Bayesian combined forecasts and Monte Carlo simulations to improve inflation rate predictions in Romania

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ABSTRACT

There are many proposals in literature for improving the forecast performance. In this paper we applied the regression approach and Bayesian inference to obtain more accurate forecasts of the inflation rate in the case of the Romanian economy. The necessity of using the most accurate forecasts for the inflation rate is required by the realisation of economic criteria for the accession to the eurozone and by the inflation targeting strategy of the National Bank of Romania. Considering the assumption that simple econometric models provide better forecasts than complex models, in this paper we combined various forecasts from individual models using as prior information the expectations of experts. The empirical findings for Romanian inflation rate forecasts over the horizon of 2016-2018 indicated that a fixed effects model performed better than other simple models (autoregressive moving average model, dynamic model, simple and multiple linear model, VAR, Bayesian VAR, simultaneous equations model). The Bayesian combined forecasts that used experts' predictions as priors, with a shrinkage parameter tending to infinity, improved the accuracy of all predictions using individual models, outperforming also naïve forecasts and zero and equal weights forecasts. However, predictions based on Monte Carlo simulation outperformed all the scenarios in terms of the mean error and mean absolute error.

Keywords: forecasts accuracy, Bayesian forecasts combination, shrinkage parameter, econometric model.

1. Introduction

The evolution of inflation is directly supervised in Romania in the context of the eurozone accession that requires, among other economic criteria, price stability (an inflation rate that does not exceed 1.5 percentage points the average of the first three countries with the lowest inflation rate in the eurozone). Therefore, inflation forecasting is essential in the efforts to achieve the convergence criteria in Romania. The National Bank of Romania implemented a prudent monetary policy in the last years as to keep a low level of inflation. The relationship between the inflation rate and the exchange rate evolution influences the conversion rate for RON/Euro. When Euro is adopted, the fixed conversion rate will influence the nominal revenues and all the prices. Therefore, before entering ERM2, it is necessary to have a compara-

tive price level that is bearable by the national economy, but compatible with the eurozone.

Inflation targeting should be based on accurate inflation forecasts for good implementation of the monetary policy. The evolution of the inflation rate might be described by various econometric models that could also be used to build predictions. National banks used to employ more alternative models in describing the evolution of inflation, and the predictions based on these models are later combined to get a better prediction of inflation. Recent advances in literature indicated that the combined predictions that use more individual models perform better than individual forecasts. The recent economic crisis emphasized the need to reduce the forecast uncertainty (Julio Roman, Bratu Simionescu, 2013). The reduction of forecast uncertainty has advantages at the macro-

economic and microeconomic levels by improving the decision-making process (Terceno and Vigier, 2011).

The most used method to improve forecast accuracy nowadays is the construction of combined forecasts, different ways of building them, described by Timmermann (2006). Recent advances in this field are represented by the use of Bayesian techniques. In this context, Diebold and Pauly (1990) proposed a Bayesian shrinkage method that includes prior information for building better combined forecasts. Wright (2008) and Koop and Potter (2003) employed an equal-weights or zero-weights prior mean. The Bayesian weights are calculated by Gomez, Gonzalez and Melo (2012) in the context of a rolling window estimation method using co-integrated data series of order one.

The main purpose of this paper is to provide a way for improving inflation rate forecasts in Romania. We chose only Romania in the analysis, because it had a particular evolution of the inflation rate from the transformation of the centrally planned economy to the functional market economy. This framework is completed by new challenges like inflation targeting that has been implemented since 2005 and the necessity to achieve the criteria for the entrance to the eurozone. Contrary to other countries in the region, in Romania, there are more alternative predictions for usual macroeconomic indicators, and the policy makers should know exactly what is the best forecast to be used in the decision-making process and how this forecast might be improved by combining a subjective perspective of experts with an objective perspective given by quantitative forecasting methods. The Dobrescu model for the Romanian economy has an international recognition, but the forecasts of the National Commission for Prognosis are used in the government decisions. The National Bank of Romania employs a complex model for constructing short term and medium-run forecasts. However, none of these individual predictions are based on a Bayesian combination of forecasts in order to improve the forecasts' accuracy. As a novelty for the economic literature in Romania, in this paper new inflation rate predictions are built using own econometric models and experts' expectations based on the Bayesian combination technique. After a brief literature review on inflation modelling for predictions, the methodological background is described. Empirical data are used to show the improvement of inflation rate forecasts in Romania. The paper uses a prior mean that considers the forecasts based on the Dobrescu macro-model for the Romanian economy. Starting from the conclusion of Simio-

nescu (2014) that simple econometric models perform better than the complex ones, in this paper, we will build forecasts based on usual econometric models (time series models and panel data models).

2. Literature review

Inflation forecasting is a difficult task, but many papers in literature focused on this topic by proposing various forecast methods. The paper of Atkeson and Ohanian (2001) is considered as a milestone in the economic literature related to inflation forecasting. The authors considered more standard Phillips curve forecasting models, showing that none of them performed better than a four-quarter random walk benchmark in the period 1984–1999. The next studies after Atkeson and Ohanian showed that their results are dependent on the forecast horizon and sample period. In case of other benchmark models, the results might change. For example, if the model of Stock and Watson (2007) is used as a benchmark (unobserved component-stochastic volatility model), the forecasts based on Phillips curve are not anymore better than univariate predictions.

There are single-equation or multiple-equations inflation forecasting models. In the case of single-equation models, we have four types of inflation forecasts:
a) Forecasts based only on past inflation;
b) Predictions using activity measures (forecasts based on Phillips curve);
c) Forecasts built up from other predictions;
d) Forecasts that use other predictors.

The forecasts using the past inflation use the following methods: univariate time series models, autoregressive integrated moving average – ARIMA models and time-varying or nonlinear univariate models. This type of forecasts includes also those predictions in which one or different inflation measures other than the forecasted one is/are predictors(s) (e.g. past core inflation based on the consumer price index, previous wage growth could be used for predicting the overall CPI inflation). Some of these models are often used as benchmark models: the direct autoregressive model, the random walk model used by Atkeson and Ohanian (2001) and the unobserved components-stochastic volatility model employed by Stock and Watson (2007).

Phillips curve forecasts are those that include predictions based on an activity variable like the output gap, output growth or unemployment rate in interaction with other variables to predict the inflation evolution or the changes in inflation. There are two types of Phillips

curve forecasts: backward-looking curves and New Keynesian Phillips curves, with the latter being rarely used in inflation forecasting. There are two frequently used prototypes of Phillips curves: the triangle model used by Gordon (1990) in which inflation is regressed using lagged inflation, supply shock variables and unemployment rate. This model was extended by Gordon (1998) to include the predicted values of predictors, where these forecasts are based on univariate autoregressive models for shocks, import inflation, energy and food inflation. Another usual prototype of Phillips curve eliminates the supply shock indicators and step-function restriction.

Inflation forecasting is a key element in monetary policy elaboration, whether the central banks have fixed a target for inflation rate or not. A simple Phillips curve that uses unemployment rate for predicting inflation rate is the most used forecasting method. However, many studies showed a lack of utility in using Phillips curve for inflation forecasting (Sovbetov and Kaplan, 2019; Furtula et al., 2018).

Forecasts based on other forecasts refer to those inflation predictions based on implicit or explicit expectations or other forecasts. In this case, we may have regressions using implicit expectations coming from asset prices, like predictions extracted from the structure element of the nominal Treasury debt or from Treasury inflation-protected securities yield curve. In this case, we may also have those forecasts using explicit predictions of others (mean forecasts, median forecasts from surveys such as the Survey of Professional Forecasters).

Forecasts that use other predictors refer to predictions using other variables than those regarding activity or expectations. The 1970s-vintage monetarist model is an example in this sense, with M1 growth being used for predicting inflation. In most cases, this type of forecast performs worse than the other three types, being rarely used in the literature.

In Romania, more macroeconomic models were built to predict the evolution of the inflation rate. The Dobrescu macromodel for the Romanian economy is the most used model for making predictions on macroeconomic indicators in Romania, with the consumer price index being one of them. Other predictions are provided by the National Commission for Prognosis.

The Dobrescu model for the Romanian economy was developed in the transition period from the centrally planned system to the market economy. It is the first international recognized model for the Romanian economy. The first version was released in 1996 and the last version was built in 2012, still being in use to make predictions for the following years. The model includes 6 macroeconomic blocks:
(1) Production function and output gap;
(2) Employment, capital, labour income;
(3) Domestic absorption and foreign trade;
(4) General consolidated budget and public debt;
(5) Prices, exchange rate, monetary variables;
(6) Balance of payments and external debt;
(7) Primary energy and CO_2 emissions.

The block used for predicting the inflation rate includes 10 accounting relationships and 7 econometric relations (Dobrescu, 2017). The first difference in the consumer index price and fixed capital formation was stationary, and a causality in Granger sense was detected from the inflation rate to the interest rate. The lag of the first difference in the interest rate was included in the specification of the investment price index and consumer price index with a positive sign. The results indicated that the economic operators are adapted to high interest rates that are included in the expected cash flows through the corresponding prices.

The National Commission for Prognosis has, among attributions, the elaboration of short-run, medium-run and long-run predictions for the economic and social aspects in Romania. These forecasts are strongly correlated with the stipulations of the political factor, with the strategies for development and with the national and international actual tendencies. The changes in the dynamics of recent evolution of inflation rate are presented by Liao (2014):
- Less inflation persistence;
- The Phillips curve is more flattened;
- Inflation is not anymore so sensitive to shocks.

There are several studies in the subject literature that modelled the inflation rate in Romania using econometric models. For example, for the period of 1992-2000, Budina et al. (2006) showed, using a co-integration approach, that inflation in the 1990s was a monetary phenomenon, a fact that allows us to show the utility of inflation predictions in the creation of the monetary policy in Romania. A vector error correction model was employed by Dritsakis (2004) to show the causal relationship from inflation to productivity in the period between 1990-2003. Various time series models (autoregressive and moving average models) were estimated by Baciu (2015) using data from January 1997 to August 2013 in order to predict the inflation rate in Romania. Mihai et al. (2016) used linear regression models to show that unemployment had a significant impact on the inflation rate in Romania during 2007-2014. However, these authors used a very short sample in estimations and the results should be cautiously retained.

In the context of alternative forecasts for the same indicator, it is essential to select those predictions that perform better and to improve their accuracy. One way to get more accurate predictions is to construct combined predictions. This recommendation is also among the nine generalizations of Armstrong (2005) for improving the forecasts accuracy (selection of the best forecasting method, good knowledge of the domain in which forecasts are built, use of experts' predictions, realistic representation of the economic phenomenon, use of econometric models when causal relationships among variables are well known, issue's structuration, use of simple econometric models, utilization of conservative forecasts when more sources of uncertainty are identified, use of combined forecasts). In the last conferences of the International Institute of Forecasters, a specific importance was assigned to the techniques for combing forecasts. For example, at the conference held in Seoul in 2014, a new scheme of Bayesian combination was proposed for predictions based on different models in case of Columbia's inflation (Velandia et al., 2014). Other new techniques for combining forecasts in order to improve their accuracy were proposed by Poncela et al. (2011) who combined some methods to reduce dimensionality in forecasts, using in the end the ordinary least squared method for combination. On the other hand, Tian and Zhou (2013) proposed a scheme for global minimum variance weighting which combines the usual techniques such as random walk, moving average, moment mean and GARCH-M.

However, most of the individual models for the inflation rate or those based on combination require a lot of time, data and computational power and, in most cases, the intervention of the monetary authorities cancels the utility of the model.

In this paper, a new technique of combination is proposed based on the Bayesian approach. This type of combination scheme has not been used before for predicting the inflation rate in Romania, but it is proved that it provides valuable results for improving inflation forecasts in this country.

3. Methodology

Let us start with a number of m h-step-ahead predictions of a certain variable y_t: $f^1_{t/t-h}$,..., $f^m_{t/t-h}$. According to Granger and Ramanathan (1984), we should start with a certain forecast combination:

$$y_t = \alpha' f_{t/t-h} + \varepsilon_t \qquad (1)$$

y_t – variable of interest at time t;
ε_t – error term;
$\alpha = (\alpha_0, \alpha_1, \dots, \alpha_m)'$ – vector including regression parameters;
$f_{t/t-h} = (1, f^1_{t/t-h}, \dots, f^m_{t/t-h})'$ – vector including intercept and m forecasts (vector size: m+1).

The intercept is considered to have an optimally determined bias correction.

Diebold and Pauly (1990) proposed a method that includes prior information in regression that combines forecasts by using the g-prior model of Zellner (1986). In this case, the error is independently, identically and normally distributed of null average and constant variance σ^2. A natural conjugate normal-gamma prior is employed:

$$p_0(\alpha,\sigma) \propto \sigma^{-m-v_0-2} \exp \{-\tfrac{1}{2}\, \sigma^2[v_0 s^2_0 + (\alpha - \alpha^*)' \, M \, (\alpha-\alpha^*)]\} \qquad (2)$$

α, α^*, v_0 – parameter;
σ – standard deviation;
$p_0(\alpha, \sigma)$ – prior;
m – number of forecasts;
s^2_0 – estimated variance;
M – expected value (mean).

The likelihood function has the following form:

$$L(\alpha,\sigma/Y,F) \propto \sigma^T \exp \{-\tfrac{1}{2}\, \sigma^2 (Y-F\alpha)'(Y-F\alpha)\} \qquad (3)$$

$Y = (y_1, \dots, y_{t-h})'$ – vector of variables;
$F = (f_{1/1-h}, \dots, f_{t-h/t-2h})'$ – distribution function;
$L(\alpha, \sigma/Y, F)$ – likelihood function;
T – sample volume;
$\sigma2$ – variance;
α – parameter;
h – horizon length;
σ – standard deviation.

$$p_1\left(\frac{\alpha}{Y}, F\right) \propto \left[1 + \frac{1}{v_1}(\alpha - \bar{\alpha})' s_1^{-2}(M + F'F)(\alpha - \bar{\alpha})\right]^{-\frac{m+v_1+1}{2}} \qquad (4)$$

$p_1\left(\frac{\alpha}{Y}, F\right)$ – marginal posterior;
α, v_1 – parameters;
$\bar{\alpha}$ – average of α;
F – distribution function;
σ – standard deviation;
Y – vector of variables;
m – number of forecasts.

The marginal posterior average is:

$$\bar{\alpha} = (M + F'F)^{-1}(M\alpha * + F'F\hat{\alpha}) \qquad (5)$$

where:

$\hat{\alpha}$- estimated α
$v_1 = T + v_0$
$\hat{\alpha} = (F'F)^{-1}F'Y$
$$s_1^2 = \frac{1}{v_1}[v_0 s_0^2 + Y'Y + \alpha *' M\alpha$$
$$* -\bar{\alpha}'(M + F'F)\bar{\alpha}]$$

Diebold and Pauly (1990) demonstrated the validity of the relationship for the g-prior analysis (M=gF'F):

$$\bar{\alpha} = \frac{g}{1+g}\alpha * + \frac{1}{1+g}\hat{\alpha} \qquad (6)$$

$g \in [0, \infty)$ represents the shrinkage parameter. It controls the relative weight based on a maximum likelihood estimator and the prior average in the posterior mean.

Wright (2008) used zero weight as the prior mean, but Diebold and Pauly (1990) previously used equal weights. Geweke and Whiteman (2006) built the prior distribution in Bayesian forecasting by using the experts' forecasts. In this current study, our prior weights are represented by the estimated coefficients of the regression between the h-step predictions of the experts $f_{t/t-h}^{expert}$ and the forecasts using various econometric models. In our case, the prior mean is:

$$f_{t/t-h}^{expert} = \alpha_t' f_{t/t-h} + \varepsilon_t \rightarrow \alpha *_t =$$
$$(F'_{t-w+1,t}, F_{t-w+1,t})^{-1} F'_{t-w+1,t} F_{t-w+1,t}^{expert} \qquad (7)$$

where:

$F_{t-w+1,t} = (f_{t-w+1/t-h-w+1}, \dots, f_{t/t-h})'$
$F_{t-w+1,t}^{expert} = (f_{t-w+1/t-h-w+1}^{expert}, \dots, f_{t/t-h}^{expert})$

$f_{t/t-h}^{expert}$— prior mean of experts' forecasts;
$F_{t-w+1,t}^{expert}$— vector of experts' forecasts.

In the case of non-stationary data series, Coulson and Robins (1993) employed a linear model to build the combination technique:

$$y_t - y_{t-h} = \alpha' \widetilde{f_{t/t-h}} + \varepsilon_t \qquad (8)$$

$$\tilde{f}_{t/t-h} = (1, f_{t/t-h}^1 - y_{t-h}, \dots, f_{t/t-h}^m - y_{t-h})' \qquad (9)$$

$$f_{t/t-h}^{expert} - f_{t-h/t-2h}^{expert} = \alpha_t' \bar{\bar{f}}_{t/t-h} + \varepsilon_t, \text{ where } \bar{\bar{f}}_{t/t-h} =$$
$$(1, f_{t/t-h}^1 - f^{expert}{}_{t-h/t-2h}, \dots, f_{t/t-h}^m - f^{expert}{}_{t-h/t-2h})' \qquad (10)$$

In Table 1, the extreme cases of the posterior mean used by Coulson and Robins (1993) are indicated.

Table 1: Posterior mean of the extreme cases using the method of Coulson and Robins (1993)

Prior	g→∞
Experts' forecasts	Experts' weights
Equal weights	Equal weights
Zero weights	Random walk weights

Source: own calculations.

For zero weights prior, when g tends to infinity, the posterior mean is actually a zero-weight vector. This implies a naïve forecast. The Bayesian approach with equal and zero weights priors supposes that the combination uses the forecasters' expectation as covariate.

4. Bayesian combined forecasts for the inflation rate in Romania

The experts' forecasts that are employed in this study are based on the Dobrescu macro-model for the Romanian economy. We will use the available data for inflation rate forecasts from 1997 to 2018. The data are organized into two samples. The first sample (1997-2015) is used to estimate the forecast combination model, while the second sample (2016-2018) is used in assessing the accuracy of predictions based on individual models and on a combination of models.

Romania's transition from the planned economy to the market economy was marked by high inflation rates. According to Dobrescu (2009), in the transition process downward price rigidity had a huge role, but the influence of the other determinants of inflation were, indeed, decisive. In his macromodel, Dobrescu (2009) computed sectoral prices indices under the hypothesis of zero inflation. The author calculated minimal price indices that represent lower prices at which the production might be sold. These minimal price indices are provided by taking into account the suppliers' behaviour and real price indices.

A short presentation of the evolution of the inflation rate in Romania will be made to understand the importance of inflation evolution for the overall economy and the necessity to predict it for the elaboration of the macroeconomic policies. The evolution of inflation rate (%) in Romania based on monthly average in the period 1991-2018 can be observed in Figure 1, the data being provided by National Institute of Statistics from Romania. The necessity of providing the most accurate forecasts for inflation might be explained by the National Bank of Romania strategy in the context of inflation targeting that was introduced since 2005. The Central Bank proposed to maintain the inflation rate under the level of 10%. This criterion is in connection with other objectives of the National Bank: the consolidation and increase in the credibility of the Central Bank, fiscal consolidation, gain in independence and transparency, exchange rate flexibilization, a better prediction of macroeconomic behaviours and of mechanisms that ensure the evolution of the economy.
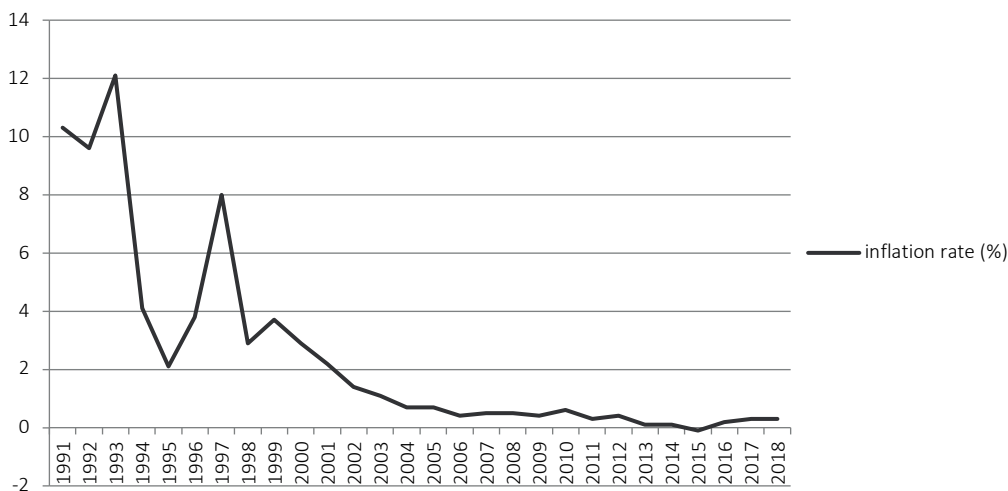

Figure 1. The evolution of inflation rate (%) in Romania based on monthly average (1991-2018)
Source: own calculations

In the 1990s, inflation was one of the main instability factors in the Romanian economic environment because of its volatility and high level. In this context, inflation forecasting and the associated costs coverage were difficult to make. The economy was characterized by persistent shocks in aggregate demand and supply which generated, in first transition years, the transformation of corrective inflation into structural inflation that might be controlled only if the monetary policy is correlated with the other macroeconomic policies. In the 1990s, the high level of inflation and its oscillations were explained by: the consequences of late restructuration of the economy, the interruptions of applied measures for stabilization, large fiscal indiscipline and inadequate wage policies. In the period between 1991-1993, inflation increased in the context of prices liberalization and fiscal reforms, achieving a maximum level in 1993 (the annual average inflation rate of more than 256%). In 1994, inflation reduced amid the resumption of economic growth and prices reforms temporizations. The economic growth reinforcement under the old structures did not bring long-run positive effects and inflation reignited in 1997 in the last phase of prices liberalization. The inflation expansion continued in 1998 and 1999 in an economic environment marked by economic decline, VAT increase, exchange rate depreciation and increases in prices for public services.

In 2000, together with the economic recovery, a new process of disinflation started, with consumer prices decreasing by 14 percentage points. In the next two years, the disinflation process accelerated and in 2003 a stagnation of disinflation was observed in the context of tensions in supply and pressures generated by consumption increase. In the next years, until 2006, the inflation rate registered a tendency of decrease, even more than expected in 2006. In 2004, the national currency appreciation, the more pronounced tendency for saving and restrictive fiscal policies sustained the disinflation process, even if the growth in consumption

and an average brute salary as well as arrears accumulation acted in the opposite sense. In 2005, the disinflation was encouraged by the national currency appreciation with respect to euro and the decrease in the dynamics of administered prices. The disinflation intensified in 2006 under the base component reduction, changes in volatile prices and a higher competition on retail market. In 2007, the volatile prices evolution and fast appreciation of national currency in nominal terms accelerated the inflation evolution. Since 2007, the inflation has changed its trajectory, with the increases in prices being attributed to: unexpected increase in the volatile prices of agricultural products, rise in the prices of some foods, exchange rate adjustment when the demand was in excess. In 2008, the inflation pressure was generated by the shocks in supply (tensions on the agri--food market, rise in the prices for agricultural import of raw materials and unprocessed products) and in demand (rise in fuel and natural gas prices). Since August 2008, these factors have begun to diminish their influence, but the demand-side effects of fiscal policy relaxation, the laxity of wage policy, the expansion of lending activity persisted.

The severe economic contraction in 2009 in Romania characterized by persistent structural rigidities on the labour market and the production market diminished the rhythm of prices reduction. In 2010, the influence of the external prices increase in the context of the global demand decrease were strongly felt on volatile food prices. In 2011, the inflation rate suddenly decreased due to volatile food prices. An unexpected increase in prices was registered in 2012 because of the internal and international shocks in supply, especially increases in the prices of vegetal raw materials. The shocks in demand (persistence of demand deficit) were represented by changes in oil prices, the exchange rate for RON/euro and adjustments in administered prices. In 2013, the inflation rate enrolled on a pronounced descendent trajectory due to the end of the effects of supply shocks and the persistence of demand deficit correlated to a good agricultural year and reductions in V the VAT rate for some bakery products. The low level of inflation in 2014 was ensured by the relative stable evolution of the exchange rate against euro and the lack of pressures on external prices. The prices decline in 2015 was explained by reduction in the VAT rate and demand deficit, the mitigation in import prices dynamics and reduction in oil prices on international markets. In 2016, the reduction in the VAT rate at the beginning of the year and the first signals from the external environment regarding the dissipation of disinflation determined an attenuation in the inflation decline in the third quarter of 2016. However, global evolution of the inflation rate in 2016 indicated a consistent disinflation. In the second quarter of 2017, the prices grew because of the pressures on a constant increase in production costs. The consumer price evolution was adjusted as to take into account the effects of fiscal changes in the first 2 months of 2017 (lower standard VAT tax, elimination of overcharging for fuels and of some non-fiscal taxes). The evolution was mainly due to exogenous factors in the context of the liberalization for natural gas intern production price and the consistent support for electric energy production based on renewable sources. The ascending trajectory accentuated in the last quarter of 2017 due to supply shocks such as growth of electricity price on the local concurrence market, increase in the price of aliments and higher excise duty on fuels. In the second quarter of 2018, the inflation rate in Romania registered the maximum value in the last five years. In September 2018, inflation reduced due to exogenous components.

The forecasters anticipated an increase in the inflation rate in Romania in the next years based on the increase in the excess of aggregate demand, more expansionist fiscal policy, increase in the disposable income and more encouraging real monetary conditions.

Some accuracy measures are calculated for comparing the forecasts accuracy (U1Theil's statistic, U2 Theil's statistic, root mean square error (RMSE), mean error (ME), mean absolute error (MAE)). Some individual econometric models are built to forecast the inflation rate in Romania using data series for the inflation rate, unemployment rate and exchange rate in the period between 1991-2013. These models are used to make predictions for the inflation rate over the horizon of 2014-2016. According to the Augmented Dickey-Fuller test and Phillips-Perron test, the data for inflation rate and unemployment rate are stationary in the first difference (d_inflation and d_unemployment), while the data for an average RON/Euro exchange rate are stationary in the second difference at 5% level of significance.

The Phillips curve cannot be identified using data series from the Romanian economy. A valid simple linear model was built on stationary data:

$$d\_inflation_t = -7.363 + 6.877 \cdot d\_unemployment_t \qquad (11)$$

For eliminating the disadvantage of a small set of data, the parameters were estimated by

bootstrapping, when the residuals are resampled using 10 000 replications:

$$d\_inflation_t = -7.382 + 6.9 \cdot d\_unemployment_t \tag{12}$$

At each increase with one per cent in the variation unemployment rate, the absolute change in the inflation rate increases by 6.9 percentage points. The Durbin-Watson tests and Breusch-Godfrey test for a lag equalled to 1 indicated errors' independence. The residuals are homoscedastic, as the White test showed.

A multiple regression model is built, adding as explanatory variable of the RON/euro average exchange rate. The multiple regression model is built using bootstrapped coefficients. The errors are homoscedastic (prob. corresponding to the White test is 0.301) and the auto-correlation is ignored.

$$inflation_t = -98.125 + 21.22 \cdot unemployment_t - 74.94 \cdot d\_excange\ rate_{t-1} \tag{13}$$

There is a negative correlation between inflation and variation in the exchange rate in Romania. The principal forces behind the national currency depreciation were unfavourable business conditions of the domestic market and lower inputs of capital.

There is a positive correlation between inflation and unemployment in Romania. The unemployment rate was significantly lower in the last years in Romania having direct implications for inflation slowing.

A simultaneous equations model is considered:

$$inflation_t = a + b\ unemployment_t + c\ exchange\ rate_t + u_t \tag{14}$$
$$exchange\ rate_t = d + e\ exchange\ rate_{t-1} + v_t \tag{15}$$

$exchange\ rate_t$ – real exchange rate at moment t

$inflation_t$ – inflation rate at moment t

$unemployment_t$ – unemployment rate at moment t

$unemployment_t, exchange\ rate_t$ – endogenous variables

$unemployment_t, exchange\ rate_{t-1}$ – exogenous variables

The type of the simultaneous equations model is fixed for choosing the most suitable model. The model is over identified, because the first equation is exactly identified and the second equation is over identified. The first equation is exactly identified, because the number of missing variables is 1, a number that equals the number of endogenous variables minus 1 (2-1=1). The second equation is over identified, because the number of missing variables in the second equation is greater than the number of endogenous variables minus 1 (2-1=1). In the case of the over identified model, the estimation method used is two stages ordinary least squares.

Stage 1: the endogenous variable $exchange\ rate_t$ (the endogenous variable in the second equation and exogenous one in the first equation) is regressed using the exogenous variables in the model ($unemployment_t, exchange\ rate_{(t-1)}$).

$$exchange\ rate_t = \alpha + \beta\ unemployment_t + \gamma\ exchange\ rate_{t-1} + w_t \tag{16}$$

According to the F test, the coefficients of independent variables are statistically significant. The Breusch-Godfrey test indicated that the errors are independent.

Stage 2: The estimated values of $exchange\ rate_t$ are introduced in the first equation.

$$inflation_t = a + b\ unemployment_t + c\ \widehat{exchange\ rate_t} + u_t \tag{17}$$

For the ARMA model, stationary data of the inflation rate are used. The best model for first differentiated inflation rate is an ARMA(1,1).

$$d\_inflation_t = -6.8813 - 0.4415 \cdot d\_inflation_{t-1} + 0.55 \cdot \varepsilon_{t-1} + \varepsilon_t \tag{18}$$

According to Figure 2, the inverse roots are inside the unit circle.

According to the White test, the errors are homoscedastic. We do not have reasons to reject the hypothesis of homoscedasticity (Prob. is 0.346, greater than 0.05). The study of the correlogram shows that the errors are independent. The Jarque-Bera test indicates that there is not enough evidence to reject the normality distribution of errors (the JB test statistic is 0.43, lower than the critical value of 5.99).

A vector-autoregressive model (VAR model) is built on stationary data series, the data series for inflation and the unemployment rate being differentiated once while the data for exchange rate were differentiated twice. Most of the
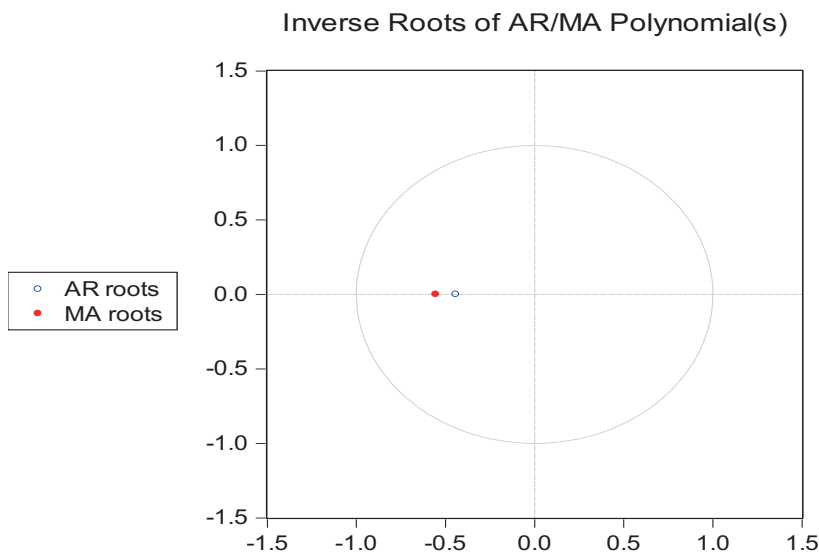
Inverse Roots of AR/MA Polynomial(s)

Figure 2. The inverse roots of ARMA(1,1)
Source: own calculations

selection criteria indicated a lag of 1. The Portmanteau test indicates error independence. Moreover, the errors are homoscedastic (prob. is 0.6514 which is greater than 0.05).

Four scenarios are used for making predictions of the variables in the first difference: baseline scenario S1 (dynamic and determinist simulation), baseline scenario S2 (static and determinist simulation), baseline scenario S3 (dynamic and stochastic simulation) and baseline scenario S4 (static and stochastic simulation). These scenarios are utilized to forecast the original variables over the horizon of 2014-2016 and are presented in Table 2.

For the unemployment rate in Romania, the best forecasts were provided by two scenarios: S1 and S3 scenarios. For the inflation rate in 2016, all the scenarios indicated deflation which did not happen in reality, but in 2017 and 2018 a slow deflation process was observed in Romania. S1 scenario was the best prediction for the inflation rate, if we consider only the scenarios based on VAR(1) model. All in all, there were not any significant differences between inflation rate scenarios based on VAR model.

The variance decomposition shows that inflation volatility is mostly due to the evolution of this indicator, but its influence decreases in time, from lag 1 to 10. Till the lag 3, the unemployment rate volatility is explained by the inflation influence, but then, till the end, the contribution of the exchange rate is more significant, more than 50% of the unemployment volatility being explained by the exchange rate. For the exchange rate, more than 65% of its volatility in each period is explained by the same indicator, even if the unemployment rate has a rather high influence (more than 32% in each period). The unemployment rate is a cause of inflation evolution, while overall the exchange rate and the unemployment rate influence the inflation rate. According to the Granger causality test, inflation and the exchange rate influence the unemployment evolution.

In the case of a shock in inflation, immediately after the shock, only the inflation rate changes, the variations in unemployment rate

Table 2: Forecasts for the inflation rate (i) (%) and unemployment rate (u) (%) using VAR(1) models (horizon 2016-2018)

Year	S1		S2		S3		S4	
	i	u	I	U	I	u	i	u
2016	-1.89	5.53	-1.89	5.4	-2.02	5.55	-1.95	5.51
2017	-1.75	5.06	-1.98	5.14	-2	5.4	-1.84	5.3
2018	-1.25	4.71	-1.88	4.74	-1.98	5.03	-1.82	5

Source: own calculations.

and exchange rate not being explained by these shocks. In the second period after that shock in inflation, 75.37% of the changes in inflation, 24.55% of the changes in unemployment and 0.07% of the changes in exchange rate are due to that shock. Only after three periods, 2.85% of the changes in exchange rate are due to a shock in inflation rate. After 4 periods, the influence of the inflation rate shock on unemployment changes became stable with a contribution of around 23.8%. In conclusion, according to variance decomposition, we can state that the inflation rate in Romania is most sensitive to direct shocks in inflation that could be controlled by the National Bank. However, a significant contribution in the inflation changes is due to the unemployment variation. In this case, the inflation rate is less sensitive to the exchange rate compared to unemployment. Therefore, for achieving price stability more attention should be attributed to the issues of the labour market than to the exchange rate control.

Bayesian VAR models were also built (BVAR(1) models) based on Minnesota and non-informative priors. These Bayesian models with intercepts are used to construct direct and repeated predictions. The impulse-response analysis is made by adapting the Matlab program of Koop and Korobilis (2010) using stationary data sets for the inflation rate, unemployment rate and exchange rate.

The BVAR model is written as: Y(t) = X(t) x A + e(t), where e(t) ~ N(0,SIGMA),A- vector with coefficients.

The data are represented as a matrix of dimensions T*M (T- number of observations, M- number of variables). The X matrix includes all the variables (intercept, dependent variables with lag, exogenous variables). In Table 3, we have the inflation rate forecasting based on BVAR(1) models with intercept over the horizon of 2016-2018.

In the case of direct forecasts using non-informative priors and repetitive forecasts using the Minnesota priors, a decrease in the inflation rate is observed from one year to another in the

period between 2016-2018. The deflation process specific to 2015 and 2016 was not reflected by the forecasts based on BVAR models.

Another type of models was built to make forecasts for the inflation rate in Romania: a panel data approach. The data used in the model consist unregistered values of the inflation rate and the unemployment rate in Romania and the forecasts provided by experts: the Dobrescu model, the National Commission for Prognosis and the European Commission during 2001-2018. The panel data regression model is written as:

$$inflation_t = c + b \cdot prediction\_inflation_{it} + d \cdot prediction\_unemployment_{it} + e \cdot unemployment_t + a_i + \varepsilon_{it} \qquad (19)$$

$inflation_t$ − actual inflation rate at time t
$unemployment_t$ − actual unemployment rate at time t
$prediction\_i_{it}$ − inflation rate forecast of expertiat time t
$prediction\_u_{it}$ − unemployment rate forecast of expertiat time t
a_i − individual effects
ε_{it} − random error

After more estimations, we decided that a fixed effects model is more suitable. Individual predictions based on econometric models were used in building combined forecasts. The shrinkage parameters took the values 0, 1 and g→∞. The prior is based on experts' forecasts, but we also employed zero-weight and equal-weight priors.

Moreover, Monte Carlo simulations were conducted in R software to provide scenarios for the inflation rate in Romania, under the subjective hypothesis that the expected annual increase will be 10% and the volatility will be

Table 3: Forecasts of the inflation rate (%) using BVAR(1) models with intercept (horizon 2016-2018)

Prior	Years	Direct forecasts	Repetitive forecasts
Non-informative prior	2016	1.3	2.06
	2017	1.01	1.18
	2018	0.56	086
Minnesota prior	2016	1.45	1.73
	2017	0.95	1.4
	2018	1.2	1.3

Source: own calculations.

20%. The initial inflation rate that is introduced in the model is the level from December 2014 (1.1%).

In Table 4, we have the measures of forecast accuracy for inflation rate forecasts in Romania. The first part of the table refers to individual models, followed by combined models. The predictions performance is dependent on the range of the shrinkage parameter g and the window size. According to the value of the mean error, the combined forecasts based on

g→∞ and experts' predictions as prior presented the lowest errors in average. Other accuracy measures such as the absolute mean error, root mean squared error and U1 Theil's coefficient confirmed that these combined predictions had the best performance. Moreover, the U2 coefficient is less than 1, which indicates that these forecasts are better than naïve predictions. The experts' forecasts proved to be more informative. In the group of combined forecasts with g=0, the equal weights forecasts were the best,

Table 4: Measures of forecast accuracy for one-year-ahead inflation rate predictions in Romania (2016-2018)

Type of models	ME	MAE	RMSE	U1 Theil's statistic	U2 Theil's statistic
Individual models					
Simple linear model	7.62	7.62	4.42	0.83	3.81
Dynamic model	6.45	6.45	3.35	0.74	3.02
Simultaneous equations model	5.14	5.14	3	0.68	2.54
ARMA model	5.19	5.19	3.02	0.79	2.61
S1 scenario using VAR(1) model	1.30	1.46	1.07	0.67	0.92
S2 scenario using VAR(1) model	1.58	1.58	1.10	0.63	0.95
S3 scenario using VAR(1) model	1.67	1.67	1.15	0.64	0.99
S4 scenario using VAR(1) model	1.54	1.54	1.10	1.69	0.95
BVAR(1) model based on non-informative prior- direct forecasts	-1.29	1.29	0.87	0.71	0.75
BVAR(1) model based on non--informative prior- repetitive forecasts	-30.08	30.08	29.17	0.99	25.15
BVAR(1) model using Minnesota prior- direct forecasts	-1.53	1.53	1.04	0.77	0.90
BVAR(1) model using Minnesota prior- repetitive forecasts	-1.81	1.81	1.17	0.77	1.01
Fixed effects model1	1.25	1.21	1.55	0.17	1.16
Fixed effects model2	-2.54	2.56	2.90	0.25	0.57
Fixed effects model3	-0.84	1.34	1.54	0.15	1.22
Combined models					
g=0					
Prior: Experts' predictions	1.33	1.33	1.64	0.19	0.99
Prior: Equal weights	-0.38	0.88	1.09	0.12	1.32
Prior: Zero weights	1.68	1.68	2.09	0.17	0.83
g=1					
Prior: Experts' predictions	-1.25	1.25	1.45	0.13	0.99
Prior: Equal weights	-3.97	3.97	3.45	0.30	0.37
Prior: Zero weights	-0.24	1.2	1.12	0.1	1.22
g→∞					
Prior: Experts' predictions	-0.11	0.65	0.78	0.07	0.65
Prior: Equal weights	-2.3	2.3	2.5	0.21	0.78
Prior: Zero weights	0.75	0.75	1.22	0.12	1.28
Model based on Monte Carlo simulations	-0.1	0.64	0.8	0.08	0.69

Source: own calculations.

while in the case of predictions with g=1, zero weights forecasts are the most accurate. All in all, for g→∞, the experts' combined predictions outperformed all the proposed forecasts based on individual and combined models. The result is in line with the expectations. The subjective information given by the experts is based on a large experience from practice which is well combined with the objective forecasts based on econometric models. The experts proved that they anticipated the sense of evolution well the in case of the inflation rate, but they have problems with the magnitude of the changes from one year to another. Moreover, the scenarios based on Monte Carlo simulations performed better than all the other predictions in terms of the mean error and the mean absolute error.

Our results which proved the superiority of the forecasts that use experts' expectations as prior are in line with the results of Diebold and Pauly (1990) and Gomez et al. (2012). These combined forecasts proved to be better than those predictions using simple econometric models. Using these improved forecasts for the inflation rate, we may have a clear image of the future measures for monetary policy and for the steps that should be made in achieving the criteria for the entrance to the eurozone. According to converge criterion related to prices stability, the inflation rate should not be by 1.5 percentage points higher than the rate of the first three countries in the eurozone with the lowest inflation. Romania faces difficulties in achieving this criterion because the country struggles with the inability to pay caused by non-performing loans, which ruined the banking system. Losses of billions of euro were then taken over to the state budget from the former Bancorex and the former Bank agricultural. In the actual context of turbulences generated by COVID-19, the National Bank of Romania decided to decrease the interest rate monetary policy by 0.5 percentage points. The governments' measures to face the recession caused by COVID-19 by offering liquid money to population will generate high inflation that should be anticipated and alternative methods should be taken to alleviate the negative effects.

5. Conclusions

In this study, starting from inflation predictions based on individual models, we proposed different Bayesian forecasts combinations. Then, we checked if these combined forecasts succeeded in improving the initial forecasts.

As a novelty for the economic literature in Romania, the Bayesian combinations were constructed using as prior the experts' expectations. This research is based on forecasts using the Dobrescu macromodel and the expectations of the European Commission and National Commission for Prognosis. The shrinkage parameter g had more values (0, 1 and g→∞). The one-step-ahead inflation forecasts were made for a period of 3 years (2016-2018). For Romania, we proved on empirical data that the Bayesian combined forecasts using experts' predictions as priors, when the shrinkage parameter tends to infinity, improved the accuracy of the predictions based on individual models. However, the predictions based on the Monte Carlo simulation outperformed all the scenarios in terms of the mean error and the mean absolute error. Our research is limited by the fact that the results are dependent on the types of the forecasts and on the window size. Moreover, a short horizon was considered due to the limited availability of data in the sample used in the estimations. In future research, a larger horizon should be considered and more experts' forecasts will be added.

The VAR analysis indicated that the inflation rate in Romania proved to be more sensitive to changes in unemployment rather than changes in exchange rate. The issues on the labour market should be a priority for the government in order to achieve prices stability. We recommend the use of econometric models that link inflation with unemployment and their utilisation for predictions. These simplistic models provide good forecasts, but a Bayesian combination that uses experts' expectations as priors should be considered in elaborating better the inflation rate forecasts in Romania.

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