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Analyzing Poverty Across Indonesian Provinces Using Panel Data Regression

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Abstract

This study aims to analyze the factors that influence poverty levels in provinces in Indonesia using panel data regression. This study uses secondary data from the Central Statistics Agency (BPS). The data used includes variables such as provincial poverty rate (TKP), gross regional product per capita (PPK), open unemployment rate (TPT), and average length of schooling (RLS). The results of the analysis show that the fixed effect model is the most appropriate model for this data, as confirmed by the Chow test and the Hausman test. RLS has a negative and significant effect on poverty rates, indicating that increased education correlates with a decrease in poverty. Meanwhile, TPT has a positive but insignificant effect at the 5% level, although it is close to significant at the 10% level. This suggests that increased unemployment tends to increase poverty. PPK has a negative but insignificant effect on poverty levels, reflecting the phenomenon of “growth without justice” where the benefits of growth are not felt equally by all segments of society. This model has a very high level of suitability, with an R-squared value of 0.996810, which means that 99.68% of the variation in poverty levels can be explained by the independent variables.
Keywords: Dynamic, Indonesia, Poverty, Panel Data Regression

Abstrak

Penelitian ini bertujuan untuk menganalisis faktor-faktor yang mempengaruhi tingkat kemiskinan di provinsi-provinsi di Indonesia menggunakan regresi data panel. Penelitian ini menggunakan data sekunder dari Badan Pusat Statistik (BPS). Data yang digunakan mencakup variabel tingkat kemiskinan provinsi (TKP), Produk Regional Bruto per kapita (PPK), Tingkat Pengangguran Terbuka (TPT), dan Rata-rata Lama Sekolah (RLS). Hasil analisis menunjukkan bahwa model efek tetap (fixed effect model) adalah model yang paling sesuai untuk data ini, seperti yang dikonfirmasi oleh Uji Chow dan Uji Hausman. RLS memiliki efek negatif dan signifikan terhadap tingkat kemiskinan, menunjukkan bahwa peningkatan pendidikan berkorelasi dengan penurunan kemiskinan. Sementara itu, TPT memiliki efek positif tetapi tidak signifikan pada tingkat 5%, meskipun mendekati signifikan pada tingkat 10%. Hal ini menyarankan bahwa peningkatan pengangguran cenderung meningkatkan kemiskinan. PPK memiliki efek negatif tetapi tidak signifikan terhadap tingkat kemiskinan, mencerminkan fenomena “pertumbuhan tanpa keadilan” di mana manfaat pertumbuhan tidak dirasakan secara merata oleh semua lapisan masyarakat. Model ini memiliki tingkat kesesuaian yang sangat tinggi, dengan nilai R-squared sebesar 0.996810, yang berarti 99,68% variasi tingkat kemiskinan dapat dijelaskan oleh variabel independen.
Kata Kunci: Dinamis, Indonesia, Kemiskinan, Regresi Data Panel

INTRODUCTION

Poverty in Indonesia is a multidimensional issue that reflects deep-rooted inequalities in the distribution of resources, access to education and health services, and opportunities for obtaining decent employment. These inequalities are shaped by a complex interplay of historical, structural, and socioeconomic factors that make poverty not merely an economic concern but also a social and developmental challenge. Although Indonesia has recorded consistent economic growth in recent decades, the benefits of such growth have not been evenly distributed across regions, leading to persistent disparities between more developed and less developed provinces. This condition reinforces the notion that poverty cannot be fully understood through monetary indicators alone, but must instead be examined through a broader lens that incorporates social welfare, human development, labor market conditions, and access to essential services.

Despite the government's efforts through programs such as the Family Hope Program (PKH), Direct Cash Assistance (BLT), and Village Funds, poverty rates in several regions remain significantly high and, in some cases, exceed the national average. These programs, while impactful in alleviating short-term poverty, have varying degrees of effectiveness depending on regional capacity, institutional quality, and local socioeconomic structures. According to the Central Statistics Agency (BPS), as of March 2024 the national poverty rate stood at 9.03%, yet provinces like Papua and West Papua recorded considerably higher rates of 26.03% and 21.74% respectively (BPS, 2024). Such disparities demonstrate that national-level strategies may not sufficiently address the unique, localized challenges that contribute to poverty in remote and underserved areas.

These significant interregional differences highlight the limitations of a one-size-fits-all approach in poverty reduction and underscore the necessity of context-sensitive policy interventions. In regions with challenging geographical conditions, limited infrastructure, and constrained access to markets, poverty tends to take different forms compared to more urbanized provinces. Consequently, understanding the structural determinants of poverty at the provincial level becomes crucial for designing policies that are both relevant and effective. A data-driven approach allows policymakers to tailor interventions based on evidence rather than assumptions, reducing the risks of misallocation of resources and inefficiency in program delivery.

Previous empirical studies have consistently shown that variables such as GDP per capita, unemployment rate, education level, and the Human Development Index (HDI) hold strong correlations with poverty levels (Todaro & Smith, 2020; Ravallion, 2016). GDP per capita reflects the intensity of economic activity and average income levels within a province, serving as an indicator of the population's purchasing power and ability to meet basic needs. However, relying solely on GDP per capita may overlook distributional issues, as high economic output does not necessarily translate into inclusive growth. This reinforces the need to incorporate additional socioeconomic indicators into poverty analysis.

The Human Development Index (HDI) provides a complementary perspective by measuring achievements in health, education, and living standards (UNDP, 2020). The Open Unemployment Rate (OUR) acts as another critical variable, reflecting the extent to which regional labor markets are able to absorb the working-age population. BPS data from 2024 indicate that several provinces continue to record relatively high unemployment rates, reflecting structural weaknesses in local economies and an imbalance between economic growth and job creation (Central Statistics Agency, 2024). High unemployment not only reduces household income but also contributes to long-term poverty traps, as unemployed individuals often face skill depreciation, reduced productivity, and increased vulnerability to economic shocks. Understanding the dynamics between labor markets and poverty is therefore pivotal for designing employment-centered poverty reduction strategies.

Education, measured through indicators such as average years of schooling, plays an equally crucial role in shaping poverty dynamics. Individuals with higher educational attainment tend to have better access to formal employment, higher earning potential, and greater economic stability. Research published in E-Journal UTMJ confirms that average years of schooling consistently exhibit a negative effect on poverty levels—meaning that higher education levels reduce the likelihood of poverty (Rahmawati & Supriyanto, 2022). This finding underscores the importance of expanding educational access, improving learning outcomes, and addressing regional disparities in educational attainment as part of a long-term poverty reduction agenda.

To analyze these interconnected variables across both space and time, panel regression emerges as an appropriate and powerful methodological approach. Panel data analysis integrates cross-sectional and time-series dimensions, enabling researchers to observe changes in poverty over time while simultaneously accounting for interprovincial differences. It also offers methodological advantages by controlling for unobserved heterogeneity and improving the efficiency of parameter estimates (Baltagi, 2008; Gujarati & Porter, 2009). Furthermore, panel regression-based predictive models allow policymakers to simulate the potential impacts of various policy scenarios, such as increasing education investment or reducing unemployment, thereby offering more informed and proactive decision-making tools.

Despite the extensive literature on poverty determinants, a significant research gap remains concerning the development of a comprehensive and context-sensitive poverty prediction model at the provincial level in Indonesia. Most previous studies examine poverty either through cross-sectional analysis or time-series analysis conducted independently, thereby limiting their ability to capture simultaneous spatial and temporal variations. Additionally, existing studies often focus on national or district-level analyses rather than province-level panel data models that integrate economic, educational, and human development indicators. This limitation is problematic because each province possesses distinct economic structures, demographic patterns, and development challenges. Failures to account for such heterogeneity may lead to misinterpretation of poverty determinants and less effective policy recommendations. Addressing this research gap is crucial for producing a more holistic and robust poverty prediction model that not only investigates causal relationships but also offers predictive capacity for evidence-based policymaking. The novelty of this study lies in its development of a province-level poverty prediction model using a fixed effect panel regression framework that simultaneously incorporates economic, educational, and human development indicators. Unlike previous studies that examine these factors separately or at broader administrative levels, this research provides a more granular, data-driven, and context-specific analytical model capable of capturing interprovincial disparities and generating more accurate policy insights. By filling this gap, the study contributes to the development of adaptive, measurable, and regionally tailored poverty alleviation strategies. Furthermore, generating a predictive model grounded in empirical data will support Indonesia’s long-term efforts toward sustainable development, equitable growth, and improved welfare across all provinces.

METHODOLOGY

This study analyzes poverty across 34 provinces in Indonesia from 2020 to 2024, uses secondary data published and obtained from various relevant institutions, and applies the panel data method

The explanation regarding the data and its sources can be seen in Table 1.

Table 1.
Data and Data Sources

No.	Data	Data Source	Unit	Symbol
1	Provincial Poverty Rate	Central Statistics Agency	Percent	TKP
2	GRDP per Capita	Central Statistics Agency	Rupiah	PPK
3	Open Unemployment Rate	Central Statistics Agency	Percent	TPT
4	Average Years of Schooling	Central Statistics Agency	Years	RLS

Source: Processed by Researcher, 2025

The data variables such as provincial poverty rates, Gross Regional Domestic Product (PPK) per capita, Open Unemployment Rate (TPT), and Average Years of Schooling (RLS).

$$TKP_{it} = \beta_0 + \beta_1 PPK_{it} + \beta_2 TPT_{it} + \beta_3 RLS_{it} + \varepsilon_{it} \quad (1)$$

Panel Data Regression Method

In estimating panel data, one of three common calculation methods is generally used: Pooled Least Squares (PLS), Fixed Effect Model (FEM), and Random Effect Model (REM). These methods have fundamental differences. PLS is the simplest approach, combining cross-sectional and time-series data using Ordinary Least Squares (OLS) without considering the dimensions of individuals or time. FEM assumes that the intercept varies across cross-sections while the slope remains constant, using dummy variables (0 and 1) in the Least Square Dummy Variables (LSDV) technique to capture intercept differences. REM, on the other hand, uses the error term approach to link cross-section and time-series data, aiming to improve estimation efficiency by addressing FEM's limitations and reducing excessive degrees of freedom (Baltagi, 2015).

Selection of Panel Data Regression Method

Panel data estimation can be performed using three main models—Common Effect (PLS), Fixed Effect (FEM), and Random Effect (REM)—with the best model determined through the Chow Test and the Hausman Test. The Chow Test is used to choose between common effect and fixed effect models, selecting fixed effect when the F-statistic probability is lower than the significance level, and common effect otherwise. The Hausman Test distinguishes between FEM and REM, where a significant chi-square statistic result leads to choosing FEM, while a non-significant result favors REM (Baltagi, 2015).

Classical Assumption Testing

Several classical assumption tests are applied to ensure the validity of the regression model. The Normality Test (Jarque–Bera) checks if data is normally distributed, with a high J–B statistic and p-value below 5% indicating non-normality. The Multicollinearity Test detects correlations among independent variables through correlation coefficients. The Heteroskedasticity Test identifies non-constant error variance using scatterplots to observe residual patterns. Lastly, the Autocorrelation Test examines data dependency within variables over time, ensuring that past values do not bias the regression parameters.

DISCUSSION AND FINDINGS

Model Significance Test

Table 2
Chow Test Results

Effects Test	Statistics	df	Prob.
Cross-section F	1038,361	-33,133	0.000
Cross-section Chi-square	944.4233	33	0.000

Source: Eviews 9 Output

Table 2 shows that the value of the Cross-section F Prob. is 0,0000 greater than the real level (α) of 5 percent, (0,0000< 0.05) then H_0 is rejected (common effect model) and H_a is accepted (fixed effect model) so it can be concluded that the fixed effect model method is better than the common effect model method for analyzing data in this study.

Table 3
Hausman Test Results

Test Summary	Chi-Sq. Statistic	Chi-Sq. df	Prob.
Random cross-section	16,115	3	0.0011

Source: Eviews 9 Output

Table 5 shows that the Cross-section F Prob. is 0,0000 greater than the real level (α) of 5 percent, (0,0000< 0.05) then H_0 is rejected (random effect model) and H_a is accepted (fixed effect model), it can be concluded that the fixed effect model method is better to use than the random effect model method in this study. Thus, the fixed effect model is the most appropriate model to use for this panel data analysis.

Classical Assumption Testing

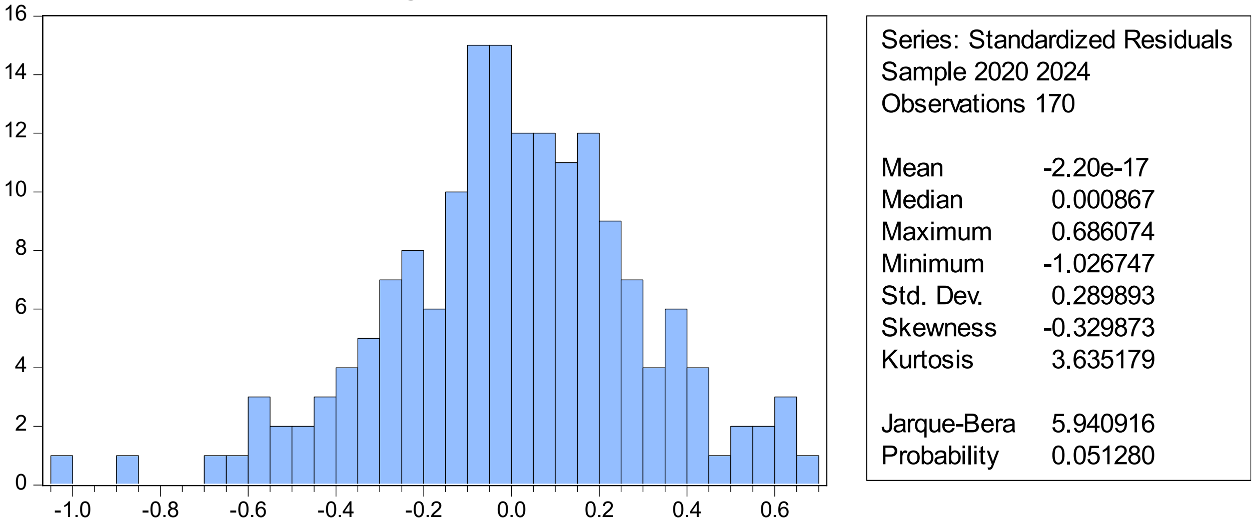

Figure 1.
Normality Test Results
Source: BPS Indonesia 2020

Based on Figure 1, the probability result is 0.0513 which is greater than α = 5% (0.05), so it can be concluded that the data is normally distributed.

Table 4
Multicollinearity Test Results

Variables	PPK	RLS	TPT
PPK	1,0000	-0.1179	-0.1011
RLS	-0.1179	1,0000	0.4962
TPT	-0.1011	0.4962	1,0000

Source: Eviews 9 Output

Based on the results of the multicollinearity test, no significant multicollinearity issues were found in this regression model. This value is well below the commonly used threshold for detecting multicollinearity, which is 0.85 (Widardjono, 2018). This low correlation value indicates that the two independent variables do not have a strong linear relationship with each other.

Table 5
Heteroscedasticity Test Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.961688	0.466947	2.059524	0.0414
RLS	-0.0702	0.049111	-1.42939	0.1552
TPT	-0.01761	0.023816	-0.73919	0.4611
PPK	-0.00054	0.000538	-1.0041	0.3172

Source: Eviews 9 Output

Based on the results of the heteroscedasticity test, it can be concluded that there is no heteroscedasticity problem in the regression model. This is indicated by the probability value (Prob.) of each variable being greater than 0.05. Furthermore, the Durbin-Watson value is 1.33018, meaning the test results are in the Accept H_0 area. Therefore, the DW test provides the conclusion that there is no autocorrelation.

Regression Results

Table 6
Fixed Effect Model Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	33.86848	0.895042	37.84009	0.0000
RLS	-2.59793	0.094137	-27.5975	0.0000
TPT	0.075751	0.04565	1.659378	0.0994
PPK	-0.00095	0.001031	-0.91693	0.3608
R-squared	0.99681	Prob(F-statistic)		0.0000
Adjusted R-squared	0.995947	Durbin-Watson stat		1.33018

Source: Eviews 9 Output

Based on the panel regression estimation results, a model equation is obtained that shows the influence of the variables Average Years of Schooling (RLS), Open Unemployment Rate (TPT), and Economic Growth Rate (PPK) on the poverty rate. The constant value (C) of 33.86848 indicates that when all independent variables are zero, the poverty rate is predicted to be 33.87%. This explanation can be described as follows, for example: if RLS increases by 1%, the poverty rate will decrease by 2.59%; assuming other factors remain constant.

The RLS variable has a coefficient of -2.597933 with a t-statistic value of -27.59745 and a p-value of 0.0000, which means it has a negative and significant effect on poverty at a 5% significance level. This means that an average increase of 1 year in education significantly reduces the poverty rate by 2.59%. The TPT variable has a positive coefficient of 0.075751 with a p-value of 0.0994, which indicates a positive but insignificant effect at a 5% significance level, although it is close to significance at a 10% level, suggesting that an increase in unemployment tends to increase poverty. Meanwhile, PPK has a coefficient of -0.000945 with a p-value of 0.3608, which means it has a negative but insignificant effect on poverty.

The model shows a very high level of fit with an R-squared value of 0.996810 and an Adjusted R-squared of 0.995947, indicating that approximately 99.68% of the variation in poverty levels can be explained by variations in RLS, TPT, and PPK. Based on Table 6, the F-statistic value of 1154.579 with a probability of 0.000000 indicates that the model is simultaneously significant in explaining the variation in poverty levels. The Durbin-Watson value of 1.330180 indicates the possibility of slight positive autocorrelation, although this is not too worrying. These findings confirm that increased education (RLS) is a key factor in reducing poverty, while unemployment and economic growth require more attention because their effects were not significant during the study period.

The estimation results show that Average Years of Education (RLS) has a negative and significant effect on poverty levels. This finding is in line with more recent human capital literature, which confirms that increased education improves workers' skills and productivity—thereby raising wages and reducing the risk of poverty (Ginting, Taufiq, & Wardaya, 2025). Recent empirical studies in the Indonesian context have also found similar relationships: increases in average length of schooling are significantly correlated with reductions in poverty and expanded access to higher-paying formal jobs (Wijaya & Suasih, 2021). Therefore, policies that prioritize investment in the quantity and quality of education remain a crucial strategy for breaking the cycle of intergenerational poverty.

Meanwhile, the Open Unemployment Rate (TPT) has a positive but insignificant effect on poverty, indicating that rising unemployment tends to increase poverty, consistent with the view that unemployment reduces household income and increases economic vulnerability (Mankiw, 2020). However, this insignificant effect may be due to the prevalence of informal workers who continue to earn income despite not being registered in the formal sector—or due to the existence of social protection and labour-market vulnerabilities that cushion the negative impact of unemployment on poverty (Setyanti, 2020; Anggara & Alfahma, 2024). This suggests that poverty-reduction efforts should not only aim at reducing unemployment quantitatively, but must also focus on creating good-quality jobs that offer stable income, decent protections, and advancement opportunities.

Furthermore, the gross regional domestic product per capita (PPK) has a negative but insignificant effect on poverty. In theory, economic growth is expected to increase public income and reduce poverty (Todaro & Smith, 2020). However, this finding aligns with more recent discussions on unequal or non-inclusive growth, which emphasize that economic expansion does not automatically lead to poverty reduction when its benefits are disproportionately captured by higher-income groups (World Bank, 2020; Klasen, 2018). In such conditions, growth tends to be concentrated among the upper-middle class, thereby limiting its capacity to lift the poor out of poverty.

CONCLUSION

Conclusion

The results of this study confirm that education plays a central role in reducing poverty levels. Average Years of Schooling has a negative and significant effect, indicating that the higher the level of education in a community, the lower the poverty rate. This finding is in line with the view that education improves individual skills and competitiveness in the labor market. The Open Unemployment Rate has a positive but insignificant effect at the five percent level, although it approaches significance at the ten percent level. This indicates that increasing unemployment tends to contribute to rising poverty, although its impact can be mitigated through the role of the informal sector and social protection programs. Meanwhile, the Economic Growth Rate has a negative but insignificant effect, indicating that economic growth has not fully provided equitable benefits to all levels of society, especially low-income groups. This research model has a very high level of fit and is simultaneously significant, although there are indications of mild positive autocorrelation that require attention in further model testing.

Suggestion

Regional governments need to strengthen policies focused on improving access to and the quality of education, given that research shows that education is a key factor in breaking the cycle of poverty. Programs to increase the average length of schooling can be realized through strengthening compulsory education policies, providing scholarships for low-income families, and improving the quality of teaching staff. Poverty alleviation efforts also need to be accompanied by the creation of quality jobs, so that people not only have jobs but also a decent and stable income. Economic growth should be directed to be more inclusive, by ensuring that the benefits of development are felt equally by all levels of society through the empowerment of micro, small, and medium enterprises and community economic programs. Furthermore, strengthening the quality of socioeconomic data and monitoring systems is essential to ensure that poverty alleviation policies can be formulated in a targeted manner and based on accurate evidence.

REFERENCES

Anggara, D., & Alfahma, A. (2024). Labor market vulnerabilities and informal employment in Indonesia. *Journal of Asian Labor Studies*, 12(1), 55–70.

Badan Pusat Statistik. (2024a). *Kemiskinan dan Ketimpangan Pengeluaran Penduduk Indonesia Maret 2024*. BPS RI.

Badan Pusat Statistik. (2024b). *Persentase Penduduk Miskin Menurut Provinsi, Maret 2024*. BPS RI.

Baltagi, B. H. (2008). *Econometric Analysis of Panel Data* (4th ed.). John Wiley & Sons.

Baltagi, B. H. (2015). *Econometrics* (5th ed.). Springer.

Becker, G. S. (1993). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education* (3rd ed.). University of Chicago Press.

Dartanto, T., & Nurkholis. (2013). The determinants of poverty dynamics in Indonesia: Evidence from panel data. *Bulletin of Indonesian Economic Studies*, 49(1), 61–84. https://doi.org/10.1080/00074918.2013.772939

Ginting, M., Taufiq, M., & Wardaya, M. (2025). Education, skills, and poverty reduction: Evidence from Indonesian labor households. *Asian Economic and Social Review*, 14(2), 211–229.

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* (5th ed.). McGraw-Hill.

Hikmah, Y. (2017). Pemodelan panel spasial pada data kemiskinan di Provinsi Papua. *Statistika*, 17(1), 1–15.

Klasen, S. (2018). Growth, inequality, and poverty: A review of the evidence. *World Development*, 110, 278–293.

Mankiw, N. G. (2020). *Principles of Economics* (9th ed.). Cengage Learning.

Oktarinda, S. (2024). Model regresi data panel pada faktor-faktor yang mempengaruhi kemiskinan di Provinsi Sumatera Selatan tahun 2020–2022. *Jurnal Penelitian Sains*, 8(1), 45–53.

Rahmawati, A., & Supriyanto, S. (2022). Pengaruh pendidikan terhadap tingkat kemiskinan di Indonesia. *E-Journal UTMJ*, 15(2), 123–135.

Rahmawati, E., & Supriyanto, E. (2022). Pengaruh pendidikan terhadap kemiskinan di Indonesia. *E-Journal UTMJ*, 11(2), 145–154.

Ravallion, M. (2012). Why don't we see poverty convergence? *American Economic Review*, 102(1), 504–523. https://doi.org/10.1257/aer.102.1.504

Ravallion, M. (2016). *The Economics of Poverty: History, Measurement, and Policy*. Oxford University Press.

Setyanti, R. (2020). Informal workers and income vulnerability in Indonesia. *Jurnal Ekonomi dan Bisnis*, 33(1), 90–104.

Suryahadi, A., Suryadarma, D., & Sumarto, S. (2012). The effects of location and sectoral components of economic growth on poverty: Evidence from Indonesia. *Journal of Development Economics*, 96(1), 96–111. https://doi.org/10.1016/j.jdeveco.2010.08.007

Todaro, M. P., & Smith, S. C. (2020). *Economic Development* (13th ed.). Pearson Education.

United Nations Development Programme. (2020). *Human Development Report 2020: The Next Frontier – Human Development and the Anthropocene*. UNDP.

Widardjono, A. (2018). Panel data modelling and poverty analysis in Indonesia. *Journal of Quantitative Economics*, 16(2), 331–347.

Widodo, E., Suriani, E., Putri, I., & Kusumandari, G. E. (2019). Analisis regresi panel pada kasus kemiskinan di Indonesia. *Prosiding Seminar Nasional Matematika*, 2, 710–717.

Wijaya, I., & Suasih, N. (2021). Education and poverty reduction in Indonesia: A panel data approach. *Economic Journal of Emerging Markets*, 13(2), 159–170.

Wooldridge, J. M. (2019). *Introductory Econometrics: A Modern Approach* (7th ed.). Cengage Learning.