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COMBINING FORECASTS BASED ON ECONOMETRIC MODELS FOR SHORT RUN MACROECONOMIC PREDICTIONS WITH HIGH DEGREE OF ACCURACY

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Abstract:
For a certain macroeconomic variable more predictions based on different methods could be made. The essential problem is to establish the most accurate forecast, using different indicators. The econometric modeling is one of the most used forecasting method. A strategy to improve the accuracy of the predictions based on econometric model is to make combined forecasts. In this paper, for inflation rate, unemployment rate and interest rate were made predictions based on ARMA procedures, VAR(2) models and models with lagged variables. For all the analyzed variables in Romania, ARMA models generate more accurate forecasts than VAR(2) models or models with lags. For inflation and interest rate optimal combination and equal-weights-scheme determined the most accurate predictions, while for *unemployment rate ARMA models remain the best forecasting method in terms of accuracy.*

Key words: forecasts, accuracy, ARMA models, inflation rate, unemployment rate, interest rate, combined forecasts

JEL Classification: E21, E27,C51, C53

I. INTRODUCTION

In establishing the monetary policy, the deciders must take into account the possible future evolution of some important macroeconomic variables as inflation rate, unemployment rate or interest rate. This fact implies the knowledge of the predictions of these indicators. In econometrics we can build forecasts starting from a valid model. The real problem appears when we have some alternative models and we must choose the one with the higher degree of accuracy.

In this article, we modeled the three selected variables and we made predictions for them. Using indicators of accuracy we demonstrated that ARMA models generate the best forecasts in Romania for unemployment rate, while combined forecasts of ARMA and VAR(2) models are the best choice for inflation and interest rate.

II. THE FORECASTS ACCURACY EVALUATION IN LITERATURE

To assess the forecast accuracy, as well as their ordering, statisticians have developed several measures of accuracy. For comparisons between the MSE indicators of forecasts, Granger and Newbold proposed a statistic. Another statistic is presented by Diebold and Mariano (1995) for comparison of other quantitative measures of errors. Diebold and Mariano test proposed in 1995 a test to compare the accuracy of two forecasts under the null hypothesis that assumes no differences in accuracy. The test proposed by them was later improved by Ashley and Harvey, who developed a new statistic based on a bootstrap inference. Subsequently, Diebold and Christoffersen have developed a new way of measuring the accuracy while preserving the cointegrating relation between variables.

Armstrong and Fildes (1995) showed that the purpose of measuring an error of prediction is to provide information about the distribution of errors form and they proposed to assess the prediction error using a loss function. They showed that it is not sufficient to use a single measure of accuracy.

Since the normal distribution is a poor approximation of the distribution of a low-volume data series, Harvey, Leybourne, and Newbold improved the properties of small length data series, applying some corrections: the change of DM statistics to eliminate the bias and the comparison of this statistics not with normal distribution, but with the T-Student one. Clark evaluated the power of equality forecast accuracy tests , such as modified versions of the DM test or those used by or Newey and West, based on Bartlett core and a determined length of data series.

In literature, there are several traditional ways of measurement, which can be ranked according to the dependence or independence of measurement scale. A complete classification is made by Hyndman and Koehler (2005) in their reference study in the field, “Another Look at Measures of Forecast Accuracy “:

- Scale-dependent measures
- Scale-independent errors:

-> *Measures based on percentage errors*

-> *Measures based on relative errors*

->*Relative measures*

- Free-scale error metrics (resulted from dividing each error at average error).

If we consider, $\hat{X}_t(k)$ the predicted value after k periods from the origin time t, then the error at future time (t+k) is: $e_t(t+k)$. In practice, the most used measures of forecast error are:

- Root Mean Squared Error (RMSE): $RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n} e_X^2(T_0 + j, k)}$
- Mean error (ME): $ME = \frac{1}{n}\sum_{j=1}^{n} e_X(T_0 + j, k)$

The sign of indicator value provides important information: if it has a positive value, then the current value of the variable was underestimated, which means expected average values too small. A negative value of the indicator shows expected values too high on average.

- Mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{j=1}^{n} \left| e_X(T_0 + j, k) \right|$$

U Theil’s statistic is calculated in two variants by the Australian Tresorery in order to evaluate the forecasts accuracy.

The following notations are used:

a- the registered results
p- the predicted results
t- reference time
e- the error (e=a-p)
n- number of time periods

$$U_1 = \frac{\sqrt{\sum_{t=1}^{n}(a_t - p_t)}}{\sqrt{\sum_{t=1}^{n} a_t^2} + \sqrt{\sum_{t=1}^{n} f_t^2}}$$

The more closer of one is U_1, the forecasts accuracy is higher.

$$U_2 = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{f_{t+1}-a_{t+1}}{a_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{a_{t+1}-a_t}{a_t}\right)^2}}$$

If U_2=1=> there are not differences in terms of accuracy between the two forecasts to compare

If U_2<1=> the forecast to compare has a higher degree of accuracy than the naive one

If U_2>1=> the forecast to compare has a lower degree of accuracy than the naive one

III. THE MODELS USED TO MAKE MACROECONOMIC FORECASTS

The variables used in models are: the inflation rate calculated starting from the harmonized index of consumer prices, unemployment rate in BIM approach and interest rate on short term. The last indicator is calculated as average of daily values of interest rates on the market. The data series for the Romanian economy are monthly ones and they are taken from Eurostat website for the period from february 1999 to october 2011. The indicators are expressed in comparable prices, the reference base being the values from january 1999.

After applying the ADF test (Augmented Dickey-Fuller test) for 1, 2 and 4 lags, we got that interest rate series is stationary, while the inflation rate (denoted rin) and the unemployment rate (denoted rsn) series have one single unit root each of them. In order to stationarize the data we differenced the series, rezulting stationary data series:

$$ri_t = rin_t - rin_{t-1}$$

$$rs_t = rsn_t - rsn_{t-1}$$

Taking into account that our objective is the achievement of one-month-ahead forecasts for August, September and October 2011, we considered necessary to update the models. We used two types of models: a VAR(2) model, an ARMA one and a model in which inflation and interest rate are explained using variables with lag. The models for each analyzed period are shown in the table below. We developed one-month-ahead forecasts starting from these models (see ***Appendix A***), then we evaluated their accuracy.

Table 1. Models used for one-month-ahead forecasts

Reference period of data series	VAR(2)
February 1999-July 2011	RI = - 0.332549643*RI(-1) - 0.09857499949*RI(-2) + 0.6959845127*RD(-1) - 0.3327243579*RD(-2) - 1.149402259*RS(-1) - 6.645103743*RS(-2) + 0.1609208367 RD = 0.03639407301*RI(-1) + 0.01505176501*RI(-2) + 0.7472206176*RD(-1) + 0.08865293152*RD(-2) + 1.645267366*RS(-1) + 0.08076722019*RS(-2) + 0.01458050352 RS = 0.0001340429611*RI(-1) + 0.0009177472885*RI(-2) - 0.001883934895*RD(-1) + 0.002434943796*RD(-2) + 0.009381493101*RS(-1) + 0.1624923521*RS(-2) - 0.0002147805616
February	RI = - 0.3123344702*RI(-1) - 0.0790328783*RI(-2) - 1.201638141*RS(-1) - 6.690049339*RS(-2)

1999-August 2011	+ 0.6969093653*RD(-1) - 0.3324227192*RD(-2) + 0.1522329367 RS = 0.0001159284236*RI(-1) + 0.0009002358633*RI(-2) + 0.009428300954*RS(-1) + 0.1625326272*RS(-2) - 0.001884763643*RD(-1) + 0.002434673502*RD(-2) - 0.0002069954542 RD = 0.03566791295*RI(-1) + 0.01434978199*RI(-2) + 1.647143759*RS(-1) + 0.08238173503*RS(-2) + 0.7471873955*RD(-1) + 0.08864209619*RD(-2) + 0.01489258624
February 1999-September 2011	RI = - 0.2950275431*RI(-1) - 0.06113106597*RI(-2) - 1.235890563*RS(-1) - 6.707442706*RS(-2) + 0.6833790828*RD(-1) - 0.319815167*RD(-2) + 0.1449318154 RS = - 3.100273337e-05*RI(-1) + 0.0007482542901*RI(-2) + 0.009719094807*RS(-1) + 0.1626802922*RS(-2) - 0.001769895183*RD(-1) + 0.002327638774*RD(-2) - 0.0001450108972 RD = 0.03589036766*RI(-1) + 0.01457988307*RI(-2) + 1.646703495*RS(-1) + 0.08215816926*RS(-2) + 0.7470134839*RD(-1) + 0.08880414745*RD(-2) + 0.01479874122

Reference period of data series	ARMA
February 1999-July 2011	$ri_t = 0{,}159 - 0{,}223 \cdot \varepsilon_{t-1} + \varepsilon_t$ $rs_t = 0{,}747 \cdot rs_{t-1} - 0{,}691 \cdot \varepsilon_{t-1} + \varepsilon_t$ $rd_t = 0{,}941 \cdot rd_{t-1} + \varepsilon_t$
February 1999-August 2011	$ri_t = 0{,}157 - 0{,}222 \cdot ri_{t-1} + \varepsilon_{1t}$ $rs_t = 0{,}748 \cdot rs_{t-1} - 0{,}691 \cdot \varepsilon_{2t-1} + \varepsilon_{2t}$ $rd_t = 0{,}941 \cdot rd_{t-1} + \varepsilon_{3t}$
February 1999-September 2011	$ri_t = 0{,}99 \cdot ri_{t-1} - 0{,}98 \cdot \varepsilon_{t-1} + \varepsilon_t$ $rs_t = 0{,}74 \cdot rs_{t-1} - 0{,}69 \cdot \varepsilon_{t-1} + \varepsilon_t$ $rd_t = 0{,}94 \cdot rd_{t-1} + \varepsilon_t$

Reference period of data series	Models having variables with lags
February 1999-July 2011	$ri_t = 0{,}115 + 0{,}215 \cdot rd_{t-1} + \varepsilon_t$ $rd_t = 0{,}098 + 0{,}257 \cdot ri_{t-2} + 0{,}264 \cdot ri_{t-1} + \varepsilon_t$
February 1999-August 2011	$rd_t = 0{,}098 + 0{,}258 \cdot ri_{t-2} + 0{,}264 \cdot ri_{t-1} + \varepsilon_t$ $ri_t = 0{,}113 + 0{,}221 \cdot rd_{t-1} + \varepsilon_t$
February 1999-September 2011	$rd_t = 0{,}098 + 0{,}257 \cdot ri_{t-2} + 0{,}264 \cdot ri_{t-1} + \varepsilon_t$ $ri_t = 0{,}11 + 0{,}226 \cdot rd_{t-1} + \varepsilon_t$

Source: own calculations using EViews.

In building the VAR models we check that the lag is 2 for stationarized variables, three of the criteria indicating this fact (see Appendix B).

The forecasts based on these models are presented in Annex A and these are made for August, Septembre and October 2011 in the version of one-step-ahead forecasts.

IV. THE ASSESSMENT OF SHORT-RUN FORECASTS ACCURACY IN ROMANIA

A generalization of Diebold-Mariano test (DM) is used to determine whether the MSFE matrix trace of the model with aggregation variables is significantly lower than that of the model in which the aggregation of forecasts is done. If the MSFE determinant is used, according Athanasopoulos and Vahid (2005), the DM test can not be used in this version, because the difference between the two models MSFE determinants can not be written as an average. In this case, a test that uses a bootstrap method is recommended.

The DM statistic is calculated as:

$$DM_t = \frac{\sqrt{T}\cdot[tr(MSFE_{ARMA\ model})_h - tr(MSFE_{VAR(2)\ model})_h]}{s} = \frac{1}{s}\cdot\sqrt{T}\cdot[\frac{1}{T}\sum_{t=1}^{T}(em_{1,1,t}^2 + em_{2,1,t}^2 + em_{3,1,t}^2 - er_{1,1,t}^2 - er_{2,1,t}^2 - er_{3,1,t}^2)]$$

T-number of months for which forecasts are developed

$em_{i,h,t}$ – the h-steps-ahead forecast error of variable i at time t for the ARMA model

$er_{i,h,t}$ – the h-steps-ahead forecast error of variable i at time t for the VAR(2)

s- the square root of a consistent estimator of the limiting variance of the numerator

The null hypothesis of the test refers to the same accuracy of forecasts. Under this assumption and taking into account the usual conditions of central limit theorem for weakly correlated processes, DM statistic follows a standard normal asymptotic distribution. For the variance the Newey-West estimator with the corresponding lag-truncation parameter set to h − 1 is used.

On 3 months we compared in terms of accuracy the predictions for all the three variables, predictions made starting from VAR(2) models and ARMA models. The value of DM statistics (34,48) is greater than the critical one, fact that shows there are significant differences between the two predictions. The accuracy of forecasts based on ARMA models is higher than that based on VAR models.

Table 2. Indicators of forecasts accuracy for the inflation rate

Inflation rate	Models used to build the forecasts		
Indicators of accuracy	VAR(2)	ARMA	Models with lag
RMSE	4,482473	0,430998	1,262643
ME	1,385	0,234863	-1,06267
MAE	3,577667	0,415137	1,062667
MPE	4,854135	0,823079	-3,72371
MAPE	12,57103	1,45622	3,723707
U1	0,021042	0,00854	0,017756
U2	41,27034	3,968221	11,62521

Source: own calculations using Excel.

VAR(2) and ARMA models have the tendency to underestimate the forecasted values of inflation rate unlike the models with lag, fact that can be seen analyzing the ME values (**Table 2**). The predictions of inflation based on ARMA models have the higher accuracy, the value close to zero for U1 confirming this observation as the other accuracy indicators that registered the lowest values. As the U2 Theil's statistic has values higher than one for al one-step-ahead forecasts, the naïve predictions are better than those based on VAR(2) models, ARMA models or models with lag for inflation rate.

Table 3. Indicators of forecasts accuracy for the unemployment rate

Unemployment rate	Models used to build the forecasts	
Indicators of accuracy	VAR(2)	ARMA
RMSE	0,022821	0,008324
ME	0,0019	0,0076
MAE	0,0219	0,0076
MPE	5,049578	15,40997
MAPE	44,41572	15,40997
U1	0,429091	0,966619
U2	0,0008	0,000292

Source: own calculations using Excel.

For the unemployment rate the VAR(2) models underestimate the forecasted values. The values registered by the indicators are contradictory, because some of the indicators of accuracy indicate a higher precision for predictions based on VAR(2) models (ME,MPE,U1), and the others consider that ARMA models should be used in forecasting the unemployment rate (RMSE, MAE,MAPE). Relative RMSE indicator is 2,74, fact that suggests a higher accuracy for predictions based on ARMA models. The unemployment rate forecasts based on both models are better than those obtained using the naïve model (**Table 3**).

Table 4. Indicators of forecasts accuracy for the interest rate

Interest rate	Models used to build the forecasts		
Indicators of accuracy	VAR(2)	ARMA	Models with lag
RMSE	0,027382	0,002357	0,023588
ME	0,026633	0,001283	0,022933
MAE	0,026633	0,00215	0,022933
MPE	36,17233	1,715201	31,05321
MAPE	36,17233	2,902297	31,05321
U1	1,346936	0,245252	1,215116
U2	0,000961	0,00008278	0,000828

Source: own calculations using Excel.

The best forecasts for the interest rate are those based on ARMA models, all the indicators of accuracy having registered the lowest values. For all the presented models we observed the underestimation tendency for the predicted values. Only ARMA models have a good accuracy, the value cloose of zero for the U2 statistics (0,245) validating this conclusion, unlike VAR models or those with lag for which U1 registered values greater than one. The forecasts based on proposed models have a higher acccuracy than those based on naive models (**Table 4**).

The most used combination approaches are: the optimal combination (OPT), with weak results according Timmermann (2006), the equal-weights-scheme (EW) and the inverse MSE weighting scheme (INV).
Bates and Granger (1969) considered two predictions p1;t and p2;t, for the
same variable Xt, derived h periods ago. If the forecasts are unbiased, the error is calculated as:

$$e_{i,t} = X_{i,t} - p_{i,t} \quad (1)$$

The errors follow a normal distribution of parameters 0 and σ_i^2. If ρ is the correlation between the errors, then their covariance is $\sigma_{12} = \rho \cdot \sigma_1 \cdot \sigma_2$. The linear combination of the two predictions is a weighted average:

$$c_t = m \cdot p_{1t} + (1-m) \cdot p_{2t} \quad (2)$$

The error of the combined forecast is:

$$e_{c,t} = m \cdot e_{1t} + (1-m) \cdot e_{2t} \quad (3)$$

The mean of the combined forecast is zero and the variance is:

$$\sigma_c^2 = m^2 \cdot \sigma_1^2 + (1-m)^2 \cdot \sigma_{2t}^2 + 2 \cdot m \cdot (1-m) \cdot \sigma_{12} \quad (4)$$

By minimizing the error variance, the optimal value for m is determined (m_{opt}):

$$m_{opt} = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2 \cdot \sigma_{12}} \quad (5)$$

The prediction error variance of the optimally combined forecast is:

$$\sigma_{opt}^2 = \frac{\sigma_1^2 \cdot \sigma_2^2 \cdot (1-\rho^2)}{\sigma_1^2 + \sigma_2^2 - 2 \cdot \rho \cdot \sigma_1 \cdot \sigma_2} \quad (6)$$

Stock and Watson (2004) were interested in the variances of the forecast errors. The individual forecasts are inversely weighted to their relative mean squared forecast error (MSE) resulting INV. In this case, the inverse weight (m_{inv}) is:

$$m_{inv} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2} \quad (7)$$

The prediction error variance of the inversely combined forecast is:

$$\sigma_{inv}^2 = \frac{\sigma_1^2 \cdot \sigma_2^2 \cdot (\sigma_1^2 + \sigma_2^2 + 2 \cdot \rho \cdot \sigma_1 \cdot \sigma_2)}{(\sigma_1^2 + \sigma_2^2)^2} \quad (8)$$

Equally weighted combined forecasts (EW) are gotten when the same weights are given to all models, disregarding all information of the covariance matrix of the prediction errors and taking the average.

The forecast error variance of EW is:

$$\sigma_{eq}^2 = \frac{1}{4}\cdot\sigma_1^2 + \frac{1}{4}\cdot\sigma_2^2 + \frac{1}{2}\cdot\sigma_1\cdot\sigma_2\cdot\rho_{12} \quad (9)$$

The combined forecasts based on the three approaches are presented in **Appendix C** and the forecasts accuracy is evaluated and compared with the accuracy of ARMA predictions.

Table 5. Indicators of forecasts accuracy for the inflation rate

Inflation rate	Approach for combined forecasts		
Indicators of accuracy	OPT	INV	EQ
RMSE	**0,26899134**	0,4140799	0,4225052
ME	-0,31784	-0,24257	**-0,23933**
MAE	**0,31784**	0,391567	0,403333
MPE	-0,01114	-0,0085	**-0,00839**
U1	**0,006325**	0,007298	0,007446
U2	2,871405	3,316775	3,383922

Source: own calculations using Excel.

For the inflation rate the best combined forecasts are those based on OPT scheme, according to RMSE, MAE and U1 indicators and those based on EQ scheme according to ME and MPE. To compare the forecast we use U1 indicator that shows a great improvement of accuracy in combining procedure (**Table 5**).

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Table 6. Indicators of forecasts accuracy for the interest rate

Interest rate	Approach for combined forecasts		
Indicators of accuracy	OPT	INV	EQ
RMSE	**0,00255941**	0,0031179	0,0027151
ME	**-0,00143**	-0,00235	-0,00185
MAE	0,003475	0,002647	**0,00238**
MPE	**-0,01896**	-0,0317	-0,02481
U1	0,025031	0,021502	**0,01866**
U2	2,259169	1,934593	1,683695

Source: own calculations using Excel.

For combined forecasts of interest rate again OPT scheme and EQ one are the best according to RMSE, ME and MPE for the first one and according to MAE and U1 for the second. A very high improvement of accuracy could be observed when we combine VAR predictions with ARMA ones (**Table 6**).

Table 7. Indicators of forecasts accuracy for the unemployment rate

Unemployment rate	Approach for combined forecasts		
Indicators of accuracy	OPT	INV	EQ
RMSE	0,00906841	**0,0082695**	0,0082959
ME	-0,008	**-0,00753**	-0,00757
MAE	0,007996	**0,007531**	0,007566
MPE	-0,16132	**-0,15285**	-0,15349
U1	0,098045	**0,09161**	0,091944
U2	0,845276	**0,829859**	0,830098

Source: own calculations using Excel.

For unemployment rate combined forecasts, the INV is the recommended scheme according to all accuracy indicators. All the predictions based on combining scheme are better than the naïve forecasts on the forecasting horizon. However, the predictions based on ARMA models are better than combined ones, according to U2 values less than 1 (**Table 7**).

V. CONCLUSIONS

Analyzing the results of this research, we recommend the use of ARMA models in making predictions about macroeconomic variables as inflation rate, unemployment rate or interest rate in Romania on a short horizon. We got the highest accuracy for these forecasts, that proved to be better even the VAR(2) models or models with lagged variables. Actually, some observations are lost when the model uses lagged variables. The superiority of ARMA models over VAR ones was demonstrated also for the economy of Pakistan by Bokhari and Feridun (2005).

Combined forecasts are a good strategy to improve the forecasts accuracy for inflation and interest rate, the optimal and equally weighted combined forecasts being the best choice. For unemployment rate inverse MSE weighting scheme generated rather accurate monthly forecasts, but the ARMA procedure remained the best.

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APPENDIX A

The one-month-ahead forecasts based on different models

One-month-ahead forecasts using VAR(2) models

	august	september	octomber
Inflation rate	21,45	31,7	28,17
Interest rate	0,038	0,0497	0,0534
Unemployment rate	0,028	0,032	0,0808

One-month-ahead forecasts using ARMA models

	august	september	octomber
Inflation rate	28,7404	27,99	28,04
Interest rate	0,07135	0,0715	0,0743
Unemployment rate	0,0375	0,0427	0,0435

One-month-ahead forecasts for interest rate and unemployment rate using the inflation rate from previous periods

	august	september	octomber
Interest rate	0,0497	0,0455	0,057
Unemployment rate	28,93	29,123	30,61

Source: own calculations using Excel.

APPENDIX B

The selection of VAR lag

VAR Lag Order Selection Criteria
Endogenous variables: RI RD RS
Exogenous variables: C
Date: 12/01/11 Time: 17:05
Sample: 1999:02 2011:07

Included observations: 142						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	259.5526	NA	5.41E-06	-3.613417	-3.550970	-3.588041
1	1006.452	1451.719	1.66E-10	-14.00636	-13.75657*	-13.90486
2	1021.749	29.08714	1.52E-10*	-14.09506*	-13.65793	-13.91743*
3	1030.278	15.85707	1.53E-10	-14.08843	-13.46396	-13.83467
4	1036.375	11.07658	1.59E-10	-14.04753	-13.23572	-13.71765
5	1048.669	21.81737*	1.52E-10	-14.09393	-13.09477	-13.68791
6	1051.139	4.279695	1.67E-10	-14.00196	-12.81547	-13.51982
7	1060.328	15.53007	1.67E-10	-14.00462	-12.63078	-13.44635
8	1068.504	13.47339	1.70E-10	-13.99301	-12.43184	-13.35861
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Source: EViews output.

APPENDIX C

Combined forecasts for inflation, interest rate and unemployment rate

Inflation rate forecasts using combining approaches based on VAR and ARMA models

Approach	August	September	October
OPT	28,21445	28,25765	28,04938
INV	28,69351	28,01386	28,04084
EQ	28,71696	28,00193	28,04042

Interest rate forecasts using combining approaches based on VAR and ARMA models

Approach	August	September	October
OPT	0,076068	0,074584	0,077257
INV	0,069985	0,070607	0,073444
EQ	0,070667	0,071054	0,073872

Unemployment rate forecasts using combining approaches based on VAR and ARMA models

Approach	August	September	October
OPT	0,03816	0,043444	0,040907
INV	0,037385	0,04257	0,043953
EQ	0,037442	0,042635	0,043726