THE BOOTSTRAP FOR MULTIPLE REGRESSION COEFFICIENT ESTIMATING WITH MULTICOLLINEARITY

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THE BOOTSTRAP FOR MULTIPLE REGRESSION COEFFICIENT ESTIMATING WITH MULTICOLLINEARLITY

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ABSTRACT

The objective of this research is to compare the properties of the estimators of the regression coefficients in cases of existing multicollinearity among independent variables by comparing the ordinary least square and the almost unbiased generalized Liu estimator with the bootstrap technique of these two methods. The criterion of comparison is the ratio of average values of the mean square errors. This study examines the residual distribution from a normal distribution with mean of 1, standard deviation of 0.05, 0.10, 0.15, 0.30 and 0.50; contaminated normal distribution with scale factors of 3, 10 with percent contaminations of 5, 10; and lognormal distribution with mean of 1.0, variance of 0.05, 0.30, 0.70 and 1.00. This study uses sample sizes of 10,30,50 and 100. The various degrees of correlation among independent variables are equal to 0.1, 0.3, 0.5, 0.7, 0.9 and 0.99 when the number of independent variables is 3 or 5. The data were obtained through simulation using a Monte Carlo technique with 500 repetitions for each case. The results for comparing the average value of mean square error are as follows:

For the residuals which have normal, contaminated normal and lognormal distribution, the almost unbiased generalized Liu estimator method generally gives the least value of average mean square error in various degree of correlation, except in cases when the degree of correlation is higher than 0.90 in which the ordinary least square method give the least value of average mean square error.

For the sample sizes of 10 with 5 independent variables under increasing variance, the almost unbiased generalized Liu estimator with bootstrap technique gives the least value of average mean square error.

The average value of mean square error varies with descending order : degree of correlation, standard deviation, the number of independent variables, scale factor, and percent contamination. The average value of mean square error varies conversely to sample sizes.

Study on bootstrap estimator especially its inferior and conspicuous technique and study about the characteristic of the element on diagonal matrix D for reducing the bias in almost unbiased generalized Liu estimator should be further pursued.

KEY WORDS:BOOTSTRAP/ORDINARY LEAST SQUARE/
ALMOST UNBIASED GENERALIZED LIU ESTIMATOR /
MULTICOLLINEARITY

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การประมาณค่าสัมประสิทธิ์การถดถอยพหุคูณในกรณีพหุสัมพันธ์ด้วยวิธีบูตสแตรป
(THE BOOTSTRAP FOR MULTIPLE REGRESSION COEFFICIENT ESTIMATING WITH MULTICOLLINEARITY)

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บทคัดย่อ

การวิจัยครั้งนี้มีวัตถุประสงค์เพื่อเปรียบเทียบการประมาณสัมประสิทธิ์ความถดถอยพหุเมื่อเกิดพหุสัมพันธ์ระหว่างตัวแปรอิสระ ด้วยวิธี ordinary least square, almost unbiased generalized Liu estimator, ordinary least square with bootstrap และวิธี almost unbiased generalized Liu estimator with bootstrap โดยใช้ค่าความแตกต่างระหว่างตัวประมาณกับค่าจริงเป็นเกณฑ์การเปรียบเทียบภายใต้การแจกแจงของค่าความคลาดเคลื่อนที่มีค่าเฉลี่ยเท่ากับ 1 สำหรับการแจกแจงแบบปกติซึ่งมีส่วนเบี่ยงเบนมาตรฐานเท่ากับ 0.05,0.10,0.15,0.30,0.50 การแจกแจงแบบปกติปลอมปน ซึ่งมีสเกลแฟคเตอร์เท่ากับ 3,10 เปอร์เซนต์การปลอมปนเท่ากับ 5,10 และการแจกแจงแบบลอกนอร์มอลซึ่งมีความแปรปรวนเท่ากับ 0.05,0.30,0.70,1.00 โดยขนาดตัวอย่างที่ใช้ในการวิจัยเท่ากับ 10,30,50 และ100 ระดับความสัมพันธ์ระหว่างตัวแปรอิสระเท่ากับ 0.1,0.3,0.5, 0.70.9,0.99 เมื่อจำนวนตัวแปรอิสระเท่ากับ เท่ากับ 3 และ 5 ตามลำดับ ข้อมูลที่ใช้ในการวิจัยได้จากการจำลองด้วยเทคนิคมอนติคาร์โลซึ่งกระทำซ้ำ 500 ครั้งในแต่ละสถานการณ์

ผลการวิจัยโดยทั่วไปพบว่า วิธี almost unbiased generalized Liu estimator มีประสิทธิภาพดีที่สุดทุกการแจกแจงของความคลาดเคลื่อนที่ระดับความสัมพันธ์ 0.1- 0.7 และวิธี ordinary least square มีประสิทธิภาพดีที่ระดับความสัมพันธ์ตั้งแต่ 0.9 ขึ้นไป

กรณีตัวอย่างมีขนาดเล็กเท่ากับ 10 วิธี almost unbiased generalized Liu estimator with bootstrap มีประสิทธิภาพดีที่สุด โดยมีแนวโน้มดีขึ้นเมื่อจำนวนตัวแปรมากขึ้น และมีแนวโน้มลดลงเมื่อความแปรปรวนลดลง

ผลการวิจัยพบว่าระดับความสัมพันธ์ การแจกแจงของความคลาดเคลื่อน จำนวนตัวแปรอิสระและขนาดตัวอย่างต่างมีผลต่อประสิทธิภาพของการประมาณค่าสัมประสิทธิ์การถดถอยพหุทั้ง 4 วิธี โดยประสิทธิภาพมีแนวโน้มดีขึ้นเมื่อขนาดตัวอย่างมากขึ้น และมีแนวโน้มลดลงเมื่อระดับความสัมพันธ์ ส่วนเบี่ยงเบนมาตรฐาน สเกลแฟคเตอร์ และจำนวนตัวแปรอิสระสูงขึ้นตามลำดับ

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CHAPTER I
INTRODUCTION

1. Rational and Justification

The used of statistical methods in medical and public health researches has increasingly involved in every steps of studies in order to improve the reach quality. Most of the objective is to study the relationship between dependent and independent variables in term of prediction. For example, imagine that you are a researcher in a hospital who is studying the effectiveness of a new treatment for a general terminal disease. One of the most widely used statistical methods is regression analysis. The general linear regression model has the form

$$Y_n = \beta_0 + \beta_1 X_{n1} + \beta_2 X_{n2} + ... + \beta_q X_{nq} + \varepsilon_n \qquad (1.1.1)$$

The technique used to estimate the parameters based on a set of observed values of these variables is the ordinary least square method. The goal finds estimates of the parameters $\beta_0, \beta_1, ..., \beta_q$ that minimize the sum of the squared differences between the actual value of y and the predicted y. The unique solution to be the normal equation is given by

$$\hat{\underset{\sim}{\beta}}_{OLS} = \left(X'X\right)^{-1}(X'Y) \qquad (1.1.2)$$

and this method has a stringent assumption that the predictors are not perfectly correlated. The most of the predictors in medical and public health research have highly correlated or multicollinearity which needed to be solved (1).

There is an intrinsic problem of multiple regression and frustrates to make sense of the data. In some cases, removing one or more variables from the model will reduce multicollinearity to an acceptable level but the objective may be change because the researcher selects only all trusty variables into the model (2). One can also say that the data are ill-conditioned in such a case which is undesirable in regression analysis. It usually leads to unreliable estimates of the regression coefficients with too large variance and covariance(3). Multicollinearity is the problem with a correlation matrix that occurs when variables are correlated. The determinant is not exactly zero, but it is zero to several decimal places. Division by a near-zero determinant produces very large and unstable numbers in the inverted matrix (4). In regression, error terms get so large that none of the coefficients is significant (5). Further, when correlation is 0.9, the precision of estimation of weighting coefficients is halved (6).

Sometimes the multicollinearity is detected but the set of independent variables is essential anyway, ridge regression might be considered for remedies. It is a controversial procedure that attempts to stabilize estimates of regression coefficients by inflating the variance that is analyzed. Since matrix $X'X$ is ill-conditioned or nearly singular one can add positive constants to the diagonal matrix and in sure that the resulting matrix is not ill-conditioned and reduces the mean square error. This technique was first proposed in 1970's by Hoerl and Kennard (7) and it is one of the biased estimation procedures which has the form

$$(X'X + cI_n)\beta = X'Y \tag{1.1.3}$$

with a resulting biased estimate for

$$\hat{\underset{\sim}{\beta}}_R(c) = (X'X + cI)^{-1}(X'Y) \tag{1.1.4}$$

; when c is a constant and c > 0.

Practically, it is difficult to determine the best value constant. In 1993 Liu Kejian (8) proposed the paper about the method of estimated multiple regression coefficient estimated by using advantage of ridge regression method combine with Stein method has the form

$$\hat{\underset{\sim}{\beta}}_L(d) = (X'X + I)^{-1}(X'Y + d\hat{\underset{\sim}{\beta}}) \tag{1.1.5}$$

; when d is constant and 0 < d < 1.

Although this method expedient to find d than c because the limit value of d between zero and one; likewise, this method bestow mean square error lower than ridge estimator, nevertheless this technique use only one constant multiply all $\hat{\underset{\sim}{\beta}}$.

Therefore in 1996 Akdeniz and Kaciranlar (9) adapted through almost unbiased generalized Liu estimator for reduce the bias less than the original Liu estimator by

$$\hat{\underset{\sim}{\beta}}_{AUG}(D) = (X'X + I)^{-1}(X'Y + D\hat{\underset{\sim}{\beta}}) \qquad (1.1.6)$$

; when D is square matrix, size p x p.

The elements on the main diagonal of the matrix D are constant and the elements off diagonal are zero in order that elements on diagonal specific each $\hat{\underset{\sim}{\beta}}$.

For estimate model parameters, the question is "Are these parameters true? How representative is this sample of the true population even limited sample size? What should do when error is not normal distribution?". These questions are particularly important when use a complex model where parameters tradeoffs can cause havoc in analysis. Bootstrap method can solve these questions by a resampling technique that has much in common with permutation tests to computer-intensive and limited to making inferences on the others hand. Repeated samples of the data with replacement are taken to build up an estimate of the distribution of the statistic of interest (10). From this may determine the bias and standard error of the statistic without resource to any statistical theory concerned. Thus the utility of the bootstrap is in situations where parametric assumptions are untenable such as error is not only normal distribution but also contaminated normal distribution and lognormal distribution (11).

The computer simulation is applied to this study in order the regression coefficient estimating between the ordinary least square method and the almost unbiased generalized Liu estimator for with and without the bootstrap technique. The data has simulated by Monte Carlo technique (12) for able so set a specify distribution as normal, contaminated normal and lognormal distributed data.

2. Research objectives

To compare the properties of the parametric regression coefficients estimating with multicollinearity situations among the ordinary least square method, the almost unbiased generalized Liu estimator and the bootstrap technique of these two methods.

3. Scope of the study

1. The Monte Carlo method simulation study is applied to generate the data sets

for normal, lognormal and normal mixture model for contaminated normal distribution.

2. The criteria for comparing the properties of the estimators are the mean square error, the standard deviation and the different average mean square error.

4. Definitions of Terms

The following terms have been defined to clarify their meaning within the context of this study.

Correlation : Correlation is a measure of the relation between two or more variables. Correlation coefficients can range from -1.00 to +1.00. The value of -1.00 represents a perfect negative correlation while a value of +1.00 represents a perfect positive correlation. A value of 0.00 represents a lack of correlation (13). This study determines the degree of correlation between 0.1-0.3 (low correlation), 0.5-0.7 (middle correlation) and 0.9-0.99 (high correlation).

Bootstrap : This is a form of randomization which is one of the alternatives to exhaustive re-randomization. The bootstrap scheme involves generating subsets of the data on the basis of random sampling with replacements as the data are sampled. Such resampling provides that each datum is equally represented in the randomization scheme; however, the bootstrap procedure has features which distinguish it from the procedure of a Monte Carlo test (14).

Box Cox Transformation : The Box-Cox transformation can be used for converting the data to a normal distribution, which then allows the process capability to be easily determined (15).

Contaminated normal distribution : This is the part form of mixture model, one part of population has a normal distribution with mean (μ), variance (σ^2) with probability (1-p) and the others have a normal distribution with mean (μ) , variance ($c\sigma^2$) with probability (p). The p and c are percent of contamination and scale factor, respectively (16).

CHAPTER II
LITERATURE REVIEW

In this chapter, the relevant literatures based on both theories and researches were emphasized into seven main parts as follow:

1. The assumptions for regression analysis
2. Multicollinearity
3. The ordinary least square method
4. The almost unbiased generalized Liu estimator method
5. The bootstrap technique
6. The theoretical probability distribution
7. The power transformation method

1. The assumptions for regression analysis

The linear regression model is the statistical analysis of the relation between two or more quantitative variables, so that one variable can be predicted from the other variables .The linear regression model is

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip} + \varepsilon_i \qquad (2.1.1)$$

$i = 1, 2, ..., n$ and p is the number of variables

or in matrix form may be written

$$\underset{\sim}{y} = X\underset{\sim}{\beta} + \underset{\sim}{\varepsilon} \qquad (2.1.2)$$

where

$$\underset{\sim}{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \quad X = \begin{bmatrix} 1 & X_{11} & \cdots & X_{1p} \\ 1 & X_{21} & \cdots & X_{2p} \\ \vdots & \vdots & & \vdots \\ 1 & X_{n1} & \cdots & X_{np} \end{bmatrix}_{n \times p}, \quad \underset{\sim}{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{p-1} \end{bmatrix}_{p \times 1}, \quad \underset{\sim}{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}_{n \times 1}$$

and the assumption in regression is following (17):

1.The design matrix, n observations on each of k variables, is fixed in repeated samples of size n. This implies that X : n x p is not stochastic. Also, n > p.

2. The n x p design matrix is of full column rank. That is, the columns of the design matrix are linearly independent. The implication is that the columns of X form a basis for a p-dimension vector space.

3. The n-dimension disturbance vector ε consists of n random variables such that $E(\varepsilon) = 0$ and $E(\varepsilon\varepsilon') = \sigma^2 I_n$ where σ^2 is an unknown parameter.

The multiple linear regression model is based on several assumptions. Provided the assumptions are satisfied so the regression estimators are optimal in the sense that they are unbiased, efficient, and consistent (18). Unbiased means that the expected value of the estimator is equal to the true value of the parameter. Efficient means that the expected value of the estimator is equal to the true value of the parameter and the estimator has a smaller variance than any other estimator. Consistent means that the bias and variance of the estimator approach zero as the sample size approaches infinity (19). These are six basic assumptions for the regression model.

1.1 Linearity : The relationship between the predictand and the predictors is linear. The multiple linear regression model applies to linear relationship. If relationships are nonlinear, there are two ways to solve this problem:

- Transform the data to make the relationships linear
- Use an alternative statistical model such as neural networks and binary classification trees.

An early step in data analysis should be simple scatter plotting to diagnose important departures from linearity (20).

1.2 Nonstochastic X : $E(\varepsilon_i X_{i,p}) = 0$. The error is uncorrelated with the individual predictors. This assumption is checked in residual analysis with scatter plots of the residuals against individual predictors. Violation of the assumption might suggest a transformation of the predictors (21).

1.3 Zero mean : $E[\varepsilon_i] = 0$. The expected value of the residuals is zero. This is not a problem because the usual method of estimating regression equations guarantees that the mean is zero (22).

1.4 Constant variance : $E[e_i^2] = \sigma^2 I_n$. The variance of the residuals is constant.

An example of violation of this assumption is a pattern of residuals whose scatter (variance) increased over time (22).

1.5 Nonautoregression : $E[\varepsilon_i \varepsilon_{i-m}] = 0, m \neq 0$. The residuals are random, or uncorrelated in time. This assumption is critical for time series applications of regression. Several methods of checking the assumption are covered later (22).

1.6 Normality : The error term is normally distributed. This assumption allows the deriving of significance tests and confidence intervals for the regression coefficients. It is also possible to make no explicit assumption about the form of the distribution and to appeal instead to the central limit theorem to justify the use of such tests. The normality assumption is the least crucial of the regression assumptions (23).

2. Multicollinearity

When two or more exogenous observation series are highly correlated or have the same predictive power with respect to the endogenous variable they are called multicollinearity (24).

Suppose two exogenous observation vectors X_1 and X_2 of a set of n exogenous variables, they are multicollinearity if

$$\forall X_i, \exists c_i \in R_0 \quad : \sum_{i=1}^{2} c_i X_i = 0 \qquad (2.2.1)$$

which means that both vectors are perfectly linearly dependent (25).

Multicollinearity is a very serious problem; for instance, if the researcher is interested in calculating elasticities. If the only aim of the researcher would be to generate forecasts, and if it would be reasonable to assume that the multicollinearity problem would not be different for the forecast period or cross-section, then multicollinearity might be considered not to be a problem at all. This is because multicollinearity will not affect the forecasts of a model but only the weights of the explanatory variables in the model (26).

How is it possible to make the distinction between the influence of x_1 on the dependent variable and the influence of x_2 on the dependent when they are linearly dependent? The answer is simple: it is not possible at all. It is easy to show this mathematically. Assume a multiple regression model with, among others, the two exogenous vectors from

$$y = Xb + \varepsilon \quad \text{, with} \quad b = (X'X)^{-1} X'y . \qquad (2.2.2)$$

Then it is obvious to see that X'X must be a non singular symmetric K*K matrix . Since we assumed that

$$X=[x_1,x_2,\ldots.] \qquad (2.2.3)$$

and since x_1 and x_2 are linearly dependent, it follows that X has determinant equal to zero and is not non-singular.

For this reason X'X is not non-singular as well, and cannot be inverted. Therefore the b vector of the ordinary least square estimation cannot be computed. It should be noted that other estimation methods like GLS and MLE will also fail (27).

2.1 Detection of multicollinearity

Since we have seen that strong linear associations between exogenous variables are not always catastrophic, it seems that good detection measures for "bad" multicollinearity are no spurious luxury (28). There are some possible diagnostics as following :

2.1.1 Correlation matrix between exogenous variables. It is obvious that the linear correlations are the easiest detection diagnostic available to the researcher. Though it should be noted that this is no good measure for "bad" multicollinearity, as stated above. As a rule of thumb, one often uses the frontier of r = 9; If $r \geq 0.9$ then multicollinearity may be considered “harmful”, if r < 0.9 it might not be harmful. (29).

2.1.2 High R-square and low T-Stats. This criterion, like the previous, does not give us clear-cut answers with respect to the harmfulness of multicollinearity (30) .

2.1.3 High R-square and low quadratic partial correlations between an exogenous variable and the dependent variable. By definition, a partial correlation coefficient between a variable X (exogenous) and another variable Y (endogenous), given that a third variable Z (exogenous) remains constant, is

$$R_{XYZ} = \text{corr}\,(U_{XZ}V_{YZ}) \qquad (2.2.4)$$

where $$U_{XZ}=X-\hat{\beta}Z \quad \text{and} \quad V_{YZ}=Y-\hat{\gamma}Z \qquad (2.2.5)$$

and β and γ are equal to the respective simple OLS parameters (30).

2.1.4 Eigenvalues. First compute the eigenvalues of the matrix X'X. In case of linear dependence between the variables the eigenvalues of all different eigenvectors will differ much from each other, such that the ratio

$$\sqrt{\frac{\lambda_{max}}{\lambda_{min}}} = \sqrt{k} \qquad (2.2.6)$$

becomes quite large. If the square root of k (e.g., the condition number) is much larger than (approx.) 30 this could be, according to many authors, a sign of destructive multicollinearity. The variance of the OLS regression parameters can be shown to be equal to the residual variance multiplied by the sum of the variance proportions of all eigenvalues. This so-called Variance Decomposition Analysis (31).

2.1.5 Determinants. When the matrix X'X contains columns or rows which are linearly dependent from each other, we call this matrix singular (and can therefore not invert it). If the matrix is only almost singular, the process of inverting yields a lot of (rounding -off) errors.

Therefore it is good to compute the determinant of X'X (without constant term): if the determinant is equal to zero, this indicates perfect multicollinearity; if the determinant is small then this is an indication of an almost singular matrix. Also note that

$$|X'X| = \prod_{i=1}^{K} \lambda_i \ . \qquad (2.2.7)$$

Obviously this diagnostic is a very weak measure for harmful multicollinearity. It would be better to use a measure which reflects the sensitivity of the parameters with respect to small changes in X'X. For this reason the author prefers a self-developed measure defined by

$$\frac{|X'X|}{|\delta I_K + X'X|} = \omega \qquad (2.2.8)$$

where δ is a small number and ω is the measure. When ω is small, the sensitivity of the parameters with respect to changes in $X'X$ is large and therefore the existing multicollinearity is destructive. When ω is equal to 1, then there is no sensitivity (as described above). In this case “a ridge regression” (e.g., a regression where the diagonal of $X'X$ is augmented by some small value) would not yield an improvement on estimating the parameters.

Also note that ω can be computed for different δ values and is therefore dependent on δ. Above that it is imperative to see that ω is not a stochastic estimator of “bad” multicollinearity (thus no statistical tests are required). Rather, it is a technical measure for which the researcher should decide what critical level should be accepted. The author’s suggestion is not to use an absolute critical level of ω, but in stead try to have ω converge to 1 (for different δ values) when building the econometric equations (32).

2.1.6 Help regressions. It is evident to see that multicollinearity always exists in case the regressors influence each other. This can be measured by the R-square of a regression of an arbitrary exogenous variable with respect to all other p - 1 exogenous variables (constant included). The higher the R-square, the higher the degree of multicollinearity. The respective F-statistic may be calculated by

$$F_i = \frac{\dfrac{R^2_{X_1 X_2 X_3 \ldots X_p}}{p-2}}{\dfrac{1-R^2_{X_1 X_2 X_3 \ldots X_p}}{T-p+1}} \quad . \tag{2.2.9}$$

The same information might be expressed in terms of the so-called Variance Inflation Factors:

$$\mathrm{VIF}_j = \frac{1}{(1-R_j^2)} \tag{2.2.10}$$

where R_j^2 is equal to the auxiliary regression’s R^2.

As the name indicates, the VIF measures the factor by which the parameter’s variance (in an orthogonal regression; hence without multicollinearity) is multiplied (e.g. inflated) (33).

2.1.7 Sensitivity of parameters. Under the assumptions of the general linear statistical model the author also suggests comparing parameters of simple and multiple regressions. In case of zero multicollinearity simple regression yields the same parameter estimation than multiple regression.

The multicollinearity problem is proportional to the sensitivity of the parameters with respect to the introduction of new exogenous variables. Based on this concept, it has developed an algorithm to compute a measure of uncertainty induced by the presence of more than just one exogenous variables. The output of this so-called Bias

Decomposition Analysis consists of a variance measure which can be shown to be caused only by multiple exogenous variables, and not by the number of observations (34).

2.2 Remedies to the multicollinearity problem

There is a brief look at some possible solutions that may be used to solve the harmful effects of the multicollinearity problem.

2.2.1 Drop spurious exogenous variables. Assume we were interested in the estimation of the model

$$Y_t = \alpha + \beta_G G_t + \beta_I I_t + \beta_H H_t + B_L L_t + \beta_A A_t + e_t \qquad (2.2.11)$$

where G, I, H, L, and A are exogenous variables.

Suppose that harmful multicollinearity would have been discovered between G, I, and H and between L and A. Then we may choose one representative of each group (e.g. G and L). All the other exogenous variables may be dropped since they do not entail any information which is not present in either G or L (35).

2.2.2 Principal components. The X'X can be diagonalized and written in terms of eigenvectors and eigenvalues. Accordingly, the linear model can be written in terms of its principal components. The first principal component can intuitively be interpreted as the summary of all exogenous variables by one column vector which explains as much of X as possible. The remaining information is entailed in the second principal component and so on. It is however important to note that the principal components are orthogonal and therefore cannot be multicollinear.

Suppose we would have computed the principal components for our model. Also assume that the principal components (PC) contain (in descending order) 90%, 5%, 4% of the total variance of the exogenous variables. In such circumstances we would retain the first three PC in our regression model since they account for 99% of the variance of X.

When having three PCs in a regression model, this means that there are three important groups of variables (within the set of X) which are explaining the endogenous variable. Cross correlations between the exogenous variables and the PC should reveal which variables may be associated with different factors (this is necessary for interpretation purposes).

Now suppose that this regression would result in only the first PC to be significantly different from zero. In this case our model would reduce to a simple regression. The only problem with this is that we have no clue of how this model should be interpreted, since one PC cannot directly be assigned to a specific exogenous variable (but rather to a combination of all variables).

Therefore, in such circumstances, it could be better to compute the PC for both subgroups that we have detected before.

We may present the X matrix as follows

$$X = \left[\begin{bmatrix} G_1 & I_1 & H_1 \\ G_2 & I_2 & H_2 \\ . & . & . \\ G_T & I_T & H_T \\ & & \end{bmatrix}\begin{bmatrix} L_1 & & A_1 \\ L_2 & & A_2 \\ . & . & . \\ L_T & & A_T \\ & & \end{bmatrix}\right] \tag{2.2.12}$$

and compute the PC for S and T separately. This process will probably result in at least one significant PC-parameter per subgroup in a multiple regression with the endogenous, and therefore it is possible to interpret the model easily.

Note however that in this case there is no reason to assume automatically that the first PC of S and the first PC or T are not multicollinear (since both PCs have been computed separately, and since our detection of, and splitting the variables into two subgroups, might have been wrong) (36) .

2.2.3 Ridge regression. The estimator for ridge regression is

$$B_{Ridge} = (X'X + \delta I_K)^{-1} X'y \tag{2.2.13}$$

where delta is a small number which is to be added to the diagonal elements of X'X. Be aware of the fact that there exists a sensitivity of the parameters with respect to the ridge parameter delta (therefore several values for delta might be attempted before deciding upon the final ridge estimation results) (37).

2.2.4 First differences. The first differences of a time series are defined by

$$\Delta Y_t = Y_t - Y_{t-1} \tag{2.2.14}$$

and a disadvantage of this differencing is obviously the loss of one degree of freedom since the series becomes shorter. Also note that this differencing is exclusively used with time series (and has mostly no relevance with cross-section data). The relevance and interpretation will be comprehensively clarified in time series analysis.

The only relevant thing to remember now, is that differencing alters the time series so that it can be seen as the change of the series. For instance the model

$$\Delta Y_t = \alpha + \beta \Delta X_t + e_t \qquad (2.2.15)$$

illustrates the effect of the change of Xt on the change of Yt.

When a time series is differenced twice, it is not interpreted as the absolute change but rather as the acceleration of the series (38).

2.2.5 Ratio's and deflating series. It is sometimes useful to use the ratio's of two (or more) multicollinear series. In our example we could for instance redefine the exogenous variables as

rgi = G / I

rhi = H / I

rla = L / A

which does not reduce the degrees of freedom, and maintains all variables in the model. Though, care should be taken with respect to the interpretation of the estimated parameters.

Another common remedy to the multicollinearity problem is deflating time series (mostly prices, or price indexes) by some time series measuring (e.g., consumption prices. Thus, instead of working with nominal quantities it is preferred to use real quantities) (39).

2.2.6 Additional information and restrictions. Sometimes economists have additional, or a priori information about the model. This information could be in the form of knowledge about the true value of some parameter, knowledge about an upper or lower bound for parameters, or knowledge about dependencies between the sensitivity parameters of different exogenous variables.

Such information could be introduced into the model using Restricted Least Squares (RLS) or Restricted MLE (RMLE). For the moment, abstraction is made of Bayesian methods where restrictions can be imposed stochastically instead of deterministically (40).

3. The ordinary least square method

There has been a dispute about who first discovered the method of least square method. It appears that it was discovered independently by Gauss (1977-1855) and Legendre (1752-1833), that Gauss started using it before 1803 (he claimed in about 1795, but there is no corroboration of this earlier date), and that the first account was published by Legendre in 1805. When Gauss wrote in 1809 that he had used the method earlier than the date of Legendre's publication, controversy concerning the priority began (41).

The least square method is a very popular technique. It is used to computed estimations of parameters and corresponds to the problem of finding a line or curve that best fits a set of data in this form

$$\hat{\beta}_{OLS} = \left(X'X\right)^{-1}(X'Y) \qquad (2.3.1)$$

This method gives the minimum variance and unbiased estimator which is described in most introductory statistics coursed as a method for estimating the parameters in a classical straight line or multiple linear regression model. Maximum likelihood estimation and least squares estimation are different approaches that happen to give the same results for classical linear regression analyses when the dependent variable is assumed to be normally distributed (42).

4. The almost unbiased generalized Liu estimator method

The ridge trace produce, first suggested in 1962 by Hoerl And Kennard (7) Introduced the ridge trace, a method for showing in two dimensions the effects of nonorthogonality. It is then shown how to augment $X'X$ to obtain biased estimates with smaller mean square error The procedure is intended to overcome "ill-conditioned" situations where correlations between the various predictors in the model cause the $X'X$ matrix to be close to singular, giving rise to unstable parameter estimates. The estimates may gave the wrong sign or be much larger than physical or practical considerations would deem reasonable.

The ridge regression procedure, in its simplest form, is as follows. Let Z represent the appropriate centered and scaled "X matrix" when the regression problem under study is in "correlation form" .Then, for the model with all the r possible predictors $Z_1, Z_2, ..., Z_r$ in it. We can obtain parameter estimates $b_z(\theta)$ given by the equation

$$b_z(\theta) = (Z'Z + \theta I_p)^{-1} Z'Y \qquad (2.4.1)$$

where θ is a positive number. In application, the interesting values of θ usually lie in the range (0,1) and Y is not in correlation form.

The $b_Z(\theta) = \{b_{1z}(\theta), b_{2z}(\theta), ..., b_{rz}(\theta)\}'$ is an r x 1 vector with no intercept estimate. It can be seen that no intercept is needed by noting that replacement of Y by $Y - \overline{Y}1$ (where 1 = $(1,1,...,1)'$) in equation (2.4.1) would not effect the calculations at all, due to the fact that the "centering" of the predictors ensures that $Z'1 = 0$. Remembering that, because Y is not in correlation form, the factor $S_{yy}^{1/2}$ will not be needed, we can make the conversions (43)

$$b_j(\theta) = \frac{b_{jz}(\theta)}{S_{jj}^{1/2}} \qquad , j = 1,2,\ldots.r \qquad (2.4.2)$$

where $S_{jj} = \sum_{i=1}^{n} (Z_{ji} - \overline{Z}_j)^2$ and

$$b_0(\theta) = \overline{Y} - \sum_{j=1}^{r} b_j(\theta)\overline{Z}_j \qquad (2.4.3)$$

to provide the (r+1) x 1 vector.

The $b(\theta) = \{b_0(\theta), b_1(\theta), ..., b_r(\theta)\}'$ when $\theta = 0, b_j(0), j = 0,1,2,...,r$ are the usual least squares estimates, as is clear from setting $\theta = 0$ in equation (2.4.2). In fact, by removing a factor $(Z'Z)^{-1}$ from the right of the inverse matrix can express the ridge estimator in terms of the least squares estimator $b_z(0) = (Z'Z)^{-1} Z'Y$, namely,

$$\begin{aligned} b_z(\theta) &= \{I + \theta(Z'Z)^{-1}\}^{-1} b_{z(0)} \qquad (2.4.4) \\ &= Qb \end{aligned}$$

say, so that the ridge estimators are all linear combinations of the least squares estimator with coefficients determined by the matrix $\{I + \theta(Z'Z)^{-1}\}^{-1}$.

As θ is increased, the estimates become smaller in absolute value, tending to zero as θ tends to infinity. A value of θ,say θ^*, is then selected. Hoerl and Kennard say (44) :

These kinds of things can be used to guide one to a choice:

1. At a certain value of θ the system will stabilize and have the general characteristics of an orthogonal system.
2. Coefficients will not have unreasonable absolute values with respect to the factors for which they represent rates of change.
3. Coefficients with apparently incorrect signs at θ=0 will have changed to have the proper signs.
4. The residual sum pf squares will not have been inflated to an unreasonable value. It will not be large relative to the minimum residual sum of squares or large relative to what would be a reasonable variance for the process generating the data

Once θ has been selected the values $b_j(\theta)$ are used in the prediction equation. The resulting equation is made up of estimates which are not least squares and are biased but which are more stable in the sense described and which provide a smaller overall mean square error, since the reduction they achieve in variance error will more than compensate for the bias introduced (45).

Ridge regression is sometimes “justified” as a practical technique by the claim that it produces lower mean square error. The basic result is as follows. The mean square error of the ridge estimator can be written

$$\begin{aligned}\mathrm{MSE}(\theta) &= E\left\{b_z(\theta)-\beta_z\right\}'\left\{b_z(\theta)-\beta_z\right\} \\ &= E\left\{Qb-\beta_z\right\}'\left\{Qb-\beta_z\right\} \\ &= E\left\{b-\beta_z\right\}' Q'Q\left\{b-\beta_z\right\}+\beta_z'(Q-I)'(Q-I)\beta_z \ . \qquad (2.4.5)\end{aligned}$$

To get this, we have substituted for $b_z(\theta)=Qb$ from equation (2.4.4) where $Q=\left\{I+\theta(Z'Z)^{-1}\right\}^{-1}$, isolated a quadratic term in $(b-\beta_z)$, taken the expectation $E(b)=\beta_z$ in the remaining terms, performed some cancellations, and regrouped. Application of the matrix then leads to

$$\mathrm{MSE}=\sigma^2\mathrm{trace}\left\{Q(Z'Z)^{-1}Q'\right\}+\beta_z'(Q-I)'(Q-I)\beta_z \, . \qquad (2.4.6)$$

The first term, being the sum of the diagonal terms of $V(Qb) = \sigma^2 Q(Z'Z)^{-1}Q'$, is the sum of the variances of the elements of the ridge estimator Qb. The second term is a ridge "squared bias" term. If $\theta = 0$, then Q=I and the first term is the sum of the variances of the least squares estimators of the coefficients, while the second term vanishes. The value so attained would be MSE(0).

In 1993 Liu Kejian (8) considered the linear regression model $Y=X\beta+\varepsilon$, $E(\varepsilon)=0$ and $Cov(\varepsilon)=\sigma^2 I$. Motivated by an interpretation of ridge estimate $\hat{\beta}_R = (X'X+kI)^{-1}X'Y$, propose a new class of biased estimate

$$\hat{\beta}_d = (X'X+kI)^{-1}(X'Y+d\hat{\beta}) \tag{2.4.7}$$

to combat multicollinearity, where 0<d<1 is a parameter and $\hat{\beta}$ is the least squares estimate. $\hat{\beta}_d$ combines the advantages of $\hat{\beta}_R$ and Stein estimate $\hat{\beta}_s$ = c $\hat{\beta}$. Theory and simulation results show that $\hat{\beta}_d$ has the similar good property as $\hat{\beta}_R$. The advantage of $\hat{\beta}_d$ over $\hat{\beta}_R$ is that $\hat{\beta}_d$ is a linear function of d. so the selection of d is simple.

In 1995 Akdeniz and Kaciranlar (9) derived the almost unbiased generalized Liu estimator and examine an exact unbiased estimator of the bias and mean squared error of the feasible generalized Liu estimator. To compared the almost unbiased generalized Liu estimator (AUG) and ordinary least squares estimator (OLS). The almost unbiased generalized Liu estimator takes the following form

$$\hat{\beta}_{AUG}(D) \quad = \quad (X'X+I)^{-1}(X'y+D\hat{\beta}) \tag{2.4.8}$$

which D is matrix size p x p and the elements in diagonal are constant and the element outside are zero then $D = diag(d_1, d_2, ..., d_p) \quad ; 0 < d_i < 1$.

From equation (2.4.8) gets multiple regression coefficient estimating by almost unbiased generalized Liu estimating in form

$$\hat{\beta}_{AUG} = \left[I-(X'X+I)^{-1}(I-D)\right]\hat{\beta} \tag{2.4.9}$$

therefore as $\hat{\beta}_{AUG}$ has biased equal $\left[-(X'X+I)^{-1}(I-D)\right]\hat{\beta}$.

The biased is reduced when the element in diagonal of D increase and equal zero when D = I as I of $\hat{\beta}_{AUG}$ is

$$\underset{\sim}{\hat{\beta}}_{AUG_i} = \left[\frac{\lambda_i + d_i}{\lambda_i + 1}\right]\hat{\beta}_i \quad = \quad (1-\delta_i)\hat{\beta}_i \tag{2.4.10}$$

which $\delta_i = \dfrac{1-d_i}{\lambda_i + 1}$ $;0 < \delta_i < 1$ and λ_i is eigenvalue number i of matrix $X'X$.

$\hat{\beta}_i$ is element number i of multiple regression coefficient estimating by $\underset{\sim}{\hat{\beta}}_{OLS}$

And $\underset{\sim}{\hat{\beta}}_{AUG}$ has bias equal $-\delta_i\beta_i$.

Mean square error of $\underset{\sim}{\hat{\beta}}_{AUG}$ is in form

$$MSE\left[\underset{\sim}{\hat{\beta}}_{AUG}\right] = \frac{\sigma^2(\lambda_i + d_i)^2 + \lambda_i(1-d_i)^2\beta_i^2}{\lambda_i(\lambda_i+1)^2} \tag{2.4.11}$$

$$= \frac{\sigma^2}{\lambda_i}(1-\delta_i)^2 + \delta_i^2\beta_i^2$$

then $MSE\left[\hat{\beta}_{AUG}\right]$ has minimum at $d_i = \dfrac{\lambda_i(\beta_i^2 - \sigma^2)}{\lambda_i\beta_i^2 + \sigma^2}$ $;i = 1, 2, \ldots, p$.

To be due to in practical β_i and σ^2 are unknown parameter, to do that estimate parameters by unbiased estimator are $\hat{\beta}_i$ and $\hat{\sigma}^2$. Estimated appropriate d_i is made minimum mean square error equal

$$d_{i(opt)} = \frac{\lambda_i(\hat{\beta}_i^2 - \hat{\sigma}^2)}{\lambda_i\hat{\beta}_i^2 + \hat{\sigma}^2} \quad ;i = 1, 2, \ldots, p. \tag{2.4.12}$$

In 1995 Thiart et al. (46) performed to examine the relative efficiency of thirteen estimators against ordinary least square estimator across thirty combinations of orientation, variance and known parameter vector, encompassing several different degrees of collinearity. Estimation procedures included principal components, ridge and generalized ridge, jackknife, shrinkage and fractional principal component methods. Overall, in the face of collinearity, the biased estimators performed better than ordinary least square estimator, but no “optimal” estimator emerges, and a suitable choice of estimator depended on the circumstances.

Crivelli et al. (47) studied confidence intervals in ridge regression when occurred multicollinearity. The aim of this paper was reported on the use of a technique that combines the Bootstrap and the Edgeworth Expansion to obtained an approximation the distribution of some Ridge Regression estimators. Some simulation experiments carried out to compare the asymptotic confidence intervals with those obtained with this technique.

Gunst and Mason (48) compared five estimators of the coefficients in a linear regression model: least squares, principal components, ridge regression, latent root, and a shrunken estimator. Each of the caused estimators was shown to offer improvement in mean squared error over least squares for a wide range of choices of the parameters of the model. The results of a simulation involving all five estimators indicated that the principal components and latent root estimators performed the best overall, but the ridge regression estimator had a potential of a smaller mean squared error than either of these.

Obenchain (49) performed general linear hypotheses in multiple regression models. The associate probability of a ridge estimate was defined using the usual hyperllipsoidal confidence region centered at the least squares estimator, and it was argued that ridge estimates was slightly interested when they were so extreme that they laid outside of the least squares region of 90 percent confidence.

Wichern and Churchill (50) evaluated the relative performances of several mechanical selection rules, the ridge trace and the least squares procedure using computer simulation experiments.

Hemmerle and Branile (51) proposed for obtaining constrained generalized ridge estimators, with constraints placed upon β^*, to utilize a priori information concerning the signs of the model parameters along with ridge estimation. These and other ridge estimation procedures were examined and compared with least squares estimators in a Monte Carlo study which demonstrated their effectiveness.

5. The bootstrap technique

The Bootstrap is a computer-based method for assigning measures of accuracy to statistical estimate. It has became one of the major tools for producing empirical confident intervals of estimated parameters or predictors (52). Its theoretical justification is based largely on asymptotic argument for its consistency or optimality.

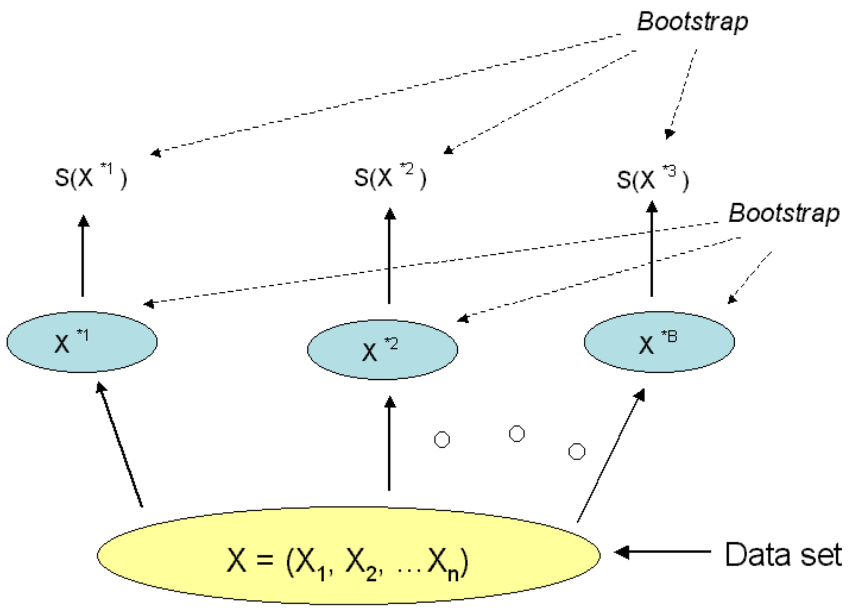

Figure 1. Schematic of the bootstrap process for estimating the standard error of a statistics s(x).

Bootstrapping is based on re-sampling with replacement. Each bootstrap sample is an independent random sample of size *n* from the empirical distribution $\hat{F}$. The elements of the bootstrap sample are the same those of the original data set. Some may appear only once in the bootstrap sample, some two or more times while some others may appear zero times. To each bootstrap sample corresponds a bootstrap replication of $\hat{\theta}$:

$$\hat{\theta}^* = s(x^*) \, .$$

The bootstrap replication is the result of applying the same function *s(.)* to x^* as was applied to *x*. Following Efron and Tibshiriani (53), the bootstrap algorithm for estimating the standard error of a parameter is summarised by the following three steps:

***Step 1*:** Select B independent bootstrap samples $x^{*1}, x^{*2}, \ldots, x^{*B}$, each consisting of *n* data values drawn with replacement from *x*.

***Step 2*:** Evaluate the bootstrap replication corresponding to each bootstrap sample,

$$\hat{\theta}^*(b) = s\left(x^{*b}\right) \qquad b = 1,2,\ldots, B. \tag{2.5.1}$$

<u>Step 3</u>**<u>:</u>** Estimate the standard error by the sample standard deviation of the B replications,

$$\hat{se}_B = \left\{ \sum_{b=1}^{B} \left[\hat{\theta}^*(b) - \hat{\theta}^*(\bullet) \right]^2 / (B-1) \right\}^{1/2} \tag{2.5.2}$$

where

$$\hat{\theta}^*(\bullet) = \sum_{b=1}^{B} \hat{\theta}^*(b) / B .$$

It can be shown that the following result holds:

$$\lim_{B \to \infty} \hat{se}_B = se_{\hat{F}} = se_{\hat{F}}(\hat{\theta}^*) \tag{2.5.3}$$

, the empirical standard deviation approaches the population standard deviation as the number of bootstrap replications grows large.

There is a total of $\binom{2n-1}{n}$ distinct bootstrap samples on which the function *s(.)* can be evaluated. When we are dealing with very small samples, we may be able to compute *s(•)* for all the distinct bootstrap samples.

In fact, the real constraint on the number *B* of bootstrap replications is computer time, which increases linearly with *B*. Based on their experience, Efron and Tibshiriani (54) proposed the following set of rules of thumb: even a small number of bootstrap replications *(B = 25)* is usually informative. *B = 50* is often enough to yield a good estimate of $se_{\hat{F}}(\hat{\theta}^*)$. Very rarely are more than *B = 200* replications necessary.

Like asymptotic methods, bootstrapping is also an approximate method. However, and unlike asymptotic methods, bootstrapping attempts to obtain small sample results. In practice, bootstrapping seems to work very well i.e., it yields a correct confidence interval. However, theory is in its infancy and the justification for the good performance of the bootstrap is asymptotic (55).

This study concentrates on the nonparametric bootstrap. These are advantages of the nonparametric bootstrap that include (56):

1. It is conceptually simple (although computationally expensive, there is no big deal nowadays).
2. It is versatile – it can be used in a wide variety of applications and contexts.
3. It involves at most weak assumptions about the distribution of the estimator.(e.g. the procedure about the distribution of animals in the survey region – which is something that affects the estimator properties).

Marine Fisheries Service (57) used Bootstrap resampling to determine the total number of salmon by catch and mortality rate. This method was developing for estimation of incidental catches of salmonids in the North Pacific squid driftnet fisheries of Japan.

Gould (58) used case about In terms of the number of replications, there is no fixed infinite number of replications because, at a formal level, that was what the Bootstrap requires. The key to the reasonably quick usefulness, was to run a finite number of replications good enough to provide data if the number of replications chosen is large enough.

Heber et al. (59) presented a method to construct a confidence neighborhood for a computed solution. Application of Bootstrap technique to physical mapping, computed a confidence value for putative local solutions derived from Bootstrap replicates of original solution.

Zhang (60) presented a Bootstrap procedure along with some results on simulation and on analysis of two real data sets of case-control study. A goodness-of-fit test for logistic regression models based on case-control study, tested the logistic regression assumption under a case-control sampling plan.

Petoxz (61) attempted to use the spatial Bootstrap for estimating rainfall variability from spatial data. The original set of rain gauge measurements attached to their geographic locations was resampled with replacements to produce a hundred new sets. For each of these sets the original semivariogram function was used to fit asurface and then to estimate the area mean precipitation. The error was estimated as the difference between the fifth and ninety-fifth percentiles as a percentage of median value.

Chiu (62) developed the use of Bootstrap confidence intervals to evaluate Iyer's criterion of individual bioequivalence. They developed a concept, individual bioequivalence. Which requires that the bioavailability of the two drugs for an individual subject was closed for some large proportion of the population. Thereafter, many different criteria have appeared to assess individual bioequivalence.

Kuppermann (63) studied Bootstrap resampling techniques to validate the multivariate model of intussusception in young children. The variables, historical, clinical, and radiographic, were selected in a multiple logistic regression analysis.

6. The theoretical probability distributions

The data distributed is divided into three cases: one is simulating under normal, contaminated normal and the other is lognormal distribution that emphasizes on the issues as follow:

6.1 Normal distribution

A purely theoretical continuous probability distribution in which the horizontal axis represents all possible values of a variable and the vertical axis represents the probability of those values occurring. The scores on the variable (often expressed as z-scores) are clustered around the mean in a symmetrical, unimodal pattern known as the bell-shaped curve or normal curve. In a normal distribution, the mean, median and mode are all the same. There are many different normal distributions, one for every possible combination of mean and standard deviation, also sometimes called the "Gaussian distribution" (64) . The probability function can be expressed following

$$f(X) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{1}{2\sigma^2}(x-\mu)^2\right\} \quad , -\infty < x < \infty$$

μ is mean of the normal distribution

σ is standard deviation must be > 0

X is value at which to evaluate the function

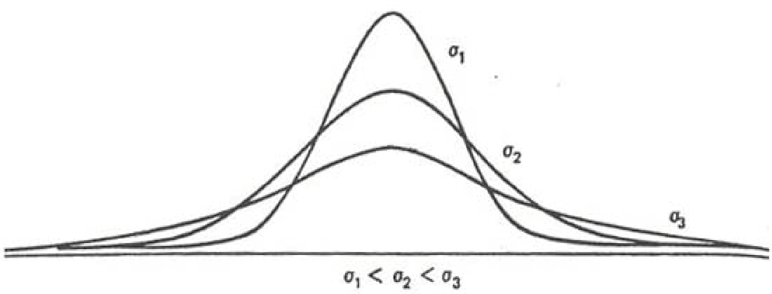

Figure 2. Three normal distributions with different standard deviations.

As a sample becomes large, the distribution of its mean (from a population with finite variance) approximates the normal distribution. It is known as the central limit theorem, a basic distribution of statistics.

Many applications arise from normal distribution such as physical phenomena, distribution of physical measurements on living organisms, intelligence test scores in research statistics, product dimensions and medicine (65).

Kunasaraphan (66) used normal distribution with mean equals to 1 and standard deviation equals to 0.1, 0.3 and 0.5 to comparison on forecasting methods between ridge regression and artificial neural network methods in multiple regression analysis.

Jaruthanasakkoon (67) compared the methods for estimation of parameters in multiple regression multiple with mean equals to 1 and standard deviation equals to0.05, 0.10 and 0.15, respectively.

6.2 Contaminated normal distribution

According to Beckman and Cook (68), outliers can be classified into discordant observations (those which appear surprising or discrepant to the investigator) and contaminants (those which are not realizations from the target distributions). One approach to the latter has been to use a two-component mixture model of the form:

$$p(x) = (1-\pi)f_1(x) + \pi f_2(x) \quad , x \in R$$

with (1-π) close to 1, $f_1(x)$ is the probability density function of interest and $f_2(x)$ is the contaminating density function.

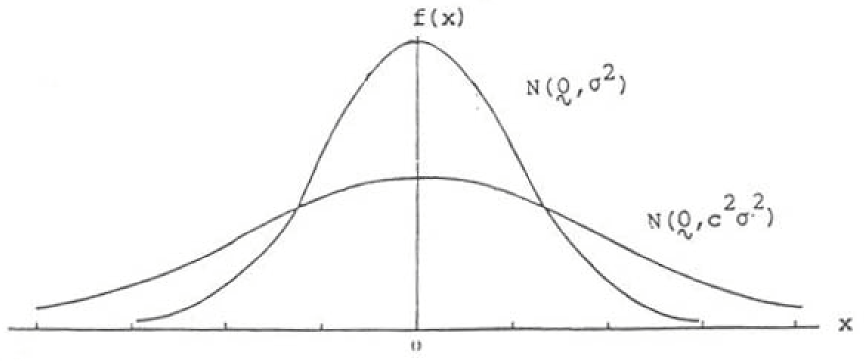

Figure 3. Graph of a scale-contaminated normal distribution.

The idea is that most observations belong to the first component sub-population but the observation is a rogue value that comes from the second component occasionally.Usually the contaminants cannot be identified as such but accommodated by suitably estimating the parameters associated with f_1 within the above model.

There are two types of contamination, namely, with location and scalar errors. The location contaminated normal distribution is the case in which $f_1(x)$ and $f_2(x)$ are both normal densities. These densities have the same standard deviation σ, but that they have different means, ξ_1 and ξ_2 respectively. Further, let 1-p bet the population proportion of component 1 so that p is the proportion from component 2, then the resulting distribution of location contamination is a mixture of two normals like this (69) :

$$f(x) = (1-p)N(\xi_1, \sigma^2) + pN(\xi_2, \sigma^2)$$

In this study, the contaminated normal model is the scalar error version in which f_1 and f_2 are both normal densities. Usually these densities have the same mean but different standard deviations, with $\sigma_2 > \sigma_1$, so that the contaminants are likely to be the extreme observations and are therefore likely to have substantial influence on statistics such as the sample mean.

Many applications arise from contaminated normal distribution such as thyroid function is evaluated by simultaneous consideration of T3, T4 and TSH. These might be related to age, diet, exercise, stress so their data generally have shown in normal mixture model like contaminated normal distribution (1) .

Ruangroj (70) used contaminated normal distribution for comparison on power of tests for normality among chi-square and Shapiro-wilk statistics with contaminated normal distribution with scale facter = 3, 10 percent of contamination = 5 and 10

6.3 Lognormal distribution

Log-normal distributions are probability distributions which are closely related to normal distributions: if X is a normally distributed random variable, then exp(X) has a log-normal distribution. In other words, the natural logarithm of a log-normally distributed variable is normally distributed. Lognormal distribution are generated by processes that follow what the economist Gibrat called the law of proportionate effect (71).The probability function can be expressed following

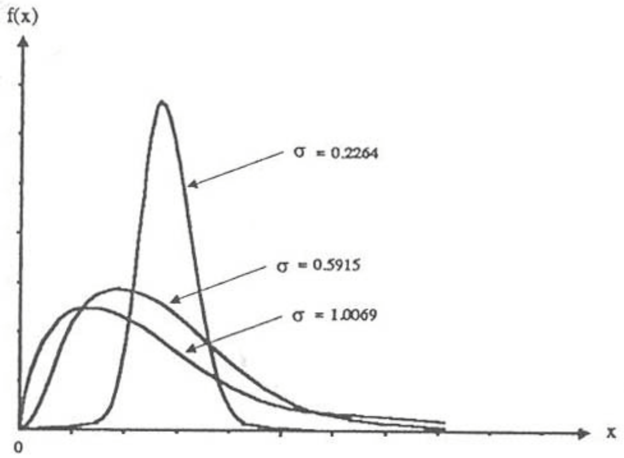

Figure 4. Graph of a lognormal distribution

$$f(X) \quad = \quad \begin{cases} \dfrac{1}{X\sigma\sqrt{2\pi}}\, e^{-\frac{1}{2}(\log_e x-\mu)/\sigma^2} & ; x>0, \sigma>0, -\infty<\mu<\infty \\ 0 & ; \text{otherwise} \end{cases}$$

μ is mean of a normally distributed variable

σ is standard deviation of a normally distributed variable

X is value at which to evaluate the function

A random variable X is said to follow a lognormal distribution if the random variable Y = log(X) is normally distributed. The expected value, standard deviation and coefficient of variation of a Lognormal random variable can be expressed in terms

$$E(X) = \exp\left(\mu+\frac{\sigma^2}{2}\right)$$

$$V(X) = \exp\left(2\mu+\sigma^2\right)\cdot\left\{\exp\left(\sigma^2\right)-1\right\}$$

$$CV(X) = \sqrt{\exp(\sigma^2)-1}$$

The distribution of particle sizes in crushing, when there have been repeated impacts, is often skewed, with a slowly decreasing right tail. The lognormal is sometimes used to fit such a distribution and utilized in technical analysis. Permits representation of random variable whose logarithm follows normal distribution. Model for a process arising from many small multiplicative errors. Appropriate when the value of an observed variable is a random proportion of the previously observed value (72).

Lognormal distribution is used to describe returns calculated over periods of a year or more. Yearly incomes in the United States are roughly log-normally distributed and use widely in distribution of sizes from a breakage process, distribution of income size, inheritances and bank deposits, distribution of various biological phenomena, life distribution of some transistor types. It is often used to model incubation times for diseases such as the cholera in Bengal from 1850 to 1950 had a cyclic feature. Asthma cases in a hospital show a peak in every first quarter of the calendar year. Diarrhea is typically high in summer or rainy months. The cyclical variation is frequently observed in a series of lognormal data (73) .

Tonchnlakun (74) presented the comparison of coefficient estimation in multiple linear regression with lognormal distribution on mean equals to 1 and variance equals to 0.05, 0.30 and 0.70 among ordinary least squares, ridge regression and ridge with stein methods.

Kunasaraphan (66) studied the comparison on forecasting methods between ridge regression and artificial neural network methods in multiple regression analysis by lognormal distribution with mean square equals to 1 and standard deviation equals to 0.2264, 0.5915, 1.0069 and standard deviation equals to 1.

7. The power transformation method

The assumptions in regression analysis include normally distributed errors of constant variance. Often these assumptions are more nearly satisfied not by the original response variable y, but by some transformations of $y, z(y)$. For nonnegative responses, one frequently used transformation is log y. The original and transformed analyses can then be compared in a number of ways. Residuals can be plotted against fitted values, assessed for normality by probability ploys for various transformations. Another comparison is through analysis of the linear model using t or F tests – a correct transformation often yields a simple linear model, with no, or just a few, interaction or quadratic terms. A formal way of comparing transformations is to embed them in a parametric family and then to make inferences about the transformation parameter λ.Transformations of three parts of the model are of differing complexity and importance (75) .

1. Transformation of the Response
2. Transformation of Explanatory Variables
3. Transformation of Both sides of the Model

This study use Transformation of Both sides of the Model by Box-Cox Transformation, it can be described as follow.

The Box-Cox transformation often yields both approximately normal errors and a multiple linear regression model. The purpose of the transformation is then to obtain normal errors of constant variance and converting the data to a normal distribution.

Suppose the tentatively used model is $Y = X\beta + \varepsilon$. Two transformations can be used. The first transformation is

$$W_i(\lambda) = \begin{cases} \dfrac{(Y_i^{\lambda} - 1)}{\lambda} & ;\lambda \neq 0 \\ \log(Y_i) & ;\lambda = 0 \end{cases} \qquad ;i = 1, 2, \ldots n \tag{2.7.1}$$

The above transformation is also called Box-Cox transformation.

$$\lim_{\lambda \to 0} W_i(\lambda) = \lim_{\lambda \to 0} \frac{Y_i^{\lambda} - 1}{\lambda} = \log(Y_i) \tag{2.7.2}$$

The other transformation is to scale $W_i(\lambda)$ by

$$V_i(\lambda) = \begin{cases} \dfrac{Y_i^{\lambda} - 1}{\lambda Y^{\lambda - 1}} & ;\lambda \neq 0 \\ Y \log(Y_i) & ;\lambda = 0 \end{cases} \tag{2.7.3}$$

where

$$Y = \sqrt[n]{Y_1 Y_2 \ldots . Y_n} = \left[\prod_{i=1}^{n} Y_i \right]^{\frac{1}{n}} \tag{2.7.4}$$

is the geometric mean of $Y_1, Y_2, \text{K}\ , Y_n$.

The model based on the transformed response is

$$W(\lambda) = \begin{bmatrix} W_1(\lambda) \\ W_2(\lambda) \\ \text{M} \\ W_n(\lambda) \end{bmatrix} = X\beta + \varepsilon \tag{2.7.5}$$

or

$$V(\lambda) = \begin{bmatrix} V_1(\lambda) \\ V_2(\lambda) \\ \vdots \\ V_n(\lambda) \end{bmatrix} = X\beta + \varepsilon \,. \qquad (2.7.6)$$

V transformation is usually preferred.

Estimation of λ

From now on, we concentrate on the transformation $V(\lambda)$. The likelihood function is

$$f(V_1(\lambda), V_2(\lambda), \ldots\ldots, V_n(\lambda), \beta_0, \beta_1, \ldots, \beta_{p-1}, \sigma^2, \lambda) = \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n e^{\frac{-[v(\lambda)-X\beta]^2[v(\lambda)-X\beta]}{2\sigma^2}}$$

Thus,

$$\frac{\partial \log f(V(\lambda), \beta, \sigma^2, \lambda)}{\partial\beta} = \frac{\partial\left[-\frac{n}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}(V(\lambda) - X\beta)^t(V(\lambda) - X\beta\right]}{\partial\beta} = 0$$

Then,

$$\Leftrightarrow \quad (X'X)\beta = X'V(\lambda) \quad \Leftrightarrow \quad b = (X'X)^{-1}X'V(\lambda)\,.$$

Furthermore,

$$\frac{\partial \log f(V(\lambda), b, \sigma^2, \lambda}{\partial\sigma^2}$$

$$= \frac{\partial\left[-\frac{n}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}(V(\lambda) - Xb)^t(V(\lambda) - Xb\right]}{\partial\sigma^2}$$

$$= \frac{\partial\left[-\frac{n}{2}\log(2\pi) - \frac{n}{2}\log(\sigma^2) - \frac{1}{2\sigma^2}(V(\lambda) - \hat{V}(\lambda))^t(V(\lambda) - \hat{V}(\lambda))\right]}{\partial\sigma^2}$$

$$= \frac{-n}{2\sigma^2} + \frac{\left[V(\lambda) - \hat{V}(\lambda)\right]^t\left[V(\lambda) - \hat{V}(\lambda)\right]}{2(\sigma^2)^2}$$

$$= 0$$

; where $\hat{V}(\lambda) = Xb = X(X^tX)^t X^t V(\lambda)$

$$\Leftrightarrow \quad \hat{\sigma}^2 \quad = \quad \frac{\left[V(\lambda)-\hat{V}(\lambda)\right]\left[V(\lambda)-\hat{V}(\lambda)\right]}{n} \quad = \quad \frac{RSS(V(\lambda))}{n}$$

where $RSS(V(\lambda)) = \left[V(\lambda)-\hat{V}(\lambda)\right]^t\left[V(\lambda)-\hat{V}(\lambda)\right]$ is the residual sum of square of $V(\lambda)$.

The maximum likelihood estimate (MLE) $\hat{\lambda}$ of λ is the maximizer of the log-likelihood. That is, $\hat{\lambda}$ maximizes

$$\log\left[f(V(\lambda), b, \hat{\sigma}^2, \lambda)\right]$$

$$= \frac{-n}{2}\log(2\pi) - \frac{n}{2}\log\left[\frac{RSS(V(\lambda))}{n}\right] - \frac{n}{2RSS(V(\lambda))}\left[V(\lambda)-\hat{V}(\lambda)\right]^t\left[V(\lambda)-\hat{V}(\lambda)\right]$$

$$= \frac{-n}{2}\log(2\pi) - \frac{n}{2}\log\left[\frac{RSS(V(\lambda))}{n}\right] - \frac{n}{2}$$

$$\propto \quad \frac{-n}{2}\log\left[\frac{RSS(V(\lambda))}{n}\right]$$

$$\Leftrightarrow \hat{\lambda} \quad \text{minimizes} \frac{n}{2}\log\left[\frac{RSS(V(\lambda))}{n}\right] \quad \Leftrightarrow \quad \hat{\lambda} \quad \text{minimizes} RSS(V(\lambda))$$

$\Leftrightarrow$ $\hat{\lambda}$ can be found by finding the value of λ which minimizes

$$RSS(V(\lambda)) = \left[V(\lambda)-\hat{V}(\lambda)\right]\left[V(\lambda)-\hat{V}(\lambda)\right].$$

The procedure of finding the approximate value of $\hat{\lambda}$

- Let $-a = \lambda_0 < \lambda_1 < \lambda_2 < \Lambda < \lambda_{2n-1} < \lambda_{2n} = a$, where $\lambda_i = \lambda_0 + \left(\frac{i}{n}\right)a$, a is some constant, and n is a very large number. For example, as $n = 100$ and $a = 1$, then $\lambda_0 = -1, \lambda_1 = -0.99, \lambda_2 = -0.98, ..., \lambda_{199} = 0.99, \lambda_{200} = 1$.
- Find all values $RSS(V(\lambda_0)), RSS(V(\lambda_1), ..., RSS(V(\lambda_{2n-1})), RSS(V(\lambda_{2n})$.

The value λ_i corresponding to smallest $RSS(V(\lambda))$ is the approximate $\hat{\lambda}$. That is $RSS(V(\lambda_i) \leq RSS(V(\lambda_j)), j \neq i$.

$100(1-\alpha)\%$ confidence interval for λ:

Let $\hat{\lambda}$ be the maximum likelihood estimate. $100(1-\alpha)\%$ confidence interval for λ consists of those values of λ satisfying

$$\mathrm{RSS}(V(\lambda)) \le \mathrm{RSS}(V(\hat{\lambda}))e^{\frac{\chi^2_{1-\alpha}}{n}}$$

Sometimes, $\hat{\lambda}$ is very close to 0, for example, $\hat{\lambda} = 0.001$. Then, we might wonder if $Y^{0.001}$ or $\log(Y)$ is more appropriate (76). Then, we can construct a $100(1-\alpha)\%$ confidence interval. Then, we can examine if 0 falls in this interval. If yes, then we use log transformation. Otherwise, we use power transformation, $Y^{0.001}$.

Several benchmark values of λ are recommended to examine by using $100(1-\alpha)\%$ confidence interval. They are following as :

$$\lambda = -1 \Rightarrow Y^{-1} = \frac{1}{Y}, \lambda = -\frac{1}{2} \Rightarrow Y^{\frac{1}{2}} = \frac{1}{\sqrt{Y}}, \lambda = 0 \Rightarrow \log(Y),$$

$$\lambda = \frac{1}{2} \Rightarrow Y^{\frac{1}{2}} = \sqrt{Y}, \lambda = 1 \Rightarrow Y = Y$$

Krataithong (77) proposed the data transformation to normal distribution for transformation of explanatory variables.

Kuo and Cliffs (78) presented the discrete data control systems by transformation of the response yields the formal way of comparing transformation in parametric statistics.

CHAPTER III
METHODOLOGY

The methodology of this study is mainly concerned with a simulation technique under comparing the properties of the estimators for the parametric regression coefficients in multicollinearity situations among the ordinary least square, the almost unbiased generalized Liu estimator method and the bootstrap of these two methods. This chapter emphasizes on the important issues as follow:

1. The criteria for the study design
2. The simulation programming
3. Statistical investigation

1. The criteria for the study design

To obtain the specified condition, the study design consists of the set up for simulation study and the simulation procedure.

1.1 Set up for simulation study

Without loss of generality, the studied data distributed under mean equals to 1 for all distribution. The following simulation factors are fixed:

1. For the normal distribution, the standard deviation equals to 0.05, 0.10, 0.15, 0.30 and 0.50.
2. For the contaminated normal distribution, scale factor equals to 3, 5 and percent of contamination equals to 5, 10 and standard deviation equals to 0.05, 0.10 and 0.15.
3. For the lognormal distribution, the variance equals to 0.05, 0.30, 0.70 and 1.00.
4. The studied sample sizes of 10, 30, 50 and 100.
5. The number of independent variables are 3 and 5.
6. The various degree of correlation among independent variables are equal to 0.1, 0.3, 0.5, 0.7, 0.9 and 0.99 that set by Wichern and Churchill formula.

7. The estimator ($\hat{\beta}$) of multiple regression coefficients
   a) determine $\hat{\beta}$ from eigenvector appropriate maximum eigenvalue of matrix $X'X$ for the least mean square error.
   b) determine $\hat{\beta}$ from eigenvector appropriate minimum eigenvalue of matrix $X'X$ for the most mean square error.
8. Each condition is performed for 500 iterations at Linux system with Intel Fortran Complier 8.1 on Dell PowerEdge 2600 Intel Xeon 3.2 GHz.

1.2 The simulation procedure

To simulate the data according to the determined criteria, The simulation procedure is illustrated in Figure 5. The step of calculating multiple regression coefficient estimating of these four methods as follows:

1. Generate random numbers for matrix X for each distribution under various degree of correlation, sample size and number of independent variables.
2. Computation of matrix $X'X$ for eigenvalue corresponds to the eigenvector of matrix for multiple regression coefficient (β) and regarding this coefficient from maximum eigenvalue corresponds to the eigenvector.
3. Generate error random sample (ε) using uniform distribution under each distribution.
4. Computation of dependent variable from matrix X that generated in step 1 multiply by multiple regression coefficient in step 2 and plus with error random sample.
5. Lognormal distribution is transformed using Box-Cox power transformation.
6. Estimate the parameter of multiple regression coefficient ($\hat{\beta}$) using the ordinary least square, the almost unbiased generalized Liu estimator and the bootstrap technique with these two methods.
7. Compute mean square error and standard deviation of multiple regression coefficient ($\hat{\beta}$) from each method.

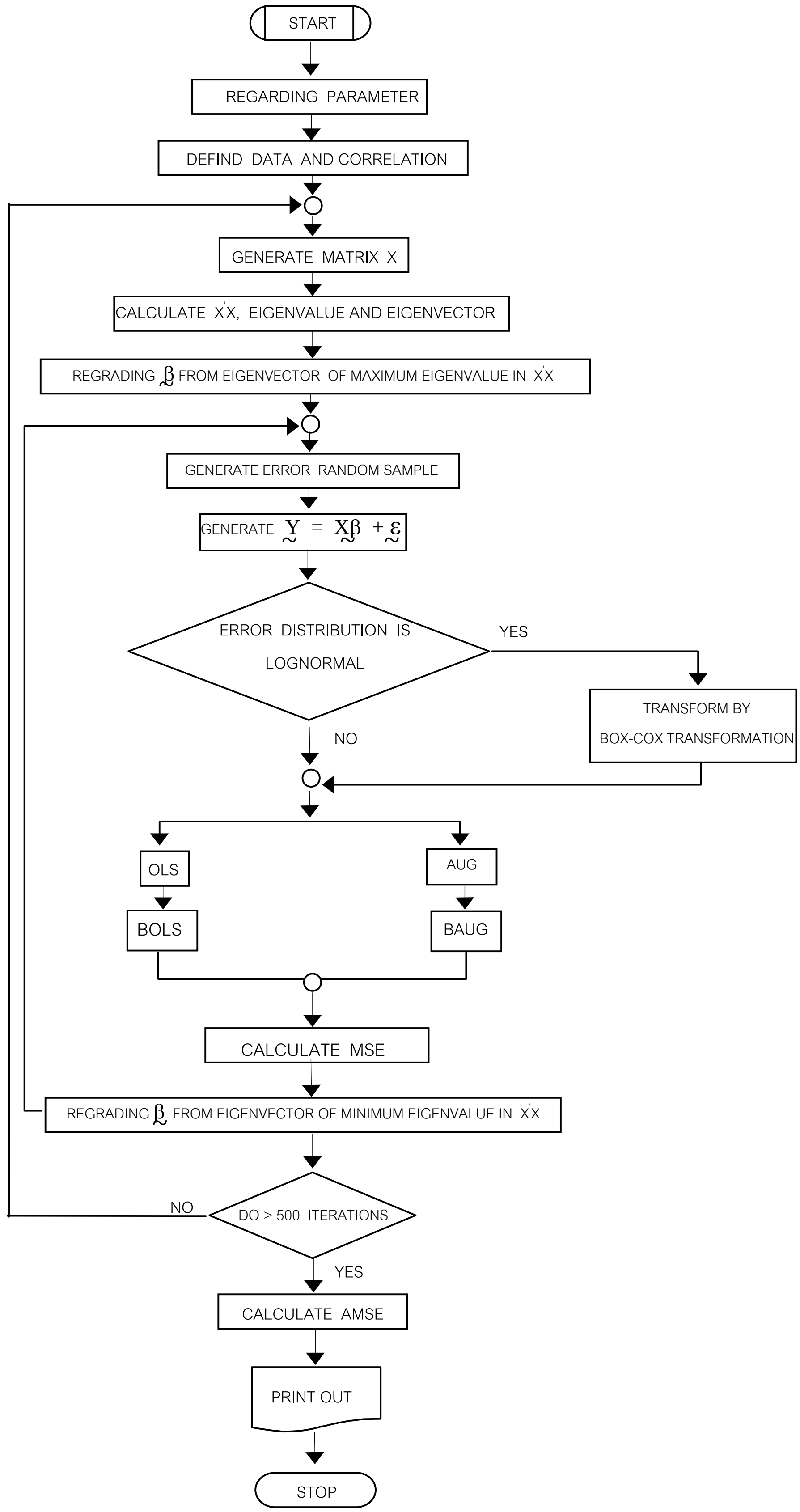

Figure 5. The flowchart of the simulation procedures.

8. Regarding the coefficient from minimum eigenvalue corresponds to the eigenvector and repeats iteration since step 2 till step 7.
9. Repeat the estimation for all 500 iterations under each criteria.
10. Compute average mean square error and standard deviation from average mean square error all 500 iterations.

2. The simulation programming

In order to simulation the data according to the criteria, the Monte Carla method used on FORTRAN 90 language. The important step in simulation procedure, display in subroutine programming were:

2.1 Seed of 65539

Kulanoot (79) used the number 65539 to generate a random number for statistics test. It makes many set of random number with uniform distribution. In Fortran program, the researcher used subroutine random (ix,iy,yfl) for generating the random number.

2.2 Population Distribution from Defining Distribution

Fortran program was used to create population under three distributions by simulating the data from Monte Carlo method. Their distributed data has generated in this step.

2.2.1 Normal Distribution

Actually, the first step for random number generation is to generate uniform random number by Box and Muller method (80). This technique yields standard normal distribution random variable under mean is zero and variance equal 1 at the same time, which was represented as Figure 6.

From picture gets

$$Z_1 = B\cos(\theta) \tag{4.2.1}$$

$$Z_2 = B\sin(\theta) \tag{4.2.2}$$

Because $B^2 = Z_1^2 + Z_2^2$ is chi-square distribution with 2 degree of freedom, which equal exponential distribution with mean equals to 2 ,then we use inverse transformation to generate random variable distribution as follows

$$B = [-2in(R)]^{\frac{1}{2}} \tag{4.2.3}$$

When R is random variable under uniform distribution.

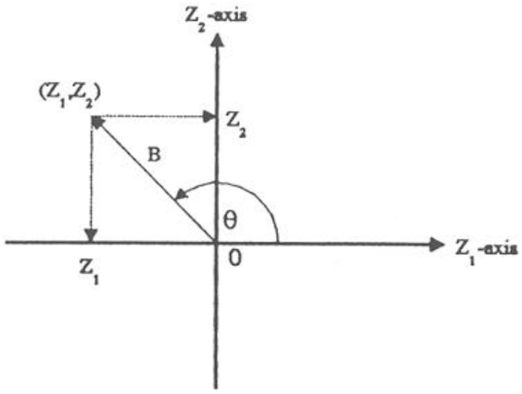

Figure 6. Box and Muller method by using generator Z_1 and Z_2 to generated normal distribution.

By Symmetry of normal distribution ,The θ is uniform between 0 to 2π radian , radius B and θ is independent. From equation (4.2.1) to (4.2.3), we can generated random number in Z-Score 2 set, which are presented

$$Z_1 = [-2\ln(R_1)]^{\frac{1}{2}} \cos(2\pi R_2) \tag{4.2.4}$$

$$Z_2 = [-2\ln(R_1)]^{\frac{1}{2}} \sin(2\pi R_2) \tag{4.2.5}$$

when R_1 and R_2 is random number constructed from subroutine random ,then we get random number into Z-Score and transform random number by equation

$$NORMAL_1 = \mu + \sigma Z_1 \tag{4.2.6}$$

$$NORMAL_2 = \mu + \sigma Z_2 \tag{4.2.7}$$

After that the uniform distributed random numbers will be transformed to be whatever distributed data are needed. Especially for this study, Fortran 90 can include subroutines that are easily used for various functions. Therefore, the subroutine for generate a uniform random number is omitted in this step.

A subroutine for generation of a standard normal distribution random numbers is required . The subroutine is used by using the statement normal (am,sd) which had two parameters, mean (μ) equals to 1 and standard deviation (σ) equals to 0.05,0.10, 0.15, 0.30 and 0.50 .

In this method, a uniform (0,1) random deviate is generated subroutine normal generates random numbers from a standard normal distribution using the Box-Muller method technique.

2.2.2 Contaminated normal distribution

For the contaminated normal distribution, one part of population has a normal distribution with mean μ, variance σ^2 with probability 1-p and the others have a normal distribution with mean μ, variance $c\sigma^2$ with probability p. The p and c are percent of contamination and scale factor, respectively. The contaminated normal distribution subroutine is based on the preceding subroutine of standard normal distribution.

This study generated function for simulate from contaminated normal distribution used by using the statement : scnor (c,p,am,sd) which had four parameters, scale factor (c) equals to 3 and 10 ,percent contaminated (p) equals to 5 and 10 , mean (μ) equals to 1 and standard deviation (σ) equals to 0.05,0.10 and 0.15 . Therefore, this subroutine produces a number X and random number is required.

2.2.3 Lognormal distribution

The first step for random number generation to generate lognormal distribution is using exponential of random number . Lognormal distribution had special importance in probability statistics, Which had two parameters mean (μ) equals to 1 and the standard deviation (σ) equals to 0.2236, 0.5477, 0.8366 and 1.0069.

The formulation is represented as a subroutine for generation of a lognormal distribution and random number is required. The subroutine is used by using statement lognor(am,sd) for transform by exponential function.

2.3 Generate independent variables into linear relationship with correlation

This study concern independent variable have collinearity which the nearest independent variables have high collinearity and the farthest independent variables have low collinearity. It can defined correlation among independent variables as follows (81): (Corr (x_1,x_2) means the correlation coefficients between x_1 and x_2)

2.3.1 The 3 independent variables

- Corr (x_1,x_2) and Corr (x_2,x_3) = 0.1 with Corr (x_1,x_3) = $(0.1)^2$ = 0.01
- Corr (x_1,x_2) and Corr (x_2,x_3) = 0.3 with Corr (x_1,x_3) = $(0.3)^2$ = 0.09
- Corr (x_1,x_2) and Corr (x_2,x_3) = 0.5 with Corr (x_1,x_3) = $(0.5)^2$ = 0.25
- Corr (x_1,x_2) and Corr (x_2,x_3) = 0.7 with Corr (x_1,x_3) = $(0.7)^2$ = 0.49
- Corr (x_1,x_2) and Corr (x_2,x_3) = 0.9 with Corr (x_1,x_3) = $(0.9)^2$ = 0.81
- Corr (x_1,x_2) and Corr (x_2,x_3) = 0.99 with Corr (x_1,x_3) = $(0.99)^2$ = 0.9801

To summarize, Corr (x_1,x_2) and Corr (x_2,x_3) equal to 0.1,0.3,0.5,0.7, 0.9 ,0.99 and Corr (x_1,x_3) equal 0.01,0.09,0.25,0.49,0.81 and 0.9801.

2.3.2 The 5 independent variables

- Corr (x_1,x_2), Corr(x_2,x_3), Corr(x_3 ,x_4) and Corr(x_4,x_5) = 0.1 with Corr(x_1,x_3), Corr(x_2,x_4) and Corr(x_3,x_5) = $(0.1)^2$ = 0.01
- Corr (x_1,x_2), Corr (x_2,x_3), Corr (x_3 ,x_4) and Corr (x_4,x_5) = 0.3 with Corr(x_1,x_3), Corr (x_2,x_4) and Corr (x_3,x_5) = $(0.3)^2$ = 0.09
- Corr (x_1,x_2), Corr (x_2,x_3), Corr (x_3 ,x_4) and Corr (x_4,x_5) = 0.5 with Corr(x_1,x_3), Corr (x_2,x_4) and Corr (x_3,x_5) = $(0.5)^2$ = 0.25
- Corr (x_1,x_2), Corr (x_2,x_3), Corr (x_3 ,x_4) and Corr (x_4,x_5) = 0.7 with Corr(x_1,x_3), Corr (x_2,x_4) and Corr (x_3,x_5) = $(0.7)^2$ = 0.49
- Corr (x_1,x_2), Corr (x_2,x_3), Corr (x_3 ,x_4) and Corr (x_4,x_5) = 0.9 with Corr(x_1,x_3), Corr(x_2,x_4) and Corr(x_3,x_5) = $(0.9)^2$ = 0.81
- Corr (x_1,x_2), Corr (x_2,x_3), Corr (x_3 ,x_4) and Corr (x_4,x_5) = 0.99 with Corr(x_1,x_3), Corr (x_2,x_4)and Corr (x_3,x_5) = $(0.99)^2$ = 0.9801

To summarize, Corr (x_1,x_2), Corr (x_2,x_3), Corr (x_3,x_4) and Corr(x_4,x_5) equal 0.1, 0.3, 0.5, 0.7, 0.9,0.99 and Corr(x_1,x_3), Corr (x_2,x_4) and Corr (x_3,x_5) equal 0.01,0.09, 0.25,0.49,0.81 and 0.9801.

This study reproduced correlation between independent variables by Wichern and Churchill (50) method to generated several level of correlation and this technique has favored such as the step for generated data in 5 independent variables and sample sizes equal 30 , The value of x is created from this equations.

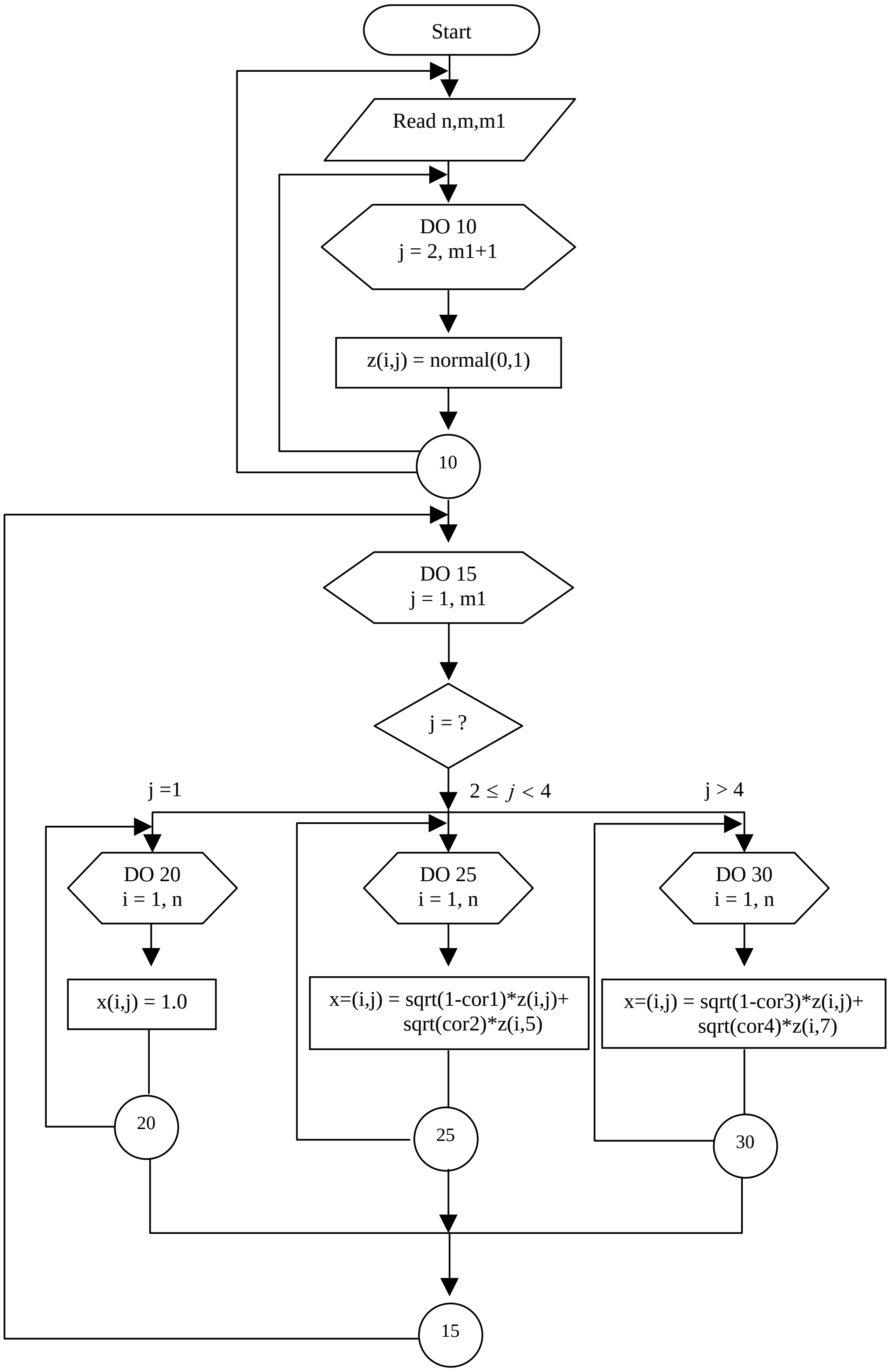

Figure 7. The flowchart of generated independent variables into linear relationship with the various degree of correlation using Wichern and Churchill.

Therefore, instead of equation (4.2.8) by α^2 = 0.99 and α_*^2 = 0.90 then data of independent variables from

$$x_{ij} = (1-0.99)^{\frac{1}{2}} Z_{ij} + (0.99)^{\frac{1}{2}} Z_{i6} \quad ; i = 1,2,\ldots\ldots,30 \quad j=1, 2, 3$$

$$x_{ij} = (1-0.90)^{\frac{1}{2}} Z_{ij} + (0.90)^{\frac{1}{2}} Z_{i6} \quad ; i = 1,2,\ldots,30 \quad j = 4,5$$

From this equations, the researcher constructs subroutine for simulated x as independent variables by using random and normal function. Then the flow chart for this study has generated function for simulate the data distributed with correlation using their formula in Figure 7.

$$x_{ij} = (1-\alpha^2)^{\frac{1}{2}} Z_{ij} + \alpha\, Z_{i6} \quad ; i = 1,2,\ldots,30 \ , \ j = 1,2,3$$

$$x_{ij} = (1-\alpha_*^2)^{\frac{1}{2}} Z_{ij} + \alpha_*\, Z_{i6} \quad ; i = 1,2,\ldots,30 \ , \ j = 4,5 \qquad (4.2.8)$$

Which Z_{i1} , Z_{i2} ,…..,Z_{i6} are independent variable are generated by standard normal distribution mean equals 0 and variance equals 1.

α^2 is correlation among independent variable X_1, X_2, X_3

α_*^2 is correlation between independent variable X_4, X_5

$\alpha\alpha_*$ is correlation between independent variable X_j (j=1,2,3) and X_4 or X_5

2.4 Data generated computation

To simulate the data as X independent variables according to the determined criteria, four important steps will be conducted as follows:

For each iteration under the same criteria in different sample sizes and level of correlation must be concise and expedient process. Actually, the first step is to run process under the sample sizes. After that various degree of correlation will be run process to be whatever distributed data are needed. A summarize cycle for sample sizes and level of correlation is illustrated in Figure 8.

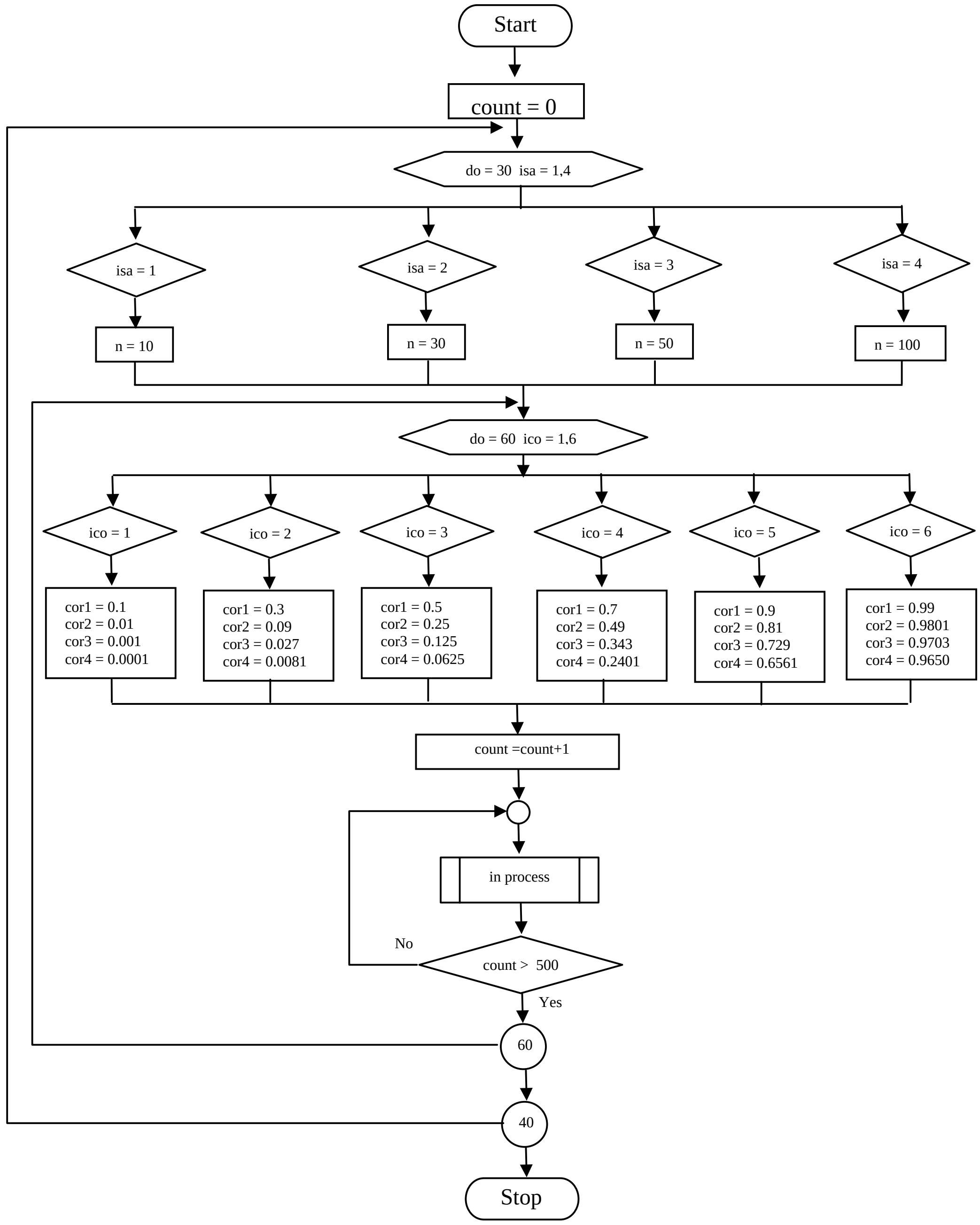

Figure 8. The flowchart for sample sizes and the various degree of correlation.

On the whole, the data generated will be checking the various degree of correlation by this step for accurately process before get through the main program. It is noted that followed the regression analysis principle. Level of correlation computing is presented in Figure 9.

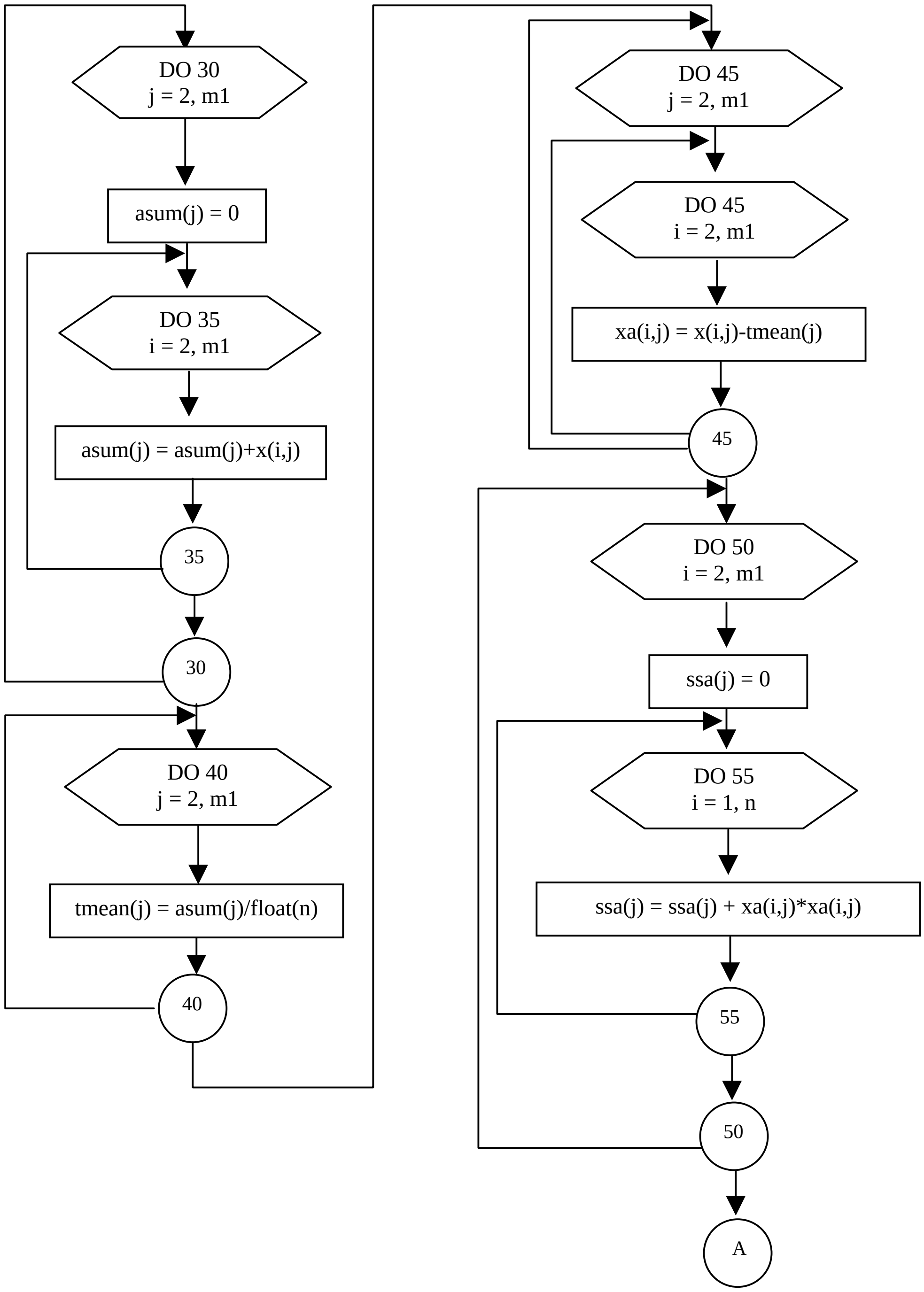

Figure 9. The flowchart for compute the various degree of correlation.

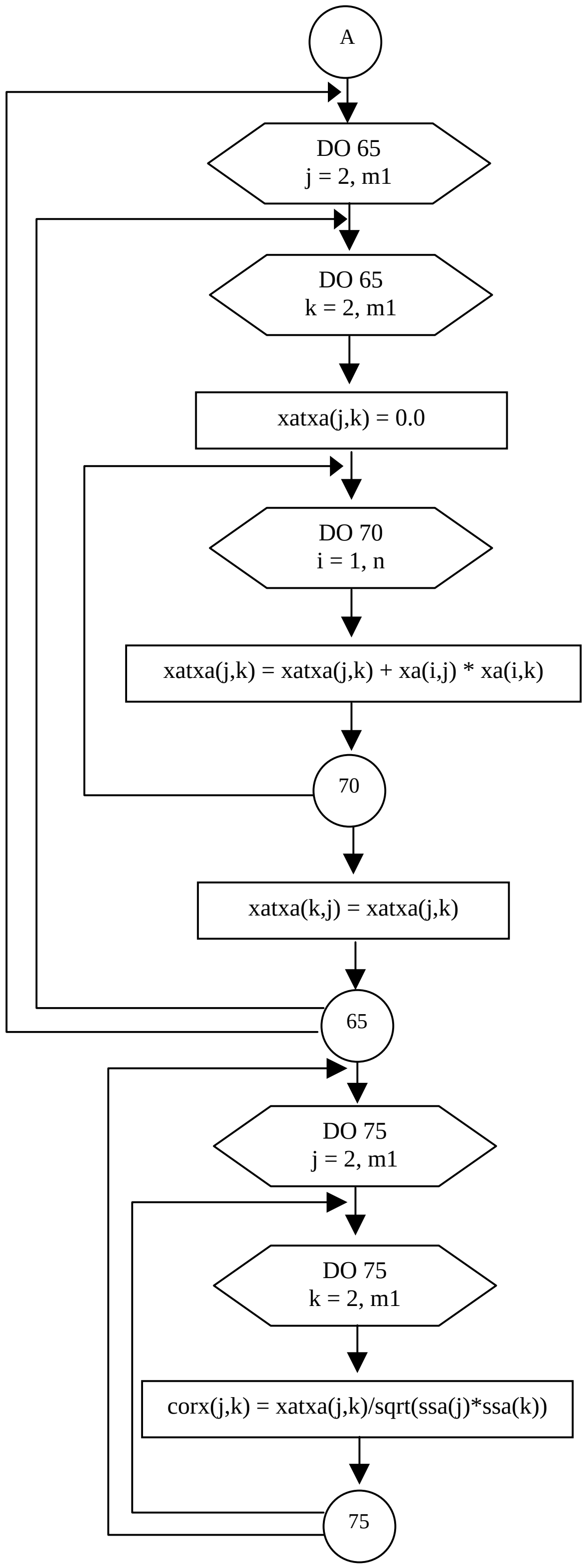

Figure 9. The flowchart for compute the various degree of correlation. (Continued)

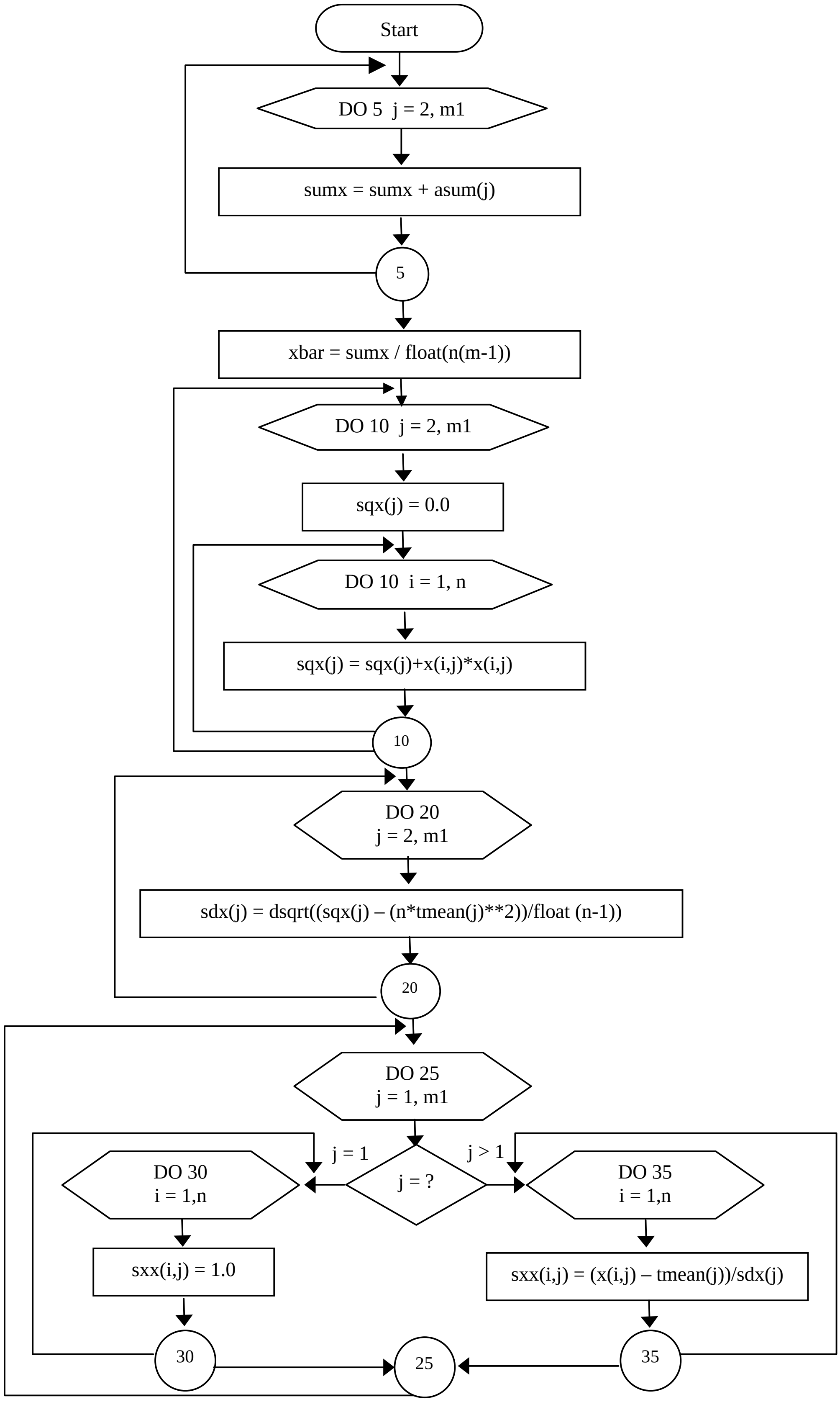

Figure 10. The flowchart for standardize data generated.

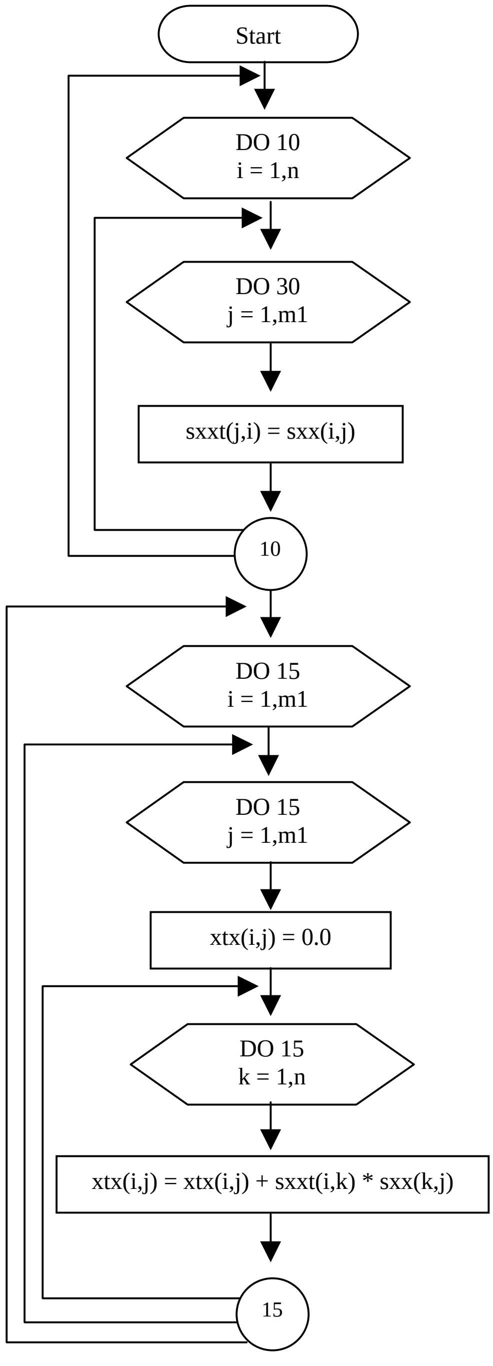

Figure 11. The flowchart for compute $X'X$ matrix.

Overall, data generated must be adjust to the same unit for reduce the sum square error, all this is due to no effective to the result. Standardized data as x independent variables as shown in Figure 10.

All of these data that generated in each round can compute $X'X$ matrix. This step will be used on the ordinary least square method and almost unbiased generalized Liu estimator method for regression coefficient estimating. $X'X$ matrix computing are illustrated in Figure 11.

2.5 Eigenvalue and eigenvectors

In this study only Jacobi's method will be used. This scope in the following two sections:

1. Transformation of coordinates.
2. Jacobi's method for eigenvalues (82).

and this numerical solution of eigenvalue and eigenvector will be generate in this step

Following the discussion on Jacobi's method for obtain eigenvalues and eigenvectors, this study examine the details for the development of a computer program from subroutine Jacobi corresponding with the procedures described in the previous sections. In particular, a step by step has shown as following (82):

1. Setting initial values of matrix V
2. Scan for largest off diagonal elements in each row
3. Find for maximum of x(i) for pivot element
4. Computing tangent, sine, cosine
5. Adjust sine, cosine for computation
6. Inspecting the value to determine a new maximum value should be computed
7. Search depleted row for new maximum
8. Changing the other elements of matrix
9. Computation of eigenvalue

After the Jacobi method has finished, the process for calculated the y dependent variable is continued. The detail in this step displayed in subroutine programming were on Figure 12.

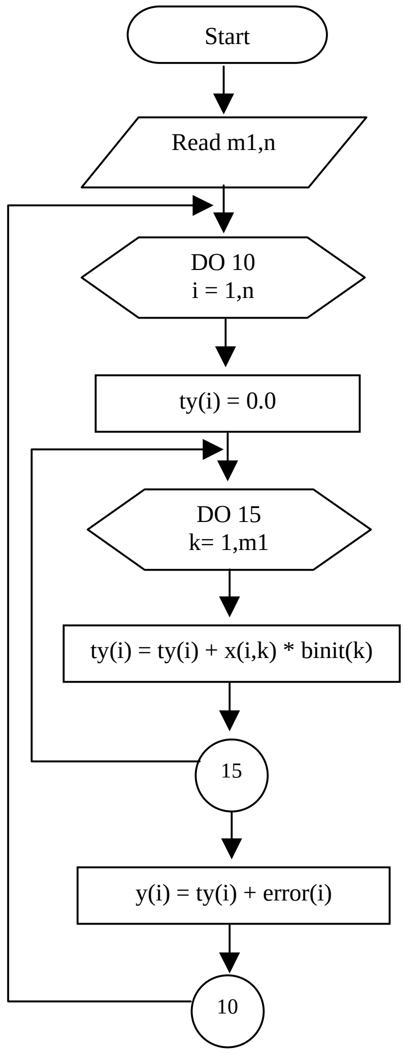

Figure 12. The flowchart for calculating y dependent variable.

2.6 The bootstrap resampling technique

The bootstrap resampling often gives a much better estimate than traditional statistical inference, the statistical calculated program by the bootstrap step are shown in Figure 13.

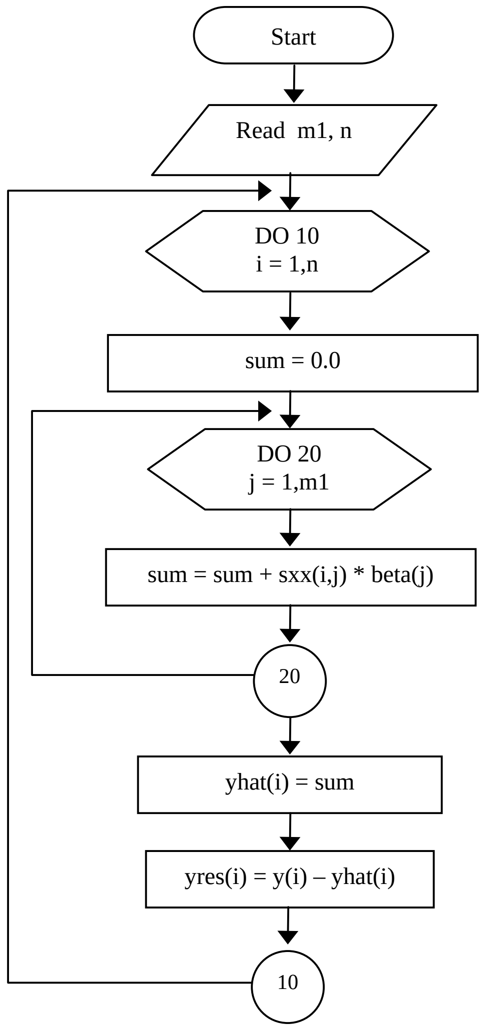

Figure 13. The flowchart for calculating the residual regression calculating in bootstrapping process.

2.6.1 The estimation of multiple regression coefficients by the ordinary least square within bootstrap technique

From model

$$\underset{\sim}{y} = X\underset{\sim}{\beta} + \underset{\sim}{\varepsilon}$$

Error is random sampling under the same continuous distribution and identically independent distribution ,then $\underset{\sim}{\varepsilon} \sim F$, i = 1,2,….,n when F is unknown probability distribution.

From the data X and $\underset{\sim}{y}$ seek for the location estimates and bootstrap in what follows (53):

1. Calculate $\underset{\sim}{\hat{\beta}}$ by Ordinary Least Square method form

$$\underset{\sim}{\hat{\beta}}_{OLS} = (X'X)^{-1}X'\underset{\sim}{y}$$

2. From $\underset{\sim}{\hat{\beta}}_{OLS}$ by Ordinary Least Square , to conduct

$$\underset{\sim}{\hat{\varepsilon}} = \underset{\sim}{y} - X\underset{\sim}{\hat{\beta}}_{OLS}$$

3. For each $\hat{\varepsilon}_1, \hat{\varepsilon}_2, ..., \hat{\varepsilon}_n$ could generate 10 sample with replacement, we get $\hat{\varepsilon}_1^*, \hat{\varepsilon}_2^*, ..., \hat{\varepsilon}_n^*$ from sample in generate step ; $\hat{\varepsilon}_j^*$ is random order j from $\hat{\varepsilon}_1, \hat{\varepsilon}_2, ..., \hat{\varepsilon}_n$.
4. $\underset{\sim}{\hat{\beta}}_{OLS}$ from step 1 and $\underset{\sim}{\hat{\varepsilon}}$ from step 3 get to construct new model.

$$\underset{\sim}{y}^* = X\underset{\sim}{\hat{\beta}} + \underset{\sim}{\varepsilon}^*$$

5. This step we bring $\underset{\sim}{y}^*$ and X to calculate $\hat{\beta}^*$ by Ordinary Least Square method.
6. Repeat step 3 to 5 for 30, 50 and 100 bootstrap sample.
7. Calculated mean square error.

2.6.2 The estimation of multiple regression coefficients by the almost unbiased generalized Liu estimator method within bootstrap technique

From model

$$\underset{\sim}{y} = X\underset{\sim}{\beta} + \underset{\sim}{\varepsilon}$$

Error is random sampling under the same continuous distribution and identically independent distribution ,then $\underset{\sim}{\varepsilon} \sim F$, i = 1,2,….,n when F is unknown probability distribution.

From the data X and $\underset{\sim}{y}$ seek for the location estimates and bootstrap in what follows (47) :

1. Calculate $\underset{\sim}{\hat{\beta}}$ by the almost unbiased generalized Liu estimator method from

   $$\underset{\sim}{\hat{\beta}}_{AUGLE}(D) = (X'X+I)^{-1}(X'\underset{\sim}{y}+D\underset{\sim}{\hat{\beta}})$$

2. From $\hat{\beta}_{\sim AUGLE}$ by the almost unbiased generalized Liu estimator, to conduct

   $$\underset{\sim}{\hat{\varepsilon}} = \underset{\sim}{y} - X\hat{\beta}_{\sim AUGLE}$$

3. For each $\hat{\varepsilon}_1,\hat{\varepsilon}_2,....,\hat{\varepsilon}_n$ could generate n sample with replacement ,we get $\hat{\varepsilon}^*_1,\hat{\varepsilon}^*_2,....,\hat{\varepsilon}^*_n$ from sample in generate step ; $\hat{\varepsilon}^*_j$ is random order j from $\hat{\varepsilon}_1,\hat{\varepsilon}_2,....,\hat{\varepsilon}_n$

4. $\hat{\beta}_{\sim AUGLE}$ from step 1 and $\underset{\sim}{\hat{\varepsilon}}$ from step 3 get to construct new model

   $$\underset{\sim}{y}^* = X\underset{\sim}{\hat{\beta}} + \underset{\sim}{\varepsilon}^*$$

5. This step we bring $\underset{\sim}{y}^*$ and X to calculate $\hat{\beta}^*$ by the almost unbiased generalized Liu estimator method.
6. Repeat step 3 to 5 for 10, 30, 50 and 100 bootstrap sample.
7. Calculate mean square error.

   This technique base on the principle of residual bootstrap regression (53) and A summarize cycle for bootstrap technique is illustrated in Figure 14.

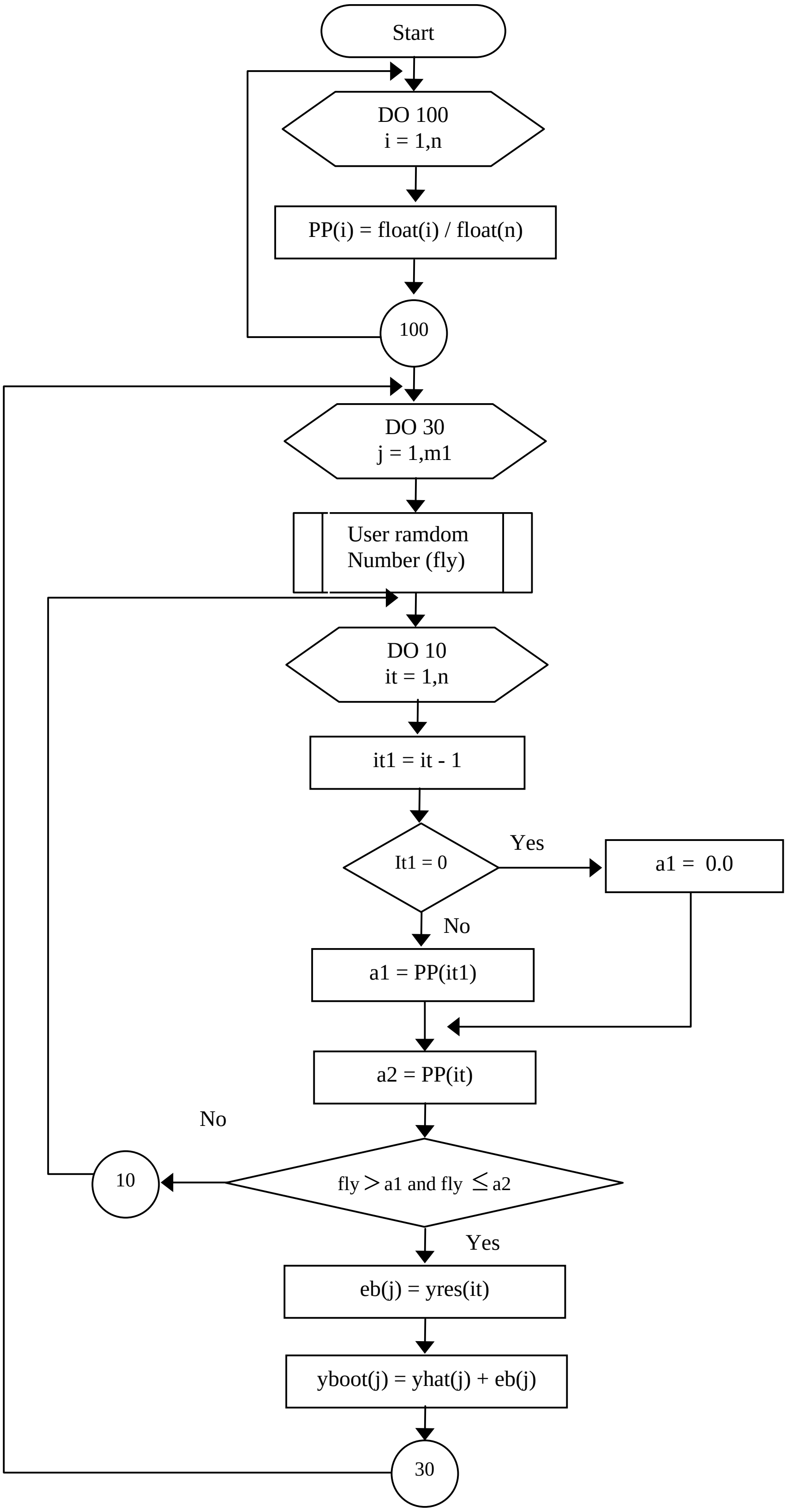

Figure 14. A flowchart for bootstrap regression.

2.7 The ordinary least square method

Following the literature review on ordinary least square method, this step offer the details for iterative and support with another subroutine. This subroutine corresponding with the procedures described in the previous chapter as shown in Figure 15.

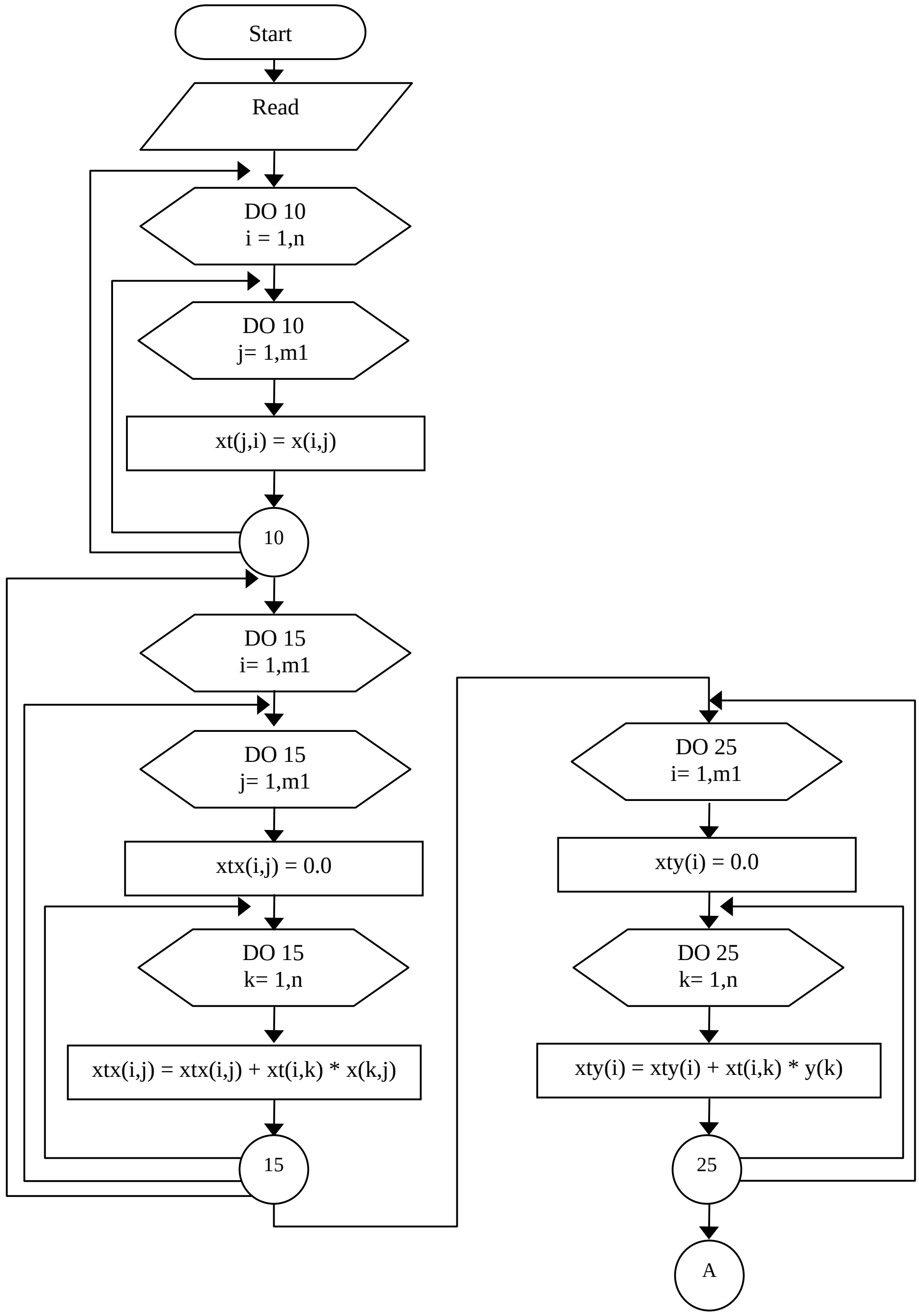

Figure 15. The flowchart for ordinary least square method.

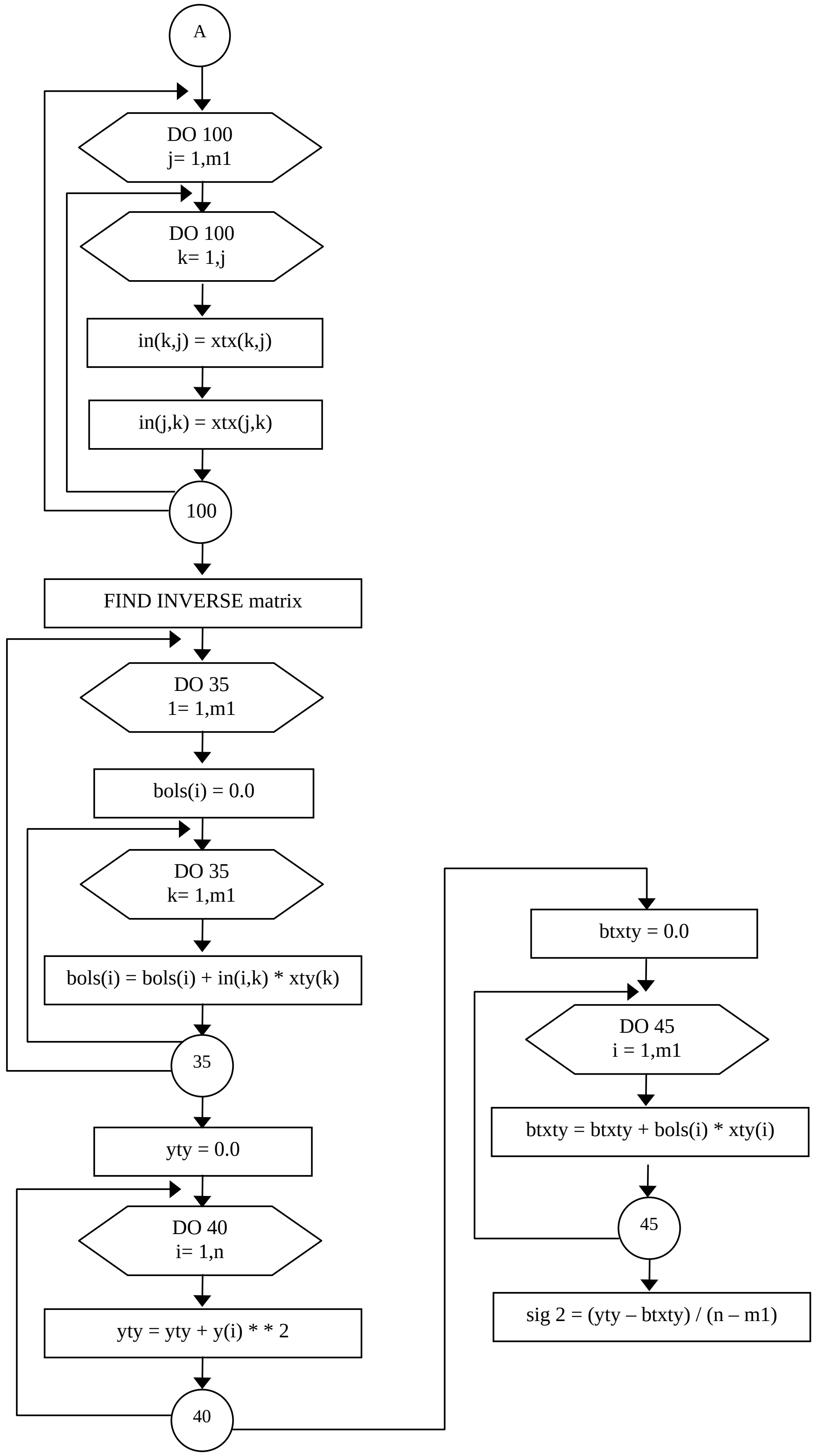

Figure 15. The flowchart for ordinary least square method. (Continued)

2.8 The almost unbiased generalized Liu estimator method

Following the literature review on almost unbiased generalized Liu estimator method, this step examine the details for iterative and support with another subroutine. This subroutine corresponding with the procedures described in the previous chapter is shown in Figure 16.

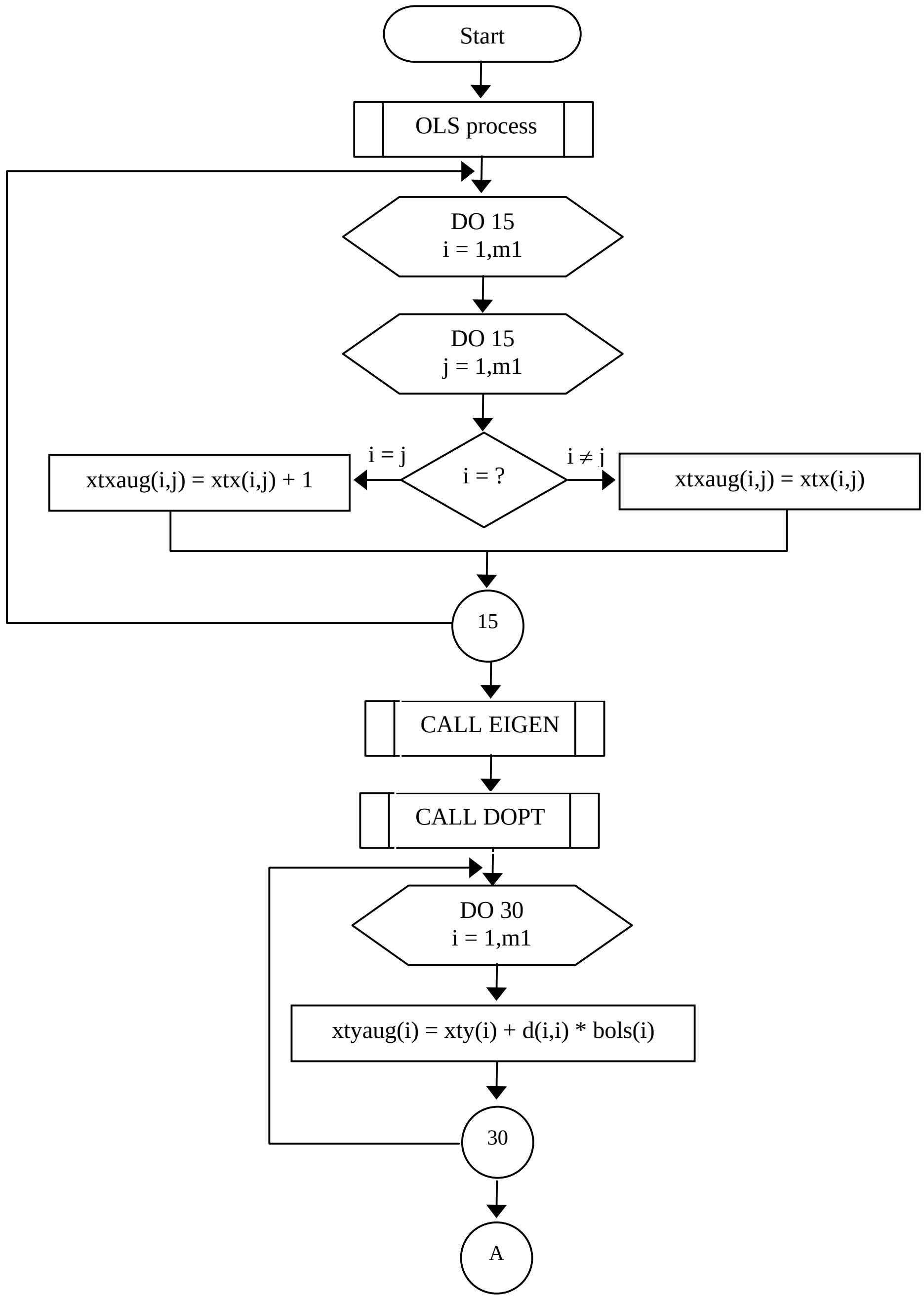

Figure 16. The flowchart for the almost unbiased generalized Liu estimator method.

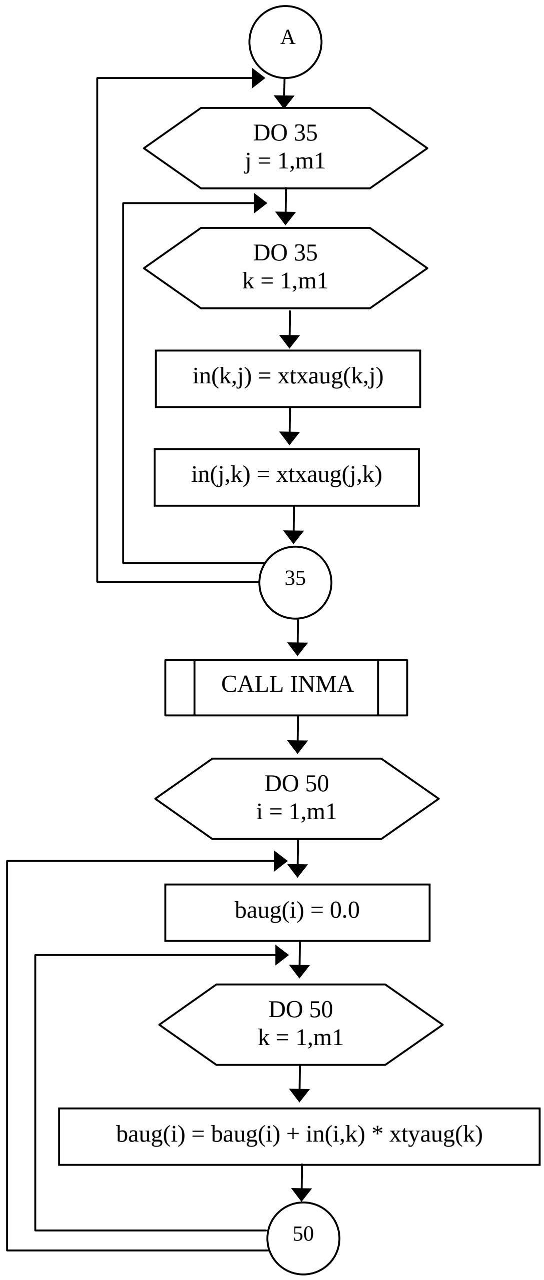

Figure 16. The flowchart for the almost unbiased generalized Liu estimator method. (Continued)

2.9 Transformation technique

Following the literature review on transformation, this step offer the details for iterative and support with another subroutine.

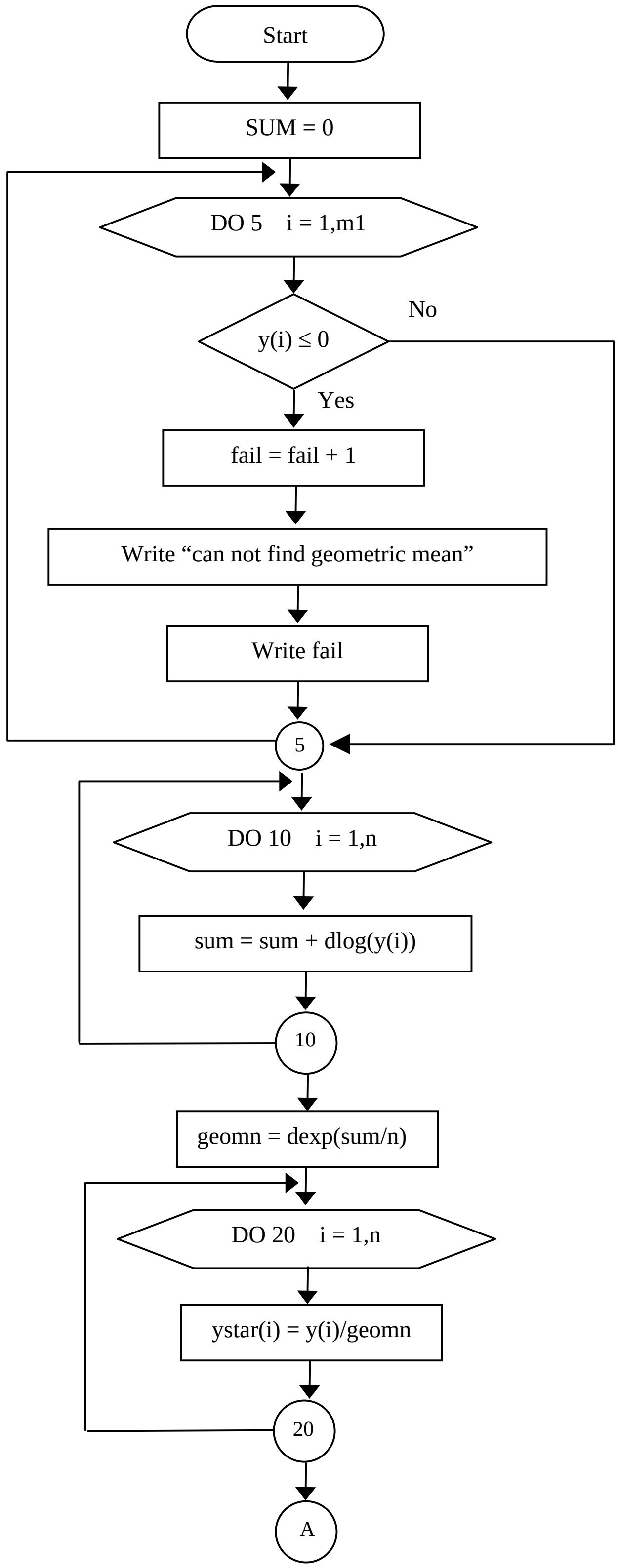

Figure 17. The flowchart for Box-Cox transformation technique.

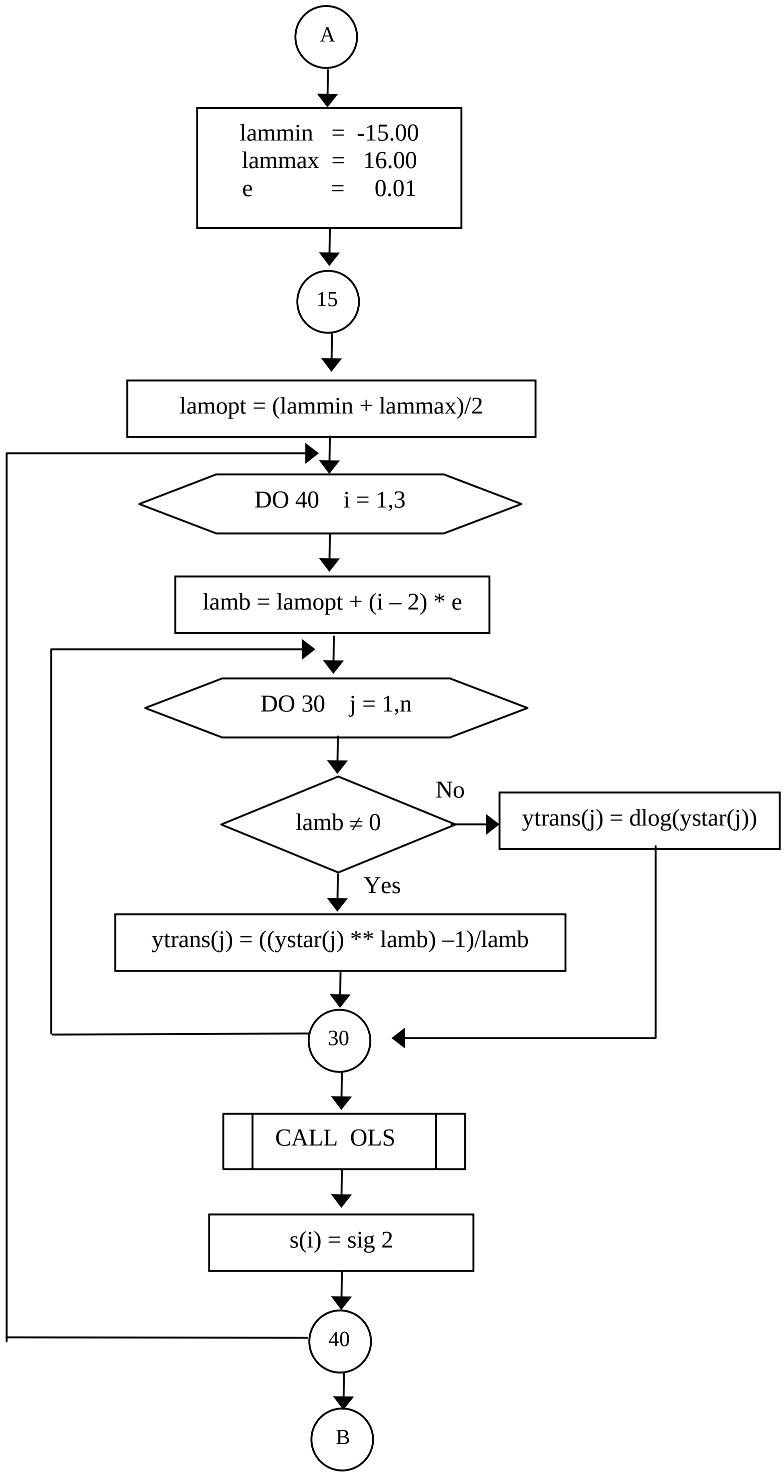

Figure 17. The flowchart for Box-Cox transformation technique.(Continued)

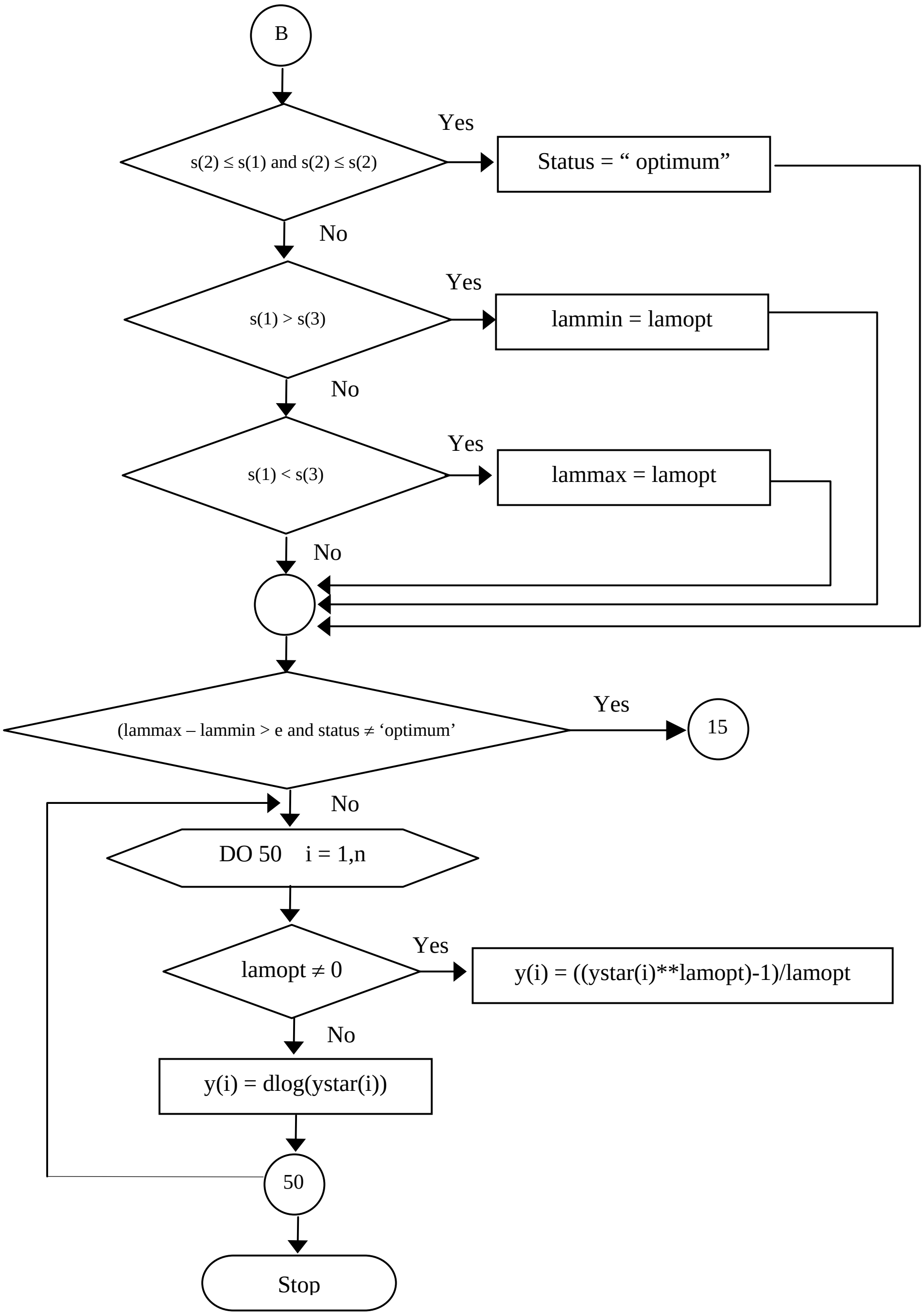

Figure 17. The flowchart for Box-Cox transformation technique.(Continued)

2.10 Program development

Program development was divided into 3 steps.

2.10.1 Starting to develop and complied the program

The first stage in developing the program was the programming operation and formulation of ordinary least square and almost unbiased generalized Liu estimator method with bootstrap technique on the Fortran 90 program.

2.10.2 Testing the operation of the program

To develop the program, each step needed to be tested to see how it worked, and to detect any potential errors in the program. The testing step was as follows:

Testing was done to detect mistakes in writing the program, such as variable declaration and variable values, command steps in the program, called subroutines or functions.

Testing of program operation by statisticians to check statistical calculations and statistical output.

2.10.3 Improving and correcting the program

Improvement and correction of the program were conducted with the operation of the program as follows:

When mistakes in these programs were detected and reported by the experts, such as specifying type variance, the series of operations of the program, call subroutines and functions, the developer of the program would improve it until it could be used in the correct way.

If the experts found that the commands or series of operations were too long or repetitive, resulting in a long operating time to obtain an outcome, and a need for more memory space being reserved for the program, the developer would correct it according to the experts’ suggestions.

When mistakes in statistical formulae or series of calculations were checked by experts, such as errors in statistical calculations or unclear statistical results, the developer would correct the program until could be used correctly.

After the researchers used the program, if they had any comments about the program, the developer would consider how to improve it according to the expert statisticians' and programmers' suggestions.

3. Statistical investigation

After data was generated in one situation, it was computed for ordinary least square, almost unbiased generalized Liu estimator and bootstrap technique with these two estimators. There are calculated according to the studied criteria and different characters of population for all studied distribution. Then, these values were compared with mean square error.

With respect to specific data situations, four method will be investigated through their average mean square error.

3.1 The mean square error (MSE)

Mean square error of multiple regression coefficient estimating each method will be investigated as follows:

$$\mathrm{MSE(OLS)} = \sum_{i=0}^{p}(\hat{\beta}_{OLS(i)} - \beta_i)^2$$

$$\mathrm{MSE(AUG)} = \sum_{i=0}^{p}(\hat{\beta}_{AUG(i)} - \beta_i)^2$$

$$\mathrm{MSE(BOLS)} = \sum_{i=0}^{p}(\hat{\beta}_{BOLS(i)} - \beta_i)^2$$

$$\mathrm{MSE(BAUG)} = \sum_{i=0}^{p}(\hat{\beta}_{BAUG(i)} - \beta_i)^2$$

p is number of independent variables

β_i is the element order i of multiple regression coefficient

$\hat{\beta}_{OLS(i)}$ is the element order i of multiple regression coefficient by ordinary least square

$\hat{\beta}_{AUG(i)}$ is the element order i of multiple regression coefficient by almost unbiased generalized Liu estimator

$\hat{\beta}_{BOLS(i)}$ is the element order i of multiple regression coefficient by ordinary least square with bootstrap technique

$\hat{\beta}_{BAUG(i)}$ is the element order i of multiple regression coefficient by almost unbiased generalized Liu estimator with bootstrap technique

3.2 The average mean square error (AMSE)

Each condition was replicated 500 times, so the average mean square error for each method is

$$\text{AMSE(OLS)} = \frac{1}{500}\sum_{i=1}^{500}\text{MSE(OLS)}_{(i)}$$

$$\text{AMSE(AUG)} = \frac{1}{500}\sum_{i=1}^{500}\text{MSE(AUG)}_{(i)}$$

$$\text{AMSE(BOLS)} = \frac{1}{500}\sum_{i=1}^{500}\text{MSE(BOLS)}_{(i)}$$

$$\text{AMSE(BAUG)} = \frac{1}{500}\sum_{i=1}^{500}\text{MSE(BAUG)}_{(i)}$$

The final step is to compare the average mean square error of estimation among the ordinary least square method, the almost unbiased generalized Liu estimation and the bootstrap technique with these two methods.

CHAPTER IV
RESULTS

The main issues in this chapter are the results of comparing four methods of multiple regression coefficient estimator under three distributions based on their mean square error. There are three parts of error distributed in different situations that are summarized in the following:

1. Results based on normal distributed data
2. Results based on contaminated normal distributed data
3. Results based on lognormal distributed data

1. Results based on normal distributed data

Formally, mean square error is the average of the square of the difference between the desired response and the actual output. To determine which estimator provides the least value, one should determine which estimator has the smallest mean square error, in other words, which estimator has value of standard deviation close to zero. Simply put, the standard deviation is a measure of the degree of dispersion of the data from the average mean square error. A large standard deviation indicates that the data points are far from the average mean square error and a small standard deviation indicates that they are clustered closely around the average mean square error. Likewise, it is the precision of those measurements. The least value of average mean square error from each method is demonstrated in Table 1 to Table 4.

1.1 The three independent variables

According to Table 1, the almost unbiased generalized Liu estimator method gives the least value of average mean square error as well as standard deviation for all various degree of correlation as variance equals to 0.05, 0.10, 0.15 and 0.50 at the smallest sample sizes of 10.

Table 1. The method of the least value of average mean square error for the various degree of correlation on normal distributed data as 3 independent variables with sample sizes of 10.

n = 10	Standard deviation			
Corr.	0.05	0.10	0.15	0.50
0.1	1.0019549 (AUG)	1.0074098 (AUG)	1.0166049 (AUG)	1.1855740 (AUG)
0.3	1.0020398 (AUG)	1.0077389 (AUG)	1.0173256 (AUG)	1.1937297 (AUG)
0.5	1.0025338 (AUG)	1.0097804 (AUG)	1.0220814 (AUG)	1.2377492 (AUG)
0.7	1.0045476 (AUG)	1.0178381 (AUG)	1.0398593 (AUG)	1.4010879 (AUG)
0.9	1.0170579 (AUG)	1.0678310 (AUG)	1.1508081 (AUG)	2.4701354 (AUG)
0.99	1.1738562 (AUG)	1.6486928 (AUG)	2.4053880 (AUG)	15.716155 (AUG)

According to Table 2, the almost unbiased generalized Liu estimator gives the least value of average mean square error for all case at the degree of correlation between 0.1 to 0.9; besides, the values of average mean square error from the ordinary least square method are slightly less than the almost unbiased generalized Liu estimator method estimator at the highest degree of correlation equals to 0.99 as the sample sizes of 30, 50 and 100.

Table 2. The method of the least value of average mean square error for the various degree of correlation on normal distributed data as 3 independent variables with sample sizes of 30, 50 and 100.

S.D.	n	Degree of correlation					
		0.1	0.3	0.5	0.7	0.9	0.99
0.05	30	1.0002955 (AUG)	1.0003022 (AUG)	1.0003690 (AUG)	1.0006237 (AUG)	1.0021656 (AUG)	1.0237617 (OLS)
	50	1.0005768 (AUG)	1.0005828 (AUG)	1.0006156 (AUG)	1.0007415 (AUG)	1.0015055 (AUG)	1.0122569 (OLS)
	100	1.0002207 (AUG)	1.0002465 (AUG)	1.0002365 (AUG)	1.0002942 (AUG)	1.0006499 (AUG)	1.0056437 (OLS)
0.10	30	1.0011431 (AUG)	1.0011671 (AUG)	1.0014336 (AUG)	1.0024553 (AUG)	1.0086825 (AUG)	1.0950026 (OLS)
	50	1.0014394 (AUG)	1.0014642 (AUG)	1.0015950 (AUG)	1.0021018 (AUG)	1.0051885 (AUG)	1.0481600 (OLS)
	100	1.0005775 (AUG)	1.0005845 (AUG)	1.0006399 (AUG)	1.0008711 (AUG)	1.0023030 (AUG)	1.0222689 (OLS)
0.15	30	1.0025381 (AUG)	1.0026015 (AUG)	1.0032041 (AUG)	1.0055124 (AUG)	1.0198771 (AUG)	1.2137224 (OLS)
	50	1.0025897 (AUG)	1.0026454 (AUG)	1.0029417 (AUG)	1.0040872 (AUG)	1.0111213 (AUG)	1.1077094 (OLS)
	100	1.0010705 (AUG)	1.0010869 (AUG)	1.0012106 (AUG)	1.0017326 (AUG)	1.0049675 (AUG)	1.0498756 (OLS)

1.2 The five independent variables

With the simulation results, the almost unbiased generalized Liu estimator with bootstrap technique gives the least value of average mean square error for various degree of correlation between 0.1 to 0.7 for each standard deviation as sample sizes of 10.

However, this is not unanimous result for various degree of correlation between 0.9 to 0.99 because the ordinary least square method, the ordinary least square method with bootstrap technique and the almost unbiased generalized Liu estimator with bootstrap technique give the least value of average mean square error for each standard deviation as sample sizes of 10. The least value of average mean square error from each method is demonstrated in Table 3.

Table 3. The method of the least value of average mean square error for the various degree of correlation on normal distributed data as 5 independent variables with sample sizes of 10.

n = 10	Standard deviation				
Corr.	0.05	0.10	0.15	0.30	0.50
0.1	4.4414304 (BAUG)	14.764510 (BAUG)	31.969254 (BAUG)	124.87324 (BAUG)	345.08819 (BAUG)
0.3	7.4430983 (BAUG)	26.771163 (BAUG)	58.984204 (BAUG)	232.93309 (BAUG)	645.25438 (BAUG)
0.5	27.070183 (BAUG)	105.21257 (BAUG)	235.48730 (BAUG)	940.35152 (BAUG)	2610.5131 (BAUG)
0.7	8.0750669 (BAUG)	29.299026 (BAUG)	64.671974 (BAUG)	255.68419 (BAUG)	708.45186 (BAUG)
0.9	9.7329964 (OLS)	35.930748 (BAUG)	79.593253 (OLS)	315.36929 (BAUG)	874.24377 (BAUG)
0.99	234.61513 (BOLS)	935.69926 (BOLS)	2104.0725 (BOLS)	8413.2881 (OLS)	23368.446 (BAUG)

According to Table 4, simulation results show that the almost unbiased generalized Liu estimator method give less mean square error than those form the ordinary least square method for each standard deviation as the largest sample sizes of 100 for various degree of correlation between 0.1- 0.9, while the ordinary least square method gives the least value of average mean square error for the highest degree of correlation at 0.99.

Table 4. The method of the least value of average mean square error for the various degree of correlation on normal distributed data as 5 independent variables with sample sizes of 100.

n = 100	Degree of correlation					
S.D.	0.1	0.3	0.5	0.7	0.9	0.99
0.05	1.0005365 (AUG)	1.0005575 (AUG)	1.0006154 (AUG)	1.0007110 (AUG)	1.0011328 (AUG)	1.0083179 (OLS)
0.10	1.0013405 (AUG)	1.0014237 (AUG)	1.0016557 (AUG)	1.0020394 (AUG)	1.0039870 (AUG)	1.0324639 (OLS)
0.15	1.0024105 (AUG)	1.0026017 (AUG)	1.0031212 (AUG)	1.0039927 (AUG)	1.0084331 (AUG)	1.0724379 (OLS)
0.30	1.0072361 (AUG)	1.0080183 (AUG)	1.0101311 (AUG)	1.0137193 (AUG)	1.0315343 (OLS)	1.2873285 (OLS)
0.50	1.0175527 (AUG)	1.0196905 (AUG)	1.0257740 (AUG)	1.0363763 (AUG)	1.0849028 (OLS)	1.7954422 (OLS)

1.3 Increasing sample sizes

According to Figure 18, the value of average mean square error tends to be higher continually as the sample sizes decreases, on the other hand, the value of average mean square error tends to be lower continually as the sample sizes increases.

1.4 Increasing the degree of correlation

With the simulation results from Table 4 and Figure 18, the value of average mean square error tends to be lower continually as the various degrees of correlation decreases. Besides that the increment of the degree of correlation yields the increasing the value of average mean square error of all four multiple regression coefficient estimating methods.

1.5 Increasing the standard deviation

According to Table 4, all cases the average mean square error provide increasing value as the standard deviation increases in the same sample sizes and various degree of correlation.

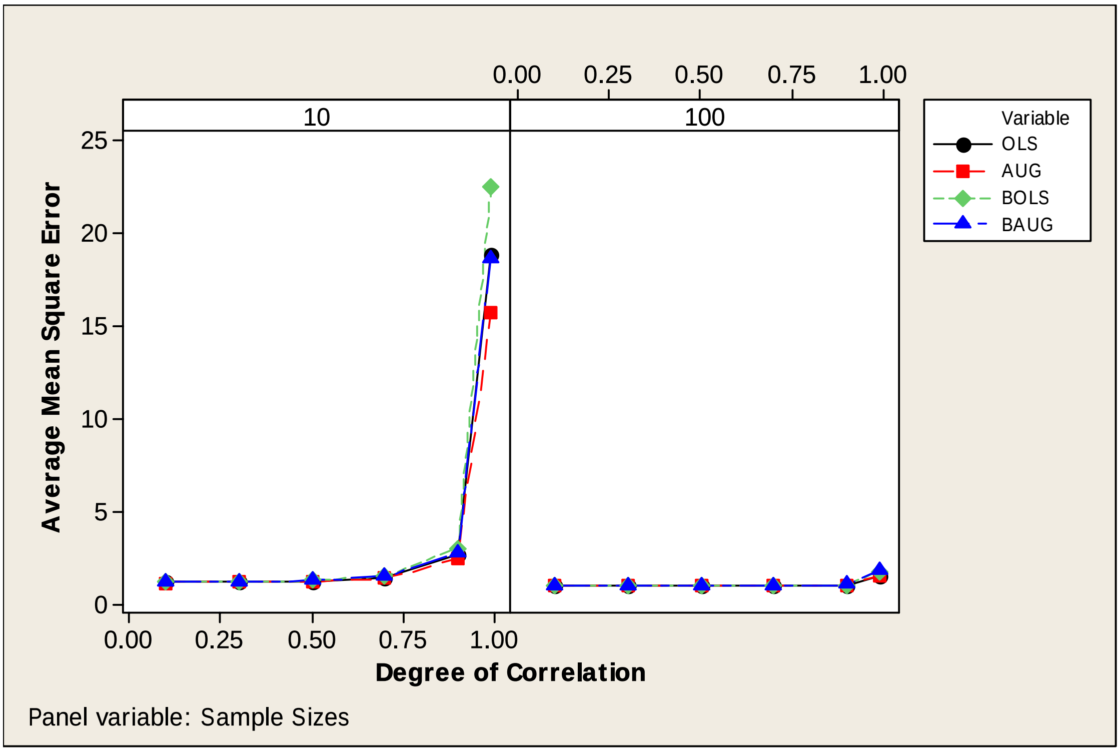

Figure 18. Scatterplot of average mean square error and various degree of correlation on normal distributed data with standard deviation equals to 0.50 as 3 independent variables.

1.6 Increasing the number of independent variables

According to Table 1 and Table 4, the value of average mean square error tends to be higher continually as the number of independent variables increases. Furthermore, the values of average mean square error from all methods are closer together, especially for smaller number of independent variables.

2. Results based on contaminated normal distributed data

2.1 The three independent variables

According to Table 5, the almost unbiased generalized Liu estimator method gives the least value of average mean square error as well as standard deviation for all various degree of correlation as variance equals to 0.05, 0.10, 0.15 at the smallest sample sizes of 10 in each scale factor and percent of contamination.

Table 5. The method of the least value of average mean square error for the various degree of correlation on contaminated normal distributed data as scale factor of 10 for 3 independent variables with sample sizes of 10.

n = 10	Degree of correlation					
S.D.	0.1	0.3	0.5	0.7	0.9	0.99
0.05	1.2113751 (AUG)	1.2209878 (AUG)	1.2617501 (AUG)	1.4567777 (AUG)	2.5980517 (AUG)	19.057431 (AUG)
0.10	1.7597142 (AUG)	1.8101077 (AUG)	1.9523407 (AUG)	2.6244678 (AUG)	7.0677200 (AUG)	72.857736 (AUG)
0.15	2.6041018 (AUG)	2.6901784 (AUG)	3.0003602 (AUG)	4.5165525 (AUG)	14.456744 (AUG)	162.57733 (AUG)

Table 6. The method of the least value of average mean square error for the various degree of correlation on contaminated normal distributed data as scale factor of 10 for 3 independent variables with sample sizes of 100.

n = 100	Degree of correlation					
S.D.	0.1	0.3	0.5	0.7	0.9	0.99
0.05	1.0062946 (AUG)	1.0066001 (AUG)	1.0081411 (AUG)	1.0141400 (AUG)	1.0502883 (OLS)	1.5281109 (OLS)
0.10	1.0266951 (AUG)	1.0279887 (AUG)	1.0344881 (AUG)	1.0607457 (AUG)	1.2017971 (OLS)	2.8347340 (AUG)
0.15	1.0627466 (AUG)	1.0661511 (AUG)	1.0821815 (AUG)	1.1428098 (AUG)	1.4545265 (OLS)	5.1059612 (AUG)

According to Table 6, the almost unbiased generalized Liu estimator gives the least value of average mean square error for all case at the degree of correlation between 0.1 to 0.7 as the largest sample sizes of 100.

However, this is not unanimous result for various degree of correlation between 0.9 to 0.99 because the ordinary least square method and the almost unbiased generalized Liu estimator give the least value of average mean square error for each standard deviation as sample sizes of 100.

2.2 The five independent variables

With the simulation results from 5 independent variables as the smallest sample sizes of 10 with standard deviation equals to 0.05, 0.10 and 0.15 , the ordinary least square gives the least value of average mean square error at the 0.1 degree of correlation. The least value of average mean square error from each method is demonstrated in Table 7.

Table 7. The method of the least value of average mean square error for the various degree of correlation on contaminated normal distributed data as 5 percent of contamination on 5 independent variables with sample sizes of 10.

n=10 S.D.	Scale Factor	Degree of correlation 0.1	0.3	0.5	0.7	0.9	0.99
0.05	3	68.617613 (OLS)	75.732483 (AUG)	361.89041 (BAUG)	794.00751 (AUG)	202.04658 (BAUG)	2475.2917 (BAUG)
	10	752.30049 (OLS)	831.35425 (AUG)	4010.9740 (BOLS)	8812.1933 (AUG)	2237.8879 (BAUG)	27495.121 (BOLS)
0.10	3	271.46885 (OLS)	299.92820 (AUG)	1444.5913 (BOLS)	3173.0313 (AUG)	804.39465 (BAUG)	9880.3482 (BAUG)
	10	3006.1961 (OLS)	3322.4114 (BOLS)	16040.890 (BOLS)	35245.773 (AUG)	8948.8871 (AUG)	109977.48 (BOLS)
0.15	3	609.55357 (BAUG)	673.58717 (AUG)	3249.0794 (BOLS)	7138.0685 (AUG)	1812.2182 (BAUG)	22242.128 (BAUG)
	10	6762.6878 (OLS)	7474.1708 (BAUG)	36090.733 (BAUG)	79301.699 (BAUG)	20130.544 (BAUG)	247444.58 (BAUG)

Furthermore, this is not unanimous result for various degree of correlation over 0.3 because the almost unbiased generalized Liu estimator, the ordinary least square and the almost unbiased generalized Liu estimator with bootstrap technique give the least value of average mean square error for various degree of correlation between 0.3 to 0.99 for each standard deviation as sample sizes of 10.

Table 8. The method of the least value of average mean square error for the various degree of correlation on contaminated normal distributed data as scale factor of 3 with sample sizes of 100.

Variables	S.D.	Degree of correlation					
		0.1	0.3	0.5	0.7	0.9	0.99
3	0.05	1.0004949 (AUG)	1.0005200 (AUG)	1.0006535 (AUG)	1.0011669 (AUG)	1.0043182 (AUG)	1.0474623 (OLS)
	0.10	1.0021830 (AUG)	1.0022769 (AUG)	1.0028209 (AUG)	1.0049081 (AUG)	1.0178459 (AUG)	1.1900426 (OLS)
	0.15	1.0050661 (AUG)	1.0053024 (AUG)	1.0065469 (AUG)	1.0113645 (AUG)	1.0407045 (OLS)	1.4277408 (OLS)
5	0.05	1.0012394 (AUG)	1.0014411 (AUG)	1.0019628 (AUG)	1.0027777 (AUG)	1.0068233 (AUG)	1.0673621 (OLS)
	0.10	1.0048507 (AUG)	1.0056410 (AUG)	1.0077536 (AUG)	1.0111287 (AUG)	1.0275769 (OLS)	1.2692964 (OLS)
	0.15	1.0108607 (AUG)	1.0126990 (AUG)	1.0175519 (AUG)	1.0253596 (AUG)	1.0619339 (OLS)	1.6058027 (OLS)

According to Table 8, simulation results show that the almost unbiased generalized Liu estimator method give less mean square error than those form the ordinary least square method for each standard deviation as the largest sample sizes of 100 for various degree of correlation between 0.1- 0.7, while the ordinary least square method gives the least value of average mean square error for the highest degree of correlation at 0.99 for all cases.

2.3 Increasing sample sizes

According to Figure 19, the average mean square error of each method is plotted versus correlation level for each variance and sample sizes. Their value of average mean square error tends to be higher continually as the sample sizes decreases, on the other hand, the value of average mean square error tends to be lower continually as the sample sizes increases.

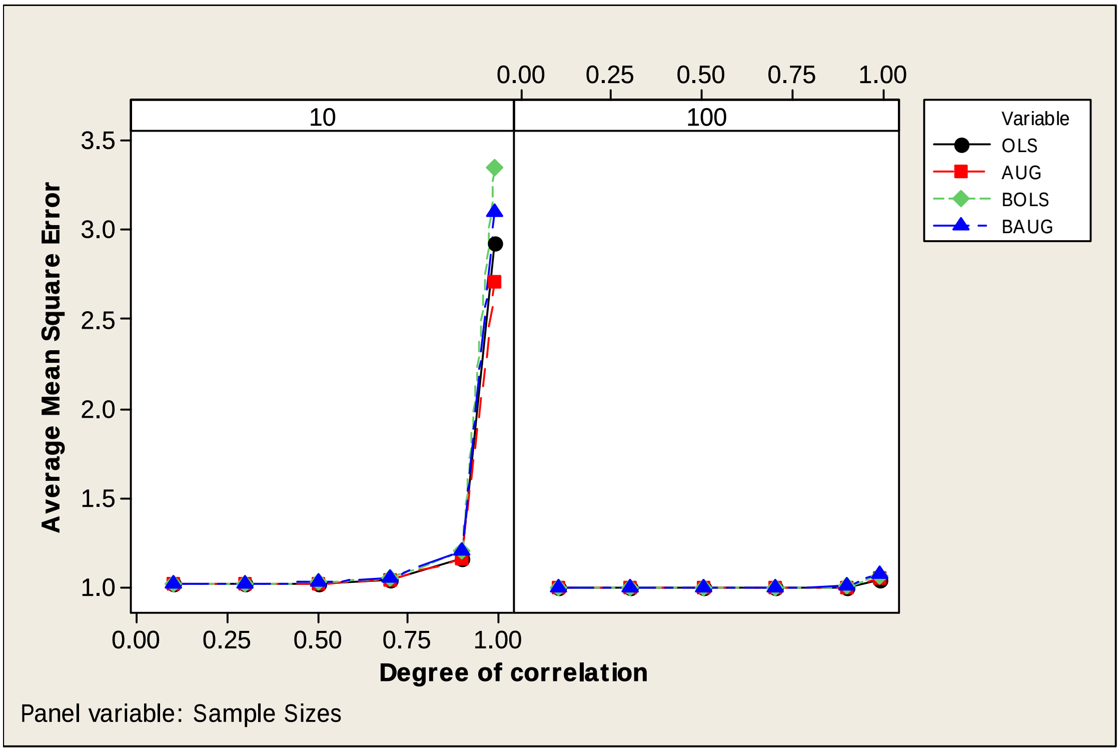

Figure 19. Scatterplot of average mean square error and various degree of correlation on contaminated normal distributed data with standard deviation equals to 0.05 as 3 independent variables and scale factor of 3.

2.4 Increasing the degree of correlation

Overall, the value of average mean square error tends to be lower continually as the various degrees of correlation decreases. Besides that the increment of the degree of correlation yields the increasing the value of average mean square error of all four multiple regression coefficient estimating methods.

2.5 Increasing the standard deviation

According to Table 7, all cases the average mean square error provides increasing value as the standard deviation increases in the same sample sizes and various degree of correlation.

2.6 Increasing the number of independent variables

According to Table 8, the value of average mean square error tends to be higher continually as the number of independent variables increases. Furthermore, the values of average mean square error from all methods are closer together, especially for smaller number of independent variables.

2.7 Increasing the scale factor

On the whole, the average mean square error tends to be higher as the scale factor increases in each sample sizes. The value of average mean square error as decreased sample sizes are significantly greater than increased sample sizes. The least value of average mean square error from each method as the different scale factor is demonstrated in Table 9.

Table 9. The method of the least value of average mean square error for the various degree of correlation on contaminated normal distributed data as 5 percent of contamination with standard deviation of 0.05 on 5 independent variables.

Sample Sizes	Scale Factor	Degree of correlation					
		0.1	0.3	0.5	0.7	0.9	0.99
10	3	68.617613 (OLS)	75.732483 (AUG)	361.89041 (BAUG)	794.00751 (AUG)	202.04658 (BAUG)	2475.2917 (BAUG)
	10	752.30049 (OLS)	831.35425 (AUG)	4010.9740 (BOLS)	8812.1933 (AUG)	2237.8879 (BAUG)	27495.121 (BOLS)
100	3	1.0012394 (AUG)	1.0014411 (AUG)	1.0019628 (AUG)	1.0027777 (AUG	1.0068233 (AUG)	1.0673621 (OLS)
	10	1.0134029 (AUG)	1.0156951 (AUG)	1.0217604 (AUG)	1.0315775 (AUG)	1.0764334 (OLS)	1.7478763 (OLS)

2.8 Increasing the percent of contamination

Overall, the percent of contamination is not significantly to change the results because there are no difference results at the percent of contamination as 5 and 10 in the same sample sizes, standard deviation, scale factor and various degree of correlation.

3. Results based on lognormal distributed data

3.1 The three independent variables

According to Table 10, the almost unbiased generalized Liu estimator method gives the least value of average mean square for all various degree of correlation as variance over 0.30 at the smallest sample sizes of 10.

Furthermore with the largest sample sizes of 100, the almost unbiased generalized Liu estimator gives the least value of average mean square error at the degree of correlation between 0.1 to 0.5 and the ordinary least square method gives the least value of average mean square error at the degree of correlation between 0.7 to 0.99 as the variance of 0.05 and 0.30. Especially at the variance over 0.70 ,the almost unbiased generalized Liu estimator is significantly greater than another methods to yields the least value of average mean square error.

Table 10. The method of the least value of average mean square error for the various degree of correlation on lognormal distributed data as 3 independent variables

Sample Sizes	Var.	Degree of correlation					
		0.1	0.3	0.5	0.7	0.9	0.99
10	0.05	1.5351730 (OLS)	1.6468077 (OLS)	1.7951781 (OLS)	2.3056435 (AUG)	3.4204311 (AUG)	12.233361 (AUG)
	0.30	2.7616895 (AUG)	2.8052041 (AUG)	3.1231331 (AUG)	4.0778070 (AUG)	10.017428 (AUG)	83.287638 (AUG)
	0.70	5.4436131 (AUG)	5.6455641 (AUG)	6.2128766 (AUG)	9.3872301 (AUG)	28.853393 (AUG)	299.16666 (AUG)
	1.00	8.8947408 (AUG)	9.8461483 (AUG)	10.787793 (AUG)	17.068465 (AUG)	61.053726 (AUG)	671.25972 (AUG)
100	0.05	6.3638027 (AUG)	6.0404287 (AUG)	5.3473765 (AUG)	4.3026765 (OLS)	4.0254631 (OLS)	4.4785636 (OLS)
	0.30	8.3784764 (AUG)	8.3911076 (AUG)	7.9096239 (AUG)	6.6717317 (OLS)	5.1652280 (OLS)	7.8729165 (AUG)
	0.70	11.072555 (AUG)	11.142029 (AUG)	11.094124 (AUG)	10.472151 (AUG)	8.8367459 (AUG)	18.503589 (AUG)
	1.00	13.876313 (AUG)	14.004678 (AUG)	14.000164 (AUG)	14.150368 (AUG)	13.309965 (AUG)	36.921196 (AUG)

3.2 The five independent variables

With the simulation results, the almost unbiased generalized Liu estimator, the ordinary least square and the bootstrap technique with these two methods give the least value of average mean square error for various degree of correlation as sample sizes of 10.

Especially at the variance over than 0.70, the almost unbiased generalized Liu estimator gives the least value of average mean square error as the degree of correlation between 0.5 to 0.99. However, this is not unanimous result for the variance not over 0.30. The least value of average mean square error from each method as the different scale factor is demonstrated in Table 11.

Table 11. The method of the least value of average mean square error for the various degree of correlation on lognormal distributed data as 5 independent variables with sample sizes of 10.

Var.	Degree of correlation					
	0.1	0.3	0.5	0.7	0.9	0.99
0.05	406.05060 (BAUG)	383.58403 (BOLS)	7074.5294 (BAUG)	258.39107 (BAUG)	690.22612 (BOLS)	8633.6589 (BAUG)
0.30	2560.7815 (BAUG)	1757.7902 (BOLS)	8340.8075 (BAUG)	1743.1813 (BAUG)	3194.5626 (AUG)	53167.753 (BAUG)
0.70	7984.5786 (AUG)	6538.2695 (AUG)	20198.773 (BAUG)	5631.7350 (BAUG)	15753.380 (BAUG)	157217.11 (BAUG)
1.00	14813.072 (AUG)	13327.549 (BAUG)	42254.995 (BAUG)	10619.408 (BAUG)	38285.004 (BAUG)	277347.54 (BAUG)

According to Table 12, simulation results show that the ordinary least square method gives the least value of mean square error as the degree of correlation between 0.5 to 0.7 at the variance not over than 0.30 for the largest sample sizes of 100.

Overall, the almost unbiased generalized Liu estimator method give the least value of mean square error for all cases as the variance over than 0.70 .

Table 12. The method of the least value of average mean square error for the various degree of correlation on lognormal distributed data as 5 independent variables with sample sizes of 100.

Var.	Degree of correlation					
	0.1	0.3	0.5	0.7	0.9	0.99
0.05	5.5373441 (AUG)	4.9095841 (OLS)	4.2285195 (OLS)	4.0459515 (OLS)	4.0697510 (OLS)	4.7275059 (AUG)
0.30	8.0305456 (AUG)	7.5995339 (AUG)	6.5889404 (OLS)	5.9545014 (OLS)	5.3907837 (AUG)	10.326555 (AUG)
0.70	11.261641 (AUG)	11.036639 (AUG)	10.422593 (AUG)	10.328995 (AUG)	9.5457900 (AUG)	28.652692 (AUG)
1.00	14.457564 (AUG)	14.326262 (AUG)	14.189358 (AUG)	14.312258 (AUG)	15.957857 (AUG)	60.916487 (AUG)

3.3 Increasing sample size

3.3.1 The 3 independent variables with variance 0.05 at correlation level 0.1-0.9, the value of average mean square error tends to be higher continually as the sample sizes increases, whereas the value of average mean square error tends to be lower as the highest correlation level.

3.3.2 The 3 independent variables with variance 0.30 at correlation level 0.1-0.7, the value of average mean square error tends to be higher continually as the sample sizes increase, whereas the value of average mean square error tends to be lower as the correlation level of 0.9-0.99.

3.3.3 The 3 independent variables with variance 0.70 and 1.014, the value of average mean square error tends to be higher continually as the sample sizes increase for all correlation level.

3.3.4 The 5 independent variables, all of cases, the value of average mean square error tends to be higher continually as the sample sizes increase.

3.3.5 The different average mean square error provide the lower value when the sample sizes increase.

3.4 Increasing the level of correlation

According to Table 11 and Table 12, most cases of value of the different average mean square error are not different pattern. Their value tends to be higher continually as the level of correlation increases.

3.5 Increasing the variance

With the simulation results, on the whole, the average mean square error tends to be higher as the variance increases.

3.6 Increasing the number of independent variables

Overall, the average mean square error tends to be higher as the independent variables increase.

CHAPTER V
DISCUSSION

This chapter is mainly concern with the discussion for the present study. Their details can be described in four parts, one is methodology discussion and the other is on comparison of those four estimators under their investigation by average mean square error.

1. The discussion of the methodology

This study generated data, which depended on five factors: distributed data, variance, sample sizes, various degree of freedom and independent variable in each criteria. There are 168 different situations examined through generated data and using the value of average mean square error.

In method procedure, to commence this study by the work of Thiart (46) that performed to examine the relative efficiency of thirteen estimator against the ordinary least square method as several various degree of correlation and the work of Crivelli (47) that reported on bootstrap technique with occurred multicollinearity in ridge regression.

Therefore, this study combines the bootstrap technique with the method from the work of Akdeniz and Kaciranlar (9) to develop the method for estimated multiple regression coefficient by using advantage ridge regression method combined with Stein method by Liu Kejian (8).

This study uses the smallest sample sizes of 10 because Efron (53) introduce bootstrap technique suitable for small sample size. Besides, increasing the sample size to 100 for notice a strange trend when sample size changed.

In programming procedure, generating data in each condition is performed for 500 iterations with respect to their distribution. The regression coefficients are assigned from eigenvector appropriates maximum eigenvalue of matrix $X'X$ for the least value of mean square error and eigenvector appropriates minimum eigenvalue of matrix $X'X$ for the most value of mean square error. Then, the multiple regression coefficient from different techniques are merged and seek for the average mean square error for four estimating method. It is different from the works of Tonchonlakun (74) which use the technique to determine the multiple regression coefficient for only the most mean square error.

This study also corrected the various degree of correlation in computing from Wichern and Churchill (50) method to generated various degree of correlation which the nearest independent variables have the highest degree of correlation.

Mute (68) transformed lognormal to normal distributed data and Krataithong (77) adept this technique to many criteria. This study works some criteria that suitable not only small sample size but also large sample size. Furthermore, this work conveys the data transform to nearly normal distribution for all coefficient of variation.

2. The discussion of the results of average mean square error

The results of this simulation data concerning average mean square error, demonstrated that almost unbiased generalized Liu estimator is prefer to sample size over 30 up for three and five independent variables at correlation level of 0.1-0.7. In the other hand, as correlation level of 0.9-0.99 is prominent for ordinary least square. The results of this study were different to work of Jaruthanasakkoon (67) because there are different to generated the various degree of correlation between the nearest variables.

Almost unbiased generalized Liu estimator within bootstrap technique mostly presented small average mean square error even in case of the smallest sample size as the number of independent variable increases. This character also employed even the distribution are normal, contaminated-normal, and lognormal.

However, this technique trends to increase the value of average mean square error when sample sizes increasing because the inferior to this technique. Moreover, the result from this technique has considerable the value of average mean square error that is similar to work of Chernick (10), Bryan (12), Crivelli (47) and Chui (62) in case of the smallest sample size.

Furthermore, the value of average mean square error for all method has been considerable and always decreased as the number of sample sizes increased. This character remained all situations examined through this study.

Moreover, when increasing of the correlation between 0.1-0.7, the value of average mean square error will be increased in all case. Due to the higher degree of correlation, the lower value of function $X'X$ matrix for promote average mean square error increasing. On account of, there is the square distance from $\underset{\sim}{\hat{\beta}}$ to $\underset{\sim}{\beta}$ in form of function $X'X$ matrix as follows:

$$E\left[L_1^2(k)\right] = \sigma^2 \sum_{i=1}^{p} \frac{\lambda_i}{(\lambda_i + k)^2} + k^2 \underset{\sim}{\beta}'(X'X + kI)^{-2} \underset{\sim}{\beta}$$

$$= Var\left(\underset{\sim}{\hat{\beta}}_{AUG}(k)\right) + \left[Bias(\underset{\sim}{\hat{\beta}}_{AUG}(k))\right]^2$$

To be due to $|X'X|$ equals multiplied with eigenvalue of $X'X$ matrix and $|X'X|$ converge to zero as increasing the degree of correlation, so some eigenvalue is tiny. From above, $E\left[L_1^2(k)\right]$ will be increased. This mean that the effective of multiple regression coefficient is weaken when the correlation levels increases.

Likewise, when the number of independent variables increases, the value of average mean square error will be increased but there are not prominent such as increasing degree of correlation.

CHAPTER VI
CONCLUSION AND RECOMMENDATIONS

1. Conclusion

This study focused on comparing multiple regression coefficient estimators when exists multicollinearity via the ordinary least square, the almost unbiased generalized Liu estimator method and the bootstrap technique with these two method. The four methods simulated by the aid of Microsoft Fortran programming. The conclusions of result are:

- The average value of mean square error varies with descending order: levels of correlation, standard deviation, the number of independent variables, scale factor, and percent of contamination.
- The average value of mean square error varies conversely to sample sizes.
- In generally, it is founded that the almost unbiased generalized Liu estimator method provides the least value of average mean square error as sample size of 30, 50 and 100 at the correlation level of 0.1-0.7 even the data is different in each distribution.
- As the smallest sample sizes of 10, the almost unbiased generalized Liu estimator with bootstrap technique is prominent in each distribution because its average mean square error gives the least value of average mean square error, especially as the independent variables increases.
- In comparing the variance of four methods, their standard deviation depends on the value of average mean square error. The higher value of average mean square error, the higher value of standard deviation. On the other hand, the standard deviation decreases as the sample size increases.

Note that the results of this study are based on only the scope of study mentioned at the beginning:

2. Recommendations

Based on the results of this study, the following recommendations can be made:

- The element on diagonal matrix D in almost unbiased generalized Liu estimator closed to zero, So using ordinary least square method instead of almost unbiased generalized Liu estimator.
- There are many serviceable subroutines for statistical tests, especially for the simulation attached to the IMSL Library of Fortran Powerstation. So this program is more markedly convenient than the others, and moreover, takes a short time for running the program.

In addition, the following suggestions have been made to guide further studies:

1. Further studies should be used other coefficient estimator for comparison with this study in various mean, variance, scale factor, percent of contamination, sample size, degree of correlation and number of independent variables.
2. This study used scalar errors for a contaminated normal distribution. So, location errors may be used with the same estimator in further studies.
3. More than 1,000 replicates should be sampled to estimate the coefficient for further studies.
4. To generate random number, it would be better to begin with 69069. Marsaglia (83) performed the beginning number of 65539 should be replace with 69069 because 65539 was found to have a serious problem.
5. Extended study on comparing of coefficient estimator by principle component, latent root and rural network.
6. This study can be further extended for multiple regression analysis with missing observations among the independent variables.
7. Extended study focused on estimation of multiple regression coefficients when residuals have skewed distribution and longer tailed distribution than normal distribution or outliers are present for broad conclusion.
8. Further studies should be used degree of correlation more than three and five independent variables and addition on negative correlation case.

9. The further studies should be focused on bootstrap technique with real data when the sample sizes are rare.
10. Extended studies should be under investigation with analysis of covariance for bootstrap technique on multiple regression and factorial experiment.
11. For further studies should be focused on the quality independent variables or selecting some independent variables are not essential requirement.
12. New flexible estimators from regression assumption are supposed to investigating with real data.

REFERENCES

1. Bernard, R. **Fundamentals of Biostatistics.** 5[nd]ed.Pacific Grove:California: Duxvury, 2000.
2. Lachin, J.M. **Biostatistical methods : the assessment of relative risks.** New York:John Wiley & Sons, 2000.
3. Pankratz, A. **Forecasting with dynamic regression models.** New York:John Wiley & Sons, 1991.
4. Allison, P.D. **Multiple regression.** Thousand Oaks:Pine Forge, 1999.
5. Kutner, M.H. **Applied linear statistical models.** Save Boston:McGraw-Hill Irwin, 2005.
6. Birkes, D. **Alternative methods of regression.** New York:John Wiley & Sons, 1993.
7. Hoerl, A.E. and Kennard, R.W. Ridge Regression : Biased Estimation for Nonorthogonal Problems . Technometrics1970; 12: 55-67.
8. Liu Kejian. A new class of biased estimate in linear regression. Communication in Statistics and Theory methods 1993; 22: 393-402 .
9. Akdeniz, F. and Kaciranlar, S.On the almost unbiased generalized liu estimator and unbiased estimation of the biased and mse. Communication in Statistics and Theory methods 1995; 24:1789-1797.
10. Chernick, M.R. **Bootstrap Methods : A practitioner's Guide.** New York : Wiley, 1999.
11. Hudnut, R.K. **The Bootstrap Fallacy : What The Self-Help Books Don't Tell You.** Cleveland Ohio:Collins,1978.
12. Bryan, F.J. **Randomization, Bootstrap And Monte Carlo Methods In Biology.** London:Chapman & Hall, 1997.
13. Graybill, F.A. **Regression analysis : concepts and applications.** Belmont California: Duxbury, 1994.
14. Hjorth, J.S. **Computer Intensive Statistical Methods: Validation Model Selection And Bootstrap.** London:Chapman & Hall, 1994.

15. Muth, E.J. **Transform methods : with applications to engineering and operations research.** Englewood Cliffs, N.J:Prentice-Hall, 1977.

16. Green, P.J. **Nonparametric regression and generalized linear models : a roughness penalty approach.** London:Chapman & Hall, 1994.

17. Neter J. and Kutner M.H. **Applied linear regression model.** 3nded. Illinois: Irwin, 1996.

18. Draper, N.R. **Applied regression analysis.** New York:Wiley, 1998.

19. Keter, J. **Applied linear statistical models.** Chicago:Irwin, 1998.

20. Kleinbaum, D.G. **Applied regression analysis and other multivariable methods.** Belmont California:Duxbury, 1998.

21. Verbeek, M. **A guide to modern econometrics.** Chichester, West sussex:John Wiley & Sons, 2004.

22. Hocking, R.R. **Methods and applications of linear models: regression and the analysis of variance.** New York:John Wiley & Sons, 1996.

23. Neter J. **Applied statistics.** Boston:Allyn & Bacon, 1993.

24. Bibby, J. **Predeuction and improved estimation in linear models.** New York: John Wiley & Sons, 1997.

25. Berry,W.D.**Understanding regression assumptions.**NewburyPark California Sage Publications, 1993.

26. Jacob C. **Applied multiple regression : correlation analysis for the behavioral science.** Mahwah, NJ:Lawrence Eribaum Associates, 2003.

27. Hoel, P.G. **Introduction to mathematical statistics.** New York:John Willey, 1984.

28. Graybill, F.A. **Regression analysis concepts and applications.** Belmont, California:Daxbury Press, 1994.

29. Miles, J. **Applying regression & correlation : a guide for students and researchers.** London:SAGE, 2001.

30. Glantz, S.A. **Primer of applied regression and analysis of variance.** New York:McGraw-Hill, 1990.

31. Keppel, G. **Data analysis for research designs : analysis of variance and multiple regression / correlation approaches.** New York:W.H. Freeman, 1989

32. Fox, J. **Regression diagnostics.** Newbury Park,California:Sage Publications, 1991.

33. Berry, W.D. **Multiple regression in practice.** Beverly Hills:Sage Publication, 1987.

34. Chatterjee, S. **Sensitivity analysis in linear regression.** New York:John Wiley & Sons, 1988.

35. Cook, R.D. **Residuals and influence in regression.** New York:Chapman, 1982.

36. Belsley, D.A. **Regression diagnostics : identifying influential data and sources of collinearity.** New York:John Wiley & Sons, 1980.

37. Weisberg, S. **Applied linear regression.** New York:John Wiley & Sons, 1990.

38. Ostrom, C.W. **Time series analysis : Regression techniques.** London: Sage,1990.

39. Rawlings, J.O. **Applied regression analysis : a research tool.** Pacific Grove California:Wadsworth & Brooks/Cole, 1988.

40. Studenmund, A.H. **Using econometrics : a practical guide.** Boston:Addison Wesley, 2000.

41. Lewis,C.M et al. **Encyclopedia of Social Sciences Research Method.** Thousand Oaks:California:Sage, 2003.

42. Rawlings, J.O. **Applied regression analysis : a research tool.** North Scituate, Mass Boston:Duxbury Press, 1978.

43. Leo Breiman. Heuristics of instability and stabilization in model selection. The Annals of Statistics 1996; 24: 2350-2383.

44. Hoerl, A.E. and Kennard, R.W. Ridge Regression : Application to nonorthogonal problems. Technometrics 1970; 12: 69-82.

45. Fox, J. **Applied regression analysis, linear models, and related methods.** Thousand Oaks, California:Sage, 1997.

46. Thiart. C. et al. A simulation of biased estimation and subset selection regression technique regression technique. Communication in Statistics and Simulation 1993; 22: 569-589.

47. Crivelli, A. and et al. Confidence intervals in ridge regression by bootstrapping the dependent variable: A simulation study. Communications in Statistics 1995; 331-352.

48. Gunst, R.F. and Mason, R.L. Biased estimation in regression : An evaluation using mean squared error. Journal of the American Statistical Association. 1997; 72:616.

49. Obenchanin, R.L. Classical F-Tests and Confidence Regions for Ridge Regression. Technometrics 1997; 19: 429-439.

50. Wichern, D.W. and Churchill, A.G. A comparison of Ridge Estimators. Technometrics 1978; 20: 30-39.

51. Hemmerle, W.J. and Branile, T.F. Explicit and Constrained Generalized Ridge Estimation. Technometrics 1978; 20; 109-120.

52. Boston, M. **The Entrepreneurial Venture : Readings Selected.** Mass: Harvard Business School Press, 1999.

53. Efron, B. and Tivshirani, R.J. **An Introduction To The Bootstrap.** New York:Chapman & Hall, 1993.

54. Kunsch, H.R. The jackknife and the Bootstrap for General Stationary Observations. The annals of Statistics 1989; 17(3): 1217-1241.

55. Felsenstein, J. **Inferring Phylogenies.** Sunderland, Mass:Sinauer Associates, 2004.

56. Oxford. **Design and Analysis of Ecological Experiments.** Oxford;New York: Oxford University Press, 2001.

57. National Marine Fisheries Service. **Incidental catches of salmonids in the 1991 on North Pacific squid driftnet fisheries.** NOAA Technical Memorand, 1991.

58. Gould, W. **STATA statistics.** SRATA cooperation, 2001.

59. Heber, S. and et al. **Application of Bootstrap Techniques to Physical Mapping.** Academic Press, 2000.

60. Zhang, Q.B. A goodness-of-fit test for logistic regression models based on case-control data [M.S. Thesis in Mathematics].Toledo:Department of Mathematics, University of Toledo,1997.

61. Petoxz, P. and Fischer O. Estimating rainfall variability from spatial data. [M.S. thesis in Technology].Sydney:University of Technology,1997.

62. Chui, L.Y. Using bootstrap confidence intervals to evaluate iyer's criterion of individual bioequivalence. [M.S. Thesis in Statistics]. Colorada : Department of Statistics, Colorado State University, 1998.

63. Kuppermann,N. and Dea, T.O. Predictors of Intussusception in Young Children. Arch Pediatr Adolesc Med 2000; 154: 250-255.

64. Abdelnoor and Jason, R.E. **A Mathematical dictionary.** 6nded.Leeds,England: Arnold-Wheaton, 1986.

65. Marcello, P. and Hauvreau, K. **Principles of biostatistics.** Pacific Grove, California:Duxbury, 2000.

66. Kunasaraphan, P. A comparison on forecasting methods between ridge regression and artificial neural network methods in multiple regression analysis with multicollinearity. [M.S. Thesis in Statistics].Bangkok: Graduate School, Chulalongkorn University, 1998.

67. Jaruthanasakkoon, S. A comparison of parameters estimating methods in multiple regression analysis by least square method, ridge regression with prior information method, and generalized liu kejian method when existing multicollinearity among in dependent variables. [M.S. Thesis in Statistics].Bangkok: Graduate School, Chulalongkorn University, 1996.

68. Beckmean, R.J. and Cook, R.D. Outliers (with discussion). Technometrics 1993; 25: 119-163.

69. Barnett, V. and Lewis, T. **Outliers in statistical data.** 2nded.New York:John Wiley & Sons, 1983.

70. Ruangroj, R. A comparison on power of tests for normality among chi-square, shapito-wilk w statistics and Shapiro-francia w' statistics. [M.S. Thesis in Biostatistics].Bangkok: Graduate School, Mahidol University, 2000.

71. Peter, A. and Theodore, C. **Encyclopedia of Biostatistics.** New York:Wiley, 1999.

72. Givilisco, S. **The concise illustrated dictionary of science and technology.** Blue Ridge Summit, 1993.

73. Dawson, B. and Robert, G.T. **Basic and clinical biostatistics.** 4th ed. Boston:McGraw Hill, 2004.

74. Tonchonlakun, T. A comparison among ordinary least squares, ridge regression, and ridge and stein methods in estimating multiple regression coefficients with multicollinearity. [M.S. Thesis in Statistics].Bangkok: Graduate School, Chulalongkorn University, 1996.

75. Muth, E.J. **Transform methods : with applications to engineering and operations research.** Englewood Cliffs, N.J.:Prentice-Hall, 1997.

76. Carroll, R.J. **Transformation and weighting in regression.** New York: Chapman & Hall,1988.

77. Krataithong, N. Data transformation to normal distribution. [M.S. Thesis in Statistics].Bangkok: Graduate School, Chulalongkorn University, 1999.

78. Kuo, B.C. **Discrete-data control systems.** Englewood Cliffs, N.J.:Pretice Hall, 1970.

79. Kulanoot A. A comparison of the power of test for homogeneity of variance using three types of test statistics. [M.S. Thesis in Statistics].Bangkok: Graduate School, Chulalongkorn University, 1985.

80. Hoerl, R. and Schuenmeyer, J.A Simulation of biased estimation and subset selection regression technique.Technometrics 1986; 28: 369-380.

81. Araveeporn, A. A comparison of coefficient estimation in multiple linear regression with multicollinearity.[M.S. Thesis in Statistics].Bangkok: Graduate School, Chulalongkorn University, 1998.

82. Shan, S.K. **Numerical methods and Computers.** Massachusetts:Addison-Wesley,Inc., 1965.

83. Karlen D. Part III: Monte carlo methods. Randaom number generation. [Online]. Ottawa: 2005. Available from: http://www.physics.carleton.ca /course/75.502/slides/monte21/p015 .html. [Accessed 2005 April 20].

84. Brian H. **Fortran 90 for Scientists and Engineers.** Cambridge:University Press, 1994.

85. Anthony, N. and Baltimore, G. **High – yield biostatistics.** Williams & Wilkins, 1995.

APPENDIX

APPENDIX A
FORTRAN SUBROUTINES USED IN THIS STUDY

```
!MAIN PROGRAM : THE BOOTSTRAP OF MULTIPLE REGRESSION     !
!COEFFICIENT ESTIMATIND IN MULTICOLLINEARITY BY ORDINARY
!LEAST SQUARE, ALMOST UNBIASED GENERALIZED LIU !ESTIMATOR !
!METHOD  AND BOOTSTRAP TECHNIQUE WITH THESE TWO !METHOD
program honest
integer m,n,count,derror,poo,nb
real am,sd,c,p
common /seed/ix,kk/no/m1,n/corr/cor1,cor2,cor3,cor4/prob/pp(100)
double precision x(100,6),tmean(6),asum(6),sxx(100,6),xtx(6,6),eigval(6),vecmax(6)
double precision vecmin (6),binit(6),error(100),y(100),xty(10)
double precision sig2,bols(6),yresols(100),yols(100)
double precision ybootols(100),xtybootols(6),bbootols(6),msebbootols
double precision baug(6),yresaug(100),yaug(100),ybootaug(100)
double precision bbootaug(6),msebbootaug
double precision mseols1,mseaug1
double precision mseols2,mseaug2
double precision mols1(500),maug1(500),abols1(500),abaug1(500)
double precision mols2(500),maug2(500),abols2(500),abaug2(500)
double precision sols,saug ,sbols,sbaug
double precision sols1,saug1 ,sbols1,sbaug1
double precision sols2,saug2 ,sbols2,sbaug2
double precision amols,amaug,ambols,ambaug
double precision amols1,amaug1,ambols1,ambaug1
double precision amols2,amaug2,ambols2,ambaug2
double precision pbolsbaug,pbaugbol
double precision pbolsbaug1,pbaugbols1
double precision pbolsbaug2,pbaugbols2
```

```
      double precision polsaug,paugols
      double precision polsaug1,paugols1
      double precision polsaug2,paugols2
      double precision polsbols,paugbaug,pbolsols,pbaugaug
      double precision polsbols1,paugbaug1,pbolsols1,pbaugaug1
      double precision polsbols2,paugbaug2,pbolsols2,pbaugaug2
      double precision sqols,sqaug,sqbols,sqbaug
      double precision sqols1,sqaug1,sqbols1,sqbaug1
      double precision sqols2,sqaug2,sqbols2,sqbaug2
      double precision rsols,rsaug,rsbols,rsbaug
      double precision avbols1,avbaug1,avbols2,avbaug2
      character(25) filename
      write(*,*) "Enter file name "
      read(*,*) filename
      open (unit=25,File=filename,status="new")
      !    SET VALUE
      write(*,*)"PLEASE KEY DISTRIBUTION"
      read(*,*) derror
      write(*,*) "Derror =",derror
      if(derror.eq.1)then
      write(*,*)"1.Please key mean and sigma"
      read(*,*)am,sd
      write(*,5)am,sd
      write (25,5)am,sd
5     format(2x,'normal distribution',2x,'mean=',f4.2,2x,'sd=',f11.9)
      else if(derror.eq.2)then
      write(*,*)"2.Please key c p mean and sigma"
      read(*,*)c,p,am,sd
      write(*,10)c,p,am,sd
      write(25,10)c,p,am,sd
10    format(2x,'scale-contaminated normal distribution  scale factor=',f4.1, &
  & 2x,'percent of contamination=',f5.2,3x,'mean=',f4.2,3x,'sd=',f11.9)
```

```
      else if(derror.eq.3)then
      write(*,*)"3.Please key mean and sigma"
      read(*,*)am,sd
      write(*,15)am,sd
      write(25,15)am,sd
15    format(2x,'lognormal distribution',2x,'mean=',f4.2,2x,'sd=',f11.9)
      end if
      write(*,*)"Please key count and m"
      read(*,*)count,m
      write(*,20)count
      write(25,20)count
20    format(/,2x,'round of simulation                    :',i4)
      write(*,25)m
      write(25,25)m
25    format(2x,'number of independent variables          :',i4)
      m1   =m+1
!     SET SAMPLE SIZE
      do 30 isa=1,4
      goto(35,40,45,50),isa
35    n=10
      goto 55
40    n=30
      goto 55
45    n=50
      goto 55
50    n=100
!     SET CORRELATION
55    do 60 ico=1,6
      goto(65,70,75,80,85,90),ico
65    cor1=0.1
      cor2=0.01
      cor3=0.001
```

```
      cor4=0.0001
      goto 95
70    cor1=0.3
      cor2=0.09
      cor3=0.027
      cor4=0.0081
      goto 95
75    cor1=0.5
      cor2=0.25
      cor3=0.125
      cor4=0.0625
      goto 95
80    cor1=0.7
      cor2=0.49
      cor3=0.343
      cor4=0.2401
      goto 95
85    cor1=0.9
      cor2=0.81
      cor3=0.729
      cor4=0.6561
      goto 95
90    cor1=0.99
      cor2=0.9801
      cor3=0.9703
      cor4=0.9650
95    ix=13
      kk=0
      write (*,*)  "Sample size            = ",n
      write (25,*) "Sample size            = ",n
      if(m.eq.3)then
      write (*,*) "correlation cor1       = ",cor1
```

```
      write (*,*) "correlation cor2       = ",cor2
      write (25,*) "correlation cor1       = ",cor1
      write (25,*) "correlation cor2       = ",cor2
      else if (m.eq.5) then
      write (*,*) "correlation cor1       = ",cor1
      write (*,*) "correlation cor2       = ",cor2
      write (*,*) "correlation cor3       = ",cor3
      write (*,*) "correlation cor4       = ",cor4
      write (25,*) "correlation cor1       = ",cor1
      write (25,*) "correlation cor2       = ",cor2
      write (25,*) "correlation cor3       = ",cor3
      write (25,*) "correlation cor4       = ",cor4
      end if
      if(n.eq.10)then
      nb=300
      write (25,*)"round of bootstrap =",nb
      else if(n.eq.30)then
      nb=500
      write (25,*)"round of bootstrap =",nb
      else if(n.eq.50)then
      nb=700
      write (25,*)"round of bootstrap =",nb
      else if(n.eq.100)then
      nb=1000
      write (25,*)"round of bootstrap =",nb
      end if
!     Calcualte probability of Sampling Random
      do 100 i=1,n
      pp(i)=float(i)/float(n)
100   continue
      sols1  =0
      saug1  =0
```

```
sbols1 =0
sbaug1 =0
sqols1 =0
sqaug1 =0
sqbols1=0
sqbaug1=0
sols2  =0
saug2  =0
sbols2 =0
sbaug2 =0
sqols2 =0
sqaug2 =0
sqbols2=0
sqbaug2=0
sols  =0
saug  =0
sbols =0
sbaug =0
sqols =0
sqaug =0
sqbols=0
sqbaug=0
do 105 poo=1,count
write (*,*) "Round = ",poo
call buildx(x,tmean,asum)
call stand(x,tmean,sxx,asum)
call calxtx(sxx,xtx)
call eigen(xtx,eigval,vecmax,vecmin)
do 110 bint=1,2
if(bint.eq.1)then
do 115 i=1,m1
binit(i)=vecmax(i)
```

```
115  continue
     if (derror.eq.1)then
     do 125 i=1,n
     error(i)=normal(am,sd)
125  continue
     else if (derror.eq.2)then
     do 130 i=1,n
     error(i)=scnor(c,p,am,sd)
130  continue
     else if (derror.eq.3)then
     do 135 i=1,n
     error(i)=lognor(am,sd)
135  continue
     end if
     call buildy(sxx,binit,error,y)
     if (derror.eq.3) then
     call boxcox(sxx,y)
     end if
     call ols(sxx,y,xtx,xty,sig2,bols)
     call ms(binit,bols,mseols1)
     mols1(poo)=mseols1
     call yresid(yresols,sxx,y,yols,bols)
     tbols1=0
     do 160 ib=1,nb
     call loop (yresols,yols,ybootols)
     call ols (sxx,ybootols,xtx,xtybootols,sig2,bbootols)
     call ms(binit,bbootols,msebbootols)
     tbols1=tbols1+msebbootols
160 continue
     avbols1=tbols1/nb
     abols1(poo)=avbols1
     call aug(sxx,y,baug)
```

```
      call ms(binit,baug,mseaug1)
      maug1(poo)=mseaug1
      call yresid(yresaug,sxx,y,yaug,baug)
      tbaug1=0
      do 180 ib=1,nb
      call loop(yresaug,yaug,ybootaug)
      call augboot(sxx,ybootaug,bbootaug)
      call ms(binit,bbootaug,msebbootaug)
      tbaug1=tbaug1+msebbootaug
180   continue
      avbaug1=tbaug1/nb
      abaug1(poo)=avbaug1
!     sum mse in vecmax
      sols1=sols1+mols1(poo)
      saug1=saug1+maug1(poo)
      sbols1=sbols1+abols1(poo)
      sbaug1=sbaug1+abaug1(poo)
!     square mse
      sqols1=sqols1+mols1(poo)**2
      sqaug1=sqaug1+maug1(poo)**2
      sqbols1=sqbols1+abols1(poo)**2
      sqbaug1=sqbaug1+abaug1(poo)**2
      else if (bint.eq.2) then
      do 215 i=1,m1
      binit(i)=vecmin(i)
215   continue
      if (derror.eq.1)then
      do 225 i=1,n
      error(i)=normal(am,sd)
225   continue
      else if (derror.eq.2)then
      do 230 i=1,n
```

```
      error(i)=scnor(c,p,am,sd)
230   continue
      else if (derror.eq.3)then
      do 235 i=1,n
      error(i)=lognor(am,sd)
235   continue
      end if
      call buildy(sxx,binit,error,y)
      if (derror.eq.3) then
      call boxcox(sxx,y)
      end if
      call ols(sxx,y,xtx,xty,sig2,bols)
      call ms(binit,bols,mseols2)
      mols2(poo)=mseols2
      call yresid(yresols,sxx,y,yols,bols)
      tbols2=0
      do 260 ib=1,nb
      call loop (yresols,yols,ybootols)
      call ols (sxx,ybootols,xtx,xtybootols,sig2,bbootols)
      call ms(binit,bbootols,msebbootols)
      tbols2=tbols2+msebbootols
260   continue
      avbols2=tbols2/nb
      abols2(poo)=avbols2
      call aug(sxx,y,baug)
      call ms(binit,baug,mseaug2)
      maug2(poo)=mseaug2
      call yresid(yresaug,sxx,y,yaug,baug)
      tbaug2=0
      do 280 ib=1,nb
      call loop(yresaug,yaug,ybootaug)
      call augboot(sxx,ybootaug,bbootaug)
```

```
      call ms(binit,bbootaug,msebbootaug)
      tbaug2=tbaug2+msebbootaug
280   continue
      avbaug2=tbaug2/nb
      abaug2(poo)=avbaug2
!     sum mse in vecmax
      sols2=sols2+mols2(poo)
      saug2=saug2+maug2(poo)
      sbols2=sbols2+abols2(poo)
      sbaug2=sbaug2+abaug2(poo)
!     square mse
      sqols2=sqols2+mols2(poo)**2
      sqaug2=sqaug2+maug2(poo)**2
      sqbols2=sqbols2+abols2(poo)**2
      sqbaug2=sqbaug2+abaug2(poo)**2
!      mse per each round
      rsols=(mols1(poo)+mols2(poo))/2
      rsaug=(maug1(poo)+maug2(poo))/2
      rsbols=(abols1(poo)+abols2(poo))/2
      rsbaug=(abaug1(poo)+abaug2(poo))/2
!     sum mse in each round
      sols=sols+rsols
      saug=saug+rsaug
      sbols=sbols+rsbols
      sbaug=sbaug+rsbaug
!     square mse in each round
      sqols=sqols+rsols**2
      sqaug=sqaug+rsaug**2
      sqbols=sqbols+rsbols**2
      sqbaug=sqbaug+rsbaug**2
      end if
110   continue
```

```
105  continue
!       average mse vecmax
        amols1=sols1/float(count)
        amaug1=saug1/float(count)
        ambols1=sbols1/float(count)
        ambaug1=sbaug1/float(count)
        write (25,*)"amols1  =",amols1
        write (25,*)"amaug1  =",amaug1
        write (25,*)"ambols1 =",ambols1
        write (25,*)"ambaug1 =",ambaug1
!       variance mse vecmax
        vols1  =(sqols1-(count*(amols1**2)))/float(count-1)
        vaug1  =(sqaug1-(count*(amaug1**2)))/float(count-1)
        vbols1 =(sqbols1-(count*(ambols1**2)))/float(count-1)
        vbaug1 =(sqbaug1-(count*(ambaug1**2)))/float(count-1)
        write(25,*) "vols1  =",vols1
        write(25,*) "vaug1  =",vaug1
        write(25,*) "vbols1 =",vbols1
        write(25,*) "vbaug1 =",vbaug1
!       standard deviation vecmax
        sdols1 =sqrt(vols1)
        sdaug1 =sqrt(vaug1)
        sdbols1=sqrt(vbols1)
        sdbaug1=sqrt(vbaug1)
        write (25,*)"sdols1 =",sdols1
        write (25,*)"sdaug1 =",sdaug1
        write (25,*)"sdbols1=",sdbols1
        write (25,*)"sdbaug1=",sdbaug1
!       comparison on 3 method and bootstrap in vecmax
        polsbols1 = ((ambols1-amols1)/amols1)*100
        pbolsols1=((amols1-ambols1)/ambols1)*100
        paugbaug1 = ((ambaug1-amaug1)/amaug1)*100
```

```
      pbaugaug1=((amaug1-ambaug1)/ambaug1)*100
      write (25,*)"polsbols1 =",polsbols1
      write (25,*)"pbolsols1 =",pbolsols1
      write (25,*)"paugbaug1 =",paugbaug1
      write (25,*)"pbaugaug1 =",pbaugaug1
!     Comparison on 3 method without bootstrap in  vecmax
      polsaug1=((amaug1-amols1)/amols1)*100
      paugols1=((amols1-amaug1)/amaug1)*100
      write (25,*)"polsaug1 =",polsaug1
      write (25,*)"paugols1 =",paugols1
!     Comparison on bootstrap with 3 method  in  vecmax
      pbolsbaug1=((ambaug1-ambols1)/ambols1)*100
      pbaugbols1=((ambols1-ambaug1)/ambaug1)*100
      write (25,*)"pbolsbaug1 =",pbolsbaug1
      write (25,*)"pbaugbols1 =",pbaugbols1
!     average mse vecmin
      amols2=sols2/float(count)
      amaug2=saug2/float(count)
      ambols2=sbols2/float(count)
      ambaug2=sbaug2/float(count)
      write (25,*)"amols2  =",amols2
      write (25,*)"amaug2  =",amaug2
      write (25,*)"ambols2 =",ambols2
      write (25,*)"ambaug2 =",ambaug2
!     variance mse vecmin
      vols2  =(sqols2-(count*(amols2**2)))/float(count-1)
      vaug2  =(sqaug2-(count*(amaug2**2)))/float(count-1)
      vbols2 =(sqbols2-(count*(ambols2**2)))/float(count-1)
      vbaug2 =(sqbaug2-(count*(ambaug2**2)))/float(count-1)
      write(25,*) "vols2  =",vols2
      write(25,*) "vaug2  =",vaug2
      write(25,*) "vbols2 =",vbols2
```

```
      write(25,*) "vbaug2 =",vbaug2
!     standard deviation in vecmin
      sdols2 =sqrt(vols2)
      sdaug2 =sqrt(vaug2)
      sdbols2=sqrt(vbols2)
      sdbaug2=sqrt(vbaug2)
      write (25,*)"sdols2 =",sdols2
      write (25,*)"sdaug2 =",sdaug2
      write (25,*)"sdbols2=",sdbols2
      write (25,*)"sdbaug2=",sdbaug2
!     comparison on 3 method and bootstrap in vecmin
      polsbols2 = ((ambols2-amols2)/amols2)*100
      pbolsols2 =((amols2-ambols2)/ambols2)*100
      paugbaug2 = ((ambaug2-amaug2)/amaug2)*100
      pbaugaug2 =((amaug2-ambaug2)/ambaug2)*100
      write (25,*)"polsbols2 =",polsbols2
      write (25,*)"pbolsols2 =",pbolsols2
      write (25,*)"paugbaug2 =",paugbaug2
      write (25,*)"pbaugaug2 =",pbaugaug2
!     Comparison on 3 method without bootstrap in  vecmin
      polsaug2=((amaug2-amols2)/amols2)*100
      paugols2=((amols2-amaug2)/amaug2)*100
      write (25,*)"polsaug2 =",polsaug2
      write (25,*)"paugols2 =",paugols2
!     Comparison on bootstrap with 3 method  in  vecmin
      pbolsbaug2=((ambaug2-ambols2)/ambols2)*100
      pbaugbols2=((ambols2-ambaug2)/ambaug2)*100
      write (25,*)"pbolsbaug2 =",pbolsbaug2
      write (25,*)"pbaugbols2 =",pbaugbols2
!     average mse in both vecmax and vecmin
      amols=sols/float(count)
      amaug=saug/float(count)
```

```
      ambols=sbols/float(count)
      ambaug=sbaug/float(count)
      write (25,*)"amols  =",amols
      write (25,*)"amaug  =",amaug
      write (25,*)"ambols =",ambols
      write (25,*)"ambaug =",ambaug
!     variance mse in both vecmax and vecmin
      vols  =(sqols-(count*(amols**2)))/float(count-1)
      vaug  =(sqaug-(count*(amaug**2)))/float(count-1)
      vbols =(sqbols-(count*(ambols**2)))/float(count-1)
      vbaug =(sqbaug-(count*(ambaug**2)))/float(count-1)
      write(25,*) "vols  =",vols
      write(25,*) "vaug  =",vaug
      write(25,*) "vbols =",vbols
      write(25,*) "vbaug =",vbaug
!     standard deviation in both vecmax and vecmin
      sdols =sqrt(vols)
      sdaug =sqrt(vaug)
      sdbols=sqrt(vbols)
      sdbaug=sqrt(vbaug)
      write (25,*)"sdols =",sdols
      write (25,*)"sdaug =",sdaug
      write (25,*)"sdbols=",sdbols
      write (25,*)"sdbaug=",sdbaug
!     comparison on 3 method and bootstrap in both vecmax and vecmin
      polsbols = ((ambols-amols)/amols)*100
      pbolsols=((amols-ambols)/ambols)*100
      paugbaug = ((ambaug-amaug)/amaug)*100
      pbaugaug=((amaug-ambaug)/ambaug)*100
      write (25,*)"polsbols =",polsbols
      write (25,*)"pbolsols =",pbolsols
      write (25,*)"paugbaug =",paugbaug
```

```
      write (25,*)"pbaugaug =",pbaugaug
!     Comparison on 3 method without bootstrap in both vecmax and vecmin
      polsaug=((amaug-amols)/amols)*100
      paugols=((amols-amaug)/amaug)*100
      write (25,*)"polsaug =",polsaug
      write (25,*)"paugols =",paugols
!     Comparison on bootstrap with 3 method  both vecmax and vecmin
      pbolsbaug=((ambaug-ambols)/ambols)*100
      pbaugbols=((ambols-ambaug)/ambaug)*100
      write (25,*)"pbolsbaug =",pbolsbaug
      write (25,*)"pbaugbols =",pbaugbols
60    continue
30    continue
      contains
!     SUBROUTINE FOR SIMULATE INDEPENDENT VARIABLES
      subroutine buildx(x,tmean,asum)
      common /seed/ix,kk/no/m1,n/corr/cor1,cor2,cor3,cor4
      double precision asum(6),tmean(6),x(100,6),z(100,7)
      do 10 j=2,m1+1
      do 10 i=1,n
      z(i,j)=0.0
      z(i,j)=normal(0.0,1.0)
10  continue
!     3 INDEPENDENT   VARIABLES
      do 15 j=1,m1
      if (j.eq.1) then
      do 20 i=1,n
      x(i,j)=1.0
20    continue
      endif
      if (j.ge.2.and.j.le.4) then
      do 25 i=1,n
```

```
      x(i,j)=sqrt(1-cor1)*z(i,j)+sqrt(cor2)*z(i,5)
25    continue
      endif
!     5 independent variables
      if (j.gt.4) then
      do 30 i=1,n
      x(i,j)=sqrt(1-cor3)*z(i,j)+sqrt(cor4)*z(i,7)
30    continue
      endif
15    continue
!     CALL CORRELATION
      call corre(x,tmean,asum)
      return
      end   subroutine
!     FUNCTION FOR SIMULATE FROM NORMAL
      real function normal(am,sd)
      common/seed/ix,kk
      real am,sd,pi
      real nor1,nor2
      real u1,u2
      pi=3.14159265
      if (kk.eq.1) goto 5
      call random(ix,iy,fly)
      u1=fly
      call random(ix,iy,fly)
      u2=fly
      nor1=sqrt(-2*alog(u1))*cos(2*pi*u2)
      nor2=sqrt(-2*alog(u1))*sin(2*pi*u2)
      normal=nor1*sd+am
      kk=1
      return
5     normal=nor2*sd+am
```

```
      kk=0
      return
      end  function
!     SUBROUTINE FOR SIMULATE FROM UNIFORM
      subroutine random(ix,iy,fly)
      real fly
      iy=ix*16807
      if(iy.lt.0)  iy=(iy+2147483647)+1
      fly=iy
      fly=fly/2147483647
      ix=iy
      return
      end  subroutine
!     SUBROUTINE FOR COMPUTE CORRELATION
      subroutine corre(x,tmean,asum)
      common /no/m1,n
      double precision tmean(6),asum(6),x(100,6)
      double precision  xatxa(100,6),xa(100,6),ssa(6),corx(6,6)
      do 30 j=2,m1
      asum(j)=0
      do 35 i=1,n
      asum(j)=asum(j)+x(i,j)
35    continue
30    continue
      do 40 j=2,m1
      tmean(j)=asum(j)/float(n)
40    continue
      do 45 j=2,m1
      do 45 i=1,n
      xa(i,j)=x(i,j)-tmean(j)
45    continue
      do 50 j=2,m1
```

```
      ssa(j)=0
      do 55 i=1,n
      ssa(j)=ssa(j)+xa(i,j)*xa(i,j)
55    continue
50    continue
      do 65 j=2,m1
      do 65 k=2,m1
      xatxa(j,k)=0.0
      do 70 i=1,n
      xatxa(j,k)=xatxa(j,k)+xa(i,j)*xa(i,k)
70    continue
      xatxa(k,j)=xatxa(j,k)
65    continue
      do 75 j=2,m1
      do 75 k=2,m1
      corx(j,k)=xatxa(j,k)/sqrt(ssa(j)*ssa(k))
75    continue
      return
      end   subroutine
!     SUBROUTINE FOR BUILD STANDARDIZE X
      subroutine stand(x,tmean,sxx,asum)
      common /no/m1,n
      double precision tmean(6),asum(6),x(100,6),sxx(100,6)
      double precision sqx(6),sdx(6),sumx,xbar
      sumx=0.0
      do 5 j=2,m1
      sumx=sumx+asum(j)
5     continue
      xbar=sumx/float(n*(m1-1))
      do 10 j=2,m1
      sqx(j)=0.0
      do 10 i=1,n
```

```
      sqx(j)=sqx(j)+x(i,j)*x(i,j)
10    continue
      do 20 j=2,m1
      sdx(j)=dsqrt((sqx(j)-(n*tmean(j)**2))/float(n-1))
20    continue
      do 25 j=1,m1
      if(j.eq.1)then
      do 30 i=1,n
      sxx(i,j)=1.0
30    continue
      else
      do 35 i=1,n
      sxx(i,j)=(x(i,j)-tmean(j))/sdx(j)
35    continue
      endif
25    continue
      return
      end   subroutine
!     SUBROUTINE FOR CALCULATE X'X
      subroutine calxtx(sxx,xtx)
      double precision sxx(100,6),sxxt(6,100)
      double precision xtx(6,6)
      common /no/m1,n
      do 10 i=1,n
      do 10 j=1,m1
      sxxt(j,i)=sxx(i,j)
10    continue
      do 15 i=1,m1
      do 15 j=1,m1
      xtx(i,j)=0.0
      do 15 k=1,n
      xtx(i,j)=xtx(i,j)+sxxt(i,k)*sxx(k,j)
```

```
15    continue
      return
      end  subroutine
!     SUBROUTINE FIND EIGEN VALUE AND EIGEN VECTOR
!     THIS IS THE MAIN PROGRAM FOR EIGENVALUE PROBLEM IN THE
!     FORM OF AX=LX
!     A IS SYMMETRICAL MATRIX
!     L ARE EIGENVALUES , X ARE EIGENVECTORS
      subroutine eigen(a,eigval,vecmax,vecmin)
      double precision a(6,6),x(6,6),eigval(6),vecmax(6),vecmin(6)
      common/no/m1,n
      call jacobi(a,1,nr,x)
      do 1 i=1,m1
      eigval(i)=a(i,i)
      vecmax(i)=x(i,2)
      vecmin(i)=x(i,m1)
1     continue
      return
      end  subroutine
!     SUBROUTINE FOR DIAGONALIZATION OF MATRIX Q BY SUCCESSIVE
!     ROTATIONS
      subroutine jacobi(q,jvec,nr,v)
      double precision q(6,6),v(6,6),ih(6),x(6)
      common/no/m1,n
!     NEXT 8 STATEMENTS FOR SETTING INITIAL VALUES OF MATRIX V
      if (jvec)10,15,10
10    do 14 i=1,m1
      do 14 j=1,m1
      if (i-j)12,11,12
11    v(i,j)=1.0
      goto 14
12    v(i,j)=0.0
```

```
14   continue
15   nr=0
!    NEXT 8 STATEMENTS SCAN FOR LARGEST OFF DIAGONAL ELEMENT
!    IN EACH ROW
!    X(I) CONTAINS LARGEST ELEMENT IN ITH ROW
!    IH(I) HOLDS SECOND SEBSCRIPT DEFINING POSITION OF ELEMENT
17   nri=m1-1
     do 30 i=1,nri
     x(i)=0.0
     nrj=i+1
     do 30 j=nrj,m1
     if(x(i)-dabs(q(i,j))) 20,20,30
20   x(i)=dabs(q(i,j))
     ih(i)=j
30   continue
!    NEXT 7 STATEMENTS FIND FOR MAXIMUM OF X(I)S FOR PIVOT
!    ELEMENT
40   do 70 i=1,nri
     if(i-1)60,60,45
45   if(xmax-x(i))60,70,70
60   xmax=x(i)
     ip=i
     jp=ih(i)
70   continue
!NEXT 2 STATEMENTS TEST FOR XMAX,IF LESS THAN 10**-8   GO TO 1000
     epsi=0.00000001
     if (xmax-epsi)1000,1000,148
148  nr=nr+1
!    NEXT 11 STATEMENTS FOR COMPUTING TANG,SIN,COS,Q(I,I),Q(J,J)
     if(q(ip,ip)-q(jp,jp)) 150,151,151
150  tang=-2.0*q(ip,jp)/(dabs(q(ip,ip)-q(jp,jp))+dsqrt((q(ip,ip)-q(jp,jp))**2+4.0*q
     (ip,jp)**2))
```

```
      goto 160
151   tang=+2.0*q(ip,jp)/(dabs(q(ip,ip)-q(jp,jp))+dsqrt((q(ip,ip)-q(jp,jp))**2+4.0*q
      (ip,jp)**2))
160   cosn=1.0/sqrt(1.0+tang**2)
      sine=tang*cosn
      qii=q(ip,ip)
      q(ip,ip)=cosn**2*(qii+tang*(2.0*q(ip,jp)+tang*q(jp,jp)))
      q(jp,jp)=cosn**2*(q(jp,jp)-tang*(2.0*q(ip,jp)-tang*qii))
      q(ip,jp)=0.0
!     NEXT 4 STATEMENTS FOR PSEUDO RANK THE EIGENVALUES
      if(q(ip,ip)-q(jp,jp))152,153,153
152   temp=q(ip,ip)
      q(ip,ip)=q(jp,jp)
      q(jp,jp)=temp
!     NEXT 6 STATEMENTS ADJUST SIN,COS FOR COMPUTATION OF
!     Q(I,K),V(I,K)
      if(sine)154,155,155
154   temp=+cosn
      goto 170
155   temp=-cosn
170   cosn=abs(sine)
      sine=temp
!     NEXT 10 STATEMENTS FOR INSPECTING THE IHS BETWEEN I+1 AND
!     N-1
!     TO DETERMINE WHETHER A NEW MAXIMUM VALUE SHOULD BE
!     COMPUTED SINCE
!     THE PRESENT MAXIMUM IS IN THE I OR J ROW
153   do 350 i=1,nri
      if(i-ip)210,350,200
200   if(i-jp)210,350,210
210   if(ih(i)-ip)230,240,230
230   if(ih(i)-jp)350,240,350
```

```
240  k=ih(i)
250  temp=q(i,k)
     q(i,k)=0.0
     nrj=i+1
     x(i)=0.0
!    NEXT 5 STATEMENTS SEARCH IN DEPLETED ROW FOR NEW
!    MAXIMUM
     do 320 j=nrj,m1
     if(x(i)-dabs(q(i,j)))300,300,320
300  x(i)=dabs(q(i,j))
     ih(i)=j
320  continue
     q(i,k)=temp
350  continue
     x(ip)=0.0
     x(jp)=0.0
!    NEXT 30 STATEMENTS FOR CHANGING THE OTHER ELEMENTS OF Q
     do 530 i=1,m1
     if(i-ip)370,530,420
370  temp=q(i,ip)
     q(i,ip)=cosn*temp+sine*q(i,jp)
     if(x(i)-dabs(q(i,ip)))380,390,390
380  x(i)=dabs(q(i,ip))
     ih(i)=ip
390  q(i,jp)=-sine*temp+cosn*q(i,jp)
     if(x(i)-dabs(q(i,jp)))400,530,530
400  x(i)=dabs(q(i,jp))
     ih(i)=jp
     goto 530
420  if(i-jp)430,530,480
430  temp=q(ip,i)
     q(ip,i)=cosn*temp+sine*q(i,jp)
```

```
      if(x(ip)-dabs(q(ip,i)))440,450,450
440   x(ip)=dabs(q(ip,i))
      ih(ip)=i
450   q(i,jp)=-sine*temp+cosn*q(i,jp)
      if (x(i)-dabs(q(i,jp))) 400,530,530
480   temp=q(ip,i)
      q(ip,i)=cosn*temp+sine*q(jp,i)
      if(x(ip)-dabs(q(ip,i)))490,500,500
490   x(ip)=dabs(q(ip,i))
      ih(ip)=i
500   q(jp,i)=-sine*temp+cosn*q(jp,i)
      if (x(jp)-dabs(q(jp,i)))510,530,530
510   x(jp)=dabs(q(jp,i))
      ih(jp)=i
530   continue
!     NEXT 6 STATEMENTS TEST FOR COMPUTATION OF EIGENVECTORS
      if(jvec)540,40,540
540   do 550 i=1,m1
      temp=v(i,ip)
      v(i,ip)=cosn*temp+sine*v(i,jp)
550   v(i,jp)=-sine*temp+cosn*v(i,jp)
      goto 40
1000  return
      end  subroutine
!     SUBROUTINE FOR COMPUTE INVERSE MATRIX
      subroutine inma(in)
      common /no/m1,n
      double precision in(6,6)
      do 5 k=1,m1
      in(k,k)=-1.0/in(k,k)
      do 10 i=1,m1
      if(i-k)15,10,15
```

```
15    in(i,k)=-in(i,k)*in(k,k)
10    continue
      do 30 i=1,m1
      do 30 j=1,m1
      if((i-k)*(j-k))35,30,35
35    in(i,j)=in(i,j)-in(i,k)*in(k,j)
30    continue
      do 5 j=1,m1
      if (j-k) 40,5,40
40    in(k,j)=-in(k,j)*in(k,k)
5     continue
      do 45 i=1,m1
      do 45 j=1,m1
      in(i,j)=-in(i,j)
45    continue
      return
      end   subroutine
!     FUNCTION FOR SIMULATE FROM SCALE CONTAMINATED NORMAL
      real function scnor (c,p,am,sd)
      real c,p,am,sd,fly,adsd
      common/seed/ix,kk
      adsd=c*sd
      call random(ix,iy,fly)
      if (fly.le.p)then
      scnor=normal(am,adsd)
      else
      scnor=normal(am,sd)
      endif
      return
      end   function
!     FUNCTION FOR SIMULATE FROM LOGNORMAL
      real function lognor (am,sd)
```

```
      real norm
      common/seed/ix,kk
      norm=normal(am,sd)
      lognor=exp(norm)
      return
      end    function
!     SUBROUTINE FOR BUILD DEPENDENT VARIABLE
      subroutine buildy(x,binit,error,y)
      double precision x(100,6),error(100)
      double precision binit(6),ty(100),y(100)
      common /no/m1,n
      do 10 i=1,n
      ty(i)=0.0
      do 15 k=1,m1
      ty(i)=ty(i)+x(i,k)*binit(k)
15    continue
      y(i)=ty(i)+error(i)
10    continue
      return
      end    subroutine
!     SUBROUTINE  FOR BOXCOX TRANSFORMATION
      subroutine boxcox(x,y)
      double precision y(100),ytrans(100),ystar(100),sum,geomn,xtx(6,6),xty(6)
      double precision sig2,bols(6),s(3)
      double precision x(100,6),lammin,lamopt,lammax,lamb
      integer fail
      character status*10
      common /no/m1,n
      sum=0.0
      do 5 i=1,n
      if(y(i).le.0) then
      fail=fail+1
```

```
      write(*,6)
6     format('can not find geometric mean')
      write(25,7)fail
7     format('fail=',i3)
      return
      end if
5     continue
      do 10 i=1,n
      sum=sum+dlog(y(i))
10    continue
      geomn=dexp(sum/n)
      do 20 i=1,n
      ystar(i)=y(i)/geomn
20    continue
      lammin=-15.00
      lammax=16.00
      e=0.01
15    lamopt=(lammin+lammax)/2
      do 40 i=1,3
      lamb=lamopt+(i-2)*e
      do 30 j=1,n
      if(lamb.ne.0)then
      ytrans(j)=((ystar(j)**lamb)-1)/lamb
      else
      ytrans(j)=dlog(ystar(j))
      end if
30    continue
      call ols(x,ytrans,xtx,xty,sig2,bols)
      s(i)=sig2
40    continue
      if(s(2).le.s(1).and.s(2).le.s(3)) then
      status='optimum'
```

```
      else if (s(1).gt.s(3))then
      lammin=lamopt
      else if (s(1).lt.s(3)) then
      lammax=lamopt
      end if
      if ((lammax-lammin).gt.e.and.(status.ne.'optimum')) goto 15
      do 50 i=1,n
      if (lamopt.ne.0)then
      y(i)=((ystar(i)**lamopt)-1)/lamopt
      else
      y(i)=dlog(ystar(i))
      end if
50    continue
      status='return'
      return
      end   subroutine
!     SUBROUTINE FOR BUILD BETA FROM OLS METHOD
      subroutine ols(x,y,xtx,xty,sig2,bols)
      double precision x(100,6),xt(6,100),in(6,6)
      double precision xtx(6,6),xty(6),bols(6),y(100)
      double precision yty,btxty,sig2
      common/no/m1,n
      do 10 i=1,n
      do 10 j=1,m1
      xt(j,i)=x(i,j)
10    continue
      do 15 i=1,m1
      do 15 j=1,m1
      xtx(i,j)=0.0
      do 15 k=1,n
      xtx(i,j)=xtx(i,j)+xt(i,k)*x(k,j)
15    continue
```

```
      do 25 i=1,m1
      xty(i)=0.0
      do 25 k=1,n
      xty(i)=xty(i)+xt(i,k)*y(k)
25 continue
      do 100 j=1,m1
      do 100 k=1,m1
      in(k,j)=xtx(k,j)
      in(j,k)=xtx(j,k)
100   continue
      call inma(in)
      do 35 i=1,m1
      bols(i)=0.0
      do 35 k=1,m1
      bols(i)=bols(i)+in(i,k)*xty(k)
35    continue
      yty=0.0
      do 40 i=1,n
      yty=yty+y(i)**2
40    continue
      btxty=0.0
      do 45 i=1,m1
      btxty=btxty+bols(i)*xty(i)
45    continue
      sig2=0.0
      sig2=(yty-btxty)/(n-m1)
      return
      end   subroutine
!     SUBROUTINE FOR CALCULATE ERROR
      subroutine yresid(yres,sxx,y,yhat,beta)
      double precision yres(100),sxx(100,6),yhat(100),y(100),beta(6),sum
      common /no/m1,n
```

```
      do 10 i=1,n
      sum=0
      do 20 j=1,m1
      sum=sum+sxx(i,j)*beta(j)
20    continue
      yhat(i)=sum
      yres(i)=y(i)-yhat(i)
  10  continue
      return
      end  subroutine
!     SUBROUTINE FOR ERROR RANDOM AND FIND Y-PREDICT FORM
!     BOOTSTRAP SAMPLE
      subroutine loop (yres,yhat,yboot)
      double precision yres(100),yboot(100),eb(100),yhat(100)
      common/no/m1,n/prob/pp(100)
      do 30 j=1,n
      call random(ix,iy,fly)
      do 10 it=1,n
      it1=it-1
      if(it1.eq.0) then
      a1=0.0
      else
      a1=pp(it1)
      end if
      a2=pp(it)
      if((fly.gt.a1).and.(fly.le.a2))then
      eb(j)=yres(it)
      goto 12
      end if
10    continue
12    yboot(j)=yhat(j)+eb(j)
30    continue
```

```
      return
      end  subroutine
!     SUBROUTINE FOR BULID BETA FROM ALMOST UNBIASED
!     GENERALIZED LIU METHOD
      subroutine aug(sxx,y,baug)
      double precision d(6,6),sxx(100,6)
      double precision xtx(6,6),xty(6),bols(6),baug(6),xtxaug(6,6)
      double precision xtyaug(6),sig2,y(100),eigval(6)
      double precision vecmax(6),vecmin(6),in(6,6)
      common /no/m1,n
      call ols(sxx,y,xtx,xty,sig2,bols)
      do 15 i=1,m1
      do 15 j=1,m1
      if (i.eq.j) then
      xtxaug(i,j)=xtx(i,j)+1
      else
      xtxaug(i,j)=xtx(i,j)
      end if
15    continue
      call eigen(xtx,eigval,vecmax,vecmin)
      call dopt(bols,sig2,eigval,d)
      do 30 i=1,m1
      xtyaug(i)=xty(i)+d(i,i)*bols(i)
30    continue
      do 35 j=1,m1
      do 35 k=1,m1
      in(k,j)=xtxaug(k,j)
      in(j,k)=xtxaug(j,k)
35    continue
      call inma(in)
      do 50 i=1,m1
      baug(i)=0.0
```

```
      do 50 k=1,m1
      baug(i)=baug(i)+in(i,k)*xtyaug(k)
50  continue
      return
      end   subroutine
!     SUBROUTINE DOPT FIND MATRIX D FOR ALMOST UNBIASED
!     GENERALIZED LIU METHOD
      subroutine dopt(bols,sig2,eigval,d)
      double precision d(6,6)
      double precision bols(6),eigval(6),p1(6),p2(6),sig2
      common/no/m1,n
      do 10 i=1,m1
      p1(i)=eigval(i)*((bols(i)**2)-sig2)
      p2(i)=(eigval(i)*(bols(i)**2))+sig2
      d(i,i)=p1(i)/p2(i)
  10  continue
      return
      end subroutine
!     Subroutine for mean squre error
      subroutine ms (binits,B,mse)
      double precision binits(6),B(6),mse
      common/no/m1,n
      mse=0.0
      do 10 I=1,m1
      mse = mse+(binits(i)-B(i))**2
10    continue
      return
      end subroutine
!     SUBROUTINE BOOTSTRAP FROM ALMOST UNBIASED GENERALIZED
!     LIU METHOD
      subroutine augboot(sxx,ybootaug,bbootaug)
      double precision sxx(100,6),d(6,6)
```

```
      double precision xtx(6,6),ybootaug(100),xtybootaug(6),sig2,augbols(6)
      double precision  xtxbootaug(6,6),eigval(6),vecmax(6),vecmin(6)
      double precision bootstrapxtyaug(6), in(6,6),bbootaug(6)
      common/no/m1,n
      call ols(sxx,ybootaug,xtx,xtybootaug,sig2,augbols)
      do 15 i=1,m1
      do 15 j=1,m1
      if(i.eq.j)then
      xtxbootaug(i,j)=xtx(i,j)+1
      else
      xtxbootaug(i,j)=xtx(i,j)
      end if
15    continue
      call eigen(xtx,eigval,vecmax,vecmin)
      call dopt(augbols,sig2,eigval,d)
      do 30 i=1,m1
      bootstrapxtyaug(i)=xtybootaug(i)+d(i,i)*augbols(i)
30    continue
      do 35 j=1,m1
      do 35 k=1,m1
      in(k,j)=xtxbootaug(k,j)
      in(j,k)=xtxbootaug(j,k)
35    continue
      call inma(in)
      do 50 i=1,m1
      bbootaug(i)=0
      do 50 k=1,m1
      bbootaug(i)=bbootaug(i)+in(i,k)*bootstrapxtyaug(k)
50    continue
      return
      end   subroutine
      end program
```

APPENDIX B
The Results of the Simulated Study

The main issues in this appendix is the results of comparing the multiple regression coefficient estimating in multicollinearity from the ordinary least square method, the almost unbiased generalized Liu estimator method and the bootstrap technique with these two methods in various situations.

With respect to specific data situations, four methods will be investigated through their average mean square error. There are three parts of results from simulated data, which are summarized in the following

1. The comparison of parameter estimation for normal distributed data
2. The comparison of parameter estimation for contaminated normal distributed data
3. The comparison of parameter estimation for lognormal distributed data

In this study, the symbol in the report is based on meaning as following:

n	:	sample sizes
Est	:	estimator method
OLS	:	The ordinary least square method
AUG	:	The almost unbiased generalized Liu estimator method
BOLS	:	The ordinary least square method with bootstrap technique
BAUG	:	The almost unbiased generalized Liu estimator method by bootstrap technique
AMSE	:	average mean square error
SD	:	standard deviation

1. The comparison of parameter estimation for normal distributed data

To designate a multiple regression coefficient estimator as four methods is considered by the departure of mean (μ) equals to 1, standard deviation (σ) equals to 0.05, 0.10, 0.15, 0.30 and 0.50 with three and five independent variables on various degree of correlation 0.10, 0.30, 0.50, 0.70, 0.90 and 0.99. The result in Table 1.1-1.10 are given below:

Table	No. of independent	Standard deviation (σ)
1.1	3	0.05
1.2	3	0.10
1.3	3	0.15
1.4	3	0.30
1.5	3	0.50
1.6	5	0.05
1.7	5	0.10
1.8	5	0.15
1.9	5	0.30
1.10	5	0.50

The result from testing the multiple regression coefficient by four method on normal distribution for the sample sizes of 10,30,50 and 100 at various degree of correlation were presented in table, respectively.

Table 1.1 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.05 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.0020868	1.0021738	1.0026811	1.0046458	1.0172698	1.1790047
		SD	0.0157312	0.0158420	0.0164459	0.0184052	0.0498669	0.4121528
	AUG	AMSE	1.0019549	1.0020398	1.0025338	1.0045476	1.0170579	1.1738562
		SD	0.0157775	0.0158635	0.0163948	0.0186761	0..0477048	0.3644596
	BOLS	AMSE	1.0025062	1.0025920	1.0032193	1.0057480	1.0208061	1.2150408
		SD	0.0158630	0.0160169	0.0168189	0.0206952	0.0648650	0.4996687
	BAUG	AMSE	1.0024012	1.0024728	1.0031429	1.0059919	1.0224175	1.2307888
		SD	0.0158772	0.0159503	0.0167851	0.0228521	0.0894769	0.7403114
30	OLS	AMSE	1.0003702	1.0003773	1.0004434	1.0006985	1.0022385	1.0237617
		SD	0.0094910	0.0094679	0.0095035	0.0094839	0.0096750	0.0259825
	AUG	AMSE	1.0002955	1.0003022	1.0003690	1.0006237	1.0021656	1.0240386
		SD	0.0094928	0.0094981	0.0094822	0.0094891	0.0096652	0.0265632
	BOLS	AMSE	1.0005322	1.0005438	1.0006344	1.0009901	1.0021656	1.0330911
		SD	0.0094572	0.0094832	0.0094602	0.0094487	0.0097171	0.0874483
	BAUG	AMSE	1.0004503	1.0004558	1.0005452	1.0008987	1.0031354	1.0342603
		SD	0.0094690	0.0094792	0.0094630	0.0094613	0.0096784	0.0309738
50	OLS	AMSE	1.0006239	1.0006298	1.0006627	1.0007887	1.0015541	1.0122569
		SD	0.0075018	0.0074974	0.0075305	0.0075065	0.0075831	0.0125326
	AUG	AMSE	1.0005768	1.0005828	1.0006156	1.0007415	1.0015055	1.0123718
		SD	0.0075140	0.0075262	0.0075363	0.0075290	0.0075675	0.0126930
	BOLS	AMSE	1.0007225	1.0007322	1.0007790	1.0009590	1.0020557	1.0174101
		SD	0.0075427	0.0075434	0.0075520	0.0075472	0.0076017	0.0134149
	BAUG	AMSE	1.0006894	1.0006972	1.0007411	1.0009197	1.0020176	1.0178622
		SD	0.0074791	0.0075049	0.0075297	0.0074895	0.0076172	0.0137894
100	OLS	AMSE	1.0002448	1.0002465	1.0002604	1.0003182	1.0006724	1.0056437
		SD	0.0048879	0.0048637	0.0049160	0.0048567	0.0048900	0.0061379
	AUG	AMSE	1.0002207	1.0002465	1.0002365	1.0002942	1.0006499	1.0056927
		SD	0.0048819	0.0048851	0.0048723	0.0048753	0.0049140	0.0062311
	BOLS	AMSE	1.0002943	1.0002971	1.0003177	1.0004023	1.0092054	1.0081903
		SD	0.0049137	0.0049493	0.0048860	0.0048754	0.0049139	0.0062387
	BAUG	AMSE	1.0002682	1.0002712	1.0002921	1.0003770	1.0008990	1.0083430
		SD	0.0049102	0.0049213	0.0048792	0.0049094	0.0048575	0.0063415

Table 1.2 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.10 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.0078447	1.0081928	1.0102219	1.0180806	1.0685768	1.7155163
		SD	0.0334910	0.0338152	0.0370296	0.0490790	0.1903877	1.6459750
	AUG	AMSE	1.0074098	1.0077389	1.0097804	1.0178381	1.0678310	1.6486928
		SD	0.0338909	0.0340649	0.0371370	0.0496260	0.1724979	1.4242830
	BOLS	AMSE	1.0094660	1.0098091	1.0123527	1.0224762	1.0827319	1.8596792
		SD	0.0341593	0.0345471	0.0392784	0.0614468	0.2521550	1.9962140
	BAUG	AMSE	1.0093356	1.0096136	1.0124010	1.0233742	1.0882082	1.8234617
		SD	0.0349529	0.0349998	0.0397459	0.0664574	0.3132780	2.6758910
30	OLS	AMSE	1.0014363	1.0014646	1.0017292	1.0027496	1.0089095	1.0950026
		SD	0.0189931	0.0189904	0.0189792	0.0190609	0.0206342	0.0991882
	AUG	AMSE	1.0011431	1.0011671	1.0014336	1.0024553	1.0086825	1.0993037
		SD	0.0189951	0.0189963	0.0189928	0.0190433	0.0206942	0.1022566
	BOLS	AMSE	1.0020651	1.0021092	1.0024703	1.0038907	1.0124676	1.1322877
		SD	0.0189890	0.0189884	0.0189771	0.0190503	0.0209953	0.1108788
	BAUG	AMSE	1.0017850	1.0018118	1.0021732	1.0036024	1.0124515	1.1437699
		SD	0.0189633	0.0189627	0.0189564	0.0190348	0.0212938	0.1168702
50	OLS	AMSE	1.0016281	1.0016519	1.0017833	1.0022874	1.0053488	1.0481600
		SD	0.0150366	0.0150202	0.0150261	0.0150905	0.0154669	0.0427813
	AUG	AMSE	1.0014394	1.0014642	1.0015950	1.0021018	1.0051885	1.0501655
		SD	0.0150260	0.0150252	0.0150353	0.0150509	0.0154710	0.0450853
	BOLS	AMSE	1.0020159	1.0020506	1.0022364	1.0029571	1.0073456	1.0687645
		SD	0.0150744	0.0150631	0.0150772	0.0151066	0.0156221	0.0466649
	BAUG	AMSE	1.0018638	1.0018970	1.0020763	1.0028005	1.0072684	1.0749349
		SD	0.0150303	0.0150360	0.0150358	0.0150707	0.0155651	0.0524999
100	OLS	AMSE	1.0006733	1.0006802	1.0007358	1.0009669	1.0023838	1.0222689
		SD	0.0098178	0.0098005	0.0097993	0.0098207	0.0098344	0.0183144
	AUG	AMSE	1.0005775	1.0005845	1.0006399	1.0008711	1.0023030	1.0230239
		SD	0.0098137	0.0097923	0.0097989	0.0097956	0.0098413	0.0191855
	BOLS	AMSE	1.0008687	1.0008796	1.0009618	1.0013004	1.0033736	1.0324530
		SD	0.0098039	0.0098271	0.0097936	0.0098052	0.0098073	0.0190715
	BAUG	AMSE	1.0007714	1.0007831	1.0008654	1.0012057	1.0033124	1.0345015
		SD	0.0097762	0.0097993	0.0098024	0.0097737	0.0098129	0.0205907

Table 1.3 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.15 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.0172736	1.0180568	1.0226224	1.0403045	1.1539208	2.6095349
		SD	0.0547873	0.0552495	0.0639059	0.0960768	0.4238605	3.7017530
	AUG	AMSE	1.0166049	1.0173256	1.0220814	1.0398593	1.1508081	2.4053880
		SD	0.0569463	0.0567086	0.0652159	0.0937969	0.3780299	3.2050490
	BOLS	AMSE	1.0208794	1.0216512	1.0274001	1.0501845	1.1857774	2.9339152
		SD	0.0566075	0.0572199	0.0700387	0.1266689	0.5636636	4.4898720
	BAUG	AMSE	1.0212504	1.0218824	1.0283235	1.0522136	1.1923763	2.7399942
		SD	0.0600523	0.0596771	0.0726049	0.1283908	0.6568007	5.8028670
30	OLS	AMSE	1.0031983	1.0032621	1.0038573	1.0061532	1.0200130	1.2137224
		SD	0.0285435	0.0285569	0.0285657	0.0287977	0.0340566	0.2213502
	AUG	AMSE	1.0025381	1.0026015	1.0032041	1.0055124	1.0198771	1.2175483
		SD	0.0285518	0.0285521	0.0285709	0.0287914	0.0346454	0.2043905
	BOLS	AMSE	1.0045987	1.0046962	1.0055079	1.0087018	1.0279966	1.2975898
		SD	0.0285405	0.0285414	0.0285690	0.0288548	0.0352636	0.2479570
	BAUG	AMSE	1.0040028	1.0040874	1.0049101	1.0081797	1.0288594	1.3080229
		SD	0.0285081	0.0284997	0.0852070	0.0288520	0.0371323	0.2181000
50	OLS	AMSE	1.0030127	1.0030662	1.0033618	1.0044961	1.0113842	1.1077094
		SD	0.0225490	0.0225559	0.0225712	0.0266292	0.0240166	0.0928268
	AUG	AMSE	1.0025897	1.0026454	1.0029417	1.0040872	1.0111213	1.1148431
		SD	0.0225451	0.0225384	0.0225700	0.0264242	0.0240496	0.0969850
	BOLS	AMSE	1.0038800	1.0039551	1.0043720	1.0059944	1.0158697	1.1540630
		SD	0.0226136	0.0226370	0.0226399	0.0227602	0.0244015	0.1017594
	BAUG	AMSE	1.0035290	1.0036024	1.0040121	1.0056596	1.0159514	1.1729434
		SD	0.0225472	0.0225481	0.0225733	0.0267703	0.2449322	0.1107823
100	OLS	AMSE	1.0012854	1.0013010	1.0014261	1.0019460	1.0051339	1.0498756
		SD	0.0147356	0.0147102	0.0147095	0.0146824	0.0148658	0.0382741
	AUG	AMSE	1.0010705	1.0010869	1.0012106	1.0017326	1.0049675	1.0530104
		SD	0.0147101	0.0147138	0.0147061	0.0146903	0.0148696	0.0415245
	BOLS	AMSE	1.0017231	1.0017473	1.0019324	1.0026945	1.0073594	1.0727882
		SD	0.0147278	0.0147289	0.0147102	0.0146854	0.0148814	0.0401625
	BAUG	AMSE	1.0015103	1.0015372	1.0017207	1.0024905	1.0072818	1.0815858
		SD	0.0147084	0.0147031	0.0146967	0.0146685	0.0148767	0.0471616

Table 1.4 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.30 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.0675867	1.0707196	1.0889820	1.1597105	1.6141756	7.4366316
		SD	0.1488054	0.1484141	0.1912584	0.3424321	1.6822480	14.800790
	AUG	AMSE	1.0679628	1.0711599	1.0887205	1.1561606	1.5604466	6.3814580
		SD	0.1523611	0.1525672	0.1848255	0.3038384	1.4768650	12.864710
	BOLS	AMSE	1.0818412	1.0849277	1.1080267	1.1991901	1.7416316	8.7342080
		SD	0.1583164	0.1585247	0.2214093	0.4740146	2.2436150	17.953520
	BAUG	AMSE	1.0888661	1.0922477	1.1150984	1.2017188	1.6931435	7.4983096
		SD	0.1623072	0.1641538	0.2122053	0.4236043	2.4285250	22.387410
30	OLS	AMSE	1.0126597	1.0129147	1.0152955	1.0244793	1.0799186	1.8547561
		SD	0.0575911	0.0576079	0.0578496	0.0600794	0.0954755	0.8817477
	AUG	AMSE	1.0101137	1.0104233	1.0128520	1.0226102	1.0855320	1.7568677
		SD	0.0579190	0.0576821	0.0579428	0.0605295	0.1075555	0.7354036
	BOLS	AMSE	1.0182037	1.0185865	1.0218301	1.0345980	1.1117641	2.1901289
		SD	0.0575726	0.0576025	0.0579429	0.0606352	0.1026483	0.9889869
	BAUG	AMSE	1.0162355	1.0167027	1.0200853	1.0344617	1.1279603	1.9763982
		SD	0.0576055	0.0576735	0.05799.33	0.0621393	0.1214392	0.7070530
50	OLS	AMSE	1.0094481	1.0096623	1.0108446	1.0153819	1.0429342	1.4282349
		SD	0.0452243	0.0452357	0.0453642	0.0460232	0.0558914	0.3626854
	AUG	AMSE	1.0078003	1.0079830	1.0092080	1.0139170	1.0435741	1.4266961
		SD	0.0451824	0.0451969	0.0453270	0.0460149	0.0574913	0.3352776
	BOLS	AMSE	1.0128971	1.0131848	1.0148487	1.0213410	1.0608472	1.6136235
		SD	0.0454203	0.0454507	0.0456020	0.0463829	0.0580845	0.3988045
	BAUG	AMSE	1.0115477	1.0117740	1.0135019	1.0203826	1.0658183	1.5979873
		SD	0.0452704	0.0452943	0.0454302	0.0463236	0.0624062	0.3179460
100	OLS	AMSE	1.0042233	1.0042858	1.0047862	1.0068659	1.0196177	1.1985844
		SD	0.0295219	0.0294875	0.0294249	0.0294423	0.0314195	0.1463254
	AUG	AMSE	1.0033707	1.0034429	1.0039416	1.0060634	1.0192006	1.2176597
		SD	0.0295019	0.0294812	0.0294281	0.0294412	0.0315796	0.1510789
	BOLS	AMSE	1.0059663	1.0060619	1.0068027	1.0098519	1.0285122	1.2902279
		SD	0.0295280	0.0294966	0.0294534	0.0294551	0.0315940	0.1545395
	BAUG	AMSE	1.0051563	1.0052727	1.0060218	1.0091911	1.0292770	1.3375071
		SD	0.0294818	0.0294689	0.0294087	0.0294358	0.0321060	0.1605571

Table 1.5 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.50 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.1860655	1.1947681	1.2454970	1.4419649	2.7043679	18.877855
		SD	0.3572795	0.3519368	0.4797288	0.9205977	4.6621040	41.106870
	AUG	AMSE	1.1855740	1.1937297	1.2377492	1.4010879	2.4701354	15.716155
		SD	0.3325856	0.3306255	0.4255696	0.7743477	4.1021700	35.799930
	BOLS	AMSE	1.2254739	1.2340469	1.2983256	1.5515859	3.0584456	22.482295
		SD	0.3863754	0.3828692	0.5692755	1.2929290	6.2229130	49.864600
	BAUG	AMSE	1.2386942	1.2462174	1.3001120	1.5081652	2.7655141	18.632152
		SD	0.3451232	0.3434890	0.4773431	1.0974180	6.5708930	61.317140
30	OLS	AMSE	1.0350174	1.0357257	1.0423390	1.0678496	1.2218475	3.3741738
		SD	0.0975864	0.0977589	0.0991952	0.1095584	0.2348370	2.4480740
	AUG	AMSE	1.0287018	1.0296257	1.0367463	1.0662968	1.2315780	2.8597249
		SD	0.0980465	0.0984001	0.0998153	0.1153603	0.2245736	2.0015570
	BOLS	AMSE	1.0503530	1.0514086	1.0604151	1.0958731	1.3102088	4.3056573
		SD	0.0976815	0.0978158	0.0996539	0.1121145	0.2575907	2.7465750
	BAUG	AMSE	1.0471124	1.0484756	1.0592468	1.1046167	1.3433667	3.2762232
		SD	0.0987704	0.0990921	0.1017173	0.1255428	0.2385444	1.9154580
50	OLS	AMSE	1.0233530	1.0239479	1.0272321	1.0398356	1.1163698	2.1866493
		SD	0.0758545	0.0759247	0.0764961	0.0794139	0.1184705	1.0021220
	AUG	AMSE	1.0189741	1.0194861	1.0229539	1.0364876	1.1239900	2.0314798
		SD	0.0757392	0.0758249	0.0764312	0.0798232	0.1325827	0.8456773
	BOLS	AMSE	1.0329109	1.0336962	1.0383135	1.0563509	1.1660956	2.7015888
		SD	0.0763231	0.0764152	0.0770650	0.0805065	0.1258025	1.102508
	BAUG	AMSE	1.0296459	1.0302862	1.0353446	1.0560516	1.1949959	2.3436736
		SD	0.0759914	0.0761281	0.0768548	0.0815802	0.1469256	0.7691926
100	OLS	AMSE	1.0107113	1.0108848	1.0122749	1.0180517	1.0534733	1.5506031
		SD	0.0494156	0.0493296	0.0492302	0.0495642	0.0591736	0.4033571
	AUG	AMSE	1.0083883	1.0086033	1.0100263	1.0160565	1.0553802	1.5903794
		SD	0.0493647	0.0493084	0.0491920	0.0495936	0.0622673	0.4649018
	BOLS	AMSE	1.0155441	1.0158082	1.0178666	1.0263374	1.0781723	1.8051609
		SD	0.0494399	0.0493723	0.0492741	0.0495961	0.0600608	0.4267089
	BAUG	AMSE	1.0134653	1.0138137	1.0159884	1.0251515	1.0874414	1.8237892
		SD	0.0493296	0.0493011	0.0491566	0.0496358	0.0665049	0.4037222

Table 1.6 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.05 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	4.4414458	7.4431062	27.096662	8.0750802	9.7329964	234.67515
		SD	50.259530	134.17600	317.33110	125.83400	118.57880	2864.6110
	AUG	AMSE	4.4414462	7.4431048	27.096796	8.0750808	9.7330134	234.67578
		SD	50.259560	134.17600	317.33430	125.83400	118.57910	2864.6280
	BOLS	AMSE	4.4414458	7.4431062	27.096662	8.0750802	9.7329964	234.61513
		SD	50.25953	134.17600	317.33110	125.83400	118.57880	2864.6100
	BAUG	AMSE	4.4414304	7.4430983	27.070183	8.0750669	9.7330026	234.79021
		SD	50.259380	134.17590	317.09190	125.83370	118.57890	2865.2840
30	OLS	AMSE	1.0000849	1.0001874	1.0004645	1.0008667	1.0030328	1.0362713
		SD	0.0091458	0.0091531	0.0091795	0.0091929	0.0094308	0.0325282
	AUG	AMSE	1.0000185	1.0001234	1.0004032	1.0008052	1.0029820	1.0372155
		SD	0.0091417	0.0091617	0.0092340	0.0091990	0.0094130	0.0336261
	BOLS	AMSE	1.0003032	1.0004351	1.0007958	1.0013480	1.0042714	1.0486103
		SD	0.0091963	0.0091857	0.0091987	0.0091832	0.0095537	0.0365891
	BAUG	AMSE	1.0002542	1.0003900	1.0007591	1.0013200	1.0042849	1.0510011
		SD	0.0091290	0.0091231	0.0091640	0.0919412	0.0095455	0.0389833
50	OLS	AMSE	1.0006051	1.0006525	1.0007837	1.0010174	1.0021395	1.0189399
		SD	0.0075237	0.0074979	0.0075333	0.0075169	0.0075911	0.0516227
	AUG	AMSE	1.0005604	1.0006085	1.0007389	1.0009769	1.0021116	1.0191692
		SD	0.0074357	0.0074989	0.0075018	0.0075415	0.0075788	0.0153707
	BOLS	AMSE	1.0007593	1.0008256	1.0010084	1.0013218	1.0028648	1.0260512
		SD	0.0075021	0.0075274	0.0075058	0.0074944	0.0076200	0.0162125
	BAUG	AMSE	1.0006893	1.0007571	1.0009389	1.0012638	1.0028375	1.0268515
		SD	0.0075138	0.0074946	0.0075092	0.0074915	0.0076359	0.0168599
100	OLS	AMSE	1.0005599	1.0005812	1.0006389	1.0007356	1.0012125	1.0083179
		SD	0.0049164	0.0049119	0.0049334	0.0049206	0.0049561	0.0071870
	AUG	AMSE	1.0005365	1.0005575	1.0006154	1.0007110	1.0011328	1.0084414
		SD	0.0048943	0.0094544	0.0049196	0.0049072	0.0049147	0.0073527
	BOLS	AMSE	1.0006334	1.0006637	1.0007464	1.0008841	1.0015640	1.0117178
		SD	0.0049125	0.0049213	0.0049740	0.0049311	0.0049016	0.0074363
	BAUG	AMSE	1.0006078	1.0006379	1.0007215	1.0008591	1.0015500	1.0120982
		SD	0.0049438	0.0049536	0.0048861	0.0049019	0.0049743	0.0077178

Table 1.7 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.10 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	14.764524	26.771173	105.38524	29.299078	35.930762	935.69935
		SD	201.03960	536.70360	1269.3230	503.33260	474.31500	11458.440
	AUG	AMSE	14.764525	26.771171	105.38393	29.299908	35.930800	935.70739
		SD	201.03960	536.70350	1269.3110	503.33260	474.31590	11458.600
	BOLS	AMSE	14.764524	26.771173	105.38524	29.299078	35.930763	935.69926
		SD	201.03960	536.70360	1269.3230	503.33260	474.31500	11458.440
	BAUG	AMSE	14.764510	26.771163	105.21257	29.299026	35.930748	935.76583
		SD	201.03950	536.70340	1267.3380	506.33140	474.31470	11458.540
30	OLS	AMSE	1.0015216	1.0019314	1.0030400	1.0046486	1.0133130	1.1462668
		SD	0.0183563	0.0184715	0.0187072	0.0187765	0.0210851	0.1274684
	AUG	AMSE	1.0012549	1.0016787	1.0028243	1.0044698	1.0133590	1.1466749
		SD	0.0183636	0.0184816	0.0187778	0.0188088	0.0212936	0.1252348
	BOLS	AMSE	1.0024130	1.0029425	1.0043906	1.0066030	1.0182887	1.1956393
		SD	0.0183676	0.0184812	0.0187775	0.0189048	0.0219475	0.1440996
	BAUG	AMSE	1.0022210	1.0027839	1.0043132	1.0066342	1.0189071	1.1985336
		SD	0.0183145	0.0184291	0.0188086	0.0189303	0.0224032	0.1389003
50	OLS	AMSE	1.0018934	1.0020831	1.0026077	1.0035426	1.0080309	1.0752326
		SD	0.0150142	0.0150494	0.0150854	0.0151001	0.0157645	0.0547931
	AUG	AMSE	1.0017160	1.0019079	1.0024303	1.0033997	1.0079819	1.0768117
		SD	0.0150293	0.0150500	0.0150849	0.0151163	0.0158449	0.0582788
	BOLS	AMSE	1.0024891	1.0027538	1.0064845	1.0074446	1.0109230	1.1036706
		SD	0.0150459	0.0150827	0.0150989	0.0151348	0.0159678	0.0592272
	BAUG	AMSE	1.0022764	1.0025497	1.0032784	1.0046088	1.0110420	1.1084747
		SD	0.0150588	0.0150544	0.0150887	0.0151787	0.0161360	0.0654218
100	OLS	AMSE	1.0014321	1.0015171	1.0017481	1.0021346	1.0040423	1.0324639
		SD	0.0098643	0.0098796	0.0098428	0.0098578	0.0100416	0.0232185
	AUG	AMSE	1.0013405	1.0014237	1.0016557	1.0020394	1.0039870	1.0334204
		SD	0.0098645	0.0098623	0.0098455	0.0098693	0.0100488	0.0244164
	BOLS	AMSE	1.0017263	1.0018477	1.0021777	1.0027288	1.0054483	1.0460634
		SD	0.0098414	0.0098501	0.0098518	0.0098642	0.0100867	0.0243563
	BAUG	AMSE	1.0016362	1.0017563	1.0020887	1.0056478	1.0054616	1.0486641
		SD	0.0098690	0.0098770	000986650	0.0098953	0.0100973	0.0266093

Table 1.8 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.15 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	31.969263	58.984208	235.86577	64.672001	79.593253	2104.0727
		SD	452.33730	1207.5830	2855.9790	1132.4970	1067.2090	25781.480
	AUG	AMSE	31.969262	58.984207	235.86289	64.672003	79.593266	2104.0759
		SD	452.33730	1207.5830	2855.9490	1132.4970	1067.2100	25781.550
	BOLS	AMSE	31.969263	58.984208	235.86577	64.672001	79.593253	2104.0725
		SD	452.33730	1207.5830	2855.9790	1132.4970	1067.2090	25781.480
	BAUG	AMSE	31.969254	58.984204	235.48730	64.671974	79.593263	2104.0735
		SD	452.33720	1207.5830	2851.6370	1132.4970	1067.2090	25781.490
30	OLS	AMSE	1.0043099	1.0052320	1.0077262	1.0113457	1.0308405	1.3299897
		SD	0.0277206	0.0280067	0.0287156	0.0291583	0.0368455	0.2860908
	AUG	AMSE	1.0037263	1.0047145	1.0073532	1.0111370	1.0315938	1.3131026
		SD	0.0276978	0.0280092	0.0289308	0.0293583	0.0380287	0.2555870
	BOLS	AMSE	1.0063295	1.0075219	1.0107838	1.0157650	1.0420518	1.4410869
		SD	0.0277494	0.0280713	0.0289298	0.0295441	0.0393270	0.3236621
	BAUG	AMSE	1.0059546	1.0072742	1.0108532	1.0162364	1.0452029	1.4157498
		SD	0.0276013	0.0279690	0.0293784	0.0300564	0.0425221	0.2700830
50	OLS	AMSE	1.0038649	1.0042917	1.0054721	1.0075755	1.0176743	1.1688780
		SD	0.0225665	0.0226225	0.0227702	0.0228816	0.0250314	0.1206962
	AUG	AMSE	1.0034717	1.0039105	1.0050858	1.0072920	1.0177858	1.1731569
		SD	0.0225686	0.0226236	0.0227405	0.0229383	0.0253751	0.1285343
	BOLS	AMSE	1.0051896	1.0057845	1.0074284	1.0102678	1.0241745	1.2328582
		SD	0.0226100	0.0226542	0.0228085	0.0299027	0.0255857	0.1307145
	BAUG	AMSE	1.0047681	1.0054017	1.0070551	1.0101318	1.0250624	1.2417920
		SD	0.0226156	0.0226883	0.0227604	0.0231010	0.0264610	0.1396883
100	OLS	AMSE	1.0026165	1.0028077	1.0033275	1.0041970	1.0084894	1.0724379
		SD	0.0147880	0.0147964	0.0148053	0.0148523	0.0154546	0.0496826
	AUG	AMSE	1.0024105	1.0026017	1.0031212	1.0039927	1.0084331	1.0738667
		SD	0.0148028	0.0214777	0.0147971	0.0148504	0.0152510	0.0516336
	BOLS	AMSE	1.0032785	1.0035514	1.0042940	1.0055342	1.0116528	1.1030367
		SD	0.0148213	0.0148089	0.0148176	0.0148753	0.0155373	0.0523221
	BAUG	AMSE	1.0030854	1.0033614	1.0041096	1.0053727	1.0118390	1.1097915
		SD	0.0148243	0.0148126	0.0148322	0.0148918	0.0156738	0.0585424

Table 1.9 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.30 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	124.87326	232.93309	940.45983	255.68422	315.36930	8413.2881
		SD	1809.3530	4830.3310	11423.930	4529.9790	4268.8410	103126.00
	AUG	AMSE	124.87326	232.93309	940.45776	255.68422	315.36932	8413.2942
		SD	1809.3530	4830.3310	11423.900	4529.9790	4268.8410	103126.10
	BOLS	AMSE	124.87326	232.93309	940.45983	255.68422	315.36930	8413.2873
		SD	1809.3530	4830.3310	11423.930	4529.9790	4268.8410	103125.90
	BAUG	AMSE	124.87324	232.93309	940.35152	255.68419	315.36929	8413.2887
		SD	1809.3530	4830.3310	11422.680	4529.9780	4268.8410	103125.90
30	OLS	AMSE	1.0207848	1.0244733	1.0344501	1.0489281	1.1269070	2.3234918
		SD	0.0570362	0.0587309	0.0634012	0.0679339	0.1157128	1.1441290
	AUG	AMSE	1.0189142	1.0229086	1.0344159	1.0511738	1.1388795	2.1482529
		SD	0.0569883	0.0587154	0.0661136	0.0740200	0.1354433	0.9804007
	BOLS	AMSE	1.0289188	1.0336932	1.0467568	1.0666927	1.1718158	2.7679415
		SD	0.0572635	0.0591856	0.0648067	0.0706658	0.1283789	1.2947220
	BAUG	AMSE	1.0285534	1.0341172	1.0506517	1.0763321	1.1980424	2.4309178
		SD	0.0569585	0.0592127	0.0710601	0.0842528	0.1499064	1.0111240
50	OLS	AMSE	1.0138785	1.0155856	1.0203072	1.0287207	1.0691160	1.6739308
		SD	0.0454506	0.0457670	0.0467264	0.0481616	0.0630727	0.4764197
	AUG	AMSE	1.0123974	1.0141263	1.0190723	1.0282946	1.0733102	1.6350476
		SD	0.0455280	0.0458228	0.0466607	0.0489262	0.0692426	0.4417156
	BOLS	AMSE	1.0191143	1.0214917	1.0280662	1.0394428	1.0950896	1.9298293
		SD	0.0455775	0.0458993	0.0469420	0.0487639	0.0661560	0.5164235
	BAUG	AMSE	1.0179322	1.0204399	1.0276700	1.0409761	1.1075922	1.8340214
		SD	0.0457329	0.0460230	0.0469485	0.0506766	0.0795019	0.4266599
100	OLS	AMSE	1.0080427	1.0088077	1.0108867	1.0143649	1.0315343	1.2873285
		SD	0.0296911	0.0297313	0.0298549	0.0302556	0.0347622	0.1923954
	AUG	AMSE	1.0072361	1.0080183	1.0101311	1.0137193	1.0320269	1.3090748
		SD	0.0296999	0.0297181	0.0298877	0.0303785	0.0354884	0.2180981
	BOLS	AMSE	1.0106915	1.0117826	1.0147527	1.0197137	1.0441878	1.4097230
		SD	0.0297147	0.0297604	0.0299398	0.0303823	0.0353372	0.2032132
	BAUG	AMSE	1.0100098	1.0111413	1.0142241	1.0195355	1.0472070	1.4481403
		SD	0.0297775	0.0297845	0.0299804	0.0306682	0.0373713	0.2176841

Table 1.10 A comparison of multiple regression coefficient estimating with normal distribution on mean equals to 1 and standard deviation equals to 0.50 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	345.08821	645.25439	2610.6062	708.45188	874.24377	23368.461
		SD	5025.9830	13417.580	31733.130	12583.260	11857.890	286461.00
	AUG	AMSE	345.08821	645.25439	2610.6023	708.45188	874.24380	23368.473
		SD	5025.9830	13417.580	31733.090	12583.260	11857.890	286461.30
	BOLS	AMSE	345.08821	645.25439	2610.6061	708.45188	874.24378	23368.459
		SD	5025.9830	13417.580	31733.130	12583.260	11857.890	286461.00
	BAUG	AMSE	345.08819	645.25438	2610.5131	708.45186	874.24377	23368.446
		SD	5025.9830	13417.580	31732.070	12583.260	11857.890	286460.80
30	OLS	AMSE	1.0616745	1.0719203	1.0996336	1.1398504	1.3564585	4.6803049
		SD	0.1007491	0.1071633	0.1250590	0.1442239	0.3009263	3.1799110
	AUG	AMSE	1.0580462	1.0701196	1.1049356	1.1548081	1.3697934	3.9680873
		SD	0.1004963	0.1094902	0.1388245	0.1646778	0.2909665	2.7823190
	BOLS	AMSE	1.0843308	1.0975981	1.1339039	1.1892937	1.4812757	5.9149411
		SD	0.1017814	0.1091004	0.1305616	0.1542748	0.3385312	3.5983430
	BAUG	AMSE	1.0885573	1.1064530	1.1572238	1.2261467	1.5017931	4.6128892
		SD	0.1027467	0.1154930	0.1571845	0.1775203	0.2867602	2.8821270
50	OLS	AMSE	1.0367944	1.0415364	1.0546520	1.0780228	1.1902318	2.8702729
		SD	0.0769191	0.0781092	0.0821659	0.0891247	0.1441713	1.3195770
	AUG	AMSE	1.0332434	1.0381407	1.0531804	1.0799850	1.2113045	2.5810682
		SD	0.0772367	0.0782345	0.0829812	0.0942833	0.1798502	1.1628570
	BOLS	AMSE	1.0512683	1.0578699	1.0761313	1.1077539	1.2623504	3.5810774
		SD	0.0772810	0.0785500	0.0830459	0.0914478	0.1539261	1.4303560
	BAUG	AMSE	1.0497888	1.0572845	1.0810556	1.1210785	1.3081012	3.0022556
		SD	0.0780013	0.0795499	0.0867085	0.1046989	0.1918456	1.1172420
100	OLS	AMSE	1.0196482	1.0217732	1.0275483	1.0372098	1.0849028	1.7954422
		SD	0.0498353	0.0500369	0.0508006	0.0526984	0.0709751	0.5307912
	AUG	AMSE	1.0175527	1.0196905	1.0257740	1.0363763	1.0907212	1.8077132
		SD	0.0498806	0.0499499	0.0509165	0.0535718	0.0779851	0.5836595
	BOLS	AMSE	1.0270067	1.0300369	1.0382870	1.0520681	1.1200514	2.1354262
		SD	0.0499191	0.0501503	0.0510258	0.0531431	0.0730386	0.5609952
	BAUG	AMSE	1.0255430	1.0287339	1.0379182	1.0540547	1.1396839	2.1090575
		SD	0.0500246	0.0500692	0.0515071	0.0550959	0.0903557	0.5203598

2. The comparison of parameter estimation for contaminated normal distributed data

To designate a multiple regression coefficient estimator as four methods is considered by the departure of mean (μ) equals to 1, standard deviation (σ) equals to 0.05,0.10 and 0.15 for percent contaminated 5, 10 and scale factor of 3, 10 with 3 and 5 independent variables on various degree of correlation 0.10, 0.30, 0.50, 0.70, 0.90 and 0.99 within 10, 30 ,50 and 100 sample sizes. The result in Table 2.1- 2.24 are given below:

Table	No. of independent variables	Standard deviation	Scale factor (%)	Percent contamination (%)
2.1	3	0.05	3	5
2.2	3	0.05	3	10
2.3	3	0.05	10	5
2.4	3	0.05	10	10
2.5	3	0.10	3	5
2.6	3	0.10	3	10
2.7	3	0.10	10	5
2.8	3	0.10	10	10
2.9	3	0.15	3	5
2.10	3	0.15	3	10
2.11	3	0.15	10	5
2.12	3	0.15	10	10
2.13	5	0.05	3	5
2.14	5	0.05	3	10
2.15	5	0.05	10	5
2.16	5	0.05	10	10
2.17	5	0.10	3	5
2.18	5	0.10	3	10
2.19	5	0.10	10	5
2.20	5	0.10	10	10
2.21	5	0.15	3	5
2.22	5	0.15	3	10
2.23	5	0.15	10	5
2.24	5	0.15	10	10

Table 2.1 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.05 at 5 percentage of contamination and scale factors of 3 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.0191853	1.0198315	1.0241204	1.0433969	1.1666687	2.9314630
		SD	0.0675310	0.0623261	0.0739645	0.1036063	0.4079286	5.3817870
	AUG	AMSE	1.0186415	1.0194624	1.0230321	1.0431092	1.1633347	2.7106937
		SD	0.0684976	0.0652333	0.0701193	0.0999443	0.3810234	5.1064890
	BOLS	AMSE	1.0234543	1.0236416	1.0290031	1.0522307	1.2020768	3.3503928
		SD	0.0712046	0.0645637	0.0802126	0.1102555	0.4453163	5.8807200
	BAUG	AMSE	1.0240466	1.0244604	1.0290917	1.0543507	1.2027403	3.1036232
		SD	0.0743006	0.0690532	0.0749968	0.1075910	0.4069992	5.8377610
30	OLS	AMSE	1.0003194	1.0004226	1.0009452	1.0030438	1.0158089	1.1945422
		SD	0.0277942	0.0277904	0.0278199	0.0281420	0.0329077	0.1958315
	AUG	AMSE	0.9996731	0.9997809	1.0003027	1.0024448	1.0157036	1.2015610
		SD	0.0277899	0.0277923	0.0278158	0.0281060	0.0333270	0.1867607
	BOLS	AMSE	1.0016878	1.0018159	1.0025305	1.0054467	1.0232762	1.2731391
		SD	0.0278987	0.0278887	0.0279379	0.0283503	0.0342937	0.2202571
	BAUG	AMSE	1.0010954	1.0012396	1.0019664	1.0049942	1.0242947	1.2892761
		SD	0.0278452	0.0278538	0.0278799	0.0282769	0.0355886	0.2002648
50	OLS	AMSE	1.0003403	1.0003859	1.0007150	1.0019758	1.0095546	1.1151065
		SD	0.0211247	0.0211378	0.0211772	0.0212704	0.0229246	0.1009395
	AUG	AMSE	0.9999258	0.9999706	1.0003008	1.0015679	1.0092938	1.1252338
		SD	0.0211397	0.0211669	0.0211774	0.0212878	0.0229019	0.1099424
	BOLS	AMSE	1.0011533	1.0012138	1.0016690	1.0034422	1.0141427	1.1634267
		SD	0.0212038	0.0212243	0.2124789	0.0213540	0.0232143	0.1088210
	BAUG	AMSE	1.0008573	1.0009162	1.0013773	1.0031835	1.0143693	1.1853862
		SD	0.0210750	0.0210792	0.0211269	0.0212164	0.0231482	0.1220469
100	OLS	AMSE	1.0007107	1.0007374	1.0008699	1.0013778	1.0044583	1.0474623
		SD	0.0156496	0.0156578	0.0156498	0.0156553	0.0159344	0.0404569
	AUG	AMSE	1.0004949	1.0005200	1.0006535	1.0011669	1.0043182	1.0512847
		SD	0.0156526	0.0156451	0.0156623	0.0156378	0.0159544	0.0457072
	BOLS	AMSE	1.0011322	1.0011655	1.0013566	1.0021059	1.0066571	1.0702298
		SD	0.0156472	0.0156449	0.0156318	0.0156511	0.0159558	0.0427689
	BAUG	AMSE	1.0009258	1.0009569	1.0011512	1.0019123	1.0066134	1.0795901
		SD	0.0157125	0.0157095	0.0156985	0.0156888	0.0160415	0.0517765

Table 2.2 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.05 at 10 percentage of contamination and scale factors of 3 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.0191853	1.0198315	1.0241204	1.0433969	1.1666687	2.9314630
		SD	0.0675310	0.0623261	0.0739645	0.1036063	0.4079286	5.3817870
	AUG	AMSE	1.0186415	1.0194624	1.0230321	1.0431092	1.1633347	2.7106937
		SD	0.067497	0.0652333	0.070119	0.099944	0.3810234	5.1064890
	BOLS	AMSE	1.0234543	1.0236416	1.0290031	1.0522307	1.2020768	3.3503928
		SD	0.071204	0.064563	0.080212	0.1102555	0.4453163	5.8807200
	BAUG	AMSE	1.0240466	1.0244604	1.0290917	1.0543507	1.2027403	3.1036232
		SD	0.074300	0.090532	0.074996	0.1075910	0.4069992	5.8377610
30	OLS	AMSE	1.0003194	1.0004226	1.0009452	1.0030438	1.0158089	1.1945422
		SD	0.027794	0.027790	0.027819	0.028142	0.032907	0.1958315
	AUG	AMSE	0.9996731	0.9997809	1.0003027	1.0024448	1.0157036	1.2015610
		SD	0.027789	0.027792	0.027815	0.028106	0.033327	0.1867607
	BOLS	AMSE	1.0016878	1.0018159	1.0025305	1.0054467	1.0232762	1.2731391
		SD	0.027898	0.027888	0.027937	0.028385	0.034293	0.2202571
	BAUG	AMSE	1.0010954	1.0012396	1.0019664	1.0049942	1.0242947	1.2892761
		SD	0.027845	0.027853	0.027879	0.028276	0.035588	0.2002648
50	OLS	AMSE	1.0003403	1.0003859	1.0007150	1.0019758	1.0095546	1.1151065
		SD	0.211247	0.021137	0.021177	0.021270	0.029246	0.1009395
	AUG	AMSE	0.9999258	0.9999706	1.0003008	1.0015679	1.0092938	1.1252338
		SD	0.012239	0.021166	0.021177	0.021287	0.029019	0.1099424
	BOLS	AMSE	1.0011533	1.0012138	1.0016690	1.0034422	1.0141427	1.1634267
		SD	0.021203	0.021224	0.021247	0.021354	0.023214	0.1088210
	BAUG	AMSE	1.0008573	1.0009162	1.0013773	1.0031835	1.0143693	1.1853862
		SD	0.021075	0.021079	0.021126	0.021216	0.023148	0.1220469
100	OLS	AMSE	1.0007107	1.0007374	1.0008699	1.0013778	1.0044583	1.0474623
		SD	0.015649	0.015657	0.0156498	0.015655	0.015934	0.0404569
	AUG	AMSE	1.0004949	1.0005200	1.0006535	1.0011669	1.0043182	1.0512847
		SD	0.015652	0.015645	0.015662	0.015637	0.015954	0.0457072
	BOLS	AMSE	1.0011322	1.0011655	1.0013566	1.0021059	1.0066571	1.0702298
		SD	0.015647	0.015644	0.015631	0.015651	0.015955	0.0427689
	BAUG	AMSE	1.0009258	1.0009569	1.0011512	1.0019123	1.0066134	1.0795901
		SD	0.015712	0.015709	0.015638	0.015688	0.016041	0.0517765

Table 2.3 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.05 at 5 percentage of contamination and scale factors of 10 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.2216836	1.2288643	1.2765182	1.4907018	2.8603886	22.469213
		SD	0.5925896	0.5085341	0.6595393	1.028864	4.4870020	59.779590
	AUG	AMSE	1.2113751	1.2209878	1.2617501	1.4567777	2.5980517	19.057431
		SD	0.5282388	0.4680380	0.5283657	0.9128608	4.1183390	56.808300
	BOLS	AMSE	1.2695510	1.2716085	1.3313319	1.5897250	3.2546822	27.124913
		SD	0.6493410	0.5420843	0.7423577	1.109329	4.9051180	65.325000
	BAUG	AMSE	1.2693843	1.2752069	1.3253707	1.5446321	2.8502213	22.601607
		SD	0.5378988	0.4777147	0.5408350	0.9157693	4.2915040	63.912300
30	OLS	AMSE	1.0241717	1.0253192	1.0311255	1.0544433	1.1962771	3.1822030
		SD	0.0953865	0.0954710	0.0967178	0.1055551	0.2102423	2.1445890
	AUG	AMSE	1.0179451	1.0192446	1.0256331	1.0525602	1.2090258	2.7002443
		SD	0.0357055	0.0958244	0.0975143	0.1109045	0.2096744	1.7304650
	BOLS	AMSE	1.0390773	1.0405394	1.0485656	1.0810431	1.2791944	4.0554555
		SD	0.0961131	0.0962596	0.0978595	0.1088556	0.2323353	2.4163580
	BAUG	AMSE	1.0355848	1.0374067	1.0473498	1.0892338	1.3156647	3.1078876
		SD	0.0967401	0.0970889	0.1002237	0.1201759	0.2192195	1.6693210
50	OLS	AMSE	1.0150312	1.0155372	1.0191939	1.0332037	1.1174125	2.2902106
		SD	0.0706648	0.0710147	0.0717580	0.0752622	0.1213147	1.0994350
	AUG	AMSE	1.0106887	1.0112460	1.0150879	1.0301826	1.1303010	2.1119650
		SD	0.0706619	0.0710784	0.0718228	0.0755122	0.1373368	0.9317834
	BOLS	AMSE	1.0242941	1.0249953	1.0300851	1.0498070	1.1687111	2.8274245
		SD	0.0708599	0.0712164	0.0720275	0.0759372	0.1274005	1.1893920
	BAUG	AMSE	1.0212501	1.0220042	1.0276448	1.0504484	1.2012439	2.4205070
		SD	0.0703820	0.0709176	0.0717289	0.0767672	0.1483819	0.8370846
100	OLS	AMSE	1.0086485	1.0089456	1.0104168	1.0160607	1.0502883	1.5281109
		SD	0.0523369	0.0522898	0.0523058	0.0529098	0.0638509	0.4202617
	AUG	AMSE	1.0062946	1.0066001	1.0081411	1.0141400	1.0524135	1.5553645
		SD	0.0523249	0.0523395	0.0523551	0.053109	0.0674677	0.4384354
	BOLS	AMSE	1.0134645	1.0138389	1.0159698	1.0242998	1.0748722	1.7812367
		SD	0.0522863	0.0522512	0.0522816	0.0529285	0.0650626	0.4485368
	BAUG	AMSE	1.0113563	1.0117535	1.0140406	1.0231446	1.0842042	1.7955886
		SD	0.0524856	0.0525437	0.0525730	0.0534926	0.0732176	0.3821967

Table 2.4 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.05 at 10 percentage of contamination and scale factors of 10 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.2216836	1.2288643	1.2765182	1.4907018	2.8603886	22.469213
		SD	0.5925896	0.5085341	0.6595393	1.0288640	4.4870020	59.779590
	AUG	AMSE	1.2113751	1.2209878	1.2617501	1.4567777	2.5980517	19.057431
		SD	0.5282388	0.4680380	0.5283657	1.1093290	4.1183390	56.808300
	BOLS	AMSE	1.2695510	1.2716085	1.3313319	1.5897250	3.2546822	27.124913
		SD	0.6493410	0.5420843	0.7423577	0.9128608	4.9051180	65.325000
	BAUG	AMSE	1.2693843	1.2752069	1.3253707	1.5446321	2.8502213	22.601607
		SD	0.5378988	0.4777147	0.5408350	0.9157693	4.2915040	63.912300
30	OLS	AMSE	1.0241717	1.0253192	1.0311255	1.0544433	1.1962771	3.1822030
		SD	0.0953865	0.0954710	0.0971785	0.1055551	0.2102423	2.1445890
	AUG	AMSE	1.0179451	1.0192446	1.0256331	1.0525602	1.2090258	2.7002443
		SD	0.0957055	0.0958244	0.0975143	0.1109045	0.2096744	1.7304650
	BOLS	AMSE	1.0390773	1.0405394	1.0485656	1.0810431	1.2791944	4.0554555
		SD	0.0961131	0.0962596	0.0978595	0.1088556	0.2323353	2.416358
	BAUG	AMSE	1.0355848	1.0374067	1.0473498	1.0892338	1.3156647	3.1078876
		SD	0.0967401	0.0970889	0.1002237	0.1201759	0.2192195	1.669321
50	OLS	AMSE	1.0150312	1.0155372	1.0191939	1.0332037	1.1174125	2.2902106
		SD	0.0706648	0.0101474	0.0171580	0.0752622	0.1213147	1.0994350
	AUG	AMSE	1.0106887	1.0112460	1.0150879	1.0301826	1.1303010	2.1119650
		SD	0.0106619	0.0710784	0.0718228	0.0755122	0.1373368	0.9317834
	BOLS	AMSE	1.0242941	1.0249953	1.0300851	1.0498070	1.1687111	2.8274245
		SD	0.0108599	0.0121646	0.0720275	0.0759372	0.1274005	1.1893920
	BAUG	AMSE	1.0212501	1.0220042	1.0276448	1.0504484	1.2012439	2.4205070
		SD	0.0103820	0.0109176	0.0717289	0.0767672	0.1483819	0.8370846
100	OLS	AMSE	1.0086485	1.0089456	1.0104168	1.0160607	1.0502883	1.5281109
		SD	0.0523369	0.0522898	0.0523058	0.0529098	0.0638509	0.4202617
	AUG	AMSE	1.0062946	1.0066001	1.0081411	1.0141400	1.0524135	1.5553645
		SD	0.0523249	0.0523395	0.0523551	0.0531091	0.0974677	0.4384354
	BOLS	AMSE	1.0134645	1.0138389	1.0159698	1.0242998	1.0748722	1.7812367
		SD	0.052286	0.0522512	0.0522816	0.0529285	0.0650626	0.4485368
	BAUG	AMSE	1.0113563	1.0117535	1.0140406	1.0231446	1.0842042	1.7955886
		SD	0.0524856	0.0525437	0.0525730	0.0534926	0.0732176	0.3821967

Table 2.5 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.10 at 5 percentage of contamination and scale factors of 3 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.0789304	1.0815154	1.0986708	1.1757770	1.6688642	8.7280417
		SD	0.2237559	0.1959809	0.2489712	0.3791778	1.619007	21.522430
	AUG	AMSE	1.0751400	1.0783546	1.0951752	1.1767083	1.6110857	7.5719389
		SD	0.2063402	0.1854019	0.2091466	0.3521464	1.484630	20.444020
	BOLS	AMSE	1.0961180	1.0968612	1.1183461	1.2113358	1.8107204	10.403998
		SD	0.2427234	0.2072700	0.2777239	0.4076629	1.769330	23.518590
	BAUG	AMSE	1.0976996	1.1002400	1.1213946	1.2173187	1.7281859	8.9138149
		SD	0.2173385	0.1958993	0.2211610	0.3614821	1.555119	23.092820
30	OLS	AMSE	1.0065806	1.0069937	1.0090840	1.0174784	1.0685385	1.7834719
		SD	0.0561692	0.0561673	0.0564322	0.0587598	0.0884537	0.7745016
	AUG	AMSE	1.0040825	1.0045819	1.0067033	1.0155392	1.0733883	1.6904852
		SD	0.0561735	0.0561999	0.0564854	0.0589172	0.0967040	0.6332753
	BOLS	AMSE	1.0119774	1.0124998	1.0153803	1.0270645	1.0983943	2.0978476
		SD	0.0564727	0.0564859	0.0568314	0.0595364	0.0956447	0.8723857
	BAUG	AMSE	1.0100148	1.0106834	1.0137395	1.0268284	1.1140095	1.9053320
		SD	0.0564405	0.0564729	0.0569108	0.0606947	0.0110420	0.6167186
50	OLS	AMSE	1.0042541	1.0044363	1.0057527	1.0107962	1.0411114	1.4633188
		SD	0.0425256	0.0423708	0.0425501	0.0433254	0.0519230	0.3971851
	AUG	AMSE	1.0026419	1.0028161	1.0041651	1.0093411	1.0421070	1.4528520
		SD	0.0422575	0.0423767	0.0425445	0.0433280	0.0564508	0.3531956
	BOLS	AMSE	1.0075651	1.0078146	1.0096436	1.0167415	1.0595460	1.6566826
		SD	0.0424016	0.0424980	0.0426792	0.0435360	0.0569419	0.4293862
	BAUG	AMSE	1.0063405	1.0065883	1.0084997	1.0160290	1.0656348	1.6241226
		SD	0.0421134	0.0422511	0.0423994	0.0433370	0.0612774	0.3333288
100	OLS	AMSE	1.0030362	1.0031431	1.0036727	1.0057045	1.0180265	1.1900426
		SD	0.0313371	0.0313093	0.0313077	0.0314140	0.0338657	0.1530978
	AUG	AMSE	1.0021830	1.0022769	1.0028209	1.0049081	1.0178459	1.2145625
		SD	0.0131339	0.0313264	0.0313161	0.0314405	0.0341837	0.1825685
	BOLS	AMSE	1.0047563	1.0048906	1.0056570	1.0086553	1.0268610	1.2811521
		SD	0.031316	0.0312928	0.0312884	0.0314087	0.0341281	0.1630772
	BAUG	AMSE	1.0039609	1.0040821	1.0048783	1.0080166	1.0277637	1.3309874
		SD	0.0134431	0.0314262	0.0314193	0.0315612	0.0350165	0.1823213

Table 2.6 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.10 at 10 percentage of contamination and scale factors of 3 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.0789304	1.0815154	1.0986708	1.1757770	1.6688642	8.7280417
		SD	0.2237559	0.1959809	0.2489712	0.3791778	1.6190070	21.522430
	AUG	AMSE	1.0751400	1.0783546	1.0951752	1.1767083	1.6110857	7.5719389
		SD	0.2063402	0.1854019	0.2091466	0.3521464	1.4846300	20.444020
	BOLS	AMSE	1.0961180	1.0968612	1.1183461	1.2113358	1.8107204	10.403998
		SD	0.2427234	0.2072700	0.2777239	0.4076629	1.7693300	23.518590
	BAUG	AMSE	1.0976996	1.1002400	1.1213946	1.2173187	1.7281859	8.9138149
		SD	0.2173385	0.1958993	0.2211610	0.3614821	1.5551190	23.092820
30	OLS	AMSE	1.0065806	1.0069937	1.0090840	1.0174784	1.0685385	1.7834719
		SD	0.0561692	0.0561673	0.0564322	0.0585759	0.0884537	0.7745016
	AUG	AMSE	1.0040825	1.0045819	1.0067033	1.0155392	1.0733883	1.6904852
		SD	0.0561735	0.0561999	0.0564854	0.0589172	0.0967040	0.6332753
	BOLS	AMSE	1.0119774	1.0124998	1.0153803	1.0270645	1.0983943	2.0978476
		SD	0.0564727	0.0564859	0.0568314	0.0595364	0.0956447	0.8723857
	BAUG	AMSE	1.0100148	1.0106834	1.0137395	1.0268284	1.1140095	1.9053320
		SD	0.0564405	0.0561472	0.0569108	0.0606947	0.1104202	0.6167186
50	OLS	AMSE	1.0042541	1.0044363	1.0057527	1.0107962	1.0411114	1.4633188
		SD	0.0422569	0.0423708	0.0425501	0.0433254	0.0551923	0.3971851
	AUG	AMSE	1.0026419	1.0028161	1.0041651	1.0093411	1.0421070	1.4528520
		SD	0.0422575	0.0423767	0.0425445	0.0433280	0.0564508	0.3531956
	BOLS	AMSE	1.0075651	1.0078146	1.0096436	1.0167415	1.0595460	1.6566826
		SD	0.0424016	0.0424980	0.0426792	0.0435360	0.0569419	0.4293862
	BAUG	AMSE	1.0063405	1.0065883	1.0084997	1.0160290	1.0656348	1.6241226
		SD	0.0421134	0.0422511	0.0423994	0.0433370	0.0612774	0.3333288
100	OLS	AMSE	1.0030362	1.0031431	1.0036727	1.0057045	1.0180265	1.1900426
		SD	0.0313371	0.0313093	0.0313077	0.0314140	0.0338657	0.1530978
	AUG	AMSE	1.0021830	1.0022769	1.0028209	1.0049081	1.0178459	1.2145625
		SD	0.0313398	0.0313264	0.0313161	0.0314405	0.0341827	0.1825685
	BOLS	AMSE	1.0047563	1.0048906	1.0056570	1.0086553	1.0268610	1.2811521
		SD	0.0313161	0.0312928	0.0312884	0.0314087	0.0341281	0.1630772
	BAUG	AMSE	1.0039609	1.0040821	1.0048783	1.0080166	1.0277637	1.3309874
		SD	0.0314431	0.0314262	0.0314193	0.0315612	0.0350165	0.1823213

Table 2.7 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.10 at 5 percentage of contamination and scale factors of 10 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.8940317	1.9227544	2.1133700	2.9701044	8.4488515	86.884149
		SD	2.3259100	1.9742750	2.579400	4.0669780	17.923190	239.10390
	AUG	AMSE	1.7597142	1.8101077	1.9523407	2.6244678	7.0677200	72.857736
		SD	1.9946840	1.7296270	2.009341	3.5795330	16.481470	227.28980
	BOLS	AMSE	2.0858736	2.0940827	2.3331062	3.3669431	10.026772	105.50774
		SD	2.5621250	2.1127850	2.915923	4.3912680	19.596830	261.28690
	BAUG	AMSE	1.9112300	1.9435902	2.0942272	2.8442290	7.8776711	86.681160
		SD	1.9938860	1.7444740	2.007463	3.5670940	17.158570	255.02670
30	OLS	AMSE	1.1143635	1.1189536	1.1421787	1.2354501	1.8027850	9.7464885
		SD	0.2041397	0.2052238	0.2145305	0.2706518	0.7695326	8.5624980
	AUG	AMSE	1.0968700	1.1027690	1.1327764	1.2347158	1.7255429	7.2854540
		SD	0.2081481	0.2106715	0.2227926	0.2687989	0.6333759	7.0088680
	BOLS	AMSE	1.1737294	1.1796107	1.2117899	1.3417646	2.1344084	13.239458
		SD	0.2069629	0.2084868	0.2201078	0.2880345	0.8624042	9.6486850
	BAUG	AMSE	1.1764103	1.1848557	1.2285794	1.3695144	1.9573153	8.5069578
		SD	0.2146497	0.2173950	0.2309729	0.2751350	0.5871673	6.7974940
50	OLS	AMSE	1.0697672	1.0717914	1.0864179	1.1424573	1.4792924	6.1704850
		SD	0.1445450	0.1464707	0.1518518	0.1770310	0.4201628	4.3914390
	AUG	AMSE	1.0556692	1.0573431	1.0750735	1.1432913	1.4795116	4.9249473
		SD	0.1452707	0.1474783	0.1543594	0.1882870	0.3991195	3.4861350
	BOLS	AMSE	1.1070159	1.1098453	1.1302320	1.2091364	1.6847609	8.3196166
		SD	0.1448022	0.1468551	0.1528367	0.1809585	0.4482779	4.7524190
	BAUG	AMSE	1.1026464	1.1050305	1.1333726	1.2336148	1.6706189	5.7456182
		SD	0.1459366	0.1483886	0.1582130	0.1934333	0.3587693	3.1567720
100	OLS	AMSE	1.0352383	1.0364266	1.0423112	1.0648867	1.2017971	3.1130876
		SD	0.1058343	0.1057051	0.1063013	0.1115202	0.1827243	1.6734690
	AUG	AMSE	1.0266951	1.0279887	1.0344881	1.0607457	1.2300417	2.8347340
		SD	0.1058974	0.1062758	0.1070125	0.1142604	0.2247916	1.5497360
	BOLS	AMSE	1.0546157	1.0561172	1.0646473	1.0979710	1.3002631	4.1257228
		SD	0.1056983	0.1055946	0.1062457	0.1119387	0.1901631	1.7877910
	BAUG	AMSE	1.0484922	1.0503593	1.0605610	1.1032786	1.3581007	3.4541228
		SD	0.1063499	0.1071692	0.1083164	0.1185365	0.2140306	1.2674030

Table 2.8 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.10 at 10 percentage of contamination and scale factors of 10 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.8940317	1.9227544	2.1133700	2.9701044	8.4488515	86.884149
		SD	2.3259100	1.9742750	2.5794000	4.0669780	17.923190	239.10390
	AUG	AMSE	1.7597142	1.8101077	1.9523407	2.6244678	7.0677200	72.857736
		SD	1.9946840	1.7296270	2.0093410	3.5795330	16.481470	227.28980
	BOLS	AMSE	2.0858736	2.0940827	2.3331062	3.3669431	10.026772	105.50774
		SD	2.5621250	2.1127850	2.9159230	4.3912680	19.596830	261.28690
	BAUG	AMSE	1.9112300	1.9435902	2.0942272	2.8442290	7.8776711	86.681160
		SD	1.9938860	1.7444740	2.0074630	3.5670940	17.158570	255.02670
30	OLS	AMSE	1.1143635	1.1189536	1.1421787	1.2354501	1.8027850	9.7464885
		SD	0.2041397	0.2052238	0.2145305	0.2706518	0.7695326	8.5624980
	AUG	AMSE	1.0968700	1.1027690	1.1327764	1.2347158	1.7255429	7.2854540
		SD	0.2081481	0.2106715	0.2227926	0.2687989	0.6333759	7.0088680
	BOLS	AMSE	1.1737294	1.1796107	1.2117899	1.3417646	2.1344084	13.239458
		SD	0.2069629	0.2084868	0.2201078	0.2880345	0.8624042	9.6486850
	BAUG	AMSE	1.1764103	1.1848557	1.2285794	1.3695144	1.9573153	8.5069578
		SD	0.2146497	0.2173950	0.2309729	0.2751350	0.5871673	6.7974940
50	OLS	AMSE	1.0697672	1.0717914	1.0864179	1.1424573	1.4792924	6.1704850
		SD	0.1445450	0.1464707	0.1518518	0.1770310	0.4201628	4.3914390
	AUG	AMSE	1.0556692	1.0573431	1.0750735	1.1432913	1.4795116	4.9249473
		SD	0.1452707	0.1474783	0.1543594	0.1882870	0.3991195	3.4861350
	BOLS	AMSE	1.1070159	1.1098453	1.1302320	1.2091364	1.6847609	8.3196166
		SD	0.1448022	0.1468551	0.1528367	0.1809585	0.4482779	4.7524190
	BAUG	AMSE	1.1026464	1.1050305	1.1333726	1.2336148	1.6706189	5.7456182
		SD	0.1459366	0.1483886	0.1582130	0.1934333	0.3587693	3.1567720
100	OLS	AMSE	1.0352383	1.0364266	1.0423112	1.0648867	1.2017971	3.1130876
		SD	0.1058343	0.1057051	0.1063013	0.1115202	0.1827243	1.6734690
	AUG	AMSE	1.0266951	1.0279887	1.0344881	1.0607457	1.2300417	2.8347340
		SD	0.1058974	0.1062758	0.1070125	0.1142604	0.2247916	1.5497360
	BOLS	AMSE	1.0546157	1.0561172	1.0646473	1.0979710	1.3002631	4.1257228
		SD	0.1056983	0.1055946	0.1062457	0.1119387	0.1901631	1.7877910
	BAUG	AMSE	1.0484922	1.0503593	1.0605610	1.1032786	1.3581007	3.4541228
		SD	0.1063499	0.1071692	0.1083164	0.1185365	0.2140306	1.2674030

Table 2.9 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.15 at 5 percentage of contamination and scale factors of 3 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.1792353	1.1850517	1.2236513	1.3971401	2.5065865	18.389735
		SD	0.4830289	0.4157836	0.5377812	0.8361554	3.6357300	48.422130
	AUG	AMSE	1.1706788	1.1786428	1.2127479	1.3760782	2.3091047	15.648673
		SD	0.4327991	0.3852542	0.4347606	0.7449676	3.3326170	46.011650
	BOLS	AMSE	1.2179912	1.2196587	1.2680288	1.4773154	2.8259307	22.160817
		SD	0.5285041	0.4427030	0.6045348	0.9011824	3.9743370	52.913810
	BAUG	AMSE	1.2201558	1.2239912	1.2669744	1.4529455	2.5243102	18.541224
		SD	0.4443699	0.3954137	0.4477366	0.7495970	3.4765180	51.799000
30	OLS	AMSE	1.0187836	1.0197131	1.0244162	1.0433037	1.1581890	2.7667891
		SD	0.0854019	0.0854565	0.0863637	0.0929713	0.1744318	1.7379390
	AUG	AMSE	1.0135870	1.0146442	1.0196922	1.0409410	1.1690728	2.4006812
		SD	0.0856016	0.0856748	0.0868289	0.0961199	0.1841947	1.4000790
	BOLS	AMSE	1.0308687	1.0320515	1.0385494	1.0648533	1.2253541	3.4741255
		SD	0.0860053	0.0861041	0.0872723	0.0955222	0.1920615	1.9580980
	BAUG	AMSE	1.0276177	1.0290740	1.0367671	1.0697441	1.2595258	2.7558899
		SD	0.0863595	0.0865650	0.0885991	0.1036083	0.1963745	1.3505350
50	OLS	AMSE	1.0117414	1.0121513	1.0151131	1.0264611	1.0946702	2.0446368
		SD	0.0635271	0.0638010	0.0643539	0.0669171	0.1020552	0.8909506
	AUG	AMSE	1.0081774	1.0086268	1.0117007	1.0237902	1.1025446	1.9254777
		SD	0.0635311	0.0638214	0.0643802	0.0670347	0.1102892	0.7471773
	BOLS	AMSE	1.0192354	1.0198023	1.0239238	1.0398978	1.1362098	2.4797676
		SD	0.0637044	0.0639898	0.0645765	0.0674462	0.1068063	0.9637566
	BAUG	AMSE	1.0166529	1.0172750	1.0217451	1.0397686	1.1609320	2.1971807
		SD	0.0632709	0.0636639	0.0642505	0.0677072	0.1244798	0.6744238
100	OLS	AMSE	1.0069763	1.0072170	1.0084086	1.0129801	1.0407045	1.4277408
		SD	0.0470700	0.0470334	0.0470401	0.0474664	0.0555547	0.3409321
	AUG	AMSE	1.0050661	1.0053024	1.0065469	1.0113645	1.0416934	1.4672055
		SD	0.0470639	0.0706894	0.0470776	0.0476086	0.0578987	0.3867890
	BOLS	AMSE	1.0108721	1.0111752	1.0129010	1.0196481	1.0606116	1.6327668
		SD	0.0470312	0.0469979	0.0470099	0.0474629	0.0564464	0.3637665
	BAUG	AMSE	1.0091383	1.0094495	1.0112858	1.0185775	1.0665415	1.6755504
		SD	0.0472167	0.0472529	0.0472601	0.0478936	0.0617858	0.3423471

Table 2.10 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.15 at 10 percentage of contamination and scale factors of 3 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.1792353	1.1850517	1.2236513	1.3971401	2.5065865	18.389735
		SD	0.4830289	0.4157836	0.5377812	0.8361554	3.6357300	48.422130
	AUG	AMSE	1.1706788	1.1786428	1.2127479	1.3760782	2.3091047	15.648673
		SD	0.4327991	0.3852542	0.4347606	0.7449676	3.3326170	46.011650
	BOLS	AMSE	1.2179912	1.2196587	1.2680288	1.4773154	2.8259307	22.160817
		SD	0.5285041	0.4427030	0.6045348	0.9011824	3.9743370	52.913810
	BAUG	AMSE	1.2201558	1.2239912	1.2669744	1.4529455	2.5243102	18.541224
		SD	0.4443699	0.3954137	0.4477366	0.7495970	3.4765180	51.799000
30	OLS	AMSE	1.0187836	1.0197131	1.0244162	1.0433037	1.1581890	2.7667891
		SD	0.0854019	0.0854565	0.0863637	0.0929713	0.1744318	1.7379390
	AUG	AMSE	1.0135870	1.0146442	1.0196922	1.0409410	1.1690728	2.4006812
		SD	0.0856016	0.0856748	0.0868289	0.0961199	0.1841947	1.4000790
	BOLS	AMSE	1.0308687	1.0320515	1.0385494	1.0648533	1.2253541	3.4741255
		SD	0.0860053	0.0861041	0.0872723	0.0955222	0.1920615	1.9580980
	BAUG	AMSE	1.0276177	1.0290740	1.0367671	1.0697441	1.2595258	2.7558899
		SD	0.0863595	0.0865650	0.0885991	0.1036083	0.1963745	1.3505350
50	OLS	AMSE	1.0117414	1.0121513	1.0151131	1.0264611	1.0946702	2.0446368
		SD	0.0635271	0.0638010	0.0643539	0.0669171	0.1020552	0.8909506
	AUG	AMSE	1.0081774	1.0086268	1.0117007	1.0237902	1.1025446	1.9254777
		SD	0.0635311	0.0638214	0.0643802	0.0670347	0.1102892	0.7471773
	BOLS	AMSE	1.0192354	1.0198023	1.0239238	1.0398978	1.1362098	2.4797676
		SD	0.0637044	0.0639898	0.0645795	0.0674462	0.1068063	0.9637566
	BAUG	AMSE	1.0166529	1.0172750	1.0217451	1.0397686	1.1609320	2.1971807
		SD	0.0632709	0.0636639	0.0642505	0.0677072	0.1244798	0.6744238
100	OLS	AMSE	1.0069763	1.0072170	1.0084086	1.0129801	1.0407045	1.4277408
		SD	0.0470700	0.0470334	0.0470401	0.0474664	0.0555547	0.3409321
	AUG	AMSE	1.0050661	1.0053024	1.0065469	1.0113645	1.0416934	1.4672055
		SD	0.0470639	0.0470689	0.0470776	0.0476086	0.0578987	0.3867890
	BOLS	AMSE	1.0108721	1.0111752	1.0129010	1.0196481	1.0606116	1.6327668
		SD	0.0470312	0.0469979	0.0470099	0.0474629	0.0564464	0.3637665
	BAUG	AMSE	1.0091383	1.0094495	1.0112858	1.0185775	1.0665415	1.6755504
		SD	0.0472167	0.0472529	0.0472601	0.0478936	0.0617858	0.3423471

Table 2.11 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.15 at 5 percentage of contamination and scale factors of 10 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	3.0170443	3.0816704	3.5105555	5.4382079	17.765388	194.24480
		SD	5.2192570	4.4196150	5.7767250	9.1253190	40.311090	537.97320
	AUG	AMSE	2.6041018	2.6901784	3.0003602	4.5165525	14.456744	162.57733
		SD	4.4573760	3.8493350	4.4987180	8.0522830	37.089020	511.43320
	BOLS	AMSE	3.4489678	3.4674224	4.0053227	6.3316542	21.316269	236.14849
		SD	5.7560270	4.7331790	6.5359860	9.8560510	44.077490	587.88580
	BAUG	AMSE	2.8479344	2.9070066	3.2384267	4.9007775	16.172926	193.47087
		SD	4.4481290	3.8907300	4.4987250	8.0326250	38.611880	573.37820
30	OLS	AMSE	1.2705755	1.2809031	1.3331596	1.5430201	2.8195238	20.692856
		SD	0.3343623	0.3381643	0.3664263	0.5194281	1.6970430	19.255690
	AUG	AMSE	1.2295785	1.2399138	1.2915223	1.4732201	2.4522013	14.743752
		SD	0.3336338	0.3345335	0.3540482	0.4490694	1.3249430	15.708470
	BOLS	AMSE	1.4039564	1.4172139	1.4896727	1.7821644	3.5656420	28.552009
		SD	0.3411405	0.3461976	0.3808368	0.5626836	1.9076940	21.698760
	BAUG	AMSE	1.3861392	1.3996134	1.4652525	1.6838310	2.7753814	17.336028
		SD	0.3340131	0.3355165	0.3513707	0.4297315	1.2059670	15.271760
50	OLS	AMSE	1.1642081	1.1687625	1.2016720	1.3277607	2.0856396	12.640823
		SD	0.2259382	0.2312441	0.2478668	0.3216028	0.9160128	9.8782720
	AUG	AMSE	1.1372985	1.1402079	1.1808726	1.3094916	1.9417919	9.4966337
		SD	0.2276245	0.2325112	0.2514983	0.3102930	0.8045629	7.9667870
	BOLS	AMSE	1.2481653	1.2545500	1.3004408	1.4779881	2.5481494	17.476576
		SD	0.2261387	0.2318976	0.2504427	0.3323370	0.9814770	10.691200
	BAUG	AMSE	1.2436977	1.2478147	1.3050101	1.4745436	2.2116717	11.184435
		SD	0.2288747	0.2332063	0.2534996	0.3028168	0.6641375	7.2366600
100	OLS	AMSE	1.0797691	1.0824429	1.0956833	1.1464782	1.4545265	5.7549301
		SD	0.1617668	0.1615924	0.1640333	0.1812997	0.3739036	3.7628620
	AUG	AMSE	1.0627466	1.0661511	1.0821815	1.1428098	1.4648049	5.1059612
		SD	0.1621246	0.1634655	0.1672999	0.1903060	0.3613091	3.6406120
	BOLS	AMSE	1.1234537	1.1268349	1.1460324	1.2210135	1.6761727	8.0334585
		SD	0.1615320	0.1614131	0.1640619	0.1829545	0.3927960	4.0208010
	BAUG	AMSE	1.1155169	1.1205945	1.1462047	1.2413345	1.6764801	6.2915657
		SD	0.1640127	0.1663103	0.1715665	0.1968076	0.3130737	3.0430890

Table 2.12 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.15 at 10 percentage of contamination and scale factors of 10 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	3.0170443	3.0816704	3.5105555	5.4382079	17.765388	194.24480
		SD	5.2192570	4.4196150	5.7767250	9.1253190	40.311090	537.97320
	AUG	AMSE	2.6041018	2.6901784	3.0003602	4.5165525	14.456744	162.57733
		SD	4.4573760	3.8493350	4.4987180	8.0522830	37.089020	511.43320
	BOLS	AMSE	3.4489678	3.4674224	4.0053227	6.3316542	21.316269	236.14849
		SD	5.7560270	4.7331790	6.5359860	9.8560510	44.077490	587.88580
	BAUG	AMSE	2.8479344	2.9070066	3.2384267	4.9007775	16.172926	193.47087
		SD	4.4481290	3.8907300	4.4987250	8.0326250	38.611880	573.37820
30	OLS	AMSE	1.2705755	1.2809031	1.3331596	1.5430201	2.8195238	20.692856
		SD	0.3343623	0.3381643	0.3664263	0.5194281	1.6970430	19.255690
	AUG	AMSE	1.2295785	1.2399138	1.2915223	1.4732201	2.4522013	14.743752
		SD	0.3336338	0.3345335	0.3540482	0.4490694	1.3249430	15.708470
	BOLS	AMSE	1.4039564	1.4172139	1.4896727	1.7821644	3.5656420	28.552009
		SD	0.3411405	0.3461976	0.3808368	0.5626836	1.9076940	21.698760
	BAUG	AMSE	1.3861392	1.3996134	1.4652525	1.6838310	2.7753814	17.336028
		SD	0.3340131	0.3355165	0.3513707	0.4297315	1.2059670	15.271760
50	OLS	AMSE	1.1642081	1.1687625	1.2016720	1.3277607	2.0856396	12.640823
		SD	0.2259382	0.2312441	0.2478668	0.3216028	0.9160128	9.8782720
	AUG	AMSE	1.1372985	1.1402079	1.1808726	1.3094916	1.9417919	9.4966337
		SD	0.2276245	0.2325112	0.2514983	0.3102930	0.8045629	7.9667870
	BOLS	AMSE	1.2481653	1.2545500	1.3004408	1.4779881	2.5481494	17.476576
		SD	0.2261387	0.2318976	0.2504427	0.3323370	0.9814770	10.691200
	BAUG	AMSE	1.2436977	1.2478147	1.3050101	1.4745436	2.2116717	11.184435
		SD	0.2288747	0.2332063	0.2534996	0.3028168	0.6641375	7.2366600
100	OLS	AMSE	1.0797691	1.0824429	1.0956833	1.1464782	1.4545265	5.7549301
		SD	0.1617668	0.1615924	0.1640333	0.1812997	0.3739036	3.7628620
	AUG	AMSE	1.0627466	1.0661511	1.0821815	1.1428098	1.4648049	5.1059612
		SD	0.1621246	0.1634655	0.1672999	0.1903060	0.3613091	3.6406120
	BOLS	AMSE	1.1234537	1.1268349	1.1460324	1.2210135	1.6761727	8.0334585
		SD	0.1615320	0.1614131	0.1640619	0.1829545	0.3927960	4.0208010
	BAUG	AMSE	1.1155169	1.1205945	1.1462047	1.2413345	1.6764801	6.2915657
		SD	0.1640127	0.1663103	0.1715665	0.1968076	0.3130737	3.0430890

Table 2.13 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.05 at 5 percentage of contamination and scale factors of 3 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	68.617613	75.732484	361.89835	794.00820	202.32829	2475.4719
		SD	953.45610	1604.1190	7631.1270	14347.330	2458.9650	31902.020
	AUG	AMSE	68.617615	75.732483	361.89833	794.00751	202.34325	2475.4740
		SD	953.45610	1604.1190	7631.1270	14347.310	2459.1900	31902.060
	BOLS	AMSE	68.617614	75.732484	361.89835	794.00822	202.32828	2475.4717
		SD	953.45610	1604.1190	7631.1270	14347.330	2458.9650	31902.010
	BAUG	AMSE	68.617706	75.732516	361.89041	794.02450	202.04658	2475.2917
		SD	953.45780	1604.1190	7630.9500	14347.550	2454.7330	31899.480
30	OLS	AMSE	1.0048324	1.0058352	1.0086111	1.0127127	1.0336969	1.3446862
		SD	0.0275229	0.0277286	0.0284181	0.0291960	0.0387636	0.3054325
	AUG	AMSE	1.0042786	1.0053025	1.0081677	1.0122761	1.0340386	1.3319117
		SD	0.0275073	0.0277723	0.0284583	0.0293118	0.0393135	0.2799641
	BOLS	AMSE	1.0069791	1.0082699	1.0118370	1.0173296	1.0451193	1.4582298
		SD	0.0275240	0.0277245	0.0285139	0.0294882	0.0410144	0.3387171
	BAUG	AMSE	1.0066336	1.0079911	1.0117468	1.0173999	1.0475450	1.4348306
		SD	0.0276042	0.0279167	0.0286882	0.0299445	0.0427467	0.2912721
50	OLS	AMSE	1.0032069	1.0036002	1.0046763	1.0066118	1.0161606	1.1579445
		SD	0.0214744	0.0215005	0.0215644	0.0216896	0.0237856	0.1119580
	AUG	AMSE	1.0028386	1.0032590	1.0043462	1.0063123	1.0162787	1.1639645
		SD	0.0214765	0.0214944	0.0215853	0.0217182	0.0238613	0.1183001
	BOLS	AMSE	1.0045220	1.0050784	1.0066031	1.0092670	1.0224839	1.2195417
		SD	0.0215343	0.0216004	0.0216894	0.0218555	0.0243807	0.1237617
	BAUG	AMSE	1.0042209	1.0048248	1.0063874	1.0091715	1.0235335	1.2328402
		SD	0.0215439	0.0215876	0.0217131	0.0219215	0.0247374	0.1310873
100	OLS	AMSE	1.0014457	1.0016443	1.0021653	1.0029656	1.0069322	1.0673621
		SD	0.0147165	0.0147222	0.0147231	0.0147296	0.0149944	0.0430712
	AUG	AMSE	1.0012394	1.0014411	1.0019628	1.0027777	1.0068233	1.0696771
		SD	0.0147214	0.0147183	0.0147304	0.0147340	0.0149762	0.0456551
	BOLS	AMSE	1.0020593	1.0023375	1.0030828	1.0042572	1.0100586	1.0980693
		SD	0.0147742	0.0147352	0.0147517	0.0147593	0.0149881	0.0451026
	BAUG	AMSE	1.0019160	1.0022001	1.0029502	1.0041573	1.0102185	1.1050590
		SD	0.0146978	0.0146968	0.0146871	0.0146745	0.0149636	0.0497003

Table 2.14 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.05 at 10 percentage of contamination and scale factors of 3 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	68.617613	75.732484	361.89835	794.00820	202.32829	2475.4719
		SD	953.45610	1604.1190	7631.1270	14347.330	2458.9650	31902.020
	AUG	AMSE	68.617615	75.732483	361.89833	794.00751	202.34325	2475.4740
		SD	953.45610	1604.1190	7631.1270	14347.310	2459.1900	31902.060
	BOLS	AMSE	68.617614	75.732484	361.89835	794.00822	202.32828	2475.4717
		SD	953.45610	1604.1190	7631.1270	14347.330	2458.9650	31902.010
	BAUG	AMSE	68.617706	75.732516	361.89041	794.02450	202.04658	2475.2917
		SD	953.45780	1604.1190	7630.9500	14347.550	2454.7330	31899.480
30	OLS	AMSE	1.0048324	1.0058352	1.0086111	1.0127127	1.0336969	1.3446862
		SD	0.0275229	0.0277286	0.0284181	0.0291960	0.0387636	0.3054325
	AUG	AMSE	1.0042786	1.0053025	1.0081677	1.0122761	1.0340386	1.3319117
		SD	0.0275240	0.0277723	0.0284583	0.0293118	0.0393135	0.2799641
	BOLS	AMSE	1.0069791	1.0082699	1.0118370	1.0173296	1.0451193	1.4582298
		SD	0.0275073	0.0277248	0.0285139	0.0293118	0.0410447	0.3387171
	BAUG	AMSE	1.0066336	1.0079911	1.0117468	1.0173999	1.0475450	1.4348306
		SD	0.0276042	0.0279167	0.0286882	0.0299445	0.0127467	0.2912721
50	OLS	AMSE	1.0032069	1.0036002	1.0046763	1.0066118	1.0161606	1.1579445
		SD	0.0214744	0.0215055	0.0215644	0.0216896	0.0237856	0.1119580
	AUG	AMSE	1.0028386	1.0032590	1.0043462	1.0063123	1.0162787	1.1639645
		SD	0.0214765	0.0214944	0.0215853	0.0217182	0.0238613	0.1183001
	BOLS	AMSE	1.0045220	1.0050784	1.0066031	1.0092670	1.0224839	1.2195417
		SD	0.0215343	0.0216004	0.0216894	0.0218555	0.0243807	0.1237617
	BAUG	AMSE	1.0042209	1.0048248	1.0063874	1.0091715	1.0235335	1.2328402
		SD	0.0215439	0.0215876	0.0217131	0.0219215	0.0247374	0.1310873
100	OLS	AMSE	1.0014457	1.0016443	1.0021653	1.0029656	1.0069322	1.0673621
		SD	0.0147165	0.0147222	0.0147231	0.0147296	0.0149944	0.0430712
	AUG	AMSE	1.0012394	1.0014411	1.0019628	1.0027777	1.0068233	1.0696771
		SD	0.0147214	0.0147183	0.0147304	0.0147340	0.0149762	0.0456551
	BOLS	AMSE	1.0020593	1.0023375	1.0030828	1.0042572	1.0100586	1.0980693
		SD	0.0147742	0.0147352	0.0147517	0.0147593	0.0149881	0.0451026
	BAUG	AMSE	1.0019160	1.0022001	1.0029502	1.0041573	1.0102185	1.1050590
		SD	0.0146978	0.0146968	0.0146871	0.0146745	0.0196369	0.0497003

Table 2.15 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.05 at 5 percentage of contamination and scale factors of 10 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	752.30049	831.35425	4010.9741	8812.1959	2237.9735	27495.123
		SD	10593.930	17823.510	84790.270	159414.70	27321.830	354466.80
	AUG	AMSE	752.30050	831.35425	4010.9742	8812.1933	2237.9744	27495.126
		SD	10593.930	17823.510	84790.270	159414.70	27321.840	354466.80
	BOLS	AMSE	752.30049	831.35425	4010.9740	8812.1962	2237.9736	27495.121
		SD	10593.930	17823.510	84790.270	159414.70	27321.830	354466.80
	BAUG	AMSE	752.30070	831.35440	4010.9916	8812.2381	2237.8879	27495.286
		SD	10593.930	17823.510	84790.660	159415.60	27320.540	354482.70
30	OLS	AMSE	1.0632892	1.0744325	1.1052749	1.1508489	1.3840067	4.8394433
		SD	0.097957	0.1045252	0.1259005	0.1456992	0.3258785	3.3932500
	AUG	AMSE	1.0599905	1.0750477	1.1110698	1.1608457	1.3990996	4.0734538
		SD	0.100791	0.1144673	0.1348108	0.1564183	0.3179935	2.9579920
	BOLS	AMSE	1.0866962	1.1010146	1.1406229	1.2017166	1.5106232	6.1007812
		SD	0.098911	0.1063372	0.1301757	0.1544737	0.3590459	3.7634550
	BAUG	AMSE	1.0914685	1.1127915	1.1641217	1.2333575	1.5283953	4.7413382
		SD	0.1079124	0.1226882	0.1490185	0.1703808	0.3133971	3.0206600
50	OLS	AMSE	1.0339372	1.0383070	1.0502644	1.0717692	1.1778672	2.7532437
		SD	0.072926	0.073733	0.076421	0.082159	0.1354767	1.2209950
	AUG	AMSE	1.0307744	1.0358118	1.0500435	1.0746157	1.2009450	2.4849710
		SD	0.072722	0.074310	0.079202	0.086353	0.1604389	1.0620130
	BOLS	AMSE	1.0482079	1.0544010	1.0713684	1.1009832	1.2478453	3.4373794
		SD	0.073378	0.074485	0.077996	0.084882	0.1462138	1.3534990
	BAUG	AMSE	1.0476393	1.0557137	1.0790603	1.1161043	1.2990511	2.8971543
		SD	0.073461	0.076494	0.086262	0.097799	0.1786845	1.0212780
100	OLS	AMSE	1.0154715	1.0176780	1.0234679	1.0323592	1.0764334	1.7478763
		SD	0.0490940	0.0492514	0.0498870	0.0512716	0.0638583	0.4608299
	AUG	AMSE	1.0134029	1.0156951	1.0217604	1.0315775	1.0805063	1.8064640
		SD	0.0490730	0.0492707	0.0500567	0.0516212	0.0674181	0.5486898
	BOLS	AMSE	1.0226448	1.0257421	1.0340281	1.0470690	1.1115267	2.0894233
		SD	0.049195	0.0493644	0.0500224	0.0513815	0.064995	0.4862216
	BAUG	AMSE	1.0214095	1.0247450	1.0339200	1.0491838	1.1277916	2.1136616
		SD	0.0489690	0.0492638	0.0502768	0.0520255	0.0732704	0.4872758

Table 2.16 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.05 at 10 percentage of contamination and scale factors of 10 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	752.30049	831.35425	4010.9741	8812.1959	2237.9735	27495.123
		SD	10593.930	17823.510	84790.270	159414.70	27321.830	354466.80
	AUG	AMSE	752.30050	831.35425	4010.9742	8812.1933	2237.9744	27495.126
		SD	10593.930	17823.510	84790.270	159414.70	27321.840	354466.80
	BOLS	AMSE	752.30049	831.35425	4010.9740	8812.1962	2237.9736	27495.121
		SD	10593.930	17823.510	84790.270	159414.70	27321.830	354466.80
	BAUG	AMSE	752.30070	831.35440	4010.9916	8812.2381	2237.8879	27495.286
		SD	10593.930	17823.510	84790.660	159415.60	27320.540	354482.70
30	OLS	AMSE	1.0632892	1.0744325	1.1052749	1.1508489	1.3840067	4.8394433
		SD	0.0979573	0.1045252	0.1259005	0.1456992	0.3258785	3.3932500
	AUG	AMSE	1.0599905	1.0750477	1.1110698	1.1608457	1.3990996	4.0734538
		SD	0.1007916	0.1144673	0.1348108	0.1564183	0.3179935	2.9579920
	BOLS	AMSE	1.0866962	1.1010146	1.1406229	1.2017166	1.5106232	6.1007812
		SD	0.0989117	0.1063372	0.1301757	0.1544737	0.3590459	3.7634550
	BAUG	AMSE	1.0914685	1.1127915	1.1641217	1.2333575	1.5283953	4.7413382
		SD	0.1079124	0.1226882	0.1490185	0.1703808	0.3133971	3.0206600
50	OLS	AMSE	1.0339372	1.0383070	1.0502644	1.0717692	1.1778672	2.7532437
		SD	0.0729262	0.0737331	0.0764215	0.0821590	0.1354767	1.220995
	AUG	AMSE	1.0307744	1.0358118	1.0500435	1.0746157	1.2009450	2.4849710
		SD	0.0717221	0.0743108	0.0792029	0.0863537	0.1604389	1.062013
	BOLS	AMSE	1.0482079	1.0544010	1.0713684	1.1009832	1.2478453	3.4373794
		SD	0.0733787	0.0448585	0.0779969	0.0848821	0.1462138	1.353499
	BAUG	AMSE	1.0476393	1.0557137	1.0790603	1.1161043	1.2990511	2.8971543
		SD	0.0734612	0.0764946	0.0862623	0.0977999	0.1786845	1.021278
100	OLS	AMSE	1.0154715	1.0176780	1.0234679	1.0323592	1.0764334	1.7478763
		SD	0.0490949	0.0492514	0.0498870	0.0512716	0.0638583	0.4608299
	AUG	AMSE	1.0134029	1.0156951	1.0217604	1.0315775	1.0805063	1.8064640
		SD	0.0490731	0.0492707	0.0500567	0.0516212	0.0674181	0.5486898
	BOLS	AMSE	1.0226448	1.0257421	1.0340281	1.0470690	1.1115267	2.0894233
		SD	0.0491951	0.0493644	0.0500224	0.0513815	0.0649952	0.4862216
	BAUG	AMSE	1.0214095	1.0247450	1.0339200	1.0491838	1.1277916	2.1136616
		SD	0.0489692	0.0492638	0.0502768	0.0520255	0.0732704	0.4872758

Table 2.17 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.10 at 5 percentage of contamination and scale factors of 3 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	271.46885	299.92820	1444.5914	3173.0314	806.31114	9898.8867
		SD	3813.8180	6416.4670	30524.500	57389.300	9835.8570	127608.10
	AUG	AMSE	271.46885	299.92820	1444.5914	3173.0313	806.33893	9898.8880
		SD	3813.8180	6416.4670	30524.500	57389.300	9836.2750	127608.10
	BOLS	AMSE	271.46885	299.92820	1444.5913	3173.0315	806.31114	9898.8862
		SD	3813.8180	6416.4670	30524.500	57389.300	9835.8570	127608.10
	BAUG	AMSE	271.46890	299.92837	1444.5958	3173.0352	804.39465	9880.3482
		SD	3813.8190	6416.4710	30524.600	57389.280	9807.0750	127258.70
30	OLS	AMSE	1.0217971	1.0258087	1.0369119	1.0533186	1.1372554	2.3812127
		SD	0.0560315	0.0575434	0.0628196	0.0681901	0.1244574	1.2211200
	AUG	AMSE	1.0199877	1.0243799	1.0368124	1.0539099	1.1455259	2.1877540
		SD	0.0563521	0.0583676	0.0650656	0.0705777	0.1295489	1.0505750
	BOLS	AMSE	1.0302694	1.0354265	1.0496882	1.0716753	1.1828680	2.8353208
		SD	0.0561897	0.0578880	0.0638232	0.0705240	0.1356982	1.3544040
	BAUG	AMSE	1.0300860	1.0363117	1.0535041	1.0785698	1.2066952	2.4795896
		SD	0.0572865	0.0604451	0.0689443	0.0778601	0.1473736	1.0737370
50	OLS	AMSE	1.0123917	1.0139649	1.0182695	1.0260113	1.0642066	1.6313422
		SD	0.0432878	0.0433921	0.0439524	0.0451640	0.0595682	0.4411061
	AUG	AMSE	1.0110295	1.0127190	1.0173120	1.0255613	1.0687935	1.6091865
		SD	0.0431293	0.0434620	0.0442532	0.0454425	0.0626463	0.4217301
	BOLS	AMSE	1.0175644	1.0197927	1.0258983	1.0365580	1.0894275	1.8776596
		SD	0.0433772	0.0436522	0.0444483	0.0459470	0.0629023	0.4887391
	BAUG	AMSE	1.0167254	1.0192770	1.0262004	1.0382761	1.1036021	1.8076015
		SD	0.0432491	0.0438094	0.0451993	0.0473036	0.0736216	0.4153802
100	OLS	AMSE	1.0056306	1.0064249	1.0085093	1.0117102	1.0275769	1.2692964
		SD	0.0294225	0.0294478	0.0295721	0.0298040	0.0324926	0.1667092
	AUG	AMSE	1.0048507	1.0056410	1.0077536	1.0111287	1.0278677	1.2988089
		SD	0.0294188	0.0294570	0.0295620	0.0297517	0.0327741	0.2142534
	BOLS	AMSE	1.0081765	1.0092909	1.0122733	1.0169688	1.0401739	1.3922166
		SD	0.0294883	0.0295159	0.0296221	0.0298353	0.0327176	0.1756077
	BAUG	AMSE	1.0076400	1.0087619	1.0118541	1.0169715	1.0426677	1.4436747
		SD	0.0293562	0.0293893	0.0295396	0.0296700	0.0337820	0.2129585

Table 2.18 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.10 at 10 percentage of contamination and scale factors of 3 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	271.46885	299.92820	1444.5914	3173.0314	806.31114	9898.8867
		SD	3813.8180	6416.4670	30524.500	57389.300	9835.8570	127608.10
	AUG	AMSE	271.46885	299.92820	1444.5914	3173.0313	806.33893	9898.8880
		SD	3813.8180	6416.4670	30524.500	57389.300	9836.2750	127608.10
	BOLS	AMSE	271.46885	299.92820	1444.5913	3173.0315	806.31114	9898.8862
		SD	3813.8180	6416.4670	30524.500	57389.300	9835.8570	127608.10
	BAUG	AMSE	271.46890	299.92837	1444.5958	3173.0352	804.39465	9880.3482
		SD	3813.8190	6416.4710	30524.600	57389.280	9807.0750	127258.70
30	OLS	AMSE	1.0217971	1.0258087	1.0369119	1.0533186	1.1372554	2.3812127
		SD	0.0560315	0.0575434	0.0628196	0.0681901	0.1244574	1.2211200
	AUG	AMSE	1.0199877	1.0243799	1.0368124	1.0539099	1.1455259	2.1877540
		SD	0.0563521	0.0583676	0.0650656	0.0705777	0.1295489	1.0505750
	BOLS	AMSE	1.0302694	1.0354265	1.0496882	1.0716753	1.1828680	2.8353208
		SD	0.0561897	0.0578880	0.0638232	0.0705240	0.1356982	1.3544040
	BAUG	AMSE	1.0300860	1.0363117	1.0535041	1.0785698	1.2066952	2.4795896
		SD	0.0572865	0.0604451	0.0689443	0.0778601	0.1473736	1.0737370
50	OLS	AMSE	1.0123917	1.0139649	1.0182695	1.0260113	1.0642066	1.6313422
		SD	0.0431878	0.0433921	0.0439524	0.0451640	0.0595682	0.4411061
	AUG	AMSE	1.0110295	1.0127190	1.0173120	1.0255613	1.0687935	1.6091865
		SD	0.0431293	0.0434620	0.0442532	0.0451125	0.0626463	0.4217301
	BOLS	AMSE	1.0175644	1.0197927	1.0258983	1.0365580	1.0894275	1.8776596
		SD	0.0433772	0.0436522	0.0444483	0.0459470	0.0629023	0.4887391
	BAUG	AMSE	1.0167254	1.0192770	1.0262004	1.0382761	1.1036021	1.8076015
		SD	0.0432491	0.0438094	0.0451993	0.0473036	0.0736216	0.4153802
100	OLS	AMSE	1.0056306	1.0064249	1.0085093	1.0117102	1.0275769	1.2692964
		SD	0.0294225	0.0294478	0.0295721	0.0298040	0.0324926	0.1667092
	AUG	AMSE	1.0048507	1.0056410	1.0077536	1.0111287	1.0278677	1.2988089
		SD	0.0294188	0.0294570	0.0295620	0.0297517	0.0327741	0.2142534
	BOLS	AMSE	1.0081765	1.0092909	1.0122733	1.0169688	1.0401739	1.3922166
		SD	0.0294883	0.0295159	0.0296221	0.0298353	0.0327176	0.1756077
	BAUG	AMSE	1.0076400	1.0087619	1.0118541	1.0169715	1.0426677	1.4436747
		SD	0.0293562	0.0293893	0.0295396	0.0296700	0.0337820	0.2129585

Table 2.19 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.10 at 5 percentage of contamination and scale factors of 10 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	3006.1961	3322.4114	16040.891	35245.776	8948.8885	109977.49
		SD	42375.680	71294.010	339161.10	637658.80	109287.30	1417867.0
	AUG	AMSE	3006.1961	3322.4114	16040.891	35245.773	8948.8871	109977.49
		SD	42375.680	71294.010	339161.10	637658.80	109287.30	1417867.0
	BOLS	AMSE	3006.1961	3322.4114	16040.890	35245.777	8948.8887	109977.48
		SD	42375.680	71294.010	339161.10	637658.90	109287.30	1417867.0
	BAUG	AMSE	3006.1963	3322.4114	16041.000	35245.803	8948.9720	109982.01
		SD	42375.680	71294.010	339163.50	637659.30	109288.60	1417945.0
30	OLS	AMSE	1.2613822	1.3059552	1.4293250	1.6116209	2.5442520	16.365998
		SD	0.2378403	0.2790453	0.3961511	0.4922913	1.2719310	13.579630
	AUG	AMSE	1.2485602	1.2975268	1.4081831	1.5527524	2.2954101	12.881356
		SD	0.2461094	0.2769909	0.3427383	0.4056445	1.0015990	11.865260
	BOLS	AMSE	1.3546280	1.4118809	1.5702920	1.8147220	3.0504620	21.411129
		SD	0.2450547	0.2910472	0.4191715	0.5349430	1.4082820	15.060080
	BAUG	AMSE	1.3640921	1.4266022	1.5560301	1.7270708	2.5519569	15.249671
		SD	0.2469381	0.2741596	0.3271963	0.3757710	0.9163129	12.206680
50	OLS	AMSE	1.1342955	1.1517750	1.1996043	1.2856239	1.7100159	8.0115218
		SD	0.1543526	0.1598577	0.1796254	0.2185244	0.4826521	4.8759380
	AUG	AMSE	1.1275723	1.1504546	1.2149516	1.3022348	1.6881723	6.5029177
		SD	0.1579929	0.1698343	0.2038984	0.2357345	0.4710177	4.2050870
	BOLS	AMSE	1.1910856	1.2158677	1.2837598	1.4022323	1.9896872	10.747826
		SD	0.1564757	0.1636826	0.1880032	0.2328347	0.5293061	5.4060870
	BAUG	AMSE	1.2018962	1.2375716	1.3323609	1.4378765	1.9076269	7.7965937
		SD	0.1665823	0.1830756	0.2187413	0.2341331	0.4094497	4.1173970
100	OLS	AMSE	1.0613788	1.0702047	1.0933642	1.1289295	1.3052263	3.9909979
		SD	0.0995658	0.1010202	0.1064657	0.1179301	0.1975110	1.8426860
	AUG	AMSE	1.0542637	1.0648051	1.0930217	1.1333362	1.3373986	3.8351709
		SD	0.1001015	0.1023273	0.1114917	0.1190087	0.2287234	2.0962100
	BOLS	AMSE	1.0903761	1.1027709	1.1359192	1.1880763	1.4459043	5.3574913
		SD	0.0997404	0.1013089	0.1070803	0.1190011	0.2045935	1.9459840
	BAUG	AMSE	1.0885480	1.1059345	1.1530646	1.2166204	1.5161728	4.7695724
		SD	0.1006661	0.1045411	0.1202450	0.1285877	0.2210564	1.8361690

Table 2.20 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.10 at 10 percentage of contamination and scale factors of 10 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	3006.1961	3322.4114	16040.891	35245.776	8948.8885	109977.49
		SD	42375.680	71294.010	339161.10	637658.80	109287.30	1417867.0
	AUG	AMSE	3006.1961	3322.4114	16040.891	35245.773	8948.8871	109977.49
		SD	42375.680	71294.010	339161.10	637658.80	109287.30	1417867.0
	BOLS	AMSE	3006.1961	3322.4114	16040.890	35245.777	8948.8887	109977.48
		SD	42375.680	71294.010	339161.10	637658.90	109287.30	1417867.0
	BAUG	AMSE	3006.1963	3322.4114	16041.000	35245.803	8948.9720	109982.01
		SD	42375.680	71294.010	339163.50	637659.30	109288.60	1417945.0
30	OLS	AMSE	1.2613822	1.3059552	1.4293250	1.6116209	2.5442520	16.365998
		SD	0.2378403	0.2790453	0.3961511	0.4922913	1.2719310	13.579630
	AUG	AMSE	1.2485602	1.2975268	1.4081831	1.5527524	2.2954101	12.881356
		SD	0.2461094	0.2769909	0.3427383	0.4056445	1.0015990	11.865260
	BOLS	AMSE	1.3546280	1.4118809	1.5702920	1.8147220	3.0504620	21.411129
		SD	0.2450547	0.2910472	0.4191715	0.5349430	1.4082820	15.060080
	BAUG	AMSE	1.3640921	1.4266022	1.5560301	1.7270708	2.5519569	15.249671
		SD	0.2469381	0.2741596	0.3271963	0.3757710	0.9163129	12.206680
50	OLS	AMSE	1.1342955	1.1517750	1.1996043	1.2856239	1.7100159	8.0115218
		SD	0.1543526	0.1598577	0.1796254	0.2185244	0.4826521	4.8759380
	AUG	AMSE	1.1275723	1.1504546	1.2149516	1.3022348	1.6881723	6.5029177
		SD	0.1579929	0.1698343	0.2038984	0.2357345	0.4710177	4.2050870
	BOLS	AMSE	1.1910856	1.2158677	1.2837598	1.4022323	1.9896872	10.747826
		SD	0.1564757	0.1636826	0.1880032	0.2328347	0.5293061	5.4060870
	BAUG	AMSE	1.2018962	1.2375716	1.3323609	1.4378765	1.9076269	7.7965937
		SD	0.1665823	0.1830756	0.2187413	0.2341331	0.4094497	4.1173970
100	OLS	AMSE	1.0613788	1.0702047	1.0933642	1.1289295	1.3052263	3.9909979
		SD	0.0995656	0.1010202	0.1064657	0.1179301	0.1975110	1.8426860
	AUG	AMSE	1.0542637	1.0648051	1.0930217	1.1333362	1.3373986	3.8351709
		SD	0.1001015	0.1023273	0.1114917	0.1190087	0.2287234	2.0962100
	BOLS	AMSE	1.0903761	1.1027709	1.1359192	1.1880763	1.4459043	5.3574913
		SD	0.0997404	0.1013089	0.1070803	0.1190011	0.2045935	1.9459840
	BAUG	AMSE	1.0885480	1.1059345	1.1530646	1.2166204	1.5161728	4.7695724
		SD	0.1006661	0.1045411	0.1202450	0.1285877	0.2210564	1.8361690

Table 2.21 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.15 at 5 percentage of contamination and scale factors of 3 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	609.55367	673.58717	3249.0795	7138.0701	1812.9488	22271.241
		SD	8581.0830	14437.040	68680.120	129125.90	22130.680	287118.10
	AUG	AMSE	609.55367	673.58717	3249.0796	7138.0685	1812.9565	22271.243
		SD	8581.0830	14437.040	68680.120	129125.90	22130.800	287118.10
	BOLS	AMSE	609.55367	673.58717	3249.0794	7138.0704	1812.9488	22271.240
		SD	8581.0830	14437.040	68680.120	129126.00	22130.680	287118.00
	BAUG	AMSE	609.55357	673.58731	3249.1526	7138.0946	1812.2182	22242.128
		SD	8581.0810	14437.050	68681.760	129126.50	22119.700	286574.30
30	OLS	AMSE	1.0508941	1.0599202	1.0849026	1.1218175	1.3106753	4.1095792
		SD	0.0869200	0.0917934	0.1079601	0.1232449	0.2660671	2.7483030
	AUG	AMSE	1.0480187	1.0593288	1.0877942	1.1293874	1.3279033	3.4987403
		SD	0.0889978	0.0976555	0.1123358	0.1328300	0.2696439	2.4015870
	BOLS	AMSE	1.0698710	1.0814698	1.1135535	1.1630370	1.4132462	5.1312728
		SD	0.0875951	0.0931118	0.1111879	0.1300091	0.2927100	3.0481750
	BAUG	AMSE	1.0729488	1.0893367	1.1307870	1.1891985	1.4419760	4.0597485
		SD	0.0941972	0.1052348	0.1262495	0.1488147	0.2718264	2.4464270
50	OLS	AMSE	1.0275545	1.0310941	1.0407795	1.0581985	1.1441379	2.4201929
		SD	0.0653844	0.0659853	0.0679516	0.0721485	0.1132406	0.9894794
	AUG	AMSE	1.0248429	1.0288522	1.0400228	1.0594009	1.1613333	2.2352847
		SD	0.0651949	0.0663022	0.0696147	0.0721485	0.1307341	0.8719287
	BOLS	AMSE	1.0391270	1.0441430	1.0578855	1.0818729	1.2008309	2.9743536
		SD	0.0657568	0.0665900	0.0691798	0.0747962	0.1217338	1.0967940
	BAUG	AMSE	1.0382888	1.0446307	1.0625750	1.0918773	1.2443191	2.5866835
		SD	0.0656659	0.0677958	0.0742488	0.0828790	0.1528267	0.8374755
100	OLS	AMSE	1.0125548	1.0143420	1.0190318	1.0262338	1.0619339	1.6058027
		SD	0.0441688	0.0442738	0.0447289	0.0457070	0.0549736	0.3734443
	AUG	AMSE	1.0108607	1.0126990	1.0175519	1.0253596	1.0646784	1.6701048
		SD	0.0441439	0.0442748	0.0448301	0.0458485	0.0578170	0.4755726
	BOLS	AMSE	1.0183514	1.0208600	1.0275714	1.0381349	1.0903457	1.8824420
		SD	0.0442589	0.0443697	0.0448320	0.0457842	0.0557984	0.3939303
	BAUG	AMSE	1.0172923	1.0199370	1.0272168	1.0393278	1.1016231	1.9316087
		SD	0.0440498	0.0442390	0.0449042	0.0460315	0.0617868	0.4273486

Table 2.22 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.15 at 10 percentage of contamination and scale factors of 3 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	609.55367	673.58717	3249.0795	7138.0701	1812.9488	22271.241
		SD	8581.0830	14437.040	68680.120	129125.90	22130.680	287118.10
	AUG	AMSE	609.55367	673.58717	3249.0796	7138.0685	1812.9565	22271.243
		SD	8581.0830	14437.040	68680.120	129125.90	22130.800	287118.10
	BOLS	AMSE	609.55367	673.58717	3249.0794	7138.0704	1812.9488	22271.240
		SD	8581.0830	14437.040	68680.120	129126.00	22130.680	287118.00
	BAUG	AMSE	609.55357	673.58731	3249.1526	7138.0946	1812.2182	22242.128
		SD	8581.0810	14437.050	68681.760	129126.50	22119.700	286574.30
30	OLS	AMSE	1.0508941	1.0599202	1.0849026	1.1218175	1.3106753	4.1095792
		SD	0.0869200	0.0917934	0.1079601	0.1232449	0.2660671	2.7483030
	AUG	AMSE	1.0480187	1.0593288	1.0877942	1.1293874	1.3279033	3.4987403
		SD	0.0889978	0.0976555	0.1123358	0.1328300	0.2696439	2.4015870
	BOLS	AMSE	1.0698710	1.0814698	1.1135535	1.1630370	1.4132462	5.1312728
		SD	0.0875951	0.0931118	0.1111879	0.1300091	0.2927100	3.0481750
	BAUG	AMSE	1.0729488	1.0893367	1.1307870	1.1891985	1.4419760	4.0597485
		SD	0.0941972	0.1052348	0.1262495	0.1488147	0.2718264	2.4464270
50	OLS	AMSE	1.0275545	1.0310941	1.0407795	1.0581985	1.1441379	2.4201929
		SD	0.0653844	0.0659853	0.0679516	0.0721485	0.1132406	0.9894794
	AUG	AMSE	1.0248429	1.0288522	1.0400228	1.0594009	1.1613333	2.2352847
		SD	0.0651949	0.0663022	0.0696147	0.0747962	0.1307341	0.8719287
	BOLS	AMSE	1.0391270	1.0441430	1.0578855	1.0818729	1.2008309	2.9743536
		SD	0.0657568	0.0665900	0.0691798	0.0742456	0.1217338	1.0967940
	BAUG	AMSE	1.0382888	1.0446307	1.0625750	1.0918773	1.2443191	2.5866835
		SD	0.0656659	0.0677958	0.0742488	0.0828790	0.1528267	0.8374755
100	OLS	AMSE	1.0125548	1.0143420	1.0190318	1.0262338	1.0619339	1.6058027
		SD	0.0441688	0.0442738	0.0447289	0.0457070	0.0549736	0.3734443
	AUG	AMSE	1.0108607	1.0126990	1.0175519	1.0253596	1.0646784	1.6701048
		SD	0.0441439	0.0442748	0.0448301	0.0458485	0.0578170	0.4755726
	BOLS	AMSE	1.0183514	1.0208600	1.0275714	1.0381349	1.0903457	1.8824420
		SD	0.0442589	0.0443697	0.0448320	0.0457842	0.0557984	0.3939303
	BAUG	AMSE	1.0172923	1.0199370	1.0272168	1.0393278	1.1016231	1.9316087
		SD	0.0440498	0.0442390	0.0449042	0.0460315	0.0617868	0.4273486

Table 2.23 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.15 at 5 percentage of contamination and scale factors of 10 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	6762.6878	7474.1709	36090.750	79301.753	20133.748	247448.09
		SD	95345.260	160411.50	763112.30	1434733.0	245896.50	3190200.0
	AUG	AMSE	6762.6878	7474.1709	36090.750	79301.754	20133.780	247448.08
		SD	95345.260	160411.50	763112.30	1434733. 0	245897.00	3190200.0
	BOLS	AMSE	6762.6878	7474.1709	36090.749	79301.756	20133.748	247448.07
		SD	95345.260	160411.50	763112.30	1434733.0	245896.50	3190199.0
	BAUG	AMSE	6762.6879	7474.1708	36090.733	79301.699	20130.544	247444.58
		SD	95345.270	160411.50	763112.00	1434731.0	245848.30	3190126.0
30	OLS	AMSE	1.5942787	1.6945681	1.9721500	2.3823160	4.4807360	35.579665
		SD	0.4455129	0.5534837	0.8408847	1.0669830	2.8510750	30.560390
	AUG	AMSE	1.5116373	1.5910524	1.8018280	2.0889686	3.6162266	27.509319
		SD	0.3995286	0.4726239	0.6771280	0.8013382	2.2377510	26.799740
	BOLS	AMSE	1.8037953	1.9325989	2.2890072	2.8390161	5.6195163	46.931045
		SD	0.4656363	0.5848895	0.8967102	1.1674930	3.1594410	33.891020
	BAUG	AMSE	1.6958683	1.7839302	1.9961025	2.3170173	4.0222220	32.710174
		SD	0.3736179	0.4265581	0.5809433	0.6887776	2.0281690	27.592250
50	OLS	AMSE	1.3010749	1.3404040	1.4480199	1.6415638	2.5964458	16.774834
		SD	0.2513847	0.2676820	0.3256596	0.4313289	1.0596350	10.966920
	AUG	AMSE	1.2761306	1.3233674	1.4369793	1.5734581	2.3298101	13.138791
		SD	0.2576147	0.2783006	0.3253952	0.3808568	0.9227434	9.5424720
	BOLS	AMSE	1.4286330	1.4844000	1.6371741	1.9037473	3.2255258	22.931340
		SD	0.2570507	0.2779202	0.3471466	0.4665118	1.1662440	12.159660
	BAUG	AMSE	1.4196047	1.4810897	1.6256910	1.7842332	2.6505411	15.898109
		SD	0.2622043	0.2802942	0.3174427	0.3406675	0.7805853	9.4526890
100	OLS	AMSE	1.1377218	1.1575801	1.2096890	1.2897109	1.6863786	7.7293648
		SD	0.1536016	0.1586280	0.1763032	0.2113550	0.4183283	4.1481990
	AUG	AMSE	1.1228794	1.1496192	1.2148524	1.3010967	1.7274102	6.9275004
		SD	0.1549471	0.1633166	0.1911203	0.2201342	0.4568138	4.0718280
	BOLS	AMSE	1.2031939	1.2310862	1.3056734	1.4230218	2.0031327	10.804204
		SD	0.1538563	0.1592621	0.1780799	0.2148135	0.4362949	4.3817730
	BAUG	AMSE	1.2011574	1.2443055	1.3435148	1.4569729	1.9680402	8.8807013
		SD	0.1566224	0.1713753	0.2035427	0.2148304	0.3710944	3.511759

Table 2.24 A comparison of multiple regression coefficient estimating with contaminated normal distribution on mean equals to 1, standard deviation equals to 0.15 at 10 percentage of contamination and scale factors of 10 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	6762.6878	7474.1709	36090.750	79301.753	20133.748	247448.09
		SD	95345.260	160411.50	763112.30	1434733.0	245896.50	3190200.0
	AUG	AMSE	6762.6878	7474.1709	36090.750	79301.754	20133.780	247448.08
		SD	95345.260	160411.50	763112.30	1434733.0	245897.00	3190200.0
	BOLS	AMSE	6762.6878	7474.1709	36090.749	79301.756	20133.748	247448.07
		SD	95345.260	160411.50	763112.30	1434733.0	245896.50	3190199.0
	BAUG	AMSE	6762.6879	7474.1708	36090.733	79301.699	20130.544	247444.58
		SD	95345.270	160411.50	763112.00	1434731.0	245848.30	3190126.0
30	OLS	AMSE	1.5942787	1.6945681	1.9721500	2.3823160	4.4807360	35.579665
		SD	0.4455129	0.5534837	0.8408847	1.0669832	2.8510750	30.560390
	AUG	AMSE	1.5116373	1.5910524	1.8018280	2.0889686	3.6162266	27.509319
		SD	0.3995286	0.4726239	0.6771280	0.8013382	2.2377510	26.799740
	BOLS	AMSE	1.8037953	1.9325989	2.2890072	2.8390161	5.6195163	46.931045
		SD	0.4656363	0.5848895	0.8967102	1.1674930	3.1594410	33.891020
	BAUG	AMSE	1.6958683	1.7839302	1.9961025	2.3170173	4.0222220	32.710174
		SD	0.3736179	0.4265581	0.5809433	0.6887776	2.0281690	27.592250
50	OLS	AMSE	1.3010749	1.3404040	1.4480199	1.6415638	2.5964458	16.774834
		SD	0.2513847	0.2676820	0.3256596	0.4313289	1.0596350	10.966920
	AUG	AMSE	1.2761306	1.3233674	1.4369793	1.5734581	2.3298101	13.138791
		SD	0.2576147	0.2783006	0.3253952	0.3808568	0.9227434	9.5424720
	BOLS	AMSE	1.4286330	1.4844000	1.6371741	1.9037473	3.2255258	22.931340
		SD	0.2570507	0.2779202	0.3471466	0.4665118	1.166244	12.159660
	BAUG	AMSE	1.4196047	1.4810897	1.6256910	1.7842332	2.6505411	15.898109
		SD	0.2622043	0.2802942	0.3174427	0.3406675	0.7805853	9.4526890
100	OLS	AMSE	1.1377218	1.1575801	1.2096890	1.2897109	1.6863786	7.7293648
		SD	0.1536016	0.1586280	0.1763032	0.2113550	0.4183283	4.1481990
	AUG	AMSE	1.1228794	1.1496192	1.2148524	1.3010967	1.7274102	6.9275004
		SD	0.1549471	0.1633166	0.1911203	0.2201342	0.4568138	4.0718280
	BOLS	AMSE	1.2031939	1.2310862	1.3056734	1.4230218	2.0031327	10.804204
		SD	0.1538563	0.1592621	0.1780799	0.2148135	0.4362949	4.3817730
	BAUG	AMSE	1.2011574	1.2443055	1.3435148	1.4569729	1.9680402	8.8807013
		SD	0.1566224	0.1713753	0.2035427	0.2148304	0.3710944	3.5117590

3. A comparison of parameter estimation for lognormal distributed data

To determine the conditions for comparing the multiple regression coefficient by two estimators which are the ordinary least square and almost unbiased generalized Liu estimator when within and without bootstrap technique. The criteria are set as variance (σ^2) equals to 0.05, 0.30, 0.70 and 1.00 in the population mean (μ) equals to 1. The results in Table 3.1-3.8 are given below:

Table	No. of dependent variable	Variance
3.1	3	0.05
3.2	3	0.30
3.3	3	0.70
3.4	3	1.00
3.5	5	0.05
3.6	5	0.30
3.7	5	0.70
3.8	5	1.00

The result from testing the multiple regression coefficient in four method on lognormal distribution for the sample sizes of 10,30,50 and 100 at various degree of correlation is presented in table, respectively.

Table 3.1 A comparison of multiple regression coefficient estimating with lognormal distribution on mean equals to 1 and variance equals to 0.05 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	1.5351730	1.6468077	1.7951781	2.3059914	3.5712253	14.430716
		SD	1.6935940	1.7348290	1.8007490	1.9580750	3.2669130	28.966010
	AUG	AMSE	1.5581169	1.6657490	1.8128569	2.3056435	3.4204311	12.233361
		SD	1.6860010	1.7304940	1.7922030	1.9281270	2.9279960	23.937750
	BOLS	AMSE	1.5542868	1.6669727	1.8217487	2.3624870	3.7864084	16.938813
		SD	1.7062120	1.7497530	1.8192220	2.0006560	3.6450380	33.092210
	BAUG	AMSE	1.5926912	1.7023251	1.8529120	2.3639331	3.5599035	13.636966
		SD	1.6997830	1.7450330	1.8058810	1.9504220	3.2570650	27.542480
30	OLS	AMSE	3.3076444	3.2550437	3.4551728	3.7028385	4.0176622	5.9613171
		SD	1.9958900	2.0320730	1.7746920	1.2151440	0.8446583	3.1184930
	AUG	AMSE	3.3113981	3.2592253	3.4617101	3.7200556	4.0589068	5.4857924
		SD	1.9903240	2.0261870	1.7699490	1.2148290	0.8403146	2.6463000
	BOLS	AMSE	3.3196744	3.2674534	3.4697930	3.7262448	4.0937361	6.7738583
		SD	2.0010120	2.0379190	1.7802150	1.2207110	0.8644060	3.4081500
	BAUG	AMSE	3.3338918	3.2819992	3.4892509	3.7649418	4.1600116	5.8381384
		SD	1.9941090	2.0300870	1.7743930	1.2216850	0.8499275	2.5130600
50	OLS	AMSE	4.3073864	4.3570208	4.3026075	4.0076497	4.0780559	5.0185945
		SD	2.2153850	2.0825720	1.5577750	0.8320125	0.2903658	1.2577500
	AUG	AMSE	4.3068575	4.3564345	4.3034856	4.0143270	4.1149246	4.8733242
		SD	2.2110830	2.0784230	1.5540000	0.8301334	0.3036263	1.0669510
	BOLS	AMSE	4.3168350	4.3670255	4.3136744	4.0227892	4.1229683	5.4851972
		SD	2.2192840	2.0863770	1.5614680	0.8348570	0.2984982	1.3532170
	BAUG	AMSE	4.3216480	4.3714439	4.3211639	4.0417910	4.1939660	5.1450847
		SD	2.2130780	2.0800360	1.5556730	0.8320609	0.3076251	0.9742209
100	OLS	AMSE	6.3662664	6.0425185	5.3482982	4.3026765	4.0254631	4.4785636
		SD	1.8213310	1.9569960	1.8124260	1.0228550	0.1380563	0.5152906
	AUG	AMSE	6.3638027	6.0404287	5.3473765	4.3048854	4.0420562	4.5060833
		SD	1.8194710	1.9549260	1.8101750	1.0211060	0.1420569	0.5356067
	BOLS	AMSE	6.3728489	6.0490162	5.3550362	4.3107968	4.0476263	4.7062953
		SD	1.8232070	1.9588450	1.8144030	1.0248110	0.1402500	0.5364925
	BAUG	AMSE	6.3715254	6.0483951	5.3562327	4.3177110	4.0855550	4.7132076
		SD	1.8200940	1.9557100	1.8109090	1.0218060	0.1490971	0.4783991

Table 3.2 A comparison of multiple regression coefficient estimating with lognormal distribution on mean equals to 1 and variance equals to 0.30 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	2.9120021	2.9309046	3.3299099	4.5230257	11.950106	103.58890
		SD	3.2115070	2.9637740	3.7812940	6.2667770	33.823210	361.84270
	AUG	AMSE	2.7616895	2.8052041	3.1231331	4.0778070	10.017428	83.287638
		SD	2.7893140	2.6615150	3.2454190	5.0608480	27.933380	292.34460
	BOLS	AMSE	3.0679456	3.0985677	3.5469641	4.9543383	13.672806	123.63356
		SD	3.3997000	3.2306430	4.0867620	7.1634440	38.036880	416.09450
	BAUG	AMSE	2.8624709	2.9211935	3.2528089	4.2909537	10.831873	94.699932
		SD	2.8185180	2.7855340	3.2957300	5.4124340	30.728830	323.40640
30	OLS	AMSE	5.3060544	5.1587092	5.1731953	5.2083499	5.9447776	22.322329
		SD	2.8400300	2.8077290	2.5707700	2.3232680	3.5049570	32.788290
	AUG	AMSE	5.2512894	5.1053738	5.1192401	5.1246775	5.5455771	17.101538
		SD	2.7592240	2.7257860	2.4746790	2.1712620	2.9034830	27.448870
	BOLS	AMSE	5.4400591	5.2935630	5.3263467	5.4334811	6.6046055	29.294899
		SD	2.9234550	2.8892510	2.6607220	2.4499610	3.9043870	36.591910
	BAUG	AMSE	5.3914153	5.2464539	5.2676692	5.2952334	5.8398066	19.446140
		SD	2.8130680	2.7817150	2.5240510	2.2069650	2.8037950	26.476470
50	OLS	AMSE	6.9654351	6.8217132	6.4735015	5.6883218	5.4221908	13.423510
		SD	2.4302420	2.4533980	2.4259810	2.0590670	1.6556230	12.765220
	AUG	AMSE	6.9285523	6.7852982	6.4464744	5.6672032	5.3019280	10.910692
		SD	2.3983130	2.4187890	2.3871820	1.9991230	1.4264880	10.264450
	BOLS	AMSE	7.0756650	6.9319193	6.5925460	5.8421862	5.8173954	17.478736
		SD	2.4757840	2.5010940	2.4780430	2.1244900	1.8156440	14.253830
	BAUG	AMSE	7.0577418	6.9151358	6.5833677	5.8264584	5.5457103	12.440743
		SD	2.4326980	2.4563880	2.4221850	2.0329470	1.3814680	9.6146660
100	OLS	AMSE	8.4037612	8.4145333	7.9276257	6.6717317	5.1652280	8.6759696
		SD	1.2723520	1.2827700	1.7675320	2.1653500	1.2207320	4.1980340
	AUG	AMSE	8.3784764	8.3911076	7.9096239	6.6720592	5.1808112	7.8729165
		SD	1.2612220	1.2719580	1.7536660	2.1373520	1.1935380	3.8247970
	BOLS	AMSE	8.4714358	8.4835217	8.0014180	6.7631760	5.3661319	10.657099
		SD	1.2888050	1.2995680	1.7874840	2.1965920	1.2659060	4.6169140
	BAUG	AMSE	8.4605698	8.4764465	8.0031317	6.7861967	5.3579418	8.9485863
		SD	1.2753170	1.2858290	1.7677650	2.1528920	1.1962310	3.3665460

Table 3.3 A comparison of multiple regression coefficient estimating with lognormal distribution on mean equals to 1 and variance equals to 0.70 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	6.3672873	6.6393690	7.3729315	11.458273	36.990948	385.15186
		SD	11.355420	11.862690	14.044220	35.060810	164.72940	1848.8670
	AUG	AMSE	5.4436131	5.6455641	6.2128766	9.3872301	28.853393	299.16666
		SD	8.8379490	9.2986960	10.780000	28.027040	120.85010	1333.3470
	BOLS	AMSE	6.9996276	7.4073339	8.2603150	13.058465	43.640668	465.43260
		SD	12.375480	13.309190	15.714130	38.734040	189.09740	2257.8640
	BAUG	AMSE	5.7480908	6.0612571	6.6417559	10.045082	31.799019	344.69304
		SD	8.9213490	9.7826090	11.085860	28.650090	129.59540	1532.0910
30	OLS	AMSE	9.1134887	9.2364169	9.3038172	9.4830898	13.070479	87.288752
		SD	5.2303390	5.1663610	5.5819230	7.3861890	17.984030	245.73800
	AUG	AMSE	8.4214156	8.5513740	8.5040489	8.4022074	10.663807	63.379492
		SD	4.3163430	4.3466260	4.4861940	5.5130850	13.942150	197.57540
	BOLS	AMSE	9.8156432	9.9663005	10.147778	10.622994	16.052018	117.80762
		SD	5.8720290	5.8108420	6.4101320	8.5260360	21.016140	278.95840
	BAUG	AMSE	8.8574050	8.9994117	8.9762220	8.8843976	11.649732	73.975732
		SD	4.5860630	4.6074720	4.7419680	5.5162750	13.591020	198.68510
50	OLS	AMSE	10.659961	10.633851	10.140139	9.8039308	10.523431	43.249009
		SD	3.6034610	3.6431130	3.9232050	4.4066210	7.6749100	68.038290
	AUG	AMSE	10.233119	10.225644	9.7138806	9.2115285	9.2576213	33.254207
		SD	3.2563580	3.3168470	3.5554500	3.7981530	5.9493090	55.781950
	BOLS	AMSE	11.204789	11.181376	10.717627	10.594465	12.438833	60.422666
		SD	3.9497110	3.9850640	4.2926600	4.9539340	9.0022500	79.045840
	BAUG	AMSE	10.619766	10.604203	10.086171	9.6114526	9.9906721	39.472948
		SD	3.4264720	3.4729880	3.6992060	3.9478120	5.9092660	54.267330
100	OLS	AMSE	11.267411	11.336987	11.318706	10.800362	9.4724806	22.808500
		SD	2.0935010	2.1809500	2.4141980	3.6693330	4.0114550	21.739450
	AUG	AMSE	11.072555	11.142029	11.094124	10.472151	8.8367459	18.503589
		SD	1.7711140	1.8336160	1.9368520	2.8534060	3.4600240	18.652750
	BOLS	AMSE	11.589540	11.665813	11.689165	11.307711	10.518756	31.239378
		SD	2.4429460	2.5337130	2.8276870	4.3371420	4.5162670	25.959520
	BAUG	AMSE	11.342576	11.416976	11.380128	10.789080	9.3341627	23.286468
		SD	1.908937	1.9706590	2.0689710	2.9781670	3.4923420	17.952510

Table 3.4 A comparison of multiple regression coefficient estimating with lognormal distribution on mean equals to 1 and variance equals to 1.00 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	11.118994	12.301312	13.775181	21.822934	80.110416	879.81643
		SD	28.238640	30.754110	36.671750	89.777310	473.44800	5295.8290
	AUG	AMSE	8.8947408	9.8461483	10.787793	17.068465	61.053726	671.25972
		SD	21.767060	23.654540	26.716470	67.939190	332.70810	3587.8810
	BOLS	AMSE	12.562113	14.043401	15.926334	25.315158	94.772917	1064.0811
		SD	30.969200	34.278340	41.791630	99.836630	542.43380	6560.4330
	BAUG	AMSE	9.5499339	10.723771	11.794693	18.414921	67.148821	773.31214
		SD	21.966630	24.604540	27.643710	68.150870	347.50850	4211.8190
30	OLS	AMSE	13.716445	13.756802	14.352367	15.993483	26.357191	203.12629
		SD	10.658670	10.122180	12.555330	19.089430	64.103930	755.73140
	AUG	AMSE	11.748133	11.833906	12.070874	12.788066	19.539952	144.70705
		SD	7.6142170	7.3802910	8.6513840	12.514680	44.801480	591.92580
	BOLS	AMSE	15.464504	15.550449	16.471960	19.041740	33.777033	275.17649
		SD	12.688230	12.137520	15.240490	23.104660	74.753050	866.80780
	BAUG	AMSE	12.675365	12.792794	13.088879	13.951388	21.845807	170.68058
		SD	8.3185280	8.0918830	9.2609000	12.803170	43.138800	603.49640
50	OLS	AMSE	14.461279	14.750979	14.441365	14.669693	18.302626	94.370422
		SD	6.2066240	6.2920770	6.9355620	8.4939790	18.710770	181.17870
	AUG	AMSE	13.232810	13.524217	13.111879	12.882908	15.059247	71.105416
		SD	4.9729680	5.0753100	5.5941020	6.5226060	14.376490	145.43010
	BOLS	AMSE	15.761951	16.076667	15.888961	16.645677	23.044696	134.45430
		SD	7.3280650	7.4067630	8.1834580	10.187340	22.72176	217.07830
	BAUG	AMSE	13.996242	14.284603	13.876323	13.710904	16.713789	86.037983
		SD	5.4278330	5.5074220	6.0332490	6.8818420	14.336100	146.09550
100	OLS	AMSE	14.556083	14.700013	14.843080	15.427138	15.151237	46.679867
		SD	6.5160240	7.2665730	8.4125600	13.794310	8.5476400	64.188060
	AUG	AMSE	13.876313	14.004678	14.000164	14.150368	13.309965	36.921196
		SD	4.2405400	4.8497520	4.8736360	7.3296310	6.4063430	52.373180
	BOLS	AMSE	15.391516	15.548626	15.803036	16.809931	17.839251	66.637582
		SD	8.8369520	9.5278270	11.061300	18.109460	10.332990	80.034750
	BAUG	AMSE	14.406544	14.533519	14.547233	14.742334	14.407800	48.096726
		SD	5.1332060	5.6666440	5.6933600	8.0492170	6.6390480	53.672420

Table 3.5 A comparison of multiple regression coefficient estimating with lognormal distribution on mean equals to 1 and variance equals to 0.05 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	406.05061	383.58403	7074.5304	258.39107	690.22612	8633.6650
		SD	6969.1230	7523.9980	126078.60	3185.9790	10143.580	95543.060
	AUG	AMSE	406.05061	383.58403	7074.5301	258.39107	690.22615	8633.6647
		SD	6969.1230	7523.9980	126078.60	3185.9790	10143.580	95543.070
	BOLS	AMSE	406.05061	383.58403	7074.5303	258.39107	690.22613	8633.6644
		SD	6969.1230	7523.9980	126078.60	3185.9790	10143.580	95543.050
	BAUG	AMSE	406.05060	383.58403	7074.5294	258.39107	690.22613	8633.6589
		SD	6969.1230	7523.9980	126078.60	3185.9790	10143.580	95543.000
30	OLS	AMSE	3.6397888	3.6842605	3.7784721	3.9360127	4.1947296	7.2374504
		SD	1.5321140	1.2825040	1.0323450	0.8185813	0.7747278	4.0584100
	AUG	AMSE	3.6535295	3.7017228	3.8073258	3.9745000	4.2252667	6.5493455
		SD	1.5280730	1.2791400	1.0341680	0.8204600	0.7559930	3.4675640
	BOLS	AMSE	3.6595815	3.7068276	3.8090956	3.9802154	4.3068258	8.3490582
		SD	1.5390050	1.2894400	1.0417630	0.8306457	0.8149368	4.6111380
	BAUG	AMSE	3.6917627	3.7456746	3.8656376	4.0518580	4.3429549	7.1030341
		SD	1.5337790	1.2857330	1.0439350	0.8312467	0.7594146	3.5456410
50	OLS	AMSE	4.1940840	4.0985461	4.0222673	4.0415282	4.1395058	5.5698205
		SD	1.6465210	1.3057810	0.6248605	0.3448929	0.3059829	1.4980870
	AUG	AMSE	4.1985447	4.1056168	4.0372386	4.0647018	4.1870282	5.2825087
		SD	1.6418420	1.3015280	0.6242472	0.3476806	0.3233002	1.2981520
	BOLS	AMSE	4.2082336	4.1138348	4.0419273	4.0683393	4.2041468	6.2064421
		SD	1.6510300	1.3094380	0.6274495	0.3490354	0.3178932	1.6164630
	BAUG	AMSE	4.2211877	4.1327204	4.0762122	4.1165857	4.2872367	5.6591335
		SD	1.6430180	1.3033140	0.6276277	0.3546191	0.3267262	1.2366510
100	OLS	AMSE	5.5377156	4.9095841	4.2285195	4.0459515	4.0697510	4.7436052
		SD	1.8525530	1.6033410	0.8867956	0.3489242	0.1585920	0.7179368
	AUG	AMSE	5.5373441	4.9109808	4.2337649	4.0553411	4.0963834	4.7275059
		SD	1.8497430	1.6001420	0.8845838	0.3484024	0.1652304	0.6532639
	BOLS	AMSE	5.5466993	4.9186981	4.2388113	4.0595688	4.1017003	5.0518807
		SD	1.8553900	1.6060190	0.8887972	0.3501331	0.1627941	0.7523623
	BAUG	AMSE	5.5492360	4.9244619	4.2519843	4.0809923	4.1571124	4.9909977
		SD	1.8504130	1.6002100	0.8847964	0.3497038	0.1737405	0.5920935

Table 3.6 A comparison of multiple regression coefficient estimating with lognormal distribution on mean equals to 1 and variance equals to 0.30 as 5 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	2560.7815	1757.7902	8340.8101	1743.1813	3194.5626	53167.763
		SD	47920.980	28731.420	98177.180	22896.300	49391.000	607151.60
	AUG	AMSE	2560.7815	1757.7902	8340.8085	1743.1813	3194.5626	53167.762
		SD	47920.980	28731.420	98177.150	22896.300	49391.000	607151.60
	BOLS	AMSE	2560.7815	1757.7902	8340.8100	1743.1813	3194.5626	53167.759
		SD	47920.980	28731.420	98177.180	22896.300	49391.000	607151.50
	BAUG	AMSE	2560.7815	1757.7902	8340.8075	1743.1813	3194.5626	53167.753
		SD	47920.980	28731.420	98177.150	22896.300	49391.000	607151.30
30	OLS	AMSE	5.4280723	5.5064991	5.4104596	5.7101466	7.4107422	35.897109
		SD	3.1297390	3.2514170	2.8138270	3.8376580	10.868010	100.57160
	AUG	AMSE	5.2955464	5.3244644	5.2168618	5.3743335	6.4799413	27.752607
		SD	2.6444600	2.3818670	2.3627440	2.2044450	5.6028900	65.320060
	BOLS	AMSE	5.6421574	5.7550326	5.7434202	6.1489787	8.4663535	46.272129
		SD	3.5751180	3.9451930	3.8217670	4.9831330	13.448180	126.54390
	BAUG	AMSE	5.4530626	5.4890390	5.3993388	5.5867387	6.8477222	32.067075
		SD	2.7395020	2.5010940	2.6195660	2.4800820	5.8065880	69.220990
50	OLS	AMSE	6.5230886	6.2650417	5.7375537	5.4906763	5.9270040	17.796965
		SD	2.4193540	2.3498570	1.9771180	1.6520370	1.7884990	13.992590
	AUG	AMSE	6.4740173	6.2300577	5.6960161	5.4124698	5.6302390	14.419264
		SD	2.3584020	2.2907540	1.8959740	1.5509270	1.4146610	11.513510
	BOLS	AMSE	6.6721759	6.4258008	5.9312884	5.7396170	6.4939290	23.324723
		SD	2.4793870	2.4140350	2.0593910	1.7618050	2.0433990	16.354510
	BAUG	AMSE	6.6166980	6.3816360	5.8622270	5.5853404	5.9319167	17.032187
		SD	2.3875840	2.3238320	1.9261300	1.5674890	1.4095760	11.681640
100	OLS	AMSE	8.0536594	7.6138524	6.5889404	5.9545014	5.4423517	10.925676
		SD	1.7975530	2.0588540	2.2286850	1.9869410	1.3225430	6.5851630
	AUG	AMSE	8.0305456	7.5995339	6.5970500	5.9570942	5.3907837	10.326555
		SD	1.7795910	2.0326020	2.1931110	1.9458930	1.2581540	6.3667250
	BOLS	AMSE	8.1509002	7.7167603	6.7051554	6.0977859	5.7351891	13.632379
		SD	1.8230520	2.0892110	2.2707680	2.0339570	1.4079540	7.1663730
	BAUG	AMSE	8.1394732	7.7202881	6.7339825	6.1038859	5.6064372	11.869219
		SD	1.7973260	2.0532630	2.2143870	1.9645530	1.2652800	5.8300450

Table 3.7 A comparison of multiple regression coefficient estimating with lognormal distribution on mean equals to 1 and variance equals to 0.70 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	7984.5786	6538.2695	20198.793	5631.7350	15753.380	157217.16
		SD	151971.40	92094.660	209050.20	69459.700	296928.40	1766226.0
	AUG	AMSE	7984.5786	6538.2695	20198.793	5631.7350	15753.380	157217.16
		SD	151971.40	92094.660	209050.20	69459.700	296928.40	1766226.0
	BOLS	AMSE	7984.5786	6538.2695	20198.793	5631.7350	15753.380	157217.15
		SD	151971.40	92094.660	209050.20	69459.700	296928.40	1766225.0
	BAUG	AMSE	7984.5786	6538.2695	20198.773	5631.7350	15753.380	157217.11
		SD	151971.40	92094.660	209050.00	69459.700	296928.40	1766224.0
30	OLS	AMSE	11.543971	12.100911	11.502080	15.606848	30.933658	245.95276
		SD	42.492570	52.537330	30.697790	100.18250	304.74400	2752.1940
	AUG	AMSE	9.5347982	9.4657089	9.3295424	11.465551	19.828004	171.41787
		SD	19.602590	18.166900	16.532880	48.733370	143.02090	1756.2750
	BOLS	AMSE	13.258408	14.189652	14.564967	18.889924	38.394309	318.83361
		SD	59.928770	76.923130	69.351940	133.99690	376.90190	3475.9990
	BAUG	AMSE	10.155508	10.214128	10.535711	12.195442	21.348787	193.41876
		SD	24.269720	26.129010	33.644140	53.466840	146.78810	1846.6920
50	OLS	AMSE	10.592354	10.357516	10.170425	10.498997	12.027173	59.948209
		SD	4.0732290	4.2735080	4.7886720	5.7746200	9.3480700	77.778190
	AUG	AMSE	9.9800898	9.6825678	9.2936769	9.3334681	10.041108	45.924552
		SD	3.5689920	3.6954330	3.8987920	4.4896390	7.2282860	65.216060
	BOLS	AMSE	11.329729	11.155859	11.152285	11.763895	14.577061	83.201496
		SD	4.5368190	4.7730900	5.4788390	6.7705770	11.582000	98.042950
	BAUG	AMSE	10.370130	10.065669	9.6930006	9.7733033	11.040814	57.049806
		SD	3.7134950	3.8146440	4.0363750	4.5375160	7.3709110	71.509970
100	OLS	AMSE	11.537866	11.343778	10.814493	10.909543	10.455488	31.971344
		SD	2.1920060	2.5779400	3.3072070	3.8196320	5.1723020	31.445190
	AUG	AMSE	11.261641	11.036639	10.422593	10.328995	9.5457900	28.652692
		SD	2.0178410	2.3483570	2.9799720	3.3631150	4.4151140	30.113600
	BOLS	AMSE	11.991675	11.838707	11.411659	11.704724	11.930077	43.506216
		SD	2.3758500	2.7772380	3.5756710	4.1883460	5.9648740	36.310540
	BAUG	AMSE	11.564509	11.343925	10.734061	10.666018	10.112021	35.566826
		SD	2.0820410	2.4052410	3.0339340	3.4002870	4.4648980	29.676530

Table 3.8 A comparison of multiple regression coefficient estimating with lognormal distribution on mean equals to 1 and variance equals to 1.00 as 3 independent variables.

n	Est	Value	Various degree of correlation					
			0.1	0.3	0.5	0.7	0.9	0.99
10	OLS	AMSE	14813.072	13327.549	42254.996	10619.408	38285.004	277347.67
		SD	281296.40	200450.80	514226.10	124651.20	760245.90	3025007.0
	AUG	AMSE	14813.072	13327.549	42254.995	10619.408	38285.004	277347.67
		SD	281296.40	200450.80	514226.10	124651.20	760245.90	3025007.0
	BOLS	AMSE	14813.072	13327.549	42254.995	10619.408	38285.004	277347.65
		SD	281296.40	200450.80	514226.10	124651.20	760245.90	3025006.0
	BAUG	AMSE	14813.072	13327.549	42255.003	10619.408	38285.004	277347.54
		SD	281296.40	200450.80	514226.20	124651.20	760245.90	3025004.0
30	OLS	AMSE	28.478511	31.735886	27.064424	52.932994	133.41341	1180.2037
		SD	289.58220	356.07260	194.36000	730.76870	2179.6020	19625.030
	AUG	AMSE	18.742673	18.411858	18.589150	31.959390	71.937792	792.89459
		SD	131.05640	123.06750	102.63580	375.91710	1035.6420	12813.390
	BOLS	AMSE	36.409361	42.034722	43.075161	68.279520	167.18689	1513.5778
		SD	414.43260	530.51350	473.91940	970.03030	2691.5510	24749.730
	BAUG	AMSE	21.128037	21.884135	25.268200	34.240290	76.637897	866.72978
		SD	164.35760	181.85830	230.11200	395.43810	1055.0090	13477.650
50	OLS	AMSE	15.416059	15.342990	15.994798	17.461247	23.195704	130.85262
		SD	7.4894520	8.0755010	10.362980	16.048180	27.979260	229.39170
	AUG	AMSE	13.661035	13.394976	13.446560	14.258270	18.109530	97.757999
		SD	5.7879830	6.0178590	7.1289040	11.243740	23.933530	181.52790
	BOLS	AMSE	17.233026	17.305011	18.452033	20.597389	29.615431	185.52774
		SD	9.0249310	9.7073390	12.615070	19.164120	35.341770	297.31950
	BAUG	AMSE	14.464966	14.171965	14.246119	15.119754	20.419858	123.98251
		SD	6.2551570	6.3789290	7.4084590	11.072760	23.549350	201.04970
100	OLS	AMSE	15.340031	15.335393	15.544843	16.070363	18.584970	66.882792
		SD	3.9857210	4.4500930	5.4257180	6.8589710	12.627540	79.980960
	AUG	AMSE	14.457564	14.326262	14.189358	14.312258	15.957857	60.916487
		SD	3.2617410	3.5545060	4.1575880	5.3529110	10.278040	100.27080
	BOLS	AMSE	16.425476	16.529200	17.028234	18.024296	22.536925	94.198946
		SD	4.6269370	5.1310500	6.2943290	8.0204350	15.305430	97.189480
	BAUG	AMSE	15.011679	14.887239	14.759737	14.925785	17.319622	78.135782
		SD	3.4403550	3.6913980	4.2530550	5.3925130	10.441150	102.74120

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