INCOME JOURNAL OF ECONOMICS DEVELOPMENT
Volume 7, No. 2, July 2027, pp. 507-521
e-ISSN: 3025-3225, DOI : 10.54065/ijed.7.2.2027.926

Analysis of the Impact of Education Levels and Labor Force Participation Rates on Unemployment in Sumatra Province (2019–2025)

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Article Info

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Keywords:
Education Level, Labor Force Participation Rate, Unemployment, Panel Data Regression, Sumatra

Abstract

Employment is an important aspect of the Indonesian economy. One of the employment problems on the island of Sumatra is unemployment. This study aims to analyze the effect of education level and Labor Force Participation Rate (LFPR) on unemployment in the provinces of Sumatra during 2019–2025. This study uses secondary data. The analytical method used in this study is panel data regression processed using EViews 12 software. The results show that the Fixed Effect Model (FEM) is the most appropriate model. Based on the regression results, education level has a negative and significant effect on unemployment. Meanwhile, the Labor Force Participation Rate (LFPR) has a positive but insignificant effect on unemployment. Based on the simultaneous test, education level and LFPR simultaneously affect unemployment, with a coefficient of determination (R-squared) of 0.814484. This indicates that 81.44% of the variation in the unemployment rate in Sumatra can be explained by Education Level and LFPR, while the remaining 18.56% is explained by other factors outside the model.

How to Cite:
Rismahani, A., Fadilah, M. A., & Nengsih, T. A. (2027). Analysis of the impact of education levels and labor force participation rates on unemployment in Sumatra Province (2019–2025). Income Journal of Economics Development, 7(2), 507-521. https://doi.org/10.54065/ijed.7.2.2027.926

1. Introduction

The employment sector is an inseparable part of the main indicators as well as a driving force of the national economy (Haider et al., 2023; Sultana et al., 2022). This indication can be seen from the contribution of labor force productivity, which is expected to continue increasing every year in order to support community competitiveness toward the vision of Golden Indonesia 2045 (Widodo et al., 2025). In addition to providing positive chain effects for the advancement of other sectors, inequality caused by the surge in new labor force entrants that is not in line with job vacancies in the regions remains a fundamental obstacle that triggers an accumulation of unemployment (Rahmawati et al., 2024). Therefore, creating high economic growth is crucial to absorbing this abundant productive workforce (Hamzah & Fitriyah, 2025; Chaerul, 2023).

The Sumatra region is the target of this study because employment dynamics in this economic corridor have shown relatively complex fluctuations in recent years. Since the economic contraction caused by the COVID-19 pandemic in 2020, there have been strong indications that regions in Sumatra need to recover by optimizing their human capital potential. Recovery policies have begun to operate, but labor absorption has not been optimal because several provinces are still struggling to reduce their open unemployment rates (Aprilia et al., 2025). Efforts to restore post-COVID-19 economic stability in Sumatra also constitute a major challenge after the region experienced a 1.5% surge in open unemployment. Restrictions on activities during that period massively reduced community productivity and triggered a wave of large-scale layoffs by companies (Mohamed, 2024).

The competitiveness of a region is largely determined by the performance of its own labor market. This condition is influenced by several factors, such as economic slowdown, mismatches in job skills, changes in economic structure, and external shocks such as crises or pandemics (Ulfiyah et al., 2026). This is consistent with the actual condition in Indonesia, where open unemployment is one of

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the main indicators of labor-market imbalance and reflects the imbalance between the number of job seekers and available employment opportunities (Uparaman & Muzakir, 2023; Baharuddin, 2022). If unemployment is allowed to persist, it will create social problems due to declining productivity. This condition causes individuals to have no income, thereby reducing their purchasing power, which ultimately hampers economic growth and increases poverty (Jeray et al., 2023). In addition to socioeconomic aspects, an alarming increase in the number of unemployed people can also trigger a decline in community welfare. To maintain this stability, local governments must be able to maintain a balance between labor supply and demand and encourage improvements in the quality of the labor force.

The effectiveness of a region in reducing its unemployment rate is strongly influenced by how well the quality of management and economic development planning are implemented in that region (Lazuardi & Santoso, 2024). High economic growth or an increase in the value added of goods and services (GRDP) is not always accompanied by adequate job creation in the real sector. The phenomenon of growth without job creation (jobless growth) tends to occur when economic activity is dominated by capital-intensive rather than labor-intensive sectors (Widodo et al., 2025). Another negative impact is the emergence of a skill mismatch between the qualifications possessed by the labor force and the actual needs of the modern industrial sector (Dewi, 2023).

One indicator of regional progress can be observed through an analysis of the community's education level. An analysis of education level is needed to determine the condition of workforce competencies in a region so that it can subsequently assist local governments in making better decisions. Panel data regression analysis is conducted to analyze macro indicators such as labor participation ratios with the aim of maximizing economic development performance in the future (Anggraini & Armida, 2025).

Employment conditions in the Sumatra region are reflected in fluctuations in the open unemployment rate (TPT) during the 2019–2025 period. Based on the data presented in Figure 1, ten provinces experienced complex employment fluctuations. Almost all provinces experienced a significant increase in unemployment in 2020 due to the impact of the COVID-19 pandemic, with the Riau Islands recording the highest rate, exceeding 10%. The data also show that provinces such as West Sumatra, North Sumatra, and Aceh consistently belonged to the relatively high-TPT group, although after 2020 they began to show a gradual downward trend as the economic recovery progressed. Figure 1 explains that local government policy management must immediately formulate effective labor absorption strategies to reduce labor-market imbalance in the coming years (Minah & Sekaringsih, 2023).

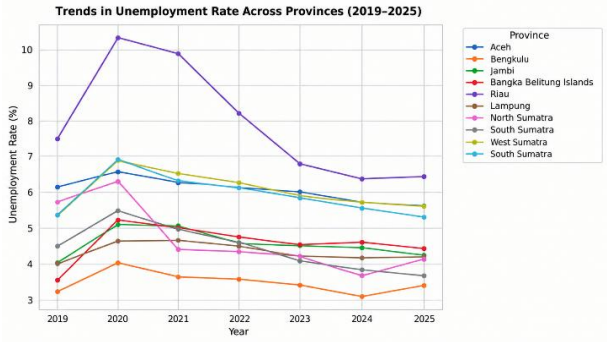


Figure 1. Line Graph of the Open Unemployment Rate in the Sumatra Region, 2019–2025

Several previous studies have examined employment using panel data regression methods. In their study on the Effect of Population, Provincial Minimum Wage (UMP), and Labor Force Participation Rate (LFPR) on Unemployment in West Sumatra during 2020–2024, found that all independent variables simultaneously had a significant effect on the unemployment rate, with a coefficient of determination of 76.45% (Anggraini & Armada, 2025). Partially, population had a significant negative effect, while the minimum-wage increase policy was positively associated with unemployment because it encouraged labor efficiency by companies. On the other hand, the LFPR variable was found to have no significant partial effect on open unemployment in the region because the labor supply tended to be absorbed into the informal sector.

Another study conducted by previous studied on employment in West Nusa Tenggara showed that the Average Years of Schooling variable had a positive but insignificant effect on open unemployment due to a mismatch between the qualifications of educated graduates and available job vacancies (Bachri & Salmah, 2025). However, the LFPR had a strong negative and significant effect on the open unemployment rate in the region. Meanwhile, research by previous studied stated that population density was proven to be the

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dominant determinant affecting the Open Unemployment Rate (TPT) in regional employment modeling in East Nusa Tenggara (Setiawan et al., 2024).

Current employment research often relies only on general open-unemployment indicators without distinguishing specific regional characteristics. Therefore, this study offers a comprehensive evaluation to analyze regional employment performance using a combination of Education Level (Average Years of Schooling) and Labor Force Participation Rate (LFPR) variables estimated through the Fixed Effect Model (FEM), which was selected based on the Chow and Hausman tests to eliminate autocorrelation and heteroscedasticity problems. Another advantage of this study is the expanded data coverage from 2019 to 2025, capturing a complete picture of the economic transition from the pandemic period to the long-term recovery phase across the provinces of Sumatra.

Hypothesis Developmen

The research model explaining the relationships among the research variables was developed based on previous studies from the literature review. Figure 2 illustrates the relationship between education level and labor force participation rate on unemployment in the provinces of Sumatra studied during 2019–2025, measured using the Open Unemployment Rate (TPT).

The analysis of unemployment is based on labor economics theory, which explains that the unemployment rate is influenced by various economic and social factors, including education level and labor force participation rate (Sidabutar & Putri, 2024). Education reflects the quality of human resources that supports productivity in the labor market. Meanwhile, labor force participation indicates the proportion of the working-age population that is economically active. Higher education tends to increase employment opportunities and reduce unemployment (Zilda et al., 2025). On the other hand, the impact of the labor force depends heavily on the absorption capacity of the labor market and the negative correlation trend it produces. This study uses education level and labor force participation as independent variables, while the open unemployment rate is the dependent variable (Siregar, 2020). The analysis focuses on the provinces of Sumatra during the 2019–2025 period to examine this effect.

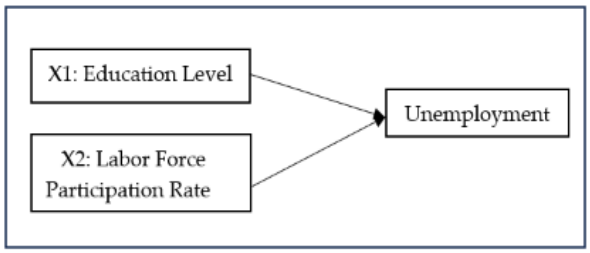


Figure 2. Research Model

Ha: Education Level Affects the Unemployment Rate

Education level is the primary instrument for measuring the quality of human capital that determines the productivity, skills, and adaptive capacity of the productive-age population to labor-market dynamics (Ismeti & Hameli, 2026). Adequate and continuous access to education theoretically expands individuals' opportunities to acquire academic competencies and competitiveness required by industry (Fatonah et al., 2023). This increase in qualifications at the macro level is projected to align the availability of skills with the needs of the business market, thereby sustainably reducing open unemployment in the provinces of Sumatra (Saputri & Samsuddin, 2025).

This is consistent with the findings of previous studied, who examined macro employment dynamics in Indonesia and found that education had a negative and significant effect on the unemployment rate. Similar findings were obtained by in their study in West Java Province, which showed that the education index was one of the main determinants significantly affecting fluctuations in the open unemployment rate through a panel data regression approach (Fatonah et al., 2023).

Ha: Labor Force Participation Rate Affects the Unemployment Rate

The Labor Force Participation Rate (LFPR) represents the ratio of active involvement of the productive-age population in real economic activities, both those who are already employed and those who are still seeking employment (Permatasari et al., 2024). Fluctuations in the LFPR reflect the actual labor supply of a region that is ready to contribute to the regional economy (Alkalbeo et al., 2023). High labor-market participation can act as a trigger for reducing open unemployment when it is accompanied by the availability of proportional employment opportunities for the active labor force (Febriansyah & Cahyono, 2026).

This is consistent with the findings of previous studied, who examined regional

employment determinants and found that the labor force participation rate had a negative and significant effect on unemployment (Adianita et al., 2024). In a study of the Sumatra region, stated that fluctuations in labor supply require local governments to allocate budgets and facilitate the creation of business opportunities in order to address unemployment problems (Islamiah et al., 2021).

Ha: Education Level and LFPR Simultaneously Affect the Unemployment Rate

The structural combination of Education Level and Labor Force Participation Rate is believed to simultaneously influence variations in unemployment rates in a region (Fatonah et al., 2023). The relationship between these two employment aspects plays a central role in determining macro labor-market equilibrium, where graduate quality and labor-force mobility interact simultaneously. The government's failure to integrate the quality of labor supply (education) and the quantity of market participation (LFPR) has direct implications for regional socioeconomic vulnerability, particularly through an increase in the absolute number of unemployed people (Permatasari et al., 2024). Thus, the simultaneous interaction between fluctuations in education level and the availability of the labor force is expected to have strong explanatory power for changes in the Open Unemployment Rate (TPT) in the provinces of Sumatra.

This is consistent with the empirical testing conducted by previous studied using panel data regression analysis, which demonstrated that regional employment characteristics, including the education index and its accompanying economic variables, jointly exerted a very strong significant effect, with an R^2 contribution reaching 94.10%, on the unemployment rate (Fatonah et al., 2023). This simultaneous theoretical explanation is supported by previous studied, who confirmed that macro labor-market interaction strongly depends on how the quality of labor supply is combined with market absorption capacity (Stijepic, 2021).

However, a comparative study using province-scale pooled data by previous studied, as well as partial dynamics in the regional another studied, indicates that the integration of these indicators often proceeds slowly at the regional level because of disparities in development-budget absorption and minimum-wage policies that are biased against employment expansion (Permatasari et al., 2024). This inconsistency in joint interaction patterns provides a strong basis for testing the explanatory power of these two independent variables simultaneously in the provinces of Sumatra during 2019–2025.

2. Literature Review

2.1 Unemployment Rate

Unemployment is one of the important issues in the field of employment because it is directly related to economic conditions and community welfare. The unemployment rate can describe the condition of the labor market in a region, particularly regarding the balance between the number of people seeking employment and the availability of job opportunities. When the number of job seekers exceeds the available employment opportunities, the unemployment rate tends to increase. Therefore, unemployment is not only an individual problem for those who have not obtained employment but also an important indicator that needs to be considered in economic development (Sari et al., 2023).

The Open Unemployment Rate (OUR) is one of the indicators used to describe unemployment conditions. Open unemployment refers to people who are part of the labor force but have not obtained employment and are still seeking employment. A high unemployment rate indicates an imbalance in the labor market, particularly when the available labor supply cannot be optimally absorbed by existing employment opportunities. Thus, the unemployment rate can indicate that a region's ability to provide employment opportunities remains insufficient in comparison with the number of people entering the labor market (Kettanurak, 2025).

Unemployment also has broad social and economic impacts on society. Individuals who do not have employment experience limitations in earning income. The decline in income can reduce people's purchasing power and eventually affect economic activity. High unemployment may also increase the risk of various social problems because people face difficulties in fulfilling their basic needs. Therefore, unemployment is closely related to productivity, income, economic growth, and community welfare (Jeray et al., 2023).

In addition to the availability of employment opportunities, the unemployment rate is also related to the quality of the labor force. Changes in labor market requirements

may create a mismatch between workers' skills and the qualifications required for available jobs. This condition is known as a skill mismatch, which occurs when workers' education or abilities do not correspond to the needs of the labor market. Such a mismatch may make it difficult for individuals to obtain employment even when they have a certain level of educational attainment (Aprilia et al., 2025).

Unemployment can also be affected by changes in economic conditions. Economic slowdowns, structural changes, crises, and external shocks can affect the ability of businesses and economic sectors to absorb labor. This condition was particularly evident during the COVID-19 pandemic, when economic activities were disrupted and unemployment increased in various regions. In the provinces of Sumatra, almost all provinces experienced an increase in unemployment in 2020, which gradually declined as economic recovery took place (Sari et al., 2023).

Therefore, the unemployment rate can be considered an important indicator for assessing the success of employment development. Efforts to reduce unemployment are not only related to creating employment opportunities but also require improvements in human resource quality so that workers possess skills that correspond to labor market needs. Local governments need to consider the balance between the size of the labor force, the quality of workers, and the capacity of the economy to provide employment opportunities. With such a balance, labor absorption is expected to increase and the unemployment rate can be reduced (Yi et al., 2024).

2.2 Level of education

Education level is one of the indicators that can be used to assess the quality of human resources in a region. Education plays an important role in developing individuals' knowledge, skills, abilities, and competencies, thereby improving their readiness to enter the labor market. In the context of employment, education does not merely function as a process of acquiring knowledge but also represents an investment in human capital. The better the quality of education received by the population, the greater the ability of workers to adapt to changes in labor market requirements.

Education is closely related to labor productivity. Individuals who receive education can acquire better knowledge and skills, enabling them to perform their jobs more effectively. This improvement in quality can ultimately increase workers' competitiveness in obtaining employment opportunities. In studies of employment, education level is frequently used as one of the factors explaining changes in unemployment because education is associated with the quality of the labor force available in a region (Fatonah et al., 2023).

Education can also increase an individual's opportunity to obtain employment that corresponds to their abilities. Certain educational qualifications are among the considerations in the recruitment process, particularly for jobs requiring specific skills and expertise. As education levels increase, individuals are expected to possess competencies that are more aligned with the needs of businesses and industries. Therefore, improvements in education can help reduce the gap between workers' skills and labor market requirements (Putranto et al., 2024).

In relation to unemployment, education tends to have a negative relationship with unemployment. This means that an increase in education level is expected to be followed by a decrease in the unemployment rate. Better education can improve the quality of human resources, thereby providing workers with greater opportunities to obtain employment. In addition, education can enhance individuals' ability to adapt to technological developments and changes in the structure of employment within the economy (Zilda et al., 2025).

However, a higher level of education does not automatically guarantee that an individual will obtain employment. There is still a possibility of a mismatch between educational qualifications and the requirements of available jobs. This condition indicates that improvements in education need to be accompanied by alignment between the competencies obtained through education and labor market requirements. Thus, quality education should not only be assessed based on the length of time an individual spends in education but also based on the competencies acquired and their relevance to labor market needs (Hakim et al., 2025).

Several previous studies support the relationship between education level and unemployment. In their study of the open unemployment rate in West Java, found that education indicators were among the factors affecting the unemployment rate (Fatonah et al., 2023). Meanwhile, the previous studied found

that education had a negative and significant effect on the unemployment rate in Indonesia (Lazuardi & Santoso, 2024). These findings indicate that improvements in education can contribute to enhancing labor quality and increasing people's opportunities to obtain employment.

Based on the discussion above, education level can be considered one of the important factors determining the employment conditions of a region. Improvements in education are expected to enhance the quality, skills, productivity, and competitiveness of workers. When these improvements are aligned with labor market requirements, workers' opportunities to obtain employment will increase, thereby helping to reduce the unemployment rate.

2.3 Labor Force Participation Rate

The Labor Force Participation Rate (LFPR) is an indicator that describes the involvement of the working-age population in economic activities. LFPR represents the proportion of the working-age population that belongs to the labor force, including both employed individuals and those who are actively seeking employment. Therefore, LFPR provides an overview of the size of the labor supply available in a region. The higher the LFPR, the larger the proportion of the working-age population that is actively participating in the labor market (Permatasari et al., 2024).

LFPR plays an important role in describing labor market conditions because it indicates the extent to which the working-age population is willing and able to participate in economic activities. Individuals who are part of the labor force can contribute to production activities through the work they perform. Therefore, changes in LFPR can reflect changes in the number of people entering the labor market and potentially affect employment conditions in a region.

An increase in LFPR essentially indicates an increase in the number of people who are active in the labor market. However, such an increase does not necessarily lead directly to a decrease in the unemployment rate. This depends largely on the ability of a region to provide employment opportunities. If the increase in the labor force can be absorbed by available employment opportunities, an increase in LFPR may be accompanied by an increase in the number of employed people. Conversely, if employment opportunities do not increase proportionally, some of the additional labor force may become unemployed (Asmara & Saleh, 2024).

This condition indicates that the relationship between LFPR and unemployment is closely associated with the absorption capacity of the labor market. An increase in the number of people entering the labor force may become a problem if it is not accompanied by the creation of sufficient employment opportunities. Therefore, an increase in LFPR needs to be accompanied by policies capable of expanding employment opportunities and increasing economic activities that can absorb labor. Local governments have an important role in creating such conditions through economic development and employment policies.

The relationship between LFPR and unemployment may also differ across regions. Each region has different economic characteristics, employment structures, and labor absorption capacities. In regions with relatively broad employment opportunities, an increase in LFPR can contribute to an increase in the number of employed people. However, in regions where employment opportunities are limited, an increase in the number of people entering the labor force may intensify competition for jobs and potentially increase the number of unemployed people (Egeten et al., 2023).

Previous studies have also shown different findings regarding the relationship between LFPR and unemployment. The previous studied found that LFPR had a negative and significant effect on the unemployment rate (Bachri & Salmah, 2025). This finding indicates that increased labor force participation can be associated with a decrease in unemployment when workers can be absorbed by available employment opportunities. Meanwhile, the previous studied found that LFPR had a negative but insignificant effect on the open unemployment rate (Wahyuni et al., 2025). These differences in research findings indicate that the effect of LFPR on unemployment is not always the same and may be influenced by the conditions of the labor market in each region.

The previous studied also found that LFPR had no significant effect on unemployment in West Sumatra (Anggraini & S, 2025). This condition indicates that a high level of labor force participation does not necessarily correspond to a significant change in the

unemployment rate. One possible explanation is the capacity of the labor market to absorb additional workers. Therefore, an increase in LFPR needs to be accompanied by the creation of adequate employment opportunities so that the increasing labor force can be optimally absorbed.

Based on the discussion above, LFPR is an important indicator for analyzing the employment conditions of a region. LFPR describes the proportion of the working-age population that is active in the labor market, while the unemployment rate represents the proportion of the labor force that has not obtained employment. The relationship between the two depends largely on the balance between the available labor force and the ability of the economy to create employment opportunities. Therefore, an increase in LFPR needs to be accompanied by employment creation policies so that growth in the labor force can contribute to labor absorption and help reduce unemployment.

3. Research Methods

3.1 Research Approach

This study uses a quantitative approach with a descriptive-associative research design. A quantitative approach is used because the research involves numerical data that can be measured and analyzed statistically to examine the relationship between the independent and dependent variables. The associative approach is intended to identify and explain the relationship between education level, Labor Force Participation Rate (LFPR), and unemployment in the provinces of Sumatra. The quantitative approach allows the researcher to test the proposed relationships between variables based on statistical evidence (Sugiyono, 2013).

The descriptive aspect of this study is used to describe the development of unemployment, education level, and LFPR during the 2019–2025 period. Meanwhile, the associative aspect is used to examine whether education level and LFPR have an effect on the unemployment rate. Therefore, the research does not only describe the development of each variable but also analyzes the relationship between the variables using an econometric model.

3.2 Data Type and Data Sources

The data used in this study are secondary data. Secondary data refer to data that have previously been collected and published by institutions or other parties and are subsequently utilized by researchers for research purposes. In this study, the data were obtained primarily from publications of Statistics Indonesia (Badan Pusat Statistik/BPS). The use of secondary data is appropriate because the variables analyzed in this research, namely the Open Unemployment Rate (OUR), Average Years of Schooling (AYS), and Labor Force Participation Rate (LFPR), are available in official statistical publications.

The study covers 10 provinces located on the island of Sumatra over the 2019–2025 period. The data therefore consist of observations across provinces and years, allowing differences between regions and changes over time to be analyzed simultaneously. The use of BPS data also provides a consistent statistical basis for comparing the employment conditions of different provinces during the observation period. The original study specifies that the data consist of OUR, AYS as an indicator of education level, and LFPR for 10 provinces in Sumatra from 2019 to 2025.

3.3 Population and Sample

The population of this study consists of provinces located on the island of Sumatra that are included in the observation of employment indicators during the research period. The sample consists of 10 provinces in Sumatra observed annually from 2019 to 2025. Thus, the research covers 10 cross-sectional units and 7 time-series periods, resulting in 70 province-year observations.

The selection of the provinces and observation period is intended to provide a regional perspective on the relationship between education, labor force participation, and unemployment. The 2019–2025 period also covers conditions before the COVID-19 pandemic, the economic disruption during the pandemic, and the subsequent recovery period. This enables the analysis to capture variations in employment conditions across provinces and over time.

3.4 Data Collection Technique

The data collection technique used in this study is documentation. Documentation involves collecting relevant information from existing documents, publications, reports, books, journal articles, and official statistical sources. In this research, the documentation

technique was applied by collecting secondary statistical data from BPS publications and supporting information from books and previous studies.

The use of documentation is considered appropriate because the research variables have already been systematically recorded and published by official institutions. The collected data were subsequently organized according to province and year before being processed into panel data. The previous studied explains that documentation can be used as a data collection technique by utilizing existing records or documents relevant to the research (Sugiyono, 2013). The original study also states that the documentation technique was used to collect data from books, journal articles, and BPS publications.

3.5 Research Variables

This study consists of one dependent variable and two independent variables. The dependent variable is the Open Unemployment Rate (OUR), while the independent variables are education level and Labor Force Participation Rate (LFPR). Education level is represented by Average Years of Schooling (AYS), which describes the average number of years of formal education completed by the population. AYS is used as an indicator of the educational characteristics of the population because it can provide an overview of the quality of human resources in a region.

LFPR represents the proportion of the working-age population that participates in the labor market. It includes individuals who are employed as well as those who are actively seeking employment. Therefore, LFPR is used to represent the degree of labor market participation within each province. The dependent variable, OUR, represents the proportion of the labor force that is unemployed. The use of OUR allows the research to measure the employment condition of each province in a comparable form. The original research identifies OUR as the dependent variable and AYS and LFPR as the independent variables.

3.6 Panel Data Analysis

The analytical method used in this study is panel data regression. Panel data combine cross-sectional data and time-series data. Cross-sectional data in this research consist of 10 provinces in Sumatra, while the time-series dimension covers the period from 2019 to 2025. The combination of these two dimensions allows the researcher to observe differences among provinces as well as changes over time.

Panel data regression is useful for analyzing regional economic and employment phenomena because it can take into account differences among observational units and changes across periods. Panel data analysis can be applied to economic and business research by combining cross-sectional and time-series observations (Basuki, 2021). This approach enables the researcher to obtain more comprehensive information than using only cross-sectional or time-series data. The use of panel regression in this study is intended to estimate the effect of education level and LFPR on unemployment while considering the characteristics of provinces and changes during the observation period. The original research also applies panel regression to analyze the effect of the independent variables on the dependent variable.

3.7 Panel Model Selection

Before estimating the final regression model, model selection is required to determine the most appropriate panel data estimation technique. The three commonly considered models are the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). Each model has different assumptions regarding individual or regional effects.

The Common Effect Model (CEM) assumes that differences among cross-sectional units do not create specific individual effects, so all observations are treated relatively uniformly. The Fixed Effect Model (FEM) assumes that each cross-sectional unit may have specific characteristics that remain constant over time and may affect the dependent variable. Meanwhile, the Random Effect Model (REM) assumes that individual effects are random and are not correlated with the explanatory variables.

In this study, model selection is conducted using the Chow Test and Hausman Test. The Chow Test is used to determine whether the CEM or FEM is more appropriate. If the FEM is selected, the Hausman Test is subsequently used to determine whether FEM or REM is more suitable. Model selection is an important stage in panel data analysis because the selected estimation model must correspond to the characteristics of the data.

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3.8 Classical Assumption Tests

Classical assumption testing is conducted to assess whether the estimated regression model satisfies the requirements necessary for obtaining reliable statistical estimates. In this study, the classical assumption tests include normality, multicollinearity, heteroskedasticity, and autocorrelation tests. The normality test is used to examine the distributional characteristics of the research variables or residuals. The multicollinearity test is conducted to determine whether there is a strong correlation among the independent variables. High correlation among explanatory variables may make it difficult to identify the individual effect of each variable on the dependent variable. The heteroskedasticity test is used to determine whether the variance of the residuals is constant across observations. A regression model is considered preferable when the residual variance is relatively constant. The autocorrelation test is used to identify whether residuals from one observation are correlated with residuals from another observation.

3.9 Hypothesis Testing

After the appropriate panel regression model has been determined and the model assumptions have been evaluated, hypothesis testing is conducted to determine the statistical significance of the estimated relationships. The t-test is used to examine the partial effect of each independent variable on the dependent variable. In this research, the t-test is used to determine whether education level individually affects unemployment and whether LFPR individually affects unemployment. The F-test is used to examine the simultaneous effect of the independent variables on the dependent variable.

Therefore, the F-test determines whether education level and LFPR jointly have a significant effect on the unemployment rate. In addition, the coefficient of determination (R^2) is used to measure the proportion of variation in the dependent variable that can be explained by the independent variables included in the regression model. A higher R^2 indicates that a larger proportion of variation in the dependent variable can be explained by the model, although it does not by itself establish a causal relationship.

3.10 Data Processing Software

The data analysis in this study was performed using EViews 12. The software was used to organize and process panel data, estimate the regression model, conduct panel model selection tests, perform classical assumption tests, and conduct hypothesis testing. The use of EViews is consistent with the panel regression approach employed in this study and facilitates the estimation of economic and employment models involving cross-sectional and time-series observations. The research uses panel regression because the data combine 10 provinces and seven years of observation. The use of EViews 12 allows the characteristics of both dimensions to be incorporated into the estimation process and supports the selection of the most appropriate panel regression model.

3.11 Panel Data Regression Model

The Panel Data Regression Model in this study is formulated as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \varepsilon_{it}$$

Description:

Y_{it} = Unemployment Rate
X_{1it} = Education Level
X_{2it} = Labor Force Participation Rate(LFPR)
β_0 = Constant
β_1, β_2 = Regression Coefficient
ε_{it} = Error Term

4. Results and Discussion

Research Results

4.1 Panel Data Regression Model Selection

The initial stage of panel data regression analysis is to determine the best estimation type among the Fixed Effect Model (FEM), Random Effect Model (REM), and Common Effect Model (CEM), using a series of formal tests, namely the Chow Test and Hausman Test (Kartiningrum et al., 2022). In determining the most appropriate panel data estimation model to examine the effect of Education Level (X1) and Labor Force Participation Rate/LFPR (X2) on Unemployment (Y) in the provinces of Sumatra during 2019–2025, several stages of model testing were conducted as follows:

Table 1. Model Selection

Test	p-value	Testing	Best Model
Chow	0.0000	FEM VS CEM	FEM
Hausman	0.0000	FEM VS REM	FEM
LM	-	CEM VS REM	-

Based on the panel data model testing results presented in the table, the Chow test

INCOME JOURNAL OF ECONOMICS DEVELOPMENT
Volume 7, No. 2, July 2027, pp. 507-521
e-ISSN: 3025-3225, DOI : 10.54065/ijed.7.2.2027.926

results show a p-value of 0.0000. Because this probability value is smaller than the 0.05 significance level (0.0000 < 0.05), H0 is rejected and H1 is accepted. Therefore, the more appropriate model is the Fixed Effect Model (FEM).

The Hausman Test then produced a probability value for Cross-section random of 0.0000. This value is also smaller than 0.05 (0.0237 < 0.05), so the statistical decision is to reject H0. The conclusion is that the final model most appropriate for this study is the Fixed Effect Model (FEM). Model Selection Conclusion**:** Because the Fixed Effect Model (FEM) was consistently selected in both the Chow and Hausman tests, the best model used in this study is the Fixed Effect Model (FEM). Therefore, the Lagrange Multiplier (LM) Test no longer needs to be conducted.

4.2 Classical Assumption Tests

Normality Test

The results of the Normality Test are as follows:

Table 2. Normality Test

Variable	Statistic	Value
Y	Skewness	1.270973
	Kurtosis	5.502119
X1	Skewness	0.328296
	Kurtosis	2.368397
X2	Skewness	-0.472880
	Kurtosis	2.318146

Based on Table 2, the normality test results are determined from Skewness and Kurtosis. Variable Y has a skewness value of 1.271 and a kurtosis value of 5.502, meaning that the values are normally distributed because each falls within the range of -2 to +2 for skewness and -7 to +7 for kurtosis. Similarly, variable X1 has a skewness value of 0.328 and a kurtosis value of 2.368, while variable X2 has a skewness value of -0.473 and a kurtosis value of 2.318. Each variable is normally distributed because the normality test results fall within the range of -2 to +2 for skewness and -7 to +7 for kurtosis.

Multicollinearity Test

The results of the multicollinearity test are as follows:

Table 3. Multicollinearity Test

	X1	X2
X1	1.000000	-0.093423
X2	-0.093423	1.000000

The multicollinearity test results in the table above show that all correlation values among the independent variables are below 0.85. Specifically, the correlation coefficient between X1 and X2 is -0.093423 (< 0.85). Therefore, it can be concluded that the model is free from multicollinearity problems among the independent variables and is suitable for proceeding to the heteroscedasticity test.

Heteroscedasticity Test

The results of the heteroscedasticity test are as follows:

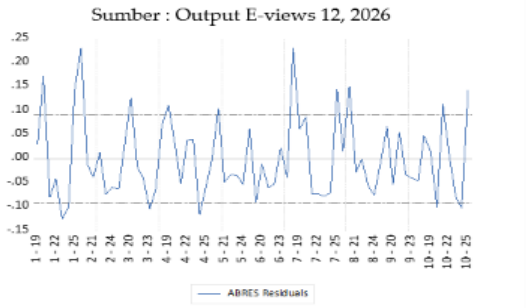


Figure 3. Heteroscedasticity Test

Based on the heteroscedasticity test above, it can be seen that the residual graph (blue) does not cross the boundaries (500 and -500), meaning that the residual variance is the same or that there is no indication of heteroscedasticity. Therefore, the research data pass the heteroscedasticity test.

Autocorrelation Test

Based on the results of the Fixed Effect model estimation, the Durbin-Watson Statistic value is 1.518451. This value is within the range of 1.5 to 2.5, so it can be concluded that the panel data regression model does not experience autocorrelation. Thus, the classical assumption concerning autocorrelation has been fulfilled.

4.3 Panel Data Regression Test (Fem Model)

The Panel Data Regression Test is used to examine the effect of independent variables on the dependent variable in the form of cross-sectional and time-series data (Basuki, 2021). This study uses Education Level (X1), Labor Force Participation Rate/LFPR (X2), and Unemployment (Y) as variables. Based on the panel data regression results using the Fixed Effect Model estimation, the following equation is obtained:

$$Y = 16.58740 - 1.652535X1 + 0.052854X2$$

The explanation is as follows: 1) The Constant Coefficient (C) is 16.58740, meaning that if the Education Level (X1) and Labor Force Participation Rate/LFPR (X2) variables do not change or have a value of 0, the Unemployment Rate (Y) in the provinces of Sumatra is 16.59%. 2) The Education Level (X1) coefficient is -

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1.652535, indicating that every 1-unit increase in Education Level, assuming the LFPR variable remains constant, is associated with a 1.65% decrease in the Unemployment Rate (Y). This negative relationship indicates that the higher the education level of the population, the greater its real impact in reducing unemployment in the provinces of Sumatra. 3) The coefficient of the LFPR variable (X2) is 0.052854, indicating that every 1% increase in LFPR, assuming Education Level remains constant, is estimated to increase the Unemployment Rate (Y) by 0.05%. However, this effect is not statistically significant because its probability value is much greater than 0.05.

4.4 Partial And Simultaneous Hypothesis Testing

Partial Test (t-Statistic Test)

Table 4. t-test

Variable	Coefficient	Std. Error	t-value	p-value
Constant (C)	16.58740	5.135544	3.229921	0.0020
Tingkat Pendidikan	-1.652535	0.562353	-2.938609	0.0047
TPAK	0.052854	0.113136	0.467173	0.6421

Based on the t-test results, Education Level (X1) has a probability value of 0.0047 < 0.05, meaning that Education Level (X1) has a significant effect on Y. The coefficient value of -1.652535 indicates that Education Level (X1) has a negative effect on Y (Unemployment). Meanwhile, LFPR (X2) has a probability value of 0.6421 > 0.05, meaning that LFPR (X2) does not have a significant effect on Y. The coefficient value of 0.052854 indicates a positive direction of the relationship, but it is not statistically significant.

Simultaneous Test (F-Statistic Test) and Coefficient of Determination (R-Squared)

Table 5. F-test

p-value for F-test	0.000000
R^2	0. 814484

Based on the F-test results, the F-statistic value is 23.14929 with a Prob(F-statistic) of 0.000000. Because the probability value is less than 0.05, it can be concluded that Education Level (X1) and LFPR (X2) simultaneously have a significant effect on variable Y. Therefore, it can be concluded that Education Level and LFPR jointly affect unemployment. Based on the table above, the R-squared value is 0.814484. This means that 81.44% of the dependent variable, namely unemployment, can be explained by the independent variables, namely Education Level and LFPR. Meanwhile, the remaining 18.56% can be explained by other factors outside the model.

5. Discussion

5.1 The Effect of Education Level on Unemployment

Education Level has a negative and significant effect on the unemployment rate. The hypothesis-testing results show that Education Level has a probability value of 0.0047, which is smaller than 0.05, indicating a statistically significant effect on unemployment. The coefficient value of -1.652535 indicates that every increase in Education Level will reduce the unemployment rate. This indicates that the higher the education level of the population, the greater the opportunity for them to obtain jobs that are suitable for labor-market needs, thereby reducing the number of unemployed people. Higher education can also improve the quality of human resources, skills, and labor competitiveness, which ultimately can reduce the unemployment rate (Stijepic, 2021). This is consistent with the findings of previous studied, who examined macro employment dynamics in Indonesia and found that education had a negative and significant effect on the unemployment rate (Ismeti & Hameli, 2026). Similar findings were also obtained by previous studied in their study in West Java Province, which showed that the education index was one of the main determinants significantly affecting fluctuations in the open unemployment rate through a panel data regression approach (Fatonah et al., 2023).

5.2 The Effect of Labor Force Participation Rate on Unemployment

The Labor Force Participation Rate (LFPR) does not have a significant effect on the unemployment rate. The results show that the LFPR probability value is 0.6421, which is greater than 0.05, meaning that it does not have a statistically significant effect on unemployment. Nevertheless, the coefficient value of 0.052854 indicates a positive direction of the relationship. This means that an increase in LFPR tends to be followed by an increase in the unemployment rate, but the relationship is not strong enough to serve as a basis for explaining changes in the unemployment rate.
This condition may occur because an increase in the number of people entering the labor force is not always accompanied by the availability of adequate employment opportunities, causing the effect of LFPR on unemployment to become

insignificant (Egeten G et al., 2023). This is consistent with the findings of previous studied, who examined employment dynamics in Indonesian provinces (Wahyuni et al., 2025). Their study found that the Labor Force Participation Rate (LFPR) had a negative but insignificant effect on the open unemployment rate because the increase in the labor force was not accompanied by sufficient employment opportunities.

Based on the simultaneous test (F-test), an F-statistic value of 23.14929 was obtained with a Prob(F-statistic) value of 0.000000. A probability value smaller than 0.05 indicates that Education Level and LFPR jointly have a significant effect on the unemployment rate. Thus, the two variables simultaneously explain changes in the unemployment rate. This result indicates that unemployment is not influenced by only one factor, but also by a combination of various factors related to the quality of human resources and labor-market conditions (Nabila et al., 2026).

Based on the simultaneous testing, all independent variables in the model jointly affect the dependent variable. This is consistent with the research of (Wahyuni et al., 2025). Through the F-test, that study demonstrated that the variables Labor Force Participation Rate (LFPR), Literacy Rate, and Average Years of Schooling simultaneously had a significant effect on the Open Unemployment Rate (TPT).

6. Conclusion

Based on the results of the study, it can be concluded that the level of education has a negative and significant effect on the unemployment rate in Sumatra. This indicates that an increase in the level of education can help reduce unemployment because education can improve the quality of human resources, skills, productivity, and the competitiveness of the workforce in responding to labor market demands. Meanwhile, the Labor Force Participation Rate (LFPR) does not have a significant effect on the unemployment rate. Although the direction of the relationship is positive, an increase in labor force participation is not necessarily followed by a decrease in unemployment. This condition indicates that an increase in the number of people entering the labor force needs to be accompanied by adequate job opportunities so that they can be optimally absorbed into the labor market.

Simultaneously, the level of education and LFPR have a significant effect on the unemployment rate. These results indicate that unemployment is not influenced by a single factor but is related to the quality of human resources and the ability of the labor market to absorb the workforce. Therefore, improving the quality of education needs to be accompanied by policies that support the creation of broader job opportunities that are in accordance with workers' competencies. Thus, efforts to reduce the unemployment rate in Sumatra need to be carried out through an integrated approach involving improvements in the quality of education, workforce competency development, and the expansion of employment opportunities. These efforts are expected to increase labor absorption and support improvements in the welfare of the population.

References

Adianita, H., Susilowati, D., & Karisma, D. A. P. (2024). Analysis of labor force participation levels and number of employment through education on unemployment rates in Indonesia. *Golden Ratio of Data in Summary, 4*(2). https://doi.org/10.32662/golder.v0i0.3408

Akalbeo, B., Martinez-Vazquez, J., & Yedgenov, B. (2023). Fiscal decentralization and structural versus cyclical unemployment levels. *European Journal of Political Economy, 80*, 102477. https://doi.org/10.1016/j.ejpoleco.2023.102477.

Anggraini, Y., & Armida, S. (2025). The effect of population, provincial minimum wage (UMP), and labor force participation rate (LFPR) on unemployment in West Sumatra in 2020–2024. *Jurnal Pendidikan Tambusai, 9*(3), 39109–39119. https://doi.org/10.31004/jptam.v9i3.34932

Aprilia, P., Ritonga, M., & Murdy, K. (2025). Analisis pengaruh tingkat pendidikan dan upah terhadap pengangguran di Provinsi Sumatera Barat tahun 2019–2023. *Jurnal Ekonomi Manajemen Sistem Informasi, 6*(5), 3228–3238. https://doi.org/10.38035/jemsi.v6i5.5184.

Asmara, G. D., & Saleh, R. (2024). Determinants of unemployment: Empirical evidence from Indonesia. *Widya Cipta: Jurnal Sekretari dan Manajemen, 8*(2). https://doi.org/10.31294/widyacipta.v8i2.21753

Bachri, D. A., & Salmah, E. (2025). Pengaruh laju pertumbuhan ekonomi, tingkat partisipasi angkatan kerja, dan rata-rata lama sekolah terhadap pengangguran. *Journal of Trends Economics and Accounting Research, 6*(2), 196–205. https://doi.org/10.47065/jtear.v6i2.2352

Baharuddin, F. (2022). The effect of unemployment and gross regional domestic product on inflation in South Sulawesi Province. *Income Journal of Economics Development, 2*(2), 49–54. https://doi.org/10.54065/ijed.2.2.2022.96

Basuki, A. T. (2021). *Panel data analysis in economic and business research: Equipped with the use of EViews*.

Chaerul. (2023). Influence Amount Resident, Level Education And Unemployment Against Poverty In Regency Pangkajene And Island. *Income Journal Of Economics Development*, *3*(2), 61–65. https://doi.org/10.54065/ijed.3.2.2023.176

Dewi, A. K. (2023). Analysis effect of human development index (HDI), regency/city minimum wage (UMK), investment and unemployment rate on the number of poor people in Bali Province in 2012–2021. *Wiga: Jurnal Penelitian Ilmu Ekonomi, 13*(1), 94–101. https://doi.org/10.30741/WIGA.V13I1.933.

Egeten G, M., Kawung M V, G., & Tolosang D, K. (2023). Analysis of the effect of education level and labor force size on the open unemployment rate in cities in North Sulawesi Province. *Jurnal Berkala Ilmiah Efisiensi, 23*(3), 25–36.

Fatonah, S., Fitriani, F., & Indrasetianingsih, A. (2023). Application of panel data regression to the problem of the open unemployment rate in West Java. *Unisda Journal of Mathematics and Computer Science (UJMC), 9*(1), 21–30. https://doi.org/10.52166/ujmc.v9i1.4232

Febriansyah, H., & Cahyono, H. (2026). The impact of the unemployment rate and the number of people living in poverty on the labor participation rate in Indonesia, 2020–2024. *Indonesian Journal of Advanced Research, 5*(9), 1671–1682. https://doi.org/10.55927/ijar.v5i9.17253.

Haider, A., Jabeen, S., Rankaduwa, W., & Shaheen, F. (2023). The nexus between employment and economic growth: A cross-country analysis. *Sustainability, 15*(15), 11955. https://doi.org/10.3390/su151511955

Hakim, D. R., Disman, & Dahlan, D. (2025). Horizontal educational mismatch among Indonesian graduates: Is there any earnings penalty? *Education Economics, 33*(5), 747–774. https://doi.org/10.1080/09645292.2024.2401998.

Hamzah, M., & Fitriyah. (2025). Causality between economic growth and unemployment in Indonesia. *E-Jurnal Ekonomi Pembangunan, 14*(8). https://doi.org/10.24843/EEB.2025.v14.i08.p06.

Islamiah, N., Rahmatia, Paddu, H., & Zamhuri, M. Y. (2021). Direct and indirect effect of macro economic factors in the west of Indonesia. *Golden Ratio of Social Science and Education, 1*(1). https://doi.org/10.52970/grsse.v1i1.107

Ismeti, E., & Hameli, K. (2026). The effect of education on economic growth and unemployment rate – A comparative analysis between Kosovo and Germany. *International Journal of Comparative Education and Development, 28*(1), 20–35. https://doi.org/10.1108/IJCED-07-2025-0098.

Jeray, J., Putra, S. Y., & Harahap, E. F. (2023). Pengaruh pengangguran, tenaga kerja dan inflasi terhadap pertumbuhan ekonomi di Indonesia. *Menara Ekonomi: Penelitian dan Kajian Ilmiah Bidang Ekonomi, 9*(1), 95–103. https://doi.org/10.31869/me.v9i1.4496.

Kartiningrum, E. D., Notobroto, H. B., Widjanarko, O. B., Kumarijati, N. E., & Yuswatiningsih, E. (2022). *Application of regression and correlation in research data analysis*.

Kettanurak, S. (2025). Job employment and vertical mismatch: Evidence from Thailand. *Asian-Pacific Economic Literature, 39*(2), 122–133. https://doi.org/10.1111/apel.12447

Lazuardi, M. A., & Santoso, D. B. (2024). Analisis tingkat pengangguran terbuka dan upah minimum di Provinsi Jawa Barat. *Journal of Development Economic and Social Studies, 3*(3).

https://doi.org/10.21776/jdess.2024.03.3.23.

Minah, N., & Sekaringsih, R. B. (2023). Determinants of unemployment rate in Indonesia (2011–2021 period). *Bulletin of Islamic Economics, 2*(1). https://doi.org/10.14421/bie.2023.021-04

Mohamed, A. A. (2024). Economic growth and unemployment nexus: Empirical test of Okun's law in Somalia. *Journal of Economic Structures, 13*, Article 16. https://doi.org/10.1186/s40008-024-00337-y

Nabila, A. P. A., Maranda, D., Susanti, R., Laga, S. A. D., & Setyanto, A. R. (2026). The effect of labor force growth on the unemployment rate in Southern Sumatra, 2014–2019. *Jurnal Intelek Dan Cendikiawan Nusantara, 2*(6), 11227–11238.

Permatasari, D., Winanto, A. R., & Abas, S. (2024). The effect of labor force participation rate, provincial minimum wage, and inflation on the open unemployment rate in Indonesia in 2010–2023. *JPEK (Jurnal Pendidikan Ekonomi Dan Kewirausahaan), 8*(3), 1179–1188. https://doi.org/10.29408/jpek.v8i3.28267

Putranto, F. G. F., Natalia, C., & Pitriyani, N. K. D. (2024). Closing the gap between education and labor market requirement: Do vocational education matter? *The Journal of Indonesia Sustainable Development Planning, 5*(3), 181–191. https://doi.org/10.46456/jisdep.v5i3.614

Rahmawati, Y., Izzati, R. N., & Luthfiyyah, F. N. (2024). Pengaruh tingkat partisipasi angkatan kerja, indeks pembangunan manusia, dan upah minimum terhadap pengangguran di Banten. *Independent: Journal of Economics, 4*(3), 49–59. https://doi.org/10.26740/independent.v4i3.65189.

Sari, V. K., Cahyadin, M., Ignasiak-Szulc, A., & Ahmad, R. (2023). Threshold levels of poverty and unemployment rates on economic growth in Indonesia during COVID-19 pandemic. *Jurnal Ekonomi dan Studi Pembangunan, 15*(1), 74–87. https://doi.org/10.17977/um002v15i12023p074

Setiawana, E., Fitriyani, N., & Harsyiah, L. (2024). Modeling the open unemployment rate in Indonesia using panel data regression analysis. *Eigen Mathematics Journal, 7*(1), 34–43. https://doi.org/10.29303/emj.v7i1.184.

Sidabutar, M. A. R., & Putri, N. T. (2024). The influence of education, UMP, inflation, and investment on unemployment rates in Indonesia. *Cita Ekonomika: Jurnal Ilmu Ekonomi, 18*(2), 76–85. https://doi.org/10.51125/citaekonomika.v18i2.16162.

Siregar, T. H. (2020). Impacts of minimum wages on employment and unemployment in Indonesia. *Journal of the Asia Pacific Economy, 25*(1), 62–78. https://doi.org/10.1080/13547860.2019.1625585.

Stijepic, D. (2021). A cross-country study of skills and unemployment flows. *Journal for Labour Market Research, 55*, Article 9. https://doi.org/10.1186/s12651-021-00289-x

Sugiyono. (2013). *Quantitative, qualitative, and research and development methods*.

Sultana, N., Rahman, M. M., & Khanam, R. (2022). Informal sector employment and economic growth: Evidence from developing countries in SDG perspective. *Sustainability, 14*(19), 11989. https://doi.org/10.3390/su141911989

Suparman, S., & Muzakir, M. (2023). Regional inequality, human capital, unemployment, and economic growth in Indonesia: Panel regression approach. *Cogent Economics & Finance*. https://doi.org/10.1080/23322039.2023.2251803

Ulfiyah, N., Sari, D. D., & Ningsih, S. (2026). Analisis tingkat pengangguran terbuka (TPT) Provinsi Jawa Tengah tahun 2016–2025. *Jurnal Riset Multidisiplin Edukasi, 3*(3), 376–384. https://doi.org/10.71282/jurmie.v3i3.1783.

Wahyuni, L., Wati, N. K., Ardiansyah, M. F. N., Erhan, W. S., Afandi, M. I., Hasan, B., & Dinianti, B. T. (2025). The effect of labor force participation rate, literacy rate, average years of schooling, and dependency burden on the open unemployment rate in Indonesia, 2018–2023. *Jurnal Publikasi Ekonomi dan Akuntansi, 5*(3), 716–727. https://doi.org/10.51903/jupea.v5i3.4503.

Widodo, E., Alhaqq, F. H. A., Ginastuti, A. P.,

Alifyah, H., & Pramudita, Z. N. (2025). Panel data regression analysis for modeling the open unemployment rate in West Java Province in 2019–2022. *Emerging Statistics and Data Science Journal, 3*(3), 650–661. https://doi.org/10.20885/esds.vol3.iss.3.art18.

Yi, M., Mueller, S., & Stegmaier, J. (2024). Industry mix, local labor markets, and the incidence of trade shocks. *Journal of Labor Economics, 42*(3). https://doi.org/10.1086/724569

Zilda, A. T., Pramita, C. H., Apriliyana, M. I., Pramana, A. B. A., Mega, D. A., & Utami, D. T. (2025). Analisis pengaruh tingkat pendidikan dan pengangguran terhadap pendapatan masyarakat di Indonesia. *Determinasi: Jurnal Penelitian Ekonomi Manajemen dan Akuntansi, 3*(3), 329–337. https://doi.org/10.23917/determinasi.v3i3.483.