“Government debt forecasting based on the Arima model”

AUTHORS	Fedir Zhuravka https://orcid.org/0000-0001-8368-5743 https://www.webofscience.com/wos/author/record/P-4821-2014 Hanna Filatova https://orcid.org/0000-0002-7547-4919 https://www.webofscience.com/wos/author/record/AHC-9824-2022 John O. Aiyedogbon https://orcid.org/0000-0001-5095-875X

ARTICLE INFO	Fedir Zhuravka, Hanna Filatova and John O. Aiyedogbon (2019). Government debt forecasting based on the Arima model. *Public and Municipal Finance*, *8*(1), 120-127. doi:10.21511/pmf.08(1).2019.11
DOI	http://dx.doi.org/10.21511/pmf.08(1).2019.11
RELEASED ON	Friday, 17 January 2020
RECEIVED ON	Tuesday, 03 December 2019
ACCEPTED ON	Saturday, 28 December 2019

LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License

JOURNAL	"Public and Municipal Finance"
ISSN PRINT	2222-1867
ISSN ONLINE	2222-1875
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
23	5	2

© The author(s) 2026. This publication is an open access article.

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10, Sumy, 40022, Ukraine

www.businessperspectives.org

Fedir Zhuravka (Ukraine), **Hanna Filatova** (Ukraine), **John O. Aiyedogbon** (Nigeria)

GOVERNMENT DEBT FORECASTING BASED ON THE ARIMA MODEL

Abstract

The paper explores theoretical and practical aspects of forecasting the government debt in Ukraine. A visual analysis of changes in the amount of government debt was conducted, which has made it possible to conclude about the deepening of the debt crisis in the country. The autoregressive integrated moving average (ARIMA) is considered as the basic forecasting model; besides, the model work and its diagnostics are estimated. The EViews software package illustrates the procedure for forecasting the Ukrainian government debt for the ARIMA model: the series for stationarity was tested, the time series of monthly government debt was converted into stationary by making a number of transformations and determining model parameters; as a result, the most optimal specification for the ARIMA model was chosen.

Based on the simulated time series, it is concluded that ARIMA tools can be used to predict the government debt values.

Keywords debt, debt sustainability, modeling, time series analysis, Ukraine

JEL Classification H60, H63

Received on: 3rd of December, 2019
Accepted on: 28th of December, 2019

© Fedir Zhuravka, Hanna Filatova, John O. Aiyedogbon, 2019

Fedir Zhuravka, Doctor of Economics, Professor, Department of the International Economic Relations, Sumy State University, Ukraine.

Hanna Filatova, Ph.D. Student, Department of the International Economic Relations, Sumy State University, Ukraine.

John O. Aiyedogbon, Ph.D., Associate Professor, Department of Economics, Bingham University, Nigeria.

This is an Open Access article, distributed under the terms of the Creative Commons Attribution 4.0 International license, which permits unrestricted re-use, distribution, and reproduction in any medium, provided the original work is properly cited.

INTRODUCTION

Government debt is not only a means of fundraising to finance public needs, but also an effective tool to stabilize the country's economic development, whose predictive values allow making effective management decisions at the state level and developing effective measures to improve the economic and debt situation.

Despite the advanced mathematical tools for data forecast, choosing the appropriate method that provides adequate forecasts is one of the main tasks that arise in forecasting the amount of government debt.

There are many different methods of forecasting economic information in modern statistical theory. Most of them relate to time series forecasting, without additional information, i.e. without analyzing the impact of other factors. Of course, such analyses are incomplete, but their results are often more accurate than other forecasting techniques. Constructing an ARIMA model is one of such methods. Its main idea is that some time series are a set of random variables that depend on time, but changes in the entire time series have certain rules that can be represented by the corresponding mathematical model. When analyzing the mathematical model, one can understand the structure and characteristics of the time series more deeply and achieve optimal predictive values.

Different factors, such as GDP, inflation, industrial production index, exchange rate, as well as other factors of the country's economic life,

http://dx.doi.org/10.21511/pmf.08(1).2019.11

may influence the change in the value of the government debt indicator. Collecting, processing, and analyzing selected factors to build a multivariate regression model can be time consuming and require significant resources that do not correspond to the end result. For this reason, it is more appropriate to use time series-based forecasting methods, such as an ARIMA time series model.

1. LITERATURE REVIEW

Time series analysis, in particular, ARIMA analysis, is widely used in the scientific literature to predict macroeconomic variables. The ARIMA model (autoregressive integrated moving average), a time series prediction method, was first developed and applied in the mid-1970s by two American scientists J. Box and D. Jenkins (Box, Jenkins, & Reinsel, 1994). The use of Box-Jenkins processes makes it possible to build an accurate and adequate model for the short-term forecast, but because of the data non-stationarity, this method needs improvement to build a more accurate long-term forecast.

Gnegne and Jawadi (2013), Martinez (2015), and Ericsson (2017) examine methods and features of forecasting government debt for different countries.

The government debt dynamics for the United States of America and the United Kingdom are examined by applying non-linearity tests and threshold autoregressive models (Gnegne & Jawadi, 2013). The research gives understanding that the dynamics of government debt have different threshold effects (due to economic downturns, oil shocks, and debt crises); their consideration can improve the modeling and forecasting of the government debt development.

In the context of analyzing the government borrowing forecast, it is important to focus on Ericsson (2017), who looks at different approaches to testing for potential bias and proposes the use of impulse indicator saturation (IIS) to find out how biased the forecasts are. This indicator can also be applied to the government debt in Ukraine.

Despite significant scientific contributions to ARIMA's research, developing such models for government debt and key debt sustainability indicators is in its infancy.

Goswami and Hossain (2013) use a time series forecasting tool (ARIMA model) to analyze debt sustainability in Bangladesh for the period 2013–2033. The objects of the study are public debt, external debt and debt sustainability indicators; the predicted values are compared with the thresholds and stress tests applied to the external debt.

It should be noted that carrying out such a study for some debt sustainability indicators in Ukraine (for example, the government debt to GDP ratio, government external debt to annual exports of goods and services) can be problematic (because annual data are not enough to make adequate forecasts).

Nikoloski and Nedanovski (2017) and Navapan and Boonyakunakorn (2017) consider the varieties of ARIMA models that simultaneously take into account lag variables of the studied indicator and exogenous factors. In particular, Nikoloski and Nedanovski provide a detailed analysis of the dynamics of government debt and its structure in the Republic of Macedonia over 16 years. The study carefully examines how certain factors affect government debt to project its future trend.

Predicting the value of Ukraine's government debt by scientists is usually inseparable from other socio-economic indicators of the country. For this purpose, one-factor and multi-factor regression models are used to extrapolate future values. Yashchenko (2014) uses a four-equation system to predict external and internal debt on the basis of revenues and expenditures of the state budget of Ukraine and to determine the correlation dependence between the variables.

ARIMA models are rarely used to predict Ukraine's public debt.

When predicting the direct government debt of Ukraine and considering the cyclicality factor, Caruk (2007) found that the use of taxonomies of forecasting methods can significantly simplify the process of choosing the optimal forecast model according to the existing limitations, resources and

tasks set by a researcher. A multicriteria approach to selecting the optimal ARIMA model specification is proposed.

Therefore, many issues concerning the formation of a holistic view of the ARIMA model construction to forecast the amount of public debt, taking into account the specifics of current economic transformations, have not been fully resolved. In addition, the analysis of government debt and its impact on the economy requires continuous improvement of research methods, especially in terms of dynamic comparisons and forecasting of data.

The purpose of the paper is to analyze the dynamics of government debt and to predict its future values using the ARIMA model.

2. METHODS

The main research methods are scientific abstraction, generalization and systematization; they are used to consider scientific literature and substantiate basic theoretical propositions. Besides, the time series analysis method (ARIMA model) is employed to analyze the dynamics and trends of changing public debt and predict its future values.

To build the ARIMA time series model, EViews software is used, which has a considerable range of capabilities for primary data analysis, their graphical display, etc.

The factual base of the research consists of reporting and analytical information of the Ministry of Finance of Ukraine, as well as articles of Ukrainian and foreign scientists, materials of international organizations and their scientific calculations.

ARIMA modeling is a procedure for determining the parameters p, d, and q, where p is the order of the component AR, d is the order of the integrated series, and q is the order of the component MA. The process of analyzing data and building an ARIMA model can be presented in several steps:

1. Time series analysis (plotting of dynamics of indicators and, accordingly, analysis of the graph's appearance: the presence of a trend, cycle, seasonality, and zero values).
2. Checking the time series for stationarity. Determining an integration parameter d. In the case of non-stationarity of the time series, the order of integration, namely the form in which it behaves as a stationary series (e.g., first or second differences, taking logarithms, seasonality adjustments, etc.) should be defined and justified (Lukianenko & Zhuk, 2013).
3. Model evaluation uses regression methods to obtain estimates of the parameters included in the model. The autocorrelation coefficient (ACF) and the partial autocorrelation coefficient (PACF) of sequence, as well as the autocorrelation order p and the moving average order q of the ARMA model are calculated.
4. Testing the basic prerequisites of regression analysis and checking the model for adequacy.
5. Using the model for forecasting.

In practice, varieties of ARIMA models, such as ARMAX models, are also used; they simultaneously consider lag variables of the studied indicator and exogenous factors. This model is a kind of hybrid of linear multivariate regression and ARIMA models. Being specified correctly, the ARMAX models make it possible to reduce forecasting errors and prove more effective than multivariate regression models or even pure ARIMA models (Lukianenko & Zhuk, 2013).

3. RESULTS

Let's build the ARIMA model for the government debt of Ukraine and determine the predictive value of this indicator for the next few months. There is a time series of monthly data on the amount of the government debt of Ukraine from December 2011 to October 2019, in UAH million.

The first stage is a visual analysis of changes in the volume of the government debt of Ukraine (a simple linear graph was selected based on the raw data with an additional histogram of the distribution along the axis). Figure 1 shows results.

It should be noted that over the last few years, there has been a steady tendency to increase the

http://dx.doi.org/10.21511/pmf.08(1).2019.11

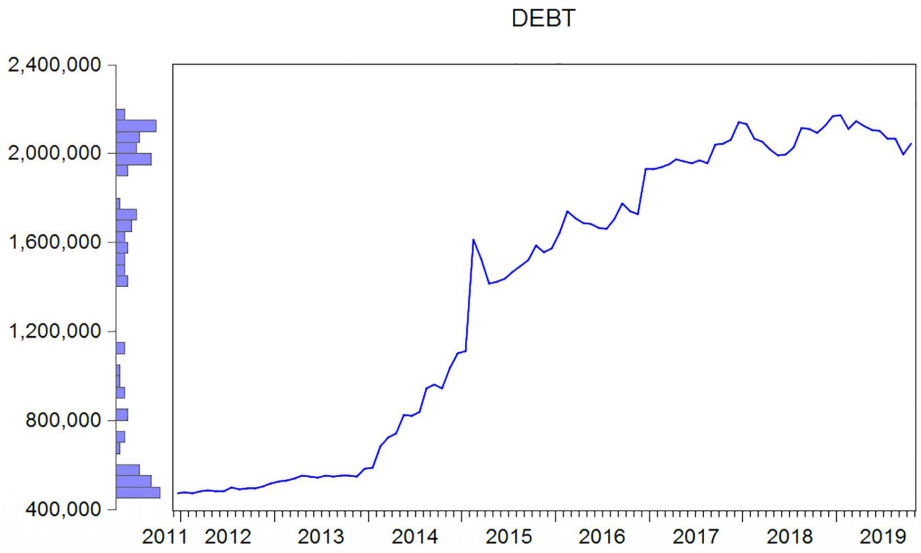


Figure 1. The schedule of the time series of the Ukraine's government debt for 2011–2019, UAH mln

government debt of Ukraine; it is determined by the irrational pursuit of debt policy, high cost of attracting new loans, unstable debt refinancing in previous years, currency risks of the debt, etc.

During 2011–2013, there was a slight increase in government debt, with a minimal growth rate for this period.

Figure 1 shows that since 2014, there has been a rapid aggravation of the debt stability of Ukraine. The period from January 2014 to the beginning of 2015 can be called the extensive growth phase, with a peak value in February 2015. The distribution histogram, which is further represented on the left, has three peaks.

The next step is to check the time series for stationarity. The Dickey-Fuller test is the most common time-series test for stationarity. Figure 2 shows the results of testing the series for stationarity in its original form.

Null Hypothesis: DEBT has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.163521	0.9117
Test critical values:	1% level	-4.058619	
	5% level	-3.458326	
	10% level	-3.155161	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DEBT)
Method: Least Squares
Date: 12/21/19 Time: 10:10
Sample (adjusted): 2012M01 2019M10
Included observations: 94 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DEBT(-1)	-0.044961	0.038642	-1.163521	0.2477
C	37777.01	17777.16	2.125031	0.0363
@TREND("2011M12")	858.8846	919.1242	0.934460	0.3525

R-squared	0.019427	Mean dependent var	16726.81
Adjusted R-squared	-0.002124	S.D. dependent var	66401.89
S.E. of regression	66472.38	Akaike info criterion	25.07836
Sum squared resid	4.02E+11	Schwarz criterion	25.15952
Log likelihood	-1175.683	Hannan-Quinn criter.	25.11114
F-statistic	0.901440	Durbin-Watson stat	2.111877
Prob(F-statistic)	0.409579		

Figure 2. The results of the Dickey-Fuller test to verify the time series in the stationarity equations

Null Hypothesis: D(DEBT) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.892150	0.0000
Test critical values:	1% level	-4.059734	
	5% level	-3.458856	
	10% level	-3.155470	

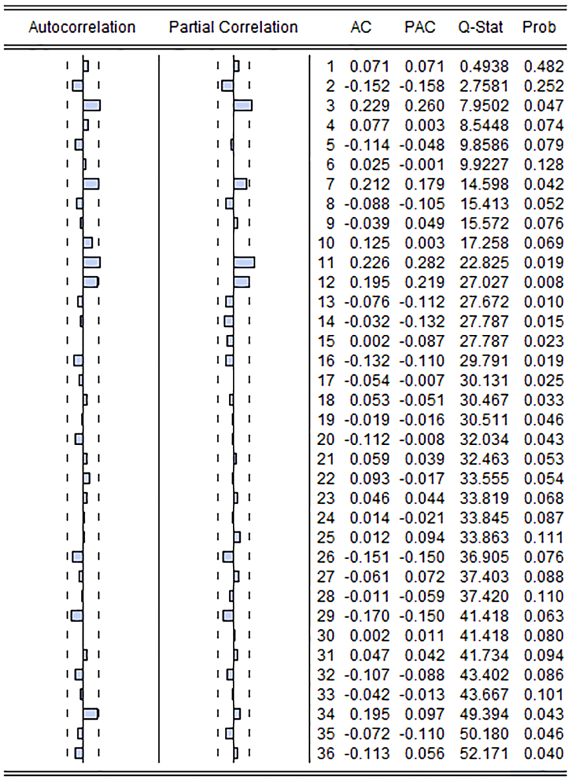
*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DEBT,2)
Method: Least Squares
Date: 12/21/19 Time: 04:38
Sample (adjusted): 2012M02 2019M10
Included observations: 93 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DEBT(-1))	-0.937579	0.105439	-8.892150	0.0000
C	23959.43	11143.72	2.150038	0.0342
@TREND("2011M12")	-168.7212	197.6233	-0.853752	0.3955

R-squared	0.467688	Mean dependent var	490.2688
Adjusted R-squared	0.455859	S.D. dependent var	68991.59
S.E. of regression	50892.29	Akaike info criterion	24.54454
Sum squared resid	2.33E+11	Schwarz criterion	24.62623
Log likelihood	-1138.321	Hannan-Quinn criter.	24.57752
F-statistic	39.53686	Durbin-Watson stat	1.973199
Prob(F-statistic)	0.000000		

Figure 3. The results of the time series check in the first differences for stationarity



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.071	0.071	0.4938	0.482
		2	-0.152	-0.158	2.7581	0.252
		3	0.229	0.260	7.9502	0.047
		4	0.077	0.003	8.5448	0.074
		5	-0.114	-0.048	9.8586	0.079
		6	0.025	-0.001	9.9227	0.128
		7	0.212	0.179	14.598	0.042
		8	-0.088	-0.105	15.413	0.052
		9	-0.039	0.049	15.572	0.076
		10	0.125	0.003	17.258	0.069
		11	0.226	0.282	22.825	0.019
		12	0.195	0.219	27.027	0.008
		13	-0.076	-0.112	27.672	0.010
		14	-0.032	-0.132	27.787	0.015
		15	0.002	-0.087	27.787	0.023
		16	-0.132	-0.110	29.791	0.019
		17	-0.054	-0.007	30.131	0.025
		18	0.053	-0.051	30.467	0.033
		19	-0.019	-0.016	30.511	0.046
		20	-0.112	-0.008	32.034	0.043
		21	0.059	0.039	32.463	0.053
		22	0.093	-0.017	33.555	0.054
		23	0.046	0.044	33.819	0.068
		24	0.014	-0.021	33.845	0.087
		25	0.012	0.094	33.863	0.111
		26	-0.151	-0.150	36.905	0.076
		27	-0.061	0.072	37.403	0.088
		28	-0.011	-0.059	37.420	0.110
		29	-0.170	-0.150	41.418	0.063
		30	0.002	0.011	41.418	0.080
		31	0.047	0.042	41.734	0.094
		32	-0.107	-0.088	43.402	0.086
		33	-0.042	-0.013	43.667	0.101
		34	0.195	0.097	49.394	0.043
		35	-0.072	-0.110	50.180	0.046
		36	-0.113	0.056	52.171	0.040

Figure 4. The correlogram graph of the series in the first differences

The calculated and critical values of McKinnon's τ-statistics are the key indicators of the Dickey-Fuller test. Figure 2 shows that the calculated value of the τ-statistic is –1.163521 and it is greater (lies to the right) than the critical values at the 1, 5, and 10% significance levels. Besides, p-value = 91% (p-value > 10%) is the minimum probability that a row has a single root and is not stationary. Therefore, the null hypothesis of having a single root in the time series cannot be rejected.

The observed series was transformed to bring it to the stationary process. Since there is an anomalous value in this series (February 2015) that is not typical for the whole series, it was decided to replace it with an average value (between the previous and the next) to prevent the results from being distorted.

The results of using the Dickey-Fuller test in the first differences indicate the stationarity of the transformed series (Figure 3). The value of McKinnon's calculated τ-statistic (–8.89) is less (lies to the left) than the critical values at 1, 5, and 10%; therefore, the null hypothesis on a single root (non-stationarity) in some of the first differences is rejected with a minimum probability of making a 0% mistake (since p-value equals zero).

Thus, the model will be built for the time series in the first differences, with order of integration 1; at this stage, the study has AR(?)I(1)MA(?).

Consider the graphs of the autocorrelation and partial autocorrelation function of a series of Ukraine's government debt (see Figure 4) to determine the general specification of the future ARIMA model and the number of lags for each component.

The correlogram graph is analyzed based on the key properties of the graphs of ACF/PACF functions for MA, AR and ARMA processes (Figure 5) (Lukianenko & Zhuk, 2013).

The visual analysis of the correlogram (ACF/PACF functions) makes it possible to determine whether the selected data set is a pure AR or MA process or a mixed ARMA process. The conclusion on the maximum number of lags can be made only in cases of pure processes. In a mixed process, special identification procedures (for example, the Hannan-Rissanen procedure) should be used.

http://dx.doi.org/10.21511/pmf.08(1).2019.11

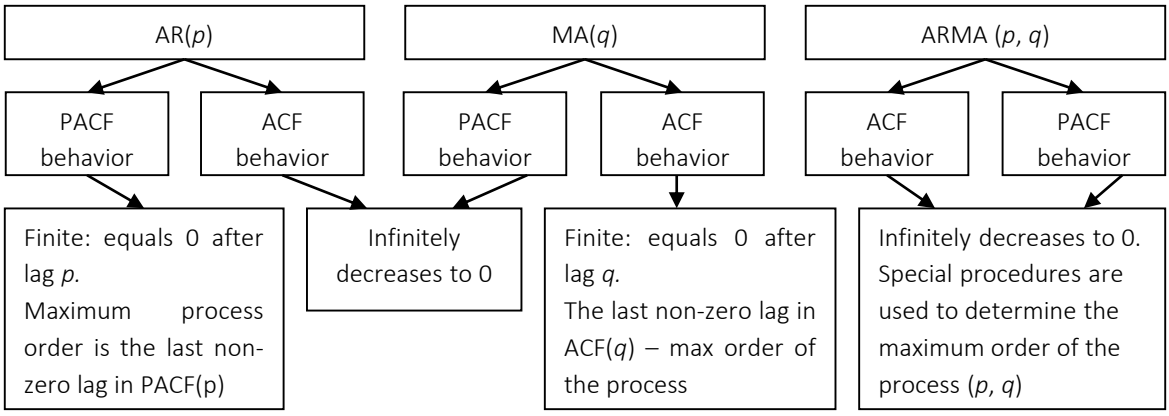


Figure 5. Properties of ACF and PACF functions for MA, AR, and ARMA processes

Consider the graphs of the ACF and PACF functions to determine the type of the process and the number of lags to be included in the model. Figure 4 indicates that the 11th lag, the 3rd lag and probably the 1st lag are significant. The process is mixed, as evidenced by the visual analysis of the ACF/PACF charts.

Given that judgment is very subjective, special procedures must be used to establish a more accurate model and identify the order of AR and MA components.

Since the process is not a pure autoregressive or moving average process, the order of AR and MA components using the Hannan-Rissanen procedures was determined. According to these procedures, the AR component was determined using the least-squares method (the optimal lags for inclusion in the model are those for which the value of the AIC information criterion is minimal) (Greene, 2012).

After determining the optimal AR component, it is necessary to form a set of the model residues for later use in determining the optimal order of the MA component of the ARMA/ARIMA model.

Numerical criteria only give some term (value), which makes it possible to conclude that the model is adequate. It should also be noted that the most accurate estimation is given by the Schwartz-Rissanen information criterion (SIC) and the Hannan-Quinn criterion (HQ), since as $t \to \infty$ they completely identify the true model. Independent use of the Akaike criterion (AIC) results in an inadequate increase in the number of model parameters.

To construct the predicted values of the transformed time series of the government debt of Ukraine, parameter estimates for 96 specifications of the ARIMA model with the number of parameters p, q, d from 1 to 12 were determined. Accordingly, the models with the lowest SIC and AIC are selected for further analysis. Table 1 gives the most significant model specifications.

Table 1. Test results for ARMA (p, q)

(p, q)	Adjusted *R*-squared	AIC	SIC
(1,1)	0.993870	24.52944	24.61061
(0,3)	0.994125	24.48702	24.56819
(1,3)	0.994146	24.48344	24.56461
(1,0)	0.993891	24.51559	24.56970
(1,12)	0.994072	24.49588	24.57705

Consecutive evaluation of the AR components showed that minimum AIC (24.48344) and SIC (24.56461) criteria were reached for the ARIMA (1; 1; 3) general specification.

Therefore, this ARIMA model (1, 1, 3) most accurately describes the trend of government debt dynamics and provides the highest accuracy for further forecasting; equation (1) reflects the model specification in EViews format:

$$\left(d\left(debt\right)cd\left(debt\left(-1\right)\right)resids_tmp\left(debt\left(-3\right)\right)\right). \quad (1)$$

The proposed model allows obtaining the forecast values of government debt in Ukraine (the forecasting results in the next five months are shown

Table 2. Forecast of the government debt amount in Ukraine, UAH mln

Period	November 2019	December 2019	January 2020	February 2020	March 2020
Ukraine' government debt, UAH mln	1,998,365	2,019,533	2,049,131	2,030,689	1,992,106

in Table 2). As Table 5 shows, the projected growth of government debt has been decreasing since 2020 in the forecast horizon.

MAPE criterion (average absolute error of the percentage forecast) is one of the most used indicators serving for estimating the model's predictive quality. For this case, the MAPE value = 12.9%, which indicates a high predictive quality of the model. The ARIMA model for forecasting government debt ratios confirmed its positive predictive properties. Therefore, it is advisable to recommend the implementation of this technique.

CONCLUSION

Forecasts of trends in economic variables are very complex operations. To make them, the economy relies on econometric modeling. The obtained forecasts are subject to additional practical and theoretical processing to get the most relevant and accurate results. Quite often, it is necessary to rely on predictive values of indicators when making operational decisions, without digging into a detailed analysis of the factors that influence their change. The ARIMA model works on this principle.

The model consists of AR, I and MA, where, AR is the autoregressive model, I represents the integration and indicates the order of a single integer, and MA is the moving average model.

Summing up the ARIMA simulation of Ukraine's government debt, one can state that the government debt indicators for a certain period represented a non-stationary time series that can be led to a stationary one by performing a series of transformations (in particular, replacing anomalous values by the average of a series) and taking first order difference from the time series created. To forecast the value of the government debt of Ukraine, parameter estimates for the 96 specifications of the ARIMA model were identified. The most optimal specification of the ARIMA model (1, 1, 3) was selected. The model can generally be used in practice, but it requires further improvements and calculations.

REFERENCES

1. Berti, K. (2013). Stochastic government debt projections using the historical variance-covariance matrix approach for EU countries. *Economic and Financial Affairs: Economic Paper, 480,* 1-26. Retrieved from https://ec.europa.eu/economy_finance/publications/economic_paper/2013/ecp480_en.htm
2. Box, G., Jenkins, G. M., & Reinsel, G. (1994). *Time Series Analysis: Forecasting & Control* (3rd ed.) (614 p.). Prentice Hall.
3. Caruk, O. V. (2007). Statystychne prohnozuvannja derzhavnoho borhu Ukrainy na osnovi protsesiv Boksa-Dzhenkinsa [Statistical forecasting of Ukraine's government debtbased on Box-Jenkins]. *Problemy statystyky – Statistics Problems, 8,* 1-8.
4. Demyanov, R. S. (2017). *Ispolzovaniye metoda Boksa-Dzhenkinsa dlia prognozirovaniya vremennykh riadov [Using the Box-Jenkins method to predict time series].* (In Russian). Retrieved from http://nauka-rastudent.ru/39/4071/
5. Doronina, A. I. (2016). Time-series models. The example of oil products consumption in France. *Financial university under the Government of the Russian Federation,* 1-21. Retrieved from http://economy.bsu.by/wp-content/uploads/2016/10/naft_ar_ma.pdf
6. Drehmann, M., & Juselius, M. (2012). Do debt service costs affect macroeconomic and financial stability? *BIS Quarterly Review,* 21-34. Retrieved from https://www.bis.org/publ/qtrpdf/r_qt1209e.htm
7. Ericsson, N. R. (2017). How biased are U.S. government forecasts of the federal debt? *International Journal of Forecasting, 33*(2), 543-559. https://doi.org/10.1016/j.ijforecast.2016.09.001
8. Gardner, E., &Giovanni, J. D. (2008). A simple stochastic approach to debt sustainability applied to Lebanon. *IMF Working Paper, 8,* 1-25. Retrieved from https://www.imf.org/en/Publications/WP/Issues/2016/12/31/A-Simple-Stochastic-Approach-to-Debt-Sustainability-Applied-to-Lebanon-21891

http://dx.doi.org/10.21511/pmf.08(1).2019.11

9. Gnegne, Y., & Jawadi, F. (2013). Boundedness and nonlinearities in government debtdynamics: A TAR assessment. *Economic Modelling, 34,* 154-160. https://doi.org/10.1016/j.econmod.2013.04.006

10. Goswami, G. G., & Hossain, M. M. (2013). From Judgmental Projection to Time Series Forecast: Does it Alter the Debt Sustainability Analysis of Bangladesh? *Bangladesh Development Studies, XXXVI*(3). Retrieved from https://bids.org.bd/uploads/publication/BDS/36/36-3/1_Judgmental%20Projection.pdf

11. Greene, W. H. (2012). Econometrics analysis. *New York University,* 325-335.

12. Kantorovych, G. G. (2002). Analiz vremennykh riadov [Time series analysis]. *Ekonomicheskiy zhurnal – VSHE Economic Journal, 3,* 379-401. (In Russian)

13. Lihua, M., & Chao, H. (2017). ARIMA model forecast based on EViews software. *IOP Conf. Series: Earth and Environmental Science*. Retrieved from https://iopscience.iop.org/article/10.1088/1755-1315/208/1/012017/pdf

14. Lukianenko, I. G., & Zhuk, V. M. (2013). *Analiz chasovykh riadiv. Pobudova ARIMA, ARCH/GARCH modelei z vykorystanniam paketa E.Views [Time series analysis. Construction of ARIMA, ARCH/GARCH models using E.Views package]* (187 p.). Kyiv: NaUKMA; Agrar Media Grup. (In Ukrainian). Retrieved from http://ekmair.ukma.edu.ua/handle/123456789/9085

15. Martinez, A. B. (2015). How good are US government forecasts of the federal debt? *International Journal of Forecasting, 31*(2), 312-324. https://doi.org/10.1016/j.ijforecast.2014.08.014

16. Martyniuk, V. P. (2011). *Prohnozuvannia nadkhodzhennia podatkovykh platezhiv do derzhavnoho biudzhetu za dopomohoiu vykorystannia ARIMA-modeli [Predicting tax payments to the state budget using the ARIMA model].* (In Ukrainian). Retrieved from http://dspace.tneu.edu.ua/bitstream/316497/1383/1/30.PDF

17. Medeiros, J. (2012). Stochastic debt simulation using VAR models and a panel fiscal reaction function: results for a selected number of countries. *European Economy Economic Paper, 459.* Retrieved from https://ideas.repec.org/p/euf/ecopap/0459.html

18. Ministry of Finance of Ukraine. (n.d.). *Statystychni materialy shchodo derzhavnoho ta harantovanoho derzhavoiu borhu Ukrainy [Statistics on government debt and government guaranteed Ukraine's debt].* Retrieved from https://www.mof.gov.ua/uk/derzhavnij-borg-ta-garantovanij-derzhavju-borg

19. Navapan, K., & Boonyakunakorn, P. (2017). Forecasting the Growth of Total Debt Service Ratio with ARIMA and State Space Model. *Predictive Econometrics and Big Data, Studies in Computational Intelligence, 753,* 492-501.

20. Nikoloski, A., & Nedanovski, P. (2017). Government debt dynamics and possibilities for its projection. The case of the Republic of Macedonia. *DIEM: Dubrovnik International Economic meeting,* 720-734.

21. Rajaraman, I., & Mukhopadhyay, A. (2004). Univariate Time-Series Analysis of Public Debt. *Journal of Quantitative Economics, 2*(2), 122-134. Retrieved from https://link.springer.com/article/10.1007/BF03404612

22. Utkina, A. Ja. (2015). *Vremennyye riady. Modelirovaniye processov tipa ARIMA (p, d, q) [Time series. Modeling ARIMA-type processes (p, d, q)].* (In Ukrainian). Retrieved from https://docplayer.ru/26841530-Itkina-a-ya-vremennye-ryady-modelirovanie-processov-tipa-arima-p-d-q-ekonometricheskiy-paket-eviews-pozvolyaet-dovolno-legko-modelirovat-sluchaynye.html

23. Yashchenko, L. O. (2014). Prohnosuvannia derzhavnoho borhu na osnovi dokhodiv ta vydatkiv derzhavnoho biudzhetu Ukrainy [Forecasting government debton the basis of revenues and expenditures of the Ukraine's government budget]. *Statystyka Ukrainy – Statistics of Ukraine, 2,* 14-19. (In Ukrainian).