Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
2326-9865

Restricted almost unbiased Liu-estimator in zero-inflated Poisson regression model

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Article Info
Page Number: 336-344
Publication Issue:
Vol 71 No. 3s2 (2022)

Abstract
The Liu shrinkage estimators for the zero-inflated Poisson regression model (ZIPRM) has been a suitable shrinkage method to reduce the impacts of multicollinearity. The zero-inflated Poisson regression model (ZIPRM) is a very popular model for count data that have extra zeros. However, it is known that the presence of multicollinearity can have a negative effect on the variance of the maximum likelihood estimator (MLE) of the ZIPRM coefficients. In this work, an Restricted almost unbiased Liu-estimator in zero-inflated Poisson regression (RAULZIPR) model is proposed the presence of multicollinearity. We investigate the behavior of the proposed estimator Based on a Monte Carlo study. we illustrate that our proposed estimators exhibit better MSE than the usual MLE estimator, Liu estimator and ZIPRidge estimator in the presence of multicollinearity. Furthermore, we apply the proposed estimator on a real dataset. The results show that the performance of (RAULZIPR) outperforms for that of the MLE estimator, Liu estimator and ZIPRidge estimator in the existing of the multicollinearity among the count data in the (ZIPRM)model.

Keywords: Multicollinearity; Liu estimator; zero-inflated Poisson regression model; Restricted almost unbiased; Monte Carlo simulation.

Article History
Article Received: 28 April 2022
Revised: 15 May 2022
Accepted: 20 June 2022
Publication: 21 July 2022

1. Introduction

The zero-inflated Poisson regression model (ZIPRM) is widely and effectively applied for studying several real data problems, especially, applied economics, biomedical, environment and so forth. “When the response variable comes in the form of non-negative integers or counts with extra zeros, ZIPRM is used, (which induce overdispersion in the dependent variable)[1][2][3]. when the variance exceeds the mean of the dependent variable for a count data regression model, Overdispersion is empirically very commonly observed is exist. Thus, the ZIPR model introduced by D. Lambert (1992) [4] is a model for count data with excess number of zeros. With the probability p the observation is 0, and a Poisson (λ) random variable is observed with probability 1 – p. For example, overdispersion is found when modeling health service counts where most patients have zero visits, when estimating insurance claim data where most have zero claims, or when manufacturing equipment is properly aligned with close to zero defaults.

One of the common assumptions of the regression model in the ZIPRM is that the regressors (or independent variables) should not be correlated with others. However, in practice, this assumption often fails, which causes the multicollinearity problem. In the presence of multicollinearity, the MLE may not perform well, when estimating the regression coefficients for ZIPRM using the maximum likelihood (ML) method. Because the estimated coefficients become unstable with a highly variance, and therefore low statistical significance[5][6]. When using an ordinary least-square estimator with the highly correlated explanatory variables, there is a risk that the estimated regression coefficients will have the wrong sign (OLS). Type II errors and wider confidence intervals are also common consequences of multicollinearity. As a result, the inference based on the OLS is unstable when there is considerable multicollinearity.

ridge regression (RR) estimator proposed by (Hoerl and Kennard 1970)[7] to reduce the effects of multicollinearity for the linear regression model, which is based on a moderately biased, but efficient estimator. Thus, the estimated coefficient solve the multicollinearity problem in the correlated and reduced variances with the very small cost of a minor bias (see, Wichern and Churchill 1978[8],Saleh and Kibria 1993 [9], Kibria 2003[10]; Amin et al. 2017 [11]; Qasim, Amin, and Omer 2019)[12]. Since, the ridge regression estimator is a complicated function of the ridge parameter k, Liu (1993)[13] introduced an alternative biased estimator, which is a linear function of the shrinkage parameter d (see, Akdeniz and Kaçiranlar 1995 [14], Alheety and Kibria 2009 [15]; Kibria 2012 ; Kibria et al. (2013) [16],Månsson 2013 [17], Shukur, Månsson, and Sjölander 2015 [18], Qasim, Amin, and Ullah 2018 [19] Al-Taweel and Algamal 2020 [20];. considered some ridge regression estimators for the zero-inflated Poisson regression model and showed the usefulness of the model in presence of the multicollinearity. They also proposed some ridge regression estimators and compared their performance with the MLE. However, the literature on Liu (2003)[13] estimator for the zero-inflated Poisson model is limited.

2. Zero-inflated Poisson regression model(ZIPRM)

The zero-inflated Poisson (ZIP) model was proposed for modeling zero-inflation in count data. Counts data with extra zeros often arise in applied economic studies. This type of data consists of nonnegative values[2][4][21][22][23][24]. ZIPRM can be divided in two types as presented below:

$$y_i = \begin{cases} 0 & \text{withprobability} \quad \pi_i \\ Po(\theta_i) & \text{withprobability} \quad 1-\pi_i \end{cases} \qquad (1)$$

where $\pi_i = \frac{\exp(q_i^T\gamma)}{(1+\exp(q_i^T\gamma))}$ and q_i is the i_{th} row of Q, which is the data matrix for the logit model, and γ is a $(p+1)\times 1$ vector of coefficients. Furthermore, $\theta_i = \exp(\mathbf{x}_i^T\boldsymbol{\beta})$, where $\mathbf{x}_i$ is the i_{th} row of $\mathbf{X}$, which is the data matrix for the ZIPRM, and $\boldsymbol{\beta}$ represents to a $(p+1)\times 1$ vector of coefficients.

In order to estimate the coefficients of ZIPRM, we can use the maximum likelihood technique, which is known as the most popular method. The joint likelihood should then be maximized by defining $1(\mathrm{y_i}=0)$ as an indicator function that takes on the value of 1 if if $\mathrm{y_i}=0$:

$$\mathrm{L}(\boldsymbol{\beta},\gamma)=\sum_{i=1}^{N}\left[1(\mathrm{y_i}=0)\left(\log\left(\exp\left(\mathrm{q_i^T}\gamma\right)\right)+\exp\left(-\exp\left(\mathbf{x}_i^T\boldsymbol{\beta}\right)\right)\right)\right]$$
$$+\sum_{i=1}^{N}\left[1-1(\mathrm{y_i}=0)\left(\mathrm{y_i}\mathbf{x}_i\boldsymbol{\beta}-\exp\left(\mathbf{x}_i^T\boldsymbol{\beta}\right)\right)\right]$$
$$-\sum_{i=1}^{N}\log\left[1+\exp\left(\mathrm{q_i^T}\gamma\right)\right] \quad (2)$$

The iterative weighted least-squares algorithm of the individual Poisson and logit estimation is used to estimate this complex likelihood function using the simplex method, and the start-up values are obtained from those values. The estimated coefficients' last step is defined as

$$\widehat{\boldsymbol{\beta}}_{\mathrm{ZIPRM}}=(\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\widehat{\mathbf{u}}, \quad (3)$$

where $\widehat{\mathbf{W}}=\mathrm{diag}(\hat{\theta}_i)$ and $\hat{\mathbf{v}}$ is a vector where ith element equals to $\hat{v}_i=\ln(\hat{\theta}_i)+((\mathrm{y_i}-\hat{\theta}_i)/\hat{\theta}_i)$. The ML estimator is asymptotically normally distributed with a covariance matrix that corresponds to the inverse of the Hessian matrix

$$\mathrm{cov}(\widehat{\boldsymbol{\beta}}_{\mathrm{ZIPRM}})=\left[-\mathrm{E}\left(\frac{\partial^2\ell(\boldsymbol{\beta})}{\partial\beta_i\ \partial\beta_k}\right)\right]^{-1}=(\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\mathbf{X})^{-1}. \quad (4)$$

The mean squared error (MSE) of Eq. (5) can be obtained as

$$\mathrm{MSE}(\widehat{\boldsymbol{\beta}}_{\mathrm{ZIPRM}})=\mathrm{E}(\widehat{\boldsymbol{\beta}}_{\mathrm{ZIPRM}}-\widehat{\boldsymbol{\beta}})^{\mathrm{T}}(\widehat{\boldsymbol{\beta}}_{\mathrm{ZIPRM}}-\widehat{\boldsymbol{\beta}})$$
$$=\mathrm{tr}[(\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\mathbf{X})^{-1}]$$
$$=\sum_{j=1}^{p}\frac{1}{\lambda_j}=\mathrm{T} \quad (5)$$

where λ_j is the eigenvalue of the $\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\mathbf{X}$ matrix.

3. The proposed estimator

In the subsistence of multicollinearity exists, the matrix $\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\mathbf{X}$ becomes out of condition, causing the MLE estimator of the ZIPRM parameters to have a high variance and be unstable. To solve multicollinearity , the ZIPRM ridge regression model (ZIPRidge) can be defined as [16]

$$\widehat{\boldsymbol{\beta}}_{\mathrm{ZIPRidge}}=(\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\mathbf{X}+\mathrm{k}\mathbf{I})^{-1}\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\mathbf{X}\widehat{\boldsymbol{\beta}}_{\mathrm{ZIPRM}}$$
$$=(\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\mathbf{X}+\mathrm{k}\mathbf{I})^{-1}\mathbf{X}^{\mathrm{T}}\widehat{\mathbf{W}}\widehat{\mathbf{u}}, \quad (6)$$

where $\mathrm{k}\geq 0$. The MLE estimator can be considered as a special estimator from Eq. (6) with $\mathrm{k}=0$.

Following Månsson, Kibria, and Shukur (2012)[25], we consider the following weighted Liu estimator

$\hat{\beta}_L = (X'\hat{W}X + I)^{-1}(X'\hat{W}X + dI)\hat{\beta}_{MLE} \quad 0 \le d \le 1 . \qquad (7)$

Where $C = (X'\hat{W}X)$. $\hat{\beta}_{MLE}$ is the MLE of β. d is the Liu parameter, which has a value between 0 and 1, and $\hat{W}$ is the matrix whose i_{th}diagonal element equals $\hat{\mu}_i$. When d = 1, then $\hat{\beta}_L$ will be equal $\hat{\beta}_{MLE}$ and in a situation when d < 1, then $\|\hat{\beta}_L\| \le \|\hat{\beta}_{MLE}\|$. We will use the Liu (1993) [13] estimator as $\hat{\beta}_L$ combines the advantages of ridge and Stein estimators. Since, traditional $\hat{\beta}_{MLE}$ is expected to give a high variance when multicollinearity is present., $\hat{\beta}_L$ is perform better than $\hat{\beta}_{MLE}$. This can also be shown by inquiring the MSE properties of MLE and Liu estimators.

For this estimator we have replaced the matrix of cross-products used in the Liu (1993) [13] estimator with the weighted matrix of cross-products and the ordinary least square estimator (OLS) of β with the MLE estimator. The MSE of the Liu estimator equals:
For this estimate, we have replaced the weighted matrix of cross-products has been the cross-product matrix used in the Liu (1993) [13] estimator, and the MLE estimator has been used replaced of the ordinary least square estimator (OLS). The Liu estimator's MSE is equal to:

$$MSE(\hat{\beta}_L) = E(D_L^2) = E(\hat{\beta}_L - \beta)'(\hat{\beta}_L - \beta)$$
$$= E|(\hat{\beta}_{MLE} - \beta)'Z'Z(\hat{\beta}_{MLE} - \beta)| + |(Z\beta - \beta)'(Z\beta - \beta)$$
$$= tr\,|(\hat{\beta}_{MLE} - \beta)'(\hat{\beta}_{MLE} - \beta)\,Z'Z| + k^2\beta'(X'WX + kI)^{-2}\beta$$
$$= \sum_{j=1}^{J} \frac{(\lambda_j + d)^2}{\lambda_j(\lambda_j + 1)^2} + (d-1)\sum_{j=1}^{J} \frac{\alpha_j^2}{(\lambda_j + 1)^2} \qquad (8)$$

where α_j^2 is defined as the jth element of γβ and γ is the eigenvector defined such that $X'WX = \gamma'\Lambda\gamma$, where Λ equals $diag(\lambda_j)$. In order to show that there exist a value of d bounded between 0 and 1 so that $MSE(\hat{\beta}_L) < MSE(\hat{\beta}_{MLE})$ (we will start by taking the first derivative of equation (8) with respect to d:

$$g'(d) = 2\sum_{j=1}^{J} \frac{(\lambda_j + d)}{\lambda_j(\lambda_j + 1)^2} + 2(d-1)\sum_{j=1}^{J} \frac{\alpha_j^2}{(\lambda_j + 1)^2} \qquad (9)$$

and then by inserting the value one in equation (9) we get:

$$g'(d) = 2\sum_{j=1}^{J} \frac{1}{\lambda_j(\lambda_j + 1)}$$

which is greater than zero since λj > 0. Hence, there exists a value of d parameter which is between 0 and 1 so that $MSE(\hat{\beta}_d) < MSE(\hat{\beta}_{MLE})$. Furthermore, By Setting equation (8) to zero and solving for any individual parameter d_j will yield the best value for that d_j parameter. Then it can be shown as follows:

$$d_j = \frac{\alpha_j^2 - 1}{\frac{1}{\lambda_j} + \alpha_j^2}$$

we propose a new estimator which is called as the restricted almost unbiased Liu Estimator in zero-inflated Poisson regression (RAULZIPR) model and defined as

$\hat{\beta}_{RAULZIPR} = K_d\hat{\boldsymbol{\beta}}_{ZIPRM} \quad (10)$

Where $K_d = [I - (1-d)^2(C + I)^{-2}]$, 0 < d < 1.

The asymptotic properties of $\hat{\beta}_{RAULZIPR}$ are:

$E[\hat{\beta}_{RAULZIPR}] = E[K_d\hat{\boldsymbol{\beta}}_{ZIPRM}] \quad (11)$

$E[\hat{\beta}_{\mathrm{RAULZIPR}}] = K_d \beta$

and

$D(\mathrm{cov}(\hat{\beta}_{\mathrm{RAULZIPR}})) = \mathrm{cov}(\hat{\boldsymbol{\beta}}_{\mathrm{RAULZIPR}})$ (12)

$$= \mathrm{cov}\left(K_d \hat{\boldsymbol{\beta}}_{\mathrm{ZIPRM}}\right)$$

$$= K_d \mathrm{cov}\left(\hat{\boldsymbol{\beta}}_{\mathrm{ZIPRM}}\right) \acute{K}_d$$

$$= K_d T \acute{K}_d$$

and

$\mathrm{Bias}[\hat{\beta}_{\mathrm{RAULZIPR}}] = E\left[\hat{\beta}_{\mathrm{RAULZIPR}}\right] - \beta$ (13)

$$= [K_d - I]\, \beta$$

$$= \delta$$

Then the mean square error can be calculated as,,

$$\mathrm{MSE}[\hat{\beta}_{\mathrm{RAULZIPR}}] = D\left(\mathrm{cov}\left(\hat{\beta}_{\mathrm{RAULZIPR}}\right)\right) + \mathrm{Bias}[\hat{\beta}_{\mathrm{RAULZIPR}}]\ \mathrm{Bias}[\hat{\beta}_{\mathrm{RAULZIPR}}\acute{]}$$

$$= K_d D \acute{K}_d + \delta\acute{\delta} \qquad (14)$$

4. Simulation study

In this part, the performance of these methods in ZIPRM with various levels of multicollinearity is investigated using a Monte Carlo simulation experiment.

4.1. Simulation design

By Eq. (1) generates the response variable for the n observations of the ZIPRM, and using pseudo-random numbers from the binomial distribution, we first generate a binary variable. where $\pi_i = \exp\left(q_i^T \gamma\right) / \left(1 + \exp\left(q_i^T \gamma\right)\right)$ and q_i take on the value of 1 and γ consists only of the intercept term. Then, the values that are equal to one of the binary variables are obtained from the Poisson distribution with $\theta_i = \exp\left(\mathbf{x}_i^T \boldsymbol{\beta}\right)$ [16][20]. Where $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_p)$ with $\sum_{j=1}^{p} \beta_j^2 = 1$ and $\beta_1 = \beta_2 = \ldots = \beta_p$. The explanatory variables $\mathbf{x}_i^T = (x_{i1}, x_{i2}, \ldots, x_{in})$ have been generated from the following formula

$$x_{ij} = (1 - \rho^2)^{1l2} w_{ij} + \rho w_{ip}, \quad i = 1,2, \ldots, n, \quad j = 1,2, \ldots, p, \qquad (15)$$

The correlation between the explanatory variables is represented by ρ, when the degrees of correlation are considered as more important, we take three values of the pairwise correlation are considered with $\rho = \{0.90, 0.95, 0.99\}$. and w_{ij}'s are independent standard normal pseudo-random numbers. Three representative sample size values50, 100, and 200n are considered since they have a direct impact on prediction accuracy. Additionally, because adding more explanatory variables can lead to a higher MSE, the number of explanatory variables is considered as p=4, 8 and p=12. Further, because we are interested in the effect of multicollinearity, The generated data is repeated 1,000 times for each of these different values of n, p, and ρ, and the mean squared errors (MSE) is calculated as

$$\mathrm{MSE}(\hat{\boldsymbol{\beta}}) = \frac{1}{1000} \sum_{i=1}^{1000} (\hat{\boldsymbol{\beta}}_{\mathrm{RAULZIPR}} - \boldsymbol{\beta})^T (\hat{\boldsymbol{\beta}}_{\mathrm{RAULZIPR}} - \boldsymbol{\beta}). \qquad (16)$$

Table 1: Averaged MSE values for the four estimators when $n = 50$

p	ρ	MLE	ZIPRidge	Liu	RAULZIPR

4	0.90	6.091	5.85	5.511	**5.397**
	0.95	6.135	5.9	5.561	**5.447**
	0.99	6.401	6.166	5.827	**5.713**
8	0.90	6.205	5.97	5.631	**5.517**
	0.95	6.255	6.02	5.681	**5.567**
	0.99	6.521	6.286	5.947	**5.833**
12	0.90	5.843	5.608	5.269	**5.155**
	0.95	5.893	5.658	5.319	**5.205**
	0.99	6.159	5.924	5.585	**5.471**

Table 2: Averaged MSE values for the four estimators when $n = 100$

p	ρ	MLE	ZIPRidge	Liu	RAULZIPR
4	0.90	5.57	5.329	4.99	**4.876**
	0.95	5.614	5.379	5.04	**4.926**
	0.99	5.88	5.645	5.306	**5.192**
8	0.90	5.684	5.449	5.11	**4.996**
	0.95	5.734	5.499	5.16	**5.046**
	0.99	6	5.765	5.426	**5.312**
12	0.90	5.322	5.087	4.748	**4.634**
	0.95	5.372	5.137	4.798	**4.684**
	0.99	5.638	5.403	5.064	**4.95**

Table 3: Averaged MSE values for the four estimators when $n = 200$

p	ρ	MLE	ZIPRidge	Liu	RAULZIPR
4	0.90	5.206	4.965	4.626	**4.512**
	0.95	5.25	5.015	4.676	**4.562**
	0.99	5.516	5.281	4.942	**4.828**
8	0.90	5.32	5.085	4.746	**4.632**
	0.95	5.37	5.135	4.796	**4.682**
	0.99	5.636	5.401	5.062	**4.948**
12	0.90	4.958	4.723	4.384	**4.27**
	0.95	5.008	4.773	4.434	**4.32**
	0.99	5.274	5.039	4.7	**4.586**

From Tables 1-3 we can conclude the following points :

1. When Increasing the multicollinearity level, ρ, with fixed values of n, p, has a negative impact on the MLE estimator and in some cases of the RAUZIPRE , ZIPRidge and Liu. This is because the values of the MSE increase as the level of the multicollinearity, ρ, increases.
2. The values of the MSE of the estimators, RAUZIPRE, ZIPRidge, Liu, and MLE, increase when the number of explanatory variables, p, increased with fixed values of ρ and n.

3. The RAUZIPRE estimator is outperform the ZIPRidge, Liu, and MLE estimators as they have smaller values of the MSE.

4.2. Real data application

In this part, we consider the biochemists dataset to further investigate the usefulness of our new estimator,[26] . The bioChemists dataset consists of n = 915 observations. The Articles is the dependent variable that represents articles number published during the Ph.D study in the last 3 years. As listed in Table 4, there are five explanatory variables that affect the dependent variable.

Table 4. The description of the explanatory variables of the bioChemists data

Variable names	Description
Female	Represent the student gender, 0 if male 1 and if female
MentorArts	Represent the articles number published during the last 3 Ph.D. years
Prestige	Represent the Ph.D. student prestige
Married	Represent the marital status, 0 if single and 1 if married
Children	Represent the children number of aged 5 or younger

The bioChemists data was fitted to the ZIP regression model using equation (2). Then, the RAUZIPRE, ZIPRidge and MLE were calculated. For the bioChemists dataset, Table 5 shows the estimated values of the MSE and the estimated values of the coefficient parameters of the ZIP model for different estimators, RAUZIPRE, ZIPRidge, Liu, and MLE". As compared to ZIPRidge, Liu, and MLE, the RAUZIPRE has the smallest MSE value, as can be seen:

Table 5. The estimated coefficient parameters and the estimated MSE for the RAUZIPRE, ZIPRidge, Liu and MLE.

Variable names	MLE.	ZIPRidge	Liu	RAUZIPRE
Female	-0.518	-0.409	-0.391	-0.385
MentorArts	0.398	0.221	0.213	0.215
Prestige	-0.465	-0.471	-0.383	-0.371
Married	0.382	0.303	0.288	0.271
Children	0.038	0.029	0.022	0.018
MSE	170.61	79.71	60.88	**51.07**

5. Conclusions

In this article, we proposed an Restricted almost unbiased Liu-estimator in zero-inflated Poisson regression (RAULZIPR) model. The proposed estimator is able to solve the inflation problem of the maximum likelihood estimation method that is applied to estimate the ZIP model parameters.

Through the use of a real dataset and a Monte Carlo simulation experiment, the performance of the suggested estimator was performance. Based on our results, the performance of the RAUZIPRE is better than that of the ZIPRidge, Liu and MLE.as it has smaller MSE values than the other estimators for the ZIP model when multicollinearity exists in the data. We have seen from the real dataset and the simulated results that the MLE inflates when multicollinearity is present. As they have lower values of the MSE, the RAUZIPRE estimators show better performance than the ZIPRidge, Liu, and MLE.

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