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Modeling the Number of Maternal Deaths in East Java Province Using MM-Estimation and GM-Estimation Robust Regression

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ABSTRACT

Maternal Mortality Rate (MMR) is one of the targets of the Sustainable Development Goals (SDGs), and MMR is set to be less than 70 per 100,000 live births by 2030. The MMR in Indonesia in 1991-2020 decreased from 390 to 189 per 100,000 live births. The reduction in MMR is still far from the target set by the SDGs. In 2022, the number of maternal deaths in Indonesia was 3,572, with East Java Province as a large contributor of 486 deaths. The aims of the research are the number of maternal deaths (Y), the number of mothers experiencing hypertension (X_1), the number of mothers experiencing bleeding (X_2), the number of mothers experiencing infections (X_3), and the number of specialized hospitals (X_4). The methods used in this research are MM-Estimation and GM-Estimation robust regression. Robust regression was used because the data has outliers, so the residuals are not normally distributed. The results showed that the MM-Estimation and GM-Estimation model has an Adjusted R-squared value of 85.98% and 91.88% and AIC value of 201.1614 and 183.4612, with all independent variables significantly affecting maternal mortality. Based on the analysis, it is concluded that the robust regression GM-Estimation model is better than the MM-Estimation model because it has a larger Adjusted R-squared value and a smaller AIC value. The robust regression GM-Estimation model has the following equation: $\hat{y}$=1.893021+1.331650x_1+1.653501x_2+2.099621x_3-1.139574x_4.

Keywords:

Robust Regression; MM-Estimation; GM-Estimation; Maternal Mortality

INTRODUCTION

Public welfare is the goal of development. Public welfare can be achieved if there are specific targets and indicators. On September 25, 2015, precisely at the United Nations (UN) headquarters, the Sustainable Development Goals (SDGs) agenda was agreed upon by countries in the world as a global development goal that ends in 2030. The Sustainable Development Goals (SDGs) have 17 goals and 169 targets. One of the seventeen goals, the third, is to ensure healthy lives and promote the well-being of people of all ages. One of the goals, target 3.1, sets the maternal mortality rate (MMR) to be less than 70 per 100,000 live births by 2030 (United Nations, 2016).

Improving a healthy life and the population's welfare can be assessed through indicators in the form of MMR (Kementerian Kesehatan RI, 2023). Maternal Mortality Rate (MMR) is all deaths within the scope of every 100,000 live births. The definition of maternal mortality in this indicator is all deaths during the period of pregnancy, childbirth, and postpartum caused by its management but not due to other causes such as accidents or injuries (Say et al., 2014).

Maternal mortality in Indonesia decreased from 1991 to 2020, from 390 to 189 per 100,000 live births. However, the decline in MMR is still far from the SDG's target. The number of maternal deaths, compiled from the records of the family health program at the Ministry of Health, increases every year. In 2022, number of maternal deaths in Indonesia amounted to 3,572. East Java Province is one of the regions with the highest mortality rate, contributing to a sizable number of 486 deaths (Kementerian Kesehatan RI, 2023).

Knowing the factors that cause maternal mortality can reduce maternal mortality. If the causative factors are known, then early treatment can occur. Based on the causes, most maternal deaths in 2022 were related to hypertension in pregnancy, bleeding, and heart disease (Kementerian Kesehatan RI, 2023). These factors can be modeled using regression analysis. Modeling in regression analysis is used to see the relationship between the dependent and independent variables (Kamel & Abonazel, 2023). Ordinary least squares (OLS) are one of several methods used to estimate regression model parameters. Ordinary Least Squares (OLS) is a method used to estimate the parameters of a regression model by minimizing the sum of the squares of the residuals (Rasheed et al., 2014).

The data does not fulfill the normality assumption regarding maternal mortality in East Java in 2022. The normality assumption is not fulfilled because there are outliers in the data (Pek et al., 2018). An outlier is data that is far from the distribution of other data. Several methods exist to identify an outlier, including the DFFITS (Difference fitted value FITS) method. DFFITS displays the value of changes in the predicted value for a point when that point is excluded (Ayinde et al., 2015). One method to analyze data that has outliers is robust regression.

Research on the number of maternal deaths using robust regression has previously been conducted using data on the number of maternal deaths in Indonesia in 2019 (Andriany et al., 2021). The results of the study showed that the number of people with hypertension in pregnancy, the percentage of pregnant women getting K1 services, the rate of deliveries assisted by health workers, and the number of pregnant women positive for Human Immunodeficiency Virus (HIV) using the Least Trimmed Squares (LTS-estimation) method were able to explain the variable number of maternal deaths with R^2_{adj}Of 100%. In 2021, there was research on maternal mortality of pregnancy in Central Java using robust MM-estimation regression (Prahutama & Rusgiyono, 2021). Results showed that the percentage of pregnant women who made the first visit to a midwife or doctor affected the number of maternal mortality with an R^2 Of 22.27%. In 2023, there was research on maternal mortality in East Java using a panel regression approach (Febriyanto et al., 2023). The results of the study showed that pregnant women using blood-added pills affected maternal mortality in the panel regression analysis utilizing the Random Effect Model.

This study will conduct robust regression analysis with MM-estimation and GM-estimation. The data used is the number of maternal deaths in East Java in 2022 with independent variables of the number of patients with hypertension in pregnancy, the number of mothers experiencing postpartum hemorrhage, the number of mothers experiencing postpartum infections, and the number of specialized hospitals in each district/city. The two estimates will be compared, and the better model will be based on the Adjusted R-Squared (R^2_{adj}) and Akaike Information Criterion (AIC) values.

METHOD

Instrument

The data used in this study are secondary data obtained through the East Java Provincial Health Office in a publication entitled East Java Provincial Health Profile in 2022 and the official website of the Central Bureau of Statistics through bps.go.id. The data is from each district/city in East Java in 2022. The variables used in this study consist of one dependent variable (Y) and four independent variables (X) shown in Table 1.

Table 1. Research Variables

Variable	Description
Y	Number of Maternal Deaths in East Java Province
X_1	Number of Mothers with Hypertension in Pregnancy
X_2	Number of Mothers experiencing Postpartum Hemorrhage
X_3	Number of Mothers with Postpartum Infections
X_4	Number of Specialized Hospitals

Methods

This quantitative research used hypothesis testing, statistical analysis, and interpretation of the analysis results. The analysis method used in this research is robust regression with MM-estimation and GM-estimation.

Linear regression is an analysis used to obtain the relationship between one dependent variable and one or more independent variables. If more than one independent variable is used, this analysis is called multiple linear regression analysis (Montgomery et al., 2021). The model for multiple linear regression can be written as follows.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon$$

where y is the dependent variable, $\beta_0 \ldots \beta_k$ is the regression parameter, $x_1 \ldots x_k$ is the k-th independent variable, k is the number of independent variables, and ε is the error and a normally distributed random variable. In linear regression analysis, four classic assumption tests must be fulfilled, including the normality, homoscedasticity, non-autocorrelation, and non-multicollinearity tests.

The method used in this study is robust regression using MM-Estimation and GM-Estimation. Robust regression is used when the model precedes an outlier and does not meet the normality assumption (Sabzekar & Hasheminejad, 2021). MM-estimation procedure to estimate the regression parameter with S-estimation, which minimizes the scale of the residual and then proceeds with M-estimation (Susanti et al., 2014). The initial estimator of modeling in robust regression analysis using MM-estimation is the S-estimation, which minimizes the scale estimator of the residuals. S-estimation can be defined as follows (Rousseeuw & Yohai, 1984; Yu & Yao, 2017). (1)

$$\hat{\beta}_s = min_\beta \hat{\sigma}_s(e_1, e_2, \ldots, e_n)$$

with determining the minimum robust scale estimator $\hat{\sigma}_s$ and satisfying

$$\underset{\beta}{min} \sum_{i=1}^{n} \rho\left(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta}{\hat{\sigma}_s}\right) \tag{2}$$

where,

$$\hat{\sigma}_s = \begin{cases} \frac{median\,|e_i - median\,(e_i)|}{0.6745} & ,\text{iteration} = 1 \\ \sqrt{\frac{1}{nK}\sum_{i=1}^{n} w_{is}\, e_i{}^2} & ,\text{iteration} > 1 \end{cases} \tag{3}$$

The K value used is 0.199. The solution of $\hat{\beta}_s$ is by finding the derivative of β So that the following equation is obtained.

$$\sum_{i=1}^{n} x_{ij}\psi\left(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta}{\hat{\sigma}_s}\right) = 0 \quad j = 0,1,\ldots,k \tag{4}$$

ψ is an huber objective function and can be written as follows.

$$\psi(u_i) = \rho(u_i) = \begin{cases} \frac{1}{2}u_i^2 & ,|u_i| \le c \\ |u_i|c - \frac{1}{2}u_i^2 & ,|u_i| > c \end{cases} \tag{5}$$

with $u_i = \frac{e_i}{\hat{\sigma}_s}$ and a turning constant c = 1.345. At the same time, the Huber weighting function can be written as follows.

$$w_i(u_i) = \frac{\psi(u_i)}{(u_i)} = \begin{cases} 1 & ,|u_i| \le c \\ \frac{c}{|u_i|} & ,|u_i| > c \end{cases} \tag{6}$$

After minimizing the scale estimator of the bias using S-estimation, the next step is to calculate the robust regression coefficient estimator using M-estimation. The basic principle of M-estimation is to minimize the residual function ρ, which can be written in the following equation (Huber, 1964; Yu & Yao, 2017).

$$\hat{\beta}_M = \underset{\beta}{min}\, \rho\left(y_i - \sum_{j=0}^{k} x_{ij}\beta_j\right) \tag{7}$$

and we have to solve,

$$\hat{\beta}_M = \underset{\beta}{min} \sum_{i=1}^{n} \rho(u_i) = \underset{\beta}{min} \sum_{i=1}^{n} \rho\left(\frac{e_i}{\hat{\sigma}_M}\right) = \underset{\beta}{min} \sum_{i=1}^{n} \rho\left(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta_j}{\hat{\sigma}_M}\right) \tag{8}$$

with $\hat{\sigma}_{\mathrm{M}} = \frac{median|e_i - median(e_i)|}{0,6745}$. The solution of $\hat{\beta}_M$ is finding the derivative of β so that the following equation is obtained.

$$\sum_{i=1}^{n} x_{ij}\psi\left(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta}{\hat{\sigma}_M}\right) = 0 \qquad j = 0,1, \dots, k \tag{9}$$

with ψ is the Huber objective function, the derivative of ρ, and can be written as follows.

$$\psi(u_i) = \rho(u_i) = \begin{cases} \frac{1}{2}u_i^2 & , |u_i| \le c \\ |u_i|c - \frac{1}{2}u_i^2 & , |u_i| > c \end{cases}$$

with $u_i = \frac{e_i}{\hat{\sigma}_M}$ and a turning constant c = 1.345. The Huber weighting function can be written as follows.

$$w_i(u_i) = \frac{\psi(u_i)}{(u_i)} = \begin{cases} 1 & , |u_i| \le c \\ \frac{c}{|u_i|} & , |u_i| > c \end{cases}$$

MM-estimation uses the principle of M-estimation to calculate robust regression coefficient estimators. However, in MM-estimation, the robust scale estimator used comes from S-estimation. MM-estimation is the solution of

$$\sum_{i=1}^{n} \rho'_1(u_i)X_{ij} = 0 \text{ or } \sum_{i=1}^{n} \rho'_1\left(\frac{Y_i - \sum_{j=0}^{k} X_{ij}\hat{\beta}_j}{s_{MM}}\right)X_{ij} \tag{10}$$

S_{MM} is the standard deviation obtained from the residual of S-estimation, and ρ is a Huber weights function and can be formulated using the following equation.

$$\rho(u_i) = \begin{cases} \frac{1}{2}u_i^2 & , |u_i| \le c \\ |u_i|c - \frac{1}{2}u_i^2 & , |u_i| > c \end{cases}$$

The parameter estimator $\hat{\beta}$ in robust MM-estimation regression is obtained using Iteratively Reweighted Least Square (IRLS) until it converges with Huber weight.

GM-estimation is an extension of M-estimation. It is motivated by using a weight function to limit the influence of outliers on variables x_i. The following equation generally defines GM estimation (Wilcox, 2012).

$$S(\beta_j) = \arg\min_{\beta} \sum_{i=1}^{n} w_{iGM}\rho\left(\frac{e_i}{v(x_i)}\right) \tag{11}$$

with $v(x_i)$ as the weighting function for variable x_i. The $\hat{\beta}$ estimator obtained is not invariant scale, therefore the value of $\frac{e_i}{\hat{\sigma}}$ will be used instead of e_i with $\hat{\sigma}$ being the scale factor that needs to be estimated. Therefore, from equation we get the equation is obtained

$$S(\beta_j) = \sum_{i=1}^{n} w_{iGM}\rho\left(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta_j}{v(x_i)\hat{\sigma}}\right) \tag{12}$$

Equation (12) can be solved by derivate β and equating to zero, thus obtaining the following equation

$$\sum_{i=1}^{n} w_{iGM}\psi\left(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta_j}{v(x_i)\hat{\sigma}}\right)x_{ij} = 0 \qquad j = 0,1, \dots, k \tag{13}$$

The weight used is the Schweppe weight, with $w_{iGM} = \sqrt{1 - h_{ii}}$ and $v(x_i) = w_{iGM}$ and we get

$$w_{i.kGM} = w_{iGM}\frac{\psi\left(\frac{u_i}{v(x_i)}\right)}{(u_i)} = \frac{w_{iGM}}{u_i}\psi\left(\frac{u_i}{v(x_i)}\right) = \frac{\sqrt{1-h_{ii}}}{u_i}\psi\left(\frac{u_i}{\sqrt{1-h_{ii}}}\right) \tag{14}$$

with $u_i = e_i/\hat{\sigma}$, $\hat{\sigma} = 1{,}48M_k$, and M_k is the median of the largest $(n-k)$ of $|e_i|$ and $\psi(x) = \max\{-K, \min(K, x)\}$ is Huber's influence function with $K = 2\sqrt{k + 1/n}$. The parameter estimator $\hat{\beta}$ in robust GM-estimation regression is obtained by Iteratively Reweighted Least Square (IRLS) until it converges with Schweppe weight.

Procedures

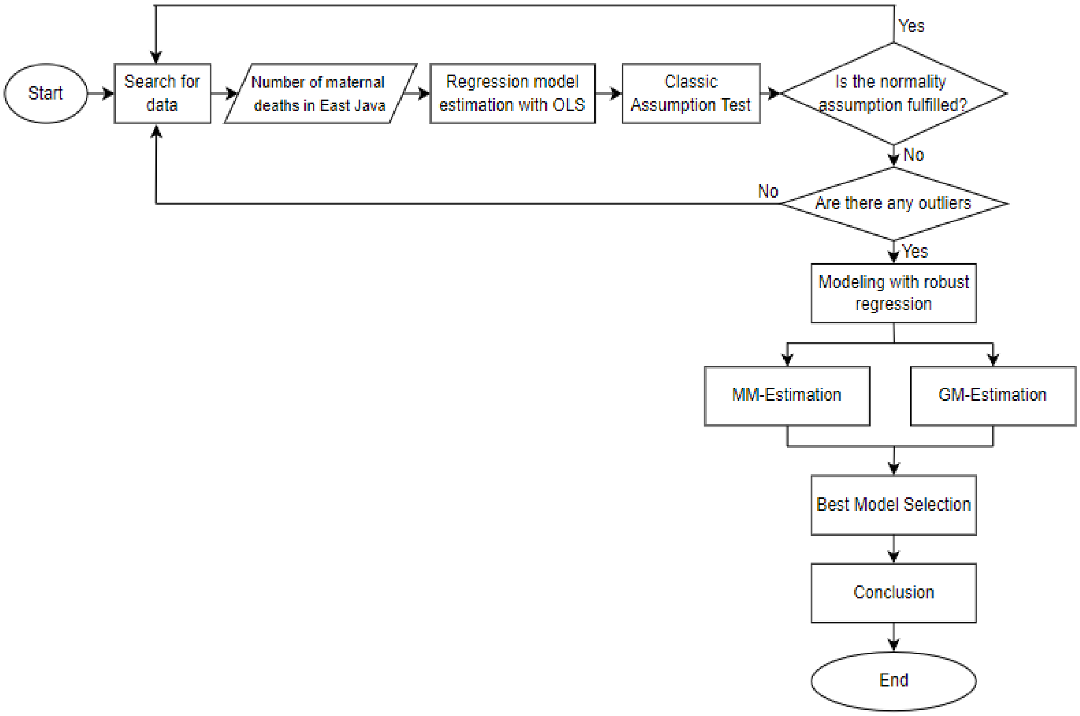

Figure 1. Steps in Conducting the Analysis

RESULTS AND DISCUSSION

Modeling Maternal Mortality in East Java with Ordinary Least Squares

The first step in regression modeling is to estimate the model parameters with Ordinary Least Squares (OLS). Using the Ordinary Least Squares (OLS), the regression model equation is obtained as follows.

$$\hat{y} = 2.1240 + 1.7727x_1 + 1.4663x_2 + 2.2264x_3 - 1.1212x_4$$

The regression model means that every increase of one mother experiencing hypertension in pregnancy will increase the number of maternal deaths by 1.7727 deaths, every increase of one mother experiencing postpartum bleeding will increase the number of maternal deaths by 1.4663 deaths, every increase of one mother experiencing postpartum infection will increase the number of maternal deaths by 2.2264 deaths, and every increase of one specialized hospital will reduce the number of maternal deaths by 1.1212 deaths.

After obtaining the regression model, it will then be tested for classical assumptions. The results of the classical assumption test are presented in Table 2 and show that the model fulfills the classical assumption test on the homoscedasticity, non-autocorrelation, and non-multicollinearity tests. However, the normality test concluded that the model did not fulfill the assumptions. This means that the regression model's residuals are not normally distributed. One reason the model is not normally distributed is that there are outliers. For this reason, outlier detection is carried out using Difference fitted value FITS (DFFITS). The results of outlier detection are presented in Table 3.

Based on Table 3, the |DFFITS| value in the 14th, 26th, and 31st observations is greater than the comparison value of 0.7254763, so it can be concluded that the three observations are outliers. Since the normality assumption model is not met and there are outliers, the next step is to perform a regression model using robust regression. Robust regression is used because the model produced by robust regression is robust to outliers.

Modeling Maternal Deaths in East Java with Robust Regression MM-Estimation

MM-estimation modeling begins with determining the initial estimate of regression coefficients using OLS and continues by finding the value of the robust scale estimator using S-estimation. The iteration results of the S-estimation model are presented in Table 4. Table 4 shows that the iteration in S-estimation stops at the fourth iteration because the coefficient has converged at that iteration. Next, we will calculate the value of the robust regression coefficient estimator using M-estimation. The iteration results of the MM-estimation model are presented in Table 5.

Based on Table 5, the coefficients converged at the 17th iteration, so the robust MM-estimation regression model for maternal mortality cases in East Java follows.

$$\hat{y} = 2.055029 + 1.432630x_1 + 1.590078x_2 + 2.175865x_3 - 1.134480x_4$$

The regression model means that every increase of one mother experiencing hypertension in pregnancy will increase the number of maternal deaths by 1.432630 deaths, every increase of one mother experiencing postpartum bleeding will increase the number of maternal deaths by 1.590078 deaths, every increase of one mother experiencing postpartum infection will increase the number of maternal deaths by 2.175865 deaths, and every increase of one specialized hospital will reduce the number of maternal deaths by 1.134480 deaths.

Based on the results of the calculations carried out, the Adjusted R-squared value is 85.98%, which means that the independent variables used in the model, such as the number of mothers with hypertension in pregnancy, the number of mothers experiencing postpartum hemorrhage, the number of mothers experiencing postpartum infections, and the number of specialized hospitals can explain 85.98% of the variation in the dependent variable number of maternal deaths. In comparison, the remaining 14.02% is influenced by other variables not included in the model. All independent variables in the robust MM-estimation regression model significantly affect the dependent variable. The results of the significance test are presented in Table 6.

In the robust MM-estimation regression model, outlier detection is carried out to see if there is a decrease in the outlier value from the OLS model that has been carried out. The results of the outlier detection of the robust MM-estimation regression model are shown in Table 7. Based on Table 7, the |DFFITS| value in the 9th, 26th, and 37th observations is greater than the comparison value of 0.7254763, so it can be concluded that the three observations are outliers. This shows that the outlier value from the MM-Estimation robust regression model does not decrease from the OLS model.

Modeling Maternal Deaths in East Java with Robust Regression GM-Estimation

GM-estimation modeling begins by determining the initial estimate of regression coefficients using OLS and continues by calculating the value of the robust regression coefficient estimator using GM-estimation. The iteration results of the GM-estimation model are presented in Table 8. Based on Table 8, the coefficients converged at the 46th iteration, so the robust GM-estimation regression model for maternal mortality cases in East Java follows.

$$\hat{y} = 1.893021 + 1.331650x_1 + 1.653501x_2 + 2.099621x_3 - 1.139574x_4$$

The regression model means that every increase of one mother experiencing hypertension in pregnancy will increase the number of maternal deaths by 1.331650 deaths, every increase of one mother experiencing post portal bleeding will increase the number of maternal deaths by 1.653501 deaths, every increase of one mother experiencing postpartum infection will increase the number of maternal deaths by 2.099621 deaths, and every increase of one specialized hospital will reduce the number of maternal deaths by 1.139574 deaths.

Based on the results of the calculations carried out, the Adjusted R-squared value is 91.88%, which means that the independent variables used in the model, such as the number of mothers with hypertension in pregnancy, the number of mothers experiencing postpartum hemorrhage, the number of mothers experiencing postpartum infections, and the number of specialized hospitals can explain 91.88% of the variation in the dependent variable number of maternal deaths. In comparison, the remaining 8.12% is influenced by other variables not included in the model. All independent variables in the robust GM-estimation regression model significantly affect the dependent variable. The results of the significance test are presented in Table 9.

In the GM-estimation robust regression model, outlier detection is carried out to see if there is a decrease in the outlier value from the OLS model that has been carried out. The results of the GM-estimation robust regression model outlier detection found that in the model, there is no |DFFITS| value greater than the comparison value of 0.7254763, so it can be concluded that there are no outliers in all observations. This shows a decrease in the outlier value of the OLS model, which previously had three outliers to zero outliers in the robust GM-estimation regression.

Best Model Selection

After conducting robust regression analysis with MM-estimation and GM-estimation on the number of maternal deaths in East Java Province, a better model will be selected from the MM-estimation and GM-estimation models. A better model is selected by comparing the Adjusted R-squared (R^2_{adj}) and the AIC value of the estimation model. A better model estimation has a larger Adjusted R-squared (R^2_{adj}) and a smaller AIC value. The model comparison is shown in Table 10.

Table 10 shows that the GM-estimation robust regression model has a more considerable Adjusted R-squared and a smaller AIC value than the MM-estimation robust regression model. Therefore, it can be concluded that the GM-estimation robust regression model is better for estimating the number of maternal deaths in East Java province in 2022 than the MM-estimation robust regression model.

CONCLUSION

Based on the results of the analysis and discussion that has been done, several conclusions are obtained as follows: a) The robust MM-estimation regression model for the number of maternal deaths in East Java in 2022 has an Adjusted R-Squared (R^2_{adj}) value of 85.98% and an AIC value of 201.1614 with the number of mothers experiencing hypertension in pregnancy, the number of mothers experiencing postpartum hemorrhage, the number of mothers experiencing postpartum infections, and the number of specialized hospitals having a significant effect on the model, b) The robust GM-estimation regression model for the number of maternal deaths in East Java in 2022 has an Adjusted R-Squared (R^2_{adj}) value of 91.88% and an AIC value of 183.4612 with the number of mothers experiencing hypertension in pregnancy, the number of mothers experiencing postpartum hemorrhage, the number of mothers experiencing postpartum infections, and the number of specialized hospitals having a significant effect on the model, c) The better robust regression model for the number of maternal deaths in East Java in 2022 is the GM-estimation robust regression model. This model is considered better because it has a more considerable Adjusted R-squared value and a smaller AIC value than the MM-estimation robust regression model. The GM-estimation robust regression model has the following equation:

$$\hat{y} = 1.893021 + 1.331650x_1 + 1.653501x_2 + 2.099621x_3 - 1.139574x_4$$

Suggestions from this research for future researchers include comparing it with other estimates not included in this study, such as LMS-estimation and GS-estimation. In addition, future researchers can also add other independent variables that affect the number of maternal deaths. This research is also open to constructive criticism and suggestions for improving sharper analysis. The results of this study are expected to provide insight to the government, especially the East Java provincial government, to pay attention to the number of maternal deaths in East Java, which is expected to continue to decrease each year.

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APPENDIX

Table 2. Classic Assumption Test Results

Regression Assumption	Test	Test Result	Critical Area	Decision
Normality	Kolmogorov-Smirnov	$D = 0{,}51503$	$D > D_{(n,\alpha)} = 0.210$	Not normally distributed
Homoscedasticity	Breusch-Pagan	$BP = 3{,}0063$	$\text{BP} > \chi^2_{(0.05,4)} = 9.4877$	The residuals are homos cedasticity
Non-autocorrelation	Durbin-Watson	$DW = 2{,}2623$	$d_L = 1.2614$ $d_U = 1.7223$	There is no auto correlation
Non-multicollinearity	VIF	$VIF < 10$ for all variables	$VIF < 10$	There is no multi collinearity

Table 3. Outlier OLS Regression Model

No.	Data	|DFFITS| Value
1.	14	0.7457359
2.	26	0.8362321
3.	32	0.7931060

Table 4. Iteration Results of the S-estimation

Iteration	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
1	1.901743	1.648689	1.511575	2.153860	-1.188109
2	2.179143	1.680579	1.486325	2.221324	-1.109974
3	2.124006	1.772684	1.466298	2.226352	-1.121209
4	2.124006	1.772684	1.466298	2.226352	-1.121209

Table 5. Iteration Results of the MM-estimation

Iteration	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
1	2.124006	1.772684	1.466298	2.226352	-1.121209
2	1.901743	1.648689	1.511575	2.153860	-1.188109
3	1.982307	1.542263	1.546850	2.177511	-1.156348
4	2.035034	1.479149	1.570249	2.184657	-1.142412
5	2.050653	1.449409	1.582524	2.182225	-1.137445
6	2.055224	1.438801	1.587164	2.178479	-1.135635
7	2.055556	1.434878	1.588982	2.176855	-1.134944
8	2.055321	1.433441	1.589674	2.176230	-1.134658
9	2.055156	1.432921	1.589931	2.175997	-1.134546
10	2.055079	1.432734	1.590025	2.175912	-1.134504
11	2.055048	1.432667	1.590059	2.175882	-1.134489
12	2.055036	1.432643	1.590071	2.175871	-1.134483
13	2.055032	1.432635	1.590075	2.175867	-1.134481
14	2.055030	1.432632	1.590077	2.175865	-1.134480
15	2.055030	1.432630	1.590078	2.175865	-1.134480
16	2.055029	1.432630	1.590078	2.175865	-1.134480
17	2.055029	1.432630	1.590078	2.175865	-1.134480

Table 6. The result of the Significance Test Robust MM-estimation Regression

Variable	|t-*value*|	t-table	Decision
X_1 (Number of Mothers with Hypertension in Pregnancy)	5.645	2.03452	Significance
X_2 (Number of Mothers Experiencing Postpartum Hemorrhage)	7.499	2.03452	Significance
X_3 (Number of Mothers Experiencing Postpartum Infections)	4.818	2.03452	Significance
X_4 (Number of Specialized Hospitals)	2.587	2.03452	Significance

Table 7. Outlier MM-Estimation Robust Regression Model

No.	Data	|DFFITS| Value
1.	9	1.48334102
2.	26	0.78171884
3.	37	1.64798761

Table 8. Iteration Results of the GM-estimation

Iteration	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
1	2.319341	1.592837	1.504169	2.183128	-1.109553
2	2.285723	1.452921	1.558937	2.116683	-1.130709
3	2.061930	1.400737	1.596495	2.104604	-1.137624
4	1.984708	1.399801	1.604483	2.086329	-1.140920
5	1.994434	1.387762	1.604921	2.058629	-1.127514
6	1.984886	1.381852	1.608876	2.038065	-1.114567
7	1.950094	1.386193	1.612779	2.021056	-1.109561
8	1.914914	1.392083	1.617981	2.005310	-1.109949
9	1.884342	1.394809	1.622348	2.002241	-1.108252
10	1.853190	1.392017	1.628182	2.015440	-1.106761
11	1.817383	1.385803	1.636628	2.037411	-1.108744
12	1.788956	1.376058	1.645303	2.063261	-1.112176
13	1.808616	1.363343	1.648075	2.080888	-1.116793
14	1.823314	1.355109	1.650727	2.087847	-1.123529
15	1.828781	1.350308	1.653247	2.090655	-1.130433
16	1.832940	1.347137	1.654775	2.092392	-1.136289
17	1.839332	1.344605	1.655297	2.094033	-1.141155
18	1.857597	1.341001	1.654076	2.096547	-1.144399
19	1.869997	1.338250	1.653487	2.097859	-1.143151
20	1.875466	1.336578	1.653696	2.098355	-1.142747
21	1.880504	1.335095	1.653778	2.098812	-1.141707
22	1.883991	1.333949	1.653948	2.099119	-1.141073
23	1.887074	1.333133	1.653859	2.099350	-1.140532
24	1.889034	1.332623	1.653778	2.099463	-1.140251
25	1.890420	1.332289	1.653685	2.099531	-1.140024
26	1.891277	1.332074	1.653633	2.099564	-1.139885
27	1.891872	1.331931	1.653589	2.099586	-1.139781
28	1.892250	1.331837	1.653562	2.099598	-1.139715
29	1.892510	1.331775	1.653541	2.099606	-1.139668
30	1.892679	1.331733	1.653529	2.099611	-1.139637
31	1.892794	1.331706	1.653520	2.099614	-1.139616
32	1.892869	1.331687	1.653514	2.099616	-1.139602
33	1.892920	1.331675	1.653510	2.099617	-1.139593
34	1.892953	1.331667	1.653507	2.099618	-1.139587

Table 8. Iteration Results of the GM-estimation (continued)

Iteration	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
35	1.892976	1.331661	1.653505	2.099619	-1.139582
36	1.892991	1.331657	1.653504	2.099619	-1.139579
37	1.893001	1.331655	1.653503	2.099619	-1.139578
38	1.893008	1.331653	1.653502	2.099620	-1.139576
39	1.893013	1.331652	1.653502	2.099620	-1.139575
40	1.893016	1.331652	1.653502	2.099620	-1.139575
41	1.893018	1.331651	1.653502	2.099620	-1.139575
42	1.893019	1.331651	1.653502	2.099620	-1.139574
43	1.893020	1.331651	1.653501	2.099620	-1.139574
44	1.893020	1.331650	1.653501	2.099620	-1.139574
45	1.893021	1.331650	1.653501	2.099620	-1.139574
46	1.893021	1.331650	1.653501	2.099620	-1.139574

Table 9. The Result of the Significance Test Robust GM-estimation Regression

Variable	|t-*value*|	t-table	Decision
X_1 (Number of Mothers with Hypertension in Pregnancy)	6.405	2.03452	Significance
X_2 (Number of Mothers Experiencing Postpartum Hemorrhage)	10.921	2.03452	Significance
X_3 (Number of Mothers Experiencing Postpartum Infections)	6.551	2.03452	Significance
X_4 (Number of Specialized Hospitals)	3.937	2.03452	Significance

Table 10. The Model Comparison Between MM-Estimation and GM-Estimation

Model	Adjusted R-Squared (R^2_{adj})	AIC	Number of Outliers	Significance Variable
MM-estimation	85.98%	201.1614	3 Outlier	4 Variable
GM-estimation	91.88%	183.4612	0 Outlier	4 Variable

BIOGRAPHIES OF AUTHORS

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