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Building a Large Bayesian Vector Autoregression Model for Kazakhstan

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Abstract

With a view to forecast the key macro indicators, in the recent years, the central banks worldwide as well as different international organizations have been actively developing and using the tools of the Bayesian vector autoregression models. This Paper presents the conducted assessment of their effectiveness in forecasting the economic activity, inflation, exchange rate and TONIA rate in Kazakhstan for various horizons up to one year in comparison with simpler models; it also shows the practicability of using such models. The search for optimum parameters of the estimated BVAR-model was conducted on the basis of forecast accuracy on the test sample.

Key Words: forecasts of macroeconomic indicators, Bayesian vector autoregression models, Bayesian methods.

JEL-classification: C32, C52, C53, C82, E17

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Contents

1. Preamble

As part of the monetary policy implementation, central banks need a complete understanding of not only the current economic situation, but also of the forecasting dynamics of key macroeconomic indicators. Based on the forecasts, monetary policy decisions are made and communication with the public is established.

To that end, the central bank staff engaged in the macroeconomic forecasting have an ongoing assignment to build and fine-tune assessment approaches that take into account the entire volume of useful information available at the time of forecasting. The National Bank of Kazakhstan makes this effort on a regular basis.

So, a short-term (up to 1 year) inflation forecasting (Tuleuov O., 2017) is carried out by combining forecasts from different models based on their accuracy over the testing period. Such models include multiple regression models (OLS), random walk models (RW), linear trend models (LTAR) and Bayesian vector autoregression models (BVAR).

As for the economic activity forecasts, the study (Mekenbayeva K. and Zhuzbayev A., 2017) presented the main methods of short-term forecasting of GDP, which, when combined, result in the final forecast. Such methods include multiple regression models (OLS), autoregression models (ARIMA), Bayesian autoregression models (BVAR) as well as mixed-data sampling models (MIDAS). There was a similar combination of forecasts also in the study (Zhuzbayev A., 2017) for estimation of short-term economic indicator[2], where multiple regression models, autoregression models (AR-models), and Bayesian vector autoregression models (BVAR) were used as the base models.

In addition to the forecast combination, which allows taking into account the advantages of several methods, in the study (Orlov, 2019) the GDP was forecasted by constructing and evaluating a dynamic factor model. Assessment of factors for several sectors (real and external, financial, monetary, price) enabled to cover a fairly wide set of monthly data in estimation of the quarterly equation for GDP.

Besides, in the study (Mekenbayeva K., Musil K., 2017), assessments of factors were built on the basis of quarterly surveys of enterprises in the real sector conducted by the National Bank and served as explanatory variables in determining the output gap in the current quarter.

As it follows from the above, at present the National Bank of Kazakhstan is already using BVAR-models with a view to forecast the economic activity (STEI and GDP) and inflation. However, such models have not been discussed separately. To this end, the purpose of this study was to analyze the forecasting accuracy of the BVAR-models under various prior distributions and various parameters of the prior distribution itself.

As a result, the assessment of efficiency of constructed BVAR-models in forecasting the economic activity, inflation, exchange rate and TONIA index for various horizons of up to one year as compared to simpler models was conducted and practicability of using such models was shown.

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[2] Short-term economic indicator (STEI) is a monthly indicator that characterizes a change in the physical output in key sectors of Kazakhstan's economy: the industry, construction, agriculture, trade, transport and communication.

The paper consists of several parts. The second section provides an overview of references that descries various aspects of the BVAR-model estimation, the third section describes the used data and the methodology of searching for optimum parameters of a BVAR-model while ensuring the forecasting accuracy versus alternative models. The fourth section shows the outcomes of the search for optimum parameters as well as gives a comparison of the forecasting accuracy on various forecasting horizons and with a different number of variables. Finally, the fifth section presents findings and recommendations for future studies.

2. Overview of References

Any vector autoregression model (including a Bayesian model) is presented as

$$y_t = \sum_{k=1}^{r} A^r \, y_{t-r} + c + \varphi Z_t + \epsilon_t, \ (1)$$

where $y_t = \left(y_{1,t}, \dots, y_{m,t}\ \right)'$ – vector of m values of endogenous variables at the time t , r – number of lags, A^r – a coefficient matrix with r lag of dimension $m \times m$, c – dimensional constant vector m, Z_t – vector of d values of exogenous factors at time t, φ – coefficient matrix of exogenous factors of dimension $m \times d$, ϵ_t – random error vector of equations at time t of dimension m, $\epsilon_t \sim N(0, \Sigma)$, Σ – covariance matrix m of equations in the dimension $m \times m$, or in short

$$y_t' = x_t' B + \epsilon_t', \ (2)$$

where $B = (A^1, \dots, A^r, c, \varphi)'$ – dimension matrix $(mr + d + 1) \times m$, $x_t = (y_{t-1}', \dots, y_{t-r}', 1, Z_t')$ – dimension vector $mr + d + 1$.

Going directly to the history of application of the Bayesian approach to vector autoregression and basic methods, one should note that the Bayesian approach itself is the dependence of the statistical data under consideration on a family of parameters that are random variables themselves (a detailed review of the Bayesian approach in statistics - Ayvazyan, 2008). Having only a prior distribution of parameters before the observations, after actual implementation of data an updated, the so-called posterior distribution of parameter probabilities is calculated with the help of the Bayes formula:

$$p(\theta|y) = p(\theta)p(y|\theta) / \int p(\theta)p(y|\theta)d\theta \propto p(\theta)p(y|\theta), \ \ (3)$$

where $p(\theta|y)$ – posterior distribution of parameter probabilities, $p(\theta)$ – prior distribution of parameter, $p(y|\theta)$ – likelihood function.

An assumption about a multidimensional normal distribution of random errors in the type (2) BVAR-model allows obtaining the likelihood function for endogenous variables depending on parameters. Prior distribution of the parameter vector itself is determined via the distribution of individual elements of coefficient matrices B and covariance matrix Σ.

In turn, the use of the Bayesian approach became popular due to the fact that in evaluation of VAR models with a large number of variables, moderate number of lags and a relatively small number of observations, the problem of excessive parameterization could arise when the number of estimated parameters was too large in relation to the sample size, which could lead to biased estimates of the coefficients and, ultimately, to poor quality forecasts (for example, Gupta, Kabundi, 2008).

The idea of using the Bayesian approach to vector autoregressions was based on the principle of reducing the redundant parameterization described above in the presence of a large amount of data. Another popular reduction technique is the use of factor models. In the context of Kazakhstan, these methods are discussed in the studies (Mekenbayeva K., Musil K., 2017) and (Orlov, 2019).

Researchers from the University of Minnesota and the Federal Reserve Bank of Minneapolis were the first to use the Bayesian approach method in the studies (Litterman,1980, 1986) and (Doan, Litterman, and Sims 1984), whereby the most popular and simple method of selecting a prior parameter distribution (with further modifications – for example, the paper by Sims, Zha, 1998) was given the name of Litterman, Litterman-Minesota or simply Minnesota.

The Minnesota prior distribution implies that elements in the coefficient matrix B are distributed normally, a prior mean for the first lag of own variable may be set (usually, for stationary data it is taken to be equal to 0, and for non-stationary data – 1), and for the rest of coefficients is equal to zero. Thus, a prior distribution is based on the assumption that variables behave as AR(1)-processes, including white noise and random walk. Having said this, prior standard variances are presented as

$$V_{i,j}^{r} = \begin{cases} \left(\frac{\lambda_1}{r^{\lambda_3}}\right)^2, i = j \\ \left(\frac{\lambda_1 \lambda_2 \sigma_i}{r^{\lambda_3} \sigma_j}\right)^2, i \neq j, \end{cases} \quad (4)$$

where $V_{i,j}^{r}$ – prior variance for coefficient of j-variable in i-equation with lag r, hyperparameters $\lambda_1, \lambda_2, \lambda_3$ – set numerical values, σ_i – i-diagonal element of known covariance matrix of the residuals Σ.

The last matrix is calculated by evaluating the individual AR-models for each variable (single estimate) and constructing the corresponding VAR-model and estimating the residual covariance matrix, while assuming the diagonal form of such a matrix (diagonal estimate) or without imposing any restrictions (full estimate).

The main disadvantage of the Minnesota prior distribution is a rather strict constraint on the constancy of the residual covariance matrix. This limitation can be weakened by using the conjugate normal-inverse prior Wishart distribution. The latter distribution, like the Minnesota distribution, is conjugate, that is, the posterior and prior distributions belong to the same class of distributions, which enables to obtain an analytical form for the posterior distribution (Kadiyala, Karlsson, 1997).

Conjugate normal-inverse Wishart prior distribution is represented as

$$\beta|\Sigma \sim N(\beta, H \otimes \Sigma) \quad (5)$$

$$\Sigma \sim IW(S, \nu) \quad (6),$$

where $\beta = vec(B)$ – vectorization of the coefficient matrix B, Σ – covariance matrix of the residuals, $\otimes$ symbol means the Kronecker product of matrices, IW – inverse Wishart distribution, matrices H, S and numerical value ν – the set hyperparameters. Here, the β distribution coincides with the Minnesota distribution. Despite the fact that contrary to the Minnesota Distribution, the covariance matrix is not pre-determined, a dependence of the moments of prior distributions of parameters from each other for different equations arises. Hence, both distributions are used in equal measure and there is no obvious preference of one method to the other.

Apart from the above distributions, independent normal-inverse Wishart prior distribution is applied, which requires using special numerical methods (Koop, Korobilis, 2010) and implies an independence between β and Σ, Sims-Zha approaches for structural VAR-models, 2012). The latter method assumes the structure of distribution of the normal-inverse Wishart prior distribution, however, it implies that hyperparameters of this distribution are also random values with hyperpriors from the given distributions (a hierarchy appears – hyperpriors determine the initial parameters). The values of hyperpriors correspond to the maximum of the system's likelihood function. In order to estimate the maximum, numerical methods from the MCMC (Monte Carlo Markov Chain) family are used, such as the Metropolis–Hastings algorithm, the Gibbs algorithm (Chib, Siddhartha, 1995; Geman, Geman, 1984).

A detailed description of BVAR-models may be also found in the studies (Blake, Mumtaz, 2012) (Demeshev, Malakhovskaya, 2016, II).

As for practical studies, the Bayesian approach to vector autoregressions at present is widely used by leading central banks worldwide (for example, Banbura, Marta, Domenico Giannone, and Lucrezia Reichlin, 2010 for the EU and Bloor, Matheson, 2009 for the New Zealand). In turn, the studies of both the central banks' staff and other economists from emerging economies and the EAEU appear. So, in the Bank of Russia (Deryugina, Ponomarenko, 2015), they have built a BVAR-model by the GLP method and compared its forecast with alternative models; the Central Bank of Armenia (Pogosyan, 2015) compared a relative quality of BVAR and FAVAR-models concurrently; the National Bank of Belarus (Bezborodova, Michalenok, 2015) used the Bayesian approach method for assessing the monetary policy transmission mechanism; and at the Central Bank of Turkey (Öğünç, 2019), they compared a relative forecasting accuracy of several specifications of BVAR-models to get the inflation forecast. In addition, the forecasting quality of BVAR-models based on the Russian data was assessed in the studies (Lomivorotov, 2015) and (Demeshev, Malakhovskaya, 2015, 2016). The key conclusions in these papers are that BVAR-models in most cases outperform alternative models (autoregression and vector autoregression) and also that not always the greatest forecasting accuracy of BVAR-models for developing countries is achieved based on the maximum quantity of reviewed variables; this can be explained by the fact that time series are still not long enough.

3. Data and Methodology Used

3.1 Data Description

In order to build the vector autoregression models on a monthly basis, the present study used 15 macroeconomic variables, 10 of which were endogenous and the rest were exogenous (Annex 1, Table 1). All monthly variables were taken from December 2004 through April 2020 and represented the basis index where December 2004 acted as the base. For quarterly VAR- and BVAR-models, 15 variables were also used (10 endogenous and 5 exogenous) in the basis form, with the 4th quarter of 2004 being the base. The monthly variables were translated into quarterly ones by averaging or replacing with the quarterly equivalents. Quarterly data were taken from the fourth quarter of 2004 to the first quarter of 2020. For those variables whose data became available after December 2020 (transfers from the National Fund), a value that was equal to 100 before the appearance of the data was assumed. The data from the Bureau of National Statistics with the ASPR of Kazakhstan (the BNS ASPR RK), National Bank of Kazakhstan (the NBRK), Kazakhstan Stock Exchange (KASE), Kazakhstan's Ministry of Finance, the US Energy Information Administration (EIA), and statistics authorities of China, Russia, and the European Union (the EU) served as the sources.

3.2 Methodology of the Searching Technique for an Optimum Set of the BVAR-Model Parameters and Ensuring its Forecasting Accuracy

All derivations in this study were made with the help of Eviews software (a program code for a monthly BVAR-model from the family with 15 variables – Annex 2).

At first, for all variables, except the overnight interest rate index TONIA, the natural logarithm was taken. Further, all variables were exposed to the deseasonalization procedure by using the X13-ARIMA-SEATS standard method. Variables were both monthly and quarterly.

In order to build monthly vector autoregression models for 5 endogenous variables, the following data were used: on the short-term economic indicator (STEI), CPI, nominal exchange rate of the tenge against the US Dollar, TONIA index, money supply in the tenge; for 6 variables – an exogenous price of oil was added to the abovementioned variables; in respect of 15 variables – the following indicators have been additionally included: endogenous fixed capital investments, retail sales, real wages, price index in the manufacturing industry, new housing price index as well as exogenous transfers from the National Fund, the weighted average index of industrial output in the trading partner countries, inflation in Russia, production of oil and gas condensate.

In turn, for quarterly vector autoregression models with 5, 6 and 15 variables, the same data have been used, only except for STEI and external industrial output the GDP and the weighted average GDP of the trading partner countries were used, and fixed capital investments, real wages, retail sales and the housing price index were replaced with the gross fixed capital formation (GFCF), spending on final consumption, GDP deflator and GFCF deflator.

Further, in order to assess the forecast quality, the period of May 2018 through April 2020 was chosen as a test period for the monthly models, and for the quarterly models – the period from the 2nd quarter of 2018 to the 4th quarter of 2019. Despite the fact that forecasts can be made for all endogenous variables of the model, 4 key variables – STEI (for the quarterly model – GDP), CPI, exchange rate, and TONIA were selected for the analysis.

In order to assess the degree of accuracy of the BVAR-model forecasts for such variables, alternative models have been taken – a naïve model (white noise for TONIA as a stationary variable and a shifted random walk for the rest of non-stationary variables) and the same VAR-model. The choice of such models was stipulated by the fact that in essence such models represent extreme points of the family of prior distribution parameters of the reviewed BVAR-models, when a completely zero variance of the parameters excludes the possibility of relying on the data, thus resulting in a naive model; and when the variance is equal to infinity there is no a priori knowledge of the parameters, which leads to the estimation of the coefficients only through the data, that is, to the VAR model.

The overall scheme of getting an optimum BVAR-model and assessing its quality versus alternative models looked as follows:

- forecasts of the abovementioned key variables for 1, 3, 6, 9, 12 months ahead (for 1, 2, 3, 4 quarters ahead for the quarterly models) were performed for each point within the test period with the use of alternative models. In doing so, if the forecasting horizon went beyond the test period, the forecast was not performed and the models were constantly revaluated from the very beginning of the sample to the point within the test period (the so-called landmark window strategy). Apart from that, in order to simplify the outcome presentation, forecasts beyond the selected months were not stored. Finally, the VAR-model was evaluated for various lags from 1 to 5 for the monthly data and from 1 to 4 for the quarterly data with an aim to compare the forecasting accuracy with the relevant BVAR-model;
- for each forecasting month (quarter), a root-mean-square error (RMSE) of this variable was calculated for points within the test period; in doing so, only those points were taken where the forecast for the given number of months (quarters) ahead was lying within the test period. Moreover, for each forecasting month (quarter) an average RMSE of the model as an arithmetic mean of the RMSE of 4 key variables was then derived;
- for monthly and quarterly data, a cycle was launched for the BVAR parameters (separately for the Minnesota distribution and separately for the conjugate normal-inverse Wishart distribution). The number of lags (from 1 to 5 for the monthly data and from 1 to 4 for the quarterly data) served as parameters for both distributions, a prior mean of the coefficient at the first lag of own variable μ_1 (from 0 to 1 with a step of 0.2), the total rigidity of the system or a prior standard deviation of the coefficient at the first lag of own variable λ_1 (from 0.2 to 1 with a step of 0.2), proportionality factor of the prior variance of coefficients at lags of other variables λ_2 (from 0.19 to 0.99 with a step of 0.2), coefficient of the rate of reduction in a prior variance with the increase in the lag of variables λ_3 (from 0.19 to 0.99 with a step of 0.2), as well as the method for evaluation of the covariance matrix of the residuals (uni method via autoregression models, diagonal, complete)

- at a pre-determined set of BVAR parameters similarly to a naïve model and VAR-model, the RMSE of key variables and the average RMSE of the entire model were evaluated
- for each monthly (quarterly) forecast and for each of the key variables, the ratio of RMSE of the BVAR-model to relevant indicators of alternative models was calculated. In addition, for each monthly (quarterly) forecast, the relevant ratio of the mean for the RMSE variables as the indicator of overall (average for key variables) relative forecast quality was computed;
- if the latter ratio is less than one for all forecasting horizons and both for the naïve model and the VAR-model, then we will say that this BVAR-model is "generally" forecasting better and we would call it a good model, while storing the values of such parameters;
- among the BVAR-models esteemed by the algorithm, attention is attracted by the models that, for each forecasting horizon and for each variable, give a minimum RMSE value and corresponding minimum ratios of the RMSE to the RMSE of alternative models as well as give minimum ratios of the average RMSE to the average RMSE of alternative models for each forecasting horizon. Both the minimum values themselves and the parameters at which they are obtained are stored (a similar procedure of optimum parameters – Kadiyala, Karlsson, 1997).

It should be noted that this procedure was performed for models with 5, 6, 15 variables.

4. Discussion of Outcomes

4.1 Outcomes of the Search for Optimum Parameters of BVAR-Models

Based on the application results of the above described scheme in searching for optimum parameters of the BVAR-model ("the Scheme"), 67 500 monthly equations and 54 000 quarterly equations were estimated in total. The Scheme outcomes are presented in Tables 1 and 2. The first symbol means a type of a prior distribution (LM – Litterman-Minnesota, NW – a conjugate normal-inverse Wishart distribution); the 2nd symbol – the number of variables in the model; the 3rd symbol – the number of lags in the system, the 4th symbol – a method for estimating the covariance matrix of the residuals ("uni" – Univariate AR, "diag" – Diagonal VAR, "full" – Full VAR); the 5th-8th symbols – the above described parameters λ_1, μ_1, λ_2, λ_3, respectively[3]. As follows from the results in respect of different forecasting horizons and different variables, there is no unique prior distribution, the number of variables and a set of parameters of the BVAR-model that would serve as "champions" for the majority of cases. Nonetheless, for the monthly TONIA index, a "victory" of the model with the normal-inverse Wishart distribution, 5 variables and 5 lags is observed, and for the quarterly data the "victory" is given to the Minnesota distribution.

These outcomes indicate that the possibility of using only one BVAR model for forecasting several variables at a time and for various periods could be not quite

[3] The Table shows not the parameter values themselves but the increment numbers whose range and limits were presented above.

optimal. Hence, the approach based on the concurrent use of different BVAR-models or their combination might be more justified and correct.

Table 1

A Set of Optimum Parameters and the View of a Monthly BVAR-Model, which Minimizes a Mean-Squared Error of the Forecast for the Given Variable and the Given Forecasting Horizon

Forecast length	Variables			
	STEI	CPI	USDKZT	TONIA
1 month	NW_15_1_full_3_0_1_3	LM_6_3_uni_1_5_1_1	NW_6_3_uni_3_5_1_2	NW_5_5_uni_1_4_3_4
3 month	LM_15_5_diag_1_5_5_1	LM_6_2_full_1_5_1_1	NW_15_5_full_5_4_3_5	NW_5_5_uni_1_3_1_5
6 month	LM_6_5_uni_1_0_1_3	NW_15_5_full_3_5_3_4	LM_5_5_full_2_5_2_1	NW_5_5_uni_3_3_4_2
9 month	NW_6_1_full_4_0_3_2	NW_15_4_uni_2_5_2_3	LM_5_1_full_2_5_1_1	NW_5_5_uni_4_5_3_2
12 month	NW_6_1_uni_1_0_1_1	NW_5_5_uni_1_5_1_1	LM_15_5_uni_4_5_1_1	NW_5_5_full_4_5_5_5

Source: the author's derivations

Table 2

A Set of Optimum Parameters and the View of a Quarterly BVAR-Model, which Minimizes a Mean-Squared Error of the Forecast for the Given Variable and the Given Forecasting Horizon

Forecast length	Variables			
	GDP	CPI	USDKZT	TONIA
1 quarter	LM_5_4_uni_3_5_1_5	LM_6_1_full_1_5_5_1	LM_5_2_uni_1_5_1_5	LM_5_4_diag_1_0_1_1
2 quarter	LM_5_4_uni_4_4_1_5	LM_5_4_uni_1_0_3_2	LM_5_4_full_2_0_1_5	LM_5_4_full_4_3_1_1
3 quarter	LM_6_3_diag_5_0_1_4	LM_6_4_uni_1_1_2_1	LM_5_4_full_2_0_1_5	LM_5_4_full_1_5_5_2
4 quarter	LM_6_3_diag_5_0_1_4	LM_6_4_uni_1_2_3_5	LM_5_4_full_2_0_1_5	LM_5_4_diag_1_1_3_2

Source: the author's derivations

4.2 Forecast Accuracy

Based on the Scheme's application, for each variable and each forecasting horizon, the minimum ratios of the RMSE of the BVAR-model to the RMSE of the two reviewed alternative models were found, and for each forecasting horizon - the ratio of the average on key variables RMSE in the context of the two classes of prior distribution and the number of variables in the system. The results of assessment of such relative accuracy of forecasts of the BVAR-model are put together in Tables 3-8.

Table 3

The Ratio of the Average on Key Variables RMSE of the Monthly BVAR-Model of Two Types to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 month	0.779	0.776	0.901	0.789	0.774	0.815
Minnesota	3 month	0.91	0.876	1.093	0.886	0.867	0.847
Minnesota	6 month	0.922	0.931	1.104	0.899	0.883	0.883
Minnesota	9 month	0.839	0.899	0.927	0.889	0.876	0.911
Minnesota	12 month	0.775	0.866	0.685	0.847	0.881	0.845
Normal Wishart	1 month	0.782	0.85	0.861	0.789	0.84	0.815
Normal Wishart	3 month	0.892	0.894	0.881	0.873	0.902	0.74
Normal Wishart	6 month	0.819	0.909	0.811	0.882	0.923	0.717
Normal Wishart	9 month	0.734	0.894	0.687	0.889	0.931	0.771
Normal Wishart	12 month	0.678	0.877	0.613	0.866	0.955	0.822

Source: the author's derivations

Table 4

The Ratio of the Average on Key Variables RMSE of the Quarterly BVAR-Model of Two Types to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 quarter	0.677	0.83	1.7	0.452	0.582	0.377
Minnesota	2 quarter	0.646	0.797	1.736	0.537	0.565	0.431
Minnesota	3 quarter	0.623	0.739	1.565	0.411	0.574	0.518
Minnesota	4 quarter	0.533	0.686	1.296	0.312	0.404	0.318
Normal Wishart	1 quarter	0.93	1.022	1.022	0.788	0.756	0.321
Normal Wishart	2 quarter	0.948	1.027	1.002	1.06	0.758	0.326
Normal Wishart	3 quarter	1.021	1.014	0.977	1.178	1	0.379
Normal Wishart	4 quarter	1.065	0.971	1.005	1.104	0.775	0.326

Source: the author's derivations

Table 5

The Ratio of RMSE of the Monthly BVAR-Model from the Minnesota Family to the RMSE of the Naïve Model and VAR-Model for Given Variable, for Given Forecasting Horizon and for Given Number of Variables in the Model

Variable	# variables	BVAR to RW Forecasting horizon, months					BVAR to VAR Forecasting horizon, months				
		1	3	6	9	12	1	3	6	9	12
STEI	**5**	0.965	0.879	0.649	0.502	0.446	0.926	0.875	0.867	0.853	0.937
STEI	**6**	0.811	0.693	0.518	0.403	0.354	0.877	0.802	0.782	0.786	0.866
STEI	**15**	0.673	0.68	0.585	0.481	0.448	0.934	0.958	0.932	0.903	0.875
CPI	**5**	0.772	0.929	0.952	1.156	1.056	0.689	0.787	0.762	0.754	0.767
CPI	**6**	0.72	0.808	0.841	0.803	0.683	0.633	0.729	0.754	0.681	0.637
CPI	**15**	1.345	1.85	1.653	1.693	1.15	0.773	0.777	0.769	0.919	0.902
USDKZT	**5**	0.901	0.972	0.788	0.546	0.46	0.889	0.933	0.931	0.889	0.766
USDKZT	**6**	0.83	0.819	0.956	0.898	0.847	0.871	0.954	0.946	0.952	0.927
USDKZT	**15**	0.88	0.981	1.032	0.616	0.392	0.791	0.792	0.826	0.779	0.556
TONIA	**5**	0.437	0.794	1.063	1.02	0.937	0.577	0.732	0.81	0.739	0.666
TONIA	**6**	0.649	0.947	1.131	1.179	1.151	0.567	0.676	0.71	0.669	0.666
TONIA	**15**	0.503	0.673	0.622	0.654	0.636	0.44	0.578	0.626	0.603	0.6

Source: the author's derivations

Table 6

The Ratio of RMSE of the Monthly BVAR-Model from the Normal Wishart Family to the RMSE of the Naïve Model and VAR-Model for Given Variable, for Given Forecasting Horizon and for Given Number of Variables in the Model

Variable	# variables	BVAR to RW Forecasting horizon, months					BVAR to VAR Forecasting horizon, months				
		1	3	6	9	12	1	3	6	9	12
STEI	**5**	0.968	0.88	0.649	0.502	0.446	0.941	0.908	0.93	0.935	0.976
STEI	**6**	0.767	0.737	0.592	0.403	0.335	0.916	1.017	1.062	0.976	0.929
STEI	**15**	0.584	0.719	0.56	0.457	0.371	0.864	0.799	0.718	0.655	0.609
CPI	**5**	0.778	0.951	0.855	0.751	0.511	0.692	0.865	0.774	0.662	0.411
CPI	**6**	0.88	0.921	0.92	0.97	0.969	0.772	0.835	0.909	0.895	0.924
CPI	**15**	0.938	1.053	0.839	0.62	0.549	0.539	0.45	0.351	0.33	0.43
USDKZT	**5**	0.907	0.995	0.839	0.607	0.536	0.911	0.976	0.972	0.906	0.766
USDKZT	**6**	0.814	0.816	0.954	0.872	0.8	0.898	0.957	0.924	0.861	0.785
USDKZT	**15**	0.851	0.794	0.871	0.742	0.538	0.778	0.641	0.697	0.938	0.763
TONIA	**5**	0.342	0.478	0.513	0.393	0.401	0.473	0.464	0.401	0.285	0.285
TONIA	**6**	0.737	0.955	1.075	1.148	1.2	0.629	0.682	0.682	0.68	0.71
TONIA	**15**	0.614	0.791	0.884	0.846	0.819	0.553	0.736	0.838	0.753	0.732

Source: the author's derivations

Table 7

The Ratio of RMSE of the Quarterly BVAR-Model from the Minnesota Family to the RMSE of the Naïve Model and VAR-Model for Given Variable, for Given Forecasting Horizon and for Given Number of Variables in the Model

Variable	# variables	BVAR to RW				BVAR to VAR			
		Forecasting horizon, quarters				Forecasting horizon, quarters			
		1	2	3	4	1	2	3	4
GDP	**5**	0.846	0.618	0.437	0.29	0.416	0.438	0.377	0.49
GDP	**6**	0.874	0.669	0.425	0.278	0.428	0.533	0.581	0.435
GDP	**15**	1.032	0.783	0.428	0.371	0.348	0.266	0.19	0.141
CPI	**5**	0.523	0.5	0.36	0.124	0.451	0.282	0.163	0.061
CPI	**6**	0.519	0.505	0.296	0.065	0.464	0.304	0.145	0.035
CPI	**15**	2.178	2.246	1.978	1.465	0.259	0.343	0.593	0.426
USDKZT	**5**	0.928	0.853	0.801	0.841	0.537	0.435	0.298	0.255
USDKZT	**6**	1.25	1.347	1.636	1.714	0.826	0.785	0.724	0.656
USDKZT	**15**	2.002	2.223	2.459	2.245	0.464	0.575	0.603	0.462
TONIA	**5**	0.182	0.208	0.06	0.05	0.279	0.352	0.086	0.049
TONIA	**6**	0.226	0.287	0.107	0.065	0.312	0.356	0.314	0.103
TONIA	**15**	0.23	0.292	0.085	0.138	0.092	0.119	0.015	0.032

Source: the author's derivations

Table 8

The Ratio of RMSE of the Quarterly BVAR-Model from the Normal Wishart Family to the RMSE of the Naïve Model and VAR-Model for Given Variable, for Given Forecasting Horizon and for Given Number of Variables in the Model

Variable	# variables	BVAR to RW				BVAR to VAR			
		Forecasting horizon, quarters				Forecasting horizon, quarters			
		1	2	3	4	1	2	3	4
GDP	**5**	1.094	0.967	0.932	0.876	0.591	0.787	0.945	1.485
GDP	**6**	0.96	0.775	0.617	0.481	0.543	0.73	0.817	0.745
GDP	**15**	1.166	0.916	0.526	0.395	0.451	0.307	0.226	0.14
CPI	**5**	0.569	0.553	0.5	0.268	0.595	0.654	0.502	0.264
CPI	**6**	0.727	0.689	0.496	0.134	0.615	0.606	0.424	0.108
CPI	**15**	0.659	0.645	0.399	0.209	0.159	0.148	0.093	0.052
USDKZT	**5**	1.417	1.544	2.012	2.36	0.96	0.977	1.057	1.061
USDKZT	**6**	1.471	1.577	1.881	2.019	0.971	0.913	0.878	0.822
USDKZT	**15**	1.745	1.904	2.343	2.549	0.415	0.532	0.519	0.483
TONIA	**5**	0.234	0.335	0.29	0.15	0.673	0.652	0.466	0.248
TONIA	**6**	0.329	0.345	0.182	0.128	0.467	0.502	0.731	0.243
TONIA	**15**	0.342	0.357	0.144	0.164	0.161	0.163	0.031	0.034

Source: the author's derivations

Judging from these tables, the outcomes of this study for the monthly data are generally repeating the estimation results obtained for the Russian economy in the studies (Demeshev, Malakhovskaya, 2015, 2016).

Also, it is important to mention that nearly for all forecasting horizons and the number of variables, the average of the RMSE variables of the BVAR model is smaller than that of the alternative models, which indicates the “average” superiority of the BVAR-models (for all cases – the normal-inverse Wishart distribution). The only exception is the Minnesota distribution with 14 variables for 3 and 6 months.

If we turn to the relative quality of forecasts of individual variables, then the relative forecast error of the BVAR model is always less than 1 for STEI. Also, the error is less than 1 for both distributions in all cases with respect to VAR. At the same time, the number of "outliers" in the normal-inverse Wishart distribution is somewhat smaller, which confirms some superiority in the "average" of this distribution over the Minnesota distribution for the monthly data.

At the same time, as for the Russian data, there is no pronounced reduction in the relative error with an increase in the number of variables, which is observed in developed countries. (De Mol, Giannone, Reichlin, 2008; Banbura, Giannone, and Reichlin, 2010). Nonetheless, in case of the normal-inverse Wishart distribution, one may note some improvement in the relative forecast accuracy for 15 variables in respect of the STEI, CPI and the exchange rate.

As for the quarterly data, despite the generally worse performance than in the monthly data, especially with respect to the naïve model, the normal-inverse Wishart distribution for all variables has a more pronounced reduction in error for 15 variables relative to the VAR-model.

5. Findings and Recommendations for Future Studies

This study involved the assessment of effectiveness of BVAR-models in forecasting the economic activity, inflation, exchange rate and TONIA rates in Kazakhstan for various horizons of up to 1 year as compared to simpler alternative models (a naïve model and a VAR-model). The models were built on both a monthly basis and a quarterly basis for 5, 6 and 15 variables for the Minnesota prior distributions and the conjugate normal-inverse Wishart distribution.

The search for the optimum parameters of the evaluated BVAR-model took place on the basis of the forecast accuracy on the testing sample as compared to the corresponding alternative models. Parameters included the type of distribution, the number of variables, the number of lags, a method for estimation of the covariance matrix of the residuals as well as the numerical parameters of the prior distribution itself. For each forecasting horizon, both the parameters that give the BVAR-model (for the given type of a prior distribution and the number of variables) a minimum ratio of the RMSE on individual variables and a minimum average on the RMSE variables to the corresponding averages of alternative models were factored in.

For all forecasting horizons and the number of variables, the average on RMSE variables of a monthly BVAR-model with the normal-inverse Wishart distribution appeared to be smaller than in case of alternative models, whereas for the Minnesota distribution this relationship held true almost in all cases. This fact indicates that generally both types of BVAR-models outperform alternative models in terms of accuracy.

At the same time, an important outcome of the study is that there is no obvious improvement in the accuracy of the BVAR-model forecasts as compared to both alternative models as the number of variables increases. Nonetheless, for the prior normal-inverse Wishart distribution with the increase in the number of variables such relationship is present in case of the VAR-model, especially for the quarterly data.

Therefore, it makes sense to use the BVAR-models in the regular forecasting practice, especially in case of their “competition” with the VAR-models. In this instance, the BVAR-model with the prior normal-inverse Wishart distribution looks more appropriate. However, since no common Bayesian model was found for all forecasting periods and all variables, a broad class of BVAR-models is recommended to be considered for performing the forecasts both in respect of the prior distribution parameters and the distributions themselves.

Further research in this field may be dealing with a broader range of prior distributions and their parameters with a view to study further the forecasting features of the Bayesian method and also to use this approach in obtaining qualitative assessment regarding the degree of correlation among macroeconomic variables.

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Annex 1

Table 1

List of variables for evaluation of vector autoregression models (on a monthly and quarterly basis)

N	Variable Name	Variable Type	Information Source
1	Short-term economic indicator (STEI), December 2004=100	Endogenous	BNS ASPR RK, the author's derivations
2	Index of physical volume of retail sales, December 2004=100	Endogenous	BNS ASPR RK, the author's derivations
3	Real monthly wage, December 2004=100	Endogenous	BNS ASPR RK, the author's derivations
4	Index of physical volume of fixed capital investments, December 2004=100	Endogenous	BNS ASPR RK, the author's derivations
5	Consumer price index, December 2004=100	Endogenous	BNS ASPR RK, the author's derivations
6	Producer price index in the manufacturing industry, December 2004=100	Endogenous	BNS ASPR RK, the author's derivations
7	New house selling price index, December 2004=100	Endogenous	BNS ASPR RK, the author's derivations
8	Index of the nominal exchange rate of the tenge against the US Dollar	Endogenous	NBRK, the author's derivations
9	Money supply in the tenge, December 2004=100	Endogenous	NBRK, the author's derivations
10	TONIA Index, в %	Endogenous	KASE
11	Brent average monthly oil price, December 2004=100	Exogenous	EIA, the author's derivations
12	The weighted average industrial output index in the EU, China, Russia in terms of average exports from Kazakhstan, December 2004=100	Exogenous	NBRK, national statistics authorities of China, Russia, and the EU; the author's derivations

13	Consumer price index in Russia, December 2004=100	Exogenous	Rosstat, the author’s derivations
14	Volume of transfers from the National Fund to the state budget of Kazakhstan, December 2004 =100	Exogenous	Kazakhstan’s Ministry of Finance, the author’s derivations
15	Production of oil and gas condensate, December 2004=100		BNS ASPR RK, the author’s derivations
16	Index of physical volume of Kazakhstan’s GDP, the 4th quarter of 2004=100	Endogenous	BNS ASPR RK, the author’s derivations
17	Index of physical volume of gross fixed capital formation, the 4th quarter of 2004=100	Endogenous	BNS ASPR RK, the author’s derivations
18	Deflator of gross fixed capital formation, the 4th quarter of 2004=100	Endogenous	BNS ASPR RK, the author’s derivations
19	Kazakhstan’s GDP deflator, the 4th quarter of 2004=100	Endogenous	BNS ASPR RK, the author’s derivations
20	Index of physical volume of spending on final consumption, the 4th quarter of 2004=100	Endogenous	BNS ASPR RK, the author’s derivations
21	GDP of the main trading partner countries торговых партнеров (the EU, China, Russia) weighted average based on quarterly exports from Kazakhstan, 4th quarter of 2004=100	Exogenous	NBRK, national statistics authorities of China, Russia, the EU; the author’s derivations

Source: compiled by the author based on the information from the BNS ASPR RK, NBRK, KASE, Kazakhstan’s Ministry of Finance, EIA, national statistics authorities of China, Russia and the EU.

Annex 2

Eviews code for evaluating the BVAR model and selecting its optimal parameters

```
Pagecreate(Page=Data_M) M 2004M12 2021M04
Pageselect Data_M

Import   ...\BVAR_BAZA_Q.xlsx Range=index_M Colhead=2 Namepos=last Na="#N/A" @Freq M 2004M12 @Smpl
@All
Pagestruct(End=2021M04)

Scalar Obs_number = @ilast(Stei)

Sample SeasNA 2004M12 2020M03

Sample Seas 2004M12 2020M04

Sample LST 2020M04 2020M04

'IDENTIFYING THE START DATE AND THE END DATE FOR PSEUDO-REAL FORECAST EXPERIMENT PERIOD
String Startdate = "2018M05"
String Enddate = "2020M04"

'TRANSFORMING THE STRING DATE OBJECT INTO THE SCALAR OBJECT
Scalar Num1 = @Dtoo(Startdate)
Scalar Num2 = @Dtoo(Enddate)

'LENGTH OF PSEUDO-REAL FORECAST EXPERIMENT PERIOD
Scalar Num_Max = Num2-Num1+1

'LOOP BY SEASONAL ADJUSTMENT OF VARIABLES
For %Nam STEI Indust Mining Manufact Invest Retail Wholesale RealInc RealWage NewHouse CPI IndustPrice
ManufactPrice HousePrice OilExtract Transfert NEER REER NEERwoOil REERwoOil USDKZT TONIA KASE LoanBus
LoanInd CashCirc MoneyBase TengeMoneySupply M3MoneySupply OilPrice FAO RusCPI ExtDemand ChinaIndust
EUIndust RusIndust

'TAKE LOGS OF ALL SERIES EXCEPT FOR TONIA PERCENT RATE
If %Nam<>"TONIA" Then
{%Nam}=log({%Nam})
Endif

'GETTING CURRRENT DATE VALUE OF EACH VARIABLE THROUGH VECTOR OBJECT
Smpl LST
Stomna({%Nam},V_{%Nam})
Smpl @All

'IF CURRRENT DATE VALUE IS NOT AVALAIBLE THEN USE SHORTENED SAMPLE FOR SEASONAL
ADJUSTMENT
If V_{%Nam}(1)=NA Then
Smpl SeasNA
{%Nam}.x13(save="d11", arimasmpl=SeasNA)  @x11()
Rename {%Nam}_d11 {%Nam}_sa

'ELSE USE ALL SAMPLE FOR SEASONAL ADJUSTMENT
Else
Smpl Seas
{%Nam}.x13(save="d11", arimasmpl=Seas)  @x11()
Rename  {%Nam}_d11 {%Nam}_sa
Endif

'DELETE INTERIM OBJECTS
Delete V_{%Nam} {%Nam}

Smpl @All

'IDENTIFYING UNIT ROOT STATUS OF VARIABLES
```

```
Freeze(Tab_{%Nam}) {%Nam}_sa.uroot(exog=none)

Scalar Stationar_Status_{%Nam}=0

If Tab_{%Nam}(7,5)<=0.05 Then
Stationar_Status_{%Nam}=1
Endif

'DELETE INTERIM OBJECTS
Delete Tab_{%Nam}

Next

'INITIAL VALUE ASSINGMENT OF CRITERIA FOR SELECTING THE BEST BVAR PARAMETERS IF AT LEAST ONE
"GOOD" BVAR IS FOUND
Vector (5) Min_BVV =1000
Vector (5) Min_BVRW =1000

Vector (5) Min_STEI =1000
Vector (5) Min_CPI =1000
Vector (5) Min_USDKZT =1000
Vector (5) Min_TONIA =1000

Vector (5) Min_BVV_STEI =1000
Vector (5) Min_BVV_CPI =1000
Vector (5) Min_BVV_USDKZT =1000
Vector (5) Min_BVV_TONIA =1000
Vector (5) Min_BVRW_STEI =1000
Vector (5) Min_BVRW_CPI =1000
Vector (5) Min_BVRW_USDKZT =1000
Vector (5) Min_BVRW_TONIA =1000

'FILLING IN THE HEADERS OF THE RESULTS TABLE IF AT LEAST ONE "GOOD" BVAR IS FOUND
Table (31,3) Tab_Results
Tab_results(1,1) = "Indicator"
Tab_results(1,2) = "Set of parameteres"
Tab_results(1,3) = "Value"
Tab_results(2,1) = "1 month RMSE BVAR to VAR"
Tab_results(3,1) = "3 month RMSE BVAR to VAR"
Tab_results(4,1) = "6 month RMSE BVAR to VAR"
Tab_results(5,1) = "9 month RMSE BVAR to VAR"
Tab_results(6,1) = "12 month RMSE BVAR to VAR"
Tab_results(7,1) = "1 month RMSE BVAR to RW"
Tab_results(8,1) = "3 month RMSE BVAR to RW"
Tab_results(9,1) = "6 month RMSE BVAR to RW"
Tab_results(10,1) = "9 month RMSE BVAR to RW"
Tab_results(11,1) = "12 month RMSE BVAR to RW"
Tab_results(12,1) = "1 month RMSE STEI"
Tab_results(13,1) = "3 month RMSE STEI"
Tab_results(14,1) = "6 month RMSE STEI"
Tab_results(15,1) = "9 month RMSE STEI"
Tab_results(16,1) = "12 month RMSE STEI"
Tab_results(17,1) = "1 month RMSE CPI"
Tab_results(18,1) = "3 month RMSE CPI"
Tab_results(19,1) = "6 month RMSE CPI"
Tab_results(20,1) = "9 month RMSE CPI"
Tab_results(21,1) = "12 month RMSE CPI"
Tab_results(22,1) = "1 month RMSE USDKZT"
Tab_results(23,1) = "3 month RMSE USDKZT"
Tab_results(24,1) = "6 month RMSE USDKZT"
Tab_results(25,1) = "9 month RMSE USDKZT"
Tab_results(26,1) = "12 month RMSE USDKZT"
Tab_results(27,1) = "1 month RMSE TONIA"
Tab_results(28,1) = "3 month RMSE TONIA"
Tab_results(29,1) = "6 month RMSE TONIA"
Tab_results(30,1) = "9 month RMSE TONIA"
Tab_results(31,1) = "12 month RMSE TONIA"
Tab_results(32,1) = "1 month BVAR to VAR STEI"
Tab_results(33,1) = "3 month BVAR to VAR STEI"
```

```
Tab_results(34,1) = "6 month BVAR to VAR STEI"
Tab_results(35,1) = "9 month BVAR to VAR STEI"
Tab_results(36,1) = "12 month BVAR to VAR STEI"
Tab_results(37,1) = "1 month BVAR to VAR CPI"
Tab_results(38,1) = "3 month BVAR to VAR CPI"
Tab_results(39,1) = "6 month BVAR to VAR CPI"
Tab_results(40,1) = "9 month BVAR to VAR CPI"
Tab_results(41,1) = "12 month BVAR to VAR CPI"
Tab_results(42,1) = "1 month BVAR to VAR USDKZT"
Tab_results(43,1) = "3 month BVAR to VAR USDKZT"
Tab_results(44,1) = "6 month BVAR to VAR USDKZT"
Tab_results(45,1) = "9 month BVAR to VAR USDKZT"
Tab_results(46,1) = "12 month BVAR to VAR USDKZT"
Tab_results(47,1) = "1 month BVAR to VAR TONIA"
Tab_results(48,1) = "3 month BVAR to VAR TONIA"
Tab_results(49,1) = "6 month BVAR to VAR TONIA"
Tab_results(50,1) = "9 month BVAR to VAR TONIA"
Tab_results(51,1) = "12 month BVAR to VAR TONIA"
Tab_results(52,1) = "1 month BVAR to RW STEI"
Tab_results(53,1) = "3 month BVAR to RW STEI"
Tab_results(54,1) = "6 month BVAR to RW STEI"
Tab_results(55,1) = "9 month BVAR to RW STEI"
Tab_results(56,1) = "12 month BVAR to RW STEI"
Tab_results(57,1) = "1 month BVAR to RW CPI"
Tab_results(58,1) = "3 month BVAR to RW CPI"
Tab_results(59,1) = "6 month BVAR to RW CPI"
Tab_results(60,1) = "9 month BVAR to RW CPI"
Tab_results(61,1) = "12 month BVAR to RW CPI"
Tab_results(62,1) = "1 month BVAR to RW USDKZT"
Tab_results(63,1) = "3 month BVAR to RW USDKZT"
Tab_results(64,1) = "6 month BVAR to RW USDKZT"
Tab_results(65,1) = "9 month BVAR to RW USDKZT"
Tab_results(66,1) = "12 month BVAR to RW USDKZT"
Tab_results(67,1) = "1 month BVAR to RW TONIA"
Tab_results(68,1) = "3 month BVAR to RW TONIA"
Tab_results(69,1) = "6 month BVAR to RW TONIA"
Tab_results(70,1) = "9 month BVAR to RW TONIA"
Tab_results(71,1) = "12 month BVAR to RW TONIA"

'INITIAL VALUE ASSINGMENT OF CRITERIA FOR SELECTING THE BEST BVAR PARAMETERS IF "GOOD" BVAR
IS NOT FOUND
Vector (5) A_Min_BVV =1000
Vector (5) A_Min_BVRW =1000

Vector (5) A_Min_STEI =1000
Vector (5) A_Min_CPI =1000
Vector (5) A_Min_USDKZT =1000
Vector (5) A_Min_TONIA =1000

Vector (5) A_Min_BVV_STEI =1000
Vector (5) A_Min_BVV_CPI =1000
Vector (5) A_Min_BVV_USDKZT =1000
Vector (5) A_Min_BVV_TONIA =1000
Vector (5) A_Min_BVRW_STEI =1000
Vector (5) A_Min_BVRW_CPI =1000
Vector (5) A_Min_BVRW_USDKZT =1000
Vector (5) A_Min_BVRW_TONIA =1000

'FILLING IN THE HEADERS OF THE RESULTS TABLE IF "GOOD" BVAR IS NOT FOUND
Table (31,3) A_Tab_Results
A_Tab_results(1,1) = "Indicator"
A_Tab_results(1,2) = "Set of parameteres"
A_Tab_results(1,3) = "Value"
A_Tab_results(2,1) = "1 month RMSE BVAR to VAR"
A_Tab_results(3,1) = "3 month RMSE BVAR to VAR"
A_Tab_results(4,1) = "6 month RMSE BVAR to VAR"
A_Tab_results(5,1) = "9 month RMSE BVAR to VAR"
A_Tab_results(6,1) = "12 month RMSE BVAR to VAR"
A_Tab_results(7,1) = "1 month RMSE BVAR to RW"
```

```
A_Tab_results(8,1) = "3 month RMSE BVAR to RW"
A_Tab_results(9,1) = "6 month RMSE BVAR to RW"
A_Tab_results(10,1) = "9 month RMSE BVAR to RW"
A_Tab_results(11,1) = "12 month RMSE BVAR to RW"
A_Tab_results(12,1) = "1 month RMSE STEI"
A_Tab_results(13,1) = "3 month RMSE STEI"
A_Tab_results(14,1) = "6 month RMSE STEI"
A_Tab_results(15,1) = "9 month RMSE STEI"
A_Tab_results(16,1) = "12 month RMSE STEI"
A_Tab_results(17,1) = "1 month RMSE CPI"
A_Tab_results(18,1) = "3 month RMSE CPI"
A_Tab_results(19,1) = "6 month RMSE CPI"
A_Tab_results(20,1) = "9 month RMSE CPI"
A_Tab_results(21,1) = "12 month RMSE CPI"
A_Tab_results(22,1) = "1 month RMSE USDKZT"
A_Tab_results(23,1) = "3 month RMSE USDKZT"
A_Tab_results(24,1) = "6 month RMSE USDKZT"
A_Tab_results(25,1) = "9 month RMSE USDKZT"
A_Tab_results(26,1) = "12 month RMSE USDKZT"
A_Tab_results(27,1) = "1 month RMSE TONIA"
A_Tab_results(28,1) = "3 month RMSE TONIA"
A_Tab_results(29,1) = "6 month RMSE TONIA"
A_Tab_results(30,1) = "9 month RMSE TONIA"
A_Tab_results(31,1) = "12 month RMSE TONIA"
A_Tab_results(32,1) = "1 month BVAR to VAR STEI"
A_Tab_results(33,1) = "3 month BVAR to VAR STEI"
A_Tab_results(34,1) = "6 month BVAR to VAR STEI"
A_Tab_results(35,1) = "9 month BVAR to VAR STEI"
A_Tab_results(36,1) = "12 month BVAR to VAR STEI"
A_Tab_results(37,1) = "1 month BVAR to VAR CPI"
A_Tab_results(38,1) = "3 month BVAR to VAR CPI"
A_Tab_results(39,1) = "6 month BVAR to VAR CPI"
A_Tab_results(40,1) = "9 month BVAR to VAR CPI"
A_Tab_results(41,1) = "12 month BVAR to VAR CPI"
A_Tab_results(42,1) = "1 month BVAR to VAR USDKZT"
A_Tab_results(43,1) = "3 month BVAR to VAR USDKZT"
A_Tab_results(44,1) = "6 month BVAR to VAR USDKZT"
A_Tab_results(45,1) = "9 month BVAR to VAR USDKZT"
A_Tab_results(46,1) = "12 month BVAR to VAR USDKZT"
A_Tab_results(47,1) = "1 month BVAR to VAR TONIA"
A_Tab_results(48,1) = "3 month BVAR to VAR TONIA"
A_Tab_results(49,1) = "6 month BVAR to VAR TONIA"
A_Tab_results(50,1) = "9 month BVAR to VAR TONIA"
A_Tab_results(51,1) = "12 month BVAR to VAR TONIA"
A_Tab_results(52,1) = "1 month BVAR to RW STEI"
A_Tab_results(53,1) = "3 month BVAR to RW STEI"
A_Tab_results(54,1) = "6 month BVAR to RW STEI"
A_Tab_results(55,1) = "9 month BVAR to RW STEI"
A_Tab_results(56,1) = "12 month BVAR to RW STEI"
A_Tab_results(57,1) = "1 month BVAR to RW CPI"
A_Tab_results(58,1) = "3 month BVAR to RW CPI"
A_Tab_results(59,1) = "6 month BVAR to RW CPI"
A_Tab_results(60,1) = "9 month BVAR to RW CPI"
A_Tab_results(61,1) = "12 month BVAR to RW CPI"
A_Tab_results(62,1) = "1 month BVAR to RW USDKZT"
A_Tab_results(63,1) = "3 month BVAR to RW USDKZT"
A_Tab_results(64,1) = "6 month BVAR to RW USDKZT"
A_Tab_results(65,1) = "9 month BVAR to RW USDKZT"
A_Tab_results(66,1) = "12 month BVAR to RW USDKZT"
A_Tab_results(67,1) = "1 month BVAR to RW TONIA"
A_Tab_results(68,1) = "3 month BVAR to RW TONIA"
A_Tab_results(69,1) = "6 month BVAR to RW TONIA"
A_Tab_results(70,1) = "9 month BVAR to RW TONIA"
A_Tab_results(71,1) = "12 month BVAR to RW TONIA"


'DECLARING OBJECTS FOR MAIN VARIABLES AND EQUATION TYPES
For %Nam1 STEI_sa  CPI_sa  USDKZT_sa TONIA_sa
For %ModType V  RW
```

```
Matrix (Num_max-11,1) Mat_{%ModType}_12_{%Nam1}
Matrix (Num_max-8,1) Mat_{%ModType}_9_{%Nam1}
Matrix (Num_max-5,1) Mat_{%ModType}_6_{%Nam1}
Matrix (Num_max-2,1) Mat_{%ModType}_3_{%Nam1}
Matrix (Num_max,1) Mat_{%ModType}_1_{%Nam1}
Next
Next


'LOOP BY PSEUDO-REAL FORECAST EXPERIMENT PERIOD

For !J=1 To Num_Max

'SAMPLE FROM BEGINNING POINT TO THE SINGLE POINT IN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
Smpl @All
Smpl @First @First-1+(Num1-1)+(!J-1)

'ESTIMATION OF VAR MODEL
Var Var14_{!J}.ls 1 5 STEI_sa Invest_sa RealWage_sa Retail_sa CPI_sa ManufactPrice_sa HousePrice_sa
USDKZT_sa  TONIA_sa TengeMoneySupply_sa  @ c OilPrice_sa Transfert_sa(-3) ExtDemand_sa(-1) RusCPI_sa(-1)
OilExtract_sa

'ESTIMATION OF SIMPLE INDIVIIDUAL VARIABLE EQUATIONS
Equation Eq_STEI_{!J}.ls STEI_sa STEI_sa(-1) c
Equation Eq_CPI_{!J}.ls CPI_sa CPI_sa(-1) c
Equation Eq_USDKZT_{!J}.ls USDKZT_sa USDKZT_sa(-1) c
Equation Eq_TONIA_{!J}.ls TONIA_sa  c

'DECLARING OF SCALAR ASSOCIATED WITH 1 YEAR AHEAD FORECAST DATE NUMBER
Scalar Temp =  (Num1-1)+!J-1+12

'IF 1 YEAR AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp<=Obs_number Then

'1 YEAR AHEAD FORECAST WITH VAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J+11
Var14_{!J}.forecast(e) v

'1 YEAR AHEAD FORECAST WITH SIMPLE INDIVIIDUAL VARIABLE EQUATIONS
Eq_STEI_{!J}.forecast(e) STEI_sa_rw
Eq_CPI_{!J}.forecast(e) CPI_sa_rw
Eq_USDKZT_{!J}.forecast(e) USDKZT_sa_rw
Eq_TONIA_{!J}.forecast(e) TONIA_sa_rw

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_v  Invest_sa_v RealWage_sa_v Retail_sa_v ManufactPrice_sa_v HousePrice_sa_v

'LOOP BY MAIN VARIABLES AND 2 TYPES OF MODELS
For %Name STEI_sa CPI_sa  USDKZT_sa TONIA_sa
For %ModType1 V  RW

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_{%ModType1}_{%Name}
Temp_Er_{%ModType1}_{%Name}=abs({%Name}-{%Name}_{%ModType1})
Stomna(Temp_Er_{%ModType1}_{%Name}, Vec_Er_{%ModType1}_{%Name})

'SAVING 1, 3, 6, 9 12 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-
REAL FORECAST EXPERIMENT PERIOD
Mat_{%ModType1}_12_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(12)
Mat_{%ModType1}_9_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(9)
Mat_{%ModType1}_6_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(6)
Mat_{%ModType1}_3_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(3)
Mat_{%ModType1}_1_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(1)

'DELETE INTERIM OBJECTS
Delete {%Name}_{%ModType1}  Temp_Er_{%ModType1}_{%Name}  Vec_Er_{%ModType1}_{%Name}

Next
```

```
Next

Else

'IF ONLY 9 MONTH AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp-3<=Obs_number Then

'9 MONTH AHEAD FORECAST WITH VAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J+8
Var14_{!J}.forecast(e) v

'9 MONTH AHEAD FORECAST WITH SIMPLE INDIVIIDUAL VARIABLE EQUATIONS
Eq_STEI_{!J}.forecast(e) STEI_sa_rw
Eq_CPI_{!J}.forecast(e) CPI_sa_rw
Eq_USDKZT_{!J}.forecast(e) USDKZT_sa_rw
Eq_TONIA_{!J}.forecast(e) TONIA_sa_rw

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_v  Invest_sa_v RealWage_sa_v Retail_sa_v ManufactPrice_sa_v HousePrice_sa_v

'LOOP BY MAIN VARIABLES AND 2 TYPES OF MODELS
For %Name STEI_sa CPI_sa  USDKZT_sa TONIA_sa
For %ModType1 V  RW

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_{%ModType1}_{%Name}
Temp_Er_{%ModType1}_{%Name}=abs({%Name}-{%Name}_{%ModType1})
Stomna(Temp_Er_{%ModType1}_{%Name}, Vec_Er_{%ModType1}_{%Name})

'SAVING 1, 3, 6, 9 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-
REAL FORECAST EXPERIMENT PERIOD
Mat_{%ModType1}_9_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(9)
Mat_{%ModType1}_6_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(6)
Mat_{%ModType1}_3_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(3)
Mat_{%ModType1}_1_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(1)

'DELETE INTERIM OBJECTS
Delete {%Name}_{%ModType1}  Temp_Er_{%ModType1}_{%Name}  Vec_Er_{%ModType1}_{%Name}

Next
Next

Else

'IF ONLY 6 MONTH AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp-6<=Obs_number Then

'6 MONTH AHEAD FORECAST WITH VAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J+5
Var14_{!J}.forecast(e) v

'6 MONTH AHEAD FORECAST WITH SIMPLE INDIVIIDUAL VARIABLE EQUATIONS
Eq_STEI_{!J}.forecast(e) STEI_sa_rw
Eq_CPI_{!J}.forecast(e) CPI_sa_rw
Eq_USDKZT_{!J}.forecast(e) USDKZT_sa_rw
Eq_TONIA_{!J}.forecast(e) TONIA_sa_rw

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_v  Invest_sa_v RealWage_sa_v Retail_sa_v ManufactPrice_sa_v HousePrice_sa_v

'LOOP BY MAIN VARIABLES AND 2 TYPES OF MODELS
For %Name STEI_sa CPI_sa  USDKZT_sa TONIA_sa
For %ModType1 V RW

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_{%ModType1}_{%Name}
Temp_Er_{%ModType1}_{%Name}=abs({%Name}-{%Name}_{%ModType1})
```

```
Stomna(Temp_Er_{%ModType1}_{%Name}, Vec_Er_{%ModType1}_{%Name})

'SAVING 1, 3, 6 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-REAL
FORECAST EXPERIMENT PERIOD
Mat_{%ModType1}_6_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(6)
Mat_{%ModType1}_3_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(3)
Mat_{%ModType1}_1_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(1)

'DELETE INTERIM OBJECTS
Delete {%Name}_{%ModType1}  Temp_Er_{%ModType1}_{%Name}  Vec_Er_{%ModType1}_{%Name}

Next
Next

Else

'IF ONLY 3 MONTH AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp-9<=Obs_number Then

'3 MONTH AHEAD FORECAST WITH VAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J+2
Var14_{!J}.forecast(e) v

'3 MONTH AHEAD FORECAST WITH SIMPLE INDIVIIDUAL VARIABLE EQUATIONS
Eq_STEI_{!J}.forecast(e) STEI_sa_rw
Eq_CPI_{!J}.forecast(e) CPI_sa_rw
Eq_USDKZT_{!J}.forecast(e) USDKZT_sa_rw
Eq_TONIA_{!J}.forecast(e) TONIA_sa_rw

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_v  Invest_sa_v RealWage_sa_v Retail_sa_v ManufactPrice_sa_v HousePrice_sa_v

'LOOP BY MAIN VARIABLES AND 2 TYPES OF MODELS
For %Name STEI_sa CPI_sa USDKZT_sa TONIA_sa
For %ModType1 V RW

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_{%ModType1}_{%Name}
Temp_Er_{%ModType1}_{%Name}=abs({%Name}-{%Name}_{%ModType1})
Stomna(Temp_Er_{%ModType1}_{%Name}, Vec_Er_{%ModType1}_{%Name})

'SAVING 1, 3 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-REAL
FORECAST EXPERIMENT PERIOD
Mat_{%ModType1}_3_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(3)
Mat_{%ModType1}_1_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(1)

'DELETE INTERIM OBJECTS
Delete {%Name}_{%ModType1}  Temp_Er_{%ModType1}_{%Name}  Vec_Er_{%ModType1}_{%Name}

Next
Next

Else

'IF ONLY 1 MONTH AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp-11<=Obs_number Then

'1 MONTH AHEAD FORECAST WITH VAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J
Var14_{!J}.forecast(e) v

'1 MONTH AHEAD FORECAST WITH SIMPLE INDIVIIDUAL VARIABLE EQUATIONS
Eq_STEI_{!J}.forecast(e) STEI_sa_rw
Eq_CPI_{!J}.forecast(e) CPI_sa_rw
Eq_USDKZT_{!J}.forecast(e) USDKZT_sa_rw
Eq_TONIA_{!J}.forecast(e) TONIA_sa_rw
```

```
'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_v  Invest_sa_v RealWage_sa_v Retail_sa_v ManufactPrice_sa_v HousePrice_sa_v

'LOOP BY MAIN VARIABLES AND 2 TYPES OF MODELS
For %Name STEI_sa CPI_sa USDKZT_sa TONIA_sa
For %ModType1 V RW

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_{%ModType1}_{%Name}
Temp_Er_{%ModType1}_{%Name}=abs({%Name}-{%Name}_{%ModType1})
Stomna(Temp_Er_{%ModType1}_{%Name}, Vec_Er_{%ModType1}_{%Name})

'SAVING 1 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-REAL
FORECAST EXPERIMENT PERIOD
Mat_{%ModType1}_1_{%Name}(!J)= Vec_Er_{%ModType1}_{%Name}(1)

'DELETE INTERIM OBJECTS
Delete {%Name}_{%ModType1}  Temp_Er_{%ModType1}_{%Name}  Vec_Er_{%ModType1}_{%Name}

Next
Next


Endif
Endif
Endif
Endif
Endif

'DELETE EQUATIONS ESIMATED WITH NOT FULL SAMPLE
If !J<>Num_Max Then
Delete Var14_{!J} Eq_STEI_{!J} Eq_CPI_{!J} Eq_USDKZT_{!J} Eq_TONIA_{!J}
Endif

Next


'LOOP BY MAIN VARIABLES AND 2 TYPES OF MODELS
For %Name2 STEI_sa CPI_sa  USDKZT_sa TONIA_sa
For %ModType V RW

'VECTOR WITH COMPONENTS WHICH ARE RMSEs FOR DIFFERENT LENTH OF FORECAST
Vector (5) RMSE_Var14_{%ModType}_{%Name2}

'CALCULCATION OF RMSE FOR DIFFERENT LENTH OF FORECAST
Vector (1) TTemp=@csumsq(Mat_{%ModType}_1_{%Name2})
RMSE_Var14_{%ModType}_{%Name2}(1) = (TTemp(1)/(Num_max))^(1/2)

Vector (1) TTemp=@csumsq(Mat_{%ModType}_3_{%Name2})
RMSE_Var14_{%ModType}_{%Name2}(2) =(TTemp(1)/(Num_max-2))^(1/2)

Vector (1) TTemp=@csumsq(Mat_{%ModType}_6_{%Name2})
RMSE_Var14_{%ModType}_{%Name2}(3) = (TTemp(1)/(Num_max-5))^(1/2)

Vector (1) TTemp=@csumsq(Mat_{%ModType}_9_{%Name2})
RMSE_Var14_{%ModType}_{%Name2}(4) = (TTemp(1)/(Num_max-8))^(1/2)

Vector (1) TTemp=@csumsq(Mat_{%ModType}_12_{%Name2})
RMSE_Var14_{%ModType}_{%Name2}(5) = (TTemp(1)/(Num_max-11))^(1/2)

'DELETE INTERIM OBJECTS
Delete  Mat_{%ModType}_1_{%Name2}   Mat_{%ModType}_3_{%Name2}   Mat_{%ModType}_6_{%Name2}
Mat_{%ModType}_9_{%Name2}  Mat_{%ModType}_12_{%Name2}   TTemp

Next

Next
```

```
!Count=0
Scalar Counter = 0

'LOOP BY PARAMETRES OF LIT-MIN BVAR
For %init uni diag full
For !L1=1 to 5
For !M=0 to 5
For !L2=1 to 5
For !L3=1 to 5
For !Lag=5 to 5

'INTERIM TABLE FOR POSITIONINIG IN THE LOOP
Table (6,1) XXX
XXX(1,1)=%init
XXX(1,2)=!L1
XXX(1,3)=!M
XXX(1,4)=!L2
XXX(1,5)=!L3
XXX(1,6)=!Lag

'DECLARING OBJECTS FOR MAIN VARIABLES AND EQUATION TYPES
For %Nam1 STEI_sa  CPI_sa  USDKZT_sa  TONIA_sa
Matrix (Num_max-11,1) Mat_B_12_{%Nam1}
Matrix (Num_max-8,1) Mat_B_9_{%Nam1}
Matrix (Num_max-5,1) Mat_B_6_{%Nam1}
Matrix (Num_max-2,1) Mat_B_3_{%Nam1}
Matrix (Num_max,1) Mat_B_1_{%Nam1}
Next

'LOOP BY PSEUDO-REAL FORECAST EXPERIMENT PERIOD
For !J=1 To Num_Max

'SAMPLE FROM BEGINNING POINT TO THE SINGLE POINT IN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
Smpl @All
Smpl @First @First-1+(Num1-1)+(!J-1)

'ESTIMATION OF BVAR MODEL
Var bVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{!J}.bvar(prior=lit,initcov={%init},l1=!L1/5,l2=!L2/5-0.01,l3=!L3/5-
0.01,mu1=!M/5) 1 {!Lag} STEI_sa Invest_sa RealWage_sa Retail_sa CPI_sa ManufactPrice_sa HousePrice_sa
USDKZT_sa  TONIA_sa TengeMoneySupply_sa   @ c OilPrice_sa  Transfert_sa(-3)  ExtDemand_sa(-1) RusCPI_sa(-1)
OilExtract_sa

'DECLARING OF SCALAR ASSOCIATED WITH 1 YEAR AHEAD FORECAST DATE NUMBER
Scalar Temp =  (Num1-1)+!J-1+12

'IF 1 YEAR AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp<=Obs_number Then

'1 YEAR AHEAD FORECAST WITH BVAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J+11
bVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{!J}.forecast(e) b

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_b  Invest_sa_b RealWage_sa_b Retail_sa_b ManufactPrice_sa_b HousePrice_sa_b

'LOOP BY MAIN VARIABLES
For %Name STEI_sa CPI_sa  USDKZT_sa TONIA_sa

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_B_{%Name}
Temp_Er_B_{%Name}=abs({%Name}-{%Name}_B)
Stomna(Temp_Er_B_{%Name}, Vec_Er_B_{%Name})

'SAVING 1, 3, 6, 9 12 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-
REAL FORECAST EXPERIMENT PERIOD
Mat_B_12_{%Name}(!J)= Vec_Er_B_{%Name}(12)
Mat_B_9_{%Name}(!J)= Vec_Er_B_{%Name}(9)
Mat_B_6_{%Name}(!J)= Vec_Er_B_{%Name}(6)
```

```
Mat_B_3_{%Name}(!J)= Vec_Er_B_{%Name}(3)
Mat_B_1_{%Name}(!J)= Vec_Er_B_{%Name}(1)

'DELETE INTERIM OBJECTS
Delete {%Name}_B Temp_Er_B_{%Name}  Vec_Er_B_{%Name}

Next

Else

'IF ONLY 9 MONTH AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp-3<=Obs_number Then

'9 MONTH AHEAD FORECAST WITH BVAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J+8
bVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{!J}.forecast(e) b

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_b  Invest_sa_b RealWage_sa_b Retail_sa_b ManufactPrice_sa_b HousePrice_sa_b

'LOOP BY MAIN VARIABLES
For %Name STEI_sa CPI_sa  USDKZT_sa TONIA_sa

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_B_{%Name}
Temp_Er_B_{%Name}=abs({%Name}-{%Name}_B)
Stomna(Temp_Er_B_{%Name}, Vec_Er_B_{%Name})

'SAVING 1, 3, 6, 9 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-
REAL FORECAST EXPERIMENT PERIOD
Mat_B_9_{%Name}(!J)= Vec_Er_B_{%Name}(9)
Mat_B_6_{%Name}(!J)= Vec_Er_B_{%Name}(6)
Mat_B_3_{%Name}(!J)= Vec_Er_B_{%Name}(3)
Mat_B_1_{%Name}(!J)= Vec_Er_B_{%Name}(1)

'DELETE INTERIM OBJECTS
Delete {%Name}_B Temp_Er_B_{%Name}  Vec_Er_B_{%Name}

Next

Else

'IF ONLY 6 MONTH AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp-6<=Obs_number Then

'6 MONTH AHEAD FORECAST WITH BVAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J+5
bVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{!J}.forecast(e) b

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_b  Invest_sa_b RealWage_sa_b Retail_sa_b ManufactPrice_sa_b HousePrice_sa_b

'LOOP BY MAIN VARIABLES
For %Name STEI_sa CPI_sa  USDKZT_sa TONIA_sa

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_B_{%Name}
Temp_Er_B_{%Name}=abs({%Name}-{%Name}_B)
Stomna(Temp_Er_B_{%Name}, Vec_Er_B_{%Name})

'SAVING 1, 3, 6 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-REAL
FORECAST EXPERIMENT PERIOD
Mat_B_6_{%Name}(!J)= Vec_Er_B_{%Name}(6)
Mat_B_3_{%Name}(!J)= Vec_Er_B_{%Name}(3)
Mat_B_1_{%Name}(!J)= Vec_Er_B_{%Name}(1)

'DELETE INTERIM OBJECTS
```

```
Delete {%Name}_B Temp_Er_B_{%Name}  Vec_Er_B_{%Name}

Next

Else

'IF ONLY 3 MONTH AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp-9<=Obs_number Then

'3 MONTH AHEAD FORECAST WITH BVAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J+2
bVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{!J}.forecast(e) b

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_b  Invest_sa_b RealWage_sa_b Retail_sa_b ManufactPrice_sa_b HousePrice_sa_b

'LOOP BY MAIN VARIABLES
For %Name STEI_sa CPI_sa USDKZT_sa TONIA_sa

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_B_{%Name}
Temp_Er_B_{%Name}=abs({%Name}-{%Name}_B)
Stomna(Temp_Er_B_{%Name}, Vec_Er_B_{%Name})

'SAVING 1, 3 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-REAL
FORECAST EXPERIMENT PERIOD
Mat_B_3_{%Name}(!J)= Vec_Er_B_{%Name}(3)
Mat_B_1_{%Name}(!J)= Vec_Er_B_{%Name}(1)

'DELETE INTERIM OBJECTS
Delete {%Name}_B Temp_Er_B_{%Name}  Vec_Er_B_{%Name}

Next

Else

'IF ONLY 1 MONTH AHEAD FORECAST WITHIN PSEUDO-REAL FORECAST EXPERIMENT PERIOD
If Temp-11<=Obs_number Then

'1 MONTH AHEAD FORECAST WITH BVAR MODEL
Smpl @All
Smpl @First-1+(Num1-1)+!J @First-1+(Num1-1)+!J
bVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{!J}.forecast(e) b

'DELETE INTERIM OBJECTS
Delete TengeMoneySupply_sa_b  Invest_sa_b RealWage_sa_b Retail_sa_b ManufactPrice_sa_b HousePrice_sa_b

'LOOP BY MAIN VARIABLES
For %Name STEI_sa CPI_sa USDKZT_sa TONIA_sa

'SAVING MAIN VARIABLES FORECSAT ERRORS
Series Temp_Er_B_{%Name}
Temp_Er_B_{%Name}=abs({%Name}-{%Name}_B)
Stomna(Temp_Er_B_{%Name}, Vec_Er_B_{%Name})

'SAVING 1 MONTH AHEAD FORECAST ERRORS FOR DIFFERENT STARTING DATES WITHIN PSEUDO-REAL
FORECAST EXPERIMENT PERIOD
Mat_B_1_{%Name}(!J)= Vec_Er_B_{%Name}(1)

Delete {%Name}_B Temp_Er_B_{%Name}  Vec_Er_B_{%Name}

Next

Endif
Endif
Endif
Endif
Endif
```

```
'DELETE EQUATIONS ESIMATED WITH NOT FULL SAMPLE
If !J<>Num_Max Then
Delete BVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{!J}
Endif

Next

'DECLARING VECTOR THAT COMPONENT IS THE MAIN VARIABLES AVERAGE RATIO OF BVAR RMSE TO
ALTERNATIVE MODEL RMSE FOR A GIVEN FORECAST HORIZON
Vector(5) RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}=0
Vector(5) RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}=0

'LOOP BY MAIN VARIABLES
For %Name2 STEI_sa CPI_sa  USDKZT_sa TONIA_sa

'DECLARING VECTOR WITH COMPONENTS THAT ARE BVAR RMSEs FOR DIFFERENT LENTH OF FORECAST
Vector (5) RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}

'CALCULCATION OF BVAR RMSE FOR DIFFERENT LENTH OF FORECAST
Vector (1) TTemp=@csumsq(Mat_B_1_{%Name2})
RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(1) = (TTemp(1)/(Num_max))^(1/2)

Vector (1) TTemp=@csumsq(Mat_B_3_{%Name2})
RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(2) =(TTemp(1)/(Num_max-2))^(1/2)

Vector (1) TTemp=@csumsq(Mat_B_6_{%Name2})
RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(3) = (TTemp(1)/(Num_max-5))^(1/2)

Vector (1) TTemp=@csumsq(Mat_B_9_{%Name2})
RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(4) = (TTemp(1)/(Num_max-8))^(1/2)

Vector (1) TTemp=@csumsq(Mat_B_12_{%Name2})
RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(5) = (TTemp(1)/(Num_max-11))^(1/2)

'DELETE INTERIM OBJECTS
Delete  Mat_B_1_{%Name2}   Mat_B_3_{%Name2}   Mat_B_6_{%Name2}   Mat_B_9_{%Name2}
Mat_B_12_{%Name2}   TTemp

'DECLARATION OF A VECTOR THAT COMPONENT IS THE RATIO OF BVAR RMSE TO ALTERNATIVE MODEL
RMSE FOR A GIVEN FORECAST HORIZON (AND GIVEN VARIABLE)

Vector(5) RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}
Vector(5) RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}

'LOOP BY THE LENTH OF FORECAST
For !A=1 To 5

'CALCULATING BVAR RMSE TO ALTERNATIVE MODEL RMSE RATIO FOR A GIVEN FORECAST HORIZON (AND
GIVEN VARIABLE)
RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(!A)=RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3
}_{!Lag}_{%Name2}(!A)/RMSE_Var14_V_{%Name2}(!A)
RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(!A)=RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!
L3}_{!Lag}_{%Name2}(!A)/RMSE_Var14_RW_{%Name2}(!A)

'CALCULATING THE MAIN VARIABLES AVERAGE RATIO OF BVAR RMSE TO ALTERNATIVE MODEL RMSE FOR A
GIVEN FORECAST HORIZON
RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!A)=RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag
}(!A)+(1/4)*RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(!A)
RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!A)=RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(
!A)+(1/4)*RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}(!A)
Next

Next

'IF THE MAIN VARIABLES AVERAGE RATIO OF BVAR RMSE TO BOTH ALTERNATIVE MODEL RMSE FOR ALL
FORECAST HORIZONS IS LESS THAN 1 ("GOOD BVAR') THEN
If RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(1)<1 and
RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(2)<1 and
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RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(3)<1 and
RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(4)<1 and
RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(5)<1 and
RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(1)<1 and
RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(2)<1 and
RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(3)<1 and
RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(4)<1 and
RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(5)<1 Then

'INCREASE COUNTER OF THAT SET OF BVAR "GOOD" PARAMETRES
Counter=Counter+1

!Count=!Count+1

Show Counter

'SAVING DESCRIPTION OF THAT "GOOD" BVAR
Freeze(Tab_{!Count}) BVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{Num_max}.results

'SAVING THAT "GOOD" BVAR  SET OF PARAMETRES IN INDIVIDUAL TABLE
Table (6,1) Tab_Temp_{!Count}
Tab_Temp_{!Count}(1,1)=%init
Tab_Temp_{!Count}(2,1)=!L1
Tab_Temp_{!Count}(3,1)=!M
Tab_Temp_{!Count}(4,1)=!L2
Tab_Temp_{!Count}(5,1)=!L3
Tab_Temp_{!Count}(6,1)=!Lag

'SAVING THAT "GOOD" BVAR RMSE AND AVERAGE RATIO OF THAT "GOOD" BVAR RMSE TO BOTH
ALTERNATIVE MODEL RMSE (FOR A GIVEN VARIABLE AND A GIVEN FORECAST HORIZON)
For %Name3 STEI_sa CPI_sa  USDKZT_sa TONIA_sa
For %Mtype B BVV BVRW

Vector(5)
RMSE_Var14_{%Mtype}_{!Count}_{%Name3}=RMSE_Var14_{%Mtype}_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name
3}

Next
Next

'SAVING THE MAIN VARIABLES AVERAGE RATIO OF THAT "GOOD» BVAR RMSE TO BOTH ALTERNATIVE
MODEL RMSE (FOR A GIVEN FORECAST HORIZON)
Vector(5) RMSE_BVARtoVAR_{!Count}=RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}
Vector(5) RMSE_BVARtoRW_{!Count}=RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}

'LOOP BY THE LENTH OF FORECAST
For !Z=1 To 5

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF THE MAIN VARIABLES AVERAGE RATIO
OF "GOOD" BVAR RMSE TO VAR RMSE
If  RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z) < Min_BVV(!Z)  Then
Tab_results(1+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(1+!Z,3) = RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z)
Min_BVV(!Z) = RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF THE MAIN VARIABLES AVERAGE RATIO
OF "GOOD" BVAR RMSE TO SIMPLE EQUATION RMSE
If  RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z) < Min_BVRW(!Z)  Then
Tab_results(6+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(6+!Z,3) = RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z)
Min_BVRW(!Z) = RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF "GOOD" BVAR RMSE FOR STEI VARIABLE
If  RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z) < Min_STEI(!Z)  Then
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Tab_results(11+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(11+!Z,3) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Min_STEI(!Z) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF "GOOD" BVAR RMSE FOR CPI VARIABLE
If  RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z) < Min_CPI(!Z)  Then
Tab_results(16+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(16+!Z,3) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Min_CPI(!Z) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF "GOOD" BVAR RMSE FOR USDKZT
VARIABLE
If  RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z) < Min_USDKZT(!Z)  Then
Tab_results(21+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(21+!Z,3) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Min_USDKZT(!Z) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF "GOOD" BVAR RMSE FOR TONIA
VARIABLE
If  RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z) < Min_TONIA(!Z)  Then
Tab_results(26+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(26+!Z,3) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Min_TONIA(!Z) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF "GOOD" BVAR RMSE TO VAR
RMSE FOR STEI VARIABLE
If  RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z) < Min_BVV_STEI(!Z)  Then
Tab_results(31+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(31+!Z,3) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Min_BVV_STEI(!Z) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF "GOOD" BVAR RMSE TO VAR
RMSE FOR CPI VARIABLE
If  RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z) < Min_BVV_CPI(!Z)  Then
Tab_results(36+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(36+!Z,3) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Min_BVV_CPI(!Z) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF "GOOD" BVAR RMSE TO VAR
RMSE FOR USDKZT VARIABLE
If  RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z) < Min_BVV_USDKZT(!Z)  Then
Tab_results(41+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(41+!Z,3) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Min_BVV_USDKZT(!Z) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF "GOOD" BVAR RMSE TO VAR
RMSE FOR TONIA VARIABLE
If  RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z) < Min_BVV_TONIA(!Z)  Then
Tab_results(46+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(46+!Z,3) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Min_BVV_TONIA(!Z) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Endif
```

```
'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF "GOOD" BVAR RMSE TO
SIMPLE EQUATION RMSE FOR STEI VARIABLE
If  RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z) < Min_BVRW_STEI(!Z)  Then
Tab_results(51+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(51+!Z,3) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Min_BVRW_STEI(!Z) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF "GOOD" BVAR RMSE TO
SIMPLE EQUATION RMSE FOR CPI VARIABLE
If  RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z) < Min_BVRW_CPI(!Z)  Then
Tab_results(56+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(56+!Z,3) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Min_BVRW_CPI(!Z) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF "GOOD" BVAR RMSE TO
SIMPLE EQUATION RMSE FOR USDKZT VARIABLE
If  RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z) < Min_BVRW_USDKZT(!Z)  Then
Tab_results(61+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(61+!Z,3) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Min_BVRW_USDKZT(!Z) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF "GOOD" BVAR RMSE TO
SIMPLE EQUATION RMSE FOR TONIA VARIABLE
If  RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z) < Min_BVRW_TONIA(!Z)  Then
Tab_results(66+!Z,2) =%init +"_" +@Str(!L1)+"_"
+@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)+"_"+@Str(!Count)
Tab_results(66+!Z,3) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Min_BVRW_TONIA(!Z) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Endif

Next

Endif

Show XXX
Show Tab_results


'IF "GOOD" BVAR IS NOT FOUND THEN
If Counter =0 Then

'LOOP BY THE LENTH OF FORECAST
For !Z=1 To 5

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF THE MAIN VARIABLES AVERAGE RATIO
OF BVAR RMSE TO VAR RMSE
If  RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z) < A_Min_BVV(!Z)  Then
A_Tab_results(1+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(1+!Z,3) = RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z)
A_Min_BVV(!Z) = RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF THE MAIN VARIABLES AVERAGE RATIO
OF BVAR RMSE TO SIMPLE EQUATION RMSE
If  RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z) < A_Min_BVRW(!Z)  Then
A_Tab_results(6+!Z,2) =%init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(6+!Z,3) = RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z)
A_Min_BVRW(!Z) = RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF BVAR RMSE FOR STEI VARIABLE
If  RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z) < A_Min_STEI(!Z)  Then
A_Tab_results(11+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
```

```
A_Tab_results(11+!Z,3) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
A_Min_STEI(!Z) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF BVAR RMSE FOR CPI VARIABLE
If  RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z) < A_Min_CPI(!Z)  Then
A_Tab_results(16+!Z,2) =%init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(16+!Z,3) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
A_Min_CPI(!Z) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF BVAR RMSE FOR USDKZT VARIABLE
If  RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z) < A_Min_USDKZT(!Z)  Then
A_Tab_results(21+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(21+!Z,3) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
A_Min_USDKZT(!Z) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF BVAR RMSE FOR TONIA VARIABLE
If  RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z) < A_Min_TONIA(!Z)  Then
A_Tab_results(26+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(26+!Z,3) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
A_Min_TONIA(!Z) = RMSE_Var14_B_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF BVAR RMSE TO VAR RMSE FOR
STEI VARIABLE
If  RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z) < A_Min_BVV_STEI(!Z)  Then
A_Tab_results(31+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(31+!Z,3) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
A_Min_BVV_STEI(!Z) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF BVAR RMSE TO VAR RMSE FOR
CPI VARIABLE
If  RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z) < A_Min_BVV_CPI(!Z)  Then
A_Tab_results(36+!Z,2) =%init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(36+!Z,3) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
A_Min_BVV_CPI(!Z) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF BVAR RMSE TO VAR RMSE FOR
USDKZT VARIABLE
If  RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z) < A_Min_BVV_USDKZT(!Z)  Then
A_Tab_results(41+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(41+!Z,3) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
A_Min_BVV_USDKZT(!Z) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF BVAR RMSE TO VAR RMSE FOR
TONIA VARIABLE
If  RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z) < A_Min_BVV_TONIA(!Z)  Then
A_Tab_results(46+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(46+!Z,3) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
A_Min_BVV_TONIA(!Z) = RMSE_Var14_BVV_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF BVAR RMSE TO SIMPLE
EQUATION RMSE FOR STEI VARIABLE
If  RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z) < A_Min_BVRW_STEI(!Z)  Then
A_Tab_results(51+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(51+!Z,3) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
A_Min_BVRW_STEI(!Z) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_STEI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF BVAR RMSE TO SIMPLE
EQUATION RMSE FOR CPI VARIABLE
If  RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z) < A_Min_BVRW_CPI(!Z)  Then
A_Tab_results(56+!Z,2) =%init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
```

```
A_Tab_results(56+!Z,3) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
A_Min_BVRW_CPI(!Z) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_CPI_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF BVAR RMSE TO SIMPLE
EQUATION RMSE FOR USDKZT VARIABLE
If  RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z) < A_Min_BVRW_USDKZT(!Z)  Then
A_Tab_results(61+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(61+!Z,3) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
A_Min_BVRW_USDKZT(!Z) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_USDKZT_sa(!Z)
Endif

'FOR A GIVEN FORECAST HORIZON SEARCH FOR THE MINIMUM OF RATIO OF BVAR RMSE TO SIMPLE
EQUATION RMSE FOR TONIA VARIABLE
If  RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z) < A_Min_BVRW_TONIA(!Z)  Then
A_Tab_results(66+!Z,2) = %init +"_" +@Str(!L1)+"_" +@Str(!M)+"_"+@Str(!L2)+"_"+@Str(!L3)+"_"+@Str(!Lag)
A_Tab_results(66+!Z,3) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
A_Min_BVRW_TONIA(!Z) = RMSE_Var14_BVRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_TONIA_sa(!Z)
Endif

Next

Show A_Tab_results

Endif


'DELETE INTERIM OBJECTS
For %Name2 STEI_sa CPI_sa USDKZT_sa TONIA_sa
For %Mtype B BVV BVRW
Delete RMSE_Var14_{%Mtype}_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{%Name2}
Next
Next

'DELETE INTERIM OBJECTS
Delete RMSE_BVARtoVAR_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}
RMSE_BVARtoRW_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}

'DELETE INTERIM OBJECTS
Delete BVar14_{%init}_{!L1}_{!M}_{!L2}_{!L3}_{!Lag}_{Num_max}


Next
Next
Next
Next
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Next
```

Annex 3

Table 1

The Ratio of the Average on Key Variables RMSE of the Monthly BVAR-Model of Two Types with 1 lag to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 month	0.915	0.876	1.018	0.95	0.9	0.888
Minnesota	3 month	1.042	0.987	1.158	0.956	0.932	0.893
Minnesota	6 month	1.07	1.043	1.142	0.98	0.951	0.905
Minnesota	9 month	0.974	1.022	1.166	0.999	0.964	0.911
Minnesota	12 month	0.935	1.01	1.227	0.995	0.97	0.916
Normal Wishart	1 month	0.87	0.953	0.933	0.895	0.972	0.866
Normal Wishart	3 month	0.963	0.991	0.986	0.894	0.939	0.796
Normal Wishart	6 month	0.99	1.045	0.958	0.923	0.963	0.792
Normal Wishart	9 month	0.902	1.063	0.935	0.977	0.998	0.789
Normal Wishart	12 month	0.884	1.018	1.018	0.978	0.974	0.822

Source: the author's derivations

Table 2

The Ratio of the Average on Key Variables RMSE of the Monthly BVAR-Model of Two Types with 2 lags to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 month	0.806	0.796	0.929	0.851	0.809	0.824
Minnesota	3 month	0.975	0.897	1.17	0.886	0.879	0.87
Minnesota	6 month	0.996	0.963	1.204	0.899	0.912	0.914
Minnesota	9 month	0.899	0.936	1.141	0.928	0.931	0.988
Minnesota	12 month	0.832	0.895	1.034	0.953	0.942	0.999
Normal Wishart	1 month	0.883	0.907	0.895	0.918	0.911	0.826
Normal Wishart	3 month	0.961	0.993	0.904	0.887	0.972	0.74
Normal Wishart	6 month	0.941	1.012	0.872	0.882	0.978	0.74
Normal Wishart	9 month	0.88	1.026	0.799	0.949	1.039	0.771
Normal Wishart	12 month	0.851	1.032	0.849	0.995	1.099	0.867

Source: the author's derivations

Table 3

The Ratio of the Average on Key Variables RMSE of the Monthly BVAR-Model of Two Types with 3 lags to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 month	0.779	0.776	0.919	0.832	0.778	0.815
Minnesota	3 month	0.922	0.876	1.126	0.917	0.867	0.847
Minnesota	6 month	0.937	0.931	1.17	0.908	0.883	0.883
Minnesota	9 month	0.846	0.899	1.023	0.89	0.876	0.971
Minnesota	12 month	0.8	0.868	0.813	0.896	0.881	0.99
Normal Wishart	1 month	0.83	0.896	0.884	0.869	0.886	0.815
Normal Wishart	3 month	0.911	0.907	0.914	0.898	0.902	0.757
Normal Wishart	6 month	0.906	0.971	0.839	0.917	0.952	0.717
Normal Wishart	9 month	0.871	0.964	0.732	0.965	0.977	0.774
Normal Wishart	12 month	0.839	0.92	0.697	0.985	0.97	0.941

Source: the author's derivations

Table 4

The Ratio of the Average on Key Variables RMSE of the Monthly BVAR-Model of Two Types with 4 lags to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 month	0.782	0.786	0.916	0.789	0.78	0.82
Minnesota	3 month	0.915	0.879	1.122	0.887	0.898	0.853
Minnesota	6 month	0.927	0.943	1.156	0.95	0.924	0.9
Minnesota	9 month	0.839	0.916	1.022	0.889	0.907	0.966
Minnesota	12 month	0.782	0.866	0.792	0.866	0.903	0.973
Normal Wishart	1 month	0.782	0.85	0.875	0.789	0.84	0.826
Normal Wishart	3 month	0.915	0.894	0.925	0.887	0.913	0.762
Normal Wishart	6 month	0.927	0.909	0.843	0.95	0.923	0.77
Normal Wishart	9 month	0.839	0.894	0.699	0.889	0.931	0.781
Normal Wishart	12 month	0.782	0.877	0.68	0.866	0.955	0.941

Source: the author's derivations

Table 5

The Ratio of the Average on Key Variables RMSE of the Monthly BVAR-Model of Two Types with 5 lags to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 month	0.789	0.788	0.901	0.795	0.774	0.825
Minnesota	3 month	0.91	0.88	1.093	0.89	0.892	0.863
Minnesota	6 month	0.922	0.939	1.104	0.972	0.927	0.904
Minnesota	9 month	0.848	0.913	0.927	0.903	0.899	0.934
Minnesota	12 month	0.775	0.876	0.685	0.847	0.903	0.845
Normal Wishart	1 month	0.815	0.953	0.861	0.806	0.972	0.848
Normal Wishart	3 month	0.892	0.991	0.881	0.873	0.939	0.78
Normal Wishart	6 month	0.819	1.045	0.811	0.926	0.963	0.797
Normal Wishart	9 month	0.734	1.063	0.687	0.928	0.998	0.833
Normal Wishart	12 month	0.678	1.018	0.613	0.915	0.974	0.826

Source: the author's derivations

Table 6

The Ratio of the Average on Key Variables RMSE of the Quarterly BVAR-Model of Two Types with 1 lag to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 quarter	0.715	0.862	1.785	0.831	0.813	0.678
Minnesota	2 quarter	0.663	0.797	1.736	0.834	0.838	0.736
Minnesota	3 quarter	0.664	0.739	1.569	0.827	0.706	0.697
Minnesota	4 quarter	0.616	0.703	1.381	0.756	0.598	0.699
Normal Wishart	1 quarter	0.963	1.022	1.038	1.059	0.827	0.446
Normal Wishart	2 quarter	0.948	1.027	1.002	1.163	0.905	0.459
Normal Wishart	3 quarter	1.021	1.014	1.052	1.308	1.249	0.552
Normal Wishart	4 quarter	1.065	0.971	1.101	1.612	1.459	0.666

Source: the author's derivations

Table 7

The Ratio of the Average on Key Variables RMSE of the Quarterly BVAR-Model of Two Types with 2 lags to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 quarter	0.72	0.861	1.855	0.754	0.695	0.635
Minnesota	2 quarter	0.683	0.819	1.894	0.788	0.709	0.626
Minnesota	3 quarter	0.662	0.788	1.672	0.811	0.749	0.518
Minnesota	4 quarter	0.605	0.746	1.452	0.692	0.695	0.5
Normal Wishart	1 quarter	0.93	1.022	1.022	0.92	0.827	0.412
Normal Wishart	2 quarter	1	1.027	1.011	1.06	0.905	0.384
Normal Wishart	3 quarter	1.082	1.014	0.977	1.394	1.249	0.379
Normal Wishart	4 quarter	1.127	0.971	1.005	1.647	1.459	0.38

Source: the author's derivations

Table 8

The Ratio of the Average on Key Variables RMSE of the Quarterly BVAR-Model of Two Types with 3 lags to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 quarter	0.704	0.869	1.828	0.591	0.62	0.569
Minnesota	2 quarter	0.664	0.838	1.885	0.549	0.565	0.654
Minnesota	3 quarter	0.653	0.795	1.636	0.629	0.648	0.579
Minnesota	4 quarter	0.562	0.747	1.412	0.393	0.435	0.507
Normal Wishart	1 quarter	1.071	1.03	1.227	0.986	0.756	0.445
Normal Wishart	2 quarter	1.28	1.137	1.203	1.122	0.758	0.447
Normal Wishart	3 quarter	1.599	1.219	1.279	1.541	1	0.479
Normal Wishart	4 quarter	1.82	1.261	1.337	1.448	0.775	0.461

Source: the author's derivations

Table 9

The Ratio of the Average on Key Variables RMSE of the Quarterly BVAR-Model of Two Types with 4 lags to the Same Values in the Naïve Model and VAR-Model for Given Forecasting Horizon and for Given Number of Variables in the Model

BVAR-method	Forecast length	BVAR to RW			BVAR to VAR		
		The number of variables			The number of variables		
		5	6	15	5	6	15
Minnesota	1 quarter	0.677	0.83	1.7	0.452	0.582	0.377
Minnesota	2 quarter	0.646	0.811	1.75	0.537	0.66	0.431
Minnesota	3 quarter	0.623	0.748	1.565	0.411	0.574	0.53
Minnesota	4 quarter	0.533	0.686	1.296	0.312	0.404	0.318
Normal Wishart	1 quarter	1.136	1.168	1.363	0.788	0.812	0.321
Normal Wishart	2 quarter	1.378	1.309	1.329	1.212	1.159	0.326
Normal Wishart	3 quarter	1.689	1.372	1.308	1.178	1.122	0.456
Normal Wishart	4 quarter	1.755	1.416	1.307	1.104	0.88	0.326

Source: the author's derivations