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The Application of Partial Proportional Odds Model on Determinants Analysis of Household Food Insecurity Level in Papua, Indonesia

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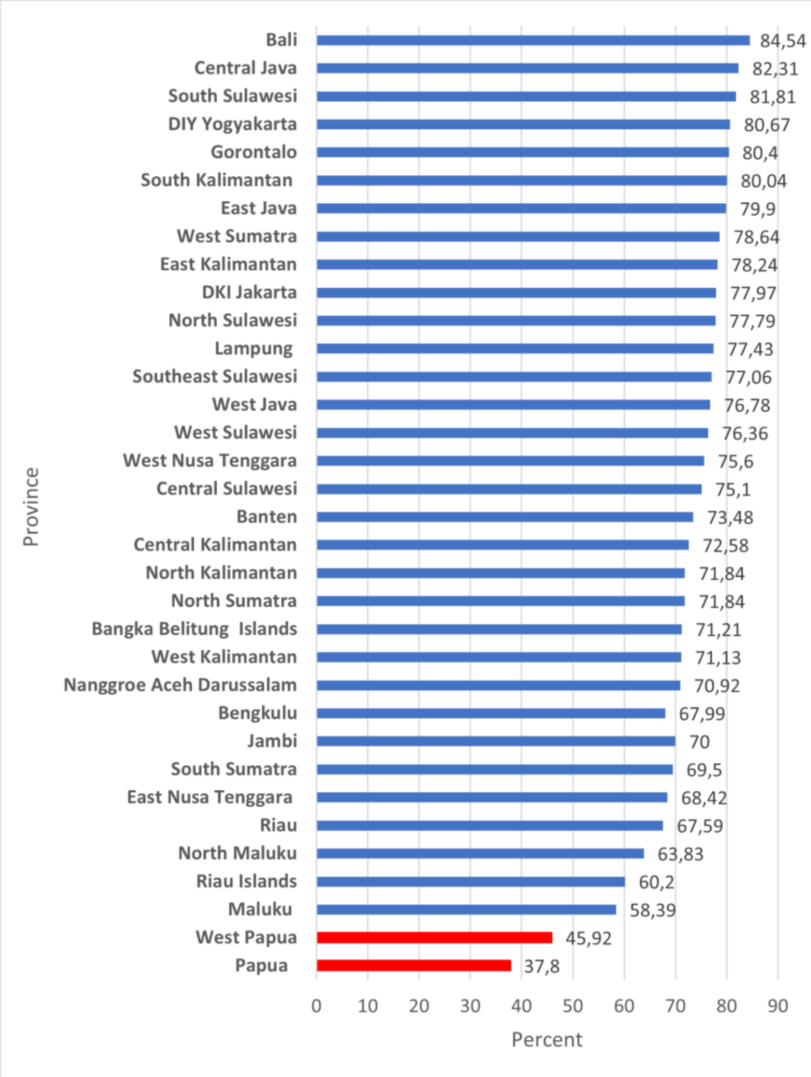
Abstract

Introduction/Main Objectives: Food insecurity in Papua, Indonesia, is still high. However, the study on that issue is limited. This research aims to analyze the determinants of food insecurity in Papua. **Background Problems:** An ordinal logistic regression can be used. However, this model generally requires the parallel lines assumption. However, somehow, the assumption is often violated. **Novelty:** This study used a model that relaxes the assumption of parallel lines. This model can capture the condition that some parameters are assumed to meet parallel lines and some do not. **Research Methods:** In this case, the partial proportional odds model was applied to find the determinant of household food insecurity status by using the National Socioeconomic Survey (SUSENAS) data. **Finding/Results:** The results show that a female head of household, age 60 years and above, junior high school education and below, has a higher tendency to be at least mildly food insecure, and the effect is the same for each level of food insecurity. Household heads who do not work, work in agriculture, and have household drinking water sources that are not feasible can aggravate the food insecurity level. Meanwhile, food assistance provided by the government influences reducing food insecurity levels.

1. Introduction

Food is one of the most basic needs of humanity to sustain life, causing the demand for food needs to increase as the number of people increases with positive population growth. Therefore, food security must be considered by the government. Food security is a condition that describes the sufficiency of food needs from the national level to individuals or households in terms of quantity, quality, safety, distribution, and affordability. The UN is committed to realizing food security through the Sustainable Development Goals(SDGs) in the second goal in target 2.1 regarding the right to food [1]. The government can monitor food security achievements through the Food Security Index (FSI).

Figure 1 shows two provinces with the lowest FSI values: Papua Province at 37.80 percent and West Papua Province at 45.92 percent. According to BPN [2], this figure shows that these provinces are classified as vulnerable to food insecurity. These provinces are located on the Papua Islands. We know that this region, especially Papua Indonesia region, faces various difficulties in achieving, maintaining, and improving the quality of sustainable food security. So, it is common for food insecurity to occur on this island. However, to mitigate more severe food insecurity, it is necessary to find the determining factors of the level of food insecurity at the individual/household level.



Source: BPN, 2022

Figure 1. Household food security index of 34 provinces in Indonesia 2022

Food insecurity is when a person does not have sufficient physical and economic access to nutritious food on an ongoing basis for normal growth and development and an active and healthy life. In terms of the prevalence of people with moderate or severe food insecurity, based on the 2022 food insecurity experience scale, the provinces of Papua region have a higher prevalence than the national figure of 4.85 percent, namely Papua province at 6.77 percent and West Papua province at 10.31 percent.

The government can monitor the state of food insecurity in Papua through the Food Security and Vulnerability Atlas (FSVA) to alleviate food insecure areas. FSVA categorizes the status of food security into six priority categories: the first is a category of highly vulnerable to food insecurity, and the last is a category of food security [3].

Figure 2 shows that most Papua districts are highly vulnerable to food insecurity. The food condition in this region is different from the achievement of the second goal of the SDGs indicators, making the Papua region an urgency in overcoming the problem of food insecurity at a macro level. In addition, food insecurity issues in this region will affect the status of food insecurity at the household level. Two components cause food insecurity at the household level: inadequate access to nutritious and safe food supplies and inadequate utilization of food by households. This fact makes it important to assess the status of food insecurity at the household level because household food insecurity can affect regional food access uncertainty directly.

Source: BPN, 2022

Figure 2. Food Security and Vulnerability Atlas (FSVA) in Indonesia by District 2022

The categorization in FSVA only provides an overview of the state of vulnerability to food insecurity at the regional level. However, it cannot be used to describe food insecurity at the household level. Meanwhile, household food insecurity is urgent in overcoming food insecurity problems at a regional level. Solving this food insecurity problem needs to consider the prioritization of households affected by food insecurity based on the level of food insecurity. Thus, FAO distinguishes household food insecurity based on levels into four categories. They are food security, mild food insecurity, moderate food insecurity, and severe food insecurity. There are many measurements for food insecurity, but according to Leroy et al. [4], the Food Insecurity Experience Scale (FIES) indicator is more standard than others. The FIES indicator was measured by eight questions about worry about getting food, eating healthily, the kinds of food that are eaten, eating a meal or not, eating less than usual, running out of food, feeling hungry or not, and any condition without food for a day.

Many studies have been conducted to examine the problem of food insecurity. These studies have various kinds of determination of food insecurity status, the methods applied, and the variables used. Borku et al. [5] and Ndhleve et al. [6] determined food insecurity with Household Food Insecurity Access Prevalence (HFIAP). Furthermore, Smith [7], Grimaccia & Naccarato [8], and Sheikomar [9], determine food insecurity status with the Food Insecurity Experience Scale (FIES).

Generally, they use binary logistic regression. Only Grimacia and Naccarato [8] applied ordinal logistic regression among researchers who used FIES. They made FIES into nine categories according to 8 FIES questions plus food security if all 8 FIES questions are answered "no". Because there are too many categories, many cell contents are zero. Of course, this will affect the modeling. Therefore, FAO itself classifies food insecurity into four categories. In addition, they still used the conventional ordinal logistic model with proportional odds so that it is not visible which variables have worsened food insecurity potentially. Besides that, the ordinal logistic regression with proportional odds model requires the assumption of parallel lines to be met. The assumption of parallel lines means that the categories in the dependent variable are parallel to each other so that the model has the same value for each category of different response variables. When the assumption is violated, a partial proportional odds model can be used if only some independent variables violate the parallel lines assumption or the non-proportional odds model if all independent variables violate the parallel lines assumption [10].

Existing research employing determinant analysis to assess household food insecurity in Papua remains limited. Given the widespread prevalence of severe food insecurity in many regions, further investigation is necessary to develop effective mitigation strategies. Ordinal logistic regression analysis, with categories aligned with the FAO's four-tier classification, can be employed to examine the influence of various factors on the severity of food insecurity. This study proposes a more flexible ordinal logistic model to avoid the restrictive parallel lines assumption inherent in the proportional odds model.

2. Material and Methods

2.1. Data

This study was undertaken in Papua and West Papua Provinces. The household food insecurity status can be measured by Statistics Indonesia (BPS) through the National Socioeconomic Survey (SUSENAS) according to questions R1701 to R1708. We used SUSENAS in March 2022. In this study, we have 20 975 household samples.

The dependent variable of this study is the household food insecurity level. The household food insecurity level is determined based on responses to the FIES questions on household access to food over the past year contained in Block XVII details of questions 1701-1708 in the March 2022 SUSENAS KOR questionnaire (VSEN22.K). The details of these questions are shown in Figure 3.

- *R1701. During the last year, did you or other household members* ***worry*** *that you would not have enough food due to a lack of money or other resources? (Yes/No)*
- *R1702. During the last year, was there a time when you or other household members* ***could not eat healthy*** *and nutritious food due to a lack of money or other resources? (Yes/No)*
- *R1703. During the last year, did you or other household members eat* ***only a few kinds of food*** *because you did not have money or other resources? (Yes/No)*
- *R1704. During the last year, have you or other household members* ***ever missed a meal*** *on a particular day because you did not have enough money or other resources to get food? (Yes/No)*
- *R1705. During the last year, did you or other household members* ***eat less than you should*** *have due to a lack of money or other resources? (Yes/No)*
- *R1706. During the last year, did the household* ***run out of food*** *due to lack of money or other resources? (Yes/No)*
- *R1707. During the last year, did you or other household members* ***feel hungry but did not eat*** *due to lack of money or other resources to obtain food? (Yes/No)*
- *R1708. During the last year, have you or other household members* ***gone without food*** *for a day due to a lack of money or other resources? (Yes/No)*

Source: BPN, 2022

Figure 3. FIES questions in SUSENAS March 2022 questionnaire

The FIES questions are asked at the household level, represented by the household head/partner/household members aged 15 years and above. Table 1 provides the criteria for categorizing the level of food insecurity.

Table 1. Operational definition of dependent variable

Food Insecurity Levels	Code	Condition
Food Security	1	All question items R1701-R1708 are answered "No."
Mild Food Insecurity	2	At least one question in R1701-R1703 is answered "Yes" and all questions in R1704 - R1708 are "No"
Moderate Food Insecurity	3	At least one question in R1704 - R1706 is answered "Yes," and the questions in R1707 and R1708 are "No".
Severe Food Insecurity	4	There is an answer "Yes" in R1707 and/or in R1708

Meanwhile, the independent variables used in this study are derived from the sociodemographic characteristics of household heads and standard household living conditions included in the March 2022 SUSENAS KOR responses (VSEN22.K). Table 2 explains the operational definitions of the independent variables used in the study.

Table 2. Operational definition of independent variable

Independent Variables	Categories
Head of household's sex	Female
	Male*
Head of household's age	Less than 60 years*
	60 years and above
Head of household's education	Junior high school and below
	More than junior high school*
Head of household's work	Working at non-agriculture*
	Working at agriculture
	Not working
Drinking water source	Yes*
	No
Food aid recipient	Yes
	No*

**reference category*

2.2. Ordinal Logistic Regression Analysis

Ordinal logistic regression is a statistical analysis method for modeling the relationship between an ordinal dependent variable and one or more explanatory variables. An ordinal variable is a categorical variable with clear category levels. Meanwhile, the explanatory variables may be either continuous or categorical.

Ordinal logistic regression can be used when the dependent variable has at least three categories and the absolute distance between levels is unknown [11]. Several models are often used and can be distinguished based on how the logit is formed, such as the adjacent-category model, continuation ratio, and cumulative logit [12]. Based on these three models, the cumulative logit model is the easiest to interpret [10]. According to the assumptions that must be met, there are three types of cumulative logit models: proportional odds model, partial proportional odds model, and non-proportional odds model.

Proportional odds model (POM)

The proportional-odds model is an ordinal logistic model in which the intercepts depend on the jth category, but the slopes are all equal. The form of the cumulative logit model of proportional odds property is written as equation (1).

$$logit[P(Y > j)] = \alpha_j + \boldsymbol{\beta}'\boldsymbol{x} = \alpha_j + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p,\ j = 1,\ \ldots,\ J-1 \tag{1}$$

Based on equation (1), it is implied that there are $J-1$ models formed. For example, if there are three categories of response variable/dependent variable, then two cumulative logit models will be formed. The α_j is the unknown parameter's variable estimator, meaning that each cumulative logit has its intercept. $\boldsymbol{\beta}$ is a vector $p \times 1$ of regression coefficient parameter (slopes), where p is the number of the parameters.

$logit[P(Y > j)]$ is the logit of the cumulative probability of an analysis unit belonging to a category higher than j ($j+1$ or $j+2, \ldots$), where j is the dependent variable category. According to Agresti [11], the probability to be at or below the jth category can be defined as follows:

$$P(Y \leq j) = \pi_1 + \pi_2 + \cdots + \pi_j, \qquad j = 1, \ldots, J-1 \tag{2}$$

Where π_j is the probability (odds) of category j. and the probability of being above the jth category is thus the complement of the cumulative probability:

$P(Y > j) = 1 - P(Y \leq j)$

Then, the logit function of the cumulative odds as equation (1) can be expressed by equation (3) [13].

$$logit[P(Y > j)] = log\left[\frac{P(Y > j)}{1 - P(Y > j)}\right] = log\left[\frac{P(Y > j)}{P(Y \leq j)}\right] = \alpha_j + \boldsymbol{\beta}'\boldsymbol{x}, \quad j = 1, \dots, J \tag{3}$$

This model applies simultaneously to all $J - 1$ cumulative probabilities and assumes an identical effect of the predictors (independent variable) for each cumulative probability. The Proportional Odds Model (POM) ensures that the predicted odds for category j are no smaller than that of a category lower than category j and no larger than that of a category higher than category j. This model has assumptions that must be met. Specifically, the slope of the model must be the same for all logits [13]. This assumption is known as cumulative logit parallelity or parallel lines. The parallel lines assumption means that the categories in the dependent variable are parallel to each other so that the model has the same value for each category of different response variables [14]. If these assumptions are violated, the results of ordinal regression may not be valid.

Partial proportional odds model (PPOM)

When a parallel line assumption is not met in the POM model, it can occur because only some are not met. The partial proportional odds model (PPOM) is present to cover this. PPOM can be applied when some independent variables violate the parallel lines assumption. PPOM allows the slopes of some independent variables to violate the parallel lines assumption while others fulfill the parallel lines assumption. The cumulative probability of the partial proportional odds model for a dependent variable with j categories is as follows [15]:

$$logit[P(Y > j)] = \alpha_j + \boldsymbol{\beta}'\boldsymbol{x} + \boldsymbol{\gamma}_j'\boldsymbol{u}, \quad j = 1, \dots, J - 1 \tag{4}$$

$\boldsymbol{\beta}$ is a vector of regression parameters (slopes) of independent variables that meet the parallel line assumption, and $\boldsymbol{\gamma_i}$ is a vector of parameters of independent variables that violate the parallel line assumption (different slopes for each jth dependent variable category).

Non-proportional odds model (NPOM)

The parallel line assumption violation in the POM model can also occur because all independent variables do not meet the assumption. A Non-proportional Odds Model (NPOM) can be applied when all independent variable coefficients violate the parallel line assumption. This model has varying slopes for each category of the dependent variable. The cumulative probability of the non-proportional odds model is as follows [15]:

$$logit[P(Y > j)] = \alpha_j + \boldsymbol{\gamma}_j'\boldsymbol{u}, \quad j = 1, \dots, J - 1 \tag{5}$$

Parallel Lines Assumption Test

The parallel lines assumption means that the association between dependent and independent variables does not change for the categories of dependent variables. The parallel line assumption test can be done to determine whether the proportional odds model can be applied or not. This assumption can be tested through the likelihood ratio test to present an overall test of the parallel lines assumption on each independent variable [16]. The null hypothesis in this test is that the value of the regression coefficient (slope) is the same across all logit models ($j = 1, \dots, J - 1$). A rejection of this null hypothesis thus implies that the assumption is violated, whereas failure to reject this hypothesis supports the assumption.

$$PL = -2\, ln\left[\frac{L_0}{L_1}\right] \sim \chi^2_{p(J-2)} \tag{6}$$

Where, L_0 is the maximum likelihood value of the model with independent variables assuming parallel lines and L_1 is the maximum likelihood value of the model with independent variables that does not assume parallel lines. The null hypothesis can be rejected if $PL > \chi^2_{\alpha;p(J-2)}$ or $p - value < \alpha$.

Furthermore, the Brant test of parallel lines can identify the suitable model when the parallel lines assumption is not met. The Brant test compares separate estimates of each predictor. The hypothesis used in the Brant test is as follows,

H_0 : $\boldsymbol{R\beta}^* = \boldsymbol{0}$ (regression coefficients (slope) of all logit models are the same)
H_1 : $\boldsymbol{R\beta}^* \neq \boldsymbol{0}$

where

$$\boldsymbol{R} = \begin{bmatrix} I & -I & 0 & \cdots & 0 \\ I & 0 & -I & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ I & 0 & 0 & \cdots & -I \end{bmatrix}_{(J-2)p\times(J-1)p} \qquad \boldsymbol{\beta}^* = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \vdots \\ \beta_{J-1} \end{bmatrix}_{(J-1)p\times 1}$$

The test statistic is as follows:

$$\chi^2_{hit} = \left(\boldsymbol{R\widehat{\beta}}^*\right)^T \left[(\boldsymbol{R}) \left(\boldsymbol{Asy.Var}\left(\boldsymbol{\widehat{\beta}}^*\right)\right) \left(\boldsymbol{R^T}\right)\right]^{-\boldsymbol{1}} \left(\boldsymbol{R\widehat{\beta}}^*\right) \tag{7}$$

where, $\boldsymbol{Asy.Var}\left(\boldsymbol{\widehat{\beta}}^*\right)$ is a covariance estimation matrix of regression coefficient estimate, $\boldsymbol{R}$ is a contrast matrix, and $\boldsymbol{I}$ is the design of matrix $\boldsymbol{R}$, depending on the contrast to be compared in the parameters, the sum of the contrast coefficients in each row is zero. The decision will be obtained when the null hypothesis can be rejected if $\chi^2_{hit} > \chi^2_{\alpha;(J-2)}$ or $p-value < \alpha$. Based on the Brant test results, NPOM can be applied, when it shows that all predictors violate the parallel lines assumption. PPOM can be applied when it shows that only some predictors violate the parallel lines assumption.

Model Fit Test

To ensure which model is suitable, we can compare the models and call it the model fit test [14]. Model fit testing in PPOM for large samples can be done through the likelihood ratio (LR) test. The LR test in this model is carried out by comparing a simpler model with a more complex model. In this case, the LR test is carried out between POM and PPOM, and between PPOM and NPOM. The model fit testing hypothesis is as follows:

a. POM vs PPOM
H_0 : The POM model better fits the data
H_1 : The PPOM model better fits the data

Test statistics:

$$LR_1 = -2\ ln\left[\frac{L_{POM}}{L_{PPOM}}\right] \sim \chi^2_{v_1} \tag{8}$$

L_{POM} is the maximum likelihood of POM, while L_{PPOM} is the maximum likelihood of PPOM and $v_1$is the degree of freedom calculated from the difference in the number of parameters of the POM and PPOM models. The decision will be obtained when the null hypothesis is rejected if $LR_1 > \chi^2_{(\alpha;v_1)}$ or $p-value < \alpha$ so that it can be concluded that PPOM fits the data better than POM.

b. PPOM vs NPOM
H_0 : The PPOM model better fits the data
H_1 : The NPOM model better fits the data

Test Statistics:

$$LR_2 = -2\ ln\left[\frac{L_{PPOM}}{L_{NPOM}}\right] \sim \chi^2_{v_2} \tag{9}$$

L_{NPOM} is the maximum likelihood of NPOM and v_2 is calculated form the difference in the number of parameters of the PPOM and NPOM model. The decision will be obtained when the null hypothesis is rejected if $LR_2 > \chi^2_{(\alpha;v_2)}$ or $p-value < \alpha$ so that it can be concluded that NPOM fits the data better than PPOM.

According to Parry [17], there are many software options for running ordinal logistic regression models, such as SPSS, SAS, R and STATA. Williams [18] proposed the **gologit2** module in STATA. This model can directly check the parallel lines assumption in the POM model and, at the same time, can also test the model fit between the PPOM and NPOM models if the parallel lines assumption is violated.

3. Empirical Result and Discussion

3.1. Households Sample in Papua Indonesia 2022 Overview

Based on the results of the March 2022 SUSENAS presented in Figure 4 regarding the percentage level of household food insecurity in the Papua Indonesia region in 2022, the households sample generally experienced food security, which amounted to 82.31 percent. However, around 17.69 percent of households are still experiencing food insecurity. Of the 17.69 percent of households experiencing food insecurity, there are 6.69 percent of households experiencing mild food insecurity, 4.9 percent of households experiencing moderate food insecurity, and 6.2 percent of households experiencing severe food insecurity. This finding indicates that 6.69 percent of households are worried about uncertainty in food access; 4.9 percent of households experience a decrease in the quality and quantity of food and are not sure they can obtain food due to limited household resources; and 6.2 percent of households experience food shortages and do not eat for one or more days despite being hungry due to limited household resources.

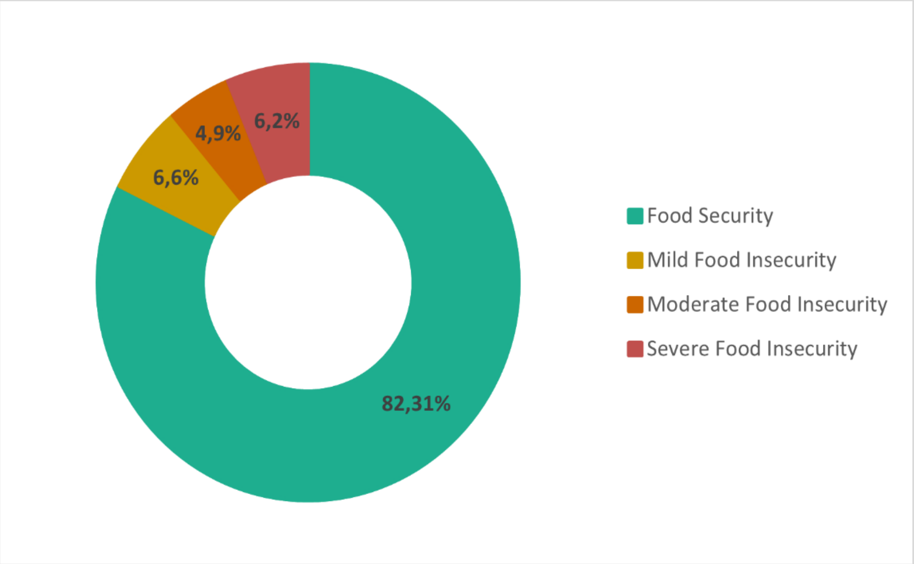


Figure 4. Percentage of households sampled by food insecurity level in Papua Indonesia region in 2022

Table 3 shows that the sample distribution of households experiencing food insecurity has characteristics derived from the gender of the female head of household, the age of the head of household is 60 years and above, the education level of the head of household is junior high school or below, the head of household is not working, work in agriculture, the household receives food assistance, and the household has inadequate drinking water sources. When viewed from the severity level, the most severe level of food insecurity appears to have more household samples for these characteristics. However, the difference is mostly similar to the level below it. The most severe looks were quite different when the head of the household was not working, working in agriculture, the family's source of drinking water was not feasible and not receive food assistance from the government.

Table 3. Percentage of sample households by food insecurity level and household characteristics in Papua Indonesia in 2022

Independent Variables	Categories	Food Security	Food Insecurity		
			Mild	Moderate	Severe
Head of household's sex	Female	78.60%	7.00%	7.06%	7.35%
	Male*	82.64%	6.56%	4.68%	6.12%
Head of household's age	Less than 60 years*	82.66%	6.53%	4.85%	5.97%
	60 years and above	80.08%	7.04%	5.08%	7.80%
Head of household's education	Junior high school and below	81.62%	6.45%	5.06%	6.87%
	More than junior high school*	83.35%	6.82%	4.60%	5.22%
Head of household's work	Working at non-agriculture*	83.18%	7.78%	4.52%	4.53%
	Working at agriculture	82.24%	5.84%	4.96%	6.96%
	Not working	78.26%	7.52%	6.07%	8.15%
Drinking water source	Feasible*	82.61%	7.51%	5.04%	4.85%
	Not feasible	82.01%	5.70%	4.72%	7.57%
Food aid recipient	Yes	61.73%	21.07%	8.47%	8.73%
	No*	83.35%	5.86%	4.70%	6.09%

3.2. Determinants Analysis of Household Food Insecurity Level in Papua Indonesia in 2022

First, we perform ordinal logistic regression modelling with proportional odds, then we check the parallel line assumption. The parallel line statistic test has a Chi-Square value of 148.56, and the p-value is 0.000. The p-value is less than the significance level (α=0,05). This finding indicates that with a significance level of 5 percent, the model does not meet the parallel lines assumption. Then perform a Brant test to know which predictors (independent variables) violate the parallel lines assumption. The Brant test statistic values produced based on formula (6) are listed in Table 4.

Table 4. Parallel lines assumption test results with brant test

Independent variables	Categories	*Chi-Square*	*p-value*	df
Head of household's sex	Female	3.76	0.153	2
Head of household's age	60 years and above	2.14	0.342	2
Head of household's education	Junior high school and below	0.08	0.960	2
Head of household's work	Working at agriculture	12.26	0.002*	2
	Not working	6.23	0.004*	2
Drinking water source	Not feasible	78.41	0.000*	2
Food aid recipient	Yes	19.86	0.000*	2

* Significance at level 0.05

The independent variables that meet the parallel line assumption have a p-value greater than the significance level ($\alpha = 0.05$). From Table 4, it can be seen that of the six variables, only three met the parallel line assumption, such as gender, age, and the education level of the household head. The other three variables, such as the economic activity of the household head, access to feasible drinking water, and the food aid recipient status, violate the parallel line assumption. This result shows that only some variables met the parallel line assumption. This indicates that the ordinal logistic model with proportional odds isn't suitable.

A model-fitting test was done to determine which of the three types of ordinal logistic regression models is the most appropriate. The test results can be seen in Table 5. From these results, we can decide that the partial proportional odds (PPOM) model is the most appropriate.

Table 5. Model fit test result

Model Hypothesis	*Chi-square*	*p-value*	Decision
H_o : $POM\ model\ better\ fits\ the\ data$ H_1 : $PPOM\ model\ better\ fits\ the\ data$	166.07	0.000*	Reject H_o
H_o : $PPOM\ model\ better\ fits\ the\ data$ H_1: $NPOM\ model\ better\ fits\ the\ data$	8.72	0.1899	Do not reject H_o

* Significance at level 0.05

The partial proportional odds model was then applied to determine the household food insecurity level in the Papua Indonesia region. Three logit models were formed because there are four levels of dependent variable categories: Model 1 (at least mild food insecurity versus food security), Model 2 (at least moderate food insecurity versus food security and mild food insecurity), and Model 3 (severe food insecurity versus food security to moderate food insecurity). The results of partial parameter testing are in Table 6.

Table 6. Partial proportional odds model results

		Model 1 (at least mild food insecurity versus food security) $g(y) = \log\frac{P(Y>1)}{P(Y\le 1)}$			Model 2 (at least moderate food insecurity versus food security and mild food insecurity) $g(y) = \log\frac{P(Y>2)}{P(Y\le 2)}$			Model 3 (severe food insecurity versus food security to moderate food insecurity) $g(y) = \log\frac{P(Y>3)}{P(Y\le 3)}$		
Variables	Categories	$\hat{\beta}$	Se($\hat{\beta}$)	*p-value*	$\hat{\beta}$	Se($\hat{\beta}$)	*p-value*	$\hat{\beta}$	Se($\hat{\beta}$)	*p-value*
Intercept	-	-1.632	0.036	0.000	-2.406	0.047	0.000	-3.31	0.066	0.000
Head of household's sex	Female	0.145	0.051	0.004*	0.145	0.051	0.004*	0.145	0.051	0.004*
Head of household's age	60 years and above	0.139	0.052	0.008*	0.139	0.052	0.008*	0.139	0.052	0.008*
Head of household's education	Junior high school and below	0.114	0.039	0.004*	0.114	0.039	0.004*	0.114	0.039	0.004*
Head of household's work	Working at agriculture	0.233	0.044	0.000*	0.363	0.053	0.000*	0.435	0.071	0.000*
	Not working	0.346	0.084	0.000*	0.529	0.096	0.000*	0.665	0.122	0.000*
Drinking water source	Not feasible	0.005	0.038	0.898	0.220	0.044	0.000*	0.458	0.059	0.000*
Food aid recipient	Yes	0.675	0.061	0.000*	0.418	0.073	0.000*	0.408	0.093	0.000*

* Significance at level 0.05

Based on the results presented in Table 6, it can be seen that for all logit models, each independent variable generally produces a p-value smaller than the significance level ($\alpha = 0.05$). This finding shows that with a significance level of 5 percent, each variable affects to distinguish between households group with food insecurity and no food insecurity, moderate food insecurity from the level below it, and severe food insecurity from the level below it significantly. However, in Model 1 the source of feasible drinking water does not affect significantly. This result means that the variable can not distinguish significant groups of food-secure households from those with food insecurity. Interpretation of the effects per variable is easier if using the odds ratio. The odds ratio values for each variable category are presented in Table 7.

Table 7. Odds Ratio

Variables	Categories	*Odds Ratio* (OR) Model 1 (Y = 2,3,4 vs Y = 1)	Model 2 (Y = 3,4 vs Y = 1,2)	Model 3 (Y = 4 vs Y = 1,2,3)
Intercept		0.195	0.09	0.037
Head of household's sex	Female	1.156	1.156	1.156
Head of household's age	60 years and above	1.149	1.149	1.149
Head of household's education	Junior high school and below	1.121	1.121	1.121
Head of household's work	Working at Agriculture	1.261	1.437	1.545
	Not working	1.413	1.697	1.579
Drinking water source	Not feasible	1.005	1.247	1.581
Food aid recipient	Yes	1.963	1.519	1.503

The head of household's sex, age, and education level fulfill the parallel lines assumption. So, these variables have the same influence on each level of food insecurity. We can see from Table 7. This table depicts the same odds ratio of these variables in Models 1, 2, and 3. However, the other three variables (head of household working status, feasibility of drinking water sources, and food recipient status) violate this assumption. Hence, the effects in these three models are different. More details about each variable effect can be expressed as follows.

Head of Household's Sex

Assuming other influencing variables are constant, the odds of a female head of household experiencing at least mild food insecurity is 1.156 times greater than that of a male. Likewise, her probability of experiencing at least moderate food insecurity and of experiencing severe food insecurity is 1.156 times greater than that of a male head of household. This result is similar to the results of Smith et al. [7], Grimaccia and Naccarato [8], and Nigusu and Shewadinber [19]; households headed by women are more likely to experience food insecurity than households headed by men. Female-headed households have limitations in accessing resources that affect food production and access, so they experience food insecurity compared to male-headed households [6].

Head of Household's Age

Compared to households with a head of household under 60, those aged 60 years and above are 1.149 more likely to experience mild food insecurity (compared to food security), assuming other variables are constant. 1.149 is more likely to experience moderate and severe food insecurity (compared to maximum mild food insecurity), and 1.149 is more likely to experience severe food insecurity (compared to maximum moderate food insecurity). This result is related to Gebre's [20], the older the household head, the more likely they are to experience food insecurity. The older the household head, the more food insecurity they will experience due to decreased productivity and efficiency in doing work [21]. In addition, households with older heads of household are usually multigenerational, with more older people to feed and unable to contribute to income generation, increasing the incidence of food insecurity [7].

Head of Household's Education

Assuming other variables are constant, for households with the education level of head households junior high school and below, the odds of being very or somewhat likely to have food insecurity (severe, moderate, or mild) versus likely to have no food insecurity is 1.121 times that of households whose heads have more than junior high school. This finding is similar to the statement from Ndheleve et al. [6] and Birhane et al. [22] that household heads who have low education are more vulnerable to food insecurity. The higher the level of formal education of the household head, the lower the household food insecurity because the education of the household head is important in improving the quality of life and providing opportunities to obtain decent work so that they have sufficient income to meet food needs [23].

Head of Household's Work

Households in which the head of household did not work (assuming other variables are constant) are 1.413 times more likely to experience mild food insecurity or more (compared to food security) than those working in non-agriculture, 1.697 times more likely to experience moderate or severe food insecurity (versus food security or mild food insecurity), and 1.925 times more likely to experience severe food insecurity (versus food security or no more than moderate food vulnerability). Meanwhile, household heads working in agriculture tend 1.262 times to experience mild food insecurity or more (compared to food security) than those working in non-agriculture, 1.437 times to experience moderate and severe food insecurity (compared to food security or mild food insecurity), and 1.545 times to experience severe food insecurity (compared to food security or no more than moderate food vulnerability).

Thus, in the Papua Indonesia region in 2022, households where the head of household did not work and work in agriculture tend to aggravate food insecurity more than non-agriculture households. This result is in line with Etana and Tolossa [24], that unemployed household heads have a higher potential for food insecurity than employed household heads because unemployed household heads cannot buy food in terms of quality and quantity. In addition, household heads working in the agricultural sector earn smaller salaries and have lower welfare than non-agricultural workers, so they cannot fulfill their food needs. [25].

Drinking water source

The same thing happens with access to infeasible drinking water. Households with infeasible drinking water sources tend to increase food insecurity than households with feasible drinking water sources. The odds of households with infeasible drinking water sources being more likely to experience moderate and severe food insecurity are 1.247 times greater than that of feasible drinking water sources (versus food security or mild food insecurity), and the odds to be more likely severe are 1.581 times.

Similar research results such as Azwardi, et al [26] also prove that households with adequate drinking water sources tend to be food insecure. When drinking water does not come from a proper source, it will increase the risk of individuals getting diseases due to contamination of drinking water. Hence, the food utilization dimension needs to be realized.

Food aid recipient

The provision of food assistance from the Government in Papua appears to have different effects on the household food insecurity level. We see that the higher the severity, the lower the odds ratio. Assuming other variables are constant, households receiving food assistance are 1.963 times more likely to experience mild food insecurity or more (versus food security) than households not receiving food assistance, 1.519 times more likely to experience moderate and severe food insecurity (versus food security or mild food insecurity), and 1.503 times more likely to experience severe food insecurity (versus food security or no more than moderate food vulnerability).

The decrease in the odds ratio shows that this program has successfully reduced the severity of food insecurity. Nonetheless, the odds ratio value is still quite high (more than 1.5), so this program has yet to be able to address food insecurity fully. In addition, Amrullah [27] shows that the provision of food assistance has a small impact, so more than alleviating household food insecurity is needed to depend on food assistance received.

4. Conclusions

This study empirically shows a violation of the parallel lines assumption in the usual ordinal regression model (proportional odds model), and the partial proportional odds model is more appropriate to describe the determinants of household food insecurity levels. Based on this model, households in the Papua region of Indonesia with characteristics of female heads of household, aged 60 years and above, junior high school education or below, have an unsafe drinking water source, do not receive food assistance, farmers, and worse if they do not work have a greater tendency to experience food insecurity at least mild insecurity.

In addition, with the proportional odds model, we can find out which variables can worsen the level of food insecurity or, vice versa, reduce the severity. The employment status of the head of the household, which reflects a household's economic conditions, can aggravate the food insecurity level; if he works as a farmer or does not work at all, the higher the severity level. Thus, access to infeasible drinking water can also worsen food insecurity. However, on the contrary, food assistance from the government can reduce the severity of food insecurity. Thus, the government should continue to run the program accompanied by education on how the family economy improves and socialization of the importance of education.

Ethics approval

Not required.

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Competing interests

All the authors declare that there are no conflicts of interest.

Underlying data

Derived data supporting the findings of this study are available from the corresponding author on request.

Credit Authorship

Rolyn Abigael: Writing, Visualization, Software. **Cucu Sumarni**: Conceptualization, Methodology, Supervision. **Ray Sastri:** Reviewing and Editing,

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