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ПЕРЕТВОРЕННЯ СПОЖИВАННЯ І ЙОГО НАСЛІДКИ ДЛЯ УКРАЇНСЬКОГО ТОВАРИСТВА

Розглянуто зміни структури споживання в українському суспільстві за останні 25 років, а також проаналізовано вплив цієї трансформації на українських споживачів. Досліджено ринкові сили та їхній вплив на поведінку споживачів. І, нарешті, зроблено висновок про те, що ринкові сили, які концентруються на українському ринку, привели до трансформації моделей споживання і поведінки споживачів. У науковому дослідженні також представлено критичний аналіз наслідків для українського суспільства і можливих варіантів ринкових моделей.

Ключові слова: споживання, споживча поведінка, український споживач, українська економіка, українське суспільство.

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ПРЕОБРАЗОВАНИЕ ПОТРЕБЛЕНИЯ И ЕГО ПОСЛЕДСТВИЯ ДЛЯ УКРАИНСКОГО ОБЩЕСТВА

Рассмотрены изменения структуры потребления в украинском обществе за последние 25 лет, а также проанализировано влияние этой трансформации на украинских потребителей. Исследуются рыночные силы, и их влияние на поведение потребителей. И, наконец, сделан вывод о том, что рыночные силы, присутствующие на украинском рынке, привели к трансформации моделей потребления и поведения потребителей. В этом научном исследовании также представляется критический анализ последствий для украинского общества и возможных вариантов рыночных моделей.

Ключевые слова: потребление, потребительское поведение, украинский потребитель, украинская экономика, украинское общество.

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MACROECONOMIC FORECASTING USING BAYESIAN VECTOR AUTOREGRESSIVE APPROACH

There are many arguments that can be advanced to support the forecasting activities of business entities. The underlying argument in favor of forecasting is that managerial decisions are significantly dependent on proper evaluation of future trends as market conditions are constantly changing and require a detailed analysis of future dynamics. The article discusses the importance of using reasonable macro-econometric tool by suggesting the idea of conditional forecasting through a Vector Autoregressive (VAR) modeling framework. Under this framework, a macroeconomic model for Georgian economy is constructed with the few variables believed to be shaping business environment. Based on the model, forecasts of macroeconomic variables are produced, and three types of scenarios are analyzed – a baseline and two alternative ones. The results of the study provide confirmatory evidence that suggested methodology is adequately addressing the research phenomenon and can be used widely by business entities in responding their strategic and operational planning challenges. Given this set-up, it is shown empirically that Bayesian Vector Autoregressive approach provides reasonable forecasts for the variables of interest.

Keywords: forecasting, macroeconomic modeling, bayesian VAR, litterman prior, scenario analysis, IFRS 9.

Introduction. Forecasting, in general, plays a significant role in many aspects of modern business administration. It represents an important part in operation planning and decision-making process, which in turn are prerequisites for successful business management. Since forecasting involves estimation of business-relevant factors both in quantitative and qualitative terms in short-, medium- and/or long-run, organizational decisions and strategy, of course, are incomplete without direct projections of future trends or at least, without making a quantitative assessment of those trends [3]. Benefits, yielded by accurate and timely forecasts, are huge. First of all, managerial decisions are greatly dependent on proper evaluation of future trends as market conditions are constantly changing and require a detailed analysis of future dynamics. Accordingly, managerial decisions are made in a continuous manner, and are applied to short-term, as well as medium and long term horizons. This circumstance puts on the agenda the need for organized activities, which will involve reasonable predictions of future trends and in this regard, forecasting process is an effective method to improve the quality of decisions by reducing losses from unexpected developments (Shim 2000). In addition, forecasts of a firm's financial indicators (e.g., sales), raises organization's success by allowing cost optimization, efficient distribution of resources and rational budgeting. One more important benefit of forecasting is that projection of important factors, based on all available and relevant information, facilitates integration of plans and strategies in various departments of a firm and helps design a mutual action plan. Also, it facilitates discussions between the parties involved in forecasting process, enhancing team spirit, encouraging coordination and developing a broader and clearer vision of the firm's goals and objectives. Meanwhile, forecasting process helps a manager to identify "weak points" enabling her to effectively manage and deal with them [20].

Financial institutions (and of course, other non-financial firms as well) typically make four kinds of forecasts:

- *Competition forecast*, assessing future moves and tactics of competitors on the market;
- *Technological forecast,* following evolution dynamics of innovations and technological advances;
- *Social forecasts*, studying customers' behavior, taste and sentiment;
- *Economic/financial forecast*, evaluating and predicting financial performance indicators, as well as industrial/macroeconomic indicators.

From practical point of view, the most effective one among aforementioned forecasting activities is *economic/financial forecasting*, as long as it is based on a quantitative framework, results in unambiguous conclusions and therefore, is one of the most important components in decision-making process. It also makes it possible to clearly define different scenarios and analyze possible developments. In addition, as is well known, communication of a quantitative forecast is much easier and more productive compared with the alternative – an expert judgment – because the latter is excessively dependent on the forecaster's subjective beliefs and at the same time, it does not allow elimination of systematic forecast errors since it is usually unknown how data were used in assessments.

As noted above, facing the new requirements under IFRS 9 to use more forward-looking information in credit loss assessments, financial institutions are expected to rely more on *macroeconomic forecasts*. Importance of such forecasts stems from the fact that macroeconomic stance shapes business environment and may significantly affect future business activity.

Typically, business environment is influenced by the following 6 basic macroeconomic indicators:

- Current and expected growth of gross domestic product (GDP);
- Changes in price level and expected inflation
- Trend in total savings
- Rate of unemployment
- Government macroeconomic policy
- Economic and financial environment overseas

Current and expected GDP growth causes changes in demand for a firm's goods and services as far as, on one hand, it is in fact in line with income dynamics of existing and potential consumers. Also, its positive and negative trend significantly influences expectations and purchasing decisions of customers in the economy. On the other hand, consumption is a major component of a country's GDP (70 %-90 %), the dynamics of which, obviously, represents valuable information for consumer product manufacturers in learning behavior, choices and decisions of buyers.

Growth of total savings means for business entities a greater access to financial capital with favorable conditions. This primarily refers to interest rates, which typically fall in times of excess savings. In contrast, scarcity of total savings increases the cost of financial resources and deteriorates credit conditions.

Low inflation, which is seen as an evidence for price stability in a macroeconomic sense, is an important factor for sustainable business environment. In particular, low-inflation helps economic agents avoid volatility, thus facilitating optimal decision-making and planning, and reduces costs related to uncertainty. In contrast, high inflation (or high deflation) creates additional uncertainty and impediments both for firms and consumers.

Unemployment rate in a country, as a rule, is a less relevant indicator shaping business environment in the short term; however, in longer term, high unemployment has a negative impact on consumer demand even in case of high GDP growth rates. Note that if GDP growth is not inclusive, typically it is not associated with job growth and income growth among population.

The macro-economic policies, including monetary, fiscal and structural policies, are one of the most important factors in forming business environment. Economic-cycle-adjusted monetary and fiscal policies, as well as the optimal structural reforms significantly contribute to entrepreneurial activity and boost expectations among economic agents.

Foreign economic and financial developments are vital for sustainable growth of international trade and global financial integration. Unsurprisingly, a firm, which has close ties with export markets and foreign capital markets, is potentially very sensitive to developments in the international arena. A firm's competitiveness is influenced by dynamics of foreign demand, interest rates on attracted foreign resources, exchange rates, etc.

Recently, macroeconomic forecasts have raised particular interest among financial enterprises. Under the new International Financial Reporting Standards (IFRS), accounting rules for financial instruments are set to be altered substantially from 2018. In particular, IFRS 9, which lists the standards for classification and measurement of financial instruments, as well as impairment of financial assets and hedge accounting, introduces a new approach based on more forward-looking information to account for expected credit losses. In other words, these standards require that the loss be recognized not after a credit event but before it – at the very moment of originating a debt-type instrument (the so-called "day one loss"). This in principle means that a bank, while concluding a financial contract, instantly recognizes the "expected" credit loss from it and is not "waiting" for any credible evidence of a credit event (for example, a loan payment past due). This also means that the bank should use all available forward-looking information to assess the potential credit losses and make reasonable predictions of factors that could potentially affect future cash flows from the financial instrument (IFRS 9 Financial Instruments, 2014). Therefore, financial institutions are expected to intensify forecasting activities and extensively rely on projections made through various models.

In this paper, we construct a macroeconomic model for Georgian economy with few variables believed to be shaping business environment (see *Model Description, Data and Diagnostics* section), and carry out scenario generation to analyze likely developments. As noted in IFRS staff paper on incorporation of forward-looking scenarios [13], "relatively simple modelling may be sufficient without the need for a large number of detailed simulations of scenarios", so, we intentionally maintain a rudimental (but straightforward) set-up of the model and scenarios. In particular, we produce conditional forecasts of key macroeconomic variables in vector autoregressive (VAR) framework with Bayesian estimation approach, and construct three types of scenarios – a baseline and two alternative ones.

The paper is organized as follows. The following section makes a literature review focusing on accumulated knowledge in macroeconomic forecasting. The methodology section describes the tools and technique employed in estimation and forecasting exercise. Next, model properties and data are described. The results section provides quantitative outcomes of unconditional and conditional forecasts of key macroeconomic variables along with fan charts. The last section concludes.

Literature Review. Forecasting has been emerging as a necessary tool for economic experts along with the development of macroeconomic analysis. In particular, strengthening Keynesian school in academic circles after World War II substantially raised interest in forecasting instruments. In this respect, two fundamental works – Klein (1946) and Klein and Goldberger [14] – should be noted. These works were the first attempt to model Keynesian economy with mathematical apparatus – systems of linear equations. Later, Brookings Institute (USA) developed a relatively sophisticated and complex econometric model which consisted of about 400 equations with vast computer resources having been spent on it (Fromm and Klein 1965). These developments made it particularly relevant to produce official forecasts on a regular basis in the US, Great Britain and the Scandinavian countries.

At the end of the 60s, in academic circles, certain skepticism emerged towards traditional linear equations systems based on Keynesian models. The three main reasons are believed to have caused this: 1) the structural Keynesian models had ambiguous microeconomic fundamentals (Phelps 1970), which made the interaction of variables in the model suspicious; 2) models relied on unrealistic adaptive expectations concept while rational expectations idea gradually was becoming more convincing to researchers [21] 3) conventional rule-based decision-making analysis turned out to be flawed in producing conditional forecast after publication of a classic work by Robert Lucas [18] (known as the "Lucas critique"), because parameters involved in decision-making practices changed with the change in policy. That was when the concept of the so-called "Fundamental Parameters" emerged and based on this concept a new trend in macroeconomic modeling developed.

With decreasing popularity of structural Keynesian macroeconomic models, non-structural models started to enjoy growing interest in academic circles. Non-structural models were predicting variables based on autoregressive and moving average processes rather than within theoretical macroeconomic framework. Sims [22] developed vector-autoregressive (hereinafter – VAR) modeling framework, which, with different modifications, has been extensively used for forecasting purposes. The essential feature of the methodology is that in contrast to the structural framework, the variables are no longer separated as "exogenous" (Independent) and "endogenous" (dependent). Under this approach, each variable is modeled based on both its own historical path and other lagged variables, with some error terms accounted for. By avoiding "unrealistic structural assumptions" [2], VAR models turned out to be the most efficient among existing alternatives (Diebold 1998). In James Hamilton's famous book [12] on time series analysis the nature of vector-autoregressive models was described in detail and also, structural vector-autoregressive models were extensively discussed. The latter enables a researcher to take into account the structural relationships between variables while setting up a VAR model. However, as it turned out later, this approach may be accompanied by two significant obstacles. First of all, due to the abundance of the estimated parameters, a VAR model may face a problem of insufficient degrees of freedom, which, on the one hand, is caused by a multitude of variables, and on the other hand, increasing lags in the specification (so-called overfitting). This leads to the fact that the instead of estimation of parameters a simple description the data is carried out, and the model at least loses its abilities to produce reasonable forecast.

Litterman [17] proposed a Bayesian methodology which seemed to offer a workaround of overfitting problem. According to this approach, as far as a structure of true population parameters in a VAR model is vague, it is better not to put great importance (weight) on a specific value of the model parameter (for example, by restricting coefficients to zero). Instead, the vagueness of the model parameters is recommended to describe with the so-called *prior probability distribution*. As a result, the initial degree of uncertainty, given with the prior, can be improved by information coming from data. In this case, the improvement is carried out from a "signal" and not from "noise", which provides reduction in overfitting risk. It is vital to accurately select a prior and the Litterman approach offers specific rules for forming it. It is believed that due to above-mentioned reasons, Bayesian vector-autoregressive models (BVAR) perform much better in terms of forecasting than the classic reduced-form VAR alternatives or structural models [2].

Abundance of estimated parameters, of course, limits the possibility to include desired number of variables into classical VAR model. The Bayesian approach successfully copes with this problem. In a paper published by the European Central Bank [1], it is clearly shown that with a proper selection of prior probability distribution for parameters, BVAR represents a powerful forecasting tool for large data panels from developed economies. The same study indicates that valuable alternatives in terms of performance are only *factor models*, whose structure is based on the assumption that large data sets can be described through relationships among a few common factors (see e.g. [7]). However, in-sample and out-of-sample forecasting results suggest that BVAR generally is a better choice even when considering factor-augmented Bayesian VAR model (so-called BFAVAR). In recent years, a rich volume of publications accumulated that address various aspects of Bayesian VAR modeling. Some of them are worth noting. Korobilis [16] finds that Bayesian variable selection methods can be used to find restrictions based on the evidence in the data, and at the same time improve over the forecasts of unrestricted VAR models as well. A paper by Koop [15] develops a mechanism that solves certain computational and theoretical issues when the undertaken model is large.

It should be noted that of course, structural econometric models still continue to play significant role in forecasting practices, and in this regard, it is important to mention dynamic stochastic general equilibrium models (DSGE). The framework of such model was first proposed in a seminal work by Rotemberg and Woodford [19], and it gained substantial popularity since the publication of a paper by Galí and Monacelli [9]. This model has many uses in central banks' policy analysis and medium and long term projections; however, forecasting quality does not exceed that in BVAR alternatives (see e.g. Coenen and Warne [4], and Wickens [24]). In addition, DSGE modeling requires a lot of intellectual resources and costs are justified only in cases when it is used by monetary or fiscal bodies to carry out fundamental macroeconomic analysis [23].

Methodology. In this paper, we employ the idea of *conditional forecasting* through a vector autoregressive (VAR) modeling framework. By construction, a VAR model captures all the dynamic interlinkages among the variables included in the model. Therefore, estimated parameters and error covariance can be used to construct forecast paths for these variables both unconditional and conditional on assumed trajectory of a variable (or a set of variables). For clarity, suppose a forecaster expects the monetary policy rate to remain unchanged for the following time periods. Obviously, the model forecasting procedure is required to incorporate this condition in future projections of the variables as unconditional evolution of the system might be well different from that one conditioned on constant interest rate path due to existing correlations among the macroeconomic variables. Meanwhile, conditioning technique not only helps increase the overall forecast accuracy whenever conditioning information turns out to be correct ex post, it also allows for a variety of scenarios to be generated and analyzed.

In essence, the scenario generation in this paper will be implemented through reduced-form VAR model and will rest on all the reduced-form innovations that are compatible with imposed conditions. Hence, we intentionally avoid the task of identification of any structural shocks and maintain the simplicity of the framework without a loss of performance. [6;1].

Since the seminal work of Sims [22], VAR models have gained considerable popularity in modern macroeconomics having been used primarily for forecasting purposes. However, these models proved to be rather uneconomical in the sense that faced with a large set of parameters to estimate (which is typical even in case of small VARs), one needs to employ a sufficiently long time series. Scarcity of data exerts a negative impact on the accuracy of model parameter estimates and, of course, casts doubt on the credibility of the projected results [5]. For example, most of the macro-economic data in Georgia are only available from the years 1996-2000 for obvious reasons, and at the same time, the majority of them are reported in yearly or quarterly frequency. Consequently, the existing volume of data makes it almost impossible to properly estimate a standard reduced-form VAR model that contains three or more endogenous variables. This has an adverse effect on intentions of business forecasters to include all the relevant variables from their desired set of macro- and industry-specific variables.

As noted above, although a traditional VAR modeling may yield inaccurate estimated dependencies between the variables, it may perfectly fit the data (the so-called *overfitting*) solely due to the fact that the model simply contains many variables. In general, the number of estimated parameters increases geometrically in relation to the number of variables and proportionately to the number of lags. In this case, often there is a situation in which the estimators are influenced by the "noise" and not the informative "signal" coming from data. In this situation it is recommended to impose certain restrictions to reduce the parametric space and therefore, the question is how to construct effectively a procedure for setting up appropriate restrictions.

Obviously, the problem of overfitting could be solved with imposing zero restrictions on model parameters. However, Litterman [17] proposed an alternative. According to his judgement, as far as a researcher cannot be completely sure that a particular model coefficient is exactly trivial, he should not ignore the possible variation of the corresponding variable. For this reason, instead of focusing on specific values, the uncertainty around the true magnitude of a parameter can be described with a (prior) probability distribution. Further, the degree of uncertainty can be substituted by the information that comes as a "signal" from the data eventually resulting in posterior probability distribution. Since the procedure reflects a well-known *Bayes Rule* in statistics, VAR models employing this approach have been named *Bayesian*.

Bayesian Estimation of a VAR Model with Litterman Prior. Consider a typical reduced-form VAR:

$$Y_t = B_1Y_{t-1} + B_2Y_{t-2} + \ldots + B_pY_{t-p} + Dz_t + u_y \quad t = 1,\ldots,T \qquad 1$$

where Y_t is an $n \times 1$ vector of endogenous variables and u_t is an $n \times 1$ vector of residuals. The latter is distributed identically, normally and independently with variance-covariance $n \times n$ matrix V, and $B_l, L = 1,2,\ldots,p$ and D are $n \times n$ and $n \times d$ matrices, respectively. z_t is a $d \times 1$ vector of exogenous variables.

(1) can be rewritten into a more compact form:

$$Y_t = X_t\beta + u_t, \qquad t = 1,\ldots,T \qquad 2$$

where $X_t = L_n \otimes W_{t-1}$ is an $n \times nk$ matrix ($k = np + d$), $W_{t-1} = (Y'_{t-1},\ldots,Y'_{t-p},z'_t)'$ is an $k \times 1$ vector, and $\beta = vec(B_1, B_2,\ldots,B_p,D)$ is an $nk \times 1$ vector. (Symbol $\otimes$ stands for the Kroneker product of matrices; *vec* is vectorization operator creating a column vector from a matrix by stacking its column vectors below one another). The unknown parameters to be estimated are β and V.

The conditional probability density function (pdf) of the parameters given the data Y, according to the Bayes Rule, is

$$f(\beta,V \mid Y) = \frac{f(\beta,V,Y)}{f(Y)} = \frac{f(Y \mid \beta,V)f(\beta,V)}{f(Y)}$$

Note that $f(Y \mid \beta,V)$ is simply a likelihood function, $L(Y \mid \beta,V)$, and $f(Y)$ does not depend on parameters. Therefore, the conditional probability density function of the parameters given the data (called the *posterior pdf*) is proportional to the product of the likelihood of the data given the parameters and the pdf of these parameters (called the *prior pdf*):

$$f(\beta,V \mid Y) \propto L(Y \mid \beta,V)f(\beta,V)$$

The posterior density $f(\beta,V \mid Y)$ summarizes all the information known about the parameters after observing the data and consequently, can be used to derive point estimators for β and V (for example, by simply taking the mean of $f(\beta,V \mid Y)$). In turn, a *prior density* $f(\beta,V)$ represents subjective beliefs (or complete ignorance) of a researcher about the parameters before observing the data. The choice of a prior distribution is a significant step in setting up of the model. There are a number of alternatives proposed in the academic literature; however, in this paper we follow the technique called Litterman (Minnesota) prior as this prior is relatively simple to implement.

Under Litterman approach, the prior distribution reflects three statistical properties of macroeconomic time series:

A. Macroeconomic time series are characterized by a trend;

B. The data from the recent past contain more valuable information about the current state of a variable rather than distant ones;

C. Own past values contain much more information about the current state of a variable than values of other variables from the same past time period.

Bayesian VAR modeling implements aforementioned statistical properties through the following restrictions (as we will see below, these restrictions are technically implemented by the so-called hyper-parameters, each of which bears a defined function):

A. Expected value of all lag coefficients other than the first lag is set to zero;

B. Variance of coefficients is inversely proportional to the order of the lag;

C. Coefficients have more prior variance in own equation than in other equations.

Consider the m-th $(1 \le m \le n)$ equation from (2) after stacking the observations from 1 to T:

$$Y_m = X\beta_m + u_m, \quad 1 \le m \le n$$

where β_m are the $k \times 1$ parameter vector of the m-th equation, Y_m and u_m are $T \times 1$ vectors, and X is a stacked X_t. Litterman (1986) proposes a multivariate normal prior distribution for β_m,

$$\beta_m \sim N(\beta_m^*, \Omega_m^*),$$

with prior mean, β_m^*, and diagonal covariance matrix of β_m, Ω_m^*.

Next, some restrictions are imposed in order to specify β_m^* and Ω_m^*. The *hyper-parameter*, λ_1, reflects the restriction A (noted above) and represents the prior mean of the coefficient on the first lag of the endogenous variable in equation m; the prior parameter vector becomes $\beta_m^* = (0,0,...\lambda_1,0,0)$ with λ_1 standing on the m-th position. λ_2 reflects the restriction B and characterizes a lag-decay of the prior variance of coefficients. The restriction C is implemented through the hyper-parameter λ_3. There are three more hyper-parameters, λ_4, λ_5 and λ_6, which control the tightness of lags of the endogenous variable, the degree of uncertainty on the coefficients of the deterministic and/or exogenous variables in equation m, and overall tightness, respectively. Formally, diagonal elements of Ω_m^* are derived as follows:

$$\operatorname{var}(\beta_m^*) = \begin{cases} \dfrac{\lambda_6\lambda_4}{l^{\lambda_2}}, \text{ for } m-\text{th lagged endogenous variable} \\ \dfrac{\lambda_6\lambda_3}{l^{\lambda_2}} * \dfrac{\sigma_{mm}}{\sigma_{jj}}, \text{ for } j-\text{th lagged endogenous variable} \\ \lambda_6\lambda_{5\sigma}\sigma_{mm}, \text{ for deterministic and exogenous variable} \end{cases}$$

where $l = 1,...,p$.

Next, error covariance matrix in (2) is assumed fixed and diagonal: $V = \sigma_{mm}^2 I_T$ (this means that the only parameters to be estimated are β).

As a result, the posterior density for m-th equation coefficients takes the form:

$$f(\beta_m \mid Y) = N(\hat{\beta}_m, \widehat{\Omega}_m),$$

where the posterior variance, $\widehat{\Omega}_m$, is

$$\widehat{\Omega}_m = (\Omega_m^{*-1} + \sigma_{mm}^{-2} X'X)^{-1}$$

and the posterior mean, $\hat{\beta}_m$, is

$$\hat{\beta}_m = \widehat{\Omega}_m(\Omega_m^{*-1}\beta_m^* + \sigma_{mm}^{-2} X'Y_m)$$

Since hyper-parameters mostly are responsible for controlling the tightness of the variance of model coefficients, the technique is usually referred as *Bayesian shrinkage*.

Scenario Generation. We find it sufficient to construct three types of scenarios under Bayesian VAR framework: baseline, pessimistic and optimistic. In practice, one can pick an unconditional forecast for the baseline scenario since the former corresponds to the forecast assuming no explicit restrictions on future evolution of the system. On the contrary, a pessimistic scenario can be built upon the assumption that macroeconomic situation is worse than projected by the baseline. Typically, this might be implemented through assigning lower values to the GDP growth variable via conditioning mechanism. The set-up of an optimistic scenario would be straightforward.

Model Description, Data and Diagnostics. We set up a 6-variable and 2-lag quarterly VAR model and apply Bayesian estimation technique to the parameters. The following priors were used (the parametrization is similar to the one commonly used in empirical literature):

- white-noise prior: $\lambda_1 = 0$;
- lag-decay prior: $\lambda_2 = 1$;
- restriction C prior: $\lambda_3 = \sqrt{12}$;
- other priors: $\lambda_4 = \lambda_5 = \lambda_6 = 1$.

The database, employed in the estimation procedure, includes both monthly and quarterly data. The Consumer Price Index (CPI) is constructed and provided by the National Statistics Office of Georgia. The index is computed at monthly frequency and the base date is 2010. The data are available since January 2000. The policy rate is a short-term refinancing rate set by the National Bank of Georgia and is considered a reference point for market rates. The data on it is in monthly frequency starting from January 2008. The data on Lari/US Dollar exchange rate are provided by the National Bank of Georgia at monthly frequency (monthly averages) starting from September, 1995. Money remittances are the inflows measured in US dollars and compiled by the National Bank of Georgia at monthly frequency starting from January 2000. Exports are measured in US dollars and provided by the National Statistics Office of Georgia at monthly frequency starting from January 1995. Real GDP volumes are available from Q1 2003 and are calculated at constant 2010 prices by the National Statistics Office of Georgia.

The monthly data are converted into quarterly via averaging and year-on-year growth rates are computed (except for the interest rate). The estimation procedure exploits the following set of variables:

- Real GDP Y/Y Growth
- Headline Y/Y Inflation (based on CPI)
- Policy Rate
- GEL/USD Exchange Rate Y/Y Change
- Remittances Y/Y Growth
- Exports Y/Y Growth

Since the data panel is unbalanced (ragged-edge data) we first estimate the model on balanced panel, i.e. over the range where data points for all the variables are available.

Then, the periods with missing observations are fitted through conditional forecasting.

Bayesian shrinkage results in the eigenvalues lying inside the unit circle which is an evidence of VAR stability (see Fig. 1).

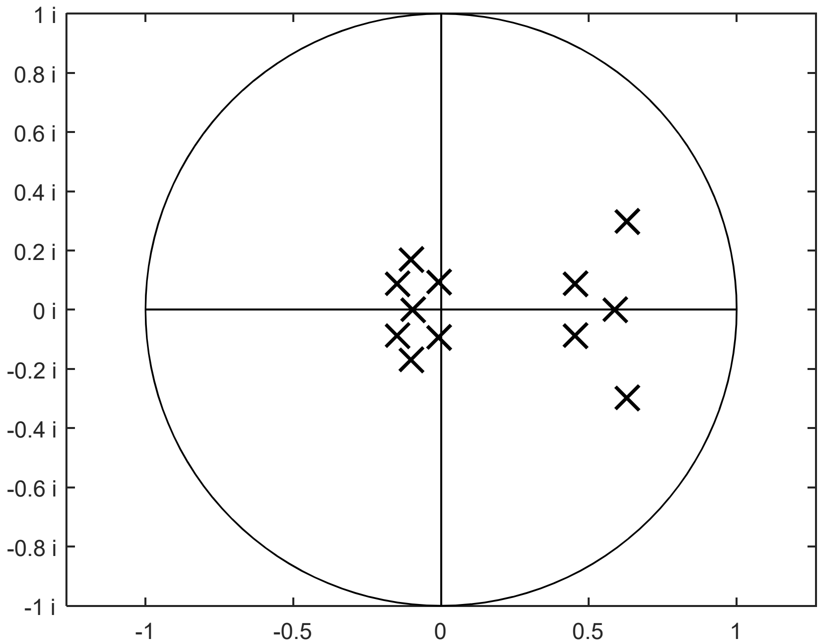

Fig. 1. Eigenvalues of the BVAR model

In order to assess forecasting performance of the BVAR model, we undertake an *out-of-sample forecasting analysis*. We divide the sample period by *estimation* and *validation* sub-samples. The estimation sub-sample is used for estimating model parameters and validation sub-sample serves as a source for computing forecast errors. The division procedure starts in 2012Q3, the BVAR model is estimated and a forecast for 8 subsequent periods is made. The differences between actual and predicted values on the validation range are saved. The procedure moves to 2012Q4 and repeats estimation/validation steps. Eventually, after iterating through all possible estimation samples, root mean squared forecast errors (RMSFE) are computed for each 1-, 2-, …, 8-quarter horizons to assess forecasting performance over different time spans. In Table 1 below, computed RMSFEs are compared to the same forecast error metrics of a Random-Walk model (which represents a naïve alternative of the form $Y_t = Y_{y-1} + w_t$) by taking a ratio of the former to the latter. As can be seen from the table, BVAR generally performs better than the counterpart.

Table 1. **Ratio of BVAR Model RMSFE to Random-Walk Model RMSFE**

	1-q	2-q	3-q	4-q	5-q	6-q	7-q	8-q
Real GDP Y/Y Growth	0.65	0.83	0.7	0.73	0.44	0.41	0.41	0.39
Headline Y/Y Inflation (based on CPI)	1.04	0.88	0.75	0.57	0.37	0.19	0.2	0.26
Policy Rate	0.95	0.85	0.78	0.66	0.73	0.71	0.63	0.69
GEL/USD Exchange Rate Y/Y Change	1.06	1.11	0.94	1.02	0.91	0.9	0.85	0.82
Remittances Y/Y Growth	0.74	0.8	0.67	0.52	0.35	0.33	0.3	0.27
Exports Y/Y Growth	0.94	0.75	0.71	0.65	0.6	0.67	0.54	0.5

Results. The scenario generation results are summarized in the form of point forecasts of key macroeconomic variables – the GDP growth, the headline inflation, the policy rate and the GEL/USD exchange rate depreciation – below in Table 2 Fig. 2 depicts the probability distribution of baseline forecasts.

Baseline Scenario. As noted, the *baseline* scenario corresponds to the unconditional forecast of the macroeconomic variables included in the model. Under this scenario, predicted real GDP growth in 2017 on average stands at 3.7 % which is slightly below the consensus forecast of 4.0 % (IMF, 2016), and the headline inflation is projected to reach almost 3.0 % by end-2017 – the figure to be set as an inflation target for 2018 by the National Bank of Georgia. The monetary policy eases throughout 2017 as the policy rate decreases roughly by 1pp and floats near the neutral one (the neutral rate is estimated between 5.5 % and 6.0 % by the National Bank of Georgia). The Georgian Lari depreciates against the US dollar by annual 6.0 %.

Table 2. **The Scenarios for Key Macroeconomic Variables**

		Real GDP Growth, %			Headline Inflation, %			Policy Rate, %			GEL/USD exchange rate, change, %		
		Baseline	*Optimistic*	*Pessimistic*	*Baseline*	*Optimistic*	*Pessimistic*	*Baseline*	*Optimistic*	*Pessimistic*	*Baseline*	*Optimistic*	*Pessimistic*
2017	Q1	3.26	3.80	2.60	1.91	1.80	2.05	5.81	5.80	5.83	2.55	2.07	3.19
	Q2	3.56	4.70	2.40	2.43	2.25	2.57	5.58	5.58	5.60	4.00	3.02	5.36
	Q3	3.85	4.60	2.50	2.72	2.71	2.80	5.52	5.52	5.52	5.34	3.90	7.27
	Q4	3.99	4.90	2.50	2.98	2.92	3.09	5.55	5.56	5.53	6.14	4.75	8.22
2018	Q1	4.04	4.44	3.37	3.18	3.19	3.15	5.62	5.62	5.60	6.53	5.29	8.49
	Q2	4.02	4.22	3.67	3.32	3.31	3.31	5.69	5.69	5.69	6.66	5.78	8.09
	Q3	3.95	4.05	3.79	3.40	3.36	3.44	5.75	5.74	5.76	6.67	6.13	7.57
	Q4	3.88	3.92	3.81	3.43	3.38	3.50	5.79	5.78	5.82	6.65	6.35	7.15
2019	Q1	3.81	3.83	3.77	3.43	3.39	3.50	5.82	5.80	5.85	6.63	6.50	6.87
	Q2	3.75	3.77	3.72	3.42	3.39	3.48	5.83	5.81	5.86	6.64	6.59	6.73
	Q3	3.71	3.73	3.69	3.41	3.38	3.45	5.83	5.82	5.86	6.65	6.64	6.67
	Q4	3.69	3.71	3.66	3.39	3.38	3.41	5.82	5.82	5.85	6.68	6.68	6.67
2020	Q1	3.67	3.69	3.65	3.38	3.38	3.39	5.82	5.82	5.84	6.70	6.71	6.69
	Q2	3.66	3.68	3.64	3.38	3.38	3.38	5.81	5.82	5.83	6.72	6.72	6.71
	Q3	3.66	3.67	3.64	3.37	3.38	3.37	5.81	5.82	5.83	6.74	6.73	6.73
	Q4	3.64	3.66	3.62	3.37	3.37	3.37	5.79	5.83	5.83	6.74	6.74	6.75

Optimistic Scenario. Under the optimistic scenario, we condition the forecast on higher GDP growth than that obtained in the baseline and compare results with the latter. In particular, the growth in 2017 is set to 4.5 % on average [11]. As one can imply from Table 2, headline prices rise at a slightly lower rate while the Lari depreciation is not as large as in the baseline. The policy rate is virtually analogous to the baseline figures.

Pessimistic Scenario. Under the pessimistic scenario, the GDP is set grow at 2.5 % on average in 2017. This condition is associated with higher headline inflation and Lari depreciation. The policy rate path is again broadly similar to that in the baseline.

Fan charts. A fan chart is a common way in finance and monetary policy to visualize probability distribution of forecasts. Below in Fig. 2 we present fan charts of the forecasts for GDP growth, headline inflation, policy rate and GEL/USD exchange rate depreciation under the baseline scenario. The mean forecasts (i.e. the point forecasts) are given by a solid line. Above and below the line, the colored shapes indicate intervals based on forecast standard deviations multiplied by factors of 0.1, 0.25, 0.5, and 0.75.

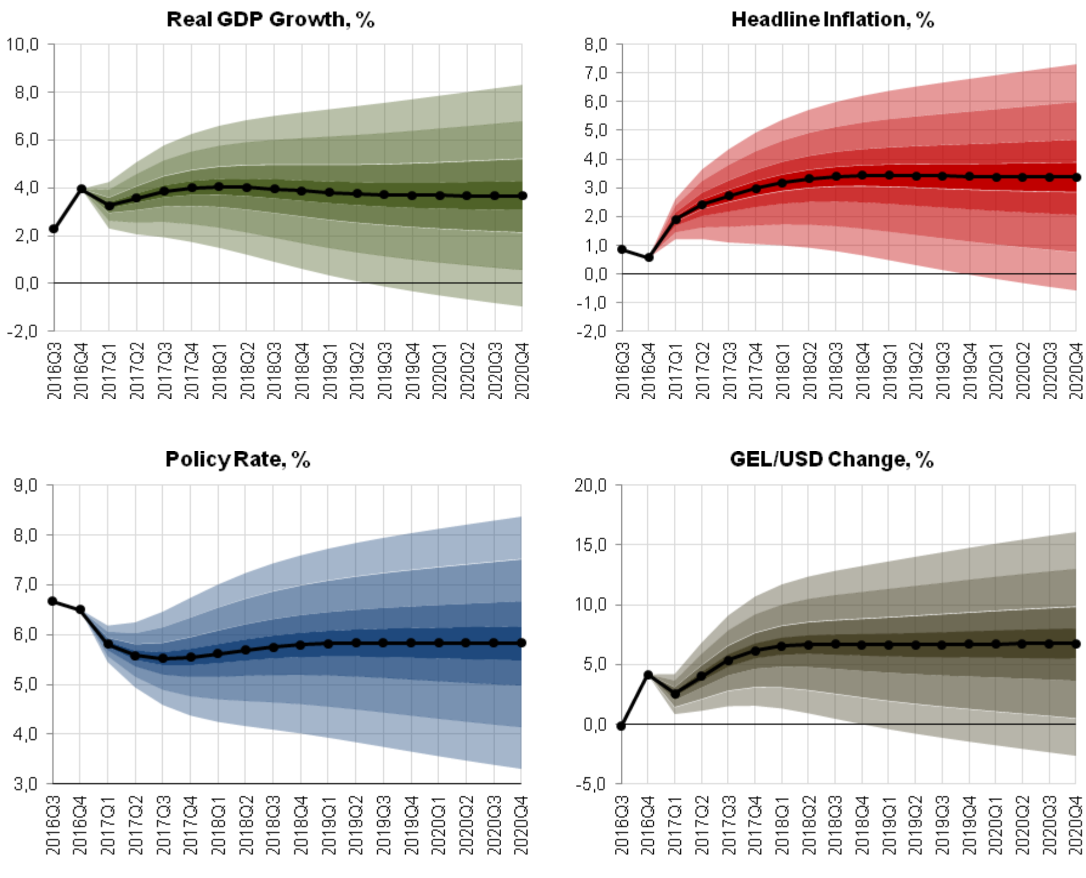

Fig. 2. Fan Charts of Key Macroeconomic Variables

Conclusion. This paper proposes a flexible and efficient way of generating macroeconomic scenarios based on unconditional and conditional forecasts. The technique is based on Bayesian VAR framework which is viewed as a convenient tool to produce accurate predictions. The baseline scenario forecasts are broadly in line with consensus forecasts by such renowned institutions as the International Monetary Fund, the Asian Development Bank, the National Bank of Georgia, etc. The technique might be particularly useful to financial institutions which are required to incorporate more forward-looking information while making all necessary adjustments to accounting rules of financial instruments under the new IFRS standards. The framework involves a model consisting of six macroeconomic variables; however, it would be a reasonable direction of further research to extend the model over any desired set of factors enabling an investigator to make more inclusive forecasts.

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МАКРОЕКОНОМІЧНЕ ПРОГНОЗУВАННЯ З ВИКОРИСТАННЯМ БАЙЄСІВСЬКОГО ПІДХОДУ ДО ВЕКТОРНОЇ АВТОРЕГРЕСІЇ

Є багато аргументів, які можуть бути висунуті для підтримки прогнозування діяльності господарюючих суб'єктів. Основним аргументом на користь прогнозування є те, що управлінські рішення у значній мірі залежать від правильної оцінки майбутніх тенденцій, оскільки ринкові умови постійно змінюються і вимагають детального аналізу майбутньої динаміки. У статті розглянуто важливість використання розумного макроеконометричного інструменту, запропонувавши ідею умовного прогнозування за допомогою системи моделювання векторної авторегресії (VAR). У межах зазначеної структури, макроекономічна модель економіки Грузії будується з кількома змінними, як прийнято вважати, формування бізнес-середовища. На основі моделі вироблено прогнози макроекономічних показників і проаналізовано три типи сценаріїв – базовий рівень і два альтернативних із них. Результати дослідження надають підтверджуючі докази того, що запропонована методика адекватної адресації дослідного феномена може широко використовуватися господарюючими суб'єктами в задоволенні своїх стратегічних та оперативних завдань планування. З огляду на цю настанову, емпірично доведено, що байєсівський підхід до векторної авторегресії дає обґрунтовані прогнози для змінних, що представляють інтерес.

Ключові слова: прогнозування, макроекономічне моделювання, байєсівська VAR, Litterman сценарій, сценарний аналіз, IFRS 9.

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МАКРОЭКОНОМИЧЕСКОЕ ПРОГНОЗИРОВАНИЕ С ИСПОЛЬЗОВАНИЕМ БАЙЕСОВСКОГО ПОДХОДА К ВЕКТОРНОЙ АВТОРЕГРЕССИИ

Есть много аргументов, которые могут быть выдвинуты для поддержки прогнозирования деятельности хозяйствующих субъектов. Основным аргументом в пользу прогнозирования является то, что управленческие решения в значительной степени зависят от правильной оценки будущих тенденций, поскольку рыночные условия постоянно меняются и требуют детального анализа будущей динамики. В статье рассматривается важность использования разумного макроэконометрического инструмента, предложена идея условного прогнозирования с помощью системы моделирования векторной авторегрессии (VAR). В рамках этой структуры, макроэкономическая модель экономики Грузии строится с несколькими переменными, как считается, формирования бизнес-среды. На основе модели произведено прогнозы макроэкономических показателей и три типа сценариев анализируются – базовый уровень и два альтернативных из них. Результаты исследования дают подтверждающие доказательства того, что предложенаяметодика адекватной адресации исследовательского феномена может широко использоваться хозяйствующими субъектами в удовлетворении своих стратегических и оперативных задач планирования. Учитывая эту установку, эмпирически показано, что байесовский подход к векторной авторегрессии дает обоснованные прогнозы для переменных, представляющих интерес.

Ключевые слова: прогнозирование, макроэкономическое моделирование, байесовская VAR, Litterman сценарий, сценарный анализ, IFRS 9.