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Unveiling Tomorrow's Labor Market: A Data-Driven Forecast of Open Unemployment in Bandung Regency (2025–2029)

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Abstract:

Unemployment remains a persistent challenge in Bandung Regency, where labor market volatility reflects broader structural issues in West Java. Reliable forecasting of the Open Unemployment Rate (OUR) is therefore essential for designing evidence-based labor policies and anticipating future dynamics. This study employs annual time-series data of OUR from 2007 to 2024 (18 observations) sourced from the Central Statistics Agency (BPS). Using the Box-Jenkins ARIMA methodology, the analysis involved stationarity testing with the Augmented Dickey-Fuller test, model identification, parameter estimation, and diagnostic checking through the Portmanteau test. ARIMA(0,1,1) was selected as the most parsimonious model, yielding forecasts that project a decline in OUR from 6.36% in 2024 to 3.21% in 2029. While this projection suggests an optimistic labor market trajectory approaching the natural rate of unemployment, the result is contingent on economic stability and sustained interventions. The findings underscore the policy urgency of enhancing vocational training, aligning education with industry needs, and fostering labor-intensive investments to ensure the forecasted gains are realized.

Keywords: *Forecasting, Unemployment, ARIMA, Bandung Regency*

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1. Introduction

Unemployment is a fundamental macroeconomic issue that not only reflects the health of an economy but also has broad social impacts, ranging from increased poverty to a potential rise in crime rates. This issue is a central concern in the global development agenda, particularly within the framework of Sustainable Development Goal (SDG), which targets decent work and inclusive economic growth (Siddikee et al., 2022). Therefore, the ability to project future unemployment rates becomes a vital instrument for governments in designing proactive and evidence-based policies. On the international stage, statistical forecasting methodologies, especially the Autoregressive Integrated Moving Average (ARIMA) model, have proven to be reliable tools. Studies in various countries, such as forecasting SDG indicators in Bulgaria and projecting the housing price index in Malaysia in line with the 2018-2025 national policy objectives, demonstrate the effectiveness of ARIMA in capturing

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historical data patterns to produce accurate short- to medium-term projections (Ionescu et al., 2021; Zamri et al., 2024).

In the national context, Indonesia faces complex unemployment challenges, influenced by structural factors such as the quality of the labor force, minimum wages, and urbanization (Latifah et al., 2025). A significant body of research has confirmed the relevance and reliability of the ARIMA model for forecasting various economic indicators in Indonesia. Huruta (2024) comprehensively applied ARIMA to predict the national unemployment rate, yielding highly accurate projections (MAPE < 10%) relevant for long-term planning in anticipation of the demographic dividend. Other studies by Sulaiman & Juarna (2021) and Mahmudah (2017) also affirm that ARIMA, with its ability to handle non-stationary data through differencing, is well-suited for Indonesian unemployment data. The vulnerability of Indonesia's labor market became starkly evident during the COVID-19 pandemic, which caused a significant spike in unemployment due to economic slowdowns and mass layoffs, a phenomenon well-documented by Krisnandika et al. (2021) and Darmawan & Mifrahi (2022).

When the analysis is narrowed to the regional level, West Java Province presents a paradox. Despite being one of the main drivers of the national economy, the province consistently records one of the highest Open Unemployment Rates (OUR) in Indonesia. Research by Adipratomo et al. (2024) reveals a crucial finding that economic growth and the Human Development Index (HDI) in West Java do not significantly affect the reduction of OUR, while population growth exacerbates it. This indicates deeper structural problems, such as a skills mismatch and economic growth that is not labor-intensive. This finding is reinforced by Septiyanto & Tusianti (2020), who, through spatial analysis, found that the Labor Force Participation Rate (TPAK) and the Regency/City Minimum Wage are significant factors affecting OUR in West Java. These structural issues underscore that policies focused solely on increasing GRDP at the provincial level will not be sufficiently effective. Therefore, analysis at a more granular level, namely the regency or city level, becomes imperative for formulating more targeted interventions in addressing the research gap (Rayhan & Saputra, 2025).

Table 1. Open Unemployment Rate (OUR) of Bandung Regency (2007-2024)

Year	Open Unemployment Rate (%)
2007	17.37
2008	14.40
2009	12.27
2010	10.69
2011	10.42
2012	11.60

Year	Open Unemployment Rate (%)
2013	10.12
2014	3.94
2015	4.03
2016	8.89
2017	3.92
2018	5.07
2019	5.51
2020	8.58
2021	8.32
2022	6.98
2023	6.52
2024	6.36

Source: Central Statistics Agency (BPS), processed

Bandung Regency, as one of the main economic buffers in West Java, faces unique labor dynamics (Adipratomo et al., 2024). Historical OUR data in Bandung Regency from 2007 to 2024 show significant fluctuations, as presented in Table 1. High volatility is evident, with a sharp decline in 2014 and a significant spike in 2020 coinciding with the COVID-19 pandemic. This unstable data pattern presents a challenge and a primary justification for conducting forecasting using a reliable statistical method. According to Huruta (2024), in this case, ARIMA is a feasible method to be used for forecasting local unemployment trends based on the available regional time-series data. By understanding future trends, the Bandung Regency Government can take anticipatory steps. Based on this background, this study formulates the following research question: What is the projection of the Open Unemployment Rate (OUR) in Bandung Regency for the 2025-2029 period based on historical data using the Autoregressive Integrated Moving Average (ARIMA) model, and what policy implications can be drawn from the forecasting results for the Bandung Regency Government? The main benefit of this research is to provide a quantitative, evidence-based tool that can be used by local policymakers to design more proactive, measurable, and responsive labor strategies for future labor market dynamics, in line with practices that have proven effective in various economic contexts.

2. Theoretical Background

Open Unemployment Rate: From a theoretical perspective, Open Unemployment Rate (OUR) measures the percentage of the labor force that is jobless but actively seeking employment or preparing to start a business (Ahn & Hamilton, 2022). This indicator is a direct reflection of the gap between labor supply and demand in the market. Theoretically, the discourse on unemployment is dominated by two main schools of thought. The Classical Theory posits that the labor market, if left free, will always reach equilibrium at full employment through a flexible wage mechanism (Garegnani, 2024). In this view, unemployment is voluntary and temporary, arising from wage rigidity, such as the imposition of a minimum wage above the market equilibrium level or the power of labor unions demanding higher wages. When wages are forced above the equilibrium level, the quantity of labor supplied will exceed the quantity demanded, creating a labor surplus known as unemployment (Cairó et al., 2022; Eeckhout & Weng, 2024)

Conversely, the Keynesian Theory, pioneered by John Maynard Keynes, argues that unemployment can be involuntary and persistent (Kahn, 2022). According to Keynes, the primary cause is a lack of aggregate demand in the economy. A decline in aggregate demand suppresses production levels, which in turn reduces the demand for labor, thus creating unemployment even when wages are flexible. Within the Keynesian framework, the economy can become trapped in an underemployment equilibrium, where government intervention through expansionary fiscal and monetary policies is necessary to boost aggregate demand and restore the economy to full employment (Piluso & Colletis, 2021).

In addition to these two main perspectives, modern theory classifies unemployment into several types for a more in-depth analysis (Bougrine, 2020). Frictional Unemployment is temporary and unavoidable, occurring when workers are in the process of moving from one job to another or when new graduates first enter the labor market (Axtell et al., 2019). It is considered a part of a healthy, dynamic labor market. Structural Unemployment arises from a fundamental mismatch between the skills possessed by the labor force and the qualifications required by industries (Adely et al., 2021). This type of unemployment is more persistent and is often caused by technological changes, shifts in the economic structure from agriculture to industry or services, or globalization. Addressing it requires long-term policies such as educational reform, reskilling programs, and enhancing labor mobility. Lastly, Cyclical Unemployment is unemployment that fluctuates with the business cycle or economic conjuncture. This unemployment increases during periods of recession or economic slowdown (when aggregate demand falls) and decreases during periods of economic expansion, consistent with the Keynesian view (Gertler et al., 2022).

Research on the regional open unemployment rate (TPT) emphasizes that TPT is heterogeneous across regions and influenced by temporal dynamics (persistence) as well as spatial interdependence, meaning that changes in TPT in one area are often associated with patterns in neighboring regions (Mendez & Siregar, 2023). Crossprovince and panel studies in Indonesia indicate that macroeconomic and structural variables such as regional economic growth (GRDP/GDP), inflation, regional minimum wage (UMR), human capital quality (HDI), and the level of investment (including FDI) have a significant influence on TPT fluctuations. These findings remain consistent in panel analyses and cross-sectional regressions examining the past decade (Siregar, 2022).

In addition to macro determinants, the literature also highlights structural and labor market factors such as deindustrialization, shifts toward the informal sector, and skills mismatches as contributors to unemployment, particularly among youth. Research results show that open unemployment continues to be a major challenge in Indonesia, requiring policies that foster the creation of quality jobs and strengthen the linkages between vocational education and labor market needs (Grabowski & Self, 2020). Methodologically, this implies the necessity of conducting analysis and forecasting at more granular levels (province/regency/city) using time-series methods capable of capturing both temporal autocorrelation and space-time interdependencies. Empirical studies on unemployment in the forecasting context generally recommend combining approaches (e.g., ARIMA models) to produce more reliable projections for the formulation of regional policy interventions (Rayhan & Saputra, 2025).

Economic Forecasting: Economic forecasting is the process of making predictions about future economic conditions using historical data and statistical or econometric models (Petropoulos et al., 2022). In the context of public policy, accurate forecasting is an essential foundation for effective decision-making, from government budgeting and setting inflation targets to planning for infrastructure and social development. Among the various methods available, the Autoregressive Integrated Moving Average (ARIMA) model, developed by Box and Jenkins, is one of the most established and widely used methodologies for time series analysis (Kontopoulou et al., 2023).

The Box-Jenkins methodology is a comprehensive, iterative approach to finding the best ARIMA model to represent a time series data. This process consists of three main stages: identification, estimation, and diagnostic checking (Shumway & Stoffer, 2017). The identification stage aims to tentatively determine the order of the ARIMA(p,d,q) model. This process begins with checking for data stationarity. A time series is said to be stationary if its mean, variance, and autocovariance do not change over time. Stationarity is a critical prerequisite as it allows historical data patterns to be used for future projections. Formal stationarity tests like the Augmented Dickey-Fuller (ADF) test are used to detect the presence of a unit root in the data. If the data is non-stationary, a differencing process (order d) is performed until stationarity is achieved. Once the data is stationary, the autoregressive (p) and moving average (q) orders are identified by analyzing the patterns in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Theoretically, for a pure AR(p) process, the ACF plot will decay exponentially or sinusoidally, while the PACF plot will cut off after lag p. Conversely, for a pure MA(q) process, the ACF plot will cut off after lag q, and the PACF plot will decay gradually.

The second stage is estimation, where the parameters of the tentatively identified model (coefficients ϕ for AR and θ for MA) are estimated. The commonly used estimation method is Maximum Likelihood Estimation (MLE), which finds the parameter values that are most likely to have produced the observed data. From several candidate models that may arise from the identification stage, the best model is selected based on the principle of parsimony (the simplest model that still adequately explains the data). Information criteria such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) are used as a guide, where the model with the lowest AIC/BIC value is preferred.

The final stage, diagnostic checking, is the validation of the model to ensure that the chosen model is adequate. This check focuses on the analysis of the model's residuals. If the model has successfully captured all systematic information from the data, its residuals should be white noise—that is, random, uncorrelated, and normally distributed with a mean of zero and constant variance. A formal test like the Ljung-Box Q-statistic is used to check for the absence of autocorrelation in the residuals. If the residuals do not meet the white noise assumption, the process must return to the identification stage to find a better model. Once the model is validated, it can be used to forecast future values.

3. Methodology

This study employs a quantitative approach with time series analysis to model and project the Open Unemployment Rate (OUR). The adopted methodology is designed to be replicable and to provide transparent and statistically accountable results.

The data used in this research is secondary data in the form of annual Open Unemployment Rate (OUR) in Bandung Regency, measured in percent. The data spans 18 observations from 2007 to 2024. All data is sourced from the official publications of the Central Statistics Agency (BPS), which ensures the validity and reliability of the data used. The data is subsequently processed using the STATA version 17 application to generate the analysis.

The primary analytical method applied is the Autoregressive Integrated Moving Average (ARIMA) model, which is part of the Box-Jenkins methodology. This method was chosen for its proven ability to analyze and forecast univariate time series data, especially economic data that often exhibit trends and autocorrelation patterns. The general form of a non-seasonal ARIMA(p,d,q) model can be mathematically represented as follows:

$$(1-\phi_1 B-\cdots-\phi_p B^p)(1-B)^d Y_t=c+(1+\theta_1 B+\cdots+\theta_q B^q)\epsilon_t$$

Where Y_t is the value of OUR at time period t, p is the order of the Autoregressive (AR) component, d is the order of the differencing process to achieve stationarity, q is the order of the Moving Average (MA) component, ϕ is the parameter coefficient for the AR component, θ is the parameter coefficient for the MA component, B is the backshift operator ($B^kY_t=Y_{t-k}$), c is the model constant, ϵ_t is the white noise error term or residual at time t, assumed to be normally distributed with a mean of zero and constant variance.

The analytical process in this study systematically follows the Box-Jenkins methodology, which consists of five main steps:

1) Model Identification: This initial stage aims to determine whether the time series data is stationary and to identify the tentative order for the ARIMA(p,d,q) model.
   - Stationarity Test: Data stationarity, meaning the mean and variance of the data are constant over time, is a primary prerequisite for ARIMA modeling. A formal stationarity test is conducted using the Augmented Dickey-Fuller (ADF) test. The null hypothesis (H0) of the ADF test is that the data has a unit root (is non-stationary). If the probability (p-value) is greater than the significance level (α=0.05), then H0 is not rejected, and the data needs to be transformed through differencing (d) to achieve stationarity.
   - Determination of Model Order (p,q): Once the data is stationary, the tentative orders for the AR (p) and MA (q) components are identified by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the differenced data. The patterns in these correlograms provide clues about potential models. For instance, if the ACF plot cuts off after lag q and the PACF plot tails off exponentially, it suggests an MA(q) model.
2) Parameter Estimation: After several candidate ARIMA(p,d,q) models are identified, the model parameters (ϕ, θ, and c) are estimated using the Maximum Likelihood Estimation (MLE) method with the aid of statistical software.
3) Model Evaluation and Selection: From the several estimated candidate models, the best model is selected based on the principles of parsimony and accuracy. The primary criteria used are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The model with the lowest AIC and BIC values is considered the best, as it can explain the data well without using excessive parameters.3 Additionally, the Mean Absolute Percentage Error (MAPE) is calculated to measure the model's forecasting accuracy.
4) Diagnostic Checking: The selected best model is then diagnostically checked to ensure that its residuals meet the white noise assumption (independent and identically distributed, with a zero mean and constant variance). A formal test is conducted using the Ljung-Box Q test. The null hypothesis (H0) of this test is that the residuals have no autocorrelation. If the p-value is greater than 0.05,

H0 is not rejected, which means the model is considered adequate and has successfully captured all systematic information from the data.

5) Forecasting: After the ARIMA model is validated through diagnostic checking, it is used to forecast OUR values for the upcoming period, from 2025 to 2029. The forecasting results are presented as point forecasts along with 95% confidence intervals to provide a range of uncertainty for the generated projections.

4. Empirical Findings/Result

Model Identification
Data Stationarity Test

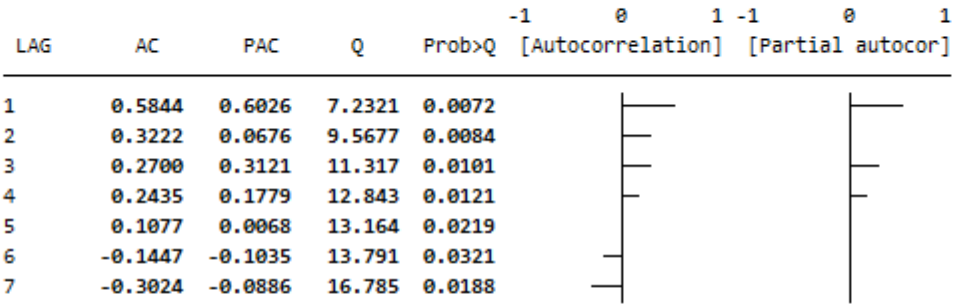
The first step in ARIMA modeling is to ensure the time series data is stationary. A formal stationarity test was conducted using the Dickey-Fuller test. The test on the data at the initial level yielded a p-value of 0.0675, which is greater than the 0.05 significance level. This indicates that the data is non-stationary. Therefore, a first-order differencing process (d=1) was performed. After differencing, the Dickey-Fuller test was applied again, resulting in a p-value of 0.0003, which is significantly smaller than 0.05. Thus, the data became stationary after the first differencing, and the order of integration was set to d=1. The complete results of the stationarity test are presented in Table 2.

Table 2. Dickey-Fuller Stationarity Test Results

Data Level	Z(t) Test Statistic	Probability (p-value)	Description
Level	-2.739	0.0675	Non-Stationary
First Difference	-4.441	0.0003*	Stationary

Source: Data processing results with STATA 17, 2024, note: *Significance level α=0.05

Determination of Tentative Model Order (p,q)



LAG	AC	PAC	Q	Prob>Q
1	0.5844	0.6026	7.2321	0.0072
2	0.3222	0.0676	9.5677	0.0084
3	0.2700	0.3121	11.317	0.0101
4	0.2435	0.1779	12.843	0.0121
5	0.1077	0.0068	13.164	0.0219
6	-0.1447	-0.1035	13.791	0.0321
7	-0.3024	-0.0886	16.785	0.0188

Figure 1. ACF and PACF plots
Source: Data processing results with STATA 17, 2024

Once the data was confirmed to be stationary at the first difference, the tentative orders for the Autoregressive (AR) and Moving Average (MA) components were identified. Analysis of the correlogram on the initial level data, as shown in the provided figure, displays an Autocorrelation Function (ACF) pattern that tails off slowly. This pattern is a strong indication of non-stationary data and reinforces the decision to perform differencing. Subsequently, after the differencing process, an analysis was conducted on the ACF and PACF plots of the differenced data. The ACF plot of the differenced data shows a significant spike at lag 1 and then cuts off, while the PACF plot shows a pattern that tails off gradually. This pattern is a strong characteristic of an MA(1) process, making ARIMA(0,1,1) the most potential model. To ensure the selection of the most optimal model, other candidate models such as ARIMA(1,1,0) and ARIMA(1,1,1) were also estimated for comparison.

Parameter Estimation and Model Selection

The parameters of the three candidate models were estimated, and the best model was selected by comparing the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. The model with the lowest AIC and BIC values is considered the most parsimonious and best-fitting model. Table 3 presents the estimation and comparison results of the candidate models.

Table 3. Estimation and Comparison of Candidate ARIMA Models

Model	Coefficient	Coefficient Value	Std. Error	z-Statistic	Prob.	AIC	BIC
ARIMA(0,1,1)	**MA(1)**	**-0.336**	**0.288**	**-1.17**	**0.244**	**85.338**	**87.838**
	Constant	-0.598	0.417	-1.43	0.151		
ARIMA(1,1,0)	AR(1)	-0.144	0.305	-0.47	0.637	85.927	88.426
	Constant	-0.634	0.570	-1.11	0.267		
ARIMA(1,1,1)	AR(1)	0.337	0.912	0.37	0.712	86.949	90.282
	MA(1)	-0.623	0.866	-0.72	0.472		
	Constant	-0.577	0.600	-0.96	0.336		

Source: Data processing results with STATA 17, 2024

Based on Table 3, the ARIMA(0,1,1) model shows the lowest AIC (85.338) and BIC (87.838) values compared to the other candidate models. Although the MA(1) coefficient and the constant in this model are not statistically significant at the 5% significance level (Prob. > 0.05), the model selection in the Box-Jenkins methodology prioritizes the information criteria (AIC/BIC) to obtain the most parsimonious model. Therefore, ARIMA(0,1,1) was chosen as the best model for forecasting.

Diagnostic Checking

The selected ARIMA(0,1,1) model was then diagnostically checked to ensure its residuals are white noise (random and have no autocorrelation). The Portmanteau (Q-statistic) test was performed on the model's residuals, and the results are presented in Table 4.

Table 4. Residual Diagnostic Test Results (Portmanteau Test)

Statistic	Value	Degrees of Freedom (df)	Probability
Portmanteau (Q)	4.2841	6	0.6383

Source: Data processing results with STATA 17, 2024

The test results show a probability value of 0.6383, which is much larger than the 0.05 significance level. This means the null hypothesis that the residuals have no autocorrelation is not rejected. In other words, the residuals are random, and the ARIMA(0,1,1) model is adequate in explaining the historical data patterns and is suitable for forecasting.

Forecasting

After validation, the ARIMA(0,1,1) model was used to project the OUR of Bandung Regency for the period 2025–2029. The forecasting results are presented in Table 5.

Table 5. Projection of Open Unemployment Rate (OUR) in Bandung Regency (2025-2029)

Year	Projected OUR (%)
2025	5.60
2026	5.01
2027	4.40
2028	3.80
2029	3.21

Source: Data processing results with STATA 17, 2024

The new forecasting results show a much faster and more significant downward trend in OUR. The projection indicates that OUR will decrease from 6.36% in 2024 to 5.61% in 2025, and continue to decline drastically to 3.21% by 2029. This significant reduction over five years presents a very optimistic outlook for the labor market conditions in Bandung Regency, as shown in Figure 2.

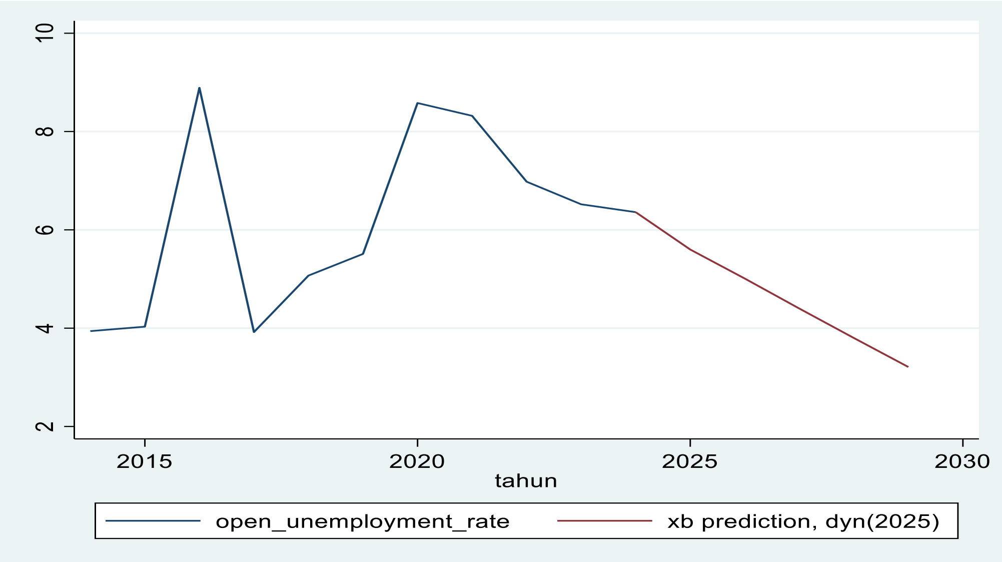


Figure 2. Forecast graph of OUR in Bandung Regency (2025-2029)
Source: Data processing results with STATA 17, 2024

5. Discussion

The forecasting results present a notably optimistic scenario for the labor market in Bandung Regency, projecting a sharp and consistent decline in the Open Unemployment Rate from 5.61% in 2025 to 3.21% by 2029. A OUR of 3.21% is exceptionally low and approaches what economists define as the "natural rate of unemployment," which primarily consists of unavoidable frictional and structural unemployment. According to Eeckhout & Weng, (2024), this suggests a potential transition towards a highly efficient labor market where cyclical unemployment, as described by Keynesian theory, is minimized. If realized, this would signify a robust economic recovery and strong labor absorption capacity within the regency.

However, this optimistic projection must be interpreted with considerable caution, especially when contextualized with the broader literature and the model's inherent limitations. The forecast appears to contradict the established paradox in West Java, where studies have shown that high economic growth does not always translate into significant reductions in unemployment due to deep-seated structural issues like skills mismatch.

An evaluation of the model points towards the latter. First, the ARIMA model is univariate, meaning its forecast is based solely on the past patterns of the unemployment data itself, without considering external causal factors such as investment levels, specific government policies, or shifts in industrial structure. Second, the historical data is extremely volatile, with sharp shocks such as the significant drop in 2014 and the spike in 2020. A model trained on such data can be heavily influenced by the most recent trend in this case, the strong recovery post-2020 and may extrapolate this short-term momentum into the future without the ability to account for potential new shocks.

Therefore, the primary policy implication is not one of complacency but of proactive vigilance. The forecast should be viewed not as a guaranteed outcome but as a potential best-case scenario that can only be achieved under stable economic conditions and with effective, sustained policy interventions. The optimistic projection should motivate policymakers to aggressively address the known structural impediments to employment. This includes strengthening vocational training centers to reduce skills mismatch, further aligning educational curricula with industry demands, and creating an attractive environment for labor-intensive investments. The forecast provides a target, but achieving it requires deliberate action to build a resilient and adaptive labor market that can weather future uncertainties and make this optimistic trend a reality.

6. Conclusions

This study successfully developed and validated a forecasting model for the Open Unemployment Rate (OUR) in Bandung Regency using the ARIMA methodology with annual time series data from 2007 to 2024. Based on a series of identification, estimation, and validation processes, the ARIMA(0,1,1) model was selected as the most suitable and parsimonious model. Based on this model, the projection for the 2025–2029 period shows a very significant and optimistic downward trend in the OUR. The unemployment rate is projected to decrease drastically from 5.61% in 2025 to 3.21% in 2029, indicating the potential for a very rapid improvement in labor market conditions.

The main implication of this finding is that although labor market conditions are projected to improve, the gradual rate of improvement is not sufficient to significantly reduce the unemployment rate in the medium term. This sends a strong signal to the Bandung Regency Government that relying on existing economic trends will not be adequate. Therefore, targeted and proactive policy interventions are needed. Some policy recommendations for regional government that can be drawn are: first, to intensify job creation programs focused on labor-intensive and highly competitive sectors to accelerate labor absorption. Second, given the high uncertainty reflected in the wide confidence intervals, the government needs to strengthen social safety nets and adaptive labor policies to increase the resilience of the labor market to potential future economic shocks. Third, to align the curricula of formal education and vocational training with the real needs of local industries to address the problem of skills mismatch, which is one of the root causes of structural unemployment.

This study has limitations that must be acknowledged. As a univariate model, ARIMA can only forecast based on the internal patterns of historical data and cannot incorporate or explain the influence of external causal variables such as economic growth, investment, inflation, or education levels. The high volatility in the historical data also limits the precision of long-term forecasting.

For future research, the use of multivariate econometric models such as Vector Autoregression (VAR) or Vector Error Correction Model (VECM) is recommended to analyze the dynamic relationships between OUR and other macroeconomic variables. Additionally, panel data analysis combining data from across regions in West Java, as has been done in some reference studies, could provide a deeper understanding of the determinants of unemployment at the local level, thereby generating more specific and effective policy recommendations. To improve the accuracy of the analysis, future studies may use higher-frequency data such as monthly or quarterly data. The use of Machine Learning may also be considered to enhance the accuracy of the analysis.

References:

Adely, F. I. J., Mitra, A., Mohamed, M., & Shaham, A. (2021). Poor education, unemployment and the promise of skills: The hegemony of the “skills mismatch” discourse. *International Journal of Educational Development, 82,* 102381. https://doi.org/10.1016/j.ijedudev.2021.102381

Adipratomo, Y., Hutagaol, P., & Tanjung, D. (2024). Penyebab tingginya angka pengangguran di Jawa Barat. *SEIKAT: Jurnal Ilmu Sosial, Politik Dan Hukum, 3,* 158–165. https://doi.org/10.55681/seikat.v3i2.1274

Ahn, H. J., & Hamilton, J. D. (2022). Measuring labor-force participation and the incidence and duration of unemployment. *Review of Economic Dynamics, 44,* 1–32. https://doi.org/10.1016/j.red.2021.04.005

Axtell, R. L., Guerrero, O. A., & López, E. (2019). Frictional unemployment on labor flow networks. *Journal of Economic Behavior & Organization, 160,* 184–201. https://doi.org/10.1016/j.jebo.2019.02.028

Bougrine, H. (2020). *Credit, Money and Crises in Post-Keynesian Economics.* Edward Elgar Publishing. https://doi.org/10.4337/9781786439550.00016

Cairó, I., Fujita, S., & Morales-Jiménez, C. (2022). The cyclicality of labor force participation flows: The role of labor supply elasticities and wage rigidity. *Review of Economic Dynamics, 43,* 197–216. https://doi.org/10.1016/j.red.2021.02.001

Darmawan, A. S., & Mifrahi, M. N. (2022). Analisis tingkat pengangguran terbuka di Indonesia periode sebelum dan saat pandemi COVID-19. *Jurnal Kebijakan Ekonomi Dan Keuangan, 1*(1), 111–118. https://doi.org/10.20885/JKEK.vol1.iss1.art11

Eeckhout, J., & Weng, X. (2024). The technological origins of the decline in labor market dynamism. *Journal of Economic Dynamics and Control, 169,* 104962. https://doi.org/10.1016/j.jedc.2024.104962

Garegnani, P. (2024). Two routes to effective demand: Comment on Kregel. In P. Garegnani & R. Ciccone (Eds.), *Capital Theory, the Surplus Approach, and Effective Demand: An Alternative Framework for the Analysis of Value, Distribution and Output Levels* (pp. 435–444). Springer International Publishing. https://doi.org/10.1007/978-3-031-23643-3_12

Gertler, M., Huckfeldt, C., & Trigari, A. (2022). Temporary layoffs, loss-of-recall and cyclical unemployment dynamics. https://doi.org/10.3386/w30134

Grabowski, R., & Self, S. (2020). Industrialization and deindustrialization in Indonesia. *Asia & the Pacific Policy Studies, 7*(1), 95–111. https://doi.org/10.1002/app5.295

Huruta, A. (2024). Predicting the unemployment rate using autoregressive integrated moving average. *Cogent Business & Management, 11*. https://doi.org/10.1080/23311975.2023.2293305

Ionescu, G., Jianu, E., Patrichi, I., Ghiocel, F., Lili, T., & Iancu, D. (2021). Assessment of sustainable development goals (SDG) implementation in Bulgaria and future developments. *Sustainability, 13,* 12000. https://doi.org/10.3390/su132112000

Kahn, R. F. (2022). Unemployment as seen by the Keynesians. In M. C. Marcuzzo & P. Paesani (Eds.), *Richard F. Kahn: Collected Economic Essays* (pp. 225–239). Springer International Publishing. https://doi.org/10.1007/978-3-030-98588-2_11

Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. (2023). A review of ARIMA vs. machine learning approaches for time series forecasting in data driven networks. *Future Internet, 15*(8), 255. https://doi.org/10.3390/fi15080255

Krisnandika, V., Aulia, D., & Jannah, L. (2021). Dampak pandemi COVID-19 terhadap pengangguran di Indonesia. *JISIP (Jurnal Ilmu Sosial Dan Pendidikan), 5.* https://doi.org/10.36312/jisip.v5i3.2227

Latifah, T., Syarif, A., & Taufiqurrahman, T. (2025). Analisis pengaruh upah dan tenaga kerja terhadap pengangguran di Indonesia dalam perspektif ekonomi Islam. *Ekonomi, Keuangan, Investasi dan Syariah (EKUITAS), 6*(4). https://doi.org/10.47065/ekuitas.v6i4.7148

Mahmudah, U. (2017). Predicting unemployment rates in Indonesia. *Economic Journal of Emerging Markets, 9*(1), 20–28. https://doi.org/10.20885/ejem.vol9.iss1.art3

Mendez, C., & Siregar, T. H. (2023). Regional unemployment dynamics in Indonesia: Serial persistence, spatial dependence, and common factors. *Letters in Spatial and Resource Sciences, 16*(1), 40. https://doi.org/10.1007/s12076-023-00364-6

Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Barrow, D. K., Ben Taieb, S., Bergmeir, C., Bessa, R. J., Bijak, J., Boylan, J. E., Browell, J., Carnevale, C., Castle, J. L., Cirillo, P., Clements, M. P., Cordeiro, C., Cyrino Oliveira, F. L., De Baets, S., Dokumentov, A., … Ziel, F. (2022). Forecasting: Theory and practice. *International Journal of Forecasting, 38*(3), 705–871. https://doi.org/10.1016/j.ijforecast.2021.11.001

Piluso, N., & Colletis, G. (2021). A Keynesian reformulation of the WS-PS model: Keynesian unemployment and Classical unemployment. *Economia Politica, 38*(2), 447–460. https://doi.org/10.1007/s40888-021-00222-y

Rayhan, E., & Saputra, P. (2025). An analysis of the determinants of unemployment rate in West Java. *Journal of Development Economic and Social Studies, 4,* 77–90. https://doi.org/10.21776/jdess.2025.04.1.07

Septiyanto, W. G., & Tusianti, E. (2020). Analisis spasial tingkat pengangguran terbuka di provinsi Jawa Barat. *Jurnal Ekonomi Indonesia, 9*(2). https://doi.org/10.52813/jei.v9i2.40

Shumway, R. H., & Stoffer, D. S. (2017). ARIMA models. In R. H. Shumway & D. S. Stoffer (Eds.), *Time series analysis and its applications: With R examples* (pp. 75–163). Springer International Publishing. https://doi.org/10.1007/978-3-319-52452-8_3

Siddikee, M. N., Zahid, J. R., Sanjida, A., & Oshchepkova, P. (2022). Sustainable economic growth and unemployment nexus of SDG 2030: Bangladesh in Asia. *SN Business & Economics, 2*(1), 12. https://doi.org/10.1007/s43546-021-00190-2

Siregar, T. H. (2022). Investigating the effects of minimum wages on employment, unemployment and labour participation in Java: A dynamic spatial panel approach. *Bulletin of Indonesian Economic Studies, 58*(2), 195–227. https://doi.org/10.1080/00074918.2021.1914817

Sulaiman, A., & Juarna, A. (2021). Peramalan tingkat pengangguran di Indonesia menggunakan metode time series dengan model ARIMA dan Holt-Winters. *Jurnal Ilmiah Informatika Komputer, 26,* 13–28. https://doi.org/10.35760/ik.2021.v26i1.3512

Zamri, M., Rifin, M., & Amit, N. (2024). Application of the ARIMA model in house price index in Malaysia. *Jurnal Intelek, 19,* 184–192. https://doi.org/10.24191/ji.v19i2.26615