Privieit Social Sciences Journal
E-ISSN 2798-6314
P-ISSN 2798-866X
DOI:10.55942/pssj.v5i6.617

Volume 5
Issue 6
June Edition 2025

Income inequality across provinces in Indonesia: An empirical analysis of human development, economic performance, and labor market conditions

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Received 17 May 2025
Revised 15 June 2025
Accepted 29 June 2025

ABSTRACT

Income inequality is one of the structural challenges faced by many countries, including Indonesia. This phenomenon reflects an unequal distribution of income across regions, which can lead to social injustice and hinder the process of economic development. This study aims to analyze the effects of the Human Development Index (HDI), economic growth, and unemployment rates on income inequality across 34 provinces in Indonesia over the period 2019–2024. The method employed is panel data regression analysis. The findings reveal that the unemployment rate has a positive and significant effect on income inequality. The HDI shows a significant negative effect, while economic growth does not exhibit a statistically significant impact. These findings highlight the importance of policies that prioritize job creation and human development in addressing inequality. Economic growth strategies should also be designed to be more inclusive.

Keywords: Income inequality, Human Development Index, economic growth, unemployment, panel data

1. INTRODUCTION

Income inequality remains a persistent structural issue in Indonesia's economic development agenda. Despite the implementation of various development policies, disparities between regions and individuals continue to be significant. While numerous macroeconomic indicators suggest positive growth, income inequality remains high, as reflected in the stagnant or increasing Gini ratio observed in several periods. This condition indicates that the benefits of development have not been evenly distributed across all segments of society. The Gini ratio is a commonly used metric to measure income inequality, capturing the extent to which income is unevenly distributed within a population. Inequality manifests in income gaps between individuals, groups, or regions. According to data from the Central Statistics Agency (Badan Pusat Statistik, BPS) covering 34 provinces from 2019 to 2024, several provinces have persistently high Gini ratios. For example, the Gini ratio in Jakarta reached 0.431 in 2023, while in West Papua it stood at 0.385 during the same year. Globally, income inequality is not limited to developing countries; it is also prevalent in advanced economies. In the United States, a 2021 report by the Pew Research Center found that the top 20% of households held over 50% of national income (Pew Research Center, 2021). This underscores the universality of income inequality and the urgent need for comprehensive attention and action.

This phenomenon aligns with the Kuznets hypothesis (Kuznets, 1995), which posits that in the early stages of economic growth, income inequality tends to rise, and only begins to decline once a certain income threshold is reached implying an inverted U-shaped relationship between economic growth and income inequality. However, the relevance of this hypothesis in the Indonesian context remains contested. Data suggest that some regions with high economic growth still experience significant inequality. For instance, Central Sulawesi recorded an economic growth rate of 15.22% in 2022, yet its Gini ratio remained high at 0.305. Numerous previous studies have sought to explain the determinants of income inequality from both theoretical and empirical perspectives. Common analytical frameworks focus on human development, economic growth, and labor market dynamics. The Human Development Index (HDI) is considered a crucial indicator for assessing the quality of human capital, encompassing access to education, healthcare, and a decent standard of living. Economic growth is often associated with aggregate welfare improvements but does not necessarily lead to equitable income distribution. Meanwhile, high unemployment rates may lead to economic exclusion and exacerbate income disparities.

Some empirical studies suggest that income inequality in Indonesia does not strictly follow the Kuznets curve. For example, Sutomo et al. (2024) found that despite economic growth, income inequality between provinces remained pronounced, implying that additional factors influence income distribution. Moreover, provinces with high HDI values do not always exhibit lower inequality. For example, Jakarta, which recorded the highest HDI (82.46 in 2023), also had the highest Gini ratio, suggesting that economic growth and human development have not translated uniformly into equitable outcomes. This study aims to contribute empirically to the understanding of how HDI, economic growth, and unemployment rates affect income inequality across Indonesian provinces. By employing panel data regression on 34 provinces over the period 2019–2024, the study seeks to provide robust empirical evidence to inform the formulation of inclusive and equitable development policies.

2. RESEARCH METHODS

This study adopts a quantitative approach utilizing panel data regression methods. The data used are secondary data collected from 34 provinces in Indonesia covering the period from 2019 to 2024. The dependent variable in this study is the Gini Ratio, which serves as a proxy for income inequality. The independent variables include the Human Development Index (HDI), Economic Growth (EG), and the Open Unemployment Rate (UR). To estimate the panel regression model, three main approaches are commonly employed: the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM) (Basuki & Prawoto, 2019). Among these, the model that provides the most robust statistical fit is selected as the basis for analysis. Therefore, to determine the most appropriate model whether Pooled Least Squares (PLS/CEM), FEM, or REM the Chow test and Hausman test are conducted as preliminary diagnostic procedures. Data analysis is performed using EViews software, and all data are obtained from Badan Pusat Statistik (Statistics Indonesia). The general form of the panel data regression model employed in this study is specified as follows:

$$INEQit = \alpha + \beta 1HDIit + \beta 2EGit + \beta 3URit + uit$$

where iii denotes the cross-sectional unit (province) and ttt represents the time unit (year).

2.1. Panel Data Regression Models

2.1.1. Common Effect Model (CEM)

The Common Effect Model, also known as the Pooled Least Squares (PLS) model, assumes no variation in intercepts or slope coefficients across time or individuals. Time-series and cross-sectional data are pooled and analyzed simultaneously. Parameter estimation is conducted using the Ordinary Least Squares (OLS) method. This model does not account for heterogeneity among provinces or time periods. The general form of the equation is as follows:

$$Yit = \beta 0 + \beta 1X1it + \beta 2X2it + \cdots + \beta kXkit + \varepsilon it$$

2.1.2. Fixed Effect Model (FEM)

The Fixed Effect Model accounts for individual heterogeneity by allowing each cross-sectional unit (province) to have its own intercept. This method is particularly useful for controlling for omitted variables that vary across entities but are constant over time. The general form of the FEM equation is:

$$Yit = \alpha i + k = 1\sum p\beta kXkit + \varepsilon it$$

where αi represents the intercept specific to each province.

2.1.3. Random Effect Model (REM)

The Random Effect Model serves as an alternative to FEM by assuming that individual-specific effects are randomly distributed across cross-sectional units and uncorrelated with the explanatory variables. This approach overcomes the loss of degrees of freedom associated with FEM due to the inclusion of dummy variables. The general form of the REM equation, as described by Setiawan and Kusrini (2010), is:

$$Yit = \beta 0 + \delta it + k = 1\sum p\beta kXkit + \varepsilon it$$

where δit captures the random individual effects.

2.2. Model Selection Criteria

To determine the most appropriate panel regression model, the Chow test is used to choose between the Common Effect Model and the Fixed Effect Model, while the Hausman test is employed to decide between the Fixed Effect Model and the Random Effect Model (Basuki & Prawoto, 2019). The decision rules are as follows:

Table 1. Model Criteria

Test	P-Value Criterion	Model Selection
Chow Test	Prob > 0.05	Common Effect Model (CEM)
	Prob < 0.05	Fixed Effect Model (FEM)
Hausman Test	Prob > 0.05	Random Effect Model (REM)
	Prob < 0.05	Fixed Effect Model (FEM)

3. RESULTS AND DISCUSSIONS

3.1. Chow Test for Model Selection

The Chow test is conducted to compare the Common Effect Model (CEM) and the Fixed Effect Model (FEM) in panel data regression (Basuki & Prawoto, 2019). Model selection is based on the p-value of the cross-section test. If the p-value > 0.05, the Common Effect Model is preferred. Conversely, if the p-value < 0.05, the Fixed Effect Model is deemed more appropriate.

Table 2. Chow Test Results

Effects Test	Statistic	d.f.	Prob.
Cross-section F	96.696186	(33,166)	0.0000
Cross-section Chi-square	610.381924	33	0.0000

Source: Processed using EViews, 2025

The results indicate that both the Cross-section F and Chi-square tests yield a probability value of 0.0000, which is less than 0.05. Therefore, it can be concluded that the Fixed Effect Model (FEM) is more appropriate than the Common Effect Model (CEM) for this panel data analysis. Based on this result, the next step involves conducting the Hausman test to determine whether FEM or REM (Random Effect Model) is the most suitable

3.2. Hausman Test for Model Selection

The Hausman test is employed to determine the more appropriate model between the Fixed Effect Model (FEM) and the Random Effect Model (REM). The decision rule is based on the p-value of the cross-section random test. If the p-value is greater than 0.05, it indicates that the Random Effect Model is more suitable. Conversely, a p-value less than 0.05 suggests that the Fixed Effect Model should be used, as it implies the presence of correlation between individual-specific effects and the explanatory variables.

Table 3. Hausman Test Results

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	4.931181	3	0.1769

Source: Processed using EViews, 2025

The results show that the probability value of the Cross-section random test is 0.1769, which is greater than the 0.05 threshold. Therefore, it can be concluded that the Random Effect Model (REM) is the most appropriate model to be used in this study.

3.3. Classical Assumption Testing

According to Gujarati (2004) and Basuki & Prawoto (2019), one of the advantages of panel data is that classical assumption tests such as normality and autocorrelation are not mandatory. Nevertheless, to ensure the robustness of the model, this study conducted a classical assumption test, specifically a multicollinearity test, to verify that there is no high correlation among the independent variables, which could potentially bias the model estimates.

3.3.1. Multicollinearity Test

The results of the multicollinearity test reveal that no significant multicollinearity exists among the independent variables, as the correlation coefficients between variables do not exceed the threshold of 0.90 (Ghozali, 2013:83). Thus, it can be concluded that the regression model is free from multicollinearity issues.

Table 4. Multicollinearity Test Results

	HDI (IPM)	Economic Growth (PE)	Unemployment Rate (PG)
IPM	1.000	-0.0046	0.1901
PE	-0.0046	1.000	-0.3022
PG	0.1901	-0.3022	1.000

Source: Processed using EViews, 2025

3.4. Regression Estimation Results

Based on the Hausman test, the Random Effect Model (REM) was found to be more appropriate than both the Fixed Effect Model (FEM) and the Common Effect Model (CEM). Therefore, the regression results discussed in this study are based on the REM estimation. The estimated regression equation is as follows.

Table 4. Random Effect Model Regression Output

Variable / Statistic	Coefficient / Value	Std. Error	t-Statistic	p-Value
Dependent Variable: Gini Ratio (INEQ)				
Constant (C)	0.412315	0.047318	8.713659	0.0000
Human Development Index (IPM)	-0.001191	0.000651	-1.829722	0.0688
Economic Growth (PE)	0.000271	0.000230	1.177673	0.2403
Unemployment Rate (PG)	0.003296	0.000671	4.915395	0.0000
Model Fit Statistics				
R-squared	0.128787			
Adjusted R-squared	0.115653			
F-statistic	9.805723			
Prob (F-statistic)	0.000005			
Standard Error of Regression (S.E.)	0.010376			
Durbin-Watson statistic	1.257610			
Mean dependent variable	0.034181			
S.D. dependent variable	0.011019			
Sum squared residuals	0.021442			
Random Effects Specification				
Cross-section random (S.D.)	0.042397		Rho:	0.9440
Idiosyncratic random (S.D.)	0.010328		Rho:	0.0560

Source: Processed using EViews, 2025

$$INEQit = 0.412315 - 0.001191 \cdot HDIit + 0.000271 \cdot EGit + 0.003296 \cdot URit$$

The estimation results using the Random Effect Model (REM) show that the Human Development Index (HDI) variable has a negative coefficient of -0.001191 and is statistically significant at the 10% level (p-value: 0.0688). This suggests that improvements in human development quality tend to reduce income inequality, aligning with the "development as freedom" concept by Sen (1999), which emphasizes the importance of individual capabilities in addressing social disparities. This finding is also supported by Yoertiara (2022), Febrianto (2017), and Ersad et al. (2022), who found that HDI has a significantly negative effect on income inequality.

According to Syamsir & Rahman (2018), reflecting the UNDP perspective, human development should be centered around individuals as the primary subjects positioning people as the ultimate goal of national development, rather than merely tools for achieving it. Alvan, as cited in Yoertiara (2022), also argues that in order to achieve higher levels of GDP and per capita income and to reduce income inequality, regional or national development should focus on improving the Human Development Index. HDI encompasses three main dimensions: health, education, and a decent standard of living. Better access to education enhances individuals' knowledge and skills, which in turn boosts productivity and income. Therefore, the higher a region's HDI, the lower its income inequality tends to be.

The economic growth variable has a positive coefficient of 0.000271, but it is not statistically significant (p-value: 0.2403). The positive direction indicates that economic growth has not yet generated sufficient distributive impact, in line with the Kuznets inverted-U hypothesis (Todaro & Smith, 2010), which posits that inequality tends to rise in the early stages of economic development. The unemployment rate variable shows a positive and statistically significant effect on income inequality, with a coefficient of 0.003296 and a p-value of 0.0000. This indicates that rising unemployment contributes to higher income inequality. Theoretically, this occurs because unemployment reduces individuals' opportunities to participate in income distribution. This finding aligns with Ersad et al. (2022), who reported that unemployment significantly increases income inequality in the southern region of Sumatra.

The R-squared value of 0.128787 (approximately 12.9%) indicates that the model explains around 12.9% of the variation in income inequality. The F-statistic probability of 0.000005 further confirms that the overall model is statistically significant. These findings are consistent with the studies of Ferreira et al. (2021) and Anand & Ravallion (1993), who emphasize that economic growth must be complemented by equal access to education and employment. Consequently, policy focus should be directed toward improving the quality and accessibility of education and healthcare, developing labor training programs aligned with market demand, and fostering inclusive economic growth through the empowerment of MSMEs and local economic sectors.

4. CONCLUSION

Economic growth at the district/city level in North Sumatra Province has contributed to increasing regional income inequality. This finding aligns with the Kuznets hypothesis, which posits that income inequality tends to rise during the early stages of economic development, particularly during periods of rapid growth and structural transformation. However, as development progresses and a more advanced stage is reached, income distribution is expected to improve, leading to a decline in inequality. This relationship forms an inverted U-shaped curve between economic development and income inequality. This study demonstrates that income inequality in Indonesia is significantly influenced by unemployment rates and the quality of human development, while economic growth has not shown a statistically significant effect on inequality. The policy implications of these findings underscore the critical importance of reducing unemployment and enhancing the Human Development Index (HDI) to promote equitable welfare distribution. The government must develop integrated and simultaneous policies targeting both labor market improvements and human capital development to ensure that economic growth is inclusive and benefits all segments of the population.

Ethical approval

Not Applicable.

Informed consent statement

Not Applicable.

Authors' contributions

Al Bina conceptualized the research framework and led the data collection process. Leni Kurnia Optari was responsible for data analysis and interpretation, while Heni Widiya contributed to the literature review, manuscript writing, and editing. All authors reviewed and approved the final manuscript.

Research Funding

The authors have no funding sources available for this study.

Statement of Disclosure

The authors declare no conflicts of interest.

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