

The Impact of Population Size, Unemployment Rates, and the Minimum Wage on Poverty in Indonesia: A Panel Data Analysis of 33 Provinces from 2015 to 2023

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Abstract: Poverty is a socioeconomic issue that remains a key focus of development in Indonesia. Poverty rates are influenced by various factors, including population size, unemployment rates, and minimum wage policies. This study aims to analyze the impact of population size, unemployment rates, and minimum wages on poverty rates in Indonesia. The research method employed is a quantitative approach using panel data analysis covering 33 provinces in Indonesia over the 2015–2023 period. The data used are secondary data obtained from the Central Statistics Agency (BPS) and other relevant sources. The analysis techniques employed include the selection of panel data models (Common Effect Model, Fixed Effect Model, and Random Effect Model) as well as testing of classical assumptions. The results indicate that, simultaneously, population size, unemployment rates, and minimum wage policies have a significant impact on poverty rates in Indonesia. These findings indicate that population size, unemployment rates, and minimum wage policies are contributing factors to the high poverty rate in Indonesia. Therefore, the government is

Abstrak: Kemiskinan merupakan permasalahan sosial ekonomi yang masih menjadi fokus utama pembangunan di Indonesia. Tingkat kemiskinan dipengaruhi oleh berbagai faktor, antara lain jumlah penduduk, tingkat pengangguran, dan kebijakan upah minimum. Penelitian ini bertujuan untuk menganalisis pengaruh jumlah penduduk, tingkat pengangguran, dan upah minimum terhadap tingkat kemiskinan di Indonesia. Metode penelitian yang digunakan adalah pendekatan kuantitatif dengan analisis data panel yang mencakup 33 provinsi di Indonesia selama periode 2015–2023. Data yang digunakan merupakan data sekunder yang diperoleh dari Badan Pusat Statistik (BPS) dan sumber terkait lainnya. Teknik analisis yang digunakan meliputi pemilihan model data panel (Common Effect Model, Fixed Effect Model, dan Random Effect Model) serta pengujian asumsi klasik. Hasil penelitian menunjukkan bahwa secara simultan jumlah penduduk, tingkat pengangguran, dan upah minimum berpengaruh signifikan terhadap tingkat kemiskinan di Indonesia. Temuan ini mengindikasikan

expected to formulate policies focused on controlling population growth, reducing unemployment rates, and improving workers' welfare to sustainably reduce poverty levels.

Keywords: Poverty; Population; Unemployment Rate; Minimum Wage.

bahwa jumlah penduduk, tingkat pengangguran dan kebijakan upah minimum menjadi faktor penyebab tingginya tingkat kemiskinan di Indonesia. Oleh karena itu, pemerintah diharapkan dapat merumuskan kebijakan yang berorientasi pada pengendalian pertumbuhan penduduk, penurunan tingkat pengangguran, serta peningkatan kesejahteraan pekerja guna menekan tingkat kemiskinan secara berkelanjutan.

Kata Kunci: Kemiskinan; Jumlah Penduduk; Tingkat Pengangguran; Upah Minimum.

A. Introduction

Poverty is one of the development issues that remains a major challenge for developing countries, including Indonesia. The existence of poverty not only reflects the population's limited economic capacity to meet basic needs, but also indicates restricted access to education, healthcare, employment opportunities, and various other productive resources (Qulsum et al., 2024). Therefore, poverty alleviation has become one of the primary goals of national development, as reflected in various government policies and the global development agenda through the Sustainable Development Goals (SDGs), particularly the first goal: to end poverty in all its forms everywhere (Sultanova, 2024). From a development economics perspective, poverty is a multidimensional phenomenon influenced by various economic, social, demographic, and institutional factors (Abdulwasaa & Kawale, 2023). Poverty is not only related to low income, but also reflects an individual's limited ability to access the resources needed to achieve a decent standard of living. Therefore, poverty reduction efforts cannot be achieved solely by increasing people's incomes; they also require improvements in various aspects that affect the overall well-being of society (Hakobyan & Gevorgyan, 2025). Poverty is the inability to live a decent life. The factors contributing to poverty are always linked to a

lack of skills, health issues, limited capital, high livelihood risks, and low productivity (Sharath, 2020). Poverty then manifests itself as vulnerability, marginalization, powerlessness, dependency, and social exclusion. This complexity indicates that poverty alleviation must be addressed through comprehensive, cross-sectoral efforts. This definition is very general in nature and does not yet provide the necessary technical and operational tools (Siziba & Mapuva, 2023). (Suresh, 2023) defines poverty, first, as low income measured accurately based on consumption and expenditure levels. Second, poverty due to material deprivation, which is viewed not only in terms of income but also the lack of other material factors such as housing, clothing, transportation and communication, as well as access to education, health, and other social services. Third, poverty is due to a lack of capabilities not only material but also non-material; a person is considered poor if they are unable to live productively and creatively in accordance with their needs and interests. Fourth, poverty is due to multidimensional deprivation or lack and deprivation.

In recent decades, Indonesia has made significant progress in reducing poverty rates. Various social protection programs, infrastructure development, expanded access to education, and increased employment opportunities have contributed to improvements in people’s well-being. However, this reduction in poverty rates has not yet been fully accompanied by equitable distribution of well-being across regions (Sinaga, 2022).

Table 1. Poverty Rates in Indonesia’s 33 Provinces, 2015–2023 (percent)

Provinces	Years								
	2015	2016	2017	2018	2019	2020	2021	2022	2023
Aceh	17,08	16,73	16,89	15,97	15,32	14,99	15,33	14,64	14,45
Sumut	10,53	10,53	10,22	9,22	8,83	8,75	9,01	8,42	8,15
Sumbar	7,31	7,09	6,87	6,65	6,42	6,28	6,63	5,92	5,95
Riau	8,42	7,98	7,78	7,39	7,08	6,28	7,12	6,78	6,68
Jambi	8,86	8,41	8,19	7,92	7,6	7,58	8,09	7,62	7,58
Sumsel	14,25	13,54	13,19	12,8	12,71	12,66	12,84	11,9	11,87
Bengkulu	17,88	17,32	16,45	14,43	15,23	15,03	15,22	15,62	14,04
Lampung	14,35	14,49	13,69	13,14	12,62	12,34	12,62	11,57	11,11
Kep.bangka	5,4	5,22	5,2	5,25	4,62	4,53	4,9	4,45	4,52
Kep. Riau	6,24	5,98	6,06	6,2	5,9	5,92	6,12	6,24	5,69

DKI Jakarta	3,93	3,75	3,77	3,57	3,47	4,53	4,72	4,69	4,44
Jabar	9,53	8,95	8,71	7,45	6,91	7,88	8,4	8,06	7,62
Jateng	13,58	13,23	13,01	11,32	10,8	11,41	11,79	10,93	10,77
DIY	14,91	13,34	13,02	12,13	11,7	12,28	12,8	11,34	11,04
Jatim	12,34	12,05	11,17	10,98	10,37	11,09	11,4	10,38	10,35
Banten	5,9	5,42	5,45	5,24	5,09	5,92	5,92	6,66	6,17
Bali	4,74	4,25	4,25	4,01	3,79	3,78	4,53	4,57	4,25
NTB	17,1	16,48	16,07	14,75	14,56	13,97	14,14	13,68	13,85
NTT	22,61	22,19	21,85	21,35	21,09	20,9	20,99	20,05	19,96
Kalbar	8,03	16,48	7,88	7,77	7,49	7,17	7,15	6,73	6,71
Kalteng	5,94	5,66	5,37	5,17	4,98	4,82	5,16	5,28	5,11
Kalsel	4,99	4,85	4,73	4,54	4,55	4,38	4,83	4,49	4,29
Kaltim	6,23	6,11	6,19	6,03	5,94	6,1	6,54	6,31	6,11
Kal.Utara	6,24	6,23	7,22	7,09	6,63	6,8	7,36	6,77	6,45
Sulut	8,65	8,34	8,1	7,8	7,66	7,62	7,77	7,28	7,38
Sulteng	14,66	14,45	14,14	14,01	13,48	12,92	13	12,33	12,41
Sulsel	9,39	9,4	9,38	9,06	8,69	8,72	8,78	8,63	8,7
Sul Tenggara	12,9	12,88	12,81	11,63	11,24	11	11,66	11,17	11,43
Gorontalo	18,32	17,72	17,65	16,81	15,52	15,22	15,61	15,42	15,15
Sulbar	12,4	11,74	11,3	11,25	11,02	10,87	11,29	11,75	11,49
Maluku	19,51	19,18	18,45	18,12	17,69	17,44	17,87	15,97	15,42
Maluku Utara	6,84	6,33	6,35	6,64	6,77	6,78	6,89	6,23	6,46
Papua barat	25,82	25,43	25,1	23,01	22,17	21,37	21,84	21,33	20,49
Papua	28,17	28,54	27,62	27,74	27,53	26,64	21,84	26,56	26,03

Source: Badan Pusat Statistik (BPS)

Provincial poverty data for 2015–2023 show significant disparities among provinces in Indonesia. In 2023, the highest poverty rate was recorded in Papua Province at 26.03 percent, followed by West Papua at 20.49 percent and East Nusa Tenggara at 19.96 percent. In contrast, several provinces such as Bali, South Kalimantan, and the Bangka Belitung Islands have poverty rates below five percent. These differences indicate that the benefits of development have not been felt equally across all regions in Indonesia. In addition to highlighting regional disparities, provincial poverty data for the 2015–2023 period also reveal dynamics worth examining. In general, most provinces have experienced a downward trend in poverty, though the rate of decline varies. Aceh Province, for example, saw its poverty rate drop from 17.08 percent in 2015 to 14.45 percent in 2023. On the other hand, Papua still has a very high poverty rate, despite a decrease from 28.17 percent to 26.03 percent over the same period. This situation indicates that economic growth and the development

policies implemented have not yet been fully effective in addressing the root causes of poverty in each region (Cuesta et al., 2020).

Another trend evident in the data is the rise in poverty rates in several provinces during the 2020–2021 COVID-19 pandemic. DKI Jakarta saw its poverty rate rise from 3.47 percent in 2019 to 4.72 percent in 2021. West Java's rate increased from 6.91 percent to 8.40 percent, while Central Java's rose from 10.80 percent to 11.79 percent over the same period. These conditions indicate that poverty is highly vulnerable to economic shocks that affect production, household income, and employment opportunities. Therefore, understanding the factors that influence poverty is crucial as a basis for formulating more effective development policies (Hallegatte et al., 2020).

One factor believed to influence poverty rates is population size. According to the classical theory proposed by Malthus, population growth that outpaces production growth can put pressure on resource availability, thereby potentially increasing poverty (Muhammad, 2008). The larger the population, the greater the need for jobs, education, healthcare, and various other public facilities. If population growth is not matched by an increase in the region's economic capacity, it will put pressure on the labor market and income distribution, which could ultimately increase the number of people living in poverty. However, modern development theory views the population not merely as a burden on development, but also as a resource for development when supported by adequate human capital. A productive population can drive economic growth through increased production, consumption, and investment. Therefore, the relationship between population size and poverty is an interesting empirical issue because it reveals varying effects across regions depending on each region's economic characteristics (Desmawan et al., 2023). In addition to population size, the unemployment rate is a factor that is theoretically closely linked to poverty. According to labor market theory, unemployment occurs when a portion of the labor force is unable to secure income-generating employment. These conditions reduce households' ability to meet their basic needs, thereby increasing the risk of poverty. Individuals who are unemployed tend to

face income uncertainty and limited access to various social services, which ultimately results in low levels of well-being (Ehlert, 2025). Consequently, high unemployment rates are often linked to an increase in the number of poor people in a region.

Another factor believed to influence poverty is the minimum wage. Conceptually, minimum wage policies are designed to protect workers by ensuring they earn enough to meet their basic living needs. Raising the minimum wage is expected to boost purchasing power and reduce poverty by increasing workers' household incomes. According to the efficiency wage theory, higher wages can increase labor productivity and workers' well-being (Dervishi, 2023). However, some studies also suggest that increases in the minimum wage that are not in line with productivity may reduce labor demand, thereby leading to unemployment. Therefore, the impact of the minimum wage on poverty remains a subject of debate in various empirical studies. Numerous studies have been conducted on the relationship between population size, unemployment, minimum wage, and poverty at both the national and regional levels. However, the findings of previous studies remain inconsistent. Some studies have found that population size and unemployment rates have a positive effect on poverty, while the minimum wage has a negative effect on poverty. On the other hand, some studies have found that the effects of these variables are not significant or even suggest a different direction of the relationship. These differing research findings indicate that the relationship between economic factors and poverty still requires further study using a broader data set and a longer observation period. Given these conditions, this study analyzes the effects of population size, unemployment rates, and minimum wages on poverty across 33 provinces in Indonesia during the 2015–2023 period using a panel data approach. The use of panel data allows for the combination of the time series and cross-sectional dimensions, thereby enabling more efficient estimates and accommodating the heterogeneity of characteristics across each province (Stankov & Roganović, 2025). In addition, the study period covers conditions before, during, and after the COVID-19 pandemic, and is thus expected to provide a more comprehensive

picture of poverty dynamics in Indonesia. This study is important because its findings are expected to provide empirical insights into the factors influencing interprovincial poverty in Indonesia. The research findings are also expected to provide input for both the central and local governments in formulating more effective policies on population, labor, and wages to support the accelerated reduction of poverty and the sustainable.

B. Research Method

This study employs a quantitative research design. This study examines the relationship between the poverty rate as the dependent variable and population size, unemployment rate, and minimum wage as independent variables. The data used in this study are secondary data sourced from the Central Statistics Agency of each province, analyzed using panel data analysis specifically, combining time-series data (covering the period 2015–2023) and cross-sectional data from 33 provinces in Indonesia.

$$\text{Poverty}_{it} = \alpha + \beta_1 \text{POP}_{it} + \beta_2 \text{UNEMP}_{it} + \beta_3 \text{UMP}_{it} + \varepsilon_{it}$$

Poverty _{it}	: Poverty rates by province in Indonesia
α	: Constant
$\beta_1, \beta_2, \beta_3$: The regression coefficients for each independent variable
POP _{it}	: Annual population by province
UNEP _{it}	: Annual unemployment rate by province
UMP _{it}	: Annual minimum wage by province
ε_{it}	: Error term

Panel data is a combination of cross-sectional and time-series data. Cross-sectional data consists of data on one or more variables collected for a number of individuals at a single point in time. Time-series data, on the other hand, consists of data on one or more variables collected over time. Thus, in panel data, the same cross-sectional units are observed over time (Zamore, 2022). The data analysis technique uses the Common Effects Model (CEM). In panel data, the Common Effects Model assumes that the intercept and slope values for each variable are the same across all cross-sectional units and time series (Das, 2019). Fixed Effects Model (FEM): In a fixed

effects model for panel data, it is assumed that the slope coefficients for each variable are constant, but the intercepts vary across cross-sections. Dummy variables can be used to account for these differences in intercepts, which is why this model is also known as the least squares dummy variable model (Ahmad & Raupong, 2023). Random Effects Model (REM): In the random effects model, differences in individual and time characteristics are accounted for in the model's error term. Since there are two components contributing to the error individual and time the random error in the random effects model must also be decomposed into a time-specific error and a combined error.(Al-Juwari et al., 2024).

The Chow test was used to determine the appropriate panel data model. The Chow test is used to determine whether a common-effects model or a fixed-effects model is most appropriate for estimating panel data. The Chow test compares the common-effects model with the fixed-effects model (Levendis, 2023). The Hausman test, which examines whether there is a correlation between the regression and individual effects, is used to determine whether a fixed-effects or random-effects model is more appropriate (Chen et al., 2020). The t-test, or partial test, is a test used to determine whether an independent variable has a significant partial effect on the dependent variable. It tests the significance level of the correlation coefficient used to determine the strength of the relationship between variable X and variable Y (Ramani et al., 2025). F-Test: This test is used to determine whether two independent variables, taken simultaneously or together, have a significant effect on the dependent variable. The F-test is used to test the significance of the combined effect of all independent variables (X) on the dependent variable (Y) (Ross & Willson, 2017). Coefficient of Determination (R^2) Test: This analysis is used to determine the extent to which the independent variable influences the dependent variable (Borsa & Fekete, 2026).

C. Result and Discussion

The panel data analysis in this study was conducted through several stages of testing to obtain the most appropriate estimation model. The use of panel data allows for the combination of cross-sectional and time-series data, thereby enabling more efficient estimates and accommodating the heterogeneity of characteristics across provinces. Before interpreting the regression results, descriptive statistical tests, panel data model selection, and classical assumption tests were first conducted to ensure that the model used could adequately explain the relationships between variables (Maylani & Sari, 2025).

Table 2. Result of Descriptive Statistical Test

	POV	POP	UMP	UNEMP
Mean	10.83716	15.28873	14.85967	5.187484
Median	9.140000	15.23165	14.83812	4.785000
Maximum	28.54000	17.72608	15.80711	10.95000
Minimum	3.470000	13.25264	14.20405	1.400000
Std. Dev.	5.618864	1.012829	0.256892	1.816770
Skewness	1.043687	0.557403	0.398410	0.731258
Kurtosis	3.651379	3.077022	3.201966	3.315354
Jarque-Bera	60.96319	15.92123	8.615349	28.53959
Probability	0.000000	0.000349	0.013465	0.000001
Sum	3316.170	4678.352	4547.058	1587.370
Sum Sq. Dev.	9629.348	312.8758	20.12800	1006.699
Observations	306	306	306	306

The results of the descriptive statistics show that poverty rates vary significantly across provinces. The average poverty rate of 10.84 percent, with a standard deviation of 5.62, indicates that there are still significant disparities in welfare between regions. The maximum rate of 28.54 percent and the minimum rate of 3.47 percent demonstrate that development success has not been evenly distributed. The population variable is relatively more stable than the other variables, whereas the unemployment rate shows

considerable variation, potentially making it one of the sources of differences in poverty rates across provinces. Overall, the descriptive statistics indicate data heterogeneity, which supports the use of a panel data approach.

Table 3. Chow Test Result

Redundant Fixed Effects Tests			
Equation: Untitled			
Test cross-section fixed effects			
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Effects Test	Statistic	d.f.	Prob.
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Cross-section F	353.568635	(33,269)	0.0000
Cross-section Chi-square	1160.556111	33	0.0000
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Discussion of the Chow Test: The cross-sectional F-statistic value of 0.0000 indicates that the Fixed Effects model is superior to the Common Effects model. These results suggest that each province has unique characteristics that influence poverty levels, so it is inappropriate to assume that they share the same intercept.

Table 4. Result of Hausman test

Correlated Random Effects - Hausman Test			
Equation: Untitled			
Test cross-section random effects			
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Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
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Cross-section random	6.020670	3	0.1106
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Based on the table above, it can be seen that the probability value of 0.1106 is greater than 0.05; therefore, the REM model is selected. Based on the results of the Chow test, the fixed-effects model is more appropriate than the Common Effects Model (CEM). Furthermore, the results of the Hausman test indicate that the probability value is greater than 0.05, so the Random Effects Model is more appropriate to use than the Fixed-Effects Model; the Lagrange Multiplier test was not performed because the CEM was eliminated in the Chow test. Thus, the panel data regression model used in this study is the Random Effects Model (REM).

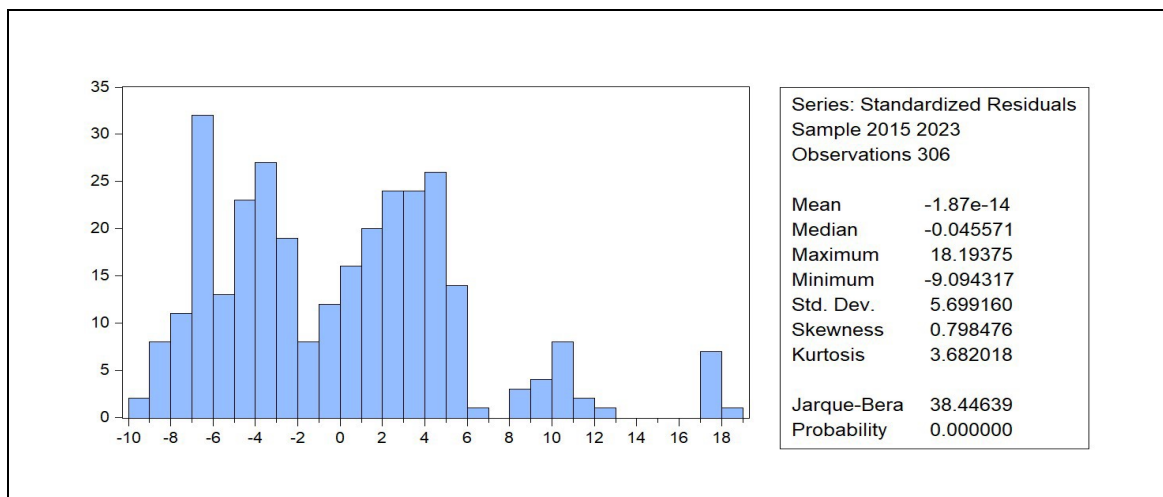


Figure 1. Result of Normality Test

From the table above, it can be seen that the Jarque-Bera statistic is 38.44639 with a p-value of 0.000, which is less than 0.05; therefore, it can be concluded that the data are not normally distributed. Although the Jarque-Bera test results indicate that the residuals are not normally distributed, based on the Central Limit Theorem, if $N > 30$, it can be assumed that the data meets the assumption of normality. Since the sample size in this study is $306 > 30$, regression analysis can still be performed.

Table 5. Result of the Multicollinearity Test

	POP	UMP	UNEMP
POP	1.000000	-0.227120	0.260542
UMP	-0.227120	1.000000	0.310722
UNEMP	0.260542	0.310722	1.000000

Based on the table above, it can be seen that the correlation coefficients of the variables are less than 0.85; therefore, it can be concluded that there is no multicollinearity or that the data passed the multicollinearity test.

Table 5. Result of the Heteroscedasticity Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	44.48803	6.384111	6.968555	0.0000
POP	-0.764836	0.403515	-1.895431	0.0590
UNEMP	0.117140	0.043252	2.708307	0.0071
UMP	-1.936923	0.250175	-7.742280	0.0000

Based on the table above, the p-values for each variable can be seen. The p-value for the POP variable is $0.0590 > 0.05$, the p-value for the UNEMP variable is < 0.05 , and the p-value for the UMP variable is $0.00 < 0.05$. Therefore, it can be concluded that the UNEMP and UMP variables exhibit signs of heteroscedasticity. The test results indicate the presence of heteroscedasticity in several variables. This condition is commonly found in panel data covering regions with diverse economic characteristics. Therefore, the research findings should be interpreted with caution, and further research is recommended using robust standard errors (Mahrani et al., 2025).

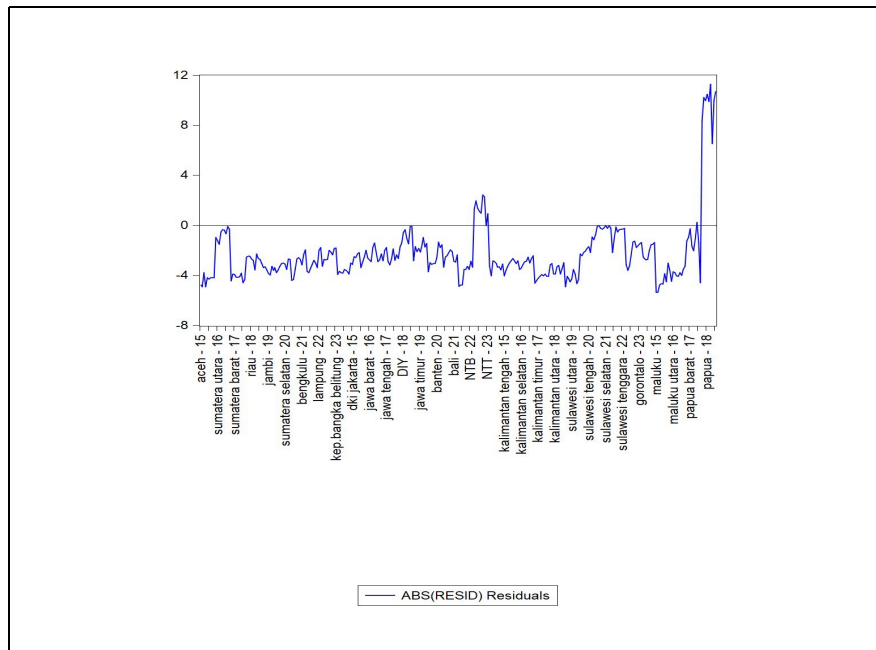


Figure 2. ABS. Residual

Table 7. Autocorrelation Test Results

R-squared	0.262432	Mean dependent var	0.555077
Adjusted R-squared	0.255105	S.D. dependent var	1.010196
S.E. of regression	0.871873	Sum squared resid	229.5689
F-statistic	35.81784	Durbin-Watson stat	1.354119
Prob(F-statistic)	0.000000		

Based on the test results, the Durbin-Watson statistic is 1.354119. This value is insufficient to serve as a basis for concluding whether or not autocorrelation exists in the panel data model. The interpretation of autocorrelation in panel data should utilize a more appropriate test, such as the panel serial correlation test. Therefore, the Durbin-Watson result in this study is presented only as supporting information and is not used as the primary basis for decision-making (Kim, 2022).

Table 8. Result of the Panel Data Regression Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	85.49731	10.29687	8.303236	0.0000
POP	-2.324668	0.692307	-3.357857	0.0009
UMP	-2.690419	0.357161	-7.532796	0.0000
UNEMP	0.165747	0.060684	2.731319	0.0067

Regression Equation Formula

$$POV = 85.49731 - 2.324668 \text{ POP} - 2.324668 \text{ UNEMP} + 0.165747 + e_{it}$$

The results of the estimation indicate that population size (POP) and the provincial minimum wage (UMP) have a significant negative effect on the poverty rate, while the unemployment rate (UNEMP) has a significant positive effect. These findings suggest that variations in poverty across provinces in Indonesia are influenced not only by labor market conditions but also by demographic dynamics and wage policies. The negative population growth rate indicates that population growth during the study period was correlated with a decline in the poverty rate. These findings indicate that the population is not always a burden on development, but can serve as a driver of development if it is predominantly made up of people of working age and supported by improvements in human capital (Farah & Sugiyanto, 2024). In many provinces across Indonesia, population growth has gone hand in hand with increased economic activity, market expansion, and a growing productive workforce, thereby driving an increase in community income. These findings support the view of modern development theory that regards the population as an asset to development provided that its quality and productivity continue to improve (Kotschy et al., 2020).

The unemployment rate variable has a positive and significant effect on poverty. Economically speaking, unemployment leads to a loss of household income, thereby

reducing people's ability to meet their basic needs. The higher the unemployment rate in a province, the greater the risk of an increase in the number of people living in poverty. This finding is consistent with labor market theory, which states that limited job opportunities reduce people's well-being and increase their vulnerability to poverty. This trend was also evident during the COVID-19 pandemic, when rising unemployment in various provinces was followed by an increase in poverty rates (Dakhilullah, 2022).

The provincial minimum wage variable has a significant negative effect on poverty. These results indicate that an increase in the minimum wage is correlated with a decrease in the poverty rate. An increase in the minimum wage can boost workers' purchasing power, improve households' ability to meet their basic needs, and reduce the economic vulnerability of low-income groups. These findings suggest that wage policies that take into account the cost of a decent standard of living have the potential to serve as a tool for poverty reduction, particularly for formal-sector workers who receive wages in accordance with applicable regulations (Susanto & Windyastuti, 2023).

Table 9. Result of the F-Test

Weighted Statistics			
R-squared	0.205957	Mean dependent var	0.563412
Adjusted R-squared	0.198069	S.D. dependent var	1.011398
S.E. of regression	0.905713	Sum squared resid	247.7355
F-statistic	26.11073	Durbin-Watson stat	1.222486
Prob(F-statistic)	0.000000		

From the table above, we can see that the F-statistic is 26.11073 and the probability (F-statistic) is $0.0000 < 0.5$; therefore, we can conclude that variable X has a significant effect on variable Y.

Table 10. Test of the Coefficient of Determination (R^2)

R-squared	0.262432	Mean dependent var	0.555077
Adjusted R-squared	0.255105	S.D. dependent var	1.010196
S.E. of regression	0.871873	Sum squared resid	229.5689
F-statistic	35.81784	Durbin-Watson stat	1.354119
Prob(F-statistic)	0.000000		

Based on the test results, the adjusted R-squared value was 0.255105, or approximately 25.51 percent. This value indicates that 25.51 percent of the variation in poverty levels can be explained by the variables of population size, unemployment rate, and minimum wage, while the remaining 74.49 percent is explained by factors outside the model, such as economic growth, education levels, the human development index, inflation, income inequality, and various government social policies.

D. Conclusion

Based on the results of a panel data analysis of 33 provinces in Indonesia over the 2015–2023 period, it can be concluded that population size, unemployment rate, and minimum wage have a significant impact on poverty levels in Indonesia. Collectively, these three independent variables play a crucial role in explaining variations in poverty rates across provinces and over time. Based on the data analysis, variable X has a significant effect of 25.5105% on variable Y. Overall, the findings of this study suggest that poverty alleviation policies in Indonesia need to be implemented in an integrated and sustainable manner.

The government is expected to strengthen population growth control by improving the quality of education and healthcare, promoting the creation of productive jobs to reduce unemployment rates, and establishing fair minimum wage policies that are responsive to the public's need for a decent standard of living. With well-targeted and synergistic policies across sectors, it is hoped that poverty rates in Indonesia can be reduced evenly across all provinces.

E. Bibliography

- Abdulwasaa, M. A., & Kawale, S. V. (2023). Determinants of Poverty: A Mini-Review. *Current Journal of Applied Science and Technology*, 42(21), 27–36. <https://doi.org/10.9734/cjast/2023/v42i214161>
- Ahmad, N. A., & Raupong, R. (2023). Estimation Of Parameter Regression Panel Data Model Using Least Square Dummy Variable Method. *Jurnal Matematika, Statistika Dan Komputasi*, 20(1), 221–228. <https://doi.org/10.20956/j.v20i1.27530>
- Al-Juwari, M., Radhi, K. H., & Al-Mamouri, A. O. (2024). Analytical Explanations of the Concept of the Fixed Term and the Random Error Term in Econometric Models. *International Journal of Religion*, 5(8), 1037–1045. <https://doi.org/10.61707/jk5d4748>
- Borsa, B., & Fekete, A. (2026). Influence of random variations on the relationship between variables. In *Agricultural Engineering, Volume 4: Power, processing and systems* (pp. 2507–2514). CRC Press. <https://doi.org/10.1201/9781003763529-54>
- Chen, J., Yue, R., & Wu, J. (2020). Testing for individual and time effects in the two-way error component model with time-invariant regressors. *Economic Modelling*, 92, 216–229. <https://doi.org/10.1016/j.econmod.2020.01.002>
- Cuesta, J., Negre, M., Revenga, A., & Silva-Jauregui, C. (2020). Is it really possible for countries to simultaneously grow and reduce poverty and inequality? Going beyond global narratives. *Oxford Development Studies*, 48(3), 256–270. <https://doi.org/10.1080/13600818.2020.1784864>
- Dakhilullah, M. F. (2022). Pengaruh Upah Minimum Dan Pengangguran Terhadap Kemiskinan di Pulau Jawa Sebelum dan Selama Pandemi Covid-19. *Wawasan : Jurnal Ilmu Manajemen, Ekonomi Dan Kewirausahaan*, 1(1), 60–75. <https://doi.org/10.58192/wawasan.v1i1.239>
- Das, P. (2019). Panel Data Analysis: Static Models. In *Econometrics in Theory and Practice* (pp. 457–497). Springer Singapore. https://doi.org/10.1007/978-981-32-9019-8_15
- Dervishi, B. (2023). The effect of minimum wage increases on inflation. *International Journal of Research in Business and Social Science (2147- 4478)*, 12(3), 258–262. <https://doi.org/10.20525/ijrbs.v12i3.2512>
- Desmawan, D., Fitrianovaline, A., Latuconsina, A. D., Siregar, M. N., Ramdani, M. N., & Fauzan, N. (2023). Analisis Laju Pertumbuhan Penduduk Terhadap Kemiskinan Provinsi Banten 2017-2019. *Jurnal Manajemen Akuntansi (JUMSI)*, 3(2), 554–558. <https://doi.org/10.36987/jumsi.v3i2.4102>
- Ehlert, M. (2025). Unemployment as a Social Problem. In *The Blackwell Encyclopedia of Sociology* (pp. 1–5). Wiley. <https://doi.org/10.1002/9781405165518.wbeosu003.pub3>

- Farah, A., & Sugiyanto, F. X. (2024). Contribution of Demographic Factors to Indonesia's Economic Growth. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi Dan Pembangunan*, 171–181. <https://doi.org/10.23917/jep.v25i2.23816>
- Hakobyan, M., & Gevorgyan, P. (2025). The Interaction Between Economic Growth And Poverty In The Context Of Inclusive Development. *Crisis Management and Technologies*, 1–14. <https://doi.org/10.61746/18292984-2025.1cmt-62>
- Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From Poverty to Disaster and Back: a Review of the Literature. *Economics of Disasters and Climate Change*, 4(1), 223–247. <https://doi.org/10.1007/s41885-020-00060-5>
- Kim, H. (2022). A finite sample correction for the panel Durbin–Watson test. *Applied Economics*, 54(28), 3197–3205. <https://doi.org/10.1080/00036846.2020.1869172>
- Kotschy, R., Suarez Urtaza, P., & Sunde, U. (2020). The demographic dividend is more than an education dividend. *Proceedings of the National Academy of Sciences*, 117(42), 25982–25984. <https://doi.org/10.1073/pnas.2012286117>
- Levendis, J. D. (2023). *Static Panel Data Models* (pp. 385–414). https://doi.org/10.1007/978-3-031-37310-7_13
- Mahrani, Karuna, E. E., & El Darman, A. A. (2025). Model Regresi Data Panel Robust terhadap Kemiskinan di Provinsi Sulawesi Selatan. *Jurnal Riset Statistika*, 93–100. <https://doi.org/10.29313/jrs.v5i2.8637>
- Maylani, E., & Sari, R. F. (2025). Panel Data Regression Modeling of North Sumatra Province's Gross Regional Domestic Product for 2019-2023. *VYGOTSKY*, 7(2), 155–168. <https://doi.org/10.30736/voj.v7i2.1279>
- Muhammad, A. (2008). Population, Poverty and Environment, the Interlinkages. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.1553586>
- Qulsum, U., Anggraini, J., & Putri, E. (2024). Analysis Of Poverty As A Main Problem Of The Indonesian Economy And Its Overcome. *Perspektif: Journal of Social and Library Science*, 2(2), 60–66. <https://doi.org/10.70489/perspektif.v2i2.297>
- Ramani, R., Haziri, A., Idrizi, S., Shaqiri, M., Kamberi, L., & Ibraimi, A. (2025). Statistical Tests For Dependent And Independent Solutions And Their Application. *JNSM - Journal of Natural Sciences and Mathematics of UT*, 10(19–20), 419–423. <https://doi.org/10.62792/ut.jnsm.v10.i19-20.p3110>

- Ross, A., & Willson, V. L. (2017). Hierarchical Multiple Regression Analysis Using at Least Two Sets of Variables (In Two Blocks). In *Basic and Advanced Statistical Tests* (pp. 61–74). SensePublishers. https://doi.org/10.1007/978-94-6351-086-8_10
- Sharath, A. M. (2020). The Challenges of Poverty, Types and Its Causes. *International Research Journal on Advanced Science Hub*, 2(Special Issue ICAMET 10S), 81–85. <https://doi.org/10.47392/irjash.2020.203>
- Sinaga, A. P. A. (2022). Poverty Perspectives And Reduction Strategies In Indonesia. *Three Seas Economic Journal*, 3(3), 1–9. <https://doi.org/10.30525/2661-5150/2022-3-1>
- Siziba, E., & Mapuva, J. (2023). Towards A Reconceptualization Of Poverty: Implications For Its Eradication And Policy. *Journal of Asian and African Social Science and Humanities*, 9(1), 34–45. <https://doi.org/10.55327/jaash.v9i1.299>
- Stankov, B., & Roganović, M. (2025). Challenges of panel data series application in research of various economic phenomena. *Ekonomija: Teorija i Praksa*, 18(3), 89–100. <https://doi.org/10.5937/etp2503089S>
- Sultanova, K. (2024). Sustainable Development Goals Through Poverty Alleviation Efforts. *Frontline Marketing, Management and Economics Journal*, 4(5), 35–42. <https://doi.org/10.37547/marketing-fmmej-04-05-03>
- Suresh, J. (2023). Poverty is Lack of Capabilities: A Literature Review. *International Journal of Research and Innovation in Social Science*, VII(III), 462–476. <https://doi.org/10.47772/IJRISS.2023.7305>
- Susanto, J., & Windyastuti, W. (2023). Increasing The Minimum Wage As A Means Of Poverty Alleviation. *Jurnal Litbang Sukowati : Media Penelitian Dan Pengembangan*, 7(2), 72–87. <https://doi.org/10.32630/sukowati.v7i2.400>
- Zamore, S. (2022). Panel Data Analysis: A Simplified Summary. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4307599>