A COMPARISON OF POLYTOMOUS MODEL WITH PROPORTIONAL ODDS AND NON-PROPORTIONAL ODDS MODEL ON BIRTH SIZE CASE IN INDONESIA

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Abstract: The proportional odds model (POM) and the non-proportional odds model (NPOM) are very useful in ordinal modeling. However, the proportional odds assumption is often violated in practice. In this paper, the non-proportional odds model is chosen as an alternative model when the proportional odds assumption is not violated. This paper aims to compare Proportional Odds Model (POM) and Non-Proportional Odds Model (NPOM) in cases of birth size in Indonesia based on the 2017 Indonesian Demographic and Health Survey (IDHS) data. The results showed that in the POM there was a violation of the proportional odds assumption, so the alternative NPOM model was used. NPOM had better use than POM. The goodness of fit shows that the deviance test failed to reject H0, and the value of Mac Fadden R2 is higher than POM. The risk factors that have a significant influence on all categories of birth size are the residence and gender of the child.

1. INTRODUCTION

The polytomous model is a model used for response data with more than two categorical values. If the response variable has an ordinal scale, then the most often used model is the Cumulative Logit Model. Cumulative Logit Models are divided into three groups, namely the Proportional Odds Model (POM), the Non-Proportional Odds Model (NPOM), and the Partial Proportional Odds Model (PPOM) (Ari & Yildiz, 2014). In the proportional odds model, each logit commuted has a different intercept but the same β effect (Agresti, 2010). Therefore, this model provides an important assumption, namely the assumption of "proportionality" or parallelity to the cumulative logit (Budyanra & Azzahra, 2017; Dolgun & Saracbasi, 2014).

The logit parallels assumption is sometimes not hold, that the POM analysis may lead to inaccurate results. Thus, it is necessary to consider the use of other models to overcome the unfulfilled assumptions in POM. Alternative models that can be used when the proportionality assumption sometimes does not hold are the Non-Proportional Odds Model (NPOM) and the Partial Proportional Odds Model (PPOM) (Ari & Yildiz, 2014). The Non-Proportional Odds (NPOM) model allows different β values for each cumulative logit (Tutz & Berger, 2020). However, in the Partial Proportional Odds (PPOM) model, only some of the independent variables have a proportional odds structure.

The ordinal logit model is widely used by several countries in cases of Low Birth Weight (LBW). In Indonesia, low birth weight cases are still a concern of the government because based on the results of the 2007 Health Statistics, the causes of most neonatal death cases are complications of asphyxia cases, infections, and low birth weight. The results of the 2013 Health Statistics stated that the range of LBW children percentage in Indonesian's provinces was 7.2 - 16.8% and the national average was 10.2% (Kemenkes, 2015a). This percentage is still above the target of the 2019 strategic plan, which is 8% (Kemenkes, 2015b). Several LBW studies related to the development of statistical models have been carried out, such as the classification of LBW with a nonparametric approach using the Weighted Probabilistic Neural Network method (Yasin & Ispriyansti, 2017), and analysis of risk factors for LBW cases using LASSO and Fused LASSO selection techniques (Kurniawati et al., 2020). Besides, Khan et al. (2018) also identified LBW in Bangladesh using a mixed logistic model and Adeyemi et al. (2016) developed a spatial effect on the LBW model in Nigeria using a semiparametric multinomial ordinal model.

Risk factors that affect the birth size of a baby can be analyzed by using the POM and NPOM models. Both of these models are appropriate to use because the category of birth size is an ordinal scale. When the proportionality assumption in POM is not violated, then NPOM can be used as an alternative model in determining the risk factors for LBW. Therefore, this study will compare and analyze the Indonesian LBW model based on the birth size using the Proportional Odds Model (POM) and the Non-Proportional Odds Model (NPOM) in determining the risk factors for LBW.

2. LITERATURE REVIEW
2.1. Cumulative Logit Model

The cumulative logit model is the easiest model to interpret and apply. Two cumulative ordinal logit models that will be compared in this study are:

a. Proporsional Odds Model (POM)

If the response variable (Y) has an ordinal scale with the J category, then the logit value used is also stratified, with J-1 as the cut-off point which is estimated through the cumulative odds value. The cumulative odds at Y are given as

$$P(Y \leq j) = \pi_1 + \cdots + \pi_j, \quad j = 1, \dots, J$$

with $P(Y \leq 1) < P(Y \leq 2) < \cdots < P(Y \leq J) = 1$ (Agresti, 2010). The Cumulative Logit Model is expressed in the form:

$$logit\{\gamma_j(\mathbf{x})\} = log\{\gamma_j(\mathbf{x})/(1 - \gamma_j(\mathbf{x}))\} = \theta_j - \boldsymbol{\beta}'\mathbf{x}, \qquad j = 1, \dots, J-1 \quad (1)$$

Where $\gamma_j(\mathbf{x}) = P(Y \leq j|\mathbf{x})$ is the cumulative odds. Each cumulative logit model has its intercept with values $\theta_1 \leq \theta_2 \leq \cdots \leq \theta_{J-1}$, and $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_k)'$ is the vector of the regression parameter. In the proportional odds model (POM), each cumulative logit has its own threshold value. The coefficient β will be the same for each category of the response variable. The cumulative logit model in equation (1) is also called the proportional odds model (Agresti, 2010).

b. Odds Non-Proporsional Model (NPOM)

The proportionality assumptions of the cumulative logit line do sometimes not hold, for the response variable with an ordinal value. Therefore, the Non-Proportional Odds Model (NPOM) is used as an alternative model to build a model if the proportional assumptions does not hold (Arı and Yildiz, 2014). The non-proportional odds model also

uses a cumulative logit where the coefficients will be different for each category. Therefore, the effect of the probabilities of the independent variable for the dependent variable will not be the same. The most significant difference between POM and NPOM is in the parameter values. NPOM has different parameter values for each response category, namely:

$$logit\{\gamma_m(\mathbf{x})\} = log\{\gamma_m(\mathbf{x})/(1-\gamma_m(\mathbf{x}))\}$$
$$= \tau_m - \boldsymbol{\beta}'_m\mathbf{x}, \quad m = 1, \dots, M-1 \tag{2}$$

Where $\gamma_m(\mathbf{x}) = P(Y \leq m|\mathbf{x})$ is the cumulative odds, τ_m is an unknown parameter with the value $\tau_1 \leq \tau_2 \leq \cdots \leq \tau_{M-1}$, and $\boldsymbol{\beta} = (\beta_{m1}, \beta_{m2}, \dots, \beta_{mk})'$ is the vector of the regression parameter. The β coefficient will be different for each category of the dependent variable (Arı and Yildiz, 2014). Testing the significance of the partial $\boldsymbol{\beta}$ parameter uses the Wald test, with test statistics (Agresti, 2010):

$$z = \frac{(\hat{\beta}_m - \beta_0)}{SE(\hat{\beta}_m)} \sim \chi^2_{\alpha,1} \tag{3}$$

2.2. Odds ratio

The odds ratio (OR) is used to interpret the proportional odds model (1), It is the comparison of the cumulative odds with its complement. The OR value of $Y \leq j$ when $X = x_1$ and $X = x_2$ (Agresti, 2010), is

$$\frac{\gamma_j(x_1)/(1-\gamma_j(x_1))}{\gamma_j(x_2)/(1-\gamma_j(x_2))} = \exp\{-\beta^T(x_1-x_2)\} \tag{4}$$

The odds of the $Y \leq j$ when $X = x_1$ is $\exp\{-\beta^T(x_1-x_2)\}$ times the odds when $X = x_2$. The odds ratio (OR) of cumulative odds is called the cumulative odds ratio. The log value of the cumulative OR is proportional to the distance between x_1 and x_2 (Agresti, 2015). In other words, the correlation between the independent variable and the response variable did not change for each category of the response variable, and the parameter estimates did not change for each cut-off point (Ari & Yildiz, 2014).

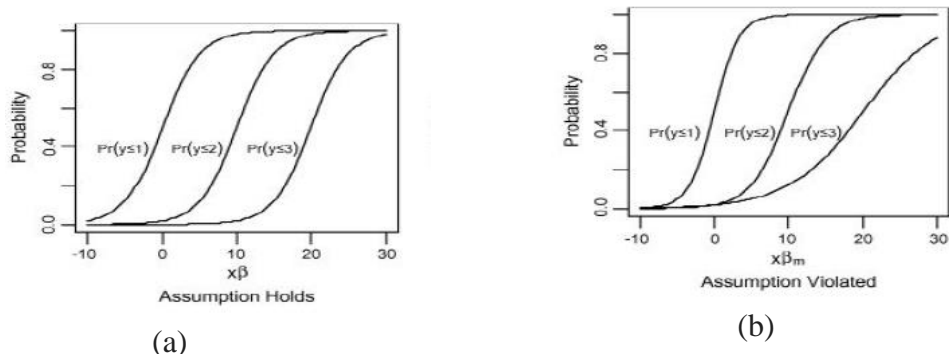## 2.3. Proportionality Assumptions

The Cumulative Logit Model for the four response categories showing the proportionality of each cumulative probability is shown in Figure 1. When the assumptions are violated, it means that there is no proportionality between the categories as shown in Figure 1b. In testing the proportionality assumption, the likelihood ratio test, Wald test, and Brant test can be used (Agresti, 2015; Fullerton & Xu, 2012). In ordinal logistic regression, these tests are used to test the equivalence of various categories and decide whether or not the assumption is valid.

If the assumptions are not valid, the interpretation of the results will be wrong. Therefore, a correct alternative model is needed to replace the ordinal logistic regression model. The hypothesis used to test the similarity of the coefficient of the independent variable β_k in each category is stated as follows (Ari & Yildiz, 2014):

$$H_0: \beta_{1j} = \beta_{2j} = \cdots = \beta_{(K-1)j} = \beta \qquad j = 1,2,\dots,J \tag{5}$$

The test statistic used to check the proportional odds assumption is the likelihood ratio test, based on the value of:

$$LR = -2\{l_{POM} - l_{NPOM}\}$$

(a)   (b)

Source: (Ari & Yildiz, 2014)

Figure 1. Cumulative Logit Models that Holds and
Violated the Proportionality Assumptions

2.4. Goodness of Fit Test

Testing the goodness of fit of the model can be done through the Deviance test with the following hypotheses:

H_0: The model fit the data

H_1: The model do not fit the data

The deviation test statistic is obtained by comparing the saturated model likelihood with the obtained model (Agresti, 2015):

$$Deviance = -2 \log[L(\hat{\mu}) - L(y)] \tag{6}$$

The testing criteria are carried out by comparing the deviance value in Equation (6) with $\chi^2_{\alpha,n-p-1}$.

3. RESEARCH METHOD

The research data was obtained from 2017 Indonesian Demographic and Health Survey (IDHS) regarding the birth of a baby. The number of babies being observed in this study was 16,336 children (BPS, 2017).

The response variable observed in this study was the birth size in five different categories (polytomous). The explanatory variables were LBW risk factors, namely mother's employment status, wealth quantile, area of residence, birth order, and gender. Categories of the Response and Explanatory Variables are shown in Table 1. The analysis stage begins with processing the data using the VGAM packages developed by (Yee, 2010) in the R-studio software (Yee, 2021).

4. RESULT AND DISCUSSION
4.1. Data Description

Babies born with a very lightweight called LBW. These babies weight less than 2500 g. In this study, the number of babies weighs heavier than 4000 g are used as a reference line in POM and NPOM. The majority of babies born in Indonesia have an average birth weight of 3000-3499 grams (39.1%) and less than 10% of babies born are very light or very heavy (Table 2).

Table 1. Categories of the Response and Explanatory Variables

Variable	Scale	Category		
Y Birth Size	Ordinal	< 2500 g	Very small	1
		2500 - 2999 g	Small	2
		3000 - 3499 g	Average	3
		3500 - 4000 g	Large	4
		> 4000 g	Very large	0
X1 Mother's Employment Status	Ordinal	Employed		0
		Unemployed		1
X2 Wealth Quantile	Ordinal	Lowest (Very Poor)		0
		Low (Poor)		1
		Middle (Middle Class)		2
		High (Rich)		3
		Highest (Very Rich)		4
X3 Area of Residence	Nominal	Urban areas		0
		Rural Areas		1
X4 Birth Order	Nominal	Less than the third order		0
		More or equal to the third order		1
X4 Gender	Nominal	Female		0
		Male		1

Table 2. Contingency Table of Birth Size Data with Explanatory Variables

Variable	Very small	Small	Average	Large	Very large	Total
Mother's employment status						
Employed (0)	621	2171	3392	1792	632	8608
	(0.501)	(0.515)	(0.531)	(0.534)	(0.534)	
Unemployed (1)	617	2042	2996	1563	510	7728
	(0.498)	(0.484)	(0.469)	(0.465)	(0.446)	
Wealth Quantile						
Very Poor	244	918	1178	697	244	3281
	(0.197)	(0.217)	(0.184)	(0.207)	(0.213)	
Poor (1)	382	989	1423	713	335	3842
	(0.308)	(0.235)	(0.222)	(0.212)	(0.293)	
Middle Class (2)	220	809	1249	669	210	3157
	(0.177)	(0.192)	(0.195)	(0.199)	(0.183)	
Rich (3)	213	769	1264	641	190	3077
	(0.172)	(0.182)	(0.197)	(0.191)	(0.166)	
Very Rich (4)	179	728	1274	635	163	2979
	(0.144)	(0.172)	(0.199)	(0.189)	(0.142)	
Area of residence						
Urban Areas (0)	611	1999	2961	1638	637	7846
	(0.493)	(0.474)	(0.463)	(0.488)	(0.557)	
Rural Areas (1)	627	2214	3427	1717	505	8490
	(0.506)	(0.525)	(0.536)	(0.511)	(0.442)	
Birth Order						
Less than the 3rd order (0)	800	2983	4262	2104	586	10735
	(0.646)	(0.708)	(0.667)	(0.627)	(0.513)	
More than the 3rd order (1)	438	1230	2126	1251	556	5601
	(0.353)	(0.291)	(0.332)	(0.372)	(0.486)	

Gender							
Female (0)		637	2204	3165	1479	452	7937
		(0.514)	(0.523)	(0.495)	(0.440)	(0.395)	
Male (1)		601	2009	3223	1876	690	8399
		(0.485)	(0.476)	(0.504)	(0.559)	(0.604)	
	Total	1238	4213	6388	3355	1142	16336

Babies born with the weight less than 2500 gram are called Low Birth Weight (LBW). In this study, the number of babies weights heavier than 4000 g are used as a reference line in POM and NPOM. The majority of babies born in Indonesia have an average birth weight of 3000-3499 grams (39.1%) and less than 10% of babies born are very light or very heavy (Table 2).

4.2. Proportional Odds Model (POM)

The results of the Proportional Odds Model (POM) analysis show that the risk factors that have a significant effect on the LBW rate are the mother's employment status, area of residence, birth order, and gender. The estimated value of β in POM is assumed to have the same proportionality for each category of y. However, when the proportionality assumption is violated, the results of the Proportional Odds Model (POM) cannot be used. Based on the assumptions test results of hypothesis (4), the likelihood ratio is 181.95 with df = 24 and a P-value of 0,000. It indicates that the proportional odds assumption is violated or not fulfilled. Therefore, the estimation results using POM in Table 3 cannot be concluded, because the conclusions may either be valid or invalid.

Table 3. Analysis Results of Proportional Odds Model (POM)

Variable	POM	
	Estimate	P-value
(Intercept):1	-2.364^{**}	< 2e-16
(Intercept):2	-0.545^{**}	< 2e-16
(Intercept):3	1.132^{**}	< 2e-16
(Intercept):4	2.763^{**}	< 2e-16
X1(1)	0.065^{*}	0.026
X2(1)	0.105^{*}	0.016
X2(2)	-0.067	0.141
X2(3)	-0.079	0.091
X2(4)	-0.120^{*}	0.013
X3(1)	0.141^{**}	0.000
X4(1)	-0.305^{**}	< 2e-16
X5(1)	-0.256^{**}	< 2e-16

Significant with $^{**} \alpha = 1\%$, $^{*} \alpha = 5\%$

4.3. Test of Proportional Odds Assumption

The proportional odds assumption must be fulfilled in building the POM model. The assumption is that the proportionality values in each category of response variables exist. In addition to the likelihood ratio test, the proportionality value parallels can also be observed through graphs. In Figure 2, it can be seen that there is no proportionality between two or

more lines in each category on Y. It indicates a possible violation of the proportionality assumption.

4.4. Non-Proportional Odds Model (NPOM)

When the proportionality assumption is violated, the results of the POM analysis can no longer be used. Thus, we need an alternative model to estimate the risk factors for the newborn size, one of the alternatives is the Non-Proportional Odds Model (NPOM). The results of the NPOM analysis in Table 4 show that the estimated values of $\boldsymbol{\beta}$ are different for each cumulative logit. The estimated values of $\boldsymbol{\beta}$ were obtained as much as j-1. However, not all of them had a significant effect on the newborn size. The estimation of parameters in this NPOM forms 16 cumulative logit equations (Table 4). One of the cumulative logits for the LBW babies (j = 1) is expressed as:

$$
\begin{aligned}
\text{Logit}\left(P(Y \leq 1|\text{x})\right) = \ & -2.576 + 0.093 \ (\text{Mother's employment})_i^1 \\
& +0.351(\text{Wealth Quantile}^*)_i^1 \\
& -0{,}094 \ (\text{Wealth Quantile}^*)_i^2 \\
& -0{,}119 \ (\text{Wealth Quantile}^*)_i^3 \\
& -0{,}285 \ (\text{Wealth Quantile}^*)_i^4 \\
& +0{,}150 \ (\text{Residence }^*)_i^1 + 0{,}027 \ (\text{Birth Order})_i^1 \\
& -0{,}130 \ (\text{Gender}^*)_i^1
\end{aligned}
$$

Mother's employment status (X1) and birth order (X4) did not have a significant effect on category j = 1. The influence of risk factors on the size of LBW was seen from the odds ratio value.

(a) X1

(b) X2

(c) X3

(d) X4
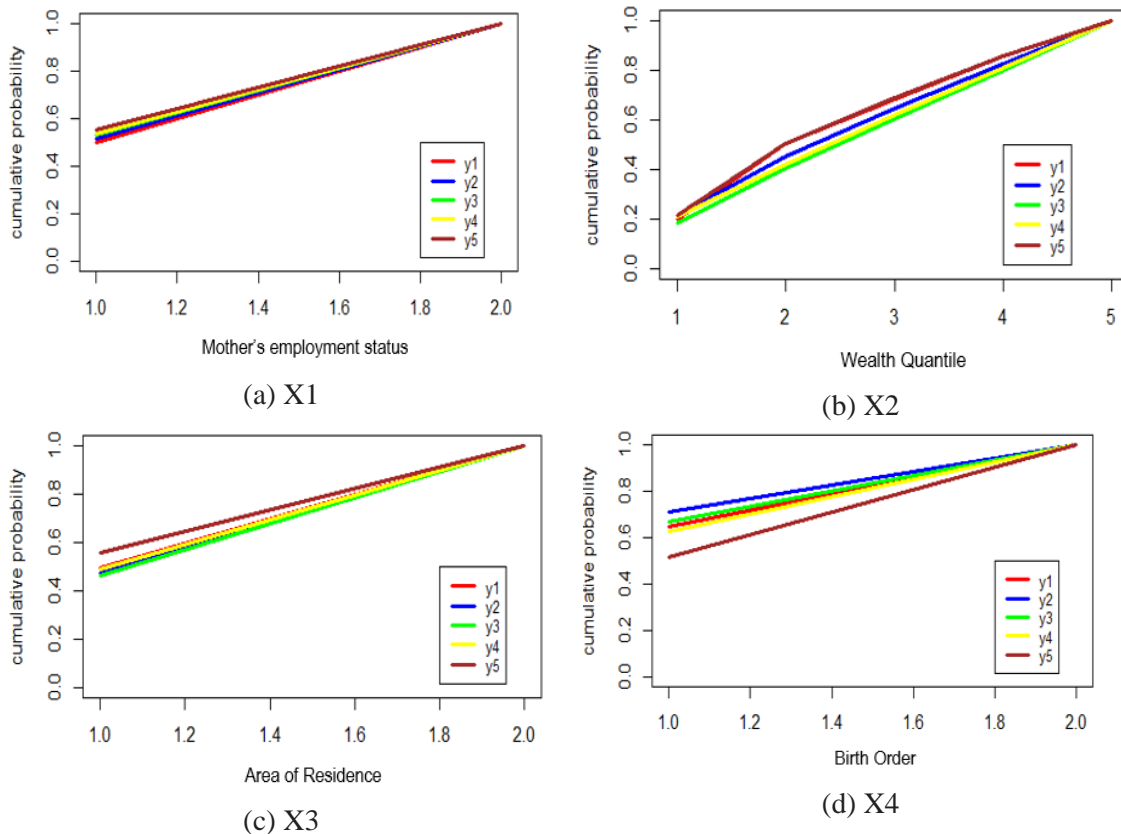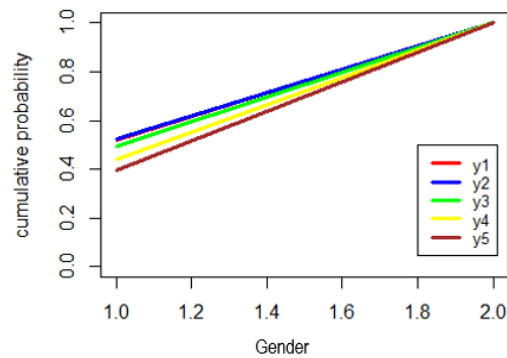
(e) X5

Figure 2. The Cumulative Odds of the Independent Variables in Each Response Category

4.5. Odds ratio

The influence of the explanatory variables can be seen from the odds ratio. Based on the variables that have a significant effect on the birth size model, it can be seen that the value of the reference line from the odds ratio is the very large baby (weight > 4000 gr). The highest odds ratio value is 1.421. It means that the largest tendency for LBW babies occurs in mothers who come from poor families than mothers from very poor families. The tendency of mothers who come from very poor families to give birth to LBW is 1.330 times that of mothers with very rich families. Mothers who live in rural areas are also more likely to give birth to LBW babies by 1.162 times than mothers who live in urban areas. Furthermore, based on the sex of the baby, it turns out that the tendency of LBW condition for female babies is 1.139 times higher than male babies.

Table 4. Non-Proportional Odds Model Analysis Result (NPOM)

Parameter	Estimate	Pr(>|z|)	*OR*	Parameter	Estimate	Pr(>|z|)	*OR*
(Intercept):1	-2.576**	< 2e-16	0.076	X2(3):3	0.032	0.580	1.032
(Intercept):2	-0.486**	< 2e-16	0.615	X2(3):4	0.115	0.263	1.121
(Intercept):3	1.107**	< 2e-16	3.026	X2(4):1	-0.285**	0.007	0.752
(Intercept):4	2.841**	< 2e-16	17.136	X2(4):2	-0.270**	0.000	0.763
X1(1):1	0.093	0.120	1.097	X2(4):3	0.026	0.662	1.026
X1(1):2	0.058	0.083	1.060	X2(4):4	0.232**	0.034	1.262
X1(1):3	0.060	0.093	1.062	X3(1):1	0.150**	0.025	1.162
X1(1):4	0.108	0.080	1.115	X3(1):2	0.114**	0.002	1.121
X2(1):1	0.351**	0.000	1.421	X3(1):3	0.163**	0.000	1.177
X2(1):2	0.056	0.264	1.058	X3(1):4	0.233**	0.001	1.262
X2(1):3	0.131**	0.015	1.140	X4(1):1	0.027	0.660	1.028
X2(1):4	-0.082	0.357	0.921	X4(1):2	-0.260**	0.000	0.771
X2(2):1	-0.094	0.333	0.910	X4(1):3	-0.354**	< 2e-16	0.702
X2(2):2	-0.147**	0.006	0.863	X4(1):4	-0.616**	< 2e-16	0.540
X2(2):3	0.011	0.839	1.011	X5(1):1	-0.130**	0.028	0.878
X2(2):4	0.078	0.426	1.082	X5(1):2	-0.213**	0.000	0.808
X2(3):1	-0.119	0.232	0.888	X5(1):3	-0.313**	< 2e-16	0.731
X2(3):2	-0.192**	0.000	0.825	X5(1):4	-0.389**	0.000	0.678

Significant with ** α = 5%.

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In addition to LBW conditions, there were more small birth size babies from very poor families than the three other economic groups. Odds ratio of middle-class, rich, and very rich families, are 1.159, 1.212, and 1.311 respectively. Apart from economic factors, other factors that have a significant effect on the small birth size of babies (BW 2500 - 3000 gr) are the area of residence, birth order, and the sex of the baby. The tendency of mothers who live in rural areas to give birth to very small babies was 1.162 times higher than mothers who live in urban areas. Mothers who have given birth to babies less than 3 times tend to give birth to small babies 1.30 times compared to mothers who have given birth 3 times or more. Furthermore, female babies tended to be born with a small size or 1,238 times more likely than male babies.

4.6. Goodness of Fit

The goodness of fit indicator uses the Deviation value and Mc Fadden's R^2 (Table 5). The goodness of fit test based on the deviance value for the NPOM model is 277,042 with a P-value = 0.605. It shows that the NPOM model is suitable for use or following the data. Meanwhile, the POM result rejects the null hypothesis/H_0 (P-value = 0.000), meaning that there is not enough evidence to state that the POM model is feasible or following the data. Furthermore, the goodness of the model is explained through Mc Fadden's R^2 value. The Non-proportional Odds Model is able to explain about 60% of the variation in the birth size. This value is much greater than the goodness of fit value of the Proportional Odds model, which is 32.1%.

Table 5. Goodness of Fit

Goodness of Fit Indicator	POM	NPOM
Deviance	458.989	277.042
P-value	0.000	0.605
Mc Fadden's R^2	0.321	0.591

5. CONCLUSION

The results of this study indicate that if the proportional odds assumption on POM is not violated, then the NPOM alternative model can be used. NPOM model is better than POM because it has the lowest Deviance and the highest Mac Fadden R^2. Based on the NPOM model, several risk factors that have a positive effect are obtained on LBW conditions, namely residence (rural) and wealth quintile (lower economic class). Therefore, to reduce the rate of LBW, the government and the health workers need to pay attention to the condition of families who live in rural areas and families with lower economic class.

The results of the NPOM analysis showed that there are still several categories of explanatory variables that do not have a significant effect. Therefore, the further research about other cumulative logit models for LBW cases can still be developed, such as Partial Proportional Odds Model (PPOM). The Partial Proportional Odds Model is used when some β parameter values are not the same for each category.

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