American Journal of Economics and Business Management

Vol. 7 Issue 12 | pp. 1534-1543 **| ISSN:** 2576-5973

Available online @ https://www.globalresearchnetwork.us/index.php/ajebm

Article

Forecasting and Planning of Financing of Economically Disadvantaged Enterprises Based on the ARIMA Model

Nuriddin Javliev[1]

[1]Tashkent State University of Economics, Tashkent, Uzbekistan

* Correspondence: **n.javliev@tsue.uz**

Abstract: *This article analyzes the causes of the economic crisis arising in the conditions of economic instability, slow payment circulation, risk of non-payment, current inflation and insufficient qualifications of managers. In this direction, researches carried out by economists are studied and their opinions are presented. In fact, as a result of special attention paid to entrepreneurship by the Uzbek government in recent years, the entrepreneurship sector has become a leading branch of the economy. Scientific research dedicated to the development of a financial mechanism on the subject is also important for innovative development and increasing social welfare. Proposals and recommendations aimed at supporting and developing various sectors of the economy were developed through these processes.*

Key words: *Insolvency, risk, risk management, macroeconomic stability, forecasting, refinancing rate, inflation.*

Citation: Nuriddin J. Forecasting and Planning of Financing of Economically Disadvantaged Enterprises Based on the ARIMA Model *American Journal of Economics and Business Management 2024*, 7(12), 1534-1543.

Received: 10th Oct 2024
Revised: 29th Oct 2024
Accepted: 24th Nov 2024
Published: 12th Dec 2024

1. INTRODUCTION

In the market economy, the subjects of the economy, being economically completely free, join the competition. If this struggle opens the door of incomparable opportunities to some market subjects, it may cause others to enter a dead end. In the conditions of perfect competition, victory or defeat is inevitable and it is very difficult to stop it. In other words, continuous competition always increases the possibility of economic failure or bankruptcy options. Every enterprise-institution that is newly established has some that have stopped their activity. Non-competitive enterprises are forced to give way to others.

Studying the theoretical-practical-methodical aspects of the issues of economic helplessness, determining the directions for solving problems and shortcomings is considered an urgent issue of today.

The urgency of financing economically disadvantaged enterprises is important not only for ensuring economic stability, but also for innovative development and increasing social welfare. Through these processes, it will be possible to support and develop various sectors of the economy.

In order to identify signals about crisis events of the enterprise, it is necessary to constantly monitor its business and financial indicators, because their analysis allows an objective assessment of the situation. The same indicators may have different meanings and trends at different stages of the life cycle of a firm's competitive advantages. Therefore, the analysis of the dynamics of indicators in its stages allows to determine the development trends of crisis events based on quantitative and qualitative assessment.

Methodology.

Systematic approach, factor analysis, statistical and financial analysis, expert assessment, information processing, mathematical modeling and other methods were used in the research process.

Literature review.

The importance of econometric models in the assessment and forecasting of various risks, the causes of the problems and needs of financially insolvent enterprises, the factors affecting them, is increasing more and more. Various methodologies and considerations for effective forecasting and financial support of these types of enterprises are being put forward.

According to Timothy Bates and others, one of the main obstacles to the success of economically disadvantaged enterprises is the struggle with a lack of capitalization. The minimum level of capital formation in enterprises leads to the need for financial support and financing programs for credit practitioners, which reduces access to business loans.

According to Bruce Chapman , government-provided investment loans are emphasized as an important factor in reducing financial risks for enterprises to achieve economic success, especially for disadvantaged enterprises [1].

Enterprises are considering it as a hybrid system for data preprocessing, module selection and feature evaluation, and forecasting of their financing risks. This system is an effective and reliable tool for small and medium enterprises in providing high accuracy and reliability [2].

These systems include forecasting and planning modules to assess the need for financial resources and plan financial provision for enterprise development [3]. They represent quantitative and qualitative methods to ensure comprehensive financial security planning.

Many econometric models have been developed by foreign researchers to forecast the financing of economically insolvent enterprises.

H.Ran developed an innovative approach using the method of relative weighted neurosophical value distances in forecasting the financial stress of companies and organizations [4]. The results of econometric forecasting are effective in analyzing financial distress and offer a potentially valuable tool for stakeholders in the event of credit risk and bankruptcy.

Erfina Dukalang and others used the CA-Score model as the most accurate and reliable model for forecasting financial difficulties in companies [5]. The results showed that the highest and most reliable method for predicting financial problems was the CA-Score model with an accuracy rate of 97.14% and a type II error of 2.86%. Compared with the Altman, Zavgren, Ohlson, Taffler and CA-Score models, the Ohlson model was superior with an accuracy rate of 94.29% and a type II error of 5.71%.

R. Chavez and others developed a predictive indicator of corporate bankruptcy, financial difficulties in an environment of asymmetric information flow to companies, investors and authorities [6]. The authors' data sources for the study consisted of 10 years (2011-2020) of indicators, analyzing data from 905 different corporations and 82 indicators each, the results showed that most companies are financially did not face difficulties and only 651 companies experienced financial distress.

Dong Meiga applied the logistic regression model to predict financial difficulties for digital economy enterprises. The scientist analyzes the 100 digital economy enterprises in China's A-share in 2017 and 2021 and combines their characteristics to systematically model the financial indicators and the first three periods of financial difficulties [7].

Li et al., in forecasting financial distress, noted that corporate financial distress is a process related to the interests of the enterprise and stakeholders, and elements of corporate governance [8].

Dr. Jyoti Nair et al developed econometric model-based forecasts for financial distress among manufacturing companies in India [9]. The authors developed a model predicting financial distress among manufacturing companies in India using logistic regression and data sources using 18 financial ratios of 574 companies in 34 industries in the manufacturing sector for the period 2005-2019.

Aidas Malakauska, a foreign economist, used logistic regression, artificial neural networks and random forest methods to evaluate binomial classifiers using data from 12,000 companies in forecasting financial difficulties for small and medium-sized enterprises based on econometric models [10]. The results showed that financial stress was viewed as a serious problem in the company's ability to cover its obligations, rather than the possibility of bankruptcy.

Inggar Nur Arini compared the four models Altman model, Springate model, Taffler model and Grover model in assessing financial stress in companies. . The author, research data analyzed 60 annual reports and global retail companies for 2018-2019. According to the results of the study, the Grover model has the highest level of accuracy, providing 76.67% positive conclusions.

Feng Shen et al. developed a dynamic financial distress forecasting model with multiple forecasting outcomes in an unbalanced data environment, emphasizing the importance of corporate financial distress to companies, investors, and regulators [11].

The authors conducted an empirical experiment on 373 distressed companies and 1,119 matched ordinary Chinese listed companies from 2007 to 2017. According to the results of the study, the ANS-REA model is a reliable tool for forecasting financial stress and offers a significant advantage over existing methods by effectively managing the problems associated with the change of concept in asymmetric data flows.

Frank Ranganai Matenda et al used a logistic regression model to model the risk of corporate default under difficult economic and financial conditions in emerging economies [12]. The study shows that accounting information is important in distinguishing between defaulting and non-defaulting private firms, especially during recessions in developing economies. This represents the importance of financial ratios in assessing default risk.

Analysis and results.

We developed forecast indicators for the financing of economically disadvantaged enterprises for the coming years 2025-2029 based on the ARIMA model.

The use of econometric models, especially successful models such as ARIMA, to forecast the financing of economically disadvantaged enterprises in order to ensure sustainable growth and financial profitability from an economic point of view, is increasing its relevance in today's scientific research.

The ARIMA model is the optimal choice for financial forecasting when efficiently handling time series data [13]. In particular, it has been recognized as a high-performing model in research involving capital investments and stock market forecasts, as well as in forecasting financial performance and investment trends.

Economically disadvantaged enterprises are allowed to forecast cash flow and financial needs in the ARIMA model, which lays the groundwork for optimizing financial management and planning [14].

A hybrid ARIMA-SVR model is used to forecast uncertain financial data, which offers a more reliable forecasting system [15]. Despite its strengths, ARIMA's reliance on historical data can limit its ability to detect sudden market changes or outliers, requiring the use of additional models for comprehensive forecasting [16].

A case study from the Dutch company Lady explains the application of the ARIMA model in financial forecasting and decision-making in real-world scenarios, explaining its practical benefits [17].

The econometric equation of the ARIMA model has the following form.

The ARIMA (AutoRegressive Integrated Moving Average) model is a statistical method successfully used in forecasting future values in time series data. It includes an autoregressive (AR) part, a moving average (MA) part, and accounts for non-stationary data by differencing to stabilize the sequence.

ARIMA model formula contains three components ARIMA is defined as (p, d, q), where: p represents the number of lagged observations (autoregressive part) in the model. d - how many times the raw observations differ (integrated part)

q is the size of the moving average window (moving average part). The general form of the ARIMA(p, d, q) model can be expressed as follows:

$yt=c+\boldsymbol{\mu}1yt-1+\boldsymbol{\mu}\,2yt-2+\cdots+\boldsymbol{\mu}\,pyt-p+\boldsymbol{\tau}1et-1+\,2et-2+\cdots+\boldsymbol{\tau}\,qet-q+et$ (1) where, yt is the value of time series differenced at time t (after difference d times), the c-constant term, $\boldsymbol{\mu}$i=(for i=1,2,…, p)-means the coefficients of the autoregressive part, $\boldsymbol{\tau}$j=(j=1, 2,…, for q) are the coefficients of the moving average part.

Explanation of components

1. Autoregressive (AR) part: $\boldsymbol{\mu}1yt-1$, $\boldsymbol{\mu}\,2yt-2$,…, $\boldsymbol{\mu}\,pyt-p$-terms represent the autoregressive part, where the current value of the series is regressed on past values.

2. Integrated (I) part: parameter d refers to the differentiation process used to make the series stationary. The differentiation operation can be written as:

yt′=yt−yt−1 (if d=1) (2)

At the same time, a higher level of differentiation can be used in the development of prognostic indicators for research.

Moving average (MA) part: The terms $\boldsymbol{\tau}$1et−1, $\boldsymbol{\tau}$2et−2,…, $\boldsymbol{\tau}$ qet−q represent the moving average part, where the current value is affected by past error terms. In the development of econometric research, using the data of the Statistical Agency under the President of the Republic of Uzbekistan (https://stat.uz/uz/), the number of enterprises and organizations not operating in the sector of the economy in 2014-2023, 37 quarterly observations were made. containing z. The resulting factor according to the econometric forecast is expressed as follows. The number of non-operating enterprises and organizations in the section of economic sectors - non_operat_company (Dependent variable).

An analytical graphical representation of the dependent variable at the initial stage of econometric forecasting is presented below (see Figure 1).

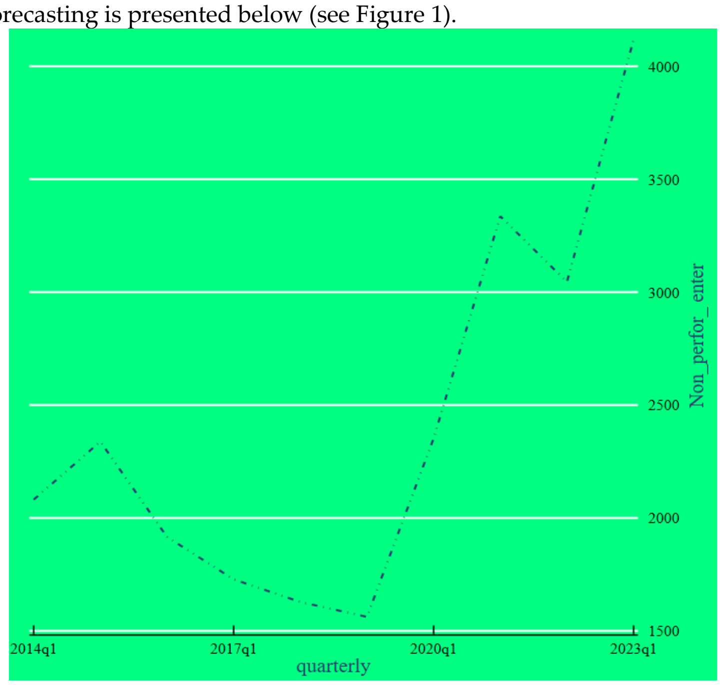

Figure 1. Analytical graph of the number of enterprises and organizations not operating in the sector of the economy over time*

* Author's development

According to chart 1, the number of non-operating enterprises and organizations in the sector of the economy showed a sharp increase in the last quarter of 2019. This indicates that these types of enterprises coincided with the period of the COVID-2019 pandemic. Even in the post-pandemic period, this trend will continue to a certain extent and provides a forecast of further growth in the future.

At the next stage of the research, the stationarity of the outcome factor was checked and the Unit-Root test was used to determine it (see Table 1).

Table 1

Unit-Root test of the number of enterprises and organizations not operating in the cross-section of economic sectors*

Non_operat_company	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value for Z(t)
	-5.680	-3.689	-2.975	-2.619	0.0000

* Author's development

According to Table 1, the number of non-operating enterprises and organizations in the sector of the economy generated a value of -5,680. It can be seen that this result is below the 1%, 5% and 10% limits of statistical significance.

In addition, McKinnon's value is minimum with Z(t)=0.0000, which shows from this test that the number of enterprises and organizations that are not operating in the sector of the economy is stationary.

The results of the Unit-Root test and the MacKinnon value showed the statistical significance of the non-operating enterprises and organizations in the sector of the economy to the gross income of the national economy and confirmed the stationarity of the data.

According to Table 1, the parameter ծ of the ARIMA model produced a value of d=2, which presented a positive fit indicating that the time series reached stationarity after being differentiated twice.

In the next step, the value of p, which determines the indirect correlation between the time series lags of the model, is given. (See Figure 2).

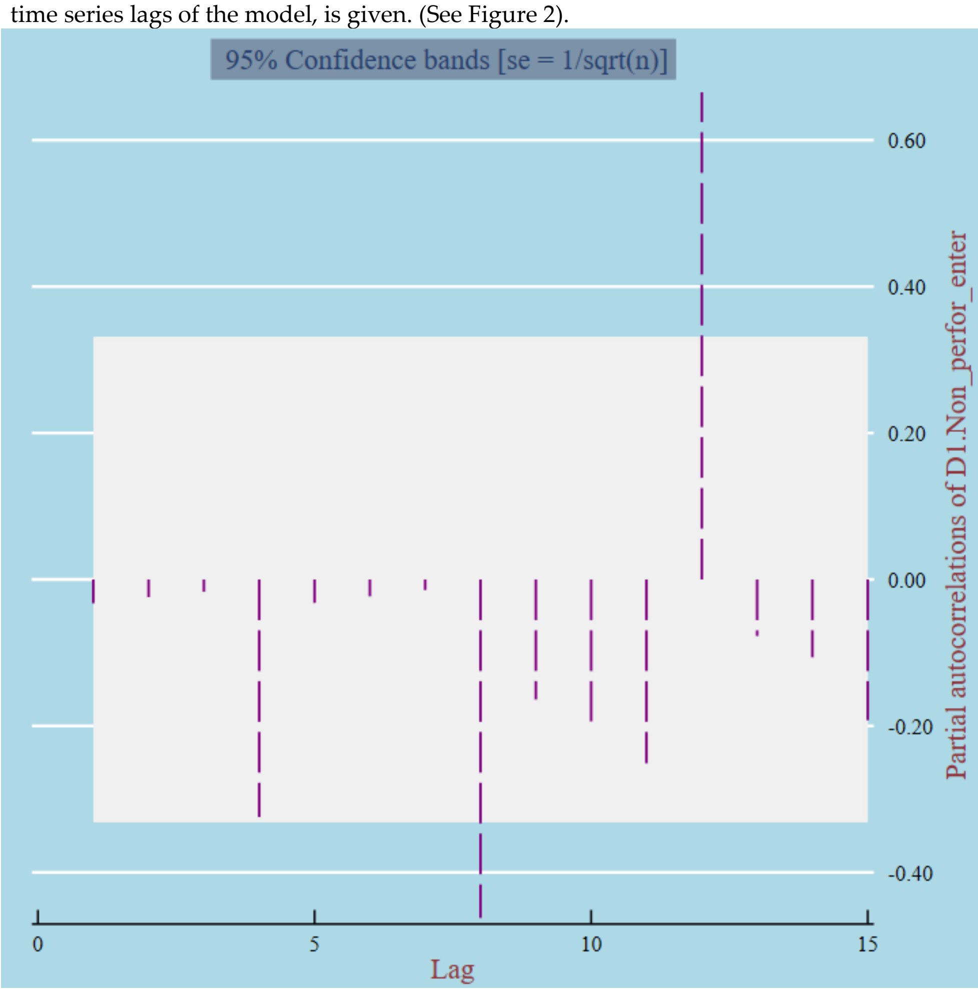

Figure 2. Indirect correlation plot between lags of the model*
* Author’s development

According to Figure 2, except for two lags, all other lags provided confidence intervals in the autocorrelation analysis. According to him, most of the delays are statistically significant and are within confidence limits. According to the ARIMA model, ensuring that the lags fit within the confidence interval is critical to fitting the model correctly.

In this case, it is appropriate to use a p-value of 0.1 or 2.

In the next step of the ARIMA model, the value of q, which describes the direct correlation between the lags of the model, was determined. (See Figure 3).

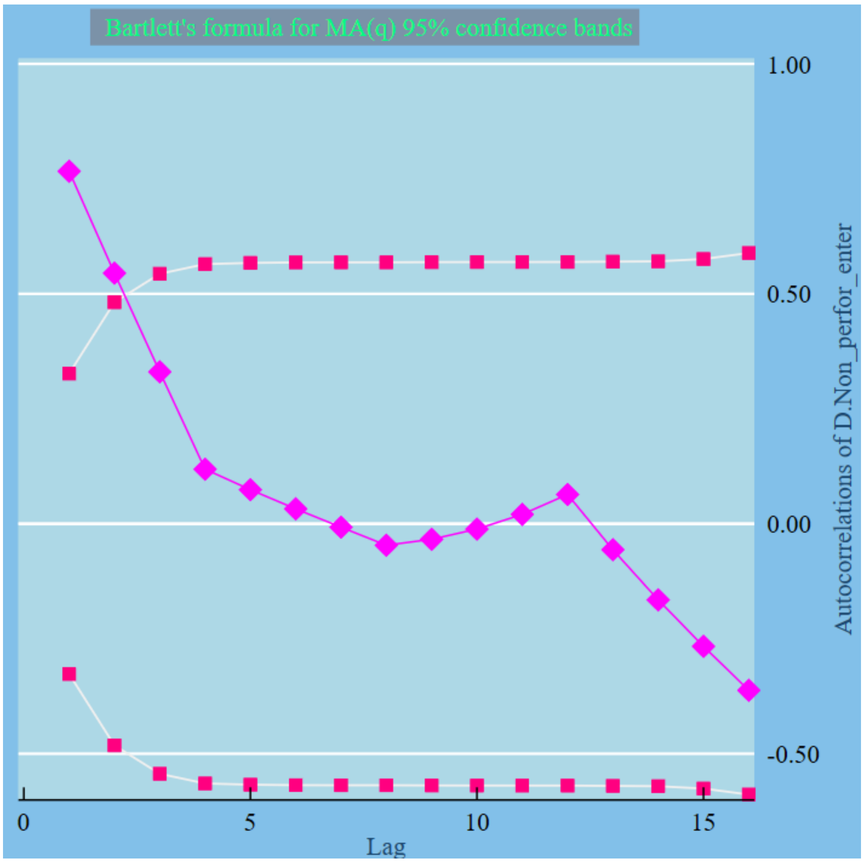

Figure 3. Direct correlation plot between lags of the model *
* Author's development

Figure 3 shows the strong correlation between the lags in the ARIMA model, with all lag values falling within the specified confidence interval. This indicates that the lag values are statistically significant and a good fit for the model. Choosing one of these values corresponds to determining the value of the moving average parameter q in the ARIMA model.

Since the observed data for the study are suitable and lie within a confidence interval of 0 to 2, it is recommended to choose a value of q within this range.

ARIMA invariant optimal models in model forecasting ARIMA(0,1,1), ARIMA(0,1,2), ARIMA(1,1,1), ARIMA(1,1,0) ARIMA(1,1,2) and ARIMA(2,01) models were used. Among these, the ARIMA(1,1,2) model with the best result was selected (see Table 2).

The ARIMA (1,1,2) regression equation is given below.

Table 2

ARIMA (1,1,2) model econometric equation indicators

D.Non_perfor_enter	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	60.134	59.767	1.01	.0414	-57.007	177.274	*
L	.547	.237	2.30	.021	.082	1.012	**
L	.078	.279	0.28	.078	-.469	.625	*
L2	.658	.117	5.63	0	.429	.888	***
Constant	82.569	9.539	8.66	0	63.874	101.264	***

Mean dependent var	56.556	SD dependent var	137.827
Number of obs	36	Chi-square	46.249
Prob > chi2	.	Akaike crit. (AIC)	431.868

*** p<.01, ** p<.05, * p<.1
* Author's development

According to Table 2, the ARIMA(1,1,2) model had the following form. $\Delta Y_t = 60.13 + 0.54 Y_{t-1} - 0.07 \varepsilon_{t-1} + 0.65 \varepsilon_{t-2} + \varepsilon_t$ **(2)**

At the next stage, the ARIMA1,1,2 model was developed for the analysis of the average values of the resulting variable and the graphical representation of the residuals. (See Figure 4 and Table 3).

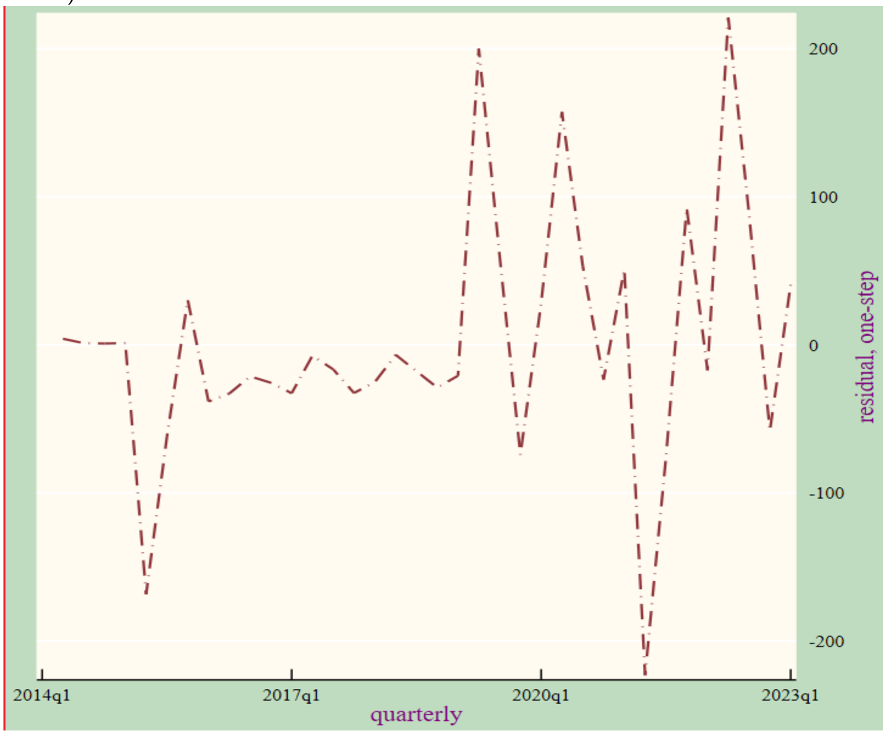

Figure 4. ARIMA (1,1,2) model is a graph of residual values by outcome variable*

* Author's development

Table 3. ARIMA (1,1,2) model residual values of the resulting factor*

Variable factor	Number of observations	Mean value	Standart deviations	Minimum value	Maximum value
Residual value	36	.5935287	84.21365	-223.0585	220.9507

* Author's development

Based on Table 3 and Figure 4 , the ARIMA(1,1,2) model has achieved stochastic equilibrium as shown by visualizing the residuals at the given time intervals. The closeness of the residuals to zero and their random distribution indicate that the model adequately takes into account the autocorrelation structure in the data.

At the next stage, the validity of the ARIMA (1,1,2) model was evaluated based on certain criteria. This includes testing the stationarity of the residuals and estimating the autoregressive (AR) and moving average (MA) residuals. In addition, the convergence of the model in the unit circle was also checked. (See Figure 5).

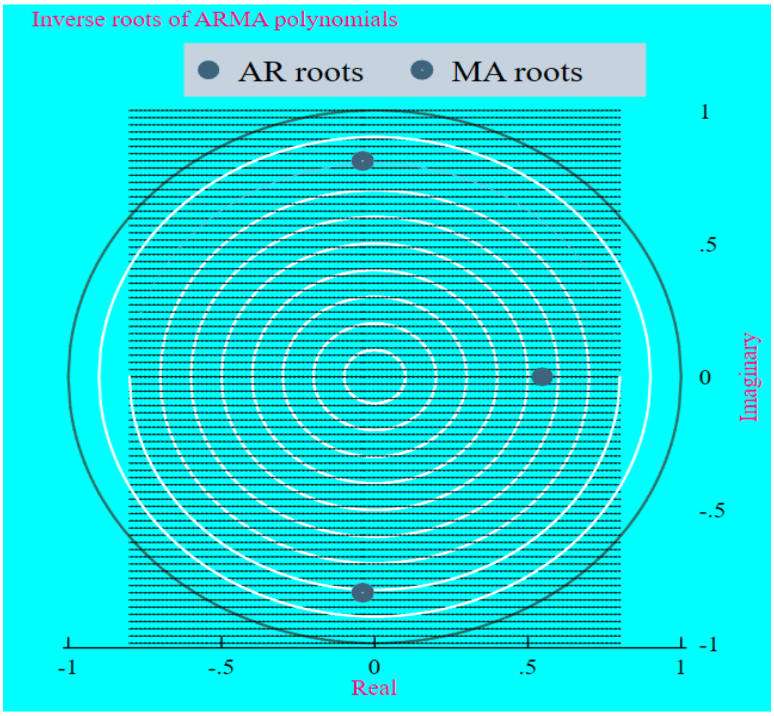

Figure 5. Area of MA values under the AR (2,1,0) model*
* Author's development

Forecast indicators of the number of enterprises and organizations not operating in the sector of the economy from 2025 to 2029 without taking into account random (exogenous and endogenous) factors according to the ARIMA(1,1,2) model using the stata program for research developed (see Table 4)

Table 4
Forecast indicators of the number of enterprises and organizations not operating in the sector of the economy in 2025-2029

Years	Pessimistic forecast	An optimistic forecast	forecast
2025	4 691	4 965	4 828
2026	4 934	5 208	5 071
2027	5 174	5 448	5 311
2028	5 415	5 689	5 552
2029	5 655	5 929	5 792

* Author's development

According to the research, the indicators of the resulting factor for the years 2014-2024 and 2025-2029 are shown in the forecast graphs of this organization. (See Figure 5).

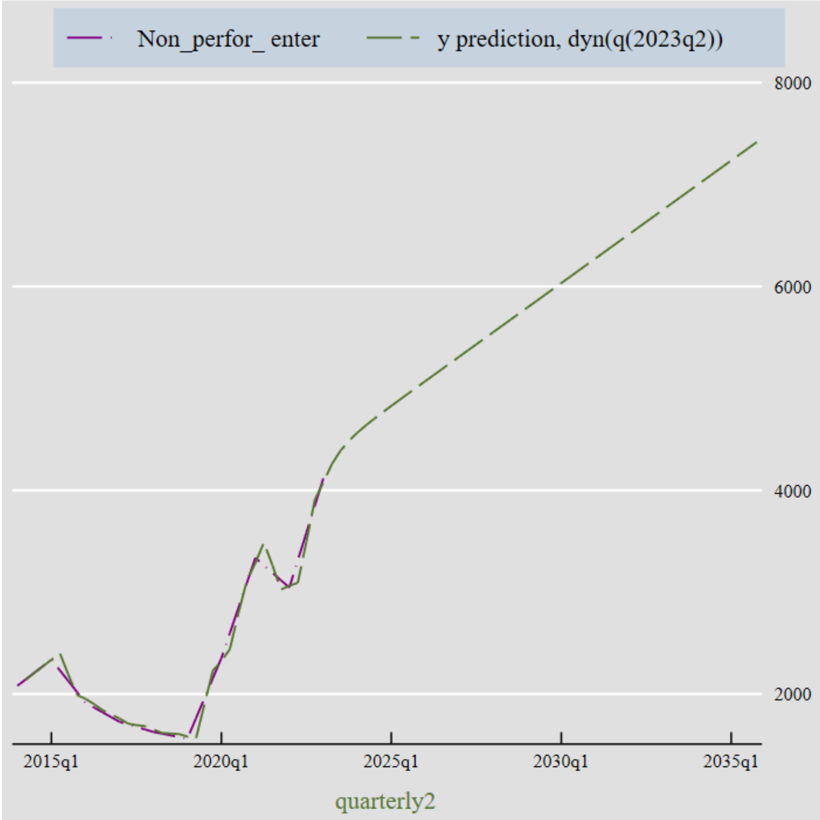

Figure 6. Graph of dependent variable for 2014-2024 and forecast for 2025-2029*
* Author's development

According to Figure 6, the number of enterprises and organizations that are not operating in the sector of the economy in 2014-2024 and 2025-2029, the number of enterprises and organizations that are not operating in the sector of the economy and forecast graphs are depicted. According to him, since the two lines are located almost next to each other, the direction graph indicates the reliability of forecast indicators for the coming years without taking into account random factors.

Conclusion

The econometric forecast for the years 2024-2029 based on the ARIMA (1,1,2) model of the number of non-operating enterprises and organizations in the sector of the economy presented by the Statistical Agency under the President of the Republic of Uzbekistan was explained as follows.

1. According to the results of the research, the indicator of the number of enterprises and organizations not operating in the sector of the economy presented by the Statistical Agency under the President of the Republic of Uzbekistan based on the ARIMA (1,1,2) model in 2025-2029, taking into account the random factors without receiving 4,828 in 2025, 5,071% in 2026, It was forecasted to reach 5,311 in 2027, 5,552 in 2028 and 5,792 in 2029, without taking into account random factors. ***Forecast growth rate***: The number of enterprises and organizations operating in the social sectors is projected to grow steadily between 2025 and 2029. This gradual increase indicates that structural changes have occurred in economic sectors.
2. The ARIMA model effectively captures the underlying trends and random factors and provides a reliable forecast for decision makers. This forecast is important in developing a strategy aimed at reducing the number of non-performing enterprises and improving overall economic activity.
3. Evaluation of strategic planning. Expected growth from 4,828 in 2025 to 5,792 in 2029 will provide stakeholders with a clear vision for strategic planning. Taking into account the forecast indicator, the government and business sectors will increase the need to create targeted state programs to improve efficiency and re-engage inactive enterprises.

4. Allocation of financial resources: Knowing these future trends allows for more efficient allocation of resources. Financial, technological, and human resources can be directed to sectors with high potential for recovery and innovation, reducing the likelihood of businesses going out of business.

Enabling Economic and Financial Reform: Projected data suggest the need for reforms to address factors that cause businesses to fail. Early intervention and sector-specific strategies can reverse this trend and promote economic stability and growth.

References

1. Aidas, Malakauskas., Aušrinė, Lakštutienė. (2021). Financial distress prediction for small and medium enterprises using machine learning techniques. The Engineering Economics, 32(1):4-14. doi: 10.5755/J01.EE.32.1.27382.
2. Anzhela, Y., Petrova., Margarita, Deyneka. (2022). Arima-models: modeling and forecasting prices of stocks. Internauka, doi: 10.25313/2520-2294-2022-2-7921
3. Bokai, Zhang. (2019). Research on Fixed Assets Investment Forecast Based on ARIMA Model. doi: 10.1109/ICEMME49371.2019.00083
4. Bruce, Chapman., Ric, Simes. (2005). Profit Related Loans for Economically Disadvantaged Regions. Research Papers in Economics,
5. Dong, Mei, Li., Kaiyao, Xu., Yun, Daisy, Li., Yu, Jiang., Ming, Tang., Yangdan, Lu., Chun, Cheng., Chunxiao, Wang., Guanbing, Mo. (2022). Financial Distress Prediction for Digital Economy Firms: Based on PCA-Logistic. Journal of Risk Analysis and Crisis Response, 12(1) doi: 10.54560/jracr.v12i1.319
6. Dr., Jyoti, Nair., Dr., JK, Sachdeva. (2022). Predictive Modelling for Financial Distress amongst Manufacturing Companies in India. Journal of Global Economy, 18(4):261-276. doi: 10.1956/jge.v18i4.665
7. Erfina, Dukalang., Irfan, Zamzam., Zulkifli, Abu. (2024). Analysis of Financial Distress Predictions Using Altman, Zavgren, Fulmer, Ohlson, Taffler, and Ca-Score Models as Early Warning Systems in Manufacturing Companies. Nominal Barometer Riset Akuntansi dan Manajemen Indonesia, 13(1):81-97. doi: 10.21831/nominal.v13i1.65081
8. Feng, Shen., Yongyong, Liu., Run, Wang., Wei, Zhou. (2020). A dynamic financial distress forecast model with multiple forecast results under unbalanced data environment. Knowledge Based Systems, 192:105365-. doi: 10.1016/J.KNOSYS.2019.105365
9. Frank, Ranganai, Matenda., Mabutho, Sibanda., Eriyoti, Chikodza., Victor, Gumbo. (2020). Corporate default risk modeling under distressed economic and financial conditions in a developing economy. Journal of Credit Risk, doi: 10.21314/JCR.2020.267
10. I., Litvin., M, M, Fesenko., Olena, Hurman., Halina, Nahorniak., Oksana, M., Kuzmenko. (2022). Forecast-planning system of financial support for the development of industrial enterprises. Revista Amazonia Investiga, 11(53):132-145. doi: 10.34069/ai/2022.53.05.13.
11. Khyrina, Airin, Fariza, Abu, Samah., Nurul, Azifah, Mohd, Khalid., Jamaluddin, Jasmis., Noor, Afni, Deraman., Lala, Septem, Riza., Zainab, Othman. (2024). Autoregressive Integrated Moving Average (ARIMA) Algorithm Adaptation for Business Financial Forecasting. Journal of Advanced Research in Applied Sciences and Engineering Technology, 38(1):37-47. doi: 10.37934/araset.38.1.3747
12. Khyrina, Airin, Fariza, Abu, Samah., Nurul, Azifah, Mohd, Khalid., Jamaluddin, Jasmis., Noor, Afni, Deraman., Lala, Septem, Riza., Zainab, Othman. (2024). Autoregressive Integrated Moving Average (ARIMA) Algorithm Adaptation for Business Financial Forecasting. Journal of Advanced Research in Applied Sciences and Engineering Technology, 38(1):37-47. doi: 10.37934/araset.38.1.3747
13. R., Chaves., André, Luis, Debiaso, Rossi., Luis, Echecopar, García. (2023). Financial Distress Prediction in an Imbalanced Data Stream Environment. Lecture Notes in Computer Science, 168-179. doi: 10.1007/978-3-031-40725-3_15
14. Ran, H. (2023). MABAC method for multiple attribute group decision making under single-valued neutrosophic sets and applications to performance evaluation of sustainable microfinance groups lending. Plos one, 18(1), e0280239.
15. Yi, Chen., Jifeng, Guo., Junqin, Huang., Bin, Lin. (2022). A novel method for financial distress prediction based on sparse neural networks with International Journal of Machine Learning and Cybernetics, 13(7):2089-2103. doi: 10.1007/s13042-022-01566-y
16. Zhangong, Huang., Huwei, Li. (2024). ARIMA-SVR-based risk aggregation modeling in the financial behavior. Kybernetes, doi: 10.1108/k-01-2024-0249
17. Zongguo, Ma., Xu, Wang., Yan, Hong, Hao. (2023). Development and application of a hybrid forecasting framework based on improved extreme learning machine for enterprise financing risk. Expert systems with applications, 215:119373-119373. doi: 10.1016/j.eswa.2022.119373.