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Do BVAR Models Forecast Turkish GDP Better Than UVAR Models?

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Author's contribution

The sole author designed, analyzed and interpreted and prepared the manuscript.

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ABSTRACT

Forecasting gross domestic product (GDP) is crucial for developing macroeconomic policies and managements. Vector autoregression models are one of the commonly used multivariate time series models for forecasting. The Bayesian vector autoregression models are used to avoid problems of multicollinearity and over parameterization that occur in general with the use of vector autoregression models. The aim of this paper is to forecast Turkish GDP using Bayesian vector autoregression models with quarterly data from 2005q4 to 2013q3 and compare the results with unrestricted vector auto regression models. The out-of-sample forecasting accuracy of these models are compared with unrestricted vector autoregression models. The results confirm the accuracy of Bayesian vector auto regression models for forecasting GDP. On the other hand unrestricted vector autoregressionmodels are most accurate for exchange rates except the first quarter and for interest rate in the first two quarter forecasts.

Keywords: Vector autoregression; forecasting; bayesian methods; forecast accuracy.

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1. INTRODUCTION

Macroeconomic forecasting is one of the primary objects of multivariate time series models, including vector autoregressions (VAR), factor augmented autoregressions additionally time-varying parameter forms of these models. Most research subjects of interest to empirical macroeconomists involve several variables and, thus, must be processed using multivariate time series methods. VAR models have been among the most popular since proposed and developed by Sargent [1], Sims [2] as a solution to the large-scale macroeconometric models. Although these models capture the linear interdependencies among time series by not requiring as much knowledge about the influences to a variable as opposed to simultaneous equations, they have a large number of parameters and so over-parameterization problems may arise (Si [3]). Bayesian vector autoregression (BVAR) model, which shrink parameters by including relevant prior beliefs, has become increasingly popular as a way of getting over these problems (Litterman [4]; Doan, Litterman and Sims [5]; Litterman [6]; Koop and Korobilis [7]). The Bayesian approach combines prior beliefs with data and suggests an objective procedure for blending beliefs and data for economic forecasting. In structural models, over fitting is tried to avoid by reducing the number of parameters, contrary to this in BVAR models lots of coefficients are allowed to be in the model but the influence of the data on them is reduced (Todd [8]). The BVAR models allow for flexible modeling and enhanced forecast performance in high dimensions (Huang [9]).

Forecasting macroeconomic variables is crucial for developing appropriate macroeconomic policies. Macroeconomic policy determination requires a compensating of risks and uncertainties. Although economic policies are not based upon just economic forecasts, risk decisions in the economic outlook and policy validity take an important place. Governments use macroeconomic forecasts in order to evaluate and develop economic policy. GDP, demonstration of wealth, is a measure of output which ensures macroeconomic management, so GDP forecasts are capital importance. This study focuses on the comparison of out-of-sample forecasts of GDP by using BVAR and unrestricted vector autoregression (UVAR) models. The indicators that prove the mechanism of the whole economy such as monetary aggregate, unemployment rate, exchange rates and interest rates are included in the VAR models. The model which has the best forecast success is chosen in order to forecast Turkish GDP. The BVAR models are estimated with various alternative values of the prior distribution's hyperparameters in the literature and their values are determined minimizing the forecast errors. As far as we know, BVAR modelling has not been used for the macroeconomic variables of the Turkish economy before and this is the only study that compares the forecasting successes of BVAR and VAR models for macroeconomic variables in order to GDP forecasting.

The paper is organised as follows: The next section is including the literature review of the BVAR framework, methodology takes part in the third section, data and empirical results are presented in the fourth section. The final section provides conclusions.

2. LITERATURE REVIEW

There is a growing literature on macroeconomic variables using BVAR models for forecasting in the literature. Litterman [4]; [6] and Todd [8] are among the first ones suggesting the use of these models. When we focus on GDP forecasting, Andersson and Karlsson [10], Caraiani [11], Spulbăr, Niţoi and Stanciu [12], Giannone, Lenza and Primiceri [13] and Österholm and Stockhammar [14] can be regarded as in the first group. Andersson and Karlsson [10] forecast U.S. GDP growth using BVAR models and compare the accuracy with autoregressive (AR) models. They find that overall the forecast combinations perform very well. Caraiani [11] forecasts Romanian GDP using BVAR, ordinary least squares (OLS) and UVAR models. The results show that the BVAR models outperforms the standard models. Spulbăr, Niţoi and Stanciu [12] use BVAR models with different priors in order to analyse the relationships between the macroeconomic variables in Romania. Giannone, Lenza and Primiceri [13] forecast the GDP, GDP deflator and federal funds rate using BVARs with small, medium and large number of variables and compare the results with VAR models. They find that BVARs' forecasting accuracy improve with the size of the model and the largest BVAR produces better one step ahead forecast. Österholm and Stockhammar [14] study the effects of euro area shocks on GDP growth in Sweden using a BVAR model.

The studies that aspire the forecasting of inflation rate and unemployment rate can be regarded as in the second group. Kadiyala and Karlsson [15] estimate U.S. forecasting model of Litterman [6] and also an unemployment rate forecasting model for Sweden using BVAR with different priors in order to examine their forecasting performance. As a result of the forecasting comparisons they report that OLS and the model with diffuse prior give the worst forecasts. Robertson and Talman [16] forecast unemployment rate, the inflation rate and the GDP rate using VAR, restricted VAR and BVAR models with Litterman [6]and also Waggoner and Zha [17] priors. They mention that restricted VAR performs very well for the inflation and GDP growth. Kenny, Meyler and Quinn [18] estimate BVAR models for forecasting Irish inflation. They confirm that Bayesian techniques improve forecasting performance. Canova [19] forecasts inflation rates in Italy using two BVAR models with different priors and compare the forecasting accuracy with autoregressive integrated moving average (ARIMA) and UVAR models. The findings show while UVAR performs poorly, the BVAR model with default prior choices is better than UVAR but not better than ARIMA model. The BVAR model with optimally chosen priors performs the best. Adolfson, Andersson and Lindé [20] compare the forecasting performances of BVAR and dynamic stochastic general equlibrium (DSGE) models for inflation and interest rate with the central bank of Sweden forecasts in terms of the actual forecasts and root mean square errors (RMSE). They have shown that BVAR and DSGE models have as good inflation forecasting performances as central banks procedures. Huang [9] estimate BVAR models for forecasting China's inflation and output growth and examine how different priors affect the results. They suggest that the Minnesota prior of Littermann [6] is the best among all priors used.

The background studies can be considered generally according to use BVAR models for macroeconomic forecasting. Cicarelli and Rebucci [21] estimated BVAR models with different priors for European monetary system. Smets and Wouters [22] estimate a DSGE model for the U.S. economy and compare the out-of-sample forecasts with VAR and BVAR models. They find that the DSGE model has considerably better forecasts than both the VAR and BVAR model over longer horizons up to three years. The BVAR model performs worse than the simple VAR model at longer horizons. Korobilis [23,24] estimate large BVAR models with Bayesian model selection methods for forecasting macroeconomic variables. Caldara [25] assess the effects of fiscal policy shocks using BVAR models. Koop, Pesaran and Smith [26] examine the forecasting performances of small, medium and large BVARs with alternative priors using a U.S. macroeconomic data and compare with the factor methods ultimately he finds that BVAR models forecast better than factor methods. Gürkaynak, Kısacıkoğlu and Rossi [27] compare the forecasting accuracy of Smets and Wouters [22] DSGE models with AR, VAR, BVAR and random walk models. The results show that none of the forecasting models is efficient and there is no single best forecasting method. While DSGE models have better forecasting accuracy at long horizons for output growth, simple AR models forecast better at short horizons. Bańbura, Giannone and Reichlin [28] show that BVAR model is appropriate for large dynamic models and their forecasting performance for small monetary models can be improved by adding additional macroeconomic variables. Auer [29] analyzes the impact of monetary policy shocks in the U.S. and Canada using BVAR, based on the approach proposed by Bańbura, Giannone and Reichlin [28]. Deryugina and Ponomarenko [30] estimate large BVAR with the 14 major price and monetary macroeconomic indicators in Russia. Giannone et al. [31] estimate BVAR models for the Euro area that captures the dynamic inter-relationships between the main components of the harmonized index of consumer prices and their determinants. The model achieves accurate conditional and unconditional forecasts in real-time. They also find a significant pass-through effect of oil-price shocks on core inflation and a strong Phillips curve at the time Great Recession. Apart from these studies, Chandramowli and Lahr [32] forecast long-term electricity demand for New Jersey using autoregressive moving average with exogenous variables, VAR and BVAR models. The VAR model gives the best forecasting results for electricity demand. Crompton [33] forecast China's energy consumption using BVAR methodology. Si [3] examines the effects of credit derivatives on bank credit supply by BVAR model.

3. METHODOLOGY

The VAR(p) model can be denoted as,

$$y_t = a_0 + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t \quad (1)$$

where y_t is an $mx1$ vector containing observations on m time series variables for $t = 1,2,\ldots,T$, a_0 is an $mx1$ vector of intercepts, A_j is an mxm matrix of coefficients with the p maximum number of lag and ε_t is an $mx1$ vector of errors, in other words vector of exogenous shocks. ε_t is assumed to be i.i.d. $N(0, \Sigma)$. Exogenous variables or deterministic terms can be added to the VAR if required (Koop and Korobilis [34]).

If VAR model is expressed in terms of the matric-variate Normal distribution Y is defined to be a Txm matrix which stacks T observations on each dependent variable in columns next to one another. The matrix notation will be,

$$x_t = \left[1\; y_{t-1} \cdots y_{t-p}\right], \quad X = \begin{bmatrix} x_1 \\ \cdot \\ \cdot \\ x_T \end{bmatrix}, \quad B = \begin{bmatrix} a_0 \\ A_1 \\ \cdot \\ \cdot \\ A_p \end{bmatrix} \tag{2}$$

and $\beta = vec(B)$. Model (1) can be written as,

$$y = (I_m \otimes X)\beta + \varepsilon, \quad \varepsilon \sim N(0, \Sigma \otimes I_m) \tag{3}$$

In large dimensional systems, these models generate inaccurate out-of sample forecasts because of the large estimation uncertainty of the parameters (Giannone, Lenza and Primiceri [13]). Litterman [4] suggests to combine the likelihood function with some informative prior distributions. The likelihood function can be demonstrated in two parts as distribution for β given Σ and Σ^{-1} has a Wishart distribution,

$$\beta|\Sigma, y \sim N\left(\hat{\beta}, \Sigma \otimes (X'X)^{-1}\right) \tag{4}$$

and

$$\Sigma^{-1}\big|y \sim W(S^{-1}, T-K-M-1) \tag{5}$$

where $\hat{\beta} = vec(\hat{B})$ and $\hat{B} = (X'X)^{-1}X'Y$ is the OLS estimate of B and S can be defined as,

$$S = \left(Y - X\hat{B}\right)'\left(Y - X\hat{B}\right) \tag{6}$$

In BVAR estimation different priors can be used and the choice of priors is debated. Here we give place to the Litterman/Minnesota, Sims-Zha Normal-Wishart, Koop and Korobilis (Ko-Ko) Minnesota priors.

Litterman [6] states his prior, in other words Minnesota prior, according to three features of macroeconomic time series. Macroeconomic time series feature trend, more recent values of series usually contain more information on its current value of the series than past values, past values of a given variable contain more information on its current state than past values of other variables. If these regularities are applied, then (1) becomes a multivariate random walk (Cicarelli and Rebucci [21]). Sims and Zha [35] assume the prior conditional covariance matrix of the coefficients follows the same pattern that Litterman gave to the prior covariance matrix on reduced form coefficients. Sims and Zha [35] propose the conditional standard deviation of the coefficient on lag l of variable j in equation i given by,

$$\frac{\lambda_0 \lambda_1}{\sigma_j l^{\lambda_3}} \tag{7}$$

where λ_0 controls the tightness of beliefs on Σ, λ_1 controls overall tighteness of beliefs around the random walk prior and λ_3 controls the rate at which prior variance shrinks with increasing lag length, $\sigma_1, \ldots, \sigma_m$ vector of parameters are the scale factors. Sims and Zha [35] also suggest two extra dummies which are for unit roots (μ_5) and trends (μ_6). The natural joint prior for normal data is the Normal-Wishart distribution in the case that fixed and diagonal variance-covariance assumption is relaxed.

In Ko-Ko Minnesota/Litterman prior Σ is assumed to be known. Koop and Korobilis [36] indicate the prior covariance matrix V_0 as a diagonal matrix with the $\mathrm{v}_{\mathrm{ij,l}}$ elements $(l = 1, \ldots, p)$

$$v_{ij,l} = \begin{cases} \dfrac{\mathrm{a}_1}{\mathrm{p}^2} \text{ for coefficients on own lags} \\ \dfrac{(\mathrm{a}_2\sigma_\mathrm{i})}{(\mathrm{p}^2\sigma_\mathrm{j})} \text{ for coefficients on lags of variable } \mathrm{i} \neq \mathrm{j} \\ \mathrm{a}_3\sigma_\mathrm{i} \text{ for coefficients on exogenous variables} \end{cases} \tag{8}$$

where σ_i^2 is the *i* th diagonal element of Σ. These hyperparameters are related to the parameters of Sims and Zha [35] as $\mathrm{a}_1 = \lambda_1$, $\mathrm{a}_2 = \lambda_1\lambda_2$, $\mathrm{a}_3 = (\lambda_0\lambda_4)^2$. The conditional posteriors are derived,

$$\beta|\hat{\Sigma}, Y \sim N(\bar{\beta}, \bar{\mathrm{V}}) \tag{9}$$

in here the estimator for β looks like multivariate least square estimator,

$$\overline{V} = \left(V_0^{-1} + \left(\widehat{\Sigma}^{-1} \otimes X'X\right)\right)^{-1} \tag{10}$$

$$\bar{\beta} = \overline{V}\left(V_0^{-1}B_0 + \left(\widehat{\Sigma}^{-1} \otimes X'X\right)\widehat{B}\right) \tag{11}$$

4. DATA AND EMPIRICAL RESULTS

In this study, the indicators that prove the mechanism of the whole economy such as monetary aggregate, unemployment rate, exchange rates and interest rates are included in the VAR models in order to compare out-of-sample forecasts of GDP by using BVAR and UVAR models. GDP and monetary aggregate (M2) are at 2010 constant prices, unemployment rate is percentage of labor force, exchange rates are received as dollars/turkish lira, interest rate is deposit-oriented interest rate yield on three months (The unemployment data is downloaded from the oecd online statistics, the other series are completely avaliable in the central bank of turkey online statistics). All series are seasonally adjusted. Meanwhile, in order to reduce heteroscedasticity, all variables are transformed into natural logarithms. Although the five series have trend behaviour, the variables are not pre-transformed to achieve stationarity as BVAR framework allows the presence of trend in the series. The in-sample period contains quarterly data from 2005q4 to 2013q3 because of the availability of unemployment rate is from 2005q4. After estimating models within this period four step ahead forecasts are also made. RMSEs are used to evaluate the performance of each model.

The literature has suggested that improvement in forecasting performance can be obtained byimposing additional priors that constrain the sum of coefficients (Sims and Zha [35]; Robertson and Tallman [16]). In this study BVAR models are estimated with Ko-Ko Minnesota/Litterman prior using different hyperparameters, in order to obtain more robust results we also estimate the models using Sims and Zha prior with different hyperparameters. Doan [37] suggests the priors should be chosen as symmetric with an overall tightness of $\lambda_1 = 0.2$ and the relative weight $\lambda_2 = 0.5$ for small sized models. Caraiani [11] estimate BVAR models with the hyperparameters of $\lambda_1 = 0.1$ and $\lambda_2 = 0.5$ with the lag decay of 1 and 2. The relative weight is taken as 0.005 in Korobolis [24], Kadiyala and Karlsson [15]. Sims and Zha [35] suggest $\lambda_0 = 1$, $\lambda_1 = 0.2$, $\lambda_3 = 1$ and 1 for unit root and trend dummies. Hyperparameters are set following the approaches in Sims and Zha [35], Doan [37], Österholm and Stockhammar [14], Kadiyala and Karlsson [15], Canova [19], Korobolis [24] and also this informations are combined with the data features.

After specifying hyperparameters BVAR models with Minnesota (0.1,0.5,1), Minnesota (0.2,0.5,1), Minnesota (0.1,0.5,2), Minnesota (0.2,0.5,2), Minnesota (0.2,0.005,1), Minnesota (0.1,0.005,1), Minnesota (0.2,0.005,2), Minnesota (0.1,0.005,2), Minnesota Normal-Wishart (1,0.1), Minnesota Normal-Wishart (1,0.2), Minnesota Normal-Wishart (1,0.05), Sims-Zha Normal Wishart (1,0.2,1,1), Sims-Zha Normal Wishart (1,0.6,1,1), Sims-Zha Normal Wishart (1,0.1,1,5), Sims-Zha Normal Wishart (10,2,1,5) are estimated. For each VAR specification lag length is specified using LR test. The hyperparameter that states prior mean is chosen 1 in the all Minnesota priors because the series have unit roots. An UVAR model with the 2 lag length is also estimated for the comparison of forecasting accuracy of the models. All series are seasonally adjusted and in order to reduce heteroscedasticity, all variables are transformed into natural logarithms. The difference operator is applied to variables to provide stationarity. Each model's four step forecast performances are evaluated by RMSEs which are presented in Table 1 and in Table 2.

The RMSEs of the forecasted models in Table 1 show that classical UVAR model is clearly dominated by BVAR models for each step of GDP forecasts. Only in the second quarter the model with Sims-Zha Normal Wishart (1,0.1,1,5) prior gives the best result, in the other quarters even though different prior usage changes the model goodness, the model with Minnesota priors gives better results and for the one step ahead forecast the model with Minnesota (0.1,0.005,2) prior gives the best forecasting performance with the minimum RMSE. As the aim of this study is to forecast GDP this model will be used for forecasting. The results confirm the accuracy of forecasting using BVAR models for GDP. This provision is also valid for monetary aggregate forecasts. In Table 1, it is seen that BVAR models generate better forecasts than UVAR model. On the other hand the forecasting results for UVAR models are most accurate for exchange rate except the first quarter and for interest rate in the first two quarter forecasts as this results are seen from Table 2. While BVAR models give the minimum RMSEs for the first three step forecasts of unemployment rate, UVAR model is the best for last quarter.

In order to forecast quarterly GDP in the short run the best BVAR model is used for forecasting. The actual GDP for the period between 2005Q4-2014Q3 and the forecasted GDP from 2013Q4 to 2014Q3 can be seen from Fig. 1. The acceleration after 2013Q3 and the decline before 2014Q3 is clearly seen from the actual values. Even if the forecasted values not exactly fit the actual values, it can be said that forecasted values reflect the GDP tendency well.

Table 1. RMSE of VAR Forecasts

	Quarters ahead			
Models	**1**	**2**	**3**	**4**
GDP				
Unrestricted VAR	0.019574	0.032160	0.027221	0.027649
Minnesota (0.1,0.5,1)	0.006335	0.011856	0.015726	0.019942
Minnesota (0.2,0.5,1)	0.005684	0.012806	0.015180	0.018209
Minnesota (0.1,0.5,2)	0.006699	0.011392	0.016247	0.021056
Minnesota (0.2,0.5,2)	0.006411	0.012289	0.015350	0.019162
Minnesota (0.2,0.005,1)	0.005720	0.015998	0.015625	0.015653*
Minnesota (0.1,0.005,1)	0.006081	0.014529	0.014804*	0.017018
Minnesota (0.2,0.005,2)	0.005516	0.014622	0.015160	0.016156
Minnesota (0.1,0.005,2)	0.005492*	0.012095	0.015050	0.017370
Minnesota Normal-Wishart (1,0.1)	0.012873	0.009888	0.024785	0.034993
Minnesota Normal-Wishart (1,0.2)	0.013029	0.010866	0.026021	0.035865
Minnesota Normal-Wishart (1,0.05)	0.012746	0.010476	0.024421	0.035721
Sims-Zha Normal Wishart (1,0.2,1,1)	0.016862	0.013697	0.031107	0.043064
Sims-Zha Normal Wishart (1,0.6,1,1)	0.018146	0.014552	0.032466	0.043514
Sims-Zha Normal Wishart (1,0.1,1,5)	0.011037	0.009532*	0.021677	0.031252
Sims-Zha Normal Wishart (10,2,1,5)	0.012786	0.010208	0.022336	0.031048
MONETARY AGGREGATE				
Unrestricted VAR	0.013436	0.012135	0.017145	0.022217
Minnesota (0.1,0.5,1)	0.025948	0.025581	0.018981	0.017497
Minnesota (0.2,0.5,1)	0.026215	0.023478	0.019611	0.016831
Minnesota (0.1,0.5,2)	0.027252	0.021630	0.020608	0.018404
Minnesota (0.2,0.5,2)	0.030607	0.025313	0.022229	0.021024
Minnesota (0.2,0.005,1)	0.027536	0.021287	0.019003	0.018440
Minnesota (0.1,0.005,1)	0.023764	0.021841	0.019202	0.016593
Minnesota (0.2,0.005,2)	0.027209	0.020297	0.019916	0.016156
Minnesota (0.1,0.005,2)	0.026144	0.020901	0.020950	0.018237
Minnesota Normal-Wishart (1,0.1)	0.021131	0.015741	0.015667	0.013986
Minnesota Normal-Wishart (1,0.2)	0.022872	0.019568	0.016090	0.016230
Minnesota Normal-Wishart (1,0.05)	0.016535	0.013805	0.014788	0.012431*
Sims-Zha Normal Wishart (1,0.2,1,1)	0.015931	0.014007	0.014182*	0.015861
Sims-Zha Normal Wishart (1,0.6,1,1)	0.012230*	0.011944*	0.014872	0.017659
Sims-Zha Normal Wishart (1,0.1,1,5)	0.023391	0.019384	0.016044	0.014447
Sims-Zha Normal Wishart (10,2,1,5)	0.020847	0.018442	0.016340	0.015074

*Note: * indicates the minimum RMSE*

Table 2. RMSE of VAR Forecasts

	Quarters ahead			
Models	**1**	**2**	**3**	**4**
UNEMPLOYMENT				
Unrestricted VAR	0.020916	0.034839	0.032211	0.041619*
Minnesota (0.1,0.5,1)	0.045039	0.045805	0.068734	0.108987
Minnesota (0.2,0.5,1)	0.037891	0.042154	0.064714	0.099885
Minnesota (0.1,0.5,2)	0.047475	0.046078	0.076298	0.118983

	Quarters ahead			
Models	**1**	**2**	**3**	**4**
	UNEMPLOYMENT			
Minnesota (0.2,0.5,2)	0.051452	0.049498	0.074428	0.115198
Minnesota (0.2,0.005,1)	0.010578*	0.014527	0.019459*	0.052321
Minnesota (0.1,0.005,1)	0.017970	0.014244	0.025073	0.058545
Minnesota (0.2,0.005,2)	0.019555	0.014826	0.027514	0.062214
Minnesota (0.1,0.005,2)	0.019433	0.017980	0.033018	0.065645
Minnesota Normal-Wishart (1,0.1)	0.062742	0.071150	0.106437	0.151539
Minnesota Normal-Wishart (1,0.2)	0.064462	0.076866	0.105922	0.154804
Minnesota Normal-Wishart (1,0.05)	0.056091	0.067341	0.103086	0.151318
Sims-Zha Normal Wishart (1,0.2,1,1)	0.039130	0.044335	0.073276	0.123722
Sims-Zha Normal Wishart (1,0.6,1,1)	0.031108	0.034979	0.065655	0.115704
Sims-Zha Normal Wishart (1,0.1,1,5)	0.029879	0.027221	0.047802	0.089806
Sims-Zha Normal Wishart (10,2,1,5)	0.014210	0.012199*	0.033875	0.080697
	EXCHANGE RATE			
Unrestricted VAR	0.026607	0.029436*	0.027117*	0.041176*
Minnesota (0.1,0.5,1)	0.039550	0.073545	0.071944	0.067329
Minnesota (0.2,0.5,1)	0.034582	0.071014	0.068321	0.068152
Minnesota (0.1,0.5,2)	0.040013	0.070831	0.072582	0.065818
Minnesota (0.2,0.5,2)	0.041000	0.070781	0.072851	0.068541
Minnesota (0.2,0.005,1)	0.073340	0.113294	0.119243	0.129396
Minnesota (0.1,0.005,1)	0.062777	0.104212	0.113074	0.123255
Minnesota (0.2,0.005,2)	0.068084	0.111415	0.111077	0.129057
Minnesota (0.1,0.005,2)	0.067046	0.105570	0.114560	0.114946
Minnesota Normal-Wishart (1,0.1)	0.027814	0.061177	0.062881	0.057366
Minnesota Normal-Wishart (1,0.2)	0.028493	0.063126	0.062273	0.060546
Minnesota Normal-Wishart (1,0.05)	0.014924*	0.054375	0.056855	0.055802
Sims-Zha Normal Wishart (1,0.2,1,1)	0.056633	0.097931	0.102781	0.101401
Sims-Zha Normal Wishart (1,0.6,1,1)	0.052022	0.088624	0.089485	0.090888
Sims-Zha Normal Wishart (1,0.1,1,5)	0.060140	0.101035	0.098091	0.104789
Sims-Zha Normal Wishart (10,2,1,5)	0.037122	0.066026	0.064933	0.064244
	INTEREST RATE			
Unrestricted VAR	0.214595*	0.299393*	0.347992	0.382753
Minnesota (0.1,0.5,1)	0.255090	0.322154	0.324386	0.312585
Minnesota (0.2,0.5,1)	0.238188	0.308615	0.311862	0.305628
Minnesota (0.1,0.5,2)	0.250651	0.334409	0.327925	0.313225
Minnesota (0.2,0.5,2)	0.235603	0.304228	0.316370	0.298504
Minnesota (0.2,0.005,1)	0.267284	0.328087	0.339691	0.325947
Minnesota (0.1,0.005,1)	0.277766	0.337795	0.349878	0.339181
Minnesota (0.2,0.005,2)	0.267256	0.343642	0.348238	0.332411
Minnesota (0.1,0.005,2)	0.275907	0.355223	0.365751	0.353257
Minnesota Normal-Wishart (1,0.1)	0.234352	0.299630	0.302516*	0.292238
Minnesota Normal-Wishart (1,0.2)	0.238121	0.300592	0.306150	0.283559*
Minnesota Normal-Wishart (1,0.05)	0.233165	0.313477	0.310043	0.307348
Sims-Zha Normal Wishart (1,0.2,1,1)	0.323146	0.417385	0.449520	0.431682
Sims-Zha Normal Wishart (1,0.6,1,1)	0.361837	0.449023	0.474574	0.479251
Sims-Zha Normal Wishart (1,0.1,1,5)	0.312554	0.409737	0.418544	0.429990
Sims-Zha Normal Wishart (10,2,1,5)	0.363014	0.450407	0.483947	0.463610

*Note: * indicates the minimum RMSE*

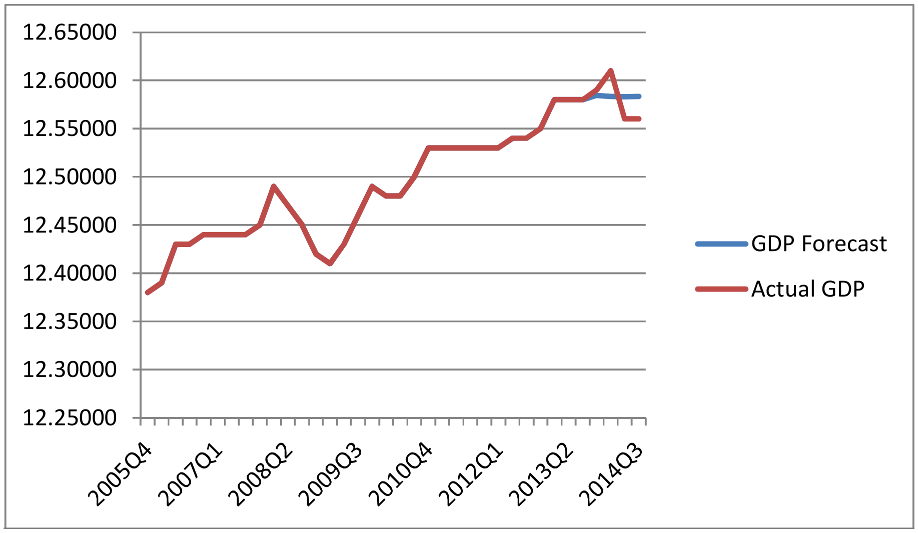

Fig. 1. GDP forecasts for 2013Q4-2014Q3

5. CONCLUSION

In this study the macroeconomic indicators as monetary aggregate, unemployment rate, exchange rates and interest rates are taken part in the VAR models in order to compare out-of-sample forecasts of GDP by using Bayesian vector autoregressive and unrestricted vector autoregressive models. The in-sample period contains quarterly data from 2005q4 to 2013q3.

BVAR models are estimated with Ko-Ko Minnesota/Litterman prior using different hyperparameters, in order to obtain more robust results models are also estimated using Sims and Zha [35] prior with different hyperparameters. Each model's four step ahead forecast performances are evaluated by RMSE.

The results confirm the accuracy of BVAR models for forecasting GDP. BVAR models are also have better forecasting performance for monetary aggregate. UVAR model forecasts are dominated by BVAR forecasts for GDP and monetary aggregate. On the other hand the forecasting results for UVAR models are most accurate for exchange rate except the first quarter and for interest rate in the first two quarter forecasts. UVAR model has also the best forecasting performance for unemployment rate in the last quarter.

Smets and Wouter [22] show that smaller variable VAR or AR model actually reduces the mean squared forecast error of the macroeconomic aggregates when comparing with larger BVAR models. Gürkaynak, Kısacıkoğlu and Rossi [27] indicate that there is no single best forecasting method and AR models are most accurate at short horizons. Our findings coincide with these studies in the literature. As far as we know, BVAR modelling has not been used for the macroeconomic variables of the Turkish economy before and this is the only study that compares the forecasting successes of BVAR and VAR models for macroeconomic variables for the purpose of GDP forecasting.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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