

BVAR models in short-term prediction of modern central banks: empirical evidence of the euro area

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Abstract: It has been more than a decade since central banks, in the face of the global financial crisis, implemented unconventional initiatives. Monetary authorities' actions have led to a reduction of main interest rates to historically low levels and huge expansion of central banks' balance sheet. So far, they still have not returned to the pre-crisis framework and implemented the normalisation process. Nowadays, there is observed a trend to use econometric models in monetary policy to forecast macroeconomic variables and plan normalising activities. The main aim of the study is empirical verification of BVAR model in short-term predicting, that might be used by the European Central Bank in its normalisation process. The conducted research indicate that the large BVAR model for the Eurozone has a significant predictive value in short-term forecasting. At the same time indicating its considerable precision and accuracy in prediction, with a high degree of objectivity and flexibility.

Keywords: normalisation process; central bank; BVAR model; European Central Bank; euro area; prediction; forecasting.

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Biographical notes: Aleksandra Nocoń, PhD, is an Assistant Professor in the Department of Banking and Financial Markets at the University of Economics in Katowice (Poland). She has published 7 monographs and more than 70 scientific articles, including in top international Journals. Her research interests concentrate on banking, central banking, monetary policy and new regulatory architecture. Since 2012, she has been the Head of the annual individual research projects for the development of young scientists at the University of Economics in Katowice. In the years of 2013–2016, she carried out the research grant, which was funded by the National Science Centre.

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1 Introduction

It has been almost a decade since central banks, in the face of the global financial crisis, implemented a set of unconventional initiatives. The end of the first decade of the 21st century has started a new period in central banking – a period of non-standard and unconventional monetary policy instruments, used in so far unprecedented scale and scope. Monetary authorities' actions, undertaken in response to the spreading out of the global economy instability, have included unprecedented interventions that have led to a reduction of main interest rates to historically low (zero or, in some cases, even negative) levels, huge expansion of central banks' balance sheet and changes in their communication system with stakeholders.

The problem with a return to traditional (standard) monetary policy is all the more complicated and ambiguous, because till 2019 central banks still have not withdrawn non-standard instruments and have not returned to the procedures and strategies, used before the global financial crisis. Not only monetary policy, but also the whole economic policy of many developed countries, has not completed unconventional activities, implemented after 2008.

The main aim of the study is empirical verification of BVAR model (*Bayesian vector autoregression model*) in short-term prediction of macroeconomic and financial indicators, that might be used by the European Central Bank in its normalisation process. Verification concerned the assessment of forecasts developed for the one-year time horizon – short-term predicting. Thus, the study verifies a research hypothesis which states that the Bayesian vector autoregression model might be a useful tool in the decision-making process of monetary authorities, regarding the normalisation of their monetary policy.

The paper consists of two parts: theoretical and empirical. First one is based on wide, critical evaluation of literature studies. It focuses on the essence of monetary policy normalisation process and then on macroeconomic prediction models used by central banks in recent years. The second part of the paper concentrates on Bayesian vector autoregression model and its empirical verification from the point of view of their application in the normalisation process of modern central banks. Additionally, the following research methods were used: cause and effect analysis, observation method, document analysis method as well as synthesis method.

Macroeconomic and financial variables used in adopted BVAR models, included data for the euro area from the databases of the European Central Bank, Federal Reserve Economic Data, European Commission, World Development Indicators, Bloomberg and OECD.

2 Literature review: theoretical background

The normalisation process of monetary policy is a procedure how to *exit* from non-standard monetary policy and return to pre-global financial crisis framework. In a broader perspective, it is a process related to withdrawal of unconventional instruments and stabilisation of banking sector conditions. The assumptions of normalisation process of monetary policy are therefore precisely defined by monetary authorities in their *exit strategies*. Thereby, they take into account determinants of selected economy, banking

sector as well as central banks, indicating necessary actions, that have to be taken to restore the previous monetary policy order.

Monetary policy normalisation is a long-term process and – in assumptions – includes several simple operations, relating to (Yamaoka and Syed, 2010; Pyka and Nocoń, 2017):

- halting extraordinary interventions
- downsizing and normalising central bank's balance sheet
- selling purchased assets, if necessary
- raising short-term interest rates.

However in practice, uncertainty about perspectives for economic activity, inflation rate, or functioning of the monetary transmission mechanism may complicate implementation of the *exit strategy*. The normalisation process should, therefore, be developed to promote sustainable economic growth in a long-term, while it also should be flexible to respond immediately to changing macroeconomic environment (Fic, 2010).

According to Trichet (2009), very important in normalisation process is appropriate preparation for the *exit* from non-standard monetary policy. Central banks must ensure that unconventional operations will be quickly withdrawn and excess liquidity will be absorbed, when macroeconomic conditions improve. Thus, in the case of extraordinary refinancing operations, conducted by central banks, their maturity has been fixed in advance, while in the case of outright purchases additional decisions are required, whether purchased securities will be held in balance sheet till maturity or in a specific date they will be resold.

Currently, central banks mainly focus at the assumptions of the normalisation process of their monetary policy. The global financial crisis has not negated the inflation target as the overriding objective of monetary policy. Furthermore, it even increased an interest in the need to control an average rate of price changes. In the context of normalising activities, the most important issue for monetary authorities still remains control of inflation level, while supporting the economic growth.

In the modern monetary policy, there might be also observed a trend to use econometric models for construction of forecasts of selected macroeconomic variables, assessment consequences of undertaken monetary policy instruments and actions, simulation of economic reactions to specific shocks, as well as in the development of alternative monetary policy scenarios (Štefanovičová and Zeman, 2010). Central banks, in the process of selection and construction of forecasting models in monetary policy, take into account analytical needs, research objectives, as well as tasks that these models will have to fulfil (see Table 1) (Brubakk et al., 2006).

The above-mentioned tasks justify the need to use econometric models in monetary policy. In central banks, the following macroeconometric models are most often used in the forecasting process (Amisano and Geweke, 2013):

- dynamic factor models (DFM models)
- dynamic stochastic general equilibrium models (DSGE models)
- vector autoregression models (VAR models).

Table 1 Macroeconometric prediction models' tasks and their characteristic

<i>Tasks</i>	<i>Characteristic</i>	<i>Justification</i>
Shock identification and forecasting	<ol style="list-style-type: none"> 1. The need to forecast macroeconomic variables 2. Forecasts of changes and economic development 	<ol style="list-style-type: none"> 1. Monetary policy transmission mechanism has the most significant impact on the inflation rate in the 2–3 years horizon 2. The need to identify the main factors determining economic changes 3. Predicting behaviours in conditions of uncertainty and risk 4. The need for an overall assessment of the macroeconomic sphere
Analysis of risk and conducted monetary policy	<ol style="list-style-type: none"> 1. Identification and assessment of risk around the central projection path 	<ol style="list-style-type: none"> 1. An attempt to explain the problem of uncertainty and risk accompanying central bank's decisions 2. The ability to identify and present economic dependencies, implications, alternative assumptions and types of risk
Communication	<ol style="list-style-type: none"> 1. Analysis of effectiveness of the inflation expectations channel in the monetary policy transmission mechanism 	<ol style="list-style-type: none"> 1. Transparency, open communication and a clearly presented forecast (along with presentation of accompanying uncertainty) allow stakeholders to understand decisions undertaken by a central bank 2. Market participants respond to newly acquired information, taking a position towards decisions as well as achievement of central bank's objectives and tasks

Source: Own work based on Brubakk et al. (2006)

There are many advantages and arguments to use the above forecasting models in monetary policy. First of all, they represent three main types of macroeconometric models, used to forecast in central banks. Secondly, they differ in terms of ways in which they try to use the *General Equilibrium Theory* as a source of information in the formulation of models and conducting statistical inference. Thirdly, these models adopt different approaches to gathering information, in particular when the main aim is to obtain useful predictions about complex phenomena, constructed for relatively few data. Nevertheless, in many methodological studies it is indicated that the most fruitful is a combination of these models, especially when they are varied (Geweke and Amisano, 2011).

Dynamic factor models (DFM) are used in short-term macroeconomic forecasting. Central banks use them as a tool to support short-term forecasting of key macroeconomic variables (Baranowski et al., 2010; Bernanke and Boivin, 2003; Breitung and Eickmeier, 2005). The essence of DFM is the aggregation a large number of potential explanatory variables to several mutually independent factors, which are then used to predict the selected variable (Acedański, 2013, p.193). Identification of factors included in the model is usually made on the basis of the principal component analysis (PCA) or its modifications. A prognostic equation describing dependence between a predicted variable and explanatory variables is usually linear. In the equation, in addition to the factors, may also occur delays as well as autoregressive components.

Dynamic stochastic general equilibrium models (DSGE models) are much younger forecasting models, which are widely used in monetary policy. They constitute a monetary policy tool that is able to describe the monetary policy transmission mechanism, starting from a monetary impulse (monetary policy decisions) finally to reaction of main macroeconomic variables (Kokoszcyński, 2004, pp.191–192). Therefore, they are an extremely valuable method, ensuring a consistent basis for performing analyses and formulating monetary policy forecasts. In particular, DSGE models influence the process of identifying sources of fluctuations, answer questions about structural changes, anticipate changes in monetary and economic policy, conduct analyses and counterfactual experiments (Tovar, 2008, pp.1–4).¹ In central banks DSGE models, used as an analytical tool, allow simulations to illustrate an impact of shock, to which an interest rate was subjected, on inflation and GDP. Nowadays, there are also used to quantify the macroeconomic effects of unconventional monetary policy implemented by central banks after the global financial crisis (Wang, 2019, pp.361–389).

In the prognostic process, the third most frequently used macroeconometric model in monetary policy is *vector autoregression model* (VAR model). Vector autoregression models are commonly used in macroeconomics for structural analysis and forecasting since the groundbreaking work of Sims (1980). Since seminal work by Sims (1980), the VAR models have also become a workhorse for many central bankers around the globe (Siranova and Kotlebova, 2018, pp.56–75). An important feature of the VAR models is their flexibility, which allows identification of complex dependencies between macroeconomic variables. However, their use to estimate a large number of parameters, also determines the need to increase the assumed degrees of freedom, and thus results in the need to adopt broad confidence intervals for estimated coefficients. Therefore, it would seem that VAR models should be used in studies that take into account a small number of variables. On the other hand, it can lead to the problem of omitted-variables bias (OVB), significantly weakening the conducted structural analysis and forecasting effectiveness.²

The use of vector autoregression models is very wide. In the 1990s, Bikker (1999) – a Dutch econometrician, used them for forecasting and modelling national economies, as well as researching dependencies between economies of different countries (Bikker, 1993, p.141). Canova (1995) studied relations between production value of Germany, the USA and Japan. Together with J. Pina, he also referred them to currency policy. In turn, Sturm and de Haan (1995) analysed connections between the real budget deficit and real growth of national income. Finally, Bagliano and Favero (1998) used VAR models to analyse the monetary transmission mechanism in the USA.

3 Methodological considerations

Imperfections resulting from the use of VAR models in forecasting process of central banks justify a need to search for new methods of forecasting variables in monetary policy. Against this background, in recent years there has been undertaken research to use a new approach to vector autoregression models – *Bayesian vector autoregression models* (BVAR models). They are a useful tool to forecast macroeconomic variables (Moreira et al., 2014, pp.1–12). The main argument that confirms legitimacy of adopting the BVAR methodology in central banks' forecasting process is the fact that in the case of large models – i.e., those with a large number of explanatory variables (containing about 30 variables and more), Bayesian approach allow to avoid problems with over-parameterisation that could occur in classic VAR models (Ghysels and Marcellino, 2018). This phenomenon could occur in a situation of the use of standard VAR model estimated for such a large set of variables. The second argument of the BVAR model is possibility of minimising an impact of the over-fitting problems. This problem occurs when a statistical model has too many parameters in relation to the size of research sample, which was a basis for its construction (Canova and Pina, 2005; Hawkins, 2004). Considering the above, Bańbura et al. (2010) indicate that it is the appropriate tool for large, dynamic macroeconometric models. An important advantage of the BVAR models is their objectivity and flexibility. They give researcher an opportunity to exchange information within a research sample in a completely transparent manner. This possibility allows to build a model that takes into account not only the stochastic behaviour of economic variables, but also an uncertainty associated with existing dependencies within the analysed economic system. This kind of flexibility leads to forming a better model in terms of economic forecasting compared to structural models with more restrictions, as well as a more accurate model than traditional VAR models, which coefficients are estimated based on the least squares method, burdened by – the previously mentioned – the over-fitting problems. Therefore, the BVAR model enables characterisation of the future path of economic variables in probabilistic terms. Objectivity of this type of model is also an important advantage, because the researcher can easily reproduce forecasts.

On the other hand, the BVAR models are not without flaws. Ciccarelli and Rebucci (2003) conclude that a main limitation of BVAR models is that the correct identification and selection of variables is extremely important for the final obtained results. In many cases, selection of variables is based on incomplete or incorrect information, and thus hinders and subjectivises decisions regarding adoption of a particular set of parameters. Other disadvantage of the BVAR models is also the lack of economic interpretation. Another criticism of BVAR models (also referring to classic VAR models) is the fact that they do not explicitly include long-term dependencies between variables. This theory postulates that certain variables follow a common path in time, or at least that they do not diverge continuously – it means that they are cointegrated.

However, there is more and more empirical evidence that confirms validity of the use of BVAR models in forecasting macroeconomic variables. They indicate high quality of the obtained results (more accurate forecasts) in comparison to the majority of alternative methods, also univariate time series models or large-scale macro-models (Ruja, 2004). The BVAR models have been particularly used in forecasting variables of the real

economy, including a volume of global output, an unemployment rate and balance of payments, especially in the long-term (McNees, 1986). Bayesian vector autoregression models are also increasingly used by central banks in monetary policy (see: Kasuya and Tanemura (2000), Alvarez et al. (1998) as well as Kenny et al. (1998)). Kasuya and Tanemura (2000) confirmed earlier achievements, recognising the Bayesian vector autoregression model as more effective compared to the VAR model. Alvarez et al. (1998) estimated the BVAR model for the Spanish economy, comparing the results to those obtained from the VAR model. They concluded that in predicting price variables, superiority of the BVAR model over the other models is obvious, and differences between them are quite significant. Kenny et al. (1998) used the BVAR model to forecast inflation in Ireland. Their results confirmed a significant improvement of forecasts, obtained by the use of Bayesian approach.

Modern approach to the use of BVAR models is represented by Kapetanios et al. (2012), Lenza et al. (2010) and Ghysels and Marcellino (2018). Their results confirm validity of the BVAR models in forecasting macroeconomic variables, used in the decision making process by monetary authorities (policymakers). This study uses the methodology developed by Kapetanios et al. (2012) and Lenza et al. (2010) and their experience in construction of macroeconomic forecasts from the point of view of monetary policy normalisation process of the European Central Bank. While in Ghysels and Marcellino (2018) there are empirical examples of the use of BVAR model for the GDP growth in the Euro area.

4 Methodology

Based on the above presented arguments, adoption of the BVAR model's methodology in the process of forecasting macroeconomic variables for monetary policy objectives seems to be fully justified. The BVAR model adopted in empirical research was developed strictly in accordance with the methodology proposed by Kapetanios et al. (2012) and Lenza et al. (2010). The general BVAR model takes the following form:

$$Y_t = \theta_0 + \theta_1 Y_{t-1} + \dots + \theta_p Y_{t-p} + e_t$$

where:

Y_t – represents a large vector of random variables included in large data set at time t , i.e., $y_{1t}, y_{2t}, \dots, y_{nt}$

e_t – represents an n -dimensional vector white-noise error term

θ_0 – represents an n -dimensional vector of constant

$\theta_1 \dots \theta_p$ – represent $n \times n$ autoregressive parameter matrices.

Explanatory (endogenous) variables included in the model are a set of macroeconomic indicators – general economic and financial market parameters of the euro area. The research covered 27 indicators (see Appendix 1), characteristic for the euro area economy, which also illustrates the specificity of its financial markets. These variables are permanent, which is a strong argument to include them in the constructed BVAR model (Kapetanios et al., 2012; Litterman, 1985).

In the research it was decided to use a large unlimited Vector Autoregression model with Bayesian estimation (*Litterman Minnesota prior*). This model allows to include a series of interactions between variables without burdening by the multidimensional model (De Moll et al., 2008, pp.318–328). Such a model can have at least several applications:

- it can be used for scenario analysis, in the form of a conditional forecast
- a model can be introduced even if some conditions are not met
- a model can provide an assessment of the risk of obtained forecasts, as the effect of the model is the distribution of projections.

Kapetanios et al. (2012) argue that, in general, simple autoregression and random walk models generate good-quality forecasts for macroeconomic and financial variables. Therefore, in the conducted research, the method of forecasting based on the random walk process with drift (Zagdański and Suchwałko, 2016) was chosen for each variable in the BVAR model, in accordance with the previous scientific studies, undertaken and analysed in the literature (Hausken and Ncube, 2013). Thus, the adopted model is expressed by the following formula:

$$Y_t = \theta_0 + Y_{t-1} + e_t$$

The elements on the diagonal θ_1 are striving to 1, while other components of the matrix $\theta_1 \dots \theta_p$ tend to 0, which also indicates that the first delay is the most important predictor in each equation in the BVAR model. In other words, the expected value of the matrix θ_1 is:

$$E(\theta_1) = 1 \times I$$

In addition, assumptions regarding the distribution of coefficients are adopted, specifying moments for θ_1 in accordance with the following formula:

$$E[\theta_k^{(ij)}] = \begin{cases} 1 & \text{if } i = j, k = 1 \\ 0 & \text{otherwise} \end{cases} \quad V[\theta_k^{(ij)}] = \left(\frac{\lambda_0 \lambda_1}{\sigma_j k^{\lambda_3}} \right)^2$$

where:

$\theta_k^{(ij)}$ – represent the element in position (i, j) in the matrix θ_k

E – expectation operator,

V – variance

λ_0, λ_1 and λ_3 – shrinkage parameters.

The research concentrated on the construction of forecasts for selected macroeconomic indicators, using large BVAR models. In the model, endogenous variables were a set of general economic and financial parameters, including: consumer price index, domestic production volume, interest rates, Treasury securities yields, monetary aggregates, unemployment rate, real estate prices, oil prices, share prices, consumer confidence indicator, exchange rates, etc. Thus, selection of the adopted variables in BVAR models was not accidental or random. It was made fully based on the methodology developed and presented by Kapetanios et al. (2012).

The BVAR models for the euro area included daily, monthly and quarterly data. The analysed models contained data for 101 periods. The analyses were started from January 2005 to June 2013, assuming that the last 5 years of collected data (i.e., until June 2018) will be a basis for evaluation of the model's prediction. In the case of some explanatory variables, their logarithmised value were used. While for the remaining variables, which by their definition are indicators, their real values were assumed (see Appendix 1).

Table 2 Evaluation of the annual prediction for the euro area model

<i>Variables</i>	<i>h</i>	<i>RMSE</i> ¹ (<i>Root mean square error</i>)	<i>MAE</i> ² (<i>Mean absolute error</i>)	<i>MAPE</i> ³ (<i>Mean absolute percentage error</i>)	<i>Theil</i> ⁴ (<i>Theil inequality coefficient</i>)
E12	12	0.581961	0.559699	77.35662	0.645049
E13	12	0.436676	0.406607	78.79279	0.599003
E14	12	0.196018	0.176582	79.73860	0.563346
E17	12	0.072041	0.045625	0.386698	0.003034
E18	12	0.005438	0.004951	0.247849	0.001363
E19	12	0.004415	0.003894	0.195156	0.001105
E20	12	0.490177	0.445968	28.23286	0.185039
E21	12	0.073751	0.065368	3.107120	0.017941
E22	12	0.052792	0.049423	1.436797	0.007621
E24	12	0.009159	0.008304	6.628813	0.035589
E25	12	0.002752	0.002152	0.106824	0.000683
E27	12	0.214130	0.181378	59.70943	0.573699
E3	12	0.560220	0.503699	16.26213	0.087071
E4	12	0.319918	0.258732	18.83986	0.121409
E5	12	0.923731	0.795474	64.57495	0.620920
W1	12	0.090816	0.074204	2.571882	0.016123
W2	12	0.695884	0.586116	18.79147	0.125293

¹*Root Mean Square Error* (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are. RMSE is a measure of how spread out these residuals are. Root mean square error is commonly used in climatology, forecasting, and regression analysis to verify experimental results.

²*Mean Absolute Error* (MAE) is defined as the expected value of the square of the difference between the estimator and the parameter.

³*Mean Absolute Percentage Error* (MAPE) is a statistical measure of how accurate a forecast system is. It measures this accuracy as a percentage, and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values.

⁴*Theil inequality coefficient* (Theil) is a relative accuracy measure that compares the forecasted results with the results of forecasting with minimal historical data. It also squares the deviations to give more weight to large errors and to exaggerate errors, which can help eliminate methods with large errors.

Source: Own work

5 Results

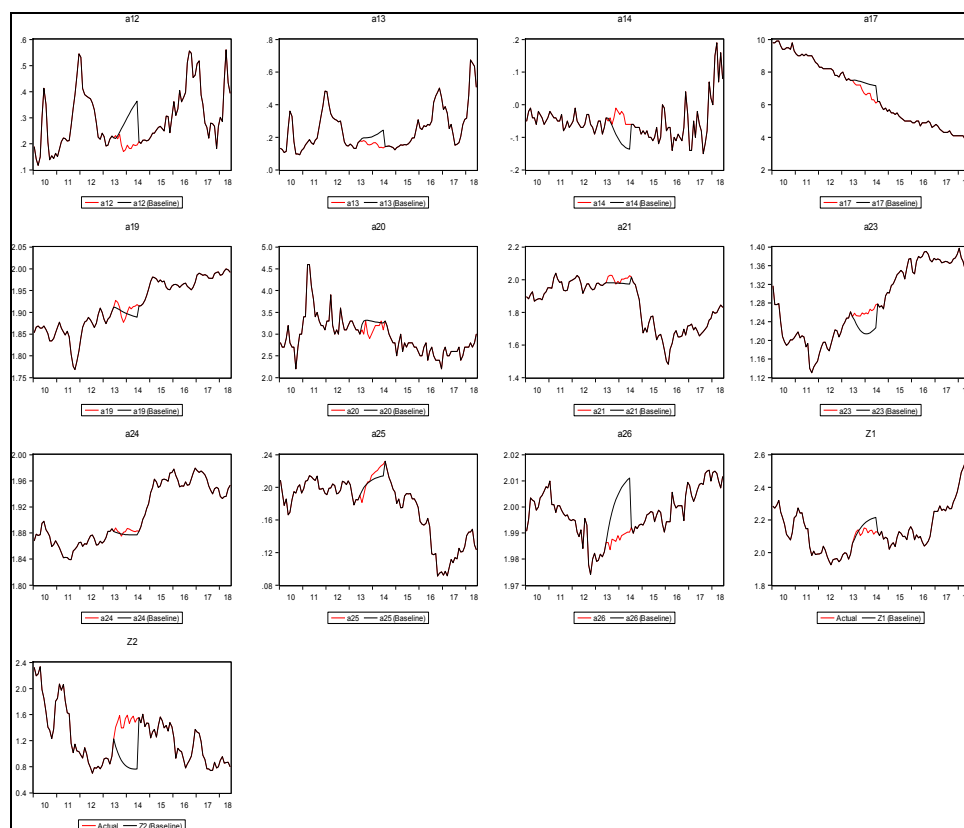
Due to the fact that some variables in the model for the Eurozone were characterised by a high correlation (0.8–0.9), two indicators were developed to avoid multicollinearity and overestimation of model’s data. The following two indicators were developed:

- W1: E1, E2, E10, E11, E15, E16, E23, E26,
- W2: E6, E7, E8, E9.

Finally, 15 variables and two indicators were included in the analyses.

Based on the Schwarz information criterion, it was adopted 1 row of delays (SC = -55.95). In order to determine accuracy of forecasts for 12 periods (1 year), forecasts for the period between July 2013 and June 2014 were determined. Table 2 presents the results of their evaluation.

Figure 1 Annual forecast for the Eurozone (see online version for colours)



Source: Own work

Values of predictive indicators do not allow a satisfactory prognostic assessment of the model. Acceptable values presenting the optimum level of forecast, based on the obtained RMSE error values, can be seen for the following variables: E18, E19, E21, E24 and E25. Similar results were received from the analysis of the *Mean Absolute Percentage Error* –

MAPE. Errors at a level significantly below 10% were obtained for the following variables: E17, E18, E19, E21, E22, E25 and for the W1 indicator. The *Theil inequality coefficient* (Theil) values that indicate the high quality of the model occurred only for variables: E17, E18, E19, E22 and E25. Thus, acceptable values indicating an optimal forecast level can only be seen for the following variables: E17, E18, E19, E21, E22, E24, E25 and for the W1 indicator. For the remaining variables, the RMSE or U Theila values are relatively high and may lead to errors. Figure 1 illustrates differences between real values and one-year forecasts.

6 Summary and conclusions

After more than a decade of extraordinary monetary policy, further stimulation of a banking sector seems to be inconvenient even for central banks themselves. First of all, monetary authorities have a need to return to traditional policy (to normality), because too long period of unconventional interventions may undermine their public commitment to maintain price stability. Secondly, they are afraid that the environment of low interest rates can generate factors that also contributed to instability at the beginning of the 21st century. At the same time, leading to another destabilisation in the near future. Finally third, non-standard monetary policy, conducted over a long period of time, can undermine monetary authorities' credibility, so one of the main attributes of modern central banks. All above considerations makes that the process of monetary policy normalisation of modern central banks seems to be necessary and undoubtedly fully justified.

From the monetary policy normalisation process point of view, it seems that an effective method of forecasting macroeconomic variables, particularly important for central banks, is a key tool facilitating the decision-making process, regarding identification of time, pace and methods of normalisation. It gives monetary authorities an instrument through which they are able to anticipate changes of macroeconomic and financial variables, also taking into account consequences of specific monetary policy instruments and decisions. The Bayesian vector autoregression model presented in the study currently finds an increasing number of supporters among central banks as an effective method of forecasting. The conducted research indicate that the large BVAR model has a significant predictive value in short-term forecasting. The results presented in the paper are only a part of wider research project, which aimed at verification of accuracy of the BVAR models in monetary policy, and then determination of forecasts of macroeconomic variables that will form a basis for central bank decision-making, regarding normalising activities of their monetary policy. So far obtained results – for the one-year prediction, confirm legitimacy of using the BVAR model for this purpose. At the same time indicating its considerable precision and accuracy in short-term forecasting, with a high degree of objectivity and flexibility left to a researcher. Thus, for short-term forecasting, they confirm the adopted research hypothesis that the Bayesian vector autoregression model might be a useful tool in the decision-making process of monetary authorities, regarding the normalisation of their monetary policy. At the same time, they are a basis for further in-depth research and studies of whether the BVAR model can be used in medium- and long-term forecasting.

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Notes

¹Counterfactual experiments present alternative scenarios of future economy behaviour, which means “what would have been if” and allow to assess the future and current economic situation.

²The problem of *omitted-variable bias (OVB)* in statistical estimation is an error of estimation resulting from omission – not taking into account some factors or explanatory variables in the model. The consequence of the error is wrong assignment of an impact of missing variables to included elements (More: Barreto and Howland, 2006; Clarke, 2005; Wooldridge, 2009).

Appendix 1

Explanatory variables used to estimate the models for the euro area

<i>Number</i>	<i>Code of variable</i>	<i>Variable</i>	<i>Data</i>	<i>Log</i>
1	E1	Euro Area Harmonized Index of Consumer Prices)	Monthly	X
2	E2	Euro Area Industrial Production Index	Quarterly	X
3	E3	10-Year EAGB Yield – 3-Month Treasury Bill Rate Spread	Monthly	
4	E4	5-Year EAGB Yield – 3-Month Treasury Bill Rate Spread	Monthly	
5	E5	2-Year EAGB Yield – 3-Month Treasury Bill Rate Spread	Monthly	
6	E6	20-Year EAGB Yield	Monthly	
7	E7	15-Year EAGB Yield	Monthly	
8	E8	7-Year EAGB Yield	Monthly	
9	E9	3-Year EAGB Yield	Monthly	
10	E10	Main Refinancing Operation Rate	Monthly	
11	E11	6-Month EUR Libor	Daily	
12	E12	3-Month EUR Libor-T-Bill Spread	Daily	
13	E13	3-Month EUR Libor-MRO Rate	Daily	
14	E14	3-Month T-Bill – MRO Rate Spread	Monthly	
15	E15	Euro Area M2 Money Stock	Monthly	
16	E16	Euro Area M1 Money Stock	Monthly	
17	E17	Euro Area Unemployment Rate	Monthly	
18	E18	Euro Area House Price Index	Quarterly	
19	E19	Euro area Consumer Confidence Index	Monthly	
20	E20	Euro Area Future Tendency of Inflation (Inflation Perception)	Monthly	X
21	E21	Average Oil Price	Monthly	X

Appendix 1 (continued)*Explanatory variables used to estimate the models for the euro area*

<i>Number</i>	<i>Code of variable</i>	<i>Variable</i>	<i>Data</i>	<i>Log</i>
22	E22	Euro Stoxx 50 Index	Monthly	X
23	E23	EUR Real Effective Exchange Rate	Monthly	
24	E24	USD-EUR Exchange Rate	Daily	X
25	E25	US Industrial Production Index	Monthly	
26	E26	CPI	Monthly	X
27	E27	Effective US Federal Funds Rate	Monthly	

Log – data logarithmisation (X – yes).