ORIGINAL PAPER

Assessing the Impact of Financial Risk on Organizations by Modeling the Unemployment Rate Using the ARIMA Model

Cezar Cătălin Ene[1)]

Abstract:
The unemployment rate is a critical macroeconomic indicator that directly influences the financial stability and risk exposure of organizations, yet the dynamic relationship between unemployment fluctuations and corporate financial risk remains insufficiently explored through rigorous quantitative methods. This article aims to model and forecast Romania's unemployment rate using the ARIMA methodology, thereby assessing its implications for organizational financial risk within an international comparative framework. Monthly unemployment rate data were sourced from the European Central Bank database, covering the period January 1997 to November 2024, totaling 335 observations. The series was log-transformed to stabilize variance, and stationarity was tested using the Augmented Dickey-Fuller test, which confirmed the original series as non-stationary ($p = 0.5935$); first-order differencing successfully achieved stationarity ($p = 0.0000$). Following the Box-Jenkins methodology implemented in EViews 12, multiple ARIMA specifications were evaluated based on the Bayesian Information Criterion, adjusted R^2, and standard error of regression. The ARIMA(1, 2, 2) model was selected as optimal, with statistically significant AR(1) and MA(2) coefficients of −0.9843 and −0.9975, respectively. Residual diagnostics confirmed white noise behavior through the Ljung-Box Q-statistic, and model stability was validated via inverse root analysis. Forecast evaluation demonstrated strong predictive accuracy, yielding an RMSE of 0.042, a Theil inequality coefficient of 0.012, and a covariance proportion of 81.7%. These findings confirm that ARIMA models effectively capture Romania's unemployment dynamics across major economic disruptions, including the 2008 financial crisis and the COVID-19 pandemic, offering practical value for managers, investors, and policymakers seeking to anticipate labor market shifts and mitigate associated financial risks.

Keywords: *unemployment rate, ARIMA, financial risk, time series forecasting, Box-Jenkins*

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1. Introduction

The unemployment rate is one of the most relevant macroeconomic indicators, reflecting labor market conditions and directly influencing the financial stability of organizations. Its fluctuations affect corporate revenues, investment capacity, and, implicitly, financial risk exposure particularly in contexts marked by economic crises, pandemics, or geopolitical turbulence. The existing literature has consistently documented the connection between unemployment and corporate financial performance, yet most studies adopt either an aggregate macroeconomic perspective or focus primarily on social effects. Less explored are the dynamic relationships between unemployment rate variations and the financial risks perceived at the organizational level, particularly through rigorous quantitative methods such as ARIMA modelling (Box & Jenkins, 1970).

The ARIMA methodology has demonstrated strong forecasting performance across a wide range of economic and financial applications. Meher et al. (2021) confirmed its applicability in forecasting pharmaceutical stock performance, while Kumar et al. (2021, 2023) highlighted its effectiveness in volatile commodity markets. Da Veiga et al. (2024) applied ARIMA models to critical health-sector time series, including the unemployment rate, achieving forecast accuracy exceeding 95%. Ariyo et al. (2014) and Khan & Alghulaiakh (2020) further validated the model's predictive robustness for short-term stock price forecasting, with the latter reporting a MAPE-based accuracy of 99.74%. Despite this breadth of application, the use of ARIMA for linking unemployment dynamics to organizational financial risk remains a relatively underexplored avenue in the literature.

This study addresses that gap by applying the Box-Jenkins methodology to monthly unemployment rate data for Romania, covering the period January 1997 to November 2024 (335 observations), sourced from the European Central Bank database. The methodological approach follows Spulbăr & Ene (2024), who demonstrated the effectiveness of ARIMA in capturing and forecasting fluctuations in closing prices of stocks listed on the Bucharest Stock Exchange. The primary objective is to identify the optimal ARIMA specification for forecasting Romania's unemployment rate and to assess the implications of these dynamics for organizational financial risk. The scientific contribution lies in the application of a rigorous time-series framework to bridge labor market forecasting and financial risk assessment, offering practical value for managers, investors, and policymakers seeking to anticipate labor market shifts and mitigate associated financial risks.

2. Literature Review

The use of ARIMA models in forecasting economic and financial variables has been extensively explored in the literature. Meher et al. (2021) demonstrated their applicability in analysing the stock performance of Indian pharmaceutical companies (2017–2019), confirming the need for stationarity through the Augmented Dickey-Fuller test and selecting model specifications based on AIC and adjusted R^2. Similarly, Kumar et al. (2021) applied ARIMA to time series forecasting across volatile markets, identifying optimal models using AIC and BIC criteria, with first-order differencing employed to achieve stationarity.

In commodity markets, Kumar et al. (2023) forecasted weekly natural rubber RSS-1 prices in India (2002–2019) using the Box-Jenkins methodology, selecting ARIMA(1,1,4) based on significant coefficients, low AIC and Schwarz Criterion values, and i.i.d. residuals — confirming the model's robustness for financial risk management in price-volatile sectors. Fattah et al. (2018) extended the application to demand forecasting in a Moroccan food company (2010–2015), where ARIMA(1,0,1) outperformed competing specifications based on AIC and SBC criteria, contributing to supply chain optimisation.

Comparative studies have further contextualised ARIMA's relative strengths. Divisekara et al. (2020) evaluated ARIMA and GARCH models across 51 financial instruments from eight sectors, finding that GARCH outperforms ARIMA in volatility modelling, while underscoring the importance of model selection tailored to sector-specific data characteristics. In the public health domain, Da Veiga et al. (2024) applied ARIMA to five critical Brazilian health-sector time series (2000–2020), including the unemployment rate, with selected models such as ARIMA(1,0,2) and ARIMA(2,2,1) achieving forecast accuracy exceeding 95% as validated by MAPE and U-Theil statistics.

For short-term stock price forecasting, Ariyo et al. (2014) applied the Box-Jenkins methodology to data from the New York and Nigerian stock exchanges, with ARIMA(2,1,0) selected as optimal for Nokia stock index analysis, validated through BIC and white noise residual diagnostics. Khan & Alghulaiakh (2020) further confirmed ARIMA's predictive strength by forecasting Netflix stock prices (2015–2020), with ARIMA(1,1,33) achieving 99.74% accuracy based on MAPE and out-of-sample validation tests.

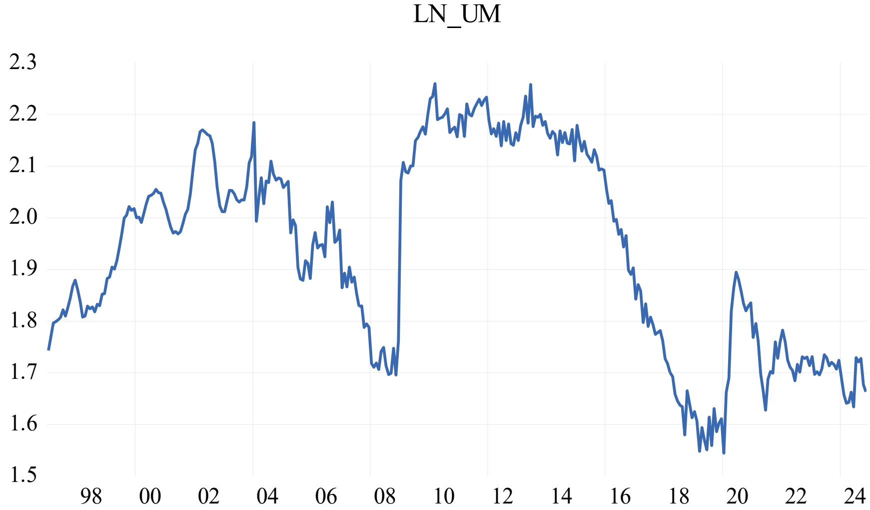
3. Methodology

The unemployment rate was selected as the primary variable for this study given its direct link to corporate financial stability, investment attractiveness, and organizational resilience to economic shocks, with the analysis focused on Romania due to the specificities of its national economy and data availability. Monthly data were sourced from the European Central Bank (ECB) database, covering January 1997 to November 2024, yielding 335 observations, well above the minimum recommended by Box & Tiao (1975), and encompassing key structural events including Romania's EU accession in 2007, the 2008 global financial crisis, and the COVID-19 pandemic. Prior to modelling, the series was log-transformed to stabilise variance and reduce the influence of extreme values, a standard practice for economic time series (Spulbăr & Ene, 2024). The dataset contained no missing values and was split into training and test sets to enable rigorous out-of-sample forecast evaluation.

Statistical modelling was performed using EViews 12, following the Box-Jenkins (1970) methodology across three stages: identification, estimation, and diagnostic checking. The ARIMA(p, d, q) specification was identified through ACF and PACF analysis, with stationarity verified via the Augmented Dickey-Fuller (ADF) test and differencing applied where required. Model selection relied on the AIC, Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQC), while residual validation used the Ljung-Box Q-statistic to confirm white noise behaviour. Spulbăr & Ene (2024) applied this same methodology to forecast BRD and Banca Transilvania (TLV) closing prices on the Bucharest Stock Exchange, confirming ARIMA's capacity to capture Romanian financial market dynamics.

Figure 1 illustrates the time evolution of the log-transformed variable LN_UM. The series is visibly non-stationary, exhibiting significant fluctuations and shifting mean levels across sub-periods — indicating the presence of trends or time-varying seasonality that render it unsuitable for direct modelling and requiring pre-processing to achieve stationarity.

Figure 1. Logarithmic evolution of Romania's unemployment rate (1997–2024)



Source: Author's contribution

To transform the series into a stationary one, differencing is applied. Differencing involves computing the variation between consecutive values of the series, eliminating trends and stabilising the mean. If the series remains non-stationary after first-order differencing, the process may be repeated. The parameter d in the ARIMA model indicates how many times the series has been differenced to achieve stationarity. In the present case, differencing of LN_UM was necessary to eliminate the evident trend visible in the graph.

The LN_UM series exhibits fluctuations that reflect major economic events and structural changes in the labour market. Growth phases between 2002 and 2008 correspond to an economic expansion cycle, while the post-2008 decline reflects the impact of the global financial crisis. Variations around 2020 are associated with the effects of the COVID-19 pandemic. These phenomena underscore the necessity of differencing and the careful identification of parameters p, d, and q to correctly capture the series dynamics.

The ARIMA model is specified through three fundamental parameters:

- **p:** the number of autoregressive (AR) terms, indicating how many past values of the series are used to predict the current value. The value of p is determined using the Partial Autocorrelation Function (PACF).
- **d:** the number of differencing operations required to achieve stationarity, as discussed above.
- **q:** the number of moving average (MA) terms, representing the influence of past residuals on the current value. The value of q is determined using the Autocorrelation Function (ACF).

4. Findings and discussion

To assess the stationarity of the LN_UM series, the Augmented Dickey-Fuller (ADF) test was applied, with results presented in Table 1. The ADF test investigates the presence of a unit root, a characteristic indicative of non-stationarity, under the null hypothesis that the series contains a unit root.

Table 1. Augmented Dickey-Fuller Test Statistics Before Differencing

Null Hypothesis: LN_UM has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=36)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.377885	0.5935
Test critical values:	1% level	-3.449797	
	5% level	-2.870004	
	10% level	-2.571349	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LN_UM)
Method: Least Squares
Date: 01/12/25 Time: 16:25
Sample (adjusted): 1997M03 2024M11
Included observations: 333 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_UM(-1)	-0.014930	0.010835	-1.377885	0.1692
D(LN_UM(-1))	-0.133957	0.054610	-2.452966	0.0147
C	0.028592	0.021103	1.354893	0.1764

R-squared	0.025759	Mean dependent var	-0.000318
Adjusted R-squared	0.019855	S.D. dependent var	0.037967
S.E. of regression	0.037588	Akaike info criterion	-3.715311
Sum squared resid	0.466236	Schwarz criterion	-3.681004
Log likelihood	621.5993	Hannan-Quinn criter.	-3.701631
F-statistic	4.362638	Durbin-Watson stat	1.972971
Prob(F-statistic)	0.013488		

Source: Author's contribution

The results show a t-statistic of −1.377885, which exceeds the critical values at the 1% (−3.449797), 5% (−2.870004), and 10% (−2.571349) significance levels. Furthermore, the associated p-value of 0.5935 surpasses the conventional significance threshold of 0.05. Consequently, the null hypothesis of non-stationarity cannot be rejected, confirming that the LN_UM series requires further transformation before it can be used in an ARIMA model.

The non-stationarity of the series indicates the presence of long-term trends or variations that may compromise the accuracy of the analysis. To address this, first-order differencing was applied a process that computes the variation between consecutive values, eliminating trends and stabilising the mean. Following differencing, the series was re-tested using the ADF test to confirm that stationarity had been achieved.

Table 2. Augmented Dickey-Fuller Test Statistics for First-Order Differencing

Null Hypothesis: D(LN_UM) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=36)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-20.99856	**0.0000**
Test critical values:	1% level	-3.449797	
	5% level	-2.870004	
	10% level	-2.571349	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LN_UM,2)
Method: Least Squares
Date: 01/12/25 Time: 17:23
Sample (adjusted): 1997M03 2024M11
Included observations: 333 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LN_UM(-1))	-1.141890	0.054379	-20.99856	0.0000
C	-0.000346	0.002063	-0.167913	0.8668

R-squared	0.571210	Mean dependent var	-0.000120
Adjusted R-squared	0.569914	S.D. dependent var	0.057393
S.E. of regression	0.037639	Akaike info criterion	-3.715580
Sum squared resid	0.468918	Schwarz criterion	-3.692709

Log likelihood	620.6441	Hannan-Quinn criter.	-3.706460
F-statistic	440.9394	Durbin-Watson stat	1.974083
Prob(F-statistic)	0.000000		

Source: Author's contribution

The ADF test results following first-order differencing, reported in Table 2, confirm that the LN_UM series achieves stationarity. The t-statistic of −20.99856 is substantially below the critical values at the 1% (−3.449797), 5% (−2.870004), and 10% (−2.571349) significance levels, and the associated p-value of 0.0000 indicates very high statistical significance. The null hypothesis of a unit root is therefore rejected. This result is essential for ARIMA modelling, as stationarity is a prerequisite for the application of this class of models. Through differencing, long-term trends and seasonal variations are eliminated, enabling the model to capture short-term fluctuations and generate more accurate forecasts.

The ADF test applied after second-order differencing of the LN_UM series, reported in Table 3, confirms that the series remains stationary. The t-statistic of −12.16212 is well below the critical values at the 1% (−3.450223), 5% (−2.870192), and 10% (−2.571449) significance levels, with an associated p-value of 0.0000. The null hypothesis of a unit root is again rejected.

Table 3. Augmented Dickey-Fuller Test Statistics for Second-Order Differencing

Null Hypothesis: D(LN_UM,2) has a unit root
Exogenous: Constant
Lag Length: 6 (Automatic - based on SIC, maxlag=36)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.16212	0.0000
Test critical values:	1% level	-3.450223	
	5% level	-2.870192	
	10% level	-2.571449	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LN_UM,3)
Method: Least Squares
Date: 01/12/25 Time: 17:27
Sample (adjusted): 1997M10 2024M11
Included observations: 326 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

D(LN_UM(-1),2)	-4.833670	0.397437	-12.16212	0.0000
D(LN_UM(-1),3)	2.812381	0.367896	7.644502	0.0000
D(LN_UM(-2),3)	2.030113	0.319074	6.362512	0.0000
D(LN_UM(-3),3)	1.478403	0.258815	5.712193	0.0000
D(LN_UM(-4),3)	0.959136	0.194456	4.932410	0.0000
D(LN_UM(-5),3)	0.537248	0.124043	4.331128	0.0000
D(LN_UM(-6),3)	0.158810	0.056113	2.830166	0.0049
C	-0.000169	0.002181	-0.077276	0.9385

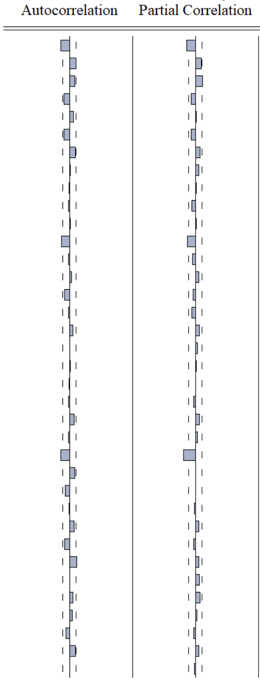
R-squared	0.859864	Mean dependent var	2.35E-05
Adjusted R-squared	0.856779	S.D. dependent var	0.104048
S.E. of regression	0.039377	Akaike info criterion	-3.607054
Sum squared resid	0.493065	Schwarz criterion	-3.514124
Log likelihood	595.9499	Hannan-Quinn criter.	-3.569970
F-statistic	278.7461	Durbin-Watson stat	2.031785
Prob(F-statistic)	0.000000		

Source: Author's contribution

The application of second-order differencing confirms stationarity; however, the results obtained after first-order differencing were already sufficient to ensure this property. It is worth noting that a second differencing operation may add unnecessary complexity to the model without meaningful gains in stationarity, given that the series had already become stationary after the first differencing. The adjusted R-squared of 0.856779 and the extremely low p-value indicate that the model accounts well for the variation in the data.

Figure 2. Correlogram of Romania's Unemployment Rate Time Series After First-Order Differencing

Date: 01/12/25 Time: 17:31
Sample (adjusted): 1997M02 2024M11
Included observations: 334 after adjustments

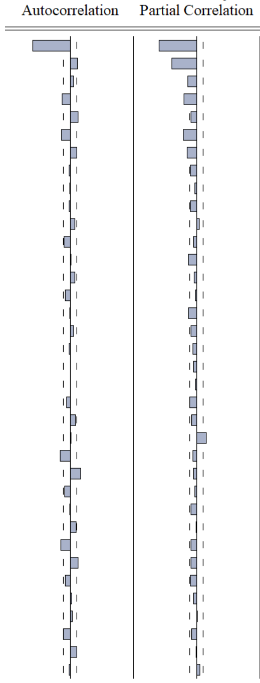


Lag	AC	PAC	Q-Stat	Prob
1	-0.142	-0.142	6.7798	0.009
2	0.111	0.093	10.981	0.004
3	0.088	0.119	13.622	0.003
4	-0.083	-0.069	15.954	0.003
5	0.067	0.025	17.462	0.004
6	-0.086	-0.070	19.991	0.003
7	0.092	0.081	22.918	0.002
8	0.023	0.051	23.101	0.003
9	-0.000	0.011	23.101	0.006
10	-0.015	-0.055	23.184	0.010
11	0.015	0.016	23.260	0.016
12	-0.124	-0.126	28.609	0.005
13	-0.024	-0.044	28.813	0.007
14	0.037	0.050	29.298	0.010
15	-0.075	-0.035	31.294	0.008
16	-0.012	-0.060	31.348	0.012
17	0.056	0.069	32.456	0.013
18	0.007	0.033	32.471	0.019
19	0.011	0.015	32.514	0.027
20	-0.002	0.005	32.516	0.038
21	-0.019	-0.028	32.646	0.050
22	0.080	0.071	34.924	0.039
23	-0.009	0.040	34.953	0.053
24	-0.145	-0.196	42.616	0.011
25	0.082	0.005	45.066	0.008
26	-0.069	0.001	46.781	0.007
27	-0.004	-0.015	46.789	0.010
28	0.074	0.057	48.816	0.009
29	-0.079	-0.030	51.123	0.007
30	0.117	0.062	56.165	0.003
31	0.001	0.070	56.166	0.004
32	0.058	0.079	57.427	0.004
33	0.046	0.032	58.230	0.004
34	-0.056	-0.028	59.408	0.004
35	0.102	0.064	63.302	0.002
36	0.002	-0.011	63.304	0.003

Source: Author's contribution

Figure 3. Correlogram of Romania's Unemployment Rate Time Series After Second-Order Differencing

Date: 01/12/25 Time: 17:31
Sample (adjusted): 1997M03 2024M11
Included observations: 333 after adjustments



Lag	AC	PAC	Q-Stat	Prob
1	-0.612	-0.612	125.81	0.000
2	0.123	-0.403	130.87	0.000
3	0.065	-0.146	132.28	0.000
4	-0.139	-0.204	138.84	0.000
5	0.130	-0.090	144.63	0.000
6	-0.144	-0.215	151.68	0.000
7	0.108	-0.155	155.64	0.000
8	-0.020	-0.100	155.78	0.000
9	-0.004	-0.032	155.78	0.000
10	-0.020	-0.100	155.92	0.000
11	0.075	0.042	157.89	0.000
12	-0.105	-0.046	161.70	0.000
13	0.017	-0.130	161.81	0.000
14	0.076	-0.038	163.80	0.000
15	-0.078	-0.016	165.91	0.000
16	-0.002	-0.137	165.91	0.000
17	0.052	-0.088	166.86	0.000
18	-0.024	-0.062	167.05	0.000
19	0.007	-0.049	167.07	0.000
20	0.002	-0.015	167.07	0.000
21	-0.052	-0.113	168.04	0.000
22	0.083	-0.074	170.52	0.000
23	0.020	0.156	170.66	0.000
24	-0.159	-0.053	179.75	0.000
25	0.165	-0.049	189.65	0.000
26	-0.093	-0.028	192.81	0.000
27	-0.007	-0.096	192.83	0.000
28	0.102	-0.005	196.65	0.000
29	-0.154	-0.096	205.34	0.000
30	0.137	-0.097	212.22	0.000
31	-0.075	-0.100	214.31	0.000
32	0.030	-0.048	214.64	0.000
33	0.040	0.011	215.25	0.000
34	-0.114	-0.080	220.08	0.000
35	0.114	-0.001	224.92	0.000
36	-0.019	0.063	225.05	0.000

Source: Author's contribution

For the first-order differenced series (Figure 2), the Autocorrelation Function (AC) and Partial Autocorrelation Function (PAC) values indicate a gradual decline in autocorrelation at the initial lags, yet several lags remain statistically significant (e.g., lags 1, 2, and 24). This suggests that the series, while more stationary than in its raw form, retains a residual structure that requires further modelling through autoregressive (p) or moving average (q) components. The Q-statistics and associated p-values confirm the presence of significant autocorrelations at multiple lags.

For the second-order differenced series (Figure 3), the correlogram shows a more pronounced decline in autocorrelations across all lags, with AC and PAC values becoming smaller. The statistical significance of residual autocorrelations also diminishes, indicating that the series becomes nearly fully decorrelated after second-order differencing. However, applying a second differencing operation removes useful information about short-term relationships within the series, which may reduce the accuracy of both the economic interpretation and the predictive performance of the model.

Based on the results presented in Table 4, the selection of ARIMA(1, 2, 2) is justified by several criteria. The model was chosen as it yields an adjusted R^2 of 0.565565, the highest among all tested specifications indicating a superior capacity to explain data variation. Additionally, the standard error of regression (S.E.) of 0.038001 is relatively low, suggesting minimal residual error.

Table 4. ARIMA Model Selection Based on Statistical Performance Criteria

Model	BIC	Adjusted R^2	S.E. of Regression
ARIMA(1, 2, 1)	-3.64345	0.569002	0.037679
ARIMA(2, 2, 1)	-3.635295	0.564821	0.037861
ARIMA(6, 2, 1)	-3.630396	0.563241	0.03793
ARIMA(7, 2, 1)	-3.631235	0.563157	0.037933
ARIMA(4, 2, 1)	-3.62964	0.562874	0.037946
ARIMA(1, 2, 2)	**-3.625772**	**0.565565**	**0.038001**
ARIMA(13, 2, 1)	-3.623289	0.559915	0.038074
ARIMA(23, 2, 1)	-3.622775	0.559643	0.038085
ARIMA(1, 2, 24)	**-3.307815**	**0.388098**	**0.044895**
ARIMA(1, 2, 4)	**-3.291798**	**0.376945**	**0.045302**
ARIMA(1, 2, 25)	**-3.291044**	**0.376885**	**0.045304**
ARIMA(1, 2, 29)	-3.289402	0.375897	0.04534
ARIMA(1, 2, 6)	**-3.28917**	**0.375395**	**0.045359**
ARIMA(1, 2, 5)	-3.27951	0.369215	0.045582
ARIMA(12, 1, 24)	**-3.712318**	**0.038832**	**0.037193**

Source: Author's contribution

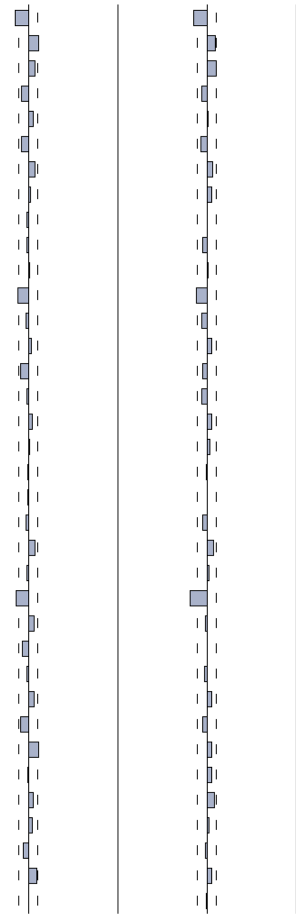
The remaining models in the table that are not highlighted do not exhibit statistical significance, excluding them from final consideration regardless of potentially comparable BIC values.

The ARIMA(1, 2, 2) model also offers a favourable trade-off between complexity and performance, with a BIC of −3.625772, near-optimal relative to the other tested specifications. This value suggests that the model does not introduce unnecessary parameters that could lead to overfitting, maintaining an appropriate balance between model accuracy and parsimony.

The residual correlogram for the ARIMA(1, 2, 2) model confirms that the model satisfies the requirements for a stable univariate process. Diagnostic analysis was conducted using the Ljung-Box Q-statistic, under the null hypothesis that the residuals are white noise. that is independent and identically distributed.

Figure 4. Autocorrelation and Partial Autocorrelation Analysis of Model Residuals

Date: 01/12/25 Time: 23:20
Sample (adjusted): 1997M03 2024M11
Q-statistic probabilities adjusted for 2 ARMA terms



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.153	-0.153	7.9007	
		2	0.117	0.096	12.535	
		3	0.078	0.112	14.584	0.000
		4	-0.077	-0.064	16.595	0.000
		5	0.056	0.015	17.661	0.001
		6	-0.082	-0.066	19.933	0.001
		7	0.082	0.069	22.210	0.000
		8	0.026	0.056	22.444	0.001
		9	-0.009	0.001	22.471	0.002
		10	-0.010	-0.047	22.503	0.004
		11	0.009	0.009	22.533	0.007
		12	-0.118	-0.117	27.333	0.002
		13	-0.032	-0.058	27.699	0.004
		14	0.039	0.054	28.242	0.005
		15	-0.085	-0.048	30.787	0.004
		16	-0.009	-0.055	30.818	0.006
		17	0.046	0.055	31.567	0.007
		18	0.008	0.037	31.592	0.011
		19	-0.000	-0.001	31.592	0.017
		20	-0.001	0.007	31.593	0.025
		21	-0.031	-0.043	31.926	0.032
		22	0.080	0.074	34.233	0.025
		23	-0.019	0.030	34.370	0.033
		24	-0.143	-0.191	41.802	0.007
		25	0.073	-0.012	43.710	0.006
		26	-0.067	0.008	45.347	0.005
		27	-0.015	-0.031	45.425	0.007
		28	0.074	0.059	47.413	0.006
		29	-0.088	-0.044	50.259	0.004
		30	0.118	0.064	55.365	0.002
		31	-0.005	0.061	55.372	0.002
		32	0.062	0.084	56.793	0.002
		33	0.043	0.027	57.474	0.003
		34	-0.050	-0.021	58.421	0.003
		35	0.099	0.061	62.065	0.002
		36	0.006	-0.001	62.081	0.002

Source: Author's contribution

In the residual correlogram, the absence of significant spikes in the AC and PAC plots indicates no meaningful autocorrelation in the residuals. These results confirm that the selected ARIMA model is appropriate for the analysed time series, with residuals satisfying the conditions required to be considered white noise. This property is important for model validation, as it indicates that all available information has been captured by the model and that the generated forecasts are reliable.

To ensure the validity of the estimated ARIMA(1, 2, 2) process, the AR (autoregressive) and MA (moving average) roots were verified to lie inside the unit circle as a necessary condition for confirming model stationarity and ensuring reliable forecasts.

Table 5 demonstrates that all AR and MA roots are positioned inside the unit circle, with moduli of 0.984346 for the AR component and 0.998726 for the MA components. This confirms that the estimated ARIMA model is both stationary and invertible, reinforcing its robustness and reliability for forecasting the analysed variable.

Table 5. Stability and Invertibility of the ARIMA Model: AR/MA Polynomial Roots

Inverse Roots of AR/MA Polynomial(s)
Specification: D(LN_UM, 2) C AR(1) MA(2)
Date: 01/12/25 Time: 23:20
Sample: 1997M01 2024M11
Included observations: 333

AR Root(s)	Modulus	Cycle
-0.984346	0.984346	

No root lies outside the unit circle.
ARMA model is stationary.

MA Root(s)	Modulus	Cycle
-0.998726	0.998726	
0.998726	0.998726	

No root lies outside the unit circle.
ARMA model is invertible.

Source: Author's contribution

The ARIMA(1, 2, 2) model estimated via Maximum Likelihood yielded relevant results for the analysis of the second-order differenced dependent variable. The autoregressive AR(1) and moving average MA(2) coefficients are both statistically significant, with p-values below the conventional threshold of 0.05. The AR(1) coefficient of −0.9843 indicates a strong negative relationship between the current value of the series and its lagged value, while the MA(2) coefficient of −0.9975 reflects a significant contribution of the second-order moving average component to the dynamics of the series.

Table 6. Estimated Parameters and Performance Statistics for the ARIMA(1, 2, 2) Model

Dependent Variable: D(LN_UM,2)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/12/25 Time: 22:56
Sample: 1997M03 2024M11
Included observations: 333
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.50E-05	2.40E-05	-1.039873	0.2992
AR(1)	-0.984346	0.020064	-49.06052	0.0000
MA(2)	-0.997454	0.068991	-14.45773	0.0000
SIGMASQ	0.001427	8.97E-05	15.90989	0.0000

R-squared	0.565565	Mean dependent var	-0.000120
Adjusted R-squared	0.561603	S.D. dependent var	0.057393
S.E. of regression	0.038001	Akaike info criterion	-3.671516
Sum squared resid	0.475092	Schwarz criterion	-3.625772
Log likelihood	615.3074	Hannan-Quinn criter.	-3.653275
F-statistic	142.7683	Durbin-Watson stat	2.305608
Prob(F-statistic)	0.000000		

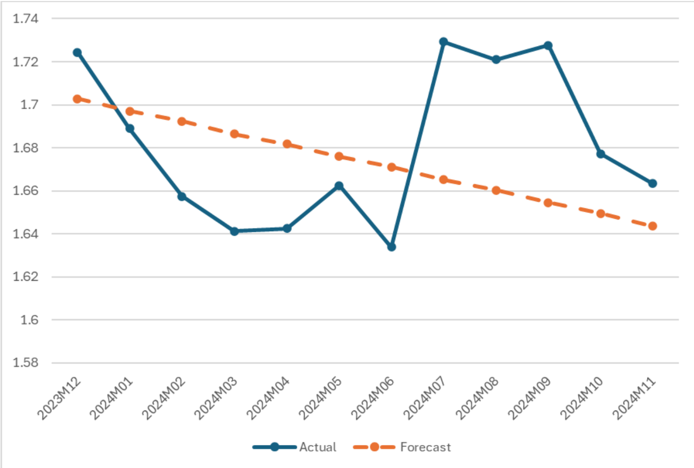
Inverted AR Roots	-.98	
Inverted MA Roots	1.00	-1.00

Source: Author's contribution

The model's goodness-of-fit indicators provide additional insight into its performance. The adjusted R-squared of 0.5616 indicates that approximately 56% of the variability in the differenced series is explained by the model, a reasonable level of fit for an ARIMA model applied to economic data. The Akaike (AIC), Schwarz (SIC), and Hannan-Quinn (HQ) information criteria yield values of −3.6715, −3.6258, and −3.6533, respectively, suggesting that the selected model offers an appropriate balance between complexity and fit. The Durbin-Watson statistic of 2.3056 indicates a low probability of autocorrelation among the residuals, confirming that the model satisfies the requirements of a stable and valid forecasting process.

The comparative plot of actual versus forecasted values for the ARIMA(1, 2, 2) model highlights several important aspects. The general trajectory of the forecasted values follows a downward path, suggesting that the model captures a long-term declining component in Romania's unemployment rate over the analysed period. This is a positive finding, indicating that the model reflects the overall direction of the historical data and produces forecasts that are consistent with macroeconomic expectations.

Figure 5. Actual and Forecasted Values of the Unemployment Rate for the Period 2023M12–2024M11



Source: Author's contribution

Another notable aspect is the close alignment between actual and forecasted values in the first half of the analysed interval, particularly for December 2023 and January 2024, where discrepancies are minimal. This reflects the model's adequate capacity to generate short-term forecasts based on historical patterns.

Furthermore, despite notable deviations at certain points (such as June 2024), the model's forecasts remain within a reasonable range of the actual values, indicating overall model consistency.

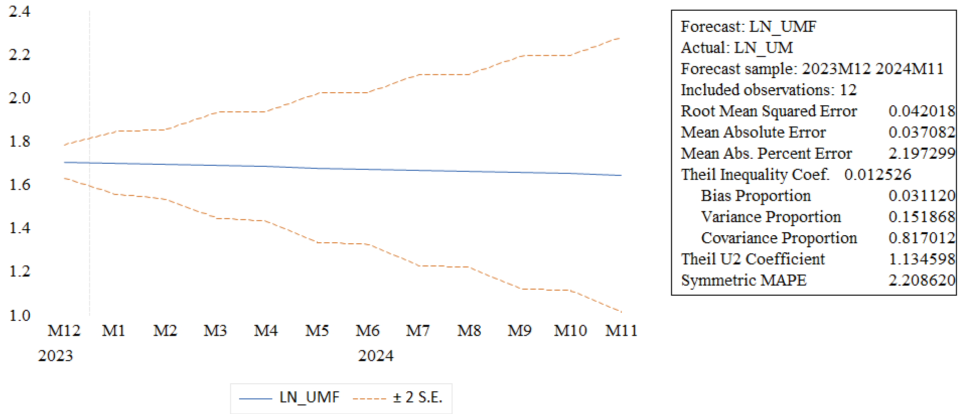
Table 7. Actual and Forecasted Values for the ARIMA(1, 2, 2) Model

Date	Actual	Forecast
2023M12	1.724347	1.702742
2024M01	1.688918	1.696974
2024M02	1.657375	1.692299
2024M03	1.641309	1.686498
2024M04	1.642532	1.681756
2024M05	1.662526	1.675922
2024M06	1.633882	1.671113
2024M07	1.729245	1.665246
2024M08	1.721021	1.66037
2024M09	1.727622	1.654469
2024M10	1.677326	1.649528
2024M11	1.663356	1.643593

Source: Author's contribution

The figure below presents the forecast generated by the ARIMA(1, 2, 2) model for the logarithmic unemployment rate, along with two standard error bands. The forecasted curve (LN_UMF) follows a steady downward trajectory, suggesting that the model anticipates a gradual decline in the unemployment rate over the coming months. This projection is consistent with the long-term trend identified in the historical time series.

Figure 6. Forecasted Unemployment Rate with ±2 Standard Error Confidence Intervals



Source: Author's contribution

The confidence intervals represented by the dotted lines (±2 standard deviations) indicate an acceptable level of forecast uncertainty, providing additional information on the potential variability of the estimates. These intervals remain relatively stable throughout the analysed period, suggesting that the model does not identify major risks of instability or extreme variations.

The accuracy indicators included in the figure provide important information about model quality. The Root Mean Squared Error (RMSE) is low, at approximately 0.042, indicating a small average error between forecasted and actual values. The Theil inequality coefficient (0.012) and the covariance proportion (81.7%) confirm that the majority of variations are correctly captured by the model, with a low share of bias and variance errors.

5. Conclusions

This study applied the Box-Jenkins ARIMA methodology to monthly unemployment rate data for Romania, covering the period January 1997 to November 2024, with the objective of modelling unemployment dynamics and assessing their implications for organizational financial risk. Following log-transformation and stationarity testing via the Augmented Dickey-Fuller test, the ARIMA(1, 2, 2) model was identified as the optimal specification, demonstrating statistically significant AR(1) and MA(2) coefficients of −0.9843 and −0.9975, respectively, alongside satisfactory goodness-of-fit indicators including an adjusted R^2 of 0.5616 and a Durbin-Watson statistic of 2.3056. Residual diagnostics confirmed white noise behaviour, and inverse root analysis validated the stationarity and invertibility of the estimated process.

Forecast evaluation over the out-of-sample period December 2023 to November 2024 demonstrated strong predictive accuracy, with an RMSE of 0.042, a Theil inequality coefficient of 0.012, and a covariance proportion of 81.7%. The forecasted trajectory indicates a gradual decline in Romania's unemployment rate, consistent with the long-term trend observed across the historical series and with macroeconomic conditions in the post-pandemic period. These results confirm that ARIMA models are capable of effectively capturing the structural dynamics of the Romanian labour market, including the effects of major disruptions such as the 2008 global financial crisis and the COVID-19 pandemic.

From a practical standpoint, the findings carry direct implications for managers, investors, and policymakers. Accurate forecasting of unemployment trends enables organisations to anticipate shifts in consumer demand, labour costs, and credit risk exposure, thereby supporting more informed strategic and financial decision-making. Investors may use such models to better assess macroeconomic conditions prior to capital allocation, while policymakers can leverage these forecasts to design timely labour market interventions aimed at reducing unemployment-related financial vulnerabilities.

Future research directions include extending the comparative analysis to multiple countries to identify regional differences in labour market sensitivity and financial risk exposure. Additionally, hybrid modelling approaches, combining ARIMA with machine learning techniques such as LSTM networks, may further improve forecast accuracy, particularly in periods of structural breaks or heightened economic volatility (Spulbăr & Ene, 2024).

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Article Info

Received: April 14 2026
Accepted: June 22 2026

How to cite this article:

Ene, C. C. (2026). Assessing the Impact of Financial Risk on Organizations by Modeling the Unemployment Rate Using the ARIMA Model. *Revista de Științe Politice. Revue des Sciences Politiques,* no. 90, pp. 101-117.