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Zero Inflated Poisson Regression Analysis in Maternal Death Cases on Java Island

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ABSTRACT

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The basic regression model used to analyze the count data is the Poisson regression. However, applying the Poisson regression model is unsuitable for excess zero data because it can cause overdispersion where the variance data is greater than its mean. One of the developments of the Poisson regression model can overcome this condition, Zero Inflated Poisson Regression (ZIP). In the health sector, the death of pregnant women on the Java island is an event that still rarely occurs and forms an excess zero data structure. However, the analysis of cases of maternal mortality using ZIP regression has never been studied in more depth. In this article, the maternal mortality cases in Java were modelled using ZIP regression to specify the variables that had a significant effect. The initial analysis results indicated the occurrence of overdispersion due to excess zero where there are 52% zero values in the data. The ZIP regression applied in this research provides enhancements to the Poisson regression based on the Vuong test. The results showed that the variables that had a significant effect on the maternal death cases in Java in the count model are the percentage of maternal health service coverage and the percentage of coverage of postpartum visit coverage, while in the zero-inflation model, the percentage of deliveries in health facilities and the percentage of obstetric complications treatment.

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1. Introduction

Statistical analysis to describe the relationships between the explanatory variables and the count data type response variable is Poisson regression analysis [1]. The assumption must be met in the Poisson Regression is the equidispersion condition (variance value is the same as the average value). However, events in the field state that there is often a violation of assumptions in the Poisson Regression, namely the overdispersion condition (variance value is greater than the mean value) [2] caused by many things, namely heterogeneity between observations, the correlation between observations, use of link functions that do not appropriate, improper a systematic component implementation or the excess zero presence [3]. If Poisson regression is still used, the standard error value of the parameter estimates will be too small and can lead to inappropriate conclusions [4].

One of the development models of Poisson Regression that can be used to overcome the overdispersion problem of overdispersion caused by excess zero data is Zero Inflated Poisson Regression (ZIP) [5]. The data with the ZIP distribution is a mixture distribution of the primary count data distribution, Poisson, with a degenerated distribution whose mass is concentrated at zero [6] [7]. If an observation has a ZIP distribution, the excess zero value may come from two different populations. The first population is a population with all elements worth zero, which is called a zero state with probability π_i and the second population is a population with a Poisson distribution where the parts can be zero or non-zero which is called a Poisson state with probability $1 - \pi_i$ [6].

ZIP regression has often been applied to the education, manufacturing, health, and production fields. In the health sector, data on maternal mortality in Java is a count-type event that rarely occurs. It fulfills the Poisson distribution assumption and forms an excess zero data structure so that it is suitable when analyzed with ZIP regression. Several previous studies related to Zero Inflated Poisson Regression have been carried out on data with zero excess with case studies, including modeling the amount of customer claims in the health insurance in Morocco by Mouatassim and Ezzahid [8] and the number of deaths due to diphtheria in East Java by Fittriyah et al. [9]. The results of the two studies concluded that Zero Inflated Poisson Regression is better in modeling the excess zero data than Poisson Regression and Negative Binomial Regression. Based on these advantages, this study will be carried out using Zero Inflated Poisson Regression Analysis to analyze the factors that influence maternal mortality due to infection in Java Island where Java Island is the island with the largest contributor to maternal deaths due to infection in Indonesia with a percentage of 46% of the total of all cases [10]

2. Research Methods

2.1 Data Description

The analyzed data is acquired from the Publication of Health Profiles for each province on Java island. It consisted of 119 observations from all districts/cities on Java Island with six explanatory variables. The following Table 1, shows the description of each explanatory variable:

Table 1. Variables description

Variable	Description
Y	Number of maternal deaths due to infection
X_1	Percentage of pregnant women who get Td2+
X_2	Percentage of Deliveries in Health Facilities
X_3	Percentage of Maternal Health Service Coverage
X_4	Percentage of Postpartum Visit Coverage
X_5	Percentage of Coverage of Iron Tablets
X_6	Percentage of Obstetric Complications Treatment

Data source: Kemenkes RI, 2020

2.2 Data Analysis Procedure

The analysis procedures in this study are as follows :

1. Exploring the data to find out the characteristics of the data in general.
2. Do the *Chi-square* goodness-of-fit test.
   The *Chi-square* test can be applied to discrete distributions such as the Binomial and Poisson with the hypothesis as follows [11]:
   H_0: Data follow Poisson distribution
   H_1: Data do not follow the Poisson distribution
   and test statistics as follows

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

where O_i is the observed frequency and E_i is the expected frequency in each response category.

3. Identify the existence of multicollinearity.
Multicollinearity conditions can be detected by calculating the Variance Inflation Factor. The formula for VIF, is as follows [1]:

$$VIF = \frac{1}{1-R_i^2} \tag{2}$$

Where:
R_i^2 = determination coefficient
The indication of multicollinearity occurs when the VIF value is >10.

4. Specify the Poisson regression model.
Poisson regression is the count data base model by assuming a Poisson distribution of response data [12]. The general form of the Poisson regression model that relates the average number of events to the explanatory variable is as follows [13]:

$$\ln(\mu_i) = \ln(t_i) + \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}, \; i = 1,2, \dots n \tag{3}$$

where μ_i is the average of an event per unit of time at the ith observation, $\ln(t_i)$ is the offset at the i-th observation, x is the explanatory variable, β is the regression coefficient, and p is the number of explanatory variables.

5. Detect the overdispersion.
In the count data, there is often overdispersion (variance value is greater than the mean value) which results in an underestimate of the standard error value in parameter estimation [12]. According to [14], the overdispersion condition can be determined through a dispersion parameter value with the *Pearson Chi-square* approach, which is shown in the following equation:

$$\phi = \frac{\chi_p^2}{n-p} \;\; ; \; \chi_p^2 = \sum_{i=1}^{n} \frac{(y_i-\mu)^2}{Var(Y)} \tag{4}$$

where χ_p^2 is the *Pearson Chi-square* statistic with p parameter, is the mean of Y variable, $Var(Y)$ is the variance of Y variable, and is the dispersion parameter. A data experience overdispersion if $\phi > 1$ or vice versa will experience underdispersion if $\phi < 1$ [12].

6. Take action in case of overdispersion.

7. Identify the existence of zero excess in the data as one of the causes of overdispersion.
Excess zero data are generally indicated by a higher proportion of zero values compared to other values with percentages ranging from 50% to 90% [15] and can be shown by looking at the existence of a zero value that is greater than expected based on the calculation of the Poisson distribution [16].

8. Handling if there is an excees zero.

9. Specify the Zero Inflated Poisson Regression model.
ZIP regression is a development of the Poisson Regression for excess zero [17]. According to [5], if the response variable for each observation $Y_1, Y_2, \dots, Y_n$ is a random variable that is independent of each other and has a ZIP distribution, the excess zero value is likely to come from two different populations. The first population is a population with all elements are zero, which is called a zero state with probability π_i, and the second population is a population with a Poisson distribution where the parts can be zero or non-zero, which is called a Poisson state with probability$1 - \pi_i$ with the probability distribution function:

$$P(Y = y_i) = \begin{cases} \pi_i + (1-\pi_i)e^{-\mu_i}, & \text{untuk } y_i = 0 \\ (1-\pi_i)\dfrac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, & \text{untuk } y_i > 0 \end{cases} \tag{5}$$

which is denoted by $Y \sim ZIP(\mu, \pi)$ where $E(y_i) = (1-\pi_i)\mu_i$ and $Var(Y) = (1-\pi_i)(\mu_i + \mu_i^2 \pi_i)$ where ZIP will be reduced to standard Poisson model when $\pi_i = 0$.
In modeling quantified data, the time or space period in generated data is often identified. This period can be referred to as exposure. The ZIP regression model, by including an exposure t_i of each individual, can be expressed as follows [18]:

$$\ln(\mu_i) = \ln(t_i) + \boldsymbol{x}_i^T \boldsymbol{\beta} \text{ dan } \operatorname{logit}(\pi_i) = \boldsymbol{x}_i^T \boldsymbol{\gamma} \tag{6}$$

with

$\boldsymbol{\beta}_{p\times1}$ = count model parameter vector
$\boldsymbol{\gamma}_{p\times1}$ = zero-inflation model parameter vector
$\boldsymbol{x}_{i(1\times p)}^{T}$ = vector of explanatory variables at observation i
$\ln(t_i)$ = offset at observation i.

10. Estimate the Zero Inflated Poisson Regression model parameters using Maximum Likelihood Estimation and Newton Raphson iterations.

11. Test the ZIP goodness-of-fit by Vuong test.
To test whether the resulting ZIP regression is better used than the Poisson regression, the Vuong test is used with the following hypothesis [8]:
$H_0 : \bar{m} = 0$ (No fix provided by ZIP to Poisson)
$H_0 : \bar{m} > 0$ (There is a fix given by ZIP to Poisson)
with test statistics

$$V = \frac{\sqrt{n}\left(\frac{1}{n}\sum_{i=1}^{n} m_i\right)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i-\bar{m})^2}} \quad ; \quad m_i = \ln\left(\frac{p_{Poisson}(y_i|x_i)}{p_{ZIP}(y_i|x_i)}\right) \tag{7}$$

The statistical value of V will approach the Normal distribution so that at the 5% significance level, it will reject H_0 if $V >$ 1,96 or *p-value* $< \alpha$ [8].

12. Test the significance of the overall model parameters with the Maximum Likelihood Ratio Test method.
The simultaneous parameter test is derived using the Maximum Likelihood Ratio Test method with the hypothesis as follows:
$H_0 : \beta_0 = \beta_1 = \cdots = \beta_6 = \gamma_1 = \gamma_2 = \cdots = \gamma_6$
H_1 : at least one $\beta_j \neq 0$ or $\gamma_j \neq 0, j = 1,2, \ldots 6$
with test statistics as follow

$$G = 2[\ln L(\hat{\Omega}) - \ln L(\hat{\omega})] \tag{8}$$

Where:
$L(\hat{\Omega})$ = likelihood function model with all explanatory variables
$L(\hat{\omega})$ = likelihood function model without explanatory variables
The G-test statistic follows a χ^2 distribution with $df = 2p$. Rejection criteria (Reject H_0) if the value of $G > \chi^2_{(df,\alpha)}$ with a significance level of 0.05 or when *p-value* $< \alpha$ [19].

13. Test the significance of the model parameters partially by using the Wald test statistic.
Wald test is derived to determine the explanatory variables that partially affect the response variable in each model with the following hypothesis:

$$H_0 : \beta_i = 0 \qquad\qquad H_0 : \gamma_i = 0$$
$$H_0 : \beta_i \neq 0 \quad \text{and} \quad H_0 : \gamma_i \neq 0$$

with the following test statistics [20]:

$$W_i = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)} \quad \text{and} \quad W_i = \frac{\hat{\gamma}_i}{SE(\hat{\gamma}_i)} \tag{9}$$

The value squared of the Wald test statistic is indicated to have a χ^2 distribution, so reject H_0 if $W_i^2 > \chi^2_{(\alpha;df=1)}$ or *p-value* $< \alpha$, which means the i-th explanatory variable has a significant effect on response variable [21].

14. Interpret the conclusions.

3. Results And Discussion

3.1. Data Exploratory

The Java Island consists of 6 provinces in which there are 119 regencies and cities with each totaling 85 regencies and 34 cities. The distribution map of the number of maternal deaths due to infection by district/city on the island of Java in 2020 is shown as follows.

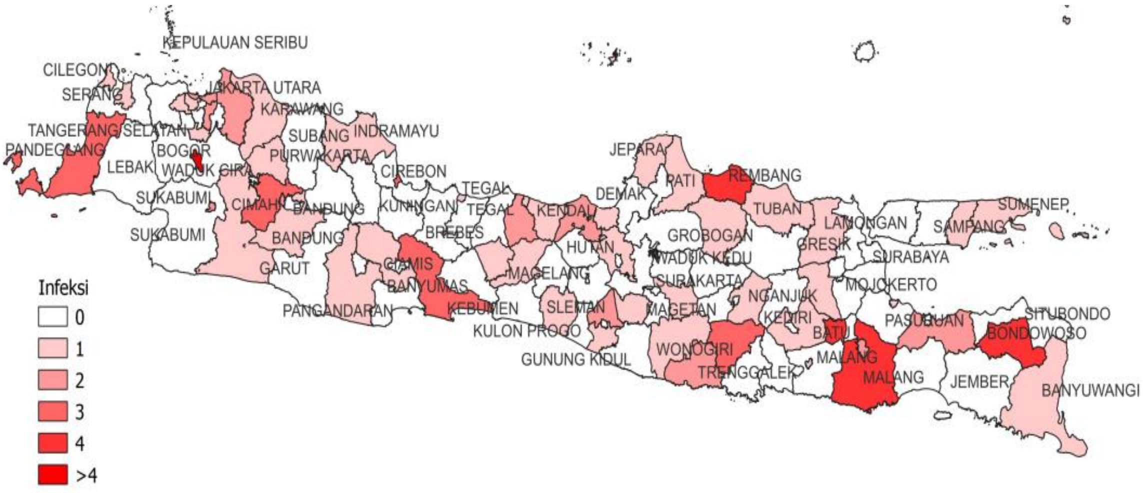

Figure 1. Distribution Map of Maternal Deaths due to Infections in Java Island in 2020

Figure 1 shows that the more maternal death cases due to infection are marked in red, while the fewer maternal death cases due to infection are marked in pink, and the state of the district/cities where there are no maternal death cases due to infection are marked in white.

3.2. Poisson Distribution Test

Chi-square test was conducted to determine whether the data on maternal mortality due to infection in Java came from the Poisson distribution or not. The test results can be shown below:

Table 2. Poisson distribution test result

Chi-square	**df**	***p-value***
5,87	$k-(c+1)=4-2=2$	0,053

Table 2 shows that the value of $\chi^2=5{,}87<\chi^2_{(0{,}05;2)}\ (5{,}99)$ and $p-value>\alpha$ so that there is not enough evidence to reject H_0 which can be concluded that the maternal mortality infection data in Java comes from the Poisson distribution.

3.3. Multicollinearity Test

Multicollinearity examination was carried out by calculating the VIF value. VIF value > 10 indicates a significant indication of multicollinearity between explanatory variables. The results of the VIF values are shown in Table 3 below:

Table 3. VIF values

Explanatory Variables	**VIF**
X_1	1,032
X_2	1,232
X_3	1,398
X_4	1,439
X_5	1,233
X_6	1,061

Table 3 above shows that the VIF value of each explanatory variable is less than ten, which can be concluded that there is no presence of multicollinearity indication between the explanatory variables.

3.4. Poisson Regression Model Specifacation

Table 2 shows that the response variable data comes from the Poisson distribution. The following shows parameter estimates of the Poisson regression model:

Table 4. Poisson regression model parameter estimates

Parameter	**Estimate Value**	***Standard Error***
β_0	$-7{,}751$	$1{,}763$
β_1	$0{,}002$	$0{,}001$
β_2	-0.006	$0{,}017$
β_3	$-0{,}039$	$0{,}017$
β_4	$0{,}005$	$0{,}015$
β_5	$0{,}013$	$0{,}006$
β_6	-0.001	$0{,}004$

Overdispersion checking is seen through the dispersion value using the *Pearson Chi-square* approach is shown in Table 5 as follows:

Table 5. Dispersion Value

Pearson Chi-square	**df**	**Dispersion**
210,911	112	1,883

Table 5 shows that the dispersion value is more than one, which can be concluded that the data has overdispersion. This condition causes the Poisson Regression to be inappropriate in modeling data on maternal mortality due to infection in Java.

3.5. Excess Zero Identification

The percentage of each value observed in the data on cases of maternal mortality due to infection in Java can be shown in Figure 2 below:

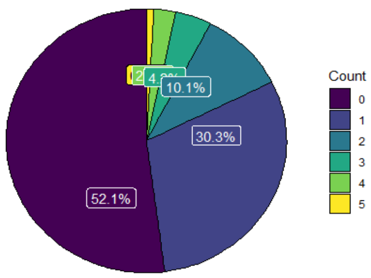

Figure 2. Percentage of each observation response

where the percentage of zero values in the data is 52.1%, so it can be concluded that the data has zero excess.

Excess zero can also be indicated by comparison the number of zero observations with the expected zero value based on the Poisson distribution calculation with the following calculation results:

Table 6. Comparison of the zero observed value with the expected zero value

Zero value observed	**Expected zero value**
62	52,9

The results in Table 6 above show that the total number of zero observed is more than the zero value based on the calculation of the Poisson distribution so that it can be concluded that the data on the response variable to maternal mortality due to infection in Java experienced zero excess.

3.6. Zero Inflated Poisson Regression Model Specification

The summary of the parameter estimation results based on the Maximum Likelihood Estimation (MLE) method with Newton Raphson iterations can be shown in Table 7 below:

Table 7. ZIP regression model parameter estimates

Parameter	**Estimate Value**	***p-value***
	Count model (Poisson *state*)	
β_0	$-6{,}748$	0,001*
β_1	0.001	0,512
β_2	0,054	0,067
β_3	$-0{,}043$	0,017*
β_4	$-0{,}068$	0,024*
β_5	0,011	0,055
β_6	0,009	0,063
	Zero-inflation model (*zero state*)	
β_0	$-8{,}341$	0,401
β_1	$-0{,}003$	0,785
β_2	0,35	0,027*
β_3	$-0{,}042$	0,578
β_4	$-0{,}248$	0,065
β_5	$-0{,}04$	0,433
β_6	0,041	0,035*
	$\boldsymbol{G = 24,523}$	

Note: *) significant at the 5% significance level

Based on the results shown in 7 above, the Zero Inflated Poisson regression model is obtained as follows:

1. Count model (Poisson *state*)
$$\ln(\mu_i) = \ln(t_i) - 6{,}748 + 0{,}001x_{1i} + 0{,}054x_{2i} - 0{,}043x_{3i} - 0{,}068x_{4i} + 0{,}011x_{5i} + 0{,}009x_{6i}$$
2. Zero-inflation model (*zero state*)
$$\text{logit}(\pi_i) = -\,8{,}341 - 0{,}003x_{1i} + 0{,}35x_{2i} - 0{,}042x_{3i} - 0{,}248x_{4i} - 0{,}04x_{5i} + 0{,}041x_{6i}$$

with $i = 1,2,\ldots n$

3.7. ZIP Regression Model Goodness-of-Fit

Based on the results of data processing using R software the Vuong statistical value was obtained, namely the average comparison of the ZIP model opportunities to the Poisson model of $\mathbf{1,98 > z_{0,05} = 1,96}$ so that there was sufficient evidence to reject $\boldsymbol{H_0}$ which can be concluded that there is an improvement given by the ZIP regression to the Poisson Regression.

3.8. Significance of ZIP Regression Parameters

Based on the results of Table 7 which shows the test statistic value $G = 24{,}523 > \chi^2_{(0,05;12)} = 21{,}026$, so there is sufficient evidence to reject H_0, which can be concluded that there is at least one significant explanatory variable which affects response variable in the model, while in partial parameter testing it is found that the significant variables which affects the number of maternal deaths cases due to infection in Java on the count model are the percentage of maternal health service coverage and the percentage of postpartum visit coverage, while the zero-inflation model is the percentage of deliveries in health facilities and the percentage of obstetric complications treatment.

Based on the estimated value of the regression coefficients listed in Table 7, it can be shown the interpretation of the significant explanatory variables, namely:

1. Poisson state model

a. Maternal health service coverage (K4)

Maternal health service coverage for pregnant women significantly influences cases of maternal mortality in Java. The estimated regression coefficient of the percentage of maternal health service coverage (X_3) is $-0{,}043$, which indicates that every 1% increase in the maternal health service coverage will cause a decrease in the average number of maternal deaths due to infection in Java by $e^{-0{,}043} = 0.958$ times, assuming all other variables remain constant. This is in line with research conducted by [22] that quality visit services for pregnant women can reduce the number of maternal deaths from various factors where in its application, routine visits for pregnant women are an effort in early detection of pregnancy problems, namely complications, infection or other risks so that early treatment can be carried out and prevent the death of pregnant women.

b. Postpartum visit coverage

Postpartum visit coverage has a negative and significant impact on cases of maternal mortality in Java. The estimated regression coefficient of the percentage of postpartum visit coverage (X_4). is $-0{,}068$, which indicates that every 1% increase in the postpartum visit coverage will cause a decrease in the average number of maternal deaths due to infection in Java by $e^{-0{,}068} = 0.934$ times, assuming all other variables remain constant. This is in line with the research conducted by [23] which showed that postpartum maternal care was associated with the risk of postpartum morbidity. This condition resulted in postpartum care that was focused on infection prevention efforts and demanded midwives to provide high-level midwifery care.

2. Zero-inflation model (zero state)

a. Deliveries in health facilities

Deliveries in health facilities significantly and positively affects the absence of cases of maternal mortality due to infection in Java. The estimated regression coefficient of the percentage of deliveries in health facilities (X_2) is $0{,}35$, which indicates that every 1% increase in the deliveries in health facilities will increase the probability that there will be no cases of maternal mortality due to infection in Java by $e^{0{,}35} = 1{,}419$ times when compared to cases of maternal death by assuming all other variables remain constant. This condition is supported by research conducted by [24], which shows a significant relationship between the place of delivery and maternal mortality. The higher the number of mothers giving birth in non-health facilities, the higher the risk of maternal death, and vice versa.

b. Obstetric complications treatment

Obstetric complications treatment significantly and positively affect the absence of cases of maternal mortality due to infection in Java. The estimated regression coefficient of the percentage of obstetric complications treatment (X_6) is $0{,}041$, which indicates that every 1% increase in the obstetric complications treatment will increase the probability that there will be no cases of maternal mortality due to infection in Java by $e^{0{,}041} = 1{,}042$ times compared to the presence of cases of maternal death by assuming all other variables remain constant. This condition is in line with research conducted by [25] that there is a significant relationship to the number of maternal deaths where one of the complications during the puerperium is puerperal infection. Therefore, it is necessary to treat complications appropriately and as soon as possible to prevent the spread of infection which can result in maternal death.

4. Conclusions

Based on the analysis and discussion results in the previous sections, several conclusions can be drawn, as follows:

1. Modeling using Poisson regression is unsuitable for modeling the data on the maternal mortality cases in Java because there is an indication of overdispersion, which is indicated by the dispersion parameter value of 1,883 and an indication of zero excess in the response variable data.
2. The appropriate predictive regression model for modeling the data on the maternal death cases in Java with an indication of zero excess is the Zero Inflated Poisson regression. This is reinforced by the Vuong test, which states that the ZIP regression model gives an improvement to the Poisson Regression.
3. In the count model (Poisson state), the percentage of maternal health service coverage and the percentage of coverage of postpartum visit coverage significantly affect maternal death cases in Java.
4. In the zero-inflation model (zero state), the percentage of deliveries in health facilities and the percentage of obstetric complications treatment significantly affect maternal death cases in Java.

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