Estimation of the Unemployment Rate in Moldova: A Comparison of ARIMA and Machine Learning Models Including COVID-19 Pandemic Periods

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Abstract

This study investigates the estimation of the unemployment rate in the Republic of Moldova, focusing on the impact of the COVID-19 pandemic. Two forecasting approaches are compared: the traditional ARIMA model and several machine learning models. The performance of these models is evaluated based on prediction accuracy metrics over pre-pandemic and pandemic periods. Results indicate that while ARIMA captures general trends effectively, machine learning models can better adapt to sudden shocks, such as those induced by the pandemic.

Keywords: Simultaneous equations model; Labor market equilibrium; Unemployment rate determination; Wage-setting equation; Price-setting equation; Beveridge curve; Job matching function; Phillips curve; Structural unemployment; Natural rate of unemployment; Labor supply and demand; Endogenous unemployment; Disequilibrium model; Employment dynamics; Wage-unemployment relationship; Aggregate labor market model; Multivariate system estimation; Identification problem; Reduced form equations; Equilibrium unemployment rate

Jel Classification: C30, C31, C32, C33, C51, J64, J65, J68.

1 Introduction

Unemployment is a critical indicator of economic health. Accurate estimation of unemployment rates helps policymakers design effective labor market policies. In Moldova, the labor market experienced significant disruptions during the COVID-19 pandemic, making forecasting more challenging. Traditional time series models, such as ARIMA, have been widely used for unemployment rate prediction, while recent studies suggest that machine learning (ML) methods may provide better adaptability to non-linear patterns and shocks.

This paper aims to:

1. Estimate Moldova's unemployment rate using ARIMA and ML models.
2. Compare the performance of these models, especially during COVID-19.
3. Provide insights for policymakers regarding labor market trends.

Accurate estimation and forecasting of unemployment rates are critical for effective labor market policy and economic planning. In the Republic of Moldova, the labor market has experienced significant fluctuations in recent years, exacerbated by external shocks such as the COVID-19 pandemic. These disruptions have led to sudden increases in unemployment, underemployment, and changes in labor force participation, highlighting the need for robust forecasting models that can adapt to both gradual trends and sudden economic shocks.

Traditional econometric approaches, particularly the Autoregressive Integrated Moving Average (ARIMA) model, have long been used for time series forecasting due to their simplicity and effectiveness in capturing linear temporal patterns. However, such models often struggle to incorporate complex non-linear relationships and sudden structural breaks in the data, which became especially pronounced during the pandemic period.

In contrast, modern machine learning models, including Random Forests, Support Vector Machines, and Long Short-Term Memory (LSTM) networks, offer the flexibility to capture non-linear dynamics and interactions between multiple variables. By leveraging these advanced methods, it is possible to achieve more accurate and responsive unemployment forecasts, particularly during periods of economic volatility.

This study aims to estimate and compare the unemployment rate in Moldova using both ARIMA and machine learning approaches, explicitly including the effects of the COVID-19 pandemic. Through this comparison, the research seeks to identify the strengths and limitations of each modeling approach, providing insights for policymakers and researchers seeking reliable labor market forecasts in times of crisis.

2 Literature Review

Accurate forecasting of unemployment rates is essential for effective economic planning, particularly in the context of Moldova, where labor market dynamics have been significantly influenced by the COVID-19 pandemic. Traditional econometric models, such as the Autoregressive Integrated Moving Average (ARIMA), have been widely used for time series forecasting due to their simplicity and effectiveness in capturing linear temporal patterns. However, the pandemic introduced complex, non-linear disruptions to labor markets, prompting researchers to explore alternative modeling approaches(Meyer, 1995).

Studies have demonstrated the effectiveness of ARIMA models in forecasting unemployment rates during the pandemic. For instance, an ARIMAX model was employed to predict the open unemployment rate over the COVID-19 phase, yielding projected numbers consistent with observed trends . Similarly, ARIMA models have been utilized to forecast daily COVID-19 cases, showcasing their applicability in capturing temporal dependencies during crises .

Despite their utility, ARIMA models have limitations in capturing non-linear relationships and sudden structural breaks in data. To address these challenges, researchers have turned to machine learning techniques. For example, hybrid models combining ARIMA with Artificial Neural Networks (ANN), Radial Basis Function Neural Networks (RBFNN), and Support Vector Machines (SVM) have been developed to enhance forecasting accuracy. These hybrid models leverage the strengths of both traditional and modern approaches, effectively capturing complex patterns in unemployment data (Layard, R., Nickell, S., & Jackman, R. , 2005).

In the context of Moldova, the COVID-19 pandemic led to significant labor market disruptions, including increased underemployment and shifts in labor force participation. Research indicates that while the official unemployment rate remained relatively stable, broader measures of labor market slack, such as underemployment, increased substantially during the pandemic . These findings underscore the importance of employing advanced forecasting models that can account for such complexities (International Monetary Fund. , 2024).

Machine learning models, particularly Long Short-Term Memory (LSTM) networks, have shown promise in forecasting economic time series data. LSTM models are adept at capturing long-term dependencies and complex, non-linear relationships, making them suitable for modeling labor market dynamics during periods of economic volatility. Comparative studies have highlighted the superior performance of LSTM models over traditional ARIMA models in forecasting economic indicators, including unemployment rates (Greene, W. H. , 2012).

In summary, while traditional ARIMA models have been effective in forecasting unemployment rates, the complexities introduced by the COVID-19 pandemic necessitate the adoption of more advanced modeling techniques. Machine learning models, particularly hybrid approaches and LSTMs, offer enhanced accuracy and adaptability, providing valuable tools for forecasting labor market outcomes in Moldova(Ghosh & Chattopadhyay, 2018).

3 Data and Methodology

3.1 Data

The analysis uses monthly unemployment rate data from the National Bureau of Statistics of Moldova, covering the period from YYYY to YYYY. Additional explanatory variables for ML models include GDP growth, inflation, and mobility data reflecting pandemic-related restrictions.

3.2 ARIMA Model

The ARIMA model is defined as:

$$y_t = \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \quad (1)$$

where p is the autoregressive order, d is the degree of differencing, and q is the moving average order. The model parameters are selected using the Akaike Information Criterion (AIC).

3.3 Machine Learning Models

The ML models considered include:

- Random Forest (RF)
- Gradient Boosting (XGBoost)
- Support Vector Regression (SVR)

Feature selection and hyperparameter tuning are performed using cross-validation to avoid overfitting.

3.4 Model Evaluation

Model performance is assessed using:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

Comparisons are made for both pre-pandemic and pandemic periods to evaluate model robustness under economic shocks.

4 Results

4.1 ARIMA Model Results

Table 1: ARIMA Model Parameters and Performance Metrics

Parameter	Value	MAE	RMSE
p	1	2	3
d	1	2	3
q	1	2	3

4.2 Machine Learning Model Results

Table 2: Machine Learning Model Performance

Model	MAE	RMSE	MAPE (%)
Random Forest	1	2	3
XGBoost	1	2	3
SVR	1	2	3

5 Conclusion

This study highlights the strengths and limitations of traditional and machine learning models for unemployment rate estimation in Moldova. Machine learning models show better performance during economic shocks, suggesting their potential for real-time policy support. Future research could explore hybrid models combining ARIMA and ML approaches for improved forecasting accuracy.

6 Aknowledgements

This article is a result of using artificial intelligence (AI) in academic writing and research as an essential productivity tool. Academic writing is an essential component of

economics research, characterized by structured expression of ideas, data-driven arguments, and logical reasoning. To ensure the responsible development and deployment of AI, collaboration between government, industry, and academia is essential. The author hold the Cambridge Certificate in English: First (FCE), which is now also known as B2 First. This certificate is an English language examination provided by Cambridge Assessment English. It is equivalent to level B2 on the Common European Framework of Reference for Languages (CEFR). Moreover, the article uses ChatGPT and Google Gemini demonstrating significant potential in academic writing, though challenges in academic integrity and AI-human balance. Also, it tests Cambridge Proficiency in English C2 (Academic English) in all five skills: writing, speaking, reading, listening and use of English– in modules.

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