Effects of the Human Development Index and Unemployment Rate on Poverty in Sumatra

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Abstract

This study analyzes the effects of the Human Development Index (HDI) and the Unemployment Rate (OUR) on poverty across 10 provinces in Sumatra during 2015–2024. The study uses secondary data from Statistics Indonesia (BPS) organized as panel data and applies the Random Effects Model (REM). The results show that the HDI has a significant negative effect on poverty, whereas the OUR has a significant positive effect on poverty in Sumatra. Taken together, HDI and OUR also have a significant effect on poverty. These findings indicate that improving human capital and expanding employment opportunities can contribute to reducing poverty levels in Sumatra.

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Introduction

Poverty is a fundamental problem that poses a major challenge to governments around the world. Poverty is defined as an individual's inability to meet basic needs such as food, clothing, health services, and housing (Hardinandar, 2019). People are considered poor when their average monthly expenditure per person falls below the poverty line. Poverty is a complex phenomenon that cannot be addressed through simple solutions (Haugthon & Khandker, 2009).

Because of its serious impacts, poverty alleviation has become a major priority in development efforts in many countries. Through the Sustainable Development Goals (SDGs), the United Nations (UN) established the first goal, "No Poverty," as a global commitment to combating poverty and improving public well-being (Arifin, 2020). The poverty rate is not only an indicator of public welfare but is also frequently used to assess the success of a region's socioeconomic development (Oktaviana et al., 2021). Therefore, a high poverty rate may indicate that the development process has not been optimal. If this condition is not addressed promptly, poverty may generate other problems, such as rising unemployment, social inequality, low human-resource quality, and increasing social and economic vulnerability within communities (Ariwuni & Kartika, 2019).

According to official data from Statistics Indonesia (BPS), the national poverty rate averaged 9.03% in March 2024 and declined to 8.57% in September 2024 (BPS, 2025). Overall, poverty levels in Sumatra are considered relatively low compared with other regions in eastern Indonesia, such as Papua and the Nusa Tenggara Islands. However, four provinces in Sumatra had poverty rates above the national threshold in 2024.

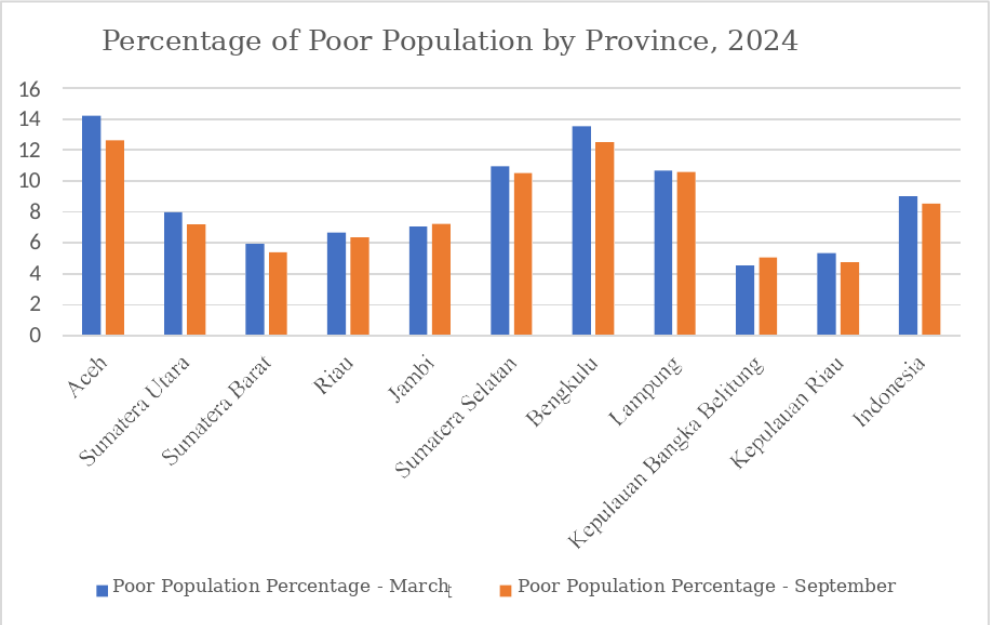


Figure 1. Percentage of Poor Population by Province, 2024
Source: Statistics Indonesia.

Based on the 2024 census on the Number and Percentage of Poor Population by Province conducted by Statistics Indonesia (BPS), Aceh Province recorded the highest poverty rate in Sumatra at 14.23% in March 2024. It was followed by Bengkulu Province, with a poverty rate of 13.56% during the same period. The poverty rate in South Sumatra Province was 10.97% in March 2024 and declined to 10.51% in September 2024. The poverty rate in Lampung Province fluctuated between 10.6% and 10.9%. Sumatra was selected as the object of this study because it displays varying levels of economic development and poverty across provinces, making it relevant for further analysis of the factors that influence poverty in the region.

There is a close relationship between unemployment and poverty. Unemployment includes working-age individuals who are not working and are looking for work, preparing a new business, believing that they are unlikely to obtain a job (discouraged workers), having been accepted for work but not yet started, or having a business but not yet begun operating it (BPS, 2024). Unemployment reduces income, which in turn lowers welfare (Hasibuan, 2021).

In addition to unemployment, the Human Development Index is also considered one of the factors influencing poverty. According to Badan Pusat Statistik (2025), the Human Development Index (HDI) is an important indicator used to measure the success of efforts to improve people's quality of life through three basic dimensions: a long and healthy life, knowledge, and a decent standard of living. When the HDI increases, poverty tends to decline because higher levels of education can raise individual income, improve welfare, and ultimately help people escape poverty (Nengsih et al., 2024).

To date, studies examining the effects of the Human Development Index (HDI) and the Unemployment Rate (OUR) on poverty have produced mixed findings. Several studies show that improvements in the HDI significantly reduce poverty, whereas higher unemployment is associated with increased poverty (Afifah, 2025; Hutabarat et al., 2025; Riyandini, 2024). Other studies, however, report contradictory findings and suggest that

unemployment has no significant effect on poverty levels (Afriansyah et al., 2026; Qomarina et al., 2025; Rohmah & Prakoso, 2022).

The inconsistency in previous findings may arise from a tendency to overlook random heterogeneity, namely unobserved differences in regional characteristics. Most previous studies used national-level data or focused on Java and assumed that regional characteristics were relatively homogeneous. Such approaches cannot fully capture Sumatra-specific trends, where large income differences exist across provinces and labor-market structures are highly sensitive to changes in the prices of major commodities. In addition, previous studies generally did not consider the influence of random external factors during recent decades.

Accordingly, the main novelty of this study lies in applying panel-data econometric regression using a Random Effects Model (REM) specification corrected with the White Cross-Section method. This approach is used to estimate relationships among variables more accurately while minimizing potential violations related to spatial autocorrelation and heteroskedasticity. It also accommodates random differences in the characteristics of the 10 provinces in Sumatra during the 2015–2024 study period. The findings are expected to clarify the relationships between HDI, OUR, and poverty and to provide considerations for local governments in formulating poverty-alleviation policies focused on improving human-resource quality and expanding employment opportunities in accordance with the characteristics of each region.

Method

Model Specification and Data

This study applies a quantitative approach using multiple linear regression analysis with panel data. Panel data (pooled data) are used because they can accommodate unobserved heterogeneity across regions that cannot be captured by ordinary linear models (Baltagi, 2021). The study uses secondary balanced-panel data covering 10 provinces in Sumatra (Aceh, North Sumatra, West Sumatra, Riau, Riau Islands, Jambi, South Sumatra, Bengkulu, Bangka Belitung Islands, and Lampung) over a ten-year period from 2015 to 2024, producing a total of 100 observations (N × T).

Based on a macro production-function framework and adopting the Two-Way Error Component Regression Model specification of Porter and Gujarati (2008), the econometric model used in this study is formulated as follows:

$$POVERTY_{it} = \beta_o + \beta_1 HDI_{it} + \beta_2 OUR_{it} + \delta_i + \gamma_t + e_{it} \quad (1)$$

Where Poverty represents the percentage of the poor population, HDI denotes the Human Development Index, and. OUR refers to the unemployment rate. β_o represents the model constant, β_1, β_2 denote the estimated coefficients of the independent variables. δ_i captures the region-specific effect, representing the cross-sectional fixed effect, γ_t accounts for the time-specific effect, representing the time fixed effect. e_{it} represents the idiosyncratic error component. i is cross-sectional for the 10 observed provinces (i = 1, 2, …, 10) and t is time-series for 2015–2024. The research data and sources are presented in Table 1.

Table 1. Operational Definitions of Variables

Variable	Operational Definition	Unit	Source
Poverty	Percentage of the population whose average monthly per capita expenditure is below the poverty line.	Percent (%)	Statistics Indonesia
Human Development Index (HDI)	Composite index measuring the quality of human development through health, education, and a decent standard of living.	Index	Statistics Indonesia
Unemployment Rate (OUR)	Percentage of unemployed persons relative to the total labor force.	Percent (%)	Statistics Indonesia

Model Selection Procedure

To ensure valid inference, this study follows the model-selection protocol based on Baltagi (2021) and Gujarati (2009):

1. **Chow Test (F-Test):** Tests the restriction of a single intercept. The results show Prob. F = 0.0000 (< 0.05), so the null hypothesis (CEM) is rejected, indicating that each province in Sumatra has unique characteristics that must be accommodated through fixed effects.
2. **Hausman Test:** Tests the correlation between regressors and regional error terms. A p-value of 0.4990 (> 0.05) indicates that differences across provinces are random and uncorrelated with the independent variables. Therefore, the Random Effects Model (REM) is selected because it is more efficient.
3. **Lagrange Multiplier (LM) Test:** Because the Chow and Hausman tests produce different model-selection indications, the Breusch–Pagan LM test is used to determine whether the REM is preferable to the Common Effects Model (CEM). The Breusch–Pagan (Both) p-value is 0.0000 (< 0.05). Thus, the null hypothesis is rejected, indicating the presence of random effects in the panel data and supporting the REM as the preferred estimation model.
4. **Standard Error Correction (White Cross-Section):** White Cross-Section (period cluster) standard errors are applied to mitigate the risks of spatial autocorrelation and heteroskedasticity, producing standard errors that are consistent and minimally biased.

Results and Discussion

Results

Descriptive Analysis of Research Variables

Before estimating the panel-data regression model, descriptive statistical analysis was conducted to provide an overview of the distributional characteristics of the variables under study. The observations cover 10 provinces in Sumatra from 2015 to 2024, for a total of 100 observations.

The descriptive statistics in Table 2 show that the average poverty rate in Sumatra during the observation period was 9.71%. A relatively wide gap is observed between the minimum value (4.52%) and the maximum value (17.52%), indicating disparities in welfare outcomes across provinces in Sumatra. For the human-capital variable, the HDI has an average value of 71.68, which falls within the "High" category. The relatively small HDI standard deviation (2.09) indicates that human-development quality across regions in

Sumatra tends to be relatively even and does not exhibit extreme volatility compared with the other variables. Meanwhile, the OUR has an average of 5.22%, with a maximum value of 10.01%. This high maximum OUR reflects labor-market disruption in certain regions that may hinder regional poverty reduction efforts.

Table 2. Descriptive Statistics of Research Variables (Sample: 2015–2024)

Statistic	POVERTY	HDI	OUR
Mean	9.7111	71.6809	5.2222
Maximum	17.52	77.97	10.015
Minimum	4.52	66.95	2.835
Std. Dev.	3.832367	2.097532	1.416394
Jarque-Bera	8.993491	2.700371	11.12423
Probability	0.011145	0.259192	0.003841
Observations	100	100	100

Source: Processed EViews 13 data (2026).

Model Selection Results: Chow Test

Before conducting further regression analysis, the study applies model-restriction testing to determine the most accurate estimation method. The first stage is the Chow Test (Redundant Fixed Effects Test), with the following results:

Table 3. Chow Test Results (Redundant Fixed Effects Tests)

Effects Test	Statistic	d.f.	Prob.
Cross-section F	752.964684	(9,88)	0.0000
Cross-section Chi-square	435.680820	9	0.0000

Source: Processed EViews 13 data (2026).

Table 3 shows that the probabilities for both Cross-section F and Cross-section Chi-square are 0.0000. Because these probabilities are far below the significance level of $\alpha = 0.05$, the null hypothesis (H0), which states that the Common Effects Model (CEM) is appropriate, is rejected. This result indicates significant unobserved heterogeneity across provinces in Sumatra, making the use of a single-intercept model (CEM) inappropriate. The Fixed Effects Model (FEM) is therefore preferred to the CEM at this stage. The next step is the Hausman Test to compare the FEM with the Random Effects Model (REM).

Model Selection Results: Hausman Test

After the Chow Test indicates the presence of region-specific effects, the Hausman Test is used to determine whether the Fixed Effects Model (FEM) or Random Effects Model (REM) is more efficient for estimating the study parameters. The results are presented below:

Table 4. Hausman Test Results (Correlated Random Effects)

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	1.390355	2	0.499

Source: Processed EViews 13 data (2026).

Based on Table 4, the Chi-Square statistic is 1.3903 with a probability value of 0.4990. Since this probability exceeds $\alpha = 0.05$, the null hypothesis (H0) fails to be rejected. This result indicates that there is no correlation between the regional error component and the independent variables in the model. Econometrically, the finding

indicates that the Random Effects Model (REM) is more efficient and appropriate than the Fixed Effects Model (FEM) for analyzing the effects of HDI and OUR on poverty in Sumatra. With the REM selected, the estimates discussed in the following sections refer to the parameters generated by the random-effects model.

Lagrange Multiplier (LM) Test Results

After the REM is indicated to be more suitable than the FEM, testing proceeds with the Lagrange Multiplier (LM) Test to determine whether the REM is preferable to the Common Effects Model (CEM).

Table 5. LM Test Results for Random Effects

Testing Method	Effect Type	Statistic	Prob.
Breusch-Pagan	Cross-section	413.4728	0.0000

Source: Processed EViews 13 data (2026).

The Lagrange Multiplier results in Table 5 show a Breusch–Pagan Cross-section probability of 0.0000. Since this value is below $\alpha = 0.05$, the null hypothesis (H0), which states that the Common Effects Model (CEM) is more appropriate, is rejected. Therefore, the Random Effects Model (REM) is the more suitable model for analyzing the effects of HDI and OUR on poverty in Sumatra.

Classical Assumption Test: Multicollinearity

The multicollinearity test is conducted to ensure that there is no perfect or strong linear correlation among the independent variables in the regression model. Multicollinearity can inflate standard errors and make t-tests unreliable. The correlation matrix among the independent variables is presented below:

Table 6. Correlation Matrix of Independent Variables

	HDI	OUR
HDI	1.000000	0.427078
OUR	0.427078	1.000000

Source: Processed EViews 13 data (2026).

Table 6 shows that the correlation between HDI and OUR is 0.4270. Referring to the criterion proposed by Gujarati (2009), multicollinearity is considered serious when the correlation among independent variables exceeds 0.80 or 0.90. Because the correlation in this model (0.4270) is well below that threshold, the model can be considered free from multicollinearity problems. This result indicates that each independent variable makes a unique and valid contribution to explaining variations in poverty across Sumatra.

Panel Data Regression Analysis: Random Effects Model

Based on the preceding model-selection results, parameter estimation is conducted using the Random Effects Model (REM) with White Cross-Section standard-error correction to ensure consistency of the results. The R-squared value of 0.7696 indicates that 76.96% of the variation in the poverty rate in Sumatra can be jointly explained by HDI and OUR. The remaining 23.04% is explained by variables outside the research model. In addition, the Prob(F-statistic) value of 0.0000 (< 0.05) demonstrates that human-capital quality and labor-market conditions jointly have a significant effect on poverty in Sumatra.

Table 7. Random Effects Model (REM) Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	44.59735	1.230031	36.25709	0.000
HDI	-0.497865	0.016375	-30.40461	0.000
OUR	0.153409	0.047747	3.212943	0.010
R-squared	0.769643		Mean dependent var	0.327433
Adjusted R-squared	0.764894		S.D. dependent var	0.819341
S.E. of regression	0.39728		Sum squared resid	15.30965
F-statistic	162.0431		Durbin-Watson stat	0.516915
Prob(F-statistic)	0			

Source: Processed EViews 13 data (2026).

Discussion

Effect of Human Capital (HDI) on Poverty

The estimated coefficient of the HDI variable is −0.4978 with a probability value of 0.0000 ($p < 0.05$). This means that each one-point increase in HDI is statistically associated with a 0.497 percentage-point reduction in the poverty rate in Sumatra. The result indicates that improvements in human development through education, health, and a decent standard of living enhance people's capacity and productivity, thereby increasing their opportunities to earn better income.

However, an increase in the Human Development Index does not always produce an immediate and uniform reduction in poverty across all provinces. Several areas, including Aceh and Bengkulu, still record relatively high poverty rates. This condition indicates that successful human development requires a balance between equal economic opportunities, higher productivity in the business sector, and job creation capable of optimally absorbing labor. Differences in economic structure across provinces in Sumatra may also contribute to variations in the poverty-reduction effect generated by improvements in welfare.

The findings are consistent with Gary Becker's Human Capital Theory, which states that investment in education and health can improve the quality and productivity of human resources as well as local incomes. Higher human-resource quality increases opportunities for people to escape poverty. These findings are also in line with Afifah (2025) and Hutabarat et al. (2025), who found that the Human Development Index has a significant negative effect on poverty.

Effect of the Labor Market (OUR) on Poverty

The coefficient of the OUR variable is 0.1534, with a probability value of 0.0106 ($p < 0.05$). This result indicates that every 1 percentage-point increase in the unemployment rate significantly increases the poverty rate by 0.153 percentage points. A high unemployment rate shows that part of the population is not optimally absorbed into the labor market, resulting in lower household income and a reduced ability to meet basic needs.

This situation is a serious issue, particularly in Sumatra, where economic conditions vary considerably across provinces. Several regions still rely on primary industries such as agriculture, plantations, and mining, yet these industries are unable to provide

sufficiently productive and stable employment opportunities. If employment growth fails to keep pace with growth in the labor force, the risk of rising unemployment and poverty will become greater.

The findings are consistent with Ragnar Nulkse's Vicious Circle of Poverty Theory, which states that low income can reduce people's ability to meet basic needs and thereby increase the risk of becoming trapped in poverty. The findings are also consistent with Riyandini (2024), who found that unemployment has a significant positive effect on poverty.

Conclusion

Based on the findings of this study, during 2015–2024 the Human Development Index (HDI) had a significant negative effect on the poverty rate in Sumatra. This indicates that improvements in education, health, and living standards contribute to poverty reduction. In contrast, the Unemployment Rate (OUR) had a significant positive effect on poverty, meaning that higher unemployment may increase the number of poor people. Taken together, HDI and OUR also had a significant effect on poverty in Sumatra. Therefore, the quality of human resources and labor-market conditions are critical factors in poverty-alleviation efforts in the region.

Policy Implications

The government is expected to improve human-resource quality by expanding equitable access to education, strengthening health services, and developing job-skills training to reduce poverty. In addition, employment opportunities and productive economic sectors should be expanded and strengthened to lower the unemployment rate. Future research is encouraged to include additional variables such as economic growth, inflation, and minimum wages so that analyses of the determinants of poverty can be more comprehensive.

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this article.

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