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REGRESSION-BASED DECOMPOSITION OF INCOME INEQUALITY IN LAMPUNG PROVINCE INDONESIA

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Abstract
This study analyzes the influence of socio-economic and infrastructure factors on gross regional domestic product per capita and measures each factor's contribution to income inequality across 15 districts/cities in Lampung Province during 2020–2025. Using panel data regression with Random Effects Model (REM) and cluster-robust standard errors, the results show the mean years of schooling and internet access have a positive and significant effect, while poverty rate, open unemployment rate, and electricity access have a negative and significant effect on GRDP per capita. Applying the Regression-based Decomposition by Fields, all variables collectively contribute 100% to explaining inequality, with open unemployment rate as the largest contributor (16.85%), followed by percentage of poor population (10.40%), electricity access (9.74%), and internet access (9.21%). Notably, mean years of schooling reduces inequality by -4.64%. The overall model explains 41.56% of total GRDP per capita inequality, while the remaining 58.44% reflects residual factors outside the model such as institutional, geographical, and structural conditions. These findings suggest that improving education quality and expanding internet infrastructure can simultaneously boost economic growth and reduce income disparities, while addressing unemployment and poverty remains critical for equitable development in Lampung Province.

Keywords: Electricity and Internet Access, Percentage of Poor Population, Mean years of schooling, Regression-Based Decomposition, Open Unemployment Rate

1. Introduction

Income inequality is one of the main challenges in economic development because it reflects an uneven distribution of growth benefits. Inequality is not only affected by income differences, but also by educational disparities, poverty, unemployment, and access to infrastructure and economic opportunities. Therefore, inequality is seen as a multidimensional phenomenon that is formed through the interaction of various social and economic factors (Bersisa & Heshmati, 2021; Soler-Martínez et al., 2025).

In Lampung Province, the decline in the Gini Ratio has not fully reflected the equitable distribution of development between districts/cities. There are still considerable gaps in Gross Regional Domestic Product per capita, mean years of schooling, poverty rate, open unemployment rate, and internet and electricity access. In particular, internet access shows a higher disparity than electricity access, indicating that there is still a gap in digital development between regions (Asy'ariati et al., 2022; Jayanthi, 2021).

Various studies show that education, poverty, unemployment, and infrastructure are important determinants of income inequality. However, the empirical results are still inconsistent because the relationship between variables is influenced by regional characteristics and levels of development. In addition, most studies only examine the influence of these variables on inequality using conventional regression analysis, so it has

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not been able to explain the relative contribution of each factor in shaping income inequality (Ezcurra & Del Villar, 2021; Marchand et al., 2020).

To overcome these limitations, this study uses the Regression-Based Inequality Decomposition approach developed by Fields (2003). In contrast to previous research that generally uses the Gini Ratio as a measure of inequality, this study uses the variance of log income from the Gross Regional Domestic Product per capita of districts/cities because it is theoretically in accordance with the income generating function framework and allows the contribution of each variable to inequality to be calculated directly.

This study aims to analyze the influence of mean years of schooling, percentage of poor population, open unemployment rate, internet access, and electricity access on the Gross Regional Domestic Product per capita of districts/cities in Lampung Province for the period 2020–2025 using panel data regression, then decomposing the contribution of each factor to income inequality using the Fields method. The results of the research are expected to enrich the literature on the decomposition of inequality at the regional level and become an input for local governments in formulating policies that not only encourage economic growth, but also increase the equitable distribution of development.

2. Theoretical Background

a. Income Inequality

Income inequality is a condition when the distribution of income is uneven between individuals and regions. From an economic development perspective, inequality reflects not only differences in income levels, but also unequal access to education, employment opportunities, and infrastructure. According to Jenkins (1999), a good measure of inequality must meet the characteristics of scale independence, population independence, and decomposability, thus allowing analysis of the sources of inequality. In line with that, Haughton and Khandker (2009) stated that decomposable measures of inequality provide more useful information for policy formulation than aggregate measures alone.

This study examines inequality between districts/cities using variance of log income as a measure of relative inequality. In contrast to the Gini Ratio, which describes the distribution of household income, the variance of log income is more suitable to be used in a regression-based decomposition framework because it allows the measurement of the contribution of each factor to inequality.

b. Income Generating Function

The Income Generating Function (IGF) approach was developed from the theory of human capital introduced by Schultz (1961), Becker (1964), and formalized by Mincer (1974). In this framework, income is seen as a function of the productive characteristics possessed by individuals and regions. Fields (2003) expands the concept so that various socioeconomic factors can be used as determinants of income in a regression function. In this study, Gross Regional Domestic Product per capita is used as a representation of regional income, while mean years of schooling, percentage of poor population, open unemployment rate, internet access, and electricity access are positioned as factors affecting regional economic productivity.

c. Regression-Based Inequality Decomposition

Regression-Based Inequality Decomposition developed by Fields (2003) is a development of the traditional inequality decomposition approach. In contrast to the method that only identifies the influence of variables on income, this approach is able to

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measure the relative contribution of each explanatory variable to income inequality based on the results of estimating income generating function.

The advantage of this method is that the contribution of each variable can have a positive or negative value. Positive values indicate that a factor increases inequality, while negative values indicate that these factors play a role in reducing inequality (Fields, 2003). Therefore, this method provides more comprehensive information for development policy formulation than conventional regression analysis.

3. Methods

This study uses a quantitative approach with panel data consisting of 15 districts/cities in Lampung Province during the period 2020–2025. Data was obtained from the Central Statistics Agency of Lampung Province. The dependent variable in this study is Gross Regional Domestic Product per capita which is transformed into a natural logarithm as a proxy for regional income. Independent variables consist of mean years of schooling, percentage of poor population, open unemployment rate, internet access, and electricity access.

This study uses income generating function as a conceptual framework based on two complementary lines of empirical analysis: (1) analyzing the influence of independent variables on dependent variables, and (2) focusing on the application of the Regression-Based Decomposition Fields Method to decompose the contribution of each of these factors to the inequality of Gross Regional Domestic Product per capita between districts/cities in Lampung Province. In general, IGF is written as:

$$\ln \mathrm{Y_i} = \alpha + \sum_{k=1}^{K} \beta_k \mathrm{X_{ki}} + \varepsilon_i$$

Where represents income, the explanatory variable k, the coefficient and is $\mathrm{yX_k}\beta_k\varepsilon$the term error. Based on this framework, the equation model in this study is formulated as:

$$lnGRDPPC_{it} = \alpha + \beta_1 EDU_{it} + \beta_2 POOR_{it} + \beta_3 UNEMP_{it} + \beta_4 INT_{it} + \beta_5 ELEC_{it} + \varepsilon_{it}$$

Description:

lnGRDPPC : Natural logarithm of per capita income
β0 : Constant
β1.β2…...β5 : The regression coefficient of each independent variable
EDU : Mean years of schooling
POOR : Percentage of Poor Population
UNEMP : Open Unemployment Rate
INT : Percentage of the population with internet access
ELEC : Percentage of households with access to electricity
i : Cross-section
t : Time Series
ε : Error Term

The stages of panel model estimation include correlation test, multicollinearity test. Furthermore, the best regression estimation model was selected through the Chow test, the Hausman test, and the Breusch/Pagan Lagrange Multiplier Test. In the data panel, the problem of classical assumption violation is not only limited to heteroscedasticity between cross-section units (districts/cities), but also has the potential to experience autocorrelation (serial correlation) in the time dimension for the same cross-section unit, where the error in period t tends to correlate with the error in period t-1 for the same region, so cluster-robust standard error is used in the selected model in this study. Then a

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hypothesis test and determination coefficient were carried out to determine the influence and significance of each independent variable on the dependent variable.

Then for regression-based decomposition, the basic model follows the log-linear specification of Fields (2003) using the previous income generating function framework. So, the variance of ln Y can be written as:

$$\sigma^2(\ln\ Y) = \sum_{k=1}^{K} \beta_k \cdot \mathrm{Cov}(X_k, \ln\ Y) + \mathrm{Cov}(\varepsilon, \ln\ Y)$$

This equation shows that the total inequality variation or ln Y can be broken down into K components that each derive from variable X, plus one residual component. The Fields (2003) method in Friderichs et al (2023) estimates the portion of the log-variance income that can be attributed to the kth explanatory factor as the contribution of the relative factor is calculated using the following formula:

$$S_k = \frac{\hat{\beta}_k \cdot \mathrm{Cov}(X_k, \ln\ y)}{\sigma^2(\ln\ y)} = 1,2, \dots, K$$

$\hat{\beta}_k$ is the coefficient of the K explanatory factor estimated from the regression, $\sigma^2(\ln y)$ is the variance of the dependent variable, and $cov(X_j, \ln y)$ is the covariance between the K factor and the dependent variable. The sign of S_k showing whether the contribution of factors X_k increases inequality or not with the criteria, $S_k > 0$ factors that increase inequality while $S_k < 0$ factors that reduce inequality. The sum of the entire weight of the inequality must be equal to R^2, as shown in the following equation. Thus, the variability that can be explained from the income generating model is reflected through the value of R^2.

$$\sum_{k=1}^{K} s_k = \frac{\sum_{k=1}^{K} \hat{\beta}_k\ \mathrm{Cov}(x_k, \ln\ y_i)}{\mathrm{Var}(\ln\ y_i)} = \frac{\mathrm{Var}(\ln\ \hat{y}_i)}{\mathrm{Var}(\ln\ y_i)} = R^2$$

When the error component is taken into account, the percentage of unexplained inequality is obtained from $S_\varepsilon = 1 - R^2$. The value s_ε reflects an inequality that cannot be explained by the variables in the model (unobserved heterogeneity). Fiorio & Jenkins (2007) show that the use of ineqrbd commands as in the Y_i income generating function model compared to $\hat{Y}_i$ can affect the decomposition result, because the error term (ε_i) is also decomposed.

4. Results and Discussion

a. Pearson Correlation Test Results

Table 1. Pearson Correlation Matrix

Variable	lnGRDPPC	EDU	POOR	UNEMP	INT	ELEC
lnGRDPPC	1.0000					
EDU	0.1464	1.0000				
POOR	-0.3479	-0.2216	1.0000			
UNEMP	0.3684	0.5610	0.0745	1.0000		
INT	0.3755	0.4652	-0.4833	0.1290	1.0000	
ELEC	0.4816	0.1291	-0.1718	0.3914	0.3665	1.0000

Source: processed data (2026)

All correlation values between independent variables are below 0.80, so there is no indication of serious multicollinearity so that all variables are suitable for use in the next panel data regression analysis.

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b. Multicollinearity Test (Variance Inflation Factor) Results

Table 2. Variance Inflation Factor (VIF) Test Results

Variable	VIF	1/VIF
EDU	2.19	0.456977
UNEMP	2.08	0.481134
INT	1.90	0.527472
ELEC	1.54	0.649745
POOR	1.37	0.731566
Mean VIF	**1.81**	

Source: processed data (2026)

All VIF values are well below the critical threshold of 10 (even below 5), with a Mean VIF of 1.81. Thus, it can be concluded that there are no serious multicollinearity problems between independent variables in the model.

c. Panel Data Regression Model Selection Results

Table 3. Recapitulation of Panel Data Regression Model Selection Results

Phase Testing	Test Statistics	p-value	Decision	Conclusion
Chow Test	740.97	0.0000	H_0 rejected	FEM is better than CEM
LM Test	189.94	0.0000	H_0 rejected	REM is better than CEM
Hausman Test	8.94	0.1113	H_0 accepted	REM was selected as the final model

Source: processed data (2026)

Based on the results of the Chow Test, the Breusch-Pagan Lagrange Multiplier Test, and the Hausman Test, the most appropriate panel data model used in this study is the Random Effect Model (REM).

d. Estimation of Selected Models with Cluster-Robust Standard Error and Hypothesis Test Results

To increase the reliability of the estimates, this study applied cluster-robust standard errors at the district/city level to correct the potential heteroscedasticity, autocorrelation, and error correlation between periods within the same region. This approach only affects the calculation of standard errors and test statistics, without changing the value of the coefficient or the direction of influence of the variable. This approach is recommended in panel data analysis by much of the econometric literature, including Wooldridge (2010), Cameron and Miller (2015), because it results in more reliable statistical inference than conventional standard errors. Therefore, the REM model with cluster-robust standard errors is used as the basis for hypothesis testing in this study.

Table 4. REM Estimation Results with Cluster-Robust Standard Error (Selected Model) and Hypothesis Test Results

Variable	Coefficient	Robust Std. Error	z-stat	P>|z|	Hypothesis Testing Decision
EDU	0.0637815	0.0232179	2.75	0.006	H_0 rejected
POOR	-0.0142447	0.0043934	-3.24	0.001	H_0 rejected
UNEMP	-0.0233447	0.0067661	-3.45	0.001	H_0 rejected

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Variable	Coefficient	Robust Std. Error	z-stat	P>|z|	Hypothesis Testing Decision
INT	0.0022549	0.0003557	6.34	0.000	H_0 rejected
ELEC	-0.0046411	0.0017968	-2.58	0.010	H_0 rejected
Constant	17.10812	0.2592085	66.00	0.000	
R-squared Within	0.9015		Wald chi2(5)		508.67
Between	0.0065		Prob > chi2		0.0000
Overall	0.0244				

Source: processed data (2026)

The equation can be written as follows:

$$lnGRDPPC_{it} = 17.10812 + 0.0637815\,EDU_{it} - 0.0142447\,POOR_{it} - 0.0233477\,UNEMP_{it} + 0.0022549\,INT_{it} - 0.0046411\,ELEC_{it} + \varepsilon_{it}$$

The value of the regression model constant is 17.10812. If the value is transformed again using the exponential function (anti-Ln), the real value of IDR 26,912,193.42 is obtained. This shows that if all independent variables, namely Mean Years of Schooling, Percentage of Poor Population, Open Unemployment Rate, Internet Access, and Electricity Access, are considered unchanged or have zero value, then the average value of Gross Regional Domestic Product per capita in Lampung Province's Regencies/Cities in the 2020-2025 period is IDR 26,912,193.42 per year assuming ceteris paribus.

Based on the estimated results, a Wald Chi-Square value of 508.67 with a probability value of 0.0000 < 0.05 indicates that the null hypothesis (H_0) is rejected. Thus, all independent variables simultaneously have a significant effect on the Gross Regional Domestic Product per capita of districts/cities in Lampung province. Then the R-squared within value is 0.9015, the R-squared between is 0.0065, and the overall R-squared is 0.0244. The high R-squared within value indicates that the model is able to explain 90.15 percent of the variation in Gross Regional Domestic Product per capita within the same district throughout the observation period.

The mean years of schooling variable has a coefficient of 0.0638 with a probability value of 0.006 < 0.05. Thus, H_0 is rejected and H_1 is accepted. This means that the mean years of schooling has a positive and significant effect on the Gross Regional Domestic Product per capita. These findings are consistent with Human Capital Theory (Becker, 1964; Mincer, 1974) which states that education investment increases labor productivity, encourages innovation, and ultimately accumulates regional per capita output.

The percentage of poor population variable has a coefficient of -0.0142 with a probability value of 0.001 < 0.05. Thus, H_0 is rejected and H_1 is accepted. This means that the percentage of the poor population has a negative and significant effect on the Gross Regional Domestic Product per capita. These results are consistent with the poverty trap theory where poverty is not only a consequence of low economic output, but also a cause that hinders further growth through low consumption capacity and human capital investment at the household level.

The open unemployment rate variable has a coefficient of -0.0233 with a probability value of 0.001 < 0.05. Thus, H_0 is rejected and H_1 is accepted. This means that the open unemployment rate has a negative and significant effect on the Gross Regional Domestic Product per capita. This finding is also in line with Solow's Growth Theory, which places labor as one of the main determinants of economic growth.

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The internet access variable has a coefficient of 0.0023 with a probability value of 0.000 < 0.05. Thus, H_0 is rejected and H_1 is accepted. This means that internet access has a positive and significant effect on the Gross Regional Domestic Product per capita. In line with the Endogenous Growth Theory (Romer, 1990) and the concept of knowledge spillover, internet access expands markets, facilitates technology diffusion, and improves the efficiency of economic transactions.

The electricity access variable has a coefficient of -0.0046 with a probability value of 0.010 < 0.05. Thus, H_0 is rejected and H_1 is accepted. This means that access to electricity has a negative and significant effect on the Gross Regional Domestic Product per capita. This can also reflect the composition of electricity use which is more consumptive than productive in some districts. This finding is in line with Jayanthi (2021), who found that increased electrification in 31 Indonesian provinces is actually associated with increasing income inequality, because the growth benefits of electricity have not been enjoyed equally.

e. Regression-based Decomposition Results

Field decomposition requires re-estimating the IGF in the form of a pooled OLS to obtain the coefficient and predicted value of ln $\hat{Y}$. This requirement is mathematically absolute, not merely a methodological choice. $\hat{\beta}_k$The OLS-based regression output showed that the model was simultaneously significant with an F(5.84) value of 11.95 and a Prob > F of 0.0000. The R-squared value of 0.4156 indicates that 41.56 percent of the variation in the Gross Regional Domestic Product per capita can be explained by the variables of Mean years of schooling, Percentage of Poor Population, Open Unemployment Rate, Internet Access, and Electricity Access. However, the results of this OLS are not positioned as the main model of the research, but only as an operational basis in the decomposition of the Fields. Here's the output of regression-based decomposition using the ineqrbd command:

Table 5. Contribution of factors to inequality using regression-based decomposition by Fields method

Variable	**Y = ln GRDPPC actual (%)**	**$\hat{Y}$ = ln GRDPPC predicted (%)**
	100 × s_f (%)	**100 × s_f (%)**
Mean Years of Schooling	-4,6368	-11,1558
Percentage of Poor Population	10,3983	25,0176
Open Unemployment Rate	16,8549	40,5515
Internet Access	9,2114	22,1619
Electricity Access	9,7363	23,4249
Residual	58,4359	–
Total	**100,0000**	**100,0000**

Source: processed data (2026)

By comparing the decomposition to the actual value (Y) and the decomposition to the predicted value ($\hat{Y}$) side by side, it can be known whether the contribution pattern of each variable is consistent or changes direction when the residual influence is excluded from the calculation. The total contribution of all variables amounts to 100%. The decomposition results in the actual column of 100 × s_f (%) show that all variables in the model contribute 41.56% to the inequality of Gross Regional Domestic Product per capita between districts/cities in Lampung Province during the period 2020–2025, while the remaining 58.44% is explained by residual components representing factors outside the

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model. In studies of the decomposition of inequality in developing countries, a relatively large residual proportion generally indicates that the model has not fully captured the institutional heterogeneity, economic structure, and spatial mechanisms that influence income distribution (Zhang et al., 2025). Among the variables analyzed, the open unemployment rate was the largest contributor to inequality with a contribution of 16.85%, followed by the percentage of poor population at 10.40%, electricity access at 9.74%, and internet access at 9.21%. On the other hand, the mean years of schooling had a negative contribution of −4.64%, which shows that increasing the equitable distribution of education plays a role in reducing income inequality between regions through a more equitable increase in productivity. These findings are in line with research by Assyifa et al. (2025), which found that the mean years of schooling has a negative and significant effect on income inequality in 34 provinces in Indonesia.

To obtain an overview of the relative contribution between variables without being influenced by residual components, decomposition is also carried out on the predicted Gross Regional Domestic Product per capita. The decomposition results showed that the sequence of contributions between variables remained consistent with the actual decomposition. The open unemployment rate remains the largest contributor to inequality at 40.55%, followed by the percentage of the poor population at 25.02%, electricity access at 23.42%, and internet access at 22.16%. In contrast, the mean years of schooling had a negative contribution of −11.16%, which shows its role in reducing income inequality between regions. The increase in the percentage contribution to the predicted decomposition does not indicate that the influence of the variable becomes substantively greater, but rather is a mathematical consequence of the elimination of the residual component. Since the residual accounts for 58.44% of the total inequality in the actual decomposition, all remaining variable contributions are re-normalized to 100%. As a result, the proportion of contribution of each variable increases relatively but still maintains the same proportional order and relationship.

f. Discussion

In the study, Budiarty et al. (2023) stated that in Lampung, the limitations of work in the countryside between planting and harvest seasons encourage residents to move to the city. Cities attract migrants because they offer greater job opportunities and higher income expectations than the area of origin. Furthermore, agricultural districts whose economies rely on the subsistence agriculture sector, such as West Lampung, Tanggamus, or Pesisir Barat, tend to have very low unemployment rates, even though many workers there are underemployed or are unpaid family workers. The large contribution of the open unemployment rate to inequality also indicates a skills mismatch between labor competence and the needs of the productive sector. Wealthy districts such as Central Lampung and South Lampung continue to move towards the mechanization of agriculture and capital-intensive manufacturing industries that require workers with specific qualifications. Therefore, reducing inequality is not enough to be done through job creation in urban areas, but needs to be accompanied by the development of the base sector in low-income districts, improving the quality of vocational training, and investing that is able to absorb local workers. This strategy is expected to strengthen regional economic capacity more evenly so as to reduce income disparities between districts/cities in Lampung Province (Karmini et al., 2022; Putri et al., 2025).

Regional inequality and poverty reinforce each other in a spatial poverty trap, especially in areas that are still dominated by the subsistence agriculture sector such as most districts in Lampung which in turn limit the local investment capacity and economic mobility of their populations, so that the gap with high-income districts/cities such as Bandar Lampung City tends to persist, and even has the potential to widen (Agustine et al., 2025). Bandar Lampung City and Metro City have a much lower percentage of poor people thanks to high money turnover and a higher minimum wage.

In general, the ratio of household electrification continues to increase; however, inequality is triggered by differences in quality, reliability, and purpose of energy supply utilization between regions. In a study based on the Williamson Index, the electricity sector had a significant effect on Indonesia's regional inequality in 2019–2021, both through household and industrial customers (Sari, 2025). The increase in electrification is related to the increase in economic growth, but it is also indicated to increase income inequality if the benefits are not evenly distributed (Jayanthi, 2021). Stable and minimally disruptive large-scale electricity supply has historically been concentrated in industrial growth areas, such as in South Lampung and Central Lampung Regencies. Meanwhile, in rural and remote areas, they tend to be served last because of higher supply costs, lower return on investment, and thinner local markets (Situmorang et al., 2023). Lampung's renewable energy potential is also spatially uneven, where South Lampung is said to have the greatest potential, while the biogas potential is also abundant in East Lampung and Central Lampung, which means that opportunities to improve access are highly dependent on local resource bases (Rahman et al., 2019). Although not in disadvantaged areas, rural households generally use electricity to meet basic needs, which has not led to the transformation of the productive sector. The gap in energy utilities for the productive sector is what causes the variable access to electricity to widen the income disparity in Lampung.

Internet diffusion appears to reduce individual inequality in a nonlinear pattern, but actually increases regional inequality when access and the ability to utilize it are uneven (Fointuna, 2025). Internet access has not fully generated equitable economic benefits because it is still influenced by the gap in the quality of digital infrastructure between regions. The concentration of high-speed internet networks in economic growth centers, especially Bandar Lampung City and Metro City, provides greater advantages for business actors in the region in adopting digital technology and expanding market access. The optimization of agricultural ICT in Lampung is hampered by weak rural internet infrastructure, slow/unstable connections, and high costs, making it difficult to adopt IoT and smart agriculture applications (Muhida, 2025). Limited network coverage in several districts, such as Pesisir barat, West Lampung, Tanggamus, and parts of Mesuji, hinders the productive use of digital technology. A study at SMAN/SMKN in Bengkunat Belimbing (Pesisir barat, 3T region) found many blank spots, very weak signals, schools without computer laboratories, and only a single GSM modem with an unstable connection (Syambas et al., 2025). This hinders digital learning and signals a sharp gap with the urban area. This condition shows that digital transformation in Lampung Province is still taking place unevenly, so it has the potential to widen productivity and income disparities between regions.

The mean years of schooling in this study was the only factor that contributed to reducing income inequality which was characterized by a negative value of −4.64% of the total inequality. This is in line with human capital theory, which holds that education investment increases labor productivity and encourages the accumulation of regional per capita output. Chen (2025) and Tchamyou (2020) found that education has a positive impact on income while reducing inequality. Furthermore, Assyifa et al. (2025) found

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that the mean years of schooling had a negative and significant effect on income inequality in 34 provinces in Indonesia. In accordance with the law of diminishing returns, regions with low initial capital but supported by evenly growing human capital will experience faster growth acceleration to catch up. It should be noted that the relationship between the mean years of schooling and economic output depends on quality while the context of additional school years alone is often insufficient without the quality of learning, institutions, and job absorption (Glawe & Wagner, 2022; Lubis et al., 2025; Yin et al., 2024).

5. Conclusion

Based on the results of panel data regression analysis using Random Effect Model (REM) with cluster-robust standard errors, this study shows that the mean years of schooling and internet access have a positive and significant effect on the Gross Regional Domestic Product per capita of districts/cities in Lampung Province. On the other hand, open unemployment rates, poor population, and access to electricity have a negative and significant effect on the Gross Regional Domestic Product per capita. Simultaneously, all independent variables have a significant effect on the Gross Regional Domestic Product per capita, which shows that the quality of human resources, labor market conditions, poverty levels, and equitable distribution of infrastructure are important factors in determining regional economic performance.

The results of the Regression-Based Inequality Decomposition show that the open unemployment rate is the largest contributor to the inequality of Gross Regional Domestic Product per capita between districts/cities in Lampung Province with a contribution of 16.85%, followed by the percentage of poor population 10.40%, electricity access 9.74%, and internet access 9.21%. In contrast, the mean years of schooling had a negative contribution of −4.64%, which shows that equal distribution of education plays a role in reducing income inequality between regions.

Overall, the model was able to explain 41.56% of the variation in the inequality of the Gross Regional Domestic Product per capita log between districts/cities in Lampung Province during the 2020–2025 period, while the remaining 58.44% was explained by factors outside the model. These findings indicate that reducing development inequality requires not only efforts to increase economic growth, but also policies oriented towards job creation, poverty alleviation, equitable distribution of education quality, and more equitable infrastructure development throughout the region.

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