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Adaptable Ridge Regression Estimation for Sure Model

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Abstract

Binkley(1982) described the possible loss in efficiency of the best linear unbiased estimator (BLUE) of parametric vector due to the presence of Multicollinearity among the explanatory variables in the different linear regression equations of SURE model. When there is linear dependence among the variables across the equations , gain in efficiency can still be made through the use of Generalized least squares (GLS). In the context of system of SUR equations , analyzing Multicollinearity will adversely affect the GLS estimator . Ridge Regression Estimation may be used in this case. In the present study, an adaptable Ridge Regression Estimation technique has been proposed for the SURE model under the problem of Multicollinearity. A procedure has been suggested for the selection of Ridge parameter to obtain adaptable Ridge Regression Estimator.

Keywords: Multicollinearity, Best linear unbiased estimator, Ridge Regression Estimator

1. Introduction

Binkley(1982) described the possible loss in efficiency of the best linear unbiased estimator of parametric vector due to the presence of Multicollinearity among the explanatory variables in the different linear regression equation of SURE model. When there is linear dependence among variables across equations ,gains in efficiency can still be made through the use of GLS when there is multicollinearity among the variables within an equation. In the context of system of SURE equations , analyzing Multicollinearity is much more complex than that in the classical linear regression model. However, the problem of Multicollinearity will adversely effect the GLS estimator. In this case, Ridge Regression estimation may be used. Ridge regression estimation is an Shrinkage estimator, is developed originally to overcome the problem of Multicollinearity in the linear regression model.

B.H . Baltagi(1988) developed the efficiency of the OLS of SUR models and M.A. Alkhamisi and G.Shukur(2007), studied about the Ridge parameters of the SUR model . Vuctres and Lvis Firinguetti(1997) has given an approach for Ridge Regression in the context of a system of SUR equations. Some Asymptotic Properties were developed for Ridge Regression in a System of SUR Equations by L. Firinguetti and H. Rubio(2008). T.F.Ma and S.G. Wang (2009), improved estimates of regression coefficients in seemingly unrelated regression model with two equations. Moawad EI- Fellah Abd El- Salam(2011), given some efficient Alternative Ridge etimators for Seemingly Unrelated Regressions.

2. Adaptable Ridge Regression Estimation for SURE model

Consider a SUR(Seemingly Unrelated Regression) model for m system of equations as

$$Y = X\,\beta + \epsilon$$

Where Y_i is (n x 1); X_i is (n X k_i); β_i is (k_i X 1) and ϵ_i is (n X 1) matrices for i th equation for regression.

And it is also assumed that

E(Є)=0, E(Є $\epsilon^{'}$)=Ω=∑ΘI_n , where ∑ ={ $\begin{matrix} \sigma_{11} & \cdots & \sigma_{1M} \\ \cdot & \cdots & \cdot \\ \sigma_{M1} & \cdots & \sigma_{MM} \end{matrix}$ }

Under the assumption that X is of full rank , The GLS estimator of β is given by

$\beta^{\sim}$ = {X'[$\sum^{-1}$ ΘI_n] X} X'[$\sum^{-1}$ ΘI_n]Y and also Var($\beta^{\sim}$)= {X'[∑^(-1) ΘI_n] X}^(-1)

When ∑ is known, $\beta^{\sim}$ gives the BLUE for β.

In practice ∑ is unknown, an unrestricted estimator of ∑ is given by

$\sum^{\sim}$ = S = ((S_{ij})) , where S_{ij} = $\frac{Y_i^{'}[I-Z(Z^{'}Z)^{\wedge}(-1)Z^{'}]Y_j}{n-p}$ = $\frac{\sum_{t=1}^{n} e_{ti}e_{tj}}{n-p}$

Here e_{ti} = the OLS residuals.

Where Z is the (n x p) matrix of n observation on all the p distinct independent variables in the model.

By defining internally studentized residuals e_{ti}^{*} 's ,an operational GLS estimator for β based on e_{ti}^{*} 's is given by

$\beta^{\sim *}$ = [X′(S^{*-1}ΘI)x $]^{-1}$x'[$S^{*-1}\theta$I]y ,where $\sum^{\sim}$= S = ((S_{ij}^{*}))

Here , S_{ij}^{*} = $\frac{\sum_{t=1}^{n} e_{ti}^{*} e_{tj}^{*}}{n-p}$

Since the presence of Multicollinearity poses a problem in SURE model , it may be useful to consider alternative estimation methods such as ridge regression estimation.

The operational ridge regression estimator for β based on internally studentized residuals is given by

$\beta_{RR}^{\sim *}$ = [X′(S^{*-1}ΘI)x + c$I_n]^{-1}$x'(S^{*-1}ΘI)y

Where C>0 is ridge regression parameter which is a constant when C=0 ,$\beta_{RR}^{\sim *}$ given $\beta^{\sim *}$.

3. SELECTION OF RIDGE PARAMETER C

The major problem with the ridge regression estimation lies in selecting a non-arbitrary, unique value of Ridge parameter C ,proper choice of C can lead to operational ridge regression estimator for β.

Generally, there always exists a C that yields a smaller mean square error (MSE) than that to be obtained by OLS estimation or GLS estimation above.

Here, C should be chosen in the interval, $0 < C < \frac{\sigma\pi}{\beta\beta}$.

Since the upper boundary of this interval is a function of unknown parameters., this result has limited practical value. The primary drawback of Ridge regression estimator is the selection of Ridge parameter C.

In the present study, Ridge parameter C may be chosen as

$$C^* = \frac{\sum_{i=1}^{n} k_i S_{11}^*}{\beta^{\sim *}\beta^{\sim *1}}$$

Thus, the operational adaptable Ridge Regression Estimator for β is given by

$$\beta_{RR}^{\sim *} = [\, X'(S^{*-1}\Theta I)x + C^* I]^{-1} x'(S^{*-1}\Theta I)y$$

The asymptotic properties of $\beta_{RR}^{\sim *}$ can be studied similar to that of the estimator given by Firinguetti and Rubio(2008).

4. Conclusions

The literature on inferential methods for SURE models has grown enormously in the fast three decades. In the present research study, an attempt has been made by developing some new inferential techniques for SURE model under the presence of problem of Multicollinearity.

An adaptable ridge regression estimation technique has been proposed for the SURE model under the problem of Multicollinearity.A procedure has been explained for the selection of Ridge parameter to obtain adaptable Ridge regression estimator.

References

[1] M.A. Alkhamisi and G. Shukur, Developing Ridge parameters for SUR model, electronic working paper series (2007), paper no. 80 , pp.1-27.

[2] B.H. Baltagi, The efficiency of OLS in a seemingly unrelated regression model, Econometric theory (1988),No.4, pp536-537.

[3] J.K. Binkley, The effect of Variable correlation on the efficiency of Seemingly Unrelated Regression in a Two equation Model, JASA (1982), Vol.77, pp890-895.

[4] T.F. Ma and S.G. Wang, The improved estimates of regression coefficients in seemingly unrelated regression model with two equations, China Journal of Applied Probability and Statistics(2009),Vol.25, pp.619-631.

[5] Moawad EI- Fellah Abd EI- Salam, The Efficiency of Some Alternative Ridge Estimators for Seemingly Unrelated Regressions, Asian Journal of Mathematics and Statistics (2011), 4(3):pp128-139.

[6] Vuctres and Lvis Firinguetti, Ridge Regression in the context of a system of seemingly unrelated regression equations, Journal of statistical computation and simulation (1997),Vol.56,pp145-162.

[7] L. Firinguetti and H. Rubio, Some Asymptotic Properties of Ridge Regression in a System of Seemingly Unrelated Regression Equations, Taylor and Francis Publishers (2008),37:15,pp.2433-2446.

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