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Negative Binomial Regression in Overcoming Overdispersion Poverty Data in Kalimantan

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ABSTRACT

Poverty is one of the problems that Indonesia still faces. Kalimantan Island has large natural resources, but experiences inequality in the distribution of wealth in the region. In this study, data on the number of poor people is used as the dependent variable. The independent variables include the percentage of households that have access to non-PLN electricity (X_1), access to proper drinking water (X_2), proper sanitation (X_3), non-own toilet facilities (X_4), HDI (X_5), Open Unemployment Rate (X_6), average wages of informal workers and main employment (X_7), population density per km^2 (X_8), monthly per capita food and non-food expenditure (X_9), the percentage of the population experiencing health issues but not seeking treatment due to lack of financial means (X_{10}), and percentage of the population aged 15 years and above who do not have a diploma (X_{11}) in 2023. A Poisson regression analysis is employed. The model accounts for the significance of every independent variable. The model was found to have overdispersion, which was resolved through negative binomial regression. The findings of the study revealed that the average wage of informal workers and primary employment, population density per km2, monthly per capita food and non-food expenditure, The percentage of the population experiencing health issues but not seeking treatment due to lack of financial means, and the percentage of the population aged 15 years and older who do not have a diploma all have a significant impact on the magnitude of the number of people living in poverty on the island of Kalimantan.

Keywords: poor, wealth, poisson regression.

INTRODUCTION

One of the issues Indonesia is still dealing with is poverty. Due to poverty's complexity and multifaceted nature, it is a development priority (Ferezagia, 2018). The government has tried several initiatives, such as poverty alleviation programs, to enhance community welfare (Sumargo & Simanjuntak, 2019). Poverty reduction initiatives are necessary for the nation's goals to be achieved where a just and wealthy society is created. Reliable data is required to support programs aimed at reducing poverty. The government can decide what actions to take to reduce if the data is provided (Ferezagia, 2018). The number and percentage of people living in poverty were first determined in 1984 by the Central Bureau of Statistics (BPS). Since 2003, BPS has regularly published data on the total population and proportion of the impoverished (Badan Pusat Statistik Kalimantan Selatan, 2024).

The island of Kalimantan possesses abundant natural resources, yet the region's wealth is distributed differently (Noorachmadan & Suliadi, 2024). With 5.67% of the population living in poverty by March 2023, Kalimantan Island has the lowest poverty rate (Badan Pusat Statistik Indonesia, 2023). Basel Population Survey (Badan Pusat Statistik Kalimantan Tengah, 2024) measures poverty using the ability to meet necessities. There are several interrelated factors that cause poverty (Adriana, 2020).

Education is the primary means of attaining a better life and good health, which are the cornerstones of welfare (Adriana, 2020). Additionally, variations in the natural resource composition contribute to regional development inequality by influencing the economic growth rate in each location (Ginting & Ginting, 2023). Geographical conditions vary from region to region, which causes variations in the number of cases of poverty (Jasmadi et al., 2016). Good services are anticipated to be provided via equitable development (Badan Pusat Statistik Kalimantan Utara, 2024).

Quality human resources are one of the primary factors contributing to the success of a country's development (Badan Pusat Statistik Kalimantan Timur, 2024). Poverty can affect various aspects such as education, health, and living conditions. Hunger, unemployment, inadequate education, and inadequate housing reflect poverty that impacts human life (Sumargo & Simanjuntak, 2019). Poverty can also be influenced by food/nutrition, sanitation, clean water, housing, and employment (Sumargo & Simanjuntak, 2019). Easy access to infrastructure such as roads, electricity, clean water, and other basic services also plays a crucial role in socio-economic activities (Andrianus & Alfatih, 2023). The poverty rate is also significantly influenced by the Human Development Index and economic progress (Alviannor & Fahrati, 2021).

METHODOLOGY

The study's data came from Kalimantan's Central Bureau of Statistics, published in numbers in 2024. The data year utilized for the observation is 2023, comprising 56 districts and cities. The number of impoverished individuals in thousands is the dependent variable used. Next, among the independent variables employed is the proportion of households with access to power that is not PLN (X_1). The percentage of households with access to a decent drinking water source (X_2), and proper sanitation (X_3). Then the variable percentage of households with non-own toilet facilities (X_4). According to research findings (Andrianus & Alfatih, 2023), the percentage of the impoverished population is significantly impacted by access to power and a suitable sanitary infrastructure.

The Human Development Index (X_5) is the independent variable utilized in this model. Then the percentage of open unemployment rate (X_6). Based on the results of research (Alviannor & Fahrati, 2021), Human Development Index and unemployment affect the poverty rate. Then the variable of average net monthly wage of informal workers and main employment is also used (X_7). Population density per square kilometer (X_8). Monthly per capita food and non-food expenditure (X_9). The percentage of the population experiencing health issues but not seeking treatment due to lack of financial means (X_{10}). Percentage of the population 15 years and over who do not have a diploma (X_{11}). Research conducted by (Adriana, 2020) found that the level of the minimum wage, as well as access to education and health care, substantially impacts the percentage of people living in poverty.

Multicollinearity Test

Multicollinearity testing is utilized to ascertain if independent variables and other variables in a model are related (Widodo & Ariani, 2018). The Variance Inflation Factor (VIF) value is used in multicollinearity tests. The multicollinearity test's premise is

H_0: No correlation exists between independent variables.

H_1: There exists a correlation between the independent variables.

Despite considering that the subsequent test statistics were utilized:

$$VIF_i = \frac{1}{1 - R_i^2}$$

where R^2 is the coefficient of determination between X_i and other variables in the model (Santi & Rahayuningsih, 2023). If the value of the VIF is more than 10, the null hypothesis is rejected, and it is concluded that the variable in question is subject to multicollinearity. In the meantime, the null hypothesis is accepted if the value of the VIF is less than 10, which ensures that the variable does not experience multicollinearity.

Poisson Regression

The Poisson Regression Model is a nonlinear model typically utilized in count models. The Poisson distribution is the distribution of a random variable that is expressed by the number of experimental outcomes that occur in a particular time interval or a particular area. The Poisson Regression Model is generally utilized in count models. the probability density function of the Poisson distribution is summarized (Fitrial & Fatikhurrizqi, 2020):

$$P(Y = y) = \frac{\mu^y \exp{(\mu)}}{y_{i!}}$$

The Poisson distribution assumes that the value of the random variable Y, denoted by the symbol μ, is equal to its variance. Therefore, the Poisson distribution assumes that the μ value of the random variable Y is the same as its variance. In Poisson regression, the natural logarithm is the relationship function that is utilized to generate a log-linear relationship between the variable that is being dependent on and the variable that is being independent of (Fitrial & Fatikhurrizqi, 2020). The equation that emerges from the model that was created is (Santi & Rahayuningsih, 2023):

$$\mu_i = \exp{(\beta_0 + \beta_{1i}X_{1i} + \beta_{2i}X_{2i} + \cdots + \beta_n X_{ni})}$$

The Poisson regression model employs maximum likelihood estimation (MLE) to arrive at parameter estimation (Fitrial & Fatikhurrizqi, 2020). The following is a use of the maximized likelihood function used in Poisson regression (Fikhri et al., 2014):

$$L(\lambda|y) = \prod_{i=1}^{n} \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i}$$

Overdispersion Test

Some presumptions must be fulfilled while modelling Poisson regression. Equidispersion is the underlying premise here. According to the premise that must be fulfilled, the dependent variable's mean value must equal the variance value (Zubedi et al., 2021). The reason for overdispersion is that variations in the data's mean and variance values prevent the equidispersion assumption from being satisfied. The overdispersion test is based on the following hypothesis:

H_0: Model has no overdispersion.

H_1: Overdispersion in model

The overdispersion test results in the decision to reject the null hypothesis or find that the model has overdispersion if the p-value is lower than the significance level.

Negative Binomial Regression

The negative binomial regression approach is one of the methods that can be utilised to avoid overdispersion in Poisson regression and other similar methods (Keswari et al., 2014). the probability density function of the negative binomial distribution takes the following form (Fitrial & Fatikhurrizqi, 2020):

$$f(y;\mu,\theta) = \frac{\Gamma(y+\theta)}{\Gamma(\theta)y!}\frac{\mu^y\theta^\theta}{(\mu+\theta)^{y+\theta}}$$

The gamma function is known to have a mean parameter μ and a dispersion value θ. As with Poisson regression, Negative Binomial regression is also a member of the family of Generalised Linear Models (GLM) (Rahmadeni & Desmita, 2016). The relationship function is in the form of a natural logarithm, and it is designed to generate a log-linear relationship between the variable that is reliant on it and the variable that is independent of it. The model is as described below (Fitrial & Fatikhurrizqi, 2020):

$$\mu_i = \exp\,(\beta_0 + \sum\nolimits_{j=1}^{k} \beta_{1j}X_{1j})$$

Maximum Likelihood Estimation (MLE) is the method utilised to estimate parameters in the Negative Binomial regression model (Zubedi et al., 2021). The following is an example of the maximised likelihood function (Santi & Rahayuningsih, 2023):

$$L(y,\mu,\theta) = \prod_{i=1}^{n} \frac{\Gamma(y+\frac{1}{\theta})}{y_i!\,\Gamma(\frac{1}{\theta})}\left(\frac{1}{1+\theta\mu}\right)^{\frac{1}{\theta}}\left(\frac{\theta\mu}{1+\theta\mu}\right)^{y}$$

Significance Test of Negative Binomial Regression Parameters

The significance test for the model is required to determine the dependent variable's impact on the model (Keswari et al., 2014). Parameter testing is carried out concurrently in stages. A simultaneous test is carried out to determine the effect that independent factors have on the dependent variable simultaneously (Fitrial & Fatikhurrizqi, 2020). The test is carried out jointly using the likelihood ratio test in conjunction with the following hypothesis (Zubedi et al., 2021):

$H_0: \beta_1 = \beta_2 = \cdots = \beta_k = 0$

H_1: at least there are 1 $\beta_j \neq 0$, dengan $j = 1,2, \dots k$

In this test, the likelihood ratio is utilized, along with the following statistical test results:

$$G = -2\ln\left(\frac{L(\hat{\omega})}{L(\hat{\Omega})}\right)$$

where $L(\hat{\omega})$ is the likelihood value for the basic model does not include independent variables and the likelihood value for the entire model, which does not include any independent variables, is denoted by $L(\hat{\Omega})$.

Suppose the value of $G > X^2_{(\alpha,k)}$, where α represents the significance level and k represents the number of parameters. In that case, the null hypothesis is rejected to take a decision. This is because the test statistic G follows the chi-square distribution. In the case of partial tests, the Wald test is utilized, and the test hypothesis consisting of the following is utilized (Zubedi et al., 2021):

$\boldsymbol{H_0: \beta_j = 0}$

$\boldsymbol{H_1: \beta_j \neq 0}$, for every $\boldsymbol{j = 1, 2, \dots, k}$

The test statistics is:

$$\boldsymbol{Z} = \frac{\widehat{\boldsymbol{\beta_J}}}{\boldsymbol{se}(\widehat{\boldsymbol{\beta_J}})}$$

where $\widehat{\beta_J}$ is the value of the estimate and $se(\widehat{\beta_J})$ is the standard error of $\widehat{\beta_J}$. The decision taken in the Wald test is that the null hypothesis is rejected if the value of $Z > Z_{\alpha/2}$ where α being the significance level.

Best Model Selection

In 1973, Akaike presented Akaike's Information Criterion, a technique for modelling results known for its impartiality as an estimator. AIC is utilized to determine how well the model fits the data. A model is considered the best if it has the lowest AIC value. One possible formulation for the AIC value is (Zubedi et al., 2021):

$$AIC = -2\ \ln L(\beta) + 2k$$

where $lnL(\beta)$ is the maximum likelihood value and k is the number of parameter (Keswari et al., 2014).

RESULTS AND DISCUSSION

Based on districts and cities in Kalimantan from 2019 to 2022, this research investigates the data by employing descriptive statistical analysis to acquire the characteristics of the independent and dependent variables.

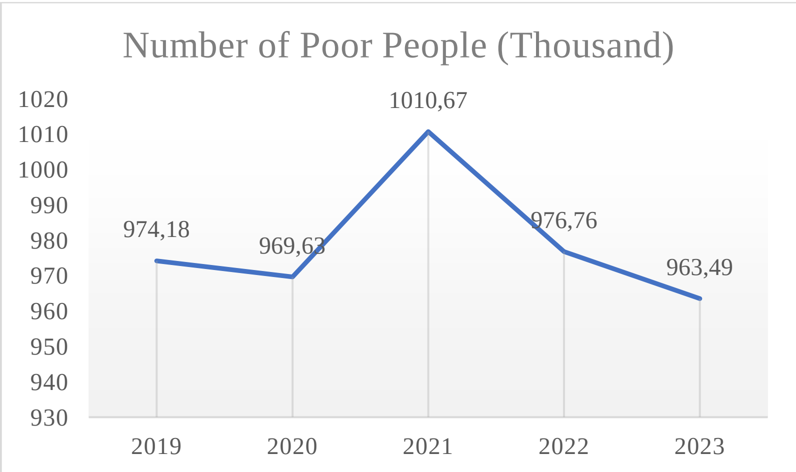

Figure 1. Graph of Kalimantan Island Poverty 2019-2023
Source: Processed from BPS Publications, in 2024

According to Figure 1, it is known that the number of people living in poverty declined from 2019 to 2020 but then climbed once more in 2021. Finally, from 2021 to 2023, the number of people living in poverty decreased to 47,180. Table 1 provides the following descriptive statistics for each variable.

Table 1. Descriptive Statistics of Research Variables.

Variable	**Minimum**	**Maximum**	**Mean**
(1)	**(2)**	**(3)**	**(4)**
Y	1,470	60,860	17,206.03
X_1	0	31.63	7.04
X_2	48.98	99.91	79.22
X_3	56.66	98.06	81.70
X_4	1.42	18.61	5.18
X_5	66.06	82.61	73.25
X_6	2.07	8.92	4.33
X_7	1,128,019	5,107,640	2,471,287.76
X_8	2	6,775	375.01
X_9	1,041,562	2,374,273	1,542,664.03
X_{10}	0	4.41	0.79
X_{11}	2.63	33.56	13.30

Source: Processed from BPS Publication in 2024

Tana Tidung District, located in Kalimantan Utara Province, has the lowest number of impoverished people. In contrast, Kutai Kartanegara District, located in Kalimantan Timur Province, has the highest number of impoverished people. This information is presented in Table 1. Even though Kalimantan Timur Province has the highest number of people living in poverty, the overall number of people living in poverty is higher in Kalimantan Barat Province and the lowest in Kalimantan Utara Province.

Multicollinearity Test

An examination of multicollinearity is performed with the help of the Variance Inflation Factor (VIF) value before the modelling process. A multicollinearity test determines the degree of correlation between each variable. As can be seen in Table 2, the results of the multicollinearity test.

Table 2. Multicollinearity Test Result

Variable	**VIF**
(1)	**(2)**
X_1	2.24
X_2	2.09
X_3	2.30
X_4	1.85
X_5	6.68
X_6	2.58
X_7	3.74
X_8	2.11
X_9	3.39
X_{10}	1.51
X_{11}	3.36

Source: Processed from BPS Publication in 2024

As demonstrated by the findings presented in Table 2, eleven of the independent variables have a VIF value greater than ten. As a result, there is no multicollinearity, and the independent variables can be utilized in modelling. It shows that there is no correlation between the variables that are considered independent.

Poisson Regression

The factors influencing Kalimantan Island's poverty rate are modelled using Poisson regression. Table 3 represents the eleven independent variables that comprise the Poisson Regression modelling findings.

Table 3. Poisson Regression

Variable	**Estimation**	**Standard Error**	**P-value**
(1)	**(2)**	**(3)**	**(4)**
Y	9.316	0.04587	2e-16
X_1	-0.02212	0.00018	2e-16
X_2	-0.007773	1.076e-04	2e-16
X_3	0.008827	1.515e-04	2e-16
X_4	-0.009929	4.101e-04	2e-16
X_5	-0.005604	6.951e-04	7.44e-16
X_6	-0.07342	8.804e-04	2e-16
X_7	5.389e-07	2.194e-09	2e-16
X_8	2.622e-04	1.061e-06	2e-16
X_9	-6.128e-07	6.363e-09	2e-16
X_{10}	0.2695	0.001155	2e-16
X_{11}	0.03748	2.933e-04	2e-16

Source: Processed from BPS Publication in 2024

As can be seen in Table 3, the equation that the Poisson Regression creates is:

$$\mu = \exp(9.316 - 0.02212X_1 - 0.007773X_2 + 0.009927X_3 - 0.009929X_4 - 0.005604X_5 - 0.07342X_6 + 0.0000005389X_7 + 0.0002622X_8 - 0.0000006128X_9 + 0.2695X_{10} + 0.03748X_{11})$$

The results of the partial test indicate that each of the independent factors significantly impacts the variable being tested. Variables X_1, X_2, X_4, X_5, X_6, and X_9 have a negative effect on the dependent variable, while variables X_3, X_7, $X_{8,}$ X_{10}, dan X_{11} have a significant positive effect on the regression model. Then, the overdispersion test is carried out. The results of the tests are presented in Table 4.

Table 4. Overdispersion Check

Overdispersion Ratio	**P-Value**
(1)	**(2)**
7,281.24	0.001

Source: Processed from Poisson Regression Model

According to the findings presented in Table 4, it is known that the p-value that is lower than the significance level (0.05) indicates that the model has overdispersion. As a result, the model will continue to be analyzed using negative binomial regression.

Negative Binomial Regression

Overdispersed count data can be modelled using Negative Binomial regression, an alternative method that can be selected. With the assistance of the R scripting language, the following equation was derived from the results of the parameter estimate for the Negative Binomial regression model:

Table 5. Negative Binomial Regression

Variable	Estimation	Standard Error	P-value
(1)	(2)	(3)	(4)
Y	8.714	3.399e+00	0.010347
X_1	-2.343e-02	1.319e-02	0.075719
X_2	-8.565e-03	8.178e-03	0.294926
X_3	9.000e-03	1.120e-02	0.421553
X_4	-4.059e-03	3.176e-02	0.898301
X_5	4.510e-03	4.989e-02	0.927973
X_6	-7.406e-02	7.300e-02	0.310299
X_7	5.578e-07	1.680e-07	0.000896
X_8	2.698e-04	9.567e-05	0.004795
X_9	-7.502e-07	4.440e-07	0.091093
X_{10}	2.221e-01	9.990e-02	0.026202
X_{11}	4.429e-02	2.224e-02	0.04641

Source: Processed from BPS Publication in 2024

According to the results in Table 5, the Negative Binomial Regression equation formed is:

$$\mu = \exp\,(8.714 + 0.0000005578X_7 + 0.0002698X_8 - 0.0000007502X_9 + 0.2221X_{10} + 0.04429X_{11})$$

Partial test results show that the variables Average monthly net wage/salary of informal workers and main employment (X_7), Population Density per square kilometer (X_8), The percentage of the population experiencing health issues but not seeking treatment due to lack of financial means (X_{10}), percentage of population 15 years and over who do not have a diploma (X_{11}) have positive significant impact on the number of impoverished individuals in thousands. While monthly per capita expenditure on food and non-food (X_9) has negative significant impact on the number of impoverished individuals in thousands. The result are same with (Adriana, 2020) that access to education, health and minimum wage are significant to the percentage of people living in poverty. To identify whether or not the regression model is subject to overdispersion, an overdispersion check will be carried out once the model has been constructed of regression. Table 6 displays the test results.

Table 6. Overdispersion Check

Overdispersion Ratio	P-Value
(1)	(2)
0.954	0.936

Source: Processed from Negative Binomial Regression Model

According to Table 6, it is common knowledge that a p-value greater than the significance level (0.05) shows no overdispersion.

Best Model Selection

The AIC value is the basis for the most recommended model selection. The AIC value of the best model is the single lowest. Table 7 displays the outcomes of the statistical analysis of the AIC values for both models.

Table 7. AIC Value

Model	AIC
(1)	**(2)**
Poisson Regression	296,022
Negative Binomial Regression	1,194.6

Source: Processed from Poisson Regression and Negative Binomial Regression

The AIC value for Negative Binomial regression is lower than Poisson regression, as indicated by the findings in Table 7. The Poisson regression model is less effective than the Negative Binomial regression model when predicting poverty on the island of Kalimantan.

CONCLUSION AND RECOMMENDATION

It is possible to conclude from this discussion that the number of people living in poverty in Kalimantan has fallen from 2019 to 2020, climbed in 2021, and decreased until 2023. A negative binomial regression model accounts for the overdispersion that occurs in the Poisson regression model. The average net compensation or salary per month of informal workers and primary employment and population density per square kilometer showed that the variables were all related. Cost of food and non-food items for each individual every month. The percentage of the population that is older than 15 years old and does not have a diploma substantially impacts the number of individuals living in poverty. A percentage of the population has health issues but does not seek treatment since there is no expense. According to the covariance (AIC) value analysis, the negative binomial regression model is the most effective model.

Considering the findings of this study, it is anticipated that the government will be able to pay greater attention to the distribution of the population and then proceed to take action in the fields of education for regions that still lack adequate educational facilities, equitable development of health facilities, and improvement of the quality of health services.

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