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NOTES

The views expressed herein are of the author and do not necessarily represent those of the Bank of Albania.

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ABSTRACT

In the context of the Bank of Albania's primary objective of achieving and maintaining price stability, generating accurate and reliable forecasts for the future rate of inflation is a necessity for its successful realization. This paper aims at offering a relatively simple, practical and inexpensive tool to forecast short-term inflation: a Bayesian vector autoregressive (BVAR) model, which unlike standard autoregressive vector (VAR) models, addresses the over-parameterization problem, allowing for the inclusion of more explanatory variables, and in this way enabling a more comprehensive explanation of inflation. We use two benchmark models: a univariate model selected from a range of time-series models, and an unrestricted VAR. The results show that the BVAR approach, which incorporates more economic information, outperforms the benchmark univariate and the unrestricted VAR models in the different time horizons of the forecast sample, but the differences between models in terms of their forecast performance are not statistically significant.

Key words: Bayesian estimation, vector autoregressive, forecasting performance

JEL Classification: C30, C52, C53, C80.

1. INTRODUCTION

Generating accurate and reliable forecasts for the future rate of inflation is a necessity for the successful fulfilment of Bank of Albania's (BoA) primary objective of achieving and maintaining price stability. This issue takes a greater importance when considering that monetary policy effects on the economy are transmitted with time lags depending on the responsiveness of financial markets and real economy to policy interventions. Forecasting inflation is not only an important decision-making tool, but also a crucial communication device. Monetary policy has become considerably more transparent over the recent decades. Open communication of monetary policy is beneficial to the stability and predictability of its transmission in the Albanian economy, and it is also essential for the accountability of an independent central bank.

BoA uses a large set of information in the policymaking process, coming from expert judgment, which is derived using both nowcasting tools, and a variety of models ranging from simple traditional time series models to more complex ones, such as quarterly projection (QPM) models. Nevertheless, the existing published papers for the econometric models used to forecast inflation in Albania are still scarce. In this context, this paper aims at actively contributing in enriching the Bank's portfolio of short-term inflation forecasting tools with a relatively simple, more practical, and inexpensive econometric model: the Bayesian vector autoregressive (BVAR) model, which has been demonstrated to have superior forecasting ability compared to alternative forecasting methods, such as univariate time series models or large-scale macro-models. Furthermore, unlike standard vector autoregressive (VAR) models, BVAR models address the over-parameterization problem, allowing for the inclusion of more endogenous variables, and thereby enabling a more comprehensive explanation for inflation. In the forecasting framework of BoA, the medium-term inflation projections are based on the information obtained from the short-term inflation projections (mainly one or two quarters ahead). Therefore, it is essential for the Bank to base its medium-term forecasts on more accurate and well performing short-term projections, which rely on the maximum information set available.

Several univariate models are estimated to forecast short-term inflation, such as unconditional mean, random walk, autoregressive integrated moving average (ARIMA) models; the best performing among them is used as a benchmark to evaluate the forecast performance of the BVAR model. In addition, an unrestricted VAR is constructed as an additional benchmark: this is the most commonly used tool to obtain projections of the main economic indicators, based solely on the information that the data series provide. The results show that the BVAR approach, which incorporates more economic information, outperforms the benchmark univariate and unrestricted VAR models in the different time horizons of the forecast sample, but the differences between models with regard to their forecast performance are not statistically significant. Although the best performing individual model of each horizon differs, the performance of the BVAR is close to the superior models of each horizon.

The paper is structured as follows. Section 2 provides a review of the existing empirical papers on BVAR models used by central banks or other institutions for analysis and forecasting purposes, and continues with a description of the theoretical background of these models. Section 3 describes the structure of the BVAR model, the selected economic indicators and the estimation and forecast procedure. Section 4 discusses the empirical results obtained by the comparative analysis and their interpretation. Final remarks are presented in Section 5.

2. THEORETICAL BACKGROUND AND EMPIRICAL RESULTS

2.1LITERATURE REVIEW

There is growing empirical evidence in the literature that BVARs set a high standard in comparison to most alternative forecasting methods such as univariate time series models or large-scale macro-models. In recent years, the models seem to be used even more systematically for policy analysis and forecasting macroeconomic variables. At present, there is considerable interest in using BVARs for these purposes in a large dataset context. In this section, we provide an overview of some of the recent empirical works on these models and their uses for analysis and forecasting purposes in central banks or other institutions (see Alvarez, Ballabriga and Jareno (1998); Kasuya and Tanemura (2000); and Kenny, Meyler and Quinn (1998)).

Using data for the Japanese economy, Kasuya and Tanemura (2000) estimate several Bayesian VAR models 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 the BVARs with that of an ordinary VAR by one-step ahead forecasts and Monte Carlo experiments: the results suggest that the selected BVARs are superior to the ordinary VAR models.

Banbura, Giannone, and Reichlin (2010) show that large unrestricted VARs can be handled by applying Bayesian shrinkage and, therefore, a VAR framework can be applied to empirical problems that require the analysis of more than a handful of time series. They use a dataset that contains 131 monthly macro-indicators covering a broad range of categories including, inter alia, income, industrial production, capacity, employment and unemployment, consumer prices, producer prices, wages, housing starts, inventories and orders, stock prices, interest rates for different maturities, exchange rates, money aggregates for the time span from January 1959 through December 2003. Overall, their results show that not only a Bayesian VAR estimated over one hundred variables is feasible, but it produces better forecasting results than the typical small VARs considered in the literature. Given that VARs have other advantages (e.g. in that impulse responses are easier to interpret), this suggests Bayesian VARs could be a useful addition to the macroeconomic forecaster’s toolbox even in cases with dozens or hundreds of variables.

Carriero, Clark, and Marcellino (2011) examine how the forecasting performance of Bayesian VARs is affected by a range of specification choices, such as the tightness of the priors, the lag length of the model, the cross-variable shrinkage, the size of the VAR, modelling in levels or growth rates; they discuss and address a set of additional relevant issues. Their dataset for includes 18 monthly macroeconomic and financial series for the United States, which are of major interest to policymakers and forecasters. Summarizing all the set of estimated results, the authors find very small losses (and sometimes even gains) on average across variables and horizons from the adoption of specification choices that make BVAR modelling quick and easy. This finding could therefore further enhance the diffusion of the BVAR as an econometric tool for a vast range of applications.

Akdogan et. al (2012) employ several econometric models such as the univariate ARIMA models, decomposition based models, a Phillips curve motivated time varying parameter model, a suit of VAR, Bayesian VAR and dynamic factor models to forecast short-term inflation in Turkey. Their result suggests that the models, which incorporate more economic information, outperformed the random walk chosen as the best performer among the other univariate models at least up to two quarters ahead.

Poghosyan (2013) estimates an unrestricted VAR, a BVAR and a Factor Augmented VAR (FAVAR) to forecast the key macroeconomic variables in Armenia such as real growth of GDP, inflation and the nominal short-term interest rate. The three models are applied to the Armenian economy using quarterly macroeconomic time series from 2000 to 2012. Based on the out-of-sample recursive and rolling forecast regression schemes and using forecast evaluation (the Root Mean Squared Error (RMSE)) criteria, the models are compared to each other regarding the performance in forecasting Armenia's key macroeconomic indicators. The ex-post results show that there is not one specific model that gives best results for any macroeconomic variables (in our case real GDP growth, inflation and nominal interest rate). One particular method gives better forecasts for real GDP growth, the other for inflation and the third for nominal interest rate.

Iversen et al. (2016) investigate the case of the Sveriges Riksbank and explicitly contrast dynamic stochastic general equilibrium (DSGE) and BVAR model real-time forecasts since 2007. They find that the BVAR model forecasts for inflation performed well both in absolute terms and relative to the DSGE model forecasts and the Riksbank's published forecasts. Another study, by Christoffel et al. (2011), examines the forecasting performance of New Area-Wide Model of the euro area (NAWM), the European Central Bank's (ECB) DSGE model, against Bayesian VAR benchmarks. They assess NAWM against four BVARs, which vary in size and type of prior and the models are re-estimated annually. They also find that the DSGE model is outperformed by a BVAR benchmark, both in terms of point and density forecasts.

Brázdik and Franta (2017) compare the forecasts based on a small-scale mean-adjusted BVAR model with the official forecasts published by the Czech National Bank (CNB) over the period 2008Q3–2016Q4. The comparison demonstrates that the BVAR approach can provide more precise inflation forecasts over the monetary policy horizon i.e. the horizon at which CNB targets its inflation target (3-7 quarters). For other macroeconomic variables, the CNB forecasts either outperform or are comparable with the forecasts based on the BVAR model.

In the case of Albania, Vika (2018) discusses some practical issues on the estimation of VAR models. Among others, he makes use of a small BVAR model to forecast the main domestic economic indicators: inflation, real economic growth, real exchange rate and key monetary policy rate, conditioning on three exogenous foreign variables, using a Normal-Wishart prior. The variables enter into the model in three forms: in levels, in annual growth rates and in quarterly growth rates. The model specification with the variables expressed in annual changes, is the preferred form to forecast the endogenous variables of the model, besides the exchange rate. Compared to an unrestricted VAR model with exactly the same variables, the Bayesian estimation reduces significantly the RMSEs for the exchange rate forecasts, but does not appear so useful for the other variables, particularly for economic growth. In this paper, we use an extended version of the BVAR used by Vika (2018), intended to forecast only inflation. Besides the Normal-Wishart prior, we use the Litterman-Minnesotta prior as well. The analysis is extended by evaluating point and density forecasts of the BVAR and comparing them to the chosen benchmarks, as it will be described in details throughout the paper.

Kristo and Hashorva (2019) use, inter alia, several BVARs to forecast Albanian inflation components with a Litterman-Minnesotta prior, diasaggregating the total CPI index into 5 composing groups. Based on the out-of-sample forecasting results, the BVAR model outperforms the other forecasting models for the category of processed foods, industrial goods and services, while unprocessed foods and energy goods are better forecasted by the multivariate regression.

2.2 THE THEORETICAL FRAMEWORK OF THE BAYESIAN VAR MODEL

This section presents the Bayesian Vector Autoregressive approach, based on Ciccarelli and Rebucci (2003), Doan et al. (1984), Kenny et al. (1998) and Litterman (1980, 1986).

A standard VAR(p) model can be written as:

$$Y_t=B_1\, Y_{(t-1)}+ B_2\, Y_{(t-2)}+ \dots +B_p\, Y_{(t-p)}+ \mu+ \varepsilon_t \qquad (1)$$

where $\mathbf{Y}_t$ is a *(nx1)* vector of endogenous variables which are stationary, μ is a *(nx1)* vector of constant coefficients and ε_t is a *(nx1)* vector of error terms, independently identically and normally distributed. The coefficient matrices $\mathbf{B}_1$ *(i=1…p)* are of dimension *(nxn)*.

As Ciccarelli and Rebucci (2003) underline, the above model, when estimated through the classical approach, leads to the so-called "over-fitting" problem, as a consequence of over adjustment, imprecise estimation and poor forecasting performance. This comes from the fact that the number of parameters to be estimated, namely $n(np+1)$, grows geometrically by the number of variables n and proportionally by the number of lags p.

One approach for solving this problem is shrinkage, where restrictions on parameters are imposed to reduce the parameter set. BVAR methods (Doan, Litterman, and Sims, 1984; Litterman, 1986; Sims and Zha, 1998) are one popular approach for achieving shrinkage, since Bayesian priors provide a logical and consistent method of imposing parameter restrictions. The general idea is to use informative priors that shrink the unrestricted model towards a parsimonious naïve benchmark, thereby reducing parameter uncertainty, and improving forecast accuracy.

Differently from frequentist statistics, Bayesian inference treats the VAR parameters as random variables, and provides a framework to update the inferred probability distributions of the unobserved parameters conditional on the observed data. By providing such a framework, the Bayesian approach allows us to incorporate prior information about the model parameters into post-sample probability statements. The 'prior' distributions about the location of the model parameters summarise pre-sample information available from a variety of sources, such as other macro or micro datasets, theoretical models, other macroeconomic phenomena, or introspection.

In the absence of pre-sample information, Bayesian VAR inference can be thought of as adopting 'non-informative' (or 'diffuse' or 'flat') priors, that express complete ignorance about the model parameters, in the light of the sample evidence summarised by the likelihood function (i.e. the probability density function of the data as a function of the parameters). Often, in such a case, Bayesian probability statements about the unknown parameters (conditional on the data) are very similar to classical confidence statements about the probability of random intervals around the true parameters value.

Doan et al. (1984), Litterman (1984a, 1984b, 1986), and Todd (1984, 1988) propose imposing probabilistic constraints, oriented towards shrinking the size of the parametric space and, as a result, lessening the above mentioned problems. These restrictions are amenable to a Bayesian interpretation and may include quite different structures, depending on the non-sample information that the analyst wants to incorporate in the model. Due to its origin, this prior is often named "Minnesota prior" or "Litterman prior". This prior has been generalized or modified to consider a wide variety of specifications, see Kadiyala and Karlsson (2007) and Karlsson (2012).

In constructing the priors, Litterman (1986) uses three of the stylized facts of time series from macroeconomics:

1. Most of the macroeconomic time series are characterized by a trend;
2. Although macroeconomic data are persistent, the most recent lags matter the most;
3. Its own lags influence a specific variable much more than the lags of other variables.

By using these stylized facts, Litterman (1986) derived a prior distribution that is actually a multivariate random-walk. Thus, for each equation, the prior distribution is centered around a random walk specification given by:

$$y_{n,t}=\mu_n+y_{n,t-1}+\varepsilon_{n,t} \tag{2}$$

Following Doan (2007, p. 378), the standard priors have the following characteristics

- For deterministic variables the priors are non-informative, namely flat;
- For the lags of endogenous variables, the priors are independent and normally distributed;
- In the case of means of prior distributions, they are set to zero. However, by default, the prior mean for the first lag of the dependent variable in each equation is one.

The only other prior to be set is the prior for the variance. According to Litterman (1986), the standard error on the coefficient estimate of lag l of variable j in equation I is given by a standard deviation of the form $S(i,j,l)$ given by:

$$S\,(i,j,l) = \frac{[yg(l)f(i,j)]s_i}{s_j} \tag{3}$$

where $f(i,j) = 1$ if $i = j$ and $f(i,j) = wij$ if $i \neq j$ and si is the standard error of the univariate regression on equation i. The ratio $\frac{s_i}{s_j}$ is for the correction of different magnitudes of the variables. The term y indicates the overall tightness and is also the standard deviation on the first own lag: The prior can be tightened by lowering this value. $g(l)$ determines the tightness on lag l relative to lag one and can be of harmonic or geometric type, with a decay factor (d) of one or two. It tightens the prior on increasing lags. $g(l)$ decays harmonically $g(l)=l^{-d}$. The geometric type of $g(l)$ tends to get tight very fast. The parameter $f(i,j)$ represents the tightness of variable j in equation i relative to variable i with the relative tightness coefficient w. For deterministic variables, the priors are uninformative. In the literature, overall tightness y, lag decay factor (d) and weight parameter $f(i,j)$ are called "hyperparameters".

3. DATA AND METHODOLOGY

Most of the existing literature on forecasting short term inflation uses a wide variety of models starting from the simplest such as univariate models, to multivariate ones such as VAR and BVAR models, as well as time varying parameters and dynamic factor models. In this paper, we will focus only on some of them, which we describe in the following section.

3.1 IDENTIFICATION OF BVAR MODEL AND DATA DESCRIPTION

In order to build up a proper forecasting BVAR model for the Albanian inflation, it seems appropriate to begin by considering three issues: (1) which are the indicators that economic theory and empirical studies suggest as the main explanatory variables, (2) which economic sectors do they belong to, and (3) which of the available statistical series best approximate the variables chosen. In keeping with this approach, the BVAR presented here, is a medium-sized model, which describes the most important dynamics and interactions between the determinants of inflation in Albania and consists of the following blocks:

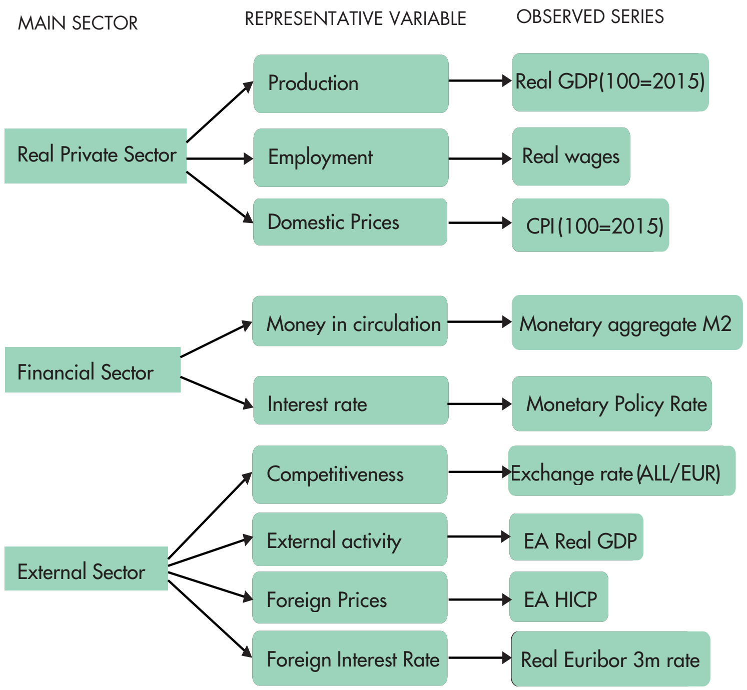
1. The real private sector, which synthesizes the decisions of domestic agents in the markets for goods and services, as well the labour market. The level of real activity in the economy will be reflected by production, captured by the series of Gross Domestic Product (GDP) in real terms, which by definition represents the final result of the production activity of resident producer units. Also, the inclusion of domestic prices is necessary, being an important point of reference in the decision process related with consumption and investment made by private agents. Prices will be represented by the Consumer Price Index (CPI), as it is the series to which private economic agents usually refer and in terms of which the central bank sets its targets. The choice of alternative series, such as National Accounts deflators, has been ruled out due to the delay in reporting, the frequency and magnitude of revisions, and, basically, the lower attention they receive from the various economic agents. The labour market will be represented by real wages, which reflect, in part, the terms on which equilibrium is established in the labour market and also indicate the possible existence of real pressures on the price formation process.
2. The financial sector is associated with the actions of the monetary authority and the financial institutions. The behaviour of this sector can be characterized by a price and a quantity variable: the monetary policy rate and the amount of money in circulation. Among the existing interest rates, the central bank

repurchase (REPO) rate is chosen to be included in the model, as it is the preferred instrument for implementing monetary policy in Albania and achieving its target. The amount of money in circulation is captured by the annual growth rate of M2, which includes M1 plus term deposits in Albanian leks of resident sectors (excluding banks and the central government).

3. The external sector, which captures the influence of the decisions of economic agents of Albania's main trading and financial partners, i.e., Euro Area (EA) countries, as trade and financial links are among the main channels for relations between different economies. Hence, the representative variables of this sector correspond to its main determinants: competitiveness and external activity. The demand for imported goods and services also depends on the country's level activity, i.e., domestic GDP, which is already included in the domestic sector. Competitiveness is captured by the real exchange rate of the domestic currency (the Albanian lek – ALL) to EA currency (EUR), as the latter is the transmitter of external effects on the economy's purchasing power and its inclusion in the model helps to capture the impact of trade via price effects. EA real GDP serves as a measure of activity in the external sector. In addition, we include in the model the foreign prices and the foreign interest rate as the main determinants of the exchange rate, and therefore include EA inflation too (the Harmonised Index of Consumer Prices – HICP).

Figure 1 illustrates the model's structure through a simplified schematic presentation. The dataset includes quarterly time series for the period 2002Q2-2018Q4. Given the size of the sample, the number of the variables has been limited to 9 indicators: 6 domestic and 3 foreign variables.

Figure 1. BVAR model's structure.


MAIN SECTOR
REPRESENTATIVE VARIABLE
OBSERVED SERIES
Real Private Sector
Production
Real GDP(100=2015)
Employment
Real wages
Domestic Prices
CPI(100=2015)
Financial Sector
Money in circulation
Monetary aggregate M2
Interest rate
Monetary Policy Rate
External Sector
Competitiveness
Exchange rate (ALL/EUR)
External activity
EA Real GDP
Foreign Prices
EA HICP
Foreign Interest Rate
Real Euribor 3m rate

The information sources utilized to obtain these data are: The data is obtained from the Bank of Albania (BoA), Albania's National Institute of Statistics (INSTAT), the European Central Bank (ECB) and Eurostat. Real production is represented by the GDP at constant prices expressed in million ALL and is INSTAT. The price level is measured by the CPI and the inflation rate by the changes on this index. Data on the later are taken from INSTAT as well. The series of real wages is calculated as a ratio of the nominal wages of the private sector to the CPI multiplied by 100. The series of nominal wages is published by INSTAT in annual terms since 2000. The quarterly data are interpolated for the period 2000-2002 using the wages of the public sector, while starting from 2003 they are interpolated in line with the wage index from the Survey of

Economic Enterprises conducted by INSTAT. For the data on the financial indicators, the REPO rate and new bank loans, we have used the Bank of Albania's database. Foreign indicators such as real EA GDP, the HICP in the EA and the Euribor rate are taken from ECB's database and Eurostat. The data on nominal exchange rate ALL/EUR are taken from Bank of Albania and the real exchange rate (RER) is calculated as a production of the nominal exchange rate with the price ratio between the foreign and the domestic price indexes. More information on the descriptive statistics and evolution over time of all the series included in the model can be found in the Appendix, Table 1, and Figures 1 and 2, respectively.

3.2 ESTIMATION PROCEDURE

The BVAR is specified in annual growth rates with the exception of the domestic and foreign monetary policy rates, which are treated as stationary. There is no need to adjust the series seasonally as while computing the annual growth rates, the seasonal component is eliminated by the difference between the same quarters of the two consecutive years. Data quality during the first decade of the transition period and some values considered as outliers compels us to start the estimation period from 2002q2. The stationarity properties of the data are assessed by applying the standard techniques: the augmented Dickey–Fuller (ADF) unit root tests. Overall, all the considered series can be characterized as integrated of order zero I(0) or in other words stationary.

Having specified the model, it is necessary to determine the optimal number of lags, which is a key issue when estimating VAR models, especially when they are intended for forecast purposes. However, this is not always an easy task as it is subject to a trade-off. On one hand, the higher the lag order, the less precise the coefficients due to a reduction in the degrees of freedom and, consequently, the lower the forecast power of the model will be. On the other hand, the lower the lag order, the more probable it is that some intertemporal dynamics are omitted, and the autocorrelation in the residuals will not be removed (Lack, 2006). The most common method in the literature to decide the number of lags is by minimizing the information criteria. In our case, the AIC (Akaike's Information Criterion) and HQ (Hannan-Quinn) information criteria suggest that the optimal number of lags is 6 quarters, with the exception of the Bayesian Information Criterion (BIC) that is quite parsimonious and suggests one lag. However, in this paper, the selection of the number of lags for the BVAR model is not based on the information criteria, but on the out-of-sample forecast performance of different specifications and the model's dynamic properties, as the model is intended for forecast purposes rather than for policy analysis. The selected number of lags that ensures the best forecast performance, measured by RMSEs, is 4 quarters. Whereas it is possible to choose the lag length optimally during estimation by including it as an argument of the maximisation problem (see below), selecting the lag length somewhat arbitrarily is not unprecedented in the literature (see Giannone et al. (2015)). Also, the results in Carriero et al. (2011) suggest that shorter lags tend to yield better forecasting performance.

Few restrictions are imposed on the behaviour of the series, by using the different types of priors most commonly found in the literature, notably the 'Minnesota' prior introduced by Litterman (1980) and Normal-Wishart. In addition to them, another restriction is that Albania is treated as a small open economy, which implies that it does not affect the three EA variables and so they enter the model as exogenous. This assumption is motivated by the negligible size of the Albanian economy and trade flows relative to EA.

An optimization procedure is used to select the best possible combination of the hyperparameters that characterize the priors in such a way that they maximize the marginal likelihood of the model, as suggested in Giannone et al. (2015). The marginal likelihood is a measure of out-of-sample forecasting performance of a model, so selecting the tightness of the priors that maximises the marginal likelihood is akin to selecting them according to the one-step-ahead out-of-sample forecasting ability of the model. We do a grid search for all possible combinations of hyperparameters and lag lengths allowing two to five lags. Overall tightness is set to range from 0.1 to 1 with increments of 0.1; the decay factor takes values of 1 and 2; values for the weight parameter are from 0 to 1. This procedure is repeated for different estimation periods and pseudo out-of-sample forecasts are produced for one to eight quarters horizons, but this procedure will be described into more details in the next section. The method for prior selection used herein outperforms other commonly used procedures, such as the one described in Litterman (1980), where the tightness of the prior is chosen by maximising the out-of-sample forecasting performance of the model over a pre-sample, and the procedure in Banbura et al. (2010), where the priors are chosen by maximising the models' in-sample fit. The procedure in Giannone et al. (2015) also addresses the trade-off between model complexity and in-sample fit, as it yields looser priors when the model involves few unknown coefficients relative to the size of the dataset and vice-versa.

After choosing the lag length and specifying the model, several diagnostic tests are performed to check for model stability, autocorrelation, heteroscedasticity and normality of residual distribution. Test results suggest that the BVAR model satisfies all the necessary assumptions of an ordinary least squares (OLS) estimation procedure.

To assess the forecasting performance of the BVAR, we start by measuring the accuracy of its central forecasts, through computing the root mean squared errors (RMSE) in the out-of-sample forecasting period (2013Q1-2018Q4) for each forecast horizon up one year and a half, obtained using two forecast strategies, which will be explained in the next section. Formally, the RMSE at horizon h is given by:

$$RMSE^{h}=\sqrt{\frac{1}{P-h+1}\sum_{t=R}^{T-h}\hat{u}_{t+h}^{2}} \qquad (4)$$

where the forecast error $\hat{u}_{t+h}$ is defined as the difference between the actual data and the mean forecast for the corresponding period, T is the length of the whole sample, which is split into an in-sample period of length R and an out-of-sample period of length P; h is the forecast horizon. This leaves us with a sequence of out-of-sample forecasts from R + h to T, to evaluate; or equivalently, we have P- h +1 forecasts. The time point of the forecast origin is denoted by t; the first origin is at point R, and the most recent is at T - h.

It is important to note that the value of the RMSE is not in itself informative (i.e. whether it is above or below a certain (threshold) value); therefore, it is necessary to set a benchmark against which to compare the BVAR model.

3.2.1 CONSIDERING POTENTIAL BENCHMARK MODELS

Univariate models are commonly used as benchmarks in the forecasting literature, as they are hardly found to be beaten by large, complicated models such as VARs and traditional structural macroeconomic models (see for instance Arratibel et al. (2009), Hofmann (2008), Stock and Watson (2008)). Moreover, they are considered convenient for short data samples as they include few explanatory variables. The univariate modelling in this study includes the following models: unconditional mean, random walk, autoregression and seasonal autoregressive integrated moving average (ARIMA). The best performing of these univariate models will be used as a benchmark for the evaluation of the forecast performance of more advanced models. We proceed with a VAR model, which in addition to the univariate models, includes more variables that incorporate information on real activity, commodity prices, exchange rates, monetary aggregates and interest rates. Due to the problem of over-parametrization and short time series, more than 5 endogenous variables cannot be included in the VAR model, while the BVAR overcomes this difficulty and allows the use of more variables.

Unconditional mean (UM). The first model considered is the unconditional mean (UM), which states that the variable of interest is equal to the average of its past without any restriction or apriori information:

$$\pi_{t+h} = \alpha + \varepsilon_{t+h} \tag{5}$$

where $h = 1,...,4$ is the forecast horizon, and π_{t+h} is the h-period ahead inflation rate. According to this model, the best inflation forecast for any horizon is the arithmetic mean of the past values of the inflation rate, implying that all forecasts are the same for all forecast horizons. It is argued that UM performs better for long horizons rather than short ones, since stationary series are mean-reverting and inflation in the long run is driven by its target (Kapetanios et al., 2007).

Random walk (RW). According to the random walk approach, the inflation forecast for any horizon h is equal to the previous actual value of inflation, as defined by the following equation:

$$\pi_{t+h} = \pi_t + \varepsilon_{t+h} \tag{6}$$

Autoregressive model (AR). Another potential benchmark is the autoregressive model of order one AR(1):

$$\boldsymbol{\pi}_{t+h} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \, \boldsymbol{\pi}_{t+h-1} + \boldsymbol{\varepsilon}_{t+h} \tag{7}$$

In this case, there is no need to introduce seasonal dummies in the equation since the forecasted inflation rate is expressed in annual terms.

Autoregressive moving average model (ARIMA). The last univariate candidate is the ARIMA model:

$$\boldsymbol{\pi}_{t+h} = \boldsymbol{\mu} + \boldsymbol{\phi}_1 \, \boldsymbol{\pi}_{t+h-1} + \ldots + \boldsymbol{\phi}_p \, \boldsymbol{\pi}_{t+h-p} - \boldsymbol{\theta}_1 \, \boldsymbol{\varepsilon}_{t+h-1} - \ldots - \boldsymbol{\theta}_q \, \boldsymbol{\varepsilon}_{t+h-q} \tag{8}$$

where $\boldsymbol{\phi}_p$ and $\boldsymbol{\theta}_q$ are the AR and moving average (MA) polynomials, respectively; p shows the number of autoregressive lags and q the number of MA lags.

Vector autoregressive model (VAR). The VAR models are relatively simple, inexpensive and practical to use, and therefore are widely used in the literature as benchmarks for other more advanced forecasting tools. The VAR approach averts the need for structural modelling by treating every endogenous variable in the system as a linear function of the lagged values of all of the endogenous variables in the system and possibly a set of exogenous variables (Hamilton, 1994):

$$y_t = B_0 + \sum_{i=1}^{p} B_i \; y_{t-i} + \ldots + \varepsilon_t \tag{9}$$

where $\mathbf{y}_t = [\mathbf{y}_{1,t},\ldots,\mathbf{y}_{m,t}]'$ is the vector of variables in the model, is the $\mathbf{m} \times \mathbf{1}$ vector of constants and $\mathbf{B}_1$ is the $\mathbf{m} \times \mathbf{m}$ matrix of coefficients of $\mathbf{y}_{t-i}$.

Due to the over-parametrization problem and short-time series, the VAR includes only four endogenous variables: inflation, real GDP growth, the real exchange rate and the monetary aggregate M2. It is conditioned on the same set of foreign variables as the BVAR: EA real GDP, EA inflation and EA 3-M Euribor. Similarly to the BVAR, the VAR is specified in annual growth rates with the exception of the domestic and foreign monetary policy rates, which are treated as stationary. Also, the choice of the optimal number of lags, based on the out-of-sample forecast performance of different specifications, is four.

3.2.2 FORECAST PROCEDURE

All the models are estimated with real-time data and have the same information sets. The real-time estimation approach means that the forecasts for endogenous variables are produced using only the information that would have been available at each forecast round. For foreign variables, we use the Eurostat forecasts available at the time that the forecasts for domestic variables are made. The whole sample period (2002Q2:2018Q4) is divided into two parts: the estimation sample and the forecasting sample. Two forecast strategies are used: expanding and rolling window. In both cases, the procedure starts with an estimation sample 2002Q2-2012Q4, and the forecasts are produced for 1 to 6-quarters ahead as we are interested in the short-term forecast performance of the models. In the second forecast round, in the case of the expanding window strategy, the estimation period expands recursively by one quarter, but its starting point will be the same. So, in this case the number of observations will increase recursively by one in each forecast round. In the rolling window strategy, the whole estimation period, including its starting point, shifts by one quarter in each forecast round. For each round, 1 to 6 quarters ahead pseudo out-of-sample forecasts are obtained using both forecast strategies. The estimation process is repeated until 2018Q3, when we can obtain the last 1-quarter ahead forecast for 2018Q4.

4. EMPIRICAL RESULTS

4.1 EVALUATING BVAR POINT FORECAST PERFORMANCE

This section sets out the main empirical findings of the paper. Root mean squared errors (RMSEs) are calculated separately for each forecast horizon as a measure of forecast performance. In general, with the exception of the random walk (RW), performances of the other univariate models are not promising. Unconditional mean displays a particularly poor performance. Differences in the forecast performance between the expanding and rolling window forecast strategies are not significant. Table 1 and 2 show the RMSEs of each of the individual models relative to the random walk for different forecast horizons, starting from 1-quarter to 6-quarters ahead, for both expanding and rolling forecast strategies.

Table 1. RMSEs relative to RW using recursive window strategy.

	Forecast horizon					
	h=1	h=2	h=3	h=4	h=5	h=6
UM	2.02	1.57	1.47	1.39	1.58	1.47
RW	1.00	1.00	1.00	1.00	1.00	1.00
AR(1)	1.17	1.23	1.29	1.30	1.32	1.36
ARMA	1.25	1.27	1.33	1.36	1.38	1.40
VAR(4)	0.89	0.91	0.95	1.02	0.98	1.03

Source: Author`s calculations.

Table 2. RMSEs relative to RW using rolling window strategy.

	Forecast horizon					
	h=1	h=2	h=3	h=4	h=5	h=6
UM	1.82	1.44	1.38	1.33	1.71	1.69
RW	1.00	1.00	1.00	1.00	1.00	1.00
AR(1)	1.12	1.15	1.20	1.21	1.57	1.60
ARMA	1.22	1.24	1.26	1.40	1.42	1.47
VAR(4)	0.85	0.87	0.90	0.93	0.96	1.05

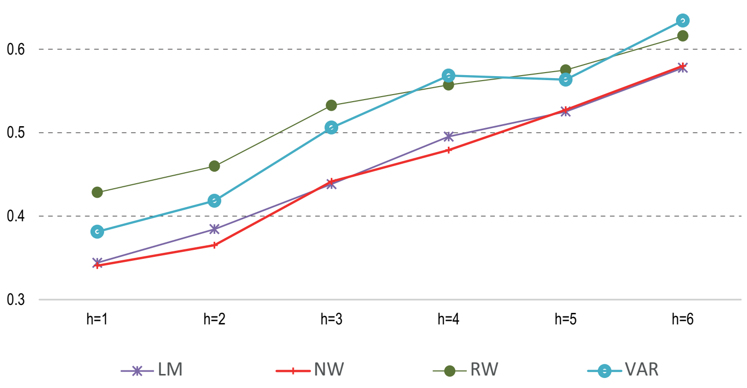
Source: Author`s calculations.

Note: The shaded cells mean that the model in the corresponding row is performing better than the RW for a certain forecast horizon, indicated by the corresponding column.

Whenever the relative RMSE is lower than one, it means that the respective model is superior to the random walk in terms of forecast performance. Using both forecast strategies, the random walk is the best performing model among the univariate models, but the VAR with 4 lags outperforms it in all the forecast horizons (except the 4 and 6-quarters ahead forecast with the expanding window strategy and 6-quarters ahead forecast with the rolling strategy), even though the differences between them are not considerable. Therefore, these two models will be used as benchmarks for the evaluation of the forecast performance of the BVAR.

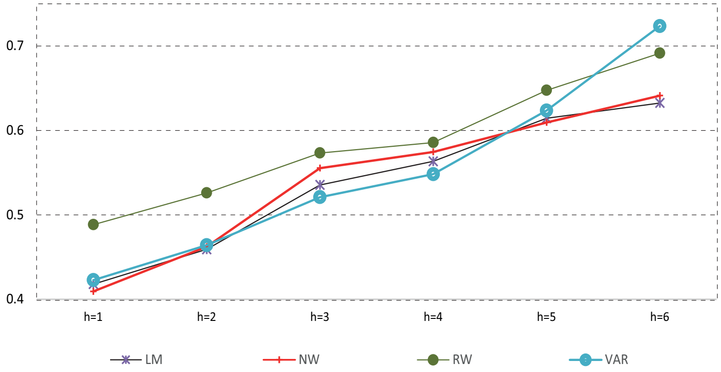
Figure 2 and 3 present the evolution of RMSEs of the BVAR using both types of priors – Litterman-Minnesota (LM) and Normal-Wishart (NW) – against the benchmark RW and VAR models for the two forecast strategies, respectively. In the case of the expanding window forecast strategy, the two BVAR models systematically outperform the benchmarks for all the forecast horizons. Whereas in the case of rolling strategy, their performance is overpassed by the VAR for the 3 and 4 quarters ahead forecasts, while for the other forecast horizons, BVARs are still the best performing models in terms of accuracy. Forecast accuracy tends to decrease as the forecast horizon expands, which is a reasonable result as with the increase in forecast horizon, it is more difficult to predict the likely path of a given variable.

Figure 2. RMSEs of the best performing models (expanding strategy)



Source: Author`s calculations.

Figure 3. RMSEs of the best performing models (rolling strategy).



Source: Author`s calculations.

To assess whether the forecast performances of the two models are statistically different on average over the out-of-sample period, we apply two tests of equal predictive ability: the Diebold-Mariano (1995) test (DM) in the case of rolling window forecast strategy, and the Giacomini and White (2003) test (GW) in the case of expanding window strategy, which is similar to the first test. To test if RMSFEs from alternative forecasts are significantly different, Diebold and Mariano (1995) proposed the following test statistic:

$$DM_h = \frac{1}{\sqrt{P-h+1}} \sum_{t=R}^{T-h} \frac{\hat{u}_{1,t+h}^2 - \hat{u}_{2,t+h}^2}{\sqrt{\hat{\Sigma}}} \qquad (10)$$

where $\hat{\Sigma}$ is an estimate of the long-run variance, P is the out-of-sample period length, and h is the forecast horizon. Under the null hypothesis $H_0: \widehat{\mathrm{E}(u}_{1,t+h}^2 - \hat{u}_{2,t+h}^2) = 0$, DM_h converges to a normal distribution. Because forecast errors are likely to be autocorrelated, the two tests are standardised by an autocorrelation and heteroskedasticity-consistent (HAC) covariance estimator, as in Newey and West (1987).

In addition to DM test which is used to assess the unconditional relative predictive ability of two alternative forecasting models, GW (2006) investigate the differences in the forecast performance between models in times of high or low uncertainty, through the following regression model:

$$\hat{u}_{1,t+h}^2 - \hat{u}_{2,t+h}^2 = \alpha + \beta X_t + e_{t+h} \qquad (11)$$

where X_t contains information that is known at the forecast origin t such as a constant, indicators of economic activity or measures of global uncertainty. If X_t contains only a constant, the Giacomini and White (2006) test is equal to the test of Diebold and Mariano (1995). Under the null hypothesis $H_0: \hat{\alpha} + \hat{\beta} E(X) = 0$, two alternative point forecasts are equally accurate conditional on X_t.

The test statistic of the conditional relative predictive ability test takes the form:

$$GW_h = (P-h+1)\bar{Z}'\hat{\Sigma}^{-1}\bar{Z} \qquad (12)$$

where $\bar{Z}$ represents the vector:

$$\left(\frac{1}{P-h+1}\sum_{t=R}^{T-h}(\hat{u}_{1,t+h}^2 - \hat{u}_{2,t+h}^2), \frac{1}{P-h+1}\sum_{t=R}^{T-h}(\hat{u}_{1,t+h}^2 - \hat{u}_{2,t+h}^2)X_t\right)' \qquad (13)$$

and $\hat{\Sigma}$ is an estimate of the long-run variance $\Sigma = lim_{P\to\infty} V((P-h+1)^{1/2}\bar{Z}$, which is estimated using a Newey-West estimator where the bandwidth is chosen optimally. Asymptotically, the GW test has a X^2 (2) distribution. If $\hat{\alpha} + \hat{\beta} X_t < 0$ the predicted h-step ahead loss of the first model is lower compared to the second one, which implies that the first model is more appropriate to be used for forecasting.

The results of both relative predictive ability tests are presented in Table 3.

Table 3. BVAR point forecast performance versus the benchmarks: DM and GW test statistics for RMSFEs, 2012-2018.

		DM(a)		GW(b)	
		4-quarters	6-quarters	4-quarters	6-quarters
BVAR (LM)	Random Walk	0.372	0.971	0.349	0.365
	Vector Auto Regressive	0.059	0.062	0.291	0.316
BVAR (NW)	Random Walk	0.351	0.754	0.351	0.372
	Vector Auto Regressive	0.055	0.057	0.049	0.051

(a) A positive (negative) number means that BVAR is more (less) accurate than the corresponding benchmark.

(b) A positive (negative) number indicates that the BVAR has a smaller (larger) predicted loss on average.

The BVAR inflation point forecast performance is comparable to the RW and VAR models. On average, all three models registered similar RMSFEs for 1 to 6-quarters ahead forecasts for the period 2013Q1-2018Q4. The two BVAR models outperform the random walk and the VAR for both forecast horizons: 4 and 6 quarters ahead, but the differences are not statistically significant. In the case of the expanding window forecast strategy, the BVAR models outperforms RW and VAR 6-quarters ahead forecasts, with an average RMSE of 0.46 (5 pp lower than VAR and 7 pp lower than RW) during 2012 and 2018, while in the case of rolling window, the BVARs are still superior, but the gains in forecast performance versus the RW and VAR are lower: 1 pp lower than VAR and 3 pp lower than RW, respectively.

Figure 4 presents the out-of-sample inflation forecasts for each of the models versus the actual data[1]. Although on average, all the models perform similarly throughout the forecast period, their behaviour changes over time.

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[1] More detailed information can be found in Figure 3, in the Appendix, which presents the forecast error series over time for the three models for three forecast horizons: 1-, 4- and 6-quarters ahead.

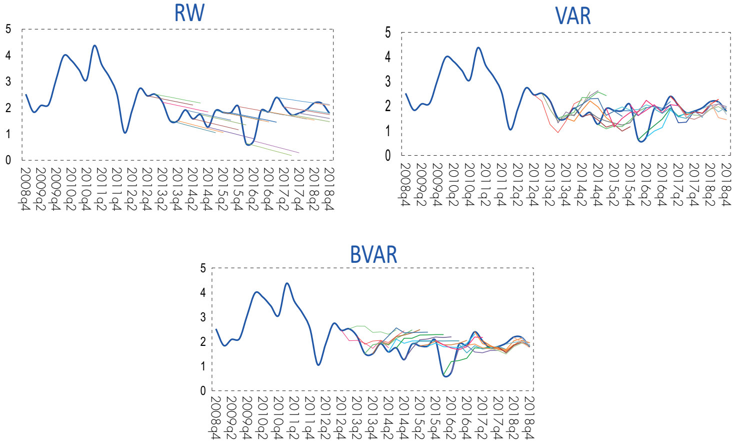


Figure 4. Out-of-sample forecasts for the period 2012-2018.

At the very beginning of the forecast sample, BVAR is slightly outperformed by the two other models, RW and VAR, whereas, in the next periods, its forecast performance improves. At some specific timepoints – like 2015Q4, 2016Q3, 2017Q1, 2107Q2, 2018Q2, 2018Q3, which are characterized by slight changes in inflation behaviour - VAR and BVAR have a superior forecast performance compared to the RW. In 2016Q1, when the actual rate of inflation reaches its lowest level over the whole forecast period at around 0.7%, all the models fail to capture accurately the future inflation movements, but the RW is the one which marks the largest forecast error. At other timepoints of the forecast horizon, such as 2014Q4 and 2016Q3, RW demonstrates a superior ability in capturing future inflation swings, whereas in other periods, for instance in 2015Q1, 2015Q4, 2017Q3, BVAR outperforms the two other models.

4.2 EVALUATING BVAR DENSITY FORECAST PERFORMANCE

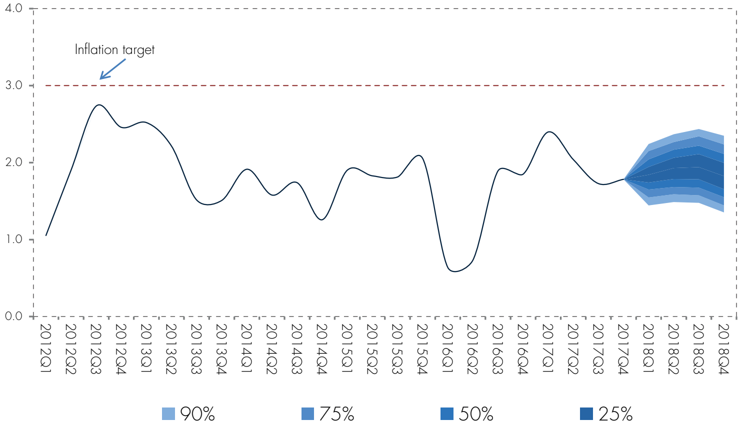
Due to uncertainty surrounding point forecasts, there is a general consensus in the literature that a central bank maximizing the probability of achieving its goal should adopt some form of "density forecasting" when conducting monetary policy (Greenspan, 2003). Many central banks thus nowadays provide quantitative information on the uncertainty associated with the main economic indicators forecasts. They calculate and publish officially prediction intervals for key economic variables (e.g. inflation and output) in order to express and communicate perceived forecast risks with professionals and the general public. This helps the public understand the degree to which the stance of monetary policy may have adjust over time in response to unpredictable economic events as the central bank seeks to meet its goals.

In this section, we assess the distributional properties (normality and symmetry) of the inflation forecast errors, which can then be used for fan-chart modelling. In addition, the performance of the density forecasts from the BVAR is evaluated relative to RW and VAR models using the Amisano and Giacomini (2007) test.

There is some work in the literature on testing the normality of forecast errors (see, e.g., Harvey and Newbold (2003), Lahiri and Teigland (1987), Makridakis and Winkler (1989), Reifschneider and Tulip (2007)). As the corresponding tests of distribution properties, give correct inference for independently and identically distributed (i.i.d.) observations, i.e. serially uncorrelated forecast errors, it is necessary to test first for the presence of autocorrelation among the forecast errors, in order to judge if we can use the skewness and kurtosis tests to assess normality of the errors. Q-statistics and the corresponding p-values are presented in Table 2 in the Appendix. The results show that serial correlation does not seem to be very problematic: the results are statistically significant in some of the cases, but only after 4 lags, and in 10% level of significance. Then, they become significant at 5% level of significance for some of the models, but only after 8 lags. As a next step, we proceed by calculating the skewness of the distributions of the forecast errors for the three models and we provide normal approximation for their respective probability histograms. Figures 4-6 in the Appendix summarize all this information for the three models for three forecast horizons: 1-, 4- and 6-quarters ahead. A Jarque-Bera test is used to analyse whether the forecast errors have the skewness and kurtosis matching a normal distribution. The null hypothesis is a joint hypothesis of the skewness being zero and the excess kurtosis being zero. Samples from a normal distribution have an expected skewness of 0 and an expected excess kurtosis of 0 (which is the same as a kurtosis of 3). The estimated results show that the null hypothesis cannot be rejected in none of the cases, implying that the forecast errors of each of the models follow a normal distribution and they are symmetric (unskewed) to the distribution mean. The mean varies across models and for different forecast horizons. It reaches its minimum value of -0.23 units in the case of the distribution of forecast errors of RW for 6-quarters ahead forecast horizon and its maximum 0.13 in the case of the distribution of forecast errors of BVAR for 6-quarters ahead forecast horizon, but in all the cases it is relatively small, which means that on average, the models have a satisfactory forecast performance.

In addition, forecast densities (or fan charts) are used to describe the degree of uncertainty around the central forecasts (see Figure 5). The gradually expanding fan, during the forecast period, reflects the increase of uncertainties over time around the central projection. A lighter shade represents the highest and lowest percentiles reflecting the level of confidence in these forecasting values. There are four degrees of shading confidence: 25%; 50%; 75%; and 90%. Inflation forecast value falling in the ranges of the darkest shade has a 25% probability to occur. Further up, the values found in the area with lighter colors have a 90% probability to occur. The fan-chart in Figure 5 shows that there are no increasing risks for inflationary pressures at the end of the forecast horizon (four quarters ahead).

Figure 5. Inflation density forecast, 2018Q1-2018Q4.



Assessing the performance of a density forecast is less trivial than for point forecasts, because we only observe one realised value of the variable of interest in each period, as opposed to its entire distribution. A related method to evaluate density forecasts is scoring rules. A scoring rule is a loss function that takes the density forecast and the actual outcome as its arguments. Following Alessandrini and Mumtaz (2013), we use the logarithmic scoring rule log f(y) where f is the density forecast and y is the observed value of the variable in question. The logarithmic score takes a high value if the forecast density assigns a high probability to the actual outturn.

The accuracy of density forecast over the out-of-sample period is measured by the average logarithmic scores defined as:

$$\frac{1}{P-h+1}\sum_{t=R}^{T-h} log f_t\left(Y_{t+h}\right) \qquad (14)$$

where P is the out-of-sample period length, and h is the forecast horizon. To test whether the log scores of various models are statistically different from each other on average over the out-of-sample period, a likelihood ratio test of Amisano and Giacomini (AG) (2007) is applied. The test statistic is given by:

$$AG_h = \frac{1}{\sqrt{P-h+1}} \sum_{t=R}^{T-h} \frac{\log f_{1,t}(Y_{t+h}) - \log f_{2,t}(Y_{t+h})}{\sqrt{\hat{\Sigma}}} \qquad (15)$$

where $\hat{\Sigma}$ is an estimate of the long-run variance. Under the null hypothesis, the two density forecasts $f_{1,t}(.)$ and $f_{2,t}(.)$ perform equally well.

Table 4. BVAR density forecast performance versus the benchmarks: Amisano and Giacomini test (AG) statistics for average log scores, 2012-2018 (a).

		AG (expanding)		AG (rolling)	
		4-quarters	6-quarters	4-quarters	6-quarters
BVAR (LM)	Random Walk	1.364	1.571	1.349	1.496
	Vector Auto Regressive	0.735	0.947	1.178	1.246
BVAR (NW)	Random Walk	0.953	1.074	1.372	1.453
	Vector Auto Regressive	0.755	0.857	0.672	0.701

(a) A positive (negative) number means that BVAR generates more (less) accurate forecasts than the benchmarks.

The BVARs inflation density forecasts perform similarly to the benchmarks for 4 and 6-quarters ahead forecast horizons, as none of the AG test statistics results statistically significant. However, it is important to note some of the limitations of this analysis. The out-of-sample period is relatively short and this not only hinders the evaluation of the performance stability of models, but also raises doubts about the reliability of the performances measured. Furthermore, the period covered by the pseudo forecast analysis includes the effects of the global financial crisis, which has been characterized by much more volatility in the behaviour of many macroeconomic variables. Therefore, our findings may be specific to the sample size as well as the considered period.

5. FINAL REMARKS

This study presents a Bayesian VAR model to forecast short-term inflation in Albania, which unlike standard autoregressive vector models, addresses the over-parameterization problem, allowing the inclusion of more endogenous variables, and enabling in this way a more comprehensive explanation of inflation. The BVAR is designed as a medium-sized model, which describes the most important dynamics and interactions between the determinants of inflation in Albania and consists of the following blocks: real private sector, financial sector and foreign sector. It includes 9 variables in total - 6 domestic and 3 foreign variables - and the dataset include quarterly time series for the period 2002Q2-2018Q4. The two most common priors found in the literature Litterman-Minnesota (LM) and Normal-Wishart (NW) are used for the estimation of the BVAR. An optimization procedure is implemented to select the best possible combination of the hyperparameters that characterize the priors in such a way that they maximize the marginal likelihood of the model. Several econometric models are considered as possible benchmarks for the BVAR, such as: unconditional mean, random walk, autoregressive integrated moving average models, unrestricted VAR. The best performing among them, random walk and VAR, are used as benchmarks to evaluate the forecast performance of the BVAR model.

The forecasting performance of the models is measured by RMSEs of the out-The point forecast accuracy of the models is measured by RMSEs of the out-of-sample forecasts for each forecast horizon up to 6 quarters, obtained using both rolling and expanding window forecast strategies, and then they are compared to each other for different time horizons. In addition, the accuracy of the density forecast for both the BVAR and the benchmarks is measured by the average logarithmic scores and they are also compared to each other. The estimated results show that the BVAR approach, which integrates more economic information, outperforms the benchmark univariate and the VAR models in the different time horizons of the forecast sample using both forecast strategies, but the differences between models on their forecast performance are not statistically significant. Nevertheless, it should be noted that due to relatively short pseudo out-of-sample period, the findings of the study might be subject to change as new data are released.

Lastly, forecast averaging (e.g. using Bayesian model averaging where all models have the same likelihood function and differ only from their prior) could be a convenient approach in dealing with the wide variety of possible prior choices, the way in which they do shrinkage and the uncertainty over which prior leads to the best forecast performance. Also, a forecast combination procedure of the BVAR with other short-term inflation forecasting models could be a successful strategy to improve forecast performance. By combining many misspecified models, each of them incorporating information from different variables, model averaging usually outdoes forecasts from individual models (Aiolfi et al., 2011). Admittedly, the presented version of the BVAR model is an illustrative example of its applicability rather than the ultimate specification. The composition of the dataset and the structure of the model may obviously be further changed depending on the issue addressed.

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APPENDIX

Table 1. Summary of descriptive statistics.

	GDP	CPI	REPO	ER	RER	M2	W	GDPEZ	CPIEZ	EURIBOR
Mean	3.99	2.49	4.41	0,14	-0.65	5.70	6.51	1.21	1.69	1.47
Median	3.95	2.40	5.00	-0.39	-1.54	5.80	4.49	1.72	1.91	1.04
Maximum	9.59	4.99	8.50	13.25	14.92	13.76	23.73	3.67	3.92	4.98
Minimum	-2.35	0.64	1.00	-9.23	-9.71	-1.47	-5.94	-5.96	-0.36	-0.33
Std. Dev.	2.48	0.95	2.14	4.18	3.93	3.95	7.62	1.93	0.98	1.59
Skewness	0.18	0.55	-0.08	0.80	1.02	-0.04	0.92	-1.91	-0.33	0.63
Kurtosis	2,95	3.08	2.17	4.34	6.02	2.24	2.91	7.05	2.57	2.26
Sum	267.1	167.0	295.8	9.4	-43.6	382.2	436.5	80.8	113.3	98.4
Obs	67	67	67	67	67	67	67	67	67	67

Figure 1. Development over time of the main domestic indicators.

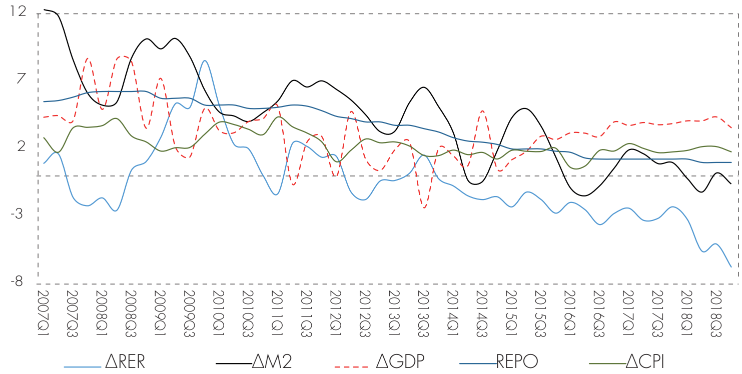


Figure 2. Development over time of the foreign indicators

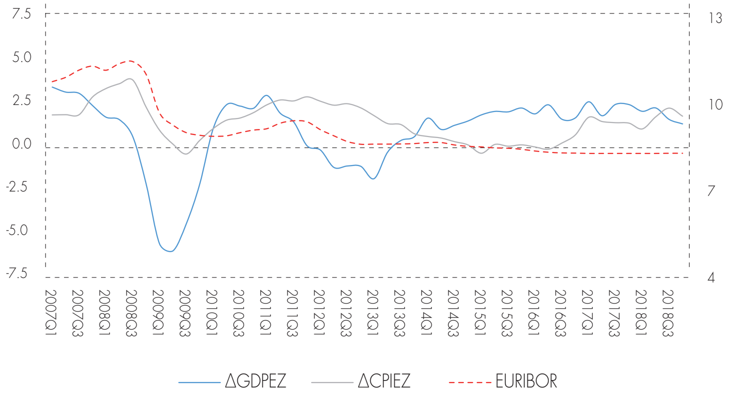


Figure 3. Forecast errors of different models for 1-, 4- and 6-quarters ahead forecasts.

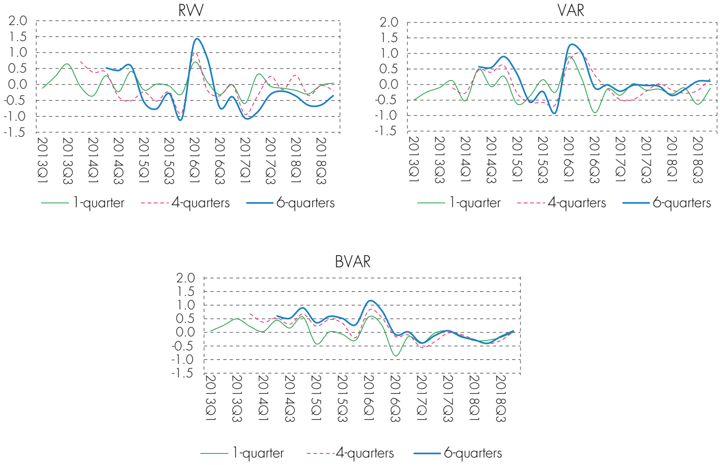
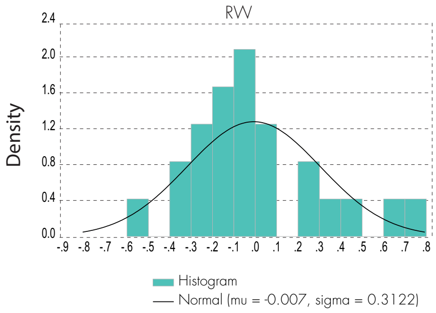


Table 2. Autocorrelation test results for the forecast errors of different models for 1-, 4- and 6-quarters ahead.

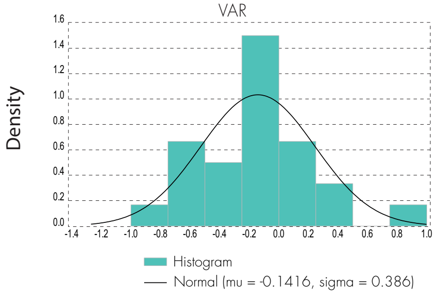
	RW			VAR			BVAR		
Lag	1-Q	4-Q	6-Q	1-Q	4-Q	6-Q	1-Q	4-Q	6-Q
1	1.976	0.047	1.212	0.529	0.701	1.208	0.444	0.619	0.018
	(0.160)	(0.829)	(0.271)	(0.467)	(0.402)	(0.272)	(0.505)	(0.432)	(0.894)
2	1.445	0.186	1.458	0.607	0.713	1.806	0.559	0.619	0.143
	(0.485)	(0.911)	(0.482)	(0.738)	(0.700)	(0.405)	(0.756)	(0.734)	(0.931)
3	1.505	0.400	2.374	1.538	1.366	4.568	0.923	1.530	0.148
	(0.681)	(0.940)	(0.499)	(0.674)	(0.713)	(0.206)	(0.820)	(0.675)	(0.986)
4	3.594	4.047	7.485	2.715	6.794	7.248	0.998	7.056	1.364
	(0.464)	(0.400)	(0.112)	(0.607)	(0.147)	(0.123)	(0.910)	(0.133)	(0.850)
5	11.711*	4.052	7.798	3.261	10.661*	8.085	3.698	10.719*	1.409
	(0.051)	(0.542)	(0.168)	(0.660)	(0.059)	(0.152)	(0.594)	(0.057)	(0.923)
6	11.843*	4.508	10.731*	3.674	11.248*	8.871	6.951	11.207*	1.458
	(0.066)	(0.608)	(0.097)	(0.721)	(0.081)	(0.181)	(0.325)	(0.082)	(0.962)
7	11.850	4.672	13.525*	4.166	13.336*	9.258	7.018	13.756*	2.037
	(0.106)	(0.700)	(0.060)	(0.760)	(0.081)	(0.235)	(0.427)	(0.056)	(0.958)
8	12.025	5.160	13.663*	4.335	13.548*	9.362	7.071	13.889*	2.762
	(0.150)	(0.740)	(0.091)	(0.826)	(0.094)	(0.313)	(0.427)	(0.085)	(0.948)
9	17.805**	5.474	15.733*	5.646	17.481**	9.382	10.524	17.741**	2.799
	(0.038)	(0.791)	(0.073)	(0.775)	(0.042)	(0.403)	(0.310)	(0.038)	(0.972)
10	24.20***	5.810	17.368*	5.736	17.701*	9.437	10.546	18.026*	3.367
	(0.007)	(0.831)	(0.067)	(0.837)	(0.060)	(0.491)	(0.394)	(0.055)	(0.971)
11	24.315**	7.757	17.910*	6.022	19.924**	9.441	10.559	20.665**	4.329
	(0.011)	(0.735)	(0.084)	(0.872)	(0.046)	(0.581)	(0.481)	(0.037)	(0.959)
12	24.317**	8.197	17.928	6.529	21.453**	9.502	11.276	22.262**	5.220
	(0.018)	(0.770)	(0.118)	(0.887)	(0.044)	(0.660)	(0.505)	(0.035)	(0.950)

Note: Numbers in the first line represent the Q-statistic, whereas the numbers in the second line within the brackets represent the corresponding p-value. Under the null hypothesis there is no serial correlation at the respective lag. * denotes significant autocorrelation at 10% level of significance; ** denotes significant autocorrelation at 5% level of significance; *** denotes significant autocorrelation at 1% level of significance.

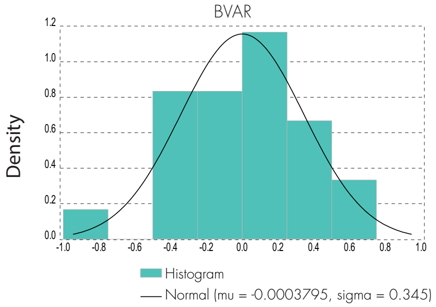
Figure 4. Distribution properties of forecast errors of RW, VAR, BVAR for 1-quarter ahead forecast horizon.



Skewness	0.615
Kurtosis	3.092
Jarque-Bera	1.524
p-value	0.467

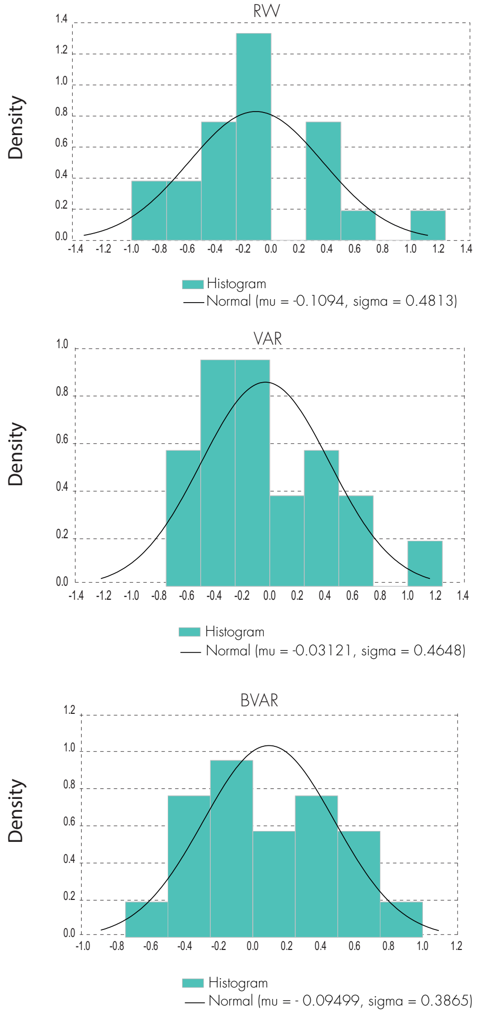


Skewness	0.546
Kurtosis	3.092
Jarque-Bera	1.803
p-value	0.406



Skewness	-0.264
Kurtosis	3.096
Jarque-Bera	0.289
p-value	0.865

Figure 5. Distribution properties of forecast errors of RW, VAR, BVAR for 4-quarters ahead forecast horizon.

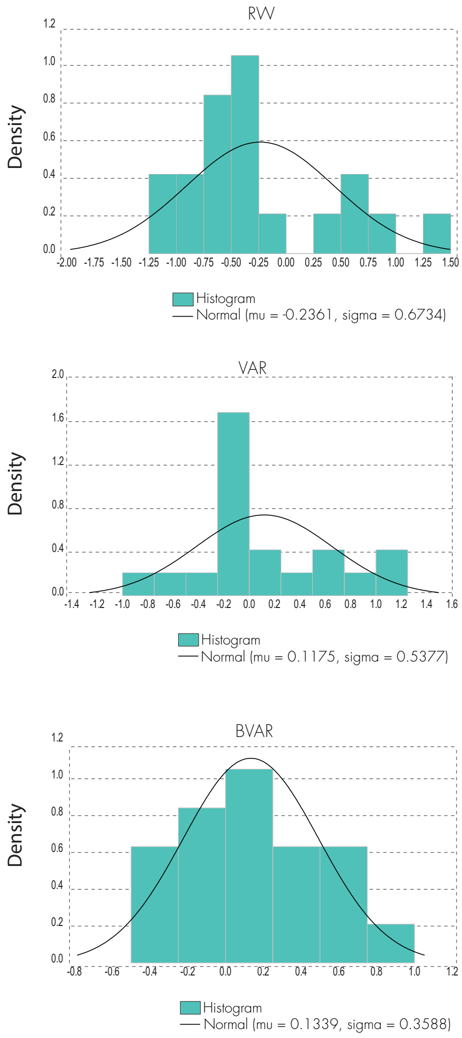


Skewness	-0.264
Kurtosis	3.096
Jarque-Bera	0.289
p-value	0.865

Skewness	0.665
Kurtosis	2.477
Jarque-Bera	1.788
p-value	0.409

Skewness	0.182
Kurtosis	1.977
Jarque-Bera	1.031
p-value	0.597

Figure 6. Distribution properties of forecast errors of RW, VAR, BVAR for 6-quarters ahead forecast horizon



Skewness	0.876
Kurtosis	2.841
Jarque-Bera	2.451
p-value	0.293

Skewness	0.439
Kurtosis	2.728
Jarque-Bera	0.667
p-value	0.716

Skewness	0.298
Kurtosis	2.029
Jarque-Bera	1.010
p-value	0.603

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