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DETERMINANTS OF POVERTY IN PAPUA PROVINCE: A PANEL DATA REGRESSION APPROACH (2021–2023)

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ABSTRACT

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Papua Province, as one of the most underdeveloped regions in Indonesia, faces the problem of chronic poverty that occurs continuously. The high percentage of poverty and the low index in the aspects of shaping human development make the analysis of the factors that cause poverty urgent and worth researching. The purpose of this study is to identify the variables that affect the poverty rate in Papua Province in 2021-2023 comprehensively and systematically to identify vulnerable factors so that they can be used as a reference for mapping poverty alleviation policies that are more effective. The method used in this study is panel data regression, considering its advantages in providing a larger amount of data so that it can provide greater information that is not only produced by cross-sectional or time series data only. The data used is a publication from Badan Pusat Statistik (BPS) for 2021-2023 with the number of poor people, average length of schooling, labor force participation rate, per capita expenditure, life expectancy, human development index, gross regional domestic product, and length of schooling as predictor variables. The approach with fixed random effect was chosen to be the most suitable model. According to the results obtained from this analysis, the factor that has a significant effect on the condition of economic insufficiency in Papua Province in 2021-2023 is the number of poor people. These findings emphasize the importance of affirming that poverty alleviation policies need to be focused on reducing the number of poor people through programs that target increasing income and access to basic needs of the community.

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1. INTRODUCTION

Poverty still remains an old classic problem that almost every country fights against. This problem is especially faced in countries that are still in the process of development [1]. Poverty is multidimensional, which is not only caused by low economic factors but also by poor health, educational conditions, and other social systems [2]. With the low level of people's welfare, poverty is the main commitment of all countries in the world [3]. Therefore, dealing with these problems requires a comprehensive, data-based approach to find out the root of the problem. This is an urgency, especially in areas that are still lagging behind in terms of development. Indonesia, as a developing country, also faces the same serious problems [4].

One of the most striking in the list of provinces with high poverty rates is Papua [5]. The proportion of poverty in Papua in September 2022 reached 26.80 percent, an increase of 0.24 percent from March 2022, making it the province with the highest poverty rate in Indonesia. The poor population in September 2022 increased by 14.20 thousand people compared to March 2022, which resulted in the number of poor people reaching 939.32 thousand people [6]. According to Badan Pusat Statistik (BPS) in March 2023, the poverty rate in Papua was recorded at 26.03 percent, where this figure decreased by 0.77 percent compared to September 2022. The number of people living in poverty in March 2023 was recorded at 915.15 thousand people, down 21.2 thousand people compared to September 2022 [7]. This percentage shows that many people in Papua still live below the poverty line. The high number of poor people is well above the national average, reflecting significant socio-economic disparities at the regional level.

One way that can be done to reduce poverty rates is to implement a countermeasure program by considering the factors that affect it [8]. The large percentage of poor people is an affirmation that the poverty alleviation program implemented by the government in the last period is not effective enough in improving the living standards of the poor [9]. High levels of poverty are inseparable from the various factors that influence them, so a more in-depth analysis of poverty is needed that is not only focused on a single point in time but also consistent over time [10].

In this context, the use of panel data becomes important and more effective. Data panels were introduced by Howles in 1950 [11]. The data panel consists of time-based data combined with one-time observations across unit (individual) data [12]. Cross-sectional data is generated from observing multiple subjects at the same time, while time series data is generated from observations of a single object from several different time periods [13]. The data panel is able to provide more data so that it provides a large amount of observations, thus providing a wider range of information [14]. Data observed over time and entities will result in a degree of freedom [15].

Therefore, this study aims to empirically analyze the factors that affect poverty in Papua in 2021-2023, seeing that there is still limited research that specifically examines determinants using a panel data approach. By using socio-economic variables such as the number of poor people, average length of schooling, labor force participation rate, per capita expenditure, life expectancy, human development index, gross regional domestic product, and school life expectancy, this study is expected to provide a comprehensive picture. The main contribution of this study is to provide relevant data-based evidence for the formulation of more contextual poverty alleviation policies in Papua.

2. METHODS

Material and Data

This research uses a quantitative approach with a panel data regression analysis method. The data used is data that has been collected previously sourced from BPS, with a period of 2021-2023 covering 9 districts/cities in Papua. The panel data regression approach was chosen because it is able to combine the advantages of the data provided by the time series and cross section so that it can capture more complex dynamics between time and individuals.

The variables used in this study consist of:

Table 1. Variables

Variable	Code
Percentage of Poor Population	(Y)
Total Poor Population	(X1)
Average School Length	(X2)
Labor Force Participation Rate	(X3)
Expenditure per Capita	(X4)
Life Expectancy Figures	(X5)
Human Development Index	(X6)
Gross Regional Domestic Product	(X7)
Old School Expectations	(X8)

The selection of these variables is based on human development theory, which shows that poverty is influenced by the economic, educational, and health dimensions [16]. In this context, poverty is not only seen from the economic aspect (the number of poor, the participation rate of the labor force, per capita expenditure, and gross regional domestic product) but also from the aspect of education (average length of school and length of school), the health aspect (life expectancy), and also the multidimensional aspect, namely the human development index.

With the panel data regression approach and the use of these variables, this analysis is expected to provide a comprehensive picture of the factors affecting the poverty rate in Papua Province in 2021 – 2023.

Research Method

In the analysis to find out the elements that have an impact on the poverty rate in Papua Province, the researchers applied the Data Regression Analysis Panel. This method was chosen because it can model the relationships between variables from a dated panel. This combination of dimensions makes the data have a richer structure, so it can provide a wider range of information [17]. In this approach, a variety of methods can be used to estimate the model. Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM) are the models used to estimate [18].

Procedure for analysis:

1. Conduct a literature study and what variables are used in analyzing the factors that affect the poverty rate.
2. Collect data and perform characteristic analysis for dependent and independent variables.
3. Conduct statistical analysis descriptively.
   Descriptive analysis involves statistical techniques that describe the characteristics of a dataset based on the collected information, without drawing conclusions applicable to the wider population [19]. In descriptive statistical analysis, data can be presented in a variety of ways, such as in the form of tables, graphs, diagrams, maps, and centering sizes [19].
4. Conduct statistical analysis using panel data regression approach.
   One widely used statistical method for analyzing panel data is regression analysis, which aims to see the influence of several predictor variables on response variables involving repeated observations over time for multiple units. The basic model representation for panel data regression [20]:

$$Y_{it} = \beta_{0it} + \sum_{k=1}^{K} \beta_k X_{kit} + e_{it} \tag{1}$$

   Where Y_{it} is the dependent variables in the observation unit and the time, β_{0it} is the intercept regression models in the unit and time, β_k is the slope coefficients for independent variables, X_{kit} is the independent variables for observation units and time periods, e_{it} is the error components in observation and time units, and K is the independent variables (k = 1,2,3,…, K)

5. Estimating panel data model parameters [18].
   a. Common Effect Model (CEM) assembling a data structure that includes both cross-sectional and longitudinal components, regardless of unit or individual and research time. The intercept and slope coefficient values of each entity based and temporal data variable in this method are assumed to be the same. The CEM equation is expressed as follows:

$$Y_{it} = \alpha + \sum_{k=1}^{K} \beta_k X_{it} + u_{it} \tag{2}$$

   Where Y_{it} is the response variables in observation units and time, β_0 is the intercept regression models on observation and time units, β_k is the slope coefficient, x_{it} is the predictor variables for observation units and time periods, e_{it} is the errors in observation and time units, i is the cross section unit, t is the time series unit, and k is the K of predictor variables (1, 2, 3, …,n).
   b. Fixed Effect Model (FEM) It is assumed that the intercept is not constant, while the slope coefficient is assumed to remain constant between cross section units. The FEM equation is expressed as follows:

$$Y_{it} = \beta_{0it} + \sum_{k=1}^{n} \beta_k X_{kit} + e_{it} \tag{3}$$

   Where Y_{it} is the response variables in observation units and time, β_0 is the intercept regression models on observation and time units, β_k is the slope coefficient, x_{it} is the predictor variables for observation units and time periods, e_{it} is the errors in observation and time units, I is the cross section unit, t is the time series unit, and k is the K of predictor variables (1, 2, 3, …,n).
   c. Random Effect Model (REM) used to deal with problems in FEM. The addition of a dummy variable to the FEM will block the original model so that there is an addition of an error term variable to the model. The REM equation is expressed as follows:

$$Y_{it} = \beta_{0it} + \sum_{k=1}^{n} \beta_k X_{kit} + \mu_i + e_{it} \tag{4}$$

   Where Y_{it} is the response variables in observation units and time, $\beta_0$is the intercept regression models on observation and time units, $\beta_k$is the slope coefficient, x_{it} is the predictor variables for time period observation units, μ_i is the error on the observation unit, e_{it} is the errors in observation and time units, i is the cross section unit, t is the time series unit, and k is the K of predictor variables (1, 2, 3, …, n).
6. Identifying the best-fitting panel regression framework [18]:
   a. Chow Test
   This test assesses the suitability of the CEM in comparison with the FEM is appropriate. If H_0 is rejected, FEM is selected and followed by the Hausman test. If H_0 is accepted, CEM is chosen, and subsequently, the Lagrange Multiplier test was performed. The Chow test statistic is as follows:

$$F_{count} = \frac{(RSS_1 - RSS_2)\ /\ (N-1)}{RSS_2/(NT - N - K)} \tag{5}$$

   Where N is the number unit, T is the number of period, K is the number of predictor component, RSS_1 is the number of square errors from CEM estimates, and RSS_2 is the number of squared errors from FEM estimates.
   b. Hausman Test

This test assesses the suitability of the FEM or REM, whichever is more appropriate. If H_0 is rejected, FEM is selected; otherwise, REM is chosen and followed by the Lagrange Multiplier test. The Hausman test statistic is as follows:

$$\chi^2(K) = (b-\beta)'[var(b-\beta)]^{-1}(b-\beta) \tag{6}$$

Where b is the Coefficient REM and β is the Coefficient FEM

c. Lagrange Multiplier Test
This test is conducted to choose between the CEM or the REM. If H_0 is rejected, REM is selected; if H_0 is accepted, CEM becomes the preferred model. The Lagrange Multiplier test statistic is as follows:

$$LM = \frac{nT}{2(T-1)} \frac{\sum_{i=1}^{n}(Te_{it})^2}{\sum_{i=1}^{n}\sum_{t=1}^{T} e^2{}_{it}} - 1 \tag{7}$$

Where n is the number of unit, T is the number of period, and e_{it} is the error components in cross section and time series units.

7. Perform an assumption validity test.
   a. Multicollinearity
   Multicollinearity tests are performed to show a strong correlation among multiple variables within a regression framework. The interdependencies between explanatory variables may be observed using the Variance Inflation Factor (VIF). The VIF value can be calculated by [21]:

$$VIF_j = \frac{1}{1-R_j^2}; j = 1,2,\ldots,k \tag{8}$$

   Decision-making criteria if the VIF value is < 10 or *the Tolerance value* is > 0.01, then it is stated that multicollinearity does not occur [22].
   b. Autocorrelation
   Autocorrelation in the concept of linear regression means that the residual components are correlated temporally in the time series component and spatially in the cross-sectional component of the data. The presence of autocorrelation can be examined using appropriate testing procedures with the Durbin-Watson test with the following test criteria:
      i. If $dU < dW < I\ dU$ then acceptance of H_0, this means that there is no autocorrelation.
      ii. If $dW < dL$ or $dW > 4 - dL$ rejection of H_0, this means that autocorrelation occurs.
      iii. If $dL < dW < dU$ or $4 - dU < dW < 4 - dL$, meaning that there is no definitive conclusion.
   c. Heteroscedasticity
   The heteroscedasticity test is carried out with the aim of testing whether in the model there is an unevenness of variance from one residual observation to another. If the variance is different, heteroscedasticity occurs, while if the variance is fixed, it is called homogeneity. The hypothesis of this test is as follows:
   H_0: No heteroscedasticity
   H_1: There is heteroscedasticity
   The heteroscedasticity test statistic is as follows [8]:

$$t_{count} = \frac{\hat{\beta}_k}{Se(\widehat{\beta_k})} \tag{9}$$

   Decision making criteria:
   Rejection of H_0 if $|t_{count}| > t_{(\frac{\alpha}{2};NT-k1)}$ or *p-value* < α (0,05).

8. Perform parameter significance tests.
   a. Overall Test

      It is performed for whether the predictor variables as a whole and together are significant to the response variables. The hypothesis is as follows:

      H_0 : The set of independent variables fails to produce a significant influence on the dependent variable.

      H_1 : The independent variables collectively have significant effect on the dependent variable.

      The overall test statistic is as follows [23]:

$$F = \frac{R^2 / (N + K - 1)}{(1 - R^2) / (NT - N - K)} \tag{10}$$

      The test criteria are when $F_{count} > F_{table(\frac{\alpha}{2};(K,(nT-K-1))}$ or *p-value* $< \alpha$ (0,05) rejection of H_0. This implies that the independent variable together has an effect on the bound variables.

   b. Partial Test

      It was undertaken to find out the relationship or significance of each element on the response variable separately. The hypothesis is as follows:

      H_0 : The partial effects of the independent variables on the dependent variable are statistically insignificant.

      H_1 : The independent variables contribute significantly to variations in the dependent variable individually

      The partial test statistic is as follows [23]:

$$t = \frac{\hat{\beta}_k}{se(\hat{\beta}_k)} \tag{11}$$

      The test criteria are when $|t_{count}| > t_{table(\frac{\alpha}{2},NT-N-K)}$ or *p-value* $< \alpha$ (0,05) rejection of H_0. As a result, predictor variable plays a role in determining the bound variable partially.

   c. Adjusted R^2

      It is used to measure the quality of the model by considering the number of predictor variables used so that it can be possible to give a more accurate picture of its ability to predict the model. The Adjusted R^2 value is in the range of 0 – 1, with values close to one drawn. The conclusion is that the determinant variables in the model structure are able to offer most of the explanatory power required to estimate the dependent variables [12].

9. Interpret the empirical findings formed from the model deemed most appropriate.

3. RESULTS

Data Exploration

Descriptive statistical methods are utilized to summarize and present an overall picture of the characteristics of the data in general.

Table 2. Descriptive Analysis of Variables in General

Variable	Minimum	Maximum	Average
Percentage of Poor Population (%)	10.5	37.91	22.1611
Total Poor Population	5.45	36.8	16.8329
Average School Length	5.87	11.84	9.3240
Labor Force Participation Rate	42.13	76.005	64.7059
Expenditure per Capita	4603	15272	8552.40
Life Expectancy Figures	58	71.07	66.8044
Human Development Index	52.18	81.14	67.7007
Gross Regional Domestic Product	38810	111387	63490.4
Old School Expectations	11.8	15.26	13.2311

As shown in Table 1, descriptive summary results indicate that the average ratio of the low-income population in Papua Province in 2021-2023 is around 22.16%. This value shows a relatively high poverty rate, with the poorest areas reaching 38% and the lowest still above 10%. The average extent of poverty among residents in Papua Province in 2021-2023 is around 18,830 people per district/city. The results of the analysis also show a significant disparity in the number of poor people between regions with the highest and lowest values. The average length of schooling for residents is approximately 9.32 years, indicating that people generally only complete their education up to the junior high school level. Around 64.71% of the working-age population in Papua Province has participated in the labor force. This indicates a moderate level of economic involvement. Per capita expenditure reflecting people's purchasing power level is at Rp. 8,552 which shows that the standard of living is still relatively low. The quality of public health shown by the life expectancy rate is quite low, only in the range between 58-71 years. The value of the human development index is relatively moderate, with an average of 67.7, but there is still inequality between regions. As shown by gross regional domestic product, there is a disparity in regional economic potential, with the highest value is Rp. 111,387, while the lowest is Rp. 38,810. The length of school expectation shown by an average of 13.23 years indicates the desire and potential for access to education up to the high school level.

Descriptive statistics are then shown in the form of a graph of the poverty rate in Papua during 2021-2023, as illustrated in Figure 1.

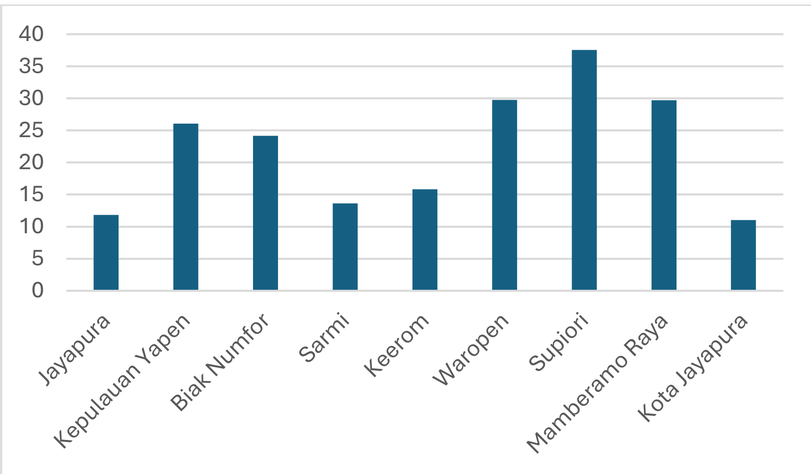

Figure 1. Poverty Rate in Papua Province

The results obtained from the percentage graph of the poverty rate in Papua show that Supiori Regency, which was then followed by Waropen Regency, had the highest poverty rate in 2021-2023. Meanwhile, the area with the lowest poverty rate in 2021-2023 in Papua is Jayapura City. The significant difference between the regions with the lowest and highest poverty is evidence of the magnitude of the existing socio-economic inequality.

Parameter Model Estimation

The next step after the data exploration aims to compute the predicted values of parameters in the panel data model.

1. Common Effect Model

$$Y_{it} = -3.710410 - 0.394801X1_{it} + 4.384703X2_{it} - 0.284710X3_{it} + 9.92E-05X4_{it} + 0.839246X5_{it} - 2.241329X6_{it} - 0.000376X7_{it} + 9.728987X8_{it}$$

2. Fixed Effect Model

$$Y_{it} = \hat{a}_i + 0.821148X1_{it} + 0.674677X2_{it} - 0.005304X3_{it} - 0.001170X4_{it} + 0.399389X5_{it} - 0.438818X6_{it} + 8.25E-05X7_{it} + 1.036541X8_{it}$$

The estimated value of intercept $\hat{a}_i$ varies for each district/city, presented in Table 3.

Table 3. Estimated Intercept for Each Regency/City

Variable	Intercept
Jayapura	-10.50833
Kepulauan Yapen	-3.066162
Biak Numfor	-10.90076
Sarmi	-2.592982
Keerom	2.908583
Waropen	11.01222
Supiori	19.61093
Mambero Raya	12.47257
Kota Jayapura	-18.93608

3. Random Effect Model

$$Y_{it} = -3.710410 - 0.394801X1_{it} + 4.384703X2_{it} - 0.284710X3_{it} + 9.92E-05X4_{it} + 0.839246X5_{it} - 2.241329X6_{it} - 0.000376X7_{it} + 9.728987X8_{it}$$

Identifying the Most Accurate Model

Chow Test

Table 4. Outcome of the Chow Test

Test Summary	P-Value
Cross-section F	0.0000

In reference to Table 4, the obtained p-value is < 0.05, so the FEM is selected.

Hausman Test

Table 5. Outcome of the Hausman Test

Test Summary	P-Value
Cross-section random	0.0000

According to Table 5, the p-value was obtained < 0.05, so the FEM was chosen to be the most suitable model.

Classical Assumption

Multicollinearity

Table 6. Outcome of the Multicollinearity Test

Variable	Value
Total Poor Population	3.197
Average School Length	1.805
Labor Force Participation Rate	1.385
Expenditure per Capita	5.756
Life Expectancy Figures	1.224
Human Development Index	1.529
Gross Regional Domestic Product	1.761
Old School Expectations	1.735

According to Table 6, the VIF value obtained was < 10, therefore, it mas be concluded that the model does not exhibit multicollinearity.

Autocorrelation

Table 7. Outcome of the Autocorrelation Test

Test Summary	Value
Durbin Watson	1.989

According to Table 7, the value obtained was > 0.05. The values obtained concluded that there are no autocorrelation symptoms under the model specification.

Heteroscedasticity

Table 8. Outcome of the Heteroscedasticity Test

Variable	P-Value
Percentage of Poor Population	0.346
Total Poor Population	0.180
Average School Length	0.647
Labor Force Participation Rate	0.898
Expenditure per Capita	0.921
Life Expectancy Figures	0.396
Human Development Index	0.399
Gross Regional Domestic Product	0.175
Old School Expectations	0.782

According to Table 8, all variables show that the p-value obtained was > 0.05. It can therefore the findings suggest the absence of symptom of unequal variance issues in the model, and the classical assumption of residual variance constant (homocedasticity) has been fulfilled.

Parameter Significance Test

Overall Test

This statistical test is conducted to assess whether the variable affected by the independent variable as a whole.

Table 9. Outcome of the Overall Test

Test Summary	P-Value
Prob (F-statistic)	0.0000

According to Table 9, the p-value obtained was < 0.05, indicating that the independent variables, including the scale of poverty, educational duration indicators, labor force participation rate, per-head spending level, survival expectancy, human development index, value of goods and services produced within a region, and length of schooling expectations, are jointly significant to the response variables.

Partial Test

This test is used to assess whether an individual independent variable is affected by a dependent variable.

Table 10. Outcome of the Partial Test

Variable	Coefficient	P-Value
Percentage of Poor Population	-3.530009	0.9861
Total Poor Population	0.821148	0.0496
Average School Length	0.674677	0.7580
Labor Force Participation Rate	-0.005304	0.8358
Expenditure per Capita	-0.001170	0.5303
Life Expectancy Figures	0.399389	0.9311
Human Development Index	-0.438818	0.8065
Gross Regional Domestic Product	8.25E-05	0.4407
Old School Expectations	1.036541	0.7337

Referring to Table 10, the number of poor people is significant because it has a p-value < 0.05, while other explanatory variables are not relevant to the regressed variable because they have a p-value of > 0.05.

Adjusted R^2

This test is used to assess the quality of the model.

Table 11. Outcome of the Adjusted R^2

Test Summary	Value
Adjusted R^2	0.9981

Based on Table 11, the Adjusted R^2 value is obtained as 0.9981 or 99.81%. This value signifies that an independent variable is able to explain 99.81% of the dependent variables, while the other 0.19% is explained through variables beyond the scope of the model.

4. DISCUSSIONS

In this study, descriptive analysis was used as a medium to explore data related to the poverty level in Papua in 2021-2023. This analysis resulted in information that Supiori Regency, which was then continued by Waropen Regency, had the highest economic difficulties in Papua Province in 2021-2023.

Regression analysis using panel data proved the significance between several variables that are suspected to have a relationship with socio-economic losses in Papua. The analysis process using this method begins with a decision on the most suitable model to be applied as a parameter estimation model. Among the models tested, FEM provides the most reliable results for modeling economic disadvantage in Papua Province in 2021-2023.

The equation of regression models with the FEM approach is presented below:

$$Y_{it} = \hat{a}_i + 0.821148X1_{it} + 0.674677X2_{it} - 0.005304X3_{it} - 0.001170X4_{it} + 0.399389X5_{it} - 0.438818X6_{it} + 8.25E - 05X7_{it} + 1.036541X8_{it}$$

Testing of the classical regression assumptions is undertaken to ensure that the model used has met the classical assumptions of regression. This test is carried out to ensure that the estimate obtained is BLUE (Best Linear Unbiased Estimator) with three test criteria. The results obtained in the classical assumption test on the selected model have met the assumptions of multicollinearity, autocorrelation and heteroscedasticity. Accordingly, the model is considered valid for the observed data for modeling the poverty level in Papua Province in 2021-2023.

To find out the results obtained statistically significant, a Parameter Significance Test was carried out with three test criteria, namely Overall Test, Partial Test and Adjusted R^2. The results obtained from the Overall Test stated that the entire set of variables examined in this study together had a significant effect on the percentage of poverty.

Meanwhile, in the Partial Test, the variable of factors that has a positive and significant as individuals to the response variable is only the variable pertaining to the number of low-income individuals. The score obtained was 0.821148. Any 1 percent uplifting the count of improverished individuals can increase poverty by 0.821148 percent. These findings are also in line with the theory of welfare economics which states that the absolute poor household count is directly proportional to the poverty rate as a percentage

The Determination Coefficient (Adjusted R^2) test measured the quality of the model, the results proved that the factor variable was able to determine the response variable by 99.81%, while the other 0.19% is explained through variables beyond the scope of the model.

This study proves that the date panel using the regression analysis approach is a suitable statistical method to model the levels and determinants that have an impact on poverty in Papua Province in 2021-2023. This is because the panel data used in this study is able to provide large observational data and also produce a level of freedom. So that great variability will result in more efficient econometric estimation.

5. CONCLUSION

This study proves that the dated panel using the regression approach is a suitable statistical approach to analyze the determinants that affect poverty in Papua Province in 2021-2023. This analysis proves that the number of poor people has a significant effect on the percentage of poverty. The quality of the resulting model proves that the factor variable can explain the response variable by 99.81%, while the other 0.19% is explained by other variables that are not included in the regression model.

According to the results of the analysis, the government should focus more on poverty alleviation programs through aspects of reducing the number of poor people. Some programs that can be carried out to lift the population above the poverty line can be focused on increasing income directly with direct cash assistance or household subsidies. Other mitigation policies can also be pursued with economic empowerment programs such as job training, business capital assistance, or access to business financing for the poor can be maximized. Policies that combine strengthening and ease of economic access will lead to better population growth, which is then expected to have an impact on reducing poverty rates.

Suggestions for further research are to expand the limitations of the problems in this study, such as adding new variables that have the potential to affect poverty and extending the observation period of the study to get a broader and deeper picture of poverty and the factors that influence it.

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