ASSESSING THE FORECASTS ACCURACY OF THE WEIGHT OF FISCAL REVENUES IN GDP FOR ROMANIA

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Abstract

The main aim of this research is to construct different forecasts for the weight of fiscal revenues in the GDP for Romania on short horizon (2011-2013) by using different types of econometric models. Using annual data from 1995, according to Granger causality test, there is a unidirectional relationship between weight of fiscal revenues (an indicator of fiscal pressure) and real GDP rate in first difference. 74.48% of the fiscal revenues weights is due to this variable, the influence very slowly decreasing till 72.56% at the 10th lag. In the first period, the variation in transformed GDP rate explains 19.25% of the variation in fiscal pressure indicator. The predictions based on a vector-autoregressive model of order 1 (VAR(1)) outperformed the forecasts based on a Bayesian VAR model, moving average process (MA(2)) and dynamic factor model. The static and stochastic simulations based on VAR(1) generated the best predictions of the fiscal pressure indicator on the horizon 2011-2013, according to absolute and relative accuracy measures, excepting the mean error. In terms of sign and directional accuracy, all the types of forecasts performed the same.

Keywords: forecasts accuracy, fiscal revenues, VAR model, impulse-response function, forecast error

JEL Classification: C51, C53, E66

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Introduction

The main objective of this research is to construct different types of econometric models for the weight of fiscal revenues in GDP in order to assess the ex-post forecasts. The VAR approach allows us to evaluate the variance decomposition of each indicator. In this way, we can determine if the variation in the variable's evolution is mainly due to the other variable or to its own evolution. The model is applied for the Romania, the data series being from 1995 to 2013, and the predictions' horizon being 2011-2013.

European Commission has launched the famous Internal Market Programme that has different objectives, one of them being the harmonization of national tax system. Therefore, it is necessary to diminish the contrary incentives for capital movements, production and goods generated by national purposes. In the context of fiscal convergence the study of the relationship between fiscal pressure indicators and different factors is important.

The main results showed the superiority of VAR models in forecasting the weight of fiscal revenues in GDP in Romania. The static and stochastic simulations of VAR(1) model generated the best predictions for fiscal pressure indicator, the model including variables like the differentiated rate of consumption and the differentiated rate of real GDP. Our contribution is given by the utilization of the econometric models for Romanian indicator, proposing also other models than those used in literature in this context (BVAR model, dynamic factor model, moving average model).

The fiscal policies may determine consistent macroeconomic effects on short run, the use of different instruments conducting to various results (Skinner, 1992).

Compared to the researches based on DSGE models, the VAR models studies recover significant effects of fiscal expansions on GDP. These are more in accordance with a positive 'Keynesian' effect on consumption, if the eventual multiplier is clearly diminished (Perotti, 2005).

Blanchard and Perotti (2002) used a semi-structural VAR that utilized external institutional information on the elasticity of fiscal indicators to GDP. The cyclical reaction of fiscal balance is eliminated and we can observe shifts to the cyclically adjusted balance as discretionary fiscal shocks.Ramey and Shapiro (1998) showed that an important role in the transmission of shocks in fiscal policy brings from labour market. Some papers compared the effects of consumptive government purchases to changes in public employment (Finn, 1998; Pappa, 2005; Cavallo, 2005). Perotti (2004) and Kamps (2004) studied the effects of government investment on GDP and labour market variables. Mountford and Uhlig (2002) obtained different types of fiscal shocks among those that conform to some a priori sign restrictions on the impulse response or variance decomposition of fiscal variables. Canova and Pappa (2002) considered only those shocks that satisfy formal sign restrictions on the responses conditional cross-correlation to the variables' orthogonalised shocks.

The article is structured as follows. After the brief introduction, the methodological background for assessing the forecasts accuracy is developed. The construction of econometric models and forecasts is presented in the next section, as well as the evaluation of predictions using the accuracy indicators. The last section concludes.

Methodological background

There are different methods used in literature to assess the forecasts accuracy. In practice, there are many cases when some indicators suggest the superiority of certain forecasts while other ones indicate that other predictions are more accurate. Therefore, it is proposed a new methodology to solve this contradiction given by the results of accuracy assessment. The method is based on different types of accuracy measures: statistics based on size errors, coefficients for comparisons and directional accuracy measures. These types of indicators were also used by Melander et al. (2007) but without any aggregation.

The prediction error at time *t* is the simplest indicator based on the comparison of the registered value with the forecasted one and it is denoted by e_t. Green and Tashman (2008) confirmed that there are two ways of computing the forecast error if $\hat{y}_t$ is the prediction at time t: $e_t = y_t - \hat{y}_t$or $e_t = \hat{y}_t - y_t$. Seven out of eleven members from International Institute of Forecasters recommended in a survey the use of the first variant ($e_t = y_t - \hat{y}_t$). This is the most utilized version in literature and it will also be used in this study.

The following summary statistics have been used: root mean squared error, mean squared error, mean error, mean absolute error, mean absolute percentage error. If the horizon length is h and the length of actual data series is n, the indicators are computed as in the following table (Table 1):

Table 1 - Summary statistics for forecasts accuracy

Indicator	Formula
Mean error- ME	$ME = \frac{1}{h}\sum_{t=n+1}^{n+h}(y_t - \hat{y}_t)$
Mean absolute error- MAE	$MAE = \frac{1}{h}\sum_{t=n+1}^{n+h}\lvert y_t - \hat{y}_t\rvert$
Root mean squared error- RMSE	$RMSE = \sqrt{\frac{1}{h}\sum_{t=n+1}^{n+h}(y_t - \hat{y}_t)^2}$
Mean squared error- MSE	$MSE = \frac{1}{h}\sum_{t=n+1}^{n+h}(y_t - \hat{y}_t)^2$
Mean absolute percentage error- MAPE	$MAPE = 100 \cdot \frac{1}{h}\sum_{t=n+1}^{n+h}\left\lvert\frac{y_t - \hat{y}_t}{y_t}\right\rvert$

The aggregate statistic for comparisons is based on U1Theil's statistic, mean relative absolute error, relative RMSE and mean absolute scaled error. $RMSE_b$ is the RMSE for the benchmark. e_t^* is the benchmark error. In our case the benchmark is represented by the naïve projection (Table 2).

Table 2 - Statistics for comparing the forecasts accuracy

Indicator	Formula
U1 Theil's statistic	$U_1 = \frac{\sqrt{\sum_{t=n+1}^{n+h}(y_t - \hat{y}_t)^2}}{\sqrt{y_t^2} + \sqrt{\hat{y}_t^2}}$
Mean relative absolute error- MRAE	$MRAE = average(\left\lvert\frac{e_t}{e_t^*}\right\rvert)$
Relative Root mean squared error- RRMSE	$RRMSE = \frac{RMSE}{RMSE_b}$
Mean absolute scaled error-MASE	$MASE = average(\frac{e_t}{\frac{1}{n-1}\sum_{t=n+1}^{n+h}\lvert y_t - y_{t-1}\rvert})$

If ME takes a positive value on the mentioned horizon with the proposed definition of the forecast error, the predictions are underestimated. For negative value of ME the forecasts are overestimated. For optimal predictions ME is zero, but this value is also met when the errors offset each other perfectly.

MSE penalizes the predictions with high errors. It considers that the high errors are more harmful than the small errors.

The positive and the negative errors cannot compensate each other like in the case of ME, which is an advantage for MSE. There is not a superior limit for MSE and it has a different unit of measurement compared to actual data. The null value is the lowest value of the indicator and it is achieved for perfect precision of the forecasts.

RMSE is equal or larger then MAE. A higher difference between these two indicators implies a higher errors variance. The errors have the same magnitude if RMSE equals MAE. The minimum value of those measures is 0, but there is not a superior limit for them. A null value for the MAPE expressed as percentage shows a perfect forecast. If MAPE is smaller than 100% the prediction is better than the naïve one. MAPE has no superior limit.

The percentage of sign correct forecasts (PSC) shows how many percent of time is sign of prediction forecasted correctly. Percentage of directional accuracy correct forecasts (PDA) shows if the expert correctly anticipates the increase or decrease of the variable. It measures the ability to correctly predict the turning points. PDA and PSC are located between 0% and 100%. According to Melander et al. (2007) the success rate of the indicators should be greater than 50% (see Table 3).

Table 3 - Measures for directional and sign accuracy

Indicator	Formula	Conditions
Percentage of sign correct forecasts- PSC	$PSC = \frac{100}{h}\sum_{t=n+1}^{n+h} z_t$	$z_t = 1, y_t \cdot \hat{y}_t > 0$ $z_t = 0, otherwise$
Percentage of directional accuracy correct forecasts- PDA	$PDA = \frac{100}{h}\sum_{t=n+1}^{n+h} z_t$	$z_t = 1, (y_t - y_{t-1})(\hat{y}_t - y_{t-1}) > 0$ $z_t = 0, otherwise$

Econometric models used in forecasting the weight of fiscal revenues in GDP in Romania

The data are represented by the weight of fiscal revenues in GDP (weight_fr), the rate of real final consumption (r_consumption) and the rate of real GDP (r_GDP) for Romanian economy. The data series were provided by Eurostat, covering the period from 1995 to 2013. According to Ng-Perron test, only the data series for the weight of fiscal revenues in GDP is stationary at 5% level of significance, for the other two series the first order differentiating being necessary to achieve the stationarity (dr_consumption and dr_GDP). The causality between the stationary data series is checked using Granger causality test as Table 4 shows.

Table 4 - The Granger causality tests

Assumption	F calculated	Prob.
dr_gdp is not Granger cause for dr_consumption	0.72193	0.5075
dr_consum is not Granger cause for dr_gdp	10.19908	0.0380
weight_fr is not Granger cause for dr_consumption	0.03390	0.9668
dr_consum is not Granger cause for weight_fr	0.62037	0.5555
weight_fr is not Granger cause for dr_gdp	9.63243	0.0496
dr_gdp is not Granger cause for weight_fr	0.88914	0.4386

Source: author's computations

There is a unidirectional relationship between consumption and GDP rate and between weight of fiscal revenues and GDP. For the other cases, a variable is not Granger cause for the other one (the associated probabilities to F statistics are higher than 0.05 and there are no reasons to reject the null hypothesis).

Table 5 - The lag selection for VAR model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-117.2227	NA	278.8361	14.14385	14.29088	14.15846
1	-104.0251	20.18462*	174.7456*	13.65001*	14.23816*	13.70847*
2	-79.38374*	28.94714	178.31612	14.54797	14.56199	14.59989

Source: author's computations

Almost all the lag length criteria, excepting logL and HQ, at 5% level indicate that a VAR(1) model is the best model. All the tests necessary to be applied for checking the validity of the estimated VAR(1) model are displayed in Table 5.

The form of the VAR model is the following:

DR_CONSUMPTION = -0.172079411481*DR_CONSUMPTION(-1) -

0.237511224857*DR_GDP(-1) + 1.01445272693*WEIGHT_FR(-1) - 29.4919062169

DR_GDP= 0.523052574718*DR_CONSUMPTION(-1) - 0.976530555311*DR_GDP(-1) + 1.70807592222*WEIGHT_FR(-1) - 48.8602780878

PONDERE_VF = 0.0327753296954*DR_CONSUM(-1) - 0.0184361823283*DR_PIB(-1) + 0.504205726203*PONDERE_VF(-1) + 14.3436867492

VAR Residual Portmanteau Tests are used to test the errors' autocorrelation for both identified model. The assumptions of the test are formulated as:

H0: the errors are not auto-correlated
H1: the errors are auto-correlated

For the lag 1 up to 12, the probabilities (Prob.) of the tests are greater than 0.05, fact that implies that there is not enough evidence to reject the null hypothesis (H0). So, we do not have enough reasons to say that the errors are auto-correlated. So, after the application of Residual Portmanteau Test, the conclusion is that there are not autocorrelations between errors for VAR(1) model as Table 6 shows.

Table 6 - Residual Portmanteau test for errors auto-correlation

Lag	Q Stat.	Prob.	Adjusted Q stat.	Prob.	Degrees of freedom
1	8.044918	NA*	8.547725	NA*	NA*
2	11.42414	0.2478	12.37751	0.1929	9
3	16.00770	0.5920	17.94326	0.4594	18
4	19.96533	0.8322	23.11863	0.6786	27
5	26.34884	0.8806	32.16193	0.6518	36
6	28.56549	0.9733	35.58766	0.8412	45
7	31.22570	0.9945	40.11002	0.9202	54
8	34.85677	0.9985	46.96871	0.9345	63
9	40.67122	0.9989	59.32442	0.8575	72
10	49.76132	0.9976	81.40037	0.4666	81
11	55.07805	0.9986	96.46445	0.3015	90
12	61.77958	0.9988	119.2496	0.0811	99

Source: author's computations

The homoskedasticity is checked using a VAR Residual LM test for the VAR(1) model. If the value of LM statistic is greater than the critical value, the errors series is heteroskedastic. LM test shows that there is a constant variance of the errors, because of the values greater than 0.05 for the probability. The Residual Heteroskedasticity test is applied in Table 7 in two variants: with cross terms and without cross terms. In this case we applied the variant without cross terms.

Table 7 - VAR Residual Heteroskedasticity Tests

No Cross Terms (only levels and squares)

Chi-square stat.	Degrees of freedom	Prob.
47.79206	36	0.0904

Dependent variable	Chi-square	F(6,10)	Prob.	Chi-square (6)
res1*res1	0.158385	0.313654	0.9155	2.692552
res2*res2	0.121999	0.231585	0.9565	2.073982
res3*res3	0.535144	1.918676	0.1730	9.097454
res2*res1	0.135212	0.260588	0.9433	2.298606
res3*res1	0.427309	1.243572	0.3619	7.264259
res3*res2	0.290599	0.682734	0.6683	4.940186

Cross Terms

Chi-square stat.	Degrees of freedom	Prob.
63.74050	54	0.1712

Dependent variable	Chi-square	F(6,10)	Prob.	Chi-square (6)
res1*res1	0.262792	0.277254	0.9611	4.467469
res2*res2	0.215751	0.213971	0.9820	3.667771
res3*res3	0.865244	4.993962	0.0228	14.70914
res2*res1	0.221981	0.221912	0.9799	3.773676
res3*res1	0.468345	0.685158	0.7078	7.961859
res3*res2	0.344221	0.408259	0.8946	5.851762

Source: author's computations

The normality tests are applied under the Cholesky (Lutkepohl) orthogonalization. If the Jarque-Bera statistic is lower than the critical value there is not enough evidence to reject the normal distribution of the errors (Table 8).

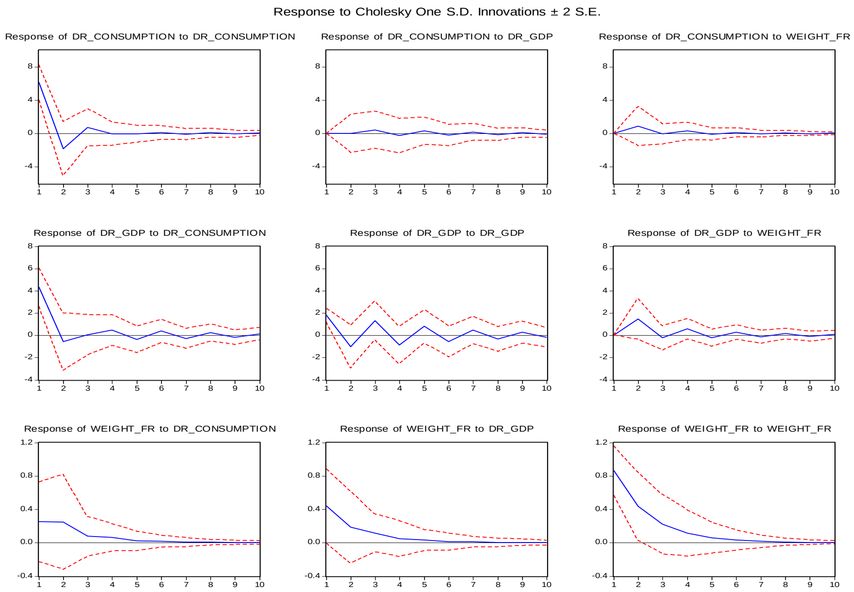
Table 8 - VAR Residual Normality Tests

Component	Jarque-Bera stat.	Degrees of freedom	Prob.
1	9.164150	2	0.0102
2	1.122952	2	0.5704
3	3.060270	2	0.2165
Common	13.34737	6	0.0378

Source: author's computations

The Residual normality test provided probabilities greater than 0.05, fact that implies that the errors series has a normal distribution when Cholesky (Lutkepohl) Orthogonalization is applied. The impulse-response analysis and the decomposition of error variance are made (Figure 1).

Figure 1 - The responses of each variable to own shocks or the other variable shocks



Source: author's computations

The variation of differences in consumption is due in the first period only to the evolution of own variable. This influence decreases in time in favor of other variables influence, the GDP weight having the highest influence that arises to 2.06%. In the first period, 84.97% of the variation in real GDP rate differences is due to the same variable, while 15.02% of the variation is explained by changes in fiscal revenues weight and neither by variation in the differences of real consumption rates. The influence of differentiated GDP rates decreases in time, at the 10th lag 28.91% of the GDP variation being explained by fiscal revenues weights and 8.94% by changes in consumption rates. 74.48% of the fiscal revenues weights is due to this variable, the influence very slowly decreasing till 72.56% at the 10th lag. In the first period, the variation in transformed GDP rate explains 19.25% of the variation in fiscal pressure indicator (Figure 9).

Table 9 - Variance decomposition of the variables

Variance decomposition of dr_consumption	Standard error	dr_consumption	dr_gdp	weight_fr
1	6.136816	100.0000	0.000000	0.000000
2	6.463070	98.16262	0.000454	1.836923
3	6.515900	97.74541	0.439033	1.815560
4	6.528369	97.37893	0.613636	2.007434
5	6.535926	97.15752	0.827505	2.014980
6	6.541446	97.02549	0.928414	2.046091
7	6.544860	96.94514	1.003822	2.051039
8	6.547045	96.89881	1.043219	2.057971
9	6.548325	96.87130	1.068517	2.060179
10	6.549095	96.85542	1.082490	2.062089
Variance decomposition of dr_gdp	Standard error	dr_consumption	dr_gdp	weight_fr
1	4.687743	84.97632	15.02368	0.000000
2	5.053626	74.44557	17.03691	8.517520
3	5.230893	69.48996	22.35222	8.157816
4	5.355474	67.04202	24.00503	8.952952
5	5.431405	65.66057	25.47254	8.866886
6	5.480612	64.97130	26.07361	8.955089
7	5.509239	64.56426	26.49841	8.937329
8	5.526530	64.34385	26.70799	8.948162
9	5.536525	64.21359	26.84150	8.944909
10	5.542418	64.14004	26.91368	8.946279
Variance decomposition of weight_fr	Standard error	dr_consumption	dr_gdp	weight_fr
1	1.000478	6.258719	19.25267	74.48861
2	1.134517	9.632787	17.71349	72.65372
3	1.163925	9.575008	17.78986	72.63513
4	1.172002	9.710745	17.70739	72.58187
5	1.173936	9.708618	17.71862	72.57276
6	1.174479	9.717911	17.71090	72.57119
7	1.174608	9.717437	17.71291	72.56965
8	1.174647	9.718308	17.71205	72.56965
9	1.174656	9.718211	17.71241	72.56938
10	1.174659	9.718321	17.71232	72.56936

Source: author's computations

The VAR model is used to make fiscal pressure- tax weight in GDP- forecasts on the horizon 2011-2013 (Table 10). For the VAR predictions four types of scenarios are considered:

- S1 scenario (Dynamic-Deterministic Simulation);
- S2 scenario (Dynamic-Stochastic Simulation);
- S3 scenario (Static-Deterministic Simulation);
- S4 scenario (Static-Stochastic Simulation).

Table 10 - Predictions of fiscal revenues weight in GDP (%) based on VAR (1) models

Year	VAR(1) model (S1)	VAR(1) model (S2)	VAR(1) model (S3)	VAR(1) model (S4)	Registered values
2011	28.35830	28.35830	28.4124	28.4124	28.50000
2012	28.58781	28.72625	28.5589	28.5249	28.50000
2013	28.76088	28.76128	28.8224	28.9024	29.00000

Source: own computations

If the comparison with actual data is made, the fourth scenario of VAR(1) model generated the most accurate predictions of the weight of fiscal revenues in GDP over 2011-2013. This scenario might be used to make predictions for 2014 and 2015.

A moving average model of order 2 was estimated for the weight of fiscal revenues in GDP:

WEIGHT_FR = 28.72402679 + [MA(1)=1.313878625,MA(2)=0.6035075711,BACKCAST=1995]

According to Jarque-Bera test, we do not have enough evidence to reject the hypothesis of normal distribution for the errors that are not serial correlated (see Appendix 1).

A dynamic model was estimated, the log likelihood being determined using stationary Kalman filter and diffuse De Jong Kalman filter (see Appendix 2).

We also estimated the BVAR(1) model using Gibbs sampler algorithm, utilizing the program in Matlab provided by Qian (2010).

The regressors are: the real GDP rate and the real consumption rate. The order in lags is 1, the number of MCMC draws is 50 000, while the number of burn-in draws is 10 000. Bayesian VAR model is identical to SUR model. Conditional posterior Sigma follows inverse Wishart. Conditional posterior Beta follows N(Dd,D).

If the model has the form Y(t) = c + Phi(1)*Y(t-1) + ... + Phi(p)*Y(t-p) + ut, where ut ~ MVN(0,Sigma) and Y(t) has d component variables, the program will display the following outputs :

- posterior draws of phi(1),…,phi(p), d*d*p*R 4-dimension array
- posterior draws of covariance matrix, d*d*R 3-dimension array
- posterior draws of the intercept in the VAR model

The constant and the posterior coefficients could be assimilated to real values of coefficients and the forecasts could be made. The predictions based on MA(2) model, dynamic factor model and BVAR(1) model are shown in Table 11.

Table 11 - Predictions of fiscal revenues weight in GDP (%) based on MA(2) model, dynamic factor model and BVAR(1) model

Year	MA(2) model	Dynamic factor model	Bayesian VAR(1)	Registered values
2011	28.26591	28.4889	28.8348	28.50000
2012	28.57522	29,77	28.8812	28.50000
2013	28.72403	29,77	28.9923	29.00000

Source: own computations

The forecasts based on MA(2) model are quite close of the registered values, but for 2012 and 2013 the predictions based on dynamic factor model are quite larger than the registered values. Different types of accuracy measures are computed for the proposed predictions in Table 12.

Table 12 - The evaluation of forecasts accuracy measures for the weight of fiscal revenues in the GDP over the horizon from 2011 to 2013

Indicator	VAR(1) model (S1)	VAR(1) model (S2)	VAR(1) model (S3)	VAR(1) model (S4)	MA(2) model	Dynamic factor model	Bayesian VAR(1)
Mean error- ME	0.0977	**0.0514**	0.0688	0.0534	0.1449	-0.6763	-0.2361
Mean absolute error- MAE	0.1562	0.2022	0.1080	**0.0700**	0.1951	0.6837	0.2412
Root mean squared error- RMSE	0.1683	0.2068	0.1193	**0.0771**	0.2134	0.8575	0.2930
Mean squared error- MSE	0.0283	0.0428	0.0142	**0.0059**	0.0455	0.7353	0.0858
Mean absolute percentage error- MAPE	54.32%	70.47%	37.54%	**24.37%**	67.89%	238.32%	84.62%
U1 Theil's statistic	0.0029	0.0036	0.0021	**0.0013**	0.0037	0.0148	0.0051
Mean relative absolute error- MRAE	3599.9816	3571.5099	3568.1191	**3567.7690**	3845.6106	3648.7242	3569.0000
Relative Root mean squared error- RRMSE	0.2831	0.3478	0.2007	**0.1297**	0.3590	1.4426	0.4928
Mean absolute scaled error-MASE	0.0059	0.0072	0.0042	**0.0027**	0.0074	0.0299	0.0102
Percentage of sign correct forecasts- PSC	100%	100%	100%	100%	100%	100%	100%
Percentage of directional accuracy correct forecasts- PDA	66.67%	66.67%	66.67%	66.67%	66.67%	66.67%	66.67%

Indicator	VAR(1) model (S1)	VAR(1) model (S2)	VAR(1) model (S3)	VAR(1) model (S4)	MA(2) model	Dynamic factor model	Bayesian VAR(1)
Mean error- ME	0.0977	**0.0514**	0.0688	0.0534	0.1449	-0.6763	-0.2361
Mean absolute error- MAE	0.1562	0.2022	0.1080	**0.0700**	0.1951	0.6837	0.2412
Root mean squared error- RMSE	0.1683	0.2068	0.1193	**0.0771**	0.2134	0.8575	0.2930
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Mean absolute percentage error- MAPE	54.32%	70.47%	37.54%	**24.37%**	67.89%	238.32%	84.62%
U1 Theil's statistic	0.0029	0.0036	0.0021	**0.0013**	0.0037	0.0148	0.0051
Mean relative absolute error- MRAE	3599.9816	3571.5099	3568.1191	**3567.7690**	3845.6106	3648.7242	3569.0000
Relative Root mean squared error- RRMSE	0.2831	0.3478	0.2007	**0.1297**	0.3590	1.4426	0.4928
Mean absolute scaled error- MASE	0.0059	0.0072	0.0042	**0.0027**	0.0074	0.0299	0.0102
Percentage of sign correct forecasts- PSC	100%	100%	100%	100%	100%	100%	100%
Percentage of directional accuracy correct forecasts- PDA	66.67%	66.67%	66.67%	66.67%	66.67%	66.67%	66.67%

Source: author's computations

In terms of directional and sign accuracy all the types of predictions have the same degree of accuracy. All the absolute and relative indicators, excepting the mean error, show that VAR(1) forecasts in the fourth scenarios are the most accurate. The lowest value for ME is registered by VAR(1) predictions after the second scenario. Excepting the anticipations based on dynamic factor model and BVAR(1) model, all the other forecasts are underestimated. The overestimations of the forecasts could be explained by the shocks in the economy that have not been taken into account by the econometric models. According to the values of MASE, all the predictions are better than the naïve ones. The errors for S4 scenario are in average 24.37% of the actual value. The values of U1 are close to zero and under 0.25, the degree of accuracy being very high.

Conclusions

In this study different econometric models were employed to predict the weight of fiscal revenues in GDP in Romania on short run (2011-2013). Moreover, the predictions were assessed using different accuracy measures. Even if in literature the VAR models are employed in this context, the study used also BVAR, ARIMA and dynamic factor models. The predictions based on a vector-autoregressive model of order 1 (VAR(1)) outperformed the forecasts based on a Bayesian VAR model, moving average process (MA(2)) and dynamic factor model. The static and stochastic simulations based on VAR(1) generated the best predictions of the fiscal pressure indicator on the horizon 2011-2013, according to absolute and relative accuracy measures, excepting the mean error. In terms of sign and directional accuracy, all the types of forecasts performed the same.

The research might be continued by using also other quantitative forecasting methods like Markov chains. It is interesting to check if this method outperforms the econometric approach in terms of forecasts accuracy.

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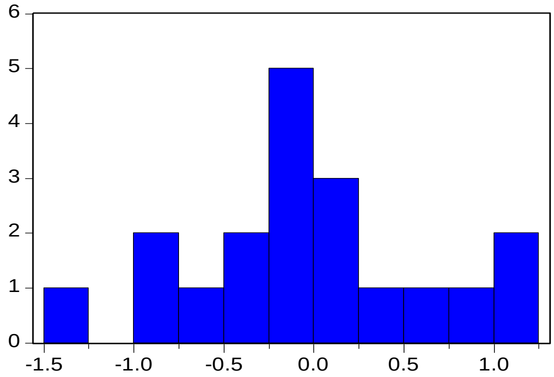
APPENDIX 1



Series: Residuals
Sample 1995 2013
Observations 19

Mean	-0.055256
Median	-0.160387
Maximum	1.177417
Minimum	-1.483526
Std. Dev.	0.689137
Skewness	0.026896
Kurtosis	2.705403
Jarque-Bera	0.070997
Probability	0.965124

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. |* . |</td><td>. |* . |</td><td>1</td><td>0.148</td><td>0.148</td><td>0.4867</td><td></td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>2</td><td>-0.121</td><td>-0.146</td><td>0.8304</td><td></td></tr>
<tr><td>.***| . |</td><td>.***| . |</td><td>3</td><td>-0.396</td><td>-0.070</td><td>4.7438</td><td>0.29</td></tr>
<tr><td>. **| . |</td><td>. *| . |</td><td>4</td><td>-0.246</td><td>-0.008</td><td>6.3572</td><td>0.42</td></tr>
<tr><td>. *| . |</td><td>. **| . |</td><td>5</td><td>-0.109</td><td>-0.189</td><td>6.6945</td><td>0.082</td></tr>
<tr><td>. |* . |</td><td>. *| . |</td><td>6</td><td>0.124</td><td>-0.070</td><td>7.1699</td><td>0.127</td></tr>
<tr><td>. |* . |</td><td>. *| . |</td><td>7</td><td>0.088</td><td>-0.152</td><td>7.4271</td><td>0.191</td></tr>
<tr><td>. |**. |</td><td>. |* . |</td><td>8</td><td>0.285</td><td>0.178</td><td>10.381</td><td>0.110</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>9</td><td>-0.004</td><td>-0.080</td><td>10.381</td><td>0.168</td></tr>
<tr><td>. **| . |</td><td>.***| . |</td><td>10</td><td>-0.304</td><td>-0.347</td><td>14.487</td><td>0.070</td></tr>
<tr><td>. *| . |</td><td>. |* . |</td><td>11</td><td>-0.123</td><td>0.074</td><td>15.247</td><td>0.084</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>12</td><td>-0.038</td><td>-0.088</td><td>15.328</td><td>0.121</td></tr>
</table>

APPENDIX 2

Dynamic-factor model

Sample: 1996 - 2013		Number of obs =	18
		Wald chi2(1) =	4.08
Log likelihood = -27.31799		Prob > chi2 =	0.0434

weight_fr	Coef.	OIM Std. Err.	z	P>|z|	[95% Conf.	Interval]
dr_gdp	.1110504	.0549907	2.02	0.043	.0032707	.2188302
_cons	28.6111	.2603924	109.88	0.000	28.10074	29.12146
Variance						
e.weight~r	1.218298	.4060995	3.00	0.001	.4223581	2.014239

Note: Tests of variances against zero are one sided, and the two-sided confidence intervals are truncated at zero.