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# Jackknifing K-L estimator in Poisson regression model

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**ABSTRACT**

At the point when there is collinearity between the reaction variable and various illustrative factors, displaying the connection between the reaction variable and a few informative factors is troublesome. While surveying count information, the Poisson relapse model (PRM) is generally utilized in applied research. A shrinkage assessor is a consistently utilized answer for the multicollinearity issue. One of these shrinkage assessors is the Kibria and Lukman assessor (K-L). In this paper, a jackknifed variant of the K-L assessor in the Poisson relapse model is proposed, which consolidates the Jackknife interaction with the K-L assessor to diminish inclination. As far as outright inclination and mean squared blunder, our Monte Carlo recreation discoveries infer that the proposed assessor can give a critical improvement over other contending assessors.

**Keywords**: Collinearity, Jackknife estimator, K-L estimator, Monte Carlo simulation, Poisson regression model

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## 1. Introduction

Statistical model being urgent in some field of scientific studies as it expresses “the link between an interest Dependent variable and other variables that explain The response variable in a linear regression model is assumed to have a normal distribution. This assumption, however, may not hold true in many real-world applications. [1].

Matrix data X correlates with a polylinear relationship between independent variables in applications, therefore (Xt, X) can inflate the variance of the maximum likelihood estimator (MLE). As a result, standard estimating approaches like MLE have a poor track record. Several writers have proposed the ridge, Liu, Liu-type, and other estimators as an alternative to MLE for dealing with multicollinearity in linear regression models. [2, 3]. G. L. Ms have now been fitted using these estimators. [4-21].

Although these shrinkage estimators are the most powerful, they have a smaller bias. By using a jackknife approach to these estimators, bias can be reduced. This approach allows to be processed experimental data in order to obtain a statistical approximation for unknown parameters. The jackknife approach offers the advantage of presenting an estimator with a minimal bias while yet giving the benefits of large samples. [8, 22, 23]”.

The major goal of this paper is to combine the Jackknife method with Kibria and Lukman's new ridge-type estimator (K-L estimator) (2020). In a Poisson regression model, the suggested estimator would effectively assist for reducing the biasness of the K-L estimator. The superiority of suggested estimator is demonstrated during a variety of simulated cases as well as a real-world application.

Estimators based on resampling techniques such as the jackknife, due to their statistical properties [Ef94], [Ko.e88], [ShTu96], are increasingly used, both in general and in particular, in the problem of linear least squares [WeWe83], to reduce the bias of the estimates [Mi74], and to estimate variances [Wo85] and confidence intervals [Kl.87], mainly. In addition, in the last two decades, this type of method has gained importance due to the computational facilities of the new times. But, as the dimension of the problems to be solved has increased in parallel, the computational facilities do not exempt from the need to search for more efficient algorithms for the calculations. In [MaSa06], conveniently using basic properties of linear algebra, a much more efficient algorithm than the standard algorithm for calculating the Jackknife Estimator for Linear Least Squares (EJMCL) is proposed, which works when the initial estimation problem is full rank.

In this article, we propose a modification to the algorithm proposed in [MaSa06], in such a way that it preserves efficiency without requiring any condition on the initial problem or on the subproblems involved in the jackknife estimation.

To achieve this purpose, initially, we recall the definition of the jackknife estimator for the full-rank linear least squares problem, then we present the standard algorithm for calculating the EJMCL and the contributions, Subsequently, without using the full rank assumption of the initial matrix of the Linear Least Squares Problem (LCSP), we present a new characterization of the solution(s) of the least squares subproblems (not necessarily full rank), required for the calculation of the EJMCL. Finally, based on this result, we propose the modification to the previously proposed algorithm, which is the central objective of this article.

## 2. K-L estimator in Poisson regression model

Count data is often utilized in health, sociology, and economic research. This data is made up of positive integer numbers. A well-known apportionment that fits this appearance of info is the Poisson distribution. To verification the relation among counter as a rejoinder variable and other hermeneutics factors, the Poisson regression model is utilized [24, 25].

The residual or Pearson deviance are pretty near to the degrees of Liberty when evaluating the fit of overdispersion models when the overdispersion parameter is estimated. Since theoretically Var(μi) = μi the overdispersion index should be equal to 1. Thus, an overdisposal index greater than 1 indicates the possible existence of overdispersion, while an overdispersion index less than 1 indicates the possible existence of underdispersion in the data.

The adequacy of the predictor linear, the link function, and the identification of outliers can all be investigated using standard residual plots. A plot of residuals can be used to revise the variance function's specification informally. V ar(μ), However, when using overdispersion models incorporating scale parameters, this may not be effective.φ.

There is a useful technique for general screening of waste by the use of a modular half-scheme, with a simulation of the shell, which takes into account the excessive scattering of the model. If the fitted model is true, then the plot of the values is expected to be the note is within the confidence limits of the envelope. for linear models these generalized diagrams provide a useful tool for checking hypotheses the model, in connection with its modification.

## 3. Jackknifing K - L estimator in PRM

For the linear regression model, Kibria and Lukman suggested a new ridge-type estimator in 2020. Kibria-Lukman (KL) estimator is the name given to this suggested estimator. [27]:

$$\beta_{kl} = (I + k\,(X^T\ X)^{-1})^{-1}\,(1 - k\,(X^7\ X)^{-1}\ X^T\ y\,, \qquad (1)$$

where k 0 is the estimated shrinkage factor, but it is larger stabilization and has a minimize mean square false than the conventional minimum squares estimate, may be defined as follows for the PRM: [28, 29]

$$\beta_{kl-prm} = (I + k\,(X^T W X)^{-1})\,(X^7\ W X)^{-1}\,X^T\ W v\,. \quad (2)$$

Eq. (10)'s bias and variance are defined as, respectively.

$$\text{Bias}\,(\beta_{kl-prm}) = 2\,k\,Q\,(X^T\ W X + k\,I\,)^{-1}\ \ldots\ldots\ldots\ldots \quad (3)$$

$$\text{Variance }(\beta_{kl-prm}) = Q\,(X^T\ WX+k\,I)^{-1}\,(X^T\ WX + kI)^{-1}\,X^T\ WX)^{-1} \ldots\ldots\ldots(4)$$
$$(X^T\ WX+kI)^{-1}(X^T\ WX+ kI)^{-1}\,Q^T$$

where Q=(q1...q2......qp) is the eigenvector matrix of the (XT W X) matrix, and = Q is the eigenvector matrix of the (XT W X) matrix. The mean square error (MSE) of Eq. (12) may be represented as follows:

$$\text{MSE }(\beta_{kl-prm}) = \Sigma\,(n1-k)2\ /\ (n1(n1+k)2 + 4k\,\Sigma\,\frac{a2}{(n+k)2} \ldots\ldots\ldots\ldots(5)$$

Estimators of shrinkage are biased estimators . The Jackknife strategy was suggested by Singh and Chaubey [30] to overcome the problem of bias in the generalized ridge estimator in a linear regression model.. Several authors have looked into the theory and use of the jackknife estimator. [1, 7-12, 15, 23, 28, 29, 31-47].
In PRM, the suggested estimator, referred to as the Jackknifed (K – L) estimator (J.K.L-PRM), can be expressed and generated.. Let A=diag (n1,n2…….. np) is the (XT WX) matrix's eigenvalues matrix, such that (QT XT WXQ=MT WM=A, where (M=XQ). Consequently. Eq. (5)'s (MLE) estimator may be rewritten as

$$\beta_{MLE} = Q0_{MLE} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

where $\acute{O}_{MLE} = \Lambda^{-1}\,M\,W\,\hat{u}$ . As a result , KL-PRM estimator of Eq. (8) is re-written as

$$\acute{O}_{MLE} = (\Lambda+k\,I)^{-1}\,(\Lambda-kI)^{-1}\,M^T\,W\tilde{v} \ldots\ldots\ldots(7)$$

$$\acute{O}_{MLE\ (-i)}$$

Taking the Jackknife method as a model [48], let $u_{(-i)}$ , $m_{(-i)}$ , $W_{(-i)}$, , respectively, the $i^{th}$ a row has been removed from the vector **u**, the $i^{th}$ The matrix's row has been removed. M, with the ith column & row and of matrix W removed. Let MLE (-i) be provided by Eq. (12) with M,W, and u replaced by M (-i), W(-i), and u(-i), respectively.

$$\acute{O}_{KI\text{-}GLM\,(-i)} = (M^T_{(-i)}\ W_{(-i)}\ M_{(-i)} + kI)^{-1}\,(M^T_{(-i)}\ W_{(-i)}\ M_{(-i)} + kI)^{-1}\,M^T_{(-i)}\,W_{(-i)}\,u_{(-i)} \ldots(8)$$

where $(M^T_{(-i)}\ W_{(-i)}\ M_{(-i)} + kI)^{-1}$ This is calculate using the Sherman - Morrison Woodbury theorem. As a result of this, Equation. (13) can be written as:

$$\acute{O}_{KI\text{-}GLM\,(-i)} = \acute{O}_{KI\text{-}GLM} - \frac{(MT\ W\ M\ +k\,I)\ (MT\ W\ M\ +k\,I)\ MT\ (v1-mt\ \acute{O}\ KI-GLM}{1-m\ t\,MT\,(-i)\,W(-i)\,M\,(-i)+k\,I)(MT(-i)W(-i)M\,(-i)-k\,I)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Using weighted pseudo-values as a starting point [48], which are represented as

$T = \acute{O}_{KI\text{-}PRM} = \acute{O}_{KI\text{-}PRM} + n\,(1-m^T_i\,(M^TW\ \ M+k\,I)^{-1}(M^TW\ \ M+k\,I)^{-1}\,\Sigma\,m^T_i(\tilde{v}_i - m^T_i\,\acute{O}_{KI\text{-}PRM} \ldots(10)$
Then there's the estimate we've presented., JKL-PRM, is defined as

$$\acute{O}_{KI\text{-}PRM} = \acute{O}_{KI\text{-}PRM} + (M^TW\ \ M+k\,I)^{-1}\,(M^TW\ \ M+k\,I)^{-1}\,\Sigma\,m^T_i(\tilde{v}_i - m^T_i\,\acute{O}_{KI\text{-}PRM} \ldots\ldots\ldots(11)$$

The bias variance and MSE of KI-PRM are defined as follows:

$$M\,S\,E\,(\acute{Ŏ}_{KI\text{-}PRM}) = \Sigma\ \frac{((n+k)2-4\ k2)2\ (n-k\ )2}{n\ (n+k\ )2} \ldots\ldots\ldots\ldots\ldots\ldots (12)$$

$$\Sigma\ \frac{(ni-k\ )2\ (\ ni+3k\ )-(\ mi+k\ )3)2\ ai2}{(ni+k)6} \ldots\ldots\ldots\ldots\ldots\ldots (13)$$

In this article, the solution set of the linear least squares subproblems that result in the calculation of the linear least squares jackknife estimator of a linear model has been fully characterized, even in the case that it is of deficient rank. This result allows modifying the algorithm proposed in [MaSa06] to calculate the aforementioned estimator, without requiring that any of the problems involved (initial or subproblems) be full rank, maintaining the same computation efficiency. As in [MaSa00], this result allows for more efficient calculations as long as the algorithm used to solve the different linear least squares subproblems required by the jackknife estimator is the same as the one used to solve the linear least squares problem initial.

It remains a challenge for us and our readers to develop a similar theory that allows us to characterize the solutions of the least squares subproblems for the generalized case of the jackknife estimator in which more than one observation is eliminated from the initial sample to pose the subproblems (Pooled Jackknife Estimator)

## 4. Results of simulation

This part performs a MonteCarlo emulation test to assess the fulfillment of the novel estimator at various degree of multiline. " A Poisson retreating sample is applied to determine a data response variable."

$$0_i = e\,x\,p(X^T{}_i\boldsymbol{\beta}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

$$X^T{}_i = (\,X_{i1}\,,\, X_{i2}, \ldots\ldots\, X_{in}\,)$$

where $\beta = (\beta_0\ ,\ \beta_1 \ldots\ldots\ \beta_p)$ with $\sum_{j=1}^{p}\beta_j^2 = 1$ and $\Sigma\beta^2{}_i = 1$ *and* $\beta_1 =.\ B_2 = \ldots.. = \beta_p$ [4, 19].

Furthermore, because the value of the intercept, $\beta_0$ , effect on the $0_i$, three values are chosen $\beta_0$ € { 1, -1} , when the value of is reduced of $\beta_0$ as a result of this, the average value of $0_i$, resulting in less variation [19, 49].

The hermeneutics variable XTi = (xi1, xi2,...... xin) were created using the formula below.

$$x_{ij} = (1 - p^2)^{1/2}\, w_{ij} + \ pw_{ip},\ \ i=1,2\ \ldots..n,\ \ j = 1,2,\ldots.,p \ldots\ldots\ldots\ldots (15)$$

where (w) denotes independent standard normal pseudo-random numbers and p denotes the correlation between explanatory components. Because sample size has a direct influence on prediction accuracy, three typical sample sizes of 30, 50, and 100 are evaluated. The numbers of hermeneutics variables is also evaluated (p=4), (p=8), and (p=12) on account of the MSE can be raised by increase the number of hermeneutics variables. We also look at three levels of pairwise correlation (p=0,90,0.95, 0.99), on account of we're mindful in the effect of multilinear, which is associated with higher correlation degrees. The average absolute bias and predicted average MSE are calculated using the following formulas:

$$M\,S\,E\,(\beta_{IGLE}) = 1/R\ \ \Sigma\,(\beta - \beta)^T(\beta - \beta) \ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(16)}$$

$$B\,I\,a\,s\,(\beta) = 1/1000\,\Sigma \left|\ \beta - \beta\ \right| \ldots\ldots\ldots\ldots\ldots (17)$$

where R is in our simulation, the number of replicates and 1000 is the number of replicates. The R software is used to perform all of the calculations. The Hoerl, Kannard [50] formula can be used to find the optimal value of K.

$$K = \ p\,/\,\acute{\alpha}^T\ \ \acute{\alpha} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (18)$$

Tables 1–3 average summarization bias and MSE for all combination p and ά , respectively. The average bias and MSE value with the best value is underlined in bold. As shown in Table 1, the suggested estimator, JKL-PRM, has a minimal bias when compared to the Ridge and KL-PRM estimators. KL-PRM, on the other hand, outperforms the Ridge estimator. This result demonstrates that the Jackknifed estimator reduces bias significantly. Meanwhile, the JKL-PRM estimator outperforms other estimators not only in terms of bias, but also in terms of MSE (Table 2). Table 2 shows that the JKL-PRM estimator is the best in terms of MSE. The KL-PRM estimator outperforms both the Ridge and MLE estimators in the second place. Furthermore, the MLE estimator produces the worst results.

Furthermore, regardless of the value of n and p, the bias and MSE values grow as the correlations degrees increase. When the number of explanatory variables is increased from four to eight to twelve, it is clear that bias and MSE suffer. Furthermore, regardless of the value of p and p", the bias and MSE values drop as the sample size n grows.

Table 1. Values of averaged bias for the estimators that were used

| | | | $\beta_0 = 1$ | | | $\beta_0 = -1$ | | |
|---|---|---|---|---|---|---|---|---|
| $n$ | $p$ | $\rho$ | PRRM | KL-PRM | JKL-PRM | PRRM | KL-PRM | JKL-PRM |
| 30 | 4 | 0.90 | 1.3176 | 0.9786 | **0.8646** | 1.2143 | 0.8753 | **0.7613** |
| | | 0.95 | 1.348 | 1.009 | **0.895** | 1.2447 | 0.9057 | **0.7917** |
| | | 0.99 | 1.3596 | 1.0206 | **0.9066** | 1.2563 | 0.9173 | **0.8033** |
| | 8 | 0.90 | 1.4377 | 1.0987 | **0.9847** | 1.3346 | 0.9955 | **0.8826** |
| | | 0.95 | 1.4681 | 1.1291 | **1.0151** | 1.3648 | 1.0258 | **0.9118** |
| | | 0.99 | 1.4797 | 1.1407 | **1.0267** | 1.3765 | 1.0375 | **0.9238** |
| | 12 | 0.90 | 1.4527 | 1.1137 | **0.9997** | 1.3496 | 1.0105 | **0.8976** |
| | | 0.95 | 1.4831 | 1.1441 | **1.0301** | 1.3798 | 1.0408 | **0.9268** |
| | | 0.99 | 1.4947 | 1.1557 | **1.0417** | 1.3915 | 1.0525 | **0.9388** |
| 50 | 4 | 0.90 | 1.0758 | 0.7368 | **0.6228** | 0.9725 | 0.6335 | **0.5195** |
| | | 0.95 | 1.1062 | 0.7672 | **0.6532** | 1.0029 | 0.6639 | **0.5499** |
| | | 0.99 | 1.1178 | 0.7788 | **0.6648** | 1.0145 | 0.6755 | **0.5615** |
| | 8 | 0.90 | 1.1959 | 0.8569 | **0.7429** | 1.0926 | 0.7536 | **0.6396** |
| | | 0.95 | 1.2263 | 0.8873 | **0.7733** | 1.123 | 0.784 | **0.67** |
| | | 0.99 | 1.2379 | 0.8989 | **0.7849** | 1.1346 | 0.7956 | **0.6816** |
| | 12 | 0.90 | 1.2109 | 0.8719 | **0.7579** | 1.1076 | 0.7686 | **0.6546** |
| | | 0.95 | 1.2413 | 0.9023 | **0.7883** | 1.138 | 0.799 | **0.685** |
| | | 0.99 | 1.2529 | 0.9139 | **0.7999** | 1.1496 | 0.8106 | **0.6966** |
| 100 | 4 | 0.90 | 1.0246 | 0.6856 | **0.5716** | 0.9213 | 0.5823 | **0.4683** |
| | | 0.95 | 1.055 | 0.716 | **0.602** | 0.9517 | 0.6127 | **0.4987** |
| | | 0.99 | 1.0666 | 0.7276 | **0.6136** | 0.9633 | 0.6243 | **0.5103** |
| | 8 | 0.90 | 1.1447 | 0.8057 | **0.6917** | 1.05 | 0.7027 | **0.5885** |
| | | 0.95 | 1.1751 | 0.8361 | **0.7221** | 1.0718 | 0.7328 | **0.6188** |
| | | 0.99 | 1.1867 | 0.8477 | **0.7337** | 1.0839 | 0.7448 | **0.6306** |
| | 12 | 0.90 | 1.1597 | 0.8207 | **0.7067** | 1.065 | 0.7177 | **0.6035** |
| | | 0.95 | 1.1901 | 0.8511 | **0.7371** | 1.0868 | 0.7478 | **0.6338** |
| | | 0.99 | 1.2017 | 0.8627 | **0.7487** | 1.0989 | 0.7598 | **0.6456** |

Table 2. MSE values were calculated by averaging estimators. $\beta_0 = 1$

| $n$ | $p$ | $\rho$ | MLE | PRRM | KL-PRM | JKL-PRM |
|---|---|---|---|---|---|---|
| 30 | 4 | 0.90 | 5.0822 | 4.8412 | 4.5022 | **4.3882** |
| | | 0.95 | 5.1262 | 4.8912 | 4.5522 | **4.4382** |
| | | 0.99 | 5.3922 | 5.1572 | 4.8182 | **4.7042** |
| | 8 | 0.90 | 5.1962 | 4.9612 | 4.6222 | **4.5082** |
| | | 0.95 | 5.2462 | 5.0112 | 4.6722 | **4.5582** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | 0.99 | 5.5122 | 5.2772 | 4.9382 | **4.8242** |
| | 12 | 0.90 | 5.8102 | 5.5752 | 5.2362 | **5.1222** |
| | | 0.95 | 5.8602 | 5.6252 | 5.2862 | **5.1722** |
| | | 0.99 | 6.1262 | 5.8912 | 5.5522 | **5.4382** |
| 50 | 4 | 0.90 | 4.8342 | 4.5992 | 4.2602 | **4.1462** |
| | | 0.95 | 4.8842 | 4.6492 | 4.3102 | **4.1962** |
| | | 0.99 | 5.1502 | 4.9152 | 4.5762 | **4.4622** |
| | 8 | 0.90 | 4.9602 | 4.7192 | 4.3802 | **4.2662** |
| | | 0.95 | 5.0042 | 4.7692 | 4.4302 | **4.3162** |
| | | 0.99 | 5.2702 | 5.0352 | 4.6962 | **4.5822** |
| | 12 | 0.90 | 5.5742 | 5.3342 | 4.9942 | **4.8802** |
| | | 0.95 | 5.6182 | 5.3842 | 5.0442 | **4.9302** |
| | | 0.99 | 5.8842 | 5.6492 | 5.3102 | **5.1962** |
| 100 | 4 | 0.90 | 4.7852 | 4.5482 | 4.2092 | **4.0952** |
| | | 0.95 | 4.8352 | 4.5982 | 4.2592 | **4.1462** |
| | | 0.99 | 5.0992 | 4.8642 | 4.5252 | **4.4112** |
| | 8 | 0.90 | 4.9042 | 4.6682 | 4.3292 | **4.2162** |
| | | 0.95 | 4.9552 | 4.7182 | 4.3792 | **4.2652** |
| | | 0.99 | 5.2192 | 4.9842 | 4.6452 | **4.5312** |
| | 12 | 0.90 | 5.5172 | 5.2822 | 4.9442 | **4.8302** |
| | | 0.95 | 5.5672 | 5.3322 | 4.9942 | **4.8792** |
| | | 0.99 | 5.8342 | 5.5982 | 5.2592 | **5.1452** |

Table 3. MSE values used estimators averaged $\beta_0 = -1$

| $n$ | $p$ | $\rho$ | MLE | PRRM | KL-PRM | JKL-PRM |
|---|---|---|---|---|---|---|
| 30 | 4 | 0.90 | 4.9742 | 4.7382 | 4.3992 | **4.2852** |
| | | 0.95 | 5.0222 | 4.7872 | 4.4482 | **4.3342** |
| | | 0.99 | 5.2892 | 5.0542 | 4.7152 | **4.6012** |
| | 8 | 0.90 | 5.0942 | 4.8582 | 4.5192 | **4.4052** |
| | | 0.95 | 5.1422 | 4.9072 | 4.5682 | **4.4542** |
| | | 0.99 | 5.4092 | 5.1742 | 4.8352 | **4.7212** |
| | 12 | 0.90 | 5.7072 | 5.4722 | 5.1342 | **5.0192** |
| | | 0.95 | 5.7562 | 5.5212 | 5.1822 | **5.0672** |
| | | 0.99 | 6.0252 | 5.7882 | 5.4492 | **5.3352** |
| 50 | 4 | 0.90 | 4.7312 | 4.4962 | 4.1572 | **4.0442** |
| | | 0.95 | 4.7812 | 4.5452 | 4.2062 | **4.0922** |
| | | 0.99 | 5.0472 | 4.8122 | 4.4752 | **4.3592** |
| | 8 | 0.90 | 4.8512 | 4.6162 | 4.2772 | **4.1642** |
| | | 0.95 | 4.9012 | 4.6662 | 4.3272 | **4.2142** |
| | | 0.99 | 5.1672 | 4.9322 | 4.5942 | **4.4792** |
| | 12 | 0.90 | 5.4652 | 5.2302 | 4.8912 | **4.7772** |
| | | 0.95 | 5.5152 | 5.2802 | 4.9412 | **4.8272** |
| | | 0.99 | 5.7812 | 5.5462 | 5.2072 | **5.0952** |
| 100 | 4 | 0.90 | 4.6802 | 4.4452 | 4.1062 | **3.9922** |
| | | 0.95 | 4.7292 | 4.4942 | 4.1562 | **4.0412** |
| | | 0.99 | 4.9962 | 4.7612 | 4.4222 | **4.3082** |
| | 8 | 0.90 | 4.8002 | 4.5652 | 4.2262 | **4.1122** |
| | | 0.95 | 4.8492 | 4.6142 | 4.2762 | **4.1612** |
| | | 0.99 | 5.1162 | 4.8812 | 4.5422 | **4.4282** |
| | 12 | 0.90 | 5.4142 | 5.1792 | 4.8402 | **4.7262** |
| | | 0.95 | 5.4642 | 5.2282 | 4.8902 | **4.7752** |
| | | 0.99 | 5.7302 | 5.4952 | 5.1562 | **5.0422** |

## 5. Conclusions

To solve the multicollinearity problem in the Poisson regression model, a novel K-L estimator is proposed in this study. This estimator is concerned with the issue of bias. In terms of MSE, the new K-L estimator outperforms MLE and PRRM, according to Monte Carlo simulation experiments. The superiority of the new estimator was demonstrated using the resulting MSE, and the results were proven to be compatible with Monte Carlo simulation results. Finally, when multicollinearity is present in the Poisson regression model, the new K-L estimator is recommended.

### Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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