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Econometric Models for Forecasting of Macroeconomic Indices

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ABSTRACT

The urgency of the research topic was stipulated by the necessity to carry out an effective controlled process by the economic system which can hardly be imagined without indices forecasting characteristic of this system. An econometric model is a safe tool of forecasting which makes it possible to take into consideration the trend of indices development in the past and their cause and effect interrelations. The aim of the article is to build econometric models for macroeconomic indices forecasting, reflecting Russia's economy stabilization processes. In the process of research econometric modeling methods were used which allow to build, estimate and control the quality of various econometric models. In the given research the following models were built and analyzed: autoregressive integrated moving average model, vector auto-regression model, simultaneous equations system; the comparison of forecast possibilities and forecast accuracy of models built; forecast values of considered macroeconomic indices for the next periods were received. As to the results of study some preference can be given to forecasting on the basis of autoregressive models. The materials of the article can be quite useful for researchers, dealing with problems of modeling and economic processes forecasting, both in their scientific and practical activity.

KEYWORDS
Autoregressive integrated moving average model, Forecasting, macroeconomic indices, Simultaneous equations system, Vector auto-regression model

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Introduction

It's hard to conceive that an effective process of an economic system management can be realized without forecasting. Qualitative forecasts call to minimize negative results of managerial decisions, to lower the uncertainty of

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their final resulting effect. So, various models including econometric ones are an effective tool of forecasting.

The econometric models differ in their tasks for which they are built, in the set of variables forecasted, types of the data, a number of observations and so on (Balash & Malinskiy, 2014; Eldyaeva, 2006; Malugin at al., 2009; Trofimov, 2015).

In the work (Aivazyan & Brodsky, 2006) the authors analyze the story of econometric modeling and macroeconomic system forecasting marking out more famous models. For example, the US economy model to build the average term forecast of basic macroeconomic indices on basis of regression system and balance equations, the Netherlands economy model (FKSEC) and that of French economy (MESANGE). What distinguished the last model mentioned was the use of cointegration theory at describing the dynamics of the most important macroeconomic indices.

State, Russia's state, scientific and business organization also implement economic indices forecasting on the basis of econometric models. In some works (Turuntseva, 2011; Aivazyan & Brodsky, 2006) a short survey of such model forecast complexes has been given which includes the Russia's economy model, worked out by the Central economic and mathematical institute under the Russian academy of sciences (CEI), a model of the macroeconomic analysis and short-term forecasting Centre, a model of the RF economic development Ministry and some others. The authors call the absence of their building methodology as one common feature of models mentioned above.

Some authors offer their own methods for building various models to analyze and forecast economic indices. So, in the works of (Ivanova, 2005) it is offered to forecast the import of goods on the basis of vector error correction models, a work of (Nikitsina, 2016) regards these models to forecast retail trade turn over. Another author (Dorokhov, 2008) makes use of vector auto-regression and cointegration models to forecast stock exchange indices, in the study of (Deryugina & Ponomarenko, 2008) a Bayesian model of vector auto-regression to forecast the real sector of economy indices has been built. In the work of (Shvaiko, 2002) the author forecasts the capacity of the primary market of state short-term bonds using vector auto-regression models, error correction models and autoregressive moving average models. The authors (Aivazyan & Brodsky, 2006) offer a system of equation for forecasting which contains cointegration and regressive econometric dependencies and balance interrelations among macroeconomic indices.

In our article we present the results of using econometric and statistical methods to forecast the macroeconomic indices of Russia's stabilization processes on the basis of built time series of indices under review.

Dealing with non-stationary time series in this research we first selected autoregressive model ARIMA (autoregressive integrated moving average) for a time series of each index. Then, proceeding from the assumption that each index considered can be influenced not only by its own preceding values but by preceding values of other indices (Sims, 1980), a vector auto-regression (VAR) model has been built. And then taking into consideration the fact how important it is to influence the indices taken as endogenous variables by other indices – exogenous variables, and having embraced their interrelations, a structural model has been built, that of simultaneous equations system (SES). All the three

types of econometric models built have been verified how they satisfy the demands of equality and how they can be used for forecasting. An estimation and comparison of forecast accuracy of models built have been made. And a point forecast of the analyzed macroeconomic indices for all models and for the next time periods has been built.

Materials and Methods

Research methods

The choice of research methods in the work was defined with due regard of initial data type – non-stationary time series of macroeconomic indices in monthly dynamics. In the process of research econometric and statistical methods (methods of econometric model building, methods of time series analysis) were used: graphical analysis of an autocorrelation and partial autocorrelation functions, tests to research stationarity, the order of time series integrity, research methods of cause and effect dependence direction, cointegration analysis, methods of building, estimation and analysis of various econometric models.

Research information basis

The article deals with macroeconomic indices describing stabilization economic processes i.e. processes that proceed in economic system for a long period of time and stabilize its state which is defined by a number of signs (Sukhanova & Shirnaeva, 2012). The basic are: relatively insignificant but stable production growth; employment rise corresponding to natural population growth; balance of foreign trade operation; practically stable prices and population welfare; budget deficit curtailment (Sukhanova & Shirnaeva, 2014). According to these signs the following macroeconomic indices were selected for forecasting (selected as endogenous variables): $Y^{(1)}$ – industrial production index (percent of corresponding period of previous year); $Y^{(2)}$ – total number of unemployed (mln person); $Y^{(3)}$ – net export (bln US dollars); $Y^{(4)}$ – consumer price index (percent of corresponding month of previous year); $Y^{(5)}$ – accrued average monthly nominal wages per employee (percent of corresponding period of previous year); $Y^{(6)}$ – fixed capital investments (percent of corresponding period of previous year).

To form the research information basis official statistical data on Short-Term Economic Indicators of the Russian Federation were used which are regularly placed on the site of the Federal Statistics Service (Short-Term Economic Indicators of the Russian Federation, 2016). Information array on all economic indices mentioned in the article presenting time-series in monthly dynamics, embraces statistical data for more than 17 years: from January 1999 to May 2016 (sampled population is 209 observations in each time series). The analysis and processing of statistical information was made using software packages Statistica, EViews, MS Excel.

Research stages

The research done included the following stages.

At the first stage a preliminary statistical time series analysis of selected macroeconomic indices was made: first that of endogenous variables and then that of exogenous variables, sorted out with due regard of revealed connections with examined endogenous variables.

At the second stage econometric modeling was carried out; econometric models were built, evaluated and analyzed. These were autoregressive integrated moving average (ARIMA) models, vector auto-regression (VAR) models and a simultaneous equations system (SES).

At the third stage test forecasting of endogenous variables (retrospective forecast) was made which allowed to estimate and compare predictive capabilities of models built.

At the fourth stage forecasting of macroeconomic indices (endogenous variables) was made concerning all models built for the following time periods. Corresponding conclusions were made.

Results

A preliminary statistical analysis of time series of macro-economic indices. Autoregressive integrated moving average (ARIMA) models

Graph analysis of initial levels, autocorrelation function (ACF) and partial autocorrelation function (PACF) of time series for indices studied $Y^{(1)}$, $Y^{(2)}$, …, $Y^{(6)}$ made possible a conclusion about the absence of a seasonal component.

A study of stationarity of the considered series with the help of the augmented Dickey-Fuller test (ADF-test) (Sukhanova & Shirnaeva, 2013) proved that time series of all indices analyzed are not stationary. To give them a stationary form the first differences of time series levels were taken. ADF-test confirmed their stationarity (Table 1; with critical values from (MacKinnon, 1990)). According to this a conclusion was made, that initial time series are first order integrated (I(1)) (Aivazyan, 2010).

Table 1. The results of time series study of macroeconomic indices for stationarity

Variable	ADF-test, *t*-statistic									
	Levels					1st differens				
	Determ. terms	Test value	Critical values			Determ terms	Test value	Critical values		
			1%	5%	10%			1%	5%	10%
$Y^{(1)}$	Constant trend	-3,2	-4,0	-3,4	-3,1	Const.	-16,2	-3,5	-2,9	-2,6
$Y^{(2)}$	Constant trend	-2,9				Const.	-9,0			

$Y^{(3)}$	Constant trend	-2,4	Const.	-19,3
$Y^{(4)}$	Constant trend	-2,3	Const.	-11,2
$Y^{(5)}$	Constant trend	-1,0	Const.	-16,8
$Y^{(6)}$	Constant trend	-2,4	Const.	-18,5

Source: authors' calculations

A time series of each index was described with processes of autoregressive moving average. Models ARIMA(*p, d, q*) were built (where *p*, *d*, *q* – are corresponding orders of auto-regression, integration, moving average). For a time series of each index possible orders of auto-regression *p* and moving average *q* were selected (Sukhanova & Shirnaeva, 2015). The analysis of built ACF and PACF graphs of each stationary time series (first differences time series) made possible a conclusion that time series of indices considered can be best (with the least number of parameters) described by a model ARIMA (1,1,0):

$$\Delta Y_t^{(i)} = \alpha_0 + \alpha_1 \Delta Y_{t-1}^{(i)} + \varepsilon_t . \qquad (1)$$

Parameters estimates of models (1) for a time series of every index $Y^{(i)}$ ($i=\overline{1,6}$), Student *t*-statistic value and probability *p* for corresponding estimates are given in Table 2.

Table 2. Results of ARIMA (1,1,0) models estimates for studied macroeconomic indices

Variable	Parameter	Parameter estimate	*t* - statistic	*p* - value
$Y^{(1)}$	α_0	0,02	0,11	0,9101
	α_1	-0,12	-1,97	0,0426
$Y^{(2)}$	α_0	-0,03	-1,69	0,0901
	α_1	0,36	5,49	0,0000
$Y^{(3)}$	α_0	0,03	1,67	0,0913
	α_1	-0,29	-4,32	0,0000
$Y^{(4)}$	α_0	-0,42	-2,05	0,0382
	α_1	0,24	3,56	0,0005
$Y^{(5)}$	α_0	-0,05	-0,27	0,7889
	α_1	-0,15	-2,14	0,0337
$Y^{(6)}$	α_0	-0,001	-1,54	0,0965
	α_1	-0,25	-3,67	0,0003

Source: authors' calculations

Parameters estimates of models built (except for some intercepts estimates) are statistically valuable at the 10% significance level. In case of a constant being insignificant it wasn't excluded from a model to get a more accurate forecast (a conclusion was made when comparing predictive properties of ARIMA (1, 1, 0) models built and estimated with a constant and without it).

The analysis of models residuals (at the 10% significance level) made possible to make a conclusion (Table 3) about the absence of autocorrelation (on the basis Breusch-Godfrey LM-test) and heteroscedasticity (on the basis White test). The analysis of built histograms built, statistical characteristics and statistical values by Jarque-Bera showed, that the distribution of residuals is close to normal.

Table 3. Test results of models ARIMA (1,1,0) residuals for studied macroeconomic indices

Variable	Breusch-Godfrey LM-test, F-statistic (probability)	White test, F-statistic (probability)
$Y^{(1)}$	1,39 (0,2189)	1,32 (0,2687)
$Y^{(2)}$	1,84 (0,1710)	0,66 (0,6853)
$Y^{(3)}$	2,14 (0,0378)	0,99 (0,4233)
$Y^{(4)}$	1,39 (0,2208)	0,28 (0,7535)
$Y^{(5)}$	2,30 (0,1132)	1,59 (0,2162)

Source: authors' calculations.

The built ARIMA models were used for forecasting considered macroeconomic indices.

Vector auto-regression (VAR) model

Supposing that each index considered can be influenced not only by its own lagged values but by lagged values of other indices, a vector autoregression (VAR) model (Tsiao & Box, 1981) was built. To build it as endogenous variables all indices $Y^{(i)}$ ($i = \overline{1,6}$) transformed to stationary form were considered. Each variable was considered as a function of all variables lagged values. To define the quantity of variable models' maximum lag p some VAR models with different lag p value were built. On the basis of Akaike and Schwarz criteria and to check up the hypothesis about statistical significance (for a concrete lag) of parameters estimates of corresponding models variables the length of the maximum lag p was determined as 3 months. So, a system of 6 equations was built corresponding to a number of endogenous variables. Each equation determines

the dependence of one endogenous variable on lag values (with lags of 1, 2, 3 months) of all model variables (transformed to a stationary form). Lagged variables with statistically insignificant parameters estimates (except for intercepts) were excluded from the model as estimates insignificance can mean that a variable with such a lag doesn't significantly influence the dynamics of the index analyzed. As a result we got the following model (*t*-statistic values considered are given in the brackets):

$$
\begin{cases}
\hat{y}_t^{(1)} = \underset{(0,71)}{0,14} - \underset{(-2,04)}{0,13}\, y_{t-1}^{(1)} + \underset{(2,56)}{0,27}\, y_{t-2}^{(3)} + \underset{(5,77)}{0,25}\, y_{t-1}^{(4)} + \underset{(2,13)}{0,14}\, y_{t-2}^{(5)} + \underset{(3,01)}{0,20}\, y_{t-3}^{(5)}, \\
\hat{y}_t^{(2)} = -\underset{(-1,57)}{0,02} - \underset{(-2,29)}{0,01}\, y_{t-1}^{(1)} + \underset{(6,30)}{0,40}\, y_{t-1}^{(2)} - \underset{(-2,52)}{0,10}\, y_{t-3}^{(2)} - \underset{(-2,84)}{0,02}\, y_{t-2}^{(3)} + \underset{(2,67)}{0,01}\, y_{t-3}^{(4)}, \\
\hat{y}_t^{(3)} = \underset{(0,25)}{0,03} + \underset{(1,85)}{0,07}\, y_{t-1}^{(1)} + \underset{(1,98)}{0,52}\, y_{t-3}^{(2)} - \underset{(-4,51)}{0,30}\, y_{t-1}^{(3)} - \underset{(-1,97)}{0,03}\, y_{t-3}^{(4)}, \\
\hat{y}_t^{(4)} = -\underset{(-1,12)}{0,33} - \underset{(-2,17)}{0,12}\, y_{t-1}^{(1)} - \underset{(-2,62)}{0,32}\, y_{t-2}^{(1)} - \underset{(-2,91)}{0,28}\, y_{t-3}^{(1)} + \underset{(2,65)}{0,18}\, y_{t-1}^{(4)} + \underset{(3,50)}{0,25}\, y_{t-3}^{(4)} - \\
\qquad - \underset{(-2,43)}{0,16}\, y_{t-1}^{(5)} + \underset{(1,98)}{0,07}\, y_{t-2}^{(6)}, \\
\hat{y}_t^{(5)} = -\underset{(-1,14)}{0,21} - \underset{(-2,10)}{0,01}\, y_{t-2}^{(1)} - \underset{(-2,52)}{1,26}\, y_{t-1}^{(2)} + \underset{(2,69)}{0,13}\, y_{t-1}^{(3)} + \underset{(2,18)}{0,23}\, y_{t-2}^{(3)} - \underset{(-3,31)}{0,23}\, y_{t-1}^{(5)} + \\
\qquad + \underset{(2,60)}{0,11}\, y_{t-2}^{(5)}, \\
\hat{y}_t^{(6)} = -\underset{(-0,65)}{0,19} + \underset{(2,79)}{0,30}\, y_{t-1}^{(1)} + \underset{(2,79)}{0,23}\, y_{t-3}^{(1)} - \underset{(-2,48)}{3,21}\, y_{t-1}^{(2)} + \underset{(2,77)}{0,35}\, y_{t-2}^{(3)} - \underset{(-2,97)}{0,16}\, y_{t-3}^{(4)} + \\
\qquad + \underset{(2,73)}{0,18}\, y_{t-3}^{(5)} - \underset{(-5,10)}{0,38}\, y_{t-1}^{(6)} - \underset{(-2,88)}{0,13}\, y_{t-2}^{(6)} - \underset{(-2,91)}{0,14}\, y_{t-3}^{(6)},
\end{cases}
\tag{2}
$$

where $y_t^{(i)}$, $y_{t-j}^{(i)}$ – are current and lagged variables transformed to a stationary form; $i = \overline{1,6}$; $j = \overline{1,3}$.

For the model built (2) the analysis of each equation residuals was carried out (Table 4), which made possible a conclusion about the absence of autocorrelation (orders 1-3) and heteroscedasticity; the residuals distribution is close to normal. Unlike of ARIMAmodels where residuals autocorrelation of the 1st order only was tested, residual's testing in a VAR model was done for 1-3 order autocorrelation.

Table 4. The results of residuals testing in VAR model equations for macroeconomic indices considered

Variable	Breusch-Godfrey LM-test, F-statistic (probability)	White test, F-statistic (probability)
$Y^{(1)}$	0,11 (0,9521)	0,47 (0,9896)
$Y^{(2)}$	2,31 (0,1185)	1,09 (0,4533)
$Y^{(3)}$	1,17 (0,3226)	1,32 (0,2838)
$Y^{(4)}$	1,32 (0,2482)	1,55 (0,2335)
$Y^{(5)}$	2,03 (0,1312)	1,29 (0,2957)
$Y^{(6)}$	0,59 (0,6208)	0,96 (0,5863)

Source: authors' calculations.

The built VAR model was used for forecasting macroeconomic indices considered.

A simultaneous equations system (SES)

To carry out a comprehensive analysis of how the examined endogenous variables $Y^{(1)}$, $Y^{(2)}$, ..., $Y^{(6)}$ are influenced by other exogenous variables and how their interconnections are modeled, a simultaneous equations system (SES) was built. For its construction, with regard of Granger test results to determine cause and effect dependence with endogenous variables $Y^{(1)}$, $Y^{(2)}$, ..., $Y^{(6)}$ to study time series stability of all indices and to carry out cointegration analysis (Sukhanova & Shirnaeva, 2013). The following indices were selected as exogenous variables: $X^{(1)}$ – commercial freight turnover (bln ton-km); $X^{(2)}$ – freight loading on railway transport (mln ton); $X^{(3)}$ – volume of work performed by economic activity "Construction" (bln rubles); $X^{(4)}$ – official US dollar / ruble exchange rate; $X^{(5)}$ – retail trade turnover (bln rubles); $X^{(6)}$ – volume of paid services rendered to population (bln rubles); $X^{(7)}$ – money income average per capita (rubles); $X^{(8)}$ – creditor indebtedness of organizations in budgets (bln rubles); $X^{(9)}$ – debtor indebtedness of organizations (bln rubles); $X^{(10)}$ – average producer prices of crude oil (rubles per ton); $X^{(11)}$ – average producer prices of naturalgas (rubles per thou cubic meter). Time series of selected exogenous variables were verified for the availability of seasonal component as well.

When it was revealed (on the basis of ACF & PACF graphs analysis) the exclusion of a seasonal component was done with regard of its type, either additive or multiplicative. The study of time series stationarity of considered variables was done with the help of augmented Dickey-Fuller test (ADF-test) both at initial levels and at first differences (Table 5).

Table 5. Time series study results of SES exogenous variables for seasonal prevalence and stationarity

Variable	Levels				1st differens		
	Seasonal component	Deterministic terms	ADF-test, *t*-statistic		Deterministic terms	ADF-test, *t*-statistic	
$X^{(1)}$	Additive	Constant, trend	-2,07		Constant	-15,72	
$X^{(2)}$	Additive	Constant, trend	-2,49		Constant	-12,73	
$X^{(3)}$	Multiplic.	Constant, trend	-1,15		Constant	-3,05	
$X^{(4)}$	None	Constant, trend	-0,91		Constant	-9,28	
$X^{(5)}$	Multiplic.	Constant, trend	-0,09		Constant	-2,89	
$X^{(6)}$	Multiplic.	Constant, trend	-2,03		Constant	-3,31	
$X^{(7)}$	Multiplic.	Constant, trend	-2,80		Constant	-4,12	
$X^{(8)}$	None	Constant, trend	-1,87		Constant	-12,71	
$X^{(9)}$	None	Constant, trend	-2,54		Constant	-18,59	
$X^{(10)}$	None	Constant, trend	-0,15		Constant	-11,17	
$X^{(11)}$	None	Constant, trend	-0,87		Constant	-9,02	
			1%	-4,00		1%	-3,46
	Critical values		5%	-3,43	Critical values	5%	-2,88
			10%	-3,14		10%	-2,57

Source: authors' calculations. Critical values from J.G. MacKinnon (1990)

As a result seasonal component was discovered and removed for variables $X^{(1)}$, $X^{(2)}$, $X^{(3)}$, $X^{(5)}$, $X^{(6)}$ and $X^{(7)}$. When studying time series stationarity of exogenous variables a conclusion was made according to ADF-test results that all time series are first-order integrated (I(1)).

One and the same order of time series integration variables for SES made possible to check these series for the cointegration availability. For time series pairs of exogenous and endogenous variables that exposed cause and effect dependence a cointegration analysis was conducted (Sukhanova & Shirnaeva, 2013). The hypothesis about the cointegration availability was checked up using R.F. Engle & C.W. Granger method (1987). The verification detected that pairs examined are cointegrated at the 10% significance level. The conclusion made

gave a chance to use base line levels of time series to build SES model, to take a long term dependence among them into consideration and to get a qualitative forecast.

With regard of cointegration analysis results and having verified how model identification conditions are performed (Shirnaeva, 2009), we got a SES structural form. As a result of its structural parameters estimation by a two-stage least squares method (Magnus, Katyshev & Peresetskij, 2004) the following SES model was received:

$$\begin{cases} \hat{Y}_t^{(1)} = \underset{(22,48)}{121,59} - \underset{(-4,07)}{2,14}\, Y_t^{(2)} - \underset{(-3,62)}{0,05}\, X_t^{(3)} - \underset{(-2,0)}{0,19}\, X_t^{(4)} + \underset{(2,23)}{0,04}\, X_t^{(6)} + \underset{(1,89)}{0,03}\, X_t^{(8)} - \\ \quad - \underset{(-1,64)}{0,001}\, X_t^{(9)} - \underset{(-1,73)}{0,005}\, X_t^{(11)},\ R^2 = 0,486 \\ \hat{Y}_t^{(2)} = \underset{(5,59)}{9,79} + \underset{(4,36)}{0,02}\, Y_t^{(4)} + \underset{(3,06)}{0,02}\, Y_t^{(6)} - \underset{(-3,85)}{0,01}\, X_t^{(1)} - \underset{(-5,27)}{0,003}\, X_t^{(3)},\ R^2 = 0,899 \\ \hat{Y}_t^{(3)} = - \underset{(-2,19)}{12,61} + \underset{(1,87)}{0,08}\, Y_t^{(1)} + \underset{(1,65)}{0,01}\, Y_t^{(6)} + \underset{(5,22)}{0,04}\, X_t^{(1)} - \underset{(-10,62)}{0,19}\, X_t^{(4)} + \underset{(12,54)}{0,001}\, X_t^{(10)},\ R^2 = 0,908 \\ \hat{Y}_t^{(4)} = \underset{(16,60)}{257,36} - \underset{(-2,89)}{3,05}\, Y_t^{(3)} - \underset{(-5,29)}{1,04}\, X_t^{(2)} + \underset{(3,48)}{0,84}\, X_t^{(4)} + \underset{(2,70)}{0,003}\, X_t^{(10)},\ R^2 = 0,583 \\ \hat{Y}_t^{(5)} = \underset{(6,82)}{141,41} - \underset{(-1,66)}{0,18}\, Y_t^{(1)} + \underset{(1,79)}{0,16}\, Y_t^{(6)} + \underset{(4,39)}{0,04}\, X_t^{(5)} + \underset{(6,19)}{0,01}\, X_t^{(7)} + \underset{(1,88)}{0,001}\, X_t^{(10)},\ R^2 = 0,879 \\ \hat{Y}_t^{(6)} = \underset{(3,49)}{88,39} + \underset{(3,41)}{0,68}\, Y_t^{(1)} - \underset{(-8,26)}{0,35}\, Y_t^{(4)} - \underset{(-2,47)}{0,15}\, X_t^{(4)} + \underset{(4,66)}{0,05}\, X_t^{(6)} + \underset{(3,75)}{0,002}\, X_t^{(10)},\ R^2 = 0,781 \end{cases} \quad (3)$$

The built system of simultaneous regression equations (3) meets all adequacy demands. Parameters estimates of model's equations are statistically significant according to t-criterion at the 5-10% significance level (in the brackets there are considered values of t-statistic and a coefficient of determination R^2); all models equations are statistically significant according to F-criterion. Residuals analysis of models equations exposed that the residuals have a distribution close to normal (histograms, statistical characteristics and Jarque-Bera test values were analyzed); autocorrelation (Breusch-Godfrey LM-test) and residuals heteroscedasticity (White test) are absent.

A SES model received can be used to analyze interconnections and to forecast the considered macroeconomic indices.

Forecasting

All the econometric models built were used to forecast studied macroeconomic indices. To compare models' predictive capabilities as to each index a retrospective forecast was realized.

For this purpose m =10 last values at the end of a time series of each index were sorted out. Every model (ARIMA, VAR, SES) was estimated according to the first ($n-m$) observation and was used to find out fitted value $\hat{Y}_{n-m+1}^{(i)}$ (n = 209). Then having added the observation each model was estimated according to the first ($n-m+1$) observations and its value $\hat{Y}_{n-m+2}^{(i)}$ was calculated and so

on. The process repeated until fitted value $\hat{Y}_n^{(i)}$ $(i = \overline{1, 6})$ was found. At figure 1 (as an example) one can see a graph of actual values and fitted values received by a method described above for $Y^{(1)}$ index. One can notice that fitted values received on all models are very close to actual values.

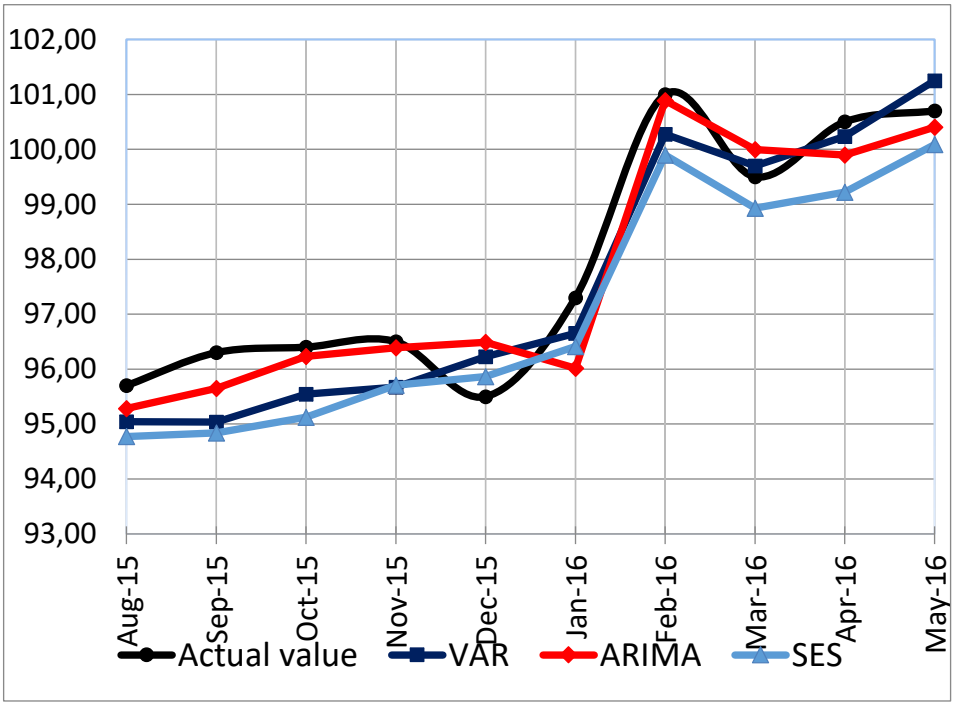

Figure 1. The results of test forecasting (retrospective forecast) for $Y^{(1)}$ (industrial production index, %) for the period from August 2015 to May 2016 according to VAR, ARIMA, SES models
Source: authors' calculations

As a criterion of estimation and comparison of forecasting accuracy of built econometric models for each $Y^{(i)}$ $(i = \overline{1, 6})$ mean relative forecast error was calculated:

$$\bar{\xi} = \frac{1}{m} \sum_{t=n-m+1}^{n} \frac{\left| Y_t^{(i)} - \hat{Y}_t^{(i)} \right|}{Y_t^{(i)}} \cdot 100\%, \qquad (4)$$

where $\hat{Y}_t^{(i)}$, $Y_t^{(i)}$ - is fitted value calculated by a method mentioned above and corresponding actual value of index $Y^{(i)}$ $(i = \overline{1, 6};\ t = \overline{200, 209};\ n = 209;\ m = 10)$.

The calculation results of mean relative forecast error (4) are placed in Table 6.

Table 6. Mean relative forecast errors (%)

Model	Variable					
	$Y^{(1)}$	$Y^{(2)}$	$Y^{(3)}$	$Y^{(4)}$	$Y^{(5)}$	$Y^{(6)}$
VAR	1,01	2,26	8,19	0,62	1,22	1,88
ARIMA	1,99	2,75	7,36	1,12	1,54	1,92
SES	6,30	6,91	12,79	8,25	5,98	7,17

Source: authors' calculations.

Insignificant forecast errors give reason to prove that models built posses rather good forecasting possibilities (Table 6). Then a forecasting of macroeconomic indices of processes studied was executed for the following months (June – December 2016) in accordance with all offered models (Table 7).

Table 7. Fitted values of macroeconomic indices for June – December 2016

Variable	Model	June	July	August	Septembe	October	November	December
$Y^{(1)}$	VAR	100,47	99,52	99,55	99,42	99,36	99,39	99,36
	ARIMA	100,30	100,72	100,75	100,77	100,79	100,81	100,83
	СОУ	98,74	99,64	98,63	96,57	98,53	98,48	99,43
$Y^{(2)}$	VAR	4,29	4,47	4,42	4,37	4,34	4,31	4,29
	ARIMA	4,21	4,16	4,13	4,10	4,07	4,04	4,02
	СОУ	4,08	4,06	4,04	4,03	4,01	3,99	3,97
$Y^{(3)}$	VAR	7,08	7,09	7,25	7,25	7,26	7,28	7,29
	ARIMA	7,04	7,09	7,11	7,13	7,16	7,18	7,21
	СОУ	6,35	6,45	7,52	6,57	8,63	7,68	8,73
$Y^{(4)}$	VAR	104,98	104,43	103,31	102,54	102,25	101,69	101,13
	ARIMA	106,98	106,59	106,18	105,77	105,35	104,93	104,52
	СОУ	95,96	95,75	95,51	95,27	95,03	94,79	94,55
$Y^{(5)}$	VAR	106,36	106,10	105,85	105,78	105,70	105,52	105,38
	ARIMA	106,13	106,09	106,04	105,99	105,94	105,90	105,85
	СОУ	92,72	95,31	83,16	94,20	93,08	93,42	95,76
$Y^{(6)}$	VAR	93,95	93,19	93,57	93,74	93,66	93,68	93,67
	ARIMA	92,21	92,21	92,21	92,21	92,21	92,21	92,20
	СОУ	93,77	95,80	94,84	94,83	93,83	93,82	93,81

Source: authors' calculations.

The results of forecasting point out at keeping the existing trends of most indices considered. One can see that changes in quantity are not essential in the forecasted period (Table 7). One should specify possible small reduction of net export volume $Y^{(3)}$ (as compared with its average quantity for the last 2 years which equals $ 10,9bln) and lowering of consumer price index $Y^{(4)}$ (the mean value of this index was 113,3% in 2015).

Discussions

The work is devoted to results of econometric modeling and macroeconomic forecasting indices: industrial production index, a number of unemployed, net export, consumer prices index, average monthly salary, investments into fixed capital.

Econometric models built in the process of work make it possible to comprehensively analyze processes under review, discover factors influencing their dynamics, to fulfil a forecast.

To compare forecast accuracy of econometric models individual authors use, as a criteria, a sample variance of forecast errors (Dorokhov, 2008) of the ratio of forecast errors mean square of models analyzed (Deryugina & Ponomarenko, 2015; Ashmarina & Khasaev, 2015). In this study to estimate and compare forecast accuracy received with the help of built econometrical models the mean relative forecast error was calculated.

Test forecasting of indices analyzed (Table 6) on the basis of autoregressive models demonstrated that mean relative forecast errors of most indices of the ARIMA and VAR models made up not more than 3% (with the exception of $Y^{(3)}$ net export). It made possible to make a conclusion that ARIMA and VAR models posess good forecast possibilities (it's confessed by other authors (Dorokhov, 2008; Nikitsina, 2016)) and are safe, convenient and effective tools of economic indices forecasting). The mean relative forecast errors received on the basis of SES model are bigger according to all indices than the corresponding values according to autoregressive models, but in the whole they don't exceed 9% (except for net export – $Y^{(3)}$). This result is good enough, even more so, forecasting according to autoregressive models was fulfilled using known values of variables (lagged values). SES forecasting has been complicated by the fact that at first it's necessary to build exogenous variables forecast. So, ARIMA type model was selected for each exogenous variable (as it was described above), and then endogenous variables forecast $Y^{(1)}$, $Y^{(2)}$, …, $Y^{(6)}$ was built.

Despite a very labour-consuming process of building and estimating structural model parameters (Eliseeva, Kurysheva & Kosteeva, 2005), SES model has a number of important advantages. It makes possible to simultaneously embrace and analyze a multitude of economic ties and interconnections of indices considered (endogenous variables) with other indices (exogenous variables), and to simulate these ties' structure. It's possible to use

these models wider than autoregressive ones, which are used mainly, for forecasting and that's the principal aim of their building.

Among possible directions of further research and perfection of represented methodology one can specify the study of the problem about possible structural moves in time series of studied macroeconomic indices. Time period taken for research (1999-2016) covers economic crisis of 2008-2009. It seems interesting to build econometric models taking two time periods under review: before and after the year of 2008, to analyze the results of such model building to check up the stability of such models (with less samples). Possibly, one should include dummy variables into econometric model (as some authors (Aivazyan & Brodsky, 2006) recommend) taking into consideration possible moves and to save the volume of original sample as a result. Other possible directions of work are an addiction of the represented indices system by other macroeconomic indices and econometric models building according to a changed set of variables.

Conclusion

In this article three types of econometrical models were built stage by stage using econometric model building methods: autoregressive integrated moving average (ARIMA) models, vector auto-regression (VAR) models and a simultaneous equations system (SES) as well.

All models built revealed good forecast possibilities and are safe and effective tools of forecast the considered macroeconomic indices. As to the results of the above presented study preference can be given to forecasting on the autoregressive models basis.

The offered methods of econometric model buildling and forecasting can be used while studying other economic processes.

The results that were received in the article can be useful for researchers dealing with modeling and forecasting of various economic processes both in scientific and practical activity.

Disclosure statement

No potential conflict of interest was reported by the authors.

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