Zero Inflated Bivariate Ordered Probit on Poverty Levels in Eastern Indonesia

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ABSTRACT – **This study examines the development of a bivariate ordinal probit regression model with zero-inflated effects. The bivariate ordinal probit regression method that can overcome zero-inflated effects is the Zero Inflated Bivariate Ordered Probit (ZIBOPR) method. ZIBOPR is a statistical method for examining the relationship between predictor variables and two correlated response variables that have levels and zero-inflated effects. A theoretical study was conducted to obtain parameter estimates for the ZIBOPR model using the Maximum Likelihood Estimator (MLE) method. The estimation equation obtained from MLE produces a non-closed form equation, so it is continued with the Bern, Hall, Hall, and Hausman (BHHH) numerical iteration method. The resulting parameters are then tested simultaneously with the Likelihood Ratio Test (LRT) and individually using the Wald test. The ZIBOPR model was applied to the case of the percentage of poor people and the poverty depth index in 176 districts/cities in Eastern Indonesia in 2023 using five predictor variables, namely life expectancy, per capita expenditure, average length of schooling, Labor Force Participation Rate (LFPR), and Infant Mortality Rate (IMR). The results showed that the ZIBOPR model parameters could be estimated using MLE and followed by BHHH numerical iteration. The resulting parameters could then be tested simultaneously using LRT and individually using the Wald test. Subsequently, ZIBOPR modeling with poverty rate levels and poverty depth index levels showed that the five parameters in the predictor variables had a significant effect on poverty rate levels and poverty depth index levels. The results of the best model selection analysis using the vuong test show that the ZIBOPR model better models the percentage of poor population and the poverty depth index than the bivariate ordinal probit regression model.**

Keywords – **BHHH, MLE, Ordinal probit regression, ZIBOPR**

I. INTRODUCTION

ZIBOPR is a statistical method used to examine the relationship between two ordinal categorical response variables, experiencing zero inflation and are correlated with each other. ZIBOPR combines binary probit regression, which models the probability of observations with categories that have excessive frequencies, particularly in handling zero inflation, and bivariate ordinal probit regression, which models two correlated response variables in data that does not experience zero inflation [1]. Based on previous research on bivariate ordinal probit regression, the parameters in the ZIBOPR model can be estimated using several methods, one of which is maximum likelihood estimation (MLE), whose log-likelihood function is then used for the numerical iteration process. The estimated parameters are then tested simultaneously using a likelihood ratio test (LRT) and tested individually with the Wald test [2].

Based on the ZIBOPR model, it can handle zero inflation, one of which occurs in the percentage of poor people and the poverty depth index of districts/cities in Eastern Indonesia, which are categorized as high or zero with a higher proportion than other categories. According to BPS [3], the 10 provinces with the highest percentage of poor people in Indonesia are dominated by Eastern Indonesia, namely 8 provinces. Similar to the percentage of poor people, the 10 provinces with the highest depth index in Indonesia are dominated by 8 provinces in Eastern Indonesia. The division of categories in both response variables is based on the quartile in each response variable. The division using quartiles is because there has been no research that divides the two response variables into ordinal categories.

The percentage of poor people and the poverty depth index in many districts/cities in Eastern Indonesia are still high. These two factors are important because poverty can cause problems in various aspects. The percentage of poor people shows how many poor people there are in a region compared to the total population of that region. Meanwhile, the poverty depth index is a measure of the average expenditure gap between each person classified as poor and the poverty line. A decrease in the poverty depth index value indicates that the average expenditure of people classified as poor tends to approach the poverty line and the expenditure gap among people classified as poor will also narrow [4].

The percentage of poor people is obtained through the National Socioeconomic Survey (SUSENAS). The percentage of poor people is the ratio between the number of poor people and the total population. People are considered poor if they live below the poverty line. Factors that influence the percentage of poor people include economic, social, geographical, and government policy factors. Knowing the poverty rate in a region is important as a reference for the government in making policies to reduce the percentage of poor people. According to the BPS [4], the percentage of poor people in Indonesia in March 2023 reached 9.36%. This figure shows that 9 out of 100 families still live below the poverty line. Meanwhile, the poverty depth index is calculated to see the extent of the difference between the poor population, especially in terms of expenditure, and the poverty line, thereby assisting the government in making policies on budget allocation. According to the BPS [5], the depth index in Indonesia in March 2023 reached 1.53%.

Research conducted by Valiant et al. [6] analyzed the factors that influence the percentage of poor people, namely Life Expectancy (LE) and Average Length of Schooling (ALS). In addition, the factors that influence the percentage of poor people according to Santoso et al [7] are ALS, the Gini ratio, and per capita expenditure. According to Syahrazad and Vidriza [8] the factors that influence the poverty depth index in Papua Province are the number of poor people and the Human Development Index (HDI). In addition, research conducted by Amset et al [9] found that the poverty depth index is per capita expenditure per province in Indonesia. The research conducted by Ayu et al [10] analyzed the factors that influence poverty indicators, namely the percentage of poor population and the poverty depth index. The factors that influence these two variables are the Infant Mortality Rate (IMR) and RLS.

Based on research conducted by Andriano et al [2], ZIBOPR parameter estimation can use the MLE method and be followed by BHHH numerical iteration. The parameters are then tested simultaneously using LRT and tested individually using the Wald test. ZIBOPR is used to identify factors that jointly influence the percentage of poor people and the poverty depth index. The ZIBOPR model is expected to overcome the excessive zeros in both variables, which are high-category zeros.

II. LITERATURE REVIEW

A. Bivariate Ordered Probit Regression

Ordinal probit regression is a regression method that uses data with two response variables consisting of more than two categories and having levels (ordinal) in those categories. Unlike the univariate ordinal probit regression model, the bivariate ordinal probit regression model can address the correlation between two ordinal responses simultaneously [11], [12]. The bivariate ordinal probit regression model is described in Equation (1) [13].

$$\begin{aligned}
&P(Y_1=0,Y_2=0)=\Phi_2(\delta_0-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha}_1,\gamma_0-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho)\\
&P(Y_1=0,Y_2=1)=\Phi(\mathbf{x}^{\mathrm{T}}\boldsymbol{\lambda})\big[\Phi_2\big(\delta_0-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha}_1,\gamma_1\\
&\qquad -\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\\
&\qquad -\Phi_2\big(\delta_0-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha},\gamma_0-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\big]\\
&\qquad\vdots\\
&P(Y_1=j,Y_2=k)=\Phi_2\big(\delta_j-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha}_1,\gamma_k-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\\
&\qquad -\Phi_2\big(\delta_j-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha},\gamma_{k-1}-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\\
&\qquad \big(-\Phi_2\big(\delta_{j-1}-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha},\gamma_k-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\\
&\qquad -\Phi_2\big(\delta_{j-1}-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha}_1,\gamma_{k-1}-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\big)\\
&\qquad\vdots\\
&P(Y_1=J,Y_2=K)=1-\Phi_2\big(\delta_J-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha}_1,\gamma_K-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\big)
\end{aligned}\tag{1}$$

where $\Phi_2(.)$ is the bivariate standard normal distribution function δ_j and $\gamma_k$are the thresholds for Y_1 and Y_2, respectively, $j=0,1,\dots,J$ and $k=0,1,\dots,K$, $\boldsymbol{\alpha}_1$ and $\boldsymbol{\alpha}_2$ are the parameters to be estimated for Y_1 and Y_2, respectively.

B. Zero Inflated Bivariate Ordered Probit

The Zero Inflated Bivariate Ordered Probit (ZIBOPR) regression model is a more advanced version of the ZIOP model. In ZIBOPR, there are two response variables that are connected or related to each other. Both of these variables have levels or ordered categories, and they use a bivariate normal distribution link function. Like the ZIOP model, both response variables in ZIBOPR have extra zeros or a higher number of zero responses. When the variables are related, using the ZIOP model is not good because the connection between them can cause problems with the results.

The general form of the probability from ZIBOPR regression is described by following Equation.

$$p(y_1,y_2)=\begin{cases}P(s=0)+P(s=1)P(r_1=0,r_2=0)\\ P(s=1)P(r_1=j,r_2=k)\end{cases}\tag{2}$$

Based on equation before, ZIBOPR Model described in Equation (3), [2].

$$\begin{aligned}
&P(y_1=0,y_2=0|s=1)=\Phi(\mathbf{x}^{\mathrm{T}}\boldsymbol{\lambda})\big[\Phi_2(-\mathbf{z}_1^{T}\boldsymbol{\alpha}_1,-\mathbf{z}_2^{T}\boldsymbol{\alpha}_2,\rho)\big]\\
&\vdots\\
&P(y_1=j,y_2=k|s=1)\\
&\qquad=[\Phi(\mathbf{x}^{\mathrm{T}}\boldsymbol{\lambda})]\left(\Phi_2\big(\delta_{j-1}-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha}_1,\gamma_{k-1}-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\right.\\
&\qquad\left.-\Phi_2\big(\delta_j-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha},\gamma_k-\mathbf{z}_2^{\mathrm{T}}\boldsymbol{\alpha}_2,\rho\big)\right)\\
&\vdots\\
&P(y_1=J,y_2=K|s=1\\
&\qquad=\Phi(\mathbf{x}^{\mathrm{T}}\boldsymbol{\lambda})\\
&\qquad+[1-\Phi(\mathbf{x}^{\mathrm{T}}\boldsymbol{\lambda})](1-\Phi_2(\delta_{J-1}-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha}_1,\gamma_{K-1}\\
&\qquad-\mathbf{z}_1^{\mathrm{T}}\boldsymbol{\alpha}_1,\rho))
\end{aligned}\tag{3}$$

where s is the binary probit regression model in the ZIBOPR model, r_1 and r_2 are the bivariate ordinal probit regression models in the ZIBOPR model $\Phi_2(.)$is the cumulative distribution function of the standard normal distribution, $\boldsymbol{\lambda}$ is the binary probit regression parameter vector in the ZIBOPR model with $\boldsymbol{\lambda}=[\lambda_0\quad\lambda_1\quad\cdots\quad\lambda_q]^T$, $\boldsymbol{x}$ is a $(q+1)\times 1$ predictor variable vector $\boldsymbol{x}=[1\quad X_1\quad X_2\quad\cdots\quad X_q]^T$, δ_j and γ_k are thresholds in ordinal probit regression where $j=0,1,2,\dots J$ and $k=0,1,2,\dots,K$, $\boldsymbol{z}$ is a vector of predictor variables in bivariate ordinal probit regression in the ZIBOPR model with

$\mathbf{z} = [1 \quad z_1 \quad z_2 \quad \cdots \quad z_p]^T$, $\boldsymbol{\alpha_1}$ and $\boldsymbol{\alpha}_2$ are the parameter vectors of the bivariate ordinal probit regression with $\boldsymbol{\alpha_1} = [\alpha_{10} \quad \alpha_{11} \quad \cdots \quad \alpha_{1p}]^T$ and $\boldsymbol{\alpha_1} = [\alpha_{20} \quad \alpha_{21} \quad \cdots \quad \alpha_{2p}]^T$.

C. Independence Test

Testing the independence of categorical variables, in this case the response variables, is done to see whether the variables are correlated with each other so that ZIBOPR analysis can be performed. If the response variables are independent, the correlation matrix between the variables will form an identity matrix. Conversely, if the response variables are correlated with each other, the correlation matrix formed will allow the analysis to continue with bivariate analysis. The statistical test used is the chi-square test with the following hypothesis [14].

H_0 : $P_{jk} = P_{j\cdot} \times P_{\cdot k}$

H_1 : The must be at least one $P_{jk} \neq P_{j\cdot} \times P_{\cdot k}; j = 0,1,\dots,J$ and $k = 0,1,\dots,K$.

Next, set the significance level (α) and the test statistic used as follows.

$$\chi^2 = \sum_{j=0}^{J}\sum_{k=0}^{K}\frac{\left(O_{jk} - E_{jk}\right)^2}{E_{jk}} \tag{4}$$

with,

$$E_{jk} = \frac{n_{j\cdot} \times n_{\cdot k}}{n_{\cdot\cdot}} \tag{5}$$

$n_{jk}$is the frequency of category j and k, with $j = 0, 1, \dots, J-1, J$ and $k = 0, 1, \dots, K-1, K$. $O_{jk}$is the observed frequency in row j and column k, and E_{jk} is the expected frequency in row j and column k obtained using equation (6) where $j = 0, 1, 2, \dots, J$ and $k = 0, 1, 2, \dots, K$. The rejection region for H_0 is $\chi^2 > \chi^2_{(\alpha;df)}$ with $df = (J-1)(K-1)$.

D. Multicollinearity

In regression modeling, the assumption that must be met is that there is no multicollinearity. Multicollinearity is a condition where two variables are correlated with each other, resulting in a large standard error of parameter estimation. Multicollinearity in regression models can be detected using the Variance Inflation Factors (VIF) value described in the following equation [15].

$$VIF_m = \frac{1}{(1 - R_m^2)} \tag{6}$$

where R_m^2 is the coefficient of determination and $m = 1,2,\dots,p$ obtained from regressing between predictor variables. Where $R_m^2$is obtained with the following equation.

$$R_m^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}\left(\hat{X}_{im} - \bar{X}_m\right)^2}{\sum_{i=1}^{n}(X_{im} - \bar{X}_m)^2} \tag{7}$$

where X_{pi} is the i-th observation value and the m-th predictor variable, and $\hat{X}_{im}$ is the estimated value of X_{im} and $\bar{X}_m = \frac{1}{n}\sum_{i=1}^{n} X_{mi}$. Based on equation (6), if the VIF value is greater than 5, then multicollinearity occurs.

E. Vuong Test

This study uses the Vuong test to compare the bivariate ordinal probit regression model and the ZIBOPR model. The Vuong test is used to compare the two models because it outperforms the Akaike Information Criterion (AIC) in terms of comparing different regression models [15].

The Vuong test calculation begins by estimating the probability of each observation $p(y_{i1}, y_{2i})$ in both models. Next, a log-likelihood function is constructed to compare the probability estimates with the likelihood ratio denoted by $m_i$where $i = 1,2,\dots,n$, obtained through the following equation [15].

$$m_i = \ln\left(\frac{\hat{p}_1(y_{1i}, y_{2i})}{\hat{p}_2(y_{1i}, y_{2i})}\right) \tag{8}$$

where $\hat{p}_1(y_{1i}, y_{2i})$ and $\hat{p}_2(y_{1i}, y_{2i})$ are estimates of the probability of observations in each model where $i = 1, 2, \dots, n$ and m_i is the natural logarithm of the probability ratio obtained from the prediction $y_i = j$ from the two different models. In this study, the ZIBOPR model is used as the first model and the bivariate ordinal probit regression model as the second model.

The hypothesis used in the Vuong test to compare the two models is as follows.

H_0: The ZIBOPR model is as good as the bivariate ordinal probit regression model.

H_1 : The ZIBOPR model is better than the bivariate ordinal probit regression model.

The Vuong v test statistic was calculated to test this hypothesis. The Vuong test statistic is as follows.

$$v = \frac{\sqrt{n}\left(\frac{1}{n}\sum_{i=1}^{n} m_i\right)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - \bar{m})^2}} \tag{9}$$

where n is the sample size used. The Vuong statistic is an asymptotic normal distribution. The rejection region H_0 is $v > Z_{(\frac{\alpha}{2})}$ so we can conclude from the test results that the ZIBOPR model is different from the bivariate ordinal probit regression model.

F. Poverty Percentage levels

The Poverty percentage levels is a reflection of how many people live below the poverty line in relation to the total population of Indonesia. The poverty line itself is a threshold value commonly used to measure a household's ability to meet its basic needs. The unit of measurement for the percentage of poor people is a percentage, which is calculated using the following equation [4].

$$\text{Poverty Percentage} = \frac{\text{Number of people live below the poverty line}}{\text{Total population}} \times 100\%$$

G. Poverty Gap Index Levels

The Poverty Depth Index shows how far below the poverty line the poor population is on average. If the poverty depth index value is equal to 0, it means that there is no gap between the income or consumption of the poor population and the poverty line. If the poverty depth index value is greater than zero, it indicates that there is an average gap between the income or consumption of the poor population and the poverty line. The higher the poverty depth index value, the deeper the level of poverty in that area. The poverty depth index is obtained through the following equation [4].

$$P_1 = \frac{1}{N}\sum_{i=1}^{I}\left(\frac{q - c_i}{q}\right) \quad (10)$$

where q is the poverty line in a region, c_i is the income or consumption of the poor, and N is the population of that region.

III. METHODOLOGY

The data used in this study is secondary data obtained from the Indonesian Central Statistics Agency. The response data used is the percentage of poor people and the poverty depth index for 2023 obtained from districts/cities in Eastern Indonesia. The amount of data used is from 176 districts/cities in Eastern Indonesia. The research variables consist of two ordinal response variables and five predictors used in binary probit and bivariate ordered probit in the ZIBOPR model, as described in Table 1.

Table 1 Research Variables

Variable	Name of Variable	Data Scale
Y_1	Poverty percentage Levels	Ordinal
Y_2	Poverty Gap Index Levels	Ordinal
X_1	Life Expectancy	Ratio
X_2	Per capita expenditure	Ratio
X_3	Average length of schooling	Ratio
X_4	Labor force participation rate	Ratio
X_5	Infant mortality rate	Ratio

The steps for researching the ZIBOPR model in cases involving the percentage of poor people and the poverty depth index are as follows.

1. Inputting data used in the study.
2. Describing data characteristics using descriptive statistics.
3. Testing correlations between response variables for bivariate analysis using equation (4).
4. Testing multicollinearity between predictor variables using the VIF criterion in equation (6).
5. Performing ZIBOPR modeling.
6. Testing parameter hypotheses simultaneously and individually.
7. Selecting the best model using the Vuong test based on equation (9).
8. Interpreting the resulting model and drawing conclusions from the analysis results.

IV. RESULTS AND DISCUSSIONS

This section described the analysis result and discuss modelling district/city poverty problems in East Indonesia using ZIBOPR.

A. Data Exploration

An overview of the characteristics of the research variables, which consist of two response variables, namely the poverty percentage levels (Y_1) and the poverty gap index levels (Y_2), as well as five predictor variables, namely life expectancy (X_1), per capita expenditure (X_2), average length of schooling (X_3), labor force participation rate (X_4), and infant mortality rate (X_5). The observation units used were 176 districts/cities in Eastern Indonesia. Descriptive statistics describing the characteristics of the predictor variables are presented in Table 2.

Table 2 Descriptive Statistics Predictor Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
X_1	68,532	3,268	55.720	74,650
X_2	9.339	2.648	2.650	17.889
X_3	8,280	1870	1710	12,530
X_4	57,576	13,014	24,210	98,090
X_5	27,262	9,423	10,610	56,690

Based on Table 2, we can see the characteristics of ratio predictor variables described through the mean, standard deviation, minimum value, and maximum value for each predictor. In this study, the percentage of poor people and the poverty depth index are categorized ordinally into four categories, which are referred to as the percentage of poor people and the poverty depth index levels, respectively. The percentage of poor people is categorized as low, lower middle, upper middle, and high. The poverty depth index is categorized as low, lower middle, upper middle, and high.

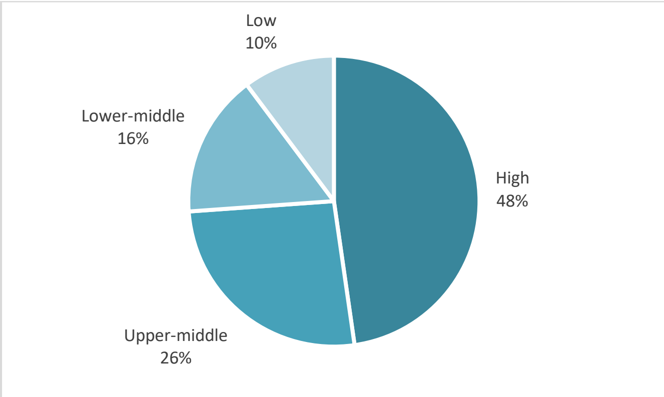

Figure 1 Proportion of Poverty Percentage Levels

Figure 1 shows that districts/cities with a high percentage of poor people have the largest proportion, at 48%. The second largest proportion is in the upper-middle category, at 26%. The third largest is in the lower-middle category, at 16%. Finally, the lowest proportion is in districts/cities in the low category, at 10%.

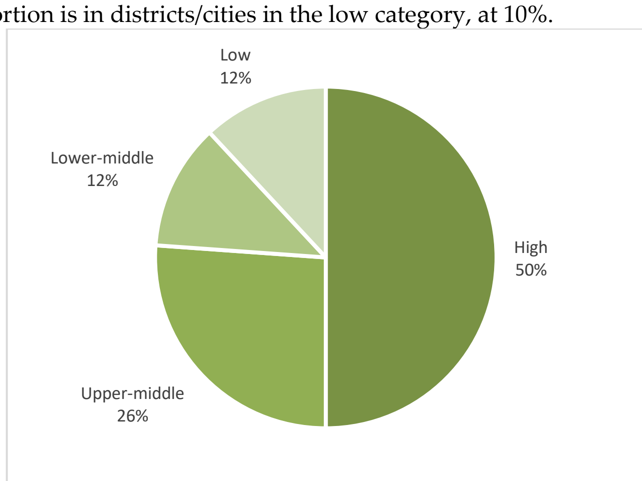

Figure 1 Proportion of Poverty Gap Index Levels

Figure 2 shows that districts/cities with a high percentage of poor people have the largest proportion, at 50%. The second largest proportion is in the upper-middle category, at 26%. The lowest is in the lower-middle category and low category, at 12%. Then, Contingency table for combined frequency for category Y_1 and Y_2 described by Table 3.

Table 3 Contingency table for Y_1 and Y_2

Variabel Respon		Y_2			
		0	1	2	3
Y_1	0	33	2	0	11
	1	6	14	8	0
	2	0	5	13	0
	3	7	0	0	77

Table 3 shows that there is an excess category compared to other categories, namely when Y_1 is categorized as 3 and Y_2 is categorized as 3, so that in the case of the percentage of poor population and the poverty depth index, there is inflation in certain categories in that category.

B. Independency Test

The independence test was conducted on two response variables in bivariate analysis. In this study, an independence analysis was conducted on the percentage of poor people and the poverty depth index. Based on Equation (4), the chi-square test statistic $\chi^2 = 178{,}23 > \chi^2_{(9;0.05)} = 16{,}919$ atau $p - Value = 0.000 < \alpha = 0{,}05$, resulting in a decision to reject H_0. Therefore, it can be concluded that there is a relationship between the percentage of poor people and the poverty depth index. Based on the results of the response variable independence test analysis, the analysis can proceed to the next stage.

C. Detecting Multicollinearity

Multicollinearity was detected through the VIF value based on Equation (6). A variable was said to be multicollinear if it had a VIF value less than 5. Table 4 below describes the VIF values for each variable.

Table 4 VIF for Predictor Variables

Variabel	Keterangan	VIF
X_1	Life Expectancy	2,051
X_2	Per capita expenditure	2,341
X_3	Average length of schooling	2,359
X_4	Labor force participation rate	1,535
X_5	Infant mortality rate	1,072

Table 4 shows that none of the predictor variables exhibit multicollinearity because they have VIF values of less than 5. Therefore, all predictor variables can be used in ZIBOPR regression modeling.

D. Modeling the Percentage of Poor Population and Poverty Depth Index Levels with ZIBOPR.

Based on the results of processing the ZIBOPR model for the response variables of the poverty percentage level and the poverty Gap index levels in districts/cities in Eastern Indonesia with five predictor variables, parameter estimation using MLE and followed by BHHH numerical iteration is presented in Table 5.

Table 5 Parameter Estimation of ZIBOPR Model

Predictor Variables	Coefficient	Standard Error	$\lvert Z_{hit} \rvert$
α_{10}	0,499	$1{,}037 \,.\, 10^{-3}$	$4{,}819 \,.\, 10^{2}$
α_{11}	$-0{,}172$	$9{,}021 \,.\, 10^{-5}$	$1{,}869 \,.\, 10^{3}$
α_{12}	0,008	$6{,}766 \,.\, 10^{-4}$	$0{,}118 \,.\, 10^{2}$
α_{13}	$-1{,}174$	$4{,}51 \,.\, 10^{-4}$	$2{,}603 \,.\, 10^{3}$
α_{14}	0,04	$4{,}50 \,.\, 10^{-4}$	$0{,}889 \,.\, 10^{2}$
α_{15}	0,186	$4{,}51 \,.\, 10^{-4}$	$4{,}124 \,.\, 10^{2}$
α_{20}	0,307	$5{,}390 \,.\, 10^{-6}$	$5{,}696 \,.\, 10^{4}$
α_{21}	0,028	$6{,}210 \,.\, 10^{-7}$	$4{,}509 \,.\, 10^{4}$
α_{22}	0,041	$9{,}337 \,.\, 10^{-7}$	$5{,}139 \,.\, 10^{3}$
α_{23}	$-0{,}005$	$9{,}728 \,.\, 10^{-7}$	$3{,}594 \,.\, 10^{5}$
α_{24}	$-0{,}017$	$8{,}388 \,.\, 10^{-7}$	$2{,}027 \,.\, 10^{4}$
α_{25}	0,028	$1{,}171 \,.\, 10^{-6}$	$2{,}391 \,.\, 10^{4}$
ρ	0,911	$1{,}179 \,.\, 10^{-4}$	$7{,}723 \,.\, 10^{3}$
λ_0	$-4{,}092$	$2{,}903 \,.\, 10^{-5}$	$1{,}401 \,.\, 10^{5}$
λ_1	2,092	$1{,}131 \,.\, 10^{-5}$	$1{,}849 \,.\, 10^{5}$
λ_2	1,622	$1{,}179 \,.\, 10^{-5}$	$1{,}376 \,.\, 10^{5}$
λ_3	1,451	$3{,}768 \,.\, 10^{-6}$	$3{,}849 \,.\, 10^{4}$
λ_4	$-0{,}888$	$8{,}54 \,.\, 10^{-6}$	$1{,}041 \,.\, 10^{5}$
λ_5	$-7{,}59$	$1{,}488 \,.\, 10^{-5}$	$5{,}098 \,.\, 10^{5}$

In Table 5, the ZIBOPR model consists of 19 parameters in the bivariate ordinal probit regression. The LRT test statistic G^2_{ZIBOPR}obtained a value of 305.933 with a p-value of 0.000, where the value of $G^2_{ZIBOPR}$is greater than $\chi^2_{(0{,}05;16)} = 26{,}296$, thus leading to the decision to reject H_0. Therefore, it can be concluded that there is at least one predictor that affects the response variable, namely the percentage of poor people and the poverty depth index.

Testing the ZIBOPR model parameter hypotheses individually using the Wald test. Based on the analysis results in Table 5, it was found that the five predictor variables had a significant effect on both response variables in the ZIBOPR binary probit model because they produced a value of $|Z_{hit}| > Z_{\alpha/2}$ (1,96) or a p-value for each predictor variable less than α (0.05). In the bivariate ordinal probit, the five predictor variables significantly affect the two response variables, namely the percentage of poor population and the poverty depth index, because they produce a value of $|Z_{hit}| > Z_{\alpha/2}$ (1,96) or a p-value for each predictor variable less than α (0,05).

E. *Best Model Selection*

The selection of the best model between a simple and a more complex model usually uses the vuong test. In this study, the vuong test was used to compare the models offered, namely ZIBOPR and the bivariate ordinal probit regression model. The Vuong test statistic $|v| = 8047260 > v_{(0{,}025)} = 1{,}96$ or $p - Value = 0{,}000 < \alpha = 0{,}05$. Therefore, the decision is that the ZIBOPR model is better than the bivariate ordinal probit regression model.

V. CONCLUSIONS AND SUGGESTIONS

Based on the results of the analysis reviewed in this study, the following conclusions were drawn.

1. Modeling the percentage of poor people and the poverty depth index in Eastern Indonesian districts/cities in 2023 using the ZIBOPR model obtained parameters that significantly influenced all predictor variables used, namely Life Expectancy, per capita expenditure, Average length of schooling, Labor force participation rate, and infant mortality rate.
2. Based on the selection of the best model using the vuong test, it was found that the ZIBOPR model was better at modeling the percentage of poor people and the poverty depth index in Eastern Indonesian districts/cities in 2023 than the bivariate ordinal probit regression model.
3. Based on the calculation of marginal effects on one of the predictor variables, namely Life Expectancy, it can be concluded that the higher the Life Expectancy value, the lower the percentage of poor population and the poverty depth index in a district/city. This shows that the Life Expectancy predictor variable affects the percentage of poor population and the poverty depth index.

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