). Based on the presented table, Bosnia and Herzegovina (BH) releases the first estimates of GDP last of all in the region. For this reason, it is very important to assess the state of total economic activity in real time based on available monthly indicators. High-frequency indicators, such as retail trade, industrial production, imports and exports of goods, foreign tourist overnight stays, labor market, credit activity and indicators of major foreign trade partners are used, in the absence of official data, for nowcasting models that aggregate monthly indicators, which already include information on the GDP trend, on a quarterly basis.

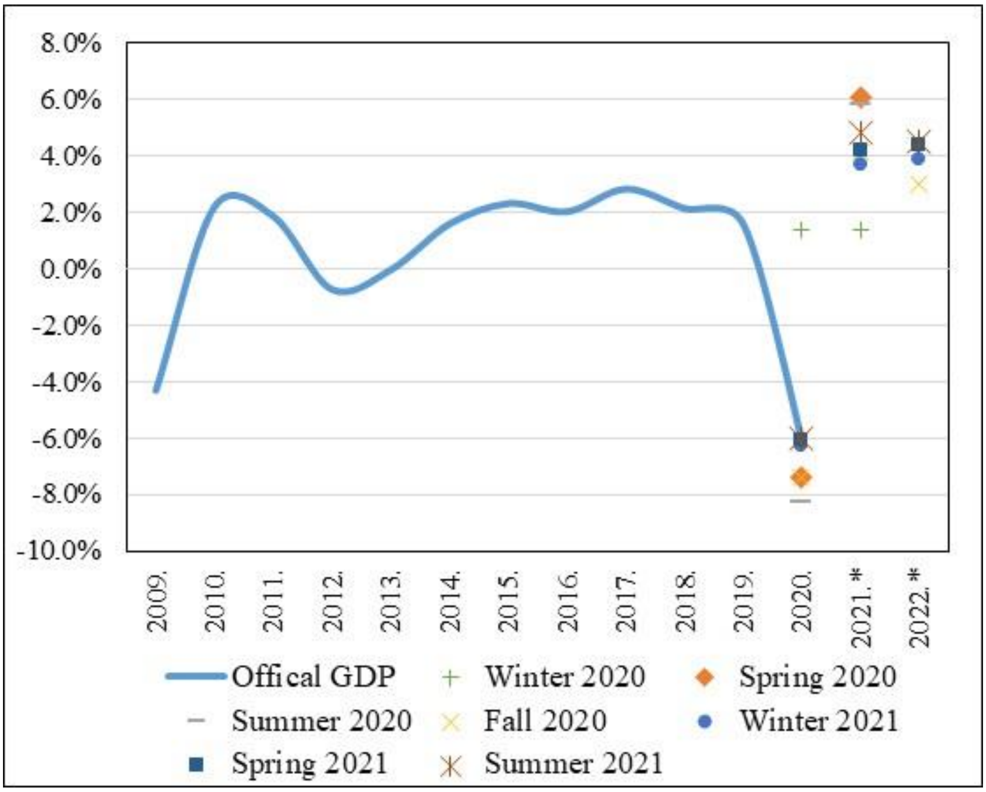
Table 1: First release of GDP and main aggregates, Q4 2020

COUNTRY	DATE
BOSNIA AND HERZEGOVINA	**5/4/2021**
ALBANIA	31/3/2021
BULGARIA	9/3/2021
CEZH REPUBLIC	2/2/2021
GREECE	5/3/2021
CROATIA	15/2/2021
HUNGARY	16/2/2021
MONTENEGRO	17/3/2021
SERBIA	1/3/2021
SLOVENIA	26/2/2021
EUROPEAN UNION	2/2/2021

Source: Eurostat, National Statistics Institutes

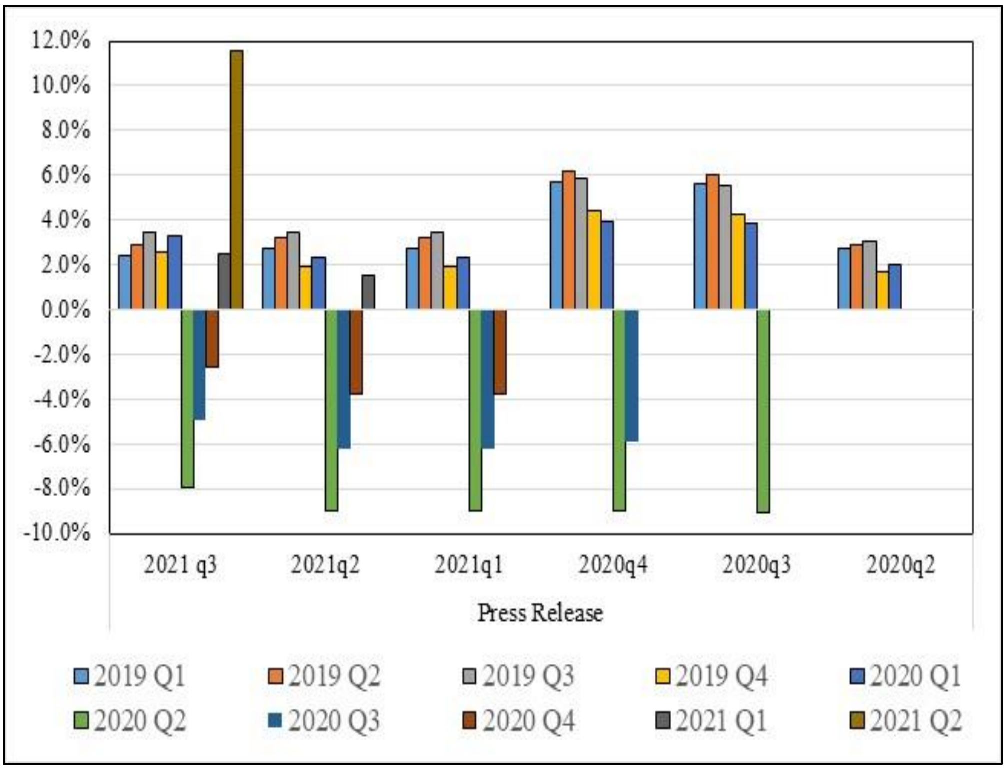
Especially in a time marked by pandemic of COVID-19, the nowcasting models of GDP and other macroeconomic variables have more profound role, comparing to the more structural projection models used for longer-term horizons. The high degree of uncertainty, which is related to the development of the epidemiological situation and spread of the new variants of virus, has a major impact on economic activity. Therefore, it is crucial to assess the performance of short-term forecasting models. The economic impact of pandemic is fundamental for policy makers, due to the extreme speed with which the crisis spread and the period during which its effects will influence economic and social activities. The pandemic caused an enormous uncertainty shock, bigger than the one during the 2008 financial crisis; therefore, the forecasting is extremely challenging during COVID-19 pandemic (Figure 1). After an initial strong coronavirus shock, the projections of EU GDP have varied significantly, in a line with the epidemiological situation and expectations of economic recovery. Additionally, the official statistics revised their estimates of economic activity with each new press releases. The revisions particularly influenced forecasting performance, especially for the BH where it is usual to have large revisions of the official estimates (Figure 2).

Figure 1: Forecasting real GDP in the EU



Source: European Commission

Figure 2: Official press releases and revisions of the BH real GDP in the pandemic



Source: BHAS

The purpose of this paper is to improve the nowcasting of GDP in BH by different methodologies, which involves filtering useful information from a large amount of data with many irregularities. These models are 'atheoretical', for which the most important criterion is how well they forecast in practice. To minimize the risk, it is possible to select several nowcasting models that have acceptable out-of-sample performance where the final nowcast represents the combination of these models. In practice, it is unlikely to have fully optimal forecasts. Therefore, the most likely situation is to have a number of sub-optimal forecasts, which are combined. The first step in this paper is to identify a selection of economic variables that might be a strong predictor of real economic activity. The models include all the variables that emerged as significant predictors of real economic activity based on the available dataset and influential research papers.

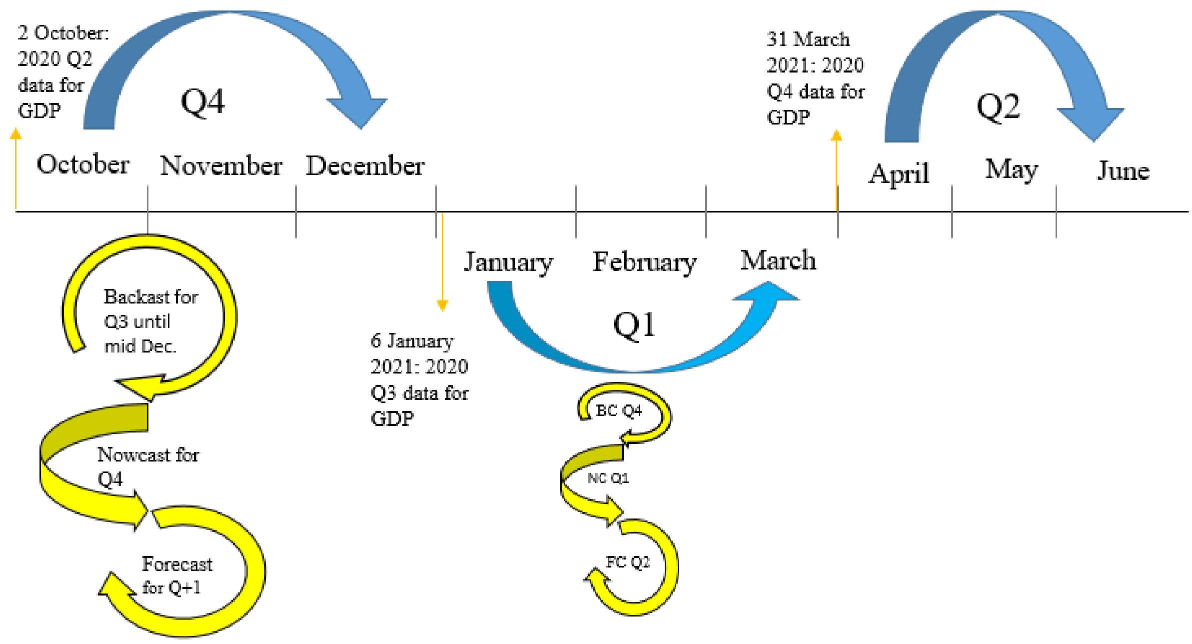
3.1. Data

The data for real GDP is collected from the Agency for Statistics of BH at the state level on a quarterly base over the period of 2007-2021. Additionally, high frequency data comes from several sources, including state statistics (BHAS), CBBH, Indirect Taxation Authority, EUROSTAT, and stock markets. Nowcasting tools integrate standard official macroeconomic information collected from National Statistical Institutes, Central Banks and other International Organizations. However, more recently, a lot of emphasis has been put on using alternative sources of high-frequency information, referred to as Big Data. Especially for the projection of foreign prices, worldwide price movements are used on a daily basis, which includes an increasing set of data available in the online catalogs.

For the calculation of factors, more than fifty time series have been taken into account, which represent: movements in trade, industrial production and turnover (domestic and foreign markets), construction, credit activity, financial sector, labor market, stock market, price indices, indicators of economic activity for main trading partners, foreign tourist overnights and foreign sentiment indicators. In the first step, factors and factor weights are estimated on a maximum sample on which there are no missing values using principle component analysis and ordinary least square (OLS). The first results show that variables for labor market; export; industrial turnover; value added tax; eurocoin (combines the positive aspects of foreign GDP, IP and surveys), foreign tourist activity from main markets and foreign sentiment indicators have the greatest individual contribution to the real GDP.

For the most part, three different sources of official data are considered for the nowcasting models: real economic data, like labor market data, sales and production; opinion surveys and financial markets data. In this paper, all recommended sources by the literature where covered. The data used in the nowcasting model has been normalized and seasonally adjusted with E-views ARIMA X12. Certain time series were affected by methodology changes, causing structural breaks that were resolved by applying different techniques in the course of the modelling itself.

Figure 3: Calendar for GDP Releases



3.2. Description of the nowcasting models

In this paper, the intention is to review different statistical approaches to nowcasting, include the results from the literature and perform an empirical exercise. Firstly, we test simple models often called "bridge equations", which are essentially regressions relating quarterly GDP growth to one monthly variables (such as retail trade or industrial production) aggregated to quarterly frequency. Moreover, the ARMA model is usually used as a benchmark forecasting model. All the methodologies link GDP with a group of other indicators (high-frequency indicators) in the following relationship:

$$GDP_t = f\left(high - frequency\ indicators_{t(or\ t-s)}\right) + \varepsilon_t$$

$$\widehat{GDP}_T = f\left(high - frequency\ indicators_{T(orT-s)}\right)$$

An equation (OLS or any other estimator) is used to forecast one period in advance:

$$y_t = \beta_0 + \beta_1 f_{1t} + \beta_2 f_{2t} + \beta_3 f_{3t} + \gamma Z_t + \varepsilon_t$$

$$\widehat{y_T} = \hat{\beta}_0 + \hat{\beta}_1 f_{1T} + \hat{\beta}_2 f_{2T} + \hat{\beta}_3 f_{3T} + \hat{\gamma} Z_T$$

The real-time data flow is inherently high-dimensional. As such, it is important to use a parsimonious model that avoid parameter proliferation but at the same time is able to capture the relevant features of the data. Most nowcasting models are based on some kind of factor analysis - the extraction of several factors from a large set of indicators. The Principal Component Analysis (PCA) method estimates one or more factors (F_t) that adequately describe the dynamics of the whole group of monthly indicators (X_t):

$$X_t = \Lambda F_t + \epsilon_t$$

The problems of the mixed frequency and ragged edge are basically missing data problems, which are easily solved by a Kalman filter:

$$Y_t = \Lambda F_t + \epsilon_t,$$
$$F_t = A_1 F_{t-1} + A_2 F_{t-2} + \cdots A_p F_{t-p} + u_t, u_t \sim N(0, Q)$$
$$\epsilon_{it} = \alpha_i \epsilon_{it-1} + \varepsilon_{it}, \epsilon_{it} \sim N(0, \sigma_i^2), i = 1, \ldots K$$

Where $Y_t = (y_t, X_1, X_2, \ldots, X_K)'$ is a vector containing GDP and all monthly indicators (different lengths), and F_t is a vector containing dynamic factors.

The vector autoregressive models (VAR), which are simple multivariate models, are also suitable tools for estimating and forecasting where all variables are treated as endogenous and the general representation of a model is:

$$Y_t = A + B(L) Y_{t-1} + \epsilon_t$$

Where Y_t is a vector of variables measured in the same sample period (t = 1, ..., T), A is vector of absolute terms, B a matrix of autoregressive coefficients and ε a vector of error terms.

Moreover, for the small and open economies VARX models are more suitable, which are been presented in the following equation:

$$Y_t = A + B(L) Y_{t-1} + C(L) Xt + \epsilon_t$$

The vector X is included to allow for the contemporaneous influence of exogenous variables, such as economic sentiment indicator of EU member states, retail turnover, oil prices and so on. In the VAR models, Bayesian shrinkage can be employed to avoid over-fitting and as well factor augmented VAR (FAVAR) models where F_t contains principal components. Bernanke and al. (2005) combine factor models with VAR in order to use large information sets and clarify the effects of monetary shocks on different indicators. These models are known as FAVAR models. The papers that have used Bayesian shrinkage to handle large information sets in the context of nowcasting are Bloor and, Matheson (2011) and Carriero, Clark, and Marcellino (2012).

The unrestricted mixed mixed-data sampling (U-MIDAS) models are tightly parametrized reduced form regressions with variables sampled at different frequencies. The models define the quarterly variables $\mathrm{xm}_{\mathrm{tq}}^{(\mathrm{i})}$, $i \epsilon \{1,2,3\}$ containing the i-th month in the quarter, yielding the following regression:

$$y_{tq} = \alpha + \beta_1 \mathrm{xm}_{\mathrm{tq}}^{(1)} + \beta_2 \mathrm{xm}_{\mathrm{tq}}^{(2)} + \beta_3 \mathrm{xm}_{\mathrm{tq}}^{(3)} + u_{tq}$$

With the use of 'Exponential Almon Lag' polynomial, the equation for mixed-data sampling (MIDAS) model is:

$$y_{tq} = \beta_0 + \beta_1 \mathrm{b}(L^{1/m};\theta) + \mathrm{x}_{\mathrm{tm}} + e_{tq}$$

3.3. Evaluating models' relative predictive ability

In addition to all mentioned models, it is important to do a quasi-out-of-sample exercise based on which to choose monthly indicators and some other details (number of factors, possible control variables, etc.) and get a sense of the average forecast error. The crucial object in measuring nowcasting performance is the loss function, which is associated with various pairs of forecasts and realizations.

In order to measure how far the realization is from the nowcast, it is important to measure the bias and dispersion of the nowcast forecast error.

Mean error measures bias:

$$ME = \frac{1}{T}\sum_{t=1}^{T} e_{t+h,t}$$

Error variance measured dispersion:

$$EV = \frac{1}{T}\sum_{t=1}^{T}\left(e_{t+h,t} - ME\right)$$

The mean square error measures both bias (ME) and dispersion (EV):

$$MSE = \frac{1}{T}\sum_{t=1}^{T} e^2{}_{t+h,t}$$

In this paper, the root mean square error (RMSE) is used to assess the model forecast accuracy and select suitable models:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e^2{}_{t+h,t}}$$

The purpose of any forecast is to build models that make accurate forecasts or models with the smallest possible forecast error. In the case where the data period is short and where official statistics often revise the data, it is worth combining the information available from the individual models. The literature indicates that the average of the results of many models frequently results in more accurate nowcasts than those obtained based on specific individual models. Simple equal weight (EW) averaging tends to work well in practice and can potentially cover the important variations of individual models:

$$y_{t+h,t}^{EW} = \frac{1}{m}\sum_{i=1}^{m} y_{t+h,t}^{M_i}$$

4. Improving the nowcasting model

For the forecast accuracy, based on a loss function, it is often of interest to distinguish whether one forecast is more accurate than another (see Appendix). When comparing alternative models, the focus is often on the overall average performance over the entire forecast sample. Simple equal weight (EW) averaging works well in stable or normal economic times, while. in the case of dramatic swings in GDP, forecasting combinations are preferred since the models are mis-specified. Comparison based on only average RMSE might be misleading since the forecasting measures is symmetric, giving equal weight to under and over prediction.

4.1. Nowcasting using new accuracy measures

A square loss is highly influenced by large errors, so at the extreme a single forecast might extremely affect the forecast assessment. That it is reason why additional evaluation methods are presented in this paper, such as the simple median or trimmed mean methods. Moreover, by using the weighted average method based on the forecasting performance of individual methods, the issue of equal weighting is solved, especially in times of high uncertainty.

For the median forecast:

$$y_{t+h,t}^{Median} = \text{median}\{y_{t+h,t}^{M_i}\}_{i=1}^{m}$$

Trimmed mean forecast: order the forecast $\{y_{t+h,t}^{M_1} \leq y_{t+h,t}^{M_2} \leq y_{t+h,t}^{M_m}\}$ and trim top/bottom λ% such that:

$$y_{t+h,t}^{TM} = \frac{1}{m(1-2\lambda)} \sum_{i=[\lambda m+1]}^{(1-\lambda)m} y_{t+h,t}^{M_i}$$

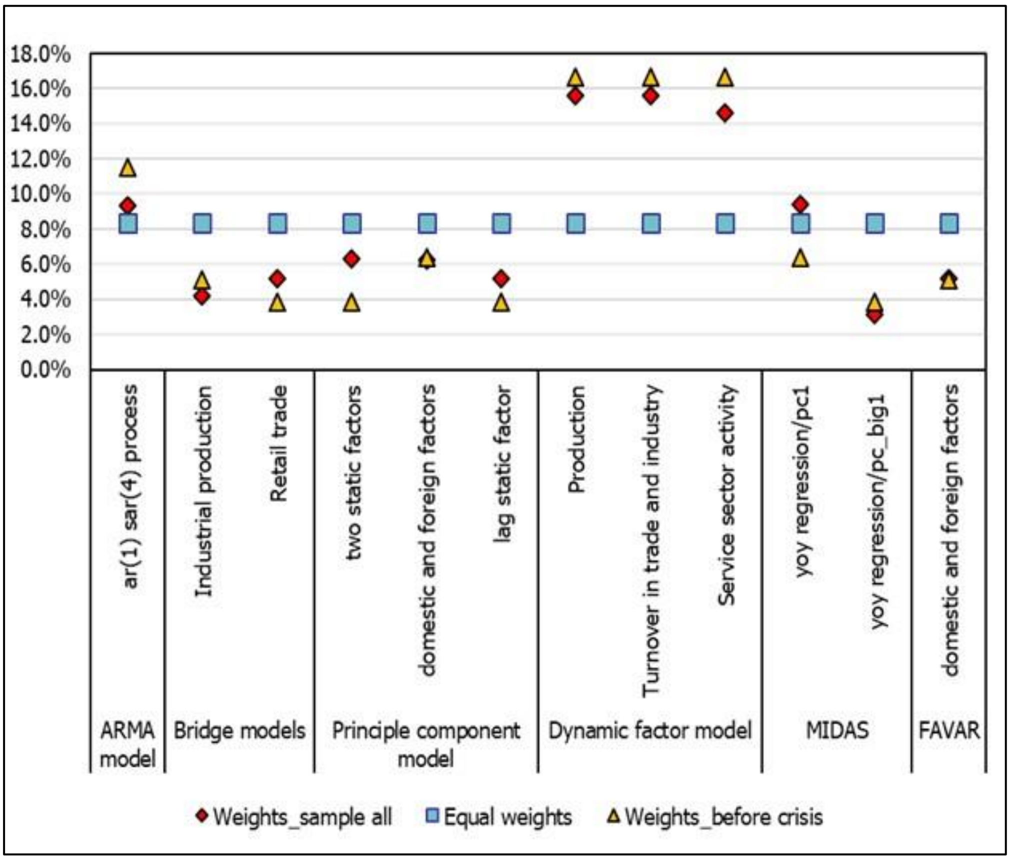
Setting weights according to the past forecast performance (MSE):

$$\omega_i^{MSE} = \frac{MSE_i^{-1}}{\sum_{i=1}^{m} MSE_i^{-1}}$$

In order to improve forecast evaluation, the optimal combination of weights of each model's performance is choosen. The individual performance of the model is based on the model's RMSE compared to the benchmark average forecast error. Additionally, including simple combination methods (median) improves the existing nowcasting model in BH, which takes into account only the simple mean. Greater weights are assigned to the models that produce more precise nowcasts (Figure 4).

Dynamic factor models that have the lowest RMSE with new evaluation method gained more weight, which is in accordance to the findings of Ankargren and Lindholm (2021). Moreover, bridge and PCA models performed worse in the pandemic times, so the weights are lower for these models which is shown in Figure 4 below. Additionally, putting greater weights on the performance before the pandemic crisis may improve nowcasts of GDP; this evaluation method will be important especially when the economy stabilizes.

Figure 4: Weights of each model in different evaluation method



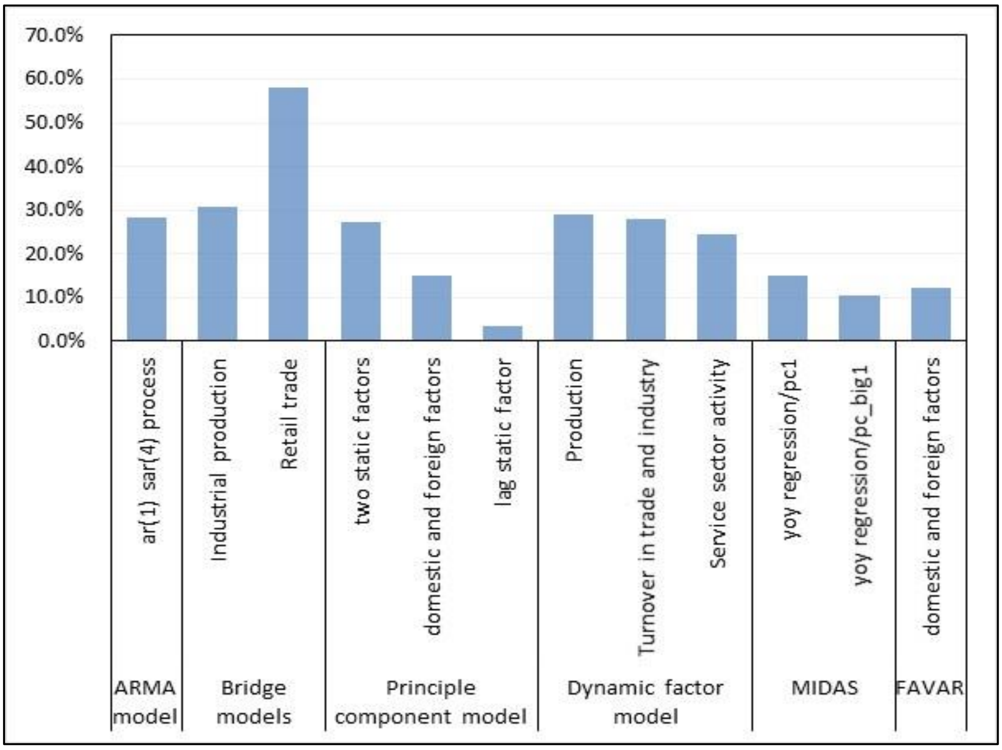
Source: Author calculations.

4.2. Nowcasting using new data sources

The choice of the variables is, in addition to the models, the core of forecasting, therefore it is crucial to choose the variables that perform constantly well with the target value. Improving the existing models' explanatory power and forecasting performance is probable by finding the variables that deliver better out-of-sample performance, which is in accordance to the Stock and Watson (2002) approach. This guarantee that the resulting factors will be correlated with the target variable and supposedly improve forecasting performance.

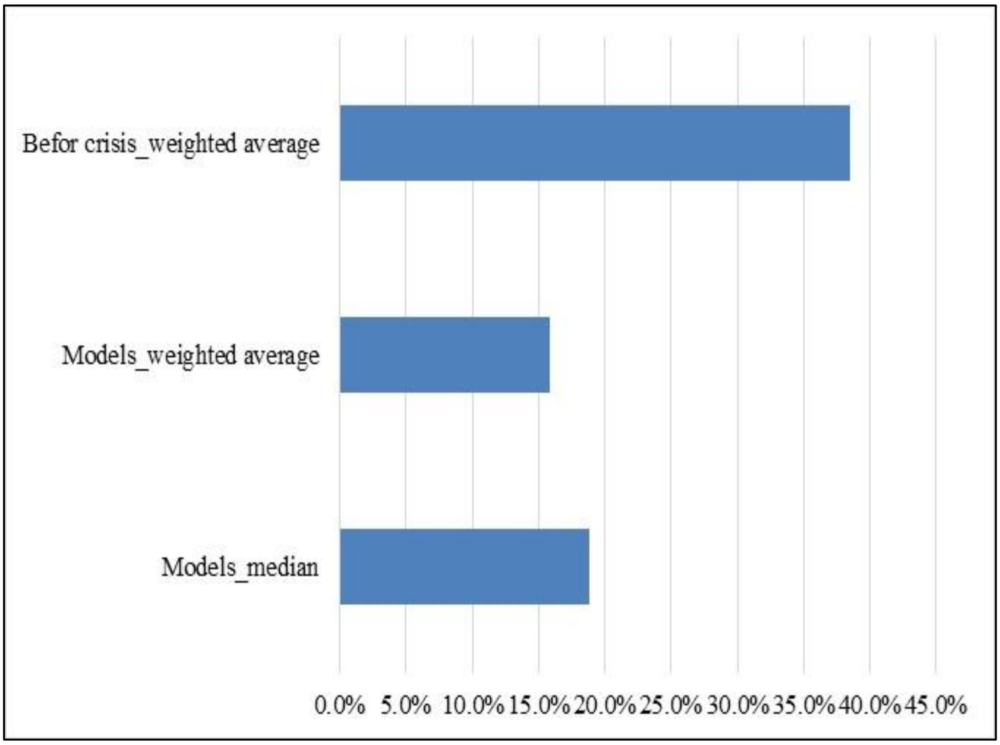
Graph 5 indicates the improvement for each model with the new set of variables, which includes some additional endogenous variables such as the wage bill and some exogenous variables. Additionally, some variables that are highly volatile in the pandemic and are not good explanatory predictor of GDP are excluded, such as tourist activity by the most important countries from which tourist are arriving in BH, since many countries in the pandemic imposed travel restrictions. This is particularly obvious for the bridge models of the retail service where the RMSE with new set of variables improved by almost 60.0%. Each model benefitted from value-added with a new set of variables (Figures 5 and 6). With the new set of variables and new evaluating methods, the loss function is substantially lower, especially when fixing the weights to the prepandemic period (Figure 6). However, the weighted average method takes into account wider sample, so it is less biased during the pandemic times.

Figure 5: RMSE improvement with new variables by each model



Source: Author calculations.

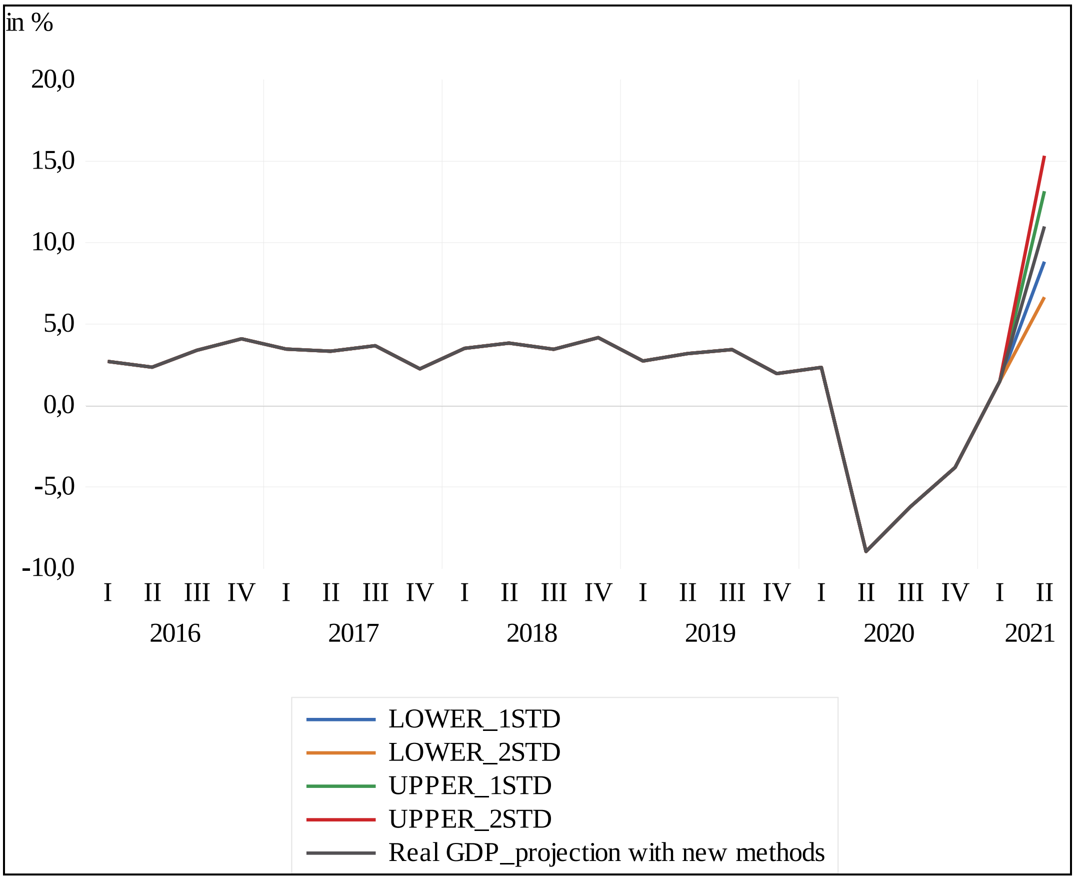
Figure 6: RMSE improvement with new variables by each model



Source: Author calculations.

Figure 7, based on the models previously described, provides an overview of the projection of real GDP growth and uncertainty surrounding the central projection using a fan chart in the period from early 2016 to the second quarter of 2021. This type of projection is mostly published in central banks because it provides the level of reliability (95% interval in this case), which is especially important for decision-making during a pandemic, when the overall economy faces many risks. The forecasts of real economic activity are more useful if presented along with the probability of the variable outcome being below or above the forecasted point estimate. Many central banks publish their forecasts in the form of fan charts, which focuses on overall forecast distribution rather than only on a single point forecast according to Britton, Fisher and Whitley (1998).

Figure 7: Nowcasting GDP, annual growth rate



Source: Author calculations. Note: STD indicates standard deviation, according to which 1STD includes an interval of 68%, while 2STD an interval of 95% confidence.

5. Concluding remarks and future recommendations

The upgraded model based on this research will enrich the nowcasting of GDP in the Bosnia and Herzegovina. Using a comprehensive method for the preselection of variables that correlates with the target and by using the other combination methods, the forecasting errors are much lower, even in times of high uncertainty. As result, out-of-sample nowcasting performance is more reliable. This paper presents the evaluation of the nowcasting performance of ARIMA, Bridge, Principle component, Dynamic factor, MIDAS and FAVAR models, with the aim of understanding, which models contribute, to the nowcasts of GDP in BH. According to the various evaluation methods, preselection of variables to give the best specifications improved the performance of all the mentioned models. The choice of the variables, in addition to that of the models, is the core of forecasting.

Additionally, the paper presents a clear divide between pre-pandemic performance and the usefulness of nowcasting during the pandemic. Simple equal weight averaging works well in normal economic times, while in the case of corona pandemic, forecasting combinations are preferred. Comparison based on the only average RMSE is misleading, since the forecasting measures are symmetric. Variables that are not good explanatory predictors during the pandemic are excluded in nowcasts of GDP, such as tourism activity.

The update of the nowcasting model is continuous work, with the integration of additional elements of the economy when data of better quality become available. The findings of this study might be subject to change as new sources of data become available. In the future, the aim is to extend the models with a number of indicators that are available on a weekly or daily basis, as current projections of GDP are limited to monthly data. Extending the official statistical reports will ultimately help achieve more accurate nowcasts. Since there is an increasing use of data from various sources, in the near future the objective is to assess whether Google search data bring some gains in nowcasting accuracy. Large databases nowadays are mostly used for short-term forecasting of macroeconomic variables. Using scanner data applications, social media and online retailers may improve many nowcasting models. Moreover, the Economic Policy Uncertainty Index that includes news about uncertainty is especially important in times of the pandemic and war tensions. Therefore, all of this higher frequency sources may improve our models in the future.

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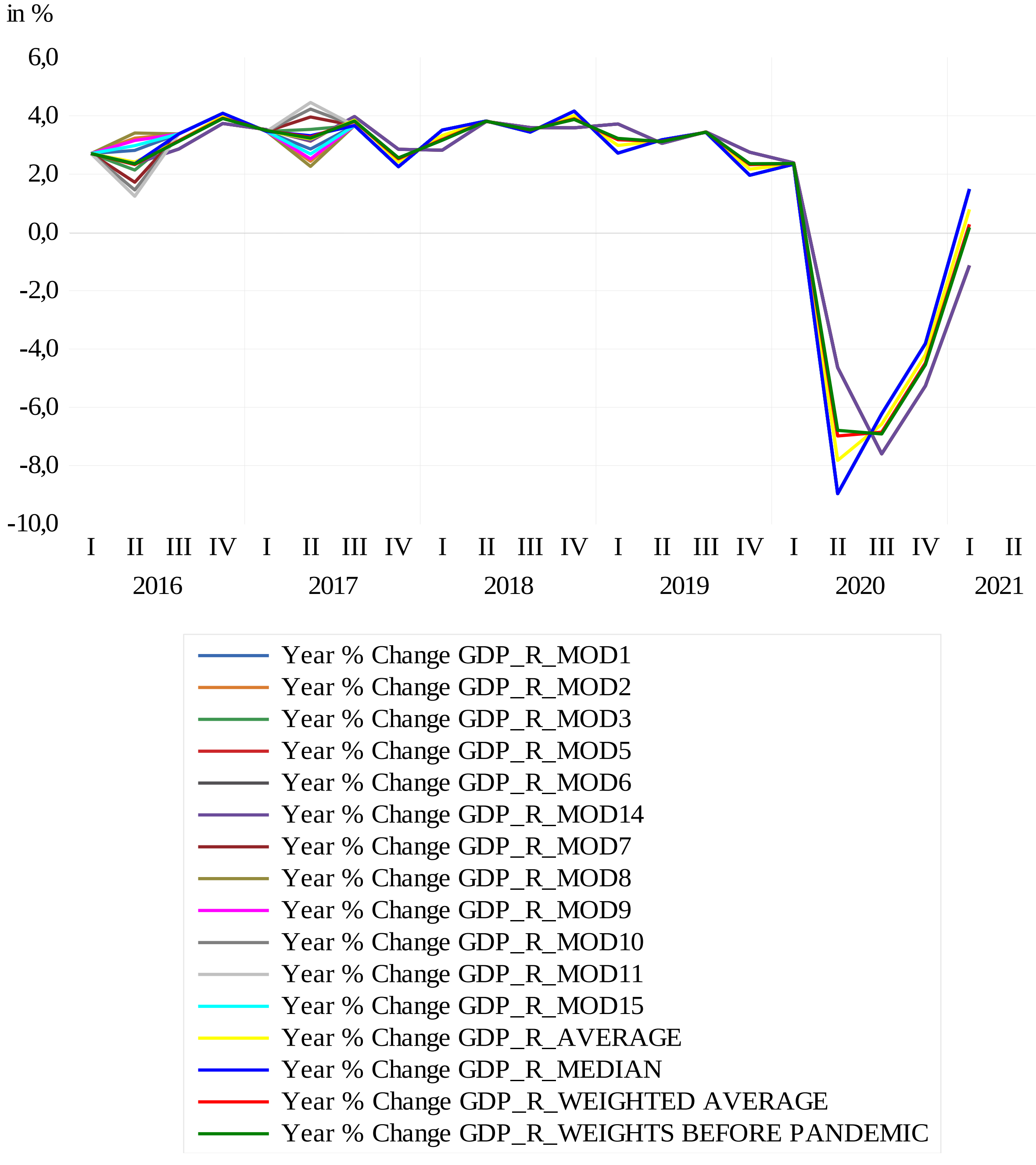
Appendix

Figure 8: Yearly growth rate of real GDP by alternative models



Source: Author calculations.