

# FORECASTS BASED ON BAYESIAN SHRINKAGE COMBINATION

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**Abstract.** *The Bayesian shrinkage combination approach was employed to improve the inflation rate predictions in Romania. Forecasters' anticipations are used as prior information, the forecasts being provided by experts in forecasting. For inflation in Romania during 2012-2014 a fixed effects model performed better than other types of econometric models (dynamic model, log-linear model, VAR model, Bayesian VAR, simultaneous equations model). The Bayesian combinations that employed experts' forecasts as priors, when the shrinkage parameter tends to infinite, improved the accuracy of all forecasts based on individual models, outperforming the naïve predictions and null and equal weights combined predictions.*

**Keywords:** *shrinkage parameter, Bayesian forecasts combination, forecasts accuracy, prior*

**JEL classification:** E37, C51, C52, C53

## 1. Introduction

In the context of inflation targeting accurate inflation predictions are necessary for having efficient monetary policies. Therefore, it is necessary to know some predictions methodologies that describe specific evolution of the inflation rate. Most of the central banks do not use only some individual models, but also suitable combined forecasts based on these models. In literature many researchers established that the combination of individual models forecasts outperform the predictions based on a single model. In the economic crisis, Julio Roman and Bratu Simionescu (2013) emphasized that the decrease of forecasts uncertainty should be one of the major objective of experts in forecasting. The lower uncertainty of forecasts will improve the decisional process at macroeconomic level, but Terceno and Vigier (2011) showed that the business decisions are also improved.

The objective of this paper is to build predictions of the inflation rate in Romania using the own econometric models, but also utilizing the Bayesian combination technique in order to improve the accuracy of

individual expectations. After a brief description of the methodology, an empirical application is proposed for The Romanian inflation rate forecasts. Prior mean that takes into account the forecasts of several forecasters are taken into account in building the combined forecasts.

## 2. Methodological background

Many papers showed that the forecasts combination performs better compared to individual predictions. However, we have to be careful in stating the conclusions, because the ex-post evaluation of combined forecasts is not enough. The unstable character of individual forecasts makes us to consider the aspects regarding the selection of the model in a simulated ex-ante approach.

An important review regarding the forecasts combination was made by Timmermann (2006). Diebold and Pauly (1990) have proposed a Bayesian shrinkage methodology in order to include prior information for improving the predictive accuracy of the combined forecasts. Authors like Wright (2008) or Koop and Potter (2003) used as prior mean zero-weights or equal-weights. Gomez, Gonzalez and Melo(2012) proposed a rolling window estimation method for co-integrated data series of order one in order to calculate the Bayesian weights.

Bjørnland et al. (2012) proposed a system for proving inflation rate predictions in Norway. The weights used in making the forecasts combination are determined from the models' performance. By using a trimmed weight mean the performance of inflation rate forecasts provided by the Norges Bank was improved.

We consider a number of  $m$   $h$ -step-ahead forecasts of the variable denoted by  $y_t$ :  $f_{t-h}^1, \dots, f_{t-h}^m$ . (Granger and Ramanathan, 1984) proposed the following forecasts combination:

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

$\alpha = (\alpha_0, \alpha_1, \dots, \alpha_m)'$  - vector of regression coefficients

$f_{t-h} = (1, f_{t-h}^1, \dots, f_{t-h}^m)'$  - vector that contains the intercept and a number of  $m$  forecasts (this vector dimension is  $m+1$ )

The intercept is introduced to ensure that the bias correction of the combined prediction is optimally determined.

Diebold and Pauly (1990) developed a method for introducing prior information in the regression of forecasts combination by using the g-prior model proposed by Zellner (1986). The model error is independently, normally and identically distributed of average 0 and variance  $\sigma^2$ . Moreover, it is used a natural conjugate normal-gamma prior:

$$p_0(\alpha, \sigma) \propto \sigma^{-m-v_0-2} \exp \left\{ -\frac{1}{2} \sigma^2 \left[ v_0 s_0^2 + (\alpha - \alpha^*)' M (\alpha - \alpha^*) \right] \right\}$$

(2)

The form of likelihood function is:

$$L(\alpha, \frac{\sigma}{\sqrt{F}} | F) \propto \sigma^T (-T) \exp \left\{ -1/2 \sigma^2 (Y - F\alpha)' (Y - F\alpha) \right\}$$

(3)

$$Y = (y_1, \dots, y_{t-h})'$$

$$F = \begin{pmatrix} f_{1-h} & \dots & f_{t-h-h} \end{pmatrix}'$$

The marginal posterior of  $\alpha$  is:

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

(4)

The marginal posterior mean is:

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

(5)

where:

$$v_1 = T + v_0$$

$$s_1^2 = \frac{1}{v_1 [v_0 s_0^2 + Y'Y + \alpha^{*'} M \alpha^* - \alpha^{*'} (M + F'F) \bar{\alpha}]}$$

$$\hat{\alpha} = (F'F)^{-1} F'Y$$

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

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

$g \in [0, \infty)$  is the shrinkage parameter. This parameter controls the relative weight between the maximum likelihood estimator and the prior mean in the posterior mean.

Wright (2008) utilized zero weight as the prior mean, while Diebold and Pauly (1990) recommended the equal weights. Geweke and Whiteman (2006) specified the prior distribution in Bayesian forecasting by including forecasters (experts) information. In this study we will use as prior weights the estimated parameters of the regression between the forecasters' h-step

predictions  $f_{t-h}^{experts}$  and the forecasts based on different econometric models. The prior mean is:

$$f_{t-h}^{expert} = \alpha_t' f_{t-h} + \varepsilon_t \rightarrow \alpha_t = (F_{t-W+1,t}^{t-h} F_{t-W+1,t}^{t-h})^{-1} F_{t-W+1,t}^{t-h} f_{t-W+1,t}^{expert}$$

(7)  
where:

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

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

For non-stationary data series, Coulson and Robins (1993) used a linear model to construct the combination technique:

$$y_t - y_{t-h} = \alpha' f_{t-h} + \varepsilon_t$$

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

$$f_{t-h}^{expert} - f_{t-h-2h}^{expert} = \alpha_t' \bar{f}_{t-h} + \varepsilon_t,$$

where

$$\bar{f}_{t-h} = (1, f_{t-h}^1 - f_{t-h-2h}^{expert}, \dots, f_{t-h}^m - f_{t-h-2h}^{expert})'$$

In the following table, Table 1, the extreme cases of the posterior mean are presented, according to the methodology of Coulson and Robins (1993).

Prior	$g \rightarrow \infty$
Experts' predictions	Experts' weights
Equal weights	Equal weights
Zero weights	Random walk weights

**Table 1. Posterior mean of the extreme cases based on methodology proposed by Coulson and Robins (1993)**

For zero weights prior, when  $g$  tends to infinite, 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.

### 3. Empirical results for the inflation rate forecasts in Romania

The experts' forecasts available data for inflation rate predictions from 1997 to 2014 are divided into two samples. The first sample (1997-2011) is utilized in estimating the forecast combination model, while the second sample (2012-2014) is useful for assessing the performance of individual models and of the models' combination.

Some accuracy measures are used to compare the forecasts accuracy (mean error- ME, mean absolute error- MAE, root mean square error- RMSE, U1Theil's statistic and U2 Theil's statistic. First of all, we proposed some individual econometric models used to predict the inflation rate in Romania.

The Phillips curve cannot be observed for data series available for Romania. However, a valid log-linear model was put in evidence:

$$\ln(\lnflation_t) = 0.798 + 0.335 \cdot unemployment_t \quad (11)$$

In order to eliminate the inconvenient of a small set of data, the parameters of a log-linear model were estimated by bootstrapping, the residuals being resampled with a number of 10 000 replications:

$$\ln(\lnflation_t) = 0.802 + 0.342 \cdot unemployment_t \quad (12)$$

In the case of a log-linear model, the coefficient of X variable has the significance of elasticity, while the slope is the product between elasticity and the ratio Y/X. At each increase with one unit of the variable X, the dependent variable Y changes in average with 0.342 or 34.2%. so, at each increase with one per cent in the unemployment rate, the inflation rate increases with 0.3248 percentage points. For this model the other assumptions are tested. The Durbin-Watson tests and Breusch-Godfrey test for a lag equalled to 1 indicated an errors' autocorrelation of order 1. The residuals are homoscedastic, according to White test.

A multiple regression model is estimated, adding as explanatory variable beside the unemployment rate the USD/ROL average exchange rate. The data series for exchange rate is not stationary being necessary a differentiation of order 1. The influence of inflation rate is eliminated from the evolution of this indicator, resulting the real exchange rate. The multiple regression model is estimated using bootstrapped coefficients. The errors are homoscedastic and the auto-correlation is ignored.

$$\lnflation_t = -195.46 + 20.09 \cdot unemployment_t - 0.0029 \cdot d_{exchange\ rate}_{t-1}$$

(13)

The following simultaneous equations model is considered:

$$\text{inflation}_t = a + b \text{unemployment}_t + c \text{exchange rate}_t + u_t$$

(14)

$$\text{exchange rate}_t = d + e \text{exchange rate}_{t-1} + v_t$$

(15)

$\text{exchange rate}_t$  - real exchange rate at time t

$\text{inflation}_t$  - inflation rate at time t

$\text{unemployment}_t$  - unemployment rate at time t

$\text{unemployment}_t, \text{exchange rate}_t$  - endogenous variables

$\text{unemployment}_t, \text{exchange rate}_{t-1}$  - exogenous variables

The type of simultaneous equations model is set up in order to choose the suitable estimation model. The model is over identified, because the first equation is exactly identified while the second one is over identified. The first equation is exactly identified, because the number of absent variables in the equation is 1, a number that equals the number of endogenous variables in the model minus 1 (2-1=1). The second equation is over identified, the number of absent variables in the second equation being greater than the number of endogenous variables minus 1 (2-1=1). The model being over identified, the estimation method is two stages ordinary least squares.

Stage 1: the endogenous variable  $\text{exchange rate}_t$ , which is endogenous in the second equation, but exogenous variable in the first equation is regressed according to the exogenous variables in the model ( $\text{unemployment}_t, \text{exchange rate}_{t-1}$ ).

$$\text{exchange rate}_t = \alpha + \beta \text{unemployment}_t + \gamma \text{exchange rate}_{t-1} + w_t$$

(16)

According to F test, the models is valid, on overall the coefficients of independent variables are statistically significant. The Breusch-Godfrey test shows independent errors.

Stage 2:  $\text{exchange rate}_t$  is introduced with the estimated values in the first equation.

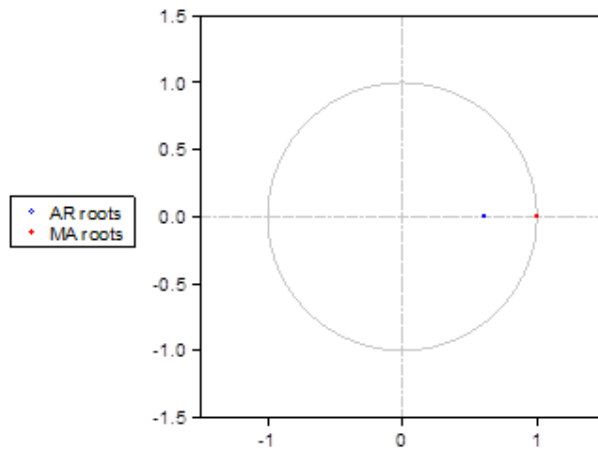
$$\text{inflation}_t = a + b \text{unemployment}_t + c \text{exchange rate}_t + u_t$$

(17)

For the ARMA model is used the first differentiated inflation rate data series which is stationary, the ADF (Augmented Dickey Fuller) showing the existence of one unit root for the level data set. The best model is an ARMA(1,1) for first differentiated inflation rate.

$$d_{inflation}_t = -0.223 + 0.047 \cdot d_{inflation}_{t-1} - 1.09 \cdot \varepsilon_{t-1} + \varepsilon_t \quad (18)$$

According to the following graphs the inverse roots are outside of the unit circle.



**Figure 1. The inverse roots of ARMA polynomial**

According to White test, the errors are homoscedastic, not having reasons to reject the hypothesis of homoscedasticity (Prob. greater than 0.05). The study of correlogram shows the errors independence. The Jarque-Bera test indicates that there is not enough evidence to reject the normality distribution of errors (the JB test statistic is 1.25, lower than the critical value of 5.99).

A vector-autoregressive model (VAR model) was proposed for the stationary data series, all of them being differentiated once. All the selection criteria indicate a lag equalled to 4. Portmanteau test indicates the errors autocorrelation, but if the model is used on long run the serial correlation could be ignored. The maximum likelihood test conducts us to the same result of serial correlation. In this case the Prob. being less than 0.05, the null hypothesis is rejected. When Cholesky orthogonalization is used, the residuals follow a normal distribution.

Four scenarios are followed to make predictions of the differentiated variables: 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 predictions are used to forecast the original variables on the horizon 2012-2014.

**Table 1. Inflation (i) (%) and unemployment rate (u) (%) predictions based on VAR(4) models (horizon 2010-2012)**

Year	S1		S2		S3		S4		Actual values	
Variable (%)	i	u	i	u	i	u	i	u	i	u
2012	4.71	4.77	5.83	4.80	7.97	4.77	8.94	5.88	3.33	6.7
2013	4.17	4.26	5.78	5.28	6.34	5.27	4.63	6.70	3.98	7.3
2014	4.01	4.06	5.56	5.80	6.97	5.77	6.94	6.88	3*	5.2*

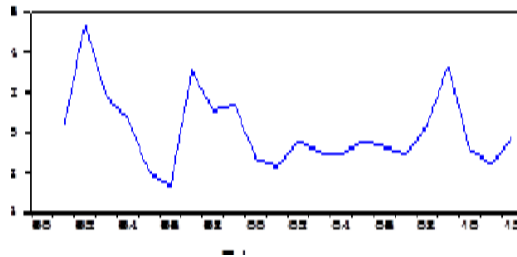
\*Values in October 2014

For the unemployment rate the best predictions for 2012 and 2013 are given by the S4 scenarios. For the inflation rate S1 predicted the best this indicator.

The evolution of the inflation data series according to the four scenarios are presented in the following graph:

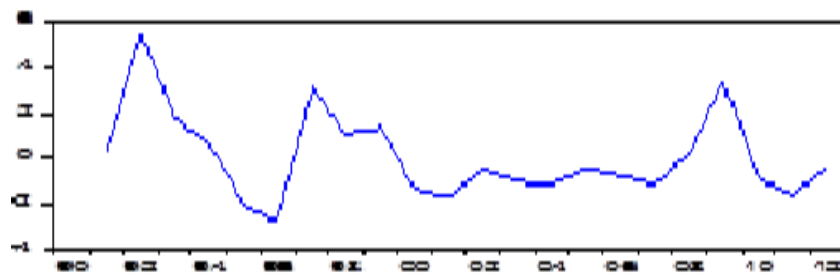
**Figure 2. The evolution of the inflation rate according to VAR(4) scenarios**

S1 scenario

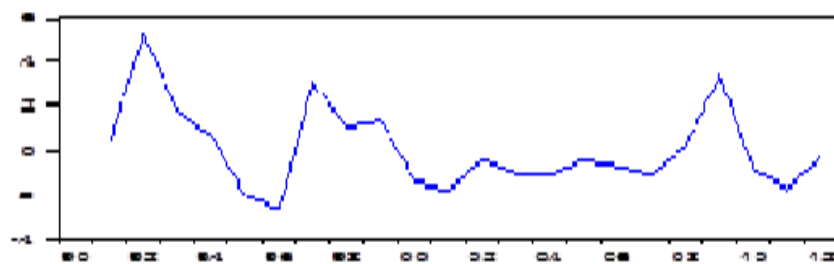


S2 scenario

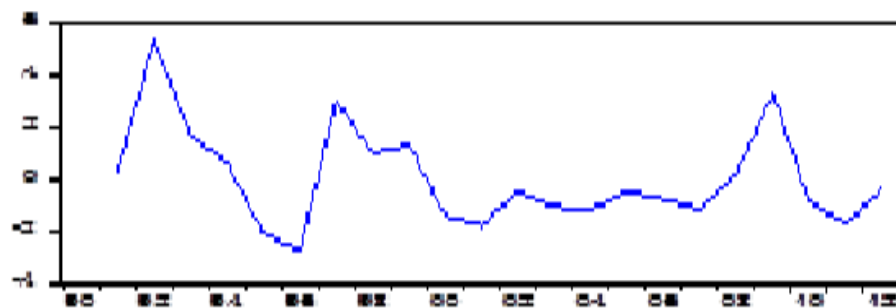




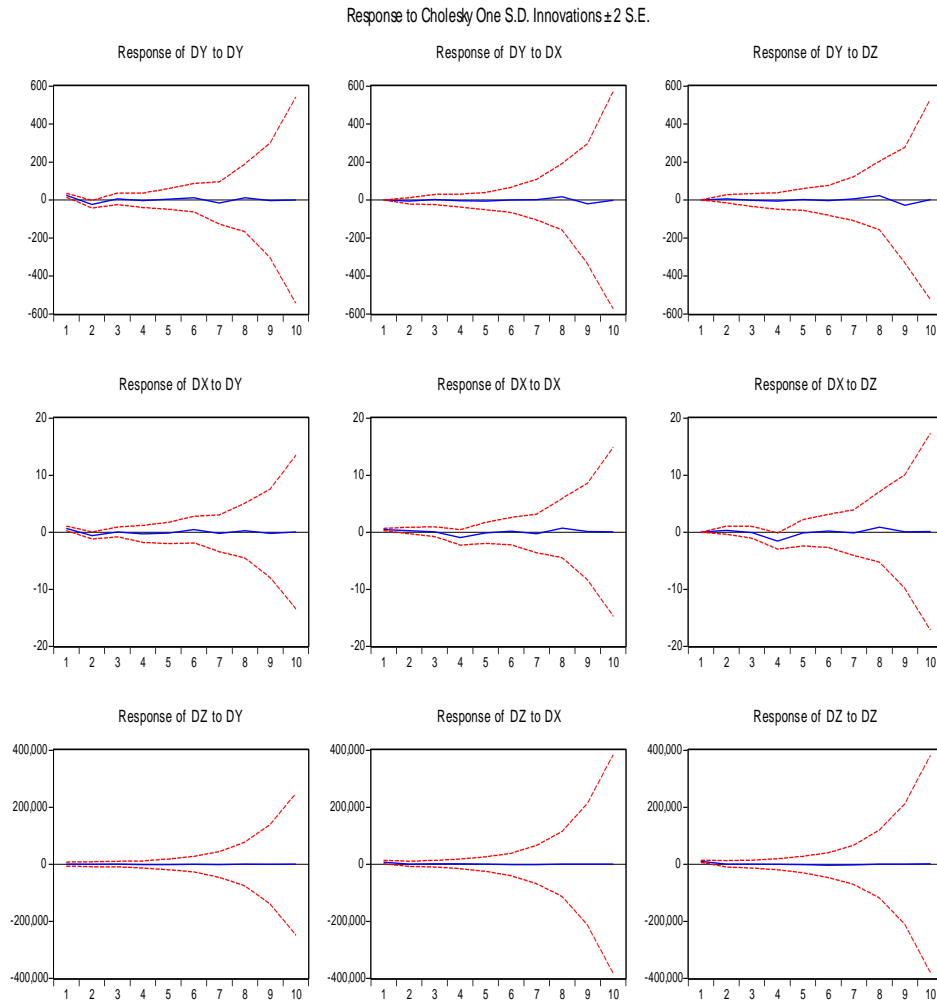
S3 scenario



S4 scenario



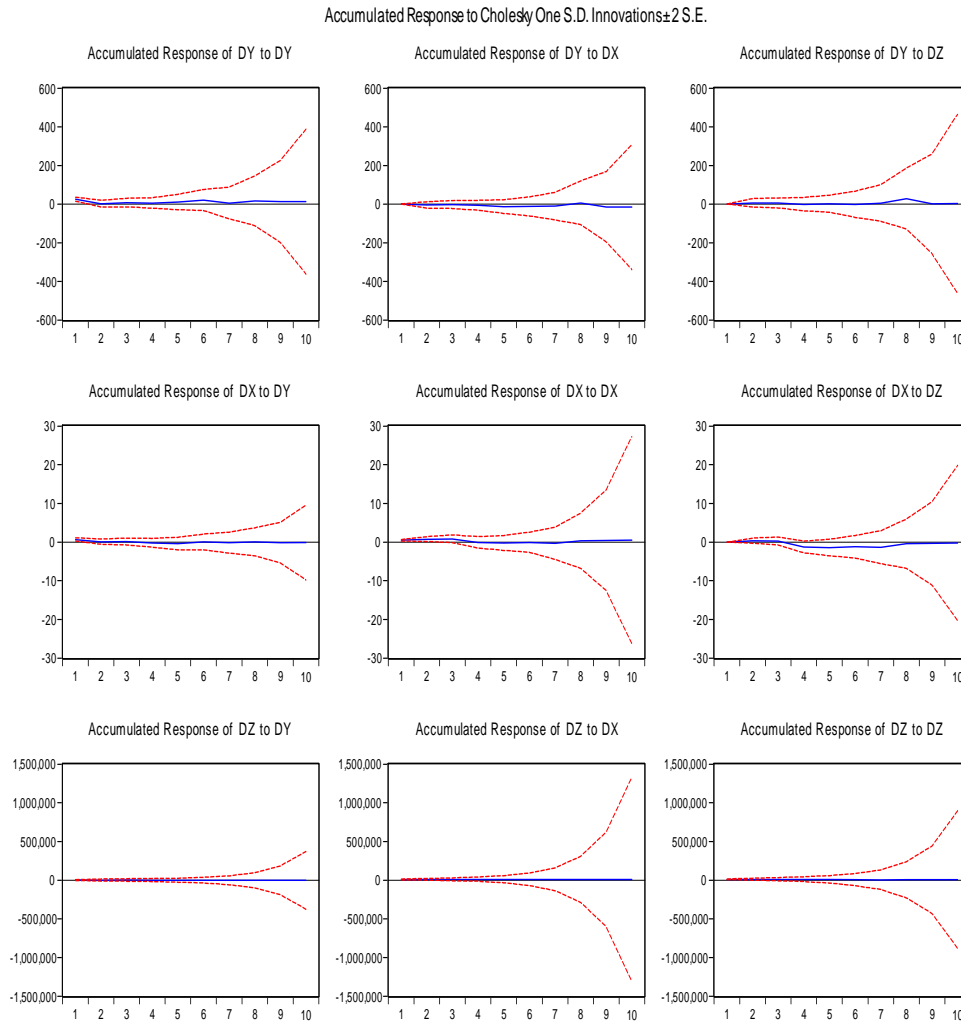
There are not significant differences between the scenarios of the inflation rate for the mentioned predictions. It is made the assessment of impulse response functions, the inflation, unemployment and exchange rate differentiated data series being denoted by DY, DX and DZ.



**Figure 3. Response to Cholesky One standard deviation innovations  $\pm 2$  standard deviations**

It was chosen the variant of multiple graphs for the response of standard errors setting Monte Carlo method with 1000 replications and 10 periods. If the variables order is changed, it is modified the scheme of shocks identification and the impulse-response function and the decomposition of errors variance. The figure shows that the response of inflation to shocks in the exchange rate is stronger than the response of the inflation to own shocks, even if the differences are insignificant. The

graphs of cumulated responses are more relevant, because the VAR model is based on the series in first difference.



**Figure 4. Accumulated Response to Cholesky One standard deviation innovations  $\pm 2$  standard deviations**

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 cause of inflation evolution, while overall the exchange rate and the unemployment rate influence the inflation rate. According to Granger causality test, the inflation and the exchange rate influence the unemployment evolution.

We estimated in Matlab BVAR(4) models using Minnesota and non-informative priors. For making the Bayesian estimation, direct and repeated predictions based on BVAR(4) models with intercept and the impulse-response analysis are elaborated, adapting the Matlab program used by (Koop and Korobilis, 2010) for stationarized data sets of inflation, unemployment and exchange rate (di, ds, dc). The BVAR model depends on the forecasting method. For repeated predictions, the model's form is:  $Y(t) = A_0 + Y(t-1) \times A_1 + \dots + Y(t-p) \times A_p + e(t)$ , p number of lags for Y (from 1 to p). The predictions with h steps use the model:  $Y(t+h) = A_0 + Y(t) \times A_1 + \dots + Y(t-p+1) \times A_p + e(t+h)$ . In both situations, the model is formulated as:  $Y(t) = X(t) \times A + e(t)$ , where  $e(t) \sim N(0, \text{SIGMA})$ , a- vector with  $a = \text{vec}(A)$ .

The data are represented as a T\*M matrix (T- number of observations, M- number of dependent macroeconomic variables). The X matrix contains all the variables (intercept, exogenous variables and dependent variables with lag).

**Table 2. Forecasts of inflation rate (%) based on BVAR(4) models with intercepts (horizon 2012-2014)**

Prior		Direct forecasts	Repetitive forecasts
Non-informative prior	2012	3.8193	2.5614
	2013	3.765	2.0554
	2014	3.654	2.2259
Minnesota prior	2012	2.5972	1.2792
	2013	1.9745	1.8845
	2014	2.005	1.9843

For direct forecasts based on non-informative priors an evident increase of the inflation rate is observed for the period 2012-2014. For the rest of the predictions a tendency of increase and decrease cannot be identified, the evolution of the predictions being irregular.

A panel data approach is applied in order to make forecasts of the inflation rate. The data are represented by the effective values of the inflation rate and unemployment rate in Romania and the predictions of 3 experts during 2001-2014.

The form of the regression model:

$$\text{inflation}_t = c + b \cdot \text{prediction}_{\text{inflation}_{it}} + d \cdot \text{prediction}_{\text{unemployment}_{it}} + e \cdot \text{unemployment}_t + a_i + \varepsilon_{it}$$

(19)

$\text{inflation}_t$  – effective inflation rate in year t

$\text{unemployment}_t$  – effective unemployment rate in year t

$\text{prediction}_{it}$  – the predicted inflation rate made by the institution i for year t

$\text{prediction}_{uit}$  – the predicted unemployment rate made by the institution i for year t

$a_i$  – individual effects

$\varepsilon_{it}$  – random error

First of all we have to decide if we should use an usual regression model or a panel data approach. The OLS estimator is biased and inconsistent, the individual effects being present. The specialists' ability, the type of model could be causes of the differences between predictions. The application of Hausman test was made in order to decide if the model with fixed effects is better than the one with random effects or else. The probability associated to Hausman statistic is less than 0.05, the fixed effects model being better. In this case two important assumptions were checked and the errors are homoscedastic and non-auto-correlated. However, we have to take into account the economic reasons for this type of model.

Starting from these individual predictions, the combined forecasts were built. The shrinkage parameters are 0, 1 and  $\frac{1}{n} \rightarrow \frac{1}{n}$ . We used a prior based on experts' expectations, but also zero-weight and equal-weight priors.

**Table 3. The accuracy of inflation one-year-ahead forecasts in Romania (horizon: 2012-2014)**

Type of models	ME	MAE	RMSE	U1 Theil's statistic	U2 Theil's statistic
<b>Individual models</b>					
Log-linear model	2.3784	2.3974	2.7024	0.4012	0.5843

Dynamic model	0.24672	1.6642	1.9584	0.2049	0.7943
Simultaneous equations model	-0.4412	1.2702	1.4018	0.2017	1.0401
ARMA model	0.8841	1.5915	1.9341	0.2104	0.7416
S1 scenario based on VAR(4) model	0.3905	1.3201	1.4204	0.1516	0.9203
S2 scenario based on VAR(4) model	-0.9200	2.2067	2.2189	0.1945	0.6626
S3 scenario based on VAR(4) model	-2.4800	2.4800	2.9941	0.2336	0.4848
S4 scenario based on VAR(4) model	-0.5967	3.1433	3.6466	0.3210	0.3986
BVAR(4) model (non-informative prior) direct forecasts	2.6022	2.9065	3.3946	0.4331	0.4405
BVAR(4) model (non-informative prior) repetitive forecasts	2.9662	2.9663	3.3806	0.4664	0.4556
BVAR(4) model (Minnesota prior) direct forecasts	3.3992	3.3942	3.8849	0.5634	0.3896
BVAR(4) model (Minnesota prior) repetitive forecasts	3.3608	3.3639	3.4946	0.5221	0.4225
Fixed effects model1 (panel data analysis)	0.2345	1.2445	1.4302	0.1534	1.0402
Fixed effects model2 (panel data analysis)	-2.2245	2.4612	2.8778	0.2302	0.5641
Fixed effects	-0.7815	1.189	1.4468	<b>0.1402</b>	0.9901

model3 (panel data analysis)					
<b><u>Combined models</u></b>					
<b><i>g=0</i></b>					
Prior: Experts' predictions	1.2399	1.2403	1.4902	0.1559	0.9775
Prior: Equal weights	-0.3602	0.8205	1.0889	<i>0.1019</i>	1.3778
Prior: Zero weights	1.8556	1.8598	2.0803	0.1339	0.7146
<b><i>g=1</i></b>					
Prior: Experts' predictions	-1.2498	1.2502	1.4509	0.1259	0.9912
Prior: Equal weights	-3.9023	3.9046	4.0205	0.2889	0.3648
Prior: Zero weights	-0.2244	1.0889	1.1187	<i>0.1058</i>	1.3197
<b><i>g → ∞</i></b>					
Prior: Experts' predictions	<b>-0.1102</b>	<b>0.6802</b>	<b>0.7894</b>	<b>0.0776</b>	<i>0.9287</i>
Prior: Equal weights	-2.2806	2.2806	2.4806	0.1987	0.5905
Prior: Zero weights	0.7385	0.7385	1.2246	0.1265	1.2709

The upper part of the table refers to individual models, the combined forecasts accuracy measures being presented in the lower part. The predictions performance depends on the window size and the range of the shrinkage parameter  $g$ . According to mean errors, the combined forecasts with ***g → ∞*** and experts' predictions as prior have the lowest errors in average. An overestimation tendency is observed for this type of combined prognoses. The absolute mean error, root mean square error and U1 Theil's coefficient indicate that this type of combined predictions has the highest performance. Moreover, the value of U2 statistic shows the superiority of these forecasts compared with the naïve expectations. The experts' forecasts are actually more informative. When  $g=0$ , the variant with equal weights

provided more accurate forecasts while for  $g=1$ , zero weights is the best choice. However, for  $g \rightarrow \infty$  the experts' combined predictions outperformed all the individual and combined models.

For a null value of  $g$ , the U1 statistic shows similar performance of the combined forecasts because the prior mean has zero weight in the posterior average. The experts' expectations are computed with less information, which determines a slightly greater value for U1 statistic.

#### 4. Conclusions

The inflation forecasts are made for inflation and unemployment rate using econometric models. Moreover, different Bayesian forecasts combinations are built. We verified if the combined forecasts improve the degree of accuracy of the initial predictions.

We employed Bayesian combinations using as prior the forecasters' expectations. The window size was 11 years, shrinkage parameter  $g$  equals 0, 1 and  $g \rightarrow \infty$ . The one-step-ahead forecasts were made for a horizon of 3 years. Indeed, the Bayesian combinations that used experts' predictions as priors, when the shrinkage parameter tends to infinite, improved the accuracy of all forecasts based on individual models. However, the Bayesian combined forecasts depend on the window size and the selected predictions.

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