Robust M-Estimator for Regression Models of Local Revenue Realization Data by Province in Kalimantan, Indonesia

Desi Yuniarti, Meiliyani Siringoringo, Ika Purnamasari, Sri Wahyuningsih, Rito Goejantoro, Wiwit Pura Nurmayanti, Thifan Octavianto

***Abstract*—The regression model that uses panel data is known as the panel data regression model. This study aims to identify robust M-estimator within a one-way panel data regression model using a fixed-effects approach. It specifically addresses panel data containing vertical outliers. The robust M-estimator is determined by employing the Mean Absolute Deviation (MAD) for the initial estimator and Huber weighting to mitigate the influence of these vertical outliers. Huber weighting is chosen because it is more suitable for panel data with time-series components, where removing observations suspected of being outliers is not appropriate. Thus, Huber weighting effectively reduces the impact of outliers without necessitating their removal. The proposed method is applied to local revenue realization (LRR) data by province in Kalimantan, Indonesia. This study evaluates the impact of plantation crop production and poultry meat production from the agricultural sector on LRR in Kalimantan. Based on the analysis, the robust M-estimator produces the smallest MSE value compared to the WG estimation method. Therefore, we conclude that this robust method is a better method for estimating LRR data by province in Kalimantan, Indonesia.**

***Index Terms*—M-estimator, outlier, panel data, regression, robust.**

I. Introduction

THE panel data regression model is a type of regression analysis that uses panel data, which integrates both cross-sectional and time-series data [1]. Panel data may contain outliers, so it requires an estimator that is robust to their influence. A robust estimator is one that is not significantly altered by removing or modifying a small percentage of the dataset. Outliers in panel data can include contamination in errors, known as vertical outliers, as well as outliers in explanatory variables, referred to as leverage points. Additionally, there are cases of concentrated outliers in several time series, including block vertical outliers and block leverage points. The presence of these outliers must be addressed, as they can introduce bias into the panel data regression estimator [2]. In [3], it is explained that outliers can affect OLS regression by altering both the magnitude and the sign of the regression coefficients. Additionally, outliers can increase the error rate and significance error of statistical estimator when using either parametric or nonparametric tests [4].

This study aims to estimate the parameters of the panel data regression model using a robust M-Estimator to reduce the influence of vertical outliers [5]. Vertical outliers are observations that are outliers in the error dimension (y-axis) but not in the independent variable space (x-axis). Vertical outliers affect OLS estimates, particularly influencing the estimated regression intercept [6]. In [3], it has also been shown that vertical outliers can increase collinearity among predictor variables.

The robust M-estimator method used in this study is the first step in the Within-Group Generalized M-Estimator (WGM) method by [2]. The WGM method first centers the data around the median, then uses the least trimmed squares (LTS) estimator to determine the initial estimate, and finally applies the Tukey bi-weight method to reduce the influence of vertical outliers in the panel data [2].

Our previous research related to the WGM method includes determining the WG estimator using median centering [7]. Furthermore, we have determined the LTS estimator for WG estimation in panel data regression models (WG-LTS). This WG-LTS method involves the elimination of observations suspected of being outliers [8]. Both approaches use the initial method to determine the WGM estimator [2].

In another study, we applied the Groupwise Principal Sensitivity Components (GPSC) method and proposed the panel influence matrix method for detecting outliers in panel data. Robust estimators are obtained by removing observations identified as outliers and then estimating parameters based on the remaining observations that have been cleaned of outliers. The outlier detection methods using GPSC and the panel influence matrix also involve the removal of observations suspected of being outliers [9]-[10].

In this study, we propose a robust method that does not remove outliers, as panel data contains time-series elements.

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Therefore, removal is inappropriate. The method we propose is the robust M-estimator, which uses the Mean Absolute Deviation (MAD) to determine the initial estimator and applies Huber weighting to reduce the influence of vertical outliers in panel data. Huber weighting is considered more appropriate because it effectively mitigates the impact of vertical outliers without requiring their removal.

The proposed method is applied to data on local revenue realization (LRR) by province in Kalimantan, Indonesia. This study aims to determine the effect of plantation crop production and poultry meat production from the agricultural sector on LRR in Kalimantan. LRR refers to the rights of the regional government recognized as an increase in net wealth derived from regional taxes, regional levies, the management of separated regional assets, and other legitimate sources of LRR. It is a crucial source of income for the region, and areas that successfully increase their LRR demonstrate their ability to optimally utilize existing potential [11]. The estimation results obtained using the robust M-estimator method will be compared with those obtained using WG estimator for the panel data regression model.

II. Robust M-Estimator for Panel Data Regression Models

Given a panel data regression model [1]:

$$y_{it} = \alpha + \mathbf{x}'_{it}\boldsymbol{\beta} + v_{it}, \quad (1)$$

with one-way error components:

$$v_{it} = \mu_i + u_{it}, \quad (2)$$

the model in Equation (1) becomes

$$y_{it} = \alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta} + u_{it}, \quad (3)$$

where $i = 1, 2, \ldots, N$ is the cross-section unit index, $t = 1, 2, \ldots, T$ is the time-series unit index, y_{it} is the it-th observation of the dependent variable Y, $\alpha_i = \alpha + \mu_i$ represents the intercept for each cross-sectional unit, $\mathbf{x}'_{it} = (x_{1_{it}}, x_{2_{it}}, \ldots, x_{K_{it}})$ is a vector of independent variables of size $1 \times K$ and $\boldsymbol{\beta}$ is a vector of model parameters of size $K \times 1$. The μ_i component of the error component represents unobserved individual-specific effects. If μ_i is assumed to be fixed, $\mu_i \sim \text{IID}N(0, \sigma_u^2)$ and $\mathbf{x}_{it}$ is assumed to be independent of u_{it} then the model in Equation (1) is called a one-way panel data regression model with a fixed-effects approach.

The Within-Group estimator (WG-estimator ($\hat{\boldsymbol{\beta}}_{WG}$)) is determined based on the following equation [1]:

$$\hat{\boldsymbol{\beta}}_{WG} = \left(\mathbf{X}^{'}\mathbf{Q}\mathbf{X}\right)^{-1}\mathbf{X}'\mathbf{Q}\mathbf{y} \quad (4)$$

assuming the inverse $\mathbf{X}^{'}\mathbf{Q}\mathbf{X}$ exists. Vector $\mathbf{y}$ is the observation vector y_{it} of size $n \times 1$ for $i = 1, 2, \ldots, N$, $t = 1, 2, \ldots, T$, $\mathbf{X}$ is the observation matrix of the independent variables of size $n \times K$. The matrix $\mathbf{Q}$ is the matrix containing the differences from the individual means.

In determining the robust M-estimator, the first step is to center each variable based on the following equation:

$$\tilde{y}_{it} = y_{it} - \frac{1}{T}\sum_{t=1}^{T} y_{it} \quad (5)$$

$$\tilde{x}_{k_{it}} = x_{k_{it}} - \frac{1}{T}\sum_{t=1}^{T} x_{it} \quad (6)$$

for $k = 1, 2, \ldots, K$. Thus, the transformed model yields the following equation, denoted as Equation (7):

$$\tilde{y}_{it} = \tilde{\mathbf{x}}'_{it}\boldsymbol{\beta} + \tilde{u}_{it} \quad (7)$$

In this study, each variable was centered using the median rather than the mean, as the median is more robust [2], [12]. Research comparing the WG estimator with mean centering to median centering has also shown that the WG estimators with median centering yields better estimation results [7]. The process for centering each variable around the median is as follows:

$$\tilde{y}_{it} = y_{it} - \operatorname*{median}_t y_{it} \quad (8)$$

$$\tilde{x}_{k_{it}} = x_{k_{it}} - \operatorname*{median}_t x_{k_{it}} \quad (9)$$

Next, the variable $\tilde{y}_{it}$ is regressed against $\tilde{x}_{k_{it}}$ to obtain the WG estimator with median centering, denoted as $\hat{\boldsymbol{\beta}}_{WG}$.

The robust M-estimator is defined as follows [13]:

$$\hat{\boldsymbol{\beta}}_M = \arg\min_{\alpha,\beta} \sum_{i=1}^{N}\sum_{t=1}^{T} \rho\left(\frac{\tilde{u}_{it}}{\hat{\sigma}}\right) \quad (10)$$

where

$$\tilde{u}_{it} = \tilde{y}_{it} - \tilde{\mathbf{x}}'_{it}\hat{\boldsymbol{\beta}}_{WG} \quad (11)$$

and ρ is a symmetric and continuous objective function. Residuals are standardized by $\hat{\sigma}$ to ensure independence from the unit of measurement of the dependent variable. In this study, the $\hat{\sigma}$ estimator is calculated using the MAD as follows:

$$\hat{\sigma} = 1.4826 \times \text{median}\left(\left|\tilde{u}_{it} - \text{median}\left(\tilde{u}_{it}\right)\right|\right) \quad (12)$$

This estimator has a high breakdown point of 50% because it is based on the median rather than the mean.

The function $\rho(\cdot)$ used in this research is the Huber function, defined as follows [5]:

$$\rho(u_{it}) = \begin{cases} \dfrac{u_{it}^2}{2} & \text{if } |u_{it}| < c \\ c|u_{it}| - \dfrac{c^2}{2} & \text{if } |u_{it}| \geq c \end{cases} \quad (13)$$

For this option, the diagonal elements of $\mathbf{W}_r$ are:

$$(W_r)_{it} = \begin{cases} 1 & \text{if } |u_{it}| < c \\ \dfrac{c}{|u_{it}|} & \text{if } |u_{it}| \geq c \end{cases} \quad (14)$$

where $c = 1.345$ is the tuning constant. The robust M-estimator for the panel data regression model in Equation (3) is as follows:

$$\hat{\boldsymbol{\beta}}_M = (\tilde{\mathbf{X}}'\mathbf{W}_r\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}'\mathbf{W}_r\tilde{\mathbf{y}} \quad (15)$$

Next, the coefficient estimate for each cross-sectional unit is obtained after determining the $\boldsymbol{\beta}$ estimate using [5]:

$$\hat{\alpha}_i = \operatorname*{median}_t y_{it} - \operatorname*{median}_t\left(\mathbf{x}'_{it}\right)\hat{\boldsymbol{\beta}} \quad (16)$$

for $i = 1, 2, \ldots, N$.

TABLE I
RESEARCH VARIABLES

Variable	Description	Units
Y	Local revenue realization	Thousand rupiahs
X_1	Total plantation crop production	Thousand tons
X_2	Total poultry meat production	Kg

TABLE II
CROSS-SECTION UNITS

i-Index	Province	Abbreviation
1	West Kalimantan	Kalbar
2	South Kalimantan	Kalsel
3	North Kalimantan	Kaltara
4	Central Kalimantan	Kalteng
5	East Kalimantan	Kaltim

TABLE III
TIME-SERIES UNITS

t-Index	Year	t-Index	Year
1	2017	5	2021
2	2018	6	2022
3	2019	7	2023
4	2020		

III. RESEARCH METHODOLOGY

This research aims to determine the robust M-Estimator for a panel data regression model using local revenue realization (LRR) data by province in Kalimantan, Indonesia [11]. The independent variable is sourced from the BPS-Statistics Indonesia publication, specifically for the agriculture, forestry, and fisheries sectors [14]. This dataset includes panel data for five provinces in Kalimantan, serving as cross-sectional units, and spans from 2017 to 2023 as time-series units. The research variables, including the cross-sectional unit index and the time-series unit index, are detailed in Table I, Table II, and Table III, respectively.

IV. RESULTS AND DISCUSSION

In this part of the discussion, we will perform a descriptive statistical analysis of the variable Y, check for the presence of vertical outliers in the research data, determine the WG estimator, and calculate the robust M-estimator. We will compare the estimation results of these two methods based on the Mean Squared Error (MSE) of each model. The analysis was conducted using R software [16]-[17].

A. Descriptive Statistics and Outliers Detection

The data pattern of the Y variable for each cross-sectional unit from 2017 to 2023 is illustrated in the descriptive statistics shown in Figure 1. According to Figure 1, East Kalimantan Province has the highest LRR, while North Kalimantan Province has the lowest LRR among the provinces in Kalimantan. Additionally, Figure 1 indicates that the LRR of each region generally increases every year, although the decline in 2020 may be attributed to the impact of the COVID-19 pandemic.

Next, we test for possible vertical outliers by analyzing the boxplot of the Y variable, as shown in Figure 2. This figure reveals several data points outside the boxplot boundaries, indicating potential vertical outliers in the dataset. Additionally, we assess vertical outliers based on standardized residual values, as depicted in Figure 3. Observations with absolute standardized residual values greater than ± 2 are considered potential vertical outliers [18]. Figure 3 also shows observations outside the boundaries, further supporting the presence of vertical outliers. Consequently, both Figure 2 and Figure 3 suggest the existence of vertical outliers in the data. Based on these findings, it is necessary to determine an estimator that is robust to vertical outliers in the LRR data by provinces in Kalimantan.

TABLE IV
CONSTANT PARAMETER ESTIMATES FOR WG ESTIMATORS ($\hat{\alpha}_i$)

Province	Parameter	Estimate
Kalbar	α_1	-1.99×10^9
Kalsel	α_2	-9.59×10^8
Kaltara	α_3	3.68×10^8
Kalteng	α_4	-2.36×10^9
Kaltim	α_5	2.45×10^9

B. Within-Group Estimator for Regression Models of Local Revenue Realization Data by Province in Kalimantan, Indonesia

Based on Equation (3), the panel data regression model for this research is:

$$y_{it} = \alpha_i + \beta_{it} x_{1_{it}} + \beta_{it} x_{2_{it}} + u_{it}, \tag{17}$$

where the research variables indexed by $i = 1, 2, \ldots, 5$ and $t = 1, 2, \ldots, 7$ are described in Table I, Table II, and Table III, respectively.

In this section, the WG estimator of the panel data regression model is determined based on Equation (4). The estimation of the panel regression model using the WG estimation method for the Local Revenue Realization (LRR) data by province in Kalimantan, Indonesia, was conducted using R software, yielding the following results:

$$\hat{y}_{it} = \hat{\alpha}_i + 388021.45 x_{1_{it}} + 36.25 x_{2_{it}}, \tag{18}$$

Table IV presents the constant parameter estimates for each cross-sectional unit. The model estimate in Equation (18) has a mean squared error (MSE) of 4.73×10^{17} and a standard error (s) of 6.88×10^8.

Based on Equation (18), it can be interpreted that an increase of one thousand tons in total plantation crop production will raise the LRR by Rp. $388,021.45$ by province in Kalimantan, assuming other variables remain fixed. Additionally, a one-kilogram increase in total poultry meat production will increase the LRR by Rp. 36.25, under the same assumption. According to the constant parameter estimates in Table IV, North Kalimantan has the highest LRR compared to other regions, followed by East Kalimantan.

C. Robust M-Estimators of Regression Model for Local Revenue Realization Data by Province in Kalimantan, Indonesia

In this section, robust M-estimators are calculated for the regression model of Local Revenue Realization (LRR) data by province in Kalimantan, Indonesia. This analysis accounts

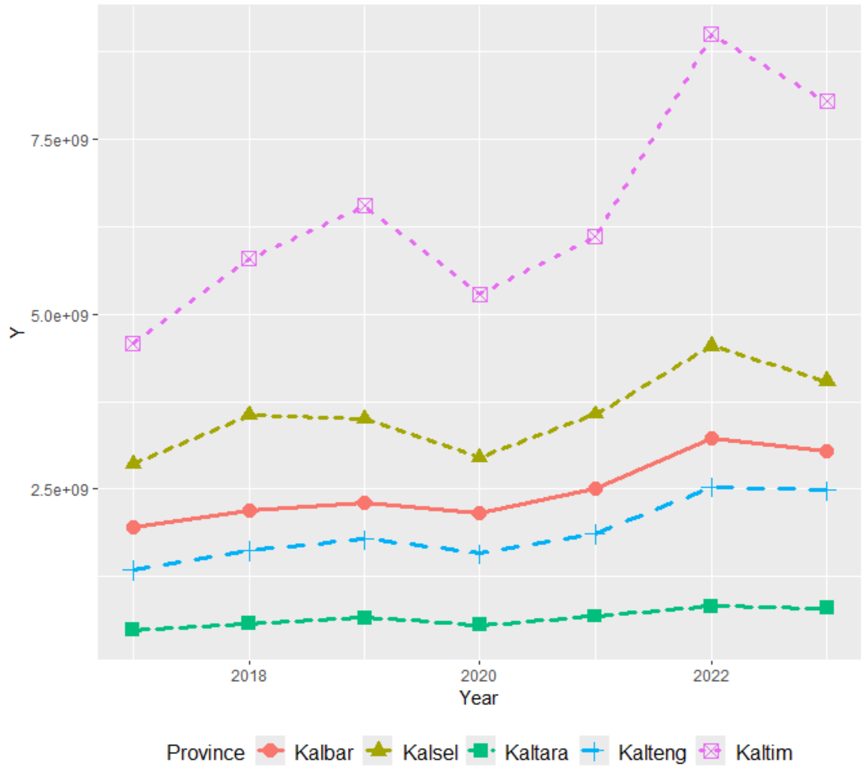

Fig. 1. Contoh gambar yang mencakup dua kolom.

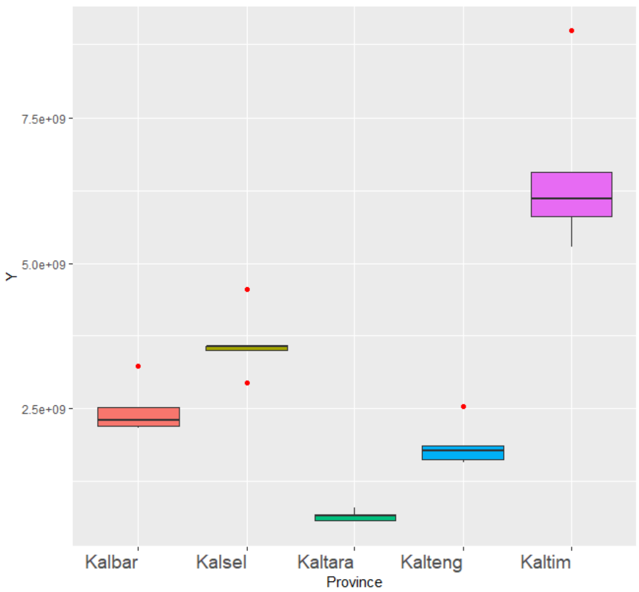

Fig. 2. Boxplot of variable Y by Province in Kalimantan

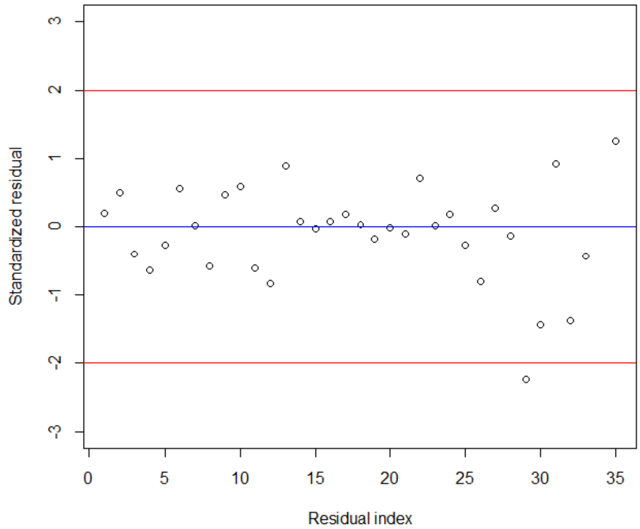

Fig. 3. Standardized residual plot

for the possibility of vertical outliers in the data. In the first step, the data for each variable is transformed using median centering based on the Equation (5)-(6).

The next step is to determine the MAD value using Equation (12) with the residuals from the OLS regression model that using median centering. The results of the analysis show that the MAD value is 2.34×10^8.

This MAD value is used to set the cut-off value for forming the $\mathbf{W}_r$ matrix, which is 25×25, as specified in Equation (14). Subsequently, robust M-estimators for the regression model are calculated using the $\mathbf{W}_r$ matrix.

Based on Equations (15)-(16), the robust M-estimators for the panel regression model of LRR data can be expressed by the following model:

$$\hat{y}_{it} = \hat{\alpha}_i + 151412.13x_{1_{it}} + 20.26x_{2_{it}}, \qquad (19)$$

The constant parameter estimates for each cross-sectional unit, derived from the robust M-estimators, are shown in Table V.

Equation (19) can be interpreted as follows: assuming other variables remain fixed, an increase of one thousand tons in plantation crop production will raise the LRR of each province in Kalimantan by Rp. $151,412.130$, while a one-kilogram increase in total poultry meat production

TABLE V
CONSTANT PARAMETER ESTIMATES FOR ROBUST M-ESTIMATORS

Province	Parameter	Estimate
Kalbar	α_1	1.19×10^8
Kalsel	α_2	1.26×10^9
Kaltara	α_3	5.82×10^8
Kalteng	α_4	-1.62×10^7
Kaltim	α_5	4.15×10^9

will increase the LRR by Rp. 20.26. Based on the constant parameter estimates in Table V, North Kalimantan has the highest LRR, followed by East Kalimantan. The LRR data regression model using robust M-estimators has an MSE value of 4.72×10^{17} and a standard error (s) of 6.87×10^8.

V. CONCLUSION

Robust analysis is used to determine the estimators of the panel data regression model for LRR data by province in Kalimantan, Indonesia, considering the potential presence of vertical outliers. The regression model estimation for this study employs two methods: the WG estimators and the robust M-estimators, which uses MAD as the initial estimator and Huber weighting to reduce the impact of vertical outliers. The comparison of these two robust estimators is based on the smallest MSE value. Huber weighting is chosen to avoid deleting observations suspected of being vertical outliers, given that the panel data includes time-series data. Based on the analysis results, the robust M-estimator produces the smallest MSE value. Therefore, we conclude that the robust M-estimator method is a better method for estimating the panel regression model of LRR data by province in Kalimantan, Indonesia.

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