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Forecasting inflation in Bosnia and Herzegovina

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Abstract

The purpose of this paper is to evaluate the performance of some leading univariate and multivariate models: ARIMA, the standard OLS VAR and Bayesian VAR models, in forecasting inflation in Bosnia and Herzegovina. Although the presented models are small and highly aggregated, they provide a convenient framework to illustrate practical forecast issues. Furthermore, they are a good starting point in the process of the forecast development.

The empirical part of this paper estimates the domestic and international transmission effects on inflation and tries to find good predictors of the inflation. A variety of inflation indicators included in the VAR models are assessed as potential predictors of inflation. They have been suggested by economic theory and existing research. A pseudo out-of-sample forecast approach is employed to assess the models' performance at different horizons using a recursive strategy. The study then evaluates the relative forecast performance of univariate model and various alternative specifications of the VAR models and offers conclusions. The results confirm the significant improvement in forecasting performance at all forecast horizons when Bayesian techniques, which incorporate information from the likelihood function and some informative prior distributions, are used.

Keywords: Bayesian VAR, model selection, inflation forecasting

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Disclaimer: The views expressed herein are of the author and do not necessarily represent those of the Central Bank of Bosnia and Herzegovina (CBBH).

Contents

1. Introduction

Bosnia and Hercegovina (BH) is a small and open economy. Due to its high dependence on the external world, it is necessary to design fiscal and monetary policies with the aim of long-term sustainable macroeconomic stability. The Central Bank of Bosnia and Herzegovina (CBBH) conducts monetary policy through a currency board arrangement (CBA) [1]. In line with the use of the CBA as a monetary strategy, the expected inflation trend in BH is in line with the expected inflation dynamics of the Eurozone. However, lack of exchange rate flexibility can amplify the impact of external shocks and make it more difficult for the central bank to anchor inflation expectations credibly. Accordingly, an unbiased analysis of the potential threats from the global economy on the BH economy are required.

Forecasting is one of the most important goals of empirical analysis. Any serious forecasting model is supposed to at least outperform naïve time series benchmark models. Numerous studies have investigated the relative accuracy of structural inflation forecasting models. One approach to compare the accuracy of the structural inflation forecasts to univariate time-series models is by using the Root Mean Square Error (RMSE). In this paper, an autoregressive integrated moving average (ARIMA) model is considered as a benchmark. The paper focuses on the development of a multiple time series model, the multivariate vector autoregressive (VAR) models, and compares it with the benchmark model. The VAR models often provide superior forecasts relative to those from univariate time series models and elaborate theory-based simultaneous equations models.

A forecasting model with a good in-sample fit does not necessarily imply that it will have a good out-of-sample performance. Therefore, pseudo out-of-sample forecasts are used in this study[2]. The study then evaluates the relative forecast performance of various alternative specifications of the VAR models and offers conclusions based on the study's findings.

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[1] CBBH maintains monetary stability by issuing domestic currency according to the CBA (1 KM: 0,51129 EUR) with full coverage in freely convertible foreign exchange funds under fixed exchange rate 1 KM: 0,51129 EUR.

[2] Experience has shown that good in-sample fit of a forecasting model does not necessarily imply good out-of-sample performance. The method of pseudo out-of sample forecast evaluation aims to address this by simulating the experience a forecaster would have using a forecasting model. In a pseudo out-of-sample forecasting exercise, one simulates standing at a given date t and performing all model specification and parameter estimation using only the data available at that date, then computing the h period ahead forecast for date t+h; this is repeated for all dates in the forecast period (Stock and Watson, 2008).

VAR models are widely used to forecast. The VAR encompasses correlation information from the observed data and uses this correlation information to forecast future movements or changes of the variable of interest. It is also used for the analysis of the system responses to different shocks/impacts.

The choice of the data sample as well as the observed variables are dictated by data availability. The Bayesian VAR (BVAR) method is quite appropriate to model data with small sample sizes, a particularly crucial advantage in applied work on emerging economies. Therefore, it is considered the appropriate methodology for this study.

The paper is organized as follows: Section 2 presents an overview of inflation dynamics in Bosnia and Herzegovina and its developments. Section 3 contains a literature review. Section 4 presents the data used in the study. Section 5 explains the methodology, the model development and the forecasting performance results. Section 6 presents the results of the structural analysis. The last section offers some concluding remarks.

2. Overview of inflation in Bosnia and Herzegovina

Bosnia and Herzegovina adopted a currency board arrangement (CBA) to achieve macroeconomic stability and credibility during the transition process. The objective of the Central Bank is to achieve and maintain the stability of the domestic currency by issuing it according to the rules of the CB regime. Under the very rigid CBA regime in BH, the reserve requirement is the only available instrument to the monetary authorities. Ghosh, Gulde, and Wolf (1998) have undertaken an empirical investigation to compare the macroeconomic performance of countries with currency boards and those with other forms of pegged exchange rate regimes. Their findings suggest that currency boards are indeed associated with better inflation performance. Low income countries (LICs) with fixed exchange rates seem to succeed in anchoring inflation expectations as much as other Emerging market and developing economies with fixed exchange rates, whereas LICs with floating exchange rates had more difficulties. This suggests that LIC central banks have not been able to secure low and stable medium-term inflation rates on their own, and their improved inflation performance may therefore have been largely imported. Therefore, if global inflation were to rise, LICs would face the risk of their own inflation rising in tandem, unless steps can be taken to improve their homegrown anti-inflation credibility (Ha, Kose, and Ohnsorge, 2019).

In BH, data on inflation, as measured by the consumer price index (CPI), is available on a monthly basis, for the period starting from January 2005, according to the EU methodological standards. Until then, there were data on the retail price index (RPI) and cost-of-living index (COLI). The classification of products used in the CPI is based on the Classification of Individual Consumption by Purpose (COICOP). The COICOP divides consumer expenditures into twelve different categories of consumer goods and services. Table 1 presents the structure of COICOP classification. The weight of food and nonalcoholic in the total consumption basket decreased from 34% in 2007 to 32% in 2018.

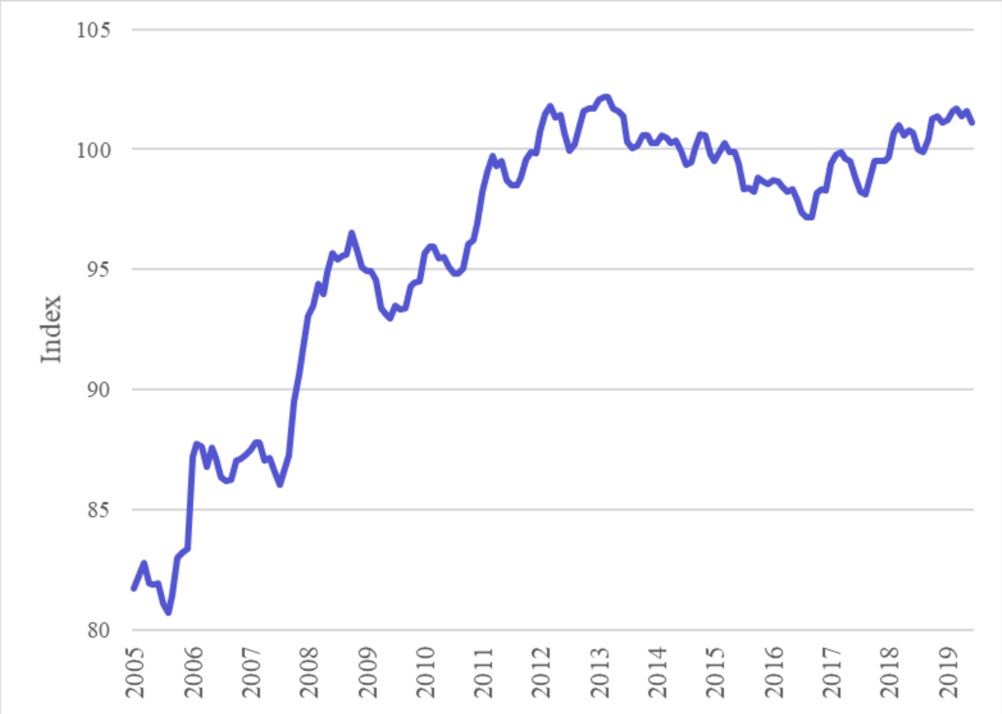
Table 1: CPI in BH by COICOP divisions and groups, year 2018

DIVISION/GROUP	
Food and nonalcoholic beverages	32.0%
Housing, water, electricity, gas and other fuels	14.5%
Transport	12.8%
Other goods and services	8.1%
Communication	5.6%
Furnishings,household equipment and maintenance	5.6%
Clothing and footwear	5.4%
Medical Care	5.1%
Alcoholic beverages and tobacco	4.3%
Hotels and restorants	3.3%
Recreation	2.4%
Education	0.7%

Source: Agency for Statistics BH

BH inflation has been moderate except in 2006, due to introduction of the value-added tax (VAT) in the BH tax system in January of that year. The price growth significantly decelerated toward the year-end and subsequent months. Besides that, a sharp increase in energy and food prices on world markets in 2008 also had large impact on changes in the CPI in BH.

Figure 1: Consumer Price Index (index base: 2015=100)



Source: Agency for Statistics BH

The standard practice of excluding food and energy from the CPI basket to draw conclusion about core inflation measure is not ideal in a country like BH, for two reasons. One is the relatively large weights of these categories of goods and the other is that not all food and energy items may exhibit high volatility, so there would be little need to exclude all of them. The analysis of the IMF Country Report (2008) has shown that the measures of core inflation that exclude food and energy deviates significantly from the inflation faced by a typical household in BH.

The first step in this paper is to identify a selection of economic variables that might be a direct or indirect predictor of inflation in BH. We will examine variables whose movements appear to have been highly correlated with inflation in the past and try to see if they may be useful in forecasting future inflation. The first attempt was to distinguish between factors originating in the global environment from those related to changes in the domestic conditions in order to examine the causes of inflation developments. The causes could be alternatively attributed to purely domestic as well as external factors.

3. Literature review

This section reviews the theoretical and empirical work which attempts to identify inflation determinants that would be most useful in predicting the future path of the inflation. It also discusses the forecasting methodologies.

In practice, it is not always easy to decompose observed inflation into its monetary, demand-pull, cost-push and structural components. The process is dynamic, and shocks to prices might be mixed. Furthermore, inflation itself may also cause future inflation.

The literature on inflation forecasting points a wide range of different modeling techniques in forecasting inflation. Well-established and widely used ones are univariate autoregressive integrated moving average (ARIMA) and multivariate vector autoregressive (VAR) models. In general, each model has its own advantages and disadvantages. The main advantage of ARIMA forecasting is that it requires data only on the time series being forecasted. The evolution of inflation expectations is an important part of the inflation process, but it is also strongly influenced by past inflation.

Fritzer et al. (2002) find that for Austrian inflation, univariate models outperform multivariate models at short horizons. Meyler, Kenny and Quinn (1998) used two approaches to identify appropriate ARIMA models for Irish inflation: the Box-Jenkins methodology and the objective penalty function methods. They stated that the ARIMA performs quite favorable compared with BVAR analysis within periods of relatively stable inflation, but may yield poor forecast values when applied to volatile and high frequency data. However, this does not mean that univariate modeling can supplant multivariate techniques. The economic significance of the ARIMA model is not clear since it does not involve any structural relationships.

The VAR model can be considered an extension of an ARIMA model. It involves multiple independent variables and therefore has more than one equation. Each equation uses as explanatory variables lags of all the variables, a constant and, possibly, a deterministic trend.

Papavangjeli (2019) estimated several univariate models to forecast short-term inflation in Albania: unconditional mean, random walk, ARIMA models, and the best performing among them is used as a benchmark to evaluate the forecast performance of a BVAR model. In addition, an unrestricted VAR - the most commonly used tool to obtain projections of the main economic indicators - is constructed as an additional benchmark. The results show that the

BVAR approach, which incorporates more economic information, outperforms the benchmark univariate and the unrestricted VAR models at different time horizons, but the differences between models in terms of their forecast performance are not statistically significant.

The study of Ogunc, Ozmenand and Sarikaya (2018) examines inflation dynamics in Turkey by estimating a Bayesian VAR model with five variables: exchange rate, import price, GDP, inflation and nominal wage. They used a Bayesian approach because they have a small sample and Bayesian VARs also have better identification facilities and capacity to incorporate expert knowledge into the estimation process.

Kasuya and Tanemura (2000) estimate several Bayesian VAR models for the Japanese economy, with 8 variables: consumer price index (CPI), money supply, real gross domestic product (GDP), GDP deflator, 10-year government bond yields, nominal exchange rate, investment and unemployment rate for the period 1973Q2-1999Q3. They compare the forecast performance of a BVARs with that of an ordinary VAR using one-step ahead forecasts and Monte Carlo experiments. The results suggest that the selected BVARs are superior to ordinary VAR models.

Bank loans and the monetary aggregate M3 are the most important variables for inflation when forecasting Swiss inflation (Lack, 2006). This result is based on the forecasts from several VAR models combined to produce one final forecast.

Arsène and Guy-Paulin (2013) investigated the link between credit to the private sector, inflation and economic growth in Cameroon (a country with fixed exchange rate regime). They find that credits cause inflation in the short term. This is explained by the fact that lending rates are too high in Cameroon, leading to an increase in the cost of production. This is then transmitted to higher prices in the economy.

The relationship between domestic market pressure and inflation depends on the openness to international trade. Specifically, the availability of imports can affect domestic inflation directly via the prices of those imports included in the price index, and indirectly through competition with domestic goods and services (Dexter et al. 2005).

Ramakrishnan and Vamvakidis (2002) analyzed the domestic and international transmission effects on inflation in Indonesia. Their results showed that the exchange rate and foreign inflation are key contributors of the domestic inflation, with a strong predictive power, while base money growth has a smaller impact on the headline CPI.

Ulke and Ergun (2011) investigated the relationship between inflation and import volume using monthly time series data for the Turkish economy over the period 1995-2010. They apply a number of econometric techniques and concluded that there is long term and short term co-integration relation between inflation and import volume.

Khalid (2005) studied the leading determinants of inflation in Pakistan. The results indicate that imported inflation, deficit-GDP ratio, seigniorage, money depth, exchange rate depreciation and domestic credit may be important determinants of inflation in Pakistan. This is consistent with the experience of many emerging economies at the early stage.

The study of Muktadir-Al-Mukit et al. (2013) attempts to investigate the relationship between inflation and imports in Bangladesh for the period of 2000 to 2011 using different econometric frameworks. Their result shows a stable, positive and significant relationship between inflation and imports.

4. Data description

The most important element for the selection of variables to be used in the exercise is availability of the data in BH. Once the variables are chosen, some of the statistical tests are performed to decide which variables should be used, and then a selection of the most useful variables for a relatively small VAR models is done. For univariate time series, forecasting is required to check whether there are structural breaks. In this paper, inflation is calculated by taking the annual rate of change in the CPI. Since food and energy prices have a relatively large weight, estimating core inflation excluding them from the CPI basket is not ideal. Therefore, in this study the headline inflation is the main variable of interest. This study focuses on the period after introduction of the value-added tax (VAT). The introduction of VAT in the BH tax system caused short-term shock to the price level, which was reflected as a one-time increase in the price index. Therefore the estimation period starts in 2007 in order to eliminate a structural break at the beginning of the sample. As the analyzed period is not that long, the monthly data is used. The comparative studies in developed countries employ longer time series and quarterly and annual data. However, transition countries generally have a short time series and work with monthly data.

In order to build the proper VAR for forecasting BH inflation, it seems appropriate to consider the indicators that economic theory, empirical studies and the country's economic structure suggest as the main explanatory variables. Based on this approach, the following variables are considered as the possible predictors of BH inflation: the index of industrial production, private sector loans, household loans, the real effective exchange rate (REER), imports, monetary aggregates (M1 and M2), international crude oil prices, international food price, EURIBOR, Harmonized Index of Consumer Prices (HICP) in Eurozone (overall index), HICP in the Eurozone (All-items excluding energy and food), the exchange rate (domestic currency KM/US dollar)[3].

Previous research has suggested that these variables had directly or indirectly influenced an inflation. Since monthly data are used, GDP is excluded as a relevant output indicator. Interpolation of the quarterly GDP in order to estimates the monthly level data was not a suitable option. Instead, industrial production is used as a proxy for the output variable.

5. Model specification

The sample period is divided into two parts: the estimation and forecast periods. The estimation period is 2007:01 to 2017:12 and the forecast period 2018:01 to 2018:12. Furthermore, a recursive (expanding window) strategy is used to simulate forecast performance 12 steps ahead. In the second forecast round, the estimation period expands by one month, but its starting point is the same. This process is repeated ten times until models are estimated with data up to 2019:09. In this way, a series of a length of 10 observations was generated for each time horizon. The forecasting period is used to compare the forecasts with the actual values of the BH inflation rate.

The models are ranked according to their forecast performance. The standard measure in the forecasting outcomes is the Root Mean Square Error (RMSE), which serves as the model selection criteria to identify the best performing model in forecasting.

[3] Source: The CPI and index of industrial production (Agency of Statistics BH), the private sector loans, the household loans, REER, the exchange rate KM/US dollar, import, M1 and M2 (Central Bank of BH), international crude oil prices, international food price (IMF – commodity prices), EURIBOR, HICP in Eurozone (European Central Bank-Statistical Data Warehouse).

5.1. The ARIMA model

The autoregressive integrated moving average (ARIMA) model is one of the widely used forecasting methods. It assumes that past values of the series and previous error terms contain information for the purposes of forecasting. An ARIMA model for non-seasonal series is denoted by ARIMA (*p*,*d*,*q*). Here, *p* and *q* indicate the order of the autoregressive (AR) part and moving average (MA) part, respectively, and *d* indicates the amount of differencing.

The ARMA process of orders *p* and *q* is defined as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$$

Where

Y_t= Endogenous variable at time t

$\phi_1, \phi_2, \ldots, \phi_p$ = *AR* coefficients

$\theta_1, \theta_2, \ldots, \theta_q$ = *MA* coefficients

ε_t =Error term at time t

ARMA models are applicable to a stationary data series, where the mean, the variance, and the autocorrelation function remain constant throughout a time period. One of the approach to the identification of ARIMA model is the Box and Jenkins methodology proposed in 1970. Box and Jenkins proposed a set of procedures for identifying and estimating time series models within the class of ARIMA models which exploits information embedded in the autocorrelation pattern of the data. Estimation is based on maximizing the likelihood function of the model.

In order to estimate parameters, *p*, *d*, and *q*, an automatic modeling method for univariate time series is used instead of the inspections of sample autocorrelation and partial autocorrelation functions. This procedure was also used by Fritzer et al. (2002) for forecasting Austrian HICP. A whole range of models are estimated and ranked according to various information criteria. More precisely, ARIMA *(p, 0, q)* is defined for $p, q \in \{0,\ldots,2\}$. Models were estimated for the period 2007:01 to 2017:12. Table 2 shows the specification of the top models. According to Akaike Information criteria (AIC), the Bayesian Information Criterion (BIC) and the Hannan–Quinn (HQ) Schwarz information criterion suggested, the ARIMA model (2,0,1) is identified as the best specification. We perform several diagnostic tests: we found no autocorrelations of residuals, we found that parameters are stable and that parameter estimates are significant. The period 2018:01 to 2019:09 was used to compare the forecast with true values of the inflation.

Table 2: Model Selection Criteria

Dependent Variable: INF_BH Sample: 2007M01 2017M12 Included observations: 132				
Model	LogL	AIC*	BIC	HQ
(2,0,1)	-77.261965	1.246393	1.35559	1.290766
(2,0,2)	-77.254266	1.261428	1.392465	1.314675
(2,0,0)	-81.904276	1.30158	1.388938	1.337078
(1,0,2)	-87.395176	1.399927	1.509124	1.4443
(1,0,1)	-95.126491	1.501917	1.589274	1.537415
(1,0,0)	-114.00917	1.772866	1.838384	1.79949
(0,0,2)	-187.481897	2.901241	2.988598	2.936739
(0,0,1)	-227.873641	3.498085	3.563604	3.524709
(0,0,0)	-310.468528	4.734372	4.77805	4.752121

Source: Author's calculation

Forecasting accuracy was measured by the *n* months ahead forecast, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Table 3 shows RMSE for 1, 6 and 12 months ahead for the first forecast period: 2018:01 to 2018:12. The best ranked model clearly outperforms the other specifications.

The root mean squared forecast error (RMSE) for the *h*-period forecasts is:

$$RMSE = \sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}\left(\hat{Y}t - Yt\right)^2}$$

Where Yt and $\hat{Y}t$ are actual and predicted value in period t

Table 3: Root Mean Squared Error (RMSE)

	1 month ahead	6 months ahead	12 months ahead
ARIMA(2,0,1)	0.949	0.509	0.559
ARIMA(2,0,2)	0.952	0.510	0.558
ARIMA(2,0,0)	0.998	0.528	0.580

Source: Author's calculation

5.2 The VAR model

The vector auto regression (VAR) model is one of the most successful and flexible models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. It has been proven that the VAR model is useful for describing the dynamic behavior of economic time series and for forecasting. The VAR models were made popular by Sims (1980) in economics and have acquired a permanent place in the toolkit of applied macroeconomists, see Chapter 4 of Canova (2007). One of disadvantages using the VAR model is that the number of variables should be related to the size of the sample. Therefore, the number of variables is restricted in the models presented in this paper. The VAR models evaluated in the selection procedure contain up to four variables.

The VAR (*p*) model, where *p* is a positive integer, can be written as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots \phi_p Y_{t-p} + \varepsilon_t$$

Where:

Y_t = vector of n variables at time *t*

C = (n x 1) vector of constants

ϕ_i = (n x n) coefficient matrices

ε_t =(n x 1) vector of errors, the errors are assumed to be independently and identically distributed, with mean zero

The first step in the modeling approach is the estimation of the numerous VAR models[4]. Three groups of the VAR models are examined. The first group includes only domestic variables: the index of industrial production, private sector loans, household loans, the real effective exchange rate (REER), the import, and the monetary aggregates (M1 and M2). Each model is restricted to three variables. All models include a constant.

At the second step, numerous VAR models are estimated using only external (foreign) variables and following the same procedure used for ARIMA models. The one with the lowest RMSE is ranked as the best. The specification in the second group of models, included BH inflation and two external variables. The external variables considered are: international crude oil prices, international food prices, EURIBOR, HICP in Eurozone (overall index), HICP in Eurozone (All-items excluding energy and food), and the exchange rate (domestic currency KM/US dollar).

Next, a new set of VAR models are constructed including the most useful variables from the two groups. Since the number of observations is limited, the models are restricted to a small number of variables to avoid large specifications. The specification with the lowest RMSE in the third group includes the following variables, specified as annual growth rates: Households loans (h_gr), Import (im), and exogenous variable, HICP in euro area- total index (inf_eu). The specification of the lag length, the key issue in the estimation of the VAR models, is selected here using the Schwarz criteria. Table 1 in the Appendix indicates the optimal choice is 2 lags, which is in line with some of the cited research papers. Note that the higher the lag order is, the less precise the coefficient estimates are due to the reduction in the degrees of freedom. Consequently, less precise coefficient estimates typically result in lower forecasting power of the model. On the other hand, the lower the lag order, the more probable it is that important dynamics are omitted, and the residuals will display autocorrelation. The result of the forecast evaluation accuracy for the standard OLS VAR for the first forecast period is presented in Table 4.

[4] Analysis of the VAR and Bayesian VAR has been done by using BEAR toolbox, a Matlab based package developed by Dieppe et al. (2016).

Table 4 : Standard OLS VAR forecast accuracy evaluation for the first forecast period

	2018m1	2018m2	2018m3	2018m4	2018m5	2018m6	2018m7	2018m8	2018m9	2018m10	2018m11	2018m12
RMSE:	**0.809**	**0.575**	**0.486**	**0.433**	**0.417**	**0.468**	**0.441**	**0.414**	**0.412**	**0.422**	**0.426**	**0.443**
MAE:	**0.809**	**0.442**	**0.368**	**0.327**	**0.331**	**0.387**	**0.363**	**0.328**	**0.335**	**0.352**	**0.362**	**0.382**
MAPE:	**271**	**140**	**100**	**80**	**69**	**64**	**56**	**50**	**47**	**45**	**43**	**43**
Theil's	**0.576**	**0.336**	**0.266**	**0.237**	**0.217**	**0.216**	**0.186**	**0.162**	**0.151**	**0.146**	**0.14**	**0.142**

5.3 The Bayesian VAR model

A major problem with using a VAR model for forecasting is over-parametrization. In an attempt to improve the forecasting performance of unrestricted VARs, a Bayesian procedure for estimating VARs has been proposed, Litterman (1980, 1986) and Doan, Litterman, and Sims (1984). Bayesian inference has its roots in Bayes' theorem. The proposal of these authors was to combine the likelihood function with some informative prior distributions, the researcher's belief about the values of coefficients. This prior is now known as the Minnesota prior. The prior we use is specified using standard values for the hyper-parameters following Dieppe et al. (2016). There are four hyperparameters, namely $\lambda = (\lambda 1, \lambda 2, \lambda 3, \lambda 4)$, which control the tightness of the prior for different coefficients, see Chapter 10 of Canova (2007). In order to optimize the hyperparameters, a grid search is used, see Table 5.

Table 5: Grid search-Bayesian VAR

	Minimum value	Maximum value	Step size
Autoregressive coefficient	0.5	1	0.1
Overall tightness (λ1)	0.05	0.2	0.01
Cross-variable weighting (λ2)	0.1	1	0.1
Lag decay (λ3)	1	2	0.2
Exogenous variable tightness (λ4)	100	1000	100
Block exogenity shrinkage (λ5)	0.001	0.001	

The AR coefficient of the prior is set to 0.9, the overall tightness $\lambda 1 = 0.2$, the cross-variable weighting $\lambda 2 = 1$, the lag decay $\lambda 3 = 1$ and the exogenous variable tightness $\lambda 4 = 100$. Furthermore, $\lambda 5$ is set to very small $\lambda 5$=0.001, which means that BH, as a small economy, cannot significantly influence the global variables. The forecasting performance of a Bayesian VAR with a combination of domestic variables (Households loans (h_gr), Import (im)), and one exogenous variable (HICP in euro area-total index (inf_eu)), for the first forecast period is presented in Table 6.

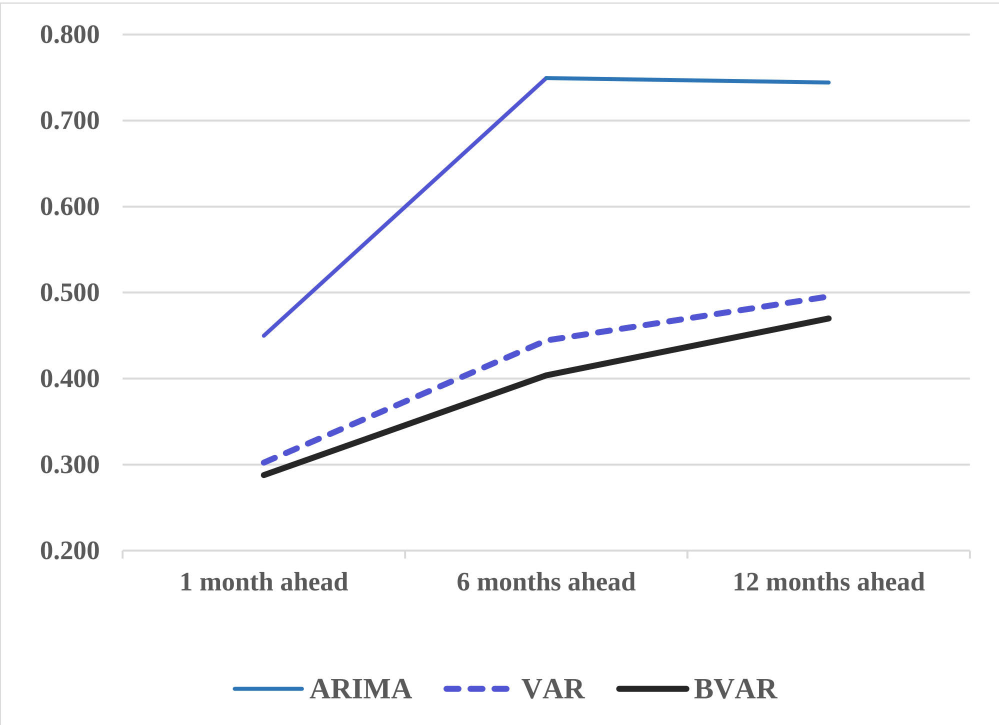
Table 6: Bayesian VAR forecast accuracy evaluation for the first forecast period

	2018m1	2018m2	2018m3	2018m4	2018m5	2018m6	2018m7	2018m8	2018m9	2018m10	2018m11	2018m12
RMSE:	**0.804**	**0.570**	**0.485**	**0.434**	**0.411**	**0.457**	**0.428**	**0.401**	**0.393**	**0.398**	**0.394**	**0.400**
MAE:	**0.804**	**0.430**	**0.366**	**0.328**	**0.323**	**0.375**	**0.346**	**0.313**	**0.315**	**0.327**	**0.329**	**0.340**
MAPE:	**269,697**	**137,970**	**99,192**	**79,777**	**68,472**	**62,733**	**55,125**	**48,840**	**45,570**	**43,475**	**41,179**	**40,146**
Theil's U:	**0.574**	**0.335**	**0.267**	**0.239**	**0.214**	**0.210**	**0.179**	**0.156**	**0.145**	**0.138**	**0.130**	**0.130**
CRPS:	**0.104**	**0.161**	**0.191**	**0.194**	**0.208**	**0.224**	**0.230**	**0.224**	**0.233**	**0.232**	**0.239**	**0.233**
Log score 1:	**-1,969**	**-0.484**	**-0.709**	**-0.793**	**-0.866**	**-1,053**	**-0.878**	**-0.880**	**-0.953**	**-0.995**	**-0.961**	**-1,011**
Log score 2:	**-1,969**	**-4,217**	**-4,286**	**-4,376**	**-4,488**	**-4,856**	**-5,445**	**-5,536**	**-5,706**	**-5,783**	**-5,851**	**-6,031**

The assessment of the forecasting performance of the BVAR model is conducted computing the RMSE for the pseudo out-of-sample forecasting period (2018:01 to 2019:09) obtained using the recursive strategy and using as a first forecast period 2018:01 and last forecast period 2018:12 (12 steps ahead). This process is repeated ten times, each time shifting the estimation period and the forecast period forward by one month until the models are estimated with data up to 2019:09.

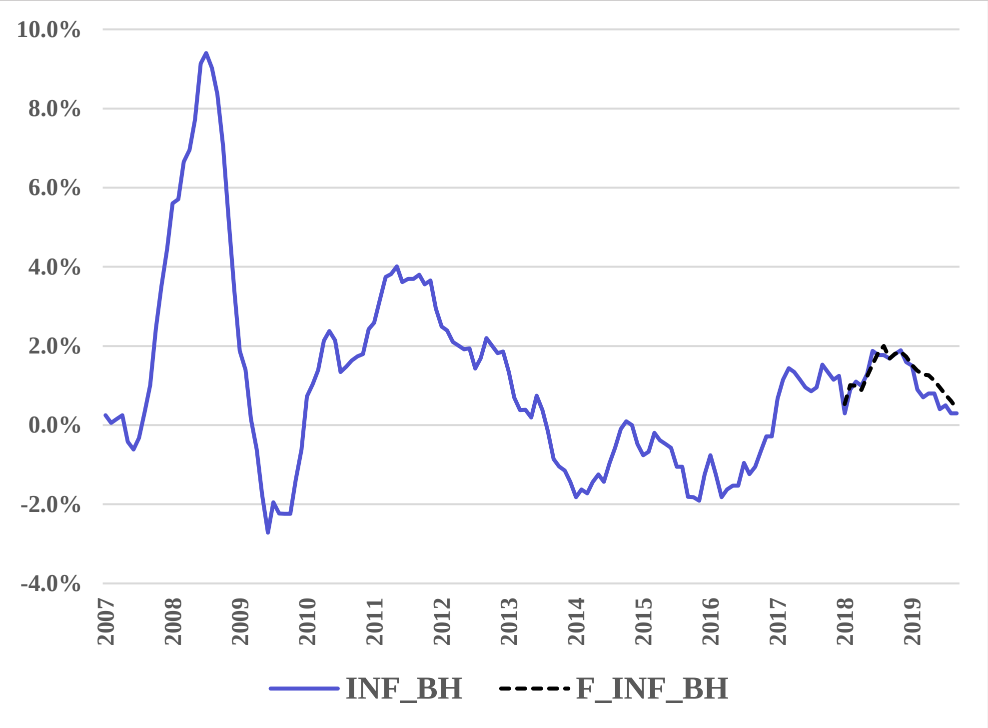
Since the RMSE is not informative by itself, it is necessary to compare its value for different models. Figure 2 presents the average evolution of RMSEs of the ARIMA, the standard OLS VAR and BVAR for the forecast horizons of one, six and twelve. The average RMSE is obtained from a series of 10 observations for each forecast horizon. The BVAR model outperforms the benchmark ARIMA model as well as the standard VAR model for all forecast horizons. Forecast accuracy tends to decrease as the forecast horizon expands. This is reasonable as it is more difficult to predict the likely path of the given variables as the forecast horizon increases.

Figure 2: Average RMSE for Inflation forecast



Source: Author's calculation

Figure 3: Inflation rate in BH, actual vs forecasted value for the BVAR



Source: Author's calculation

6. Structural analysis

Structural analysis is used here to obtain additional insights regarding the drivers of BH inflation, and the impact of domestic and foreign variables included in the Bayesian VAR model. First, a shock identification scheme is presented and used to achieve a structural interpretation of the disturbances and then we present the analysis of inflation determinants.

In structural analysis, certain assumptions about the causal structure of the data under examination are imposed, and the causal impacts of unexpected (structural) shocks to variables in the model are produced. These causal impacts are summarized here with a historical decomposition and a forecast error variance decompositions. In order to identify the model's structure, a Cholesky decomposition is used. The identification of the Cholesky decomposition is based on the following ordering: foreign variables come first and domestic variables afterwards. Due to the block exogeneity restrictions, the assumption is that shocks to the BH domestic variables can not affect foreign variables contemporaneously. In Figure 4, the historical decomposition of the annual growth rate of BH inflation is presented. The decomposition estimates how much each shock contributes to the inflation path at each time period, identifying origins and dynamics. The results suggests that HICP in Euro area has a significant effect on domestic inflation. The effect is much stronger than the effect of domestic variables. The effect of household loans on inflation is not significant. This outcome is consistent with the work of Ha, Kose, and Ohnsorge (2018), where it is shown that global shocks (global demand shocks, supply shocks, and oil price shocks) have been a more important source of domestic inflation movements in countries with stronger global trade and financial linkages, greater dependence on commodity imports, and fixed exchange rate regimes.

Figure 4. Historical decomposition

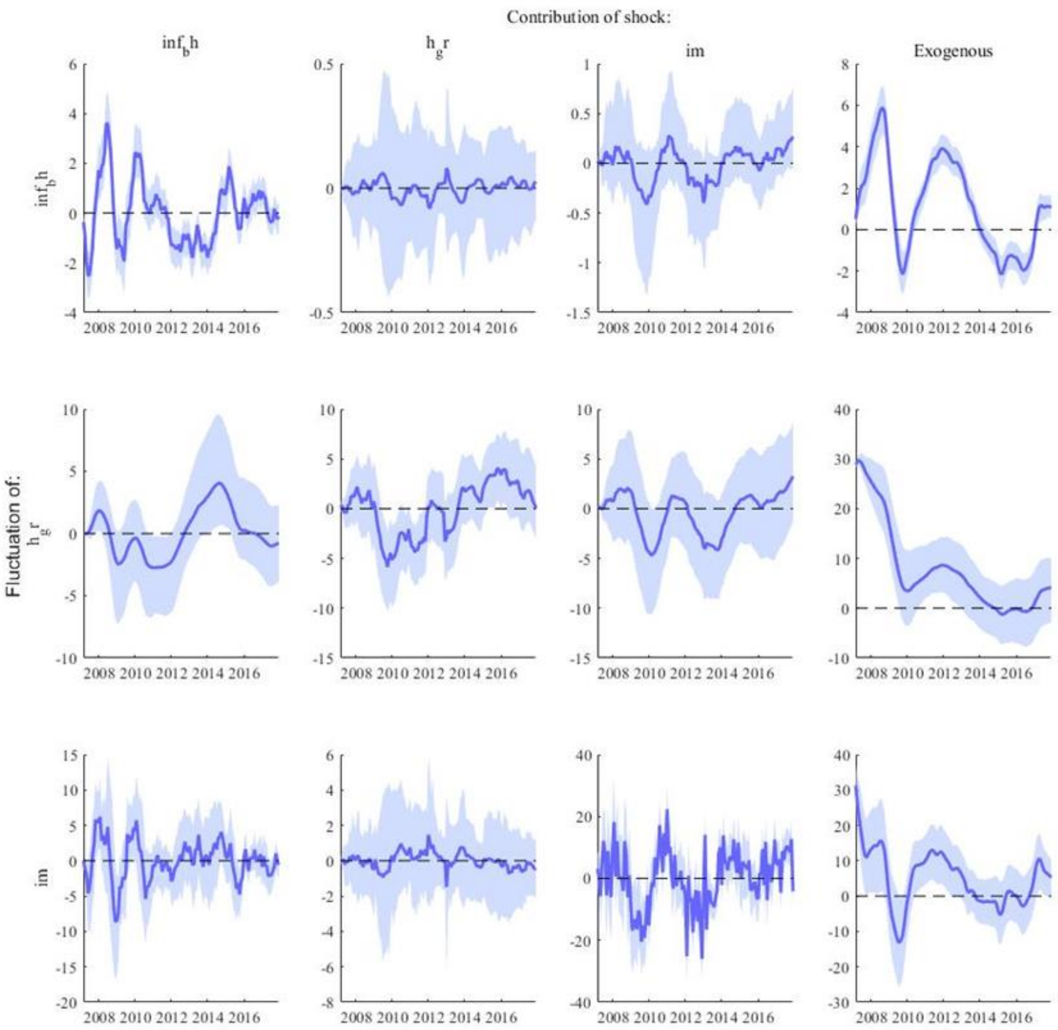
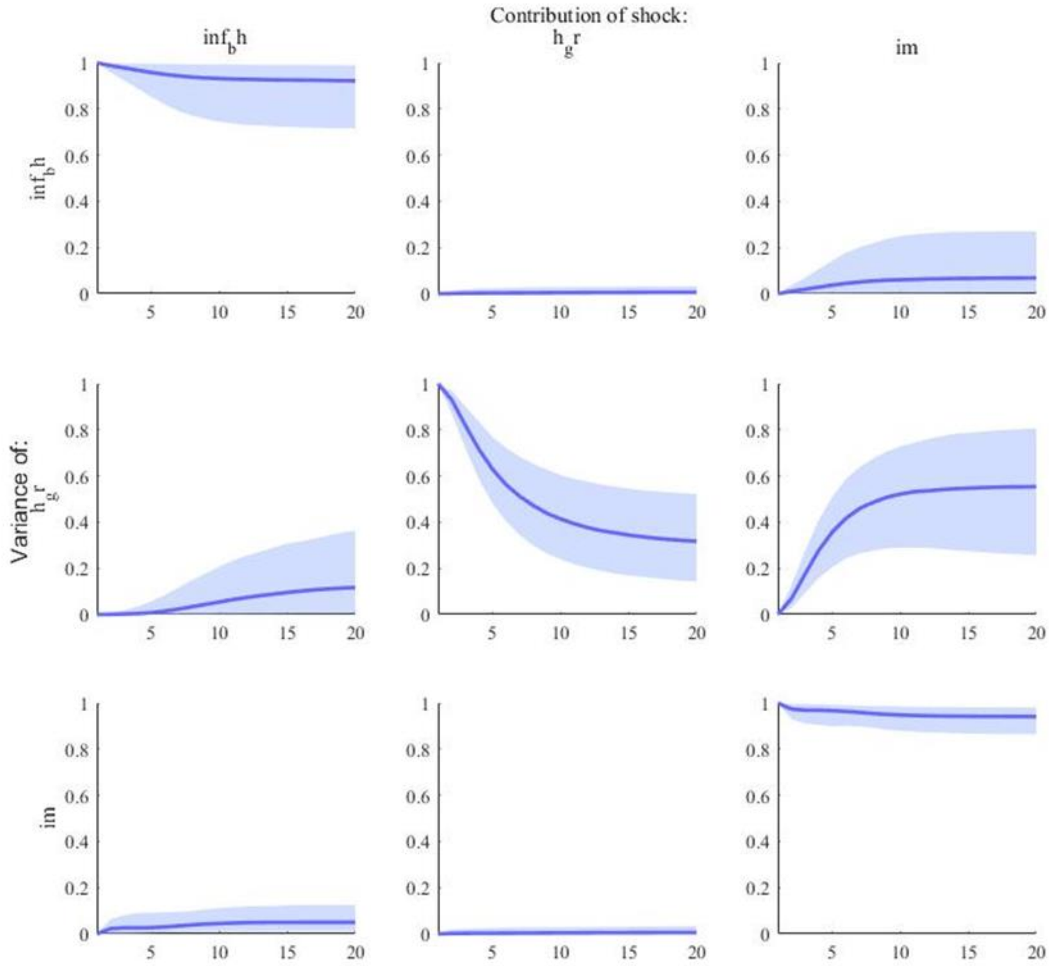


Figure 5. Forecast error variance decomposition



7. Concluding remarks

BH is a small open economy, with external imbalances and high import dependency. The CBA is a cornerstone of economic policies in the country. Inflation has been moderate since the introduction of the CBA and mainly is imported. This paper presents the evaluation of the forecasting performance of ARIMA, standard VAR and Bayesian VAR models, with the aim of understanding which model and with which variables provide the best predictions of BH inflation. According to the various information criteria, the ARIMA model (2,0,1) is identified as the best specification. The VAR models are estimated with the different groups of models. The first group include only domestic variables, and tries to identify whether there is information in domestic variables useful for forecasting the inflation. The second set of the models investigate the importance of foreign variables in forecasting BH inflation. Overall, a combination of domestic and foreign variables gives the best specification. Due to data constraints a small sample is employed. In many cases the VAR system exhibits explosive behavior. That problem might be solved using Bayesian VAR methodology. This paper finds that a Bayesian VAR is better than competing models. The estimates and forecasts of these models can be improved if one has prior information about the structure of the model in the form of knowledge of the hyperparameters of the prior.

The empirical results obtained in this study show that, in terms of forecast accuracy, the Bayesian VAR outperforms an ARIMA model and an unrestricted VAR model at all forecast horizons. The results of the structural analysis suggest that domestic inflation in BH is more affected by international factors than domestic ones. Inflation in the Euro area has a stronger and more significant effect on domestic inflation than any domestic variable.

Because the data sample is relatively short and the data availability of certain domestic variables limited, the findings of this study might be subject to change as longer data sets or data on other domestic variables become available.

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9. Appendix

Table 1: VAR Lag Order Selection Criteria

Endogenous variables: INF_BH HL_GR IM
Exogenous variables: C INF_EU
Sample: 2007M01 2017M12
Included observations: 132

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1170.795	NA	11121.10	17.83022	17.96126	17.88347
1	-746.0161	817.3770	20.43043	11.53055	11.85814	11.66367
2	-674.2163	134.8966	7.892006	10.57904	11.10318*	10.79202
3	-655.0599	35.12009	6.771220	10.42515	11.14585	10.71801
4	-638.3164	29.93546	6.029081	10.30782	11.22508	10.68055*
5	-629.7451	14.93472	6.079996	10.31432	11.42813	10.76692
6	-614.7937	25.37217*	5.570970*	10.22415*	11.53451	10.75662

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion