SCIENOVA

Analysis of Factors Affecting the Percentage of Poor Population in South Sulawesi Province Using Panel Data Regression

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Abstract

Poverty is a complex and multidimensional development challenge that affects the quality of life and societal welfare. South Sulawesi Province, as one of the most populous regions in Indonesia, faces persistent poverty issues that must be addressed to achieve sustainable development. Despite various efforts undertaken by the government, the percentage of the poor population in this province remains relatively high, influenced by income inequality, limited access to education and healthcare, and unemployment rates (BPS, 2021). This study aims to analyze the factors affecting poverty levels in South Sulawesi, focusing on the variables of open unemployment rate (X_1), mean years of schooling (X_2), and population density (X_3). The study employs panel data regression analysis, which combines time-series data (2020–2024) and cross-sectional data to provide a more comprehensive analysis. The results are expected to identify the main determinants of poverty and provide effective policy recommendations for poverty alleviation efforts in the region. Furthermore, the findings are expected to serve as a reference for future studies related to poverty and economic development issues in Indonesia

Keywords: Poverty, Panel Data, South Sulawesi, Unemployment, Education, Population Density.

1. Introduction

Poverty is one of the most complex and multidimensional development challenges, affecting the quality of life and the welfare of society. South Sulawesi Province, as one of the regions with the largest population in Indonesia, faces various poverty-related issues that need to be addressed in order to achieve sustainable development. Despite numerous efforts made by the government and other stakeholders, the percentage of the poor population in this province remains relatively high. This condition is exacerbated by factors such as income distribution inequality, limited access to education and healthcare, and high unemployment rates.

According to [1], the poverty rate in South Sulawesi reached 12.34%, indicating that a considerable proportion of the population still lives below the poverty line. In addition, the socio-economic and geographical characteristics of a region may influence poverty levels [2]. Therefore, it is important to analyze the factors affecting

poverty levels in South Sulawesi in order to formulate more effective policies. This study aims to identify the main determinants of poverty in the region and provide policy recommendations that can support sustainable poverty alleviation efforts. By understanding the significant factors influencing poverty, this study is expected to contribute to the formulation of more targeted and effective policies in reducing poverty rates in South Sulawesi Province. Furthermore, the findings are expected to serve as a reference for future studies related to poverty and economic development issues in Indonesia.

The percentage of the poor population in South Sulawesi fluctuated during the period from 2020 to 2024. After an increase in 2023, a significant decline occurred in 2024, reaching 7.77%. This decrease reflects the efforts of the government and various stakeholders in reducing poverty rates in the region.

Previous studies have examined the influence of Gross Regional Domestic Product (GRDP), unemployment rates, and the Human Development Index (HDI) on poverty, such as the study conducted by Sussy Susanti in the *Jurnal Matematika Integratif* (2013). The study revealed that poverty is a complex and multidimensional social issue influenced by various economic and social factors. In West Java Province, poverty remains a major challenge, where increasing unemployment contributes to higher poverty levels. Through panel data analysis combining time and regional dimensions, the study found that GRDP, unemployment rates, and HDI significantly affected poverty during the 2009–2011 period [3].

Furthermore, a study conducted in Bali Province showed that poverty in Bali remains a serious issue despite rapid regional economic growth [4]. The study analyzed the effects of education, inflation, population growth, unemployment, and economic growth on poverty levels using the Path Analysis method. The main finding indicated that education has a negative effect on poverty, meaning that higher levels of education are associated with lower poverty rates. This occurs because education improves skills and increases labor competitiveness.

In addition, a study regarding the factors influencing poverty in Jambi Province showed that population size has a significant effect on the number of poor people [5]. Per capita expenditure has a negative effect, meaning that increasing per capita expenditure can reduce poverty levels. On the other hand, population size has a positive effect, indicating that population growth that is not accompanied by adequate employment opportunities may increase poverty.

Based on these findings, this study focuses on analyzing poverty levels in South Sulawesi by using explanatory variables, namely the open unemployment rate (X_1), mean years of schooling (X_2), and population density (X_3), using data from 2020–2024 obtained from the Central Bureau of Statistics of South Sulawesi Province.

Although previous studies have examined the determinants of poverty in several Indonesian provinces, including West Java, Bali, and Jambi, limited empirical evidence specifically addresses the poverty dynamics of South Sulawesi using recent panel data. South Sulawesi represents a unique case because it is one of the main economic hubs in Eastern Indonesia, characterized by substantial disparities in economic development, urbanization, population distribution, and labor market conditions across its districts and municipalities. These regional characteristics may lead to different patterns in the relationship between unemployment, education, population density, and poverty compared with other provinces. Therefore, this study contributes to the existing literature by providing updated empirical evidence based on district/city panel data from 2020–2024 and by identifying the determinants of poverty that are specific to the

socio-economic context of South Sulawesi. The findings are expected to support more targeted regional poverty alleviation policies and enrich the empirical literature on poverty analysis at the subnational level in Indonesia.

Although previous studies have identified several determinants of poverty in Indonesian provinces, including Gross Regional Domestic Product (GRDP), the Human Development Index (HDI), education, unemployment, and population growth, several important issues remain unresolved. First, most existing studies focus on provinces such as West Java, Bali, and Jambi, while empirical evidence from South Sulawesi remains limited. Second, previous studies employ different explanatory variables and analytical approaches, making it unclear whether the determinants of poverty are consistent across regions. Third, few studies have investigated recent poverty dynamics using district/city panel data covering the post-pandemic recovery period (2020–2024), during which labor markets, educational conditions, and demographic characteristics changed considerably.

South Sulawesi represents a distinctive case because it serves as one of the major economic gateways in Eastern Indonesia while simultaneously exhibiting substantial disparities among its districts and municipalities. The province includes highly urbanized areas, such as Makassar, alongside predominantly rural districts with different economic structures, employment opportunities, educational attainment, and population distribution. These heterogeneous socio-economic conditions may lead to different relationships between unemployment, education, population density, and poverty compared with those reported for other Indonesian provinces. Therefore, findings obtained from other regions cannot be directly generalized to South Sulawesi.

This study addresses these research gaps by examining the determinants of poverty in South Sulawesi using district/city panel data for the 2020–2024 period. By employing panel data regression, this study captures both cross-sectional differences among districts and temporal changes over time, providing updated empirical evidence and more region-specific policy implications for poverty alleviation in South Sulawesi.

An analysis aimed at understanding the relationship between poverty and other factors must also consider changes over time, which cannot be adequately addressed using conventional statistical analysis. To overcome this issue, the required data analysis must be multidimensional, involving both cross-sectional and time-series dimensions. A data structure that combines cross-sectional (individual) and time-series dimensions is referred to as panel data. This two-dimensional structure enables researchers to observe dynamic changes in the characteristics of individuals or observations over time.

This study aims to analyze the factors influencing the percentage of the poor population in South Sulawesi Province using the panel data regression method. Panel data are chosen because of their ability to combine time-series and cross-sectional data, thereby providing a more comprehensive and accurate description of poverty dynamics in the region. The factors analyzed in this study include the open unemployment rate, mean years of schooling, and population density.

Through this study, it is expected that the relationships among these variables can be identified, thereby providing a clearer understanding of the main factors influencing poverty and serving as a basis for formulating effective policies to reduce poverty rates in South Sulawesi.

2. Materials and Methods

2.1. Open Unemployment

According to [6] open unemployment refers to individuals who are willing to work and are actively seeking or attempting to obtain employment but have not yet succeeded in finding a job. According to [7] every country in the world, whether categorized as developed or developing, consistently faces unemployment problems. The difference is that developing countries are generally unable to provide unemployment benefits to their citizens, whereas developed countries are capable of providing such guarantees.

2.2. Poor Population

According to [8] individuals whose monthly per capita expenditure falls below the national standard are classified as poor population. According to the Central Bureau of Statistics (BPS), poverty is defined as the inability to fulfill basic food needs from an economic perspective, measured in terms of expenditure rather than merely food availability.

2.3. Mean Years of Schooling

According to [9] mean years of schooling is defined as the number of years spent by the population in formal education. Under normal conditions, the mean years of schooling in a region is assumed not to decrease. Mean years of schooling serves as an indicator to determine the quality of education within a region. Higher educational attainment increases productivity, employability, and earning potential, thereby reducing poverty risk.

2.4. Population Density

Population density may affect the quality of life of the population. In areas with high population density, efforts to improve population quality become more difficult to implement. This condition may lead to socio-economic, welfare, security, land availability, clean water, and food supply problems. The most significant impact is environmental degradation.

From a human capital perspective, education plays an essential role in improving individuals' productivity, skills, and competitiveness in the labor market. Higher educational attainment generally increases employability and earning potential, enabling individuals to obtain more stable and better-paying jobs. Consequently, education is expected to reduce the risk of poverty by expanding economic opportunities and enhancing household welfare. Therefore, mean years of schooling is widely used as an important socio-economic indicator in studies examining the determinants of poverty.

2.5. Estimation of Panel Data Regression Models

There are several models that can be used to estimate panel data regression models, including the following:

2.5.1. Common Effect Model (CEM)

The *Common Effect Model* (CEM) assumes that there are no differences in the intercept and slope values of the regression results, either across individuals or over time. In general, the common effect model equation is written as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_n X_{nit} + \varepsilon_{1it} \quad (1)$$

2.5.2. Fixed Effect Model (FEM)

The estimation of panel data regression parameters using the Fixed Effect Model employs the addition of dummy variables; therefore, this method is often referred to as the Least Square Dummy Variable (LSDV) model. The regression equation in the Fixed Effect Model is:

$$Y_{it} = \beta_{1t} + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + u_{1it} \quad (2)$$

2.5.3. Random Effect Model (REM)

There are two methods used to estimate the Random Effect Model, namely the LSDV method and the Generalized Least Square (GLS) method. Since the LSDV method requires the addition of dummy variables, it results in an excessive number of variables relative to the number of observations. In addition, the degree of freedom requirement is not fulfilled; therefore, the LSDV method cannot be applied. Consequently, estimation using the GLS method is preferred because it directly estimates the model without the addition of dummy variables. The Random Effect Model is written as follows:

$$Y_{it} = \beta_{0it} + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_n X_{nit} + \mu_i + \varepsilon_{1it} \quad (3)$$

2.6. Selection of Panel Data Regression Models

Tests for selecting the appropriate panel data regression estimation model are as follows:

2.6.1. Chow Test

The Chow test is conducted to determine whether the Common Effect Model is more appropriate than the Fixed Effect Model. The test statistic is as follows [10]:

1. Hypothesis Test
   H_0 : the appropriate model for panel data regression is the model *Common Effect Model*
   H_1 : the appropriate model for panel data regression is the *Fixed Effect Model*
2. Significance Level
   $\alpha = 5\%$
3. Critical Region
   H_0 is rejected if $p - value < \alpha$ or if $F_{statistic} > F_{table}$
4. Test Statistic

$$F_{statistic} = \frac{\frac{(SSE_1 - SSE_2)}{(n-1)}}{\frac{SSE_2}{(nt-n-k)}} \quad (4)$$

Meanwhile, F_{table} is obtained from:

$$F_{table} = \alpha : dfn - 1, nt - n - k \quad (5)$$

2.6.2. Hausman Test

The Hausman test is conducted to determine whether the Fixed Effect Model is more appropriate than the *random effect model* [10].

1. Hypothesis Test

H_0 : the appropriate model for panel data regression is the *Random Effect Model*

H_1 : the appropriate model for panel data regression is the *Fixed Effect Model*

2. Significance Level
   $\alpha = 5\%$
3. Critical Region
   H_0 is rejected if p-value < α or $W \geq x^2_{table}$
4. Test Statistic
   Following the Wald criterion, the Hausman test follows a chi-square distribution as shown in the following equation:

$$W = qVarq^{-1}q \quad (6)$$

Where:

$q = \beta_{FEM} - \beta_{REM}$

$Var(q) = Var(\beta_{FEM} - \beta_{REM})$

β_{FEM} : Estimated regression parameter vector of the *Fixed Effect Model*

β_{REM} : Estimated regression parameter vector of the *Random Effecr Model*

2.6.3. Breusch–Pagan Test (Multiple Lagrange)

The Breusch–Pagan test is used to examine the existence of time effects, individual effects, or both [10].

1. Hypothesis Test
   $H_0 : \beta_{0i} = 0$ (there is no individual effect)
   $H_1 : \beta_{0i} = 0$ (there is an individual effect)
2. Time Effect Test
   $H_0 : \beta_{0i} = 0$ (there is no time effect)
   $H_1 : \beta_{0i} = 0$ (there is a time effect)

To detect the presence or absence of spatial heterogeneity in the model, the Breusch–Pagan test is applied. The formula used in the Breusch–Pagan test is as follows [11]:

$$BP = \frac{1}{2} b^T A(A^T A)^{-1} A^T \# (7)$$

2.7. Examination of the Regression Equation

2.7.1. F-Test

The F-test is used to test the regression coefficients simultaneously or collectively. In other words, it is used to determine whether the selected model is appropriate for interpreting the influence of independent variables on the dependent variable.

2.7.2. t-Test

The t-test is used to examine regression coefficients individually. The test is conducted to determine whether the population regression coefficient is equal to zero, indicating that the independent variable has no significant effect on the dependent variable, or not equal to zero, indicating that the independent variable has a significant effect on the dependent variable.

2.7.3. Coefficient of Determination Test

The coefficient of determination (Goodness of Fit), denoted by R-square, is an important measure in regression analysis because it provides information regarding the goodness of the estimated regression model.

2.8. Assumption Tests of the Panel Data Regression Model

2.8.1. Normality Test

The purpose of the normality test is to determine whether the disturbance or residual variables in a regression model follow a normal distribution [12]. One of the methods used for normality testing is the Kolmogorov–Smirnov test.

$H_0: e = 0$ (residual are normal distributed)

$H_1: e \neq 0$ (residual are not normal distributed)

2.8.2. Autocorrelation Test

The autocorrelation test is conducted to examine whether there is a correlation between disturbance errors in period t and disturbance errors in the previous period (t – 1) in a linear regression model [13]. This test is used to identify relationships among a series of observational data ordered by time and space.

$H_0: \rho = 0$ (there is no autocorrelation)

$H_1: \rho \neq 0$ (there is autocorrelation)

2.8.3. Heteroscedasticity Test

The heteroscedasticity test is conducted to determine whether the regression model has unequal variances of residuals from one observation to another [13]. The expected regression model is one in which the residual variances remain constant or homoscedastic.

$H_0: var(e_i) = 0$ (the error variance is homoscedastic)

$H_1: var(e_i) \neq 0$ (the error variance is heteroscedastic)

2.8.4. Multicollinearity Test

According to [12], the multicollinearity test aims to determine whether the regression model contains high or perfect correlations among the independent variables used. The method applied in this study is by examining the tolerance value and the *variance inflation factor*. If the VIF < 10 the model is considered free from multicollinearity problems.

2.9. Type of Research

This study uses a quantitative approach, where quantitative data refers to a research method based on numerical data. The research data consist of numbers that are measured using statistical methods as calculation tools related to the research problem in order to generate conclusions [14].

2.10. Data Source

The data were obtained from the Central Bureau of Statistics (BPS) of South Sulawesi Province; therefore, the data are secondary data. The variables obtained from BPS South Sulawesi Province include the poverty rate, open unemployment rate, mean years of schooling, and population density.

2.11. Research Variables

In this study, the poverty rate is used as the dependent variable (Y), while the open unemployment rate, mean years of schooling, and population density are used as independent variables (X).

2.12. Steps of Panel Data Analysis

1. Estimation of panel data regression models.
2. Selection of panel data regression models (estimation techniques).

3. Examination of the regression equation.
4. Assumption testing of the panel data regression model.

3. Results

3.1. Descriptive Statistics

Table 1. *Poor Population Rate (Y)*

Year	Descriptive Statistics		
	Mean	**Maximum**	**Minimum**
2020	32,36833	81,33	7,96
2021	32,70750	79,64	7,93
2022	32,39292	80,34	8,01
2023	32,86958	80,32	7,98

Table 2. Open Unemployment Rate (X_1)

Year	Descriptive Statistics		
	Mean	**Maximum**	**Minimum**
2020	4,985000	15,92	2,31
2021	4,748333	13,18	2,34
2022	3,632083	11,82	0,58
2023	3,840833	10,60	1,31

Table 3. Mean Years of Schooling (X_2)

Year	Descriptive Statistics		
	Mean	**Maximum**	**Minimum**
2020	8,147917	11,21	6,59
2021	8,272083	11,43	6,60
2022	8,360417	11,55	6,75
2023	8,518750	11,56	7,00

Table 4. Population Density (X_3)

Year	Descriptive Statistics		
	Mean	**Maximum**	**Minimum**
2020	378,0750	1423,9	137,1
2021	380,8167	1427,6	138,0
2022	394,3083	1464,6	142,7
2023	390,0917	1455,0	141,2

3.2. Panel Data Regression Model

3.2.1. Common Effect Model

$$\hat{Y} = 20.7575804 - 0.7681657X_{1it} - 0.7462211X_{2it} + 0.0553193X_{3it}$$

3.2.2. Fixed Effect Model

1. Individual Effect

$$\hat{Y}_{it} = 31{,}61061D_1 + 31{,}26637D_2 + 117{,}07537D_3 + 53{,}67333D_4 + 41{,}27108D_5 + 95{,}60136D_6 + 71{,}94044D_7 + 28{,}53670D_8 + 68{,}70471D_9 + 41{,}23156D_{10} + 61{,}31102\ D_{11} + 143{,}84481D_{12} + 57{,}98025D_{13} + 35{,}12607D_{14} + 69{,}04383D_{15} + 24{,}85637D_{16} + 56{,}52605D_{17} + 35{,}58635D_{18} + 37{,}68257D_{19} + 33{,}76019D_{20} + 43{,}47939D_{21} + 47{,}09460D_{22} + 45{,}08901D_{23} + 47{,}92440D_{24} + -0{,}75917X_{1it} - 0{,}59830X_{2it} - 0{,}3675X_{3it}$$

2. Time Effect

$$\hat{Y}_{it} = 34.301864D_1 + 34.370804D_2 + 31.575382D_3 + 33.039906D_4 - 1.602628X_{1it} - 2.350540X_{2it} + 0.066673X_{3it}$$

3. Random Effect Model

$$\hat{Y} = 14.6234136 + 0.3596422X_{1it} - 0.4800906X_{2it} + 0.0529020X_{3it}$$

3.3. Model Selection

Table 5. Chow Test

Chow Test	
F	***p-value***
308.9	$2.2e^{-16}$

Based on the test results above, the *p-value*= $2.2e^{-16}$ which is smaller than alpha, it can be said that there is insufficient evidence to accept H_0 so it can be concluded that the model selected in this test is the *Fixed effect model.*

Table 6. Hausman Test

Hausman Test	
Chi Square	***p-value***
3.5362	0.3161

Based on the test results above, the $p - value = 2.2e^{-16}$ is obtained which is greater than alpha, so it can be said that there is sufficient evidence to accept H_0 so it can be concluded that the model selected in this test is the *Random effect model.*

Table 7. Lagrange Multiplier Test

Lagrange Multiplier Test	
Chi Square	***p-value***
136.91	$2.2e^{-16}$

Based on the test results above, the $p - value = 2.2e^{-16}$ is obtained which is smaller than alpha, so it can be said that there is not enough evidence to accept H_0 sehingga dapat disimpulkan bahwa model yang terpilih pada uji ini yaitu *Random effect model.* So, the model selected after conducting the three tests above is *Random effect model.*

3.4. Classical Assumption Tests

Table 8. Normality Test

Kolmogorov–Smirnov Test	
D	***p-value***
0.11259	0.04985

Based on the output above, the *p-value* is smaller than alpha, so there is sufficient evidence to reject H_0 so it can be concluded that the data is not normally distributed.

Table 9. Autocorrelation Test

Runs Test	
Runs Statistic	***p-value***
-6.7718	0.04755

Based on the output above, the *p-value* is less than alpha, so there is sufficient evidence to reject H_0 thus concluding that autocorrelation occurs.

Table 10. Heteroscedasticity Test

Breusch–Pagan Test	
BP	***p-value***
11.711	$8.159e^{-07}$

Based on the output above, the *p-value* is less than alpha, meaning there is sufficient evidence to reject H_0 thus concluding that heteroscedasticity occurs.

Table 11. Multicollinearity Test

Variable	**VIF Value**
Open Unemployment Rate	1.301684
Mean Years of Schooling	1.269061
Population Density	1.113996

Based on the output above, it is known that the VIF values of the open unemployment rate, mean years of schooling, and population density variables are less than 10. This indicates that there is insufficient evidence to reject H_0 meaning that no multicollinearity occurs among the independent variables.

3.5. Parameter Significance Test

Table 12. Coefficient of Determination Test

Coefficient of Determination	
Adjusted R-squared	
Random Effect Model	0.33476

Based on the estimation results of the Random Effect Model, the adjusted R-squared value is 0.33476. This means that the independent variables are only able to explain 33.48% of the dependent variable, while the remaining percentage is explained by other independent variables outside the model.

Table 13. F-Test

Simultaneous Test	
F-Statistic	***p-value***
111.6	$2.2e^{-16}$

Based on the output above, the p-value is less than alpha, so there is sufficient evidence to reject H_0 and it can be concluded that variables $X_1, X_2,$ and X_3 significantly influence variable Y.

Table 14. t-Test

Variable	**z-value**	***Probability z***	**Description**
$\boldsymbol{X_1}$	2.1701	0.03000	Significant
$\boldsymbol{X_2}$	-0.5996	0.54878	Not Significant
$\boldsymbol{X_3}$	7.0926	$1.316e^{-12}$	Significant

1. The z-probability value of $X_1 < 0.05$ or $0.03000 < 0.05$, meaning there is insufficient evidence to accept H_0 therefore, we can conclude that there is a significant effect between the open unemployment rate and the poverty rate.
2. The z-probability value of $X_2 > 0.05$ or $0.054878 > 0.05$, meaning there is sufficient evidence to accept H_0 therefore, we can conclude that there is no significant effect between the average years of schooling and the poverty rate.
3. The z-probability value of $X_3 < 0.05$ or $1.316e^{-12} < 0.05$, which means there is insufficient evidence to accept H_0 so we can conclude that there is a significant influence between population density and the level of poverty.

After conducting all stages of testing, several classical assumptions were found to be violated. Therefore, corrective measures were implemented to overcome these assumption violations. The treatment applied to address the violations of normality and heteroscedasticity assumptions was logarithmic transformation of the data, while the violation of autocorrelation assumption was addressed using the GLS (*Generalized Least Square*) approach.

1. Logarithmic Transformation to Overcome Violations of Normality and Heteroscedasticity Assumptions

Table 15. Normality Test

Kolmogorov–Smirnov Test	
D	***p-value***
0.052765	0.9391

After carrying out the transformation process, the new output results are obtained as above, where the *p-value* is greater than alpha or 0.9391 > 0.05 so there is not enough evidence to reject H_0 so it can be concluded that the data is normally distributed.

Table 16. Heteroscedasticity Test

Breusch–Pagan Test	
BP	***p-value***
1.2164	0.7491

After performing the transformation process, the new output results are obtained as above, where the *p-value* is greater than alpha, or 0.7491 > 0.05 indicating insufficient evidence to reject H_0 and therefore, it can be concluded that the data is normally distributed.

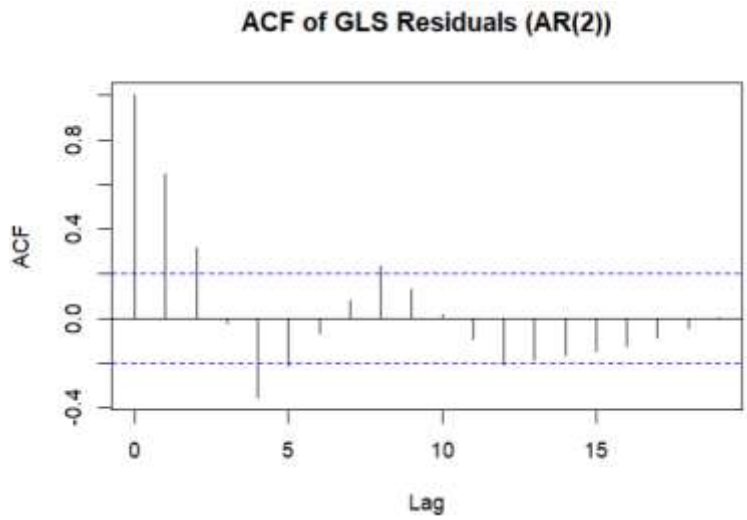
2. Using the GLS Approach to Overcome Autocorrelation Violations
The steps applied in this treatment are as follows:
   - Constructing several models, namely ARMA (1,1), ARMA (2,1), AR (2), and MA (1) models.

Table 17. Comparing the AIC values of the four models.

	AIC
ARMA (1,1) Model	383.4225
ARMA (2,1) Model	384.0751
AR (2) Model	382.1455
MA (1) Model	551.1765

After obtaining the AIC values of the four constructed models, the model with the smallest AIC value was selected, namely the AR 2 model with an AIC value of 382.1455.

   - Constructing the ACF plot of the selected model, namely the AR 2 model.



Based on the ACF plot above, it can be observed that only the initial lags (lag 1 and lag 2) are slightly high, while most ACF values remain within the significance limits. This indicates that the residuals of the model approach white noise. Therefore, it can be concluded that there is no significant autocorrelation and the autocorrelation assumption violation has been successfully resolved.

4. Discussion

This study aimed to identify the factors affecting the percentage of the poor population in South Sulawesi Province during the period 2020–2024 using panel data regression. Based on the model selection procedures, namely the Chow test, Hausman test, and Lagrange Multiplier test, the Random Effect Model (REM) was selected as the most appropriate model. The results indicate that the open unemployment rate and population density significantly influence poverty levels, while mean years of schooling does not have a statistically significant effect.

The significant positive effect of the open unemployment rate on poverty is consistent with economic theory, which states that unemployment reduces individuals' income-generating capacity and increases the risk of falling below the poverty line. Individuals who are unemployed often experience difficulties in fulfilling basic needs due to the absence of stable income sources. The result suggests that poverty reduction policies in South Sulawesi should prioritize employment creation, labor market expansion, and workforce skill development programs.

Population density was also found to have a significant positive effect on poverty. This result indicates that regions with higher population density tend to experience higher poverty rates. One possible explanation is that rapid population growth and concentration may increase competition for employment opportunities, public services, housing, and other economic resources. When economic growth and job creation are unable to keep pace with population growth, poverty may increase. Therefore, policies related to regional development, urban planning, and equitable distribution of economic activities are essential to reduce poverty in densely populated areas.

In contrast, mean years of schooling was found to have no significant effect on poverty. Although education is generally expected to improve human capital and increase earning opportunities, the result suggests that the effect of education on poverty

reduction may not be immediate. Several factors may explain this finding. First, the variation in mean years of schooling among districts and cities in South Sulawesi during the study period may not have been large enough to produce a significant statistical effect. Second, educational attainment alone may not guarantee improved economic welfare if labor market conditions are unable to absorb educated workers effectively. Third, the relatively short observation period may not fully capture the long-term benefits of education on poverty reduction.

The coefficient of determination indicates that approximately 33.48% of the variation in poverty rates can be explained by the variables included in the model. This implies that a substantial proportion of poverty variation is influenced by other factors not included in the analysis. Such factors may include economic growth, income inequality, inflation, government social assistance programs, health conditions, infrastructure availability, and regional investment levels. Consequently, future studies are encouraged to incorporate additional socio-economic indicators to improve the explanatory power of the model.

From a policy perspective, the findings emphasize the importance of integrated poverty reduction strategies. Efforts to reduce unemployment should be accompanied by policies that support entrepreneurship, vocational training, investment promotion, and local economic development. At the same time, managing population concentration through balanced regional development and improved public service distribution may help alleviate poverty pressures in densely populated areas. Although education was not found to be statistically significant in this study, improving educational quality remains essential because education contributes to long-term human capital development and sustainable economic growth.

This study contributes to the literature on poverty analysis in Indonesia by providing empirical evidence from South Sulawesi using panel data regression. Nevertheless, several limitations should be acknowledged. The study covers a relatively short period (2020–2024) and employs only three explanatory variables. Future research may extend the observation period, include additional explanatory variables, and explore spatial or dynamic panel data approaches to better understand the complex determinants of poverty at the regional level.

5. Conclusions

This study shows that the open unemployment rate and population density have a significant effect on increasing poverty in South Sulawesi during the 2020–2024 period, while mean years of schooling does not have a significant effect. The results of the panel data analysis using the Random Effect Model indicate the need for policies focused on job creation and population distribution management in order to reduce poverty.

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