

Review and classifications of the ridge parameter estimation techniques

Adewale F. Lukman^{*†} and Kayode Ayinde[‡]

Abstract

Ridge parameter estimation techniques under the influence of multicollinearity in Linear regression model were reviewed and classified into different forms and various types. The different forms are Fixed Maximum (FM), Varying Maximum (VM), Arithmetic Mean (AM), Geometric Mean (GM), Harmonic Mean (HM) and Median (M) and the various types are Original (O), Reciprocal (R), Square Root (SR) and Reciprocal of Square Root (RSR). These classifications resulted into proposing some other techniques of Ridge parameter estimation. Investigation of the existing and proposed ones were done by conducting 1000 Monte-Carlo experiments under five (5) levels of multicollinearity ($\rho = 0.8, 0.9, 0.95, 0.99, 0.999$), three (3) levels of error variance ($\sigma^2 = 0.25, 1, 25$) and five levels of sample size ($n = 10, 20, 30, 40, 50$). The relative efficiency ($RF \leq 0.75$) of the techniques resulting from the ratio of their mean square error and that of the ordinary least square was used to compare the techniques.

Results show that the proposed techniques perform better than the existing ones in some situations; and that the best technique is generally the ridge parameter in the form of Harmonic Mean, Fixed Maximum and Varying Maximum in their Original and Square Root types.

Keywords: Linear Regression Model, Multicollinearity, Ridge Parameter Estimation Techniques, Relative Efficiency.

2000 AMS Classification: 62J05, 62J07.

Received: 02.09.2015 *Accepted:* 25.12.2015 *Doi:* 10.15672/HJMS.201815671

^{*}Department of Statistics, Ladoko Akintola University of Technology, Ogbomoso, Nigeria.
Email: wale3005@yahoo.com

[†]Corresponding Author.

[‡]Department of Statistics, Ladoko Akintola University of Technology, Ogbomoso, Nigeria.
Email: kayinde@lautech.edu.ng

1. Introduction

Regression analysis is a study on relationship among variables often classified as dependent and independent variables. The dependent variable is modeled on one or more explanatory variables. The aim is often to estimate the mean value of the dependent variable in terms of the known or fixed value of the explanatory variables. The Ordinary Least Squares (OLS) estimator is the most popularly used estimator to estimate the parameters in a regression model. The estimator under certain assumptions has some very attractive statistical properties which have made it one of the most powerful estimators. One of the assumptions is that the explanatory variables are independent. However, in practice, there may be strong or perfect linear relationships among the explanatory variables. This problem is often referred to as multicollinearity problem. It is well known that the performance of OLS estimator is unsatisfactory in the presence of multicollinearity in that the regression coefficients possess large standard errors and some will even have the wrong sign (Gujarati, 1995). In literature, there are various methods existing to solve this problem. Among them is the ridge regression estimator first introduced by Hoerl and Kennard (1970). Ridge estimator has a smaller mean square error (MSE) than OLS estimator (Vinod and Ullah, 1981). Consider the standard regression model:

$$(1.1) \quad Y = X\beta + U$$

where X is an $n \times p$ matrix with full rank, Y is a $n \times 1$ vector of dependent variable, β is a $p \times 1$ vector of unknown parameters, and U is the error term such that $E(U) = 0$ and $E(UU') = \sigma^2 I_n$.

The ridge estimator is defined as:

$$(1.2) \quad \hat{\beta} = (X'X + KI)^{-1} X'Y$$

where K is a non-negative constant. It is called biasing or ridge parameter. It is observed that when $K = 0$, (2) returns OLS estimates. Ridge regression estimators are biased as K increases but give more precise estimates than OLS estimator (Mardikyan and Cetin, 2008). Hoerl *et al.* (1975) suggested that the value of K should be chosen small enough such that the mean squared error of ridge estimator is less than the mean squared error of OLS estimator. Different techniques of estimation had been proposed or suggested by various researchers. Hoerl and Kennard (1970) suggested a graphical method called ridge trace to select the value of the ridge parameter K . This is a plot of the values of individual components of $\hat{\beta}_k$ against a range of values of K ($0 < K < 1$). The minimum value for which $\hat{\beta}_k$ become stable and the wrong signs in the regression coefficient is corrected is used. Also, one can select the value of K for which the residual sum of square is not too large. The performance of the Ridge estimator with different K s had often been compared through simulation study. Most of the researchers have generated data from a normal population as explanatory variables with different number of regressors. The mean squared error (MSE) has been used severally as a performance criterion.

Several techniques had been developed to estimate K . These were reviewed and classified into different forms and various types in this paper. These classifications resulted into proposing new techniques for the ridge parameter estimation. The organization of this paper is as follows: Theoretical background of ridge regression, different methods of estimations are reviewed and proposed estimators are presented in section 2. The model, details of the Monte Carlo simulation study and performance criterion is given in Section 3. Results and discussions are presented in section 4. Some concluding remarks are given in Section 5.

2. Ridge regression and ridge estimator

2.1. Background of ridge regression. Ridge regression centers on the use of the biased parameter K which yields estimation with a smaller mean square error. Hoerl and Kennard (1970) suggested the optimum ridge parameter as:

$$(2.1) \quad K_i = \frac{\sigma^2}{\alpha_i^2}, i = 1, 2, 3, \dots, p$$

Since σ^2 and α_i^2 are generally unknown and the K_i needs to be estimated. Consequently, they suggested the replacement of σ^2 and α_i^2 by their corresponding unbiased estimators $\hat{\sigma}^2$ and $\hat{\alpha}_i^2$.

Therefore, the estimator of K_i is given as:

$$(2.2) \quad K_i = \frac{\hat{\sigma}^2}{\hat{\alpha}_i^2}$$

where $\hat{\sigma}^2 = \frac{\sum_{i=1}^n e_i^2}{n-p}$ and α_i is the i^{th} element of the vector $\hat{\alpha} = Q'\hat{\beta}$ where Q is an orthogonal matrix.

2.2. Review of methods of estimating the ridge parameter. The existing ridge parameters are reviewed as follows:

2.2.1. Estimators based on Hoerl and Kennard (1970). Hoerl and Kennard (1970) proposed $K_{HK_i} = \frac{\sigma^2}{\alpha_i^2}$. They suggested estimating ridge parameter by taking the maximum (Fixed Maximum) of α_i^2 such that the estimator of K is:

$$(2.3) \quad \hat{K}_{HK}^{FM} = \frac{\hat{\sigma}^2}{Max(\hat{\alpha}_i^2)}$$

Hoerl *et al.* (1975) proposed a different estimator of K by taking the Harmonic Mean of the ridge parameter K_{HK_i} . This estimator is given as:

$$(2.4) \quad \hat{K}_{HK}^{FM} = \frac{P\hat{\sigma}^2}{\sum_{i=1}^p \alpha_i^2}$$

Kibria (2003) proposed some new estimators of K by taking the Geometric Mean, Arithmetic Mean and Median ($p \geq 3$) of the ridge parameter K_{HK_i} . These estimators are respectively defined as:

$$(2.5) \quad \hat{K}_{HK}^{GM} = \frac{\hat{\alpha}^2}{(\prod_{i=1}^p \hat{\alpha}_i^2)^{\frac{1}{p}}}$$

$$(2.6) \quad \hat{K}_{HK}^{AM} = \frac{1}{p} \sum_{i=1}^p \left(\frac{\hat{\alpha}^2}{\hat{\alpha}_i^2} \right)$$

$$(2.7) \quad \hat{K}_{HK}^M = Median\left(\frac{\hat{\alpha}^2}{\hat{\alpha}_i^2}\right)$$

Furthermore, Muniz and Kibria (2009) proposed some estimators of K in form of Square root of Geometric Mean of K_{HK_i} and its reciprocal, the Median of the Square root of K_{HK_i} and its reciprocal, and Varying Maximum of the Square root of K_{HK_i} and its reciprocal. These estimators are respectively defined as:

$$(2.8) \quad \hat{K}_{HK}^{GMSR} = \sqrt{\frac{\hat{\sigma}^2}{(\prod_{i=1}^p \hat{\alpha}_i^2)^{\frac{1}{p}}}}$$

$$(2.9) \quad \hat{K}_{HK}^{GMRSR} = \frac{1}{\sqrt{\frac{\hat{\sigma}^2}{(\prod_{i=1}^p \hat{\alpha}_i^2)^{\frac{1}{p}}}}}$$

$$(2.10) \quad \hat{K}_{HK}^{MSR} = \text{Median}(\sqrt{\frac{\hat{\alpha}^2}{\hat{\alpha}_i^2}})$$

$$(2.11) \quad \hat{K}_{HK}^{MRSR} = \text{Median}\left(\frac{1}{\sqrt{\frac{\hat{\alpha}^2}{\hat{\alpha}_i^2}}}\right)$$

$$(2.12) \quad \hat{K}_{HK}^{MRSR} = \text{Max}(\sqrt{\frac{\hat{\alpha}^2}{\hat{\alpha}_i^2}})$$

$$(2.13) \quad \hat{K}_{HK}^{MRSR} = \text{Max}\left(\frac{1}{\sqrt{\frac{\hat{\alpha}^2}{\hat{\alpha}_i^2}}}\right)$$

2.2.2. Estimators based on Lawless and Wang (1976). Lawless and Wang (1976) proposed a different estimator of K resulting from taking the Harmonic Mean of the ridge parameter $K_{LW_i} = \frac{\sigma^2}{\lambda_i \alpha_i^2}$. The estimator is defined as:

$$(2.14) \quad \hat{K}_{LW}^{HM} = \frac{p\hat{\sigma}^2}{\sum_{i=1}^p \lambda_i \hat{\alpha}_i^2}$$

where λ_i is the eigenvalue of the matrix $X'X$.

2.2.3. Estimators based on Alkhamisi et al. (2006). Alkhamisi et al. (2006) proposed another ridge parameter $K_{AKS_i} = \frac{\sigma^2 \lambda_i}{(n-p)\sigma^2 + \lambda_i \alpha_i^2}$. They proposed estimators of K as the Arithmetic Mean and Median of the ridge parameter K_{AKS_i} . These estimators are respectively defined as:

$$(2.15) \quad \hat{K}_{AKS}^{AM} = \frac{1}{p} \sum_{i=1}^p \left(\frac{\lambda_i \hat{\sigma}^2}{(n-p)\hat{\sigma}^2 + \lambda_i \hat{\alpha}_i^2} \right)$$

$$(2.16) \quad \hat{K}_{AKS}^M = \text{Median}\left(\frac{\hat{\sigma}^2 \lambda_i}{(n-p)\hat{\sigma}^2 + \lambda_i \hat{\alpha}_i^2}\right)$$

However, a new approach of choosing the ridge parameter K suggested by Khalaf and Shukur (2005) can be seen in form of Fixed Maximum of the ridge parameter K_{AKS_i} . The estimator is defined as:

$$(2.17) \quad \hat{K}_{AKS}^{FM} = \frac{\hat{\sigma}^2 \max(\lambda_i)}{(n-p)\hat{\sigma}^2 + \max(\lambda_i)\max(\hat{\alpha}_i^2)}$$

Muniz and Kibria (2009) proposed the estimator of the ridge parameter K as the Geometric Mean of the ridge parameter K_{AKS_i} . The estimator is given as:

$$(2.18) \quad \hat{K}_{AKS}^{GMO} = \left(\prod_{i=1}^p \frac{\lambda_i \hat{\sigma}^2}{(n-p)\hat{\sigma}^2 + \lambda_i \hat{\alpha}_i^2} \right)^{\frac{1}{p}}$$

Muniz et al. (2012) proposed the estimator of the ridge parameter K as the Varying Maximum and Arithmetic Mean of the ridge parameter K_{AKS_i} . These estimators are defined respectively as:

$$(2.19) \quad \hat{K}_{AKS}^{VMO} = \text{Max}\left(\frac{\lambda_i \hat{\alpha}^2}{(n-p)\hat{\alpha}^2 + \lambda_i \hat{\alpha}_i^2}\right)$$

$$(2.20) \quad \hat{K}_{AKS}^{AMO} = \frac{1}{p} \sum_{i=1}^p \left(\frac{\lambda_i \hat{\alpha}^2}{(n-p)\hat{\alpha}^2 + \lambda_i \hat{\alpha}_i^2} \right)$$

2.2.4. Estimators based on Muniz et al. (2012). Muniz et al. (2012) proposed another ridge parameter $K_{MAO_i} = \frac{\hat{\sigma}^2 \text{Max}(\lambda_i)}{(n-p)\hat{\sigma}^2 + \text{Max}(\lambda_i)\alpha_i^2}$. They proposed estimators of K as Varying Maximum of K_{MAO_i} and its reciprocal, its square root and reciprocal of its square root, Median of the reciprocal of K_{MAO_i} , Median of the reciprocal of the square root of K_{MAO_i} , and the Geometric Mean of K_{MAO_i} , its square root and reciprocal of its square root. These estimators are defined respectively as:

$$(2.21) \quad K_{MAO_i} = \text{Max}\left(\frac{\hat{\sigma}^2 \text{Max}(\lambda_i)}{(n-p)\hat{\sigma}^2 + \text{Max}(\lambda_i)\alpha_i^2}\right)$$

$$(2.22) \quad \hat{K}_{MAO}^{VMR} = \text{Max}\left(\frac{1}{\hat{K}_{MAO}}\right)$$

$$(2.23) \quad \hat{K}_{MAO}^{VMSR} = \text{Max}\left(\sqrt{\hat{K}_{MAO}}\right)$$

$$(2.24) \quad \hat{K}_{MAO}^{VMRSR} = \text{Max}\left(\frac{1}{\sqrt{\hat{K}_{MAO}}}\right)$$

$$(2.25) \quad \hat{K}_{MAO}^{MR} = \text{Median}\left(\frac{1}{\hat{K}_{MAO}}\right)$$

$$(2.26) \quad \hat{K}_{MAO}^{MRSR} = \text{Median}\left(\frac{1}{\sqrt{\hat{K}_{MAO}}}\right)$$

$$(2.27) \quad K_{MAO_i} = \left(\prod_{i=1}^p \frac{\text{Max}(\lambda_i)\hat{\sigma}^2}{(n-p)\hat{\sigma}^2 + \text{Max}(\lambda_i)\alpha_i^2}\right)^{\frac{1}{p}}$$

$$(2.28) \quad \hat{K}_{MAO}^{GMSR} = \sqrt{\hat{K}_{MAO}^{GMO}}$$

$$(2.29) \quad \hat{K}_{MAO}^{GMRSR} = \frac{1}{\sqrt{\hat{K}_{MAO}^{GMO}}}$$

It should be noted that the Fixed Maximum of K_{MAO_i} gives the ridge parameter proposed by Khalaf and Shukur (2005) already defined in (19).

2.3. Summary of the existing and proposed ridge parameters. Following the review in section 2.2, it is observed that the parameters follow some different forms and various types. These are explained and summarized as follows:

A. Different forms of K

1. Fixed Maximum (FM): This is obtained by taking the highest value of the estimated regression coefficient or the eigenvalue or both.
2. Varying Maximum (VM): This allows the estimated regression coefficient and the eigenvalue to vary, and eventually the maximum of the estimated ridge parameter is chosen. That is, the ridge parameter with the highest estimated ridge parameters or eigenvalues or both.
3. Arithmetic Mean (AM): It involves taking the average of the estimated ridge parameters.
4. Harmonic Mean (HM): The ridge parameter is expressed as Harmonic Mean of the estimated ridge parameters.
5. Geometric Mean (GM): The ridge parameter is expressed as the Geometric Mean of the estimated ridge parameters.
6. Median (M): This involves taking the Median of the estimated ridge parameters.

B. Various types of K

1. Original form(O)
2. Reciprocal form(R)
3. Square root form(SR)

Table 1. Summary of Different Forms and Various Types for $\hat{K}_{HK_i} = \frac{\hat{\sigma}^2}{\alpha_i^2}$

Different Forms	Various types of K			
	O	R	SR	RSR
FM	$\hat{K}_{HK}^{FMO} = \frac{\hat{\sigma}^2}{Max(\alpha_i^2)}$	$\hat{K}_{HK}^{FMR} = \frac{1}{K_{HK}^{FMO}}$	$\hat{K}_{HK}^{FMSR} = \sqrt{\hat{K}_{HK}^{FMO}}$	$\hat{K}_{HK}^{FMRSR} = \frac{1}{\sqrt{K_{HK}^{FMO}}}$
	Hoerl <i>et al.</i> (1970)	proposed	proposed	proposed
VM	$\hat{K}_{HK}^{VMO} = Max(\frac{\hat{\sigma}^2}{\alpha_i^2})$	$\hat{K}_{HK}^{VMR} = Max(\frac{1}{(\frac{\hat{\sigma}^2}{\alpha_i^2})})$	$\hat{K}_{HK}^{VMSR} = Max(\sqrt{\frac{\hat{\sigma}^2}{\alpha_i^2}})$	$\hat{K}_{HK}^{VMRSR} = Max(\frac{1}{\sqrt{\frac{\hat{\sigma}^2}{\alpha_i^2}}})$
	Proposed	Proposed	Proposed	Proposed
AM	$\hat{K}_{HK}^{AMO} = \frac{1}{p} \sum_{i=1}^p \frac{\hat{\sigma}^2}{\alpha_i^2}$	$\hat{K}_{HK}^{AMR} = \frac{1}{K_{HK}^{AMO}}$	$\hat{K}_{HK}^{AMSr} = \sqrt{\hat{K}_{HK}^{AMO}}$	$\hat{K}_{HK}^{AMRSR} = \frac{1}{\sqrt{K_{HK}^{AMO}}}$
	Proposed	Proposed	Proposed	Proposed
HM	$\hat{K}_{HK}^{HMO} = \frac{p\hat{\sigma}^2}{\sum_{i=1}^p \alpha_i^2}$	$\hat{K}_{HK}^{HMR} = \frac{1}{K_{HK}^{HMO}}$	$\hat{K}_{HK}^{HMSR} = \sqrt{\hat{K}_{HK}^{HMO}}$	$\hat{K}_{HK}^{HMRSR} = \frac{1}{\sqrt{K_{HK}^{HMO}}}$
	Hoerl <i>et al.</i> (1975)	Proposed	Proposed	Proposed
GM	$\hat{K}_{HK}^{GMO} = \frac{\hat{\sigma}^2}{(\prod_{i=1}^p \alpha_i^2)^{\frac{1}{p}}}$	$\hat{K}_{HK}^{GMR} = \frac{1}{K_{HK}^{GMO}}$	$\hat{K}_{HK}^{GMSR} = \sqrt{\hat{K}_{HK}^{GMO}}$	$\hat{K}_{HK}^{GMRSR} = \frac{1}{\sqrt{K_{HK}^{GMO}}}$
	Kibria (2003)	Proposed	Proposed	Proposed
M	$\hat{K}_{HK}^M = Median(\frac{\hat{\sigma}^2}{\alpha_i^2})$	$\hat{K}_{HK}^{MR} = Median(\frac{1}{(\frac{\hat{\sigma}^2}{\alpha_i^2})})$	$\hat{K}_{HK}^{MSR} = Median(\sqrt{(\frac{\hat{\sigma}^2}{\alpha_i^2})})$	$\hat{K}_{HK}^{MRSR} = Median(\frac{1}{\sqrt{(\frac{\hat{\sigma}^2}{\alpha_i^2})}})$
	Kibria (2003)	Proposed	Proposed	Muniz and Kibria (2009)

4. Reciprocal of Square root(RSR)

In the light of this knowledge, the existing and newly proposed ridge parameters are summarized based on the previous works as follows:

2.3.1. Ridge Parameter Proposed by Hoerl and Kennard (1970). Hoerl and Kennard (1970) proposed the ridge parameter $K_{HK_i} = \frac{\sigma^2}{\alpha_i^2}$. Its estimator in the light of different forms and various types are summarized in Table 1.

Table 1 gives the summary of the different forms and various types of the Hoerl and Kennard (1970) ridge parameter. Those already in existence and the proposed ones are specified.

2.3.2. Ridge Parameter Proposed by Lawless and Wang (1976). Lawless and Wang (1976) proposed ridge parameter resulting from the Harmonic Mean of $K_{LW_i} = \frac{\sigma^2}{\lambda_i \alpha_i^2}$. Its estimator in the light of different forms and various types are summarized in Table 2.

Table 2 gives the summary of the different forms and various types of the Lawless and Wang (1976) ridge parameter. The one already in existence and the proposed are specified.

2.3.3. Ridge Parameter Proposed by Alkhamisi et al. (2006). Alkhamisi *et al.* (2006) proposed the ridge parameter $K_{AKS_i} = \frac{\sigma^2 \lambda_i}{(n-p)\sigma^2 + \lambda_i \alpha_i^2}$. Its estimator in the light of different forms and various types are summarized in Table 3.

Table 3 gives the summary of the different forms and various types of the Alkhamisi *et al* (2006) ridge parameter. Those already in existence and the proposed ones are also specified.

2.3.4. Ridge Parameter Proposed by Muniz et al. (2012). Muniz *et al.*(2012) proposed the ridge parameter $K_{MAO_i} = \frac{\hat{\sigma}^2 Max(\lambda_i)}{(n-p)\hat{\sigma}^2 + Max(\lambda_i) \alpha_i^2}$. Its estimator in the light of different forms and various types are summarized in Table 4.

Table 4 gives the summary of the different forms and various types of the Muniz *et al.* (2012) ridge parameter. Those already in existence and the proposed are specified.

Table 2. Summary of Different Forms and Various Types for $\hat{K}_{LW_i} = \frac{\delta^2}{\lambda_i \alpha_i^2}$

Different Forms	Various types of K			
	O	R	SR	RSR
FM	$\hat{K}_{LW}^{FMO} = \frac{\delta^2}{Max(\lambda_i)Max(\alpha_i^2)}$ Proposed	$\hat{K}_{LW}^{FMR} = \frac{1}{\hat{K}_{LW}^{FMO}}$ proposed	$\hat{K}_{LW}^{FMSR} = \sqrt{\hat{K}_{LW}^{FMO}}$ proposed	$\hat{K}_{LW}^{FMRSR} = \frac{1}{\sqrt{\hat{K}_{LW}^{FMO}}}$ proposed
VM	$\hat{K}_{LW}^{VMO} = Max[\frac{\delta^2}{\lambda_i \alpha_i^2}]$ Proposed	$\hat{K}_{LW}^{VMR} = Max(\frac{1}{\hat{K}_{LW}})$ Proposed	$\hat{K}_{LW}^{VMSR} = Max(\sqrt{\hat{K}_{LW}})$ Proposed	$\hat{K}_{LW}^{VMRSR} = Max(\frac{1}{\sqrt{\hat{K}_{LW}}})$ Proposed
AM	$\hat{K}_{LW}^{AMO} = \frac{1}{p} \sum_{i=1}^p \frac{\delta^2}{\lambda_i \alpha_i^2}$ Proposed	$\hat{K}_{LW}^{AMR} = \frac{1}{\hat{K}_{LW}^{AMO}}$ Proposed	$\hat{K}_{LW}^{AMS R} = \sqrt{\hat{K}_{LW}^{AMO}}$ Proposed	$\hat{K}_{LW}^{AMRSR} = \frac{1}{\sqrt{\hat{K}_{LW}^{AMO}}}$ Proposed
HM	$\hat{K}_{LW}^{HMO} = \frac{p\delta^2}{\sum_{i=1}^p \lambda_i \alpha_i^2}$ Lawless and Wang (1976)	$\hat{K}_{LW}^{HMR} = \frac{1}{\hat{K}_{LW}^{HMO}}$ Proposed	$\hat{K}_{LW}^{HMSR} = \sqrt{\hat{K}_{LW}^{HMO}}$ Proposed	$\hat{K}_{LW}^{HMRSR} = \frac{1}{\sqrt{\hat{K}_{LW}^{HMO}}}$ Proposed
GM	$\hat{K}_{LW}^{GMO} = \frac{\delta^2}{(\prod_{i=1}^p \lambda_i \alpha_i^2)^{\frac{1}{p}}}$ Proposed	$\hat{K}_{LW}^{GMR} = \frac{1}{\hat{K}_{LW}^{GMO}}$ Proposed	$\hat{K}_{LW}^{GMSR} = \sqrt{\hat{K}_{LW}^{GMO}}$ Proposed	$\hat{K}_{LW}^{GMRSR} = \frac{1}{\sqrt{\hat{K}_{LW}^{GMO}}}$ Proposed
M	$\hat{K}_{LW}^{MO} = Median(\frac{\delta^2}{\lambda_i \alpha_i^2})$ Proposed	$\hat{K}_{LW}^{MR} = Median(\frac{1}{\hat{K}_{LW}})$ Proposed	$\hat{K}_{LW}^{MSR} = Median(\sqrt{\hat{K}_{LW}})$ Proposed	$\hat{K}_{LW}^{MRSR} = Median(\frac{1}{\sqrt{\hat{K}_{LW}}})$ Proposed

Table 3. Summary of Different Forms and Various Types for $\hat{K}_{AKS_i} = \frac{\sigma^2 \lambda_i}{(n-p)\sigma^2 + \lambda_i \alpha_i^2}$

Different Forms	Various types of K			
	O	R	SR	RSR
FM	$\hat{K}_{AKS}^{FM} = \frac{\delta^2 Max(\lambda_i)}{(n-p)\delta^2 + Max(\lambda_i)Max(\alpha_i^2)}$ Khalaf and Shukur (2005)	$\hat{K}_{AKS}^{FMR} = \frac{1}{\hat{K}_{AKS}^{FM}}$ proposed	$\hat{K}_{AKS}^{FMSR} = \sqrt{\hat{K}_{AKS}^{FM}}$ proposed	$\hat{K}_{AKS}^{FMRSR} = \frac{1}{\sqrt{\hat{K}_{AKS}^{FM}}}$ proposed
VM	$\hat{K}_{AKS}^{VMO} = Max(\frac{\lambda_i \delta^2}{(n-p)\delta^2 + \lambda_i \alpha_i^2})$ Muniz et al. (2012)	$\hat{K}_{AKS}^{VMR} = Max(\frac{1}{\hat{K}_{AKS}})$ Proposed	$\hat{K}_{AKS}^{VMSR} = Max(\sqrt{\hat{K}_{AKS}})$ Proposed	$\hat{K}_{AKS}^{VMRSR} = Max(\frac{1}{\sqrt{\hat{K}_{AKS}}})$ Proposed
AM	$\hat{K}_{AKS}^{AMO} = \frac{1}{p} \sum_{i=1}^p (\frac{\lambda_i \delta^2}{(n-p)\delta^2 + \lambda_i \alpha_i^2})$ Muniz et al. (2012)	$\hat{K}_{AKS}^{AMR} = \frac{1}{\hat{K}_{AKS}^{AMO}}$ Proposed	$\hat{K}_{AKS}^{AMS R} = \sqrt{\hat{K}_{AKS}^{AMO}}$ Proposed	$\hat{K}_{AKS}^{AMRSR} = \frac{1}{\sqrt{\hat{K}_{AKS}^{AMO}}}$ Proposed
HM	$\hat{K}_{AKS}^{HMO} = p \sum_{i=1}^p (\frac{\lambda_i \delta^2}{(n-p)\delta^2 + \lambda_i \alpha_i^2})$ Lawless and Wang (1976)	$\hat{K}_{AKS}^{HMR} = \frac{1}{\hat{K}_{AKS}^{HMO}}$ Proposed	$\hat{K}_{AKS}^{HMSR} = \sqrt{\hat{K}_{AKS}^{HMO}}$ Proposed	$\hat{K}_{AKS}^{HMRSR} = \frac{1}{\sqrt{\hat{K}_{AKS}^{HMO}}}$ Proposed
GM	$\hat{K}_{AKS}^{GMO} = (\prod_{i=1}^p \frac{\lambda_i \delta^2}{(n-p)\delta^2 + \lambda_i \alpha_i^2})^{\frac{1}{p}}$ Muniz and Kibria (2009)	$\hat{K}_{AKS}^{GMR} = \frac{1}{\hat{K}_{AKS}^{GMO}}$ Proposed	$\hat{K}_{AKS}^{GMSR} = \sqrt{\hat{K}_{AKS}^{GMO}}$ Proposed	$\hat{K}_{AKS}^{GMRSR} = \frac{1}{\sqrt{\hat{K}_{AKS}^{GMO}}}$ Proposed
M	$\hat{K}_{AKS}^{MO} = (\frac{\lambda_i \delta^2}{(n-p)\delta^2 + \lambda_i \alpha_i^2})$ Alkhamisi et al.(2006)	$\hat{K}_{AKS}^{MR} = Median(\frac{1}{\hat{K}_{AKS}})$ Proposed	$\hat{K}_{AKS}^{MSR} = Median(\sqrt{\hat{K}_{AKS}})$ Proposed	$\hat{K}_{AKS}^{MRSR} = Median(\frac{1}{\sqrt{\hat{K}_{AKS}}})$ Proposed

Table 4. Summary of Different Forms and Various Types for $K_{MAO_i} = \frac{\delta^2 Max(\lambda_i)}{(n-p)\delta^2 + Max(\lambda_i)\alpha_i^2}$

Different Forms	Various types of K			
	O	R	SR	RSR
FM	$\hat{K}_{MAO}^{FM} = \frac{Max(\lambda_i)\delta^2}{(n-p)\delta^2 + Max(\lambda_i)Max(\alpha_i^2)}$ Khalaf and Shukur (2005)	$\hat{K}_{MAO}^{FMR} = \frac{1}{\hat{K}_{MAO}^{FM}}$ proposed	$\hat{K}_{MAO}^{FMSR} = \sqrt{\hat{K}_{MAO}^{FM}}$ proposed	$\hat{K}_{MAO}^{FMRSR} = \frac{1}{\sqrt{\hat{K}_{MAO}^{FM}}}$ proposed
VM	$\hat{K}_{MAO}^{VMO} = Max(\frac{Max(\lambda_i)\delta^2}{(n-p)\delta^2 + Max(\lambda_i)\alpha_i^2})$ Muniz et al. (2010)	$\hat{K}_{MAO}^{VMR} = Max(\frac{1}{\hat{K}_{MAO}})$ Muniz et al. (2010)	$\hat{K}_{MAO}^{VMSR} = Max(\sqrt{\hat{K}_{MAO}})$ Muniz et al. (2012)	$\hat{K}_{MAO}^{VMRSR} = Max(\frac{1}{\sqrt{\hat{K}_{MAO}}})$ Muniz et al. (2012)
AM	$\hat{K}_{MAO}^{AMO} = \frac{1}{p} \sum_{i=1}^p (\frac{Max(\lambda_i)\delta^2}{(n-p)\delta^2 + Max(\lambda_i)\alpha_i^2})$ Proposed	$\hat{K}_{MAO}^{AMR} = \frac{1}{\hat{K}_{MAO}^{AMO}}$ Proposed	$\hat{K}_{MAO}^{AMS R} = \sqrt{\hat{K}_{MAO}^{AMO}}$ Proposed	$\hat{K}_{MAO}^{AMRSR} = \frac{1}{\sqrt{\hat{K}_{MAO}^{AMO}}}$ Proposed
HM	$\hat{K}_{MAO}^{HMO} = p \sum_{i=1}^p (\frac{Max(\lambda_i)\delta^2}{(n-p)\delta^2 + Max(\lambda_i)\alpha_i^2})$ Lawless and Wang (1976)	$\hat{K}_{MAO}^{HMR} = \frac{1}{\hat{K}_{MAO}^{HMO}}$ Proposed	$\hat{K}_{MAO}^{HMSR} = \sqrt{\hat{K}_{MAO}^{HMO}}$ Proposed	$\hat{K}_{MAO}^{HMRSR} = \frac{1}{\sqrt{\hat{K}_{MAO}^{HMO}}}$ Proposed
GM	$\hat{K}_{MAO}^{GMO} = (\prod_{i=1}^p \frac{Max(\lambda_i)\delta^2}{(n-p)\delta^2 + Max(\lambda_i)\alpha_i^2})^{\frac{1}{p}}$ Muniz et al. (2010)	$\hat{K}_{MAO}^{GMR} = \frac{1}{\hat{K}_{MAO}^{GMO}}$ Proposed	$\hat{K}_{MAO}^{GMSR} = \sqrt{\hat{K}_{MAO}^{GMO}}$ Muniz et al. (2012)	$\hat{K}_{MAO}^{GMRSR} = \frac{1}{\sqrt{\hat{K}_{MAO}^{GMO}}}$ Muniz et al. (2012)
M	$\hat{K}_{MAO}^{MO} = Median(\frac{Max(\lambda_i)\delta^2}{(n-p)\delta^2 + Max(\lambda_i)\alpha_i^2})$ Muniz et al. (2010)	$\hat{K}_{MAO}^{MR} = Median(\frac{1}{\hat{K}_{MAO}})$ Muniz et al. (2010)	$\hat{K}_{MAO}^{MSR} = Median(\sqrt{\hat{K}_{MAO}})$ Proposed	$\hat{K}_{MAO}^{MRSR} = Median(\frac{1}{\sqrt{\hat{K}_{MAO}}})$ Muniz et al. (2010)

3. Model formulation and procedure for data generation for simulation study

Consider a linear regression model of the form:

$$(3.1) \quad Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \beta_p X_{pt} + U_t$$

$$t = 1, 2, \dots, n; p = 3, 7$$

where $U_t \sim N(0, \sigma^2)$.

The model was studied with fixed regressors, $X_{it}, i = 1, 2, \dots, p; t = 1, 2, \dots, n$ such that there exist different levels of multicollinearity among the regressors.

3.1. Procedure for generating the error terms. The error term U_t was generated to be normally distributed with mean zero and variance $U_t \sim N(0, \sigma^2)$. In this study, σ values were 0.5, 1 and 5.

3.2. Procedure for generating the explanatory variables. The procedure used by McDonald and Galarneau (1975), Wichern and Churchill (1978), Gibbons (1981) and Kibria (2003) was also used to generate the explanatory variables in this study. This is given as:

$$(3.2) \quad X_{ti} = (1 - \rho^2)^{\frac{1}{2}} Z_{ti} + \rho Z_{tp}$$

$$t = 1, 2, 3, \dots, n; i = 1, 2, \dots, p$$

where Z_{ti} is independent standard normal distribution with mean zero and unit variance, ρ is the correlation between any two explanatory variables and p is the number of explanatory variables. The values of ρ were taken as 0.8, 0.9, 0.95, 0.99 and 0.999. Thus, the inter-correlation between the variables was the same. In this study, the number of explanatory variable (p) was taken to be three (3) and seven (7).

3.3. Procedure for generating the dependent variable. The regression model is

$$(3.3) \quad Y_t = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip} + U_t$$

$$t = 1, 2, \dots, n; p = 3, 7$$

β_0 was taken to be identically zero. When $p = 3$, the values of β were chosen to be: $\beta_1 = 0.8, \beta_2 = 0.1, \beta_3 = 0.6$. When $p = 7$, the values of β were chosen to be: $\beta_1 = 0.4, \beta_2 = 0.1, \beta_3 = 0.6, \beta_4 = 0.2, \beta_5 = 0.25, \beta_6 = 0.3, \beta_7 = 0.53$. The parameter values were chosen such that $\beta' \beta = 1$ which is a common restriction in simulation studies of this type (Muniz and Kibria, 2009). We varied the sample sizes between 10, 20, 30, 40 and 50. Three different values of σ : 0.5, 1 and 5 were also used. At a specified value of n, p and σ , the fixed X s are first generated; followed by the U , and the values of Y are then obtained using the regression model. The experiment is repeated 1000 times.

3.4. Criterion for investigation. Several authors in literatures had applied the mean square error (MSE) to evaluate and compare the performance of ridge regression estimator with that of the ordinary least square estimator when there is multicollinearity. Some of these were Hoerl and Kennard (1970), Lawless and Wang (1976), Saleh and Kibria (1993), Kibria (2003), Khalaf and Shukur (2005), Alkhamisi *et al.* (2006), Mansson *et al.* (2010). To investigate whether the ridge estimator is better than the OLS estimator, the MSE is calculated using equation defined already:

$$(3.4) \quad MSE(\hat{\beta}_{ridge}) = \hat{\sigma}^2 \sum_{i=1}^p \frac{\lambda_i}{(\lambda_i + \hat{K})^2} + \hat{K}^2 \sum_{i=1}^p \frac{\hat{\alpha}_i^2}{(\lambda_i + \hat{K})^2}$$

$$(3.5) \quad MSE(\hat{\beta}_{OLS}) = \hat{\sigma}^2 \sum_{i=1}^p \frac{1}{\lambda_i}$$

where $\lambda_1, \lambda_2, \dots, \lambda_p$ are the eigenvalues of $X'X$, \hat{K} is the estimator of the ridge parameter K , $\hat{\alpha}_i$ is the i^{th} element of the vector $\hat{\alpha} = Q'\hat{\beta}$ where Q is an orthogonal matrix. This is further examined by computing the relative efficiency of the ridge regression estimator relative to OLS estimator.

$$(3.6) \quad RelativeEfficiency(RE) = \frac{MSE(\hat{\beta}_{ridge})}{\hat{\beta}(OLS)}$$

Thus, the smaller the efficiency value the better the ridge parameter. Consequently, ridge parameter estimates whose efficiency was not more than 0.75 are preferred and selected. That is, the ridge estimators whose MSE were better than that of OLS by at least 25% of OLS MSE. Furthermore, the number of times they were preferred ($RE \leq 0.75$) over the five (5) levels of multicollinearity and three (3) error variance was counted so as to know the frequency of their efficiency at each level of sample size. Thus, a maximum of fifteen (15) counts was expected.

4. Results and discussion

4.1. Summary of results with $\hat{K}_{HK_i} = \frac{\hat{\sigma}^2}{\hat{\alpha}_i^2}$. A sample of the relative efficiency of the ridge parameter based on \hat{K}_{HK_i} of Hoerl and Kennard (1970) at different forms and various types when $n=10$ is given in Appendix 1. The details are contained in the work of Lukman (2015). The frequency of the relative efficiency over the levels of multicollinearity and error variance is summarized in Table 5.

From Table 5, all the best methods in $p=7$ are also best in $p=3$. However, their order of performance differs and GMO which is best in $p=3$ is not among the best in $p=7$. It is also noted that two of the newly proposed techniques, **FMSR** and **HMSR**, are among the best five at each number of regressors. Consequently, the best techniques are: HMO, MO, FMO, **FMSR** and **HMSR**.

4.2. Summary of Results with $\hat{K}_{LW_i} = \frac{\hat{\sigma}^2}{\lambda_i \hat{\alpha}_i^2}$. A sample of the relative efficiency of the ridge parameter based on \hat{K}_{LW_i} of Lawless and Wang (1975) at different forms and various types when $n=30$ is given in Appendix 2. The details are contained in the work of Lukman (2015). The frequency of the relative efficiency over the levels of multicollinearity and error variance is summarized in Table 6.

From Table 6, the best methods are **MO**, **GMO**, **AMSR**, **GMSR** and **MSR**. All these are newly proposed techniques.

4.3. Summary of Results with $\hat{K}_{AKS_i} = \frac{\hat{\sigma}^2 \lambda_i}{(n-p)\hat{\sigma}^2 + \lambda_i \hat{\alpha}_i^2}$. The relative efficiency of the ridge parameter based on \hat{K}_{AKS_i} of Alkhamisi *et al.* (2006) at different forms and various types when $n=40$ is given in Appendix 3. The details are contained in the work of Lukman (2015). The frequency of the relative efficiency over the levels of multicollinearity and error variance is summarized in Table 7.

From Table 7, the preferred techniques are FMO, **FMSR**, **HMSR**, **MSR** and **GMSR**. It is also noted that four of the newly proposed techniques, **FMSR**, **HMSR**, **MSR** and **GMSR**, are among the best five at each number of regressors.

4.4. Summary of Results with $\hat{K}_{MAO_i} = \frac{Max(\lambda_i)\sigma^2}{(n-p)\sigma^2 + Max(\lambda_i)\alpha_i^2}$. The relative efficiency of the ridge parameter based on \hat{K}_{MAO_i} of Muniz *et al.* (2012) at different forms and various types when $n = 50$ is given in Appendix 4. The details are contained in the work of Lukman (2015). The frequency of the relative efficiency over the levels of multicollinearity and error variance is summarized in Table 8.

From Table 8, the results of $p = 3$ and $p = 7$, it can be concluded that the best methods are VMO, FMO, **FMSR**, **VMSR**, **AMSR**, **AMO**, **MSR** and **GMSR**. Among these, two are newly proposed.

Table 5: Frequency of the relative efficiency of ridge parameters based on $\hat{K}_{HK_i} = \frac{\sigma^2}{\alpha_i^2}$ estimator with Multicollinearity (5 Levels) and Error Variances (3 levels) effect partial out

Different Forms	Various Types	methods	p=3						p=7							
			n					Total	Rank	n					Total	Rank
			10	20	30	40	50			10	20	30	40	50		
Fixed Maximum	Original	FMO	15	15	15	13	13	71	3.5	15	12	15	13	13	68	1
	Reciprocal	FMR	5	2	6	7	4	24	18.5	0	4	6	7	4	21	15.5
	Square root	FMSR	14	14	15	13	12	68	5	7	10	13	13	13	56	3
	Reciprocal of Square root	FMR SR	9	8	10	8	5	40	12.5	0	5	9	8	6	28	10.5
Varying Maximum	Original	VMO	8	2	5	4	3	22	20	0	0	0	3	0	3	24
	Reciprocal	VMR	5	2	6	7	4	24	18.5	0	4	6	7	4	21	15.5
	Square root	VMSR	11	8	11	13	11	54	10	0	3	0	6	3	12	21
	Reciprocal of Square root	VMR SR	9	8	10	8	5	40	12.5	0	5	9	8	6	28	10.5
Arithmetic Mean	Original	AMO	11	6	9	8	8	42	11	0	1	0	4	0	5	23
	Reciprocal	AMR	2	0	2	2	2	8	24	1	1	1	4	1	8	22
	Square root	AMSR	11	11	11	13	11	57	9	0	6	4	11	10	31	9
	Reciprocal of Square root	AMR SR	8	5	7	4	4	28	17	2	3	6	4	3	18	17
Harmonic Mean	Original	HMO	15	15	15	15	15	75	1	10	10	15	15	15	65	2
	Reciprocal	HMR	4	0	4	4	2	14	22	0	2	6	4	1	13	20
	Square root	HMSR	13	12	13	15	13	66	6	4	9	12	14	13	52	4
	Reciprocal of Square root	HMR SR	10	5	8	5	6	34	16	0	6	6	7	4	23	14
Geometric Mean	Original	GMO	15	13	13	15	15	71	3.5	2	9	6	15	13	45	6
	Reciprocal	GMR	3	0	3	2	2	10	23	1	3	3	4	3	14	19
	Square root	GMSR	13	11	13	13	13	63	7	1	7	9	13	12	42	8
	Reciprocal of Square root	GMR SR	10	6	8	7	4	35	15	1	5	6	7	6	25	12.5
Median	Original	MO	15	14	13	15	15	72	2	2	9	8	15	13	47	5
	Reciprocal	MR	4	2	7	4	4	21	21	1	4	3	4	3	15	18
	Square root	MSR	13	11	12	13	11	60	8	1	7	9	13	13	43	7
	Reciprocal of Square root	MRSR	11	6	8	7	7	39	14	1	5	6	7	6	25	12.5

Table 6: Frequency of the relative efficiency of ridge parameters based on $\hat{K}_{LW_i} = \frac{\sigma^2}{\lambda_i \alpha_i^2}$ estimator with multicollinearity (5 levels) and error variances (3 levels) effect partial out

Different Forms	Various Types	methods	p=3						p=7							
			n					Total	Rank	n					Total	Rank
			10	20	30	40	50			10	20	30	40	50		
Fixed Maximum	Original	FMO	0	0	0	0	0	0	24	0	1	0	0	0	1	24
	Reciprocal	FMR	2	0	3	2	1	8	22	0	1	0	2	0	3	23
	Square root	FMSR	10	6	6	6	3	31	13	13	5	6	3	3	30	11
	Reciprocal of Square root	FMR SR	5	1	5	5	5	21	17	0	2	0	7	4	13	18
Varying Maximum	Original	VMO	11	7	9	6	6	39	11	0	1	0	5	0	6	21
	Reciprocal	VMR	3	0	4	2	1	10	21	0	1	0	3	0	4	22
	Square root	VMSR	11	9	11	13	10	54	1.5	0	6	4	12	9	31	10
	Reciprocal of Square root	VMR SR	6	3	6	6	5	26	15	0	3	3	7	5	18	16
Arithmetic Mean	Original	AMO	11	11	10	10	8	50	5	0	4	0	8	3	15	17
	Reciprocal	AMR	2	0	2	2	1	7	23	0	3	1	3	2	9	20
	Square root	AMSR	11	11	11	11	10	54	1.5	0	7	8	11	10	36	4
	Reciprocal of Square root	AMR SR	6	4	4	5	4	23	16	2	7	5	4	4	22	15
Harmonic Mean	Original	HMO	9	5	6	4	3	27	14	7	5	5	5	4	26	13
	Reciprocal	HMR	5	0	5	4	2	16	19	0	2	0	6	2	10	19
	Square root	HMSR	11	6	8	6	6	37	12	4	7	6	6	6	29	12
	Reciprocal of Square root	HMR SR	8	7	9	9	9	42	10	0	6	6	12	9	33	8
Geometric Mean	Original	GMO	13	9	11	8	7	48	7	2	8	8	11	10	39	2
	Reciprocal	GMR	5	0	5	4	3	17	18	0	8	7	9	8	32	9
	Square root	GMSR	12	11	11	8	7	49	6	1	8	8	10	9	36	4
	Reciprocal of Square root	GMR SR	9	8	11	10	8	46	8.5	1	8	8	10	8	35	6.5
Median	Original	MO	13	11	11	8	8	51	3.5	2	8	8	10	12	40	1
	Reciprocal	MR	4	0	5	4	2	15	20	0	7	5	7	6	25	14
	Square root	MSR	11	11	11	10	8	51	3.5	1	8	8	10	9	36	4
	Reciprocal of Square root	MRSR	9	8	11	10	8	46	8.5	1	8	8	10	8	35	6.5

Note: Proposed methods of ridge parameters are in bold form.

Table 7: Frequency of the relative efficiency of ridge parameters based on $\hat{K}_{AKSi} = \frac{\hat{\sigma} \lambda_i}{(n-p)\hat{\sigma}^2 + \lambda_i \hat{\alpha}_i^2}$ estimator with multicollinearity (5 levels) and error variances (3 levels) effect partial out

Different Forms	Various Types	methods	p=3						p=7							
			n					Total	Rank	n					Total	Rank
			10	20	30	40	50			10	20	30	40	50		
Fixed Maximum	Original	FMO	15	15	15	13	11	69	1	15	12	15	13	13	68	1
	Reciprocal	FMR	7	5	8	8	5	33	21	0	4	6	8	5	23	21
	Square root	FMSR	14	14	15	12	10	65	2	7	10	13	13	12	55	2
	Reciprocal of Square root	FMR SR	9	8	11	8	5	41	17	0	5	9	8	6	28	17
	Original	VMO	11	10	11	11	10	53	3.5	1	7	9	11	10	38	3.5
	Reciprocal of Square root	VMR	6	3	6	7	5	27	22	0	1	2	8	4	15	22
Varying Maximum	Square root	VMSR	11	11	11	10	10	53	3.5	1	7	9	11	9	37	3.5
	Reciprocal of Square root	VMR SR	9	5	9	11	9	43	15.5	0	5	6	11	9	31	15.5
	Original	AMO	13	9	11	7	5	45	13.5	3	9	10	7	7	36	13.5
	Reciprocal	AMR	9	8	11	10	8	46	11.5	0	5	7	11	10	33	11.5
	Square root	AMSR	11	11	13	8	7	50	7	2	8	12	8	7	37	7
	Reciprocal of Square root	AMR SR	11	9	11	8	10	49	9	1	6	9	11	10	37	9
Arithmetic Mean	Original	HMO	15	0	0	0	0	15	24	10	4	0	0	0	14	24
	Reciprocal	HMR	7	4	7	9	8	35	20	0	3	3	9	7	22	20
	Square root	HMSR	15	11	12	6	6	50	7	5	10	12	9	9	45	7
	Reciprocal of Square root	HMR SR	9	8	9	11	8	45	13.5	0	6	9	9	8	32	13.5
	Original	GMO	15	9	10	6	3	43	15.5	7	10	9	1	3	30	15.5
	Reciprocal	GMR	8	5	9	10	7	39	18.5	0	4	6	11	9	30	18.5
Geometric Mean	Square root	GMSR	13	11	11	9	6	50	7	2	9	13	9	9	42	7
	Reciprocal of Square root	GMR SR	9	8	11	10	8	46	11.5	0	6	9	11	9	35	11.5
	Original	MO	15	0	7	0	0	22	23	6	10	10	6	0	32	23
	Reciprocal	MR	7	5	9	9	9	39	18.5	0	4	6	9	9	28	18.5
	Square root	MSR	13	11	13	9	6	52	5	2	10	13	9	9	43	5
	Reciprocal of Square root	MR SR	9	8	11	11	8	47	10	0	6	9	11	9	35	10

Note: Proposed methods of ridge parameters are in bold form.

Table 8: Frequency of the relative efficiency of ridge parameters based on $\hat{K}_{MAOi} = \frac{Max(\lambda_i)\hat{\sigma}^2}{(n-p)\hat{\sigma}^2 + Max(\lambda_i)\hat{\alpha}_i^2}$ estimator with multicollinearity (5 levels) and error variances (3 levels) effect partial out

Different Forms	Various Types	methods	p=3						p=7							
			n					Total	Rank	n					Total	Rank
			10	20	30	40	50			10	20	30	40	50		
Fixed Maximum	Original	FMO	15	15	15	13	11	69	1.5	15	12	15	13	13	68	1.5
	Reciprocal	FMR	9	7	10	8	5	39	18	0	5	8	7	6	26	18.5
	Square root	FMSR	13	11	13	10	10	57	4	5	9	12	13	12	51	3.5
	Reciprocal of Square root	FMR SR	11	9	11	9	7	47	11	0	6	9	8	6	29	16
	Original	VMO	15	15	15	13	11	69	1.5	15	12	15	13	13	68	1.5
	Reciprocal of Square root	VMR	6	3	6	7	5	27	22	0	1	2	8	4	15	23
Varying Maximum	Square root	VMSR	13	11	13	10	10	57	4	5	9	12	13	12	51	3.5
	Reciprocal of Square root	VMR SR	9	5	9	11	9	43	16	0	5	6	11	9	31	13
	Original	AMO	15	10	13	9	7	54	6.5	10	10	12	7	7	46	7
	Reciprocal	AMR	8	8	9	11	8	44	14.5	0	4	6	11	9	30	15
	Square root	AMSR	13	12	13	10	9	57	4	5	10	13	10	10	48	5.5
	Reciprocal of Square root	AMR SR	9	8	11	8	8	44	14.5	0	5	9	11	10	35	10
Arithmetic Mean	Original	HMO	13	0	0	0	0	13	24	10	2	0	0	0	12	24
	Reciprocal	HMR	7	5	7	9	8	36	21	0	3	3	9	7	22	22
	Square root	HMSR	15	11	12	6	6	50	9	6	10	12	6	9	43	9
	Reciprocal of Square root	HMR SR	9	8	9	11	8	45	13	0	5	6	11	9	31	13
	Original	GMO	15	9	9	4	1	38	20	10	8	6	0	0	24	20.5
	Reciprocal	GMR	7	5	9	9	9	39	18	0	3	5	9	7	24	20.5
Geometric Mean	Square root	GMSR	14	11	13	9	6	55	8	5	10	12	9	9	45	8
	Reciprocal of Square root	GMR SR	9	8	11	11	8	47	11	0	5	6	11	9	31	13
	Original	MO	15	0	6	0	0	21	23	10	8	9	0	0	27	17
	Reciprocal	MR	7	5	9	9	9	39	18	0	4	6	9	7	26	18.5
	Square root	MSR	15	11	13	9	6	54	6.5	5	10	15	9	9	48	5.5
	Reciprocal of Square root	MR SR	9	8	11	11	8	47	11	0	5	8	11	9	33	11

Note: Proposed methods of ridge parameters are in bold form.

5. Summary and concluding remarks

Table 9 presents the summary of the five best ridge parameters estimation techniques having obtained their relative efficiency, counting the relative efficiency ($RE \leq 0.75$) over the five (5) levels of multicollinearity, three (3) levels of error variances and the five (5) levels of sample sizes. Thus, a maximum of seventy five (75) counts is expected.

Table 9: Summary of best ridge parameters

Ridge parameter	p=3			p=7		
	Best Method	Frequency	Best	Best Method	Frequency	Best
K_{HK}	HMO	75	HMO	HMO	65	FMO
	MO	72		MO	47	
	FMO	71		FMO	68	
	GMO	71		GMO	45	
	FMSR	68		FMSR	56	
	HMSR	66		HMSR	52	
K_{LW}	MO	51	MSR	MO	40	MO
	GMO	48		GMO	39	
	AMSR	54		AMSR	36	
	GMSR	49		GMSR	36	
	MSR	51		MSR	36	
	VMO	69		VMO/FMO	VMO	
FMO	69	FMO	68			
FMSR	57	FMSR	51			
VMSR	57	VMSR	51			
AMSR	57	AMSR	48			
AMO	54	AMO	46			
K_{LS}	MSR	54	FMO	MSR	48	FMO
	GMSR	53		GMSR	45	
	FMO	69		FMO	68	
	FMSR	65		FMSR	55	
	HMSR	50		HMSR	45	
	MSR	52		MSR	43	
K_{ALK}	GMSR	50	FMO	GMSR	42	FMO

Source: Table 5, 6, 7 and 8

From Table 9, the best estimators of the ridge parameter techniques are of the different forms and various types. These are generally Fixed Maximum Original, Varying Maximum Original, Harmonic Mean Original, Geometric Mean Original and Arithmetic Mean Square root. The best ridge parameter techniques consist of both the existing ones and newly proposed. The proposed techniques also perform better than the existing ones in some cases. Moreover, with \hat{K}_{LW_i} , the existing Harmonic Mean version is not even among the best five.

The conclusions of this paper are restricted to the simulation study that has been conducted in this paper. To make a definite statement, one might need more data from different kind of populations. However, the findings of this paper can be generalized for a great population with high confidence.

References

- [1] Alkhamisi, M., Khalaf, G. and Shukur, G. (2006). Some modifications for choosing ridge parameters. Communications in Statistics- Theory and Methods, 35(11), 2005-2020.
- [2] Gibbons, D. G. (1981). A simulation study of some ridge estimators. Journal of the American Statistical Association, 76, 131-139.
- [3] Gujarati, D.N.(1995). Basic Econometrics, McGraw-Hill, New York.
- [4] Hoerl, A.E. and Kennard, R.W. (1970). Ridge regression: biased estimation for non-orthogonal problems. Technometrics, 12, 55-67.
- [5] Hoerl, A. E., Kennard, R. W. and Baldwin, K. F. (1975). Ridge regression: Some simulation. Communications in Statistics 4 (2), 105-123.
- [6] Khalaf, G. and Shukur, G. (2005). Choosing ridge parameters for regression problems. Communications in Statistics- Theory and Methods, 34, 1177-1182.
- [7] Kibria, B. M. G. (2003). Performance of some new ridge regression estimators. Communications in Statistics-Simulation and Computation, 32, 419-435.
- [8] Lawless, J. F. and Wang, P. (1976). A simulation study of ridge and other regression estimators. Communications in Statistics A, 5, 307-323.

- [8] Lukman, A. F (2015): Review and classification of the Ridge Parameter Estimation Techniques. Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria. Unpublished P.hD. Thesis.
- [9] Mansson, K., Shukur, G. and Kibria, B. M. G. (2010). A simulation study of some ridge regression estimators under different distributional assumptions. *Communications in Statistics-Simulations and Computations*, 39(8), 1639 –1670.
- [10] Mardikyan, S. and Cetin, E. (2008). Efficient Choice of Biasing Constant for Ridge Regression, *Int.J. Contemp.Math.Sciences*, 3, 527-547.
- [11] McDonald, G. C. and Galarneau, D. I. (1975). A Monte Carlo evaluation of some ridge-type estimators. *Journal of the American Statistical Association*, 70, 407-416.
- [12] Muniz, G. and Kibria, B. M. G. (2009). On some ridge regression estimators: An empirical comparison. *Communications in Statistics-Simulation and Computation*, 38, 621-630.
- [13] Muniz, G., Kibria, B.M.G., Mansson, K., Shukur, G. (2012). On Developing Ridge Regression Parameters: A Graphical Investigation. *SORT*. 36(2), 115-138.
- [14] Saleh, A. K. Md. E. and Kibria, B. M. G. (1993). Performances of some new preliminary test ridge regression estimators and their properties. *Communications in Statistics-Theory and Methods*, 22, 2747-2764.
- [15] Vinod, D. and Ullah, A. (1981). *Recent Advances in Regression Methods*, Marcel Dekker Inc. Publication.
- [16] Wichern, D. and Churchill, G. (1978). A Comparison of Ridge Estimators. *Technometrics*, 20, 301–311.

Appendix 1: MSE of OLS and Relative efficiency of the ridge parameter based on \hat{K}_{HK}

Method	n=10 p=1															
	$\sigma = 0.5$				$\sigma = 1$				$\sigma = 5$				$\sigma = 9.99$			
	0.8	0.9	0.95	0.99	0.8	0.9	0.95	0.99	0.8	0.9	0.95	0.99	0.8	0.9	0.95	0.99
MSE OLS	0.30	1.008	1.889	22.614	219.116	0.983	2.043	4.215	28.252	206.132	1.034	2.292	11.201	11.708	119.24	
FMO	0.520	0.488	0.401	0.580	0.374	0.512	0.433	0.397	0.376	0.320	0.475	0.431	0.405	0.323	0.334	
FMR	0.771	0.840	0.935	1.003	0.998	0.729	0.831	0.915	0.974	0.966	0.799	0.705	0.724	0.708	0.667	
FMSR	0.534	0.447	0.428	0.388	0.364	0.374	0.443	0.434	0.529	0.744	0.508	0.444	0.422	0.463	0.537	
FMRSR	0.662	0.692	0.811	0.875	0.896	0.664	0.657	0.793	0.947	0.964	0.632	0.605	0.622	0.691	0.666	
VMO	0.866	0.782	0.720	0.678	0.580	0.846	0.722	0.721	0.830	0.849	0.815	0.729	0.695	0.678	0.663	
VMR	0.771	0.840	0.935	1.003	0.998	0.729	0.831	0.915	0.974	0.966	0.799	0.705	0.724	0.708	0.667	
VMRSR	0.587	0.398	0.671	0.880	0.982	0.371	0.390	0.663	0.830	0.931	0.615	0.621	0.637	0.667	0.662	
AMO	0.662	0.692	0.811	0.875	0.896	0.664	0.657	0.793	0.947	0.964	0.632	0.605	0.622	0.691	0.666	
AMR	0.703	0.614	0.617	0.570	0.532	0.652	0.605	0.625	0.780	0.735	0.725	0.664	0.643	0.646	0.656	
HMO	0.897	0.847	0.834	0.921	0.988	0.896	0.840	0.922	0.898	0.957	0.933	0.859	0.776	0.703	0.676	
HMR	0.537	0.342	0.607	0.830	0.972	0.322	0.393	0.600	0.811	0.942	0.569	0.578	0.601	0.649	0.639	
HMSR	0.791	0.706	0.711	0.657	0.585	0.789	0.704	0.763	0.864	0.934	0.832	0.716	0.637	0.626	0.630	
GMO	0.443	0.407	0.397	0.397	0.389	0.439	0.404	0.394	0.394	0.395	0.435	0.432	0.416	0.392	0.375	
GMR	0.803	0.809	0.889	0.993	0.997	0.805	0.804	0.872	0.964	0.965	0.804	0.707	0.696	0.704	0.667	
GMRSR	0.490	0.445	0.468	0.627	0.832	0.489	0.442	0.464	0.636	0.809	0.479	0.448	0.456	0.519	0.592	
MO	0.659	0.669	0.764	0.901	0.995	0.691	0.663	0.790	0.933	0.963	0.695	0.602	0.612	0.681	0.666	
MR	0.497	0.476	0.493	0.503	0.506	0.459	0.472	0.493	0.488	0.521	0.539	0.509	0.506	0.526	0.584	
MSR	0.558	0.517	0.445	0.468	0.396	0.537	0.512	0.534	0.640	0.964	0.889	0.788	0.705	0.671	0.665	
MRSR	0.470	0.474	0.566	0.748	0.927	0.467	0.471	0.531	0.793	0.899	0.496	0.506	0.556	0.604	0.641	
MRSR	0.740	0.675	0.724	0.832	0.893	0.708	0.670	0.715	0.905	0.961	0.705	0.644	0.600	0.647	0.663	
AMR	0.453	0.459	0.531	0.628	0.667	0.451	0.458	0.514	0.614	0.651	0.549	0.501	0.508	0.569	0.615	
AMRSR	0.829	0.857	0.871	0.881	0.881	0.970	1.003	1.021	1.033	1.035	0.965	0.958	0.974	0.944	0.939	
HMR	0.537	0.342	0.607	0.830	0.972	0.322	0.393	0.600	0.811	0.942	0.569	0.578	0.601	0.649	0.639	
HMSR	0.791	0.706	0.711	0.657	0.585	0.789	0.704	0.763	0.864	0.934	0.832	0.716	0.637	0.626	0.630	
GMR	0.803	0.809	0.889	0.993	0.997	0.805	0.804	0.872	0.964	0.965	0.804	0.707	0.696	0.704	0.667	
GMRSR	0.490	0.445	0.468	0.627	0.832	0.489	0.442	0.464	0.636	0.809	0.479	0.448	0.456	0.519	0.592	
MO	0.659	0.669	0.764	0.901	0.995	0.691	0.663	0.790	0.933	0.963	0.695	0.602	0.612	0.681	0.666	
MR	0.497	0.476	0.493	0.503	0.506	0.459	0.472	0.493	0.488	0.521	0.539	0.509	0.506	0.526	0.584	
MSR	0.558	0.517	0.445	0.468	0.396	0.537	0.512	0.534	0.640	0.964	0.889	0.788	0.705	0.671	0.665	
MRSR	0.470	0.474	0.566	0.748	0.927	0.467	0.471	0.531	0.793	0.899	0.496	0.506	0.556	0.604	0.641	
MRSR	0.740	0.675	0.724	0.832	0.893	0.708	0.670	0.715	0.905	0.961	0.705	0.644	0.600	0.647	0.663	

Appendix 2: MSE of OLS and Relative efficiency of the ridge parameter based on \hat{K}_{LW}

Method	n=10 p=1															
	$\sigma = 0.5$				$\sigma = 1$				$\sigma = 5$				$\sigma = 9.99$			
	0.8	0.9	0.95	0.99	0.8	0.9	0.95	0.99	0.8	0.9	0.95	0.99	0.8	0.9	0.95	0.99
MSE OLS	0.30	1.008	1.889	22.614	219.116	0.983	2.043	4.215	28.252	206.132	1.034	2.292	11.201	11.708	119.24	
FMO	0.520	0.488	0.401	0.580	0.374	0.512	0.433	0.397	0.376	0.320	0.475	0.431	0.405	0.323	0.334	
FMR	0.771	0.840	0.935	1.003	0.998	0.729	0.831	0.915	0.974	0.966	0.799	0.705	0.724	0.708	0.667	
FMSR	0.534	0.447	0.428	0.388	0.364	0.374	0.443	0.434	0.529	0.744	0.508	0.444	0.422	0.463	0.537	
FMRSR	0.662	0.692	0.811	0.875	0.896	0.664	0.657	0.793	0.947	0.964	0.632	0.605	0.622	0.691	0.666	
VMO	0.866	0.782	0.720	0.678	0.580	0.846	0.722	0.721	0.830	0.849	0.815	0.729	0.695	0.678	0.663	
VMR	0.771	0.840	0.935	1.003	0.998	0.729	0.831	0.915	0.974	0.966	0.799	0.705	0.724	0.708	0.667	
VMRSR	0.587	0.398	0.671	0.880	0.982	0.371	0.390	0.663	0.830	0.931	0.615	0.621	0.637	0.667	0.662	
AMO	0.662	0.692	0.811	0.875	0.896	0.664	0.657	0.793	0.947	0.964	0.632	0.605	0.622	0.691	0.666	
AMR	0.703	0.614	0.617	0.570	0.532	0.652	0.605	0.625	0.780	0.735	0.725	0.664	0.643	0.646	0.656	
HMO	0.897	0.847	0.834	0.921	0.988	0.896	0.840	0.922	0.898	0.957	0.933	0.859	0.776	0.703	0.676	
HMR	0.537	0.342	0.607	0.830	0.972	0.322	0.393	0.600	0.811	0.942	0.569	0.578	0.601	0.649	0.639	
HMSR	0.791	0.706	0.711	0.657	0.585	0.789	0.704	0.763	0.864	0.934	0.832	0.716	0.637	0.626	0.630	
GMO	0.443	0.407	0.397	0.397	0.389	0.439	0.404	0.394	0.394	0.395	0.435	0.432	0.416	0.392	0.375	
GMR	0.803	0.809	0.889	0.993	0.997	0.805	0.804	0.872	0.964	0.965	0.804	0.707	0.696	0.704	0.667	
GMRSR	0.490	0.445	0.468	0.627	0.832	0.489	0.442	0.464	0.636	0.809	0.479	0.448	0.456	0.519	0.592	
MO	0.659	0.669	0.764	0.901	0.995	0.691	0.663	0.790	0.933	0.963	0.695	0.602	0.612	0.681	0.666	
MR	0.497	0.476	0.493	0.503	0.506	0.459	0.472	0.493	0.488	0.521	0.539	0.509	0.506	0.526	0.584	
MSR	0.558	0.517	0.445	0.468	0.396	0.537	0.512	0.534	0.640	0.964	0.889	0.788	0.705	0.671	0.665	
MRSR	0.470	0.474	0.566	0.748	0.927	0.467	0.471	0.531	0.793	0.899	0.496	0.506	0.556	0.604	0.641	
MRSR	0.740	0.675	0.724	0.832	0.893	0.708	0.670	0.715	0.905	0.961	0.705	0.644	0.600	0.647	0.663	
AMR	0.453	0.459	0.531	0.628	0.667	0.451	0.458	0.514	0.614	0.651	0.549	0.501	0.508	0.569	0.615	
AMRSR	0.829	0.857	0.871	0.881	0.881	0.970	1.003	1.021	1.033	1.035	0.965	0.958	0.974	0.944	0.939	
HMR	0.537	0.342	0.607	0.830	0.972	0.322	0.393	0.600	0.811	0.942	0.569	0.578	0.601	0.649	0.639	
HMSR	0.791	0.706	0.711	0.657	0.585	0.789	0.704	0.763	0.864	0.934	0.832	0.716	0.637	0.626	0.630	
GMR	0.803	0.809	0.889	0.993	0.997	0.805	0.804	0.872	0.964	0.965	0.804	0.707	0.696	0.704	0.667	
GMRSR	0.490	0.445	0.468	0.627	0.832	0.489	0.442	0.464	0.636	0.809	0.479	0.448	0.456	0.519	0.592	
MO	0.659	0.669	0.764	0.901	0.995	0.691	0.663	0.790	0.933	0.963	0.695	0.602	0.612	0.681	0.666	
MR	0.497	0.476	0.493	0.503	0.506	0.459	0.472	0.493	0.488	0.521	0.539	0.509	0.506	0.526	0.584	
MSR	0.558	0.517	0.445	0.468	0.396	0.537	0.512	0.534	0.640	0.964	0.889	0.788	0.705	0.671	0.665	
MRSR	0.470	0.474	0.566	0.748	0.927	0.467	0.471	0.531	0.793	0.899	0.496	0.506	0.556	0.604	0.641	
MRSR	0.740	0.675	0.724	0.832	0.893	0.708	0.670	0.715	0.905	0.961	0.705	0.644	0.600	0.647	0.663	

Note: Proposed techniques are bolded.

Appendix 3: MSE of OLS and Relative efficiency of the ridge parameter based on \hat{K}_{AKS}

Method	n=40 p=3														
	$\sigma = 0.5$				$\sigma = 1$				$\sigma = 5$						
	0.5	0.9	0.95	0.99	0.9	0.95	0.99	0.999	0.3	0.5	0.95	0.99			
MSE OLS	0.100	0.420	0.891	4.870	12.452	0.215	0.488	0.809	4.908	13.206	0.232	0.716	1.686	8.122	87.482
FMO	0.818	0.695	0.721	0.830	0.807	0.816	0.689	0.677	0.457	0.494	0.766	0.988	0.462	0.324	0.212
FMR	0.817	0.712	0.691	0.960	1.031	0.818	0.689	0.684	0.942	1.013	0.857	0.744	0.624	0.598	0.643
FMSR	0.818	0.693	0.565	0.465	0.856	0.817	0.690	0.662	0.461	0.647	0.781	0.635	0.488	0.347	0.433
FMRSR	0.817	0.690	0.620	0.835	1.022	0.818	0.691	0.610	0.839	1.004	0.836	0.709	0.509	0.356	0.636
VMO	0.817	0.691	0.575	0.648	0.957	0.815	0.691	0.571	0.640	0.940	0.742	0.588	0.455	0.448	0.606
VMR	0.646	0.852	1.089	1.104	1.045	0.641	0.817	1.069	1.084	1.026	0.544	0.555	0.678	0.688	0.652
VMSR	0.818	0.692	0.575	0.656	0.961	0.817	0.690	0.572	0.647	0.941	0.729	0.630	0.485	0.442	0.603
VMSRS	0.894	0.389	0.712	1.006	1.001	0.693	0.863	0.901	0.897	1.013	0.685	0.480	0.470	0.626	0.644
AMO	0.891	0.822	0.718	0.934	0.847	0.800	0.820	0.726	0.929	0.934	0.856	0.781	0.920	0.400	0.588
AMR	0.727	0.601	0.607	0.863	1.009	0.727	0.508	0.508	0.846	0.991	0.755	0.591	0.482	0.320	0.824
AMSR	0.858	0.761	0.639	0.576	0.917	0.857	0.759	0.637	0.569	0.901	0.635	0.719	0.572	0.409	0.579
AMRSR	0.778	0.633	0.563	0.720	0.992	0.773	0.632	0.558	0.755	0.974	0.784	0.628	0.400	0.480	0.615
HMO	0.920	0.921	0.915	0.909	0.905	0.920	0.915	0.908	0.905	0.925	0.912	0.912	0.912	0.907	0.904
HMR	0.666	0.662	0.925	1.072	1.042	0.664	0.652	0.908	1.052	1.024	0.630	0.478	0.580	0.666	0.651
HMSR	0.884	0.831	0.767	0.611	0.545	0.883	0.830	0.877	0.610	0.558	0.879	0.824	0.757	0.576	0.416
HMSRS	0.757	0.589	0.634	0.975	1.030	0.756	0.585	0.625	0.588	1.011	0.724	0.518	0.445	0.607	0.643
GMO	0.913	0.883	0.849	0.724	0.810	0.912	0.883	0.848	0.725	0.888	0.889	0.868	0.746	0.710	0.849
GMR	0.663	0.663	0.785	1.029	1.034	0.662	0.506	0.591	1.010	1.015	0.689	0.494	0.491	0.635	0.645
GMSR	0.872	0.800	0.712	0.544	0.677	0.871	0.799	0.710	0.541	0.666	0.860	0.782	0.682	0.459	0.444
GMSRS	0.754	0.604	0.567	0.911	1.021	0.754	0.602	0.579	0.894	1.006	0.733	0.502	0.445	0.365	0.639
MO	0.917	0.902	0.890	0.871	0.858	0.916	0.902	0.890	0.871	0.928	0.912	0.898	0.875	0.868	0.855
MR	0.687	0.628	0.856	1.050	1.040	0.685	0.615	0.840	1.040	1.022	0.559	0.474	0.543	0.660	0.649
MSR	0.875	0.815	0.744	0.586	0.569	0.874	0.814	0.743	0.584	0.861	0.869	0.807	0.731	0.539	0.413
MRSR	0.790	0.595	0.609	0.957	1.020	0.790	0.592	0.600	0.940	1.011	0.709	0.584	0.440	0.396	0.642

Method	n=40 p=3														
	$\sigma = 0.5$				$\sigma = 1$				$\sigma = 5$						
	0.5	0.9	0.95	0.99	0.9	0.95	0.99	0.999	0.3	0.5	0.95	0.99			
MSE OLS	0.612	1.225	2.508	13.382	141.632	0.625	1.232	2.502	13.668	144.689	1.047	2.098	4.294	22.908	242.400
FMO	0.793	0.684	0.680	0.542	0.300	0.790	0.680	0.505	0.538	0.527	0.690	0.667	0.492	0.443	0.431
FMR	0.813	0.707	0.675	0.939	1.021	0.815	0.707	0.669	0.923	1.005	0.867	0.752	0.608	0.608	0.683
FMSR	0.810	0.684	0.591	0.406	0.641	0.788	0.681	0.478	0.502	0.632	0.748	0.614	0.507	0.394	0.418
FMRSR	0.809	0.693	0.618	0.835	1.012	0.810	0.693	0.615	0.820	0.996	0.817	0.711	0.562	0.441	0.676
VMO	0.791	0.671	0.572	0.655	0.948	0.788	0.667	0.568	0.647	0.934	0.685	0.542	0.440	0.478	0.646
VMR	0.580	0.753	0.963	1.039	1.026	0.575	0.743	0.950	1.023	1.010	0.484	0.510	0.645	0.700	0.687
VMSR	0.798	0.678	0.572	0.655	0.849	0.797	0.676	0.565	0.645	0.904	0.600	0.474	0.406	0.410	0.609
VMSRS	0.657	0.684	0.624	0.977	1.020	0.655	0.559	0.671	0.962	1.004	0.627	0.457	0.467	0.654	0.684
AMO	0.895	0.856	0.791	0.985	0.720	0.895	0.854	0.789	0.981	0.719	0.869	0.807	0.711	0.455	0.514
AMR	0.684	0.569	0.640	0.913	1.010	0.684	0.565	0.630	0.897	0.993	0.706	0.630	0.468	0.377	0.669
AMSR	0.855	0.738	0.628	0.362	0.860	0.855	0.737	0.676	0.536	0.846	0.837	0.741	0.514	0.420	0.582
AMRSR	0.706	0.604	0.503	0.800	1.000	0.706	0.603	0.500	0.785	0.978	0.734	0.588	0.472	0.310	0.656
HMO	0.926	0.920	0.915	0.906	0.900	0.926	0.920	0.915	0.906	0.900	0.924	0.918	0.913	0.904	0.897
HMR	0.627	0.602	0.825	1.024	1.025	0.625	0.504	0.512	1.007	1.008	0.591	0.445	0.549	0.689	0.686
HMSR	0.827	0.827	0.787	0.627	0.371	0.827	0.827	0.787	0.625	0.825	0.829	0.821	0.796	0.387	0.441
HMSRS	0.781	0.617	0.528	0.821	1.000	0.781	0.615	0.553	0.825	0.990	0.741	0.572	0.451	0.345	0.679
GMO	0.913	0.897	0.879	0.836	0.775	0.912	0.896	0.879	0.835	0.774	0.904	0.887	0.868	0.820	0.752
GMR	0.659	0.575	0.753	1.010	1.023	0.652	0.569	0.520	0.994	1.006	0.638	0.455	0.500	0.677	0.685
GMSR	0.867	0.807	0.753	0.839	0.810	0.867	0.807	0.754	0.586	0.862	0.839	0.794	0.713	0.323	0.433
GMSRS	0.720	0.603	0.503	0.810	1.017	0.720	0.603	0.500	0.793	1.000	0.722	0.581	0.488	0.312	0.601
MO	0.909	0.901	0.892	0.875	0.861	0.909	0.901	0.892	0.875	0.861	0.907	0.898	0.889	0.871	0.857
MR	0.658	0.576	0.775	1.018	1.024	0.657	0.569	0.533	1.001	1.007	0.631	0.446	0.518	0.684	0.686
MSR	0.863	0.811	0.746	0.607	0.383	0.864	0.810	0.745	0.602	0.578	0.891	0.804	0.732	0.558	0.435
MRSR	0.792	0.580	0.591	0.926	1.015	0.792	0.577	0.583	0.911	1.002	0.719	0.520	0.435	0.316	0.692

Appendix 4: MSE of OLS and Relative efficiency of the ridge parameter based on \hat{K}_{MAO}

Method	n=10 p=3														
	$\sigma = 0.5$				$\sigma = 1$				$\sigma = 5$						
	0.5	0.9	0.95	0.99	0.9	0.95	0.99	0.999	0.3	0.5	0.95	0.99			
MSE OLS	0.115	0.393	0.686	3.711	30.740	0.163	0.313	0.606	3.863	40.332	0.263	1.035	1.604	6.089	
FMO	0.800	0.756	0.630	0.445	0.410	0.809	0.753	0.627	0.443	0.403	0.810	0.690	0.541	0.365	0.315
FMR	0.868	0.771	0.711	0.938	1.031	0.869	0.772	0.709	0.939	1.037	0.895	0.804	0.696	0.667	0.718
FMSR	0.863	0.756	0.625	0.434	0.617	0.862	0.755	0.623	0.451	0.611	0.838	0.714	0.567	0.369	0.455
FMRSR	0.867	0.762	0.632	0.452	0.603	0.867	0.762	0.636	0.431	0.614	0.800	0.727	0.613	0.461	0.508
VMO	0.767	0.591	0.543	0.626	0.965	0.766	0.588	0.539	0.669	0.952	0.667	0.526	0.447	0.300	0.470
VMR	0.868	0.771	0.711	0.938	1.031	0.869	0.772	0.709	0.939	1.037	0.895	0.804	0.696	0.667	0.718
VMSR	0.788	0.660	0.557	0.643	0.863	0.788	0.659	0.555	0.636	0.952	0.722	0.628	0.497	0.474	0.665
VMSRS	0.857	0.782	0.658	0.422	0.608	0.857	0.782	0.636	0.411	0.824	0.800	0.727	0.643	0.381	0.209
AMO	0.792	0.690	0.529	0.560	0.867	0.791	0.628	0.527	0.555	0.857	0.729	0.579	0.453	0.400	0.614
AMR	0.629	0.538	0.749	0.710	1.005	0.629	0.539	0.749	0.701	0.990	0.937	0.872	0.757	0.539	0.681
AMSR	0.818	0.694	0.573	0.583	0.920	0.817	0.693	0.571	0.577	0.911	0.799	0.661	0.519	0.440	0.640
AMRSR	0.691														

