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Modelling and forecasting GDP using factor model: An empirical study from Bosnia and Herzegovina

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Abstract

In the most developed countries the first estimations of Gross Domestic Product (GDP) are available 30 days after the end of the reference quarter. In this paper, possibilities of creating an econometric model for making short-term forecasts of GDP in B&H have been explored. The database consists of more than 100 daily, monthly and quarterly time series for the period 2006q1-2016q4. The aim of this study was to estimate and validate different factor models. Due to the length limit of the series, the factor analysis included 12 time series which had a correlation coefficient with a quarterly GDP at the absolute value greater than 0.8. The principal component analysis (PCA) and the orthogonal varimax rotation of the initial solution were applied. Three principal components are extracted from the set of the series, thus together accounting for 73.34% of the total variability of the given set of series. The final choice of the model for forecasting quarterly B&H GDP was selected based on a comparative analysis of the predictive efficiency of the analysed models for the in-sample period and for the out-of-sample period. The unbiasedness and efficiency of individual forecasts were tested using the Mincer-Zarnowitz regression, while a comparison of the accuracy of forecast of two models was tested by the Diebold-Mariano test. We have examined the justification of a combination of two forecasts using the Granger-Ramanathan regression. A factor model involving three factors has shown to be the most efficient factor model for forecasting quarterly B&H GDP.

Keywords: efficiency, factor model, Gross Domestic Product of Bosnia and Hercegovina, unbiasedness.

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Introduction

Generaly, the country's Gross Domestic Product (GDP) serves as the basis for the creation and adoption economic development policies. Within one country, there are different interest groups which need timely and reliable forecast for trends in GDP. Miscalculation of GDP forecast leads to unreliable and wrong decisions and policies that can have immeasurable consequences for a country's economy such as: an inadequate choice of a set of policy mix of state governments, an unprofitable investment of private enterprises as well as an inadequate personal consumption. Therefore, assessing the current state of a country's economic activities and forecasting future economic developments is a vital component in a country's policy-making process. Over the past 40 years, with the development of economic theory and practice, numerous econometric GDP forecasting models have been developed. When using the classic bridge model in GDP forecasting, a problem arises when the necessary information is contained in a large number of series, and therefore the need for their inclusion in the model arises. Estimating all the model parameters may be impossible, whereas omitting relevant batches from the model may lead to misspecification and/or reduction of the prediction efficiency of the model itself. The solution to this problem is to use Principal Components Analysis (PCA). Thanks to the pioneering work of Stock, Watson (1989), factor analysis has been used as a convenient tool for current and short-term forecasting in recent years. In the papers Stock, Watson (2002a, 2002b) used static principal components.

As an alternative to static principal components, Forni et al. (2000) considered a dynamic factor estimation approach using generalized principal components where the weight of each observation is proportional to its signal-to-noise ratio. They used non-parametric techniques in factor estimation taking into account the limitations of the dynamic factor structure. Considering the fact that the findings in Buss (2010) indicate that static component analysis is a more efficient, simpler and more robust technique, a static approach is used in the paper. The approach of building a factor model involves two stages. In the first stage, the factors are extracted, and then in the second stage, a linear regression assessment performed for the dependent variable where the factor scores are predictor variables.

The present study expands existing knowledge about forecasting GDP of B&H. In particular, the problem of selecting a subset of factor bridge models by using model selection information criteria and comparison of estimated models for forecasting purposes is considered. This paper is the first study that analyses and compares a forecasting GDP of B&H using factor bridge models in two different time periods. A two-criteria approach is suggested, while in the most other papers one-criteria approach has been used. In this respect, firstly, statistical tests were conducted on historical data that ensure proper fit (in-sample validation). Secondly, statistical tests of the model's ability to allow the evaluation of the forecasting of future GDP of B&H (out-of-sample validation) were conducted. Compared to ARIMA model and classical bridge models, factor bridge model has the advantage of exploiting a large amount of information, as well as being able to evaluate the impact of broad groups of variables to GDP.

The first part of the paper provides an overview of the empirical literature, the second part describes the methodology and data used, while the third part presents the research results and provides directions for future research.

Literature review

Schumacher, Breitung (2008) studied a factor model for the short-term forecasting of GDP growth using a large number of monthly and quarterly real-time time series for the German economy. Giannone, Reichlin, Small (2008) have developed a formal method for the evaluating the marginal impact of the published monthly data on current-quarter forecasts of real US GDP growth rates. The econometric model used in this analysis was a dynamic factor model where the factors were evaluated in two stages: the principal components were first calculated and then the Kalman filter was used. Buss (2010) showed that a small static factor-augmented vector autoregression (FAVAR) model improves the performance of current vector autoregression (VAR) model forecasts along a business cycle (between business cycle phases), while dynamic factor VAR models fail to detect detect the timing and depth of the recession regardless of autoregressive moving average (ARMA) specifications. The choice between static and dynamic factor models in terms of current and future GDP forecasts is mixed. To predict German GDP growth, Marcellino, Schumacher (2010) combined a factor model based on a large set of macroeconomic variables and a mixed-frequency data sampling (MIDAS) model which considers the unbalanced database that appears in publications with lags of high and low frequency indicators. The paper concludes that factor models for estimation do not differ significantly, and the best estimates are given by simple MIDAS with a single factor lag. The results of this study showed that there is no systematic difference between the static and dynamic factor models in current forecasts.

Jovanovic, Petrovska (2010) evaluated the forecasting performance of six different models for short-term forecasting of Macedonian GDP. Comparisons were made based on root-mean-square error and the mean absolute error of the forecasts made one quarter ahead. The results showed that the static factor model outperforms other models and provides evidence that information from a large data set can improve forecasts. Liebermann (2011) conducted a fully-fledged real-time nowcasting of real GDP growth in the US using the Giannone, Reichlin, Small (2008) factor model. The paper showed that the precision of the nowcasts increases with the release of new information. The continuous updating of the model provides a more precise forecast of current quarter GDP growth relative to the Survey of Professional Forecasters (SPF). D'Agostino, Gambetti, Giannone (2011) used a dynamic factor model that forecasts recent past and current quarterly GDP of Ireland using timely data from a panel of 35 indicators. The results of the study indicate that the performance of the factor model outperforms those of the standard benchmark model.

Yiu, Chow (2011) applied the factor model proposed by Giannone, Reichlin, Small (2008) on a large data set for the current-quarter forecast of China's GDP growth rate. The data set contained 189 indicator series of several categories. The identified factor model generated out-of-sample nowcasts for China's GDP with smaller mean-squared forecast errors compared to those of the random walk benchmark model. Godbout, Lombardi (2012) evaluated the relative performance of the factor model across a variety of samples including the 2008 financial crisis. They constructed a factor model to forecast the GDP of Japan and its components using 38 series of data (including daily, monthly and quarterly variables) from 1991 to 2010. They have concluded that factor models perform well at tracking GDP movements and anticipating turning points. In the case of most GDP components, factor models produced less forecast errors than the AR model or indicator model based on PMIs (Purchasing Managers' Indicators).

Aastveit, Trovik (2012) used dynamic factor model which considers new information immediately after its publication. They used a panel of 148 non-synchronous variables and found that the financial data mostly contribute to the precision of Norway's current-quarter GDP forecasts, and the Oslo Stock Exchange data particularly. In addition to financial data, they found that labor market data and industrial production index favorably contribute to the accuracy of current forecasts. Siliverstovs (2012) evaluated forecasting performance of a large-scale factor model developed in Siliverstovs, Kholodilin (2012) in a genuine ex ante forecasting. In the paper, a forecast of GDP growth in Switzerland in real time using real-time data vintages collected at weekly frequency was performed. According to the results of the research, the factor model gives more precise out-of-sample nowcasts than the benchmark naïve model. Shahini, Haderi (2013) tested four different groups of models to forecast Albania's quarterly GDP growth. The paper used quarterly data from 2003 to 2013. Their results showed that the group of VAR model yielded the best GDP forecasting results, followed by the bridge model group and finally the ARIMA model group.

Kunovac, Špalat (2014) tested the extent to which available monthly economic indicators help in flash estimate of Croatia's GDP. A factor model was used in the paper. Model score estimates indicate that the factor models based on the dynamics of a large set of variables give better forecasts than benchmark models. Different factor models specifications produced very similar forecast performances. However, an important conclusion of the paper is that by combining the information available in certain models, when performing fast assessment, more accurate forecasts are obtained. Dias, Pinheiro, Rua (2015) evaluated the relative performance of several factor models to forecast Portugal's GDP growth using a large set of monthly series. Considering the relatively long out-of-sample period, they evaluated the behavior of different models in relation to the pre-crisis period as well as during the economic and financial crisis at the end of 2008. They concluded that factor models significantly outperform univariate autoregressive models for current and short-term forecasting a quarter ahead, while at longer horizons the forecast advantages of factor models are significantly smaller.

Research Methodology

Data

The data collected contains a large number of daily, monthly, quarterly and annual time series such as: economic statistics (prices, national accounts, foreign trade), business statistics (construction, industry, investment, ...), financial data and other type of data. In accordance to the subject of the paper, the target variable for forecasting is B&H's quarterly GDP. The paper uses quarterly GDP data of B&H starting from I quarter of 2006 to IV quarter of 2016. The use of quarterly frequencies is determined by the availability of official data. B&H quarterly time series is built by using the latest published quarterly data of the Agency for Statistics of Bosnia and Herzegovina (BHAS). The database created, in addition to data on B&H's quarterly GDP, also consists of a large number of indicators of economic activity in B&H (110 series). The series which exhibited non-stactionary behavior were transformed into stationary ones using appropriate transformations. All monthly indicators that were able to provide information within 60 days of the last quarter were taken into account. The analysis of available indicators is limited to volume or quantity indicators.

The paper analyses the GDP of B&H at current prices according to the production approach. Figure 1 shows the movement of B&H's quarterly GDP (in 000 BAM) at current prices for the period 2006-2016 year.

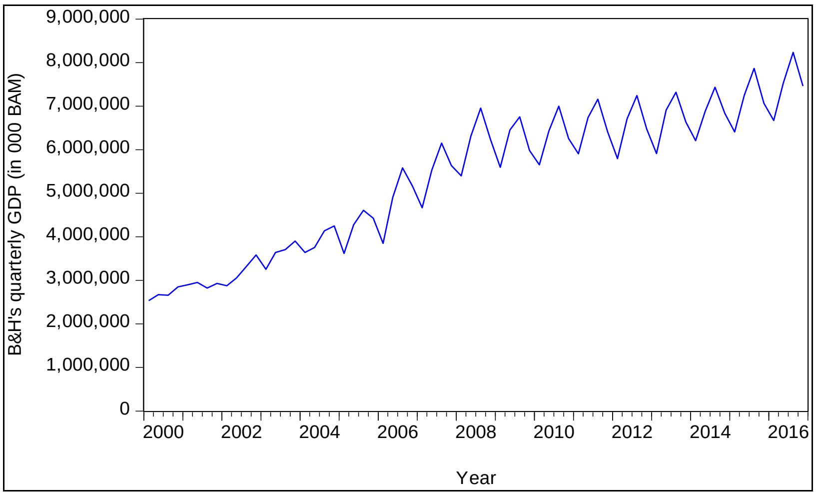

Figure 1 Line graph of B&H's quarterly GDP
Source: Authors' creation.

The graph shows that the quarterly series of GDP of B&H is not stationary, that is, there is a growing trend, that it follows the seasonal pattern and that there is an increase in variance in the observed periods. Furthermore, with the B&H GDP quarterly series, there are some deviations in the pattern of behavior in the period 2007-2009 indicating the presence of outliers or structural break during the indicated period. According to Stock, Watson (2002b) there was no extreme outliers. After graphical outlier detection, TRAMO / SEATS automatic outlier detection and correction procedure was used. The above technique did not confirm the presence of outliers in the quarterly series of GDP of B&H.

According to the Agency for Statistics of Bosnia and Herzegovina (BHAS), B&H's annual GDP grew by more than 170% in period 2000-2016. The lowest value of B&H's annual GDP was 10.71 billion BAM in 2000, while the highest recorded value of B&H GDP was 29.90 billion BAM in 2016. The average annual value of B&H GDP in the observed period was 21.21 billion BAM with a standard deviation of 6.62 billion BAM. Annual GDP growth rates in 2014, 2015 and 2016 were 2.17%, 4.49%, and 4.59%, respectively. The lowest quarterly GDP of B&H was 2.53 billion BAM in 2000q1, while the highest quarterly GDP value of 8.23 billion BAM was recorded in 2016q3. The average quarterly GDP of B&H in the observed period was 5.35 billion BAM with standard deviation of 1.63 billion BAM. Quarterly GDP growth rates (compared to the same quarter last year) in the four quarters of 2016 were 4.08%, 3.98%, 4.66% and 5.63%, respectively. Before testing the stationarity of the series, stabilization of variance was done by logarithmizing the series of quarterly GDP of B&H. The results of unit root tests for the logQGDP series are given in Table 1. The results of unit root tests of other time series are available upon request.

The results in Table 1 confirm that the logQGDP series is not stationary and that, at the significance level of 5%, the null hypothesis of the existence of a unit root cannot be rejected. Therefore, in order to achieve stationarity, its transformation was done. According to Mladenovic, Nojkovic (2012), the level of ordinary and seasonal integration was determined on the basis of analysis of variance assessment, evaluation of ordinary and partial autocorrelation function and application of unit root tests. In practice, the values of ordinary integration (d) and seasonal integration (D) are usually not greater than order 1. To determine the preliminary combination of their value, a variance assessment of the following series is used: Y_t, $(1-L)Y_t$, $(1-L^s)Y_t$, $(1-L)(1-L^s)Y_t$. The series with the lowest variance rating represents the optimal combination of values d and D. The series $(1-L)(1-L^{s})Y_{t}$ was given the lowest variance rating. The results of the unit root tests in Table 2 confirm that usually the seasonally differentiated logQGDP series follow a stationary pattern and that at the risk of error of 5%, the null hypothesis of unit root existence is rejected.

Table 1 Unit root test results for the logQGDP series

Test	logQGDP		
	Without C,T	C	C,T
ADF	*t*=2.16 (4) (*p-value*=0.9922)	*t*=-1.88 (4) (*p-value* =0.3393)	*t*=-1.05 (4) (*p-value* =0.9282)
PP	*t*=2.80 (12) (*p-value* =0.9986)	*t*=-1.82 (13) (*p-value* =0.33693)	*t*=-4.25 (16) (*p-value* =0.0065)
DF-GLS (ERS)	///	*t*=0.34 (4)	*t*=-0.89 (4)

*** Logs in unit root tests were determined automatically using the SIC criteria (ADF test and DF-GLS test) and the Newey-West method (PP test). The number in parentheses behind the test statistic is the number of logs.
Source: Authors' creation.

Table 2 Results of unit root tests for seasonally and naturally differentiated logQGDP series

Test	Seasonally and naturally differentiated logQGDP		
	Without C,T	C	C,T
ADF	*t*=-9.23 (0) (*p-value*=0.0000)	*t*=-9.16 (0) (*p-value* =0.0000)	*t*=-9.09 (0) (*p-value* =0,0000)
PP	*t*=-9.42 (2) (*p-value* =0.0000)	*t*=-9.34 (2) (*p-value* =0.0000)	*t*=-9.26 (2) (*p-value* =0.0000)
DF-GLS (ERS)	///	*t*=-7,77 (0)	*t*=-8.31 (0)

Logs in unit root tests were determined automatically using the SIC criteria (ADF test and DF-GLS test) and the Newey-West method (PP test). The number in parentheses behind the test statistic is the number of logs.
Source: Authors' creation.

For the sake of comparability all the series have been converted into quarterly base series with base in 2010. Namely, series of *monthly indices* (e.g. industrial production index) were recalculated into series of quarterly indices as the average of three corresponding monthly indices for the observed quarter and then converted into *series of quarterly indices* with the base in 2010. Quarterly values of interval time series having a cumulative property (e.g. monetary aggregate M2) were taken at the end of the observed quarter. The quarterly interval time series thus obtained were converted into quarterly index series with a base in 2010. *Current time series*, which do not have a cumulative feature (e.g. the BIFX30 market index), are converted into quarterly series as a quarterly average for the quarter for the observed quarter. The quarterly time-series were then converted into quarterly index series with the base in 2010. Potential predictor series which have a high degree of correlation with the quarterly GDP index of B&H are selected as suitable for model construction and sorted by degree of correlation (Appendix).

Methods

Considering the large data set that describes the information available, in the context of factor analysis, it starts from the assumption that there is a small number of combinations of original series that describe the behavior of the data set and explain the large amount of variability of the data set itself. With factor analysis, it tends to approximate the available set of original series (variables) to a set which possesses the same amount of information as the original space but a smaller number of dimensions that describe it. In dimensionality reduction of space from *m* dimensions of the original set, *k* ($k \leq m$) is extracted by linear combinations of latent series (variables) that explain the total variance in a significant proportion.

In accordance with the methodology of Giannone, Reichlin, Small (2008), a factor model was created in which factor scores were included as the regression variables. It is a multiple linear regression model (OLS) in which factor scores are used as a predictor of the time series. The model construction process was conducted in four stages: model identification, model parameter estimation, model evaluation and forecasting. The choice of predictor variables in the regression model was made on the basis of forward methods. It is very important to note that the procedure is repeated before each current forecast. Also, it should be noted that factors can change over time as well as the number of factors extracted. The regression parameters were evaluated by the OLS method.

In light of the diagnostic checkings, the performance of the selected model is expected to be stable in order to avoid re-modeling. In determining the major components (factors), a very large number of different variables of interest grouped into three groups can be used: a) financial variables, b) variables derived from surveys, and c) variables related to real economic activity.

The choice of series (predictor variables) was based on previous research such as: Stock, Watson (2002b), Angelini et al. (2010), Schumacher, Breitung (2008), Giannone et al. (2008), Marcellino, Schumacher (2010), Kuzin et al. (2012), Buss (2010), Bańbura et al. (2011), D'Agostino et al. (2011), Yiu, Chow (2011), Godbout, Lombardi (2012), Aastveit, Trovik (2012), Dias et al. (2015), Schumacher, Breitung (2006), Cheung, Demers (2007), Jovanovic, Petrovska (2010), Godbout, Lombardi (2012), Dimitris (2013), Kunovac, Špalat (2014).

Results and Discussion

In line with previous empirical research, the paper considered 110 potential series that can be used in factor models. For more information about the variables see Abdić (2018). According to Kuzin et al. (2012) all considered variables were stationaried. Before conducting factor analysis, the suitability of stationary time series for factor analysis was examined. According to Kinnear-Gray's criterion, a set of series is suitable for factor analysis if each selected series with at least one of the remaining series has a simple linear correlation coefficient at an absolute value larger than 0.3. The Appendix provides a list of the set of selected time series. Only 12 series were included in the analysis, which had a transformed correlation coefficient of quarterly GDP at an absolute value greater than 0.3. Observing the values of the correlation coefficients, it was concluded that the selected set of stationary series is suitable for factor analysis.

The Kaiser-Meyer-Olkin measure of sample adequacy indicates the suitability of the selected set of series for factor analysis (KMO = 0.695). Confirmation of the previous was also obtained by conducting a Bartlett test of sphericity on the selected set of series (χ^2=308.38; p-value = 0.000). This paper analyzes the common components since it takes into account the total variance of the starting series. Kaiser's eigenvalue criterion suggests that 3 common components need to be extracted and therefore, 3 components have been extracted and they together explain 73.34% of the total variability of a given batch set. The first component explains 40.91%, the second component explains 20.25% and the third component accounts for 12.18% of the total variability of the initial set of manifest series. To obtain a simpler factor structure, orthogonal varimax factor rotation was applied. There are two reasons for its use: it results in the simplification of the components in the factor structure matrix and ensures the non-collinearity of the principal components that will be used in the factor models as a variable regressor.

The factor loadings of 12 stationary series after applying the rotation with the varimax method are given in Table 3. Factor loads with an absolute value greater than 0.6 are bolded. After the rotation of the components, a simple arrangement of factor loadings of the manifest series was obtained. Furthermore, an interpretation of the obtained components was made on the basis of the factor structure matrix. Component 1 is called "trade indices", component 2 is called "production indices" and component 3 is called "financial sector indices". After performing the component analysis, three new series, component scores, were created, which were used instead of the 12 initial series. Component scores were evaluated by regression method. The selection of component scores in the regression factor model was performed by the forward method in the IBM SPSS Statistics 22 software package.

Table 3 Factor loadings after orthogonal rotation

Manifest series	**Component**		
	1	**2**	**3**
sddlogV6	**0.885**	-0.130	-0.011
sddlogV5	**0.827**	0.281	0.043
sddlogV8	**0.741**	0.169	0.366
sddlogV12	**0.700**	0.392	0.062
sddlogV10	**0.690**	0.515	0.046
sddlogV29	0.383	**0.865**	-0.007
sddlogV24	-0.045	**0.853**	0.112
sddlogV4	0.440	**0.780**	0.038
sddlogV343	0.112	0.043	**0.871**
sddlogV311	0.083	0.185	**0.865**
sddlogV345	0.153	0.112	**0.844**
sddlogV319	-0.086	-0.324	**0.521**

Source: Authors' creation.

The following 4 models were proposed as initial factor bridge model (FBM), based on the statistical significance of the model parameters:

1) FBM1: $sddlogKBDP_t = \beta_0 + \beta_1 PCA1_t + \varepsilon_t$

2) FBM2: $sddlogKBDP_t = \beta_0 + \beta_1 PCA2_t + \varepsilon_t$

3) FBM4: $sddlogKBDP_t = \beta_0 + \beta_1 PCA1_t + \beta_2 PCA2_t + \varepsilon_t$

4) FBM5: $sddlogKBDP_t = \beta_0 + \beta_1 PCA1_t + \beta_2 PCA2_t + \beta_3 PCA3_t + \varepsilon_t$

In the Eviews 8 software package, using the LS method, the parameters of the four specified FBM models were evaluated. The summaries of all models are given in Table 4. In the four models evaluated, it can be concluded from the graphical representation of the line diagram of the residuals and the histogram of the residuals that the residuals do not violate the assumption of stationarity and normality. The Jarque-Bera test confirmed that residues were normal (due to the limited scope of work, empirical test statistics are not provided). The correlograms of the SACF and SPACF residuals showed that for the first 16 logs, all sample autocorrelations fall within the 95% confidence limit and indicate that the residuals are random. The Ljung-Box residual test from the estimated models confirmed that the autocorrelations among the residuals were zero for the first 16 logs, indicating that the models provided an adequate description of the data. Also, Breusch-Godfrey LM test confirmed that there are no higher order autocorrelations among residuals. Furthermore, the results of the Breusch-Pagan-Godfrey test confirmed that there is no heteroskedasticity of the residuals. In Table 4, we can see that from the aspect of parsimony, the FBM1 and FBM2 models are the most economical because at the significance level of 5% they have one statistically significant coefficient. On the basis of the standard regression error, the adjusted coefficient of determination and the information criteria values, FBM5 is preferred. However, on the basis of the statistical significance of the estimated coefficients, the FBM4 model can be selected as the most appropriate model. Analyzing the Q statistic of residual correlograms for logs 4, 8 and 12, it can be seen that for all models the residuals are uncorrelated at the significance level of 5%. However, the empirical p-values of the Q statistics at all logs are largest for the FBM4 model. Therefore, based on Q statistics, FBM4 is preferred.

Table 4 Summary results of four FBM models

Variable	**Model**			
	FBM1	**FBM2**	**FBM4**	**FBM5**
PCA1	0.016884*** (0.004268)	///	0.016345*** (0.003567)	0.016480*** (0.003299)
PCA2	///	0.013866*** (0.004553)	0.013213*** (0.003530)	0.013209*** (0.003264)
PCA3	///	///	///	0.007907*** (0.003250)
SSR	0.008967	0.007557	0.006571	0.006821
Standard regression error (S.E.)	0.025337	0.027316	0.021160	0.019566
AIC/ BIC	-4.481355/ -4.435098	-4.330945/ -4.284688	-4.811040/ -4.718525	-4.938305/ -4.799832
Adjusted R^2	0.3230	0.2131	0.5278	0.5963
Ljung-Box residual statistics (*p-value*)	Q(4)=3.0053 (*p*=0.557) Q(8)=4.2448 (*p*=0.834) Q(12)=9.0771 (*p*=0.696)	Q(4)=1.9676 (*p*=0.742) Q(8)=3.1033 (*p*=0.928) Q(12)=6.0825 (*p*=0.912)	Q(4)=1.0045 (*p*=0.909) Q(8)=1.5430 (*p*=0.992) Q(12)=2.7184 (*p*=0.997)	Q(4)=2.2701 (*p*=0.686) Q(8)=2.7151 (*p*=0.951) Q(12)=3.9325 (*p*=0.985)

*,**,*** Coefficient significant at the level of 10%, 5%, 1%, respectively. Standard errors are in parentheses.
Source: Authors' creation.

The final selection of the FBM model for forecasting B&H's quarterly GDP was selected on the basis of a comparative analysis of the predictive effectiveness of the mentioned models for the in-sample period (2006q1-2014q4) and the out-of-sample period (2015q1-2016q4). The following is a comparison of FBM4 and FBM5 within the sample. Figure 2 provides a graphical representation of B&H's quarterly GDP, projected values of B&H's quarterly GDP based on the FBM4 and FBM5 models, and a forecast error for the in-sample period 2006q1-2014q4.

The graphs look almost identical and the projected values relatively accurately reflect trends in B&H's quarterly GDP. The FBM5 model has a lower average value of forecast errors and a smaller standard deviation of forecast errors. Based on the Jarque-Bera test, at the significance level of 5%, the hypothesis that the forecast errors of both models are normally distributed cannot be rejected. Based on the correlation charts of the SACF and SPACF forecast errors of the FBM4 model and FBM5 model, it appears that the forecast errors in both FBM4 and FBM5 model follow the Gaussian white noise process. In both models, the Ljung-Box test confirms that the first 16 logs of autocorrelation are zero among forecast errors, indicating that forecast errors are random.

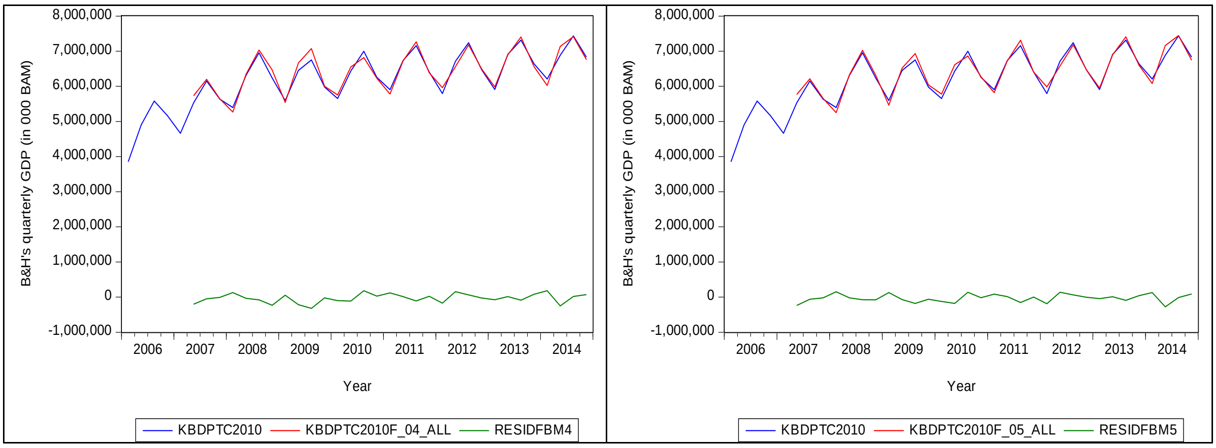

Figure 2 Quarterly GDP of B&H, forecast values of quarterly GDP of B&H and forecasting errors for the in-sample period FBM4 model (left) and FBM5 model (right)
Source: Authors' creation.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.026	-0.026	0.0224	0.881
		2	-0.036	-0.036	0.0672	0.967
		3	0.130	0.128	0.6850	0.877
		4	-0.154	-0.151	1.5782	0.813
		5	-0.050	-0.047	1.6762	0.892
		6	0.035	0.008	1.7275	0.943
		7	-0.092	-0.059	2.0896	0.955
		8	-0.023	-0.036	2.1138	0.977
		9	0.074	0.051	2.3672	0.984
		10	0.015	0.038	2.3775	0.993
		11	0.118	0.115	3.0924	0.989
		12	-0.050	-0.081	3.2296	0.994
		13	-0.017	0.002	3.2456	0.997
		14	0.007	-0.016	3.2488	0.999
		15	-0.212	-0.181	6.1160	0.978
		16	-0.014	-0.020	6.1292	0.987

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.136	-0.136	0.6348	0.426
		2	-0.180	-0.203	1.7810	0.410
		3	-0.040	-0.104	1.8401	0.606
		4	-0.151	-0.228	2.7026	0.609
		5	-0.000	-0.113	2.7026	0.746
		6	0.074	-0.043	2.9247	0.818
		7	-0.025	-0.085	2.9511	0.889
		8	-0.063	-0.136	3.1262	0.926
		9	0.093	0.018	3.5295	0.940
		10	0.001	-0.022	3.5296	0.966
		11	0.125	0.143	4.3261	0.959
		12	-0.003	0.048	4.3265	0.977
		13	-0.062	0.053	4.5437	0.984
		14	0.028	0.101	4.5922	0.991
		15	-0.232	-0.187	8.0271	0.923
		16	-0.014	-0.082	8.0405	0.948

Figure 3 Correlograms of SACF and SPACF forecast errors for the in-sample period FBM4 models (left) and FBM5 models (right)
Source: Authors' creation.

Regression of the forecast errors of an individual FBM model at a constant verified the statistical significance of the forecast errors. Based on the t-test, at the significance level of 5%, it can be concluded that there are no statistically significant errors in the FBM4 model forecasts (t = -1.33; p-value = 0.1920) and in the FBM5 model forecasts (t =-1.45; p-value=0.1569). In other words, there is no systematic error in the forecasts of these models. The impartiality and efficiency of the forecasts were tested using Mincer-Zarnowitz regression. In Tables 5 and Table 6, the Mincer-Zarnowitz regression results for the FBM4 and FBM5 models are given.

The results of the Wald joint test (F=1.5403; p-value = 0.2313) confirm that in-sample period forecasts obtained on the basis of the FBM4 model with 95% confidence are unbiased and effective. The situation with FBM5 is similar. The Wald joint test (F=1.7328; p-value =0.1946) confirms that in-sample period forecasts obtained from the FBM5 model with 95% confidence are unbiased and effective.

Table 5 Mincer-Zarnowitz Quarterly GDP regression results of forecasted in-sample period (FBM4 Model)

Variable	*Coefficient*	*Standard error*	*t-stat*	*p-value*
C	266,041.4	263,448.6	1.01	0.3209
QGDP_FBM4	0.953906	0.040700	23.44	0.0000

Source: Authors' creation.

Table 6 Mincer-Zarnowitz Quarterly GDP regression results of forecasted in-sample period (FBM5 Model)

Variable	*Coefficient*	*Standard error*	*t-stat*	*p-value*
C	237,910.3	232,840.5	1.02	0,3153
QGDP_FBM5	0.958439	0.035978	26.64	0.0000

Source: Authors' creation.

The accuracy of the forecasts of the two models is compared below. The following graphs show the forecast values of the B&H quarterly GDP series with interval limits of ±2 standard errors.

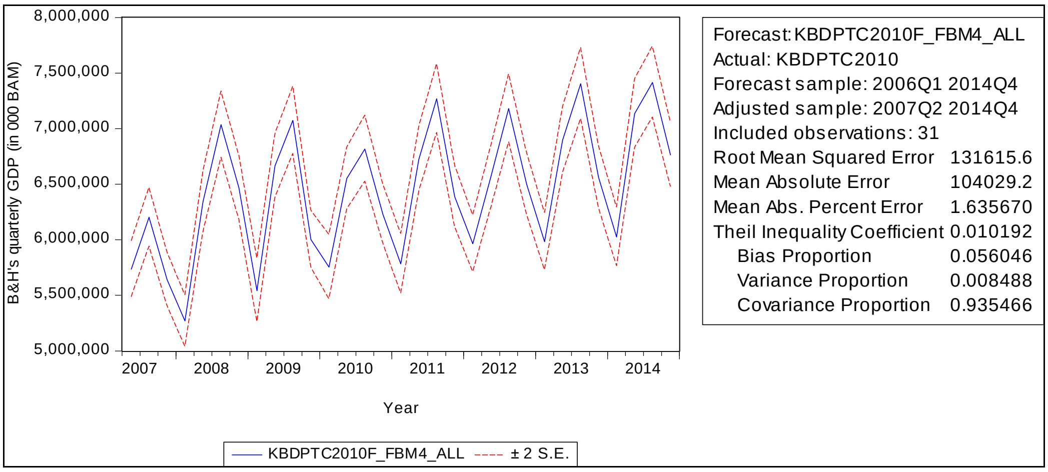

Figure 4 Forecasted values of the B&H quarterly GDP series for the in-sample period (FBM4 model)

Source: Authors' creation.

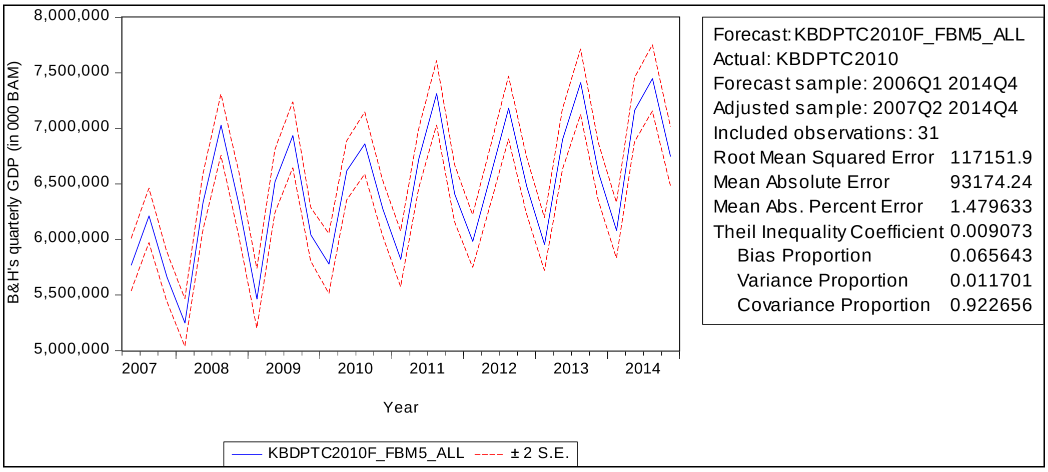

Figure 5 Forecasted values of the B&H quarterly GDP series for the in-sample period (FBM5 model)

Source: Authors' creation.

The FBM5 model has better individual metrics of estimating the accuracy of forecasts (except for the bias proportion, variance proportion and covariance proportion). The root-mean-square error in FBM4 is 131,615.6 while the root-mean-square error in FBM5 is 117,151.9. The differential of squared loss function has a mean value of 3.60E+09 with a standard deviation of 1.85E+10. The differential of squares of forecasting errors follows the white noise process. The Ljung-Box test confirms that the first 16 logs of the autocorrelation of the forecasting error squared differential are zero (Q=6.7770; p-value=0.977). However, based on the Jarque-Bera test, at the significance level of 5%, we reject the null hypothesis that the mean squared error is normally distributed (JB=47.7264; p-value=0.0000). The comparison of the forecasting accuracy of the two models mentioned above was tested by the Wilcoxon signed-rank test. Based on this test, it can be concluded that differential of the mean squared forecasting errors $\left(\bar{d} = 3.60E + 09\right)$ is statistically not significantly different from zero (z=-0.126; p-value=0.900). Therefore, it can be concluded that there is no statistically significant difference in the accuracy of forecasts using the two models mentioned. However, more efficient forecasts are given by FBM5 as it has a smaller mean forecast error.

Below, we examined the justification of a combination of the two considered forecasts using the Granger-Ramanathan regression. The coefficient of the linear correlation of the forecasts is r=0.9971, which means that there is a positive and almost perfect correlation between them. Table 7 shows the results of the regression estimation of the unconditional combination of forecasts of FBM4 and FBM5 model for B&H quarterly GDP.

Table 7 Regression results of unconditional combination of FBM4 model forecasts and FBM56 model forecasts

Variable	*Coefficient*	*Standard error*	*t-stat*	*p-value*
C	241,774.9	237.073.1	1.02	0.3165
QGDP_FBM4ALL	-0.103218	0.378848	-0.27	0.7873
QGDP_FBM5ALL	1.061076	0.378485	2.80	0.0091

Source: Authors' creation.

The results indicate that the intercept (t=1.02; p-value=0.3165) and the parameter used in the FBM4 model forecasts (t=-0.27; p-value=0.7873), at the significance level of 5%, are not statistically significantly different from zero. The parameter used in the FBM5 model forecasts (t=2.80; p-value=0.0091), at the significance level of 5%, is statistically significantly different from zero. Based on the results of the Wald joint test (F=0.6831; p-value=0.5133) with the same significance level, the null hypothesis: $\left(\beta_1, \beta_2\right) = \left(0,1\right)$ cannot be rejected and we conclude that the FBM5 model has an advantage over the FBM4 model. In addition to comparing FBM4 and FBM5 for the in-sample period, they were also compared for the out-of-sample period. Figure 6 shows B&H quarterly GDP, forecasted B&H quarterly GDP values based on the FBM4 and FBM5 models and forecast errors.

The graphs are almost identical and the forecasted values relatively accurately reflect the trends in B&H's quarterly GDP. The mean values of the forecast errors are significantly lower than the in-sample period. Also, the standard deviations of the forecast errors are significantly lower than those the in-sample period. The mean error values of the FBM4 and FBM5 forecasts are positive, with the average of the FBM5 model forecast errors being lower. Based on the Jarque-Bera test, at the significance level of 5%, the hypothesis that the forecast errors of both models are naturally distributed cannot be rejected. The correlations of the SACF and SPACF forecast errors of FBM4 and FBM5 show that the forecast errors of FBM4 and FBM5 follow the white noise process. The Ljung-Box test confirms that autocorrelations among forecast errors are zero in both FBM4 (Q=2.2380; p-value=0.946) and FBM5 (Q=2.0169; p-value= 0.959).

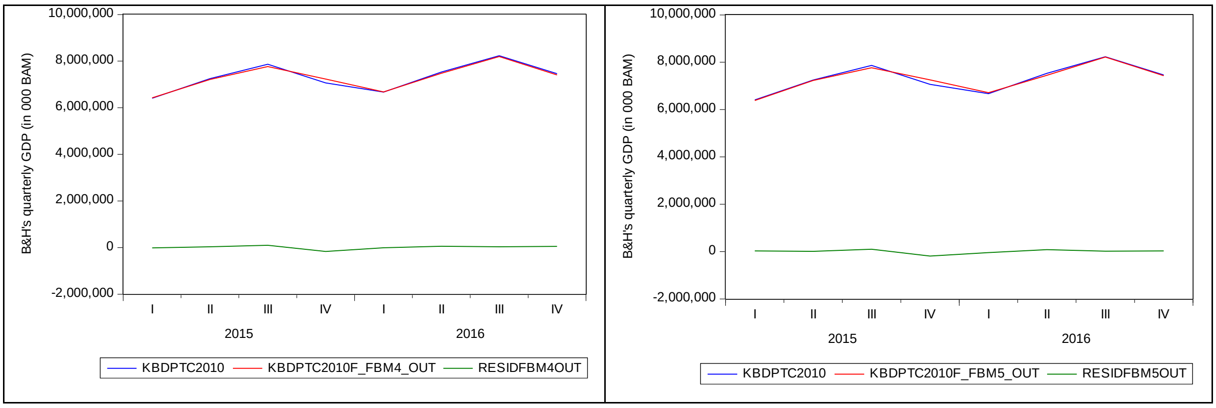

Figure 6 Quarterly GDP of B&H, projected values of quarterly GDP of B&H and forecast errors in the out-of-sample period FBM4 model (left) and FBM5 (right)
Source: Authors' creation.

Following the same procedure as in the in-sample period, it can be concluded that there are no statistically significant errors in the forecasts of the analyzed models, that the forecasts outside the sample obtained on the basis of both models are unbiased and efficient at the significance level of 5%, and that the differential of the mean squared prediction error follows the white noise process. Alos, it can be concluded that the autocorrelation among forecast errors is zero, that the mean squared prediction error is normally distributed, that the mean value of the squared prediciton errors is not statistically significantly different from zero, meaning that there is no statistically significant difference in the accuracy of the forecasts using the two models listed. However, FBM4 provides more efficient forecasts because it has a lower forecast error. Finally, based on the above, it can be concluded that FBM5 is the most representative and effective factor model in B&H's quarterly GDP forecasts:

- FBM5 is the most parsimony according to the AIC/BIC criterion,
- FBM5 has the lowest standard regression error,
- FBM5 has the best predictive performance within the sample period,
- FBM5 provides the best approximation of B&H GDP trends,
- FBM5 has the smallest root mean square error,
- FBM5 has the lowest mean absolute error,
- FBM5 has the lowest mean percentage error,
- FBM5 has the lowest Theil coefficient of inequality,
- FBM5 has the highest covariance proportion.

FBM5 was used to forecast B&H's quarterly GDP in 2017. The main assumption is that the underlying patterns in the time series will remain the same as predicted in the model in the future.

Table 8 Tabular overview of QGDP B&H forecast values (in 000 BAM) for the year 2017 by FBM5 model

Quarters	***Lower Limit Confidence Interval***	***Forecasted value***	***Upper Limit Confidence Interval***	***Forecasted value (BHAS)***
2017q1	6,790,000.00	7,068,551.32	7,360,000.00	7,074,334.00
2017q2	7,660,000.00	7,979,246.35	8,310,000.00	7,891,752.00
2017q3	8,480,000.00	8,827,772.78	9,919,000.00	8,706,847.00
2017q4	7,690,000.00	8,002,721.52	8,320,000.00	*n.a.*

*** The lower and upper limit confidence intervals were determined with a 95% confidence level.
Source: Authors' creation.

Using FBM5, it was calculated that in the first quarter of 2017, B&H GDP will amount to 7.07 billion BAM. Based on this model, GDP is projected to grow by 5.96% in the first quarter of 2017 compared to the previous quarter, which is 3.46 percentage points higher than the average growth rate in the first quarter for the last 5 years.

Conclusions

In line with previous empirical research, 110 potential series that could be used in factor models were considered. Different criteria were used when selecting manifest series suitable for factor analysis. Principal component analysis and orthogonal varimax rotation of the initial solution was applied. Three common components were extracted, which together explained 73.34% of the total variability of a given set of batches. After factor extraction, factor scores that were used in the factor model were evaluated as a predictor of the time series. When identifying and evaluating the regression model, the selection of the predictor variables (factor scores) in the regression model was made on the basis of the forward method. The intention was to reduce as many series as possible to a number of common factors with the use of factor analysis. Factor models which had the best performance based on multiple criteria were selected for forecasting. The final choice of the factor model for forecasting B&H's quarterly GDP was selected based on a comparative analysis of the predictive efficiency of the model for the in-sample period. The FBM5 factor model, which includes three major components, has proven to be the most effective factor model in B&H's quarterly GDP forecasts. The results of this empirical research have contributed to a better understanding of B&H's GDP and the creation of assumptions for modelling its short-term prediction, as well as to identify the key drivers of economic growth. Furthermore, the expected scientific contribution of the paper is reflected in the fact that this is the first scientific research conducted in B&H that included factor models. The results of this research are evident in the creation of a reliable and efficient model for the short-term forecast of B&H's GDP whose forecasts will be available no later than 60 days from the end of the observed quarter. In addition, this model has been used to produce quarterly forecasts of B&H's GDP that will allow policymakers at all levels of government, as well as, businessmen and investors on all markets to use this information to make more adequate political and managerial decisions and to construct investment and financial strategies and policies, but also for those planning personal spending. Exploiting a lot of information can lead to more precise forecasts. This is of great benefit to economic policy makers because it is possible to evaluate the impact of huge numbers of variables (both aggregated and disaggregated, soft and hard) from a large number of sources (The Central Bank of B&H and Agency for statistics of B&H) adjust the policy mix accordingly.

The paper showed that using factor models, adequate estimates of B&H's GDP can be made. However, there are limitations to the use of the factor bridge models. Static PCA is based on the restrictive assumption of serial independence of idiosyncratic components. This assumption is often too strong for economic data. In addition, the question of the appropriate method of factor estimation and factor rotation arises, and there is uncertainty regarding the correct choice of the number of factors in empirical applications. Furthermore, the unavailability and inadequacy of the required data for a number of series of real economic activity during the aforementioned research period was a significant limitation for model creation. Therefore, in order to improve all the models created, access to all the data about the trends in B&H's economy is necessary. First of all, this applies to: the producer price index of the industry in the domestic market, average consumer prices, consumer price index, foreign trade, investment, construction, tourism, population and labor market data, etc. Also, it would be interesting to include time series on the expenditure side of GDP in the research, the GDP of the EU or GDP of the countries with which B&H has the highest trade-to-GDP ratio, and international variables (e.g., oil prices, euro area prices, investment, foreign trade and output). Lastly, it would be useful to examine the justification of nonlinear combinations of two or more models.

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APPENDIX A1 Predictor variable with the highest degree of correlation with the index of QGDPB&H

Variable label	**Variable name** (*all variables are converted into quarterly index* (2010=100))	**Correlation with QGDP index** (2010=100)
V5	Retail sale of automotive fuel in specialised stores	0.9433
V24	Non - durable consumer goods	0.8977
V6	Retail sale of food, beverages and tobacco in n.s.	0.8930
V3	Gyro clearing	0.8913
V29	Processing industry	0.8859
V10	Retail sale of other household appliances in specialized stores	0.8626
V8	Other retail sale in n.s.	0.8496
V309	Retail	0.8406
V343	Claims on other sectors of the domestic economy	0.8401
V4	Total industrial production	0.8378
V326	Total deposits	0.8313
V328	Long-term loan	0.8274
V325	Other depostis	0.8190
V323	Monetary aggregate M2	0.8161
V311	Total loans	0.8143
V322	QM	0.8113
V319	Other deposits in foreign currency	0.8100
V40	Chemicals and chemical products manufacturing	0.8094
V324	Transferable deposits	0.8082
V357	The total financial sector liabilities	0.8074
V345	Total assets of the banking sector	0.8069
V12	Retail sale of other goods in s.s.	0.8055
V318	Transferable deposits in foreign currency	0.8036
V30	Manufacture of food products	0.7933

All correlations are significant at the 0.01 level (2-tailed).
Other series and their correlation coefficients are available upon request.
Source: Authors' calculations.

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