Alternative models for forecasting the key macroeconomic variables in Armenia

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Abstract: This paper uses three well known forecasting models, particularly unrestricted VAR, Bayesian VAR and Factor Augmented VAR. These models we use for forecasting the key macroeconomic variables in Armenia (real growth of GDP, inflation and nominal short-term interest rate). We apply three models to the Armenian economy using quarterly macroeconomic time series from 2000 to 2012. The main purpose of the current paper is to compare various forecasting models, in order to find that model which is more appropriate for forecasting Armenian's key macroeconomic variables. In order to answer this question we conduct out of sample forecast experiments. Based on the out of sample forecast experiments and using forecast evaluation RMSE (the Root Mean Squared Error) criteria we make comparisons between small scale (VAR, BVAR) and large scale (FAVAR) models.

Key words: VAR, BVAR, FAVAR, Forecast Accuracy, principal component, static factor model, RMSE, Armenia

JEL Classifications: C11, C13, C52, C53

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1. Introduction

In order to conduct effective monetary policy, practioners from Central Banks are interested in producing accurate forecasts of the relevant economic variables. Monetary policy decisions affect the economy with a lag, thus monetary policy authorities must be forward looking, i.e. they must know what will happen in the nearest future. Besides of that, some important macroeconomic variables, especially real GDP growth is available around two months after the reference quarter. Finally for the Central bank of Armenia having an accurate forecast for the main macroeconomic variables is an important ingredient for the inflation targeting policy purposes.

In the current paper we consider three models which are typically used for short-term forecasting purposes, particularly UVAR (Unrestricted VAR), BVAR (Bayesian VAR) and FAVAR (Factor Augmented VAR) models. First two forecasting models can be classified as small-scale, while the third model (FAVAR) can be classified as large-scale forecasting model. This is because in the third model (FAVAR) we can incorporate a large number of explanatory variables, while in the VAR and BVAR we cannot to do the same. First two models we use for forecasting the key macroeconomic variables such as real GDP growth, inflation and short-term nominal interest rate. The third model is a standard VAR model that also includes the principal components.

One of the main purposes of the current paper is to compare the above mentioned models and to see which forecasting approach produces most accurate forecasts. The models are compared with using standard measure of forecasting performance, such as the Root Mean Squared Error (RMSE) of the one-to-four quarter ahead forecast. We also use the Diebold-Mariano test, to test the hypothesis whether the differences in the forecasts obtained from different models are statistically significant.

The paper is organized as follows. In the section 2 we briefly discuss the three forecasting models (VAR, BVAR and FAVAR). In the section 3 we present the actual macroeconomic time series dynamics. In this part we also give some explanations relating with the software that has been used through the whole paper. Section 4 presents the recursive and rolling regression schemes for our experimental design. Section 5 discusses the results from the forecasting exercise. Final section gives some conclusions.

2. Overview of econometric models: VAR, BVAR and FAVAR

In this part of the paper we consider three alternative forecasting models, namely the unrestricted VAR, Bayesian VAR and FAVARs for short-term forecasting of the Armenian's macroeconomic variables. This part of the paper outlines the basics of the three forecasting models. An unrestricted VAR model is a useful tool for short-term forecasting. As it was suggested by Sims (1980) an unrestricted VAR can be presented as follows:

$$y_t = A_0 + A(L)y_t + \varepsilon_t$$

Where y is a $(n \times 1)$ vector of variables being forecasted; A(L) is a $(n \times n)$ polynomial matrix in the backshift operator L with lag length p; A0 is a $(n \times 1)$ vector of constant terms, and ε is a $(n \times 1)$ vector of error terms. We assume that $\varepsilon \sim N(0, \sigma^2 I_n)$, where I_n is a $(n \times n)$ identity matrix. As a rule in the VAR model the matrix of unknown parameters are estimated with using traditional OLS methodology. Having estimated matrix of unknown parameters it is easy to conduct forecasts for several number of periods.

From the other side in the VAR model we need to estimate a large number of parameters, especially when we try to estimate VAR model with more than one lag. It is clear, that some of the estimated parameters may be statistically insignificant. This over identification problem could cause inefficient estimates and hence a large out-of-sample forecasting error.

A widely used alternative is to use a Bayesian VAR (BVAR) model. The main idea of the BVAR approach is that we impose restrictions on the lags, particularly we assume that the coefficients should be closer to zero for longer lags and they should differ from zero for shorter lags. The restrictions are imposed by specifying normal prior distributions with zero mean and small standard deviation decreasing as the lag increase. The exception to this is that the coefficient on the first own lag of a variable has a mean of unity. This prior is known as the "Minnesota prior" due to its development at the University of Minnesota and the Reserve bank of Minneapolis (Litterman (1981, 1986)). Thus according to this approach the priors in the VAR model should follow standard AR(1) process. The variance of the priors according to the Minnesota approach can be specified as follows.

$$\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 i = j\,,\ \left(\frac{\sigma_i \lambda_1 \lambda_2}{\sigma_j l^{\lambda_3}}\right)^2,\ i \neq j\,,\ (\sigma_1 \lambda_4)^2$$

Where i refers to the dependent variable in the i-th equation and j to the independent variables in that equation. σ_i and σ_j are variances of error terms from AR(1) regression estimated via OLS using the variables in the VAR. The ratio of σ_i and σ_j in the formulas above controls for the possibility that variable i and j may have different scales. L is the lag length. The λ's are parameters set by researcher that control the tightness of the prior. An important question concerns the values of the hyper parameters that control the priors. Canova (2007) reports the following values for these parameters typically used in the literature: $\lambda_1 = 0.2$, $\lambda_2 = 0.5$, $\lambda_3 = 1 \text{ or } 2$, $\lambda_4 = 10^5$. In the BVAR model posterior coefficients matrix can be estimated analytically with using the following matrix formula. $\beta^* = (H^{-1} + \Sigma^{-1} \otimes X_t^{'} X_t)^{-1} (H^{-1} \tilde{b}_0 + \Sigma^{-1} \otimes X_t^{'} X_t \hat{b})$, where $\tilde{b}_0$ - is the vector of prior parameters, H is the diagonal matrix with prior variances on the diagonal, X is the vector of actual time series included in the model. The details of derivation Bayesian estimate is presented in Appendix 1. For example if we have two variables VAR(1) model then $\tilde{b}_0$ and H can be specified as follows:

$$y_t = c_1 + b_{11} y_{t-1} + b_{12} x_{t-1} + v_{1,t}$$
$$x_t = c_2 + b_{21} y_{t-1} + b_{22} x_{t-1} + v_{2,t}$$

$$\tilde{b}_0 = (c_1, b_{11}, b_{12}, c_2, b_{21}, b_{22})'$$

$$\tilde{b}_0 = (0,1,0,0,0,1)'$$

$$H = \begin{bmatrix} (\sigma_1 \lambda_4)^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & (\lambda_1)^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \left(\frac{\sigma_1 \lambda_1 \lambda_2}{\sigma_2}\right)^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & (\sigma_2 \lambda_4)^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \left(\frac{\sigma_2 \lambda_1 \lambda_2}{\sigma_1}\right)^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & (\lambda_1)^2 \end{bmatrix}$$

In the FAVAR model, the most important thing that we need to solve is to estimate the unobserved common factors (principal components). As a rule FAVAR model can be constructed in two steps: first is the factor extraction and the second step is the model estimation and forecasting. Factors can be extracted using three main approaches (Barhoumi et al (2008)), particularly static principal component as in Stock and Watson (2002), dynamic principal components estimated in the time domain as in Doz et al (2006 and 2007) and dynamic principal components in the frequency domain as in Forni et al (2000, 2004 and 2005). While the last two approaches are more sophisticated, studies have shown that they perform no better than the static principal component approach (Barhoumi et al 2008). Based on this finding in our paper for extraction of the principal components we use standard and widely used static principal component approach.

To determine the factors following the Stock-Watson approach, we proceed as follwos (Schumacher, 2007). We start with a collection a stationary $\mathrm{N} \times 1$ time-series vectors $\mathrm{x_t}$,

$$x_t = (x_{1t}, x_{2t}, \dots, x_{Nt})' \qquad \text{(t = 1,2,..., T).}$$

Let

$$\hat{\Gamma}_0 = \frac{1}{T}\sum_{t=1}^{T} x_t x'_t$$

Be an estimate of the variance-covariance matrix of the initial set of variables. The aim is to find r linear combinations of the time-series data

$$f_{i,t} = \hat{s}'_i x_t \qquad \text{(I = 1,2,...,r)}$$

That maximize the variance of the factors $\hat{s}'_i \hat{\Gamma}_0 \hat{s}_i$. Imposing the usual restriction that $\hat{s}'_i \hat{s}_i = 1$ and solving the optimization problem, we find that the matrix equation

$$\hat{\Gamma}_0 \hat{s}_i = \hat{\mu}_i \hat{s}_i$$

So that $\hat{\mu}_i$ denotes the i-th eigenvalue of $\hat{\Gamma}_0$ and $\hat{s}_i$ the $\mathrm{N} \times 1$ corresponding eigenvector. Thus, in order to estimate the principal components we need to find the eigenvalues and eigenvectors of $\hat{\Gamma}_0$, the variance matrix of the initial data. The number of extracted factors should also be sufficient to explain most of the variation in the initial variables. According to the static principal component approach the r eigenvectors corresponding to the first largest eigenvalues are the weights of the static factors.

Thus, having extracted factors we can begin the second step, that is estimation and forecasting step. For forecasting purposes, we use small scale VAR model containing variables of interest augmented by extracted principal components. Following the paper by Bernanke, Boivin and Eliasz (2003) the FAVAR model can be presented as follows.

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t$$

Where Yt vector of observable economic variable, F_t vector of unobservable economic variable extracted using static and dynamic approaches, $\Phi(L)$is lag polynomial of finite order, which may contain a prior restrictions as in the structural VAR. The error term ν_t is mean zero with covariance matrix Q. For the estimation of the unknown matrix of parameters the standard OLS method has been used.

Thus, above we present the basic principles of the three forecasting models that we are going to use for short-term forecasting of the Armenian's key macroeconomic indicators. Before presenting the forecasting results we need to present actual data series and specific software that has been used for estimation and forecasting through the whole paper.

3. Data

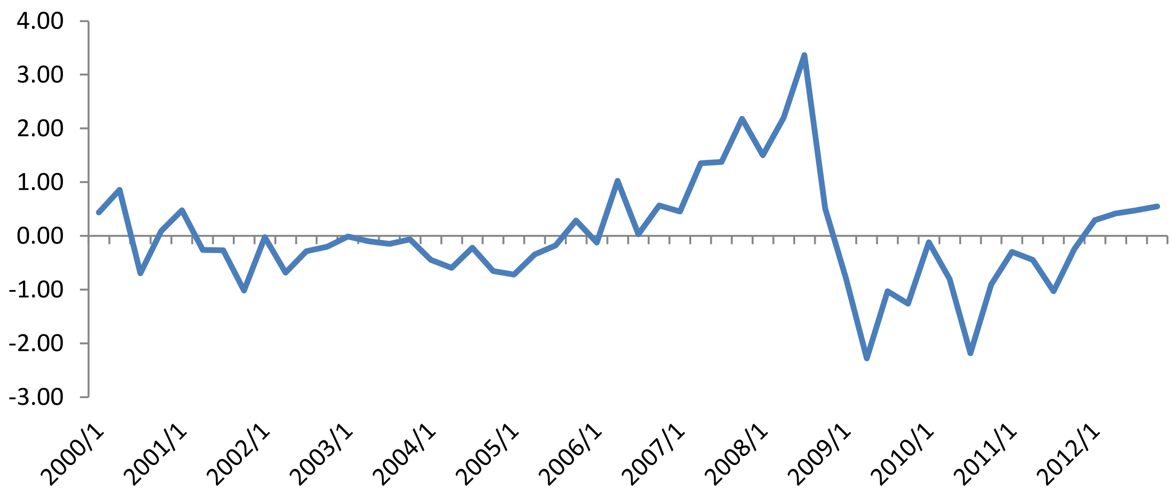
For the estimation of the small-scale VAR and BVAR models we use the following three main macroeconomic indicators, particularly real GDP growth, inflation and nominal short-term interest rate. Our data set consist of quarterly time series starting from 2000q1 to 2012q4, in total 52 observations for each variable. Now let's present the dynamics of each mentioned variables in more detail.

In order to obtain real GDP growth the following preliminary procedures have been done, first the initial level of the real GDP has been logged and then seasonally adjusted. Using seasonally adjusted data the long-run trend dynamics have been calculated (using Hodrick-

Prescott filter). Taking differences between seasonally adjusted and Hodrick-Prescott filtered data we obtain trend-gap data. Then de-trended data have been standardized to have zero mean and standard deviation equal to one. The dynamics of the standardized real GDP growth is presented in the graph 1.

Graph 1

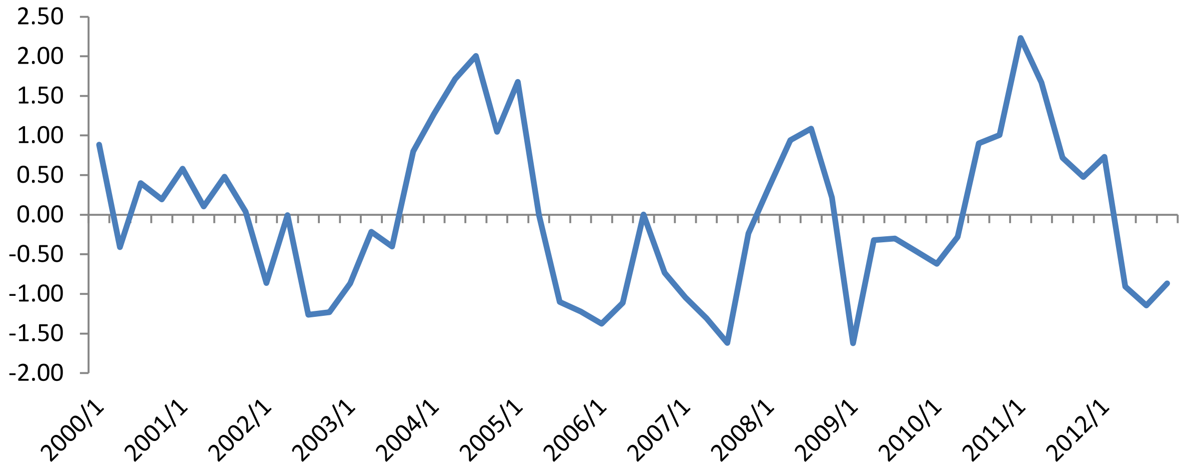
Growth rate of the standardized GDP (in % - th with respect to long-run trend dynamics)



The next important indicators that we wish to incorporate in the small scale VAR and BVAR forecasting model is inflation rate. As a rule for the inflation we use CPI index. This index have been logged and seasonally adjusted. Then using seasonally adjusted data series the long-run dynamics have been calculated (using Hodrick-Prescott filter). Taking differences between seasonally adjusted and Hodrick-Prescott filtered data we obtain trend-gap data. Then de-trended data have been standardized to have zero mean and standard deviation equal to one. The dynamics of the standardized inflation is presented in the graph 2.

Graph 2

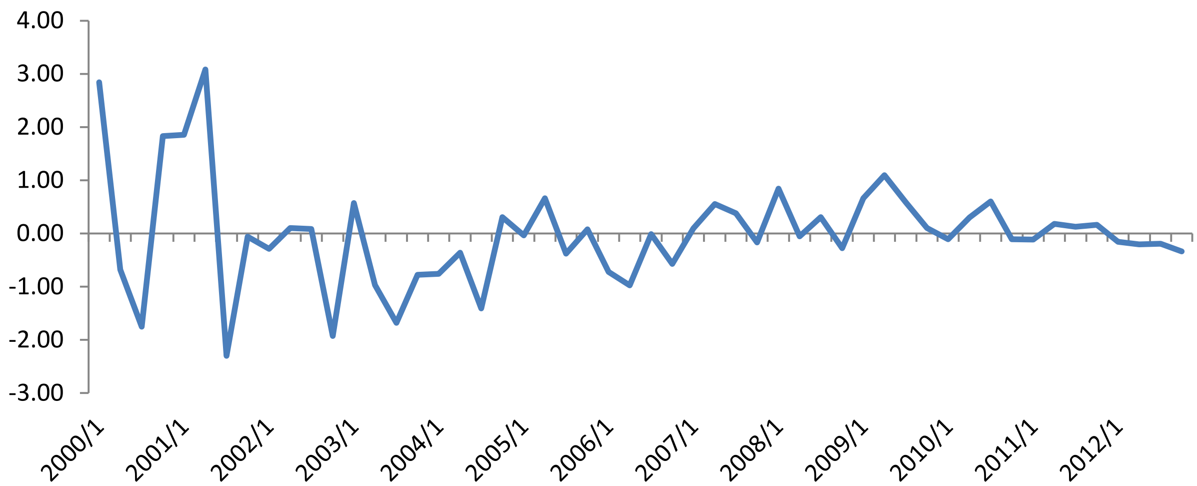
Inflation rate (in % - th with respect to long-run trend dynamics)



The third key macroeconomic variable is 360 days deposits nominal interest rate. Taking differences between actual and Hodrick-Prescott filtered data we obtain 360 days deposits nominal interest rate trend-gap data. Then de-trended data have been standardized to have zero mean and standard deviation equal to one. The dynamics of the standardized 360 days deposits nominal interest rate trend-gap data is presented in the graph 3.

Graph 3

Standardized 360 days deposit nominal interest rate dynamics (percentage points)



Relating with FAVAR model in addition to above mentioned variables we will use other macroeconomic variables. These additional variables we use to extract principal components, which from theoretical point of view should improve the forecast accuracy. This set of additional variables comprising information on national accounts, consumer price indexes, exchange rate and financial and monetary policy indicators. The sample periods spans from 2000q1 to 2012q4. The data are collected from the Central Bank of Armenia, the National Statistical Agency (NSA). The name and other important characteristics for the mentioned variables are shown in the appendix 2.

In the current working paper all calculations and forecasting experiments have been done with specially created software called Next_XL.xla. This software has been developed by the author of the current paper. For developing Next_XL.xla (which is actually Excel Add-Ins) have been used two powerful object-oriented programming languages such as Visual C# and Visual Basic. All needed functions have been created with using Visual C# (Visual Studio 2010 Professional), while for creating the user friendly interface have been used Visual Basic for Application (VBA) capabilities. For interfacing C# with Excel have been used XL DNA (written in C#) package.

NextXL.xla Add-Ins capabilities are:

1. Hodrick-Prescott filter,
2. Temporal disaggregation methods (Boot-Faibes-Lisman, Stram-Way, Low-Pass Interpolation),
3. Curve fitting and forecasting (linear, exponential, logarithmic, power),
4. Seasonal adjustment with using S(nxm) seasonal filter,
5. Linear regression analysis (OLS, IRLS),
6. Vector autoregression estimation and forecasting (VAR),
7. Bayesian vector autoregression and forecasting (BVAR)
8. Factor Augmented VAR estimation and forecasting (FAVAR),
9. Recursive and Rolling regression analysis,
10. Creating Fan Chart with using Bank of England methodology

This software from time to time is updated and we periodically add new computational and econometric algorithms.

4. Experimental design

To conduct out-of-sample forecast experiments, we use both recursive and rolling regressions. The in sample data period spans from 2000q1 to 2009q4 (40 observations, ten years), while the out-of-sample period is 2009q1 – 2012q4 (12 observations, three years).

The recursive simulation scheme proceeds as follows: First we estimate the models (VAR, BVAR, FAVAR) using subsample 2000q1 to 2009q4 (40 observations) and generate 1 to 4 steps–ahead forecasts. Then we increase the sample size by one (41 observations) and generate again 1 to 4 steps-ahead forecasts. We continue increasing the sample size by one and generating 1 to 4 steps-ahead forecast until the sample size is 48 observations. Then we increase the sample size by only one (49 observations), but only generate 1 to 3 steps-ahead forecasts (since we only have 52 observations in total). We continue increasing the sample size until we have 51 observations in the sample, in which case we can only compute the 1 step-ahead forecast. In a such a way we obtain twelve 1-step ahead forecasts, eleven 2-steps-ahead forecasts, ten 3-steps-ahead forecasts and finally nine 4-steps ahead forecasts.

While in the recursive scheme the sample size increase by one quarter at each step, in the rolling regressions we fix the sample size at 40 observations. As in the recursive regression case the forecast horizon is 1-4 quarters. The first estimation sample starts in 2000q1 and end in 2009q4, so that the forecasting quarters are 2010q1 – 2010q4. The second sample starts in 2000q2 and ends in 2010q1, with forecasting quarters are 2010q2-2011q1. We continue in this way until the 2002q4-2012q3., in which case we can only compute 1 step-ahead forecast, since we have not observations after 2012q4.

The number of forecasts is the same in both methods. The recursive scheme has the advantage of using all the data available at a certain point of time, but the rolling forecast scheme is useful if a structural change occurs in the sample (Schumacher 2007).

Next, we use the out-of-sample forecasts from both recursive and rolling regressions to compute the corresponding Root Mean Squared Errors, for each of the four forecasting horizons. More concrete, let us denote the out-of-sample period by T^* (in our case, $\mathrm{T}^* = 12$, namely 2010q1-2012q4), and the forecast horizon by h $(\mathrm{h} = 1,2,3,4)$. Then the RMSE is calculated from

$$RMSE_{ih} = \sqrt{\frac{1}{T^{*}-(h-1)}\sum_{t=1}^{T^{*}-(h-1)}(\widehat{y_{it}} - y_{it})^2},$$

Where, $\mathrm{y_{it}}$ denotes the actual value of the i-th dependent variable (in our case we have three dependent variables and therefore I = 1,2,3), $\widehat{\mathrm{y_{it}}}$ is the forecasted value of the i-th dependent variable, and $\mathrm{RMSE}_{\mathrm{ih}}$ is the root mean squared error calculated for the i-th dependent variable and the h-th forecast horizon.

5. Forecast Results

Having actual macroeconomic time series now we are able to conduct estimation and forecasting experiments with using the following three competing models:

VAR: Unrestricted Vector Autoregressive Model,

BVAR: Bayesian Vector Autoregressive Model (Minnesota prior). In the BVAR model we use the following parameters, particularly overall tightness w = 0.1, lag decay d = 1.

FAVAR: Factor augmented vector autoregressive model. As it was mentioned In the FAVAR model the principal components were calculated using static principal components approach.

For all the above mentioned models we consider only one lag model. This is because including more lags (let say 2, 3 or 4) failed to improve the forecasting performances, especially performances of the FAVAR model. In such case FAVAR model is becoming over identified and therefore from practical point of view cannot be used for forecasting purposes.

We now compare and discuss the 1-4 out of sample RMSEs of the above mentioned models. The results of calculated RMSE indices are presented in the tables 1-2.

Table 1. RMSE (2010q1 – 2012q4): Recursive regression

GDP growth	1	2	3	4	***Average***
VAR	0.69	0.86	0.81	0.53	0.72
BVAR	0.76	0.99	0.87	0.77	0.85
FAVAR	0.60	0.68	0.66	0.53	***0.62***
Inflation	1	2	3	4	***Average***
VAR	0.78	1.12	1.32	1.39	***1.15***
BVAR	0.77	1.17	1.49	1.72	1.29
FAVAR	0.92	1.23	1.38	1.36	1.22
Interest rate	1	2	3	4	***Average***
VAR	0.26	0.28	0.28	0.18	***0.25***
BVAR	0.27	0.35	0.30	0.19	0.28
FAVAR	0.36	0.27	0.33	0.30	0.32

Table 2. RMSE (2010q1 – 2012q4): Rolling regression

GDP growth	1	2	3	4	***Average***
VAR	0.70	0.86	0.81	0.53	0.73
BVAR	0.68	0.83	0.76	0.47	***0.68***
FAVAR	0.60	0.77	0.75	0.61	***0.68***
Inflation	1	2	3	4	***Average***
VAR	0.77	1.11	1.32	1.39	1.15
BVAR	0.75	1.07	1.27	1.36	***1.11***
FAVAR	0.93	1.21	1.32	1.33	1.20
Interest rate	1	2	3	4	***Average***
VAR	0.28	0.30	0.30	0.17	***0.26***
BVAR	0.26	0.33	0.32	0.17	0.27
FAVAR	0.44	0.26	0.38	0.41	0.37

Real GDP growth rate: The FAVAR model is outperforms VAR and BVAR models producing the lowest minimum average RMSEs (RMSE for recursive regression is 0.62, while RMSE for rolling scheme is 0.68).

Inflation: For the recursive regression scheme VAR outperforms both BVAR and FAVAR models producing the lowest minimum average RMSEs (1.15). For the rolling regression the

BVAR (w=0.1, d=1) outperforms both VAR and FAVAR models producing the lowest minimum average RMSEs (averaged minimum RMSE is 1.11).

Short-term nominal interest rate: The VAR model outperforms all the other models (averaged minimum RMSE = 0.25 for recursive scheme and RMSE for rolling scheme is 0.26).

Thus, from the above presented tables we see that there is not one specific model that is able at the same time to give the better forecast results for all macroeconomic variables included in the model. To summarize we can say that one method is better for example for the real GDP growth (FAVAR), while other methods are better for inflation (VAR, BVAR) and third method is better for nominal interest rate (VAR).

The next question is that whether two competing models generate the same forecasts. In order to evaluate the models forecast accuracy we perform the across model test between the VAR, BVAR and FAVAR models. The across model test is based on the well-known Diebold-Mariano (1995) test statistic. This test tests whether the forecast errors of two models are significantly different from each other. We compare the forecast errors of the different models with the forecast errors of the model with lowest RMSE. This means that we test whether the forecast of the “best” model are better than the forecasts of the remaining model. The main idea of the Diebold-Mariano statistics can be explained as follows.

Let say that $\{e_t^i\}_{t=1}^{T}$, denote the associated errors from the alternative models and $\{e_t^d\}_{t=1}^{T}$, denote the forecast errors from the alternative model. Then we can define the following statistic $s = \frac{l}{\sigma_l}$, where l is the sample mean of the loss obtained by using $l_t = \left(e_t^i\right)^2 - \left(e_t^d\right)^2$ and where σ_l is the standard error of l.The s statistic is assimptotically distributed as a standard normal random variable and can be estimated under the null hyphothesis of equal forecast accuracy, i.e. l =0. The results of the Diebold-Mariano (DM) tests are shown in the below tables.

Table 3. DM statistics (2010q1 – 2012q4): Recursive regression

Real GDP growth: FAVAR versus	1	2	3	4
VAR	-0.35	-0.66	-0.30	0.00
BVAR	-0.14	-0.66	-0.21	-0.35
Inflation: VAR versus	1	2	3	4
BVAR	0.02	-0.05	-0.16	-0.26
FAVAR	-0.37	-0.15	-0.09	0.03
Interest rate: VAR versus	1	2	3	4
BVAR	-0.09	-0.81	-0.35	-0.13
FAVAR	-0.52	0.09	-0.78	-1.24

Table 4. DM statistics (2010q1 – 2012q4): Rolling regression

Real GDP growth: BVAR versus	1	2	3	4
VAR	-0.04	-0.03	-0.04	-0.11
FAVAR	0.14	0.07	0.01	-0.21
Inflation: BVAR versus	1	2	3	4
VAR	-0.04	-0.05	-0.04	-0.06
FAVAR	-0.31	-0.16	-0.05	0.04
Interest rate: VAR versus	1	2	3	4
BVAR	0.15	-0.36	-0.34	0.00
FAVAR	-0.99	0.39	-0.83	-2.41

The DM statistics presented in the tables 4 and 5 allow us to try and reject the hypothesis that two different models generate the same forecasts. IF the DM statistic is larger (in absolute value) than some critical value (say 1.96 at the 95% level), then we reject the null hypothesis and conclude that the two models or forecasting schemes are different in the sense that they produce statistically different forecasts.

The DM statistics actually tests if the forecast from let say FAVAR model (real GDP growth) is significantly different from the forecasts from some other competing models (VAR, BVAR). As we can see from the tables 3 and 4we cannot reject the hypothesis that the forecast results from the different models are not statistically different. In other words we accept the hypothesis that the forecasts from different models are the same. Based on the Armenian's actual macroeconomic variables we can conclude that there is not strong evidence to prefer one model over the other model. All models are equally can be used for the forecasting purposes and final forecast can be obtained by averaging the different forecasts.

6. Conclusions

Forecasting plays important role in the monetary policy decision making. Policy makers must know what the future is likely to be, in order to make right moves. In this paper we compared three popular forecasting models, namely VAR, BVAR and FAVAR, using out-of-sample recursive and rolling forecast regression schemes. The three models were evaluated based on the RMSE criteria for 1-4 quarters ahead forecast horizons. The ex-post results show that there is not one specific model that gives most better results for any macroeconomic variables (in our case real GDP growth, inflation and nominal interest rate). One particular method gives better forecast for real GDP growth, other method gives better results for inflation and third method gives accurate results for nominal interest rate. At the same time when we apply Deubold-Mariano test then differences in forecasts generated by the various models are not statistically significant. Thus we can conclude that a comparison of the VAR, BVAR and FAVAR algorithms does not reveal significant differences in forecasting performance. There is not sufficient evidence to prefer one over the other model. Hence all mentioned models can be equally useful for forecasting purposes of the macroeconomic variables.

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Appendix 1

$$
\begin{gathered}
(\beta - m)' H^{-1} (\beta - m) + h(y - X\beta)'(y - X\beta) = \\
\beta' H^{-1}\beta - \beta' H^{-1} m - m' H^{-1}\beta + m' H^{-1} m + hy' y - y' hX\beta - h(X\beta)' y \\
+ h(X\beta)'(X\beta) = \beta'(H^{-1} + h(X'X))\beta - 2\beta'(H^{-1} + h(X'X))^{-1}(H^{-1}m + hX'y) + \\
((H^{-1} + h(X'X))^{-1}(H^{-1}m + hX'y))'(H^{-1} + h(X'X))((H^{-1} + h(X'X))^{-1}(H^{-1}m + hX'y)) + hy'y \\
- \beta' H^{-1} m - ((H^{-1} + h(X'X))^{-1}(H^{-1}m + hX'y))'(H^{-1} + h(X'X))((H^{-1} + h(X'X))^{-1}(H^{-1}m + hX'y)) = \\
(\beta - (H^{-1} + h(X'X))^{-1}(H^{-1}m + hX'y))'(H^{-1} + h(X'X)) + (\beta - (H^{-1} + h(X'X))^{-1}(H^{-1}m + hX'y)) + Q
\end{gathered}
$$

Appendix 2

Series	Transformation	SA
National Accounts		
GDP at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Private consumption at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Government consumption at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Gross Capital Formation at average annual prices of 2005, mln drams	Log and Δ	Yes
Export of goods and services at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Import of goods and services at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Value added of industry at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Value added of agriculture at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Value added of construction at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Value added of services at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Value added of trade and catering at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Value added of transport and communication at average annual prices of 2005, mln. Drams	Log and Δ	Yes
Net current transfers from abroad, mln drams	Log and Δ	Yes
GNDI per capita, dram	Log and Δ	Yes
Prices and exchange rates		
Consumer price index (CPI) with respect to the previous period, %	Log and Δ	Yes
Food price index, end of current period over the end of previous period, %	Log and Δ	Yes
Nonfood price index, end of current period over the end of previous period, %	Log and Δ	No
Service price index, end of current period over the end of previous period, %	Log and Δ	No
Industrial products price index, with respect to the previous period, %	Log and Δ	No
Price index in construction, with respect to the previous period, %	Log and Δ	No
Index of cargo transportation tariffs, with respect to the same period of the previous year,%	Log and Δ	No
Armenian's dram per US dollars, period average	Log and Δ	No
Employment and wages		
Employed, ths people	Log and Δ	No
Economically active population, ths people	Log and Δ	No
Average monthly nominal wages, AMD	Log and Δ	Yes
Monetary aggregates		
Money in circulation, mln. drams, end of period	Log and Δ	Yes
Monetary base, mln. drams, end of period	Log and Δ	Yes
Broad money, mln. drams, end of period	Log and Δ	Yes
Deposits interest rate in local currency, %	Log and Δ	No

Deposits interest rate in US dollars, %	Log and Δ	No
Local currency loans interest rate, %	Log and Δ	No
US dollars loans interest rate, %	Log and Δ	No
Central bank interbank interest rate, %	Log and Δ	No
Central bank refinancing interest rate, %	Log and Δ	No
Loans and Deposits		
Total credit to economy, mln. drams, end of period	Log and Δ	No
Credit to firms, mln. Drams, end of period	Log and Δ	No
US dollars credit to firms, mln. Drams, end of period	Log and Δ	No
Credit to households, mln. Drams, end of period	Log and Δ	No
US dollars credit to households, mln. Drams, end of period	Log and Δ	No
Total deposits in the banking system, mln. drams, end of period	Log and Δ	No
Armenian drams deposit in the banking system, mln. drams, end of period	Log and Δ	No
US dollars deposit in the banking system, mln. drams, end of period	Log and Δ	No