

**MODELING SEEMINGLY UNRELATED REGRESSION
(SUR) EQUATIONS WITH HETEROSCEDASTIC ERROR
AND NON-NORMAL RESPONSES**

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ABSTRACT

The Feasible Generalized Least Square (FGLS) estimator for Seemingly Unrelated Regression (SUR) models is generally efficient when the errors between equations are highly correlated and each equation satisfies all the assumptions of classical linear regression equation. However, the multivariate normal assumption on response variables in SUR model are most often not satisfied in many applications. The aim of the study was to investigate some estimators of SUR equations with heteroscedastic error and non-normal responses. The objectives of the study were to: (i) examine the performances of some estimators under different forms of heteroscedasticity with non-normal responses; (ii) determine the finite and asymptotic sample properties of SUR estimators under different forms of heteroscedasticity and non-normal response; and (iii) identify the efficient estimator of SUR model under different violations.

The Monte Carlo simulation experiment was carried out to generate the data for SUR model. Three distributions namely; Normal, Gamma and Log-Normal were considered for the response, four forms of heteroscedasticity were formulated as: Linear (LN), Quadratic (Quad), Square Root (SQRT) and Exponential (EXP)) and levels of contemporaneous correlation (C_c) were specified as: 0.0, 0.2, 0.5, 0.7 and 0.95. Four estimators; Ordinary Least Squares (OLS), Feasible Generalized Least Square (FGLS), M-Huber (Huber) and MM- Bi-Square (BISQ) were used to estimate the parameters of the models using the simulated data. Root Mean Square error (RMSE), variance and Absolute Bias (AB) criteria were used to assess the relative performances of the estimators under different conditions.

The findings of the study were that:

- (i) the performances of estimators depend on the degree of contemporaneous correlation (C_c), form of heteroscedasticity, distribution of the response and sample sizes;
- (ii) when there is absence or low contemporaneous correlation ($\rho \leq 0.2$) with small sample sizes ($n \leq 30$), OLS is the best estimator for normal response model except under Quadratic heteroscedasticity where Huber estimator was preferred;
- (iii) with moderate or high C_c ($\rho \geq 0.5$) irrespective of the form of heteroscedasticity the FGLS outperformed all other estimators for all sample sizes considered under normal responses model;
- (iv) when there is low or absence of C_c ($\rho \leq 0.2$) irrespective of the heteroscedastic structure and sample sizes, the model parameters are best estimated by BISQ under Gamma or Log-Normal responses model;
- (v) FGLS is the most efficient estimator for heteroscedastic Gamma response SUR model when C_c is moderate or high ($\rho \geq 0.5$) except in small sample under EXP heteroscedasticity where BISQ is preferred; and
- (vi) BISQ estimator is the most efficient in medium ($n=50$ or 100) and large sample sizes ($n=250$ or 500) for heteroscedastic lognormal SUR model with moderate or high C_c ($\rho \geq 0.5$) while FGLS is preferred in small samples under different forms of heteroscedasticity except Quadratic where BISQ is preferred.

The study concluded that the degrees of Cc and distribution of response variables are key determinants in modeling SUR equations with heteroscedastic non-normal responses. The study therefore recommended that BISQ estimator should be used in estimating parameter of SUR model with non-normal responses.

DEDICATION

This thesis is dedicated to my caring and loving friend and sweetheart, Mrs. Aisha Jummai Afolayan and my adorable Daughters; Hikmat, Nima't and Fareeha Afolayan.

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CERTIFICATION

This is to certify that this thesis is an original work carried out by RAZAQ BAYO AFOLAYAN with matriculation number 98/55EG082 in the Department of Statistics, Faculty of Physical Sciences, University of Ilorin. The thesis has been read and approved as fully meeting the requirements for the award of Doctor of Philosophy in Statistics of the University of Ilorin, Nigeria.

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CHAPTER ONE

GENERAL INTRODUCTION

1.0 Introduction

Seemingly Unrelated Regression (SUR) Equations is a system of M multiple regression equations in which each equation has a single dependent and K ($k \geq 1$), independent or exogenous variables as in standard regression model. The m equations have no link or relationship with one another except that their disturbances are said to be correlated.

Zellner (1962) introduced the SUR estimation procedure for systems of regression equation as against the general estimation method of ordinary least square (OLS) estimator. Prior to the introduction of SUR estimation procedure, OLS has been the traditional way of estimating the coefficient of the parameters of regression model. The OLS is a single-equation method of estimation that does not account for the interactions that may exist among the different regression equations. The OLS is unbiased, consistent and remain the most efficient estimator when all the assumptions of classical linear regression model are satisfied. The single by single equation estimation of SUR model without using the information from error terms across equations by OLS is still unbiased and consistent but seizes to be the best linear unbiased estimator (BLUE).

In view of this, the inferences taking about the parameters of the model using the statistic from OLS estimator become invalid. Zellner (1962) viewed that the disturbance terms of these equations are likely to be contemporaneously correlated because of unobservable factors that influence the disturbance term in one equation may affect the disturbance terms in other equations. Estimating these equations separately without accounting for the non-zero covariance structure of the errors leads to inefficient parameter estimates.

However, the joint estimation procedure of SUR using the information from the correlation among the errors of different equations is more efficient than the separate equation estimation procedure of the ordinary least square (OLS) and the gain in efficiency is achieved if contemporaneous correlation between the disturbances across equation is very high and other assumptions of classical regression model are satisfied, see (Judge et al 1988; Zellner, 1962&1963; Zellner & Theil, 1962).

1.1 The Classical Linear Regression Model and its Assumptions

1.1.1 The Classical Linear Regression

The linear regression model is a statistical technique used to measure the relationship between a response (dependent) variable and a set of explanatory (independent) variables. A regression model is said to be linear if the model is linear in regression parameters. In other word, linear regression model describe the relationship between the mean of the response variable and a set of independent variables assuming linearity in regression parameter, as well as normality of the response variable.

The general linear regression model is of the form:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \varepsilon_i ; i = 1, 2, \dots, n \quad (1.1)$$

Where y_i is the i^{th} value of the response variable, $x_1, x_2, \dots, x_k$ are the k explanatory variables, $\beta_0, \beta_1, \dots, \beta_k$ are the unknown parameters to be estimated and ε_i is the i^{th} random error (disturbance) term.

The equation (1.1) above could be written in matrix form as:

$$\begin{matrix} Y \\ n \times 1 \end{matrix} = \begin{matrix} X \\ n \times p \end{matrix} \begin{matrix} \beta \\ p \times 1 \end{matrix} + \begin{matrix} \varepsilon \\ n \times 1 \end{matrix}; p = k+1 \quad (1.2)$$

Where $\mathbf{Y}=(y_1, \dots, y_n)^T$ is the n observations from the response variable , $\mathbf{X}$ is the matrix consists of column of ones plus k columns containing values of explanatory variables for the n observations, $\boldsymbol{\beta}=(\beta_1, \dots, \beta_p)^T$ is the vector of model parameters and $\boldsymbol{\epsilon} = (e_1, \dots, e_n)^T$ is the random error terms.

1.1.2 Assumption of Classical Linear Regression Model

The classical linear regression model assumptions are classified according to the variables and terms in the model:

1.1.3 Assumption about the Error Terms

1. The error $(e_1, \dots, e_n)$ term is a random variable with mean equal to zero.

$$\text{i.e., } E(\epsilon_i) = 0$$

2. The error terms has unknown but constant variance σ^2 . this assumption is called homoscedasticity of error variance. However, non-constant of error variance is termed heteroscedasticity.

$$\text{i.e., } E(\epsilon_i \epsilon_j) = \begin{cases} \sigma^2 I_n & \text{for } i = j \\ 0 & \text{for } i \neq j \end{cases}$$

3. The errors are normally, independently and identically distributed.

$$\text{i.e., } \epsilon_i \sim NID(0, \sigma^2 I_n)$$

1.1.4 ASSUMPTION ABOUT THE EXPLANATORY VARIABLES

1. The values of explanatory variables X are measured without error.
2. The values of the X variables are selected in advance or fixed.

3. The X variables are linearly independent of each other. In other word, the X variables are uncorrelated, hence the determinant of matrix X^1X exist.

1.1.5 Assumption about the Response Variable

1. The model that relates the response variable to explanatory variables is linear in regression parameters (Linearity assumption).
2. The response variable is a random variable that is normally distributed with mean $X^1\beta$ and variance, σ^2 . i.e. , $y_i \sim N(X^1\beta, \sigma^2)$

1.3 Consequences of Violation of Model Assumptions

1.3.1 Heteroscedasticity

In classical linear regression, an important assumption is homoscedasticity of the error terms. Homoscedasticity means that each of the error term has the same variance. When this assumption is violated then there is a heteroscedasticity problem. In this case each observed value of the independent variables is viewed as being drawn from different distribution with different variance. Under a general linear regression mode of the form;

$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p + \varepsilon_i$, where Y_i is n x 1 vector of dependent variable, $\beta = (\beta_0, \beta_1, \beta_2, \dots, \beta_k)$ is p vector of regression parameters, X_i is a n x1 vector of k independent variables and ε_i is a vector of disturbances(error term) which is assumed to be normally, independently and identically distributed.

$E(\varepsilon_i/X) = 0$, that is ε_i has mean zero .The specification of disturbance variance matrix under both homoscedasticity and heteroscedasticity are given as;

$$E(\varepsilon\varepsilon^1) = \sigma^2 \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 1 & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} = \sigma^2 I \xrightarrow{\text{homoscedastic error}} \quad (2.2)$$

However, under heteroscedastic error terms the $E(\varepsilon\varepsilon^1) = \sigma_i^2$ and the variance–covariance matrix no longer assume a scalar matrix as in the homoscedastic error case. The Variance-Covariance matrix is then given as:

$$E(\varepsilon^1\varepsilon) = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & \sigma_n^2 \end{bmatrix} = \sigma^2 \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix} = \sigma^2 \lambda_i = \Sigma \quad (2.3)$$

$\xrightarrow{\text{heteroscedastic error}}$

In the presence of heteroscedastic error terms, the OLS estimator of unknown model parameters is still unbiased and consistent but ceases to be efficient. The OLS covariance matrix estimate is inconsistent; hence the usual t and F test no longer assume the usual distribution even at large sample sizes under the null hypothesis that it claims to test (see Green (2003)).

1.3 Justification for the Study

The notion that each separate equation satisfies the classical assumptions of the Standard Regression (CASR) model is not generally met in most practical situations.

Generally, the econometricians and Statisticians assume that disturbance term, which is an influence of innumerable many factors not accounted for in the model approaches normality according to the central limit theorem. But Bartels (1977) is of the opinion that there are limit theorems, which are just likely to be relevant when considering the sum of number of

components in regression disturbance that leads to non-normal stable distribution characterized by infinite variance. Thus the possibility of the error term following a non-normal distribution exists (Mandelbrot 1963). Furthermore, the homoscedasticity assumption of linear regression that is sometime violated in single-equation model cannot be ruled out in SUR model. When this assumption is violated, the error is said to be heteroscedastic, a condition known as heteroscedasticity.

However, heteroscedasticity arises in many applications, in cross-sectional, time-series and panel data. Most often in cross-sectional data, for instance, suppose that we wish to model the consumption Pattern/Demand equations for household of different ethnicity for a particular commodity. We expect to observe greater variation in the consumption pattern on certain commodity among high-income household than low income household because of the high discretion that high-income household have to changes in price (Green 2003). The variation also differs from one ethnic to the other depending on distribution of wealth. In applied agricultural science, the tendency of the yield distribution of some farm produce to be non-normal, left-skewed or heteroscedastic as a result of adverse weather conditions and because of biophysical and technological limitations on the maximum yields attainable during any given year was emphasized by Ramirez (1997) and the references cited therein.

The violation of each assumption has attracted the attention of many researchers especially in single regression model but the violation of homoscedasticity and /or normality in system of regression model has not been adequately exploited. When errors are non-normal and variances are non-constant, the consequences of SURE or OLS based statistics can be disastrous than when either assumption is independently violated. More so, since many real life data do not satisfy the normality assumption there is need for further investigation on the estimation methods that fit non-normal regression model with different error variance structures.

1.4 Aim and Objectives of the Study

The aim of this research work is to investigate the performance of some estimators of SUR model with heteroscedastic error and non-normal responses. The specific objectives of the study are to:

1. examine the performances of some estimators under different forms of heteroscedasticity with non-normal responses;
2. determine the finite and asymptotic sample properties of SUR estimators under different forms of heteroscedasticity and non-normal response;
3. identify the efficient estimator of SUR model under different violations; and
4. validate the simulation results using real life data set.

1.5 Scope of the study

The performances of some methods of estimating SUR models with Non-normal responses under different forms of heteroscedasticity and levels of contemporaneous correlation between the error terms in different equations were compared. The data were generated using Monte Carlo simulation for two equations with two independent variables each. Three (Normal, Log-Normal and Gamma) distributions were generated for response variable, four forms of heteroscedasticity (Exponential, Linear, Square root and Quadratic) were formulated and Five levels of contemporaneous correlation($\rho = 0.0, 0.2, 0.5, 0.7$ and 0.95) for the error terms were used.

The following estimators were considered:

- i. Ordinary Least Squares (OLS) Estimator.
- ii. Feasible generalized Least Squares (FGLS).
- iii. MM-Turkey-bi squares Estimator (BISQ).

- iv. M-Huber Estimator (HUB).

The performances of the estimators were assessed using Root Mean Squares Error (RMSE), Absolute bias (ABS) and Variance criteria.

1.6 Organization of the Study

The research work is subdivided into five chapters. General introduction, aim and objectives are presented in chapter one. Chapter two deals with review of relevant literature while chapter three focuses on methodology and procedures of Monte Carlo experiment. The results obtained from Monte Carlo experiment in chapter three are discussed in chapter four. Chapter five gives the summary of findings, conclusion and recommendations.

1.7 Notation, Abbreviation and Terminology

SUR : Seemingly Unrelated Regression

CASR: Classical Assumption of Standard Regression

OLS: Ordinary Least Squares

FGLS: Feasible Generalized least Squares

BISQ: MM-Turkey Bi-Squares Estimator

HUB: M-Huber Estimator

RMSE: Mean Squares Error

ABS : Absolute Bias

CHAPTER TWO

REVIEW OF LITERATURE

2.1 Introduction

SUR Model is found to be related to many statistical models, for instance, when the errors from different equations are uncorrelated the model reduced to a collection of separate multiple regression equation which can be estimated separately by OLS estimator. SUR model can also be viewed as a special case of simultaneous equation model involving M dependent variables with p distinct exogenous variable or an unrestricted reduced form of Simultaneous equations model in which all its independent variables are purely exogenous. Above all, SUR model is also related to multivariate regression model which has a wider application in the statistical literature. All the analysis of these models relies on some assumptions which if not met could lead to bias of estimates and consequently invalid inference. So the literature review is presented according to the violation of the Normality and homoscedasticity assumptions in the model. We also discuss some of the estimation procedures in linear regression model in the presence of heteroscedasticity, including the robust estimators.

2.2 Review of Related Work on Seemingly Unrelated Regression Model

After the Proposed Aitken's Generalized Least Squares (AGLS) estimator by Zellner (1962), much extensive theoretical and empirical applications of the work have been recorded in econometrics, statistics and other areas in recent time. For instance, finite sample properties of SUR estimator (SURE) have been studied in the literature (e.g. Zellner, 1962 & 1963; Kakawani, 1967, Zellner & Huang, 1962; Zellner & Theil, 1962) by asymptotic expansions (e.g. Srivastava and Maekawa, 1995), or by simulation (e.g. Kmenta & Gilbert, 1968). Several other researchers also work on SUR model under the violation of basic model assumptions in

different data generating processes, such as time series, Panel, Cross-sectional etc. For example, Kmenta and Gilbert (1970), considered the problem of estimating a system of regression equations in which the disturbances are both serially and contemporaneously correlated. They developed an estimator that is consistent and efficient than SURE in situation in which each of the disturbance follows a first order auto regressive scheme. Other works within the SUR frame-work with autocorrelated disturbances and error component can be found in (Guilkey and Schmidt (1973); Avery (1977);Walter Kramer (1980); Baltagi (1980); Egger (2001); Messemer and parks (2004)).

Takada et al (1995), presented methods of resolving the problem of non-singularity in the covariance matrix of the errors in the SUR model and proposed an efficient procedure of estimation. The empirical study of the estimator was investigated by studying the diffusion processes of video cassette recorders across different geographic regions in the US, which exhibits a singular covariance matrix. The empirical results show that the procedure is efficient in tackling the problem and provide plausible estimation results.

The efficiency of SUR model when exogenous variables across-equations are correlated was investigated by Yahya et al (2008). In their work, it was established that at large sample size ($n \geq 50$), the SURE would still be efficient if correlation exists among the exogenous variable in SUR model.

However, under small and moderate sample sizes, they recommended a Tolerable non-orthogonal correlation point (TNCP) of ± 0.2 under which SUR estimator would still be efficient.

SUR model also gained an appreciable application in econometrics and applied sciences:

Sparks (2004) developed a SUR procedure that is applicable to environmental situations especially when missing and censored data are inevitable.

In actuarial science, Singh and Ullah (1974) extended Zellner's (1962) SUR model to credibility regression model with random coefficient and proposed estimators that are asymptotically more efficient than Zellner's estimator (see also Pistelis (2001)). In share equation systems with random coefficient, Mandy & Martins-Filho (1993) proposed a consistent and asymptotically efficient estimator for SUR systems that have additive heteroscedastic contemporaneous correlation. They followed Amemiya (1977) by using Generalized Least Squares (GLS) to estimate the parameter of the covariance matrix.

Also O'Donnell et al (1999) and wilde et al (1999) developed SUR estimators that are applicable in agricultural economics. Recently, Cadavez and Henningsen (2012) found out that SUR estimator performed better than the OLS estimator in predicting the carcass composition of lambs. Percy (1992) studied the problem of prediction of SUR model from Bayesian perspective; using Jeffrey's invariant prior Percy obtained the posterior density function of post sample observations through Gibbs Sampling procedure. More recently, Lang, Adebayo & Fahrmeir (2002), Adebayo (2003), and Lang et al (2003) in their works also extended the usual parametric SUR model to semi-parametric SUR and Geo-additive SUR model within a Bayesian context. Also Foschi (2004), Foschi et al (2003) and Foschi & Kontoghiorghes (2002, 2003) provided some new numerical procedures that could successively and efficiently solve a large scale of SUR model.

Other works within the SUR frame-work could be found in Rose & Lynch (2001), Carroll et al (2006), Conniffe (1984), Prucha (1984), Binkley & Nelson (1988), Dwivedi & Srivastava (1978), Maeshiro (1980), Ravankar (1974, 1976), Kakwani (1967), Telsor (1964), Mehta & Swamy (1976), Gallant (1975), McElroy (1977).

2.3 Violation of Heteroscedasticity with other Assumptions

Heteroscedastic regression models in which the variance of the disturbance term is assumed to be proportional to one of the regressors raised to a certain power have been considered by a number of authors, including Geary(1996), Goldfeld and Quandt(1967), Kmenta, Lancaster and Park(1966). The variance of the disturbance term is assumed to be of the form:

$$\sigma_i^2 = \sigma^2 X_i^\lambda$$

Where X_i is n vectors of observation on independent variables and λ is constant denoting the degrees of heteroscedasticity. Park (1966) proposed a two stage estimation procedure that estimated the variance σ^2 and the λ in the first stage, the estimated values of σ^2 and λ are used in the second stage to estimate the weight and weighted least squares (EWLS) estimates of the coefficient in the actual regression equation. Park (1966) work was extended by Harvey (1976) by assuming a multiplicative Heteroscedastic error in which the variance of the disturbances may not necessarily be related to the explanatory variables in the model. He used Maximum Likelihood estimation procedure to estimate simultaneously the model parameters as well as the heteroscedastic parameters under the assumption that the error terms in the model are normally distributed. The estimator was found to be efficient when the disturbances are normally distributed and the variance of error term is known to be of the form;

$$\sigma_i^2 = e^{z_i^1 \beta}$$

Where z_i is a p x1 vector of observation which may or may not be related to regressor variables and β is a p x1 vector of parameters.

Lewis and Linzer (2004) observed that heteroscedasticity may be introduced in regression equation when dependent variable is based on estimates or aggregates. He opined that if the sampling error that generate the estimates or aggregate in the dependent variable is not constant across observation, the regression error will be heteroscedastic. He however, assumed that regression residual could be divided into sampling and Non sampling errors. The performance of three estimators: Ordinary Least Squares (OLS), Weighted Least Squares (WLS) and Feasible Generalized Least Squares (FGLS) were compared through Monte Carlo experiment. The study reveals that when sampling error component is small relative to the total variation in the dependent variable and when the sampling error does not vary greatly from observation to observation, OLS with Huber – White Standard error (HC0), and Efron Standard errors (HC3) for small samples yield good results. However, if the sampling error comprises of a large share of the variation in the response variable and it varies greatly across observation, FGLS is more efficient than OLS and WLS. The relative gain of FGLS to OLS is about 10% in small sample and even greater in large sample sizes. WLS standard error estimates are misleading and even worse than OLS estimates.

Ayinde and Ipinyomi (2006) investigated the effect of correlation between the error terms and equation identification problem on estimators of a system of simultaneous equations model. They employed Monte Carlo approach using two equations with one exactly identified and the other over identified. The level of correlation between error terms were specified as: $\lambda=0.3, 0.6$, and 0.9 at three sample sizes, $n= 20, 50$ and 100 . Six estimators (OLS, LIMLE, ILS, FIMLE2SLS and 3SLS) were examined under different conditions .

The performance of each estimator was examined using the following criteria: Bias, Absolute Bias, Variance and RMSE.

Johnson et al (2010) extended the work by Ayinde et. al (2006) by examined the effect of multicollinearity, Correlation between error terms and status of Identification of equations on some estimation methods in simultaneous equations model using Monte Carlo approach. Their study considered two equations Model, with one equation exactly identified and the other over identified.

The following estimation methods were compared; Ordinary Least Squares (OLS), Indirect Least Squares (ILS), Limited Information Maximum Likelihood (LIML), Two Stage Least Squares (2SLS), Full-Information Maximum Likelihood (FIML) and Three Stage Least Squares (3SLS).

Four levels of multicollinearity among the exogenous variables (ρ) and three levels of correlation between error terms (λ) were considered respectively as; $\rho = 0.3, 0.6, 0.8, 0.9, 0.99$ and $\lambda = 0.3, 0.6, 0.9$. The experiments were run in 250 replicate at three sample sizes (20, 50 and 100).

Their results show that the OLS estimator is best in estimating the parameters of the exactly identified equation at severe level of multicollinearity ($\rho \rightarrow 1$) at all sample sizes. At other levels of multicollinearity, the best estimator is FIML or 3SLS except when the correlation between error terms is low ($\lambda = 0.3$). At this instance, the best estimators are LIML and 2SLS. The parameters of over Identification model are best estimated with FIML or 3SLS at all levels of Multicollinearity, Correlation between error terms and sample sizes.

Habshah et al (2013) examined the performance of Two-stage robust weighted Least Squares (TSRWLS) estimator in heteroscedastic multiple regression model in the presence of outlier. The TSWLS procedure is related to M- estimation method except that the initial estimate of the residuals is obtained using Least Trimmed of Squares (LTS) instead of OLS in the estimation procedure of Huber robust estimator. These were investigated extensively using

Monte Carlo Simulation. In their study they employed a multiple linear regression model of the form:

$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \sigma_i \varepsilon_i$, $i = 1, 2, \dots, n$; where $\varepsilon_i \sim N(0,1)$ and Exponential heteroscedastic structure of the form $\sigma^2_i = \sigma^2 \exp(ax_{1i} + ax_{2i}^2)$ with $\sigma^2 = 1$ and $a=0.4$ or 0.8 . The regression coefficient are fixed as; $\beta_0 = \beta_1 = \beta_2 = 1$

In order to introduce outlier in the model, the errors were generated from contaminated Normal distribution using Cauchy distribution as; $\varepsilon_i \sim \alpha N(0,1) + (1-\alpha) \text{Cauchy}(0, 10)$, where α is the percentage of outlier in the model. Relative RMSE and relative bias were used to determine the best estimator. The study observed that when the error term is Homoscedastic with no outlier all the three estimators were fairly close in term of relative biases. However, the performance of OLS and KNN reduces with an increase in the percentage of outlier and produced poor estimates when errors are heteroscedastic. Habshah Midi et al noted that irrespective of the percentages of outliers TSRWLS maintained lower bias and smallest RMSE and does not break down before 50% contamination.

Olanrewaju (2013) noted that one of the problems of time series data is autocorrelation of the error terms and extended the work of Yahay et al(2008) to situations where disturbances in different equations follow a first order autocorrelation. The effect of multicollinearity, autocorrelation and correlation between the errors terms on some methods of estimation of system of simultaneous equation were investigated through Monte Carlo experiment. He implored seemingly unrelated regression model and assumed first order autocorrelation of the error term. The performances of Ordinary Least Squares (OLS), Three Stage Least Squares (3SLS), Feasible Generalized Least Squares (FGLS), Maximum Likelihood (ML), Full Information Maximum Likelihood (FML) and Multivariate Regression (MR) were investigated extensively at different levels of multicollinearity, autocorrelation and

correlation between the error terms. The results of the study shows that ML estimator is preferred when there is presence of autocorrelation and multicollinearity in the model. However, when there is correlation between the error term SUR and 3SLS should be preferred.

Alabi and Oyejola (2015), Opined that most economic variables do not take negative values and as such assuming normal distribution for the exogenous variables in economic model is unrealistic. In addition to the problems of multicollinearity and identification status, they considered situation where the exogenous variables in simultaneous Equation model is uniformly distributed. The performances of four estimators; Ordinary Least Squares (OLS), Two Stage Least Squares (2SLS), Three Stage Least Squares (3SLS) and Full Information Maximum Likelihood (FIML), were examined using Monte Carlo simulation. Four structural equation models were formed such that the first and third are exactly identified while the second and fourth are over identified. The levels of correlation between the exogenous variables and error terms were specified respectively as $\rho = 0.3, 0.6, 0.8, 0.9, 0.99$ and $\lambda = 0.3, 0.6, 0.9, \text{ and } 0.99$. Their Monte Carlo experiments were run 5000 times at different sample sizes ($n=10, 20, 30, 50, 100, 250$ and 500).

Their study revealed that under uniformly distributed exogenous variables with exactly identified equation, OLS is the best estimator at various sample sizes considered. Meanwhile under over identified equation, 2SLS is best in low and medium sample sizes while 3SLS is best in large sample. However, when the exogenous variables are normally distributed, in small sample with both exact and over identified equations OLS is the best estimator while in large sample 2SLS\3SLS and FIML performance is equivalent.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Introduction

3.1 Monte Carlo Simulation

Monte Carlo is a statistical tool or technique used for executing and evaluating problems express in mathematical model. The method uses a set of random numbers of various sizes generated from a specified probability distribution as input variables with fixed model parameters. The probability distributions are chosen such that the random numbers generated matches the data that best represent the phenomena we wish to evaluate. The method is commonly used for models that are complex, non-linear, or involves many uncertain parameters.

Monte Carlo simulation is a powerful tool that has been applied to diverse of problems ranging from neutron diffusion problem in atomic bomb to traffic, forecasting and others.

The term Monte Carlo was named after the city of Monte Carlo in Monaco, which is known for gambling such as roulette, dice, and slot machines, by Ulam and Nicholas Metropolis (Hoffman, 1998; Metropolis and Ulam, 1949).

In contrast to the physical experiment, Monte Carlo simulation performs random sampling and conducts a large number of experiments on computer to mimic real life problems. The statistical characteristics of the outcome of the experiments are observed and conclusion on the model output is drawn in reference to the properties of the true model parameters.

In econometric, the asymptotic properties of an estimator are known theoretically but needs to be proved analytically. The Monte Carlo approach has been found useful in evaluating the finite and asymptotic properties of various estimators. The approach is more appealing in this

area because the true values of the parameters in our model is unknown, and couple with the fact that the real life observation on economic variables are in most cases do not satisfies the economic model assumptions. Monte Carlo simulation allows the researcher to fix the model parameters and the generation of data set that are in conformity with the real life situations and, therefore the data generated can be regarded as data obtained from controlled laboratory experiment.

The following steps are required in the Monte Carlo simulation process:

1. The researcher specifies a model and assign a numeric values for model parameters.

$$Y = f(x)$$

2. Generate a set of random inputs from assumed probability distribution for the independent variables ($x_1, x_2, \dots, x_k$) in accordance with model specification.
3. Generate random inputs for the error terms from the distribution specifies for the error terms.
4. Obtain values for the response or dependent variable using the specified values of model parameters, values for set of independent variable and the error terms.

Repeat steps 2-4, N times; $N > 0$. Obtain the estimates of the model parameters for each replication using several estimation procedures. Analyze the results using summary statistics, graphs and some estimation properties.

3.2. Feasible Generalized Least Squares and Ordinary Least Squares

Estimation in (SUR) Model

The SUR model is given by

$$Y_i = X_i \beta_i + \varepsilon_i \quad i = 1, \dots, M \quad (3.0)$$

Where Y_i is $n \times 1$ vector denoting observations for the i equation and X_i is a $n \times k$ matrix of non-stochastic regressors, β_i is a $k \times 1$ vector of parameter and $n \times 1$ vector of disturbances ε_i .

The equation (3.0) could be written compactly as;

$$Y = X\beta + \varepsilon \quad (3.1)$$

And in matrix form as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & \cdots & 0 \\ 0 & X_2 & \cdots & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \cdots & X_m \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_m \end{bmatrix} \quad (3.2)$$

$$mn \times 1 \quad mn \times \sum_{i=1}^m K_i \quad \sum_{i=1}^m k_i \times 1 \quad mn \times 1$$

The assumption regarding the disturbances in equation (3.0) is that the disturbances are contemporaneously correlated with mean, $E(\varepsilon) = 0$ and variance-covariance of the disturbances given as Ω is $E(\varepsilon\varepsilon') = \text{Var}(\varepsilon) = \Omega = \Sigma \otimes I$ where $\otimes$ is the Kronecker product operator, I is an identity matrix of order $N \times N$ and $\Sigma = ((\sigma_{ij}))$ is an $M \times M$ symmetric and positive definite matrix such that:

$$E(\varepsilon_i \varepsilon'_j) = \begin{cases} \sigma_{ii} I & \text{for } i = j, \\ \sigma_{ij} I & \text{for } i \neq j, \end{cases} \quad \begin{matrix} j = 1, \dots, m \\ i = 1, \dots, m \end{matrix} \quad (3.3)$$

where Ω is an $m \times m$ matrix of the form:

$$E(\varepsilon_i \varepsilon'_j) = \text{var.}(\varepsilon_i) = \Omega = \begin{pmatrix} \sigma_{11} I & \sigma_{12} I & \cdots & \sigma_{1m} I \\ \sigma_{21} I & \sigma_{22} I & \cdots & \sigma_{2m} I \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m1} I & \sigma_{m2} I & \cdots & \sigma_{mm} I \end{pmatrix} \quad (3.4)$$

Estimating $k \times 1$ vector of parameters in the equation (3.1) is equivalent to applying OLS to each equation since the covariance matrix is no longer scalar of the form $\sigma^2 I$. The ordinary least-squares (OLS) estimator of β for separate equation in equation (3.1) is given as

$$\hat{\beta} = (X'X)^{-1}X'y \quad (3.5)$$

The OLS estimator of equation (3.1) is unbiased and consistent but less efficient

And its variance-covariance matrix is

$$V(\hat{\beta}) = (X'X)^{-1}X'\Omega X(X'X)^{-1} \quad (3.6)$$

Aitken (1962) suggested an infeasible estimator called generalized least square (GLS) estimator for a known $m \times m$ positive definite variance-covariance matrix Ω using a Weighted Least Square (WLS) approach.

The idea is to transform the model in (3.1) such that the disturbances covariance matrix in (3.6) becomes $\Omega = \sigma^2 I$. That is, transform the joint model in (3.1) by a square and invertible but non-diagonal weighting matrix A , such that

$$A\Omega A' = I_n \Leftrightarrow \Omega = (A'A)^{-1} \quad (3.7)$$

Multiplying the compact SUR model in (3.1) by A , we obtain

$$AY = AX\beta + A\epsilon \quad (3.8)$$

With $Y^* = AY$, $X^* = AX$, $\epsilon^* = A\epsilon$, then model (3.1) becomes

$$Y^* = X^*\beta + \epsilon^* \quad (3.9)$$

The $E(\epsilon^* \epsilon^{*'}) = E(A\epsilon \epsilon' A') = AE(\epsilon \epsilon')A' = A\Omega A' = I_m$, thus the transformed model now has a diagonal variance-covariance matrix with all its off-diagonal elements zero. That is $E(\epsilon^*) = 0$ and $\text{Var}(\epsilon^*) = \sigma^2 I_{nm}$.

The generalized least square (GLS) estimator of β in (3.9) is given by

$$\widehat{\beta}_{GLS} = (X^*X^*)^{-1}X^{*'}Y^* = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}Y \quad (3.10)$$

And its variance- covariance matrix is

$$V(\beta_{GLS}) = \sigma^2(X'\Omega^{-1}X)^{-1} \quad (3.11)$$

However, in practice the value of the covariance matrix Ω is generally unknown. Zellner (1962) suggested replacing Ω by its consistent estimator $\widehat{\Omega}$ and then estimate the parameters in SUR model in two steps called Feasible GLS (FGLS) estimator given as

$$\widehat{\beta}_{FGLS} = (X'\widehat{\Omega}^{-1}X)^{-1}X'\widehat{\Omega}^{-1}Y \quad (3.12)$$

Where $\widehat{\Omega} = S \otimes I$ is an $m \times m$ matrix based on single equation of OLS disturbances and $S = (s_{ij})$, where $s_{ij} = \varepsilon_i' \varepsilon_j / n - k$, see (Yahya et.al, 2008).

3.3 Robust M- Regression Estimator

M-estimators for regression which was introduced by Huber (1973), is a generalization of the OLS estimation procedure by minimizing the sum of a less rapidly increasing function (objective function) of the residuals instead of minimizing the sum of squared residuals as;

$$\hat{\beta} = \min \sum_{i=1}^n \rho(y_i - X_i' \beta) \quad (3.13)$$

Equivalent to M-Estimator of location, the robustness of the estimator is determined by the choice of weight function. The solution is not scale equivariance, and thus the residuals must be standardized by a robust scale estimator $\hat{\sigma}_e$ usually the median absolute deviation (MAD). Differentiating the objective function in (3.13) and setting the partial derivative to zero gives the score function:

$$\hat{\beta} = \min \sum_{i=1}^n \psi((y_i - X_i' \beta) / \hat{\sigma}_e) \chi_i' = 0 \quad (3.14)$$

Where ψ is the derivative of the objective function ρ . The equation (3.14) is a P system of normal equations. Then ψ is replaced by appropriate weights that decrease as the size of the residual increases, defined by $w(\varepsilon) = \frac{\psi(\varepsilon)}{\varepsilon}$ and $w_i = w(\varepsilon)$. Hence (3.14) becomes

$$\hat{\beta} = \min \sum_{i=1}^n \omega_i ((y_i - X_i' \beta) / \hat{\sigma}_e) \chi_i' = 0 \quad (3.15)$$

In solving the equation in (3.15) with respect to β , an iterative procedure called Iterative Re-Weighted Least Squares (IRWLS) is employed as follows;

1. Set the iteration counter $t=0$ and select the initial estimates $\beta^{(0)}$ from initial OLS estimates.
2. Calculate the residual from OLS in (1) and set as $\epsilon^{(0)}$
3. Select any weight function of choice and applied to the initial OLS residuals to create an initial weights, $w(\epsilon^{(0)})$
4. The first iteration, $t=1$, uses weighted least squares (WLS) to minimize $\sum \omega_i^1 \epsilon_i^2$ and obtain $\beta^{(1)}$. In matrix form, W represent an $n \times n$ diagonal matrix of individual weights, the solution is

$$\widehat{\beta^{(1)}} = (X'WX)^{-1} X'WY$$

5. At each iteration t , calculate the residual $\epsilon^{(t-1)}$ and associated weights $w(\epsilon^{(t-1)})$ from previous iteration
6. Solve for new WLS estimates $\widehat{\beta^{(t)}} = (X'W^{(t-1)}X)^{-1} X'W^{(t-1)}Y$, where $W^{(t-1)} = \text{diag}(W_i^{(t-1)})$, the current weight matrix and X is the model matrix, with χ_i' as its i^{th} row.

7. Steps 4-6 are repeated until the estimated coefficients converge.

M-estimates based on Huber's ψ function were used in this study with Objective and bi-weight function defined respectively as:

$$\rho(\varepsilon)_{huber} = \begin{cases} \frac{1}{2}\varepsilon^2 & \text{for } |\varepsilon| \leq k \\ k|\varepsilon| - \frac{1}{2}k^2 & \text{for } |\varepsilon| > k \end{cases} \quad (3.16)$$

$$w_{huber} = \begin{cases} 1 & \text{for } |\varepsilon| \leq k \\ \frac{k}{|\varepsilon|} & \text{for } |\varepsilon| > k \end{cases} \quad (3.17)$$

Huber's ψ functions have computational advantage but sensitive to leverage points, See (Maronne *et al* (2006) for more details. The choice of the turning point, $k= 1.345$ by Huber (1981) produced a relative efficiency of approximately 95% when the error density is normal.

3.4 ROBUST MM- REGRESSION ESTIMATOR

MM-estimator is robust estimator which combines the high breakdown point of S-estimator and high efficiency of M estimator. Breakdown point is a measure of the proportion of outliers that can be addressed before these observations affect the model. The S-estimator proposed by Rousseeuw and Yohai (1984), minimizes the dispersion of the residuals, expressed as:

$$\min \frac{1}{n} \sum_i^n \rho\left(\frac{\varepsilon_i}{\hat{\sigma}_e}\right) \quad (3.18)$$

Where $\hat{\sigma}_e$ is the estimate of residual scale and ρ is the weight function.

The MM-estimator requires three stages. The first stage finds the regression parameter using S estimator which is consistent and has high breakdown point of 50% but not necessarily efficient. In the second stages, M estimator of the residuals scale is calculated using the residuals obtained from initial S estimator. The M estimator of the regression parameter as described in section 3.3 is then used in the third stage to estimate the regression parameter

that is consistent, robust to outlier with high efficiency and asymptotically normally distributed (Maronna *et al* (2006)). The MM uses the Turkey's objective function:

$$w_{bisquare} = \begin{cases} \frac{k^2}{6} \{1 - [1 - (\varepsilon/k)\} & \text{for } |\varepsilon| \leq k \\ \frac{k^2}{6} & \text{for } |\varepsilon| > k \end{cases} \quad (3.19)$$

And Turkey bi-weight functions as:

$$w_{bisquare} = \begin{cases} \{[1 - (\varepsilon/k)^2]^2\} & \text{for } |\varepsilon| \leq k \\ (0) & \text{for } |\varepsilon| > k \end{cases} \quad (3.20)$$

Where the constant, $k = 4.685$ produced 95% relative efficiency (Susanti *et al.*, 2014). Turkey's biweight has a bounded function ρ that can handle the leverage point problems., See (Maronne *et al* (2006) for more details.

3.5 Model Specification and Values for Parameters in Simulation Study

The simulation work considers a system of SUR equations containing two distinct linear regression equations to examine the performances of different estimators of simultaneous equation model. Under the violation of homoscedasticity and /or normality assumption of individual regression equations in SUR model. The finite and asymptotic sample properties of these estimators are investigated.

A variety of error structures were considered to represent common types of heteroscedasticity that generally found in cross-sectional data. In view of this, the study specified four forms of heteroscedasticity namely; Linear, exponential, Square root and Quadratic heteroscedastic error and three different distributions for error /response variable were considered, including Normal distribution as a special case. These distributions include: Log-normal, Gamma and Normal distribution.

The observations were generated given the two linear regression models and the specified parameters as follows:

$$y_{i1} = \beta_{10} + \beta_{11}X_{i1} + \beta_{12}X_{i2} + \varepsilon_{i1} \quad (3.13.1)$$

$$y_{i2} = \beta_{20} + \beta_{21}X_{i1} + \beta_{22}X_{i2} + \varepsilon_{i2} ; \text{ for } i= 1, \dots, n \quad (3.13.2)$$

The values of the model parameters were set as follows;

$$\beta_{10} = -20, \beta_{11} = 15, \beta_{12} = 13, \beta_{20} = 11.5, \beta_{21} = 10.0, \text{ and } \beta_{22} = 6.5$$

In the Monte-Carlo simulation work, the explanatory variables were generated as random variate from uniform distribution, three different distributions for the error terms, $\varepsilon^1 = (\varepsilon_1, \varepsilon_2)$ as given in equations (3.13.1) & (3.13.2) were considered. This was intended to generate the response variables that are normal or non-normal through the error terms. The distributions considered are: Normal, lognormal, and Gamma distributions.

Therefore, the error terms $\varepsilon^1 = (\varepsilon_1, \varepsilon_2)$ were generated from different distributions as stated above but with the same Variance-covariance matrix Σ to establish different levels of contemporaneous correlation (0, 0.2, 0.4, 0.5, and 0.95) between the error terms in equations (3.13.1) and (3.13.2).

The 4×1 vector of errors were generated as $\varepsilon = C^1 R_n$, where C^1 is the transpose of the cholesky decomposition of the 4×4 positive definite matrix Σ in equation (3.14) and the element of R_n is a $N \times 4$ matrix containing independently distributed multivariate normal or non-normal (Gamma & Lognormal).

The variance –covariance matrix used is given as:

$$\Sigma = \begin{pmatrix} 1.0 & 0.2 & 0.4 & 0.5 \\ 0.2 & 1.0 & 0.95 & 0.3 \\ 0.5 & 0.3 & 0.3 & 1.0 \end{pmatrix} \quad 3.14$$

3.5.1 Forms of Heteroscedasticity

The study considered four heteroscedastic structures coined from Harvey (1976) additive and multiplicative heteroscedastic model but in our model we assumed that the variance of the error varies as the mean of the responses. These two General forms are:

$$(i) \text{ Var}(\varepsilon^1 \varepsilon) = \sigma^2 E(y_i)^\theta \text{ and } (ii) \text{ Var}(\varepsilon^1 \varepsilon) = \sigma^2 e^{E(y_i)} ; \theta \geq 0,$$

See Sakia (1992).Emanating from the two above, four heteroscedastic structures were formulated, namely:

- (a) Exponential form (EXP): $h_{i1} = \sigma^2 \exp (\alpha_1 + \gamma_{20} X_{i1} + \gamma_{21} X_{i2})$
- (b) Linear forms (LN): $h_{i2} = \sigma^2 (\alpha_1 + \gamma_{20} X_{i1} + \gamma_{21} X_{i2})$
- (c) Square Root (SQR): $h_{i3} = \sigma^2 (\alpha_1 + \gamma_{20} X_{i1} + \gamma_{21} X_{i2})^{0.5}$
- (d) Quadratic (QUAD): $h_{i4} = \sigma^2 (\alpha_1 + \gamma_{20} X_{i1} + \gamma_{21} X_{i2})^2 \quad i= 1,2.$

Where α_1, γ_{20} and, γ_{21} are arbitrary constant fixed for each sample size as ; α_1 0.6,

$$\gamma_{20}=0.8 , \quad \gamma_{21} = 0.4, \text{ and } \sigma^2=1$$

In order to assess the asymptotic and small sample properties of the various estimators under the violation of normality assumption of the responses, homoscedasticity assumption of the

error terms and, the level of correlation among errors across equations, the entire simulation experiments was performed for various sample sizes (n): n=500, 250,100,50,30,20 with 100 replicates in each case. However, the model specification, form of heteroscedasticity and distributions used in this work are in consonant with what is in the literature with little modification, See (Cribari-Neto and Lima, 2012; Takada et.al, 1995; Carroll, 1982: Kmenta & Gilbert, 1968).

3.6 DATA GENERATION PROCEDURE

The simulations of observations for the two regression equation model of (3.13.1 & 3.13.2) were given as follows:

1. The exogenous variables $[X_1, X_2]$ were generated from uniform distribution with parameters $a=0.5$ and $b= -0.5$, $U(0.5, -0.5)$ for various sample sizes
2. The error terms $[\varepsilon_{i1}, \varepsilon_{i2}]$ in equation (3.13.1 & 3.13.2) were drawn from normal distribution with variances covariance matrix given in equation(3.14)
3. The error terms $[\varepsilon_{i1}, \varepsilon_{i2}]$ in equation (3.13.1 & 3.13.2) were also drawn from gamma(4, 1) distribution with variances covariance matrix given in equation(3.14)
4. The error terms $[\varepsilon_{i1}, \varepsilon_{i2}]$ in equation (3.13.1 & 3.13.2) were drawn from lognormal distribution with variances covariance matrix given in equation(3.14)

The heteroscedastic structure for error variance, h_{ij} as given in section 3.3.1 were generated using the specified values: $\alpha_1 = 0.6$, $\gamma_{20}=0.8$, $\gamma_{21} = 0.4$, $\sigma^2=1$ based on generated exogenous variables $[X_1, X_2]$

1000 replications were used for different sample sizes 20, 30, 50, 100, 250 and 500. For each replication, the value of the parameters $\beta_1 = (\beta_{10}, \beta_{11}, \beta_{12})$ and $\beta_2 = (\beta_{20}, \beta_{21}, \beta_{22})$ were estimated under normal, gamma and lognormal error using the following estimators:

- I. Feasible Generalized Least Squares (FGLS)
- II. Ordinary Least Squares (OLS)
- III. Huber M-Estimator (Huber)
- IV. Turkey Bi-Squares MM- Estimator (BISQ)

The performances of the estimators at different heteroscedastic structures, contemporaneous correlations , distributions of the response variables and sample sizes were evaluated using Root Mean Squares(RMSE) , Absolute Bias (ABS) , Variance(VAR) and their Relative Efficiency (RE) to OLS. The relative efficiency of an estimator is the measure of the degree to which the estimator performs similar to common method (OLS). The relative efficiency of two unbiased estimators, θ_1 and θ_2 , of the parameter θ , is defined as:

$RE = \frac{RMSE(\theta_1)}{RMSE(\theta_2)}$, Where θ_1 is OLS estimator and θ_2 is another estimator. If the relative efficiency is 1, then it means that the estimator is as efficient as the OLS if the error distribution of the data is normal. A relative efficiency of 1.2 for instance, implies the estimator is 20% more efficient than OLS estimator.

The RMSE of the regression parameters estimator of $\beta=(\beta_{10}, \beta_{11}, \beta_{12}, \beta_{20}, \beta_{21}, \beta_{22})$ is calculated as:

$$RMSE = \frac{1}{K} \sqrt{\sum_{i=1}^2 \sum_{j=0}^2 (\beta_{ijk} - \hat{\beta}_{ijk})^2} , \text{ with } k = 1000 \text{ the number of iterations.}$$

CHAPTER FOUR

4.0 Presentation and Discussion of Results

3.4 Introduction

The results of the performances of the estimators considered at different levels of contemporaneous correlation (ρ), forms of heteroscedasticity under Normal, Gamma and lognormal response models are presented in this chapter.

The performance of an estimator was assessed based on each of the criteria highlighted in chapter 3. An estimator is said to be efficient or best under a criterion if it has the least value of the criterion. The results were presented based on the distribution of the response variable (Gamma, Lognormal and Normal) under different forms of heteroscedasticity, contemporaneous correlation at different sample sizes using RMSE, variance and Absolute bias criteria. Tables 4.1-10(A-C) show the results on the performances of estimators for Normal, Gamma and Lognormal model on the basis of RMSE, relative efficiency (RE), Variance and absolute bias of model parameter estimates.

4.1.1 RMSE of Parameter Estimates for Normal Response Model for Exponential Heteroscedasticity

Table 4.1A shows the empirical results of the estimators under RMSE criterion with relative efficiency (RE) when error is normally distributed, exponentially heteroscedastic and at different levels of C_c between the error terms in the two equations. The results show that with sample sizes $n=20$ & 30 at low C_c ($\rho = 0.2$), OLS has the minimum RMSE in estimating the model parameters compared to other estimators. The relative efficiency of all other estimator (compared with OLS) is less than 1. The OLS is the most preferred estimator while FGLS and Huber estimators show equivalent behavior.

At moderate sample size $n=50$ with low C_c FGLS, Bi-SQ and OLS estimator performed equally well but Huber is the most efficient. When the sample size is large, all the estimators are consistent and their RMSE is almost the same. However, FGLS remain the most efficient.

Also, when the correlation is moderate or high ($\rho \geq 0.5$), the FGLS has the minimum RMSE with efficiency gain of 4% (RE=1.04) over OLS estimator. Meanwhile the performances of Huber and Bi-SQ estimator are equivalent with that of OLS most especially when the sample size is large ($n \geq 50$).

Table 4.1A: Empirical Result of Estimators for Exponential Heteroscedastic Normal Error Model.

(n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	10.0200		10.4146		10.6142	-	10.7729	-	10.1354	-
	FGLS	10.1960	0.98	10.6635	0.98	10.2235	1.04	9.4879	1.14	4.7483	2.13
	HUBER	10.2541	0.98	10.7502	0.97	10.8785	0.98	11.0847	0.97	10.5437	0.96
	BI-SQ	10.3843	0.96	10.9863	0.95	11.1206	0.95	11.5202	0.94	10.7944	0.94
30	OLS	7.7712		8.3260	-	8.2051	-	8.1789	-	8.2941	-
	FGLS	7.9676	0.98	8.3994	0.99	7.9191	1.04	7.4135	1.10	3.4593	2.40
	HUBER	7.9757	0.97	8.4810	0.98	8.3834	0.98	8.2812	0.99	8.5076	0.97
	BI-SQ	8.0965	0.96	8.5565	0.97	8.4880	0.97	8.4239	0.97	8.5379	0.97
50	OLS	6.1907		6.2732	-	6.1810	-	6.4304	-	5.9509	-
	FGLS	6.2386	0.99	6.1816	1.01	5.6953	1.09	5.7721	1.11	2.5192	2.36
	HUBER	6.1332	1.01	7.2331	0.87	6.1274	1.01	6.4262	1.00	6.0101	0.99
	BI-SQ	6.1511	1.01	6.2347	1.01	6.1068	1.01	6.4551	1.00	6.0090	0.99
100	OLS	4.3631		4.2235	-	4.2589	-	4.4930	-	3.9530	-
	FGLS	4.3636	1.00	4.1370	1.02	3.8753	1.10	3.9459	1.14	1.6292	2.43
	HUBER	4.3797	1.00	4.2187	1.00	4.2603	1.00	4.4716	1.00	3.9966	0.99
	BI-SQ	4.3902	0.99	4.2593	0.99	4.2996	0.99	4.5010	1.00	4.0142	0.98
250	OLS	2.6025		2.6958	-	2.7006	-	2.7543	-	2.6092	-
	FGLS	2.5993	1.00	2.7190	0.99	2.4966	1.08	2.4816	1.11	1.0975	2.38
	HUBER	2.6276	0.99	2.7456	0.98	2.7623	0.98	2.8152	0.98	2.6573	0.98
	BI-SQ	2.6550	0.98	2.7467	0.98	2.7554	0.98	2.8312	0.97	2.6625	0.98
500	OLS	1.8587		1.8388	-	1.8490	-	1.8984	-	1.8820	-
	FGLS	1.8591	1.00	1.8000	1.02	1.6988	1.09	1.7045	1.11	0.7199	2.61
	HUBER	1.8552	1.00	1.8763	0.98	1.8972	0.97	1.9371	0.98	1.9199	0.98
	BI-SQ	1.8556	1.00	1.8785	0.98	1.9068	0.97	1.9400	0.98	1.9322	0.97

However, the RMSE of FGLS reduces tremendously as Cc increases. In particular, when Cc is high ($\rho=0.95$), the relative efficiency of FGLS is 2 to 2.6 times that of OLS estimator.

4.1.2 RMSE of Parameter Estimates for Normal Response Model for Linear Heteroscedasticity

Table 4.2A shows the simulation results for estimating the model parameters when error is linearly heteroscedastic and normally distributed at different levels of contemporaneous correlation.

Table 4.2A: Empirical Result of Estimators for Linear Heteroscedastic Normal Response Model.

(N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMS E	RE	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS FGLS HUBER BI-SQ	3.5736		3.6955		3.7673		3.8308		3.5980	
		3.6355	0.98	3.7899	0.98	3.6421	1.03	3.3841	1.13	1.7500	2.06
		3.6337	0.98	3.7909	0.97	3.8325	0.98	3.9084	0.98	3.7329	0.96
		3.6977	0.97	3.8902	0.95	3.9294	0.96	4.0763	0.94	3.8183	0.94
30	OLS FGLS HUBER BI-SQ	2.7706		2.9567		2.9150		2.9098		2.9428	
		2.8416	0.98	2.9871	0.99	2.8179	1.03	2.6414	1.10	1.2693	2.32
		2.8232	0.98	2.9877	0.99	2.9582	0.99	2.9325	0.99	3.0002	0.98
		2.8699	0.97	3.0227	0.98	3.0024	0.97	2.9852	0.97	3.0121	0.98
50	OLS FGLS HUBER BI-SQ	2.2077		2.2312		2.2001		2.2899		2.1174	
		2.2266	0.99	2.1981	1.02	2.0288	1.08	2.0581	1.11	0.9315	2.27
		2.1713	1.02	2.1999	1.01	2.1640	1.02	2.2728	1.01	2.1222	1.00
		2.1728	1.02	2.2054	1.01	2.1598	1.02	2.2856	1.00	2.1277	1.00
100	OLS FGLS HUBER BI-SQ	1.5531		1.4992		1.5133		1.5978		1.4065	
		1.5542	1.00	1.4681	1.02	1.3786	1.10	1.4062	1.14	0.6049	2.33
		1.5476	1.00	1.4876	1.01	1.5023	1.01	1.5766	1.01	1.4107	1.00
		1.5516	1.00	1.5046	1.00	1.5198	1.00	1.5887	1.01	1.4222	0.99
250	OLS FGLS HUBER BI-SQ	0.9210		0.9574		0.9604		0.9779		0.9273	
		0.9202	1.00	0.9432	1.02	0.8899	1.08	0.8833	1.11	0.4092	2.27
		0.9219	1.00	0.9675	0.99	0.9737	0.99	0.9912	0.99	0.9393	0.99
		0.9350	0.99	0.9702	0.99	0.9736	0.99	0.9994	0.98	0.9435	0.98
500	OLS FGLS HUBER BI-SQ	0.6627		0.6532		0.6564		0.6743		0.6674	
		0.6628	1.00	0.6398	1.02	0.6042	1.09	0.6070	1.11	0.2688	2.48
		0.6574	1.01	0.6620	0.99	0.6688	0.98	0.6835	0.99	0.6768	0.99
		0.6582	1.01	0.6637	0.98	0.6736	0.97	0.6854	0.98	0.6828	0.98

With low Cc ($\rho=0.2$), OLS estimator maintained minimum RMSE at small sample sizes ($n=20$ & $n=30$). At moderate to large samples ($n \geq 50$), all the estimators performed similar manner but FGLS has the least RMSE with relative efficiency of 102% compared to OLS estimator. However, the efficiency of Huber and Bi-SQ relative to OLS is 101%, 100% and 101%, 101% respectively for sample sizes 50 & 100.

Table 4.3A: Empirical Result of Estimators for Square-Root Heteroscedastic Normal Response Model

Sample Size (n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	3.9519		4.1325	-	4.2131	-	4.2655	-	4.0172	-
	FGLS	4.0213	0.98	4.2239	0.98	4.0395	1.04	3.7457	1.14	1.8043	2.23
	HUBER	4.0668	0.97	4.2897	0.96	4.3487	0.97	4.4163	0.97	4.1909	0.96
	BI-SQ	4.1029	0.96	4.3686	0.95	4.4205	0.95	4.5822	0.93	4.2761	0.94
30	OLS	3.0663		3.2968	-	3.2467	-	3.2265	-	3.2888	-
	FGLS	3.1420	0.98	3.3177	0.99	3.1259	1.04	2.9233	1.10	1.3223	2.49
	HUBER	2.5519	1.20	3.3775	0.98	3.3412	0.97	3.2892	0.98	3.3935	0.97
	BI-SQ	3.2055	0.96	3.4095	0.97	3.3697	0.96	3.3396	0.97	3.4025	0.97
50	OLS	2.4282		2.4832	-	2.4455	-	2.5397	-	2.3502	-
	FGLS	2.4456	0.99	2.4481	1.01	2.2513	1.09	2.2784	1.11	0.9551	2.46
	HUBER	2.4293	1.00	2.4795	1.00	2.4395	1.00	2.5545	0.99	2.3915	0.98
	BI-SQ	2.4382	1.00	2.4812	1.00	2.4331	1.01	2.5656	0.99	2.3875	0.98
100	OLS	1.7240		1.6711	-	1.6821	-	1.7717	-	1.5594	-
	FGLS	1.7232	1.00	1.6386	1.02	1.5300	1.10	1.5519	1.14	0.6177	2.52
	HUBER	1.7422	0.99	1.6806	0.99	1.6963	0.99	1.7813	0.99	1.5910	0.98
	BI-SQ	1.7459	0.99	1.6890	0.99	1.7035	0.99	1.7853	0.99	1.5885	0.98
250	OLS	1.0368		1.0650	-	1.0652	-	1.0889	-	0.9915	-
	FGLS	1.0350	1.00	1.0476	1.02	0.9817	1.09	0.9788	1.11	0.4110	2.41
	HUBER	1.0547	0.98	1.0937	0.97	1.0991	0.97	1.1222	0.97	1.0550	0.94
	BI-SQ	1.0591	0.98	1.0916	0.98	1.0944	0.97	1.1260	0.97	1.0558	0.94
500	OLS	0.7327		0.7263	-	0.7309	-	0.7482	-	0.7446	-
	FGLS	0.7328	1.00	0.7112	1.02	0.6715	1.09	0.6708	1.12	0.2677	2.78
	HUBER	0.7353	1.00	0.7472	0.97	0.7561	0.97	0.7707	0.97	0.7647	0.97
	BI-SQ	0.7350	1.00	0.7470	0.97	0.7580	0.96	0.7707	0.97	0.7665	0.97

When the Cc is moderate or high ($\rho \geq 0.5$) and error is linearly heteroscedastic the RMSE for FGLS increases drastically with efficiency gain of 2 to 2.4 times that of OLS.

The Huber and Bi-SQ compete favorably well with OLS at small sample and equivalent in large samples ($n \geq 50$).

4.1.3 RMSE of Parameter Estimates for Normal Response Model for Square Root Heteroscedasticity

Table 4.3A (for $n \leq 30$) shows similar picture as Table 4.2A does under low contemporaneous correlation (0.2) when error is linearly Heteroscedastic. OLS is the most efficient estimator. The relative efficiency of other estimator is less than 100% indicating OLS minimum RMSE.

However, as the sample size increases ($n \geq 50$), all the estimators performed almost equally with FGLS being the most efficient estimator showing relatively minimum RMSE. While the RE of other estimators reduces, FGLS maintained relative efficiency of 102%.

When correlation is 0.5 under Square root Heteroscedasticity, OLS still retained its efficiency at small sample size but OLS performance decreases with increase in Cc. Meanwhile the efficiency of FGLS increases with an increase in contemporaneous correlation.

For sample sizes $N \geq 50$ and $\rho = 0.5$, Huber and Bi-SQ estimator behave equally well but below the OLS. However, FGLS remain the best and most efficient estimator.

4.1.4 RMSE of Parameter Estimates for Normal Response Model for Quadratic Heteroscedasticity

Table 4.4A presents the RMSE and RE for the model parameters when error is normally distributed and the variance structure for the error is quadratic. At $\rho = 0.2$ under quadratic form of heteroscedasticity, the results reveal that neither OLS nor FGLS could maintain the small sample property as it does under other forms of heteroscedasticity. However, Huber estimator outperforms all other estimator showing relative minimum RMSE at sample sizes $n \leq 30$. At sample sizes $n \geq 50$, Huber, Bi-SQ and FGLS perform almost in similar manner with

efficiency gain of 5%, 4% and 2%, for n=50, 5%, 3% and 2%, for n=100, 4%, 1% and 1% for n=250 and 4%, 2% and 2%, for n=500 respectively, relative to OLS. Therefore at $\rho=0.2$, quadratic heteroscedastic error and $n \geq 50$, FGLS is the most efficient estimator.

When Cc is moderate ($\rho=0.5$), the FGLS and Huber estimator perform equally well with both estimators showing relatively minimum RMSE. Most importantly at sample size $n \leq 30$, the efficiency of FGLS and Huber relative to OLS are the same (102% and 103% for sample sizes 20 & 30 respectively. Meanwhile OLs perform better than Bi-SQ. At sample sizes

Table 4.4A: Empirical Result of Estimators for Quadratic Heteroscedastic Normal Response Model

(n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	3.0700		3.1123		3.1733		3.2547		3.0511	
	FGLS	3.1223	0.98	3.2049	0.97	3.1195	1.02	2.9447	1.11	1.8609	1.64
	HUBER	2.9966	1.02	3.0809	1.01	3.1246	1.02	3.2184	1.01	3.0790	0.99
	BI-SQ	3.1210	0.98	3.2400	0.96	3.2532	0.98	3.3741	0.96	3.1854	0.96
30	OLS	2.3816		2.5113		2.4837		2.5031		2.4812	
	FGLS	2.4452	0.97	2.5483	0.99	2.4188	1.03	2.2998	1.09	1.3165	1.88
	HUBER	2.3382	1.02	2.4356	1.03	2.4142	1.03	2.4118	1.04	2.4406	1.02
	BI-SQ	2.4040	0.99	2.5083	1.00	2.4967	0.99	2.4830	1.01	2.4746	1.00
50	OLS	1.9256		1.8945		1.8723		1.9568		1.8089	
	FGLS	1.9449	0.99	1.8659	1.02	1.7426	1.07	1.7798	1.10	0.9945	1.82
	HUBER	1.8053	1.07	1.8003	1.05	1.7581	1.06	1.8744	1.04	1.7300	1.05
	BI-SQ	1.8103	1.06	1.8175	1.04	1.7794	1.05	1.8929	1.03	1.7763	1.02
100	OLS	1.3294		1.2747		1.2933		1.3695		1.2080	
	FGLS	1.3324	1.00	1.2458	1.02	1.1877	1.09	1.2281	1.12	0.6533	1.85
	HUBER	1.2658	1.05	1.2087	1.05	1.2213	1.06	1.2754	1.07	1.1546	1.05
	BI-SQ	1.2781	1.04	1.2410	1.03	1.2562	1.03	1.3018	1.05	1.1919	1.01
250	OLS	0.7702		0.8176		0.8239		0.8342		0.7963	
	FGLS	0.7709	1.00	0.8084	1.01	0.7768	1.06	0.7685	1.09	0.4571	1.74
	HUBER	0.7348	1.05	0.7871	1.04	0.7930	1.04	0.8036	1.04	0.7724	1.03
	BI-SQ	0.7625	1.01	0.8062	1.01	0.8100	1.02	0.8217	1.02	0.7872	1.01
500	OLS	0.5718		0.5574		0.5594		0.5774		0.5662	
	FGLS	0.5721	1.00	0.5468	1.02	0.5193	1.08	0.5273	1.10	0.3041	1.86
	HUBER	0.5406	1.06	0.5376	1.04	0.5458	1.02	0.5573	1.04	0.5492	1.03
	BI-SQ	0.5485	1.04	0.5452	1.02	0.5549	1.01	0.5658	1.02	0.5612	1.01

($n \geq 50$), the performance of Bi-SQ estimator improves with increase in sample size. The performances of FGLS, Huber and Bi-SQ are almost equivalent but FGLS is the most efficient with efficiency gain of 6 to 9% relative to OLS.

With high C_c ($\rho \geq 0.7$), the performances of Huber and Bi-SQ is very encouraging under Quadratic heteroscedasticity than under Linear, Exponential and Square Root Heteroscedasticity. The two estimators perform better than OLS while FGLS is the most efficient estimator. However, the gain in efficiency of FGLS relatively to OLS increases at relative slow rate in Quadratic heteroscedasticity at $\rho = 0.95$ than in other forms of heteroscedasticity.

4.2 RMSE of the Parameter Estimates for Gamma Response Model

4.2.1 Gamma Response Model with Exponential Heteroscedasticity

Table 4.1.1B & 4.1.2B shows the results of simulation when form of heteroscedasticity is Exponential for Gamma response model at various contemporaneous correlations.

At small sample sizes $n \leq 30$, when there is absence of correlation ($\rho = 0.0$) between the error terms in different equations, the performance OLS and FGLS estimators is similar using RMSE criterion while the Huber and Bi-squares perform better than the OLS and FGLS estimators. The relative efficiency of Huber and Bi-squares estimators to OLS is 23% and 30% respectively. However as the level of correlation increases ($0.2 \leq \rho \leq 0.7$), the performances of Huber and Bi-squares estimators decreases with relative efficiency from 21% to 14% and 27% to 16% respectively but still better than OLS and FGLS. Nevertheless, the performance of FGLS has improved tremendously and better than OLS. In summary, in terms of RMSE, the most efficient estimator under exponential heteroscedastic error terms, response Gamma model at small sample sizes $n \leq 30$ with both absence of correlation or moderately high correlation ($\rho = 0.0$ or $0.2 \leq \rho \leq 0.7$), is Bi-squares estimator. When the

correlation is almost perfect ($\rho = 0.95$) at sample sizes $n \leq 50$, FGLS shows better efficiency over other estimators.

Table 4.1B: Empirical Result of Estimators for Exponential Heteroscedastic Gamma Response Model.

(n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	RE	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	48.9384		53.2834		56.4428		18.1692		55.7569	
	FGLS	49.4507	0.99	52.2794	1.02	52.7690	1.07	16.5943	1.09	38.9281	1.43
	HUBER	39.7426	1.23	44.0038	1.21	48.0720	1.17	15.9618	1.14	49.4964	1.13
	BI-SQ	37.7426	1.30	42.0488	1.27	46.6847	1.21	15.7030	1.16	48.3997	1.15
30	OLS	41.6984		40.2076		43.1733		14.5887		45.5751	
	FGLS	42.6573	0.98	40.3472	1.00	42.3686	1.02	13.9337	1.05	33.8621	1.35
	HUBER	34.8722	1.20	34.9920	1.15	38.6882	1.12	13.1156	1.11	40.5911	1.12
	BI-SQ	32.8739	1.27	34.0380	1.18	37.8853	1.14	12.7619	1.14	39.3795	1.16
50	OLS	35.6911		37.5678		40.5786		13.6563		41.8095	
	FGLS	35.9675	0.99	37.3849	1.00	39.4048	1.03	12.9898	1.05	33.1375	1.26
	HUBER	29.6377	1.20	31.4056	1.20	35.2072	1.15	11.6860	1.17	36.3063	1.15
	BI-SQ	27.6269	1.29	29.4435	1.28	33.5609	1.21	11.1159	1.23	34.9453	1.20
100	OLS	30.2379		31.7156		35.0625		11.2856		37.0484	
	FGLS	30.4133	0.99	31.6426	1.00	34.4978	1.02	10.8856	1.04	31.8901	1.16
	HUBER	24.8286	1.22	26.5312	1.20	30.5373	1.15	9.7781	1.15	32.0775	1.15
	BI-SQ	22.4362	1.35	24.5602	1.29	28.8979	1.21	9.2712	1.22	30.5703	1.21
250	OLS	26.5354		28.7715		32.4383		10.2531		34.2529	
	FGLS	26.5522	1.00	28.6184	1.01	31.9222	1.02	9.8907	1.04	31.6721	1.08
	HUBER	21.8165	1.22	23.7330	1.21	27.8342	1.17	8.7382	1.17	29.7591	1.15
	BI-SQ	19.3993	1.37	21.2960	1.35	25.8080	1.26	8.0430	1.27	27.9974	1.22
500	OLS	25.0425		27.1047		30.8832		9.8702		32.9058	
	FGLS	25.0446	1.00	26.9882	1.00	30.5509	1.01	9.7188	1.02	31.7810	1.04
	HUBER	20.3845	1.23	22.5394	1.20	26.6674	1.16	8.4001	1.18	28.7197	1.15
	BI-SQ	17.5187	1.43	19.9602	1.36	24.5184	1.26	7.6486	1.29	26.7832	1.23

As sample sizes increases, specifically at $n \geq 50$ in the absence of correlation, OLS and FGLS are equivalent and consistent. Huber and Bi-squares continuously maintained better performance over OLS and FGLS. The relative efficiency of Huber and Bi-squares over OLS is between 20% to 23% and 29% to 43% for Huber and Bi-squares respectively. At sample size $n > 50$, the increase in the levels of contemporaneous correlation could not improve the

efficiency of FGLS over Huber and Bi-squares, even at ($\rho = 0.95$). This is to reaffirm that FGLS or OLS is not the best estimator for modeling non-normal response model regardless of the levels of contemporaneous correlation between the error terms in different models. The robust Bi-square is the most efficient estimator for modeling exponential heteroscedastic error terms with Gamma response.

4.2.2 Gamma Response Model with Linear Heteroscedasticity

Table 4.2.1B & 4.2.2B present the simulation results for linear heteroscedastic error terms with Gamma response model using RMSE criterion.

At small sample sizes $n=20$ and 30 in the absence of correlation between the error terms in different equation the best estimator is Bi-square followed by Huber estimators. The OLS and FGLS performance is similar but less efficient. The relative efficiency of Huber and Bi-squares over OLS is 24% and 31% respectively. However, OLS is better than FGLS by 1%.

When the correlation is between ($0.2 \leq \rho \leq 0.7$) with Gamma response, using RMSE as criterion for comparison among the estimators, Bi-square is the best estimator when $n \leq 30$. At this instance, the FGLS estimator has improved better than the OLS estimator with its relative efficiency of 2% to 9% over OLS.

When the correlation is almost perfect ($\rho = 0.95$) at sample sizes $n \leq 50$ is the most efficiency estimator. The relative efficiency of FGLS, Bi-squares and Huber over OLS is 40%, 16% and 13% respectively.

As sample size (n) increases from 100 to 500 in the absence of correlation ($\rho = 0.0$), Bi-squares has the least RMSE with relative efficiency ranges from 32% to 46% over OLS estimator. The relative efficiency of Huber over OLS ranges between 21% and 24% for

n=100 and n=500 respectively. At this instance, OLS and FGLS estimators perform equally but inefficient.

Table 4.2b: Empirical Result of Estimators for Linear Heteroscedastic Gamma Response Model.

Size (N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	17.4738		19.0721		20.2419		18.1692		20.0198	
	FGLS	17.6751	0.99	18.6980	1.02	18.9324	1.07	16.5943	1.09	14.3510	1.40
	HUBER	14.0940	1.24	15.6530	1.22	17.1400	1.18	15.9618	1.14	17.6933	1.13
	BI-SQ	13.3016	1.31	14.8602	1.28	16.5680	1.22	15.7030	1.16	17.2214	1.16
30	OLS	14.9606		14.4826		15.5946		14.5887		16.4194	
	FGLS	15.3106	0.98	14.5438	1.00	15.3472	1.02	13.9337	1.05	12.6029	1.30
	HUBER	12.4170	1.20	12.5255	1.16	13.8967	1.12	13.1156	1.11	14.5674	1.13
	BI-SQ	11.6346	1.29	12.0957	1.20	13.5373	1.15	12.7619	1.14	14.0566	1.17
50	OLS	12.8514		13.5459		14.7112		13.6563		15.1595	
	FGLS	12.9458	0.99	13.4864	1.00	14.3242	1.03	12.9898	1.05	12.4099	1.22
	HUBER	10.5812	1.21	11.2362	1.21	12.6825	1.16	11.6860	1.17	13.1266	1.15
	BI-SQ	9.7515	1.32	10.4707	1.29	12.0275	1.22	11.1159	1.23	12.5601	1.21
100	OLS	11.0226		11.5854		12.8668		11.2856		13.6125	
	FGLS	11.0868	0.99	11.5624	1.00	12.6829	1.01	10.8856	1.04	11.9745	1.14
	HUBER	8.9679	1.23	9.6362	1.20	11.1547	1.15	9.7781	1.15	11.7497	1.16
	BI-SQ	8.0108	1.38	8.8424	1.31	10.4765	1.23	9.2712	1.22	11.1324	1.22
250	OLS	9.7849		10.6328		12.0312		10.2531		12.7244	
	FGLS	9.7899	1.00	10.5786	1.01	11.8600	1.01	9.8907	1.04	11.9257	1.07
	HUBER	7.9391	1.23	8.6981	1.22	10.2642	1.17	8.7382	1.17	11.0071	1.16
	BI-SQ	6.9769	1.40	7.7312	1.38	9.4530	1.27	8.0430	1.27	10.3020	1.24
500	OLS	9.3250		10.1139		11.5485		9.8702		12.3231	
	FGLS	9.3260	1.00	10.0740	1.00	11.4399	1.01	9.7188	1.02	11.9806	1.03
	HUBER	7.5034	1.24	8.3325	1.21	9.9060	1.17	8.4001	1.18	10.6914	1.15
	BI-SQ	6.3784	1.46	7.3251	1.38	9.0570	1.28	7.6486	1.29	9.9201	1.24

When the Cc is between ($0.2 \leq \rho \leq 0.7$) , as expected the increase in contemporaneous correlation has no effect in either OLS or Robust estimators' performances yet Robust estimators (Huber and Bi-squares) still perform better than FGLS that uses information from the correlation between the error terms in different equations in its estimation procedure.

When the correlation is almost perfect ($\rho = 0.95$), FGLS performance has improved over OLS and closely with Huber estimator. The relative efficiency of Bi-squares, Huber and FGLS over OLS is at least 22%, 15% and 7% respectively.

In summary, for all ranges of sample sizes considered in the absence of correlation between the error terms in different equations the best estimator is Bi-squares.

When the correlation is between ($0.2 \leq \rho \leq 0.7$) at sample size $n \leq 50$, Bi-squares remain the best estimator.

At large sample sizes $n \geq 100$, irrespective of the levels of correlation (ρ) using RMSE as a criterion for comparison among estimators, Bi-squares is the best estimator. However, at almost perfect ($\rho = 0.95$) for sample sizes $n \leq 50$, FGLS is the most efficient estimator.

4.2.3 Gamma Response Model Quadratic Heteroscedasticity

Table 4.4.1B & 4.4.2B present RMSE for model parameter estimates when the form of heteroscedasticity is Quadratic at various levels of contemporaneous correlation.

When there is absence of correlation ($\rho = 0.0$) at various sample sizes $n \leq 500$ using RMSE criterion Bi-squares estimator is the best. The Huber estimator performs better than OLS and FGLS. However, OLS and FGLS performances are the same in all the sample sizes considered in the absence of correlation between the error terms in different equations. The relative efficiency of Bi-squares and Huber estimators to OLS ranges between 43-62% and 28-32% respectively.

When the correlation is between ($0.2 \leq \rho \leq 0.7$) at various sample sizes $n \leq 500$, Bi-squares is still the best estimator in terms of RMSE criterion followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but not adequate

enough. The relative efficiency of Bi-squares, Huber and FGLS to OLS is between 23-50%, 16-28% and 2-9% respectively.

.Table 4.4b: Empirical Result of Estimators for Quadratic Heteroscedastic Gamma Response Model.

Size (n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS FGLS HUBER BI-SQ	15.7196		17.4250		18.6547		16.3042		18.6189	
		15.9398	0.99	17.0247	1.02	17.5311	1.06	14.9592	1.09	14.7004	1.27
		11.9388	1.32	13.5095	1.29	14.9993	1.24	13.6042	1.20	15.6746	1.19
		11.0095	1.43	12.1901	1.43	13.8981	1.34	12.9409	1.26	14.7387	1.26
30	OLS FGLS HUBER BI-SQ	13.8251		13.6360		14.8116		13.4543		15.4397	
		14.1131	0.98	13.7545	0.99	14.7079	1.01	13.0711	1.03	12.9701	1.19
		10.7919	1.28	11.1510	1.22	12.6172	1.17	11.5837	1.16	13.2526	1.17
		9.5816	1.44	10.1984	1.34	11.7420	1.26	10.9769	1.23	12.3104	1.25
50	OLS FGLS HUBER BI-SQ	12.0607		12.7230		14.0179		12.9020		14.3303	
		12.1399	0.99	12.7103	1.00	13.7843	1.02	12.3966	1.04	12.7289	1.13
		9.2592	1.30	10.0157	1.27	11.5892	1.21	10.5025	1.23	12.0544	1.19
		8.0565	1.50	8.9175	1.43	10.5777	1.33	9.5535	1.35	11.1543	1.28
100	OLS FGLS HUBER BI-SQ	10.6977		11.2727		12.6389		10.9737		13.4029	
		10.7655	0.99	11.2464	1.00	12.4916	1.01	10.6905	1.03	12.3458	1.09
		8.1734	1.31	8.8939	1.27	10.4945	1.20	9.0030	1.22	11.2286	1.19
		6.8636	1.56	7.8101	1.44	9.4957	1.33	8.1924	1.34	10.3040	1.30
250	OLS FGLS HUBER BI-SQ	9.7436		10.6126		12.0916		10.2504		12.8416	
		9.7464	1.00	10.5613	1.00	11.9581	1.01	9.9840	1.03	12.3351	1.04
		7.4162	1.31	8.2680	1.28	9.9358	1.22	8.3729	1.22	10.7515	1.19
		6.1574	1.58	7.0109	1.51	8.8251	1.37	7.4274	1.38	9.7586	1.32
500	OLS FGLS HUBER BI-SQ	9.4274		10.2604		11.7584		10.0161		12.5784	
		9.4289	1.00	10.2324	1.00	11.6878	1.01	9.9070	1.01	12.3774	1.02
		7.1578	1.32	8.0467	1.28	9.7109	1.21	8.1833	1.22	10.5649	1.19
		5.8028	1.62	6.8186	1.50	8.6134	1.37	7.2168	1.39	9.5240	1.32

When the correlation is almost perfect ($\rho = 0.95$) at sample size $n=20$ using RMSE as criterion for comparison, FGLS is the best estimator with efficiency of 27% over OLS. At this point, FGLS and Bi-squares performances are equivalent. The efficiency of Bi-squares relative to OLS is 26% while that of Huber is 19%. As the sample size (n) increases from 30 to 500, the Bi-squares performance increases due to the increase in sample size. The best

estimator when $\rho = 0.95$ and $n \geq 30$ using RMSE as criteria is Bi-squares estimator followed by Huber estimator. The efficiency of Bi-squares, Huber and FGLS relative to OLS are between 25-32%, 17-19% and 2-19% respectively.

Table 4.3B: Empirical Result of Estimators for Square Root Heteroscedastic Gamma Response Model

Size (N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	19.4824		21.0770		22.2896		20.3061		22.0092	
	FGLS	19.6357	0.99	20.7398	1.02	20.8561	1.07	18.5565	1.09	14.7949	1.49
	HUBER	16.0002	1.22	17.6017	1.20	19.1789	1.16	18.1502	1.12	19.6521	1.12
	BI-SQ	15.2403	1.28	16.9086	1.25	18.7179	1.19	17.9021	1.13	19.3522	1.14
30	OLS	16.4870		15.8436		16.9579		16.1435		18.0095	
	FGLS	16.8591	0.98	15.8666	1.00	16.5743	1.02	15.2418	1.06	12.7284	1.41
	HUBER	13.9113	1.19	13.8713	1.14	15.2793	1.11	14.6148	1.10	16.1147	1.12
	BI-SQ	13.1743	1.25	13.5524	1.17	15.0069	1.13	14.2551	1.13	15.7288	1.15
50	OLS	14.1120		14.8337		15.9132		14.9277		16.4559	
	FGLS	14.2213	0.99	14.7413	1.01	15.3919	1.03	14.0605	1.06	12.3486	1.33
	HUBER	11.8412	1.19	12.5333	1.18	13.9382	1.14	13.0005	1.15	14.3419	1.15
	BI-SQ	11.1380	1.27	11.8316	1.25	13.3684	1.19	12.5146	1.19	13.8974	1.18
100	OLS	11.7568		12.2908		13.4842		12.0253		14.2158	
	FGLS	11.8194	0.99	12.2608	1.00	13.2333	1.02	11.4781	1.05	11.7290	1.21
	HUBER	9.7836	1.20	10.3691	1.19	11.8350	1.14	10.6118	1.13	12.3910	1.15
	BI-SQ	8.9623	1.31	9.6957	1.27	11.3016	1.19	10.2327	1.18	11.9050	1.19
250	OLS	10.1442		10.9466		12.2517		10.5345		12.8986	
	FGLS	10.1536	1.00	10.8881	1.01	12.0243	1.02	10.0324	1.05	11.5661	1.12
	HUBER	8.4945	1.19	9.1543	1.20	10.6267	1.15	9.1417	1.15	11.3148	1.14
	BI-SQ	7.6690	1.32	8.3269	1.31	9.9581	1.23	8.5775	1.23	10.7342	1.20
500	OLS	9.4011		10.1342		11.4903		9.8813		12.1910	
	FGLS	9.4014	1.00	10.0845	1.00	11.3335	1.01	9.6658	1.02	11.5884	1.05
	HUBER	7.7923	1.21	8.5566	1.18	10.0419	1.14	8.5671	1.15	10.7693	1.13
	BI-SQ	6.8188	1.38	7.6808	1.32	9.3323	1.23	7.9384	1.24	10.1479	1.20

4.2.4 Gamma Response Model with Square-Root Heteroscedasticity

Table 4.3B presents the RMSE for the model parameter estimates for Gamma response model with Square root Heteroscedasticity at various levels of contemporaneous correlation for different sample sizes.

When there is absence of correlation ($\rho = 0.0$) for all the sample sizes considered using RMSE criterion Bi-squares is the most efficient estimator followed by Huber estimator. OLS and FGLS perform in similar manner with OLS efficiency over FGLS is 1%. While the efficiency of Bi-squares and Huber estimators to OLS ranges from 28-38% and 19-22% respectively.

When the correlation is ($0.2 \leq \rho \leq 0.7$) at various sample sizes $n \leq 500$, using RMSE criterion Bi-squares is still the best estimator followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but perform below Bi-squares and Huber estimators. The relative efficiency of Bi-squares, Huber and FGLS to OLS is between 17-32%, 11-20% and 2-9% respectively.

When the correlation is almost perfect ($\rho = 0.95$) at sample size $n=20, 30, 50$ and 100 using RMSE as criterion for comparison among estimator of Gamma response model, FGLS is the best estimator with efficiency between 21-49% over OLS. The efficiency of Bi-squares relative to OLS is between 15- 20% while that of Huber is between 12- 15%.

As the sample size (n) increases from 100 to 500, the Bi-squares performance increases due to the increase in sample size. The best estimator when $\rho = 0.95$ and $n > 100$ using RMSE as criteria is Bi-squares estimator.

4.2.5 Gamma Response Model with Homoscedastic Error Term

Table 4.5B presents RMSE for model parameter estimates when the error terms homoscedastic at various levels of contemporaneous correlation for different sample sizes.

When there is absence of correlation ($\rho = 0.0$) between the error terms in different equations and error terms is homoscedastic using RMSE criterion, the best estimator is Bi-squares at different sample sizes ($n \geq 20$). The Huber estimator performs better than OLS and FGLS

but below Bi-squares estimator. At this point, it shows clearly that when response is non-normal, OLS or FGLS is less efficient.

Table 4.5B: Empirical Result of Estimators for Homoscedastic Gamma Response Model

Sample Size (N)	Estimator	$\rho=0.0$		$\rho=0.2$		$\rho=0.5$		$\rho=0.7$		$\rho=0.95$	
		RMSE	RE	RMSE	RE	RMSE	RE	RMSE	RE	RMSE	RE
20	OLS FGLS HUBER BI-SQ	22.7647		24.3944		25.8178		23.8179		25.6066	
		22.8307	1.00	24.1065	1.01	24.2715	1.06	21.8774	1.09	16.8463	1.52
		18.8108	1.21	20.5622	1.19	22.4032	1.15	21.3922	1.11	22.9194	1.12
		17.9699	1.27	19.6576	1.24	21.7162	1.19	21.0180	1.13	22.4364	1.14
30	OLS FGLS HUBER BI-SQ	19.1940		18.5527		19.8854		19.0428		21.3412	
		19.5614	0.98	18.5333	1.00	19.3577	1.03	17.8327	1.07	14.6193	1.46
		16.2468	1.18	16.2024	1.15	17.9091	1.11	17.0774	1.12	19.1322	1.12
		15.3560	1.25	15.7288	1.18	17.4842	1.14	16.5405	1.15	18.6055	1.15
50	OLS FGLS HUBER BI-SQ	16.6502		8.6736		18.7456		17.5877		19.5068	
		16.7676	0.99	8.7207	0.99	18.0749	1.04	16.4477	1.07	13.6843	1.43
		13.9511	1.19	7.5122	1.15	16.5335	1.13	15.4502	1.14	16.9501	1.15
		13.1377	1.27	6.8585	1.26	15.8402	1.18	14.8094	1.19	16.4477	1.19
100	OLS FGLS HUBER BI-SQ	13.6673		14.3013		15.5410		14.0942		16.3450	
		13.7130	1.00	14.2533	1.00	15.1872	1.02	13.4207	1.05	12.4152	1.32
		11.3899	1.20	11.9373	1.20	13.5278	1.15	12.4344	1.13	14.2139	1.15
		10.4954	1.30	11.1793	1.28	12.9387	1.20	11.9938	1.18	13.7115	1.19
250	OLS FGLS HUBER BI-SQ	11.7760		12.4805		13.7955		11.9508		14.5030	
		11.7945	1.00	12.4412	1.00	13.5271	1.02	11.3328	1.05	11.7934	1.23
		9.9413	1.18	10.5096	1.19	12.0408	1.15	10.4224	1.15	12.7663	1.14
		8.9876	1.31	9.6541	1.29	11.3971	1.21	9.8569	1.21	12.2149	1.19
500	OLS FGLS HUBER BI-SQ	10.5230		11.2493		12.5674		10.8907		13.1193	
		10.5230	1.00	11.2191	1.00	12.3788	1.02	10.6087	1.03	11.5541	1.14
		8.8316	1.19	9.5866	1.17	11.0783	1.13	9.5153	1.14	11.7642	1.12
		7.8623	1.34	8.7151	1.29	10.4116	1.21	8.9211	1.22	11.2537	1.17

When the correlation is ($0.2 \leq \rho \leq 0.7$) at various sample sizes $n \leq 500$ and the error term is homoscedastic using RMSE criterion, Bi-squares is the best estimator followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but perform below Bi-squares and Huber estimators. The relative efficiency of Bi-squares, Huber and FGLS to OLS reduces under homoscedastic error term than when the error is heteroscedastic (13-29%, 11-20% and 2-9% respectively).

When the correlation is almost perfect ($\rho = 0.95$) for homoscedastic error terms at sample size $n=20, 30, 50, 100$ and 250 using RMSE as criterion for comparison among estimators of Gamma response model, FGLS is the best estimator with efficiency between 23-52% over OLS. The efficiency of Bi-squares relative to OLS is between 14- 19% while that of Huber is between 12- 15%. When the error terms are homoscedastic and response variables followed Gamma distribution with contemporaneous correlation of $\rho = 0.95$ for $n \leq 250$ FGLS is the most efficient estimator.

4.3 RMSE of the Estimated Parameters for Lognormal Response Model

4.3.1 Model with Homoscedastic Error Terms

Table 4.5C shows the RMSE of parameter estimates at different levels of contemporaneous correlation under Log-Normal error for different sample sizes.

When there is absence of correlation ($\rho=0.0$) between the error terms in different equations with homoscedastic error term, the performances of FGLS and OLS are equivalent in all sample sizes. Huber estimator performs better than FGLS and OLS in all sample sizes but consistently below Bi-square estimator. In other word, when error term is homoscedastic and there is absence of contemporaneous correlation, the best estimation is Bi-square for all the sample sizes considered. The efficiency of Bi-squares and Huber estimator relative to OLS is between 77-94% and 46-74% respectively.

When the level of contemporaneous correlation is between ($0.2 \leq \rho \leq 0.7$) , the performances of FGLS has improved relative to OLS estimator under homoscedastic error term. The Huber and Bi-Square performances are very close but Bi-square has the least RMSE, hence is the best estimator. The efficiency of Bi-squares, Huber and FGLS estimators relative to OLS is between 36-93% and 26-74% and 3-11% respectively in small sample ($n \leq 30$) and 48-82%, 34-64% and 4-16% in large sample ($n > 30$) respectively.

Table 4.5C: Empirical Result of Estimators for Homoscedastic Log-Normal Response Model

(N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	RE	RMSE	RE	RMSE	RE	RMSE	RE	RMSE	RE
20	OLS FGLS HUBER BI-SQ	12.0126		12.8694		13.0645		12.2208		12.5437	
		11.9776	1.00	12.4684	1.03	11.7997	1.11	10.5070	1.16	6.8847	1.82
		6.9230	1.74	7.3719	1.75	8.0886	1.62	8.4039	1.45	8.0928	1.55
		6.1802	1.94	6.6653	1.93	7.4669	1.75	7.6407	1.60	7.6611	1.64
30	OLS FGLS HUBER BI-SQ	9.4463		10.1367		10.3840		8.3974		10.9124	
		9.6638	0.98	10.0050	1.01	9.9882	1.04	7.8349	1.07	6.5792	1.66
		5.9919	1.58	6.4711	1.57	7.2942	1.42	6.6386	1.26	7.6528	1.43
		5.0005	1.89	5.6157	1.81	6.6167	1.57	6.1655	1.36	7.1529	1.53
50	OLS FGLS HUBER BI-SQ	8.0818		8.3995		8.9329		8.4031		8.6097	
		8.1491	0.99	8.0562	1.04	8.2417	1.08	7.2154	1.16	5.9595	1.44
		4.6957	1.72	5.2247	1.61	5.9385	1.50	5.5454	1.52	6.2282	1.38
		4.1496	1.95	4.6072	1.82	5.3337	1.67	5.0475	1.66	5.6769	1.52
100	OLS FGLS HUBER BI-SQ	6.3926		6.8213		7.3211		6.5572		7.8440	
		6.3673	1.00	6.7749	1.01	7.0683	1.04	6.0188	1.09	5.4643	1.44
		4.1505	1.54	4.4938	1.52	5.2097	1.41	4.8101	1.36	5.6188	1.40
		3.5525	1.80	3.9597	1.72	4.7150	1.55	4.3906	1.49	5.1317	1.53
250	OLS FGLS HUBER BI-SQ	5.2832		5.5418		6.0972		5.3565		6.5076	
		5.2935	1.00	5.4455	1.02	5.8693	1.04	5.0344	1.06	5.0069	1.30
		3.4596	1.53	3.7838	1.46	4.4502	1.37	3.9608	1.35	4.8552	1.34
		2.8553	1.85	3.2745	1.69	3.9860	1.53	3.6109	1.48	4.4216	1.47
500	OLS FGLS HUBER BI-SQ	4.6414		5.0183		5.5626		4.8292		5.8318	
		4.6387	1.00	4.9866	1.01	5.4229	1.03	4.5853	1.05	4.8930	1.19
		3.1698	1.46	3.5086	1.43	4.1414	1.34	3.6012	1.34	4.4910	1.30
		2.6203	1.77	3.0080	1.67	3.6803	1.51	3.2215	1.50	4.0844	1.43

When the contemporaneous correlation is almost perfect ($\rho=0.95$), using RMSE criterion for homoscedastic error term the best estimator is FGLS at sample sizes $n=20$ and 30 . The relative efficiency of FGLS to OLS is 82% and 66% for $n=20$ and 30 respectively. The efficiency of Bi-squares and Huber estimators relative to OLS is 64% and 55% respectively for $n=20$ and 53% and 43% respectively for $n=30$.

At sample sizes $n=50$ and 100 for homoscedastic error when the distribution of the response variables is Log-normal and $\rho=0.95$, the best estimator is Bi-Square followed by FGLS, then Huber estimator with relative efficiency of 53%, 44% and 40% respectively.

When $n > 100$ and $\rho = 0.95$ under homoscedastic error with Log-normal response model using RMSE criterion Bi-squares is the best estimator followed by Huber estimator, the FGLS with efficiency of 43%, 34% and 19% respectively relative to OLS.

4.3.2 Lognormal Response Model with Linear Heteroscedasticity

Table 4.2C: Empirical Result of Estimators for Linear Heteroscedastic Log-Normal Response Model

(N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	8.8286		9.1976		9.3411		8.9448		9.3507	
	FGLS	8.8475	1.00	8.9352	1.03	8.5285	1.10	7.9661	1.12	5.8328	1.60
	HUBER	5.1583	1.71	5.4769	1.68	6.0686	1.54	6.2740	1.43	6.1141	1.53
	BI-SQ	4.6902	1.88	4.9994	1.84	5.6641	1.65	5.7974	1.54	5.7898	1.62
30	OLS	7.2994		7.6821		7.9373		6.5206		8.3090	
	FGLS	7.4482	0.98	7.5110	1.02	7.4944	1.06	6.0106	1.08	5.6652	1.47
	HUBER	4.5887	1.59	4.7942	1.60	5.4906	1.45	5.0006	1.30	5.7488	1.45
	BI-SQ	3.8333	1.90	4.1773	1.84	4.9734	1.60	4.6331	1.41	5.2953	1.57
50	OLS	6.3812		6.5198		6.9569		6.4560		6.6432	
	FGLS	6.4231	0.99	6.2464	1.04	6.4550	1.08	5.6194	1.15	5.3025	1.25
	HUBER	3.6362	1.75	4.0667	1.60	4.6787	1.49	4.2713	1.51	4.9152	1.35
	BI-SQ	3.1549	2.02	3.5506	1.84	4.2205	1.65	3.8871	1.66	4.5308	1.47
100	OLS	5.0739		5.3207		5.7904		5.1095		6.1059	
	FGLS	5.0643	1.00	5.2957	1.00	5.6596	1.02	4.8208	1.06	5.0810	1.20
	HUBER	3.2434	1.56	3.5267	1.51	4.1603	1.39	3.7415	1.37	4.4784	1.36
	BI-SQ	2.6976	1.88	3.0161	1.76	3.6703	1.58	3.3550	1.52	3.9888	1.53
250	OLS	4.2975		4.6522		5.2216		4.5001		5.5098	
	FGLS	4.3058	1.00	4.6044	1.01	5.1083	1.02	4.2843	1.05	4.9683	1.11
	HUBER	2.8263	1.52	3.1832	1.46	3.8358	1.36	3.3033	1.36	4.1850	1.32
	BI-SQ	2.2855	1.88	2.6771	1.74	3.3526	1.56	2.9172	1.54	3.7355	1.47
500	OLS	3.9472		4.3022		4.8915		4.1586		5.1979	
	FGLS	3.9465	1.00	4.2893	1.00	4.8345	1.01	4.0688	1.02	4.9588	1.05
	HUBER	2.7109	1.46	3.0645	1.40	3.7083	1.32	3.1124	1.34	4.0412	1.29
	BI-SQ	2.1942	1.80	2.5830	1.67	3.2455	1.51	2.7268	1.53	3.6060	1.44

Table 4.2C presents the RMSE of parameter estimates for linear heteroscedastic error terms with Log-normal response model at different levels of Contemporaneous correlation at different sample sizes.

When there is absence of correlation ($\rho=0.0$) with Log-Normal response model under linear heteroscedastic error terms, Bi-Square estimator is the best estimator at all sample sizes ($n \leq 500$), Huber estimator performs in similar manner but with slightly higher RMSE than Bi-Square estimator in all the sample sizes. FGLS and OLS performances are the same in all the sample sizes. The efficiency of Bi-squares and Huber relative to OLS is between 80-90% and 46-71% respectively.

When the correlation is between ($0.2 \leq \rho \leq 0.7$) under Log-normal response using RMSE criterion, the performances of FGLS have improved slightly than OLS at sample sizes $n \geq 50$ but both estimators performances are close as sample size increases. Huber estimator performs better than FGLS and OLS in all sample sizes. However, the best estimator is Bi-Squares estimator in all sample sizes considered. The efficiency of Bi-squares, Huber and FGLS relative to OLS is between 41-84%, 30-68% and 1-15% respectively.

When the correlation is almost perfect ($\rho=0.95$) under Log-normal, the performance of FGLS is better than Huber estimator at sample size $n \leq 30$ only using RMSE criteria. OLS remain the worse estimator. The best estimator, under Log-normal response model and Linear heteroscedastic error term with $\rho=0.95$ notwithstanding the sample size, is Bi-Square estimator.

4.3.3 Lognormal Response Model with Square-Root Heteroscedasticity

Table 4.3C presents the RMSE for the model parameter estimates for Log-normal response model when the form of heteroscedasticity is Square root at various levels of contemporaneous correlation for different sample sizes.

When there is absence of correlation ($\rho = 0.0$) for all the sample sizes considered using RMSE criterion Bi-squares is the most efficient estimator followed by Huber estimator. OLS and FGLS performances are the same. The efficiency of Bi-squares and Huber estimators

relative to OLS decreases between 91-75% and 73-44% respectively as the sample sizes increases.

Table 4.3C: Empirical Result of Estimators for Square Root Heteroscedastic Log-Normal Response Model

Sample Size (n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	10.1096		10.6296		10.7499		10.2037		10.5527	
	FGLS	10.1077	1.00	10.3068	1.03	9.7430	1.10	8.9211	1.14	6.0272	1.75
	HUBER	5.8605	1.73	6.1988	1.71	6.8002	1.58	7.1312	1.43	6.8191	1.55
	BI-SQ	5.2970	1.91	5.6916	1.87	6.3875	1.68	6.6965	1.52	6.4871	1.63
30	OLS	8.1282		8.6166		8.8316		7.1967		9.2632	
	FGLS	8.3049	0.98	8.4525	1.02	8.3899	1.05	6.6513	1.08	5.7943	1.60
	HUBER	5.1424	1.58	5.4364	1.58	6.1519	1.44	5.6364	1.28	6.4456	1.44
	BI-SQ	4.3090	1.89	4.7558	1.81	5.6082	1.57	5.2389	1.37	6.0195	1.54
50	OLS	6.9890		7.1883		7.6265		7.1684		7.2640	
	FGLS	7.0423	0.99	6.8765	1.05	7.0291	1.08	6.1639	1.16	5.2841	1.37
	HUBER	4.0212	1.74	4.4831	1.60	5.1007	1.50	4.7392	1.51	5.3240	1.36
	BI-SQ	3.5513	1.97	3.9465	1.82	4.6167	1.65	4.3319	1.65	4.9234	1.48
100	OLS	5.4897		5.7731		6.2110		5.5478		6.5865	
	FGLS	5.4739	1.00	5.7389	1.01	6.0275	1.03	5.1421	1.08	5.0178	1.31
	HUBER	3.5461	1.55	3.8223	1.51	4.4538	1.39	4.0914	1.36	4.7811	1.38
	BI-SQ	3.0143	1.82	3.3393	1.73	3.9979	1.55	3.7223	1.49	4.3300	1.52
250	OLS	4.5501		4.8648		5.4015		4.6958		5.7016	
	FGLS	4.5597	1.00	4.7963	1.01	5.2380	1.03	4.4120	1.06	4.8285	1.18
	HUBER	2.9933	1.52	3.3334	1.46	3.9685	1.36	3.4769	1.35	4.3178	1.32
	BI-SQ	2.4552	1.85	2.8450	1.71	3.5136	1.54	3.1320	1.50	3.9065	1.46
500	OLS	4.0545		4.4028		4.9535		4.2471		5.2324	
	FGLS	4.0529	1.00	4.3815	1.00	4.8618	1.02	4.1030	1.04	4.8044	1.09
	HUBER	2.8102	1.44	3.1427	1.40	3.7653	1.32	3.2005	1.33	4.0866	1.28
	BI-SQ	2.3130	1.75	2.6848	1.64	3.3308	1.49	2.8462	1.49	3.6846	1.42

When the correlation is ($0.2 \leq \rho \leq 0.7$) at various sample sizes $n \leq 500$, using RMSE criterion Bi-squares is still the best estimator followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but perform below Bi-squares and Huber estimators. The relative efficiency of Bi-squares, Huber and FGLS to OLS decreases between 87-49%, 71-32% and 14-0% respectively as sample size increases.

When the correlation is almost perfect ($\rho = 0.95$) at sample size $n=20$ and 30 using RMSE as criterion for comparison among estimator of Log-normal response model, the best estimator is FGLS, with efficiency between 75-60% over OLS. The efficiency of Bi-squares relative to OLS is between 63- 54% while that of Huber is between 55- 44%.

As sample size (n) increases from 50 to 500 , the Bi-squares performance increases due to the increase in sample size. The best estimator when $\rho = 0.95$ and $n>50$ using RMSE as criteria is Bi-squares estimator.

4.3.4 Lognormal Response Model with Exponential Heteroscedasticity

Table 4.1C shows the RMSE for model parameter estimates when form of heteroscedasticity is Exponential for Log-normal response model at various contemporaneous correlations under different sample sizes.

When there is absence of correlation ($\rho = 0.0$) between the error terms in different equations for all sample sizes($n \geq 20$) considered, the performance OLS and FGLS estimators is similar using RMSE criterion while the Huber and Bi-squares perform better than the OLS and FGLS estimators. The relative efficiency of Huber to OLS for $n=20$ and 500 are 72% and 45% respectively while the efficiency of Bi-squares estimator to OLS for $n=20$ and 500 are 89% and 78% respectively. The best estimator, under Log-normal response model with exponential form of heteroscedasticity in the absence of contemporaneous correlation regardless of the size of the sample (n), is Bi-squares estimators.

Table 4.1C: Empirical Result of Estimators for Exponential Heteroscedastic Log-Normal Response Model

Size (N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS FGLS HUBER BI-SQ	25.0143		26.2779		26.6188		25.4774		26.2837	
		25.0325	1.00	25.4698	1.03	24.1547	1.10	22.4390	1.14	15.7842	1.67
		14.5473	1.72	15.4203	1.70	17.0134	1.56	17.7494	1.44	17.1125	1.54
		13.2250	1.89	14.1225	1.86	15.9088	1.67	16.4142	1.55	16.2453	1.62
30	OLS FGLS HUBER BI-SQ	20.4314		21.5892		22.2181		18.2034		23.2252	
		20.8668	0.98	21.1206	1.02	20.9926	1.06	16.7653	1.09	15.2764	1.52
		12.8698	1.59	13.5083	1.60	15.3809	1.44	14.0775	1.29	16.0969	1.44
		10.7703	1.90	11.8119	1.83	13.9726	1.59	13.0834	1.39	14.9079	1.56
50	OLS FGLS HUBER BI-SQ	17.7262		18.1308		19.2874		18.0153		18.4034	
		17.8507	0.99	17.3590	1.04	17.8412	1.08	15.5954	1.16	14.1654	1.30
		10.1306	1.75	11.3165	1.60	12.9588	1.49	11.9248	1.51	13.5697	1.36
		8.8824	2.00	9.9134	1.83	11.7042	1.65	10.8775	1.66	12.5253	1.47
100	OLS FGLS HUBER BI-SQ	14.0237		14.6908		15.9111		14.1182		16.8135	
		13.9930	1.00	14.6132	1.01	15.5028	1.03	13.2180	1.07	13.5588	1.24
		8.9867	1.56	9.7312	1.51	11.4137	1.39	10.3660	1.36	12.2723	1.37
		7.5435	1.86	8.4016	1.75	10.1478	1.57	9.3609	1.51	11.0061	1.53
250	OLS FGLS HUBER BI-SQ	11.7486		12.6644		14.1599		12.2458		14.9403	
		11.7727	1.00	12.5161	1.01	13.8072	1.03	11.5937	1.06	13.2024	1.13
		7.7316	1.52	8.6743	1.46	10.4030	1.36	9.0180	1.36	11.3358	1.32
		6.2860	1.87	7.3339	1.73	9.1352	1.55	8.0220	1.53	10.1658	1.47
500	OLS FGLS HUBER BI-SQ	10.6672		11.6154		13.1601		11.2199		13.9557	
		10.6642	1.00	11.5737	1.00	12.9772	1.01	10.9314	1.03	13.1609	1.06
		7.3619	1.45	8.2888	1.40	9.9939	1.32	8.4194	1.33	10.8719	1.28
		5.9939	1.78	7.0197	1.65	8.7794	1.50	7.4152	1.51	9.7356	1.43

When the level of correlation increases between ($0.2 \leq \rho \leq 0.7$), the performances of Bi-squares estimators decreases with increase in sample size from $n=20$ to $n=500$ with relative efficiency of 86% and 51% respectively and the relative efficiency of Huber also decreases from 70% to 32% for $n=20$ to $n=500$ respectively. The performance of FGLS has improved tremendously and better than OLS as the level of correlation increases but OLS performance increases as the sample increases. In summary, in terms of RMSE, the most efficient estimator under exponential heteroscedastic error terms, response Log-normal model and

contemporaneous correlation between $(0.2 \leq \rho \leq 0.7)$ for different sample sizes, is Bi-squares estimator.

When the correlation is almost perfect ($\rho = 0.95$) at sample sizes $n = 20$, FGLS shows better efficiency over other estimators. When $n=30$ FGLS perform better than OLS and Huber estimators but below Bi-squares estimator. When $n>50$, the increase in the levels of contemporaneous correlation could not improve the efficiency of FGLS over Huber and Bi-squares estimators. The robust Bi-square is the most efficient estimator for modeling exponential heteroscedastic error terms with Log-normal response except for $n \leq 20$ and $\rho = 0.95$ in which FGLS is the best estimator.

4.3.5 Lognormal Response Model with Quadratic Heteroscedasticity

Table 4.4C presents RMSE for model parameter estimates when the form of heteroscedasticity is Quadratic at various levels of contemporaneous correlation under Log-normal response model.

When there is absence of correlation ($\rho = 0.0$) at various sample sizes $n \leq 500$ using RMSE criterion Bi-squares estimator is the best. The Huber estimator performs better than OLS and FGLS. However, OLS and FGLS performances are the same in all the sample sizes considered in the absence of correlation between the error terms in different equations. The relative efficiency of Bi-squares and Huber estimators over OLS ranges between 93-103% and 52-83% respectively.

When the correlation is between $(0.2 \leq \rho \leq 0.7)$ at various sample sizes $n \leq 500$, Bi-squares is still the best estimator in terms of RMSE criterion followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but not adequate

enough. The relative efficiency of Bi-squares, Huber and FGLS to OLS is between 96-54%, 66-36% and 1-12% respectively.

Table 4.4C: Empirical Result of Estimators for Quadratic Heteroscedastic Log-Normal Response Model

Sample Size (n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E	RMSE	R.E
20	OLS	7.4728		7.8516		8.1148		7.8187		8.2916	
	FGLS	7.5177	0.99	7.6554	1.03	7.5412	1.08	7.1670	1.09	5.9045	1.40
	HUBER	4.3789	1.71	4.7190	1.66	5.3389	1.52	5.3292	1.47	5.4425	1.52
	BI-SQ	3.8697	1.93	4.0996	1.92	4.7916	1.69	4.5978	1.70	5.0408	1.64
30	OLS	6.4850		6.8403		7.2110		6.0238		7.5054	
	FGLS	6.6032	0.98	6.6927	1.02	6.8100	1.06	5.5599	1.08	5.7851	1.30
	HUBER	3.9691	1.63	4.1469	1.65	4.8528	1.49	4.3379	1.39	5.0636	1.48
	BI-SQ	3.1725	2.04	3.4899	1.96	4.2299	1.70	3.9069	1.54	4.4559	1.68
50	OLS	5.9633		5.9762		6.4435		5.8411		6.2698	
	FGLS	5.9908	1.00	5.7674	1.04	6.0677	1.06	5.2130	1.12	5.5219	1.14
	HUBER	3.2554	1.83	3.6487	1.64	4.2847	1.50	3.7945	1.54	4.5676	1.37
	BI-SQ	2.6764	2.23	3.0891	1.93	3.7616	1.71	3.3563	1.74	4.1036	1.53
100	OLS	4.8240		5.0543		5.5697		4.8679		5.8472	
	FGLS	4.8231	1.00	5.0346	1.00	5.4848	1.02	4.6905	1.04	5.2218	1.12
	HUBER	2.9393	1.64	3.2563	1.55	3.9001	1.43	3.4155	1.43	4.2320	1.38
	BI-SQ	2.3388	2.06	2.6658	1.90	3.3206	1.68	2.9474	1.65	3.6567	1.60
250	OLS	4.1698		4.5669		5.1741		4.4433		5.4748	
	FGLS	4.1773	1.00	4.5344	1.01	5.0988	1.01	4.2874	1.04	5.1414	1.06
	HUBER	2.6566	1.57	3.0304	1.51	3.7053	1.40	3.1425	1.41	4.0670	1.35
	BI-SQ	2.0870	2.00	2.4842	1.84	3.1615	1.64	2.6796	1.66	3.5344	1.55
500	OLS	3.9443		4.3079		4.9304		4.1715		5.2601	
	FGLS	3.9446	1.00	4.3015	1.00	4.8983	1.01	4.1116	1.01	5.1294	1.03
	HUBER	2.5904	1.52	2.9661	1.45	3.6316	1.36	3.0216	1.38	3.9766	1.32
	BI-SQ	2.0376	1.94	2.4384	1.77	3.1074	1.59	2.5786	1.62	3.4708	1.52

When the correlation is almost perfect ($\rho = 0.95$) regardless of the size of the sample (n) using RMSE as criterion for comparison, Bi-squares is the best estimator with relative efficiency between 52-68% over OLS. At this point, FGLS lost its efficiency in small sample.

In summary, the best estimator for modeling Log-normal response model with Quadratic heteroscedasticity at different levels of contemporaneous correlation notwithstanding the size of the sample using RMSE criterion is Bi-squares estimator.

4.4 Variance and Absolute Bias of Parameter Estimates for Normal Response Model

4.4.1 Exponential Heteroscedasticity

Table 4.6A shows the results of simulation when form of heteroscedasticity is Exponential for Normal response model at various contemporaneous correlations using Absolute Bias (ABS) criterion.

When there is absence of correlation ($\rho = 0.0$) between the error terms in different equations at different sample sizes, the performance OLS and FGLS estimators is similar using

Absolute bias criterion while the Huber and Bi-squares performances is worst when $n=20$. The best estimator for Normal response model with Exponential heteroscedastic error terms in the absence of contemporaneous correlation using Absolute bias criterion at sample sizes $n \leq 50$ is OLS estimators. Huber and Bi-squares show equivalent performances with OLS at sample sizes $n=30$ & $n=50$.

When the level of correlation increases between ($0.2 \leq \rho \leq 0.7$), the performances of all the estimators in terms of ABS are approximately the same at various sample sizes when $\rho = 0.2$ & $\rho = 0.5$ under Normal response model with exponential heteroscedastic error terms. Nonetheless, OLS is the most preferred estimator at various samples when $\rho = 0.2$. The performances of FGLS has improved relatively to other estimators at various samples when $\rho = 0.7$ while OLS, Huber and Bi-squares estimators show equivalent performances. However, FGLS is the most preferred estimator at various samples when $\rho = 0.5$ & $\rho = 0.7$. In summary, in terms of Absolute bias, the most efficient estimator under exponential

heteroscedastic error terms, Normal response model at various samples with both absence of correlation or low correlation($\rho = 0.2$) is OLS estimator.

Table 4.6A: Empirical Result of Estimators for Exponential Heteroscedastic Normal Response Model.

Sample Size(N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS FGLS HUBER BI-SQ	7.8478	16.8514	8.3810	18.4415	8.5653	19.1860	8.5458	19.7791	8.2059	17.4820
		7.9634	17.4832	8.4570	19.2436	8.0690	17.6900	7.5908	15.3438	3.7533	3.8515
		17.7492	17.7492	8.6525	19.6335	8.7876	20.1554	8.8509	20.9404	8.4351	18.8078
		18.2845	18.2845	8.7642	20.5039	8.9375	21.0749	9.1041	22.6274	8.5344	19.7347
30	OLS FGLS HUBER BI-SQ	6.2249	10.4523	6.6829	11.8164	6.6109	11.4862	6.5288	11.2847	6.5928	11.7877
		6.3088	10.9591	6.7391	11.9798	6.4140	10.6346	5.9543	9.2268	2.7906	2.0208
		6.3996	11.0003	6.8158	12.2417	6.7339	11.9860	6.6163	11.5825	6.7950	12.4088
		6.4761	11.3209	6.8998	12.4453	6.8519	12.2911	6.7712	11.9765	6.8327	12.4910
50	OLS FGLS HUBER BI-SQ	4.9449	6.4609	5.0754	6.6769	4.9705	6.4936	5.1175	7.0446	4.7779	6.0897
		5.0065	6.5729	5.0285	6.4646	4.6028	5.4629	4.6005	5.7058	1.9944	1.0756
		4.9141	6.3282	5.0004	6.5794	4.8713	6.3819	5.0987	7.0214	4.7781	6.2419
		4.9518	6.3605	5.0107	6.6048	4.8793	6.3538	5.1213	7.0925	4.7860	6.2488
100	OLS FGLS HUBER BI-SQ	3.5186	3.3192	3.2900	3.0421	3.3267	3.0809	3.5656	3.4051	3.1392	2.7025
		3.5172	3.3216	3.2677	2.9399	3.0429	2.5740	3.1834	2.6528	1.3058	0.4485
		3.4914	3.3445	3.2659	3.0260	3.3424	3.0768	3.5736	3.3925	3.1852	2.7526
		3.5040	3.3637	3.3038	3.0943	3.3780	3.1427	3.5981	3.4419	3.1896	2.7799
250	OLS FGLS HUBER BI-SQ	2.0758	1.1572	2.1648	1.2489	2.1645	1.2542	2.1773	1.2971	2.1016	1.1773
		2.0767	1.1547	2.1473	1.2123	2.0324	1.0747	1.9799	1.0550	0.8809	0.2036
		2.0982	1.1765	2.1937	1.2977	2.2060	1.3155	2.2243	1.3608	2.1242	1.2227
		2.1213	1.2018	1.3013	1.3013	2.1978	1.3105	2.2290	1.3792	2.1308	1.2279
500	OLS FGLS HUBER BI-SQ	1.4891	0.5874	1.4872	0.5781	1.4989	0.5862	1.5255	0.6202	1.5216	0.6066
		1.4872	0.5875	1.4503	0.5541	1.3654	0.4952	1.3887	0.4981	0.5739	0.0876
		1.4789	0.5866	1.5257	0.6024	1.5470	0.6176	1.5567	0.6485	1.5626	0.6303
		1.4730	0.5876	1.5247	0.6038	1.5510	0.6238	1.5615	0.6506	1.5688	0.6379

When the correlation is almost perfect ($\rho = 0.95$) at various samples under Normal response model with exponential heteroscedastic error terms, FGLS is the most efficiency estimator. OLS, Huber and Bi-squares performances are approximately the same. All the estimators are consistent. Therefore, under Normal response model with exponential heteroscedastic error terms with contemporaneous correlation $\rho \geq 0.5$, FGLS is the best estimator.

VARIANCE

Table 4.6A presents the variance (VAR) of parameter estimates when the form of heteroscedasticity is Exponential for Normal response model at various contemporaneous correlations for different sample sizes.

When there is absence of correlation ($\rho = 0.0$) between the error terms in different equations for exponential heteroscedastic error terms with Normal response model at different sample sizes, the best estimator is OLS using variance criterion. However, FGLS performs closely to OLS and better than the Huber and Bi-squares estimators at various sample sizes.

When the contemporaneous correlation is $\rho = 0.2$, regardless of the sample size using variance criterion the best estimator is OLS estimator. However, FGLS, Huber and Bi-squares estimators also show equivalent performances with OLS especially when $n \geq 50$. When the level of correlation increases from $\rho = 0.5$ to $\rho = 0.95$, FGLS shows distinct performances compared to OLS, Huber and Bi-squares estimators when $n \leq 30$ but as sample size increases all the estimators perform equivalently, yet in terms of variance criterion FGLS is the most efficient estimator.

4.4.2 Linear Heteroscedasticity

Table 4.7A presents the Absolute bias (ABS) estimates of parameters for Normal response model with linear heteroscedastic error terms at various contemporaneous correlations for different sample size.

When there is absence ($\rho=0.0$) of or low ($\rho=0.2$) correlation between the error terms in different equations, OLS is the most efficient estimator when $n \leq 30$. The FGLS, Huber and Bi-SQ estimators also perform closely with OLS estimator. At sample sizes $n=50$ & $n=100$ Huber estimator is the most preferred estimator using Absolute bias criterion. However, when

the response variable is normally distributed, error terms is linearly heteroscedastic and there is low or absence of contemporaneous correlation between the error terms from different equations, at samples $n=20$ & 30 OLS is the most preferred estimator. At samples $n=50$ & 100 , Huber estimator is the most preferred estimator using ABS criterion.. However, as the sample size increases from $n=250$ to $n=500$, all the estimators perform equally.

Table 4.7A: Empirical Result of Estimators for Linear Heteroscedastic Normal Response Model.

Sample Size (N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	2.7927	2.1474	2.9675	2.3264	3.0375	2.4212	3.0345	2.5058	2.9112	2.2071
	FGLS	2.8328	2.2260	3.0040	2.4350	2.8705	2.2491	2.7073	1.9559	1.3842	0.5256
	HUBER	2.8207	2.2336	3.0423	2.4457	3.0905	2.5055	3.1142	2.6086	2.9802	2.3599
	BI-SQ	2.8785	2.3241	3.0940	2.5750	3.1508	2.6355	3.2159	2.8390	2.5190	2.4712
30	OLS	2.2150	1.3313	2.3778	1.4940	2.3531	1.4537	2.3250	1.4317	2.3390	1.4888
	FGLS	2.2454	1.3961	2.4002	1.5184	2.2837	1.3494	2.1217	1.1743	1.0238	0.2734
	HUBER	2.2612	1.3834	2.4050	1.5235	2.3816	1.4973	2.3406	1.4568	2.3991	1.5491
	BI-SQ	2.2881	1.4278	2.4383	1.5577	2.4264	1.5430	2.3950	1.5083	2.4140	1.5608
50	OLS	1.7586	0.8241	1.8044	0.8470	1.7707	0.8348	1.8245	0.8956	1.7016	0.7737
	FGLS	1.7837	0.8395	1.7888	0.8198	1.6423	0.6953	1.6424	0.7272	0.7420	0.1480
	HUBER	1.7349	0.7951	1.7664	0.8241	1.7220	0.7993	1.8045	0.8821	1.6860	0.7818
	BI-SQ	1.7463	0.7958	1.7707	0.8299	1.7240	0.7983	1.8120	0.8928	1.6908	0.7872
100	OLS	1.2518	0.4225	1.1702	0.3847	1.1809	0.3904	1.2731	0.4319	1.1147	0.3432
	FGLS	1.2523	0.4232	1.1630	0.3717	1.0851	0.3271	1.1346	0.3377	0.4838	0.0620
	HUBER	1.2325	0.4197	1.1516	0.3780	1.1780	0.3843	1.2595	0.4233	1.1225	0.3443
	BI-SQ	1.2380	0.4223	1.1676	0.3876	1.1939	0.3941	1.2687	0.4302	1.1283	0.3503
250	OLS	0.7352	0.1454	0.7684	0.1580	0.7688	0.1589	0.7733	0.1641	0.7448	0.1491
	FGLS	0.7354	0.1452	0.7632	0.1536	0.7234	0.1370	0.7064	0.1340	0.3271	0.0285
	HUBER	0.7383	0.1455	0.7711	0.1618	0.7751	0.1642	0.7806	0.1694	0.7487	0.1534
	BI-SQ	0.7482	0.1497	0.7746	0.1630	0.7751	0.1644	0.7849	0.1727	0.7534	0.1547
500	OLS	0.5303	0.0749	0.5282	0.0731	0.5318	0.0741	0.5430	0.0785	0.5393	0.0765
	FGLS	0.5296	0.0749	0.5152	0.0702	0.4862	0.0628	0.4950	0.0634	0.2688	0.0123
	HUBER	0.5235	0.0740	0.5385	0.0753	0.5453	0.0771	0.5504	0.0811	0.5500	0.0786
	BI-SQ	0.5223	0.0743	0.5388	0.0757	0.5477	0.0782	0.5520	0.0816	0.5538	0.0799

When the correlation increases between $\rho =0.5$ and $\rho =0.95$ with linearly heteroscedastic error term and normal response, FGLS is the most preferred estimator using ABS criterion at

different sample sizes. However, OLS is slightly better than Huber and Bi-squares estimator at different sample sizes.

VARIANCE

Table 4.7A present the variance (VAR) estimate of parameters in Normal response model with linear heteroscedastic error terms at different levels of Contemporaneous correlation (ρ) at different sample sizes (n).

When there is absence of correlation ($\rho=0.0$) or low correlation ($\rho=0.2$) with Normal response model under linear heteroscedastic error terms, OLS estimator is the best estimator at samples $n=20$ & 30 . FGLS, Huber and Bi-squares in that order, all show equivalent performances but with slightly higher variance than OLS estimator at samples $n=20$ & 30 . When $\rho=0.0$ and $n=50$ & 100 , Huber estimator is the most preferred estimator using variance criterion but when $\rho=0.2$ and $n=50$ & 100 , FGLS estimator is the most preferred estimator using variance criterion. However, when contemporaneous correlation is between $\rho=0.0$ and $\rho=0.2$ all the estimators performance is approximately the same.

At $\rho=0.5$ and 0.7 , and for $n \leq 30$ under Normal response using variance criterion, FGLS shows continuous improved performances than OLS, Huber and Bi-squares estimators has the contemporaneous correlation increases but as the sample size increases all the estimators show equal performance. Nonetheless, FGLS is the most preferred estimator.

When the correlation is almost perfect ($\rho=0.95$) under Normal response model, the performance of FGLS is better than OLS, Huber and Bi-squares estimators at different sample sizes ($n \leq 500$) using variance criterion. At this instance Bi-squares estimator remains the worse estimator. The best estimator, under Normal response model and Linear heteroscedastic error term with $\rho=0.95$ notwithstanding the sample size, is FGLS estimator.

4.4.3 Square-Root Heteroscedasticity

Table 4.8A shows the empirical results of the estimators under RMSE criterion with relative efficiency (RE) when response variables are normally distributed with Square-root heteroscedastic error terms.

Table 4.8A: Empirical Result of Estimators for Square Root Heteroscedastic Normal Response Model.

Sam ple Size (N)	Estima tor	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS FGLS HUBER BI-SQ	3.0986	2.6192	3.3230	2.8972	3.0160	3.0160	3.3784	3.0948	3.2557	2.7407
		3.1472	2.7184	3.3456	3.0136	2.7555	2.7555	2.9945	2.3853	1.4246	0.5522
		3.1787	2.7882	3.4545	3.1216	3.2136	3.2136	3.5263	3.3188	3.3613	2.9670
		3.2025	2.8491	3.4883	3.3269	3.3252	3.3252	3.6194	3.5723	3.3966	3.0947
30	OLS FGLS HUBER BI-SQ	2.4604	1.6241	2.6368	1.8484	2.6062	1.7940	2.0176	1.0973	2.6105	1.8478
		2.4923	1.7018	2.6545	1.8655	2.5252	1.6536	1.8108	0.8877	1.0615	0.2939
		2.5518	1.7333	2.7092	1.9368	2.6742	1.8983	2.0224	1.1062	2.6998	1.9671
		2.5751	1.7692	2.7430	1.9716	2.7142	1.9313	2.0344	1.1168	2.7143	1.9771
50	OLS FGLS HUBER BI-SQ	1.9438	0.9921	2.0062	1.0441	1.9661	1.0147	2.5732	1.7527	1.8860	0.9480
		1.9651	1.0083	1.9832	1.0121	1.8130	0.8523	2.3495	1.4311	0.7492	0.1536
		1.9475	0.9913	1.9894	1.0398	1.9389	1.0091	2.6269	1.8215	1.9019	0.9854
		1.9620	0.9978	1.9944	1.0427	1.9457	1.0052	2.6819	1.8772	1.9053	0.9829
100	OLS FGLS HUBER BI-SQ	1.3881	0.5162	1.2958	0.4756	1.3145	0.4800	1.4054	0.5286	1.2414	0.4198
		1.3873	0.5160	1.2888	0.4603	1.1971	0.4004	1.2515	0.4098	0.4974	0.0642
		1.3872	0.5271	1.3000	0.4793	1.3311	0.4867	1.4235	0.5371	1.2686	0.4350
		1.3929	0.5298	1.3105	0.4856	1.3398	0.4924	1.4281	0.5404	1.2651	0.4342
250	OLS FGLS HUBER BI-SQ	0.8263	0.1830	0.8577	0.1945	0.8559	0.1947	0.8614	0.2021	0.8347	0.1838
		0.8262	0.1824	0.8500	0.1885	0.8014	0.1658	0.7808	0.1638	0.3312	0.0284
		0.8398	0.1889	0.8779	0.2054	0.8816	0.2076	0.8906	0.2156	0.8463	0.1923
		0.8454	0.1906	0.8746	0.2049	0.8766	0.2062	0.8909	0.2174	0.8481	0.1927
500	OLS FGLS HUBER BI-SQ	0.5870	0.0910	0.5870	0.0901	0.5925	0.0914	0.5995	0.0961	0.6030	0.0948
		0.5863	0.0910	0.5727	0.0863	0.5377	0.0772	0.5447	0.0769	0.2131	0.0281
		0.5857	0.0918	0.6075	0.0952	0.6160	0.0977	0.6188	0.1022	0.6231	0.0998
		0.5834	0.0918	0.6061	0.0951	0.6169	0.0981	0.6202	0.1021	0.6236	0.1002

When there is absence of contemporaneous correlation ($\rho = 0.0$) under square root heteroscedasticity of error terms, OLS is the most efficient estimator when $n \leq 30$. At these instances, the relative efficiency of other estimator is less than 100% indicating OLS

minimum RMSE. However, as the sample size increases ($n \geq 50$), all the estimators' performances are the same.

When the correlation increases between ($0.2 \leq \rho \leq 0.7$), the performances of FGLS relative to OLS increases from 3% to 13% when $n \leq 30$ but reduces from 8% to 11% when $n \geq 50$. However, OLS performs better than Huber and Bi-SQ in small sample size but both estimators' performances are equivalent in large samples.

Table 4.10A: Empirical Result of Estimators for Quadratic Heteroscedastic Normal Response Model.

Sample Size (n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	2.3901	1.5910	2.4879	1.6649	2.5490	1.7328	2.5756	1.8225	2.4506	1.6014
	FGLS	2.4212	1.6458	2.5458	1.7546	2.4727	1.6636	2.3501	1.4930	1.4772	0.6036
	HUBER	2.3117	1.5297	2.4458	1.6291	2.4892	1.6779	2.5419	1.7829	2.4195	1.6163
	BI-SQ	2.4251	1.6688	2.5404	1.7997	2.5832	1.8202	2.6524	1.8926	2.4636	1.7276
30	OLS	1.8838	0.9881	2.0311	1.0867	2.0155	1.0646	1.9942	1.0673	1.9754	1.0696
	FGLS	1.9144	1.0365	2.0567	1.1140	1.9601	1.0034	1.8395	0.8984	1.0465	0.3008
	HUBER	1.8575	0.9621	1.9635	1.0243	1.9599	1.0098	1.9169	0.9957	1.9735	1.0386
	BI-SQ	1.8904	1.0186	2.0183	1.0855	2.0210	1.0825	1.9732	1.0585	1.9918	1.0707
50	OLS	1.5145	0.6309	1.5404	0.6153	1.5115	0.6016	1.5703	0.6568	1.4559	0.5685
	FGLS	1.5446	0.6444	1.5231	0.5952	1.4138	0.5166	1.4283	0.5461	0.8084	0.1725
	HUBER	1.4297	0.5537	1.4517	0.5594	1.4034	0.5348	1.4956	0.6072	1.3734	0.5263
	BI-SQ	1.4374	0.5580	1.4701	0.5721	1.4234	0.5504	1.5085	0.6204	1.4002	0.5573
100	OLS	1.0726	0.3131	1.0074	0.2797	1.0172	0.2868	1.0904	0.3191	0.9587	0.2546
	FGLS	1.0738	0.3146	0.9976	0.2696	0.9491	0.2444	0.9948	0.2586	0.5106	0.0734
	HUBER	1.0123	0.2852	0.9413	0.2529	0.9587	0.2575	1.0161	0.2809	0.9179	0.2335
	BI-SQ	1.0235	0.2911	0.9686	0.2673	0.9898	0.2727	1.0345	0.2931	0.9457	0.2484
250	OLS	0.6124	0.1030	0.6540	0.1160	0.6570	0.1177	0.1206	0.1206	0.6282	0.1102
	FGLS	0.6140	0.1032	0.6493	0.1135	0.6243	0.1048	0.1023	0.1023	0.0360	0.0360
	HUBER	0.5908	0.0941	0.6233	0.1083	0.6244	0.1102	0.1130	0.1131	0.6101	0.1044
	BI-SQ	0.6145	0.1011	0.6383	0.1141	0.6396	0.1154	0.1188	0.1188	0.6228	0.1081
500	OLS	0.4571	0.0563	0.4490	0.0537	0.4520	0.0542	0.4682	0.0579	0.4556	0.0555
	FGLS	0.4569	0.0564	0.4405	0.0517	0.4199	0.0469	0.4292	0.0484	0.0159	0.0159
	HUBER	0.4295	0.0508	0.4386	0.0504	0.4448	0.0521	0.4528	0.0547	0.0523	0.0523
	BI-SQ	0.4337	0.0525	0.4431	0.0521	0.4485	0.0541	0.4569	0.0568	0.0545	0.0545

When the contemporaneous correlation is almost perfect ($\rho = 0.95$), using RMSE criterion the performances of FGLS better than other estimators. The efficiency of FGLS relative to any other estimators is between 106% and 146% for $n=20$ and $n=500$ respectively. Huber and Bi-SQ estimator perform equally well but below the OLS. However, FGLS remain the best and most efficient estimator.

4.4.4 Quadratic Heteroscedasticity

Table 4.10A presents the RMSE and RE for the parameters of normal response model with quadratic heteroscedastic error terms for different levels of contemporaneous correlations at various sample sizes.

When there is absence of correlation ($\rho = 0.0$) or low correlation ($\rho = 0.2$), at various sample sizes $n \leq 500$ using RMSE criterion under quadratic form of heteroscedasticity, the results reveal that neither OLS nor FGLS could maintain the small sample property as it does under other forms of heteroscedasticity. The best estimator in the absence of contemporaneous correlation ($\rho = 0.0$) under quadratic form of heteroscedasticity with normally distributed responses is Huber estimator. When $\rho = 0.2$ and $n \leq 30$, Huber estimator outperforms all other estimator showing relative minimum RMSE with relative efficiency of 1%-3% over OLS. However, OLS performs better than FGLS and Bi-SQ. At sample sizes $n \geq 50$ and $\rho = 0.2$, Huber, Bi-SQ and FGLS perform almost in similar manner with efficiency gain of 5%, 4% and 2%, for $n=50$, 5%, 3% and 2%, for $n=100$, 4%, 1% and 1% for $n=250$ and 4%, 2% and 2%, for $n=500$ respectively, relative to OLS. Therefore at $\rho=0.2$, quadratic heteroscedastic error and $n \geq 50$, Huber is the most efficient estimator.

When $\rho=0.5$, the FGLS and Huber estimator perform equally well with both estimators showing relatively minimum RMSE. Most importantly at sample size $n \leq 30$, the efficiency of FGLS and Huber relative to OLS are the same (102% and 103% for sample sizes 20 & 30

respectively. Meanwhile OLS performs better than Bi-SQ. At sample sizes ($n \geq 50$), the performance of Bi-SQ estimator improves with increase in sample size. The performances of FGLS, Huber and Bi-SQ are almost equivalent but FGLS is the most efficient with efficiency gain of 6 to 9% relative to OLS.

With moderately high correlation ($\rho \geq 0.7$), the performances of Huber and Bi-SQ is very encouraging under Quadratic heteroscedasticity than under Linear, Exponential and Square Root heteroscedasticity. The two estimators perform better than OLS while FGLS is the most efficient estimator.

When the correlation is almost perfect ($\rho = 0.95$) at different sample sizes (n), using RMSE as criterion for comparison, FGLS is the best estimator with efficiency of 64% over OLS when $n=30$ and 86% when $n=500$. However, the gain in efficiency of FGLS relatively to OLS increases at relative slow rate in Quadratic heteroscedasticity when $\rho=0.95$ than in other forms of heteroscedasticity.

4.4.5 Homoscedasticity

Table 4.5A shows the RMSE of parameter estimates at different levels of contemporaneous correlation under Normal response model with homoscedastic error term for different sample sizes.

When there is absence of correlation ($\rho=0.0$) between the error terms in different equations with homoscedastic error term, the OLS remain the most efficiency at sample sizes $n \leq 50$. However, when $n \geq 100$ both FGLS and OLS performance are the same Meanwhile Huber and Bi-SQ also show equivalent performance in large sample sizes ($n \geq 100$).

When the level of contemporaneous correlation is between ($0.2 \leq \rho \leq 0.7$), the performances of FGLS has improved relative to OLS estimator under homoscedastic error term. The

efficiency of FGLS relative to OLS when $n \leq 50$ is between 0%-1% for $\rho=0.2$ and 11%-14% for $\rho=0.7$. Meanwhile OLS performs better than Huber and Bi-Square estimators at various sample sizes.

Table 4.6.5A: Empirical Result of Estimators for Homoscedastic Heteroscedastic Normal Response Model.

Sample Size (N)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS FGLS HUBER BI-SQ	3.4978	3.3170	3.7969	3.7504	3.8685	3.9050	3.8353	3.9709	3.7214	3.5482
		3.5562	3.4453	3.8072	3.8687	3.6101	3.5150	3.3913	3.0539	1.6098	0.6964
		3.6058	3.5323	3.9547	4.0822	4.0246	4.2069	4.0310	4.3279	3.8421	3.8122
		3.6461	3.6370	4.0109	4.2636	4.0981	4.4183	4.1347	4.6601	3.9153	4.0684
30	OLS FGLS HUBER BI-SQ	2.7771	2.0571	2.9798	2.3791	2.9374	2.3049	2.8982	2.2360	2.9651	2.3788
		2.8181	2.1542	2.9902	2.3822	2.8453	2.1136	2.6715	1.8313	1.1748	0.3727
		2.9055	2.2196	3.0836	2.5195	3.0476	2.4703	2.9908	2.3498	3.0815	2.5722
		2.9355	2.2667	3.1238	2.5810	3.0860	2.5140	3.0427	2.4199	3.0903	2.5783
50	OLS FGLS HUBER BI-SQ	2.1920	1.2443	2.2736	1.3354	2.2260	1.2948	2.2773	1.3945	2.1359	1.2053
		2.2041	1.2605	2.2407	1.2975	2.0459	1.0898	2.0439	1.1322	0.8345	0.1908
		2.2136	1.2718	2.2663	1.3451	2.2047	1.2976	2.2965	1.4249	2.1664	1.2623
		2.2360	1.2937	2.2742	1.3520	2.2266	1.3053	2.3111	1.4382	2.1837	1.2682
100	OLS FGLS HUBER BI-SQ	1.5693	0.6552	1.4711	0.6116	1.4910	0.6141	1.5897	0.6725	1.4077	0.5344
		1.5653	0.6543	1.4601	0.5929	1.3569	0.5118	1.4169	0.5217	0.5569	0.0808
		1.5869	0.6840	1.4835	0.6200	1.5183	0.6303	1.6246	0.6956	1.4462	0.5610
		1.5899	0.6835	1.4948	0.6268	1.5272	0.6346	1.6293	0.6987	1.4414	0.5567
250	OLS FGLS HUBER BI-SQ	0.9470	0.2401	0.9785	0.2491	0.9723	0.2485	0.9820	0.2594	0.9541	0.5581
		0.9460	0.2390	0.9673	0.2408	0.9075	0.2099	0.8862	0.2104	0.3681	0.0347
		0.9699	0.2520	1.0102	0.2676	1.0119	0.2693	1.0259	0.2802	0.9697	0.2492
		0.9706	0.2513	1.0063	0.2663	1.0082	0.2673	1.0269	0.2821	0.9700	0.2484
500	OLS FGLS HUBER BI-SQ	0.6641	0.1150	0.6640	0.1155	0.6719	0.1175	0.6750	0.1225	0.6878	0.1222
		0.6632	0.1150	0.6503	0.1107	0.6089	0.0993	0.6148	0.0976	0.2390	0.0151
		0.6623	0.1169	0.6961	0.1234	0.7069	0.1272	0.7079	0.1321	0.7123	0.1296
		0.6613	0.1170	0.6929	0.1228	0.7060	0.1270	0.7082	0.1315	0.7104	0.1291

When the contemporaneous correlation is almost perfect ($\rho=0.95$), using RMSE criterion for homoscedastic error term the best estimator is FGLS at various sample sizes. The relative efficiency of FGLS to OLS is 131% and 183% for $n=20$ and 500 respectively. The Bi-squares and Huber estimators' performance is close to that of OLS. The efficiency of OLS relative to

Bi-squares and Huber when sample size is between 20 and 500 is 4% -3% and 7%-3% respectively.

Therefore, when the distribution of the response variables is normal with homoscedastic error term and $\rho=0.95$, the best estimator is FGLS at various sample sizes.

4.5 Variance and Absolute Bias of Parameter Estimates for Gamma Response Model

4.5.1 Exponential Heteroscedasticity

Table 4.6B shows the results of simulation when form of heteroscedasticity is Exponential for Gamma response model at various contemporaneous correlations using Absolute Bias (ABS) criterion.

When there is absence of correlation ($\rho = 0.0$) between the error terms in different equations at different sample sizes, the performance OLS and FGLS estimators is similar using Absolute bias criterion while the Huber and Bi-squares perform better than the OLS and FGLS estimators. The best estimator for Gamma response model with Exponential heteroscedastic error terms in the absence of contemporaneous correlation using Absolute bias criterion is Bi-squares estimators.

When the level of correlation increases between ($0.2 \leq \rho \leq 0.7$), the performances of FGLS has improved better than OLS when $n \leq 30$ but not better than Huber and Bi-squares estimators, The best estimator is Bi-squares estimator followed by Huber estimator. In summary, in terms of Absolute bias, the most efficient estimator under exponential heteroscedastic error terms, response Gamma model at small sample sizes $n \leq 30$ with both absence of correlation or moderately high correlation is Bi-squares estimator.

Table 4.6B: Empirical Result of Estimators for Exponential Heteroscedastic Gamma Response Model

(n)	Estimator	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	38.9043	298.3050	42.4267	342.0166	45.2599	353.3735	14.4450	322.2785	44.9773	39.5182
	FGLS	38.9580	306.8145	41.5374	324.6244	42.5139	288.7675	13.3623	72.6076	33.9322	30.1565
	HUBER	31.5632	184.3239	35.4219	216.6098	38.9840	236.7875	12.7667	241.7423	39.9836	29.6442
	BI-SQ	29.7231	169.2190	33.7542	202.3546	37.7269	228.1048	12.5731	237.0042	39.1679	29.6607
30	OLS	34.0014	183.7002	32.8068	145.4872	36.1973	145.7394	11.8025	160.4993	38.4786	20.2790
	FGLS	34.7438	196.7047	32.9200	147.2494	35.6919	134.5275	11.4733	28.6241	31.4352	16.8289
	HUBER	28.3834	122.6679	28.5609	106.7507	32.5515	112.9839	10.5696	118.9762	34.8311	16.4196
	BI-SQ	26.5699	113.3827	27.5700	108.0639	31.6704	114.4559	10.2301	115.0664	33.7527	16.2088
50	OLS	30.1415	105.9478	31.5366	111.4988	34.7977	109.7373	11.3993	104.4844	36.3714	15.2408
	FGLS	30.2955	108.5580	31.3945	109.7622	33.8840	96.5634	10.8407	17.4670	31.3160	12.3730
	HUBER	24.9232	70.0070	26.5504	72.5695	30.2504	77.6719	9.8466	72.4365	31.5930	10.5243
	BI-SQ	22.8740	66.3125	24.9090	66.9500	28.8249	73.8366	9.3864	71.8937	30.0884	9.9736
100	OLS	26.5173	50.7551	27.8866	49.0389	31.4297	47.9131	9.9373	51.7192	33.3522	6.1520
	FGLS	26.6316	52.1447	27.8519	48.4165	31.1568	42.6097	9.6697	7.8149	31.0367	4.8706
	HUBER	21.9039	31.8744	23.6322	30.2212	27.6823	32.8114	8.6628	33.1435	29.1188	4.4990
	BI-SQ	19.6239	29.2124	21.5628	29.0633	25.8957	32.5412	8.1152	32.0964	27.5081	4.5574
250	OLS	24.1558	20.4853	26.2925	23.3005	30.1104	23.2746	9.4732	23.6352	31.8266	2.7165
	FGLS	24.1657	20.6189	26.1529	22.5128	29.7620	19.7437	9.3020	3.0974	31.2927	1.8482
	HUBER	20.0077	13.0108	21.9826	13.2134	26.0955	14.6520	8.1302	14.9958	27.9404	1.7598
	BI-SQ	17.6439	12.7538	19.6514	12.0669	24.1072	13.8630	7.4416	14.3664	26.1501	1.6765
500	OLS	23.7234	9.5063	25.7023	10.1605	29.5856	10.0929	9.4017	9.2937	31.8457	1.2811
	FGLS	23.7240	9.5286	25.6089	9.7854	29.4055	8.5119	9.3502	1.5450	31.5806	0.9788
	HUBER	19.3450	5.4914	21.4639	5.8774	25.6493	6.4323	8.0508	6.4426	27.7935	0.7732
	BI-SQ	16.4715	5.1699	18.8753	5.2584	23.4844	6.0728	7.2954	6.3805	25.7722	0.7119

When the correlation is almost perfect ($\rho = 0.95$) at sample sizes $n \leq 30$, FGLS is the most efficiency estimator. Huber and Bi-squares perform well but less efficient at $n=20$ and 30 .

When $n \geq 50$ and $\rho = 0.95$ Bi-squares is the most efficient estimator. OLS and FGLS estimators are consistent and both perform equally in large samples. Huber estimator performs closely well with Bi-squares estimator.

VARIANCE

Table 4.6B present the variance (VAR) of parameter estimates when the form of heteroscedasticity is Exponential for Gamma response model at various contemporaneous correlations for different sample sizes.

When there is absence of correlation ($\rho = 0.0$) between the error terms in different equations for exponential heteroscedastic error terms with Gamma response model at different sample sizes, the best estimator is Bi-squares using variance criterion. However, Huber performs closely to Bi-squares and better than the OLS and FGLS estimators at various sample sizes. OLS performs better than FGLS when $n \leq 30$ and both perform similarly in large samples ($n \geq 50$).

When the level of correlation increases between ($0.2 \leq \rho \leq 0.7$), regardless of the sample size using variance criterion the best estimator is Bi-squares estimator. However, the performances of FGLS has improved better than OLS when $n \leq 30$ and contemporaneous correlation is between $0.2 \leq \rho \leq 0.5$ but less efficient than Huber and Bi-squares estimators. When $\rho = 0.7$, the performance of FGLS, Huber and Bi-squares are equivalent in small samples ($n \leq 30$). But in large samples ($n \geq 50$), OLS and FGLS perform equally while Huber also performs closely with Bi-squares estimator. Above all, Bi-squares is the best estimator followed by Huber estimator.

When the correlation is almost perfect ($\rho = 0.95$) at different sample sizes ($n \leq 500$), using variance criterion FGLS is the most efficiency estimator.

At this instance, the performance of both Huber and Bi-squares is poor relative to FGLS.

4.5.2 Linear Heteroscedasticity

Table 4.7B presents the Absolute bias (ABS) estimates of parameters for Gamma response model with linear heteroscedastic error terms at various contemporaneous correlations for different sample size.

At small sample sizes $n=20$ and 30 in the absence of correlation ($\rho = 0.0$) between the error terms in different equation the best estimator is Bi-square followed by Huber estimators using Absolute bias criterion. The OLS and FGLS performance is similar but less efficient.

When sample size increases between $n=50$ and $n=500$, FGLS and OLS are both consistence and exhibiting equal performance but not as efficient as Huber and Bi-squares estimators.

Table 4.7B: Empirical Result of Estimators for Linear Heteroscedastic Gamma Response Model

Sample	Estimat or	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
n		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	13.8735	37.6831	15.0779	43.7647	16.1320	45.2447	14.4450	39.5182	16.0813	41.0228
	FGLS	13.9294	38.8682	14.7655	41.4550	15.1621	37.0133	13.3623	30.1565	12.4797	9.7531
	HUBER	11.1615	23.1478	12.4903	27.4101	13.8156	29.9448	12.7667	29.6442	14.2041	30.5166
	BI-SQ	10.4512	21.1119	11.8448	25.3230	13.3229	28.6250	12.5731	29.6607	13.8698	29.7592
30	OLS	12.1230	23.4221	11.8045	18.4118	13.0363	18.4142	11.8025	20.2790	13.8408	20.2728
	FGLS	12.4061	25.1201	11.8312	18.6388	12.8825	17.0607	11.4733	16.8289	11.7058	3.8589
	HUBER	10.0882	15.4881	10.2301	13.3662	11.6842	14.1152	10.5696	16.4196	12.4461	14.8758
	BI-SQ	9.3549	14.2532	9.7979	13.4378	11.3054	14.2426	10.2301	16.2088	12.0020	14.2736
50	OLS	10.8034	13.4223	11.3346	14.0985	12.6082	13.8940	11.3993	15.2408	13.1707	13.2657
	FGLS	10.8546	13.7252	11.3056	13.8790	12.3268	12.2593	10.8407	12.3730	11.7626	2.4211
	HUBER	8.8699	8.8129	9.4678	9.0955	10.8787	9.7482	9.8466	10.5243	11.3996	9.2128
	BI-SQ	8.0422	8.2499	8.8086	8.3993	10.2869	9.2739	9.3864	9.9736	10.7762	9.0901
100	OLS	9.6776	6.4329	10.1996	6.2062	11.5706	6.0664	9.9373	6.1520	12.2737	6.5185
	FGLS	9.7147	6.6145	10.1923	6.1415	11.5002	5.4266	9.6697	4.8706	11.6747	1.0687
	HUBER	7.8946	4.0043	8.6050	3.8280	10.1581	4.1592	8.6628	4.4990	10.7001	4.1942
	BI-SQ	6.9806	3.6187	7.7558	3.6635	9.4111	4.1062	8.1152	4.5574	10.0458	4.0614
250	OLS	8.9486	2.5898	9.7797	2.9741	11.2384	2.9685	9.4732	2.7165	11.9273	3.0102
	FGLS	8.9532	2.6059	9.7308	2.8758	11.1293	2.5282	9.3020	1.8482	11.7930	0.4351
	HUBER	7.2980	1.6260	8.0889	1.6726	9.6674	1.8602	8.1302	1.7598	10.4075	1.9085
	BI-SQ	6.3504	1.5890	7.1420	1.5141	8.8724	1.7414	7.4416	1.6765	9.6920	1.8151
500	OLS	8.8835	1.1982	9.6580	1.2932	11.1285	1.2877	9.4017	1.2811	11.9845	1.1730
	FGLS	8.8825	1.2016	9.6315	1.2438	11.0812	1.0849	9.3502	0.9788	11.9124	0.2205
	HUBER	7.1592	0.6851	7.9910	0.7380	9.5821	0.8103	8.0508	0.7732	10.4046	0.8077
	BI-SQ	6.0140	0.6500	6.9664	0.6629	8.7243	0.7623	7.2954	0.7119	9.6022	0.7975

When the correlation is between ($0.2 \leq \rho \leq 0.7$) with Gamma response, using Absolute bias as criterion for comparison among the estimators, Bi-square is the best estimator at different sample sizes. At this instance, the FGLS estimator has improved better than the OLS estimator but inefficient.

When the correlation is almost perfect ($\rho = 0.95$) at sample sizes $n \leq 30$ using Absolute bias criterion FGLS is the most efficiency estimator. As sample size (n) increases from 50 to 500 , the performances of FGLS, Huber and Bi-squares are the same but Bi-square estimator has the least value of Absolute bias, hence the most efficient estimator when $n \geq 50$ and $\rho = 0.95$.

.VARIANCE

Table 4.7B present the variance (VAR) estimate of parameters in Gamma response model with linear heteroscedastic error terms at different levels of Contemporaneous correlation (ρ) at different sample sizes (n).

When there is absence of correlation ($\rho=0.0$) with Gamma response model under linear heteroscedastic error terms, Bi-Square estimator is the best estimator at all sample sizes ($n \leq 500$). Huber estimator performs in similar manner but with slightly higher variance than Bi-Square estimator in all the sample sizes. FGLS and OLS performances are the same but not efficient in all the sample sizes.

At $\rho=0.2$ and 0.5 , and for $n \leq 30$ under Gamma response using variance criterion, the performances of FGLS have improved slightly than OLS at this instances but both estimators performances are close as sample size increases. Huber estimator performs better than FGLS and OLS in all sample sizes. However, the best estimator is Bi-Squares estimator in all sample sizes considered.

When $\rho=0.7$ and $n \leq 30$ under Gamma response using variance criterion, the performances of FGLS, Huber and Bi-squares are approximately the same. Bi-squares still has the least variance even at $n > 30$, hence the best estimator when $\rho=0.7$ and $n \leq 500$ using variance as criterion is Bi-squares estimator.

When the correlation is almost perfect ($\rho=0.95$) under Gamma response model, the performance of FGLS is better than OLS, Huber and Bi-squares estimators at different sample sizes ($n \leq 500$) using variance criterion. OLS remain the worse estimator. The best estimator, under Gamma response model and Linear heteroscedastic error term with $\rho=0.95$ notwithstanding the sample size, is FGLS estimator.

4.5.3 Quadratic Heteroscedasticity

Table 4.8B presents Absolute bias (ABS) estimate of parameters for Gamma response model with Quadratic heteroscedastic error term at various levels of contemporaneous correlation under different sample sizes.

When there is absence of correlation ($\rho = 0.0$) at various sample sizes $n \leq 500$ using Absolute bias criterion Bi-squares estimator is the best. The Huber estimator performs better than OLS and FGLS. However, OLS and FGLS performances are the same in all the sample sizes considered.

When the correlation is between ($0.2 \leq \rho \leq 0.7$) at various sample sizes $n \leq 500$, Bi-squares is still the best estimator in terms of Absolute bias criterion followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but not better than Huber and Bi-squares estimators.

When the correlation is almost perfect ($\rho = 0.95$) at various sample size $n \leq 500$ using Absolute bias as criterion for comparison, Bi-squares is the best estimator. Huber and FGLS estimators performance is the same but less efficient than Bi-squares estimator when $n \leq 30$ and $\rho = 0.95$ using absolute bias criterion. At this point, FGLS lost its efficiency in small sample.

As the sample size (n) increases from 50 to 500, the Huber performs better than FGLS and OLS. Therefore, the best estimator when $\rho = 0.95$ and $n \leq 500$ using Absolute bias as criteria is Bi-squares estimator followed by Huber estimator.

Table 4.8B: Empirical Result of Estimators for Quadratic Heteroscedastic Gamma Response Model

		Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	12.4511	26.6953	13.5463	33.5431	14.7841	34.8919	12.8842	29.3209	14.9449	31.0275
	FGLS	12.5339	27.8702	13.3075	31.4415	14.0614	29.0589	12.1362	22.5462	12.7507	10.8057
	HUBER	9.4925	15.3602	10.6214	19.1025	12.0997	21.0349	10.7800	20.1921	12.6332	21.0797
	BI-SQ	8.5301	14.6453	9.5016	16.2835	11.0816	18.9565	10.2091	19.4141	11.8216	19.9024
30	OLS	11.2152	17.8117	11.4379	13.7373	12.6724	13.7843	11.1220	14.6163	13.2673	14.9887
	FGLS	11.4318	19.0160	11.5372	14.0031	12.6772	13.0351	10.9349	12.5819	11.9368	4.5208
	HUBER	8.7269	10.8148	9.3374	9.0509	10.7965	9.6741	9.5868	10.9648	11.4216	10.1692
	BI-SQ	7.5597	9.5357	8.4374	8.5458	9.9818	9.1050	9.0352	10.9269	10.5092	9.1547
50	OLS	10.2073	9.8651	10.8543	10.3007	12.1703	10.1594	10.9416	11.0805	12.6227	9.4771
	FGLS	10.2702	10.0186	10.8352	10.2311	12.0657	9.1918	10.6186	9.2938	12.0521	2.7677
	HUBER	7.7765	5.9383	8.5044	6.1453	10.0745	6.5744	8.8813	7.0085	10.6404	6.3134
	BI-SQ	6.5939	5.4089	7.4765	5.4942	9.1169	6.0943	7.9975	6.3939	9.7039	6.0648
100	OLS	9.5473	4.7312	10.1431	4.5539	11.5913	4.4778	9.8212	4.6124	12.3956	4.7239
	FGLS	9.5949	4.8812	10.1163	4.5278	11.5112	4.0909	9.6793	3.7716	12.0091	1.3069
	HUBER	7.2913	2.7189	8.0729	2.5901	9.7058	2.8017	8.0604	3.0095	10.4563	2.8817
	BI-SQ	6.0017	2.2960	6.9672	2.4452	8.6780	2.7448	7.2107	3.0290	9.4932	2.8110
250	OLS	9.1173	1.9307	9.9705	2.2469	11.5054	2.2515	9.6459	2.0485	12.2971	2.2661
	FGLS	9.1176	1.9371	9.9270	2.1773	11.4248	1.9559	9.5168	1.4557	12.1771	0.5911
	HUBER	6.9349	1.1288	7.8341	1.1688	9.5244	1.3069	7.9370	1.2044	10.3751	1.3410
	BI-SQ	5.6532	1.0410	6.5760	0.9776	8.4178	1.1412	6.9848	1.1052	9.3837	1.2080
500	OLS	9.1287	0.8540	9.9505	0.9506	11.4773	0.9535	9.6874	0.9822	12.3518	0.8432
	FGLS	9.1296	0.8581	9.9333	0.9154	11.4469	0.8157	9.6457	0.7692	12.2997	0.2796
	HUBER	6.9538	0.4701	7.8485	0.5038	9.5273	0.5508	7.9770	0.5390	10.4034	0.5436
	BI-SQ	5.5624	0.4478	6.6081	0.4558	8.4261	0.5071	7.0082	0.4914	9.3511	0.5250

VARIANCE

Table 4.8B presents the variance (VAR) estimates of parameter for Gamma response model with Quadratic heteroscedastic error terms at various levels of contemporaneous correlation under different sample sizes.

When there is absence of correlation ($\rho = 0.0$) at various sample sizes $n \leq 500$ using variance criterion Bi-squares estimator is the best. The Huber estimator performs better than OLS and

FGLS. OLS performs better than FGLS when $n \leq 30$, however both estimators are the same as n increases $n \geq 50$.

When the correlation between $(0.2 \leq \rho \leq 0.7)$ at various sample sizes $n \leq 500$, Bi-squares is still the best estimator in terms of variance criterion followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases better than OLS but less efficient.

When the correlation is almost perfect ($\rho = 0.95$) regardless of the size of the sample (n) using variance as criterion for comparison, FGLS is the best estimator.

In summary, the best estimator for modeling Gamma response model with Quadratic heterocedasticity at different levels of contemporaneous correlation (ρ) notwithstanding the size of the sample (n) using variance criterion is Bi-squares except when Cc is almost perfect ($\rho = 0.95$) where FGLS estimator is best.

4.5.4 Square -Root Heteroscedasticity

Table 4.9B presents the Absolute bias (ABS) for the model parameter estimates for Gamma response model with Square root Heteroscedasticity at various levels of contemporaneous correlation for different sample sizes.

When there is absence of correlation ($\rho = 0.0$) for all the sample sizes considered using absolute bias criterion Bi-squares is the most efficient estimator followed by Huber estimator. OLS and FGLS performance is the same but inefficient.

When the correlation is $(0.2 \leq \rho \leq 0.7)$ at various sample sizes $n \leq 500$, using absolute bias criterion Bi-squares is still the best estimator followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but perform below Bi-squares and Huber estimators.

When the correlation is almost perfect ($\rho = 0.95$) at sample size $n \leq 50$ using Absolute bias as criterion for comparison, FGLS is the best estimator. As the sample size (n) increases from 100 to 500, the Bi-squares performance increases due to the increase in sample size. Therefore, the best estimator when $\rho = 0.95$ and $n \geq 100$ using Absolute bias as criteria is Bi-squares estimator followed by Huber estimator.

Table 4.9B: Empirical Result of Estimators for Square-Root Heteroscedastic Gamma Error Model

		Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	15.5379	46.8817	16.9475	52.3300	18.0619	53.9462	16.4128	48.1030	17.9369	49.6074
	FGLS	15.5316	47.9326	16.6751	50.0068	16.9986	44.0565	15.1519	36.9473	13.0484	10.2828
	HUBER	12.7813	29.4889	14.3036	34.0688	15.7383	37.1771	14.8104	37.3045	16.0758	37.7839
	BI-SQ	12.0525	27.1414	13.6209	32.2669	15.1932	36.4129	14.5332	37.5430	15.7462	37.7110
30	OLS	13.6558	28.2675	13.0580	22.6252	14.3538	22.6456	13.2642	25.2612	15.3767	25.0355
	FGLS	13.9061	30.2789	13.1186	22.8371	14.1010	20.8036	12.6818	20.6934	11.8670	4.1104
	HUBER	11.4307	19.1879	11.3619	16.8414	12.9287	17.7823	11.8428	20.6918	13.9668	18.8371
	BI-SQ	10.7626	17.8357	11.0105	17.0673	12.6158	17.9775	11.5171	20.2880	13.6387	18.4591
50	OLS	12.0503	12.0503	12.5920	17.4197	13.7516	17.1504	12.6258	18.8419	14.4178	16.4644
	FGLS	12.0926	12.0926	12.5388	17.1048	13.3338	15.0097	11.9390	15.1091	11.6289	2.5325
	HUBER	10.0414	10.0414	10.6954	11.5533	12.0758	12.3988	11.0794	13.4410	12.5943	11.4794
	BI-SQ	9.2877	9.2877	10.1127	10.7211	11.6045	11.8273	10.6867	12.8164	12.1259	11.4560
100	OLS	10.3805	7.9269	10.8789	7.6692	12.1073	7.4850	10.6917	7.5197	12.8580	8.0878
	FGLS	10.4331	8.1277	10.8544	7.5706	11.9127	6.6440	10.2754	5.9027	11.3656	1.0972
	HUBER	8.7137	5.0770	9.2721	4.7847	10.7256	5.1948	9.5126	5.6238	11.2957	5.2305
	BI-SQ	7.8939	4.7439	8.5715	4.6168	10.1417	5.1558	9.0933	5.7623	10.7556	5.0671
250	OLS	9.2690	3.1802	9.9709	3.5978	11.3040	3.5890	9.6772	3.2940	11.4656	14.2158
	FGLS	9.2778	3.2031	9.9251	3.4776	11.1385	3.0406	9.3016	2.2340	11.2812	11.7290
	HUBER	7.8193	2.0532	8.4595	2.0822	9.9054	2.2953	8.4488	2.1997	10.2003	12.3910
	BI-SQ	7.0071	2.0217	7.7085	1.9143	9.2782	2.1973	7.9074	2.1212	9.5834	11.9050
500	OLS	8.8454	1.4954	9.5338	1.5872	10.9249	1.5741	9.2891	1.5415	11.6965	1.4614
	FGLS	8.8440	1.4977	9.4908	1.5290	10.8127	1.3263	9.1746	1.1782	11.4903	0.2109
	HUBER	7.3540	0.8798	8.1002	0.9360	9.5986	1.0220	8.1153	0.9637	10.3386	1.0243
	BI-SQ	6.4138	0.8141	7.2490	0.8354	8.8981	0.9692	7.5111	0.8939	9.7055	1.0208

VARIANCE

Table 4.9B present the variance (VAR) estimates of parameter for Gamma response model with Square-root heteroscedastic error terms at various levels of contemporaneous correlation under different sample sizes.

When there is absence of correlation ($\rho = 0.0$) at various sample sizes $n \leq 500$ using variance criterion Bi-squares estimator is the best. The Huber estimator performs better than OLS and FGLS. OLS performs better than FGLS at different samples; however both estimators are very close as n increases.

When the correlation is between $\rho = 0.2, 0.5$ and $n=20$, Bi-squares is still the best estimator in terms of variance criterion followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but better than Huber estimator.

When $\rho = 0.7$ and $n=20$, FGLS is the most efficient estimator. As sample sizes increases Bi-squares performs better than FGLS while the performance of both Huber and FGLS estimators are the same. Therefore, when $\rho = 0.7$ and $n \geq 30$ using variance criterion Bi-squares is the best estimator.

When the correlation is almost perfect ($\rho = 0.95$) regardless of the size of the sample (n) using variance as criterion for comparison, FGLS is the best estimator.

In summary, the best estimator for modeling Gamma response model with Square-Root heteroscedastic error term at different levels of contemporaneous correlation (ρ) notwithstanding the size of the sample (n) using variance criterion is FGLS estimator.

4.5.5 Homoscedasticity

Table 4.10B shows the absolute for model parameter estimates when the error terms homoscedastic at various levels of contemporaneous correlation for different sample sizes.

When there is absence of correlation ($\rho = 0.0$) between the error terms in different equations and error terms is homoscedastic using absolute criterion, the best estimator is Bi-squares at different sample sizes ($n \geq 20$). The Huber estimator performs better than OLS and FGLS

but below Bi-squares estimator. This reaffirms the conclusion reached at this instance using RMSE criteria that when response is non-normal, OLS or FGLS is inefficient.

When the correlation is between $0.2 \leq \rho \leq 0.7$ at various sample sizes $n \leq 500$ and the error term is homoscedastic using absolute criterion, Bi-squares is the best estimator followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but perform below Bi-squares and Huber estimators.

When the correlation is almost perfect ($\rho = 0.95$) for homoscedastic error terms at sample size $n=20, 30, 50$, and 100 using absolute bias as criterion for comparison among estimators of Gamma response model, FGLS is the best estimator. When the error terms are homoscedastic and response variables followed Gamma distribution with contemporaneous correlation of $\rho = 0.95$ for $n \geq 250$ using absolute bias criteria Bi-squares is the most efficient estimator.

VARIANCE

Table 4.10B presents the variance for model parameter estimates when the error terms homoscedastic at various levels of contemporaneous correlation for different sample sizes.

When there is absence of correlation ($\rho=0.0$) between the error terms in different equations with homoscedastic error term, the performances of FGLS and OLS are equivalent in all

Sample sizes. Huber estimator performs better than FGLS and OLS in all sample sizes but consistently below Bi-square estimator. In other word, when error term is homoscedastic and there is absence of contemporaneous correlation using variance criterion, the best estimation is Bi-square for all the sample sizes considered.

When the correlation is between $\rho = 0.2, 0.5$ at different samples (n), Bi-squares is still the best estimator in terms of variance criterion followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but better than OLS.

When $\rho = 0.7$ and $n=20$, FGLS is the most efficient estimator. As sample sizes increases Bi-squares performs better than FGLS while the performance of both Huber and FGLS estimators are the same. Therefore, when $\rho = 0.7$ and $n \geq 30$ using variance criterion Bi-squares is the best estimator.

Table 4.10B: Empirical Result of Estimators for Homoscedastic Gamma Response

Model

(n)	Estimators	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	18.3028	60.2981	20.0308	64.7234	21.4191	66.5395	19.5817	60.6129	21.3760	62.2420
	FGLS	18.3147	61.0370	19.9059	62.4491	20.3507	54.5295	18.0846	47.1355	15.0746	12.3506
	HUBER	15.1558	38.4598	16.9533	43.5057	18.7062	47.3985	17.7104	47.6469	19.0766	48.1818
	BI-SQ	14.3319	35.9607	15.9786	41.3552	17.9059	46.3364	17.2089	48.3334	18.4999	47.9582
30	OLS	16.2289	35.4569	15.6551	29.0662	17.0792	29.1613	15.9489	32.8297	18.4508	32.2917
	FGLS	16.4161	37.8340	15.7173	29.2614	16.9272	26.6190	15.1231	26.7197	13.5917	5.2832
	HUBER	13.5503	24.4292	13.4466	22.0403	15.2843	23.3922	14.0348	26.8810	16.7256	24.7777
	BI-SQ	12.7213	22.8585	12.9594	22.1641	14.8459	23.3588	13.5841	26.0755	16.2862	24.2761
50	OLS	14.4533	21.1280	15.2035	22.4510	16.5258	22.0643	15.1945	24.2388	17.4330	21.1668
	FGLS	14.5559	21.7638	15.0700	22.0215	15.9860	19.2305	14.3018	19.2966	12.9721	3.1358
	HUBER	11.9942	14.1938	13.0106	15.2191	14.6510	16.3675	13.3588	17.7747	15.1992	14.7478
	BI-SQ	11.1234	13.8073	12.2076	14.1282	14.0485	15.5809	12.7948	16.8870	14.7718	14.7542
100	OLS	12.3017	10.1679	12.9198	9.8826	14.2420	9.6410	12.7669	9.5974	14.9181	10.4531
	FGLS	12.3340	10.3905	12.8145	9.7363	13.9004	8.5231	12.2479	7.5259	11.9955	1.3899
	HUBER	10.2695	6.5892	10.8486	6.0547	12.3908	6.5978	11.2592	7.1814	13.1317	6.7078
	BI-SQ	9.3214	6.3309	10.0442	5.8775	11.7590	6.5795	10.7434	7.4016	12.6072	6.5107
250	OLS	11.0457	4.0814	11.6284	4.5242	12.9574	4.5148	11.1035	4.1570	13.6697	4.5835
	FGLS	11.0640	4.1129	11.6103	4.3736	12.7704	3.8227	10.6900	2.8560	11.5309	0.5285
	HUBER	9.3077	2.6557	9.8671	2.6385	11.3770	2.8944	9.7278	2.8082	12.0687	2.9507
	BI-SQ	8.3180	2.6245	9.0010	2.4576	10.7041	2.8110	9.1437	2.7231	11.5070	2.8701
500	OLS	9.9691	1.9391	10.7242	2.0229	12.0525	1.9977	10.3629	1.9323	12.6084	1.8942
	FGLS	9.9647	1.9393	10.7099	1.9549	11.9049	1.6936	10.1087	1.4928	11.3744	0.2432
	HUBER	8.4009	1.1446	9.1997	1.2107	10.6747	1.3183	9.0960	1.2302	11.3426	1.3358
	BI-SQ	7.4347	1.0532	8.3392	1.0898	10.0146	1.2593	8.5026	1.1491	10.8467	1.3312

When the contemporaneous correlation is almost perfect ($\rho=0.95$), using variance criterion for homoscedastic error term the best estimator is FGLS in all the sample sizes considered.

4.6 Variance and Absolute Bias of Parameter Estimates for Log-Normal Response Model

4.6.1 Homoscedasticity

Table 4.6C shows the absolute for lognormal response model parameter estimates with homoscedastic error terms at various levels of contemporaneous correlation for different sample sizes.

When $\rho = 0.0$ and error terms is homoscedastic using absolute bias criterion, the best estimator is Bi-squares regardless of the sample sizes. The Huber estimator performs better than OLS and FGLS but below Bi-squares estimator.

When the correlation is between $0.2 \leq \rho \leq 0.7$ at various sample sizes $n \leq 500$ and the error term is homoscedastic using absolute criterion, Bi-squares is the best estimator followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but perform below Bi-squares and Huber estimators.

When the correlation is almost perfect ($\rho = 0.95$) for homoscedastic error terms at sample sizes $n=20$ and 30 using absolute bias as criterion for comparison among estimators of Lognormal response model, FGLS is the best estimator. However, when the error terms are homoscedastic and response variables followed Lognormal distribution with contemporaneous correlation of $\rho = 0.95$ for $n \geq 50$ using absolute bias criteria Bi-squares is the most efficient estimator.

Table 4.5.1C: Empirical Result of Estimators for Homoscedastic Log- Normal Response Model

(n)	Estimators	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	8.9777	18.0813	9.4284	20.2352	9.7905	19.3432	9.2616	18.5791	9.7542	16.6827
	FGLS	9.0610	18.0177	9.3768	18.5561	9.2724	14.4659	8.5545	12.4396	6.1058	2.1366
	HUBER	5.4928	5.0762	6.1148	5.1648	6.7550	5.6490	6.7943	7.7122	6.8999	5.1216
	BI-SQ	4.7845	4.2727	5.4223	4.4085	6.1854	5.0345	6.1451	6.3934	6.5525	4.7948
30	OLS	7.5001	10.1060	7.9050	11.4119	8.3866	10.6199	7.0469	7.1208	8.8156	11.1283
	FGLS	7.6608	10.7043	7.8947	10.9414	8.1694	9.3770	6.5647	5.7612	5.9239	1.4619
	HUBER	4.9560	3.2896	5.4998	3.5340	6.3405	4.0167	5.5857	4.1304	6.7189	4.0400
	BI-SQ	4.2121	2.1937	4.7084	2.6917	5.6736	3.3062	5.1115	3.8066	6.2478	3.5267
50	OLS	6.4155	6.7655	6.8785	6.5727	7.4186	6.5730	6.7894	6.9109	7.5497	4.9016
	FGLS	6.4783	6.8994	6.8439	5.6688	7.1733	4.8894	6.1004	4.2326	5.5844	0.8578
	HUBER	4.1415	1.4815	4.6087	1.6968	5.3002	1.9273	4.8395	2.2213	5.6361	1.8856
	BI-SQ	3.6185	1.2584	4.0579	1.3359	4.7618	1.5212	4.4097	1.8382	5.1401	1.5772
100	OLS	5.5222	2.9164	5.9617	2.9258	6.5153	2.8452	5.8220	2.7426	6.9639	3.1065
	FGLS	5.5081	2.8833	5.9102	2.8673	6.3007	2.4635	5.4158	1.9788	5.2500	0.3466
	HUBER	3.7666	0.8068	4.0802	0.8009	4.7823	0.9016	4.3250	1.1547	5.1814	0.9635
	BI-SQ	3.2263	0.5965	3.5872	0.6582	4.3257	0.7654	3.9414	1.0204	4.7373	0.8309
250	OLS	4.7839	1.1923	5.0348	1.1457	5.6034	1.1682	4.8859	1.1026	5.9764	1.3071
	FGLS	4.7890	1.2056	4.9612	1.0427	5.4251	0.9318	4.6695	0.7684	4.8857	0.1454
	HUBER	3.2461	0.2821	3.5722	0.2897	4.2208	0.3511	3.7090	0.4268	4.6002	0.4056
	BI-SQ	2.6860	0.1818	3.0649	0.2277	3.7582	0.2960	3.3428	0.4000	4.1835	0.3489
500	OLS	4.3461	0.5653	4.6836	0.6212	5.2432	0.6218	4.5120	0.5784	5.5352	0.6042
	FGLS	4.3422	0.5641	4.6580	0.5958	5.1270	0.5088	4.3173	0.3965	4.7994	0.0757
	HUBER	3.0162	0.1432	3.3686	0.1485	3.9924	0.1753	3.4313	0.1926	4.3363	0.1865
	BI-SQ	2.4993	0.1050	2.8900	0.1166	3.5486	0.1466	3.0719	0.1629	3.9386	0.1614

VARIANCE

Table 4.6C presents the variance estimates of parameters for lognormal response model with homoscedastic error terms at various levels of contemporaneous correlation for different sample sizes.

When there is absence of correlation ($\rho=0.0$) between the error terms in different equations with homoscedastic error term, the performances of OLS is better than FGLS in small sample but are equivalent in all sample sizes. Huber estimator performs better than FGLS and OLS in all sample sizes but consistently below Bi-square estimator. In other word, when error term is homoscedastic and there is absence of contemporaneous correlation using variance criterion, the best estimation is Bi-square for all the sample sizes considered.

When the correlation is between $0.2 \leq \rho \leq 0.7$ and at different samples (n) in terms of variance criterion for comparison among estimators, Bi-squares is the most efficient estimator followed by Huber estimator. The performances of FGLS continue to improve better than OLS as the level of correlation increases.

When the contemporaneous correlation is almost perfect ($\rho=0.95$), using variance criterion for homoscedastic error term, the best estimator is FGLS in all the sample sizes considered.

4.6.2 Linear Heteroscedasticity

Table 4.7C presents the absolute bias estimates of parameters in lognormal response model with linear heteroscedastic error terms at different levels of Contemporaneous correlation for different sample size.

When there is absence of correlation ($\rho=0.0$) with Log-Normal response model under linear heteroscedastic error terms Using absolute bias criterion, the best estimator is Bi-square irrespective of the sample size. However, Huber estimator performs closely well with Bi-square estimator. OLS estimator performs better than FGLS in small sample size ($n \leq 30$).

When contemporaneous correlation is between ($0.2 \leq \rho \leq 0.7$), FGLS performs better than OLS in all the sample sizes using absolute bias criterion. Huber estimator performs better than FGLS and OLS in all sample sizes. However, the best estimator is Bi-Squares estimator in all sample sizes considered.

When the correlation is almost perfect ($\rho=0.95$) under Lognormal response model with linear heteroscedastic error term, the performance of FGLS could not maintain it's efficient at small sample size. OLS remain the worse estimator. The best estimator, under Log-normal response model and Linear heteroscedastic error term with $\rho=0.95$ notwithstanding the sample size, is Bi-Square estimator.

Table 4.7C: Empirical Result of Estimators for Linear Heteroscedastic-Log- Normal Response Model

(n)	Estimators	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	6.6057	10.5140	6.8112	11.4355	7.1323	10.8144	6.8672	10.7669	7.1245	10.2836
	FGLS	6.6755	10.5637	6.6662	10.6510	6.6458	8.5020	6.2754	7.9946	5.1129	1.5386
	HUBER	4.0610	2.9723	4.3644	3.1929	4.9353	3.4713	4.9894	4.8170	5.0074	3.1996
	BI-SQ	3.6336	2.5528	3.9342	2.6962	4.5163	3.0962	4.5822	4.1471	4.7161	2.9851
30	OLS	5.6365	6.3757	5.7598	7.3216	6.1493	6.9462	5.2122	4.6581	6.5051	7.1993
	FGLS	5.7180	6.7563	5.6971	6.9107	5.8949	5.9493	4.8929	3.6312	5.0646	1.1362
	HUBER	3.6840	2.0840	3.9422	2.1231	4.6005	2.4899	4.1136	2.5131	4.8596	2.4780
	BI-SQ	3.1423	1.4607	3.4176	1.5958	4.1427	2.0732	3.7792	2.2941	4.5202	2.1175
50	OLS	4.9490	4.5014	5.1962	4.2114	5.6376	4.1726	5.0838	4.3979	5.5563	3.0566
	FGLS	4.9820	4.6072	5.1403	3.5591	5.4460	3.0422	4.6516	2.6309	4.9213	0.6590
	HUBER	3.1250	0.9444	3.4966	1.0669	4.0987	1.1983	3.6138	1.3854	4.3371	1.1688
	BI-SQ	2.6990	0.7670	3.0416	0.8332	3.6865	1.0029	3.2570	1.1927	4.0232	1.0518
100	OLS	4.2163	1.8614	4.4910	1.8639	4.9831	1.8087	4.3326	1.7608	5.3179	1.9094
	FGLS	4.2184	1.8407	4.4865	1.8061	4.9463	1.5562	4.1613	1.2758	4.8978	0.2537
	HUBER	2.8862	0.5047	3.1432	0.4853	3.7625	0.5600	3.2608	0.7273	4.0959	0.5930
	BI-SQ	2.4146	0.3676	2.6869	0.3803	3.3206	0.4522	2.9143	0.6296	3.6316	0.4880
250	OLS	3.8125	0.7503	4.2013	0.7443	4.7931	0.7478	4.0815	0.6995	5.0804	0.8288
	FGLS	3.8165	0.7585	4.1746	0.6874	4.7400	0.6039	3.9675	0.4788	4.8911	0.1103
	HUBER	2.6311	0.1661	2.9944	0.1770	3.6427	0.2148	3.0785	0.2640	3.9671	0.2556
	BI-SQ	2.1186	0.1089	2.5065	0.1346	3.1749	0.1729	2.7002	0.2399	3.5376	0.2107
500	OLS	3.6626	0.3626	4.0130	0.3822	4.6199	0.3869	3.8790	0.3650	4.9375	0.3801
	FGLS	3.6621	0.3614	4.0126	0.3692	4.6060	0.3239	3.8563	0.2617	4.9115	0.0642
	HUBER	2.5961	0.0873	2.9448	0.0909	3.5903	0.1093	2.9700	0.1197	3.9315	0.1172
	BI-SQ	2.0927	0.0619	2.4730	0.0714	3.1327	0.0901	2.5881	0.1022	3.4961	0.0999

VARIANCE

Table 4.7C presents the variance (VAR) estimate of parameters in lognormal response model with linear heteroscedastic error terms at different levels of Contemporaneous correlation (ρ) at different sample sizes (n).

When there is absence of correlation ($\rho=0.0$) with Lognormal response model under linear heteroscedastic error terms, Bi-Square estimator is the best estimator at all sample sizes ($n \leq 500$). Huber estimator performs in similar manner but with slightly higher variance than Bi-Square estimator in all the sample sizes. OLS performs better than FGLS but both are equivalent as sample size increases.

When the contemporaneous correlation between $(0.2 \leq \rho \leq 0.7)$, at different samples under Lognormal response using variance criterion, the performances of FGLS have improved slightly than OLS at this instances but both estimators performances are close as sample size increases. Huber estimator performs better than FGLS and OLS in all sample sizes. However, the best estimator is Bi-Squares estimator in all sample sizes considered.

When the correlation is almost perfect ($\rho=0.95$) under Lognormal response model, the performance of FGLS is better than OLS, Huber and Bi-squares estimators at different sample sizes ($n \leq 500$) using variance criterion. OLS remain the worse estimator. The best estimator, under Lognormal response model with Linear heteroscedastic error term when $\rho=0.95$ notwithstanding the sample size, is FGLS estimator.

4.6.3 Square -Root Heteroscedasticity

Table 4.8C presents the absolute bias estimate of parameters in lognormal response model when the form of heteroscedasticity is Square-Root at various levels of contemporaneous correlation for different sample sizes.

When there is absence of correlation ($\rho = 0.0$) for all the sample sizes considered using absolute criterion Bi-squares is the most efficient estimator followed by Huber estimator. OLS and FGLS performances are the same.

When the contemporaneous correlation is $(0.2 \leq \rho \leq 0.7)$ at various sample sizes $n \leq 500$, using absolute bias criterion Bi-squares is the best estimator followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but perform below Bi-squares and Huber estimators.

When the correlation is almost perfect ($\rho = 0.95$) at sample size $n=20$ and 30 using absolute bias as criterion for comparison among estimator of Log-normal response model, the best

estimator is FGLS. As sample size (n) increases from 50 to 500, the Bi-squares performance increases due to the increase in sample size. The best estimator when $\rho = 0.95$ and $n \geq 50$ using absolute bias as criteria is Bi-squares estimator.

Table 4.8C: Empirical Result of Estimators for Square-Root Heteroscedastic Log-Normal Response Model

(n)	Estimators	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	7.5778	13.5231	7.8083	14.8036	8.0874	14.0660	7.7922	13.7253	8.0610	12.8553
	FGLS	7.6306	13.5402	7.7218	13.6798	7.5758	10.7902	7.1748	9.7231	5.2803	1.6781
	HUBER	4.6383	3.8178	5.0440	3.9915	5.5834	4.3367	5.7215	6.0420	5.6776	3.9752
	BI-SQ	4.0938	3.2385	4.5651	3.4315	5.1919	3.9370	5.3164	5.3604	5.4391	3.7208
30	OLS	6.3250	7.8943	6.5987	8.9827	6.9639	8.4391	5.8951	5.6439	7.3478	8.8036
	FGLS	6.4518	8.3608	6.5369	8.5337	6.7145	7.3233	5.4838	4.4691	5.1732	1.1914
	HUBER	4.1841	2.5953	4.5537	2.7068	5.2559	3.1162	4.6920	3.1926	5.5540	3.1366
	BI-SQ	3.5847	1.7680	3.9354	2.0441	4.7488	2.6018	4.3052	2.9148	5.2016	2.7355
50	OLS	5.4774	5.4774	5.7964	5.1870	6.2336	5.1624	5.6805	5.4376	6.1925	3.7849
	FGLS	5.5348	5.5348	5.7505	4.4182	6.0207	3.7894	5.1353	3.2697	4.9042	0.6722
	HUBER	3.5014	3.5014	3.9226	1.3369	4.5203	1.5104	4.0621	1.7394	4.7703	1.4688
	BI-SQ	3.0772	3.0772	3.4340	1.0386	4.0866	1.2273	3.6873	1.4702	4.4193	1.2831
100	OLS	4.6150	2.2858	4.9252	2.2920	5.3697	2.2254	4.7827	2.1556	5.7376	2.3889
	FGLS	4.6082	2.2592	4.9017	2.2292	5.2522	1.9125	4.5214	1.5470	4.8085	0.2651
	HUBER	3.1911	0.6340	3.4042	0.6189	3.9928	0.7057	3.5924	0.9123	4.3345	0.7481
	BI-SQ	2.7224	0.4666	2.9690	0.4993	3.5908	0.5849	3.2658	0.7953	3.9239	0.6322
250	OLS	4.0248	0.9296	4.3752	0.9052	4.9249	0.9157	4.2449	0.8592	5.1973	1.0202
	FGLS	4.0347	0.9397	4.3050	0.8297	4.8062	0.7336	4.0537	0.5897	4.7253	0.1120
	HUBER	2.7655	0.2162	3.1137	0.2243	3.7312	0.2716	3.2050	0.3322	4.0676	0.3191
	BI-SQ	2.2691	0.1403	2.6421	0.1734	3.2873	0.2246	2.8792	0.3074	3.6685	0.2703
500	OLS	3.7220	0.4445	4.0816	0.4781	4.6324	0.4813	3.9354	0.4506	4.9097	0.4702
	FGLS	3.7200	0.4433	4.0584	0.4597	4.5689	0.3969	3.8295	0.3142	4.7391	0.0624
	HUBER	2.6642	0.1109	2.9820	0.1153	3.5947	0.1370	3.0208	0.1506	3.9243	0.1463
	BI-SQ	2.1822	0.0801	2.5487	0.0904	3.1808	0.1140	2.6784	0.1283	3.5321	0.1260

VARIANCE

Table 4.8C presents the variance (VAR) estimates of parameter for lognormal response model with Square-root heteroscedastic error terms at various levels of contemporaneous correlation under different sample sizes.

When there is absence of correlation ($\rho = 0.0$) at various sample sizes $n \leq 500$ using variance criterion Bi-squares estimator is the best. The Huber estimator performs better than OLS and

FGLS. OLS performs better than FGLS at different samples; however both estimators perform similarly as sample (n) size increases.

When the contemporaneous correlation is between ($0.2 \leq \rho \leq 0.7$) at various sample sizes $n \leq 500$, using variance criterion Bi-squares is the best estimator followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but perform below Bi-squares and Huber estimators.

When the correlation is almost perfect ($\rho = 0.95$) regardless of the size of the sample (n) using variance as criterion for comparison, FGLS is the best estimator.

In summary, the best estimator for modeling Lognormal response model with Square-Root heteroscedastic error term at different levels of contemporaneous correlation (ρ) notwithstanding the size of the sample (n) using variance criterion is FGLS estimator.

4.6.4 Exponential Heteroscedasticity

Table 4.9C shows the absolute bias for model parameter estimates when form of heteroscedasticity is Exponential for Log-normal response model at various contemporaneous correlations under different sample sizes.

When there is absence of correlation ($\rho = 0.0$) between the error terms in different equations for all sample sizes ($n \geq 20$) considered, the performance OLS and FGLS estimators is similar using absolute bias criterion while the Huber and Bi-squares perform better than the OLS and FGLS estimators. The best estimator, under Log-normal response model with exponential form of heteroscedasticity in the absence of contemporaneous correlation regardless of the size of the sample (n), is Bi-squares estimators.

When the level of correlation increases between ($0.2 \leq \rho \leq 0.7$), The performance of FGLS has improved tremendously and better than OLS as the level of correlation increases but OLS

performance increases as the sample increases. In summary, in terms of absolute bias, the most efficient estimator under exponential heteroscedastic error terms, Log-normal response model and contemporaneous correlation between ($0.2 \leq \rho \leq 0.7$) for different sample sizes, is Bi-squares estimator.

When the correlation is almost perfect ($\rho = 0.95$) at sample sizes $n=20$ and 30 using absolute bias criterion, FGLS perform better than OLS and Huber estimators but below Bi-squares estimator. When $n>50$, the increase in the levels of contemporaneous correlation could not improve the efficiency of FGLS over Huber and Bi-squares estimators. Bi-square is the most efficient estimator for modeling exponential heteroscedastic error terms with Log-normal response at different samples (n).

Table 4.9C: Empirical Result of Estimators for Exponential Heteroscedastic-Log-Normal Response Model

(n)	Estimators	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	18.7411	84.2573	19.3200	92.9754	20.1127	88.2160	19.4480	87.5328	19.9955	81.3880
	FGLS	18.8835	84.4240	19.0031	85.9887	18.7471	68.1827	17.8100	63.3310	13.8164	11.3566
	HUBER	11.4813	23.7355	12.3803	25.2619	13.8760	27.5134	14.1530	38.4415	14.0864	25.3840
	BI-SQ	10.2228	20.3542	11.2036	21.4838	12.7766	24.6031	13.0315	32.8956	13.3527	23.6895
30	OLS	15.7860	50.2977	16.3222	57.7503	17.3324	54.6221	14.6739	36.6712	18.2807	56.4632
	FGLS	16.0693	53.3380	16.1281	54.5819	16.5902	46.8779	13.7285	28.6594	13.6469	8.3039
	HUBER	10.3771	16.4678	11.1960	16.9731	12.9973	19.7244	11.6242	20.1493	13.7152	19.6970
	BI-SQ	8.8815	11.3795	9.6918	12.8013	11.7082	16.3992	10.6875	18.4208	12.7842	16.9177
50	OLS	13.7837	35.1708	14.5016	33.0413	15.6714	32.7809	14.1998	34.6143	15.4676	24.1593
	FGLS	13.8951	35.9710	14.3561	28.0605	15.1160	23.9878	12.9251	20.7875	13.1317	4.7207
	HUBER	8.7484	7.4513	9.7958	8.4615	11.3752	9.5419	10.1162	11.0247	12.0194	9.3092
	BI-SQ	7.6228	6.1785	8.5605	6.5601	10.2787	7.8371	9.1596	9.4024	11.1644	8.2277
100	OLS	11.6652	14.7288	12.3874	14.6764	13.6567	14.2419	11.9848	13.8743	14.6029	15.1720
	FGLS	11.6534	14.5664	12.3495	14.2324	13.4915	12.2168	11.4373	9.9797	13.0382	1.8534
	HUBER	8.0302	3.9938	8.6478	3.8739	10.2682	4.4294	9.0511	5.7900	11.1692	4.6939
	BI-SQ	6.7725	2.9220	7.4630	3.0852	9.1289	3.6295	8.1434	5.0304	9.9742	3.9136
250	OLS	10.3902	5.9279	11.3992	5.8339	12.9411	5.8884	11.0468	5.5283	13.6977	6.5550
	FGLS	10.4029	5.9933	11.2833	5.3656	12.7342	4.7288	10.6832	3.7759	12.9767	0.7987
	HUBER	7.1533	1.3352	8.1263	1.4108	9.8229	1.7094	8.3571	2.1039	10.6868	2.0226
	BI-SQ	5.8041	0.8713	6.8278	1.0830	8.5957	1.3923	7.3889	1.9244	9.5830	1.6799
500	OLS	9.8102	2.8548	10.7883	3.0455	12.3466	3.0756	10.4041	2.8885	13.1602	3.0117
	FGLS	9.8081	2.8455	10.7579	2.9388	12.2751	2.5605	10.2845	2.0450	13.0206	0.4541
	HUBER	7.0226	0.6952	7.9086	0.7249	9.6104	0.8679	7.9882	0.9514	10.5255	0.9269
	BI-SQ	5.6911	0.4972	6.6881	0.5699	8.4267	0.7206	7.0084	0.8115	9.3958	0.7959

VARIANCE

Table 4.9C presents the variance (VAR) of parameter estimates when the form of heteroscedasticity is Exponential for Lognormal response model at various contemporaneous correlations for different sample sizes.

when there is absence of correlation ($\rho = 0.0$) between the error terms in different equations for exponential heteroscedastic error terms with Lognormal response model at different sample sizes, the best estimator is Bi-squares using variance criterion. However, Huber performs better than the OLS and FGLS estimators at various sample sizes. OLS performs better than FGLS when $n \leq 30$ and both perform similarly in large samples ($n \geq 50$).

When the level of correlation increases between ($0.2 \leq \rho \leq 0.7$), regardless of the sample size using variance criterion the best estimator is Bi-squares estimator. However, the performances of FGLS has improved better than OLS at various sample sizes and contemporaneous correlation is between $0.2 \leq \rho \leq 0.5$ but less efficient than Huber and Bi-squares estimators. Huber also performs closely with Bi-squares estimator. Above all, Bi-squares is the best estimator followed by Huber estimator.

When the correlation is almost perfect ($\rho = 0.95$) at different sample sizes ($n \leq 500$), using variance criterion FGLS is the most efficiency estimator.

At this instance, the performance of both Huber and Bi-squares is inefficient relative to FGLS.

4.6.5 Quadratic Heteroscedasticity

Table 4.10C presents absolute bias (ABS) estimate of parameters for lognormal response model with Quadratic heteroscedastic error term at various levels of contemporaneous correlation under different sample sizes.

When there is absence of correlation ($\rho = 0.0$) at various sample sizes $n \leq 500$ using Absolute bias criterion Bi-squares estimator is the best followed by Huber estimator. However, OLS and FGLS performances are the same but inefficient in all the sample sizes considered.

When the correlation is between ($0.2 \leq \rho \leq 0.7$) at various sample sizes $n \leq 500$, Bi-squares is still the best estimator in terms of absolute bias criterion followed by Huber estimator. The performances of FGLS continue to improve as the correlation increases but not better than Huber and Bi-squares estimators.

Table 4.4.1C: Empirical Result of Estimators for Quadratic Heteroscedastic-Log-Normal Response Model

(n)	Estimators	Cc $\rho=0.0$		Cc $\rho=0.2$		Cc $\rho=0.5$		Cc $\rho=0.7$		Cc $\rho=0.95$	
		ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR	ABS	VAR
20	OLS	5.5776	7.1082	5.9473	7.8517	6.3853	7.3944	6.0000	7.7055	6.4607	7.2857
	FGLS	5.6695	7.1851	5.8179	7.4189	5.9648	6.0929	5.5417	6.1359	5.1577	1.6486
	HUBER	3.4450	1.9739	3.7437	2.1990	4.3761	2.4044	4.1618	3.2487	4.5161	2.2492
	BI-SQ	3.0103	1.6319	3.2105	1.6890	3.8451	2.0197	3.5832	2.4728	4.1179	2.0670
30	OLS	5.0224	4.5449	5.2087	5.3522	5.6877	5.1782	4.8244	3.5368	5.9814	5.2727
	FGLS	5.0895	4.8209	5.1618	5.0323	5.4489	4.3877	4.5646	2.7241	5.1783	1.2977
	HUBER	3.1833	1.4295	3.3918	1.4173	4.0369	1.7014	3.5697	1.6606	4.2837	1.6355
	BI-SQ	2.5418	0.9678	2.8341	1.0570	3.5154	1.3379	3.1511	1.5033	3.8043	1.2731
50	OLS	4.6763	3.4076	4.7672	3.0009	5.2970	2.9512	4.6378	3.0978	5.3719	2.2519
	FGLS	4.6619	3.4998	4.7693	2.5319	5.1971	2.1653	4.3776	1.8955	5.0709	0.8129
	HUBER	2.7556	0.6648	3.1383	0.7283	3.7831	0.8136	3.2292	0.9267	4.0797	0.7941
	BI-SQ	2.2727	0.4893	2.6342	0.5597	3.2896	0.6930	2.8265	0.7950	3.6348	0.7164
100	OLS	4.1070	1.3723	4.3986	1.3637	4.9595	1.3257	4.2378	1.3042	5.2364	1.3582
	FGLS	4.1082	1.3621	4.3939	1.3215	4.9369	1.1621	4.1344	0.9931	5.0255	0.3151
	HUBER	2.6264	0.3331	2.9704	0.3212	3.6144	0.3717	3.0310	0.4852	3.9508	0.3961
	BI-SQ	2.0842	0.2354	2.4223	0.2327	3.0758	0.2800	2.5890	0.4078	3.4073	0.3094
250	OLS	3.8042	0.5358	4.2294	0.5589	4.8594	0.5561	4.1068	0.5209	5.1306	0.6097
	FGLS	3.8075	0.5421	4.2153	0.5237	4.8335	0.4604	4.0253	0.3667	5.0477	0.1440
	HUBER	2.5310	0.1054	2.9097	0.1175	3.5806	0.1442	2.9752	0.1779	3.9243	0.1749
	BI-SQ	1.9824	0.0684	2.3738	0.0879	3.0471	0.1108	2.5211	0.1554	3.4100	0.1363
500	OLS	3.7402	0.2658	4.1061	0.2716	4.7448	0.2778	3.9696	0.2663	5.0848	0.2761
	FGLS	3.7416	0.2650	4.1049	0.2658	4.7358	0.2430	3.9519	0.2047	5.0739	0.0854
	HUBER	2.5191	0.0589	2.9011	0.0612	3.5670	0.0740	2.9408	0.0798	3.9131	0.0791
	BI-SQ	1.9744	0.0392	2.3770	0.0479	3.0465	0.0604	2.4996	0.0669	3.4107	0.0660

When the correlation is almost perfect ($\rho = 0.95$) at various sample size $n \leq 500$ using absolute bias as criterion for comparison, Bi-squares is the best estimator. Huber and FGLS

estimators performance is the same but less efficient than Bi-squares estimator when $n \leq 30$ and $\rho = 0.95$ using absolute bias criterion, FGLS lost its efficiency in small sample.

As the sample size (n) increases from 50 to 500, the Huber performs better than FGLS and OLS. Therefore, the best estimator when $\rho = 0.95$ and $n \leq 500$ using absolute bias as criteria is Bi-squares estimator followed by Huber estimator.

VARIANCE

Table 4.10C presents the variance (VAR) estimates of parameter for lognormal response model with Quadratic heteroscedastic error terms at various levels of contemporaneous correlation under different sample sizes.

When there is absence of correlation ($\rho = 0.0$) at various sample sizes $n \leq 500$ using variance criterion Bi-squares estimator is the best. The Huber estimator performs better than OLS and FGLS. OLS performs better than FGLS when $n \leq 30$, however both estimators are the same as n increases $n \geq 50$.

When the correlation between ($0.2 \leq \rho \leq 0.7$) at various sample sizes $n \leq 500$, Bi-squares is still the best estimator in terms of variance criterion followed by Huber estimator. The performances of FGLS continue to improve better than OLS as the correlation increases but less efficient.

When the correlation is almost perfect ($\rho = 0.95$) for quadratic heteroscedastic error terms at sample size $n=20$ using variance as criterion for comparison among estimators of Lognormal response model, FGLS is the best estimator. However, when sample sizes increases from $n=30$ to $n=500$ and $\rho = 0.95$ for Lognormal response model using variance criterion, Bi-squares is the most efficient estimator.

4.7 Real Life data Application

In order to support the claims from the simulation results, the estimators are used to estimate the coefficient of parameters in economic growth models under different aberrations in the data such as non-normal responses, and or heteroscedastic error term. The data used for this study were extracted from Pen world Table (PWT09), which contains record of economic indicator variables from different countries. The data were stationary at first difference and several diagnostic measures were taken to confirm whether the data actually satisfied the assumption of classical linear regression model.

The study considered a regression equation of the form:

$$GDP_i = \beta + \gamma Lp + \tau Cs + \delta Er + \alpha Se + \vartheta Si + \mu_i, \quad i = 1, \dots, N$$

Where $[\beta, \gamma, \tau, \delta, \alpha, \vartheta]$ are the model parameters, real GDP per capital is the response variable, Lp is number of people engaged (as proxy for labour), Cs is the Capital Stock, Er is the exchange rate, Se is the share of export, Si is the share of import and μ_i is random error term. The GDP equations for two different countries form the system of regression equations.

The system of regression equations are classified as follows:

A: Homoscedasticity and Normal response model

B: Homoscedasticity and Non-normal model

C: Heteroscedasticity and Non-normal model

4.8 Empirical Result

The results from the analysis under different classifications were presented in Table 4.2 to 4.9.

4.8.1 Model A- Real Life Dataset with Homoscedastic error and Normal response

(CHINA & CAM) $\rho=-0.2639$)

The results in Table 4.7.1 & 4.7.2 are the parameter estimates and the corresponding standard error for different estimation methods for model with valid assumptions including homoscedasticity of error terms and Normality of responses. From Table 4.7.2, all the estimators perform well with approximately the same standard error. This again affirmed that all these estimators are approximately the same when the assumptions of classical linear regression are met but FGLS has the least standard error, hence is the most preferred estimator.

Table 4.7.1: Homoscedastic error and Normal responses Model (CAM & CHINA)

Methods	EQUATION1 (parameter Estimates)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	-0.0487	-0.7294	0.663	0.0898	0.0111	0.0247
FGLS	-0.0504	-0.8228	0.7477	0.0829	0.0101	0.0238
HUBER	-0.0457	-0.7833	0.8117	0.0871	0.0122	0.0228
BISQR	-0.0472	-0.7902	0.7638	0.0822	0.0122	0.0237
	EQUATION2 (parameter Estimates)					
Methods	β_0	β_1	β_2	β_3	β_4	
OLS	-0.0078	0.3448	0.5498	0.0252	0.2483	-0.1343
FGLS	-0.0078	0.3419	0.5512	0.0867	0.1882	-0.0932
HUBER	-0.0110	0.3386	0.506	-0.0135	0.3833	-0.2658
BISQR	-0.0113	0.3397	0.5073	-0.0171	0.3932	-0.2767

Table 4.7.2: Standard error of Parameter estimates

Methods	EQUATION1 (<i>Se. (β_i)</i>)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.0252	0.1921	0.8099	0.0504	0.01	0.0228
FGLS	0.0247	0.1873	0.7934	0.0501	0.0097	0.0222
HUBER	0.0281	0.2141	0.9028	0.0562	0.0111	0.0255
BISQR	0.0273	0.2081	0.8776	0.0547	0.0108	0.0247
Methods	EQUATION2 (<i>Se. (β_i)</i>)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.0116	0.1345	0.2902	0.1444	0.1963	0.1538
FGLS	0.0114	0.1314	0.2812	0.1415	0.1902	0.1489
HUBER	0.0114	0.1320	0.2849	0.1418	0.1927	0.1510
BISQR	0.0113	0.1312	0.2831	0.1409	0.1915	0.1501

4.8.2 Model B- Real Life Dataset with Homoscedastic error and Non-normal response (SAUDI & NIGER MODEL ($\rho = -0.09577$))

Table 4.7.5 and 4.7.6 present the parameter estimates and the standard error of parameter estimates based on different estimation methods for Saudi- Niger economic growth model under the violation of the normality assumption of the response variables. From Table 4.7.6, the standard error of parameter estimates for Ordinary Least Square(OLS) and Feasible Generalized Least Square(FGLS) estimators are apparently the same and relatively larger than the Huber and Bi-Square estimators. Bi-square estimator is the preferred estimator.

Table 4.7.5: Homoscedastic error and Non- Normal responses Model (Saudi &Niger)

Methods	EQUATION1 (parameter Estimates)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	-0.007	1.29191	-0.8719	-11.589	0.24922	-0.7731
FGLS	-0.005	1.29799	-0.8314	-11.955	0.21871	-0.7768
HUBER	0.0161	1.1772	0.4978	-9.8572	0.1917	-0.4317
BISQR	0.0253	1.0251	1.0571	-11.055	0.2181	-0.1116
Methods	EQUATION2 (parameter Estimates)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.08272	0.50595	2.46963	-0.1588	-0.0438	0.0083
FGLS	0.0818	0.48418	2.47153	-0.1617	-0.039	0.01932
HUBER	0.0181	0.4482	0.8429	-0.0674	-0.0185	0.0085
BISQR	-0.0063	0.3812	0.2946	-0.0386	-0.0122	0.0237

Table 4.7.6: Standard error of Parameter estimates

Methods	EQUATION1 (Se. (β_i))					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.0776	0.6533	1.58804	4.69908	0.12841	0.21891
FGLS	0.07746	0.653	1.5828	4.68436	0.1279	0.21796
HUBER	0.0359	0.3019	0.7338	2.1714	0.0593	0.1012
BISQR	0.0346	0.2912	0.7079	2.0948	0.0572	0.0976
Methods	EQUATION2 (Se. (β_i))					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.04919	0.30156	1.36758	0.09376	0.03584	(0.06452)
FGLS	0.04913	0.30142	1.36585	0.09337	0.0357	(0.06428)
HUBER	0.0326	0.1998	0.9063	0.0621	0.0238	(0.0428)
BISQR	0.0318	0.195	0.8843	0.0606	0.0232	(0.0417)

4.8.3 MODEL C- Real Life Dataset with Heteroscedastic error and Non-normal response ((NIG&BEN))

The Table 4.7.7 and 4.7.8 contains the estimate of the model parameters and standard errors respectively for model with heteroscedastic error and Non –normal response. Bi-square estimator is the most preferred estimator for Non-normal response model with heteroscedastic error term using standard errors of parameter estimates.

Table 4.7.7: Heteroscedastic error and Non-normal responses Model (Algeria & Egypt)

Methods	EQUATION1 (parameter Estimates)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.0792	1.3737	-0.0779	0.4545	0.1063	-0.0448
FGLS	0.0797	1.3531	-0.0158	0.4464	0.109	-0.0546
HUBER	0.0186	0.8742	-0.1488	0.2014	0.0581	-0.0097
BISQR	-0.0038	0.6703	0.0506	0.1242	0.0422	0.0033
	EQUATION2 (parameter Estimates)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.0377	-0.663	3.3395	-0.022	-0.0256	0.0999
FGLS	0.0444	-0.6524	3.5317	-0.0249	-0.0259	0.0987
HUBER	-0.1288	0.0095	-2.5868	-0.0575	0.0105	0.0309
BISQR	-0.1459	0.2758	-3.3425	0.0076	0.0172	-0.0033

Table 4.7.8: Standard error of Parameter estimates

Methods	EQUATION1 ($Se.(\beta_i)$)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.0607	0.1647	1.8207	0.288	0.0993	0.0939
FGLS	0.0607	0.1645	1.8186	0.2876	0.0932	0.0937
HUBER	0.0339	0.0918	1.0149	0.1605	0.0554	0.0523
BISQR	0.0312	0.0845	0.9343	0.1478	0.051	0.0482
	EQUATION2 ($Se.(\beta_i)$)					
Methods	β_0	β_1	β_2	β_3	β_4	β_5
OLS	0.1086	0.4749	3.8216	0.1105	0.0447	0.0659
FGLS	0.1085	0.4743	3.816	0.1103	0.0447	0.0658
HUBER	0.0631	0.2761	2.2216	0.0642	0.026	0.0383
BISQR	0.0491	0.2147	1.7281	0.05	0.0202	0.0298

In conclusion, the results from real life data also support the findings from the Monte Carlo simulation.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATION

5.0 INTRODUCTION:

The results of the Monte Carlo Simulation of SUR model under the violation of homoscedasticity of error terms and Normality of the response variables through the error terms under different sample sizes(n) have been thoroughly discussed on the basis of each three properties of estimator *vis a vis* ; absolute bias, variance and root mean square error in chapter four.

In this chapter, the preference of estimator(s) under violation of error terms and distributions of the response variable considered in the study are based on all the three criteria as summarized in section 5.1 through 5.3. Recommendations were given in section 5.4. The limitations of the study, contribution to knowledge and suggestions for further study are discussed in section 5.5, 5.6 and 5.7 respectively.

5.1 SUMMARY OF FINDINGS AND CONCLUSIONS

5.1.1 Form of Heteroscedastic at different sample Size (n): Normal Response Model

From table 5.1.1, at small sample size ($n=20$ & 30) for exponential, linear and square root form of heteroscedasticity ordinary least squares (OLS) estimator is the preferred estimator while Huber estimator is the most preferred estimator under quadratic heteroscedasticity.

When $n=30$, for exponential, Linear and square root heteroscedasticity, OLS is most preferred estimator while Huber estimator is the most preferred estimator under quadratic heteroscedasticity.

When the sample size is moderate, all the estimators show equivalent performances but the most preferred estimators varies with the form of heteroscedasticity. For exponential, linear and quadratic heteroscedasticity, Huber estimator is the most preferred while OLS is the most preferred estimator under square root heteroscedasticity.

When $n=100$, Huber estimator is the most preferred for linear and quadratic heteroscedasticity while OLS and FGLS is the most preferred estimator for exponential and square root heteroscedasticity respectively.

TABLE 5.1.1: Summary of the preferred Estimators under different heteroscedastic Error structures on the basis of all criteria for Normal Response Model

	Heteroscedastic Structure			
Sample size(n)	EXP	LN	SQR	QUAD
20	OLS	OLS	OLS	Huber
30	OLS	OLS	OLS	Huber
50	Huber	Huber	OLS	Huber
100	OLS	Huber	FGLS	Huber
250	FGLS	FGLS	FGLS	Huber

5.1.2 Effect of levels of Contemporaneous Correlation and Sample sizes (n)

From table 5.2.1, when there is absence or low Contemporaneous correlation ($\rho = 0.0$ or $\rho = 0.2$) at small sample sizes ($n=20$ and $n=30$), OLS is the most preferred estimator when the error term is homoscedastic and normally distributed. At sample $n=50$, OLS is the most preferred estimator for $\rho = 0.0$ and both OLS and FGLS are preferred for $\rho = 0.2$. When $n=100$ and $n=250$, FGLS is the most preferred estimator in the absence or low contemporaneous ($\rho = 0.0$ or $\rho = 0.2$). However, when $n=500$ and there is absence of Cc under homoscedasticity and normal error term all the four estimators (OLS, FGLS, Huber and Bi-square) are preferred.

When the contemporaneous correlation is moderately high ($(\rho \geq 0.5)$) for normal and homoscedastic error, FGLS is most preferred estimator for all sample sizes ($n \leq 500$).

TABLE 5.2.1: Summary of the preferred Estimators under Different levels contemporaneous correlation on the basis of all criteria for Normal response Model.

Sample Size(n)	Levels of Contemporaneous correlation				
	$\rho = 0.0$	$\rho = 0.2$	$\rho = 0.5$	$\rho = 0.7$	$\rho = 0.95$
20	OLS	OLS	FGLS	FGLS	FGLS
30	OLS	OLS	FGLS	FGLS	FGLS
50	OLS	OLS/FGLS	FGLS	FGLS	FGLS
100	FGLS	FGLS	FGLS	FGLS	FGLS
250	FGLS	FGLS	FGLS	FGLS	FGLS
500	FGLS/OLS/Bi-SQ	FGLS	FGLS	FGLS	FGLS

5.1.3 When there is Heteroscedasticity at different contemporaneous

From table 5.3.1, at small sample size ($n=20$) and there is absence or low contemporaneous correlation ($\rho = 0.0$ or $\rho = 0.2$), under Exponential, linear and square root heteroscedasticity OLS is the most preferred estimator while Huber is the preferred estimator under quadratic heteroscedasticity. However, when the contemporaneous correlation is moderately high ($\rho \geq 0.5$), FGLS is the most preferred estimator irrespective of the form of heteroscedasticity.

When $n=30$ and there is absence or low contemporaneous correlation ($\rho = 0.0$ or $\rho = 0.2$), OLS is the most preferred estimator under different heteroscedastic structure except quadratic heteroscedasticity where Huber estimator is best. Again, when the contemporaneous correlation is moderately high ($\rho \geq 0.5$), FGLS is the most preferred estimator regardless of the form heteroscedasticity.

When $n=50$ & 100 and there is absence of contemporaneous correlation ($\rho = 0.0$), FGLS estimator is the most preferred under exponential and square root heteroscedasticity While Huber is the most preferred estimator under linear and quadratic heteroscedasticity. When there is low contemporaneous correlation ($\rho = 0.2$), FGLS is the most preferred estimator under different heteroscedastic structure except quadratic heteroscedasticity where Huber

estimator is preferred. Again, when the contemporaneous correlation is moderately high ($\rho \geq 0.5$), FGLS is the most preferred estimator regardless of the form heteroscedasticity.

When $n=250$ and there is absence contemporaneous correlation ($\rho = 0.0$), FGLS estimator is the most preferred under exponential and square root heteroscedasticity, FGLS and OLS are preferred for linear heteroscedasticity and Huber is the most preferred estimator under quadratic heteroscedasticity. When there is low contemporaneous correlation ($\rho = 0.2$), FGLS is the most preferred estimator under different heteroscedastic structure except quadratic heteroscedasticity where Huber estimator is preferred. Again, when the contemporaneous correlation is moderately high ($\rho \geq 0.5$), FGLS is the most preferred estimator regardless of the form of heteroscedasticity.

When $n=500$ and there is absence contemporaneous correlation ($\rho = 0.0$), FGLS estimator is the most preferred under exponential and linear heteroscedasticity, FGLS, Huber and OLS are preferred for square root heteroscedasticity and Huber is the most preferred estimator under quadratic heteroscedasticity. When there is low contemporaneous correlation ($\rho = 0.2$), FGLS is the most preferred estimator under different heteroscedastic structure except quadratic heteroscedasticity where Huber estimator is preferred. Also, when the contemporaneous correlation is moderately high ($\rho \geq 0.5$), FGLS is the most preferred estimator regardless of the form heteroscedasticity.

Generally for quadratic heteroscedasticity, when there is absence or low contemporaneous correlation ($\rho = 0.0$ or $\rho = 0.2$), Huber is the most preferred estimator under different sample sizes ($n \leq 500$).

TABLE 5.3.1: Summary of the preferred Estimators on the basis of all criteria for model with both heteroscedasticity and contemporaneous correlation for Normal response Model.

Sample size(n)	Form of Heteroscedasticity	Contemporaneous Correlation				
		$\rho = 0.0$	$\rho = 0.2$	$\rho = 0.5$	$\rho = 0.7$	$\rho = 0.95$
20	EXP	OLS	OLS	FGLS	FGLS	FGLS
	LN	OLS	OLS	FGLS	FGLS	FGLS
	SQR	OLS	OLS	FGLS	FGLS	FGLS
	QUAD	Huber	Huber	FGLS	FGLS	FGLS
30	EXP	OLS	OLS	FGLS	FGLS	FGLS
	LN	OLS	OLS	FGLS	FGLS	FGLS
	SQR	OLS	OLS	FGLS	FGLS	FGLS
	QUAD	Huber	Huber	FGLS	FGLS	FGLS
50	EXP	FGLS	FGLS	FGLS	FGLS	FGLS
	LN	Huber	FGLS	FGLS	FGLS	FGLS
	SQR	FGLS	FGLS	FGLS	FGLS	FGLS
	QUAD	Huber	Huber	FGLS	FGLS	FGLS
100	EXP	FGLS	FGLS	FGLS	FGLS	FGLS
	LN	Huber	FGLS	FGLS	FGLS	FGLS
	SQR	FGLS	FGLS	FGLS	FGLS	FGLS
	QUAD	Huber	Huber	FGLS	FGLS	FGLS
250	EXP	FGLS	FGLS	FGLS	FGLS	FGLS
	LN	FGLS/OLS	FGLS	FGLS	FGLS	FGLS
	SQR	FGLS	FGLS	FGLS	FGLS	FGLS
	QUAD	Huber	Huber	FGLS	FGLS	FGLS
500	EXP	FGLS	FGLS	FGLS	FGLS	FGLS
	LN	FGLS	FGLS	FGLS	FGLS	FGLS
	SQR	FGLS/Huber/ OLS	FGLS	FGLS	FGLS	FGLS
	QUAD	Huber	Huber	FGLS	FGLS	FGLS

5.2 Gamma Response Model

5.2.1 When there is presence of heteroscedasticity only in the model

From table 5.1.2, for all sample sizes ($n \leq 500$) and under different forms of heteroscedasticity for gamma response model using all criteria Bi-square estimator is the most preferred.

TABLE 5.1.2: Summary of the preferred Estimators under different heteroscedastic Error structures on the basis of all criteria for gamma Response Model.

	Heteroscedastic Structure			
Sample size(n)	EXP	LN	SQR	QUAD
20	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
30	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
50	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
100	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
250	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ

5.2.2 When the model is homoscedastic at different contemporaneous correlation (ρ)

From Table 5.2.2, it can be observed that under different sample sizes ($n \leq 500$) for low and moderate contemporaneous correlation Bi-square is the most preferred estimator. However, for almost perfect contemporaneous correlation, FGLS is the most preferred estimator under different sample sizes.

In conclusion, when the assumption of constant variance is valid but the response variable is non-normal M-bi-square robust estimator is the most preferred except when the contemporaneous correlation at least $\rho = 0.95$ where FGLS estimator is preferred.

TABLE 5.2.2: Summary of the preferred Estimators under Different levels contemporaneous correlation on the basis of all criteria for gamma response Model.

	Levels of Contemporaneous correlation				
Sample Size(n)	$\rho = 0.0$	$\rho = 0.2$	$\rho = 0.5$	$\rho = 0.7$	$\rho = 0.95$
20	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
30	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
50	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
100	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
250	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
500	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS

TABLE 5.3.2: Summary of the preferred Estimators on the basis of all criteria for model with both heteroscedasticity and contemporaneous correlation for gamma response Model.

Sample size(n)	Form of Heteroscedasticity	Contemporaneous Correlation				
		$\rho = 0.0$	$\rho = 0.2$	$\rho = 0.5$	$\rho = 0.7$	$\rho = 0.95$
20	EXP	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	LN	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	SQR	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	QUAD	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
30	EXP	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	LN	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	SQR	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	QUAD	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
50	EXP	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	LN	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	SQR	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	QUAD	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
100	EXP	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	LN	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	SQR	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	QUAD	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
250	EXP	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	LN	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	SQR	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	QUAD	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
500	EXP	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	LN	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	SQR	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS
	QUAD	Bi-SQ	Bi-SQ	FGLS	FGLS	FGLS

5.2.3 When there is Heteroscedasticity at different levels of contemporaneous correlation

From table 5.3.2, at small or moderate sample sizes ($n=20$ or $n=30, 50$) when there is absence or low contemporaneous correlation ($\rho=0.0$ or $\rho = 0.2$) regardless of the form of heteroscedasticity, Bi-square is the most preferred estimator. However, for moderately high contemporaneous correlation ($\rho \geq 0.5$) and $n=20$ or 30 , except for exponential

heteroscedasticity where Bi-square is preferred otherwise FGLS is the most preferred estimator.

When sample size is large ($n \geq 100$) and there is absence or low contemporaneous correlation ($\rho=0.0$ or $\rho = 0.2$) regardless of the form of heteroscedasticity, Bi-square is the most preferred estimator. However, for contemporaneous correlation as high as $\rho \geq 0.5$ and sample size $n \geq 50$, regardless of the form of heteroscedasticity, FGLS is the most preferred estimator.

5.3 Lognormal response model

5.3.1 Form of Heteroscedastic and Different sample Size (n)

From table 5.1.3, for all sample sizes ($n \leq 500$) and under different forms of heteroscedasticity for gamma response model using all criteria Bi-square estimator is the most preferred.

TABLE 5.1.3: Summary of the preferred Estimators under different heteroscedastic Error structures on the basis of all criteria for Log-Normal Response Model.

	Heteroscedastic Structure			
Sample size(n)	EXP	LN	SQR	QUAD
20	BI-SQ	BI-SQ	BI-SQ	BI-SQ
30	BI-SQ	BI-SQ	BI-SQ	BI-SQ
50	BI-SQ	BI-SQ	BI-SQ	BI-SQ
100	BI-SQ	BI-SQ	BI-SQ	BI-SQ
250	BI-SQ	BI-SQ	BI-SQ	BI-SQ

5.3.2 When the model is homoscedastic at different contemporaneous correlation (ρ)

From table 5.2.3, when contemporaneous correlation is as high as $\rho \leq 0.7$ regardless of the sample size for lognormal response model, Bi-square is the most preferred estimator.

When $\rho = 0.95$ assuming homoscedastic error terms, for sample sizes $n=20$ and 30 , FGLS is the most preferred estimator. However, when sample is large ($n \geq 50$) and $\rho = 0.95$, Bi-square is the most preferred estimator.

TABLE 5.2.3: Summary of the preferred Estimators under Different levels contemporaneous correlation on the basis of all criteria for Log-Normal response Model.

Sample Size(n)	Levels of Contemporaneous correlation				
	$\rho = 0.0$	$\rho = 0.2$	$\rho = 0.5$	$\rho = 0.7$	$\rho = 0.95$
20	BI-SQ	BI-SQ	BI-SQ	BI-SQ	FGLS
30	BI-SQ	BI-SQ	BI-SQ	BI-SQ	FGLS
50	BI-SQ	BI-SQ	BI-SQ	BI-SQ	BI-SQ
100	BI-SQ	BI-SQ	BI-SQ	BI-SQ	BI-SQ
250	BI-SQ	BI-SQ	BI-SQ	BI-SQ	BI-SQ
500	BI-SQ	BI-SQ	BI-SQ	BI-SQ	BI-SQ

TABLE 5.3.3: Summary of the preferred Estimators on the basis of all criteria for model with both heteroscedasticity and contemporaneous correlation for Log-Normal response Model.

Sample size(n)	Form of Heteroscedasticity	Contemporaneous Correlation				
		$\rho = 0.0$	$\rho = 0.2$	$\rho = 0.5$	$\rho = 0.7$	$\rho = 0.95$
20	EXP	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
	LN	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
	SQR	Bi-SQ	FGLS	FGLS	FGLS	FGLS
	QUAD	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
30	EXP	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
	LN	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
	SQR	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	FGLS
	QUAD	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
50	EXP	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	LN	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	SQR	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	QUAD	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
100	EXP	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	LN	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	SQR	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	QUAD	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
250	EXP	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	LN	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	SQR	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	QUAD	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
500	EXP	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	LN	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	SQR	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ
	QUAD	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ	Bi-SQ

5.3.3 Forms of Heteroscedasticity at different levels of contemporaneous correlation

From table 5.3.3, at small or moderate sample sizes ($n=20$ or $n=30, 50$) when there is absence or low contemporaneous correlation ($\rho=0.0$ or $\rho = 0.2$) regardless of the form of heteroscedasticity, Bi-square is the most preferred estimator. However, for moderately high contemporaneous correlation ($\rho = 0.5$ and $\rho = 0.7$) and at small ($n=20$) except for square root heteroscedasticity where FGLS is preferred, otherwise Bi-square is the most preferred estimator.

When the contemporaneous correlation is almost perfect ($\rho = 0.95$) and at sample sizes $n=20$ and 30 , FGLS is the most preferred estimator under different form of heteroscedasticity except quadratic heteroscedasticity where Bi-square is most preferred.

When sample size is large ($n \geq 100$) and there is absence or low contemporaneous correlation ($\rho=0.0$ or $\rho = 0.2$) regardless of the form of heteroscedasticity, Bi-square is the most preferred estimator. However, for contemporaneous correlation as high as $\rho \geq 0.5$ and $n \geq 50$, regardless of the form of heteroscedasticity, Bi-square is the most preferred estimator.

5.4 Recommendation

Modeling the interaction between different units or group regarding a particular phenomenon in Social science or behavioral sciences usually prone to the violation of homoscedasticity assumptions of the model likewise the normality assumption of the error terms. The following recommendations are hereby given for a valid inference in the presence of heteroscedasticity or non-normal response:

1. OLS estimator should be preferred in small sample when there is absence or low contemporaneous correlation under normal response except when there is quadratic heteroscedastic structure.

2. FGLS should be preferred at moderately high contemporaneous correlation with normal response regardless of heteroscedastic structure and sample sizes.
3. Turkey Bi-square robust estimator should be preferred under non-normal response regardless of heteroscedastic structure and sample sizes except when there is almost perfect contemporaneous correlation where FGLS is recommended.

5.5 Suggestion for Further Study

The following areas may be considered by researchers who wish to extend the scope of this work in future.

- 1) The study considered situations where the response in each equation assume the same distribution but which may not be practically feasible in some field ,future research may consider situations in which response variables may assume different distributions.
- 2) Future research may consider large SUR model and investigate the performances of all competing estimator of SUR model under non-normal responses.
- 3) More so, there is need for a new robust estimator in form of FGLS that account for the contemporaneous correlation when the response is Non-normal.
- 4) Furthermore, Bayesian estimation procedure for seemingly unrelated heteroscedastic regression model with Non- normal responses could also be considered.

5.6 Contribution to Knowledge

This research work has contributed to the existing knowledge by reaffirm some of the established facts in the literature and discovered an estimator that is suitable for estimating SUR model parameters under four heteroscedastic structures for normal and Non-normal responses as follows:

1. The performances of estimators depend upon the degree or levels of contemporaneous correlation, form of heteroscedasticity, distribution of the response and sample sizes.

2. When there is absence or low ($\rho=0.0$ or $\rho = 0.2$) contemporaneous correlation, the model parameter are best estimated by OLS under normal responses
3. When heteroscedastic structure is Quadratic(i.e. square of the response mean) and there is absence or low contemporaneous correlation, Huber-robust estimator should be preferred in estimating model parameters under normal responses
4. When the structure of heteroscedasticity is Linear, Exponential and Square root of the response mean at moderately high contemporaneous correlation with normal responses, FGLS should be preferred.
5. When there is low or moderately high ($\rho\leq 0.5$) contemporaneous correlation irrespective of the heteroscedastic structure, the model parameters are best estimated by Turkey-Bisquare robust estimator under Non- normal responses.
6. At moderately high contemporaneous correlation ($\rho\geq 0.5$) regardless of the heteroscedastic structure, FGLS is the most preferred estimator under gamma error.

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APPENDIX I

GRAPHICAL DESCRIPTION OF THE PERFORMANCES OF ESTIMATORS CONSIDERED IN THE STUDY

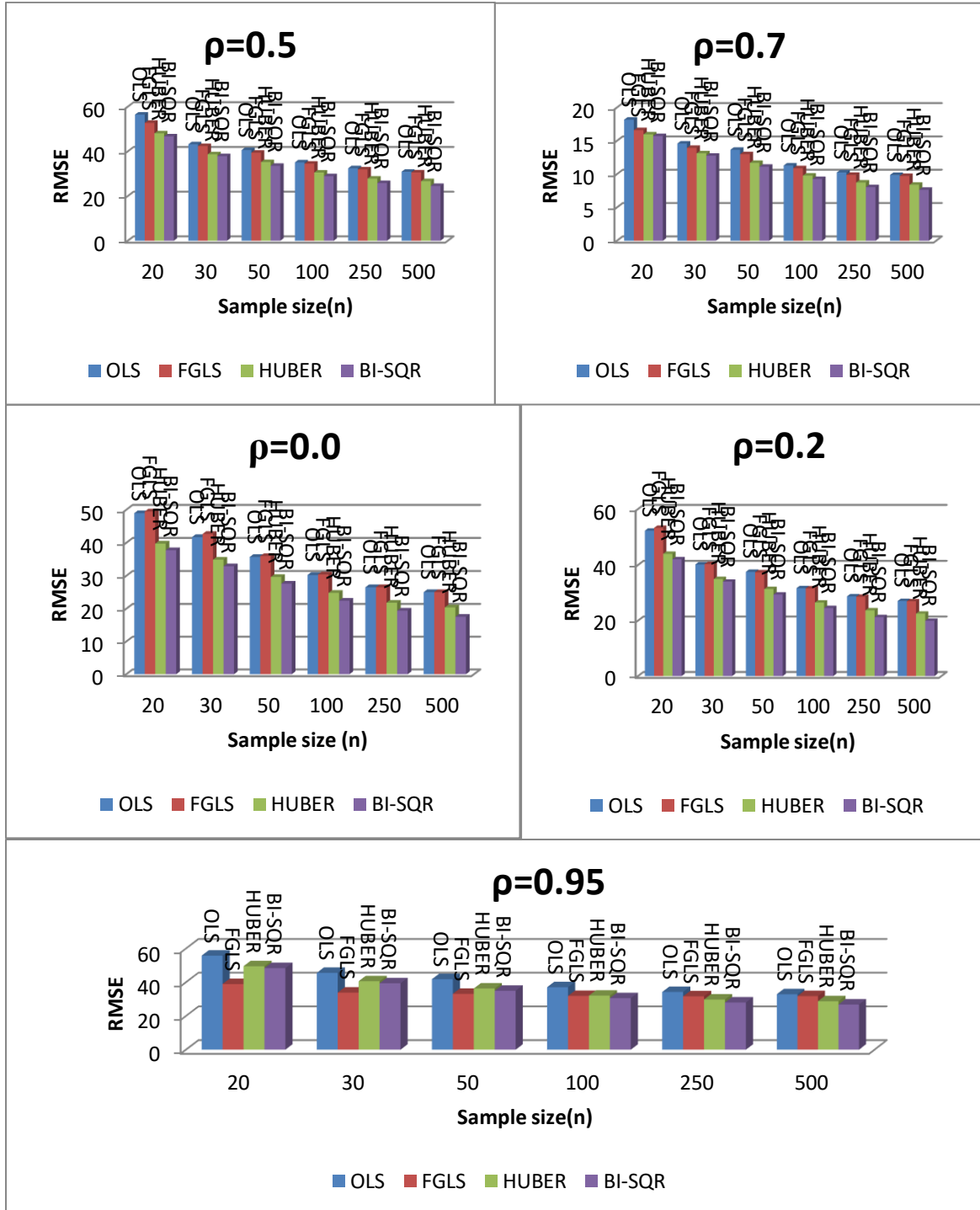


Fig. 1B: Gamma response model with Exponential Heteroscedastic Error term

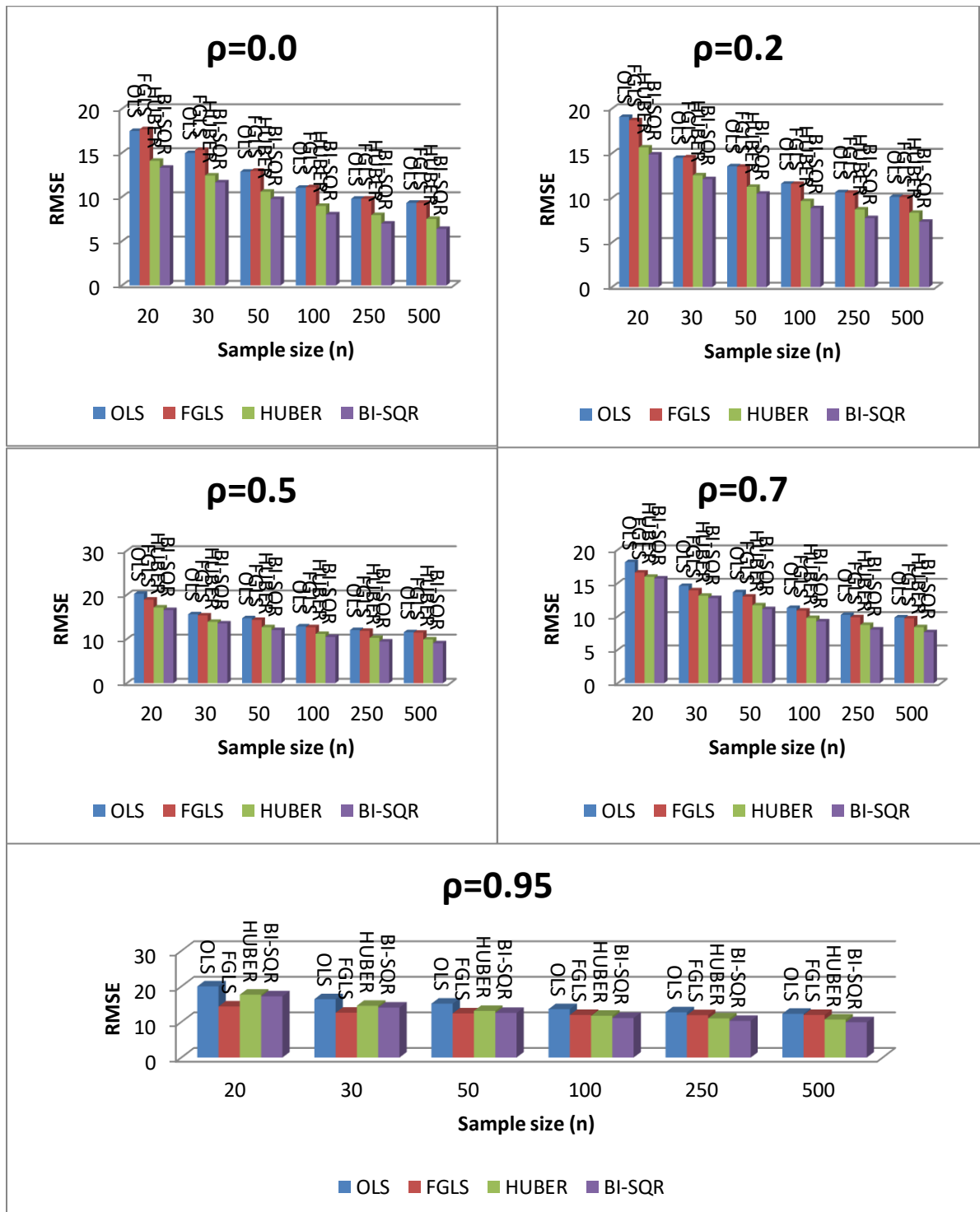


Fig. 2B: Gamma response model with Linear Heteroscedastic Error term

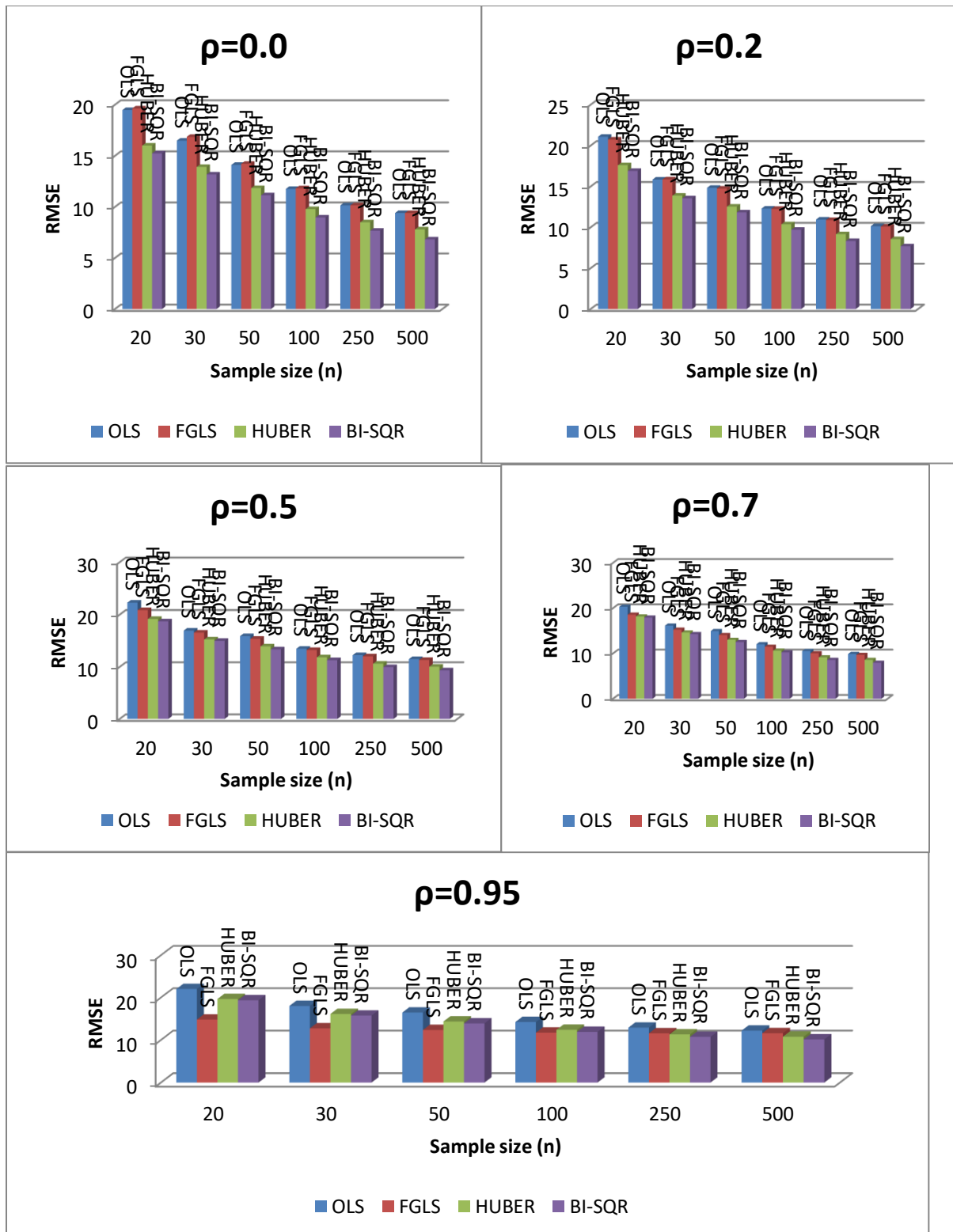


Fig. 3B: Gamma response model with Square-root Heteroscedastic Error term

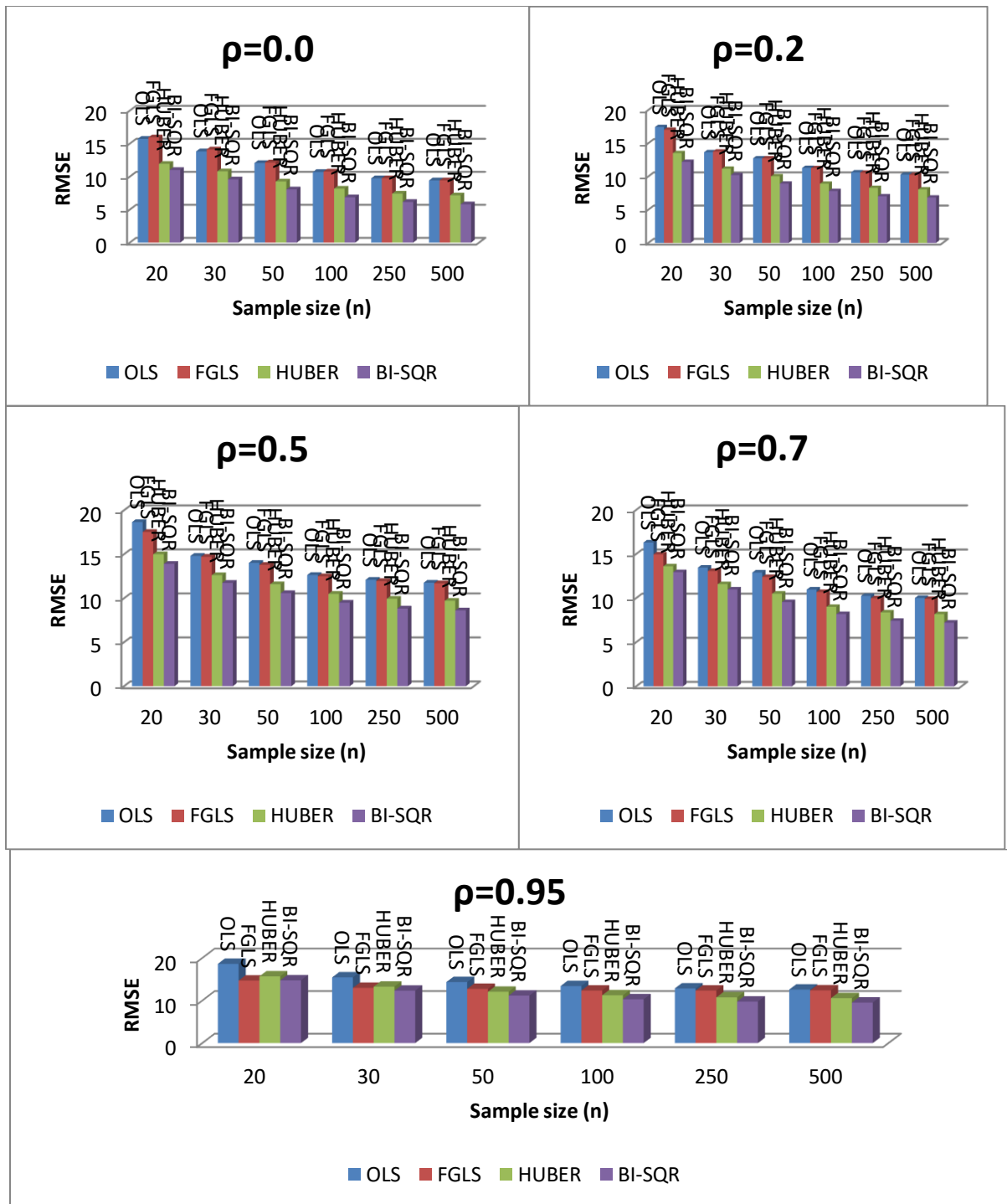


Fig. 4B: Gamma response model with Square-root Heteroscedastic Error term

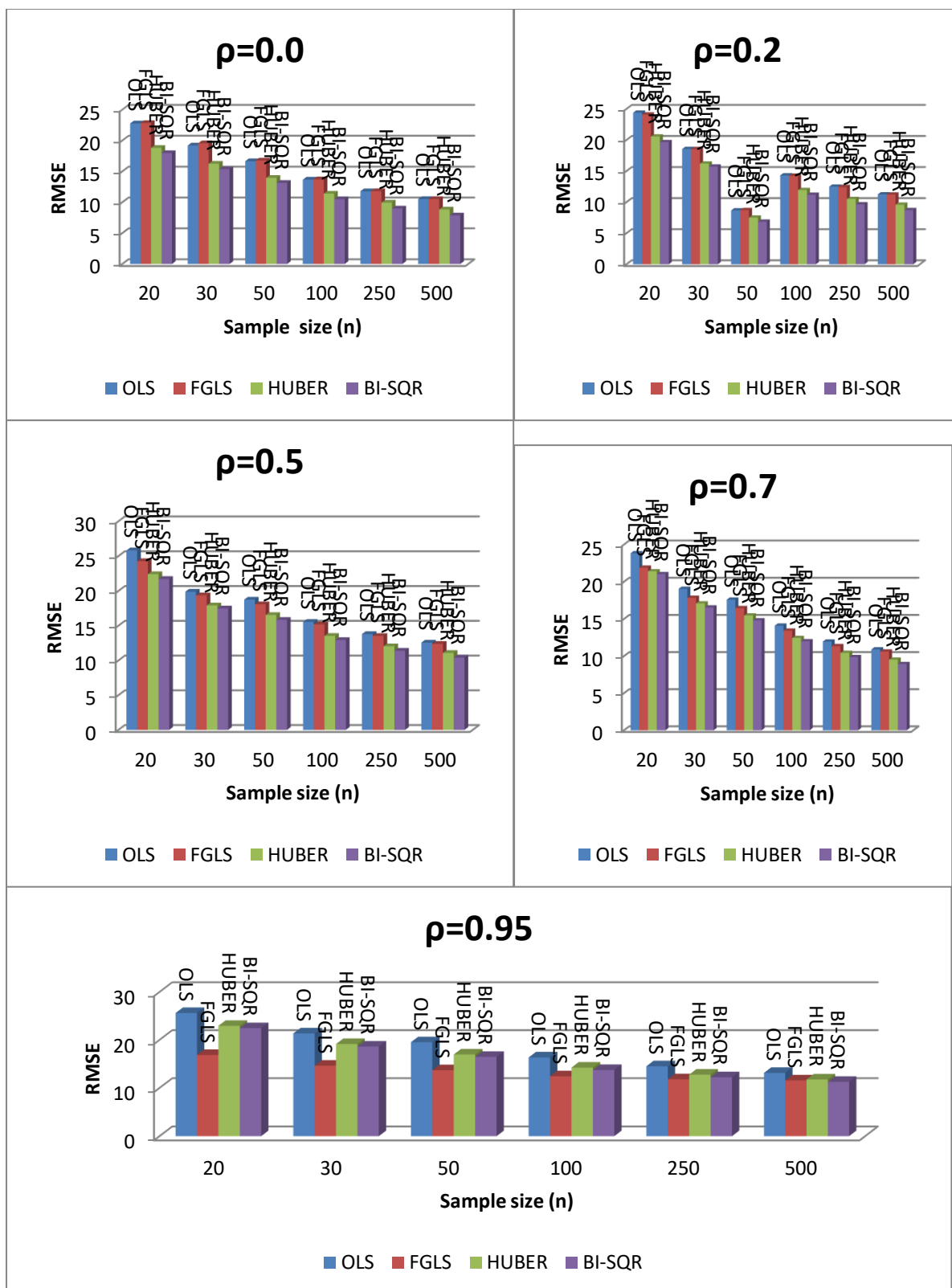


Fig.5B: Gamma response model with Homoscedastic Error term

APPENDIX C

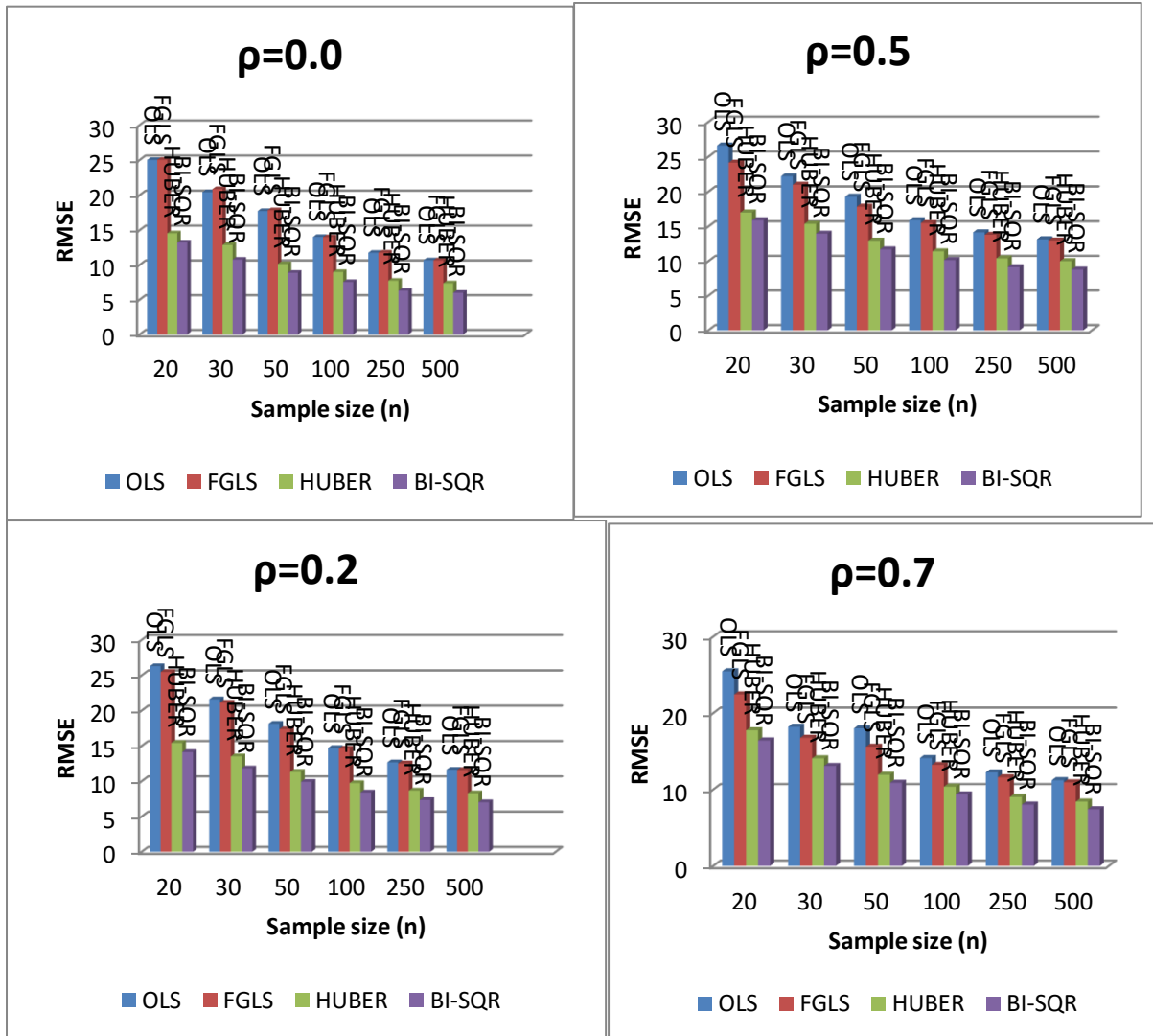


Fig.1C: Lognormal response model with Exponential heteroscedastic error terms

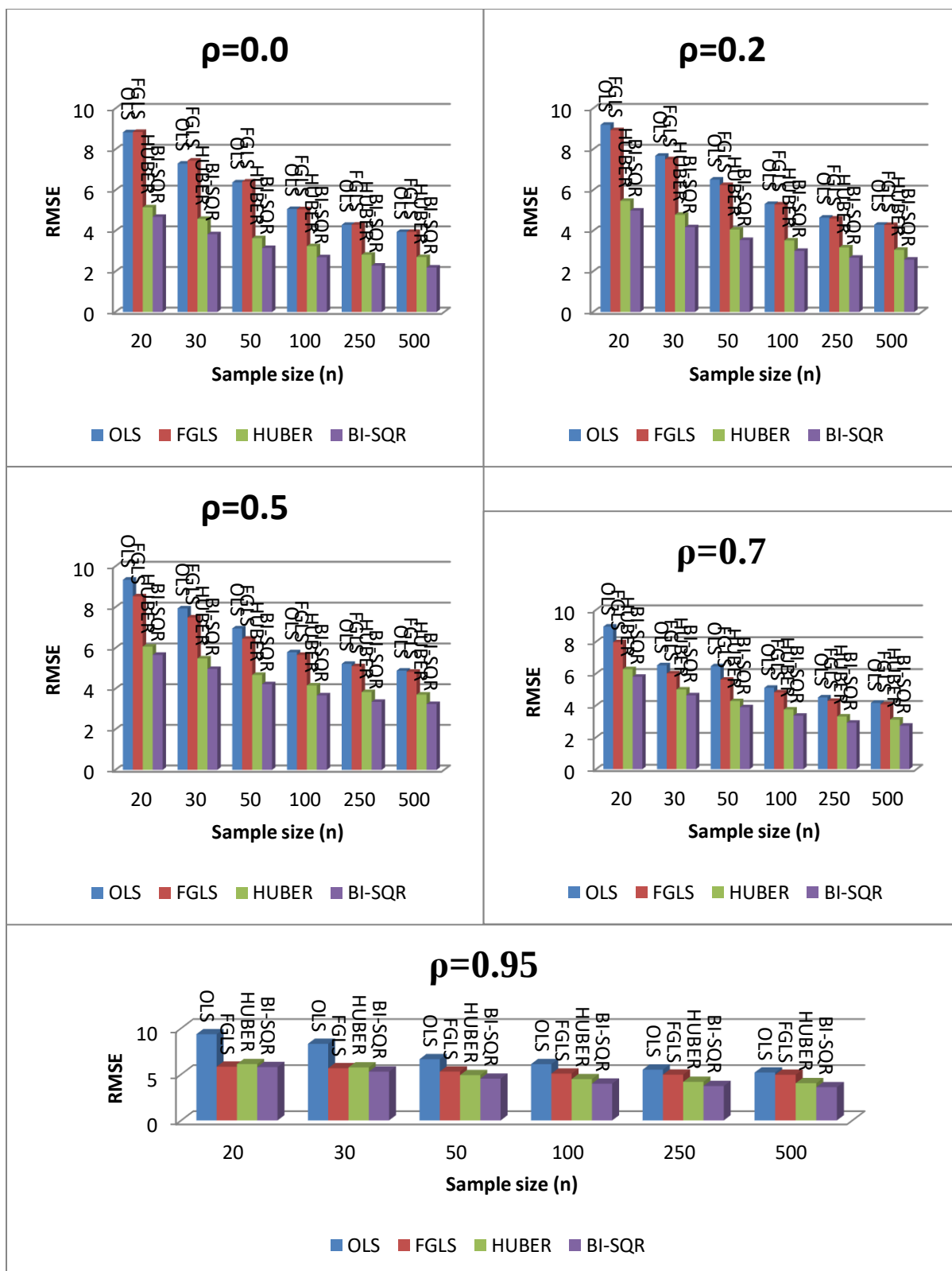


Fig.2C: Lognormal response model with Linear heteroscedastic error terms

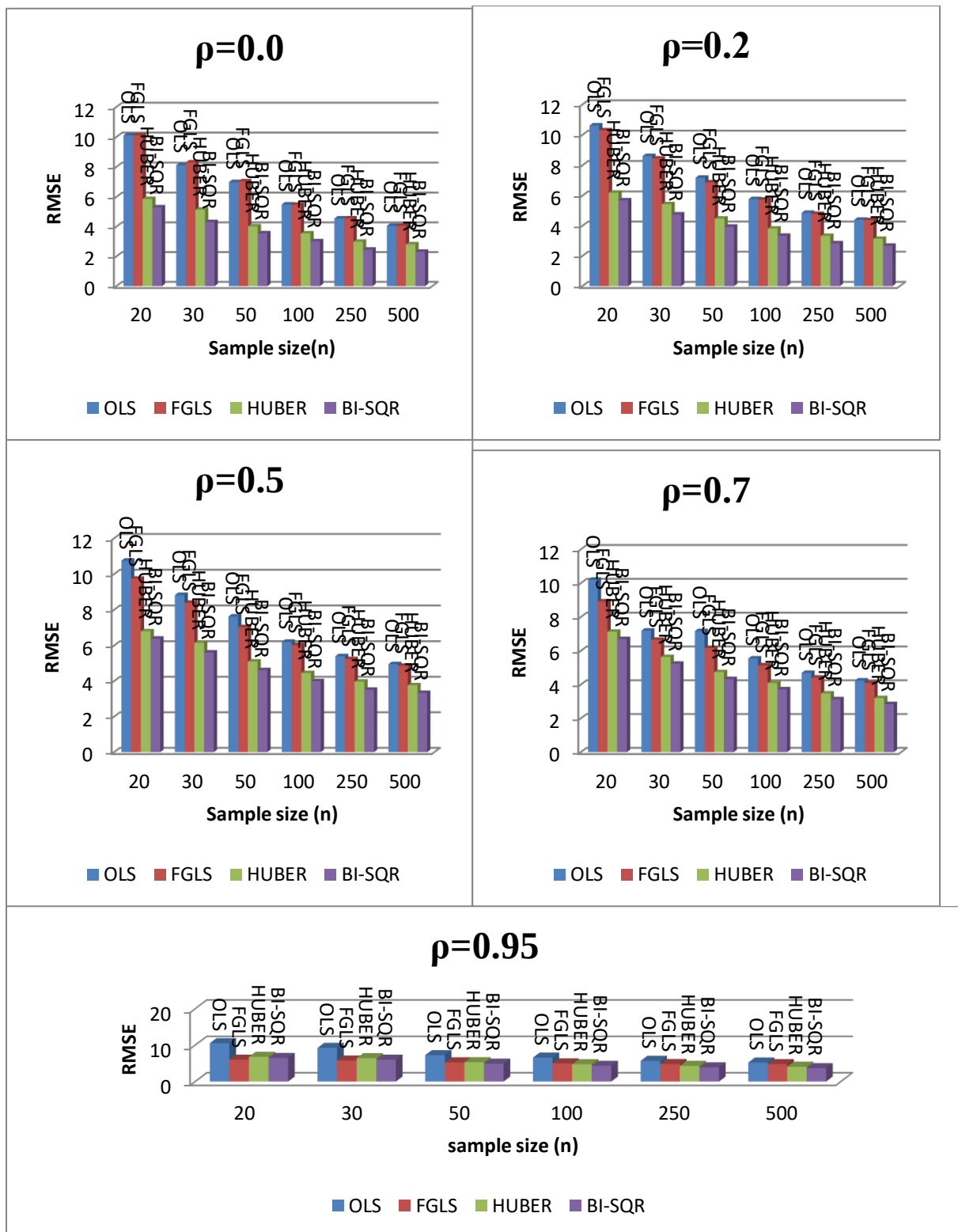


Fig. 3C: Lognormal response model with Square- root heteroscedastic error terms

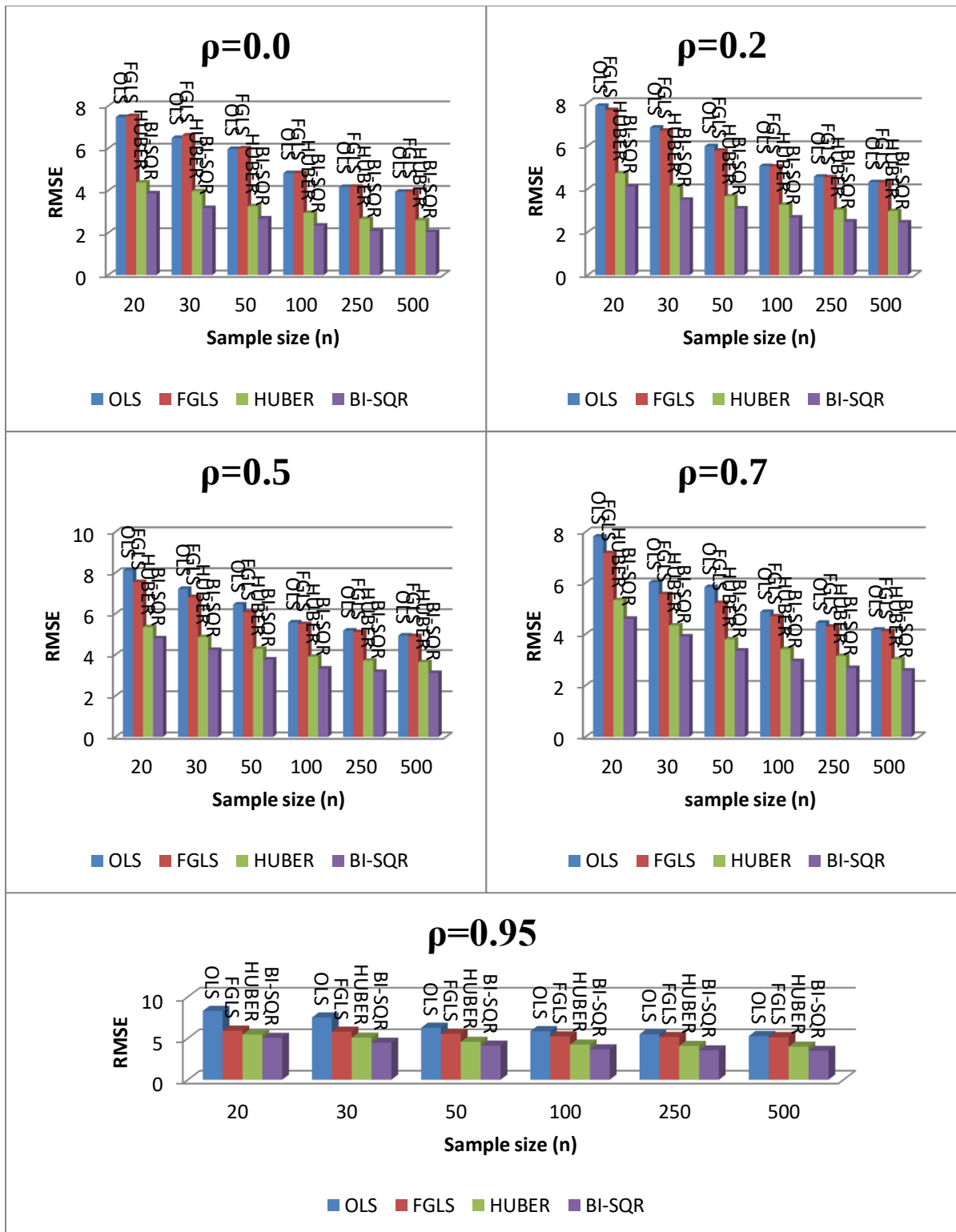


Fig.4C: Lognormal response model with Quadratic heteroscedastic error terms

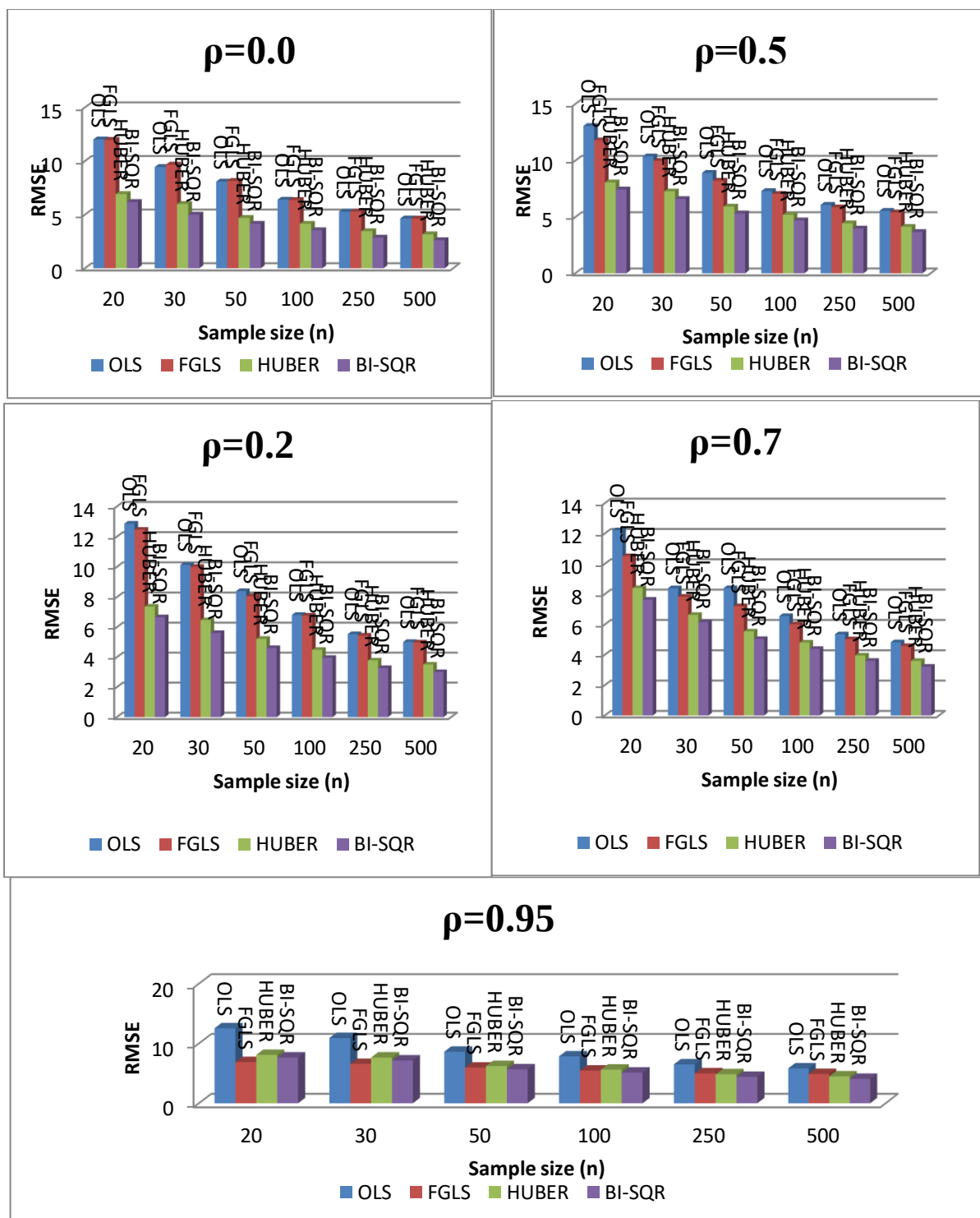


Fig. 5C: Lognormal response model with homoscedastic error terms

Fig.1.1a: Bar chart showing the Performance of Estimators using RMSE Criterion at different Sample size when Error is Normal,Uncorrelated across equations and the form of Heteroscedasticity is Exponential

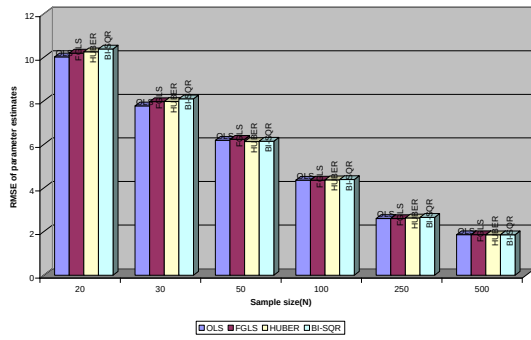


Fig.3.1a: Bar chart showing the Performance of Estimators using RMSE Criterion at different Sample size when Error is Normal,correlated error(R=0.5) and the form of Heteroscedasticity is Exponential

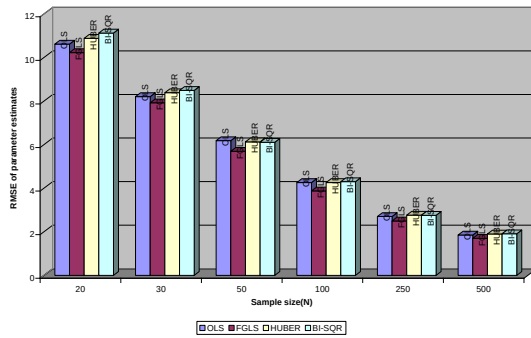


Fig.5.1a: Bar chart showing the Performance of Estimators using RMSE Criterion at different Sample size when Error is Normal,correlated error(R=0.95) and the form of Heteroscedasticity is Exponential

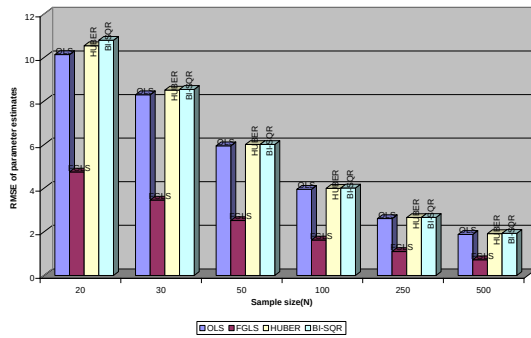


Fig.2.1b: Bar chart showing performance of estimators using RMSE criterion when error is Normal, correlated error (R=0.2) and Linearity heteroscedastic(Q=1)

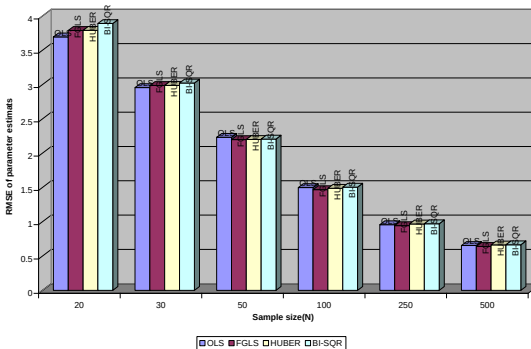


Fig.2.1a: Bar chart showing the Performance of Estimators using RMSE Criterion at different Sample size when Error is Normal,correlated error(R=0.2) and the form of Heteroscedasticity is Exponential

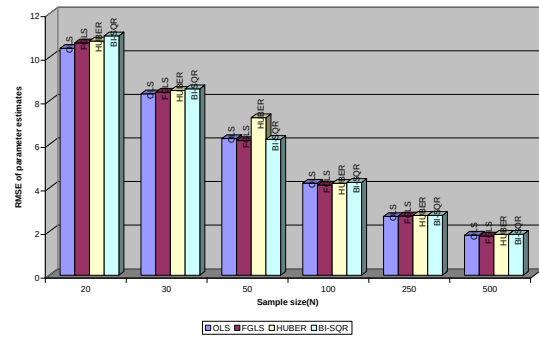


Fig.4.1a: Bar chart showing the Performance of Estimators using RMSE Criterion at different Sample size when Error is Normal,correlated error(R=0.7) and the form of Heteroscedasticity is Exponential

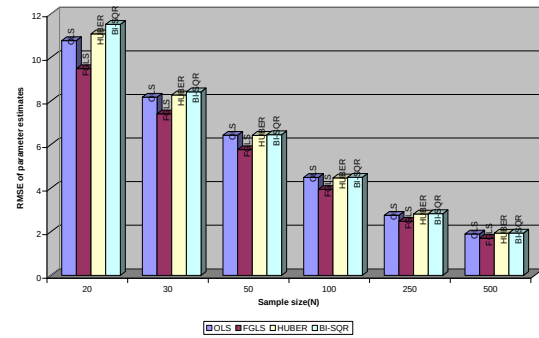


Fig.1.1b: Bar chart showing performance of estimators using RMSE criterion when error is Normal, uncorrelated across the equations and Linearity heteroscedastic(Q=1)

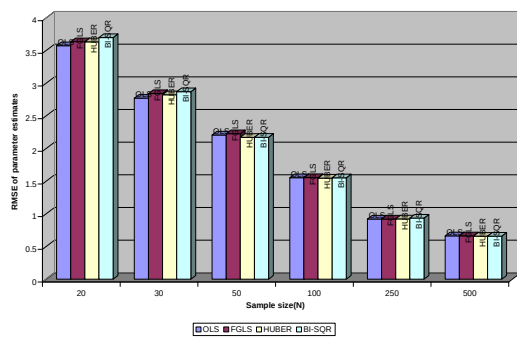


Fig.3.1b: Bar chart showing performance of estimators using RMSE criterion when error is Normal, correlated error (R=0.5) and Linearity heteroscedastic(Q=1)

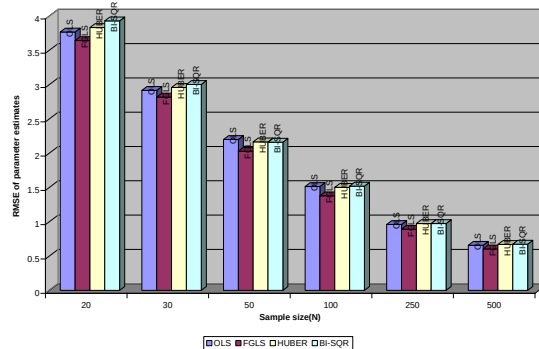


Fig.4.1b: Bar chart showing performance of estimators using RMSE criterion when error is Normal, correlated error ($R=0.7$) and Linearly heteroscedastic($Q=1$)

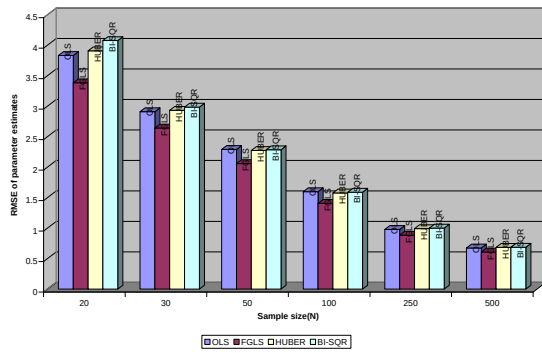


Fig.5.1b: Bar chart showing performance of estimators using RMSE criterion when error is Normal, correlated error ($R=0.95$) and Linearly heteroscedastic($Q=1$)

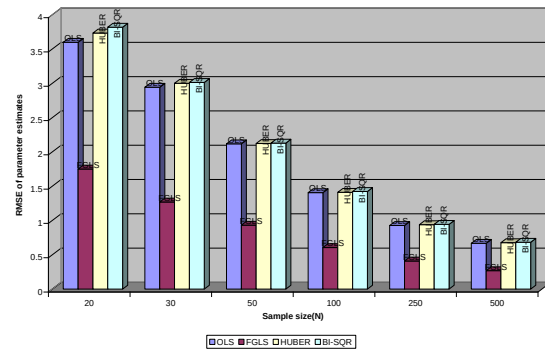


Fig.1.1c: Bar chart showing performance of estimators using RMSE criterion when error is Normal, uncorrelated across the equations and heteroscedastic($Q=0.5$)

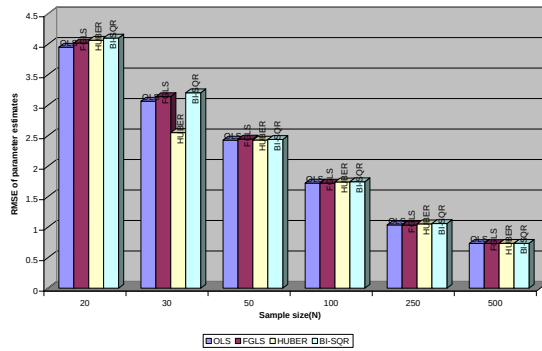


Fig.2.1c: Bar chart showing performance of estimators using RMSE criterion when error is Normal, correlated error($R=0.2$) and heteroscedastic($Q=0.5$)

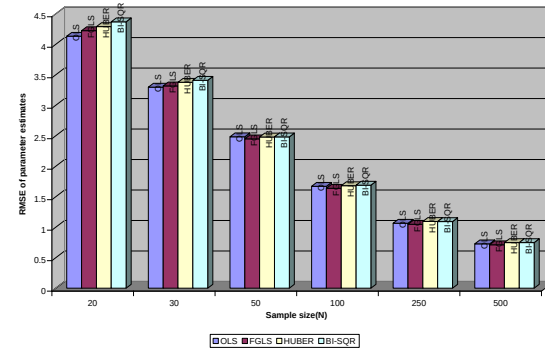


Fig.3.1c: Bar chart showing performance of estimators using RMSE criterion when error is Normal, correlated error($R=0.5$) and heteroscedastic($Q=0.5$)

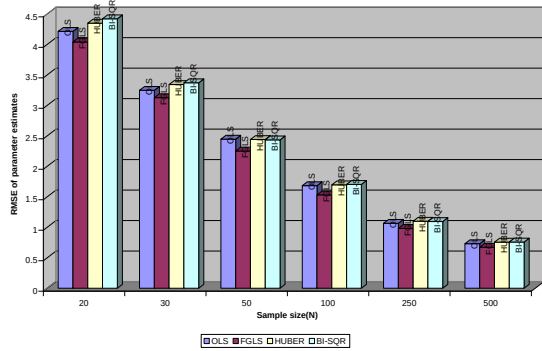


Fig.4.1c: Bar chart showing performance of estimators using RMSE criterion when error is Normal, correlated error($R=0.7$) and heteroscedastic($Q=0.5$)

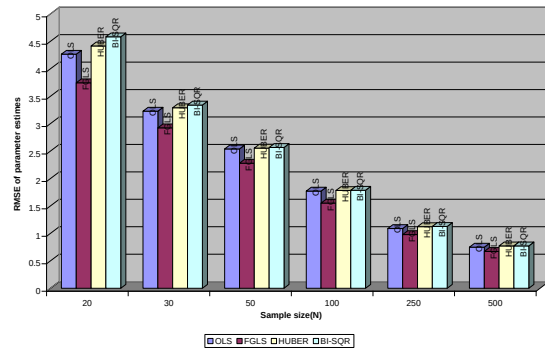


Fig.5.1c: Bar chart showing performance of estimators using RMSE criterion when error is Normal, correlated error($R=0.95$) and heteroscedastic($Q=0.5$)

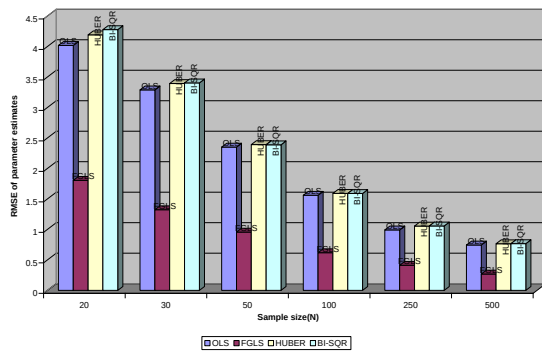


Fig.1.1g: Bar chart showing performance of estimators at different level of heteroscedasticity using RMSE criterion when error is Normal, uncorrelated across the equations

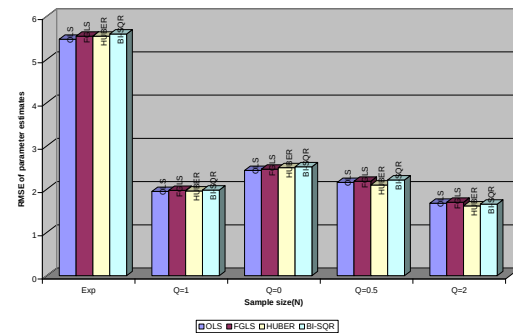


Fig.2.1g: Bar chart showing performance of estimators at different level of heteroscedasticity using RMSE criterion when error is Normal, correlated across the equations($R=0.2$)

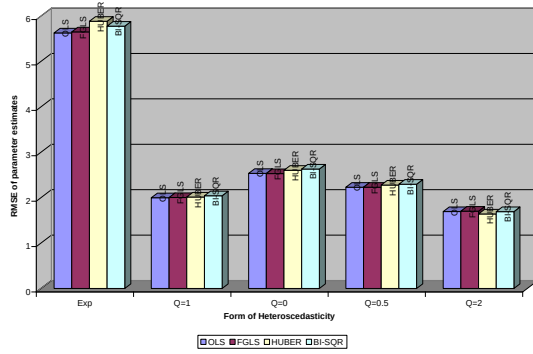


Fig.3.1g: Bar chart showing performance of estimators at different level of heteroscedasticity using RMSE criterion when error is Normal, correlated across the equations($R=0.5$)

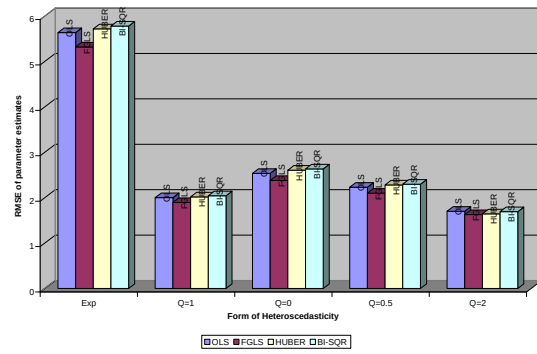


Fig.4.1g: Bar chart showing performance of estimators at different level of heteroscedasticity using RMSE criterion when error is Normal, correlated across the equations($R=0.7$)

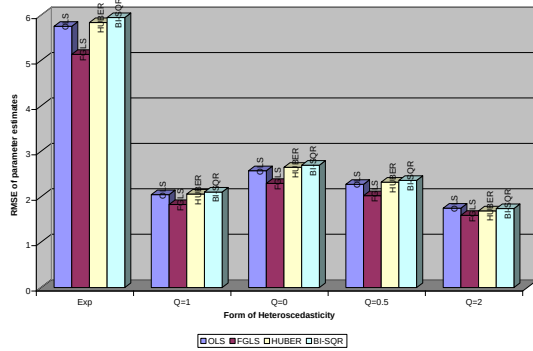
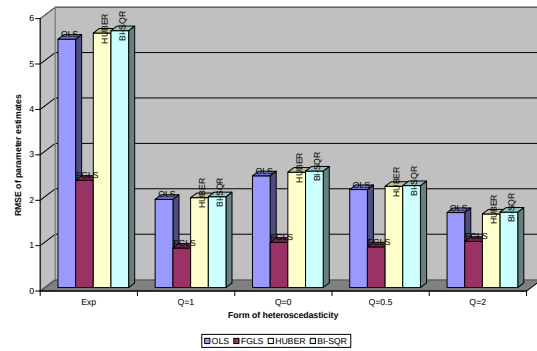
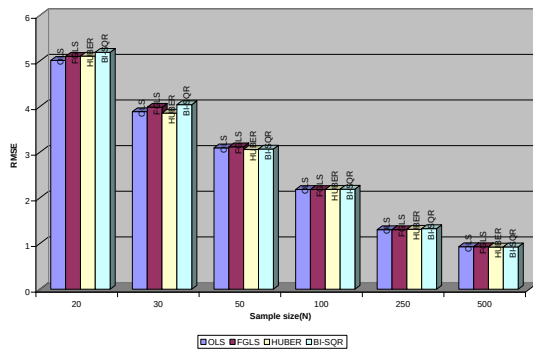


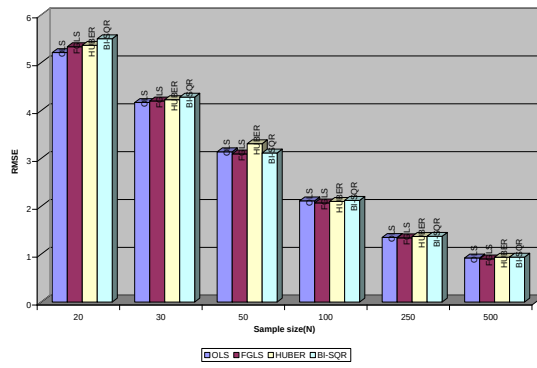
Fig.5.1g: Bar chart showing performance of estimators at different level of heteroscedasticity using RMSE criterion when error is Normal, correlated across the equations($R=0.95$)

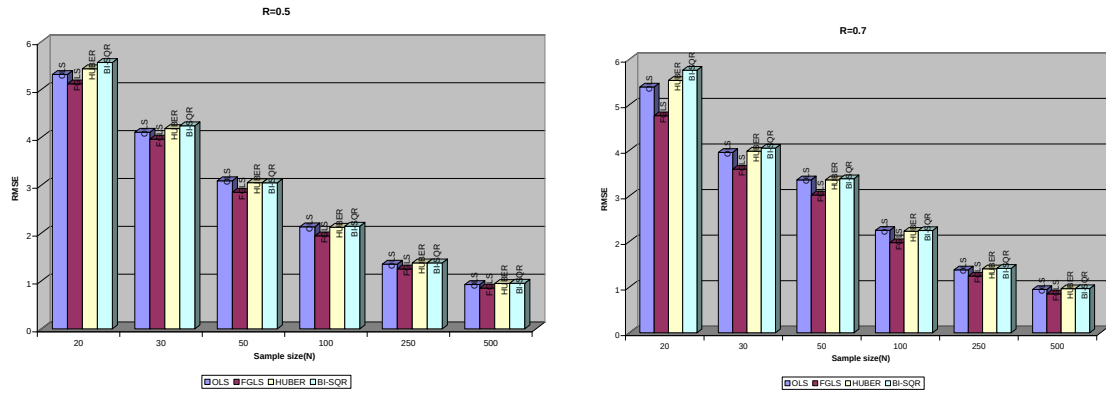


Performance of estimators at different Sample size when Contemporaneous correlation($R=0.0$)

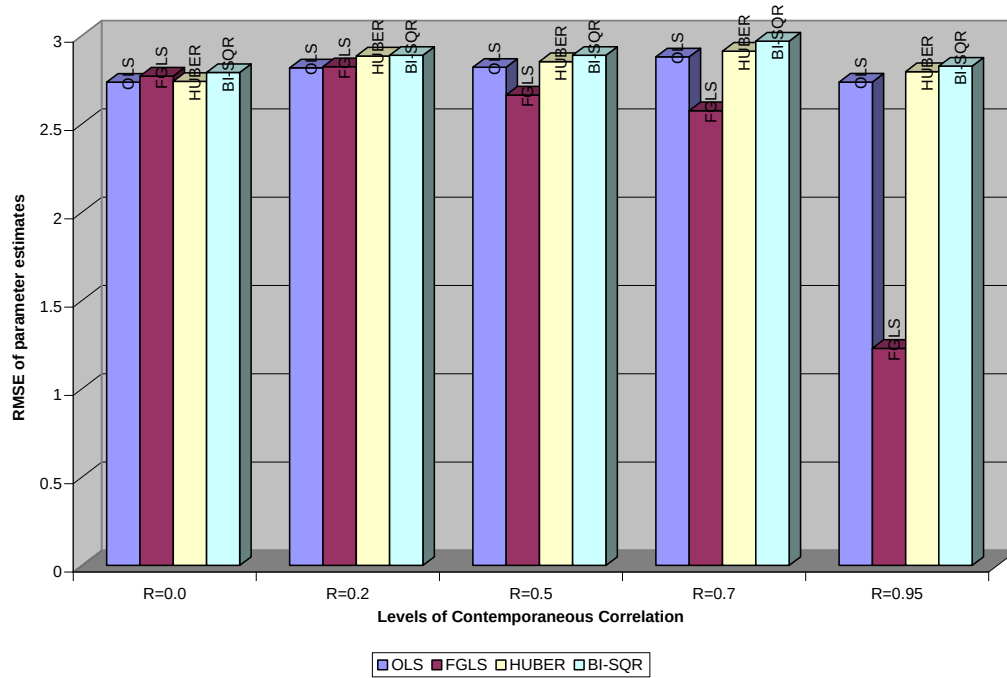


$R=0.2$





Performances of estimators at different levels of contemporaneous Correlation



APPENDIX II

TABLE 4.1.1 A: VARIANCE: When Errors are Gamma , Homoscedastic and No contemporal correlation under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g ; g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	8.139	12.91	13.8651	5.4928	9.3243	10.568	60.2981
		FGLS	7.885	12.33	14.3716	5.7009	10.076	10.679	61.0370
		Huber	4.457	8.263	8.679	4.0438	6.2005	6.8162	38.4598
		Bi-Square	4.279	7.503	7.8423	4.2698	5.7239	6.3421	35.9607
	N=30	OLS	3.588	8.539	6.7099	3.9249	6.2738	6.4207	35.4569
		FGLS	3.846	9.068	7.4918	4.0611	6.4169	6.9504	37.8340
		Huber	2.542	5.296	4.9312	3.0532	4.5159	4.0907	24.4292
		Bi-Square	2.463	4.699	4.7756	2.8813	4.3305	3.7086	22.8585
	N=50	OLS	2.087	4.93	3.8439	2.3901	4.647	3.2294	21.1280
		FGLS	2.144	4.879	4.0669	2.493	4.754	3.4271	21.7638
		Huber	1.413	3.201	2.4184	1.7191	2.9688	2.4735	14.1938
		Bi-Square	1.595	2.832	2.3324	1.8173	2.689	2.5417	13.8073
	N=100	OLS	1.215	2.274	1.3533	1.1398	2.0589	2.1271	10.1679
		FGLS	1.25	2.327	1.4153	1.1438	2.1161	2.1387	10.3905
		Huber	0.77	1.497	0.9167	0.7866	1.3097	1.3093	6.5892
		Bi-Square	0.795	1.471	0.9271	0.7934	1.2278	1.1168	6.3309
	N=250	OLS	0.384	0.794	0.6864	0.4878	1.0101	0.7188	4.0814
		FGLS	0.389	0.793	0.6965	0.4905	1.0287	0.7158	4.1129
		Huber	0.283	0.528	0.5021	0.3322	0.5387	0.4723	2.6557
		Bi-Square	0.306	0.522	0.5219	0.3471	0.4667	0.4607	2.6245
	N=500	OLS	0.235	0.341	0.4034	0.2048	0.3534	0.4018	1.9391
		FGLS	0.236	0.345	0.4032	0.2019	0.3539	0.3995	1.9393
		Huber	0.155	0.229	0.2267	0.1282	0.208	0.1984	1.1446
		Bi-Square	0.15	0.23	0.2052	0.1209	0.1837	0.1635	1.0532

TABLE 4.1.2 A: VARIANCE: When Errors are Gamma, Exponential Heteroscedastic and No contemporal correlation under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	37.08	66.4	71.3364	24.524	46.3	52.666	298.3050
		FGLS	37.35	65.71	74.8236	25.278	50.353	53.3	306.8145
		Huber	18.97	41.75	44.143	16.957	29.744	32.754	184.3239
		Bi-Square	17.12	36.02	41.7403	17.138	28.164	29.039	169.2190
	N=30	OLS	17.06	47.04	34.3171	18.376	33.187	33.727	183.7002
		FGLS	18.19	49.62	38.4491	19.35	34.725	36.367	196.7047
		Huber	11.1	27.51	25.0586	14.049	23.99	20.964	122.6679
		Bi-Square	9.986	24.28	23.3653	12.793	23.688	19.276	113.3827
	N=50	OLS	9.543	26.9	19.838	10.165	23.375	16.124	105.9478
		FGLS	9.816	26.57	20.9879	10.569	23.884	16.735	108.5580
		Huber	6.001	16.32	11.9661	7.8707	14.975	12.877	70.0070
		Bi-Square	6.222	13.52	11.0346	7.9307	14.149	13.459	66.3125
	N=100	OLS	5.528	12.09	6.85444	4.8628	10.394	11.024	50.7551
		FGLS	5.724	12.36	7.25187	4.922	10.755	11.132	52.1447
		Huber	3.42	7.585	4.5914	3.2622	6.4463	6.5689	31.8744
		Bi-Square	3.141	7.097	4.65064	2.9908	5.9354	5.3975	29.2124
	N=250	OLS	1.669	4.162	3.54889	2.133	5.1988	3.7739	20.4853
		FGLS	1.691	4.14	3.60141	2.14	5.2795	3.7673	20.6189
		Huber	1.269	2.769	2.54848	1.3953	2.6377	2.3915	13.0108
		Bi-Square	1.342	2.8	2.76793	1.351	2.2141	2.2797	12.7538
	500	OLS	1.025	1.765	2.04364	0.877	1.7831	2.0121	9.5063
		FGLS	1.032	1.784	2.04806	0.8682	1.7917	2.0045	9.5286
		Huber	0.652	1.171	1.10244	0.5334	1.0434	0.9893	5.4914
		Bi-Square	0.589	1.274	0.97084	0.4819	1.0052	0.8494	5.1699

TABLE 4.1.3 A: VARIANCE: When Errors are Gamma , Quadratic Heteroscedastic(Q=2) and No contemporaneous correlation(P=0) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	2.981	6.314	6.59852	1.9386	4.2214	4.6415	26.6953
		FGLS	3.135	6.464	6.9752	1.9783	4.6045	4.7128	27.8702
		Huber	1.351	3.693	4.00153	1.0949	2.5571	2.6623	15.3602
		Bi-Square	1.127	3.822	4.0527	1.0034	2.544	2.0969	14.6453
	N=30	OLS	1.546	4.856	3.19235	1.6042	3.3531	3.2603	17.8117
		FGLS	1.613	5.035	3.57317	1.7206	3.6065	3.4672	19.0160
		Huber	0.816	2.555	2.21217	1.0617	2.3221	1.8475	10.8148
		Bi-Square	0.667	2.374	1.95095	0.8688	2.1825	1.4926	9.5357
	N=50	OLS	0.826	2.754	1.90046	0.7567	2.1611	1.4666	9.8651
		FGLS	0.848	2.718	2.00106	0.7786	2.1924	1.4803	10.0186
		Huber	0.404	1.519	0.99453	0.5497	1.3386	1.133	5.9383
		Bi-Square	0.361	1.184	0.86789	0.5167	1.3258	1.1535	5.4089
	N=100	OLS	0.454	1.201	0.64828	0.3797	1	1.0482	4.7312
		FGLS	0.472	1.227	0.68701	0.3903	1.0428	1.0616	4.8812
		Huber	0.242	0.684	0.40316	0.2226	0.5916	0.5763	2.7189
		Bi-Square	0.183	0.592	0.38677	0.1736	0.5239	0.4364	2.2960
	N=250	OLS	0.136	0.41	0.34626	0.1709	0.4977	0.3699	1.9307
		FGLS	0.138	0.406	0.35107	0.1705	0.5028	0.369	1.9371
		Huber	0.096	0.265	0.22797	0.0939	0.234	0.2123	1.1288
		Bi-Square	0.091	0.265	0.23752	0.0782	0.1888	0.1807	1.0410
	N=500	OLS	0.079	0.172	0.18713	0.0665	0.1663	0.1826	0.8540
		FGLS	0.08	0.173	0.18838	0.0666	0.1676	0.1826	0.8581
		Huber	0.042	0.116	0.08897	0.0361	0.1002	0.0863	0.4701
		Bi-Square	0.034	0.126	0.07511	0.0314	0.1046	0.0768	0.4478

TABLE 4.1.4 A: VARIANCE: When Errors are Gamma , Linear Heteroscedastic (Q=1) and No contemporaneous correlation (P=0) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	4.557	8.442	9.14388	2.989	5.8413	6.71	37.6831
		FGLS	4.624	8.416	9.60041	3.0707	6.3616	6.7955	38.8682
		Huber	2.311	5.317	5.66391	2.0114	3.7262	4.1182	23.1478
		Bi-Square	2.033	4.543	5.3275	2.0218	3.5641	3.6225	21.1119
	N=30	OLS	2.117	6.059	4.39918	2.268	4.2306	4.3488	23.4221
		FGLS	2.255	6.399	4.92638	2.401	4.45	4.6889	25.1201
		Huber	1.345	3.535	3.18553	1.7083	3.0581	2.6558	15.4881
		Bi-Square	1.183	3.08	2.93964	1.5646	3.0452	2.4402	14.2532
	N=50	OLS	1.163	3.474	2.53886	1.2232	2.9685	2.0544	13.4223
		FGLS	1.198	3.428	2.67942	1.2691	3.0323	2.1187	13.7252
		Huber	0.717	2.083	1.50651	0.9645	1.9044	1.6373	8.8129
		Bi-Square	0.715	1.689	1.35809	0.9586	1.8152	1.7131	8.2499
	N=100	OLS	0.678	1.545	0.88035	0.5894	1.318	1.4224	6.4329
		FGLS	0.702	1.579	0.93206	0.5981	1.3654	1.4372	6.6145
		Huber	0.411	0.96	0.5876	0.3906	0.8152	0.8403	4.0043
		Bi-Square	0.364	0.886	0.58577	0.3499	0.7506	0.6825	3.6187
	N=250	OLS	0.202	0.531	0.45549	0.2564	0.6597	0.4848	2.5898
		FGLS	0.205	0.528	0.46211	0.2571	0.6695	0.4843	2.6059
		Huber	0.154	0.352	0.32247	0.1652	0.3293	0.303	1.6260
		Bi-Square	0.162	0.357	0.35258	0.1566	0.2742	0.2866	1.5890
	N=500	OLS	0.124	0.226	0.26013	0.1056	0.2272	0.2557	1.1982
		FGLS	0.125	0.228	0.26088	0.1047	0.2285	0.2549	1.2016
		Huber	0.078	0.149	0.13801	0.0638	0.1319	0.1248	0.6851
		Bi-Square	0.068	0.165	0.12055	0.0573	0.13	0.1087	0.6500

TABLE 4.1.5 A: VARIANCE: When Errors are Gamma , Linear Heteroscedastic(Q=0.5) and No contemporaneous correlation under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	5.974	10.25	11.1244	3.9669	7.239	8.3287	46.8817
		FGLS	5.926	10.02	11.6127	4.094	7.858	8.4216	47.9326
		Huber	3.163	6.543	6.9188	2.8488	4.7455	5.2701	29.4889
		Bi-Square	2.904	5.697	6.4414	2.9336	4.3803	4.7853	27.1414
	N=30	OLS	2.683	7.068	5.36117	2.908	5.0335	5.2135	28.2675
		FGLS	2.873	7.502	5.99647	3.0462	5.2206	5.6402	30.2789
		Huber	1.832	4.274	3.92783	2.2562	3.6371	3.2603	19.1879
		Bi-Square	1.687	3.762	3.70714	2.0863	3.5794	3.014	17.8357
	N=50	OLS	1.512	4.069	3.0703	1.6741	3.6495	2.5357	12.0503
		FGLS	1.556	4.019	3.24497	1.7429	3.734	2.6522	12.0926
		Huber	0.989	2.55	1.88202	1.2788	2.3497	2.0135	10.0414
		Bi-Square	1.066	2.169	1.77018	1.3194	2.1808	2.0927	9.2877
	N=100	OLS	0.888	1.839	1.07377	0.8	1.6096	1.7171	7.9269
		FGLS	0.916	1.881	1.13151	0.8069	1.6607	1.7315	8.1277
		Huber	0.556	1.185	0.72667	0.551	1.0199	1.0382	5.0770
		Bi-Square	0.535	1.128	0.74027	0.5242	0.9493	0.8677	4.7439
	N=250	OLS	0.271	0.636	0.54855	0.3439	0.8	0.5806	3.1802
		FGLS	0.274	0.634	0.55665	0.3454	0.8136	0.5793	3.2031
		Huber	0.205	0.426	0.39975	0.2318	0.4153	0.3751	2.0532
		Bi-Square	0.22	0.427	0.42719	0.232	0.3538	0.3624	2.0217
	N=500	OLS	0.167	0.272	0.31922	0.1437	0.2784	0.3157	1.4954
		FGLS	0.168	0.274	0.31956	0.142	0.2794	0.3143	1.4977
		Huber	0.11	0.183	0.17701	0.09	0.1633	0.1571	0.8798
		Bi-Square	0.101	0.191	0.15656	0.0822	0.1515	0.132	0.8141

TABLE 4.1.6 A: VARIANCE: When Errors are Gamma , Homoscedastic and contemporaneous correlation (P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	5.795	14.57	12.8511	5.7707	13.719	12.013	64.7234
		FGLS	5.526	13.19	12.8691	5.5684	13.766	11.529	62.4491
		Huber	4.098	8.94	7.93112	4.3804	8.6005	9.556	43.5057
		Bi-Square	4.684	8.55	7.41376	4.1067	7.3161	9.2846	41.3552
	N=30	OLS	2.888	4.862	5.41682	3.7053	5.5784	6.6161	29.0662
		FGLS	2.972	5.045	5.36954	3.7707	5.0878	7.0167	29.2614
		Huber	2.55	4.133	3.86117	2.9557	3.5171	5.023	22.0403
		Bi-Square	2.524	4.206	3.73239	2.9741	3.7557	4.9719	22.1641
	N=50	OLS	2.992	4.803	4.1647	2.5553	3.9329	4.0035	22.4510
		FGLS	2.791	4.714	3.93094	2.6325	4.0848	3.8685	22.0215
		Huber	2.35	2.933	2.96892	1.8362	2.6626	2.4679	15.2191
		Bi-Square	2.184	2.528	2.72942	1.8077	2.5376	2.341	14.1282
	N=100	OLS	1.243	1.859	1.76266	1.1726	1.729	2.117	9.8826
		FGLS	1.332	1.84	1.82595	1.096	1.6316	2.0111	9.7363
		Huber	0.812	1.03	1.27486	0.6929	0.937	1.308	6.0547
		Bi-Square	0.851	1.041	1.2634	0.6219	0.8919	1.2085	5.8775
	N=250	OLS	0.428	0.863	0.84493	0.5099	0.983	0.8947	4.5242
		FGLS	0.422	0.817	0.83942	0.5035	0.9344	0.8573	4.3736
		Huber	0.272	0.528	0.46022	0.3007	0.5887	0.4887	2.6385
		Bi-Square	0.281	0.482	0.42195	0.2898	0.5193	0.4635	2.4576
	N=500	OLS	0.234	0.433	0.38611	0.2294	0.3385	0.402	2.0229
		FGLS	0.231	0.418	0.35214	0.2343	0.3213	0.3983	1.9549
		Huber	0.137	0.214	0.21752	0.1477	0.2401	0.255	1.2107
		Bi-Square	0.127	0.181	0.18138	0.1233	0.2425	0.234	1.0898

Contemporaneous Correlation	sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i)= \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	26.76	78.09	66.7777	28.805	76.868	64.715	342.0166
		FGLS	25.26	69.49	64.3673	27.645	75.678	62.19	324.6244
		Huber	17.53	45.5	39.9974	19.606	45.532	48.451	216.6098
		Bi-Square	19.62	43.45	36.7523	18.544	39.631	44.366	202.3546
	N=30	OLS	12.73	24.32	28.7358	16.592	29.539	33.568	145.4872
		FGLS	13.6	25.48	28.9249	16.756	26.817	35.661	147.2494
		Huber	10.33	20.23	19.5666	12.859	18.206	25.552	106.7507
		Bi-Square	10.92	22.88	18.6257	12.071	18.133	25.436	108.0639
	N=50	OLS	13.63	25.08	21.2661	11.016	20.144	20.366	111.4988
		FGLS	12.93	24.75	20.4045	11.266	20.863	19.558	109.7622
		Huber	9.369	13.97	14.3533	8.0834	13.731	13.065	72.5695
		Bi-Square	8.102	12.01	13.3009	7.7018	13.454	12.377	66.9500
	N=100	OLS	5.517	10.07	9.08617	4.9708	8.8058	10.592	49.0389
		FGLS	5.844	10.05	9.21862	4.667	8.4818	10.152	48.4165
		Huber	3.654	5.36	6.5627	3.0443	4.9645	6.6361	30.2212
		Bi-Square	3.55	5.461	6.48465	2.6613	4.856	6.0502	29.0633
	N=250	OLS	1.966	4.617	4.47854	2.3058	5.1706	4.7627	23.3005
		FGLS	1.946	4.386	4.43344	2.2628	4.8994	4.5851	22.5128
		Huber	1.193	2.685	2.35429	1.3431	3.1614	2.476	13.2134
		Bi-Square	1.141	2.41	2.08089	1.2332	2.8282	2.374	12.0669
	N=500	OLS	1.057	2.231	2.09466	1.0134	1.7742	1.9898	10.1605
		FGLS	1.038	2.151	1.9142	1.0263	1.6996	1.9557	9.7854
		Huber	0.594	1.053	1.11732	0.6257	1.218	1.2688	5.8774
		Bi-Square	0.514	0.884	0.91583	0.4973	1.2542	1.1934	5.2584

Contemporaneous Correlation	sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i)= \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	2.235	7.728	6.31625	2.7512	8.1533	6.3588	33.5431
		FGLS	2.083	6.726	5.83943	2.6718	7.9345	6.1867	31.4415
		Huber	1.234	4.161	3.49899	1.506	4.5027	4.1999	19.1025
		Bi-Square	1.193	3.88	2.90404	1.2564	3.2872	3.7621	16.2835
	N=30	OLS	1.055	2.309	2.83323	1.3754	3.0347	3.1294	13.7373
		FGLS	1.174	2.402	2.91476	1.3758	2.8097	3.3267	14.0031
		Huber	0.709	1.843	1.72187	0.8714	1.7562	2.1496	9.0509
		Bi-Square	0.689	2.002	1.47558	0.7341	1.6114	2.034	8.5458
	N=50	OLS	1.13	2.471	1.98998	0.8522	1.9674	1.8904	10.3007
		FGLS	1.118	2.476	1.9572	0.8517	2.0231	1.8049	10.2311
		Huber	0.603	1.26	1.19178	0.5917	1.3073	1.1922	6.1453
		Bi-Square	0.441	1.11	1.02456	0.5392	1.2608	1.1182	5.4942
	N=100	OLS	0.46	1.06	0.87836	0.365	0.8446	0.9461	4.5539
		FGLS	0.476	1.075	0.86996	0.348	0.8362	0.9229	4.5278
		Huber	0.247	0.504	0.56222	0.2136	0.4899	0.5734	2.5901
		Bi-Square	0.215	0.502	0.53478	0.1847	0.4827	0.5255	2.4452
	N=250	OLS	0.171	0.466	0.43852	0.1945	0.5102	0.4673	2.2469
		FGLS	0.169	0.446	0.43374	0.1893	0.4855	0.4535	2.1773
		Huber	0.084	0.249	0.20951	0.0994	0.302	0.2249	1.1688
		Bi-Square	0.064	0.208	0.16275	0.0816	0.2583	0.2025	0.9776
	N=500	OLS	0.089	0.217	0.21181	0.0803	0.1767	0.1762	0.9506
		FGLS	0.087	0.209	0.19631	0.08	0.1719	0.1718	0.9154
		Huber	0.042	0.094	0.10024	0.043	0.1134	0.1112	0.5038
		Bi-Square	0.032	0.08	0.07678	0.037	0.121	0.1099	0.4558

TABLE 4.1.9A: VARIANCE: When Errors are Gamma , Linear Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	3.298	10.03	8.55522	3.5749	9.9568	8.3498	43.7647
		FGLS	3.104	8.898	8.16193	3.442	9.7841	8.0649	41.4550
		Huber	2.125	5.796	5.06	2.3845	5.8549	6.1897	27.4101
		Bi-Square	2.334	5.49	4.58847	2.2474	5.0423	5.6205	25.3230
	N=30	OLS	1.538	3.08	3.70718	2.0216	3.7847	4.2803	18.4118
		FGLS	1.657	3.232	3.73264	2.0351	3.4349	4.5468	18.6388
		Huber	1.225	2.551	2.50315	1.5317	2.3428	3.2128	13.3662
		Bi-Square	1.296	2.917	2.36331	1.4048	2.2774	3.1791	13.4378
	N=50	OLS	1.656	3.195	2.70348	1.3435	2.5823	2.6181	14.0985
		FGLS	1.575	3.155	2.6027	1.3673	2.6733	2.5054	13.8790
		Huber	1.097	1.755	1.79373	0.9951	1.7696	1.6851	9.0955
		Bi-Square	0.933	1.533	1.65872	0.939	1.7402	1.5957	8.3993
	N=100	OLS	0.672	1.298	1.15973	0.6	1.1208	1.356	6.2062
		FGLS	0.712	1.304	1.171	0.5648	1.0857	1.3041	6.1415
		Huber	0.445	0.69	0.83148	0.3715	0.6431	0.8469	3.8280
		Bi-Square	0.421	0.696	0.8185	0.3246	0.6304	0.7729	3.6635
	N=250	OLS	0.242	0.595	0.57971	0.2812	0.6626	0.6134	2.9741
		FGLS	0.24	0.566	0.57333	0.2761	0.6282	0.5917	2.8758
		Huber	0.143	0.342	0.30049	0.1643	0.4081	0.3142	1.6726
		Bi-Square	0.134	0.305	0.25977	0.1489	0.3654	0.3013	1.5141
	N=500	OLS	0.13	0.284	0.27348	0.1236	0.2269	0.2548	1.2932
		FGLS	0.128	0.274	0.25017	0.1247	0.2176	0.2497	1.2438
		Huber	0.072	0.132	0.14262	0.075	0.154	0.1625	0.7380
		Bi-Square	0.061	0.112	0.11607	0.0594	0.16	0.1539	0.6629

TABLE 4.1.10A: VARIANCE: When Errors are Gamma , Linear Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	4.281	11.91	10.3447	4.4146	11.486	9.896	52.3300
		FGLS	4.055	10.68	10.0964	4.2531	11.395	9.5314	50.0068
		Huber	2.922	7.139	6.26013	3.1763	6.9687	7.603	34.0688
		Bi-Square	3.279	6.848	5.78823	3.0343	6.0878	7.2298	32.2669
	N=30	OLS	2.041	3.78	4.41076	2.6683	4.4878	5.2374	22.6252
		FGLS	2.151	3.958	4.40226	2.7003	4.0664	5.5595	22.8371
		Huber	1.707	3.183	3.05621	2.1201	2.7982	3.9763	16.8414
		Bi-Square	1.781	3.469	2.94481	2.0465	2.8732	3.9529	17.0673
	N=50	OLS	2.168	3.833	3.29808	1.8104	3.1184	3.1925	17.4197
		FGLS	2.035	3.768	3.14245	1.8562	3.2358	3.0673	17.1048
		Huber	1.576	2.217	2.27298	1.3319	2.133	2.0228	11.5533
		Bi-Square	1.409	1.916	2.11612	1.2881	2.077	1.915	10.7211
	N=100	OLS	0.888	1.517	1.40261	0.8225	1.363	1.6755	7.6692
		FGLS	0.948	1.514	1.43421	0.7707	1.303	1.6004	7.5706
		Huber	0.599	0.831	1.02812	0.508	0.769	1.0491	4.7847
		Bi-Square	0.601	0.852	1.0172	0.4483	0.7396	0.9595	4.6168
	N=250	OLS	0.313	0.703	0.69049	0.3684	0.7924	0.73	3.5978
		FGLS	0.31	0.667	0.68407	0.363	0.7518	0.7017	3.4776
		Huber	0.196	0.421	0.37024	0.2193	0.4899	0.3865	2.0822
		Bi-Square	0.194	0.381	0.33057	0.2059	0.4335	0.3692	1.9143
	N=500	OLS	0.17	0.344	0.32081	0.1647	0.2713	0.3165	1.5872
		FGLS	0.167	0.332	0.29251	0.1673	0.2587	0.3116	1.5290
		Huber	0.098	0.167	0.17514	0.1039	0.1906	0.2013	0.9360
		Bi-Square	0.087	0.14	0.14428	0.0835	0.1933	0.1867	0.8354

TABLE 4.1.16A: VARIANCE: When Errors are Gamma , Homoscedastic and contemporal correlation (P=0.5) under varying sample sizes

Contemporaral Correlation	sample size	Forms of Heteroscadasticity: Var(Yi)= σ ² {E(Yi)} ^g ; g=0							
		Estimators	β ₁₀	β ₁₁	β ₁₂	β ₂₀	β ₂₁	β ₂₂	Sum(β _{i,p})
0.5	N=20	OLS	5.795	14.57	12.8511	5.8449	14.434	13.04	66.5395
		FGLS	4.856	10.62	10.0921	4.8328	13.023	11.11	54.5295
		Huber	4.098	8.94	7.93112	4.6638	10.657	11.109	47.3985
		Bi-Square	4.684	8.55	7.41376	4.585	10.195	10.909	46.3364
	N=30	OLS	2.888	4.862	5.41682	3.6944	5.5766	6.724	29.1613
		FGLS	2.65	4.633	4.84843	3.4283	4.6276	6.4318	26.6190
		Huber	2.55	4.133	3.86117	3.2103	4.2228	5.4146	23.3922
		Bi-Square	2.524	4.206	3.73239	3.1312	4.3654	5.3998	23.3588
	N=50	OLS	2.992	4.803	4.1647	2.4872	3.7078	3.91	22.0643
		FGLS	2.468	4.279	3.39598	2.3644	3.401	3.3215	19.2305
		Huber	2.35	2.933	2.96892	2.1846	3.0765	2.8541	16.3675
		Bi-Square	2.184	2.528	2.72942	2.217	3.0384	2.8836	15.5809
	N=100	OLS	1.243	1.859	1.76266	1.1486	1.7045	1.9239	9.6410
		FGLS	1.241	1.65	1.67102	0.9397	1.4045	1.6172	8.5231
		Huber	0.812	1.03	1.27486	0.8305	1.241	1.4095	6.5978
		Bi-Square	0.851	1.041	1.2634	0.7809	1.266	1.3775	6.5795
	N=250	OLS	0.428	0.863	0.84493	0.4889	1.0075	0.8819	4.5148
		FGLS	0.381	0.72	0.7338	0.4234	0.8349	0.7296	3.8227
		Huber	0.272	0.528	0.46022	0.3459	0.723	0.5651	2.8944
		Bi-Square	0.281	0.482	0.42195	0.3641	0.7123	0.5496	2.8110
	N=500	OLS	0.234	0.433	0.38611	0.2125	0.3481	0.3841	1.9977
		FGLS	0.212	0.367	0.28393	0.2024	0.2803	0.3477	1.6936
		Huber	0.137	0.214	0.21752	0.1666	0.2882	0.2955	1.3183
		Bi-Square	0.127	0.181	0.18138	0.1655	0.3025	0.3014	1.2593

TABLE 4.1.17A: VARIANCE: When Errors are Gamma , Exponential Heteroscedastic and Contemporaral Correlation(P=0.5) under varying sample sizes

Contemporaral Correlation	Sample size	Forms of Heteroscadasticity: Var(Yi)= σ ² Exp[E(Yi)]							
		Estimators	β ₁₀	β ₁₁	β ₁₂	β ₂₀	β ₂₁	β ₂₂	Sum(β _{ij})
0.5	N=20	OLS	26.76	78.09	66.7777	29.756	81.522	70.466	353.3735
		FGLS	22.1	57.93	51.3864	24.557	72.272	60.523	288.7675
		Huber	17.53	45.5	39.9974	20.954	55.96	56.853	236.7875
		Bi-Square	19.62	43.45	36.7523	20.114	52.216	55.961	228.1048
	N=30	OLS	12.73	24.32	28.7358	16.39	29.432	34.129	145.7394
		FGLS	12.31	23.95	26.2886	14.947	24.245	32.779	134.5275
		Huber	10.33	20.23	19.5666	13.578	22.175	27.098	112.9839
		Bi-Square	10.92	22.88	18.6257	12.821	22.284	26.928	114.4559
	N=50	OLS	13.63	25.08	21.2661	10.741	19.196	19.827	109.7373
		FGLS	11.61	23.01	18.1117	9.9463	17.205	16.68	96.5634
		Huber	9.369	13.97	14.3533	9.3936	15.799	14.788	77.6719
		Bi-Square	8.102	12.01	13.3009	9.3387	16.176	14.905	73.8366
	N=100	OLS	5.517	10.07	9.08617	4.8318	8.6913	9.7195	47.9131
		FGLS	5.35	9.221	8.32668	3.9729	7.3701	8.3682	42.6097
		Huber	3.654	5.36	6.5627	3.5976	6.4961	7.1413	32.8114
		Bi-Square	3.55	5.461	6.48465	3.294	6.8962	6.8552	32.5412
	N=250	OLS	1.966	4.617	4.47854	2.2337	5.2615	4.718	23.2746
		FGLS	1.745	3.896	3.88408	1.897	4.3713	3.95	19.7437
		Huber	1.193	2.685	2.35429	1.5884	3.8639	2.9669	14.6520
		Bi-Square	1.141	2.41	2.08089	1.572	3.7728	2.8867	13.8630
	N=500	OLS	1.057	2.231	2.09466	0.9504	1.8243	1.9351	10.0929
		FGLS	0.941	1.892	1.55362	0.8861	1.504	1.7349	8.5119
		Huber	0.594	1.053	1.11732	0.7149	1.5046	1.448	6.4323
		Bi-Square	0.514	0.884	0.91583	0.6893	1.587	1.4832	6.0728

TABLE 4.1.18A: VARIANCE: When Errors are Gamma , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	2.235	7.728	6.31625	2.9369	8.7155	6.9598	34.8919
		FGLS	1.847	5.949	4.83767	2.5125	7.7475	6.1652	29.0589
		Huber	1.234	4.161	3.49899	1.6366	5.4494	5.0549	21.0349
		Bi-Square	1.193	3.88	2.90404	1.4717	4.8175	4.6894	18.9565
	N=30	OLS	1.055	2.309	2.83323	1.3557	3.0384	3.1925	13.7843
		FGLS	1.101	2.341	2.69106	1.2217	2.596	3.0842	13.0351
		Huber	0.709	1.843	1.72187	0.9556	2.0962	2.3485	9.6741
		Bi-Square	0.689	2.002	1.47558	0.8319	1.9332	2.1736	9.1050
	N=50	OLS	1.13	2.471	1.98998	0.8314	1.9113	1.826	10.1594
		FGLS	1.038	2.38	1.7967	0.7374	1.6973	1.5419	9.1918
		Huber	0.603	1.26	1.19178	0.6723	1.5232	1.3247	6.5744
		Bi-Square	0.441	1.11	1.02456	0.6339	1.5934	1.2911	6.0943
	N=100	OLS	0.46	1.06	0.87836	0.3546	0.8433	0.8817	4.4778
		FGLS	0.432	1.027	0.7824	0.3026	0.7531	0.7933	4.0909
		Huber	0.247	0.504	0.56222	0.2486	0.6191	0.6208	2.8017
		Bi-Square	0.215	0.502	0.53478	0.2276	0.6789	0.586	2.7448
	N=250	OLS	0.171	0.466	0.43852	0.194	0.5147	0.4679	2.2515
		FGLS	0.154	0.406	0.38798	0.1641	0.4399	0.4036	1.9559
		Huber	0.084	0.249	0.20951	0.123	0.3667	0.2748	1.3069
		Bi-Square	0.064	0.208	0.16275	0.1106	0.3328	0.2626	1.1412
	N=500	OLS	0.089	0.217	0.21181	0.0778	0.1821	0.1762	0.9535
		FGLS	0.078	0.187	0.16467	0.0707	0.158	0.1577	0.8157
		Huber	0.042	0.094	0.10024	0.0494	0.1423	0.123	0.5508
		Bi-Square	0.032	0.08	0.07678	0.045	0.1524	0.1219	0.5071

TABLE 4.1.19A: VARIANCE: When Errors are Gamma , Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=1							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	3.298	10.03	8.55522	3.6957	10.563	9.1024	45.2447
		FGLS	2.714	7.475	6.52906	3.0615	9.3543	7.8801	37.0133
		Huber	2.125	5.796	5.06	2.5413	7.1652	7.2573	29.9448
		Bi-Square	2.334	5.49	4.58847	2.4342	6.6155	7.1625	28.6250
	N=30	OLS	1.538	3.08	3.70718	1.9857	3.7574	4.3459	18.4142
		FGLS	1.505	3.055	3.4051	1.8057	3.1012	4.1882	17.0607
		Huber	1.225	2.551	2.50315	1.6191	2.8093	3.4079	14.1152
		Bi-Square	1.296	2.917	2.36331	1.5071	2.8099	3.3493	14.2426
	N=50	OLS	1.656	3.195	2.70348	1.3158	2.4764	2.5471	13.8940
		FGLS	1.421	2.951	2.32287	1.2083	2.217	2.1387	12.2593
		Huber	1.097	1.755	1.79373	1.1578	2.0473	1.8974	9.7482
		Bi-Square	0.933	1.533	1.65872	1.1377	2.1045	1.9072	9.2739
	N=100	OLS	0.672	1.298	1.15973	0.5828	1.105	1.2491	6.0664
		FGLS	0.652	1.208	1.05597	0.4823	0.9459	1.0832	5.4266
		Huber	0.445	0.69	0.83148	0.4378	0.8371	0.9178	4.1592
		Bi-Square	0.421	0.696	0.8185	0.4005	0.8958	0.8742	4.1062
	N=250	OLS	0.242	0.595	0.57971	0.272	0.673	0.6067	2.9685
		FGLS	0.216	0.505	0.50343	0.2315	0.5618	0.5107	2.5282
		Huber	0.143	0.342	0.30049	0.1961	0.4984	0.3797	1.8602
		Bi-Square	0.134	0.305	0.25977	0.1911	0.4837	0.368	1.7414
	N=500	OLS	0.13	0.284	0.27348	0.1166	0.2334	0.2498	1.2877
		FGLS	0.115	0.241	0.20344	0.108	0.1935	0.2233	1.0849
		Huber	0.072	0.132	0.14262	0.0862	0.1929	0.1847	0.8103
		Bi-Square	0.061	0.112	0.11607	0.082	0.2023	0.1884	0.7623

TABLE 4.1.20A: VARIANCE: When Errors are Gamma , Square Root Heteroscedastic($g=0.5$) and Contemporaneous Correlation($P=0.5$) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	4.281	11.91	10.3447	4.5082	12.138	10.767	53.9462
		FGLS	3.543	8.753	7.97534	3.7191	10.822	9.2442	44.0565
		Huber	2.922	7.139	6.26013	3.3762	8.5707	8.9094	37.1771
		Bi-Square	3.279	6.848	5.78823	3.3372	8.2332	8.9275	36.4129
	N=30	OLS	2.041	3.78	4.41076	2.6364	4.4612	5.3162	22.6456
		FGLS	1.932	3.684	3.99397	2.4193	3.6665	5.1073	20.8036
		Huber	1.707	3.183	3.05621	2.2282	3.382	4.2254	17.7823
		Bi-Square	1.781	3.469	2.94481	2.1287	3.4515	4.2026	17.9775
	N=50	OLS	2.168	3.833	3.29808	1.7706	2.9665	3.1148	17.1504
		FGLS	1.814	3.471	2.7592	1.6565	2.6834	2.6249	15.0097
		Huber	1.576	2.217	2.27298	1.5673	2.4502	2.3157	12.3988
		Bi-Square	1.409	1.916	2.11612	1.5672	2.4861	2.333	11.8273
	N=100	OLS	0.888	1.517	1.40261	0.802	1.3414	1.5334	7.4850
		FGLS	0.876	1.378	1.30113	0.6577	1.1244	1.307	6.6440
		Huber	0.599	0.831	1.02812	0.6016	1.0042	1.1304	5.1948
		Bi-Square	0.601	0.852	1.0172	0.5523	1.0471	1.0871	5.1558
	N=250	OLS	0.313	0.703	0.69049	0.3537	0.8084	0.72	3.5890
		FGLS	0.278	0.59	0.59792	0.3034	0.671	0.5996	3.0406
		Huber	0.196	0.421	0.37024	0.2575	0.5925	0.4588	2.2953
		Bi-Square	0.194	0.381	0.33057	0.2605	0.5861	0.4452	2.1973
	N=500	OLS	0.17	0.344	0.32081	0.1538	0.2792	0.3065	1.5741
		FGLS	0.153	0.291	0.23596	0.1445	0.2272	0.2752	1.3263
		Huber	0.098	0.167	0.17514	0.1183	0.2319	0.2317	1.0220
		Bi-Square	0.087	0.14	0.14428	0.1157	0.2444	0.2373	0.9692

TABLE 4.1.21A: VARIANCE: When Errors are Gamma , Homoscedastic and contemporaneous correlation ($P=0.7$) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	5.795	14.57	12.8511	6.6214	10.208	10.563	60.6129
		FGLS	4.734	11.07	10.3102	5.2458	7.5523	8.2235	47.1355
		Huber	4.098	8.94	7.93112	6.2855	10.766	9.6268	47.6469
		Bi-Square	4.684	8.55	7.41376	6.6533	10.914	10.118	48.3334
	N=30	OLS	2.888	4.862	5.41682	4.3536	8.2364	7.0733	32.8297
		FGLS	2.493	3.606	4.90249	3.5149	6.0511	6.1515	26.7197
		Huber	2.55	4.133	3.86117	3.6195	6.8481	5.8689	26.8810
		Bi-Square	2.524	4.206	3.73239	3.6357	6.3006	5.6768	26.0755
	N=50	OLS	2.992	4.803	4.1647	3.3458	4.9069	4.0269	24.2388
		FGLS	2.374	3.655	3.1881	2.7496	4.2849	3.0451	19.2966
		Huber	2.35	2.933	2.96892	2.4701	4.0688	2.9834	17.7747
		Bi-Square	2.184	2.528	2.72942	2.4356	3.9465	3.063	16.8870
	N=100	OLS	1.243	1.859	1.76266	0.9823	1.786	1.9651	9.5974
		FGLS	1.058	1.389	1.58678	0.7155	1.4047	1.3729	7.5259
		Huber	0.812	1.03	1.27486	0.9071	1.5283	1.6291	7.1814
		Bi-Square	0.851	1.041	1.2634	0.9697	1.5998	1.6769	7.4016
	N=250	OLS	0.428	0.863	0.84493	0.495	0.8872	0.6382	4.1570
		FGLS	0.353	0.558	0.62927	0.3495	0.6294	0.3374	2.8560
		Huber	0.272	0.528	0.46022	0.3911	0.6429	0.5138	2.8082
		Bi-Square	0.281	0.482	0.42195	0.3853	0.6569	0.496	2.7231
	N=500	OLS	0.234	0.433	0.38611	0.2153	0.297	0.367	1.9323
		FGLS	0.192	0.292	0.31621	0.1841	0.2316	0.2768	1.4928
		Huber	0.137	0.214	0.21752	0.1615	0.2499	0.2508	1.2302
		Bi-Square	0.127	0.181	0.18138	0.1523	0.273	0.2339	1.1491

TABLE 4.1.22A: VARIANCE: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	3.298	10.03	8.55522	3.7864	7.0006	6.8481	39.5182
		FGLS	2.588	7.433	6.52215	2.9625	5.3208	5.3293	30.1565
		Huber	2.125	5.796	5.06	3.3881	7.1006	6.1746	29.6442
		Bi-Square	2.334	5.49	4.58847	3.4818	7.2442	6.522	29.6607
	N=30	OLS	1.538	3.08	3.70718	2.2408	5.2187	4.4943	20.2790
		FGLS	1.339	2.467	3.31661	1.8224	3.7823	4.1021	16.8289
		Huber	1.225	2.551	2.50315	1.8851	4.441	3.8146	16.4196
		Bi-Square	1.296	2.917	2.36331	1.8305	4.1639	3.638	16.2088
	N=50	OLS	1.656	3.195	2.70348	1.8505	3.1469	2.6888	15.2408
		FGLS	1.314	2.524	2.09143	1.4966	2.8342	2.1121	12.3730
		Huber	1.097	1.755	1.79373	1.3239	2.5651	1.9896	10.5243
		Bi-Square	0.933	1.533	1.65872	1.2994	2.5124	2.0372	9.9736
	N=100	OLS	0.672	1.298	1.15973	0.5363	1.2163	1.2699	6.1520
		FGLS	0.562	0.968	1.09675	0.3805	0.9744	0.8895	4.8706
		Huber	0.445	0.69	0.83148	0.4746	1.0487	1.0092	4.4990
		Bi-Square	0.421	0.696	0.8185	0.4867	1.0878	1.0472	4.5574
	N=250	OLS	0.242	0.595	0.57971	0.2721	0.5906	0.4369	2.7165
		FGLS	0.192	0.384	0.44974	0.1757	0.4095	0.2369	1.8482
		Huber	0.143	0.342	0.30049	0.2064	0.4316	0.3358	1.7598
		Bi-Square	0.134	0.305	0.25977	0.2067	0.4319	0.3393	1.6765
	N=500	OLS	0.13	0.284	0.27348	0.1209	0.2108	0.2615	1.2811
		FGLS	0.102	0.195	0.22238	0.1001	0.1602	0.1993	0.9788
		Huber	0.072	0.132	0.14262	0.0846	0.1748	0.1673	0.7732
		Bi-Square	0.061	0.112	0.11607	0.0782	0.1927	0.1515	0.7119

TABLE 4.1.23A: VARIANCE: When Errors are Gamma , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	2.235	7.728	6.31625	2.5973	5.4638	4.9801	29.3209
		FGLS	1.711	5.622	4.72859	2.083	4.3779	4.0241	22.5462
		Huber	1.234	4.161	3.49899	2.0361	4.9813	4.2807	20.1921
		Bi-Square	1.193	3.88	2.90404	2.0326	5.0553	4.3484	19.4141
	N=30	OLS	1.055	2.309	2.83323	1.4125	3.8133	3.1927	14.6163
		FGLS	0.946	1.989	2.55972	1.1959	2.8419	3.0494	12.5819
		Huber	0.709	1.843	1.72187	1.0726	3.0528	2.5656	10.9648
		Bi-Square	0.689	2.002	1.47558	1.0753	3.1225	2.5627	10.9269
	N=50	OLS	1.13	2.471	1.98998	1.1958	2.3158	1.9781	11.0805
		FGLS	0.898	2.056	1.5739	0.9693	2.1747	1.6217	9.2938
		Huber	0.603	1.26	1.19178	0.7972	1.7727	1.3844	7.0085
		Bi-Square	0.441	1.11	1.02456	0.7388	1.7333	1.3459	6.3939
	N=100	OLS	0.46	1.06	0.87836	0.3603	0.9448	0.9091	4.6124
		FGLS	0.383	0.811	0.87386	0.2615	0.7829	0.659	3.7716
		Huber	0.247	0.504	0.56222	0.2737	0.7663	0.6564	3.0095
		Bi-Square	0.215	0.502	0.53478	0.2773	0.8242	0.6752	3.0290
	N=250	OLS	0.171	0.466	0.43852	0.185	0.4501	0.3384	2.0485
		FGLS	0.136	0.32	0.35963	0.1172	0.3205	0.202	1.4557
		Huber	0.084	0.249	0.20951	0.1213	0.3063	0.2343	1.2044
		Bi-Square	0.064	0.208	0.16275	0.1203	0.3068	0.2428	1.1052
	N=500	OLS	0.089	0.217	0.21181	0.0846	0.1755	0.2048	0.9822
		FGLS	0.069	0.157	0.17622	0.0689	0.1363	0.1616	0.7692
		Huber	0.042	0.094	0.10024	0.0499	0.1372	0.1158	0.5390
		Bi-Square	0.032	0.08	0.07678	0.0466	0.1487	0.1082	0.4914

TABLE 4.1.24A: VARIANCE: When Errors are Gamma , Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: Var(Yi)= σ ² [E(Yi)] ^g ; g=1							
		Estimators	β ₁₀	β ₁₁	β ₁₂	β ₂₀	β ₂₁	β ₂₂	Sum(β _{ij})
0.7	N=20	OLS	3.298	10.03	8.55522	3.7864	7.0006	6.8481	39.5182
		FGLS	2.588	7.433	6.52215	2.9625	5.3208	5.3293	30.1565
		Huber	2.125	5.796	5.06	3.3881	7.1006	6.1746	29.6442
		Bi-Square	2.334	5.49	4.58847	3.4818	7.2442	6.522	29.6607
	N=30	OLS	1.538	3.08	3.70718	2.2408	5.2187	4.4943	20.2790
		FGLS	1.339	2.467	3.31661	1.8224	3.7823	4.1021	16.8289
		Huber	1.225	2.551	2.50315	1.8851	4.441	3.8146	16.4196
		Bi-Square	1.296	2.917	2.36331	1.8305	4.1639	3.638	16.2088
	N=50	OLS	1.656	3.195	2.70348	1.8505	3.1469	2.6888	15.2408
		FGLS	1.314	2.524	2.09143	1.4966	2.8342	2.1121	12.3730
		Huber	1.097	1.755	1.79373	1.3239	2.5651	1.9896	10.5243
		Bi-Square	0.933	1.533	1.65872	1.2994	2.5124	2.0372	9.9736
	N=100	OLS	0.672	1.298	1.15973	0.5363	1.2163	1.2699	6.1520
		FGLS	0.562	0.968	1.09675	0.3805	0.9744	0.8895	4.8706
		Huber	0.445	0.69	0.83148	0.4746	1.0487	1.0092	4.4990
		Bi-Square	0.421	0.696	0.8185	0.4867	1.0878	1.0472	4.5574
	N=250	OLS	0.242	0.595	0.57971	0.2721	0.5906	0.4369	2.7165
		FGLS	0.192	0.384	0.44974	0.1757	0.4095	0.2369	1.8482
		Huber	0.143	0.342	0.30049	0.2064	0.4316	0.3358	1.7598
		Bi-Square	0.134	0.305	0.25977	0.2067	0.4319	0.3393	1.6765
	N=500	OLS	0.13	0.284	0.27348	0.1209	0.2108	0.2615	1.2811
		FGLS	0.102	0.195	0.22238	0.1001	0.1602	0.1993	0.9788
		Huber	0.072	0.132	0.14262	0.0846	0.1748	0.1673	0.7732
		Bi-Square	0.061	0.112	0.11607	0.0782	0.1927	0.1515	0.7119

TABLE 4.1.25A: VARIANCE: When Errors are Gamma , Square Root Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: Var(Yi)= σ ² [E(Yi)] ^g ; g=0.5							
		Estimators	β ₁₀	β ₁₁	β ₁₂	β ₂₀	β ₂₁	β ₂₂	Sum(β _{ij})
0.7	N=20	OLS	4.281	11.91	10.3447	4.8933	8.3007	8.3756	48.1030
		FGLS	3.425	8.93	8.06728	3.8379	6.1986	6.4882	36.9473
		Huber	2.922	7.139	6.26013	4.6301	8.7276	7.626	37.3045
		Bi-Square	3.279	6.848	5.78823	4.7579	8.7759	8.0943	37.5430
	N=30	OLS	2.041	3.78	4.41076	3.0485	6.4287	5.5522	25.2612
		FGLS	1.765	2.908	3.95936	2.457	4.6634	4.9411	20.6934
		Huber	1.707	3.183	3.05621	2.5763	5.4709	4.6978	20.6918
		Bi-Square	1.781	3.469	2.94481	2.5463	5.0422	4.5048	20.2880
	N=50	OLS	2.168	3.833	3.29808	2.4404	3.8557	3.2472	18.8419
		FGLS	1.718	2.962	2.53106	1.9866	3.4127	2.4987	15.1091
		Huber	1.576	2.217	2.27298	1.782	3.1827	2.4107	13.4410
		Bi-Square	1.409	1.916	2.11612	1.7672	3.124	2.4841	12.8164
	N=100	OLS	0.888	1.517	1.40261	0.7073	1.4456	1.5586	7.5197
		FGLS	0.749	1.128	1.29123	0.5055	1.1442	1.0851	5.9027
		Huber	0.599	0.831	1.02812	0.6457	1.2435	1.276	5.6238
		Bi-Square	0.601	0.852	1.0172	0.6778	1.2965	1.3187	5.7623
	N=250	OLS	0.313	0.703	0.69049	0.3577	0.7104	0.519	3.2940
		FGLS	0.252	0.449	0.52326	0.2401	0.4948	0.2742	2.2340
		Huber	0.196	0.421	0.37024	0.2809	0.524	0.4084	2.1997
		Bi-Square	0.194	0.381	0.33057	0.2791	0.5304	0.4063	2.1212
	N=500	OLS	0.17	0.344	0.32081	0.1571	0.2442	0.3056	1.5415
		FGLS	0.136	0.232	0.26066	0.132	0.1867	0.2307	1.1782
		Huber	0.098	0.167	0.17514	0.1147	0.2052	0.2036	0.9637
		Bi-Square	0.087	0.14	0.14428	0.108	0.228	0.1861	0.8939

TABLE 4.1.26A: VARIANCE: When Errors are Gamma , Homoscedastic and contemporal correlation (P=0.95) under varying sample sizes

Contemporar Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	7.184	10.96	10.778	5.8449	14.434	13.04	62.2420
		FGLS	2.088	2.26	1.82705	1.5071	2.2383	2.4305	12.3506
		Huber	5.303	8.846	7.60329	4.6638	10.657	11.109	48.1818
		Bi-Square	5.631	8.994	7.64522	4.585	10.195	10.909	47.9582
	N=30	OLS	3.964	6.925	5.40826	3.6944	5.5766	6.724	32.2917
		FGLS	0.905	0.746	0.62522	1.1834	0.8392	0.984	5.2832
		Huber	3.259	4.364	4.30728	3.2103	4.2228	5.4146	24.7777
		Bi-Square	3.132	3.79	4.45744	3.1312	4.3654	5.3998	24.2761
	N=50	OLS	2.538	4.32	4.20446	2.4872	3.7078	3.91	21.1668
		FGLS	0.614	0.538	0.42898	0.6363	0.54	0.3789	3.1358
		Huber	1.635	2.34	2.65711	2.1846	3.0765	2.8541	14.7478
		Bi-Square	1.686	2.212	2.71659	2.217	3.0384	2.8836	14.7542
	N=100	OLS	1.41	2.219	2.04643	1.1486	1.7045	1.9239	10.4531
		FGLS	0.364	0.202	0.22303	0.2745	0.1688	0.1571	1.3899
		Huber	0.806	1.365	1.05596	0.8305	1.241	1.4095	6.7078
		Bi-Square	0.751	1.234	1.10187	0.7809	1.266	1.3775	6.5107
	N=250	OLS	0.457	0.989	0.75945	0.4889	1.0075	0.8819	4.5835
		FGLS	0.126	0.075	0.08067	0.1012	0.0795	0.0657	0.5285
		Huber	0.271	0.583	0.46292	0.3459	0.723	0.5651	2.9507
		Bi-Square	0.273	0.552	0.41899	0.3641	0.7123	0.5496	2.8701
	N=500	OLS	0.238	0.39	0.32189	0.2125	0.3481	0.3841	1.8942
		FGLS	0.045	0.04	0.03862	0.0412	0.0388	0.0392	0.2432
		Huber	0.156	0.215	0.21511	0.1666	0.2882	0.2955	1.3358
		Bi-Square	0.147	0.198	0.21758	0.1655	0.3025	0.3014	1.3312

TABLE 4.1.27A: VARIANCE: When Errors are Gamma , Exponential Heteroscedastic and Contemporar Correlation(P=0.95) under varying sample sizes

Contemporar Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	31	55.4	54.1401	29.756	81.522	70.466	322.2785
		FGLS	8.4	13.23	11.7195	7.3065	15.427	16.527	72.6076
		Huber	23.46	43.68	40.8299	20.954	55.96	56.853	241.7423
		Bi-Square	23.58	45.47	39.6606	20.114	52.216	55.961	237.0042
	N=30	OLS	17.48	35.18	27.8848	16.39	29.432	34.129	160.4993
		FGLS	3.399	4.505	4.02352	4.8425	5.9784	5.8755	28.6241
		Huber	13.53	21.23	21.366	13.578	22.175	27.098	118.9762
		Bi-Square	12.84	18.64	21.557	12.821	22.284	26.928	115.0664
	N=50	OLS	10.87	22.75	21.1027	10.741	19.196	19.827	104.4844
		FGLS	2.307	3.247	2.64182	2.5626	4.1196	2.5892	17.4670
		Huber	6.832	12.98	12.6449	9.3936	15.799	14.788	72.4365
		Bi-Square	6.843	12.21	12.4256	9.3387	16.176	14.905	71.8937
	N=100	OLS	6.311	11.3	10.862	4.8318	8.6913	9.7195	51.7192
		FGLS	1.542	1.368	1.45595	1.0501	1.3202	1.0781	7.8149
		Huber	3.428	7.055	5.42543	3.5976	6.4961	7.1413	33.1435
		Bi-Square	3.079	6.296	5.67617	3.294	6.8962	6.8552	32.0964
	N=250	OLS	2.128	5.347	3.94738	2.2337	5.2615	4.718	23.6352
		FGLS	0.485	0.511	0.55504	0.395	0.6169	0.5349	3.0974
		Huber	1.181	3.055	2.34155	1.5884	3.8639	2.9669	14.9958
		Bi-Square	1.072	2.954	2.10913	1.572	3.7728	2.8867	14.3664
	N=500	OLS	1.025	1.903	1.6558	0.9504	1.8243	1.9351	9.2937
		FGLS	0.195	0.265	0.27971	0.2006	0.2782	0.3264	1.5450
		Huber	0.664	1.029	1.08174	0.7149	1.5046	1.448	6.4426
		Bi-Square	0.593	0.938	1.09034	0.6893	1.587	1.4832	6.3805

TABLE 4.1.28A: VARIANCE: When Errors are Gamma , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	sample size	Forms of Heteroscedasticity: Var(Yi)= $\sigma^2[E(Yi)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	2.317	5.161	4.93722	2.9369	8.7155	6.9598	31.0275
		FGLS	0.777	1.934	1.91259	1.0203	2.6251	2.5375	10.8057
		Huber	1.634	3.664	3.64052	1.6366	5.4494	5.0549	21.0797
		Bi-Square	1.623	3.712	3.58855	1.4717	4.8175	4.6894	19.9024
	N=30	OLS	1.398	3.37	2.63412	1.3557	3.0384	3.1925	14.9887
		FGLS	0.379	0.858	0.71521	0.5049	1.102	0.9621	4.5208
		Huber	0.944	1.924	1.90095	0.9556	2.0962	2.3485	10.1692
		Bi-Square	0.817	1.661	1.73737	0.8319	1.9332	2.1736	9.1547
	N=50	OLS	0.794	2.212	1.90279	0.8314	1.9113	1.826	9.4771
		FGLS	0.22	0.588	0.44929	0.2696	0.7861	0.4547	2.7677
		Huber	0.463	1.331	0.99867	0.6723	1.5232	1.3247	6.3134
		Bi-Square	0.4	1.262	0.88417	0.6339	1.5934	1.2911	6.0648
	N=100	OLS	0.51	1.07	1.06417	0.3546	0.8433	0.8817	4.7239
		FGLS	0.167	0.271	0.27419	0.1095	0.2782	0.208	1.3069
		Huber	0.242	0.668	0.48376	0.2486	0.6191	0.6208	2.8817
		Bi-Square	0.197	0.636	0.48526	0.2276	0.6789	0.586	2.8110
	N=250	OLS	0.181	0.535	0.37267	0.194	0.5147	0.4679	2.2661
		FGLS	0.051	0.118	0.10662	0.056	0.1393	0.1198	0.5911
		Huber	0.082	0.289	0.20537	0.123	0.3667	0.2748	1.3410
		Bi-Square	0.064	0.261	0.1771	0.1106	0.3328	0.2626	1.2080
	N=500	OLS	0.078	0.171	0.15801	0.0778	0.1821	0.1762	0.8432
		FGLS	0.026	0.05	0.05365	0.0291	0.059	0.0618	0.2796
		Huber	0.045	0.09	0.09382	0.0494	0.1423	0.123	0.5436
		Bi-Square	0.037	0.076	0.0926	0.045	0.1524	0.1219	0.5250

TABLE 4.1.29A: VARIANCE: When Errors are Gamma , Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	sample size	Forms of Heteroscedasticity: Var(Yi)= $\sigma^2[E(Yi)]^g$; g=1							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	3.751	7.052	6.8585	3.6957	10.563	9.1024	41.0228
		FGLS	1.051	1.814	1.61408	0.909	2.1182	2.2462	9.7531
		Huber	2.872	5.492	5.18858	2.5413	7.1652	7.2573	30.5166
		Bi-Square	2.854	5.673	5.0201	2.4342	6.6155	7.1625	29.7592
	N=30	OLS	2.127	4.476	3.58144	1.9857	3.7574	4.3459	20.2728
		FGLS	0.425	0.629	0.58304	0.5932	0.8302	0.7983	3.8589
		Huber	1.631	2.702	2.70635	1.6191	2.8093	3.4079	14.8758
		Bi-Square	1.528	2.365	2.71507	1.5071	2.8099	3.3493	14.2736
	N=50	OLS	1.318	2.918	2.68986	1.3158	2.4764	2.5471	13.2657
		FGLS	0.282	0.452	0.37563	0.3256	0.611	0.3748	2.4211
		Huber	0.832	1.687	1.59179	1.1578	2.0473	1.8974	9.2128
		Bi-Square	0.813	1.583	1.54409	1.1377	2.1045	1.9072	9.0901
	N=100	OLS	0.759	1.426	1.39648	0.5828	1.105	1.2491	6.5185
		FGLS	0.187	0.192	0.20718	0.1314	0.1943	0.1566	1.0687
		Huber	0.408	0.902	0.69092	0.4378	0.8371	0.9178	4.1942
		Bi-Square	0.363	0.809	0.71901	0.4005	0.8958	0.8742	4.0614
	N=250	OLS	0.262	0.689	0.50733	0.272	0.673	0.6067	3.0102
		FGLS	0.06	0.073	0.0801	0.0513	0.0907	0.0796	0.4351
		Huber	0.143	0.391	0.29976	0.1961	0.4984	0.3797	1.9085
		Bi-Square	0.126	0.377	0.26895	0.1911	0.4837	0.368	1.8151
	N=500	OLS	0.123	0.238	0.21256	0.1166	0.2334	0.2498	1.1730
		FGLS	0.026	0.037	0.0412	0.0268	0.0408	0.0485	0.2205
		Huber	0.08	0.128	0.13651	0.0862	0.1929	0.1847	0.8077
		Bi-Square	0.07	0.117	0.13785	0.082	0.2023	0.1884	0.7975

**TABLE 4.1.30A: VARIANCE: When Errors are Gamma , Square Root
Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.95) under varying sample sizes**

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	<i>OLS</i>	5.094	8.641	8.4589	4.5082	12.138	10.767	49.6074
		<i>FGLS</i>	1.41	1.905	1.60327	1.0684	2.0516	2.2442	10.2828
		<i>Huber</i>	3.831	6.876	6.22107	3.3762	8.5707	8.9094	37.7839
		<i>Bi-Square</i>	3.952	7.122	6.139	3.3372	8.2332	8.9275	37.7110
	N=30	<i>OLS</i>	2.833	5.45	4.33881	2.6364	4.4612	5.3162	25.0355
		<i>FGLS</i>	0.569	0.603	0.55977	0.7895	0.7712	0.8176	4.1104
		<i>Huber</i>	2.269	3.346	3.38694	2.2282	3.382	4.2254	18.8371
		<i>Bi-Square</i>	2.196	2.98	3.49986	2.1287	3.4515	4.2026	18.4591
	N=50	<i>OLS</i>	1.8	3.494	3.31876	1.7706	2.9665	3.1148	16.4644
		<i>FGLS</i>	0.393	0.446	0.37235	0.4255	0.5436	0.3528	2.5325
		<i>Huber</i>	1.15	1.956	2.03966	1.5673	2.4502	2.3157	11.4794
		<i>Bi-Square</i>	1.174	1.844	2.05147	1.5672	2.4861	2.333	11.4560
	N=100	<i>OLS</i>	1.007	1.74	1.66414	0.802	1.3414	1.5334	8.0878
		<i>FGLS</i>	0.242	0.175	0.1956	0.1765	0.1659	0.1425	1.0972
		<i>Huber</i>	0.562	1.084	0.84796	0.6016	1.0042	1.1304	5.2305
		<i>Bi-Square</i>	0.517	0.976	0.88745	0.5523	1.0471	1.0871	5.0671
	N=250	<i>OLS</i>	0.337	0.813	0.61299	0.3537	0.8084	0.72	14.2158
		<i>FGLS</i>	0.081	0.064	0.0732	0.0639	0.0754	0.065	11.7290
		<i>Huber</i>	0.196	0.473	0.37224	0.2575	0.5925	0.4588	12.3910
		<i>Bi-Square</i>	0.184	0.453	0.33441	0.2605	0.5861	0.4452	11.9050
	N=500	<i>OLS</i>	0.167	0.298	0.25723	0.1538	0.2792	0.3065	1.4614
		<i>FGLS</i>	0.031	0.035	0.03685	0.0302	0.0358	0.0423	0.2109
		<i>Huber</i>	0.11	0.163	0.16945	0.1183	0.2319	0.2317	1.0243
		<i>Bi-Square</i>	0.1	0.151	0.17199	0.1157	0.2444	0.2373	1.0208

TABLE 4.1.1 B: Absolute Bias: When Errors are Gamma , Homoscedastic and No contemporal correlation under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g ; g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	3.9943	2.6834	2.945	3.8183	2.3032	2.5586	18.3028
		FGLS	3.9848	2.6463	2.8788	3.7766	2.4175	2.6107	18.3147
		Huber	3.4891	2.219	2.24	3.3211	1.8691	2.0175	15.1558
		Bi-Square	3.2875	2.2008	2.0333	3.1067	1.7459	1.9577	14.3319
	N=30	OLS	3.7952	2.2619	2.094	3.9943	2.1167	1.9668	16.2289
		FGLS	3.7812	2.2693	2.2223	3.9828	2.1119	2.0486	16.4161
		Huber	3.3992	1.7646	1.7016	3.4677	1.7067	1.5105	13.5503
		Bi-Square	3.1536	1.697	1.7043	3.1245	1.6364	1.4055	12.7213
	N=50	OLS	3.9947	1.8087	1.5705	3.9555	1.6726	1.4513	14.4533
		FGLS	3.9716	1.8314	1.6235	3.9473	1.6889	1.4932	14.5559
		Huber	3.5079	1.4511	1.1798	3.3197	1.2794	1.2563	11.9942
		Bi-Square	3.1976	1.3372	1.1657	2.9519	1.2019	1.2691	11.1234
	N=100	OLS	3.7549	1.2154	0.9647	4.0281	1.1033	1.2353	12.3017
		FGLS	3.7377	1.2253	0.9825	4.014	1.1271	1.2474	12.3340
		Huber	3.2536	0.9636	0.7937	3.4273	0.8885	0.9428	10.2695
		Bi-Square	2.9057	0.9452	0.7788	2.9908	0.865	0.8359	9.3214
	N=250	OLS	4.0892	0.6989	0.6919	4.0125	0.8428	0.7104	11.0457
		FGLS	4.0911	0.7056	0.6964	4.0146	0.849	0.7073	11.0640
		Huber	3.5454	0.5295	0.5794	3.4519	0.6163	0.5852	9.3077
		Bi-Square	3.105	0.5254	0.576	2.9702	0.5801	0.5613	8.3180
	N=500	OLS	3.9967	0.4385	0.5102	4.0323	0.4832	0.5082	9.9691
		FGLS	3.9947	0.4381	0.5083	4.0333	0.4857	0.5046	9.9647
		Huber	3.4546	0.3518	0.3865	3.4877	0.3657	0.3546	8.4009
		Bi-Square	3.0133	0.3511	0.3623	3.0456	0.3457	0.3167	7.4347

TABLE 4.1.2 B: Absolute Bias: When Errors are Gamma , Exponential Heteroscedastic and No contemporal correlation under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\};$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	6.8401	6.6567	7.0438	6.3111	6.0482	6.0044	38.9043
		FGLS	6.7789	6.6281	6.9331	6.2745	6.2998	6.0436	38.9580
		Huber	6.0463	5.1791	5.2682	5.7271	4.7885	4.554	31.5632
		Bi-Square	5.9406	4.7463	4.7335	5.5012	4.5229	4.2786	29.7231
	N=30	OLS	6.1273	6.3397	4.9217	6.6185	5.3467	4.6475	34.0014
		FGLS	6.1537	6.5069	5.2164	6.6118	5.3864	4.8686	34.7438
		Huber	5.7936	4.649	3.9766	6.0505	4.304	3.6097	28.3834
		Bi-Square	5.762	4.0397	3.7976	5.6213	4.0343	3.315	26.5699
	N=50	OLS	6.2027	5.4858	3.86	6.2494	4.5776	3.766	30.1415
		FGLS	6.1534	5.5676	3.9565	6.2367	4.5952	3.7861	30.2955
		Huber	5.943	3.9229	2.7772	5.6037	3.3801	3.2964	24.9232
		Bi-Square	5.7981	3.0627	2.6148	5.1738	3.1339	3.0907	22.8740
	N=100	OLS	5.7433	4.4119	2.9856	6.3887	4.0243	2.9636	26.5173
		FGLS	5.711	4.471	3.0424	6.3467	4.0682	2.9923	26.6316
		Huber	5.4183	3.2061	2.221	5.8183	2.97	2.2701	21.9039
		Bi-Square	5.1504	2.6563	1.9452	5.3056	2.5759	1.9906	19.6239
	N=250	OLS	6.4372	3.6529	1.9685	6.3237	3.842	1.9315	24.1558
		FGLS	6.4373	3.6421	1.981	6.3286	3.8434	1.9334	24.1657
		Huber	6.0514	2.5527	1.4804	5.8675	2.6243	1.4315	20.0077
		Bi-Square	5.5985	1.9398	1.4293	5.3413	2.0099	1.3252	17.6439
	N=500	OLS	6.3074	3.6117	1.8304	6.3245	3.7472	1.9022	23.7234
		FGLS	6.3041	3.6172	1.8297	6.3263	3.7326	1.9142	23.7240
		Huber	5.8903	2.4927	1.2445	5.9313	2.4648	1.3215	19.3450
		Bi-Square	5.4435	1.7842	0.9752	5.4889	1.7303	1.0494	16.4715

TABLE 4.1.3 B: Absolute Bias: When Errors are Gamma , Quadratic Heteroscedastic(Q=2) and No contemporaneous correlation(P=0) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	1.3681	2.7845	2.377	1.1776	2.7489	1.995	12.4511
		FGLS	1.3689	2.7903	2.3956	1.1905	2.7911	1.9975	12.5339
		Huber	1.1334	2.0129	1.7465	1.0312	2.1012	1.4673	9.4925
		Bi-Square	1.1538	1.7327	1.5736	1.1138	1.762	1.1942	8.5301
	N=30	OLS	1.142	3.0115	1.7122	1.1783	2.4911	1.6801	11.2152
		FGLS	1.1413	3.0423	1.7975	1.2025	2.5203	1.728	11.4318
		Huber	1.0372	2.1074	1.3326	1.1003	1.8928	1.2566	8.7269
		Bi-Square	1.11	1.5833	1.164	1.0813	1.5348	1.0864	7.5597
	N=50	OLS	0.8945	2.8688	1.544	0.8871	2.4069	1.606	10.2073
		FGLS	0.8883	2.9041	1.556	0.8912	2.4121	1.6186	10.2702
		Huber	0.9368	1.8751	1.0416	0.8892	1.7358	1.2979	7.7765
		Bi-Square	1.0901	1.2918	0.8184	0.9489	1.3834	1.0613	6.5939
	N=100	OLS	0.7147	2.7257	1.4945	0.82	2.5279	1.2646	9.5473
		FGLS	0.7193	2.7309	1.5097	0.816	2.5482	1.2708	9.5949
		Huber	0.8081	1.843	1.0531	0.8938	1.7745	0.9187	7.2913
		Bi-Square	0.904	1.2835	0.7902	0.9385	1.3386	0.747	6.0017
	N=250	OLS	0.7324	2.5685	1.2743	0.7279	2.6201	1.1941	9.1173
		FGLS	0.7308	2.5678	1.2775	0.729	2.6193	1.1932	9.1176
		Huber	0.939	1.7112	0.8132	0.8979	1.7608	0.8128	6.9349
		Bi-Square	1.0141	1.2147	0.6085	0.9665	1.2578	0.5916	5.6532
	N=500	OLS	0.7281	2.5533	1.239	0.7017	2.624	1.2826	9.1287
		FGLS	0.7277	2.5548	1.2391	0.7021	2.6202	1.2857	9.1296
		Huber	0.9154	1.7165	0.819	0.9097	1.7309	0.8623	6.9538
		Bi-Square	0.9978	1.1856	0.5621	0.9904	1.2106	0.616	5.5624

TABLE 4.1.4 B: Absolute Bias: When Errors are Gamma , Linear Heteroscedastic(Q=1) and No contemporaneous correlation(P=0) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	2.2567	2.4967	2.567	2.054	2.3142	2.185	13.8735
		FGLS	2.2439	2.4914	2.5396	2.0538	2.4014	2.1994	13.9294
		Huber	1.9935	1.9173	1.9201	1.874	1.8188	1.6379	11.1615
		Bi-Square	1.9715	1.7238	1.7161	1.818	1.6957	1.5262	10.4512
	N=30	OLS	2.0027	2.4611	1.7921	2.1615	2.0071	1.6985	12.1230
		FGLS	2.0138	2.5158	1.8988	2.1619	2.0358	1.7798	12.4061
		Huber	1.9102	1.7928	1.4451	1.9901	1.6304	1.3195	10.0882
		Bi-Square	1.9197	1.4981	1.3595	1.872	1.5042	1.2015	9.3549
	N=50	OLS	1.9744	2.1846	1.441	1.9983	1.7827	1.4224	10.8034
		FGLS	1.9595	2.2098	1.4664	1.9944	1.7973	1.4273	10.8546
		Huber	1.9355	1.5104	1.0301	1.8251	1.3353	1.2335	8.8699
		Bi-Square	1.9259	1.1325	0.9338	1.7035	1.2102	1.1364	8.0422
	N=100	OLS	1.8194	1.8427	1.1774	2.0368	1.6902	1.1111	9.6776
		FGLS	1.8094	1.858	1.1982	2.0212	1.7078	1.1202	9.7147
		Huber	1.7547	1.3143	0.8611	1.8924	1.2218	0.8504	7.8946
		Bi-Square	1.6954	1.0401	0.7327	1.7512	1.0168	0.7445	6.9806
	N=250	OLS	2.0487	1.6063	0.8188	2.0136	1.6758	0.7854	8.9486
		FGLS	2.0485	1.6024	0.8249	2.0154	1.6759	0.7861	8.9532
		Huber	1.975	1.1047	0.5858	1.9148	1.149	0.5687	7.2980
		Bi-Square	1.8568	0.8244	0.5413	1.7728	0.8546	0.5004	6.3504
	N=500	OLS	2.0081	1.6088	0.7815	2.0089	1.6597	0.8166	8.8835
		FGLS	2.0069	1.6107	0.7807	2.0095	1.6545	0.8202	8.8825
		Huber	1.9228	1.1082	0.5264	1.934	1.1	0.5678	7.1592
		Bi-Square	1.8066	0.7842	0.3971	1.8201	0.7719	0.4341	6.0140

TABLE 4.1.5 B: Absolute Bias: When Errors are Gamma , Linear Heteroscedastic(Q=0.5) and No contemporal correlation under varying sample sizes

Contemporall Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	3.0045	2.4447	2.7257	2.8253	2.205	2.3327	15.5379
		FGLS	2.9727	2.4268	2.6631	2.7898	2.321	2.3582	15.5316
		Huber	2.6527	1.9737	2.0536	2.517	1.7828	1.8015	12.7813
		Bi-Square	2.5629	1.8711	1.8416	2.3733	1.686	1.7176	12.0525
	N=30	OLS	2.7576	2.2607	1.9035	2.958	1.9778	1.7982	13.6558
		FGLS	2.7531	2.3053	2.0276	2.9488	1.9913	1.8801	13.9061
		Huber	2.562	1.6944	1.5435	2.6462	1.6017	1.3829	11.4307
		Bi-Square	2.4762	1.5397	1.5061	2.4219	1.533	1.2856	10.7626
	N=50	OLS	2.8608	1.8735	1.4537	2.8604	1.609	1.393	12.0503
		FGLS	2.8343	1.8811	1.4977	2.8543	1.6129	1.4123	12.0926
		Huber	2.6381	1.4185	1.0682	2.4876	1.2024	1.2267	10.0414
		Bi-Square	2.4966	1.1829	1.0329	2.2603	1.13	1.185	9.2877
	N=100	OLS	2.6759	1.3872	1.027	2.9222	1.2431	1.125	10.3805
		FGLS	2.6617	1.407	1.048	2.9072	1.2718	1.1373	10.4331
		Huber	2.425	1.0694	0.7944	2.5844	0.9738	0.8667	8.7137
		Bi-Square	2.2434	0.9392	0.7349	2.3102	0.902	0.7642	7.8939
	N=250	OLS	2.9568	1.0123	0.6571	2.9034	1.0807	0.6587	9.2690
		FGLS	2.9576	1.0118	0.6583	2.9053	1.0844	0.6605	9.2778
		Huber	2.6795	0.7374	0.521	2.6038	0.7652	0.5125	7.8193
		Bi-Square	2.4232	0.6071	0.527	2.3149	0.6319	0.503	7.0071
	N=500	OLS	2.8927	0.9246	0.5603	2.9089	0.976	0.5829	8.8454
		FGLS	2.8912	0.9269	0.5597	2.9097	0.9707	0.5859	8.8440
		Huber	2.6104	0.6592	0.393	2.6312	0.6502	0.41	7.3540
		Bi-Square	2.3521	0.5173	0.341	2.3753	0.4817	0.3464	6.4138

TABLE 4.1.6 B: Absolute Bias: When Errors are Gamma , Homoscedastic and Contemporall Correlation(P=0.2) under varying sample sizes

Contemporall Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	4.2054	2.9752	2.6606	4.6279	2.9411	2.6206	20.0308
		FGLS	4.2164	2.8171	2.6698	4.6387	2.9534	2.6105	19.9059
		Huber	3.7062	2.2671	2.2297	4.1265	2.3595	2.2643	16.9533
		Bi-Square	3.4167	2.2027	2.1242	3.9054	2.1495	2.1801	15.9786
	N=30	OLS	3.8998	1.6416	1.8676	4.4654	1.8234	1.9572	15.6551
		FGLS	3.86	1.7233	1.8262	4.478	1.773	2.0569	15.7173
		Huber	3.2888	1.4662	1.4702	4.1001	1.4329	1.6885	13.4466
		Bi-Square	2.9177	1.5292	1.4549	3.8853	1.4793	1.693	12.9594
	N=50	OLS	4.0636	1.6788	1.6118	4.6994	1.5706	1.5793	15.2035
		FGLS	3.9848	1.6504	1.5577	4.7245	1.5824	1.5702	15.0700
		Huber	3.5932	1.3055	1.3766	4.2079	1.2848	1.2425	13.0106
		Bi-Square	3.2549	1.2366	1.3152	3.9246	1.2529	1.2234	12.2076
	N=100	OLS	4.0839	1.0502	1.1151	4.4355	1.0291	1.2061	12.9198
		FGLS	4.0913	1.0293	1.1178	4.4344	0.9822	1.1597	12.8145
		Huber	3.5193	0.76	0.9042	3.9183	0.7908	0.956	10.8486
		Bi-Square	3.095	0.7802	0.8654	3.648	0.7606	0.8951	10.0442
	N=250	OLS	3.9385	0.731	0.7581	4.6634	0.7966	0.7409	11.6284
		FGLS	3.9498	0.7181	0.7634	4.6879	0.7719	0.7193	11.6103
		Huber	3.4239	0.5642	0.5549	4.1516	0.6118	0.5608	9.8671
		Bi-Square	3.0204	0.5213	0.5118	3.818	0.5825	0.5471	9.0010
	N=500	OLS	4.0323	0.533	0.5053	4.6668	0.4718	0.515	10.7242
		FGLS	4.0437	0.5239	0.4885	4.6856	0.4609	0.5074	10.7099
		Huber	3.4831	0.3807	0.3776	4.1408	0.3918	0.4257	9.1997
		Bi-Square	3.0591	0.3397	0.3463	3.7898	0.4034	0.4009	8.3392

TABLE 4.1.7B: Absolute Bias: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	6.9914	7.4499	6.3194	7.8377	7.7121	6.1162	42.4267
		FGLS	7.0169	6.8341	6.1712	7.8671	7.6452	6.0029	41.5374
		Huber	6.3824	5.5223	5.0566	7.0426	6.2389	5.1792	35.4219
		Bi-Square	6.3005	5.1897	4.7843	6.8837	5.5578	5.0382	33.7542
	N=30	OLS	6.1041	4.6638	4.4955	7.0108	5.672	4.8606	32.8068
		FGLS	6.1188	4.8668	4.4155	7.0443	5.3706	5.1041	32.9200
		Huber	5.4388	4.2294	3.5312	6.7185	4.6462	3.9968	28.5609
		Bi-Square	5.0982	4.2273	3.411	6.6217	4.2873	3.9244	27.5700
	N=50	OLS	6.5092	4.7857	3.8508	7.436	5.0451	3.9098	31.5366
		FGLS	6.3775	4.6848	3.9157	7.5097	5.0548	3.852	31.3945
		Huber	6.0464	3.4495	3.0957	7.0303	3.8548	3.0738	26.5504
		Bi-Square	5.7636	3.0183	2.9862	6.7926	3.4043	2.9438	24.9090
	N=100	OLS	6.477	3.9081	2.6785	6.8981	4.4089	3.516	27.8866
		FGLS	6.5057	3.8632	2.6552	6.9065	4.4087	3.5126	27.8519
		Huber	6.0345	2.7548	2.174	6.4532	3.4226	2.7931	23.6322
		Bi-Square	5.6231	2.2456	2.0341	6.2474	2.9634	2.4492	21.5628
	N=250	OLS	6.1982	3.8065	2.2168	7.286	4.2723	2.5127	26.2925
		FGLS	6.2323	3.77	2.1438	7.3494	4.1796	2.4778	26.1529
		Huber	5.8117	2.653	1.5699	6.9332	3.1568	1.858	21.9826
		Bi-Square	5.3996	2.0294	1.3472	6.6415	2.5889	1.645	19.6514
	N=500	OLS	6.3474	3.3869	1.9539	7.3147	4.3708	2.3288	25.7023
		FGLS	6.3703	3.3603	1.9188	7.3563	4.3054	2.298	25.6089
		Huber	5.934	2.2927	1.3639	6.9229	3.2577	1.6928	21.4639
		Bi-Square	5.4978	1.6539	1.0679	6.5813	2.6759	1.3985	18.8753

TABLE 4.1.8B: Absolute Bias: When Errors are Gamma , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.3719	2.9924	2.135	1.4108	3.4937	2.1425	13.5463
		FGLS	1.3568	2.888	2.0528	1.4261	3.427	2.1567	13.3075
		Huber	1.1542	2.1785	1.5969	1.2318	2.7221	1.738	10.6214
		Bi-Square	1.25	1.7519	1.4201	1.2517	2.2163	1.6117	9.5016
	N=30	OLS	0.9793	2.5341	1.6978	1.1163	3.2262	1.8843	11.4379
		FGLS	1.0191	2.5996	1.7061	1.1209	3.1422	1.9493	11.5372
		Huber	0.9149	2.0837	1.2746	1.0606	2.515	1.4887	9.3374
		Bi-Square	0.9326	1.829	1.13	1.1128	2.1169	1.3161	8.4374
	N=50	OLS	1.0389	2.619	1.4723	1.0046	3.0225	1.697	10.8543
		FGLS	1.0185	2.6135	1.5218	1.0301	3.0118	1.6396	10.8352
		Huber	0.9637	1.8489	1.0914	1.0614	2.2698	1.2692	8.5044
		Bi-Square	0.9952	1.4153	0.9574	1.1524	1.8672	1.089	7.4765
	N=100	OLS	0.8776	2.5525	1.204	0.7851	2.9723	1.7516	10.1431
		FGLS	0.8916	2.5413	1.1944	0.7735	2.9713	1.7442	10.1163
		Huber	0.9499	1.7527	0.8621	0.8926	2.28	1.3357	8.0729
		Bi-Square	1.0325	1.2564	0.705	0.9874	1.8895	1.0964	6.9672
	N=250	OLS	0.7353	2.5912	1.2549	0.8094	3.0344	1.5453	9.9705
		FGLS	0.7423	2.5854	1.2362	0.8253	3.0078	1.53	9.9270
		Huber	0.8856	1.7405	0.8641	0.9935	2.2269	1.1236	7.8341
		Bi-Square	0.9625	1.2378	0.6314	1.1031	1.761	0.8802	6.5760
	N=500	OLS	0.719	2.4992	1.3181	0.8079	3.0624	1.5438	9.9505
		FGLS	0.7241	2.4948	1.312	0.8194	3.0427	1.5402	9.9333
		Huber	0.9148	1.6749	0.8818	0.9935	2.2529	1.1306	7.8485
		Bi-Square	0.9917	1.1919	0.6342	1.0825	1.8047	0.9031	6.6081

TABLE 4.1.9B: Absolute Bias: When Errors are Gamma , Linear Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	2.2947	2.7671	2.2844	2.5598	2.9554	2.2166	15.0779
		FGLS	2.3013	2.5685	2.2102	2.5818	2.9061	2.1976	14.7655
		Huber	2.1097	2.0405	1.8133	2.304	2.3616	1.8613	12.4903
		Bi-Square	2.1136	1.8806	1.697	2.2646	2.0828	1.8061	11.8448
	N=30	OLS	1.9524	1.8411	1.6543	2.2592	2.2889	1.8087	11.8045
		FGLS	1.9696	1.9212	1.6286	2.2613	2.1644	1.886	11.8312
		Huber	1.7638	1.655	1.2952	2.1732	1.8735	1.4694	10.2301
		Bi-Square	1.6792	1.6124	1.2387	2.1621	1.6893	1.4163	9.7979
	N=50	OLS	2.0943	1.9132	1.4125	2.3674	2.0698	1.4775	11.3346
		FGLS	2.0523	1.8852	1.4465	2.3952	2.0871	1.4394	11.3056
		Huber	1.9682	1.372	1.1168	2.2788	1.5777	1.1544	9.4678
		Bi-Square	1.8965	1.1625	1.0706	2.2263	1.3645	1.0881	8.8086
	N=100	OLS	2.0728	1.6557	1.0025	2.1855	1.9065	1.3766	10.1996
		FGLS	2.0812	1.6441	0.9919	2.1893	1.9069	1.379	10.1923
		Huber	1.9724	1.1691	0.8085	2.08	1.4861	1.0888	8.6050
		Bi-Square	1.8672	0.9019	0.7377	2.0368	1.2669	0.9453	7.7558
	N=250	OLS	1.9727	1.6647	0.8855	2.3133	1.9013	1.0423	9.7797
		FGLS	1.9853	1.6527	0.8633	2.3364	1.8693	1.0238	9.7308
		Huber	1.8938	1.1476	0.6238	2.2473	1.4057	0.7706	8.0889
		Bi-Square	1.787	0.8602	0.5141	2.1793	1.1441	0.6572	7.1420
	N=500	OLS	2.0174	1.5285	0.8457	2.324	1.9392	1.0034	9.6580
		FGLS	2.0254	1.5232	0.8357	2.3387	1.9155	0.993	9.6315
		Huber	1.9351	1.0428	0.5845	2.2429	1.4482	0.7376	7.9910
		Bi-Square	1.8199	0.7485	0.4494	2.1569	1.1903	0.6014	6.9664

TABLE 4.1.10B: Absolute Bias: When Errors are Gamma , Linear Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	3.1118	2.7775	2.4288	3.4702	2.7873	2.3719	16.9475
		FGLS	3.1296	2.5589	2.3913	3.4719	2.7951	2.3284	16.6751
		Huber	2.81	2.0997	1.9854	3.1014	2.2756	2.0315	14.3036
		Bi-Square	2.6796	2.0158	1.8847	3.0043	2.0574	1.979	13.6209
	N=30	OLS	2.8041	1.6088	1.7128	3.2081	1.8892	1.835	13.0580
		FGLS	2.7939	1.7056	1.6694	3.2235	1.7954	1.9309	13.1186
		Huber	2.4475	1.472	1.3496	3.0277	1.5393	1.5259	11.3619
		Bi-Square	2.2359	1.514	1.3204	2.9304	1.4926	1.5173	11.0105
	N=50	OLS	2.9458	1.6451	1.471	3.4041	1.671	1.4551	12.5920
		FGLS	2.8815	1.6061	1.4768	3.4309	1.6892	1.4543	12.5388
		Huber	2.6886	1.1946	1.2159	3.1445	1.304	1.1477	10.6954
		Bi-Square	2.5108	1.1117	1.1718	2.9889	1.2067	1.1229	10.1127
	N=100	OLS	2.9652	1.1757	1.01	3.187	1.2967	1.2443	10.8789
		FGLS	2.9744	1.1734	1.0097	3.1887	1.2877	1.2205	10.8544
		Huber	2.671	0.868	0.8265	2.9033	1.0074	0.9959	9.2721
		Bi-Square	2.4265	0.7909	0.7926	2.76	0.9075	0.894	8.5715
	N=250	OLS	2.8477	1.0637	0.7658	3.3596	1.1362	0.7979	9.9709
		FGLS	2.8598	1.047	0.7425	3.3835	1.0985	0.7938	9.9251
		Huber	2.5813	0.7736	0.5409	3.1024	0.8565	0.6049	8.4595
		Bi-Square	2.3441	0.6371	0.4949	2.917	0.7477	0.5677	7.7085
	N=500	OLS	2.9131	0.8651	0.5862	3.3666	1.1316	0.6712	9.5338
		FGLS	2.9227	0.8535	0.5669	3.3833	1.1032	0.6612	9.4908
		Huber	2.6301	0.5953	0.4291	3.0956	0.8563	0.4939	8.1002
		Bi-Square	2.3815	0.4596	0.3597	2.8929	0.7147	0.4405	7.2490

TABLE 4.1.16B: Absolute Bias: When Errors are Gamma , Homoscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g ; g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	4.2054	2.9752	2.6606	5.8438	3.0173	2.7169	21.4191
		FGLS	4.2033	2.5189	2.4044	5.8857	2.8181	2.5203	20.3507
		Huber	3.7062	2.2671	2.2297	5.4604	2.6176	2.4253	18.7062
		Bi-Square	3.4167	2.2027	2.1242	5.2604	2.5086	2.3933	17.9059
	N=30	OLS	3.8998	1.6416	1.8676	5.8678	1.803	1.9993	17.0792
		FGLS	3.8629	1.7348	1.7564	5.8767	1.6789	2.0175	16.9272
		Huber	3.2888	1.4662	1.4702	5.6156	1.6146	1.8289	15.2843
		Bi-Square	2.9177	1.5292	1.4549	5.4887	1.6048	1.8507	14.8459
	N=50	OLS	4.0636	1.6788	1.6118	6.035	1.5466	1.59	16.5258
		FGLS	3.9687	1.5831	1.4317	6.0755	1.4406	1.4863	15.9860
		Huber	3.5932	1.3055	1.3766	5.5859	1.406	1.3839	14.6510
		Bi-Square	3.2549	1.2366	1.3152	5.4074	1.4154	1.419	14.0485
	N=100	OLS	4.0839	1.0502	1.1151	5.7853	1.042	1.1655	14.2420
		FGLS	4.0826	0.9873	1.0613	5.7976	0.9231	1.0486	13.9004
		Huber	3.5193	0.76	0.9042	5.3329	0.8915	0.983	12.3908
		Bi-Square	3.095	0.7802	0.8654	5.1639	0.8894	0.9652	11.7590
	N=250	OLS	3.9385	0.731	0.7581	5.9846	0.8097	0.7357	12.9574
		FGLS	3.954	0.6783	0.7171	6.0281	0.7304	0.6626	12.7704
		Huber	3.4239	0.5642	0.5549	5.551	0.6722	0.6108	11.3770
		Bi-Square	3.0204	0.5213	0.5118	5.3808	0.6646	0.6054	10.7041
	N=500	OLS	4.0323	0.533	0.5053	5.9959	0.4827	0.5033	12.0525
		FGLS	4.0446	0.4921	0.4399	6.0373	0.4256	0.4656	11.9049
		Huber	3.4831	0.3807	0.3776	5.5491	0.4387	0.4455	10.6747
		Bi-Square	3.0591	0.3397	0.3463	5.3656	0.4576	0.4463	10.0146

TABLE 4.1.17B: Absolute Bias: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	6.9914	7.4499	6.3194	9.5916	8.5007	6.4069	45.2599
		FGLS	6.9255	6.3493	5.5356	9.6726	7.9938	6.0371	42.5139
		Huber	6.3824	5.5223	5.0566	8.9314	7.2551	5.8362	38.9840
		Bi-Square	6.3005	5.1897	4.7843	8.9008	6.8143	5.7373	37.7269
	N=30	OLS	6.1041	4.6638	4.4955	9.1326	6.6404	5.1609	36.1973
		FGLS	6.1262	4.7993	4.3318	9.1867	6.1315	5.1164	35.6919
		Huber	5.4388	4.2294	3.5312	9.0439	5.7854	4.5227	32.5515
		Bi-Square	5.0982	4.2273	3.411	9.0621	5.5172	4.3545	31.6704
	N=50	OLS	6.5092	4.7857	3.8508	9.5182	5.8346	4.2993	34.7977
		FGLS	6.3643	4.5516	3.6648	9.6405	5.7892	3.8737	33.8840
		Huber	6.0464	3.4495	3.0957	9.1405	4.8943	3.6239	30.2504
		Bi-Square	5.7636	3.0183	2.9862	9.0255	4.4482	3.583	28.8249
	N=100	OLS	6.477	3.9081	2.6785	9.0438	5.4549	3.8675	31.4297
		FGLS	6.4995	3.8081	2.5364	9.0951	5.4199	3.7978	31.1568
		Huber	6.0345	2.7548	2.174	8.6586	4.7006	3.3598	27.6823
		Bi-Square	5.6231	2.2456	2.0341	8.5894	4.3691	3.0344	25.8957
	N=250	OLS	6.1982	3.8065	2.2168	9.3453	5.5015	3.0421	30.1104
		FGLS	6.2452	3.766	2.0216	9.4594	5.339	2.9309	29.7620
		Huber	5.8117	2.653	1.5699	9.0822	4.4804	2.4983	26.0955
		Bi-Square	5.3996	2.0294	1.3472	8.9932	4.0451	2.2928	24.1072
	N=500	OLS	6.3474	3.3869	1.9539	9.3984	5.5872	2.9119	29.5856
		FGLS	6.3708	3.3843	1.8735	9.4896	5.4496	2.8377	29.4055
		Huber	5.934	2.2927	1.3639	9.0875	4.6232	2.348	25.6493
		Bi-Square	5.4978	1.6539	1.0679	8.9734	4.2022	2.0893	23.4844

TABLE 4.1.18B: Absolute Bias: When Errors are Gamma , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	1.3719	2.9924	2.135	1.5974	4.2509	2.4363	14.7841
		FGLS	1.2796	2.7917	1.9341	1.5933	4.1284	2.3343	14.0614
		Huber	1.1542	2.1785	1.5969	1.4293	3.5923	2.1486	12.0997
		Bi-Square	1.25	1.7519	1.4201	1.4618	3.1863	2.0116	11.0816
	N=30	OLS	0.9793	2.5341	1.6978	1.2343	4.0391	2.1878	12.6724
		FGLS	0.994	2.5955	1.6957	1.2309	3.907	2.2542	12.6772
		Huber	0.9149	2.0837	1.2746	1.249	3.4279	1.8464	10.7965
		Bi-Square	0.9326	1.829	1.13	1.3167	3.0765	1.697	9.9818
	N=50	OLS	1.0389	2.619	1.4723	1.1575	3.8367	2.046	12.1703
		FGLS	1.0021	2.5915	1.5173	1.1867	3.805	1.9631	12.0657
		Huber	0.9637	1.8489	1.0914	1.2533	3.2185	1.6987	10.0745
		Bi-Square	0.9952	1.4153	0.9574	1.3521	2.8462	1.5507	9.1169
	N=100	OLS	0.8776	2.5525	1.204	0.996	3.8141	2.147	11.5913
		FGLS	0.8748	2.5374	1.1792	1.0172	3.7984	2.1043	11.5112
		Huber	0.9499	1.7527	0.8621	1.1196	3.2351	1.7866	9.7058
		Bi-Square	1.0325	1.2564	0.705	1.2331	2.8932	1.5577	8.6780
	N=250	OLS	0.7353	2.5912	1.2549	1.0184	3.9021	2.0036	11.5054
		FGLS	0.738	2.5906	1.2193	1.0492	3.8522	1.9755	11.4248
		Huber	0.8856	1.7405	0.8641	1.2024	3.1976	1.6343	9.5244
		Bi-Square	0.9625	1.2378	0.6314	1.3285	2.8245	1.4331	8.4178
	N=500	OLS	0.719	2.4992	1.3181	1.0384	3.9221	1.9804	11.4773
		FGLS	0.7235	2.5005	1.3074	1.0632	3.8813	1.9709	11.4469
		Huber	0.9148	1.6749	0.8818	1.2119	3.2282	1.6157	9.5273
		Bi-Square	0.9917	1.1919	0.6342	1.3237	2.8657	1.419	8.4261

TABLE 4.1.19B: Absolute Bias: When Errors are Gamma , Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	2.2947	2.7671	2.2844	3.1076	3.3187	2.3596	16.1320
		FGLS	2.2618	2.405	1.9941	3.1403	3.1274	2.2335	15.1621
		Huber	2.1097	2.0405	1.8133	2.8883	2.8148	2.149	13.8156
		Bi-Square	2.1136	1.8806	1.697	2.8915	2.6374	2.1028	13.3229
	N=30	OLS	1.9524	1.8411	1.6543	2.894	2.7571	1.9375	13.0363
		FGLS	1.9654	1.8658	1.5978	2.9147	2.5856	1.9531	12.8825
		Huber	1.7638	1.655	1.2952	2.8968	2.3907	1.6828	11.6842
		Bi-Square	1.6792	1.6124	1.2387	2.9188	2.2538	1.6025	11.3054
	N=50	OLS	2.0943	1.9132	1.4125	3.0272	2.5075	1.6535	12.6082
		FGLS	2.0502	1.827	1.3716	3.0735	2.4984	1.5061	12.3268
		Huber	1.9682	1.372	1.1168	2.9415	2.1013	1.379	10.8787
		Bi-Square	1.8965	1.1625	1.0706	2.9214	1.89	1.3459	10.2869
	N=100	OLS	2.0728	1.6557	1.0025	2.8707	2.4026	1.5663	11.5706
		FGLS	2.077	1.6401	0.9629	2.8908	2.3852	1.5442	11.5002
		Huber	1.9724	1.1691	0.8085	2.7764	2.0814	1.3503	10.1581
		Bi-Square	1.8672	0.9019	0.7377	2.7745	1.913	1.2169	9.4111
	N=250	OLS	1.9727	1.6647	0.8855	2.9668	2.4489	1.2999	11.2384
		FGLS	1.99	1.6571	0.8235	3.0084	2.3907	1.2597	11.1293
		Huber	1.8938	1.1476	0.6238	2.9201	2.0103	1.0717	9.6674
		Bi-Square	1.787	0.8602	0.5141	2.9112	1.8168	0.9831	8.8724
	N=500	OLS	2.0174	1.5285	0.8457	2.9861	2.4806	1.2703	11.1285
		FGLS	2.0255	1.5314	0.8252	3.0184	2.431	1.2497	11.0812
		Huber	1.9351	1.0428	0.5845	2.922	2.0619	1.036	9.5821
		Bi-Square	1.8199	0.7485	0.4494	2.9045	1.8743	0.9278	8.7243

TABLE 4.1.20B: Absolute Bias: When Errors are Gamma , Square Root Heteroscedastic(g=0.5) and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0.5							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	3.1118	2.7775	2.4288	4.2946	2.9965	2.4526	18.0619
		FGLS	3.109	2.328	2.139	4.3333	2.7991	2.2902	16.9986
		Huber	2.81	2.0997	1.9854	4.0196	2.587	2.2366	15.7383
		Bi-Square	2.6796	2.0158	1.8847	3.9376	2.4739	2.2016	15.1932
	N=30	OLS	2.8041	1.6088	1.7128	4.2132	2.0944	1.9204	14.3538
		FGLS	2.7868	1.684	1.6352	4.2297	1.8891	1.8762	14.1010
		Huber	2.4475	1.472	1.3496	4.109	1.8506	1.7002	12.9287
		Bi-Square	2.2359	1.514	1.3204	4.0708	1.8126	1.662	12.6158
	N=50	OLS	2.9458	1.6451	1.471	4.3645	1.7803	1.545	13.7516
		FGLS	2.8731	1.5396	1.3734	4.4085	1.7306	1.4087	13.3338
		Huber	2.6886	1.1946	1.2159	4.1207	1.5187	1.3374	12.0758
		Bi-Square	2.5108	1.1117	1.1718	4.0328	1.4267	1.3507	11.6045
	N=100	OLS	2.9652	1.1757	1.01	4.168	1.5007	1.2877	12.1073
		FGLS	2.9695	1.1275	0.9469	4.1849	1.4559	1.228	11.9127
		Huber	2.671	0.868	0.8265	3.9181	1.3173	1.1247	10.7256
		Bi-Square	2.4265	0.7909	0.7926	3.8429	1.2545	1.0343	10.1417
	N=250	OLS	2.8477	1.0637	0.7658	4.3105	1.4217	0.8946	11.3040
		FGLS	2.8642	1.036	0.6952	4.3531	1.3402	0.8498	11.1385
		Huber	2.5813	0.7736	0.5409	4.0981	1.1689	0.7426	9.9054
		Bi-Square	2.3441	0.6371	0.4949	4.0166	1.0779	0.7076	9.2782
	N=500	OLS	2.9131	0.8651	0.5862	4.3255	1.4313	0.8038	10.9249
		FGLS	2.9232	0.8418	0.5369	4.3622	1.3755	0.7731	10.8127
		Huber	2.6301	0.5953	0.4291	4.0995	1.1948	0.6499	9.5986
		Bi-Square	2.3815	0.4596	0.3597	4.0056	1.0965	0.5952	8.8981

TABLE 4.1.21B: Absolute Bias: When Errors are Gamma , Homoscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	4.2054	2.9752	2.6606	4.6535	2.5767	2.5103	19.5817
		FGLS	4.042	2.6543	2.2993	4.6901	2.2149	2.184	18.0846
		Huber	3.7062	2.2671	2.2297	4.4359	2.6373	2.4342	17.7104
		Bi-Square	3.4167	2.2027	2.1242	4.3471	2.6122	2.506	17.2089
	N=30	OLS	3.8998	1.6416	1.8676	4.2926	2.2893	1.958	15.9489
		FGLS	3.8367	1.5063	1.7932	4.2676	1.8444	1.8749	15.1231
		Huber	3.2888	1.4662	1.4702	3.9779	2.0405	1.7913	14.0348
		Bi-Square	2.9177	1.5292	1.4549	3.922	1.9756	1.7848	13.5841
	N=50	OLS	4.0636	1.6788	1.6118	4.3694	1.7944	1.6765	15.1945
		FGLS	3.9366	1.4697	1.4336	4.4385	1.6449	1.3784	14.3018
		Huber	3.5932	1.3055	1.3766	4.0682	1.6497	1.3655	13.3588
		Bi-Square	3.2549	1.2366	1.3152	3.9491	1.6163	1.4227	12.7948
	N=100	OLS	4.0839	1.0502	1.1151	4.3314	1.0548	1.1316	12.7669
		FGLS	4.0883	0.9203	0.9987	4.3424	0.9487	0.9495	12.2479
		Huber	3.5193	0.76	0.9042	4.0442	0.9753	1.0562	11.2592
		Bi-Square	3.095	0.7802	0.8654	3.9526	0.9878	1.0624	10.7434
	N=250	OLS	3.9385	0.731	0.7581	4.3229	0.7238	0.6293	11.1035
		FGLS	3.9807	0.6138	0.6413	4.369	0.5979	0.4873	10.6900
		Huber	3.4239	0.5642	0.5549	3.9937	0.6541	0.5371	9.7278
		Bi-Square	3.0204	0.5213	0.5118	3.8901	0.6738	0.5264	9.1437
	N=500	OLS	4.0323	0.533	0.5053	4.3571	0.4419	0.4933	10.3629
		FGLS	4.0406	0.4224	0.4454	4.4114	0.3724	0.4165	10.1087
		Huber	3.4831	0.3807	0.3776	4.0529	0.3975	0.4042	9.0960
		Bi-Square	3.0591	0.3397	0.3463	3.9599	0.4115	0.3861	8.5026

TABLE 4.1.22B: Absolute Bias: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	2.2947	2.7671	2.2844	2.5839	2.3514	2.1635	14.4450
		FGLS	2.1951	2.5447	1.9659	2.5981	2.1223	1.9362	13.3623
		Huber	2.1097	2.0405	1.8133	2.4985	2.2864	2.0183	12.7667
		Bi-Square	2.1136	1.8806	1.697	2.5073	2.2711	2.1033	12.5731
	N=30	OLS	1.9524	1.8411	1.6543	2.2546	2.3024	1.7977	11.8025
		FGLS	1.9292	1.9026	1.5369	2.2352	2.0851	1.7843	11.4733
		Huber	1.7638	1.655	1.2952	2.119	2.1086	1.628	10.5696
		Bi-Square	1.6792	1.6124	1.2387	2.1154	1.9918	1.5926	10.2301
	N=50	OLS	2.0943	1.9132	1.4125	2.1858	2.1193	1.6743	11.3993
		FGLS	1.9898	1.9148	1.2502	2.2293	2.0183	1.4384	10.8407
		Huber	1.9682	1.372	1.1168	2.1074	1.8537	1.4286	9.8466
		Bi-Square	1.8965	1.1625	1.0706	2.1253	1.7331	1.3984	9.3864
	N=100	OLS	2.0728	1.6557	1.0025	2.134	1.8733	1.199	9.9373
		FGLS	2.0756	1.5803	0.9517	2.1562	1.8277	1.0782	9.6697
		Huber	1.9724	1.1691	0.8085	2.1084	1.5691	1.0352	8.6628
		Bi-Square	1.8672	0.9019	0.7377	2.1196	1.4677	1.0211	8.1152
	N=250	OLS	1.9727	1.6647	0.8855	2.141	1.8383	0.971	9.4732
		FGLS	2.0143	1.5912	0.8457	2.1853	1.7683	0.8973	9.3020
		Huber	1.8938	1.1476	0.6238	2.083	1.5494	0.8326	8.1302
		Bi-Square	1.787	0.8602	0.5141	2.1021	1.4021	0.7762	7.4416
	N=500	OLS	2.0174	1.5285	0.8457	2.1585	1.8593	0.9924	9.4017
		FGLS	2.0266	1.5334	0.8279	2.2011	1.7966	0.9648	9.3502
		Huber	1.9351	1.0428	0.5845	2.1195	1.5524	0.8165	8.0508
		Bi-Square	1.8199	0.7485	0.4494	2.1347	1.4064	0.7366	7.2954

TABLE 4.1.23B: Absolute Bias: When Errors are Gamma , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	1.3719	2.9924	2.135	1.4883	2.8233	2.0732	12.8842
		FGLS	1.2622	2.8641	1.9414	1.4658	2.6836	1.9191	12.1362
		Huber	1.1542	2.1785	1.5969	1.4057	2.5715	1.8733	10.7800
		Bi-Square	1.25	1.7519	1.4201	1.4415	2.477	1.8687	10.2091
	N=30	OLS	0.9793	2.5341	1.6978	1.1453	2.965	1.8005	11.1220
		FGLS	0.937	2.6493	1.5847	1.0739	2.8141	1.876	10.9349
		Huber	0.9149	2.0837	1.2746	1.0645	2.6142	1.6349	9.5868
		Bi-Square	0.9326	1.829	1.13	1.1023	2.451	1.5902	9.0352
	N=50	OLS	1.0389	2.619	1.4723	0.9965	2.9163	1.8986	10.9416
		FGLS	0.9467	2.67	1.4162	0.9957	2.8495	1.7406	10.6186
		Huber	0.9637	1.8489	1.0914	0.9541	2.4366	1.5866	8.8813
		Bi-Square	0.9952	1.4153	0.9574	1.019	2.1539	1.4567	7.9975
	N=100	OLS	0.8776	2.5525	1.204	0.7577	2.8962	1.5332	9.8212
		FGLS	0.8549	2.4997	1.2246	0.7823	2.8669	1.4509	9.6793
		Huber	0.9499	1.7527	0.8621	0.8691	2.3705	1.2562	8.0604
		Bi-Square	1.0325	1.2564	0.705	0.9673	2.1014	1.148	7.2107
	N=250	OLS	0.7353	2.5912	1.2549	0.7433	2.879	1.4421	9.6459
		FGLS	0.753	2.5346	1.2339	0.7682	2.8214	1.4058	9.5168
		Huber	0.8856	1.7405	0.8641	0.8489	2.3966	1.2014	7.9370
		Bi-Square	0.9625	1.2378	0.6314	0.9447	2.1323	1.0761	6.9848
	N=500	OLS	0.719	2.4992	1.3181	0.7358	2.9087	1.5066	9.6874
		FGLS	0.7277	2.4955	1.3051	0.7688	2.8575	1.4912	9.6457
		Huber	0.9148	1.6749	0.8818	0.8718	2.4084	1.2253	7.9770
		Bi-Square	0.9917	1.1919	0.6342	0.9673	2.1412	1.0819	7.0082

TABLE 4.1.24B: Absolute Bias: When Errors are Gamma , Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	2.2947	2.7671	2.2844	2.5839	2.3514	2.1635	14.4450
		FGLS	2.1951	2.5447	1.9659	2.5981	2.1223	1.9362	13.3623
		Huber	2.1097	2.0405	1.8133	2.4985	2.2864	2.0183	12.7667
		Bi-Square	2.1136	1.8806	1.697	2.5073	2.2711	2.1033	12.5731
	N=30	OLS	1.9524	1.8411	1.6543	2.2546	2.3024	1.7977	11.8025
		FGLS	1.9292	1.9026	1.5369	2.2352	2.0851	1.7843	11.4733
		Huber	1.7638	1.655	1.2952	2.119	2.1086	1.628	10.5696
		Bi-Square	1.6792	1.6124	1.2387	2.1154	1.9918	1.5926	10.2301
	N=50	OLS	2.0943	1.9132	1.4125	2.1858	2.1193	1.6743	11.3993
		FGLS	1.9898	1.9148	1.2502	2.2293	2.0183	1.4384	10.8407
		Huber	1.9682	1.372	1.1168	2.1074	1.8537	1.4286	9.8466
		Bi-Square	1.8965	1.1625	1.0706	2.1253	1.7331	1.3984	9.3864
	N=100	OLS	2.0728	1.6557	1.0025	2.134	1.8733	1.199	9.9373
		FGLS	2.0756	1.5803	0.9517	2.1562	1.8277	1.0782	9.6697
		Huber	1.9724	1.1691	0.8085	2.1084	1.5691	1.0352	8.6628
		Bi-Square	1.8672	0.9019	0.7377	2.1196	1.4677	1.0211	8.1152
	N=250	OLS	1.9727	1.6647	0.8855	2.141	1.8383	0.971	9.4732
		FGLS	2.0143	1.5912	0.8457	2.1853	1.7683	0.8973	9.3020
		Huber	1.8938	1.1476	0.6238	2.083	1.5494	0.8326	8.1302
		Bi-Square	1.787	0.8602	0.5141	2.1021	1.4021	0.7762	7.4416
	N=500	OLS	2.0174	1.5285	0.8457	2.1585	1.8593	0.9924	9.4017
		FGLS	2.0266	1.5334	0.8279	2.2011	1.7966	0.9648	9.3502
		Huber	1.9351	1.0428	0.5845	2.1195	1.5524	0.8165	8.0508
		Bi-Square	1.8199	0.7485	0.4494	2.1347	1.4064	0.7366	7.2954

TABLE 4.1.25 B: Absolute Bias: When Errors are Gamma , Square Root Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	3.1118	2.7775	2.4288	3.4768	2.3296	2.2882	16.4128
		FGLS	2.9959	2.5164	2.0712	3.5117	2.0134	2.0432	15.1519
		Huber	2.81	2.0997	1.9854	3.3531	2.3745	2.1878	14.8104
		Bi-Square	2.6796	2.0158	1.8847	3.3132	2.3512	2.2886	14.5332
	N=30	OLS	2.8041	1.6088	1.7128	3.1459	2.1608	1.8317	13.2642
		FGLS	2.7649	1.5528	1.6153	3.1181	1.8403	1.7905	12.6818
		Huber	2.4475	1.472	1.3496	2.9334	1.9784	1.6619	11.8428
		Bi-Square	2.2359	1.514	1.3204	2.9119	1.888	1.6469	11.5171
	N=50	OLS	2.9458	1.6451	1.471	3.1335	1.7998	1.6306	12.6258
		FGLS	2.8485	1.5715	1.2955	3.2047	1.6556	1.3632	11.9390
		Huber	2.6886	1.1946	1.2159	2.974	1.6438	1.3625	11.0794
		Bi-Square	2.5108	1.1117	1.1718	2.9384	1.5772	1.3769	10.6867
	N=100	OLS	2.9652	1.1757	1.01	3.1109	1.3195	1.1104	10.6917
		FGLS	2.9713	1.0986	0.8938	3.1285	1.2356	0.9476	10.2754
		Huber	2.671	0.868	0.8265	2.9712	1.1776	0.9984	9.5126
		Bi-Square	2.4265	0.7909	0.7926	2.9374	1.1408	1.005	9.0933
	N=250	OLS	2.8477	1.0637	0.7658	3.1127	1.1541	0.7332	9.6772
		FGLS	2.8899	0.9539	0.6611	3.158	1.0498	0.5889	9.3016
		Huber	2.5813	0.7736	0.5409	2.9368	0.9838	0.6324	8.4488
		Bi-Square	2.3441	0.6371	0.4949	2.9037	0.9241	0.6036	7.9074
	N=500	OLS	2.9131	0.8651	0.5862	3.137	1.1003	0.6875	9.2891
		FGLS	2.922	0.8601	0.5547	3.1852	1.0352	0.6173	9.1746
		Huber	2.6301	0.5953	0.4291	2.9825	0.9224	0.5561	8.1153
		Bi-Square	2.3815	0.4596	0.3597	2.9514	0.8472	0.5117	7.5111

TABLE 4.1.26B: Absolute Bias: When Errors are Gamma , Homoscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	4.6561	2.6038	2.5381	5.8438	3.0173	2.7169	21.3760
		FGLS	4.6846	1.126	1.0629	5.9355	1.1409	1.1248	15.0746
		Huber	4.1894	2.3195	2.0645	5.4604	2.6176	2.4253	19.0766
		Bi-Square	3.964	2.3494	2.0242	5.2604	2.5086	2.3933	18.4999
	N=30	OLS	4.8633	2.1177	1.7997	5.8678	1.803	1.9993	18.4508
		FGLS	4.774	0.6778	0.6593	6.0665	0.6615	0.7526	13.5917
		Huber	4.3174	1.686	1.663	5.6156	1.6146	1.8289	16.7256
		Bi-Square	3.9945	1.6062	1.7414	5.4887	1.6048	1.8507	16.2862
	N=50	OLS	4.984	1.63	1.6475	6.035	1.5466	1.59	17.4330
		FGLS	4.7898	0.5772	0.5184	6.0433	0.5555	0.4879	12.9721
		Huber	4.3802	1.1634	1.2799	5.5859	1.406	1.3839	15.1992
		Bi-Square	4.0566	1.1634	1.31	5.4074	1.4154	1.419	14.7718
	N=100	OLS	4.6743	1.1639	1.087	5.7853	1.042	1.1655	14.9181
		FGLS	4.6349	0.3547	0.3658	5.9905	0.3256	0.324	11.9955
		Huber	4.1824	0.9142	0.8279	5.3329	0.8915	0.983	13.1317
		Bi-Square	3.8954	0.8901	0.8033	5.1639	0.8894	0.9652	12.6072
	N=250	OLS	4.6317	0.815	0.6931	5.9846	0.8097	0.7357	13.6697
		FGLS	4.6721	0.2149	0.2216	6.0027	0.21	0.2096	11.5309
		Huber	4.1123	0.5861	0.5363	5.551	0.6722	0.6108	12.0687
		Bi-Square	3.7965	0.5486	0.5112	5.3808	0.6646	0.6054	11.5070
	N=500	OLS	4.6768	0.493	0.4567	5.9959	0.4827	0.5033	12.6084
		FGLS	4.6983	0.1621	0.1589	6.0525	0.1508	0.1518	11.3744
		Huber	4.1769	0.3592	0.3732	5.5491	0.4387	0.4455	11.3426
		Bi-Square	3.8473	0.3471	0.3828	5.3656	0.4576	0.4463	10.8467

TABLE 4.1.27B: Absolute Bias: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}(E(Y_i))$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	7.5781	6.9727	5.9273	9.5916	8.5007	6.4069	44.9773
		FGLS	7.443	4.4204	3.1746	9.4042	5.746	3.744	33.9322
		Huber	7.0346	6.0519	4.8744	8.9314	7.2551	5.8362	39.9836
		Bi-Square	6.9245	6.0777	4.7133	8.9008	6.8143	5.7373	39.1679
	N=30	OLS	7.8553	5.2523	4.4371	9.1326	6.6404	5.1609	38.4786
		FGLS	7.6899	3.5543	2.3954	9.666	5.2967	2.8329	31.4352
		Huber	7.2024	4.2177	4.059	9.0439	5.7854	4.5227	34.8311
		Bi-Square	6.8696	3.8211	4.1282	9.0621	5.5172	4.3545	33.7527
	N=50	OLS	8.0182	4.8928	3.8084	9.5182	5.8346	4.2993	36.3714
		FGLS	7.6736	3.9656	2.0168	9.5827	5.2711	2.8061	31.3160
		Huber	7.4034	3.7065	2.8242	9.1405	4.8943	3.6239	31.5930
		Bi-Square	7.0404	3.3226	2.6688	9.0255	4.4482	3.583	30.0884
	N=100	OLS	7.3826	4.5222	3.0813	9.0438	5.4549	3.8675	33.3522
		FGLS	7.3733	3.9554	2.2786	9.5591	5.2327	2.6376	31.0367
		Huber	7.0037	3.2557	2.1405	8.6586	4.7006	3.3598	29.1188
		Bi-Square	6.778	2.7391	1.9982	8.5894	4.3691	3.0344	27.5081
	N=250	OLS	7.2655	4.1922	2.48	9.3453	5.5015	3.0421	31.8266
		FGLS	7.39	4.2121	2.0484	9.4235	5.4178	2.8008	31.2927
		Huber	6.8896	3.0624	1.9275	9.0822	4.4804	2.4983	27.9404
		Bi-Square	6.5843	2.5492	1.6856	8.9932	4.0451	2.2928	26.1501
	N=500	OLS	7.3242	4.2939	2.3301	9.3984	5.5872	2.9119	31.8457
		FGLS	7.3673	4.3203	2.1821	9.5339	5.464	2.7131	31.5806
		Huber	6.9963	3.0921	1.6463	9.0875	4.6232	2.348	27.7935
		Bi-Square	6.7001	2.4571	1.3503	8.9734	4.2022	2.0893	25.7722

TABLE 4.1.28B: Absolute Bias: When Errors are Gamma , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	1.2866	3.3042	2.0695	1.5974	4.2509	2.4363	14.9449
		FGLS	1.0083	2.9109	1.6825	1.2987	3.8435	2.0068	12.7507
		Huber	1.232	2.5824	1.6487	1.4293	3.5923	2.1486	12.6332
		Bi-Square	1.3003	2.2621	1.5995	1.4618	3.1863	2.0116	11.8216
	N=30	OLS	1.2339	2.755	1.8173	1.2343	4.0391	2.1878	13.2673
		FGLS	1.0121	2.6973	1.4542	1.1997	3.7571	1.8166	11.9368
		Huber	1.1524	2.1673	1.5786	1.249	3.4279	1.8464	11.4216
		Bi-Square	1.1755	1.8131	1.4304	1.3167	3.0765	1.697	10.5092
	N=50	OLS	1.1104	2.9446	1.5276	1.1575	3.8367	2.046	12.6227
		FGLS	0.9553	2.8836	1.3837	1.1297	3.7734	1.9264	12.0521
		Huber	1.1551	2.2398	1.075	1.2533	3.2185	1.6987	10.6404
		Bi-Square	1.1963	1.8358	0.9228	1.3521	2.8462	1.5507	9.7039
	N=100	OLS	0.9459	2.9077	1.5849	0.996	3.8141	2.147	12.3956
		FGLS	0.8993	2.856	1.4882	1.1531	3.7436	1.8689	12.0091
		Huber	1.03	2.1863	1.0989	1.1196	3.2351	1.7866	10.4563
		Bi-Square	1.1215	1.7817	0.9059	1.2331	2.8932	1.5577	9.4932
	N=250	OLS	0.8271	2.9874	1.5586	1.0184	3.9021	2.0036	12.2971
		FGLS	0.854	2.977	1.4711	1.0475	3.8583	1.9691	12.1771
		Huber	0.9935	2.1887	1.1587	1.2024	3.1976	1.6343	10.3751
		Bi-Square	1.0795	1.7772	0.9409	1.3285	2.8245	1.4331	9.3837
	N=500	OLS	0.8061	3.0424	1.5624	1.0384	3.9221	1.9804	12.3518
		FGLS	0.8158	3.0465	1.5393	1.0797	3.8903	1.9281	12.2997
		Huber	1.0116	2.2096	1.1264	1.2119	3.2282	1.6157	10.4034
		Bi-Square	1.111	1.7446	0.8871	1.3237	2.8657	1.419	9.3511

TABLE 4.1.29B: Absolute Bias: When Errors are Gamma , Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	2.4718	2.6733	2.1504	3.1076	3.3187	2.3596	16.0813
		FGLS	2.3995	1.8711	1.2546	2.9977	2.4676	1.4893	12.4797
		Huber	2.3039	2.2842	1.764	2.8883	2.8148	2.149	14.2041
		Bi-Square	2.2929	2.233	1.7124	2.8915	2.6374	2.1028	13.8698
	N=30	OLS	2.5356	2.0433	1.6734	2.894	2.7571	1.9375	13.8408
		FGLS	2.4742	1.6101	0.9938	3.0878	2.3528	1.1872	11.7058
		Huber	2.3376	1.6327	1.5055	2.8968	2.3907	1.6828	12.4461
		Bi-Square	2.2556	1.4642	1.5071	2.9188	2.2538	1.6025	12.0020
	N=50	OLS	2.5732	2.0009	1.4084	3.0272	2.5075	1.6535	13.1707
		FGLS	2.4579	1.7922	0.8671	3.0558	2.3601	1.2294	11.7626
		Huber	2.415	1.5332	1.0297	2.9415	2.1013	1.379	11.3996
		Bi-Square	2.3136	1.3429	0.9624	2.9214	1.89	1.3459	10.7762
	N=100	OLS	2.3532	1.8709	1.2099	2.8707	2.4026	1.5663	12.2737
		FGLS	2.3548	1.7748	0.9812	3.059	2.3369	1.168	11.6747
		Huber	2.2736	1.3767	0.8417	2.7764	2.0814	1.3503	10.7001
		Bi-Square	2.222	1.1541	0.7654	2.7745	1.913	1.2169	10.0458
	N=250	OLS	2.3106	1.868	1.0331	2.9668	2.4489	1.2999	11.9273
		FGLS	2.357	1.8727	0.9109	2.9976	2.4148	1.2401	11.7930
		Huber	2.2351	1.3686	0.8017	2.9201	2.0103	1.0717	10.4075
		Bi-Square	2.1592	1.132	0.6898	2.9112	1.8168	0.9831	9.6920
	N=500	OLS	2.3245	1.9136	1.0095	2.9861	2.4806	1.2703	11.9845
		FGLS	2.3397	1.922	0.9704	3.0344	2.4379	1.208	11.9124
		Huber	2.2662	1.3904	0.7282	2.922	2.0619	1.036	10.4046
		Bi-Square	2.1962	1.1114	0.5881	2.9045	1.8743	0.9278	9.6022

TABLE 4.1.30B: Absolute Bias: When Errors are Gamma , Square Root Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	3.41	2.5006	2.2826	4.2946	2.9965	2.4526	17.9369
		FGLS	3.4197	1.352	1.0769	4.3073	1.647	1.2455	13.0484
		Huber	3.118	2.2341	1.8805	4.0196	2.587	2.2366	16.0758
		Bi-Square	3.0304	2.2731	1.8295	3.9376	2.4739	2.2016	15.7462
	N=30	OLS	3.5657	1.9175	1.6655	4.2132	2.0944	1.9204	15.3767
		FGLS	3.5	0.9387	0.7589	4.415	1.3908	0.8637	11.8670
		Huber	3.2262	1.5486	1.5323	4.109	1.8506	1.7002	13.9668
		Bi-Square	3.0272	1.4582	1.6077	4.0708	1.8126	1.662	13.6387
	N=50	OLS	3.6469	1.6236	1.4575	4.3645	1.7803	1.545	14.4178
		FGLS	3.4956	1.0085	0.5919	4.3844	1.3584	0.7902	11.6289
		Huber	3.2931	1.2176	1.1068	4.1207	1.5187	1.3374	12.5943
		Bi-Square	3.0976	1.1393	1.0789	4.0328	1.4267	1.3507	12.1259
	N=100	OLS	3.3866	1.4351	1.08	4.168	1.5007	1.2877	12.8580
		FGLS	3.3692	0.9869	0.6445	4.3662	1.3158	0.6832	11.3656
		Huber	3.1286	1.0321	0.7749	3.9181	1.3173	1.1247	11.2957
		Bi-Square	2.9739	0.9119	0.7381	3.8429	1.2545	1.0343	10.7556
	N=250	OLS	3.3442	1.145	0.7837	4.3105	1.4217	0.8946	11.4656
		FGLS	3.3881	1.0698	0.5242	4.3358	1.3657	0.7141	11.2812
		Huber	3.0789	0.823	0.6129	4.0981	1.1689	0.7426	10.2003
		Bi-Square	2.8962	0.7163	0.5589	4.0166	1.0779	0.7076	9.5834
	N=500	OLS	3.3706	1.0945	0.6708	4.3255	1.4313	0.8038	11.6965
		FGLS	3.3889	1.1015	0.5561	4.3778	1.3796	0.6863	11.4903
		Huber	3.1233	0.7928	0.4784	4.0995	1.1948	0.6499	10.3386
		Bi-Square	2.9392	0.6431	0.4259	4.0056	1.0965	0.5952	9.7055

TABLE 4.1.1C: Root Mean Squares Error: When Errors are Gamma , Homoscedastic and No contemporaneous correlation under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	4.7607	3.5886	3.7584	4.3704	3.0428	3.2438	22.7647
		FGLS	4.7042	3.5011	3.8233	4.378	3.1657	3.2584	22.8307
		Huber	4.0606	2.8833	2.9571	3.8224	2.4877	2.5997	18.8108
		Bi-Square	3.8497	2.7454	2.8015	3.6818	2.3852	2.5063	17.9699
	N=30	OLS	4.2303	2.9347	2.5778	4.4357	2.4922	2.5233	19.1940
		FGLS	4.2348	3.026	2.7245	4.4305	2.5207	2.6249	19.5614
		Huber	3.7486	2.3018	2.2096	3.86	2.1144	2.0124	16.2468
		Bi-Square	3.5164	2.1586	2.1744	3.5179	2.0707	1.918	15.3560
	N=50	OLS	4.2455	2.2212	1.9573	4.2441	2.1563	1.8258	16.6502
		FGLS	4.2304	2.2146	2.0125	4.2484	2.1805	1.8812	16.7676
		Huber	3.7019	1.782	1.5582	3.5657	1.7192	1.6241	13.9511
		Bi-Square	3.4329	1.6761	1.5313	3.2315	1.6332	1.6327	13.1377
	N=100	OLS	3.9118	1.5189	1.1826	4.1658	1.4278	1.4604	13.6673
		FGLS	3.8997	1.5384	1.2119	4.1527	1.4476	1.4627	13.7130
		Huber	3.3686	1.2313	0.9703	3.5391	1.14	1.1406	11.3899
		Bi-Square	3.0381	1.2118	0.9673	3.1194	1.1072	1.0516	10.4954
	N=250	OLS	4.1354	0.8875	0.8267	4.0722	1.0034	0.8508	11.7760
		FGLS	4.1379	0.8868	0.8329	4.0746	1.0126	0.8497	11.7945
		Huber	3.5846	0.7243	0.7121	3.4992	0.7331	0.688	9.9413
		Bi-Square	3.1534	0.7206	0.7259	3.0275	0.6841	0.6761	8.9876
	N=500	OLS	4.0256	0.5818	0.6336	4.0573	0.5933	0.6314	10.5230
		FGLS	4.0239	0.5851	0.6334	4.058	0.5932	0.6294	10.5230
		Huber	3.4766	0.4769	0.4752	3.5059	0.4538	0.4432	8.8316
		Bi-Square	3.0378	0.4771	0.453	3.0652	0.4268	0.4024	7.8623

TABLE 4.1.2 C: Root Mean Squares Error: When Errors are Gamma , Exponential Heteroscedastic and No contemporaneous correlation under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	8.4314	8.6165	9.0059	7.502	7.7955	7.5871	48.9384
		FGLS	8.3988	8.6295	9.1885	7.5371	8.1015	7.5953	49.4507
		Huber	7.2516	6.6812	6.9375	6.7847	6.2104	5.8772	39.7426
		Bi-Square	7.0784	6.1057	6.6102	6.7124	5.7641	5.4718	37.7426
	N=30	OLS	7.1273	8.1832	6.1265	7.6314	6.6536	5.9764	41.6984
		FGLS	7.1672	8.3571	6.4714	7.6446	6.8173	6.1997	42.6573
		Huber	6.5945	6.0451	5.1277	6.8798	5.5062	4.7189	34.8722
		Bi-Square	6.4747	5.2953	4.8835	6.4142	5.2804	4.5258	32.8739
	N=50	OLS	6.86695	6.68238	4.70706	6.98788	5.68387	4.76292	35.6911
		FGLS	6.83344	6.73043	4.8306	7.00452	5.72607	4.84245	35.9675
		Huber	6.42337	4.79409	3.54718	6.21676	4.42622	4.23012	29.6377
		Bi-Square	6.30611	3.94601	3.32676	5.83408	4.12465	4.08932	27.6269
	N=100	OLS	6.1988	5.38113	3.52729	6.75494	4.78732	3.58839	30.2379
		FGLS	6.18255	5.4273	3.60718	6.71962	4.85877	3.61786	30.4133
		Huber	5.72225	3.95317	2.70545	6.08951	3.58886	2.76935	24.8286
		Bi-Square	5.44388	3.29952	2.46434	5.57765	3.1675	2.4833	22.4362
	N=250	OLS	6.56426	4.08361	2.5318	6.48849	4.40372	2.46347	26.5354
		FGLS	6.56603	4.07911	2.54401	6.49378	4.41257	2.45665	26.5522
		Huber	6.15436	2.89186	1.88154	5.98404	3.04495	1.85976	21.8165
		Bi-Square	5.71592	2.34517	1.77573	5.46509	2.40818	1.68923	19.3993
	N=500	OLS	6.38735	3.84601	2.19936	6.39279	3.96222	2.25473	25.0425
		FGLS	6.38467	3.85355	2.20101	6.39386	3.94955	2.262	25.0446
		Huber	5.9448	2.70846	1.52976	5.97563	2.65733	1.56853	20.3845
		Bi-Square	5.49679	2.05352	1.22615	5.53215	1.95725	1.25283	17.5187

TABLE 4.1.3 C: Root Mean Squares Error: When Errors are Gamma ,Quadratic Heteroscedastic(Q=2) and No contemporal correlation (P=0) under varying sample sizes									
Contemporall Correlation	Sample size	Forms of Heteroscedasticity: Var(Yi)= σ^2 [E(Yi)] ^g ; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.80987	3.45508	3.07732	1.48766	3.31174	2.57796	15.7196
		FGLS	1.84662	3.49998	3.13682	1.50256	3.38697	2.56686	15.9398
		Huber	1.42979	2.51816	2.29548	1.28275	2.52937	1.88328	11.9388
		Bi-Square	1.43034	2.28325	2.2076	1.35818	2.1584	1.57168	11.0095
	N=30	OLS	1.36282	3.5995	2.20522	1.47107	3.03326	2.15321	13.8251
		FGLS	1.38456	3.62636	2.29666	1.49872	3.09622	2.21059	14.1131
		Huber	1.22607	2.53192	1.72431	1.33358	2.36483	1.61117	10.7919
		Bi-Square	1.29051	2.04141	1.52532	1.30529	2.02556	1.39346	9.5816
	N=50	OLS	1.08816	3.26595	1.87854	1.11547	2.78788	1.92468	12.0607
		FGLS	1.08683	3.29598	1.9068	1.12312	2.79082	1.93637	12.1399
		Huber	1.10021	2.18084	1.26547	1.08553	2.03733	1.58984	9.2592
		Bi-Square	1.22918	1.57366	1.03478	1.13376	1.70081	1.38427	8.0565
	N=100	OLS	0.86428	2.93561	1.67305	0.97035	2.71451	1.53987	10.6977
		FGLS	0.86898	2.94493	1.69422	0.96352	2.74142	1.55244	10.7655
		Huber	0.91315	2.0183	1.19236	0.99862	1.92724	1.12376	8.1734
		Bi-Square	0.99669	1.47927	0.9447	1.02399	1.50973	0.90924	6.8636
	N=250	OLS	0.81527	2.64628	1.40235	0.82855	2.7125	1.33866	9.7436
		FGLS	0.8153	2.64489	1.40697	0.82926	2.71268	1.33727	9.7464
		Huber	0.9882	1.78616	0.93767	0.94829	1.82542	0.93041	7.4162
		Bi-Square	1.05764	1.31189	0.74016	1.00578	1.33001	0.71196	6.1574
	N=500	OLS	0.7756	2.58647	1.31167	0.74719	2.65521	1.35122	9.4274
		FGLS	0.77515	2.58812	1.31218	0.7476	2.65167	1.35418	9.4289
		Huber	0.93812	1.74967	0.87109	0.92918	1.75931	0.91045	7.1578
		Bi-Square	1.01432	1.23718	0.62352	1.00592	1.25257	0.66926	5.8028

TABLE 4.1.4 C: Root Mean Squares Error: When Errors are Gamma ,Linear Heteroscedastic(Q=1) and No contemporal correlation(P=0) under varying sample sizes

Contemporall Correlation	Sample size	Forms of Heteroscedasticity: Var(Yi)= σ^2 [E(Yi)] ^g ; g=1							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	2.81654	3.19518	3.28371	2.47438	2.94282	2.76112	17.4738
		FGLS	2.81241	3.21435	3.34899	2.48635	3.05115	2.76184	17.6751
		Huber	2.41775	2.46105	2.52148	2.2416	2.33286	2.11925	14.0940
		Bi-Square	2.36475	2.21973	2.38645	2.2373	2.1386	1.95473	13.3016
	N=30	OLS	2.34396	3.11839	2.24431	2.51823	2.5463	2.18945	14.9606
		FGLS	2.36046	3.1798	2.36543	2.52655	2.60896	2.26942	15.3106
		Huber	2.18646	2.29072	1.85784	2.28004	2.08773	1.71418	12.4170
		Bi-Square	2.16231	1.96246	1.74989	2.14995	1.97459	1.63539	11.6346
	N=50	OLS	2.21394	2.61862	1.74859	2.26622	2.21296	1.79111	12.8514
		FGLS	2.20277	2.63938	1.78977	2.27192	2.22666	1.81534	12.9458
		Huber	2.11099	1.85013	1.29328	2.04638	1.70549	1.57492	10.5812
		Bi-Square	2.10178	1.46651	1.18003	1.9392	1.56225	1.50176	9.7515
	N=100	OLS	1.98613	2.17277	1.37481	2.17531	1.95655	1.35703	11.0226
		FGLS	1.98138	2.18848	1.40253	2.16271	1.98281	1.36891	11.0868
		Huber	1.86689	1.57521	1.0426	1.99195	1.44956	1.04172	8.9679
		Bi-Square	1.79861	1.27528	0.92447	1.84743	1.24519	0.91977	8.0108
	N=250	OLS	2.09699	1.74869	1.02168	2.07569	1.85481	0.98703	9.7849
		FGLS	2.09748	1.74702	1.02603	2.07753	1.85723	0.9846	9.7899
		Huber	2.01319	1.22295	0.73766	1.95707	1.27709	0.73118	7.9391
		Bi-Square	1.89943	0.96242	0.67035	1.816	0.98789	0.64076	6.9769
	N=500	OLS	2.03844	1.67677	0.9125	2.0347	1.72608	0.9365	9.3250
		FGLS	2.03752	1.67924	0.91317	2.03508	1.72149	0.93953	9.3260
		Huber	1.94271	1.17275	0.62973	1.9503	1.15788	0.65003	7.5034
		Bi-Square	1.82523	0.87323	0.48898	1.83558	0.84621	0.50916	6.3784

TABLE 4.1.5 C: Root Mean Squares Error: When Errors are Gamma ,Square Root Heteroscedastic(Q= 0.5) and No contemporal correlation under varying sample sizes

Contemporaral Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0	N=20	OLS	3.6548	3.2462	3.4717	3.2942	2.8678	2.9477	19.4824
		FGLS	3.6258	3.2242	3.5384	3.3034	2.9889	2.955	19.6357
		Huber	3.1429	2.5685	2.6991	2.943	2.3269	2.3198	16.0002
		Bi-Square	3.0294	2.3855	2.5714	2.8694	2.1845	2.2001	15.2403
	N=30	OLS	3.16319	2.92984	2.35411	3.35324	2.3882	2.29838	16.4870
		FGLS	3.17402	3.01028	2.4895	3.35442	2.44083	2.39007	16.8591
		Huber	2.88131	2.22414	1.99514	2.98112	2.00658	1.82303	13.9113
		Bi-Square	2.7743	2.00362	1.92786	2.74772	1.9609	1.75991	13.1743
	N=50	OLS	3.10375	2.30883	1.77729	3.13622	2.02237	1.7635	14.1120
		FGLS	3.09029	2.31936	1.82622	3.14123	2.04314	1.80101	14.2213
		Huber	2.81745	1.73255	1.37421	2.72217	1.60977	1.58502	11.8412
		Bi-Square	2.69815	1.51	1.32454	2.51762	1.5291	1.55854	11.1380
	N=100	OLS	2.83536	1.74532	1.23246	3.05473	1.55124	1.33772	11.7568
		FGLS	2.82701	1.76488	1.26336	3.04152	1.57633	1.34634	11.8194
		Huber	2.53603	1.33476	0.97617	2.68785	1.20421	1.04456	9.7836
		Bi-Square	2.35848	1.18547	0.92705	2.41993	1.11629	0.95506	8.9623
	N=250	OLS	3.00176	1.18455	0.84148	2.96141	1.32085	0.83416	10.1442
		FGLS	3.00308	1.1827	0.84628	2.96357	1.3262	0.83172	10.1536
		Huber	2.71711	0.87636	0.66811	2.64749	0.93033	0.65514	8.4945
		Bi-Square	2.46766	0.76598	0.66369	2.36404	0.77984	0.62782	7.6690
	N=500	OLS	2.9211	1.05523	0.69487	2.93325	1.08981	0.70685	9.4011
		FGLS	2.91983	1.05865	0.69541	2.93374	1.08508	0.70864	9.4014
		Huber	2.63108	0.77076	0.50014	2.64802	0.74142	0.50086	7.7923
		Bi-Square	2.37317	0.62402	0.43149	2.39238	0.57454	0.42321	6.8188

TABLE 4.1.6.C:Root Mean Square Error: When Errors are Gamma , Homoscedastic and Contemporaral Correlation(P=0.2) under varying sample sizes

Contemporaral Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	4.76517	3.80013	3.57173	5.10876	3.69994	3.44864	24.3944
		FGLS	4.72617	3.61364	3.57057	5.11067	3.70682	3.37858	24.1065
		Huber	4.17535	2.97614	2.81298	4.58791	2.93401	3.07582	20.5622
		Bi-Square	3.94197	2.91088	2.71119	4.35611	2.70492	3.03248	19.6576
	N=30	OLS	4.25056	2.1959	2.32361	4.85274	2.36877	2.56111	18.5527
		FGLS	4.22087	2.23487	2.31332	4.86879	2.25179	2.64362	18.5333
		Huber	3.65093	2.03144	1.96188	4.44263	1.88532	2.23022	16.2024
		Bi-Square	3.31844	2.06415	1.93377	4.24735	1.9464	2.21872	15.7288
	N=50	OLS	4.41299	2.181	2.03168	4.96125	1.97324	1.99089	8.6736
		FGLS	4.31761	2.16024	1.97342	4.99267	2.01103	1.95748	8.7207
		Huber	3.90362	1.70629	1.72024	4.41864	1.62401	1.56324	7.5122
		Bi-Square	3.57161	1.58433	1.65038	4.14634	1.58734	1.52236	6.8585
	N=100	OLS	4.23181	1.35652	1.33532	4.56445	1.30948	1.50374	14.3013
		FGLS	4.24935	1.34968	1.35884	4.55508	1.2722	1.46812	14.2533
		Huber	3.63175	1.00988	1.13678	4.00483	0.97126	1.1828	11.9373
		Bi-Square	3.22813	1.01554	1.1273	3.73138	0.94812	1.12885	11.1793
	N=250	OLS	3.99197	0.92845	0.91468	4.71723	0.98665	0.94153	12.4805
		FGLS	4.0024	0.90301	0.91164	4.74074	0.96201	0.92139	12.4412
		Huber	3.46298	0.72502	0.6751	4.18728	0.76349	0.69569	10.5096
		Bi-Square	3.06604	0.69142	0.64668	3.85539	0.71705	0.67751	9.6541
	N=500	OLS	4.06098	0.66092	0.61972	4.69109	0.5826	0.63401	11.2493
		FGLS	4.07184	0.65064	0.591	4.71023	0.56526	0.63013	11.2191
		Huber	3.50248	0.4649	0.46515	4.1584	0.49251	0.50312	9.5866
		Bi-Square	3.07961	0.42716	0.42427	3.80587	0.49669	0.48151	8.7151

TABLE 4.1.7C: Root Mean Squares Error: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	8.23614	9.65721	8.26468	8.73574	10.1012	8.28847	53.2834
		FGLS	8.14719	9.09213	8.16646	8.75103	10.0126	8.11002	52.2794
		Huber	7.39483	7.31845	6.34596	7.96212	7.84696	7.13548	44.0038
		Bi-Square	7.32283	6.92343	6.07338	7.87942	7.04945	6.80026	42.0488
	N=30	OLS	7.0101	5.92728	5.80899	7.99505	7.27887	6.1873	40.2076
		FGLS	6.98552	6.15635	5.82168	8.03813	6.90821	6.43728	40.3472
		Huber	6.2904	5.38286	4.71446	7.58606	5.7469	5.27136	34.9920
		Bi-Square	6.05537	5.44507	4.52247	7.46472	5.36034	5.18998	34.0380
	N=50	OLS	7.38263	6.10253	4.87857	8.13631	6.11273	4.95503	37.5678
		FGLS	7.18425	6.10979	4.89034	8.2188	6.16302	4.81871	37.3849
		Huber	6.76988	4.43147	3.90976	7.57806	4.8151	3.9013	31.4056
		Bi-Square	6.42189	3.87222	3.69736	7.33243	4.40321	3.71643	29.4435
	N=100	OLS	6.88573	4.75519	3.28925	7.24604	5.1579	4.38148	31.7156
		FGLS	6.93612	4.7245	3.30465	7.2333	5.12633	4.31774	31.6426
		Huber	6.32712	3.38969	2.67903	6.68266	4.03065	3.42208	26.5312
		Bi-Square	5.92741	2.92309	2.5835	6.45479	3.59188	3.07952	24.5602
	N=250	OLS	6.35328	4.30617	2.754	7.44099	4.83006	3.08699	28.7715
		FGLS	6.38499	4.26891	2.70988	7.50025	4.72285	3.03153	28.6184
		Huber	5.91243	3.01135	1.94223	7.02844	3.60087	2.23764	23.7330
		Bi-Square	5.50315	2.36763	1.67078	6.73274	3.02706	1.99463	21.2960
	N=500	OLS	6.42927	3.68754	2.38819	7.38293	4.56736	2.64938	27.1047
		FGLS	6.45043	3.66353	2.32556	7.425	4.49655	2.62712	26.9882
		Huber	5.98335	2.50981	1.66681	6.96745	3.43776	1.97426	22.5394
		Bi-Square	5.5438	1.87476	1.32726	6.61864	2.8986	1.69718	19.9602

TABLE 4.1.8C: Root Mean Squares Error: When Errors are Gamma ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.63955	3.90394	2.79029	1.7789	4.37765	2.93468	17.4250
		FGLS	1.59943	3.69678	2.74089	1.77234	4.32202	2.89328	17.0247
		Huber	1.41818	2.83761	2.03609	1.48709	3.35691	2.37365	13.5095
		Bi-Square	1.48884	2.44849	1.80504	1.50735	2.74482	2.19556	12.1901
	N=30	OLS	1.19844	2.89204	2.22354	1.36237	3.63948	2.32015	13.6360
		FGLS	1.23034	2.97224	2.24046	1.36899	3.54065	2.40186	13.7545
		Huber	1.11593	2.38721	1.67432	1.28716	2.8257	1.86071	11.1510
		Bi-Square	1.16964	2.11555	1.46213	1.343	2.40656	1.70156	10.1984
	N=50	OLS	1.28476	2.99854	1.87743	1.26176	3.28513	2.01539	12.7230
		FGLS	1.25431	3.0095	1.92103	1.28137	3.27907	1.96502	12.7103
		Huber	1.18184	2.11692	1.39282	1.2755	2.50239	1.54621	10.0157
		Bi-Square	1.18438	1.70154	1.19689	1.32847	2.13008	1.37618	8.9175
	N=100	OLS	1.01742	2.74677	1.4788	0.94468	3.10973	1.97525	11.2727
		FGLS	1.03481	2.73421	1.47069	0.94087	3.10751	1.95826	11.2464
		Huber	1.06382	1.88515	1.06012	0.99621	2.38402	1.50456	8.8939
		Bi-Square	1.12514	1.43533	0.88706	1.07137	2.01195	1.27923	7.8101
	N=250	OLS	0.81142	2.67875	1.41733	0.9037	3.11653	1.68491	10.6126
		FGLS	0.82177	2.66939	1.398	0.91978	3.08666	1.66573	10.5613
		Huber	0.93124	1.80998	0.97322	1.04186	2.29301	1.21864	8.2680
		Bi-Square	0.99497	1.3147	0.74295	1.13911	1.83218	0.98702	7.0109
	N=500	OLS	0.77745	2.54178	1.39538	0.85569	3.09082	1.59931	10.2604
		FGLS	0.78102	2.53588	1.38411	0.86636	3.07056	1.59447	10.2324
		Huber	0.93723	1.70241	0.93642	1.01474	2.27765	1.17823	8.0467
		Bi-Square	1.00726	1.22445	0.68854	1.09924	1.83762	0.9615	6.8186

TABLE 4.1.9C: Root Mean Squares Error: When Errors are Gamma ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	2.73262	3.60457	2.99012	2.87759	3.83792	3.0293	19.0721
		FGLS	2.70128	3.39515	2.94512	2.8843	3.8014	2.97072	18.6980
		Huber	2.45988	2.71867	2.27677	2.62034	2.98324	2.59405	15.6530
		Bi-Square	2.45641	2.53012	2.15939	2.61187	2.64455	2.45787	14.8602
	N=30	OLS	2.27709	2.30416	2.15433	2.59449	2.87071	2.28184	14.4826
		FGLS	2.27317	2.39164	2.15847	2.60896	2.73753	2.37402	14.5438
		Huber	2.0684	2.05197	1.73236	2.47764	2.27218	1.92293	12.5255
		Bi-Square	2.01597	2.03842	1.64335	2.45767	2.06522	1.87509	12.0957
	N=50	OLS	2.40603	2.38344	1.80115	2.63336	2.45934	1.86261	13.5459
		FGLS	2.33603	2.39003	1.81647	2.66283	2.47217	1.80891	13.4864
		Huber	2.22275	1.7192	1.4214	2.48557	1.92554	1.4617	11.2362
		Bi-Square	2.12537	1.47923	1.33055	2.42612	1.73173	1.37765	10.4707
	N=100	OLS	2.22274	1.95158	1.24871	2.31744	2.15216	1.69274	11.5854
		FGLS	2.2415	1.94124	1.25107	2.31345	2.14392	1.67119	11.5624
		Huber	2.08123	1.38545	0.99558	2.16659	1.68588	1.32142	9.6362
		Bi-Square	1.97574	1.15268	0.93818	2.11424	1.48466	1.17688	8.8424
	N=250	OLS	2.03255	1.82311	1.09272	2.37269	2.06659	1.24511	10.6328
		FGLS	2.04431	1.8109	1.07514	2.39417	2.02886	1.22519	10.5786
		Huber	1.93096	1.26685	0.7679	2.28321	1.54277	0.90641	8.6981
		Bi-Square	1.8238	0.97467	0.64129	2.21288	1.28533	0.7932	7.7312
	N=500	OLS	2.04905	1.61795	0.99128	2.35016	1.99623	1.10925	10.1139
		FGLS	2.05635	1.60975	0.97052	2.36495	1.97096	1.10145	10.0740
		Huber	1.95335	1.10373	0.68745	2.25938	1.49991	0.82863	8.3325
		Bi-Square	1.83645	0.81883	0.53868	2.17053	1.25507	0.70554	7.3251

TABLE 4.1.10C: Root Mean Squares Error: When Errors are Gamma ,Square Root Heteroscedastic(P= 0.5) and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	3.61783	3.58445	3.21432	3.83741	3.64604	3.17696	21.0770
		FGLS	3.58493	3.38251	3.18543	3.84512	3.62911	3.11267	20.7398
		Huber	3.2196	2.76715	2.49239	3.48462	2.8586	2.77938	17.6017
		Bi-Square	3.11101	2.67592	2.39917	3.39966	2.61498	2.70789	16.9086
	N=30	OLS	3.13848	2.09515	2.1852	3.58048	2.48987	2.35441	15.8436
		FGLS	3.12166	2.17232	2.18216	3.59667	2.34784	2.44596	15.8666
		Huber	2.76597	1.9512	1.80408	3.35504	1.97346	2.02157	13.8713
		Bi-Square	2.59896	2.0072	1.76098	3.25778	1.92063	2.00688	13.5524
	N=50	OLS	3.2831	2.13549	1.84969	3.65787	2.05065	1.85693	14.8337
		FGLS	3.19944	2.13119	1.83426	3.68896	2.07876	1.80873	14.7413
		Huber	2.9645	1.59364	1.51629	3.34762	1.64763	1.46362	12.5333
		Bi-Square	2.77478	1.44052	1.45372	3.19508	1.55429	1.41319	11.8316
	N=100	OLS	3.10996	1.51516	1.21026	3.31232	1.58598	1.55708	12.2908
		FGLS	3.12829	1.50648	1.22248	3.30615	1.56744	1.52998	12.2608
		Huber	2.77976	1.10757	1.02067	2.98863	1.2475	1.22496	10.3691
		Bi-Square	2.54612	1.02624	1.00701	2.83925	1.14848	1.12859	9.6957
	N=250	OLS	2.9016	1.2785	0.94106	3.41347	1.39469	1.01728	10.9466
		FGLS	2.91294	1.26152	0.92803	3.43616	1.35306	0.99634	10.8881
		Huber	2.61849	0.9228	0.67649	3.13715	1.05815	0.74121	9.1543
		Bi-Square	2.38469	0.77125	0.61023	2.95176	0.91938	0.68962	8.3269
	N=500	OLS	2.94188	1.00651	0.75055	3.39075	1.23442	0.81011	10.1342
		FGLS	2.95092	0.99592	0.72267	3.40764	1.20599	0.80131	10.0845
		Huber	2.64852	0.69221	0.53817	3.11215	0.95194	0.61356	8.5566
		Bi-Square	2.39952	0.54582	0.45051	2.90717	0.83145	0.54631	7.6808

TABLE 4.1.16C: Root Mean Squares Error: When Errors are Gamma , Homoscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	4.76517	3.80013	3.57173	6.28869	3.79885	3.59322	25.8178
		FGLS	4.66632	3.24197	3.16156	6.27819	3.60662	3.31685	24.2715
		Huber	4.17535	2.97614	2.81298	5.84925	3.2727	3.31674	22.4032
		Bi-Square	3.94197	2.91088	2.71119	5.65217	3.21261	3.28741	21.7162
	N=30	OLS	4.25056	2.1959	2.32361	6.17156	2.36366	2.58006	19.8854
		FGLS	4.18704	2.14161	2.19902	6.1587	2.14258	2.52877	19.3577
		Huber	3.65093	2.03144	1.96188	5.89177	2.05486	2.31817	17.9091
		Bi-Square	3.31844	2.06415	1.93377	5.76413	2.08781	2.31587	17.4842
	N=50	OLS	4.41299	2.181	2.03168	6.23565	1.91593	1.96832	18.7456
		FGLS	4.26542	2.05874	1.83659	6.26519	1.83505	1.81391	18.0749
		Huber	3.90362	1.70629	1.72024	5.77624	1.74526	1.68189	16.5335
		Bi-Square	3.57161	1.58433	1.65038	5.60664	1.73577	1.69151	15.8402
	N=100	OLS	4.23181	1.35652	1.33532	5.88278	1.30009	1.43449	15.5410
		FGLS	4.2304	1.27791	1.30078	5.87723	1.17968	1.32123	15.1872
		Huber	3.63175	1.00988	1.13678	5.40941	1.11534	1.2246	13.5278
		Bi-Square	3.22813	1.01554	1.1273	5.23817	1.12992	1.19961	12.9387
	N=250	OLS	3.99197	0.92845	0.91468	6.02486	0.99926	0.9363	13.7955
		FGLS	4.00144	0.84946	0.8528	6.06272	0.90981	0.85083	13.5271
		Huber	3.46298	0.72502	0.6751	5.58172	0.84611	0.74983	12.0408
		Bi-Square	3.06604	0.69142	0.64668	5.41417	0.83976	0.73902	11.3971
	N=500	OLS	4.06098	0.66092	0.61972	6.01338	0.59196	0.62047	12.5674
		FGLS	4.07047	0.60871	0.53033	6.05383	0.5271	0.58833	12.3788
		Huber	3.50248	0.4649	0.46515	5.56397	0.54022	0.54162	11.0783
		Bi-Square	3.07961	0.42716	0.42427	5.38083	0.55342	0.54626	10.4116

TABLE 4.1.17C: Root Mean Squares Error: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	8.23614	9.65721	8.26468	10.4626	11.0165	8.8057	56.4428
		FGLS	8.01604	8.35747	7.34042	10.4598	10.45	8.14534	52.7690
		Huber	7.39483	7.31845	6.34596	9.86605	9.27559	7.87115	48.0720
		Bi-Square	7.32283	6.92343	6.07338	9.7792	8.82241	7.76342	46.6847
	N=30	OLS	7.0101	5.92728	5.80899	9.98154	8.0566	6.38876	43.1733
		FGLS	6.91117	6.04665	5.5827	9.95958	7.42746	6.44101	42.3686
		Huber	6.2904	5.38286	4.71446	9.75883	6.93932	5.60232	38.6882
		Bi-Square	6.05537	5.44507	4.52247	9.73726	6.63179	5.49335	37.8853
	N=50	OLS	7.38263	6.10253	4.87857	10.0613	6.90767	5.24596	40.5786
		FGLS	7.07288	5.92683	4.69598	10.1383	6.75454	4.81626	39.4048
		Huber	6.76988	4.43147	3.90976	9.63583	5.97215	4.48809	35.2072
		Bi-Square	6.42189	3.87222	3.69736	9.52395	5.62812	4.4174	33.5609
	N=100	OLS	6.88573	4.75519	3.28925	9.30449	6.14924	4.67862	35.0625
		FGLS	6.89495	4.64597	3.16641	9.30878	5.99856	4.48314	34.4978
		Huber	6.32712	3.38969	2.67903	8.8619	5.33063	3.94894	30.5373
		Bi-Square	5.92741	2.92309	2.5835	8.77713	5.04758	3.63917	28.8979
	N=250	OLS	6.35328	4.30617	2.754	9.4629	5.95608	3.60584	32.4383
		FGLS	6.38204	4.23309	2.57469	9.55814	5.72993	3.44428	31.9222
		Huber	5.91243	3.01135	1.94223	9.16832	4.88612	2.91377	27.8342
		Bi-Square	5.50315	2.36763	1.67078	9.07931	4.47296	2.71417	25.8080
	N=500	OLS	6.42927	3.68754	2.38819	9.44827	5.74658	3.18335	30.8832
		FGLS	6.44351	3.65054	2.22715	9.53572	5.58453	3.10941	30.5509
		Huber	5.98335	2.50981	1.66681	9.12637	4.7816	2.59946	26.6674
		Bi-Square	5.5438	1.87476	1.32726	9.01131	4.38516	2.37608	24.5184

TABLE 4.1.18C: Root Mean Squares Error: When Errors are Gamma, Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	1.63955	3.90394	2.79029	1.92307	5.12705	3.27078	18.6547
		FGLS	1.54348	3.54151	2.54545	1.86894	4.93294	3.09882	17.5311
		Huber	1.41818	2.83761	2.03609	1.66842	4.25628	2.78274	14.9993
		Bi-Square	1.48884	2.44849	1.80504	1.73349	3.79968	2.62251	13.8981
	N=30	OLS	1.19844	2.89204	2.22354	1.51162	4.38735	2.59856	14.8116
		FGLS	1.2057	2.96998	2.17931	1.48377	4.2231	2.64599	14.7079
		Huber	1.11593	2.38721	1.67432	1.50657	3.71834	2.21483	12.6172
		Bi-Square	1.16964	2.11555	1.46213	1.56328	3.3732	2.0582	11.7420
	N=50	OLS	1.28476	2.99854	1.87743	1.41689	4.07332	2.367	14.0179
		FGLS	1.22133	2.97422	1.89557	1.42256	4.0169	2.2537	13.7843
		Huber	1.18184	2.11692	1.39282	1.46802	3.44484	1.98478	11.5892
		Bi-Square	1.18438	1.70154	1.19689	1.54201	3.11067	1.84216	10.5777
	N=100	OLS	1.01742	2.74677	1.4788	1.14859	3.92201	2.32534	12.6389
		FGLS	1.01709	2.72144	1.43612	1.14655	3.89526	2.27514	12.4916
		Huber	1.06382	1.88515	1.06012	1.22215	3.32846	1.93477	10.4945
		Bi-Square	1.12514	1.43533	0.88706	1.32134	3.00714	1.71964	9.4957
	N=250	OLS	0.81142	2.67875	1.41733	1.10127	3.96682	2.11601	12.0916
		FGLS	0.81707	2.66714	1.36755	1.12398	3.90827	2.07413	11.9581
		Huber	0.93124	1.80998	0.97322	1.25197	3.25383	1.71551	9.9358
		Bi-Square	0.99497	1.3147	0.74295	1.36911	2.88223	1.52109	8.8251
	N=500	OLS	0.77745	2.54178	1.39538	1.07482	3.945	2.02401	11.7584
		FGLS	0.77503	2.53716	1.36833	1.09565	3.90143	2.01016	11.6878
		Huber	0.93723	1.70241	0.93642	1.23191	3.24992	1.65296	9.7109
		Bi-Square	1.00726	1.22445	0.68854	1.34038	2.89186	1.46094	8.6134

TABLE 4.1.19 C: Root Mean Squares Error: When Errors are Gamma ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	2.73262	3.60457	2.99012	3.40922	4.25971	3.24564	20.2419
		FGLS	2.65414	3.14454	2.65625	3.40767	4.0533	3.0165	18.9324
		Huber	2.45988	2.71867	2.27677	3.21276	3.58823	2.88366	17.1400
		Bi-Square	2.45641	2.53012	2.15939	3.20173	3.37793	2.84238	16.5680
	N=30	OLS	2.27709	2.30416	2.15433	3.21135	3.25829	2.3894	15.5946
		FGLS	2.24631	2.36158	2.07682	3.2027	3.03786	2.42196	15.3472
		Huber	2.0684	2.05197	1.73236	3.16135	2.80034	2.08224	13.8967
		Bi-Square	2.01597	2.03842	1.64335	3.16409	2.65319	2.02229	13.5373
	N=50	OLS	2.40603	2.38344	1.80115	3.23521	2.86674	2.01863	14.7112
		FGLS	2.29676	2.33134	1.75566	3.2623	2.81276	1.86542	14.3242
		Huber	2.22275	1.7192	1.4214	3.13032	2.46917	1.71961	12.6825
		Bi-Square	2.12537	1.47923	1.33055	3.10816	2.3042	1.68002	12.0275
	N=100	OLS	2.22274	1.95158	1.24871	2.96948	2.62042	1.85383	12.8668
		FGLS	2.22688	1.91906	1.20367	2.97224	2.57398	1.78711	12.6829
		Huber	2.08123	1.38545	0.99558	2.85335	2.27176	1.56735	11.1547
		Bi-Square	1.97574	1.15268	0.93818	2.84506	2.13105	1.43382	10.4765
	N=250	OLS	2.03255	1.82311	1.09272	3.01181	2.58132	1.48965	12.0312
		FGLS	2.04297	1.8016	1.02949	3.0462	2.50434	1.4354	11.8600
		Huber	1.93096	1.26685	0.7679	2.9532	2.12952	1.21578	10.2642
		Bi-Square	1.8238	0.97467	0.64129	2.94351	1.9441	1.12565	9.4530
	N=500	OLS	2.04905	1.61795	0.99128	3.00535	2.52675	1.35808	11.5485
		FGLS	2.05351	1.60754	0.93907	3.03603	2.4701	1.33366	11.4399
		Huber	1.95335	1.10373	0.68745	2.93651	2.10764	1.11731	9.9060
		Bi-Square	1.83645	0.81883	0.53868	2.9184	1.92696	1.01766	9.0570

TABLE 4.1.20C: Root Mean Squares Error: When Errors are Gamma ,Square Root Heteroscedastic(g= 0.5) and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0.5							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	3.61783	3.58445	3.21432	4.6584	3.87253	3.34202	22.2896
		FGLS	3.53386	3.06818	2.83829	4.66051	3.66754	3.08771	20.8561
		Huber	3.2196	2.76715	2.49239	4.37337	3.29059	3.03575	19.1789
		Bi-Square	3.11101	2.67592	2.39917	4.28815	3.20887	3.03477	18.7179
	N=30	OLS	3.13848	2.09515	2.1852	4.51232	2.63736	2.38938	16.9579
		FGLS	3.09231	2.11312	2.08561	4.50396	2.38795	2.39138	16.5743
		Huber	2.76597	1.9512	1.80408	4.36914	2.28231	2.10656	15.2793
		Bi-Square	2.59896	2.0072	1.76098	4.32194	2.23242	2.08542	15.0069
	N=50	OLS	3.2831	2.13549	1.84969	4.5609	2.18222	1.90178	15.9132
		FGLS	3.15484	2.0506	1.74057	4.59072	2.12066	1.73452	15.3919
		Huber	2.9645	1.59364	1.51629	4.3049	1.92506	1.63382	13.9382
		Bi-Square	2.77478	1.44052	1.45372	4.22076	1.85117	1.62747	13.3684
	N=100	OLS	3.10996	1.51516	1.21026	4.26213	1.79412	1.59255	13.4842
		FGLS	3.1121	1.46582	1.16743	4.26197	1.71869	1.50724	13.2333
		Huber	2.77976	1.10757	1.02067	3.99341	1.58017	1.35343	11.8350
		Bi-Square	2.54612	1.02624	1.00701	3.91338	1.53598	1.27285	11.3016
	N=250	OLS	2.9016	1.2785	0.94106	4.35088	1.65489	1.12481	12.2517
		FGLS	2.91192	1.2389	0.87176	4.3875	1.55942	1.05478	12.0243
		Huber	2.61849	0.9228	0.67649	4.12913	1.36803	0.91174	10.6267
		Bi-Square	2.38469	0.77125	0.61023	4.04857	1.27584	0.86753	9.9581
	N=500	OLS	2.94188	1.00651	0.75055	4.34311	1.52328	0.92501	11.4903
		FGLS	2.94891	0.98382	0.67536	4.37856	1.45499	0.89181	11.3335
		Huber	2.64852	0.69221	0.53817	4.11375	1.28724	0.76203	10.0419
		Bi-Square	2.39952	0.54582	0.45051	4.01987	1.20173	0.71485	9.3323

TABLE 4.1.21C:Root Mean Squares Error: When Errors are Gamma , Homoscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	4.76517	3.80013	3.57173	5.24736	3.1976	3.23586	23.8179
		FGLS	4.5583	3.31797	3.19711	5.19296	2.75776	2.85329	21.8774
		Huber	4.17535	2.97614	2.81298	5.05143	3.28829	3.08801	21.3922
		Bi-Square	3.94197	2.91088	2.71119	4.97712	3.30843	3.16844	21.0180
	N=30	OLS	4.25056	2.1959	2.32361	4.76469	2.86105	2.64696	19.0428
		FGLS	4.14595	1.90268	2.20318	4.64115	2.44761	2.49209	17.8327
		Huber	3.65093	2.03144	1.96188	4.40531	2.61729	2.41056	17.0774
		Bi-Square	3.31844	2.06415	1.93377	4.34501	2.50846	2.37068	16.5405
	N=50	OLS	4.41299	2.181	2.03168	4.73332	2.20417	2.02452	17.5877
		FGLS	4.21993	1.90825	1.77658	4.7352	2.05981	1.7479	16.4477
		Huber	3.90362	1.70629	1.72024	4.35841	2.00801	1.75364	15.4502
		Bi-Square	3.57161	1.58433	1.65038	4.24344	1.97808	1.78158	14.8094
	N=100	OLS	4.23181	1.35652	1.33532	4.44218	1.33186	1.39653	14.0942
		FGLS	4.2144	1.17604	1.25864	4.42322	1.17984	1.16853	13.4207
		Huber	3.63175	1.00988	1.13678	4.15371	1.23032	1.27196	12.4344
		Bi-Square	3.22813	1.01554	1.1273	4.07224	1.25849	1.29207	11.9938
	N=250	OLS	3.99197	0.92845	0.91468	4.37925	0.94076	0.79568	11.9508
		FGLS	4.02431	0.74319	0.7893	4.40846	0.78948	0.57801	11.3328
		Huber	3.46298	0.72502	0.6751	4.04184	0.80352	0.71394	10.4224
		Bi-Square	3.06604	0.69142	0.64668	3.93877	0.81194	0.70207	9.8569
	N=500	OLS	4.06098	0.66092	0.61972	4.38147	0.55256	0.615	10.8907
		FGLS	4.06407	0.54252	0.5596	4.43205	0.47986	0.53062	10.6087
		Huber	3.50248	0.4649	0.46515	4.07259	0.50455	0.50566	9.5153
		Bi-Square	3.07961	0.42716	0.42427	3.97887	0.52479	0.48641	8.9211

TABLE 4.1.22C: Root Mean Squares Error: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	2.73262	3.60457	2.99012	3.04534	3.01763	2.77895	18.1692
		FGLS	2.59095	3.22796	2.63214	3.0029	2.69833	2.44206	16.5943
		Huber	2.45988	2.71867	2.27677	2.95049	2.94437	2.61166	15.9618
		Bi-Square	2.45641	2.53012	2.15939	2.95841	2.93337	2.6653	15.7030
	N=30	OLS	2.27709	2.30416	2.15433	2.61239	2.95309	2.28767	14.5887
		FGLS	2.21443	2.32473	1.99327	2.51191	2.58739	2.30193	13.9337
		Huber	2.0684	2.05197	1.73236	2.4702	2.70746	2.08525	13.1156
		Bi-Square	2.01597	2.03842	1.64335	2.45312	2.59108	2.01992	12.7619
	N=50	OLS	2.40603	2.38344	1.80115	2.52466	2.52027	2.02077	13.6563
		FGLS	2.26164	2.33316	1.64324	2.52435	2.4209	1.8065	12.9898
		Huber	2.22275	1.7192	1.4214	2.38165	2.1774	1.76363	11.6860
		Bi-Square	2.12537	1.47923	1.33055	2.40151	2.04244	1.73681	11.1159
	N=100	OLS	2.22274	1.95158	1.24871	2.255	2.14284	1.46475	11.2856
		FGLS	2.2055	1.81167	1.2511	2.24181	2.05616	1.31933	10.8856
		Huber	2.08123	1.38545	0.99558	2.21705	1.81755	1.28127	9.7781
		Bi-Square	1.97574	1.15268	0.93818	2.2304	1.70405	1.27014	9.2712
	N=250	OLS	2.03255	1.82311	1.09272	2.20303	1.98243	1.11927	10.2531
		FGLS	2.06104	1.70643	1.01719	2.22473	1.87738	1.00396	9.8907
		Huber	1.93096	1.26685	0.7679	2.13152	1.6814	0.95958	8.7382
		Bi-Square	1.8238	0.97467	0.64129	2.15017	1.54624	0.90678	8.0430
	N=500	OLS	2.04905	1.61795	0.99128	2.18608	1.9146	1.11125	9.8702
		FGLS	2.05145	1.59491	0.94671	2.22347	1.84016	1.06213	9.7188
		Huber	1.95335	1.10373	0.68745	2.13917	1.60715	0.90927	8.4001
		Bi-Square	1.83645	0.81883	0.53868	2.1527	1.47262	0.82936	7.6486

TABLE 4.1.23 C: Root Mean Squares Error: When Errors are Gamma ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	1.63955	3.90394	2.79029	1.8446	3.46305	2.66278	16.3042
		FGLS	1.4945	3.57342	2.47551	1.76898	3.25253	2.39424	14.9592
		Huber	1.41818	2.83761	2.03609	1.72843	3.16628	2.41758	13.6042
		Bi-Square	1.48884	2.44849	1.80504	1.7722	3.05626	2.37011	12.9409
	N=30	OLS	1.19844	2.89204	2.22354	1.40876	3.48419	2.24735	13.4543
		FGLS	1.15133	2.96839	2.07592	1.32201	3.222	2.33149	13.0711
		Huber	1.11593	2.38721	1.67432	1.3041	3.10463	1.99748	11.5837
		Bi-Square	1.16964	2.11555	1.46213	1.34564	2.95652	1.9274	10.9769
	N=50	OLS	1.28476	2.99854	1.87743	1.29053	3.25677	2.194	12.9020
		FGLS	1.16464	2.99701	1.77624	1.25051	3.1688	2.0394	12.3966
		Huber	1.18184	2.11692	1.39282	1.20852	2.73531	1.86712	10.5025
		Bi-Square	1.18438	1.70154	1.19689	1.2673	2.45619	1.7472	9.5535
	N=100	OLS	1.01742	2.74677	1.4788	0.93319	3.05341	1.74411	10.9737
		FGLS	0.98798	2.6555	1.49977	0.90137	2.999	1.64689	10.6905
		Huber	1.06382	1.88515	1.06012	1.00893	2.52544	1.45954	9.0030
		Bi-Square	1.12514	1.43533	0.88706	1.0905	2.28227	1.37207	8.1924
	N=250	OLS	0.81142	2.67875	1.41733	0.84247	2.95542	1.54505	10.2504
		FGLS	0.82511	2.59634	1.37056	0.83977	2.87704	1.47522	9.9840
		Huber	0.93124	1.80998	0.97322	0.91646	2.4591	1.28294	8.3729
		Bi-Square	0.99497	1.3147	0.74295	1.00576	2.20241	1.16662	7.4274
	N=500	OLS	0.77745	2.54178	1.39538	0.79067	2.93839	1.57241	10.0161
		FGLS	0.77349	2.52641	1.37027	0.81192	2.881	1.54391	9.9070
		Huber	0.93723	1.70241	0.93642	0.89963	2.43644	1.2712	8.1833
		Bi-Square	1.00726	1.22445	0.68854	0.99088	2.17534	1.1303	7.2168

TABLE 4.1.24C: Root Mean Squares Error: When Errors are Gamma ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	2.73262	3.60457	2.99012	3.04534	3.01763	2.77895	18.1692
		FGLS	2.59095	3.22796	2.63214	3.0029	2.69833	2.44206	16.5943
		Huber	2.45988	2.71867	2.27677	2.95049	2.94437	2.61166	15.9618
		Bi-Square	2.45641	2.53012	2.15939	2.95841	2.93337	2.6653	15.7030
	N=30	OLS	2.27709	2.30416	2.15433	2.61239	2.95309	2.28767	14.5887
		FGLS	2.21443	2.32473	1.99327	2.51191	2.58739	2.30193	13.9337
		Huber	2.0684	2.05197	1.73236	2.4702	2.70746	2.08525	13.1156
		Bi-Square	2.01597	2.03842	1.64335	2.45312	2.59108	2.01992	12.7619
	N=50	OLS	2.40603	2.38344	1.80115	2.52466	2.52027	2.02077	13.6563
		FGLS	2.26164	2.33316	1.64324	2.52435	2.4209	1.8065	12.9898
		Huber	2.22275	1.7192	1.4214	2.38165	2.1774	1.76363	11.6860
		Bi-Square	2.12537	1.47923	1.33055	2.40151	2.04244	1.73681	11.1159
	N=100	OLS	2.22274	1.95158	1.24871	2.255	2.14284	1.46475	11.2856
		FGLS	2.2055	1.81167	1.2511	2.24181	2.05616	1.31933	10.8856
		Huber	2.08123	1.38545	0.99558	2.21705	1.81755	1.28127	9.7781
		Bi-Square	1.97574	1.15268	0.93818	2.2304	1.70405	1.27014	9.2712
	N=250	OLS	2.03255	1.82311	1.09272	2.20303	1.98243	1.11927	10.2531
		FGLS	2.06104	1.70643	1.01719	2.22473	1.87738	1.00396	9.8907
		Huber	1.93096	1.26685	0.7679	2.13152	1.6814	0.95958	8.7382
		Bi-Square	1.8238	0.97467	0.64129	2.15017	1.54624	0.90678	8.0430
	N=500	OLS	2.04905	1.61795	0.99128	2.18608	1.9146	1.11125	9.8702
		FGLS	2.05145	1.59491	0.94671	2.22347	1.84016	1.06213	9.7188
		Huber	1.95335	1.10373	0.68745	2.13917	1.60715	0.90927	8.4001
		Bi-Square	1.83645	0.81883	0.53868	2.1527	1.47262	0.82936	7.6486

TABLE 4.1.25C : Root Mean Squares Error: When Errors are Gamma ,Square Root Heteroscedastic(P= 0.5) and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.7	N=20	OLS	3.61783	3.58445	3.21432	4.00183	2.94612	2.94156	20.3061
		FGLS	3.45217	3.16304	2.84522	3.96	2.55845	2.57764	18.5565
		Huber	3.2196	2.76715	2.49239	3.88775	2.9894	2.79393	18.1502
		Bi-Square	3.11101	2.67592	2.39917	3.84408	2.99256	2.8794	17.9021
	N=30	OLS	3.13848	2.09515	2.1852	3.55249	2.76908	2.40313	16.1435
		FGLS	3.05898	2.00445	2.03617	3.44238	2.35392	2.34592	15.2418
		Huber	2.76597	1.9512	1.80408	3.32822	2.56573	2.19956	14.6148
		Bi-Square	2.59896	2.0072	1.76098	3.289	2.45252	2.14646	14.2551
	N=50	OLS	3.2831	2.13549	1.84969	3.49051	2.19668	1.97223	14.9277
		FGLS	3.11729	2.00115	1.64545	3.49503	2.07968	1.72188	14.0605
		Huber	2.9645	1.59364	1.51629	3.25714	1.94825	1.72069	13.0005
		Bi-Square	2.77478	1.44052	1.45372	3.22232	1.89205	1.7312	12.5146
	N=100	OLS	3.10996	1.51516	1.21026	3.22147	1.60481	1.36365	12.0253
		FGLS	3.09356	1.33561	1.18085	3.20749	1.48334	1.17721	11.4781
		Huber	2.77976	1.10757	1.02067	3.07692	1.40232	1.22458	10.6118
		Bi-Square	2.54612	1.02624	1.00701	3.04951	1.36644	1.23742	10.2327
	N=250	OLS	2.9016	1.2785	0.94106	3.16905	1.35549	0.88884	10.5345
		FGLS	2.93277	1.12299	0.83902	3.19539	1.22	0.72218	10.0324
		Huber	2.61849	0.9228	0.67649	2.98376	1.16307	0.77711	9.1417
		Bi-Square	2.38469	0.77125	0.61023	2.95085	1.1036	0.75688	8.5775
	N=500	OLS	2.94188	1.00651	0.75055	3.16166	1.1988	0.8219	9.8813
		FGLS	2.94503	0.95953	0.69137	3.20562	1.11103	0.75319	9.6658
		Huber	2.64852	0.69221	0.53817	3.00148	1.01691	0.66985	8.5671
		Bi-Square	2.39952	0.54582	0.45051	2.96942	0.95319	0.61995	7.9384

TABLE 4.1.26C: Root Mean Squares Error: When Errors are Gamma , Homoscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; g=0							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	5.35864	3.30012	3.26708	6.28869	3.79885	3.59322	25.6066
		FGLS	4.90028	1.4959	1.34497	6.05983	1.49222	1.55314	16.8463
		Huber	4.77496	2.96219	2.74359	5.84925	3.2727	3.31674	22.9194
		Bi-Square	4.54103	2.98596	2.75723	5.65217	3.21261	3.28741	22.4364
	N=30	OLS	5.24628	2.66456	2.31508	6.17156	2.36366	2.58006	21.3412
		FGLS	4.86695	0.89575	0.78761	6.16226	0.91147	0.99524	14.6193
		Huber	4.67618	2.1177	2.0735	5.89177	2.05486	2.31817	19.1322
		Bi-Square	4.36542	1.95655	2.11572	5.76413	2.08781	2.31587	18.6055
	N=50	OLS	5.22995	2.0689	2.088	6.23565	1.91593	1.96832	19.5068
		FGLS	4.8528	0.7317	0.65969	6.09522	0.73123	0.61361	13.6843
		Huber	4.56127	1.52247	1.66294	5.77624	1.74526	1.68189	16.9501
		Bi-Square	4.25742	1.48039	1.67593	5.60664	1.73577	1.69151	16.4477
	N=100	OLS	4.82138	1.48291	1.42339	5.88278	1.30009	1.43449	16.3450
		FGLS	4.67359	0.44843	0.47615	6.01312	0.40886	0.39508	12.4152
		Huber	4.27666	1.16504	1.0228	5.40941	1.11534	1.2246	14.2139
		Bi-Square	3.98972	1.10948	1.04457	5.23817	1.12992	1.19961	13.7115
	N=250	OLS	4.68027	0.98968	0.8726	6.02486	0.99926	0.9363	14.5030
		FGLS	4.68546	0.27536	0.283	6.01101	0.281	0.2576	11.7934
		Huber	4.14486	0.75959	0.68422	5.58172	0.84611	0.74983	12.7663
		Bi-Square	3.83195	0.73973	0.65024	5.41417	0.83976	0.73902	12.2149
	N=500	OLS	4.70187	0.62187	0.56978	6.01338	0.59196	0.62047	13.1193
		FGLS	4.70301	0.20444	0.19649	6.05589	0.19687	0.19742	11.5541
		Huber	4.1953	0.46091	0.46213	5.56397	0.54022	0.54162	11.7642
		Bi-Square	3.86616	0.4429	0.46412	5.38083	0.55342	0.54626	11.2537

TABLE 4.1.27C: Root Mean Squares Error: When Errors are Gamma , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	9.07534	8.77456	7.62223	10.4626	11.0165	8.8057	55.7569
		FGLS	7.97971	5.43024	4.08787	9.78126	6.72159	4.92741	38.9281
		Huber	8.36336	7.50946	6.61081	9.86605	9.27559	7.87115	49.4964
		Bi-Square	8.18463	7.31992	6.53008	9.7792	8.82241	7.76342	48.3997
	N=30	OLS	8.79698	6.64764	5.70355	9.98154	8.0566	6.38876	45.5751
		FGLS	7.90572	4.03804	2.86552	9.91091	5.77733	3.36457	33.8621
		Huber	8.07918	5.17598	5.03549	9.75883	6.93932	5.60232	40.5911
		Bi-Square	7.72354	4.78364	5.00991	9.73726	6.63179	5.49335	39.3795
	N=50	OLS	8.66341	6.22268	4.70855	10.0613	6.90767	5.24596	41.8095
		FGLS	7.82103	4.35205	2.42132	9.71419	5.64221	3.18668	33.1375
		Huber	7.84693	4.7439	3.6194	9.63583	5.97215	4.48809	36.3063
		Bi-Square	7.5061	4.31239	3.55729	9.52395	5.62812	4.4174	34.9453
	N=100	OLS	7.79426	5.22247	3.89934	9.30449	6.14924	4.67862	37.0484
		FGLS	7.47609	4.12311	2.49574	9.61331	5.3561	2.82572	31.8901
		Huber	7.24189	3.9565	2.73763	8.8619	5.33063	3.94894	32.0775
		Bi-Square	6.99929	3.45142	2.65569	8.77713	5.04758	3.63917	30.5703
	N=250	OLS	7.40909	4.77679	3.04221	9.4629	5.95608	3.60584	34.2529
		FGLS	7.42234	4.27176	2.16602	9.44426	5.47389	2.89382	31.6721
		Huber	6.97395	3.49885	2.31811	9.16832	4.88612	2.91377	29.7591
		Bi-Square	6.66437	3.01342	2.05314	9.07931	4.47296	2.71417	27.9974
	N=500	OLS	7.39315	4.5079	2.62651	9.44827	5.74658	3.18335	32.9058
		FGLS	7.38035	4.35052	2.2447	9.54433	5.48914	2.77197	31.7810
		Huber	7.04311	3.25271	1.91649	9.12637	4.7816	2.59946	28.7197
		Bi-Square	6.74373	2.63322	1.63372	9.01131	4.38516	2.37608	26.7832

TABLE 4.1.28C: Root Mean Squares Error: When Errors are Gamma ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	1.68248	3.90153	2.71403	1.92307	5.12705	3.27078	18.6189
		FGLS	1.23648	3.19738	2.11702	1.47437	4.16787	2.50727	14.7004
		Huber	1.55689	3.10475	2.30552	1.66842	4.25628	2.78274	15.6746
		Bi-Square	1.62882	2.74962	2.20458	1.73349	3.79968	2.62251	14.7387
	N=30	OLS	1.50406	3.22433	2.21382	1.51162	4.38735	2.59856	15.4397
		FGLS	1.14886	2.85037	1.66586	1.35156	3.8996	2.05382	12.9701
		Huber	1.40324	2.52169	1.88795	1.50657	3.71834	2.21483	13.2526
		Bi-Square	1.41419	2.16453	1.73701	1.56328	3.3732	2.0582	12.3104
	N=50	OLS	1.34382	3.28784	1.84144	1.41689	4.07332	2.367	14.3303
		FGLS	1.0587	2.98273	1.53187	1.24056	3.87516	2.03991	12.7289
		Huber	1.31348	2.51686	1.32641	1.46802	3.44484	1.98478	12.0544
		Bi-Square	1.33571	2.14653	1.17718	1.54201	3.11067	1.84216	11.1543
	N=100	OLS	1.10716	3.0845	1.81525	1.14859	3.92201	2.32534	13.4029
		FGLS	0.9688	2.90254	1.5768	1.19425	3.78016	1.92322	12.3458
		Huber	1.134	2.33259	1.27664	1.22215	3.32846	1.93477	11.2286
		Bi-Square	1.20547	1.94912	1.10129	1.32134	3.00714	1.71964	10.3040
	N=250	OLS	0.90997	3.07482	1.67275	1.10127	3.96682	2.11601	12.8416
		FGLS	0.88316	2.99664	1.50656	1.07368	3.87613	1.99897	12.3351
		Huber	1.03375	2.25303	1.24337	1.25197	3.25383	1.71551	10.7515
		Bi-Square	1.10842	1.8485	1.02922	1.36911	2.88223	1.52109	9.7586
	N=500	OLS	0.85282	3.07006	1.61171	1.07482	3.945	2.02401	12.5784
		FGLS	0.83171	3.05457	1.55642	1.09297	3.89775	1.94394	12.3774
		Huber	1.03358	2.22959	1.16694	1.23191	3.24992	1.65296	10.5649
		Bi-Square	1.12738	1.76607	0.93733	1.34038	2.89186	1.46094	9.5240

TABLE 4.1.29C: Root Mean Squares Error: When Errors are Gamma ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	2.98437	3.34737	2.77345	3.40922	4.25971	3.24564	20.0198
		FGLS	2.60216	2.23447	1.60303	3.14418	2.82955	1.93761	14.3510
		Huber	2.77104	2.83061	2.40696	3.21276	3.58823	2.88366	17.6933
		Bi-Square	2.73899	2.69736	2.36305	3.20173	3.37793	2.84238	17.2214
	N=30	OLS	2.87575	2.56495	2.11966	3.21135	3.25829	2.3894	16.4194
		FGLS	2.55777	1.76982	1.18388	3.18151	2.51432	1.39556	12.6029
		Huber	2.65714	2.00554	1.86079	3.16135	2.80034	2.08224	14.5674
		Bi-Square	2.55915	1.82776	1.83012	3.16409	2.65319	2.02229	14.0566
	N=50	OLS	2.81542	2.48747	1.736	3.23521	2.86674	2.01863	15.1595
		FGLS	2.51405	1.91302	1.02141	3.10813	2.48493	1.36836	12.4099
		Huber	2.57981	1.90541	1.3223	3.13032	2.46917	1.71961	13.1266
		Bi-Square	2.48156	1.70468	1.28146	3.10816	2.3042	1.68002	12.5601
	N=100	OLS	2.50778	2.15711	1.50392	2.96948	2.62042	1.85383	13.6125
		FGLS	2.39376	1.82759	1.06289	3.08018	2.37771	1.23239	11.9745
		Huber	2.36087	1.63625	1.06013	2.85335	2.27176	1.56735	11.7497
		Bi-Square	2.30134	1.4149	1.00627	2.84506	2.13105	1.43382	11.1324
	N=250	OLS	2.36605	2.04255	1.23305	3.01181	2.58132	1.48965	12.7244
		FGLS	2.36958	1.89201	0.9534	3.00602	2.43329	1.27144	11.9257
		Huber	2.26656	1.5021	0.93989	2.9532	2.12952	1.21578	11.0071
		Bi-Square	2.18795	1.27912	0.82169	2.94351	1.9441	1.12565	10.3020
	N=500	OLS	2.35054	1.97408	1.10826	3.00535	2.52675	1.35808	12.3231
		FGLS	2.34518	1.93163	0.99122	3.03875	2.44614	1.22764	11.9806
		Huber	2.28353	1.43526	0.81111	2.93651	2.10764	1.11731	10.6914
		Bi-Square	2.21193	1.16243	0.68273	2.9184	1.92696	1.01766	9.9201

TABLE 4.1.30C: Root Mean Squares Error: When Errors are Gamma ,Square Root Heteroscedastic(P= 0.5) and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	<i>OLS</i>	4.02111	3.17737	2.93777	4.6584	3.87253	3.34202	22.0092
		<i>FGLS</i>	3.61812	1.70581	1.37641	4.42834	2.00612	1.66009	14.7949
		<i>Huber</i>	3.65183	2.77719	2.52334	4.37337	3.29059	3.03575	19.6521
		<i>Bi-Square</i>	3.53297	2.76719	2.52028	4.28815	3.20887	3.03477	19.3522
	N=30	<i>OLS</i>	3.91752	2.40051	2.15244	4.51232	2.63736	2.38938	18.0095
		<i>FGLS</i>	3.57959	1.09743	0.9123	4.50269	1.58222	1.05417	12.7284
		<i>Huber</i>	3.55728	1.88051	1.91885	4.36914	2.28231	2.10656	16.1147
		<i>Bi-Square</i>	3.36507	1.77685	1.94709	4.32194	2.23242	2.08542	15.7288
	N=50	<i>OLS</i>	3.88351	2.10968	1.81784	4.5609	2.18222	1.90178	16.4559
		<i>FGLS</i>	3.55075	1.19111	0.73617	4.43214	1.51481	0.9236	12.3486
		<i>Huber</i>	3.46173	1.59332	1.42307	4.3049	1.92506	1.63382	14.3419
		<i>Bi-Square</i>	3.27984	1.49254	1.42565	4.22076	1.85117	1.62747	13.8974
	N=100	<i>OLS</i>	3.53065	1.64668	1.38966	4.26213	1.79412	1.59255	14.2158
		<i>FGLS</i>	3.40449	1.07106	0.72558	4.38612	1.37676	0.76497	11.7290
		<i>Huber</i>	3.21626	1.26259	0.98511	3.99341	1.58017	1.35343	12.3910
		<i>Bi-Square</i>	3.05881	1.13823	0.98571	3.91338	1.53598	1.27285	11.9050
	N=250	<i>OLS</i>	3.39382	1.38387	0.99028	4.35088	1.65489	1.12481	12.8986
		<i>FGLS</i>	3.39991	1.09882	0.57364	4.34312	1.39272	0.75784	11.5661
		<i>Huber</i>	3.11027	1.02495	0.77063	4.12913	1.36803	0.91174	11.3148
		<i>Bi-Square</i>	2.9274	0.91337	0.70152	4.04857	1.27584	0.86753	10.7342
	N=500	<i>OLS</i>	3.395	1.21763	0.78699	4.34311	1.52328	0.92501	12.1910
		<i>FGLS</i>	3.39342	1.11712	0.58801	4.38122	1.39241	0.71617	11.5884
		<i>Huber</i>	3.14064	0.87939	0.58622	4.11375	1.28724	0.76203	10.7693
		<i>Bi-Square</i>	2.9561	0.72891	0.52639	4.01987	1.20173	0.71485	10.1479

TABLE 4.2.1 A: VARIANCE: When Errors are Normal , Homoscedastic and No contemporal correlation under varying sample sizes									
Contemporall Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g ; g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.399	0.63	0.61434	0.3845	0.5973	0.692	3.3170
		FGLS	0.44	0.675	0.67004	0.3812	0.5739	0.7051	3.4453
		Huber	0.415	0.66	0.69035	0.4074	0.6719	0.6873	3.5323
		Bi-Square	0.423	0.694	0.70254	0.4215	0.6844	0.7118	3.6370
	N=30	OLS	0.274	0.497	0.3582	0.1736	0.3422	0.4123	2.0571
		FGLS	0.288	0.506	0.36769	0.1834	0.3594	0.4495	2.1542
		Huber	0.276	0.513	0.37202	0.2077	0.3872	0.4635	2.2196
		Bi-Square	0.273	0.516	0.38563	0.2208	0.395	0.4758	2.2667
	N=50	OLS	0.127	0.238	0.2429	0.1445	0.2579	0.2339	1.2443
		FGLS	0.129	0.241	0.24567	0.1426	0.2679	0.2344	1.2605
		Huber	0.128	0.231	0.2248	0.1606	0.2763	0.251	1.2718
		Bi-Square	0.129	0.235	0.22425	0.1653	0.2863	0.2531	1.2937
	N=100	OLS	0.063	0.141	0.122248	0.0661	0.1328	0.1295	0.6552
		FGLS	0.063	0.14	0.123996	0.0666	0.1348	0.1261	0.6543
		Huber	0.064	0.153	0.1253	0.0715	0.1427	0.1268	0.6840
		Bi-Square	0.066	0.156	0.12381	0.0704	0.1421	0.1252	0.6835
	N=250	OLS	0.032	0.042	0.054265	0.0262	0.0434	0.0419	0.2401
		FGLS	0.032	0.042	0.053895	0.0262	0.0433	0.0421	0.2390
		Huber	0.034	0.043	0.0553	0.0288	0.0504	0.0412	0.2520
		Bi-Square	0.033	0.043	0.05599	0.0286	0.0501	0.0405	0.2513
	N=500	OLS	0.011	0.023	0.02452	0.0124	0.0224	0.0209	0.1150
		FGLS	0.011	0.024	0.02449	0.0124	0.0224	0.0209	0.1150
		Huber	0.012	0.024	0.02485	0.0125	0.0227	0.0207	0.1169
		Bi-Square	0.012	0.024	0.02509	0.0124	0.0229	0.0205	0.1170

TABLE 4.2.2 A: VARIANCE: When Errors are Normal , Exponential Heteroscedastic and No contemporal correlation under varying sample sizes									
Contemporall Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.862	3.287	3.2067	1.754	3.1778	3.564	16.8514
		FGLS	2.04	3.488	3.43531	1.7499	3.1048	3.6648	17.4832
		Huber	1.961	3.468	3.66267	1.761	3.4158	3.4806	17.7492
		Bi-Square	1.983	3.632	3.67909	1.8114	3.5348	3.6437	18.2845
	N=30	OLS	1.235	2.61	1.84375	0.7887	1.8607	2.1148	10.4523
		FGLS	1.312	2.659	1.88473	0.8539	1.9805	2.269	10.9591
		Huber	1.181	2.589	1.90617	0.8931	2.1263	2.3045	11.0003
		Bi-Square	1.196	2.635	2.02795	0.9317	2.1954	2.3356	11.3209
	N=50	OLS	0.579	1.28	1.2321	0.7065	1.3955	1.2686	6.4609
		FGLS	0.595	1.29	1.24135	0.7074	1.4612	1.2785	6.5729
		Huber	0.538	1.227	1.07699	0.7419	1.426	1.3184	6.3282
		Bi-Square	0.549	1.288	1.07685	0.7277	1.4357	1.2834	6.3605
	N=100	OLS	0.267	0.752	0.60066	0.3012	0.6929	0.7049	3.3192
		FGLS	0.267	0.748	0.61712	0.2979	0.7055	0.6866	3.3216
		Huber	0.265	0.763	0.63796	0.3019	0.7155	0.6612	3.3445
		Bi-Square	0.269	0.786	0.63082	0.3019	0.728	0.6485	3.3637
	N=250	OLS	0.136	0.215	0.27947	0.107	0.213	0.2061	1.1572
		FGLS	0.135	0.213	0.27883	0.1071	0.2139	0.2066	1.1547
		Huber	0.137	0.217	0.27214	0.1116	0.2415	0.1971	1.1765
		Bi-Square	0.138	0.22	0.27851	0.1162	0.2537	0.1954	1.2018
	500	OLS	0.052	0.125	0.131639	0.0559	0.1171	0.106	0.5874
		FGLS	0.052	0.125	0.131405	0.056	0.1171	0.1062	0.5875
		Huber	0.053	0.129	0.12811	0.0537	0.1188	0.1038	0.5866
		Bi-Square	0.053	0.132	0.12819	0.0523	0.1206	0.1012	0.5876

TABLE 4.2.3 A: VARIANCE: When Errors are Normal , Quadratic Heteroscedastic(Q=2) and No contemporaneous correlation(P=0) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.158	0.322	0.30952	0.1462	0.3197	0.3357	1.5910
		FGLS	0.17	0.335	0.32542	0.1475	0.3204	0.347	1.6458
		Huber	0.153	0.322	0.32314	0.1246	0.2973	0.3102	1.5297
		Bi-Square	0.16	0.348	0.34905	0.1335	0.3449	0.3333	1.6688
	N=30	OLS	0.101	0.256	0.17511	0.067	0.1927	0.1967	0.9881
		FGLS	0.108	0.26	0.17863	0.0743	0.2086	0.2063	1.0365
		Huber	0.087	0.238	0.17662	0.0617	0.2079	0.1905	0.9621
		Bi-Square	0.088	0.242	0.188	0.0659	0.2446	0.1906	1.0186
	N=50	OLS	0.05	0.13	0.11532	0.0655	0.1436	0.1271	0.6309
		FGLS	0.052	0.13	0.11596	0.0668	0.151	0.1289	0.6444
		Huber	0.04	0.121	0.09012	0.0571	0.1298	0.1161	0.5537
		Bi-Square	0.041	0.132	0.09173	0.0535	0.1285	0.1108	0.5580
	N=100	OLS	0.021	0.076	0.053928	0.0247	0.0665	0.0706	0.3131
		FGLS	0.021	0.076	0.05617	0.0242	0.068	0.069	0.3146
		Huber	0.019	0.071	0.05518	0.0203	0.0618	0.0583	0.2852
		Bi-Square	0.019	0.075	0.05638	0.0204	0.0645	0.0565	0.2911
	N=250	OLS	0.01	0.021	0.02637	0.0075	0.0195	0.0182	0.1030
		FGLS	0.01	0.021	0.02652	0.0075	0.0198	0.0183	0.1032
		Huber	0.009	0.02	0.02255	0.0067	0.0208	0.0157	0.0941
		Bi-Square	0.009	0.021	0.02341	0.0076	0.0238	0.0159	0.1011
	N=500	OLS	0.005	0.013	0.01318	0.0046	0.0114	0.0098	0.0563
		FGLS	0.005	0.013	0.01314	0.0046	0.0114	0.0098	0.0564
		Huber	0.004	0.012	0.011103	0.0036	0.0112	0.0086	0.0508
		Bi-Square	0.004	0.013	0.011259	0.0037	0.0117	0.0084	0.0525

TABLE 4.2.4 A: VARIANCE: When Errors are Normal , Linear Heteroscedastic (Q=1) and No contemporaneous correlation (P=0) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.23	0.421	0.41097	0.2171	0.41	0.4581	2.1474
		FGLS	0.252	0.446	0.4384	0.2169	0.4014	0.4722	2.2260
		Huber	0.24	0.439	0.46688	0.2126	0.4314	0.4445	2.2336
		Bi-Square	0.244	0.464	0.47088	0.2207	0.4551	0.4694	2.3241
	N=30	OLS	0.152	0.333	0.23715	0.0969	0.2409	0.2713	1.3313
		FGLS	0.162	0.34	0.24215	0.1057	0.2569	0.29	1.3961
		Huber	0.142	0.326	0.24311	0.1066	0.2742	0.2912	1.3834
		Bi-Square	0.144	0.334	0.25896	0.1112	0.2853	0.2945	1.4278
	N=50	OLS	0.071	0.165	0.15752	0.0879	0.1788	0.1643	0.8241
		FGLS	0.073	0.166	0.15857	0.0885	0.1879	0.1658	0.8395
		Huber	0.065	0.158	0.13557	0.0897	0.1801	0.1673	0.7951
		Bi-Square	0.066	0.166	0.13499	0.0871	0.1793	0.1628	0.7958
	N=100	OLS	0.032	0.097	0.0763	0.0367	0.0882	0.0918	0.4225
		FGLS	0.032	0.097	0.07867	0.0363	0.0899	0.0894	0.4232
		Huber	0.031	0.097	0.081211	0.0357	0.0896	0.0848	0.4197
		Bi-Square	0.032	0.1	0.08038	0.0358	0.0916	0.0828	0.4223
	N=250	OLS	0.016	0.027	0.03587	0.0127	0.0269	0.0261	0.1454
		FGLS	0.016	0.027	0.03583	0.0127	0.0271	0.0262	0.1452
		Huber	0.016	0.027	0.034291	0.0129	0.0303	0.0245	0.1455
		Bi-Square	0.016	0.028	0.035168	0.0136	0.0321	0.0245	0.1497
	N=500	OLS	0.006	0.016	0.01706	0.0069	0.015	0.0136	0.0749
		FGLS	0.006	0.016	0.01703	0.0069	0.015	0.0136	0.0749
		Huber	0.006	0.017	0.01632	0.0064	0.0151	0.0132	0.0740
		Bi-Square	0.006	0.017	0.01634	0.0063	0.0154	0.0128	0.0743

TABLE 4.2.5 A: VARIANCE: When Errors are Normal , Square Root Heteroscedastic(g=0.5) and No contemporaneous correlation under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.296	0.505	0.49452	0.2824	0.4854	0.5551	2.6192
		FGLS	0.326	0.538	0.53326	0.2811	0.4704	0.5695	2.7184
		Huber	0.313	0.535	0.56776	0.2906	0.5353	0.5457	2.7882
		Bi-Square	0.314	0.557	0.56834	0.2973	0.5436	0.5684	2.8491
	N=30	OLS	0.199	0.4	0.28704	0.1263	0.2816	0.3302	1.6241
		FGLS	0.211	0.407	0.29362	0.1357	0.2979	0.3566	1.7018
		Huber	0.196	0.406	0.29744	0.147	0.3216	0.3658	1.7333
		Bi-Square	0.195	0.409	0.31217	0.1531	0.3271	0.3721	1.7692
	N=50	OLS	0.092	0.194	0.19244	0.1096	0.2101	0.1933	0.9921
		FGLS	0.095	0.196	0.19411	0.1093	0.2199	0.1945	1.0083
		Huber	0.089	0.187	0.17237	0.1182	0.2199	0.2047	0.9913
		Bi-Square	0.09	0.194	0.17187	0.1177	0.2232	0.2014	0.9978
	N=100	OLS	0.044	0.115	0.09501	0.0483	0.1063	0.1077	0.5162
		FGLS	0.044	0.114	0.09722	0.0479	0.1081	0.1048	0.5160
		Huber	0.044	0.119	0.1004	0.0495	0.1113	0.1027	0.5271
		Bi-Square	0.045	0.122	0.09891	0.0496	0.1128	0.1013	0.5298
	N=250	OLS	0.022	0.033	0.04347	0.0179	0.0335	0.0326	0.1830
		FGLS	0.022	0.033	0.043288	0.0179	0.0335	0.0327	0.1824
		Huber	0.023	0.034	0.04313	0.0191	0.0382	0.0319	0.1889
		Bi-Square	0.023	0.034	0.043977	0.0194	0.0392	0.0312	0.1906
	N=500	OLS	0.008	0.019	0.02015	0.009	0.018	0.0166	0.0910
		FGLS	0.008	0.019	0.02012	0.009	0.018	0.0166	0.0910
		Huber	0.008	0.02	0.02	0.0089	0.0183	0.0164	0.0918
		Bi-Square	0.009	0.02	0.02004	0.0087	0.0185	0.0161	0.0918

TABLE 4.2.6 A: VARIANCE: When Errors are Normal , Homoscedastic and contemporaneous correlation (P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.477	0.728	0.75166	0.4874	0.781	0.5258	3.7504
		FGLS	0.489	0.732	0.77528	0.4927	0.7719	0.6082	3.8687
		Huber	0.523	0.751	0.86829	0.5207	0.8348	0.584	4.0822
		Bi-Square	0.525	0.78	0.88093	0.562	0.8725	0.6431	4.2636
	N=30	OLS	0.304	0.349	0.44613	0.3089	0.4883	0.4827	2.3791
		FGLS	0.305	0.347	0.442296	0.318	0.4893	0.481	2.3822
		Huber	0.306	0.396	0.46018	0.3439	0.5204	0.4935	2.5195
		Bi-Square	0.317	0.405	0.48116	0.3471	0.5195	0.5117	2.5810
	N=50	OLS	0.162	0.246	0.26547	0.1476	0.2581	0.2559	1.3354
		FGLS	0.16	0.217	0.27933	0.1459	0.2454	0.2493	1.2975
		Huber	0.157	0.247	0.258797	0.1484	0.2557	0.2777	1.3451
		Bi-Square	0.154	0.252	0.25979	0.1498	0.2598	0.2763	1.3520
	N=100	OLS	0.072	0.126	0.1293	0.06	0.0983	0.1265	0.6116
		FGLS	0.068	0.123	0.12756	0.0544	0.0997	0.1197	0.5929
		Huber	0.071	0.134	0.12389	0.0614	0.1058	0.1234	0.6200
		Bi-Square	0.072	0.134	0.12685	0.0619	0.1067	0.1256	0.6268
	N=250	OLS	0.027	0.045	0.04788	0.0279	0.0424	0.059	0.2491
		FGLS	0.026	0.046	0.046388	0.0263	0.0394	0.0566	0.2408
		Huber	0.029	0.051	0.05042	0.0303	0.0452	0.0613	0.2676
		Bi-Square	0.029	0.051	0.05026	0.0299	0.0449	0.0614	0.2663
	N=500	OLS	0.012	0.02	0.02008	0.0155	0.0202	0.0285	0.1155
		FGLS	0.011	0.02	0.01888	0.0147	0.0185	0.0267	0.1107
		Huber	0.013	0.022	0.021508	0.0167	0.022	0.0285	0.1234
		Bi-Square	0.013	0.022	0.02134	0.0162	0.0216	0.0286	0.1228

TABLE 4.2.7A: VARIANCE: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	2.21	3.819	3.88168	2.0604	3.8348	2.6365	18.4415
		FGLS	2.316	3.847	4.08768	2.1032	3.8051	3.0852	19.2436
		Huber	2.26	3.727	4.36037	2.2151	4.1162	2.9551	19.6335
		Bi-Square	2.272	3.942	4.49129	2.3466	4.2658	3.1866	20.5039
	N=30	OLS	1.366	1.838	2.3208	1.3482	2.5045	2.4381	11.8164
		FGLS	1.446	1.878	2.39364	1.3733	2.437	2.4517	11.9798
		Huber	1.328	2.007	2.33956	1.4654	2.6485	2.4532	12.2417
		Bi-Square	1.38	2.07	2.49578	1.4283	2.603	2.4678	12.4453
	N=50	OLS	0.724	1.287	1.36349	0.6608	1.3479	1.2938	6.6769
		FGLS	0.722	1.137	1.43032	0.6441	1.2721	1.2592	6.4646
		Huber	0.673	1.295	1.28277	0.6438	1.2971	1.3878	6.5794
		Bi-Square	0.657	1.318	1.29522	0.6418	1.3143	1.3787	6.6048
	N=100	OLS	0.325	0.656	0.66642	0.26	0.4926	0.6429	3.0421
		FGLS	0.306	0.632	0.66418	0.232	0.4918	0.6136	2.9399
		Huber	0.31	0.68	0.62038	0.2603	0.5396	0.6155	3.0260
		Bi-Square	0.319	0.692	0.64259	0.2606	0.5508	0.6297	3.0943
	N=250	OLS	0.119	0.237	0.25211	0.1253	0.2149	0.3001	1.2489
		FGLS	0.117	0.241	0.24424	0.1183	0.2003	0.291	1.2123
		Huber	0.122	0.263	0.24451	0.1316	0.2291	0.3075	1.2977
		Bi-Square	0.119	0.265	0.24482	0.1302	0.2287	0.314	1.3013
	N=500	OLS	0.053	0.11	0.10253	0.0661	0.1089	0.1378	0.5781
		FGLS	0.051	0.114	0.09663	0.0625	0.1012	0.1288	0.5541
		Huber	0.052	0.116	0.1065	0.0711	0.1175	0.1392	0.6024
		Bi-Square	0.052	0.119	0.10623	0.0703	0.1167	0.1403	0.6038

TABLE 4.2.8A: VARIANCE: When Errors are Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2[E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.185	0.377	0.36571	0.1486	0.3461	0.2427	1.6649
		FGLS	0.199	0.379	0.39212	0.1544	0.3438	0.2862	1.7546
		Huber	0.168	0.33	0.38224	0.1509	0.3551	0.2431	1.6291
		Bi-Square	0.172	0.373	0.40138	0.1701	0.3916	0.2915	1.7997
	N=30	OLS	0.112	0.189	0.22182	0.1031	0.2397	0.2217	1.0867
		FGLS	0.126	0.198	0.238	0.1024	0.2244	0.2251	1.1140
		Huber	0.095	0.186	0.20678	0.0988	0.2379	0.2001	1.0243
		Bi-Square	0.102	0.218	0.22366	0.0974	0.242	0.2024	1.0855
	N=50	OLS	0.058	0.128	0.12672	0.053	0.1308	0.1186	0.6153
		FGLS	0.059	0.116	0.1313	0.0507	0.1226	0.116	0.5952
		Huber	0.047	0.124	0.10903	0.0456	0.115	0.1184	0.5594
		Bi-Square	0.046	0.131	0.11178	0.0454	0.1179	0.12	0.5721
	N=100	OLS	0.027	0.064	0.06336	0.0201	0.0459	0.0589	0.2797
		FGLS	0.025	0.061	0.06387	0.0177	0.0444	0.0571	0.2696
		Huber	0.022	0.062	0.05109	0.0176	0.0484	0.0517	0.2529
		Bi-Square	0.023	0.067	0.05284	0.0179	0.0545	0.0518	0.2673
	N=250	OLS	0.01	0.023	0.02445	0.0102	0.0206	0.0275	0.1160
		FGLS	0.01	0.024	0.02369	0.0098	0.0195	0.0271	0.1135
		Huber	0.008	0.024	0.02001	0.0095	0.0209	0.026	0.1083
		Bi-Square	0.008	0.026	0.01969	0.0099	0.0226	0.0276	0.1141
	N=500	OLS	0.004	0.012	0.00969	0.0049	0.0112	0.0117	0.0537
		FGLS	0.004	0.012	0.00922	0.0045	0.0107	0.0109	0.0517
		Huber	0.003	0.011	0.0091	0.0047	0.0113	0.0109	0.0504
		Bi-Square	0.003	0.012	0.00899	0.0049	0.0119	0.0111	0.0521

TABLE 4.2.9A: VARIANCE: When Errors are Normal , Linear Heteroscedastic and Contemporal Correlation(P=0.2) under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.273	0.488	0.49797	0.248	0.4825	0.3367	2.3264
		FGLS	0.288	0.491	0.52683	0.2542	0.4796	0.3947	2.4350
		Huber	0.271	0.467	0.54973	0.2654	0.5166	0.3759	2.4457
		Bi-Square	0.275	0.5	0.57176	0.2826	0.5379	0.4079	2.5750
	N=30	OLS	0.168	0.235	0.29876	0.1632	0.319	0.3101	1.4940
		FGLS	0.18	0.242	0.31047	0.1657	0.308	0.3123	1.5184
		Huber	0.16	0.254	0.29791	0.1731	0.332	0.3063	1.5235
		Bi-Square	0.167	0.266	0.31855	0.169	0.3288	0.3083	1.5577
	N=50	OLS	0.089	0.165	0.17494	0.0807	0.172	0.1654	0.8470
		FGLS	0.089	0.146	0.183414	0.0783	0.162	0.1609	0.8198
		Huber	0.081	0.165	0.16248	0.0772	0.1629	0.1758	0.8241
		Bi-Square	0.079	0.169	0.16456	0.0769	0.1656	0.1753	0.8299
	N=100	OLS	0.04	0.084	0.08551	0.0313	0.0624	0.082	0.3847
		FGLS	0.037	0.081	0.08537	0.0279	0.0621	0.0785	0.3717
		Huber	0.037	0.086	0.07817	0.0309	0.0678	0.0779	0.3780
		Bi-Square	0.038	0.088	0.08132	0.0308	0.07	0.0796	0.3876
	N=250	OLS	0.014	0.03	0.03244	0.0153	0.0273	0.0383	0.1580
		FGLS	0.014	0.031	0.03146	0.0145	0.0255	0.0372	0.1536
		Huber	0.014	0.033	0.03068	0.0158	0.029	0.0389	0.1618
		Bi-Square	0.014	0.034	0.03074	0.0157	0.0291	0.0399	0.1630
	N=500	OLS	0.006	0.014	0.01308	0.0079	0.0141	0.0173	0.0731
		FGLS	0.006	0.015	0.01235	0.0075	0.0132	0.0162	0.0702
		Huber	0.006	0.015	0.01358	0.0084	0.015	0.0174	0.0753
		Bi-Square	0.006	0.015	0.01344	0.0084	0.015	0.0176	0.0757

TABLE 4.2.10A: VARIANCE: When Errors are Normal , Square Root Heteroscedastic($g=0.5$) and Contemporal Correlation(P=0.2) under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.2	N=20	OLS	0.354	0.584	0.60325	0.3411	0.6014	0.4138	2.8972
		FGLS	0.368	0.588	0.63111	0.3472	0.5966	0.4826	3.0136
		Huber	0.371	0.585	0.68735	0.3673	0.6476	0.4633	3.1216
		Bi-Square	0.371	0.61	0.79285	0.388	0.6633	0.502	3.3269
	N=30	OLS	0.221	0.28	0.35997	0.2198	0.3869	0.3814	1.8484
		FGLS	0.229	0.283	0.36569	0.2251	0.3807	0.3823	1.8655
		Huber	0.218	0.312	0.36582	0.2415	0.4126	0.3868	1.9368
		Bi-Square	0.226	0.318	0.38708	0.2388	0.4067	0.3958	1.9716
	N=50	OLS	0.117	0.197	0.21271	0.1068	0.2069	0.203	1.0441
		FGLS	0.117	0.174	0.22368	0.1046	0.1956	0.1974	1.0121
		Huber	0.111	0.199	0.20308	0.1056	0.2017	0.2197	1.0398
		Bi-Square	0.109	0.202	0.20502	0.1055	0.204	0.2179	1.0427
	N=100	OLS	0.052	0.101	0.10349	0.0423	0.0767	0.1005	0.4756
		FGLS	0.049	0.098	0.10274	0.038	0.0773	0.0956	0.4603
		Huber	0.051	0.106	0.09816	0.0431	0.084	0.0977	0.4793
		Bi-Square	0.052	0.106	0.100948	0.0429	0.0845	0.0995	0.4856
	N=250	OLS	0.019	0.036	0.03884	0.0202	0.0333	0.0469	0.1945
		FGLS	0.019	0.037	0.03765	0.019	0.031	0.0452	0.1885
		Huber	0.02	0.041	0.03914	0.0214	0.0356	0.0483	0.2054
		Bi-Square	0.02	0.04	0.03912	0.0212	0.0353	0.0491	0.2049
	N=500	OLS	0.008	0.016	0.01593	0.0108	0.0165	0.0219	0.0901
		FGLS	0.008	0.017	0.015	0.0103	0.0153	0.0205	0.0863
		Huber	0.009	0.018	0.016839	0.0117	0.0178	0.0222	0.0952
		Bi-Square	0.009	0.018	0.01683	0.0115	0.0177	0.0223	0.0951

TABLE 4.2.11A: VARIANCE: When Errors are Normal , Homoscedastic and contemporal correlation (P=0.5) under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.477	0.728	0.75166	0.5164	0.8834	0.549	3.9050
		FGLS	0.456	0.642	0.67953	0.4513	0.7479	0.538	3.5150
		Huber	0.523	0.751	0.86829	0.5548	0.9294	0.5799	4.2069
		Bi-Square	0.526	0.78	0.88093	0.602	1.0143	0.615	4.4183
	N=30	OLS	0.304	0.349	0.44613	0.2873	0.4815	0.4369	2.3049
		FGLS	0.276	0.32	0.37949	0.2841	0.4378	0.4161	2.1136
		Huber	0.306	0.396	0.46018	0.324	0.5361	0.4485	2.4703
		Bi-Square	0.317	0.405	0.48116	0.3248	0.5328	0.4536	2.5140
	N=50	OLS	0.162	0.246	0.26547	0.1313	0.2399	0.2499	1.2948
		FGLS	0.142	0.177	0.25057	0.1187	0.1908	0.2101	1.0898
		Huber	0.157	0.247	0.258797	0.1316	0.2269	0.2758	1.2976
		Bi-Square	0.154	0.252	0.25979	0.1351	0.2269	0.2772	1.3053
	N=100	OLS	0.072	0.126	0.1293	0.0618	0.1041	0.1214	0.6141
		FGLS	0.058	0.104	0.11503	0.0475	0.0898	0.0979	0.5118
		Huber	0.071	0.134	0.12389	0.0646	0.1117	0.1247	0.6303
		Bi-Square	0.072	0.134	0.12685	0.0648	0.1136	0.1236	0.6346
	N=250	OLS	0.027	0.045	0.04788	0.0279	0.0398	0.0609	0.2485
		FGLS	0.022	0.042	0.04048	0.0225	0.0317	0.0512	0.2099
		Huber	0.029	0.051	0.05042	0.0298	0.045	0.0636	0.2693
		Bi-Square	0.029	0.051	0.05026	0.0296	0.0438	0.0638	0.2673
	N=500	OLS	0.012	0.02	0.02008	0.0159	0.0228	0.0274	0.1175
		FGLS	0.01	0.018	0.01655	0.0138	0.0174	0.0231	0.0993
		Huber	0.013	0.022	0.02151	0.0175	0.0248	0.0287	0.1272
		Bi-Square	0.013	0.022	0.02134	0.0174	0.0246	0.0286	0.1270

TABLE 4.2.12A: VARIANCE: When Errors are Normal , Exponential Heteroscedastic and Contemporal Correlation(P=0.5) under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	2.21	3.819	3.88168	2.187	4.3599	2.7293	19.1860
		FGLS	2.184	3.382	3.67387	1.9232	3.8009	2.7259	17.6900
		Huber	2.26	3.727	4.36037	2.3882	4.5736	2.8466	20.1554
		Bi-Square	2.272	3.942	4.49129	2.5315	4.6757	3.1627	21.0749
	N=30	OLS	1.366	1.838	2.3208	1.249	2.4955	2.2161	11.4862
		FGLS	1.317	1.737	2.08162	1.2044	2.166	2.1289	10.6346
		Huber	1.328	2.007	2.33956	1.3699	2.7482	2.1933	11.9860
		Bi-Square	1.38	2.07	2.49578	1.3682	2.7534	2.2234	12.2911
	N=50	OLS	0.724	1.287	1.36349	0.5921	1.2835	1.2435	6.4936
		FGLS	0.645	0.939	1.28676	0.5227	1.0139	1.0555	5.4629
		Huber	0.673	1.295	1.28278	0.5864	1.1665	1.3782	6.3819
		Bi-Square	0.657	1.318	1.29522	0.5758	1.126	1.3818	6.3538
	N=100	OLS	0.325	0.656	0.66642	0.2716	0.5468	0.6158	3.0809
		FGLS	0.26	0.532	0.60158	0.2063	0.4656	0.5081	2.5740
		Huber	0.31	0.68	0.62038	0.2733	0.5699	0.6231	3.0768
		Bi-Square	0.319	0.692	0.6426	0.2744	0.5939	0.6212	3.1427
	N=250	OLS	0.119	0.237	0.25211	0.127	0.2056	0.313	1.2542
		FGLS	0.102	0.22	0.21319	0.1031	0.1669	0.2696	1.0747
		Huber	0.122	0.263	0.24451	0.1312	0.232	0.3228	1.3155
		Bi-Square	0.119	0.265	0.24482	0.1294	0.2272	0.3256	1.3105
	N=500	OLS	0.053	0.11	0.10254	0.0678	0.1195	0.1336	0.5862
		FGLS	0.045	0.103	0.08419	0.0575	0.0935	0.112	0.4952
		Huber	0.052	0.116	0.10649	0.0737	0.1282	0.1411	0.6176
		Bi-Square	0.052	0.119	0.10622	0.0751	0.1305	0.1417	0.6238

TABLE 4.2.13A: VARIANCE: When Errors are Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.185	0.377	0.36571	0.1595	0.3953	0.2504	1.7328
		FGLS	0.193	0.339	0.36745	0.1453	0.3607	0.2582	1.6636
		Huber	0.168	0.33	0.38224	0.1687	0.383	0.2462	1.6779
		Bi-Square	0.172	0.373	0.40138	0.1822	0.4004	0.2911	1.8202
	N=30	OLS	0.112	0.189	0.22182	0.0961	0.2423	0.2041	1.0646
		FGLS	0.117	0.187	0.21329	0.0879	0.2001	0.1981	1.0034
		Huber	0.095	0.186	0.20678	0.0927	0.2458	0.1837	1.0098
		Bi-Square	0.102	0.218	0.22366	0.094	0.2673	0.1775	1.0825
	N=50	OLS	0.058	0.128	0.12672	0.0484	0.1282	0.1119	0.6016
		FGLS	0.054	0.1	0.119708	0.042	0.1023	0.0987	0.5166
		Huber	0.047	0.124	0.10903	0.0403	0.102	0.1121	0.5348
		Bi-Square	0.046	0.131	0.111775	0.0409	0.0991	0.1216	0.5504
	N=100	OLS	0.027	0.064	0.063364	0.0215	0.054	0.0564	0.2868
		FGLS	0.022	0.053	0.05883	0.0166	0.0454	0.0487	0.2444
		Huber	0.022	0.062	0.05109	0.0186	0.0531	0.0506	0.2575
		Bi-Square	0.023	0.067	0.052838	0.0193	0.0584	0.0519	0.2727
	N=250	OLS	0.01	0.023	0.02445	0.0107	0.0203	0.0291	0.1177
		FGLS	0.009	0.022	0.021009	0.0092	0.0176	0.0263	0.1048
		Huber	0.008	0.024	0.020006	0.0095	0.0217	0.0272	0.1102
		Bi-Square	0.008	0.026	0.019694	0.0097	0.0232	0.0285	0.1154
	N=500	OLS	0.004	0.012	0.009692	0.005	0.012	0.0114	0.0542
		FGLS	0.004	0.011	0.008102	0.0042	0.0099	0.0097	0.0469
		Huber	0.003	0.011	0.00911	0.005	0.012	0.0114	0.0521
		Bi-Square	0.003	0.012	0.00899	0.0054	0.0129	0.0117	0.0541

TABLE 4.2.14A: VARIANCE: When Errors are Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.273	0.488	0.49797	0.2639	0.5493	0.3488	2.4212
		FGLS	0.273	0.433	0.476876	0.233	0.4833	0.35	2.2491
		Huber	0.271	0.467	0.549727	0.2874	0.5706	0.3596	2.5055
		Bi-Square	0.275	0.5	0.57176	0.304	0.5792	0.4056	2.6355
	N=30	OLS	0.168	0.235	0.298758	0.1511	0.3186	0.2822	1.4537
		FGLS	0.164	0.224	0.271176	0.1446	0.2737	0.2711	1.3494
		Huber	0.16	0.254	0.29791	0.1623	0.3472	0.2757	1.4973
		Bi-Square	0.167	0.266	0.31855	0.1626	0.3504	0.2785	1.5430
	N=50	OLS	0.089	0.165	0.174937	0.1749	0.0725	0.1585	0.8348
		FGLS	0.08	0.122	0.165198	0.0636	0.1302	0.1348	0.6953
		Huber	0.081	0.165	0.16248	0.0704	0.1467	0.174	0.7993
		Bi-Square	0.079	0.169	0.16456	0.0689	0.1416	0.1756	0.7983
	N=100	OLS	0.04	0.084	0.08551	0.0329	0.07	0.0784	0.3904
		FGLS	0.032	0.068	0.07751	0.025	0.0597	0.0652	0.3271
		Huber	0.037	0.086	0.07817	0.0324	0.0719	0.0785	0.3843
		Bi-Square	0.038	0.088	0.081324	0.0326	0.0757	0.0786	0.3941
	N=250	OLS	0.014	0.03	0.032443	0.0156	0.0262	0.04	0.1589
		FGLS	0.012	0.028	0.027526	0.0127	0.0215	0.0347	0.1370
		Huber	0.014	0.033	0.03068	0.0158	0.0294	0.0409	0.1642
		Bi-Square	0.014	0.034	0.030736	0.0155	0.0291	0.0413	0.1644
	N=500	OLS	0.006	0.014	0.01308	0.0081	0.0153	0.0168	0.0741
		FGLS	0.005	0.013	0.01077	0.0069	0.0121	0.0141	0.0628
		Huber	0.006	0.015	0.013528	0.0087	0.0162	0.0177	0.0771
		Bi-Square	0.006	0.015	0.01344	0.0089	0.0167	0.0178	0.0782

TABLE 4.2.15A: VARIANCE: When Errors are Normal , Square RooT Heteroscedastic(g=0.5) and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.354	0.584	0.60325	0.362	0.6828	0.4304	3.0160
		FGLS	0.345	0.516	0.56129	0.3173	0.5888	0.4266	2.7555
		Huber	0.371	0.585	0.68735	0.3947	0.7197	0.4557	3.2136
		Bi-Square	0.371	0.61	0.70285	0.4173	0.7461	0.4781	3.3252
	N=30	OLS	0.221	0.28	0.35997	0.2038	0.3841	0.3458	1.7940
		FGLS	0.208	0.261	0.31595	0.1988	0.3392	0.3308	1.6536
		Huber	0.218	0.312	0.36582	0.2274	0.4267	0.3482	1.8983
		Bi-Square	0.226	0.318	0.38708	0.2254	0.4224	0.3532	1.9313
	N=50	OLS	0.117	0.197	0.21271	0.0954	0.1956	0.1962	1.0147
		FGLS	0.104	0.143	0.20082	0.0848	0.1546	0.1653	0.8523
		Huber	0.111	0.199	0.20308	0.0959	0.1816	0.2188	1.0091
		Bi-Square	0.109	0.202	0.20502	0.0949	0.1767	0.2182	1.0052
	N=100	OLS	0.052	0.101	0.10349	0.044	0.0837	0.0962	0.4800
		FGLS	0.042	0.082	0.09285	0.0336	0.0718	0.0786	0.4004
		Huber	0.051	0.106	0.09816	0.0452	0.088	0.099	0.4867
		Bi-Square	0.052	0.106	0.10095	0.045	0.0907	0.098	0.4924
	N=250	OLS	0.019	0.036	0.038836	0.0203	0.0316	0.0487	0.1947
		FGLS	0.016	0.033	0.03285	0.0164	0.0254	0.0415	0.1658
		Huber	0.02	0.041	0.03914	0.0213	0.0356	0.0506	0.2076
		Bi-Square	0.02	0.04	0.03912	0.021	0.0348	0.051	0.2062
	N=500	OLS	0.008	0.016	0.01593	0.0111	0.0183	0.0212	0.0914
		FGLS	0.007	0.015	0.013096	0.0095	0.0142	0.0178	0.0772
		Huber	0.009	0.018	0.01684	0.0122	0.0198	0.0224	0.0977
		Bi-Square	0.009	0.018	0.01682	0.0123	0.0198	0.0224	0.0981

TABLE 4.2.16A: VARIANCE: When Errors are Normal , Homoscedastic and contemporaneous correlation (P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.477	0.728	0.751655	0.5172	0.8131	0.6843	3.9709
		FGLS	0.39	0.659	0.568135	0.3776	0.5404	0.5178	3.0539
		Huber	0.523	0.751	0.86829	0.5719	0.8788	0.7345	4.3279
		Bi-Square	0.525	0.78	0.88093	0.6566	0.9315	0.886	4.6601
	N=30	OLS	0.304	0.349	0.446127	0.2619	0.425	0.45	2.2360
		FGLS	0.263	0.296	0.34448	0.2131	0.3641	0.3507	1.8313
		Huber	0.306	0.396	0.46018	0.2829	0.4243	0.4808	2.3498
		Bi-Square	0.317	0.405	0.48116	0.2915	0.4416	0.4841	2.4199
	N=50	OLS	0.162	0.246	0.265469	0.153	0.2268	0.3409	1.3945
		FGLS	0.134	0.189	0.21803	0.1288	0.1993	0.2626	1.1322
		Huber	0.157	0.247	0.258797	0.1622	0.2401	0.3593	1.4249
		Bi-Square	0.154	0.252	0.259789	0.1638	0.2489	0.3593	1.4382
	N=100	OLS	0.072	0.126	0.1293	0.076	0.1349	0.1348	0.6725
		FGLS	0.06	0.093	0.11757	0.0588	0.1008	0.0912	0.5217
		Huber	0.071	0.134	0.123891	0.0782	0.1506	0.1374	0.6956
		Bi-Square	0.072	0.134	0.126846	0.0787	0.1502	0.1372	0.6987
	N=250	OLS	0.027	0.045	0.04788	0.0314	0.0531	0.0551	0.2594
		FGLS	0.023	0.039	0.041466	0.0256	0.0365	0.0443	0.2104
		Huber	0.029	0.051	0.05042	0.0324	0.0559	0.0611	0.2802
		Bi-Square	0.029	0.051	0.050261	0.0332	0.0576	0.0612	0.2821
	N=500	OLS	0.012	0.02	0.02008	0.0156	0.0269	0.0286	0.1225
		FGLS	0.01	0.022	0.01543	0.0115	0.018	0.0199	0.0976
		Huber	0.013	0.022	0.021508	0.0165	0.029	0.0304	0.1321
		Bi-Square	0.013	0.022	0.021343	0.0165	0.0289	0.0299	0.1315

TABLE 4.2.17A: VARIANCE: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: Var(Yi)= $\sigma^2 \text{Exp}[E(Yi)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	2.21	3.819	3.88168	2.2658	4.1471	3.4564	19.7791
		FGLS	1.828	3.529	2.94538	1.6262	2.7546	2.6613	15.3438
		Huber	2.26	3.727	4.36037	2.5278	4.4261	3.6394	20.9404
		Bi-Square	2.272	3.942	4.49129	2.8524	4.6956	4.3744	22.6274
	N=30	OLS	1.366	1.838	2.3208	1.2011	2.2347	2.3234	11.2847
		FGLS	1.188	1.518	1.87175	0.942	1.867	1.8394	9.2268
		Huber	1.328	2.007	2.339556	1.2449	2.2024	2.4606	11.5825
		Bi-Square	1.38	2.07	2.495781	1.2769	2.2838	2.4697	11.9765
	N=50	OLS	0.724	1.287	1.363489	0.7096	1.189	1.7715	7.0446
		FGLS	0.606	1.007	1.117879	0.5815	1.0109	1.382	5.7058
		Huber	0.673	1.295	1.282768	0.7124	1.2154	1.8429	7.0214
		Bi-Square	0.657	1.318	1.29522	0.722	1.2587	1.8416	7.0925
	N=100	OLS	0.325	0.656	0.66642	0.3504	0.7125	0.6955	3.4051
		FGLS	0.268	0.499	0.589225	0.2678	0.5458	0.483	2.6528
		Huber	0.31	0.68	0.620375	0.3338	0.7664	0.6817	3.3925
		Bi-Square	0.319	0.692	0.642597	0.3404	0.7624	0.6858	3.4419
	N=250	OLS	0.119	0.237	0.25211	0.1358	0.2803	0.2724	1.2971
		FGLS	0.105	0.209	0.221696	0.1076	0.1928	0.2193	1.0550
		Huber	0.122	0.263	0.244508	0.1392	0.2938	0.2984	1.3608
		Bi-Square	0.119	0.265	0.244817	0.1423	0.3071	0.3014	1.3792
	N=500	OLS	0.053	0.11	0.102536	0.0701	0.14	0.145	0.6202
		FGLS	0.045	0.124	0.079687	0.0518	0.0962	0.1015	0.4981
		Huber	0.052	0.116	0.106495	0.0717	0.1492	0.153	0.6485
		Bi-Square	0.052	0.119	0.106215	0.0718	0.1523	0.15	0.6506

TABLE 4.2.18A: VARIANCE: When Errors are Normal , Polynomial Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: Var(Yi)= $\sigma^2[E(Yi)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.7	N=20	OLS	0.185	0.377	0.365708	0.1772	0.3937	0.3241	1.8225
		FGLS	0.16	0.362	0.288849	0.1338	0.2819	0.2656	1.4930
		Huber	0.168	0.33	0.382238	0.1872	0.4077	0.3081	1.7829
		Bi-Square	0.172	0.373	0.401382	0.2122	0.3669	0.3669	1.8926
	N=30	OLS	0.112	0.189	0.221824	0.1014	0.225	0.2187	1.0673
		FGLS	0.099	0.155	0.193089	0.0794	0.1875	0.1839	0.8984
		Huber	0.095	0.186	0.206781	0.0902	0.2038	0.2142	0.9957
		Bi-Square	0.102	0.218	0.223657	0.0893	0.2127	0.2129	1.0585
	N=50	OLS	0.058	0.128	0.126724	0.0601	0.1182	0.1654	0.6568
		FGLS	0.05	0.106	0.105373	0.0494	0.1006	0.1346	0.5461
		Huber	0.047	0.124	0.10903	0.0534	0.1132	0.1602	0.6072
		Bi-Square	0.046	0.131	0.111775	0.0535	0.117	0.1612	0.6204
	N=100	OLS	0.027	0.064	0.063364	0.0292	0.0699	0.0652	0.3191
		FGLS	0.023	0.052	0.05541	0.0229	0.0568	0.0487	0.2586
		Huber	0.022	0.062	0.051093	0.0225	0.066	0.0572	0.2809
		Bi-Square	0.023	0.067	0.052838	0.0236	0.0696	0.0569	0.2931
	N=250	OLS	0.01	0.023	0.02445	0.0106	0.0278	0.0246	0.1206
		FGLS	0.009	0.022	0.022289	0.0084	0.0204	0.0204	0.1023
		Huber	0.008	0.024	0.020057	0.0096	0.0276	0.024	0.1131
		Bi-Square	0.008	0.026	0.019694	0.0099	0.0296	0.0254	0.1188
	N=500	OLS	0.004	0.012	0.009692	0.0055	0.0134	0.0131	0.0579
		FGLS	0.004	0.013	0.00794	0.0043	0.0099	0.0096	0.0484
		Huber	0.003	0.011	0.009107	0.005	0.0133	0.0128	0.0547
		Bi-Square	0.003	0.012	0.00899	0.0051	0.0146	0.0129	0.0568

TABLE 4.2.19A: VARIANCE: When Errors are Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.273	0.488	0.49797	0.2769	0.5286	0.4412	2.5058
		FGLS	0.228	0.454	0.380603	0.1986	0.3532	0.3417	1.9559
		Huber	0.271	0.467	0.549727	0.3043	0.5589	0.4574	2.6086
		Bi-Square	0.275	0.5	0.571758	0.3458	0.5954	0.5512	2.8390
	N=30	OLS	0.168	0.235	0.298758	0.1471	0.285	0.2978	1.4317
		FGLS	0.146	0.193	0.244215	0.115	0.2374	0.2381	1.1743
		Huber	0.16	0.254	0.297914	0.1506	0.2787	0.3154	1.4568
		Bi-Square	0.167	0.266	0.31855	0.1535	0.2886	0.3145	1.5083
	N=50	OLS	0.089	0.165	0.174937	0.0873	0.1523	0.227	0.8956
		FGLS	0.075	0.13	0.143615	0.0714	0.1288	0.1782	0.7272
		Huber	0.081	0.165	0.162483	0.0857	0.1546	0.2336	0.8821
		Bi-Square	0.079	0.169	0.16456	0.0871	0.1593	0.2343	0.8928
	N=100	OLS	0.04	0.084	0.085507	0.0429	0.0908	0.0891	0.4319
		FGLS	0.033	0.064	0.075194	0.0328	0.0701	0.0624	0.3377
		Huber	0.037	0.086	0.078171	0.0395	0.0961	0.0863	0.4233
		Bi-Square	0.038	0.088	0.081324	0.0404	0.0959	0.0866	0.4302
	N=250	OLS	0.014	0.03	0.032443	0.0164	0.0358	0.0347	0.1641
		FGLS	0.013	0.027	0.028642	0.013	0.0248	0.028	0.1340
		Huber	0.014	0.033	0.03068	0.0166	0.0372	0.0376	0.1694
		Bi-Square	0.014	0.034	0.030736	0.017	0.0392	0.0381	0.1727
	N=500	OLS	0.006	0.014	0.01308	0.0085	0.0177	0.0184	0.0785
		FGLS	0.006	0.016	0.010251	0.0063	0.0123	0.013	0.0634
		Huber	0.006	0.015	0.013528	0.0085	0.0188	0.0193	0.0811
		Bi-Square	0.006	0.015	0.013442	0.0085	0.0193	0.0189	0.0816

TABLE 4.2.20A: VARIANCE: When Errors are Normal , Square Root Heteroscedastic(g=0.5) and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.354	0.585	0.603253	0.3704	0.6432	0.5396	3.0948
		FGLS	0.291	0.536	0.457156	0.2659	0.4245	0.4109	2.3853
		Huber	0.371	0.585	0.687346	0.4096	0.6889	0.5768	3.3188
		Bi-Square	0.371	0.61	0.702846	0.4672	0.7295	0.692	3.5723
	N=30	OLS	0.117	0.197	0.21271	0.1129	0.1821	0.2749	1.0973
		FGLS	0.098	0.153	0.174238	0.0933	0.156	0.2131	0.8877
		Huber	0.111	0.199	0.203076	0.1158	0.1885	0.2891	1.1062
		Bi-Square	0.109	0.202	0.205016	0.1174	0.1959	0.2882	1.1168
	N=50	OLS	0.221	0.28	0.359969	0.1914	0.3401	0.361	1.7527
		FGLS	0.191	0.232	0.285366	0.1521	0.2863	0.2836	1.4311
		Huber	0.218	0.312	0.365822	0.2028	0.3389	0.3839	1.8215
		Bi-Square	0.226	0.318	0.387075	0.2083	0.3513	0.3873	1.8772
	N=100	OLS	0.052	0.101	0.10349	0.0558	0.1086	0.1082	0.5286
		FGLS	0.043	0.076	0.092207	0.0426	0.0821	0.074	0.4098
		Huber	0.051	0.106	0.098164	0.055	0.1192	0.1083	0.5371
		Bi-Square	0.052	0.106	0.100948	0.0555	0.1179	0.1084	0.5404
	N=250	OLS	0.019	0.036	0.038836	0.0222	0.0427	0.0431	0.2021
		FGLS	0.017	0.032	0.033881	0.0177	0.0292	0.0345	0.1638
		Huber	0.02	0.041	0.039139	0.0229	0.0451	0.0475	0.2156
		Bi-Square	0.02	0.04	0.039116	0.0234	0.0468	0.0478	0.2174
	N=500	OLS	0.008	0.016	0.01593	0.0112	0.0215	0.0226	0.0961
		FGLS	0.007	0.019	0.012309	0.0083	0.0145	0.0158	0.0769
		Huber	0.009	0.018	0.016839	0.0117	0.0231	0.0241	0.1022
		Bi-Square	0.009	0.018	0.016826	0.0117	0.0232	0.0236	0.1021

TABLE 4.2.21A: VARIANCE: When Errors are Normal , Homoscedastic and contemporal correlation (P=0.95) under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.358	0.642	0.599879	0.5164	0.8834	0.549	3.5482
		FGLS	0.096	0.113	0.088998	0.13	0.1464	0.1218	0.6964
		Huber	0.417	0.71	0.62115	0.5548	0.9294	0.5799	3.8122
		Bi-Square	0.44	0.742	0.655398	0.602	1.0143	0.615	4.0684
	N=30	OLS	0.259	0.407	0.507124	0.2873	0.4815	0.4369	2.3788
		FGLS	0.073	0.059	0.066885	0.0621	0.0568	0.0547	0.3727
		Huber	0.274	0.449	0.540741	0.324	0.5361	0.4485	2.5722
		Bi-Square	0.275	0.445	0.546753	0.3247	0.5328	0.4536	2.5783
	N=50	OLS	0.119	0.224	0.241515	0.1313	0.2399	0.2499	1.2053
		FGLS	0.034	0.025	0.034124	0.0295	0.0315	0.037	0.1908
		Huber	0.123	0.245	0.259583	0.1316	0.2269	0.2757	1.2623
		Bi-Square	0.123	0.248	0.258251	0.1351	0.2269	0.2772	1.2682
	N=100	OLS	0.047	0.102	0.097512	0.0618	0.1041	0.1214	0.5344
		FGLS	0.014	0.012	0.013603	0.0133	0.0135	0.0142	0.0808
		Huber	0.053	0.106	0.101831	0.0646	0.1117	0.1247	0.5610
		Bi-Square	0.051	0.103	0.099987	0.0648	0.1136	0.1236	0.5567
	N=250	OLS	0.024	0.357	0.047601	0.0279	0.0398	0.0609	0.5581
		FGLS	0.007	0.007	0.00473	0.0067	0.0042	0.0056	0.0347
		Huber	0.025	0.036	0.049178	0.0298	0.045	0.0636	0.2492
		Bi-Square	0.025	0.036	0.049848	0.0295	0.0438	0.0638	0.2484
	N=500	OLS	0.013	0.022	0.02162	0.0159	0.0228	0.0274	0.1222
		FGLS	0.003	0.003	0.002111	0.0029	0.0024	0.0017	0.0151
		Huber	0.013	0.022	0.023955	0.0175	0.0247	0.0287	0.1296
		Bi-Square	0.013	0.021	0.024173	0.0174	0.0246	0.0286	0.1291

TABLE 4.2.22A: VARIANCE: When Errors are Normal , Exponential Heteroscedastic and Contemporal Correlation(P=0.95) under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	1.652	3.572	2.98122	2.187	4.3599	2.7293	17.4820
		FGLS	0.387	0.809	0.542867	0.5123	0.9034	0.697	3.8515
		Huber	1.949	3.804	3.246362	2.3882	4.5736	2.8466	18.8078
		Bi-Square	2.047	3.934	3.384313	2.5315	4.6757	3.1627	19.7347
	N=30	OLS	1.14	2.119	2.568231	1.249	2.4955	2.2161	11.7877
		FGLS	0.301	0.388	0.365976	0.2395	0.3658	0.3606	2.0208
		Huber	1.145	2.296	2.656983	1.3699	2.7482	2.1933	12.4088
		Bi-Square	1.166	2.288	2.691397	1.3682	2.7534	2.2234	12.4910
	N=50	OLS	0.536	1.189	1.246222	0.5921	1.2835	1.2435	6.0897
		FGLS	0.128	0.176	0.199967	0.1215	0.2115	0.2387	1.0756
		Huber	0.531	1.304	1.275398	0.5864	1.1665	1.3782	6.2419
		Bi-Square	0.534	1.346	1.285405	0.5758	1.126	1.3818	6.2488
	N=100	OLS	0.221	0.542	0.505158	0.2716	0.5468	0.6158	2.7025
		FGLS	0.064	0.074	0.083624	0.0523	0.0946	0.0802	0.4485
		Huber	0.231	0.553	0.501789	0.2732	0.5699	0.623	2.7526
		Bi-Square	0.23	0.552	0.508275	0.2744	0.5939	0.6212	2.7799
	N=250	OLS	0.102	0.186	0.243653	0.127	0.2056	0.313	1.1773
		FGLS	0.024	0.045	0.03393	0.0288	0.0319	0.04	0.2036
		Huber	0.102	0.192	0.242809	0.1312	0.232	0.3228	1.2227
		Bi-Square	0.104	0.192	0.249793	0.1294	0.2272	0.3256	1.2279
	N=500	OLS	0.056	0.116	0.113248	0.0678	0.1195	0.1336	0.6066
		FGLS	0.014	0.02	0.01469	0.0109	0.0169	0.012	0.0876
		Huber	0.056	0.111	0.120028	0.0737	0.1282	0.1411	0.6303
		Bi-Square	0.057	0.111	0.122353	0.0751	0.1305	0.1417	0.6379

TABLE 4.2.23A: VARIANCE: When Errors are Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.142	0.379	0.275439	0.1595	0.3953	0.2504	1.6014
		FGLS	0.05	0.149	0.095796	0.056	0.1434	0.1092	0.6036
		Huber	0.157	0.364	0.298038	0.1687	0.383	0.2462	1.6163
		Bi-Square	0.167	0.364	0.322223	0.1822	0.4004	0.2911	1.7276
	N=30	OLS	0.089	0.208	0.230729	0.0961	0.2423	0.2041	1.0696
		FGLS	0.03	0.068	0.053153	0.0253	0.0659	0.0589	0.3008
		Huber	0.081	0.209	0.225711	0.0927	0.2458	0.1837	1.0386
		Bi-Square	0.081	0.232	0.21879	0.094	0.2673	0.1775	1.0707
	N=50	OLS	0.044	0.119	0.116832	0.0484	0.1282	0.1119	0.5685
		FGLS	0.013	0.036	0.029976	0.0149	0.0391	0.0387	0.1725
		Huber	0.038	0.127	0.106552	0.0403	0.102	0.1121	0.5263
		Bi-Square	0.042	0.143	0.111408	0.0409	0.0991	0.1216	0.5573
	N=100	OLS	0.02	0.054	0.048536	0.0215	0.054	0.0564	0.2546
		FGLS	0.008	0.014	0.014694	0.0058	0.0167	0.0136	0.0734
		Huber	0.017	0.053	0.041679	0.0186	0.0531	0.0506	0.2335
		Bi-Square	0.018	0.056	0.044565	0.0193	0.0584	0.0519	0.2484
	N=250	OLS	0.008	0.019	0.023139	0.0107	0.0203	0.0291	0.1102
		FGLS	0.003	0.008	0.007119	0.0035	0.007	0.0069	0.0360
		Huber	0.007	0.018	0.020762	0.0095	0.0217	0.0272	0.1044
		Bi-Square	0.007	0.021	0.021602	0.0097	0.0202	0.0285	0.1081
	N=500	OLS	0.005	0.011	0.011032	0.005	0.012	0.0114	0.0555
		FGLS	0.002	0.003	0.003026	0.0014	0.0038	0.0025	0.0159
		Huber	0.004	0.01	0.010035	0.005	0.012	0.0114	0.0523
		Bi-Square	0.004	0.01	0.010301	0.0054	0.0129	0.0117	0.0545

TABLE 4.2.24A: VARIANCE: When Errors are Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.204	0.463	0.37836	0.2639	0.5493	0.3488	2.2071
		FGLS	0.049	0.114	0.076408	0.0638	0.1247	0.0968	0.5256
		Huber	0.24	0.487	0.415477	0.2874	0.5706	0.3596	2.3599
		Bi-Square	0.25	0.5	0.432601	0.304	0.5792	0.4056	2.4712
	N=30	OLS	0.138	0.271	0.327804	0.1511	0.3186	0.2822	1.4888
		FGLS	0.037	0.054	0.049717	0.0296	0.0515	0.0509	0.2734
		Huber	0.137	0.29	0.336395	0.1623	0.3472	0.2757	1.5491
		Bi-Square	0.139	0.292	0.338836	0.1626	0.3504	0.2785	1.5608
	N=50	OLS	0.065	0.153	0.159627	0.0725	0.1651	0.1585	0.7737
		FGLS	0.016	0.025	0.027492	0.0156	0.0302	0.0334	0.1480
		Huber	0.063	0.166	0.161015	0.0704	0.1467	0.174	0.7818
		Bi-Square	0.064	0.174	0.163174	0.0689	0.1416	0.1756	0.7872
	N=100	OLS	0.027	0.07	0.064854	0.0329	0.07	0.0784	0.3432
		FGLS	0.008	0.011	0.011882	0.0067	0.0134	0.011	0.0620
		Huber	0.028	0.071	0.06317	0.0324	0.0719	0.0785	0.3443
		Bi-Square	0.028	0.071	0.064618	0.0326	0.0757	0.0786	0.3503
	N=250	OLS	0.012	0.024	0.031239	0.0156	0.0262	0.04	0.1491
		FGLS	0.003	0.006	0.005006	0.0037	0.0047	0.0056	0.0285
		Huber	0.012	0.025	0.030706	0.0158	0.0294	0.0409	0.1534
		Bi-Square	0.012	0.025	0.0317	0.0155	0.0291	0.0413	0.1547
	N=500	OLS	0.007	0.015	0.014542	0.0081	0.0153	0.0168	0.0765
		FGLS	0.002	0.003	0.002162	0.0014	0.0025	0.0018	0.0123
		Huber	0.007	0.014	0.015235	0.0087	0.0162	0.0177	0.0786
		Bi-Square	0.007	0.014	0.015542	0.0089	0.0167	0.0178	0.0799

TABLE 4.2.25A: VARIANCE: When Errors are Normal , Square Root Heteroscedastic(g=0.5) and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	<i>OLS</i>	0.263	0.535	0.467418	0.362	0.6828	0.4304	2.7407
		<i>FGLS</i>	0.063	0.105	0.075082	0.0836	0.1252	0.1004	0.5522
		<i>Huber</i>	0.311	0.58	0.50586	0.3947	0.7197	0.4557	2.9670
		<i>Bi-Square</i>	0.326	0.6	0.526795	0.4173	0.7461	0.4781	3.0947
	N=30	<i>OLS</i>	0.185	0.325	0.403267	0.2038	0.3841	0.3458	1.8478
		<i>FGLS</i>	0.049	0.053	0.053663	0.0396	0.0491	0.0497	0.2939
		<i>Huber</i>	0.189	0.354	0.422092	0.2274	0.4267	0.3482	1.9671
		<i>Bi-Square</i>	0.193	0.353	0.429759	0.2254	0.4224	0.3532	1.9771
	N=50	<i>OLS</i>	0.086	0.181	0.193626	0.0954	0.1956	0.1962	0.9480
		<i>FGLS</i>	0.022	0.022	0.028565	0.0198	0.0284	0.033	0.1536
		<i>Huber</i>	0.087	0.2	0.202188	0.0959	0.1816	0.2187	0.9854
		<i>Bi-Square</i>	0.087	0.203	0.203299	0.0949	0.1767	0.2182	0.9829
	N=100	<i>OLS</i>	0.035	0.083	0.078213	0.044	0.0837	0.0962	0.4198
		<i>FGLS</i>	0.01	0.01	0.011572	0.0087	0.0125	0.0113	0.0642
		<i>Huber</i>	0.038	0.085	0.079604	0.0452	0.088	0.099	0.4350
		<i>Bi-Square</i>	0.037	0.084	0.079679	0.045	0.0907	0.098	0.4342
	N=250	<i>OLS</i>	0.017	0.029	0.037929	0.0203	0.0316	0.0487	0.1838
		<i>FGLS</i>	0.004	0.006	0.004371	0.0046	0.004	0.0054	0.0284
		<i>Huber</i>	0.017	0.029	0.038448	0.0213	0.0356	0.0506	0.1923
		<i>Bi-Square</i>	0.017	0.029	0.039403	0.021	0.0348	0.051	0.1927
	N=500	<i>OLS</i>	0.009	0.018	0.017435	0.0111	0.0183	0.0212	0.0948
		<i>FGLS</i>	0.002	0.003	0.001922	0.0179	0.0021	0.0015	0.0281
		<i>Huber</i>	0.009	0.017	0.018937	0.0122	0.0197	0.0224	0.0998
		<i>Bi-Square</i>	0.009	0.017	0.019265	0.0123	0.0198	0.0224	0.1002

TABLE 4.2.1 B :Absolute Bias: When Errors are Normal , Homoscedastic and No contemporal correlation under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.4844	0.6514	0.6273	0.473	0.6161	0.6456	3.4978
		FGLS	0.4993	0.6712	0.6622	0.4734	0.5941	0.6561	3.5562
		Huber	0.5032	0.669	0.6562	0.4868	0.6424	0.6483	3.6058
		Bi-Square	0.5022	0.6804	0.6571	0.4942	0.6534	0.659	3.6461
	N=30	OLS	0.43	0.5377	0.4764	0.3574	0.4642	0.5114	2.7771
		FGLS	0.4317	0.5398	0.4731	0.3612	0.4753	0.5369	2.8181
		Huber	0.4431	0.5471	0.4792	0.3932	0.5004	0.5425	2.9055
		Bi-Square	0.442	0.5488	0.4901	0.4024	0.502	0.5502	2.9355
	N=50	OLS	0.2981	0.4014	0.4034	0.3012	0.4211	0.3667	2.1920
		FGLS	0.2989	0.4039	0.4076	0.3019	0.4242	0.3677	2.2041
		Huber	0.294	0.4031	0.3816	0.3245	0.4337	0.3769	2.2136
		Bi-Square	0.2974	0.407	0.3848	0.3293	0.4376	0.3799	2.2360
	N=100	OLS	0.1933	0.3058	0.2897	0.2071	0.2871	0.2864	1.5693
		FGLS	0.1938	0.3049	0.2889	0.2036	0.2921	0.2819	1.5653
		Huber	0.1984	0.3153	0.2902	0.2092	0.2887	0.2852	1.5869
		Bi-Square	0.2018	0.3192	0.2891	0.2069	0.2878	0.2851	1.5899
	N=250	OLS	0.1459	0.1588	0.188	0.13	0.1647	0.1597	0.9470
		FGLS	0.1442	0.1574	0.1872	0.1309	0.1655	0.1608	0.9460
		Huber	0.1479	0.1623	0.1861	0.1372	0.1827	0.1538	0.9699
		Bi-Square	0.1483	0.1626	0.187	0.1372	0.1818	0.1537	0.9706
	N=500	OLS	0.0856	0.1257	0.1291	0.088	0.124	0.1117	0.6641
		FGLS	0.0855	0.1259	0.1281	0.0878	0.1243	0.1116	0.6632
		Huber	0.089	0.126	0.1247	0.0872	0.1224	0.1131	0.6623
		Bi-Square	0.0889	0.1266	0.1254	0.0867	0.1223	0.1114	0.6613

TABLE 4.2.2 B: Absolute Bias: When Errors are Normal , Exponential Heteroscedastic and No contemporal correlation under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.0405	1.48	1.4258	0.992	1.4247	1.4849	7.8478
		FGLS	1.0755	1.5257	1.4905	0.9886	1.3883	1.4948	7.9634
		Huber	1.9608	3.4684	3.6627	1.761	3.4158	3.4806	17.7492
		Bi-Square	1.9835	3.6321	3.6791	1.8114	3.5348	3.6437	18.2845
	N=30	OLS	0.9192	1.2207	1.094	0.7507	1.0872	1.1532	6.2249
		FGLS	0.9228	1.2299	1.0875	0.7547	1.1101	1.2037	6.3088
		Huber	0.9076	1.221	1.0745	0.807	1.1808	1.2087	6.3996
		Bi-Square	0.9156	1.2353	1.1072	0.8099	1.1869	1.2212	6.4761
	N=50	OLS	0.6379	0.927	0.9013	0.6503	0.9737	0.8547	4.9449
		FGLS	0.6464	0.9348	0.9164	0.6574	0.9913	0.8602	5.0065
		Huber	0.6104	0.9217	0.835	0.6839	0.9865	0.8766	4.9141
		Bi-Square	0.6238	0.9469	0.8393	0.676	0.995	0.871	4.9518
	N=100	OLS	0.4051	0.699	0.6398	0.442	0.6594	0.6733	3.5186
		FGLS	0.407	0.6995	0.6399	0.435	0.672	0.6637	3.5172
		Huber	0.409	0.6917	0.6507	0.4369	0.6553	0.6479	3.4914
		Bi-Square	0.4135	0.7033	0.6479	0.4345	0.6595	0.6454	3.5040
	N=250	OLS	0.306	0.3637	0.4262	0.2615	0.3668	0.3515	2.0758
		FGLS	0.3045	0.3606	0.4258	0.2631	0.3682	0.3545	2.0767
		Huber	0.303	0.3712	0.4123	0.2684	0.4026	0.3407	2.0982
		Bi-Square	0.3047	0.3733	0.4154	0.2731	0.4117	0.3431	2.1213
	N=500	OLS	0.1817	0.2905	0.2948	0.1886	0.2816	0.2519	1.4891
		FGLS	0.1814	0.2906	0.2927	0.1883	0.2824	0.2519	1.4872
		Huber	0.1862	0.2955	0.2782	0.1825	0.2816	0.2549	1.4789
		Bi-Square	0.1864	0.2992	0.2789	0.1799	0.2806	0.2479	1.4730

TABLE 4.2.3 B: Absolute Bias: When Errors are Normal , Quadratic Heteroscedastic(Q=2) and No contemporaneous correlation(P=0) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.3082	0.4616	0.4397	0.2758	0.4469	0.4579	2.3901
		FGLS	0.3167	0.4715	0.4533	0.274	0.4432	0.4626	2.4212
		Huber	0.2981	0.457	0.4417	0.2547	0.427	0.4333	2.3117
		Bi-Square	0.307	0.4739	0.4653	0.2692	0.4577	0.452	2.4251
	N=30	OLS	0.2603	0.3864	0.337	0.2107	0.3455	0.344	1.8838
		FGLS	0.2644	0.3882	0.3351	0.2187	0.3517	0.3563	1.9144
		Huber	0.244	0.3668	0.3272	0.2108	0.3653	0.3433	1.8575
		Bi-Square	0.2427	0.3772	0.3307	0.2118	0.3872	0.3408	1.8904
	N=50	OLS	0.1852	0.2919	0.2746	0.1905	0.3034	0.269	1.5145
		FGLS	0.1898	0.2941	0.2793	0.1951	0.3145	0.2717	1.5446
		Huber	0.1647	0.2837	0.2421	0.1816	0.2932	0.2645	1.4297
		Bi-Square	0.1675	0.2956	0.2441	0.1748	0.2956	0.2599	1.4374
	N=100	OLS	0.1163	0.2197	0.1921	0.1253	0.2055	0.2137	1.0726
		FGLS	0.1163	0.2189	0.194	0.1243	0.2088	0.2116	1.0738
		Huber	0.1113	0.2078	0.1912	0.1133	0.1982	0.1906	1.0123
		Bi-Square	0.1138	0.2145	0.1928	0.1121	0.2017	0.1885	1.0235
	N=250	OLS	0.085	0.1154	0.1303	0.0673	0.1105	0.104	0.6124
		FGLS	0.0849	0.115	0.1307	0.068	0.1107	0.1047	0.6140
		Huber	0.0783	0.1138	0.1187	0.0639	0.118	0.098	0.5908
		Bi-Square	0.0791	0.1167	0.1219	0.0684	0.1272	0.1012	0.6145
	N=500	OLS	0.055	0.093	0.0902	0.0544	0.0869	0.0775	0.4571
		FGLS	0.0548	0.0931	0.0899	0.0544	0.0871	0.0776	0.4569
		Huber	0.0491	0.0912	0.0806	0.0485	0.0865	0.0736	0.4295
		Bi-Square	0.0503	0.0946	0.0819	0.0478	0.0869	0.0722	0.4337

TABLE 4.2.4 B: Absolute Bias: When Errors are Normal , Linear Heteroscedastic(Q=1) and No contemporaneous correlation(P=0) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.3648	0.5275	0.5088	0.3471	0.5104	0.5342	2.7927
		FGLS	0.3775	0.5439	0.5307	0.3444	0.4994	0.537	2.8328
		Huber	0.3789	0.541	0.5361	0.3399	0.5107	0.514	2.8207
		Bi-Square	0.3755	0.5547	0.5388	0.3446	0.5292	0.5357	2.8785
	N=30	OLS	0.3222	0.4359	0.3924	0.2621	0.391	0.4114	2.2150
		FGLS	0.3239	0.4392	0.3902	0.2649	0.3984	0.4288	2.2454
		Huber	0.3148	0.4316	0.3843	0.2782	0.4229	0.4295	2.2612
		Bi-Square	0.3171	0.4391	0.394	0.2783	0.4268	0.4328	2.2881
	N=50	OLS	0.2229	0.3315	0.322	0.2275	0.3471	0.3075	1.7586
		FGLS	0.2265	0.3343	0.327	0.2309	0.355	0.31	1.7837
		Huber	0.2121	0.3285	0.2962	0.2357	0.3499	0.3125	1.7349
		Bi-Square	0.2161	0.3382	0.2965	0.2327	0.3514	0.3115	1.7463
	N=100	OLS	0.1409	0.2505	0.2282	0.154	0.2354	0.2429	1.2518
		FGLS	0.1419	0.2505	0.2285	0.1518	0.2399	0.2397	1.2523
		Huber	0.1413	0.2452	0.232	0.1504	0.2326	0.231	1.2325
		Bi-Square	0.1429	0.2493	0.231	0.1499	0.235	0.2299	1.2380
	N=250	OLS	0.1066	0.1301	0.1529	0.09	0.1303	0.1254	0.7352
		FGLS	0.106	0.129	0.1528	0.0905	0.1307	0.1264	0.7354
		Huber	0.1048	0.1325	0.1468	0.091	0.1428	0.1205	0.7383
		Bi-Square	0.1053	0.1332	0.1478	0.0931	0.1465	0.1223	0.7482
	N=500	OLS	0.0636	0.1043	0.1055	0.0663	0.1003	0.0903	0.5303
		FGLS	0.0635	0.1043	0.1047	0.0662	0.1006	0.0903	0.5296
		Huber	0.0643	0.1059	0.0987	0.0633	0.1005	0.0908	0.5235
		Bi-Square	0.0645	0.1078	0.099	0.0623	0.1004	0.0884	0.5223

TABLE 4.2.5 B: Absolute Bias: When Errors are Normal , Square Root Heteroscedastic(g=0.5) and No contemporaneous correlation under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.4147	0.5821	0.5609	0.4008	0.5568	0.5833	3.0986
		FGLS	0.4291	0.5999	0.5885	0.4008	0.5399	0.5891	3.1472
		Huber	0.4362	0.6002	0.5925	0.4051	0.571	0.5737	3.1787
		Bi-Square	0.4278	0.6094	0.59	0.4062	0.5797	0.5895	3.2025
	N=30	OLS	0.3692	0.4787	0.4301	0.3028	0.4232	0.4564	2.4604
		FGLS	0.3693	0.4819	0.4264	0.3044	0.4327	0.4777	2.4923
		Huber	0.3709	0.4843	0.4268	0.3289	0.4594	0.4815	2.5518
		Bi-Square	0.3722	0.4872	0.4377	0.3321	0.4586	0.4873	2.5751
	N=50	OLS	0.2548	0.3616	0.3568	0.2589	0.3788	0.3329	1.9438
		FGLS	0.2573	0.3643	0.3628	0.2611	0.3847	0.335	1.9651
		Huber	0.2468	0.3605	0.3336	0.2756	0.3875	0.3435	1.9475
		Bi-Square	0.2513	0.3673	0.336	0.2745	0.3904	0.3425	1.9620
	N=100	OLS	0.1632	0.2746	0.2548	0.1763	0.2571	0.262	1.3881
		FGLS	0.1641	0.2745	0.2552	0.1736	0.2623	0.2576	1.3873
		Huber	0.1653	0.275	0.2588	0.176	0.2567	0.2554	1.3872
		Bi-Square	0.1676	0.2798	0.2574	0.175	0.2579	0.2552	1.3929
	N=250	OLS	0.1233	0.1421	0.1681	0.1073	0.1451	0.1405	0.8263
		FGLS	0.1225	0.1407	0.1676	0.108	0.146	0.1415	0.8262
		Huber	0.1231	0.1455	0.164	0.1115	0.1597	0.1359	0.8398
		Bi-Square	0.1238	0.1459	0.1655	0.1122	0.1618	0.1362	0.8454
	N=500	OLS	0.0726	0.1133	0.1161	0.0753	0.1104	0.0992	0.5870
		FGLS	0.0725	0.1135	0.1152	0.0752	0.1107	0.0992	0.5863
		Huber	0.075	0.115	0.1104	0.0737	0.1102	0.1014	0.5857
		Bi-Square	0.0749	0.1159	0.111	0.0729	0.1097	0.0991	0.5834

TABLE 4.2.6 B: Absolute Bias: When Errors are Normal , Homoscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.5451	0.6987	0.6814	0.5402	0.7473	0.5842	3.7969
		FGLS	0.5452	0.6951	0.677	0.5382	0.7432	0.6085	3.8072
		Huber	0.5803	0.7133	0.7317	0.5545	0.7575	0.6175	3.9547
		Bi-Square	0.5808	0.7256	0.7449	0.5736	0.7578	0.6283	4.0109
	N=30	OLS	0.431	0.4674	0.5216	0.4467	0.5573	0.5559	2.9798
		FGLS	0.4361	0.4656	0.53	0.4539	0.5556	0.549	2.9902
		Huber	0.4449	0.4888	0.5385	0.47	0.5746	0.5669	3.0836
		Bi-Square	0.4561	0.4971	0.5506	0.4743	0.5707	0.575	3.1238
	N=50	OLS	0.3162	0.3988	0.4212	0.3113	0.4147	0.4114	2.2736
		FGLS	0.32	0.3651	0.4253	0.3117	0.4064	0.4123	2.2407
		Huber	0.3125	0.4004	0.4064	0.3108	0.4119	0.4244	2.2663
		Bi-Square	0.3096	0.4086	0.4059	0.3123	0.4126	0.4252	2.2742
	N=100	OLS	0.2161	0.2789	0.2831	0.1875	0.2387	0.2669	1.4711
		FGLS	0.2103	0.276	0.28	0.1809	0.2474	0.2655	1.4601
		Huber	0.2135	0.2876	0.2812	0.19	0.2457	0.2655	1.4835
		Bi-Square	0.2145	0.2874	0.2857	0.1924	0.2464	0.2683	1.4948
	N=250	OLS	0.1329	0.1797	0.167	0.1296	0.168	0.2013	0.9785
		FGLS	0.1326	0.1826	0.1657	0.1261	0.1624	0.198	0.9673
		Huber	0.1394	0.1882	0.1753	0.1339	0.1731	0.2004	1.0102
		Bi-Square	0.1378	0.1876	0.1745	0.133	0.1728	0.2005	1.0063
	N=500	OLS	0.0877	0.1168	0.108	0.0973	0.117	0.1372	0.6640
		FGLS	0.0849	0.1191	0.1047	0.0955	0.1135	0.1326	0.6503
		Huber	0.0959	0.1236	0.1111	0.104	0.1211	0.1404	0.6961
		Bi-Square	0.0951	0.1248	0.1105	0.1023	0.1202	0.1401	0.6929

TABLE 4.2.7B: Absolute Bias: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.1872	1.6036	1.5324	1.115	1.6445	1.2983	8.3810
		FGLS	1.1953	1.5986	1.5424	1.0964	1.6558	1.3686	8.4570
		Huber	1.2174	1.5901	1.6506	1.147	1.6778	1.3696	8.6525
		Bi-Square	1.223	1.6363	1.6774	1.1619	1.686	1.3796	8.7642
	N=30	OLS	0.9153	1.1042	1.2159	0.9177	1.2759	1.2538	6.6829
		FGLS	0.9496	1.0979	1.2631	0.9318	1.2488	1.2479	6.7391
		Huber	0.9255	1.1117	1.2326	0.9542	1.3054	1.2864	6.8158
		Bi-Square	0.9539	1.1373	1.278	0.9512	1.2877	1.2916	6.8998
	N=50	OLS	0.6732	0.9063	0.9573	0.6703	0.942	0.9262	5.0754
		FGLS	0.6885	0.8544	0.9738	0.6687	0.918	0.9252	5.0285
		Huber	0.6403	0.9204	0.915	0.6556	0.9215	0.9477	5.0004
		Bi-Square	0.6299	0.9364	0.9176	0.6542	0.9216	0.9511	5.0107
	N=100	OLS	0.4628	0.6395	0.6436	0.3969	0.5396	0.6076	3.2900
		FGLS	0.4511	0.6309	0.6453	0.3745	0.5596	0.6065	3.2677
		Huber	0.4434	0.6473	0.6326	0.3887	0.558	0.5959	3.2659
		Bi-Square	0.4523	0.6497	0.6394	0.3891	0.5671	0.6064	3.3038
	N=250	OLS	0.2736	0.4101	0.3825	0.2735	0.3751	0.4501	2.1648
		FGLS	0.2735	0.4155	0.3776	0.2686	0.3643	0.4479	2.1473
		Huber	0.2773	0.422	0.382	0.276	0.3886	0.4479	2.1937
		Bi-Square	0.1187	0.2649	0.2448	0.1302	0.2287	0.314	1.3013
	N=500	OLS	0.1877	0.2773	0.248	0.2022	0.2728	0.2994	1.4872
		FGLS	0.1818	0.2815	0.2404	0.1957	0.2647	0.2863	1.4503
		Huber	0.1916	0.2839	0.2451	0.2155	0.2801	0.3094	1.5257
		Bi-Square	0.1905	0.2862	0.2456	0.2129	0.2785	0.311	1.5247

TABLE 4.2.8B: Absolute Bias: When Errors are Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.347	0.4975	0.4652	0.2992	0.4853	0.3937	2.4879
		FGLS	0.3592	0.4971	0.4795	0.2962	0.4937	0.4202	2.5458
		Huber	0.3267	0.4608	0.4872	0.2983	0.4811	0.3917	2.4458
		Bi-Square	0.3373	0.4886	0.5055	0.3024	0.4955	0.4112	2.5404
	N=30	OLS	0.2638	0.3564	0.3837	0.2494	0.3988	0.379	2.0311
		FGLS	0.28	0.3618	0.4028	0.2505	0.3819	0.3798	2.0567
		Huber	0.2475	0.3419	0.3693	0.2434	0.3903	0.3711	1.9635
		Bi-Square	0.2573	0.3633	0.3871	0.2458	0.3898	0.3748	2.0183
	N=50	OLS	0.1959	0.2892	0.29	0.1942	0.2908	0.2803	1.5404
		FGLS	0.1997	0.2767	0.2954	0.1904	0.2829	0.2782	1.5231
		Huber	0.1683	0.289	0.2681	0.1764	0.2716	0.2783	1.4517
		Bi-Square	0.167	0.2978	0.2681	0.1756	0.2745	0.2871	1.4701
	N=100	OLS	0.1343	0.2	0.2047	0.114	0.1669	0.1874	1.0074
		FGLS	0.1307	0.1989	0.2056	0.1052	0.1692	0.188	0.9976
		Huber	0.118	0.192	0.1829	0.1012	0.1721	0.1752	0.9413
		Bi-Square	0.12	0.2005	0.184	0.1029	0.1831	0.1781	0.9686
	N=250	OLS	0.0772	0.127	0.1211	0.0781	0.1154	0.1353	0.6540
		FGLS	0.0752	0.1276	0.1189	0.0781	0.1139	0.1356	0.6493
		Huber	0.0693	0.1247	0.107	0.0752	0.1168	0.1303	0.6233
		Bi-Square	0.0688	0.1289	0.1059	0.0767	0.1236	0.1344	0.6383
	N=500	OLS	0.0542	0.0894	0.0774	0.0558	0.0864	0.0859	0.4490
		FGLS	0.0529	0.0905	0.0763	0.053	0.0859	0.0818	0.4405
		Huber	0.0492	0.0877	0.0734	0.0556	0.0872	0.0855	0.4386
		Bi-Square	0.0475	0.0889	0.0723	0.057	0.09	0.0875	0.4431

TABLE 4.2.9B: Absolute Bias: When Errors are Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.4173	0.5715	0.5476	0.3853	0.5814	0.4645	2.9675
		FGLS	0.4219	0.5704	0.553	0.38	0.5872	0.4916	3.0040
		Huber	0.4216	0.561	0.5854	0.3964	0.5914	0.4866	3.0423
		Bi-Square	0.4267	0.5804	0.5981	0.4001	0.5968	0.492	3.0940
	N=30	OLS	0.3211	0.3964	0.4383	0.3179	0.4566	0.4475	2.3778
		FGLS	0.3348	0.3945	0.4567	0.3225	0.4456	0.4461	2.4002
		Huber	0.3208	0.3971	0.4412	0.3268	0.4637	0.4555	2.4050
		Bi-Square	0.3303	0.4079	0.4583	0.3256	0.4573	0.459	2.4383
	N=50	OLS	0.2369	0.3249	0.3427	0.2351	0.3347	0.3302	1.8044
		FGLS	0.2419	0.3082	0.3489	0.2341	0.326	0.3299	1.7888
		Huber	0.2214	0.3285	0.3264	0.2274	0.3261	0.3367	1.7664
		Bi-Square	0.2174	0.3341	0.3274	0.2266	0.3259	0.3393	1.7707
	N=100	OLS	0.1617	0.2282	0.231	0.1389	0.1924	0.218	1.1702
		FGLS	0.1573	0.2262	0.2327	0.1302	0.1993	0.2174	1.1630
		Huber	0.154	0.2291	0.2245	0.1343	0.1979	0.2119	1.1516
		Bi-Square	0.1568	0.2306	0.2272	0.1343	0.2029	0.2158	1.1676
	N=250	OLS	0.0949	0.1461	0.1376	0.0956	0.1337	0.1606	0.7684
		FGLS	0.0952	0.1479	0.1358	0.0942	0.1301	0.1601	0.7632
		Huber	0.0947	0.1494	0.1342	0.0955	0.1382	0.1593	0.7711
		Bi-Square	0.093	0.151	0.1332	0.0959	0.14	0.1615	0.7746
	N=500	OLS	0.0656	0.0997	0.0889	0.0702	0.0981	0.1057	0.5282
		FGLS	0.0636	0.1011	0.0862	0.0678	0.0956	0.1009	0.5152
		Huber	0.0657	0.1016	0.0876	0.0742	0.1003	0.1092	0.5385
		Bi-Square	0.0653	0.1025	0.0877	0.0735	0.0997	0.1101	0.5388

TABLE 4.2.10B: Absolute Bias: When Errors are Normal , Square Root Heteroscedastic($g=0.5$) and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.2	N=20	OLS	0.473	0.6258	0.6043	0.452	0.6534	0.5146	3.3230
		FGLS	0.475	0.6236	0.6071	0.4459	0.6546	0.5394	3.3456
		Huber	0.4923	0.6298	0.6534	0.4664	0.6676	0.545	3.4545
		Bi-Square	0.4917	0.6456	0.663	0.4741	0.6655	0.5485	3.4883
	N=30	OLS	0.3682	0.4264	0.4751	0.3726	0.4995	0.495	2.6368
		FGLS	0.378	0.4251	0.4897	0.3791	0.4917	0.4909	2.6545
		Huber	0.3747	0.4366	0.4856	0.3894	0.5142	0.5088	2.7092
		Bi-Square	0.3857	0.4441	0.501	0.3902	0.5089	0.5132	2.7430
	N=50	OLS	0.2704	0.3559	0.3774	0.2667	0.3696	0.3662	2.0062
		FGLS	0.276	0.3308	0.3833	0.2666	0.361	0.3656	1.9832
		Huber	0.2613	0.3601	0.363	0.2633	0.3646	0.3772	1.9894
		Bi-Square	0.258	0.3672	0.3639	0.2639	0.364	0.3776	1.9944
	N=100	OLS	0.1852	0.2505	0.2505	0.1586	0.2122	0.2389	1.2958
		FGLS	0.1801	0.2467	0.2524	0.151	0.2202	0.2385	1.2888
		Huber	0.1802	0.2548	0.2516	0.1582	0.2189	0.2364	1.3000
		Bi-Square	0.1822	0.2548	0.2541	0.1589	0.2206	0.24	1.3105
	N=250	OLS	0.1105	0.1608	0.1501	0.1096	0.1481	0.1786	0.8577
		FGLS	0.1103	0.1631	0.1485	0.1074	0.1439	0.1767	0.8500
		Huber	0.114	0.1671	0.1537	0.1117	0.1536	0.1777	0.8779
		Bi-Square	0.1118	0.1665	0.1523	0.1114	0.1533	0.1794	0.8746
	N=500	OLS	0.0751	0.1073	0.0972	0.0817	0.1059	0.1198	0.5870
		FGLS	0.0726	0.1091	0.0939	0.0795	0.1028	0.1149	0.5727
		Huber	0.0783	0.1113	0.0974	0.0874	0.1093	0.1239	0.6075
		Bi-Square	0.078	0.1123	0.0975	0.0861	0.1082	0.124	0.6061

TABLE 4.2.11B: Absolute Bias: When Errors are Normal , Homoscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.5451	0.6987	0.6814	0.5659	0.7695	0.6079	3.8685
		FGLS	0.5235	0.6418	0.6354	0.5207	0.7175	0.5712	3.6101
		Huber	0.5803	0.7133	0.7317	0.5866	0.7982	0.6145	4.0246
		Bi-Square	0.5808	0.7256	0.7449	0.601	0.8212	0.6247	4.0981
	N=30	OLS	0.431	0.4674	0.5216	0.4148	0.5652	0.5375	2.9374
		FGLS	0.4216	0.4558	0.5031	0.4175	0.5289	0.5184	2.8453
		Huber	0.4449	0.4888	0.5385	0.4344	0.6	0.5411	3.0476
		Bi-Square	0.4561	0.4971	0.5506	0.4358	0.5982	0.5482	3.0860
	N=50	OLS	0.3162	0.3988	0.4212	0.2894	0.3951	0.4053	2.2260
		FGLS	0.3035	0.3306	0.3977	0.2785	0.3572	0.3785	2.0459
		Huber	0.3125	0.4004	0.4064	0.2887	0.3795	0.4173	2.2047
		Bi-Square	0.3096	0.4086	0.4059	0.2943	0.3848	0.4234	2.2266
	N=100	OLS	0.2161	0.2789	0.2831	0.1955	0.2462	0.2713	1.4910
		FGLS	0.194	0.2534	0.2658	0.1661	0.2341	0.2436	1.3569
		Huber	0.2135	0.2876	0.2812	0.1966	0.2658	0.2736	1.5183
		Bi-Square	0.2145	0.2874	0.2857	0.198	0.2676	0.274	1.5272
	N=250	OLS	0.1329	0.1797	0.167	0.1302	0.1583	0.2042	0.9723
		FGLS	0.1252	0.1746	0.1557	0.1176	0.1444	0.1901	0.9075
		Huber	0.1394	0.1882	0.1753	0.1354	0.1667	0.2069	1.0119
		Bi-Square	0.1378	0.1876	0.1745	0.1351	0.1659	0.2073	1.0082
	N=500	OLS	0.0877	0.1168	0.108	0.1005	0.1222	0.1366	0.6719
		FGLS	0.0769	0.1123	0.0976	0.0913	0.1074	0.1235	0.6089
		Huber	0.0959	0.1236	0.1111	0.1069	0.128	0.1413	0.7069
		Bi-Square	0.0951	0.1248	0.1105	0.1066	0.1282	0.1408	0.7060

TABLE 4.2.12B: Absolute Bias: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	1.1872	1.6036	1.5324	1.1742	1.7051	1.3628	8.5653
		FGLS	1.1557	1.472	1.4803	1.0626	1.6135	1.285	8.0690
		Huber	1.2174	1.5901	1.6506	1.2174	1.7542	1.3579	8.7876
		Bi-Square	1.223	1.6363	1.6774	1.2452	1.7584	1.3971	8.9375
	N=30	OLS	0.9153	1.1042	1.2159	0.875	1.2917	1.2087	6.6109
		FGLS	0.9122	1.0686	1.2045	0.8688	1.1867	1.1733	6.4140
		Huber	0.9255	1.1117	1.2326	0.8981	1.3536	1.2124	6.7339
		Bi-Square	0.9539	1.1373	1.278	0.9	1.3615	1.2211	6.8519
	N=50	OLS	0.6732	0.9063	0.9573	0.6254	0.9019	0.9064	4.9705
		FGLS	0.6536	0.7833	0.9102	0.5925	0.8117	0.8514	4.6028
		Huber	0.6403	0.9204	0.915	0.6121	0.8554	0.9281	4.8713
		Bi-Square	0.6299	0.9364	0.9176	0.6073	0.8496	0.9385	4.8793
	N=100	OLS	0.4628	0.6395	0.6436	0.4124	0.559	0.6094	3.3267
		FGLS	0.4135	0.58	0.6164	0.3477	0.5354	0.5499	3.0429
		Huber	0.4434	0.6473	0.6326	0.4084	0.5946	0.6161	3.3424
		Bi-Square	0.4523	0.6497	0.6394	0.4107	0.6076	0.6183	3.3780
	N=250	OLS	0.2736	0.4101	0.3825	0.2778	0.3575	0.4631	2.1645
		FGLS	0.261	0.3963	0.3587	0.251	0.3307	0.4348	2.0324
		Huber	0.2773	0.422	0.382	0.2835	0.3789	0.4623	2.2060
		Bi-Square	0.2717	0.4247	0.3778	0.2821	0.3768	0.4647	2.1978
	N=500	OLS	0.1877	0.2773	0.248	0.2082	0.2772	0.3005	1.4989
		FGLS	0.1652	0.2665	0.2264	0.1858	0.254	0.2674	1.3654
		Huber	0.1916	0.2839	0.2451	0.2213	0.2913	0.3137	1.5470
		Bi-Square	0.1905	0.2862	0.2457	0.222	0.2945	0.3122	1.5510

TABLE 4.2.13B: Absolute Bias: When Errors are Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.347	0.4975	0.4652	0.3187	0.5091	0.4114	2.5490
		FGLS	0.3479	0.4728	0.4712	0.2907	0.4956	0.3946	2.4727
		Huber	0.3267	0.4608	0.4872	0.3223	0.4967	0.3954	2.4892
		Bi-Square	0.3373	0.4886	0.5055	0.3289	0.5035	0.4195	2.5832
	N=30	OLS	0.2638	0.3564	0.3837	0.2422	0.4076	0.3618	2.0155
		FGLS	0.2696	0.3556	0.3845	0.2341	0.3628	0.3535	1.9601
		Huber	0.2475	0.3419	0.3693	0.2391	0.4084	0.3537	1.9599
		Bi-Square	0.2573	0.3633	0.3871	0.2419	0.4242	0.347	2.0210
	N=50	OLS	0.1959	0.2892	0.29	0.1824	0.2824	0.2716	1.5115
		FGLS	0.1911	0.2574	0.2817	0.1715	0.2537	0.2583	1.4138
		Huber	0.1683	0.289	0.2681	0.1602	0.2528	0.2649	1.4034
		Bi-Square	0.167	0.2978	0.2681	0.16	0.2501	0.2804	1.4234
	N=100	OLS	0.1343	0.2	0.2047	0.1177	0.1771	0.1834	1.0172
		FGLS	0.1224	0.1851	0.197	0.1026	0.1672	0.1749	0.9491
		Huber	0.118	0.192	0.1829	0.107	0.1821	0.1768	0.9587
		Bi-Square	0.12	0.2005	0.184	0.1101	0.1946	0.1806	0.9898
	N=250	OLS	0.0772	0.1269	0.1211	0.079	0.1126	0.1402	0.6570
		FGLS	0.0746	0.1222	0.1126	0.0744	0.1061	0.1343	0.6243
		Huber	0.0693	0.1246	0.107	0.0762	0.115	0.1323	0.6244
		Bi-Square	0.0688	0.1289	0.1059	0.0772	0.1233	0.1355	0.6396
	N=500	OLS	0.0542	0.0894	0.0774	0.057	0.0873	0.0867	0.4520
		FGLS	0.0486	0.087	0.0732	0.0501	0.083	0.0779	0.4199
		Huber	0.0492	0.0877	0.0734	0.0576	0.0892	0.0877	0.4448
		Bi-Square	0.0475	0.0889	0.0723	0.0594	0.0925	0.088	0.4485

TABLE 4.2.14B: Absolute Bias: When Errors are Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.4173	0.5715	0.5476	0.4089	0.6048	0.4875	3.0375
		FGLS	0.4086	0.5273	0.5325	0.3664	0.5754	0.4605	2.8705
		Huber	0.4216	0.561	0.5854	0.4223	0.618	0.4822	3.0905
		Bi-Square	0.4267	0.5804	0.5981	0.4317	0.6171	0.497	3.1508
	N=30	OLS	0.321	0.3964	0.4383	0.305	0.4623	0.4301	2.3531
		FGLS	0.3203	0.3845	0.4358	0.3013	0.4233	0.4186	2.2837
		Huber	0.3207	0.3971	0.4412	0.3098	0.4822	0.4307	2.3816
		Bi-Square	0.3303	0.4079	0.4583	0.3111	0.4868	0.432	2.4264
	N=50	OLS	0.2369	0.3249	0.3427	0.2198	0.3232	0.3233	1.7707
		FGLS	0.2309	0.2832	0.3269	0.2074	0.2897	0.3043	1.6423
		Huber	0.2214	0.3285	0.3264	0.2121	0.3037	0.3299	1.7220
		Bi-Square	0.2174	0.3341	0.3274	0.21	0.301	0.334	1.7240
	N=100	OLS	0.1617	0.2282	0.231	0.1438	0.1991	0.2171	1.1809
		FGLS	0.1446	0.2077	0.2225	0.1218	0.1914	0.1972	1.0851
		Huber	0.154	0.2291	0.2245	0.1409	0.2108	0.2187	1.1780
		Bi-Square	0.1568	0.2306	0.2272	0.142	0.2169	0.2203	1.1939
	N=250	OLS	0.0949	0.1461	0.1376	0.0971	0.1277	0.1655	0.7688
		FGLS	0.0907	0.1412	0.129	0.088	0.1187	0.1558	0.7234
		Huber	0.0947	0.1494	0.1342	0.0979	0.1349	0.1641	0.7751
		Bi-Square	0.093	0.151	0.1332	0.0974	0.1353	0.1651	0.7751
	N=500	OLS	0.0656	0.0997	0.0889	0.0721	0.0991	0.1064	0.5318
		FGLS	0.0578	0.0962	0.0813	0.0642	0.0919	0.0948	0.4862
		Huber	0.0657	0.1016	0.0876	0.0763	0.1033	0.1108	0.5453
		Bi-Square	0.0652	0.1025	0.0877	0.0767	0.1049	0.1106	0.5477

TABLE 4.2.15B: Absolute Bias: When Errors are Normal , Square Root Heteroscedastic(g=0.5) and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0.5							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	0.3536	0.5841	0.6033	0.362	0.6828	0.4304	3.0160
		FGLS	0.3453	0.5162	0.5613	0.3173	0.5888	0.4266	2.7555
		Huber	0.3714	0.5847	0.6874	0.3947	0.7197	0.4557	3.2136
		Bi-Square	0.3706	0.6102	0.7029	0.4173	0.7461	0.4781	3.3252
	N=30	OLS	0.3682	0.4264	0.4751	0.3521	0.5061	0.4783	2.6062
		FGLS	0.3638	0.4132	0.4671	0.3509	0.4682	0.462	2.5252
		Huber	0.3747	0.4366	0.4856	0.3636	0.5325	0.4811	2.6742
		Bi-Square	0.3857	0.4441	0.501	0.3647	0.5326	0.4861	2.7142
	N=50	OLS	0.2704	0.3559	0.3774	0.2484	0.3539	0.3602	1.9661
		FGLS	0.2614	0.3025	0.3586	0.2359	0.3185	0.3361	1.8130
		Huber	0.2613	0.3601	0.363	0.2465	0.3378	0.3703	1.9389
		Bi-Square	0.258	0.3672	0.3639	0.2456	0.3366	0.3745	1.9457
	N=100	OLS	0.1852	0.2505	0.2524	0.1652	0.2198	0.2414	1.3145
		FGLS	0.1647	0.2267	0.24	0.139	0.2103	0.2165	1.1971
		Huber	0.1802	0.2548	0.2516	0.165	0.2344	0.2451	1.3311
		Bi-Square	0.1822	0.2548	0.2541	0.1654	0.2385	0.2448	1.3398
	N=250	OLS	0.1105	0.1608	0.1501	0.1111	0.1406	0.1828	0.8559
		FGLS	0.1052	0.1555	0.1406	0.1	0.1291	0.171	0.8014
		Huber	0.114	0.1671	0.1537	0.1145	0.1485	0.1837	0.8816
		Bi-Square	0.1118	0.1665	0.1523	0.1141	0.1474	0.1846	0.8766
	N=500	OLS	0.0751	0.1073	0.0972	0.0842	0.1089	0.1198	0.5925
		FGLS	0.0656	0.1032	0.0881	0.0758	0.0981	0.1069	0.5377
		Huber	0.0783	0.1113	0.0974	0.0896	0.1142	0.1252	0.6160
		Bi-Square	0.078	0.1123	0.0975	0.0897	0.1148	0.1246	0.6169

TABLE 4.2.16B: Absolute Bias: When Errors are Normal , Homoscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.5451	0.6986	0.6814	0.5695	0.7059	0.6348	3.8353
		FGLS	0.5038	0.6633	0.5973	0.4892	0.5733	0.5644	3.3913
		Huber	0.5803	0.7133	0.7317	0.592	0.7396	0.6741	4.0310
		Bi-Square	0.5808	0.7256	0.7449	0.6125	0.7625	0.7085	4.1347
	N=30	OLS	0.431	0.4674	0.5216	0.4039	0.5255	0.5489	2.8982
		FGLS	0.4117	0.4286	0.4859	0.3743	0.4891	0.4819	2.6715
		Huber	0.4449	0.4888	0.5385	0.426	0.5334	0.5591	2.9908
		Bi-Square	0.4561	0.4971	0.5506	0.431	0.5457	0.5622	3.0427
	N=50	OLS	0.3162	0.3988	0.4212	0.3117	0.3676	0.4617	2.2773
		FGLS	0.2926	0.3313	0.3744	0.279	0.3616	0.4051	2.0439
		Huber	0.3125	0.4004	0.4063	0.3167	0.3828	0.4778	2.2965
		Bi-Square	0.3096	0.4086	0.4059	0.3213	0.3859	0.4799	2.3111
	N=100	OLS	0.2161	0.2789	0.2831	0.2254	0.2947	0.2916	1.5897
		FGLS	0.1968	0.2473	0.2754	0.1944	0.2488	0.2542	1.4169
		Huber	0.2135	0.2876	0.2812	0.2285	0.315	0.2988	1.6246
		Bi-Square	0.2145	0.2873	0.2857	0.2298	0.3146	0.2973	1.6293
	N=250	OLS	0.1329	0.1797	0.167	0.1396	0.1807	0.1821	0.9820
		FGLS	0.1237	0.1662	0.1638	0.1223	0.1486	0.1616	0.8862
		Huber	0.1394	0.1882	0.1753	0.1462	0.1842	0.1927	1.0259
		Bi-Square	0.1378	0.1876	0.1745	0.1479	0.1867	0.1923	1.0269
	N=500	OLS	0.0877	0.1168	0.108	0.0999	0.1296	0.133	0.6750
		FGLS	0.0814	0.1248	0.0935	0.087	0.1116	0.1166	0.6148
		Huber	0.0959	0.1236	0.1111	0.1037	0.1359	0.1377	0.7079
		Bi-Square	0.0951	0.1248	0.1105	0.1036	0.1367	0.1376	0.7082

TABLE 4.2.17B: Absolute Bias: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	1.1872	1.6036	1.5324	1.1887	1.5799	1.4541	8.5458
		FGLS	1.0914	1.5153	1.3374	1.0053	1.321	1.3203	7.5908
		Huber	1.2174	1.5901	1.6506	1.235	1.6411	1.5166	8.8509
		Bi-Square	1.223	1.6363	1.6774	1.2739	1.6964	1.5971	9.1041
	N=30	OLS	0.9153	1.1042	1.2159	0.8593	1.1892	1.2449	6.5288
		FGLS	0.8736	0.9812	1.1325	0.7737	1.1038	1.0895	5.9543
		Huber	0.9255	1.1117	1.2326	0.8855	1.2144	1.2466	6.6163
		Bi-Square	0.9539	1.1373	1.278	0.8952	1.2393	1.2674	6.7712
	N=50	OLS	0.6732	0.9063	0.9573	0.6675	0.86	1.0531	5.1175
		FGLS	0.6153	0.7874	0.8407	0.6103	0.8177	0.9291	4.6005
		Huber	0.6403	0.9203	0.915	0.6654	0.8712	1.0864	5.0987
		Bi-Square	0.6299	0.9364	0.9176	0.6719	0.8813	1.0842	5.1213
	N=100	OLS	0.4628	0.6395	0.6436	0.4786	0.6748	0.6662	3.5656
		FGLS	0.4174	0.5719	0.6215	0.411	0.5774	0.5843	3.1834
		Huber	0.4434	0.6473	0.6326	0.4742	0.7099	0.6664	3.5736
		Bi-Square	0.4523	0.6497	0.6394	0.4798	0.7111	0.6659	3.5981
	N=250	OLS	0.2735	0.4101	0.3825	0.2893	0.4141	0.4078	2.1773
		FGLS	0.2615	0.385	0.3763	0.2548	0.342	0.3603	1.9799
		Huber	0.2773	0.422	0.382	0.3005	0.4201	0.4225	2.2243
		Bi-Square	0.2717	0.4247	0.3778	0.3025	0.4274	0.4249	2.2290
	N=500	OLS	0.1877	0.2773	0.2479	0.2111	0.2985	0.303	1.5255
		FGLS	0.173	0.2932	0.2168	0.1846	0.2573	0.2638	1.3887
		Huber	0.1916	0.2839	0.2451	0.2166	0.308	0.3115	1.5567
		Bi-Square	0.1905	0.2862	0.2456	0.2162	0.3139	0.3092	1.5615

TABLE 4.2.18B: Absolute Bias: When Errors are Normal , Polynomial Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.7	N=20	OLS	0.347	0.4975	0.4652	0.3217	0.4912	0.4529	2.5756
		FGLS	0.3217	0.4768	0.4127	0.2848	0.4361	0.418	2.3501
		Huber	0.3267	0.4608	0.4872	0.3279	0.502	0.4373	2.5419
		Bi-Square	0.3373	0.4886	0.5055	0.3418	0.5176	0.4616	2.6524
	N=30	OLS	0.2638	0.3564	0.3837	0.2431	0.3674	0.3799	1.9942
		FGLS	0.2446	0.3205	0.3643	0.2191	0.3405	0.3504	1.8395
		Huber	0.2475	0.3419	0.3693	0.2314	0.361	0.3658	1.9169
		Bi-Square	0.2573	0.3633	0.3871	0.2323	0.3698	0.3632	1.9732
	N=50	OLS	0.1959	0.2892	0.29	0.1969	0.278	0.3202	1.5703
		FGLS	0.1763	0.2671	0.253	0.1836	0.2593	0.2889	1.4283
		Huber	0.1683	0.289	0.2681	0.1825	0.2682	0.3196	1.4956
		Bi-Square	0.167	0.2978	0.2681	0.1808	0.2728	0.322	1.5085
	N=100	OLS	0.1343	0.2	0.2047	0.1339	0.2124	0.2051	1.0904
		FGLS	0.1221	0.1833	0.1951	0.1197	0.1908	0.1839	0.9948
		Huber	0.118	0.192	0.1829	0.1222	0.2083	0.1929	1.0161
		Bi-Square	0.12	0.2005	0.184	0.1252	0.2157	0.1891	1.0345
	N=250	OLS	0.0098	0.0234	0.0245	0.0106	0.0278	0.0246	0.1206
		FGLS	0.0091	0.0217	0.0223	0.0084	0.0204	0.0204	0.1023
		Huber	0.0079	0.0239	0.02	0.0096	0.0276	0.024	0.1130
		Bi-Square	0.0078	0.0265	0.0197	0.0099	0.0296	0.0254	0.1188
	N=500	OLS	0.0542	0.0891	0.0774	0.0601	0.0947	0.0927	0.4682
		FGLS	0.0499	0.092	0.0704	0.0538	0.0813	0.0819	0.4292
		Huber	0.0492	0.0877	0.0734	0.0574	0.0945	0.0906	0.4528
		Bi-Square	0.0475	0.0889	0.0723	0.0587	0.098	0.0915	0.4569

TABLE 4.2.19B: Absolute Bias: When Errors are Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.4173	0.5715	0.5476	0.4128	0.5641	0.5212	3.0345
		FGLS	0.3854	0.5411	0.4779	0.3508	0.4771	0.475	2.7073
		Huber	0.4216	0.561	0.5854	0.4269	0.5815	0.5379	3.1142
		Bi-Square	0.4267	0.5804	0.5981	0.4411	0.6031	0.5666	3.2159
	N=30	OLS	0.321	0.3964	0.4383	0.3006	0.4239	0.4448	2.3250
		FGLS	0.3052	0.3493	0.4105	0.2697	0.3931	0.3939	2.1217
		Huber	0.3207	0.3971	0.4412	0.3068	0.431	0.4438	2.3406
		Bi-Square	0.3303	0.4079	0.4583	0.3087	0.4391	0.4507	2.3950
	N=50	OLS	0.2369	0.3249	0.3427	0.2343	0.3092	0.3765	1.8245
		FGLS	0.2155	0.2865	0.3007	0.2153	0.291	0.3334	1.6424
		Huber	0.2214	0.3285	0.3264	0.2314	0.3104	0.3864	1.8045
		Bi-Square	0.2174	0.3341	0.3274	0.2327	0.3138	0.3866	1.8120
	N=100	OLS	0.167	0.2282	0.231	0.1667	0.2416	0.2387	1.2731
		FGLS	0.1465	0.2054	0.2218	0.1431	0.2081	0.2098	1.1346
		Huber	0.154	0.2291	0.2245	0.1631	0.2519	0.237	1.2595
		Bi-Square	0.1568	0.2306	0.2272	0.1651	0.2527	0.2362	1.2687
	N=250	OLS	0.0949	0.1461	0.1376	0.1002	0.1488	0.1458	0.7733
		FGLS	0.0914	0.1386	0.135	0.0891	0.1229	0.1294	0.7064
		Huber	0.0947	0.1494	0.1342	0.1034	0.1495	0.1495	0.7806
		Bi-Square	0.093	0.151	0.1332	0.1043	0.1524	0.1509	0.7849
	N=500	OLS	0.0656	0.0997	0.0889	0.0735	0.1069	0.1085	0.5430
		FGLS	0.0604	0.1051	0.0784	0.0648	0.0916	0.0947	0.4950
		Huber	0.0657	0.1016	0.0876	0.0748	0.1097	0.1109	0.5504
		Bi-Square	0.0652	0.1025	0.0877	0.0747	0.1117	0.1101	0.5520

TABLE 4.2.20 B: Absolute Bias: When Errors are Normal , Square Root Heteroscedastic($g=0.5$) and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.4729	0.6258	0.6043	0.4822	0.6234	0.5698	3.3784
		FGLS	0.4339	0.5921	0.5296	0.4089	0.5151	0.5149	2.9945
		Huber	0.4923	0.6298	0.6533	0.4991	0.6506	0.6012	3.5263
		Bi-Square	0.4917	0.6456	0.663	0.5155	0.6717	0.632	3.6194
	N=30	OLS	0.2703	0.3559	0.3774	0.2664	0.3324	0.4151	2.0176
		FGLS	0.2478	0.3028	0.3329	0.242	0.3204	0.3649	1.8108
		Huber	0.2613	0.3601	0.363	0.2676	0.3414	0.4291	2.0224
		Bi-Square	0.258	0.3672	0.3638	0.2714	0.3452	0.4288	2.0344
	N=50	OLS	0.3682	0.4264	0.4751	0.3447	0.4672	0.4916	2.5732
		FGLS	0.3522	0.3817	0.4413	0.313	0.4343	0.427	2.3495
		Huber	0.3747	0.4366	0.4856	0.359	0.477	0.4941	2.6269
		Bi-Square	0.3857	0.4441	0.501	0.3633	0.4862	0.5017	2.6819
	N=100	OLS	0.1851	0.2505	0.2524	0.1916	0.2637	0.2619	1.4054
		FGLS	0.1669	0.2234	0.245	0.1649	0.2231	0.2283	1.2515
		Huber	0.1802	0.2548	0.2516	0.192	0.2802	0.2648	1.4235
		Bi-Square	0.1821	0.2548	0.2541	0.1934	0.2792	0.2644	1.4281
	N=250	OLS	0.1105	0.1608	0.1501	0.1171	0.1611	0.1617	0.8614
		FGLS	0.105	0.1498	0.1476	0.1025	0.1329	0.143	0.7808
		Huber	0.114	0.1671	0.1537	0.1221	0.1645	0.1692	0.8906
		Bi-Square	0.1118	0.1665	0.1522	0.1233	0.1671	0.17	0.8909
	N=500	OLS	0.0751	0.1073	0.0972	0.0846	0.1162	0.1192	0.5995
		FGLS	0.0691	0.1139	0.0842	0.0735	0.1001	0.1039	0.5447
		Huber	0.0783	0.1113	0.0974	0.0875	0.1213	0.123	0.6188
		Bi-Square	0.078	0.1123	0.0975	0.0872	0.1228	0.1224	0.6202

TABLE 4.2.21B: Absolute Bias: When Errors are Normal , Homoscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.473	0.6407	0.6643	0.5659	0.7695	0.6079	3.7214
		FGLS	0.2398	0.2577	0.2369	0.2827	0.2991	0.2937	1.6098
		Huber	0.4981	0.6733	0.6714	0.5866	0.7982	0.6145	3.8421
		Bi-Square	0.5076	0.6834	0.6774	0.601	0.8212	0.6247	3.9153
	N=30	OLS	0.401	0.502	0.5447	0.4148	0.5652	0.5375	2.9651
		FGLS	0.2019	0.1932	0.2011	0.1916	0.1948	0.1922	1.1748
		Huber	0.4165	0.5199	0.5696	0.4343	0.6	0.5411	3.0815
		Bi-Square	0.4162	0.5216	0.5703	0.4358	0.5982	0.5482	3.0903
	N=50	OLS	0.2717	0.374	0.4005	0.2894	0.3951	0.4053	2.1359
		FGLS	0.1447	0.1246	0.144	0.1355	0.1377	0.148	0.8345
		Huber	0.2834	0.3837	0.4138	0.2887	0.3795	0.4173	2.1664
		Bi-Square	0.2819	0.3862	0.4132	0.2943	0.3848	0.4234	2.1837
	N=100	OLS	0.181	0.2618	0.2519	0.1955	0.2462	0.2713	1.4077
		FGLS	0.0929	0.0893	0.0966	0.0941	0.089	0.095	0.5569
		Huber	0.1902	0.2667	0.2532	0.1966	0.2658	0.2736	1.4462
		Bi-Square	0.1867	0.2639	0.251	0.198	0.2678	0.274	1.4414
	N=250	OLS	0.1289	0.1581	0.1744	0.1302	0.1583	0.2042	0.9541
		FGLS	0.0689	0.064	0.0566	0.067	0.0508	0.0608	0.3681
		Huber	0.1275	0.1586	0.1747	0.1354	0.1667	0.2069	0.9697
		Bi-Square	0.127	0.1585	0.1762	0.1351	0.1659	0.2073	0.9700
	N=500	OLS	0.0891	0.1207	0.1187	0.1005	0.1222	0.1366	0.6878
		FGLS	0.0428	0.0446	0.035	0.045	0.0395	0.0323	0.2390
		Huber	0.0927	0.1199	0.1235	0.1069	0.128	0.1413	0.7123
		Bi-Square	0.0922	0.1181	0.1245	0.1066	0.1282	0.1408	0.7104

TABLE 4.2.22B: Absolute Bias: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.9971	1.5086	1.458	1.1742	1.7051	1.3628	8.2059
		FGLS	0.4885	0.7146	0.5693	0.5792	0.7279	0.6738	3.7533
		Huber	1.0462	1.5344	1.525	1.2173	1.7542	1.3579	8.4351
		Bi-Square	1.07	1.5453	1.5183	1.2452	1.7584	1.3971	8.5344
	N=30	OLS	0.8332	1.144	1.2401	0.875	1.2917	1.2087	6.5928
		FGLS	0.4297	0.4994	0.4744	0.3889	0.5117	0.4865	2.7906
		Huber	0.8508	1.193	1.2871	0.8981	1.3536	1.2124	6.7950
		Bi-Square	0.8629	1.1919	1.2952	0.9	1.3615	1.2211	6.8327
	N=50	OLS	0.5827	0.8575	0.9041	0.6253	0.9019	0.9064	4.7779
		FGLS	0.2731	0.3362	0.3597	0.2928	0.358	0.3747	1.9944
		Huber	0.5874	0.8872	0.9079	0.6121	0.8554	0.9281	4.7781
		Bi-Square	0.5865	0.896	0.9081	0.6073	0.8496	0.9385	4.7860
	N=100	OLS	0.3844	0.5961	0.5779	0.4124	0.559	0.6094	3.1392
		FGLS	0.2108	0.2147	0.2303	0.188	0.2341	0.2279	1.3058
		Huber	0.3909	0.6062	0.5689	0.4084	0.5946	0.6161	3.1852
		Bi-Square	0.386	0.6028	0.564	0.4107	0.6076	0.6183	3.1896
	N=250	OLS	0.2521	0.3628	0.3883	0.2778	0.3575	0.4631	2.1016
		FGLS	0.124	0.1697	0.1448	0.1373	0.1444	0.1607	0.8809
		Huber	0.2492	0.368	0.3823	0.2835	0.3789	0.4623	2.1242
		Bi-Square	0.2506	0.3674	0.3893	0.2821	0.3768	0.4647	2.1308
	N=500	OLS	0.1869	0.2796	0.2691	0.2082	0.2772	0.3005	1.5216
		FGLS	0.0909	0.1135	0.0924	0.0862	0.1061	0.0848	0.5739
		Huber	0.1891	0.2727	0.2745	0.2213	0.2913	0.3137	1.5626
		Bi-Square	0.19	0.272	0.2781	0.222	0.2945	0.3122	1.5688

TABLE 4.2.23B: Absolute Bias: When Errors are Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.2888	0.4919	0.4308	0.3187	0.5091	0.4114	2.4506
		FGLS	0.1734	0.3135	0.2399	0.1893	0.2961	0.265	1.4772
		Huber	0.2893	0.4648	0.451	0.3223	0.4967	0.3954	2.4195
		Bi-Square	0.2937	0.456	0.4621	0.3288	0.5035	0.4195	2.4636
	N=30	OLS	0.2294	0.3579	0.3765	0.2422	0.4076	0.3618	1.9754
		FGLS	0.1364	0.2073	0.1733	0.1275	0.2097	0.1923	1.0465
		Huber	0.2306	0.362	0.3797	0.2391	0.4084	0.3537	1.9735
		Bi-Square	0.2286	0.3774	0.3727	0.2419	0.4242	0.347	1.9918
	N=50	OLS	0.173	0.2713	0.2752	0.1824	0.2824	0.2716	1.4559
		FGLS	0.0939	0.1579	0.141	0.1046	0.1578	0.1532	0.8084
		Huber	0.1579	0.279	0.2585	0.1602	0.2528	0.2649	1.3734
		Bi-Square	0.1582	0.2895	0.262	0.16	0.2501	0.2804	1.4002
	N=100	OLS	0.1141	0.1839	0.1825	0.1177	0.1771	0.1834	0.9587
		FGLS	0.0694	0.0924	0.0964	0.062	0.099	0.0913	0.5106
		Huber	0.103	0.1854	0.1636	0.107	0.1821	0.1767	0.9179
		Bi-Square	0.1039	0.1917	0.1648	0.1101	0.1946	0.1806	0.9457
	N=250	OLS	0.0656	0.1148	0.1161	0.079	0.1126	0.1402	0.6282
		FGLS	0.003	0.0084	0.0071	0.0035	0.007	0.0069	0.0360
		Huber	0.062	0.1136	0.1111	0.0762	0.115	0.1323	0.6101
		Bi-Square	0.0648	0.118	0.114	0.0772	0.1133	0.1355	0.6228
	N=500	OLS	0.053	0.0884	0.0832	0.057	0.0873	0.0867	0.4556
		FGLS	0.0018	0.0034	0.003	0.0014	0.0038	0.0025	0.0159
		Huber	0.0039	0.0099	0.01	0.005	0.012	0.0114	0.0523
		Bi-Square	0.004	0.0103	0.0103	0.0054	0.0129	0.0117	0.0545

TABLE 4.2.24B: Absolute Bias: When Errors are Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.3487	0.5432	0.5181	0.4089	0.6048	0.4875	2.9112
		FGLS	0.1732	0.2716	0.2125	0.2039	0.2722	0.2509	1.3842
		Huber	0.3664	0.5463	0.545	0.4223	0.618	0.4822	2.9802
		Bi-Square	0.3711	0.5454	0.5417	0.4317	0.6171	0.0122	2.5190
	N=30	OLS	0.2886	0.409	0.4439	0.305	0.4623	0.4301	2.3390
		FGLS	0.1529	0.1872	0.1729	0.1375	0.1914	0.182	1.0238
		Huber	0.2935	0.4244	0.4586	0.3098	0.4822	0.4307	2.3991
		Bi-Square	0.2975	0.4256	0.461	0.3111	0.4868	0.432	2.4140
	N=50	OLS	0.2053	0.308	0.322	0.2199	0.3232	0.3233	1.7016
		FGLS	0.0981	0.1298	0.1336	0.1049	0.1356	0.1399	0.7420
		Huber	0.2029	0.3166	0.3207	0.2121	0.3037	0.3299	1.6860
		Bi-Square	0.2031	0.3214	0.3213	0.21	0.301	0.334	1.6908
	N=100	OLS	0.1345	0.2126	0.2075	0.1438	0.1991	0.2171	1.1147
		FGLS	0.0759	0.0813	0.0868	0.0675	0.088	0.0842	0.4838
		Huber	0.1345	0.2161	0.2015	0.1409	0.2108	0.2187	1.1225
		Bi-Square	0.1332	0.2151	0.2008	0.142	0.2169	0.2203	1.1283
	N=250	OLS	0.086	0.1301	0.1384	0.0971	0.1277	0.1655	0.7448
		FGLS	0.0432	0.0639	0.055	0.0487	0.0557	0.0605	0.3271
		Huber	0.0845	0.1316	0.1358	0.0979	0.1349	0.1641	0.7487
		Bi-Square	0.0855	0.1316	0.1385	0.0974	0.1353	0.1651	0.7534
	N=500	OLS	0.065	0.1002	0.0966	0.0721	0.0991	0.1064	0.5393
		FGLS	0.0416	0.052	0.0463	0.0367	0.0499	0.0424	0.2688
		Huber	0.0648	0.0968	0.098	0.0763	0.1033	0.1108	0.5500
		Bi-Square	0.0654	0.0969	0.0992	0.0767	0.1049	0.1106	0.5538

**TABLE 4.2.25B: Absolute Bias: When Errors are Normal , Square Root Heteroscedastic(
g=0.5) and Contemporaneous Correlation(P=0.95) under varying sample sizes**

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0.5							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	<i>OLS</i>	0.4	0.583	0.5821	0.4753	0.6753	0.54	3.2557
		<i>FGLS</i>	0.1933	0.2541	0.2137	0.2316	0.2712	0.2606	1.4246
		<i>Huber</i>	0.421	0.6039	0.6027	0.4929	0.6974	0.5433	3.3613
		<i>Bi-Square</i>	0.4307	0.6087	0.6025	0.5025	0.7059	0.5463	3.3966
	N=30	<i>OLS</i>	0.3378	0.4479	0.4883	0.352	0.5061	0.4783	2.6105
		<i>FGLS</i>	0.1703	0.1832	0.1818	0.1564	0.1886	0.1811	1.0615
		<i>Huber</i>	0.347	0.4658	0.5103	0.363	0.5325	0.4811	2.6998
		<i>Bi-Square</i>	0.3512	0.4667	0.513	0.3647	0.5326	0.4861	2.7143
	N=50	<i>OLS</i>	0.2318	0.3346	0.3572	0.2484	0.3539	0.3602	1.8860
		<i>FGLS</i>	0.112	0.1182	0.1339	0.1158	0.1306	0.1386	0.7492
		<i>Huber</i>	0.2373	0.3473	0.3628	0.2465	0.3378	0.3703	1.9019
		<i>Bi-Square</i>	0.2364	0.349	0.3632	0.2456	0.3366	0.3745	1.9053
	N=100	<i>OLS</i>	0.1538	0.2342	0.227	0.1652	0.2198	0.2414	1.2414
		<i>FGLS</i>	0.0818	0.0796	0.0873	0.0771	0.0853	0.0863	0.4974
		<i>Huber</i>	0.1596	0.2383	0.2261	0.165	0.2344	0.2451	1.2686
		<i>Bi-Square</i>	0.1564	0.2357	0.2243	0.1654	0.2385	0.2448	1.2651
	N=250	<i>OLS</i>	0.1042	0.1418	0.1542	0.1111	0.1406	0.1828	0.8347
		<i>FGLS</i>	0.0522	0.0617	0.0531	0.0552	0.0507	0.0583	0.3312
		<i>Huber</i>	0.1031	0.1436	0.1529	0.1145	0.1485	0.1837	0.8463
		<i>Bi-Square</i>	0.1033	0.1432	0.1555	0.1141	0.1474	0.1846	0.8481
	N=500	<i>OLS</i>	0.0751	0.1089	0.1061	0.0842	0.1089	0.1198	0.6030
		<i>FGLS</i>	0.0356	0.0413	0.0333	0.0352	0.0373	0.0304	0.2131
		<i>Huber</i>	0.0774	0.1074	0.1093	0.0896	0.1142	0.1252	0.6231
		<i>Bi-Square</i>	0.0773	0.1064	0.1107	0.0897	0.1148	0.1246	0.6236

TABLE 4.2.1C:Root Mean Squares Error: When Errors are Normal , Homoscedastic and No contemporaneous correlation under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.64108	0.81416	0.78419	0.61718	0.76912	0.82781	4.4535
		FGLS	0.67104	0.83573	0.82086	0.61465	0.75378	0.83559	4.5317
		Huber	0.64943	0.8302	0.82812	0.63625	0.81558	0.82541	4.5850
		Bi-Square	0.65263	0.8458	0.83497	0.64752	0.82317	0.84043	4.6445
	N=30	OLS	0.52063	0.70309	0.59572	0.41465	0.58489	0.64026	3.4592
		FGLS	0.53389	0.71042	0.60389	0.4261	0.59987	0.6675	3.5417
		Huber	0.52322	0.7136	0.60758	0.45424	0.62476	0.67739	3.6008
		Bi-Square	0.52052	0.71576	0.61846	0.46847	0.63073	0.68631	3.6403
	N=50	OLS	0.36184	0.49599	0.50026	0.37846	0.50904	0.48121	2.7268
		FGLS	0.36464	0.49788	0.50296	0.37612	0.51806	0.4817	2.7414
		Huber	0.36228	0.49028	0.4801	0.39896	0.52714	0.49858	2.7573
		Bi-Square	0.36436	0.49389	0.48016	0.40471	0.53663	0.50082	2.7806
	N=100	OLS	0.25096	0.37402	0.34899	0.25764	0.36272	0.35802	1.9524
		FGLS	0.24975	0.37221	0.35121	0.25697	0.36549	0.3534	1.9490
		Huber	0.25322	0.38977	0.35332	0.26623	0.37619	0.3544	1.9931
		Bi-Square	0.25598	0.39321	0.35105	0.2642	0.37535	0.35206	1.9919
	N=250	OLS	0.1784	0.20533	0.23269	0.16113	0.20843	0.20551	1.1915
		FGLS	0.17726	0.20417	0.23177	0.16108	0.20832	0.20587	1.1885
		Huber	0.18265	0.20618	0.23544	0.16914	0.22378	0.20479	1.2220
		Bi-Square	0.1823	0.20612	0.23674	0.16847	0.22321	0.20296	1.2198
	N=500	OLS	0.10569	0.15602	0.16101	0.11071	0.14919	0.14395	0.8266
		FGLS	0.10557	0.15611	0.16113	0.11081	0.14909	0.14398	0.8267
		Huber	0.10861	0.1568	0.16229	0.11149	0.15033	0.14356	0.8331
		Bi-Square	0.10907	0.1563	0.16297	0.11087	0.15101	0.14282	0.8330

TABLE 4.2.2 C: Root Mean Squares Error: When Errors are Normal , Exponential Heteroscedastic and No contemporaneous correlation under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.38965	1.86253	1.79638	1.31877	1.77413	1.87854	10.0200
		FGLS	1.45077	1.90401	1.86493	1.31802	1.75325	1.90497	10.1960
		Huber	1.41625	1.9048	1.91204	1.32235	1.83973	1.85896	10.2541
		Bi-Square	1.41483	1.94034	1.91178	1.34293	1.87078	1.90359	10.3843
	N=30	OLS	1.10708	1.61511	1.35109	0.88365	1.36487	1.44944	7.7712
		FGLS	1.14147	1.63287	1.36599	0.91968	1.40827	1.49927	7.9676
		Huber	1.08136	1.6044	1.3739	0.94184	1.46368	1.51052	7.9757
		Bi-Square	1.08802	1.61942	1.4175	0.96301	1.4879	1.52061	8.0965
	N=50	OLS	0.77416	1.14857	1.12868	0.83638	1.18162	1.12129	6.1907
		FGLS	0.78383	1.15068	1.13422	0.83694	1.20768	1.1252	6.2386
		Huber	0.74781	1.13426	1.05584	0.85728	1.1953	1.14272	6.1332
		Bi-Square	0.75592	1.16096	1.05669	0.84911	1.20098	1.12741	6.1511
	N=100	OLS	0.51602	0.8631	0.77374	0.54622	0.8286	0.83538	4.3631
		FGLS	0.51507	0.86069	0.78387	0.54326	0.83619	0.82448	4.3636
		Huber	0.51453	0.86947	0.79748	0.54684	0.84223	0.8091	4.3797
		Bi-Square	0.51758	0.88224	0.79256	0.54692	0.84947	0.80142	4.3902
	N=250	OLS	0.36736	0.46477	0.52736	0.32548	0.462	0.45554	2.6025
		FGLS	0.36571	0.46262	0.5265	0.32555	0.46291	0.45601	2.5993
		Huber	0.36891	0.46558	0.52218	0.33294	0.48972	0.44826	2.6276
		Bi-Square	0.37023	0.46814	0.52811	0.33989	0.50167	0.44691	2.6550
	N=500	OLS	0.22744	0.3582	0.37252	0.23528	0.341	0.32423	1.8587
		FGLS	0.22719	0.3582	0.37278	0.23556	0.3409	0.32442	1.8591
		Huber	0.2291	0.36242	0.36788	0.23097	0.34367	0.32118	1.8552
		Bi-Square	0.22987	0.36587	0.36882	0.22784	0.34611	0.31712	1.8556

TABLE 4.2.3 C: Root Mean Squares Error: When Errors are Normal ,Quadratic Heteroscedastic(g=2) and No contemporal correlation (P=0) under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.40607	0.58268	0.56024	0.38113	0.56276	0.57715	3.0700
		FGLS	0.42062	0.59172	0.57645	0.38333	0.56322	0.587	3.1223
		Huber	0.39645	0.58021	0.56897	0.35209	0.54303	0.55581	2.9966
		Bi-Square	0.40407	0.60155	0.58982	0.36445	0.58488	0.57624	3.1210
	N=30	OLS	0.31798	0.50759	0.41709	0.25757	0.43951	0.44182	2.3816
		FGLS	0.33007	0.51333	0.42152	0.27138	0.45706	0.45188	2.4452
		Huber	0.29432	0.48683	0.41816	0.24755	0.45701	0.43435	2.3382
		Bi-Square	0.29521	0.49046	0.43167	0.2561	0.49624	0.43434	2.4040
	N=50	OLS	0.22682	0.36487	0.34563	0.25482	0.37815	0.35528	1.9256
		FGLS	0.23061	0.36448	0.34752	0.25731	0.38743	0.35751	1.9449
		Huber	0.20448	0.35763	0.30642	0.23778	0.35978	0.33926	1.8053
		Bi-Square	0.20822	0.37312	0.30907	0.23011	0.35865	0.33117	1.8103
	N=100	OLS	0.14544	0.27473	0.23184	0.15632	0.25669	0.26439	1.3294
		FGLS	0.14568	0.27463	0.23658	0.15472	0.25953	0.26126	1.3324
		Huber	0.13662	0.26498	0.23448	0.14182	0.24754	0.24034	1.2658
		Bi-Square	0.13724	0.27205	0.23722	0.14207	0.25285	0.23663	1.2781
	N=250	OLS	0.10131	0.14603	0.16176	0.08611	0.13972	0.13524	0.7702
		FGLS	0.10127	0.14528	0.16216	0.08631	0.14059	0.1353	0.7709
		Huber	0.09278	0.14067	0.15033	0.08133	0.14363	0.12604	0.7348
		Bi-Square	0.09466	0.14571	0.15342	0.08714	0.15359	0.12803	0.7625
	N=500	OLS	0.06834	0.11362	0.11738	0.06742	0.10648	0.09854	0.5718
		FGLS	0.06834	0.11364	0.11741	0.06753	0.10651	0.09867	0.5721
		Huber	0.06281	0.11197	0.10817	0.06006	0.10521	0.09234	0.5406
		Bi-Square	0.06381	0.11605	0.10929	0.06024	0.10792	0.09119	0.5485

TABLE 4.2.4 C: Root Mean Squares Error: When Errors are Normal ,Linear Heteroscedastic(Q=1) and No contemporal correlation(P=0) under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=1							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.48881	0.66651	0.64331	0.46407	0.63729	0.67358	3.5736
		FGLS	0.50976	0.6806	0.66657	0.46424	0.63041	0.6839	3.6355
		Huber	0.49544	0.67749	0.68287	0.45946	0.65393	0.66454	3.6337
		Bi-Square	0.49631	0.69368	0.68397	0.46888	0.67132	0.68356	3.6977
	N=30	OLS	0.38828	0.57775	0.48461	0.30977	0.49109	0.51911	2.7706
		FGLS	0.40105	0.58419	0.48968	0.32361	0.50712	0.53597	2.8416
		Huber	0.37498	0.56989	0.49061	0.32532	0.52547	0.53696	2.8232
		Bi-Square	0.37749	0.57681	0.50651	0.33266	0.53642	0.53998	2.8699
	N=50	OLS	0.27119	0.41153	0.40366	0.29504	0.4227	0.40358	2.2077
		FGLS	0.27485	0.412	0.40564	0.296	0.43284	0.40522	2.2266
		Huber	0.25967	0.40696	0.37493	0.2981	0.42451	0.40708	2.1713
		Bi-Square	0.26191	0.41694	0.37442	0.29369	0.42431	0.40154	2.1728
	N=100	OLS	0.1793	0.3102	0.27579	0.19075	0.29563	0.30147	1.5531
		FGLS	0.17918	0.30953	0.27991	0.18952	0.29853	0.29751	1.5542
		Huber	0.17718	0.31008	0.28451	0.18807	0.29799	0.28975	1.5476
		Bi-Square	0.178	0.31473	0.28294	0.18838	0.30124	0.28635	1.5516
	N=250	OLS	0.12743	0.16595	0.18889	0.11218	0.1643	0.16221	0.9210
		FGLS	0.12693	0.16521	0.18872	0.11225	0.16476	0.16237	0.9202
		Huber	0.12634	0.16577	0.18538	0.11302	0.17345	0.15792	0.9219
		Bi-Square	0.12719	0.16703	0.18771	0.11637	0.17834	0.1584	0.9350
	N=500	OLS	0.07992	0.12834	0.13413	0.08245	0.1219	0.11596	0.6627
		FGLS	0.07984	0.12832	0.13422	0.08255	0.12186	0.11604	0.6628
		Huber	0.07955	0.12964	0.13133	0.07988	0.12265	0.11432	0.6574
		Bi-Square	0.07985	0.13135	0.13169	0.07879	0.12379	0.11276	0.6582

TABLE 4.2.5 C: Root Mean Squares Error: When Errors are Normal ,Square Root Heteroscedastic(g= 0.5) and No contemporaneous correlation under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.55376	0.72986	0.70456	0.52907	0.69336	0.74131	3.9519
		FGLS	0.57887	0.7473	0.73371	0.52808	0.68246	0.75086	4.0213
		Huber	0.56552	0.74798	0.75201	0.53731	0.7281	0.73587	4.0668
		Bi-Square	0.56294	0.75976	0.75112	0.54401	0.73359	0.75151	4.1029
	N=30	OLS	0.44446	0.63139	0.53308	0.35368	0.53083	0.57287	3.0663
		FGLS	0.45741	0.63818	0.5392	0.36669	0.54612	0.59442	3.1420
		Huber	0.37092	0.48434	0.42681	0.32889	0.45937	0.48152	2.5519
		Bi-Square	0.4398	0.63818	0.55621	0.39018	0.57415	0.60697	3.2055
	N=50	OLS	0.30896	0.44754	0.44579	0.32944	0.4588	0.43765	2.4282
		FGLS	0.31232	0.44869	0.44803	0.329	0.46875	0.4388	2.4456
		Huber	0.30322	0.44207	0.42171	0.34224	0.46978	0.45027	2.4293
		Bi-Square	0.30544	0.44943	0.42163	0.34145	0.47359	0.44662	2.4382
	N=100	OLS	0.20905	0.33739	0.30772	0.21882	0.32452	0.32651	1.7240
		FGLS	0.2085	0.33623	0.31109	0.21785	0.32736	0.32219	1.7232
		Huber	0.20984	0.34355	0.31635	0.22149	0.33221	0.3188	1.7422
		Bi-Square	0.21113	0.34818	0.3138	0.2216	0.33441	0.31679	1.7459
	N=250	OLS	0.14892	0.18232	0.20811	0.133	0.18313	0.18128	1.0368
		FGLS	0.14811	0.18144	0.20756	0.13302	0.18332	0.18154	1.0350
		Huber	0.15077	0.18313	0.2079	0.13779	0.19485	0.18027	1.0547
		Bi-Square	0.15113	0.1836	0.20984	0.13871	0.1974	0.17847	1.0591
	N=500	OLS	0.09042	0.14	0.14593	0.09445	0.1336	0.1283	0.7327
		FGLS	0.0903	0.14001	0.14606	0.09455	0.13352	0.12834	0.7328
		Huber	0.09193	0.14137	0.14546	0.0938	0.13492	0.1278	0.7353
		Bi-Square	0.09219	0.14214	0.14588	0.09272	0.13554	0.12655	0.7350

TABLE 4.2.6.C:Root Mean Squares Error: When Errors are Normal , Homoscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.68838	0.84892	0.86351	0.69468	0.89076	0.7232	4.7095
		FGLS	0.69699	0.85175	0.87708	0.69895	0.89081	0.77747	4.7931
		Huber	0.72022	0.86261	0.92752	0.71813	0.92262	0.76195	4.9131
		Bi-Square	0.72184	0.87928	0.93409	0.74596	0.94048	0.79899	5.0206
	N=30	OLS	0.5485	0.58829	0.66579	0.5556	0.69526	0.69584	3.7493
		FGLS	0.54949	0.58608	0.66398	0.56541	0.69712	0.69381	3.7559
		Huber	0.55024	0.6262	0.67696	0.58603	0.71778	0.70446	3.8617
		Bi-Square	0.56023	0.63298	0.69243	0.58922	0.71713	0.7183	3.9103
	N=50	OLS	0.40503	0.49585	0.51975	0.38319	0.50585	0.50537	2.8150
		FGLS	0.40433	0.46797	0.53321	0.38115	0.49385	0.49819	2.7787
		Huber	0.40238	0.49853	0.51465	0.38355	0.50317	0.52582	2.8281
		Bi-Square	0.39886	0.5042	0.51564	0.38522	0.50718	0.52434	2.8354
	N=100	OLS	0.27155	0.3566	0.36078	0.24466	0.31296	0.35409	1.9006
		FGLS	0.26411	0.35348	0.35742	0.23231	0.31441	0.3443	1.8660
		Huber	0.2709	0.36773	0.35403	0.24807	0.32483	0.3506	1.9162
		Bi-Square	0.27097	0.36652	0.35764	0.249	0.32621	0.35365	1.9240
	N=250	OLS	0.16338	0.21266	0.21772	0.16631	0.20669	0.2421	1.2089
		FGLS	0.16153	0.21468	0.21435	0.16142	0.19852	0.23707	1.1876
		Huber	0.1712	0.22498	0.22351	0.17307	0.21301	0.24636	1.2521
		Bi-Square	0.16978	0.22478	0.22313	0.17201	0.21226	0.24668	1.2486
	N=500	OLS	0.10832	0.13927	0.14192	0.1242	0.14229	0.16792	0.8239
		FGLS	0.1065	0.14236	0.13722	0.12124	0.1367	0.16272	0.8067
		Huber	0.11361	0.14764	0.1475	0.129	0.148	0.16824	0.8540
		Bi-Square	0.11343	0.14871	0.14719	0.12733	0.14705	0.16852	0.8522

TABLE 4.2.7C: Root Mean Squares Error: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.48087	1.94474	1.96155	1.42847	1.97868	1.62028	10.4146
		FGLS	1.51616	1.95214	2.01292	1.44519	1.98633	1.75074	10.6635
		Huber	1.49745	1.92122	2.07887	1.48161	2.05706	1.71396	10.7502
		Bi-Square	1.50109	1.97594	2.10897	1.5252	2.0966	1.77846	10.9863
	N=30	OLS	1.16321	1.34908	1.51833	1.15922	1.5748	1.56134	8.3260
		FGLS	1.1966	1.36444	1.54462	1.17424	1.55531	1.56424	8.3994
		Huber	1.14722	1.40975	1.52689	1.20874	1.61935	1.56907	8.4810
		Bi-Square	1.1695	1.43165	1.57801	1.19493	1.60532	1.57708	8.5565
	N=50	OLS	0.85721	1.13376	1.17915	0.81106	1.15676	1.13528	6.2732
		FGLS	0.85927	1.0709	1.20697	0.80068	1.1249	1.11884	6.1816
		Huber	0.83259	1.14529	1.14529	1.79982	1.13397	1.17615	7.2331
		Bi-Square	0.82212	1.15165	1.14944	0.79814	1.14093	1.17238	6.2347
	N=100	OLS	0.57942	0.81348	0.82188	0.50957	0.70011	0.79903	4.2235
		FGLS	0.56182	0.79867	0.81856	0.47996	0.69818	0.77983	4.1370
		Huber	0.56696	0.8281	0.79439	0.51172	0.73396	0.78359	4.2187
		Bi-Square	0.573	0.83324	0.8073	0.51161	0.74179	0.79239	4.2593
	N=250	OLS	0.3453	0.48573	0.4996	0.35225	0.46671	0.54619	2.6958
		FGLS	0.34313	0.48939	0.49227	0.36102	0.48132	0.55185	2.7190
		Huber	0.34826	0.51087	0.49227	0.36102	0.48132	0.55185	2.7456
		Bi-Square	0.34373	0.51248	0.49257	0.35919	0.48123	0.55753	2.7467
	N=500	OLS	0.22952	0.33019	0.32055	0.25764	0.33117	0.36975	1.8388
		FGLS	0.22471	0.33663	0.3104	0.25052	0.32052	0.35725	1.8000
		Huber	0.22807	0.33951	0.32769	0.2668	0.34257	0.37162	1.8763
		Bi-Square	0.22811	0.34275	0.32761	0.26538	0.34146	0.37318	1.8785

TABLE 4.2.8C: Root Mean Squares Error: When Errors are Normal ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.428	0.61106	0.60184	0.38368	0.59586	0.49184	3.1123
		FGLS	0.44397	0.61273	0.62317	0.39219	0.59977	0.53305	3.2049
		Huber	0.40747	0.57179	0.61524	0.38708	0.60787	0.49141	3.0809
		Bi-Square	0.4132	0.60756	0.63044	0.41107	0.63978	0.53798	3.2400
	N=30	OLS	0.3325	0.43224	0.4693	0.31998	0.48738	0.46987	2.5113
		FGLS	0.35317	0.44331	0.487	0.31998	0.47172	0.47311	2.5483
		Huber	0.30679	0.42883	0.45364	0.31356	0.48532	0.44745	2.4356
		Bi-Square	0.31758	0.46507	0.47246	0.31206	0.4895	0.45163	2.5083
	N=50	OLS	0.24342	0.35752	0.35975	0.22978	0.36074	0.34332	1.8945
		FGLS	0.24558	0.34157	0.3657	0.22445	0.34942	0.33922	1.8659
		Huber	0.21971	0.35259	0.33325	0.21318	0.3381	0.3435	1.8003
		Bi-Square	0.21796	0.36198	0.33664	0.21263	0.34211	0.34615	1.8175
	N=100	OLS	0.16774	0.25456	0.25476	0.14194	0.21348	0.24221	1.2747
		FGLS	0.16248	0.24768	0.25528	0.13261	0.20971	0.23808	1.2458
		Huber	0.15116	0.24906	0.22801	0.13334	0.21991	0.22721	1.2087
		Bi-Square	0.15364	0.25939	0.23192	0.13458	0.23382	0.22761	1.2410
	N=250	OLS	0.09868	0.15233	0.15561	0.10069	0.1449	0.16538	0.8176
		FGLS	0.09872	0.15278	0.15317	0.09864	0.14081	0.16432	0.8084
		Huber	0.08841	0.15392	0.1409	0.0972	0.14611	0.16052	0.7871
		Bi-Square	0.08805	0.16195	0.13988	0.09895	0.1519	0.16545	0.8062
	N=500	OLS	0.06608	0.10829	0.09844	0.0702	0.1067	0.1077	0.5574
		FGLS	0.06467	0.10996	0.09583	0.06796	0.10444	0.10395	0.5468
		Huber	0.05838	0.10507	0.09566	0.06862	0.10601	0.10382	0.5376
		Bi-Square	0.05785	0.10816	0.0949	0.07031	0.1089	0.10512	0.5452

TABLE 4.2.9C: Root Mean Squares Error: When Errors are Normal ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.5207	0.69512	0.7025	0.49562	0.70241	0.57911	3.6955
		FGLS	0.53473	0.69766	0.72256	0.50261	0.70613	0.62618	3.7899
		Huber	0.51881	0.68009	0.73816	0.51284	0.72962	0.61135	3.7909
		Bi-Square	0.52216	0.70366	0.75247	0.52939	0.74616	0.63632	3.8902
	N=30	OLS	0.40744	0.48268	0.5447	0.40319	0.56202	0.55662	2.9567
		FGLS	0.42216	0.48985	0.55622	0.4078	0.55287	0.55816	2.9871
		Huber	0.39826	0.5016	0.54482	0.41538	0.57335	0.55426	2.9877
		Bi-Square	0.40642	0.51355	0.56378	0.41098	0.57055	0.55741	3.0227
	N=50	OLS	0.30033	0.40603	0.42242	0.28343	0.41321	0.40581	2.2312
		FGLS	0.30165	0.38398	0.43218	0.27908	0.40135	0.39985	2.1981
		Huber	0.28811	0.40706	0.40728	0.27696	0.40192	0.4186	2.1999
		Bi-Square	0.28474	0.41176	0.40945	0.27641	0.40502	0.41806	2.2054
	N=100	OLS	0.20275	0.2906	0.29452	0.17685	0.24905	0.28544	1.4992
		FGLS	0.19638	0.28476	0.29363	0.16633	0.24805	0.27893	1.4681
		Huber	0.19635	0.29431	0.28198	0.17626	0.26004	0.27868	1.4876
		Bi-Square	0.19866	0.29644	0.28731	0.17602	0.26438	0.28178	1.5046
	N=250	OLS	0.12018	0.17329	0.17922	0.12307	0.16653	0.19506	0.9574
		FGLS	0.11961	0.17445	0.17649	0.11972	0.16044	0.19248	0.9432
		Huber	0.11909	0.18124	0.1744	0.1252	0.17135	0.19626	0.9675
		Bi-Square	0.1177	0.1829	0.17456	0.12453	0.17186	0.19864	0.9702
	N=500	OLS	0.08015	0.119	0.11449	0.08928	0.11921	0.13102	0.6532
		FGLS	0.07845	0.12128	0.11098	0.0868	0.11571	0.12655	0.6398
		Huber	0.07816	0.12141	0.11675	0.09181	0.1225	0.13134	0.6620
		Bi-Square	0.07825	0.12291	0.11649	0.09171	0.12232	0.13204	0.6637

TABLE 4.2.10C: Root Mean Squares Error: When Errors are Normal ,Square Root Heteroscedastic($g= 0.5$) and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.2	N=20	OLS	0.5925	0.76058	0.77338	0.58115	0.78301	0.64184	4.1325
		FGLS	0.60433	0.7635	0.79106	0.58704	0.78552	0.69243	4.2239
		Huber	0.60693	0.761	0.82526	0.6032	0.81465	0.67866	4.2897
		Bi-Square	0.60642	0.77756	0.83432	0.61998	0.8244	0.70589	4.3686
	N=30	OLS	0.46742	0.52623	0.59796	0.46834	0.61895	0.61793	3.2968
		FGLS	0.4762	0.52943	0.60369	0.47559	0.61479	0.61798	3.3177
		Huber	0.46485	0.5559	0.60368	0.49075	0.63916	0.62313	3.3775
		Bi-Square	0.47267	0.56084	0.62132	0.4886	0.63457	0.63147	3.4095
	N=50	OLS	0.34497	0.444	0.46555	0.32597	0.45302	0.44971	2.4832
		FGLS	0.3454	0.41887	0.47721	0.3226	0.44102	0.443	2.4481
		Huber	0.33832	0.44685	0.45572	0.32378	0.44701	0.46778	2.4795
		Bi-Square	0.33426	0.4508	0.45748	0.32337	0.44941	0.46584	2.4812
	N=100	OLS	0.23158	0.31864	0.32332	0.20544	0.27636	0.31573	1.6711
		FGLS	0.2247	0.31397	0.32139	0.19412	0.27673	0.3077	1.6386
		Huber	0.22934	0.32614	0.31565	0.20797	0.28946	0.312	1.6806
		Bi-Square	0.23019	0.32632	0.31961	0.20752	0.2904	0.31492	1.6890
	N=250	OLS	0.13827	0.18992	0.19608	0.14131	0.18358	0.21582	1.0650
		FGLS	0.13715	0.19151	0.19309	0.13722	0.17645	0.21215	1.0476
		Huber	0.14222	0.20085	0.19694	0.14558	0.18944	0.21864	1.0937
		Bi-Square	0.14026	0.20037	0.1969	0.14484	0.18872	0.22047	1.0916
	N=500	OLS	0.09197	0.12753	0.12639	0.10419	0.1289	0.14733	0.7263
		FGLS	0.0902	0.13018	0.12232	0.10152	0.12447	0.14252	0.7112
		Huber	0.09345	0.13309	0.13036	0.10829	0.13348	0.14856	0.7472
		Bi-Square	0.09351	0.13403	0.13051	0.10726	0.13282	0.14889	0.7470

TABLE 4.2.11C: Root Mean Squares Error: When Errors are Normal , Homoscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.68838	0.84892	0.86351	0.71522	0.94642	0.73901	4.8015
		FGLS	0.6733	0.79903	0.82045	0.66938	0.8765	0.73126	4.5699
		Huber	0.72022	0.86261	0.92752	0.74205	0.97319	0.75866	4.9843
		Bi-Square	0.72184	0.87928	0.93409	0.77232	1.01307	0.78162	5.1022
	N=30	OLS	0.5485	0.58829	0.66579	0.53405	0.69146	0.66123	3.6893
		FGLS	0.52315	0.56402	0.6157	0.53342	0.6593	0.64419	3.5398
		Huber	0.55024	0.6262	0.67696	0.56696	0.72983	0.67128	3.8215
		Bi-Square	0.56023	0.63298	0.69243	0.56764	0.72742	0.67412	3.8548
	N=50	OLS	0.40503	0.49585	0.51975	0.36138	0.48761	0.49915	2.7688
		FGLS	0.38233	0.42515	0.50601	0.34426	0.43629	0.45738	2.5514
		Huber	0.40238	0.49853	0.51465	0.3611	0.47395	0.52339	2.7740
		Bi-Square	0.39886	0.5042	0.51564	0.36574	0.47409	0.52457	2.7831
	N=100	OLS	0.27155	0.3566	0.36071	0.24882	0.32315	0.34709	1.9079
		FGLS	0.24425	0.32457	0.33979	0.2171	0.29903	0.31131	1.7360
		Huber	0.2709	0.36773	0.35403	0.25513	0.33471	0.3529	1.9354
		Bi-Square	0.27097	0.36651	0.35764	0.25535	0.33729	0.35139	1.9391
	N=250	OLS	0.16338	0.21266	0.21772	0.16633	0.20092	0.24582	1.2068
		FGLS	0.15122	0.204	0.2006	0.14929	0.17775	0.22556	1.1084
		Huber	0.1712	0.22498	0.22351	0.17188	0.21324	0.25102	1.2558
		Bi-Square	0.16978	0.22478	0.22313	0.17105	0.21039	0.2513	1.2504
	N=500	OLS	0.10832	0.13927	0.14192	0.1257	0.1502	0.16499	0.8304
		FGLS	0.10066	0.13456	0.12826	0.11697	0.13155	0.15136	0.7634
		Huber	0.11361	0.14764	0.1475	0.13166	0.15653	0.16874	0.8657
		Bi-Square	0.11343	0.14871	0.14719	0.13135	0.15618	0.16862	0.8655

TABLE 4.2.12C: Root Mean Squares Error: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	1.48087	1.94474	1.96155	1.472	2.1061	1.64892	10.6142
		FGLS	1.47238	1.83263	1.9072	1.38283	1.98226	1.64617	10.2235
		Huber	1.49745	1.92122	2.07887	1.53931	2.16011	1.68153	10.8785
		Bi-Square	1.50109	1.97594	2.10897	1.58503	2.17972	1.76983	11.1206
	N=30	OLS	1.1632	1.34908	1.51833	1.11281	1.57487	1.4868	8.2051
		FGLS	1.14189	1.31577	1.44193	1.09787	1.4665	1.45509	7.9191
		Huber	1.14722	1.40975	1.52689	1.16559	1.65186	1.48205	8.3834
		Bi-Square	1.1695	1.43165	1.57801	1.16485	1.65321	1.49081	8.4880
	N=50	OLS	0.85721	1.13376	1.17915	0.76832	1.1289	1.11362	6.1810
		FGLS	0.8153	0.97863	1.14671	0.72296	1.00646	1.02528	5.6953
		Huber	0.83259	1.14083	1.14529	0.76286	1.07499	1.17079	6.1274
		Bi-Square	0.82212	1.15165	1.14944	0.7554	1.05584	1.17234	6.1068
	N=100	OLS	0.57942	0.81348	0.82188	0.5219	0.73976	0.78242	4.2589
		FGLS	0.51984	0.73346	0.78026	0.45232	0.68014	0.70926	3.8753
		Huber	0.56696	0.8281	0.79439	0.52534	0.75568	0.78982	4.2603
		Bi-Square	0.573	0.83324	0.8073	0.52617	0.77163	0.78831	4.2996
	N=250	OLS	0.3453	0.48573	0.4996	0.3547	0.45808	0.55716	2.7006
		FGLS	0.32196	0.46718	0.45993	0.31969	0.4101	0.51782	2.4967
		Huber	0.34826	0.51087	0.49227	0.36064	0.48495	0.56532	2.7623
		Bi-Square	0.34373	0.51248	0.49257	0.35815	0.48072	0.56773	2.7554
	N=500	OLS	0.22952	0.33018	0.32055	0.25982	0.3445	0.36444	1.8490
		FGLS	0.21096	0.3197	0.28924	0.23963	0.30612	0.33316	1.6988
		Huber	0.22807	0.33951	0.32769	0.27084	0.35639	0.37471	1.8972
		Bi-Square	0.22811	0.34275	0.32761	0.27325	0.3596	0.37545	1.9068

TABLE 4.2.13C: Root Mean Squares Error: When Errors are Normal ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	0.42802	0.61106	0.60184	0.39753	0.635	0.49989	3.1733
		FGLS	0.43714	0.57984	0.60315	0.38058	0.61215	0.50659	3.1195
		Huber	0.40747	0.57179	0.61525	0.40912	0.62624	0.49469	3.1246
		Bi-Square	0.4132	0.60756	0.63044	0.42545	0.63962	0.53691	3.2532
	N=30	OLS	0.3325	0.43224	0.4693	0.30846	0.49098	0.45026	2.4837
		FGLS	0.3411	0.43152	0.46146	0.29606	0.44548	0.44315	2.4188
		Huber	0.30679	0.42884	0.45364	0.3031	0.49372	0.4281	2.4142
		Bi-Square	0.31758	0.46507	0.47246	0.30561	0.51449	0.42145	2.4967
	N=50	OLS	0.24342	0.35752	0.35975	0.22012	0.35744	0.33407	1.8723
		FGLS	0.23599	0.31856	0.34964	0.20503	0.3199	0.31348	1.7426
		Huber	0.21971	0.35259	0.33325	0.20039	0.31806	0.33409	1.7581
		Bi-Square	0.21796	0.36198	0.33664	0.20161	0.31326	0.34795	1.7794
	N=100	OLS	0.16774	0.25457	0.25476	0.14701	0.23215	0.23708	1.2933
		FGLS	0.15216	0.22983	0.24547	0.12824	0.21223	0.21975	1.1877
		Huber	0.15115	0.24906	0.22801	0.13724	0.23046	0.22543	1.2213
		Bi-Square	0.15364	0.25939	0.23192	0.1403	0.2424	0.22851	1.2562
	N=250	OLS	0.09868	0.15233	0.15561	0.10278	0.14456	0.16994	0.8239
		FGLS	0.09404	0.14755	0.14425	0.09528	0.13409	0.16163	0.7768
		Huber	0.08841	0.15392	0.14091	0.09722	0.1485	0.16407	0.7930
		Bi-Square	0.08805	0.16195	0.13988	0.09841	0.15373	0.16795	0.8100
	N=500	OLS	0.06608	0.10829	0.09844	0.07066	0.10924	0.10668	0.5594
		FGLS	0.06092	0.10568	0.08972	0.0649	0.10004	0.09805	0.5193
		Huber	0.05838	0.10507	0.09566	0.07089	0.10914	0.10667	0.5458
		Bi-Square	0.05785	0.10816	0.0949	0.07316	0.11284	0.10803	0.5549

TABLE 4.2.14C: Root Mean Squares Error: When Errors are Normal ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.5207	0.69512	0.7025	0.51138	0.748	0.58959	3.7673
		FGLS	0.52066	0.65548	0.68711	0.48148	0.7075	0.58984	3.6421
		Huber	0.51881	0.6801	0.73816	0.534	0.76367	0.59774	3.8325
		Bi-Square	0.52216	0.70366	0.75248	0.54937	0.76791	0.63379	3.9294
	N=30	OLS	0.40744	0.48268	0.5447	0.38706	0.56276	0.53037	2.9150
		FGLS	0.40354	0.47296	0.52038	0.38047	0.52135	0.51917	2.8179
		Huber	0.39826	0.50159	0.54482	0.40124	0.5871	0.52523	2.9582
		Bi-Square	0.40642	0.51355	0.56378	0.40149	0.5897	0.52748	3.0024
	N=50	OLS	0.30033	0.40603	0.42242	0.26892	0.40493	0.39744	2.2001
		FGLS	0.28687	0.35201	0.41078	0.25209	0.36067	0.36638	2.0288
		Huber	0.28811	0.40706	0.40728	0.26438	0.38126	0.41594	2.1640
		Bi-Square	0.28474	0.41176	0.40944	0.26143	0.37446	0.418	2.1598
	N=100	OLS	0.20275	0.2906	0.29452	0.18154	0.26458	0.27929	1.5133
		FGLS	0.18182	0.26156	0.28025	0.15757	0.24342	0.254	1.3786
		Huber	0.19635	0.29431	0.28198	0.18089	0.26838	0.28034	1.5023
		Bi-Square	0.19866	0.29644	0.28731	0.18142	0.27546	0.28053	1.5198
	N=250	OLS	0.12083	0.17329	0.17922	0.12414	0.16372	0.19918	0.9604
		FGLS	0.11242	0.16674	0.16522	0.11233	0.14737	0.18584	0.8899
		Huber	0.11909	0.18124	0.17441	0.125	0.17272	0.20126	0.9737
		Bi-Square	0.1177	0.1829	0.17456	0.12418	0.17199	0.20231	0.9736
	N=500	OLS	0.08015	0.11901	0.1145	0.08995	0.12347	0.1293	0.6564
		FGLS	0.07366	0.11541	0.10346	0.08296	0.11037	0.1183	0.6042
		Huber	0.07816	0.12141	0.11675	0.09319	0.1267	0.13262	0.6688
		Bi-Square	0.07825	0.12291	0.11649	0.09439	0.12844	0.13317	0.6736

TABLE 4.2.15C: Root Mean Squares Error: When Errors are Normal ,Square Root Heteroscedastic(g= 0.5) and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	0.5925	0.76058	0.77338	0.59887	0.83311	0.65461	4.2131
		FGLS	0.58561	0.71616	0.74551	0.56149	0.77957	0.65117	4.0395
		Huber	0.60693	0.761	0.82526	0.62583	0.85693	0.67274	4.3487
		Bi-Square	0.60642	0.77756	0.83432	0.64337	0.8704	0.68845	4.4205
	N=30	OLS	0.46742	0.52623	0.59796	0.44964	0.61771	0.58772	3.2467
		FGLS	0.45377	0.50987	0.56174	0.44622	0.58037	0.57388	3.1259
		Huber	0.46485	0.5559	0.60368	0.47492	0.65108	0.59082	3.3412
		Bi-Square	0.47267	0.56084	0.62132	0.47282	0.64763	0.59437	3.3697
	N=50	OLS	0.34497	0.444	0.46555	0.3082	0.44055	0.44225	2.4455
		FGLS	0.32726	0.38155	0.45296	0.29102	0.39276	0.40572	2.2513
		Huber	0.33832	0.44685	0.45572	0.30837	0.42401	0.46627	2.4395
		Bi-Square	0.33426	0.4508	0.45748	0.30657	0.41826	0.4657	2.4331
	N=100	OLS	0.23158	0.31864	0.32332	0.20991	0.28952	0.30914	1.6821
		FGLS	0.20761	0.28789	0.30596	0.18243	0.26722	0.27892	1.5300
		Huber	0.22934	0.32614	0.31565	0.21349	0.29692	0.31478	1.6963
		Bi-Square	0.23019	0.3263	0.31961	0.21299	0.30144	0.31297	1.7035
	N=250	OLS	0.13827	0.18992	0.19608	0.14185	0.17933	0.21974	1.0652
		FGLS	0.12846	0.18236	0.1806	0.12751	0.15963	0.20317	0.9817
		Huber	0.14222	0.20085	0.19694	0.1452	0.18996	0.22392	1.0991
		Bi-Square	0.14026	0.2004	0.19687	0.1443	0.1879	0.22468	1.0944
	N=500	OLS	0.09197	0.12753	0.12639	0.10519	0.13469	0.1451	0.7309
		FGLS	0.08487	0.12336	0.11408	0.09742	0.119	0.13281	0.6715
		Huber	0.09345	0.13309	0.13036	0.10993	0.13985	0.14937	0.7561
		Bi-Square	0.0935	0.13403	0.13052	0.11038	0.14016	0.1494	0.7580

TABLE 4.2.16C: Root Mean Squares Error: When Errors are Normal , Homoscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.68838	0.84892	0.86351	0.71567	0.9016	0.82308	4.8411
		FGLS	0.62338	0.80834	0.75132	0.61176	0.73624	0.71615	4.2472
		Huber	0.72022	0.86261	0.92752	0.75252	0.93723	0.85272	5.0528
		Bi-Square	0.72184	0.87928	0.93409	0.80623	0.96618	0.93683	5.2444
	N=30	OLS	0.5485	0.58829	0.66579	0.51382	0.65029	0.68537	3.6521
		FGLS	0.5103	0.54155	0.58661	0.46868	0.60074	0.6059	3.3138
		Huber	0.55024	0.6262	0.67696	0.53236	0.65255	0.70628	3.7446
		Bi-Square	0.56023	0.63298	0.69243	0.54058	0.66516	0.70885	3.8002
	N=50	OLS	0.40503	0.49585	0.51975	0.38919	0.47437	0.58533	2.8695
		FGLS	0.36459	0.43323	0.46488	0.35719	0.44424	0.51472	2.5789
		Huber	0.40238	0.49853	0.51465	0.40076	0.489	0.60334	2.9087
		Bi-Square	0.39886	0.5042	0.51564	0.40283	0.49842	0.60278	2.9227
	N=100	OLS	0.27155	0.3566	0.36071	0.27594	0.36569	0.37275	2.0032
		FGLS	0.24508	0.30386	0.34217	0.24155	0.31707	0.30513	1.7549
		Huber	0.2709	0.36773	0.35403	0.27866	0.387	0.3738	2.0321
		Bi-Square	0.27097	0.36652	0.35764	0.27962	0.3863	0.37322	2.0343
	N=250	OLS	0.16338	0.21266	0.21772	0.17672	0.23334	0.23355	1.2374
		FGLS	0.15153	0.19759	0.2031	0.15931	0.19162	0.20944	1.1126
		Huber	0.1712	0.22498	0.22351	0.17943	0.23834	0.24588	1.2833
		Bi-Square	0.16978	0.22478	0.22313	0.18168	0.24215	0.2461	1.2876
	N=500	OLS	0.10832	0.13927	0.14192	0.12432	0.16394	0.16885	0.8466
		FGLS	0.10083	0.14932	0.12369	0.10674	0.13534	0.14254	0.7585
		Huber	0.11361	0.14764	0.1475	0.12789	0.16961	0.17385	0.8801
		Bi-Square	0.11343	0.14871	0.14719	0.12774	0.16934	0.17229	0.8787

TABLE 4.2.17 C: Root Mean Squares Error: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	1.48087	1.94474	1.96155	1.49774	2.0382	1.84985	10.7729
		FGLS	1.34827	1.86966	1.71048	1.2691	1.667	1.62344	9.4879
		Huber	1.49745	1.92122	2.07887	1.58194	2.10688	1.8983	11.0847
		Bi-Square	1.50109	1.97594	2.10897	1.6805	2.17201	2.08167	11.5202
	N=30	OLS	1.16321	1.34908	1.51833	1.1016	1.49044	1.55619	8.1789
		FGLS	1.08481	1.22616	1.36761	0.98843	1.36072	1.38582	7.4135
		Huber	1.14722	1.40975	1.52689	1.11689	1.48574	1.5947	8.2812
		Bi-Square	1.1695	1.43165	1.57801	1.13295	1.5116	1.6002	8.4239
	N=50	OLS	0.85721	1.13376	1.17915	0.83827	1.08523	1.33683	6.4304
		FGLS	0.77506	0.99936	1.05327	0.75963	1.00078	1.18396	5.7721
		Huber	0.83259	1.14083	1.14529	0.83982	1.09952	1.36814	6.4262
		Bi-Square	0.82212	1.15165	1.14944	0.84546	1.11901	1.36738	6.4551
	N=100	OLS	0.57941	0.81348	0.82188	0.59145	0.84154	0.84527	4.4930
		FGLS	0.51758	0.70287	0.7695	0.51505	0.74022	0.70068	3.9459
		Huber	0.56696	0.8281	0.79439	0.57641	0.87258	0.83316	4.4716
		Bi-Square	0.573	0.83324	0.8073	0.58211	0.86975	0.83556	4.5010
	N=250	OLS	0.3453	0.48573	0.4996	0.36783	0.53654	0.51932	2.7543
		FGLS	0.32202	0.45488	0.46985	0.32646	0.44224	0.46612	2.4816
		Huber	0.34826	0.51087	0.49227	0.37236	0.54794	0.5435	2.8152
		Bi-Square	0.34373	0.51248	0.49257	0.37646	0.55967	0.54627	2.8312
	N=500	OLS	0.22952	0.33018	0.32055	0.26338	0.37434	0.38047	1.8984
		FGLS	0.21162	0.35056	0.28115	0.22637	0.31376	0.32102	1.7045
		Huber	0.22807	0.33951	0.32769	0.26649	0.38533	0.38998	1.9371
		Bi-Square	0.22811	0.34275	0.32761	0.26664	0.3891	0.38585	1.9400

TABLE 4.2.18 C: Root Mean Squares Error: When Errors are Normal ,Polynomial Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.7	N=20	OLS	0.42802	0.61106	0.60184	0.41883	0.62853	0.56642	3.2547
		FGLS	0.39892	0.59914	0.53547	0.36402	0.53427	0.51284	2.9447
		Huber	0.40747	0.57179	0.61524	0.43058	0.64071	0.55256	3.2184
		Bi-Square	0.4132	0.60756	0.63044	0.45845	0.66159	0.6029	3.3741
	N=30	OLS	0.3325	0.43224	0.4693	0.32014	0.47262	0.47633	2.5031
		FGLS	0.31373	0.39223	0.43927	0.28683	0.43121	0.43653	2.2998
		Huber	0.30679	0.42883	0.45364	0.30109	0.45124	0.47021	2.4118
		Bi-Square	0.31758	0.46507	0.47246	0.29947	0.46082	0.46759	2.4830
	N=50	OLS	0.24342	0.35752	0.35975	0.24439	0.34215	0.40959	1.9568
		FGLS	0.22359	0.32393	0.32392	0.22192	0.31586	0.37062	1.7798
		Huber	0.21971	0.35259	0.33325	0.23002	0.33502	0.40377	1.8744
		Bi-Square	0.21796	0.36198	0.33664	0.23026	0.34066	0.40539	1.8929
	N=100	OLS	0.16774	0.25457	0.25476	0.17022	0.26424	0.258	1.3695
		FGLS	0.15036	0.22741	0.23801	0.1507	0.23992	0.2217	1.2281
		Huber	0.15115	0.24906	0.22801	0.14957	0.2562	0.24141	1.2754
		Bi-Square	0.15364	0.25939	0.23192	0.15355	0.26265	0.24069	1.3018
	N=250	OLS	0.09868	0.15233	0.15561	0.10266	0.16888	0.15601	0.8342
		FGLS	0.09503	0.14672	0.14901	0.09111	0.14447	0.1422	0.7685
		Huber	0.08841	0.15392	0.1409	0.09781	0.1684	0.1542	0.8036
		Bi-Square	0.08805	0.16195	0.13988	0.09947	0.1738	0.15854	0.8217
	N=500	OLS	0.06608	0.10829	0.09844	0.07411	0.11589	0.1146	0.5774
		FGLS	0.06111	0.11285	0.0888	0.06536	0.10082	0.09841	0.5273
		Huber	0.05838	0.10507	0.09566	0.07027	0.11537	0.11253	0.5573
		Bi-Square	0.05785	0.10816	0.0949	0.07136	0.12032	0.11317	0.5658

TABLE 4.2.19 C: Root Mean Squares Error: When Errors are Normal ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.5207	0.69512	0.7025	0.52354	0.728	0.66095	3.8308
		FGLS	0.47591	0.67076	0.61484	0.4434	0.59748	0.58167	3.3841
		Huber	0.51881	0.6801	0.73816	0.54893	0.74927	0.67308	3.9084
		Bi-Square	0.52216	0.70366	0.75247	0.58511	0.77396	0.73896	4.0763
	N=30	OLS	0.40744	0.48268	0.5447	0.38568	0.53227	0.55705	2.9098
		FGLS	0.38053	0.43756	0.49397	0.34571	0.48525	0.49843	2.6414
		Huber	0.39826	0.50159	0.54482	0.3886	0.52846	0.57072	2.9325
		Bi-Square	0.40642	0.51355	0.56378	0.39297	0.53744	0.57099	2.9852
	N=50	OLS	0.30033	0.40603	0.42242	0.29408	0.38837	0.47867	2.2899
		FGLS	0.27241	0.35941	0.37757	0.26621	0.35725	0.42522	2.0581
		Huber	0.28811	0.40706	0.40728	0.29127	0.39205	0.48703	2.2728
		Bi-Square	0.28474	0.41176	0.40944	0.29367	0.39807	0.48789	2.2856
	N=100	OLS	0.20275	0.2906	0.29452	0.20676	0.30059	0.30256	1.5978
		FGLS	0.18098	0.25248	0.27518	0.18009	0.26559	0.25184	1.4062
		Huber	0.19635	0.29431	0.28198	0.19838	0.30901	0.29658	1.5766
		Bi-Square	0.19866	0.29644	0.28731	0.20074	0.30851	0.29702	1.5887
	N=250	OLS	0.12018	0.17329	0.17922	0.12798	0.19183	0.18539	0.9779
		FGLS	0.11267	0.16314	0.16892	0.11329	0.15871	0.16655	0.8833
		Huber	0.11909	0.18124	0.17441	0.12855	0.19514	0.19281	0.9912
		Bi-Square	0.1177	0.1829	0.17456	0.13002	0.19995	0.19426	0.9994
	N=500	OLS	0.08015	0.11901	0.11449	0.09165	0.13329	0.13574	0.6743
		FGLS	0.07391	0.12615	0.10086	0.07908	0.11214	0.11486	0.6070
		Huber	0.07816	0.12141	0.11675	0.09184	0.1368	0.1385	0.6835
		Bi-Square	0.07825	0.12291	0.11649	0.09199	0.13866	0.13712	0.6854

TABLE 4.2.20 C: Root Mean Squares Error: When Errors are Normal ,Linear Heteroscedastic (g= 0.5) and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.5925	0.76058	0.77338	0.60558	0.80256	0.73093	4.2655
		FGLS	0.53817	0.7286	0.67391	0.51317	0.65395	0.63788	3.7457
		Huber	0.60693	0.761	0.82526	0.63678	0.83066	0.75569	4.4163
		Bi-Square	0.60642	0.77756	0.83432	0.68012	0.85579	0.82796	4.5822
	N=30	OLS	0.46742	0.52623	0.59796	0.43961	0.58159	0.61367	3.2265
		FGLS	0.43523	0.4797	0.53394	0.39693	0.53284	0.54468	2.9233
		Huber	0.46485	0.5559	0.60368	0.45093	0.58305	0.63079	3.2892
		Bi-Square	0.47267	0.56084	0.62133	0.45752	0.59308	0.63417	3.3396
	N=50	OLS	0.34497	0.444	0.46555	0.33425	0.42478	0.5261	2.5397
		FGLS	0.31145	0.38971	0.41569	0.30406	0.39313	0.46435	2.2784
		Huber	0.33832	0.44685	0.45572	0.33857	0.43328	0.54173	2.5545
		Bi-Square	0.33426	0.4508	0.45748	0.34088	0.44174	0.5404	2.5656
	N=100	OLS	0.23158	0.31864	0.32332	0.2361	0.32842	0.33364	1.7717
		FGLS	0.20751	0.27363	0.30376	0.20554	0.28682	0.27467	1.5519
		Huber	0.22934	0.32614	0.31565	0.23397	0.34421	0.33199	1.7813
		Bi-Square	0.23019	0.32632	0.31961	0.23502	0.34205	0.33214	1.7853
	N=250	OLS	0.13827	0.18992	0.19608	0.1486	0.20951	0.20649	1.0889
		FGLS	0.12858	0.17727	0.18367	0.13246	0.17188	0.18497	0.9788
		Huber	0.14222	0.20085	0.19694	0.15084	0.21448	0.21689	1.1222
		Bi-Square	0.14026	0.20037	0.19687	0.15246	0.21844	0.21764	1.1260
	N=500	OLS	0.09197	0.12753	0.12639	0.10552	0.14645	0.15038	0.7482
		FGLS	0.0851	0.13612	0.11049	0.09058	0.12169	0.12684	0.6708
		Huber	0.09345	0.13309	0.13036	0.10756	0.15151	0.15476	0.7707
		Bi-Square	0.09351	0.13403	0.13051	0.10754	0.15201	0.15311	0.7707

TABLE 4.2.21C: Root Mean Squares Error: When Errors are Normal , Homoscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.59541	0.80006	0.78076	0.71522	0.94642	0.73901	4.5769
		FGLS	0.30977	0.33443	0.29692	0.29692	0.35877	0.38366	1.9805
		Huber	0.64228	0.84146	0.79604	0.74205	0.97319	0.75866	4.7537
		Bi-Square	0.66023	0.85921	0.81685	0.77232	1.01307	0.78162	4.9033
	N=30	OLS	0.50706	0.63931	0.71003	0.53404	0.69146	0.66123	3.7431
		FGLS	0.26915	0.24264	0.25764	0.248	0.23985	0.23283	1.4901
		Huber	0.52085	0.67095	0.73367	0.56696	0.72983	0.67128	3.8935
		Bi-Square	0.5223	0.6686	0.73795	0.56764	0.72742	0.67412	3.8980
	N=50	OLS	0.34529	0.47541	0.48906	0.36138	0.48761	0.49915	2.6579
		FGLS	0.18504	0.15809	0.18472	0.17121	0.17666	0.19158	1.0673
		Huber	0.35316	0.49717	0.50727	0.3611	0.47395	0.52339	2.7160
		Bi-Square	0.35278	0.49987	0.50596	0.36574	0.47409	0.52457	2.7230
	N=100	OLS	0.2163	0.3183	0.31108	0.24882	0.32315	0.34709	1.7647
		FGLS	0.11876	0.10903	0.1163	0.11485	0.11612	0.11825	0.6933
		Huber	0.22342	0.32345	0.31824	0.25513	0.33471	0.3529	1.8079
		Bi-Square	0.22539	0.31994	0.31528	0.25535	0.33729	0.35139	1.8046
	N=250	OLS	0.15586	0.18831	0.21723	0.16633	0.20092	0.24582	1.1745
		FGLS	0.08458	0.0805	0.06969	0.08167	0.06437	0.07704	0.4579
		Huber	0.15807	0.19023	0.22103	0.17188	0.21324	0.25102	1.2055
		Bi-Square	0.1579	0.18999	0.22245	0.17105	0.21039	0.2513	1.2031
	N=500	OLS	0.11179	0.1473	0.14751	0.1257	0.1502	0.16499	0.8475
		FGLS	0.05445	0.05426	0.04573	0.05412	0.05017	0.04077	0.2995
		Huber	0.11482	0.1464	0.1556	0.13166	0.15653	0.16874	0.8738
		Bi-Square	0.11443	0.14482	0.15647	0.13135	0.15618	0.16862	0.8719

TABLE 4.2.22C: Root Mean Squares Error: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	1.27904	1.88606	1.74329	1.472	2.1061	1.64892	10.1354
		FGLS	0.62079	0.89474	0.73419	0.71222	0.95471	0.83165	4.7483
		Huber	1.38946	1.94661	1.82667	1.53931	2.16011	1.68153	10.5437
		Bi-Square	1.42358	1.97999	1.85629	1.58503	2.17972	1.76983	10.7944
	N=30	OLS	1.06338	1.45844	1.59777	1.11281	1.57487	1.4868	8.2941
		FGLS	0.54724	0.62005	0.60208	0.4869	0.60554	0.59751	3.4593
		Huber	1.06493	1.51721	1.62594	1.16559	1.65186	1.48205	8.5076
		Bi-Square	1.07521	1.51754	1.63633	1.16485	1.65321	1.49081	8.5379
	N=50	OLS	0.73428	1.09485	1.11095	0.76832	1.1289	1.11362	5.9509
		FGLS	0.36087	0.41943	0.44733	0.34706	0.45822	0.48627	2.5192
		Huber	0.73256	1.145	1.12386	0.76286	1.07499	1.17079	6.0101
		Bi-Square	0.73424	1.16277	1.12843	0.7554	1.05584	1.17234	6.0090
	N=100	OLS	0.46793	0.7327	0.70831	0.5219	0.73976	0.78242	3.9530
		FGLS	0.25209	0.27204	0.28905	0.2275	0.30605	0.28249	1.6292
		Huber	0.47854	0.74043	0.70678	0.52534	0.75568	0.78982	3.9966
		Bi-Square	0.47751	0.73932	0.71128	0.52617	0.77163	0.78831	4.0142
	N=250	OLS	0.31719	0.42959	0.49248	0.35469	0.45808	0.55716	2.6092
		FGLS	0.15599	0.21057	0.18362	0.16928	0.17896	0.19906	1.0975
		Huber	0.31827	0.43553	0.49258	0.36064	0.48495	0.56532	2.6573
		Bi-Square	0.32048	0.43632	0.49915	0.35815	0.48072	0.56773	2.6625
	N=500	OLS	0.237	0.33918	0.3371	0.25982	0.3445	0.36444	1.8820
		FGLS	0.11598	0.13953	0.12062	0.1037	0.12992	0.11014	0.7199
		Huber	0.238	0.33158	0.34835	0.27084	0.35639	0.37471	1.9199
		Bi-Square	0.24022	0.33142	0.35225	0.27325	0.3596	0.37545	1.9322

TABLE 4.2.23C: Root Mean Squares Error: When Errors are Normal ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.37469	0.61363	0.53041	0.39753	0.635	0.49989	3.0511
		FGLS	0.22254	0.38457	0.30924	0.23538	0.38026	0.32896	1.8609
		Huber	0.39415	0.60089	0.55397	0.40912	0.62624	0.49469	3.0790
		Bi-Square	0.40728	0.60196	0.57414	0.42544	0.63962	0.53691	3.1854
	N=30	OLS	0.29626	0.45639	0.47885	0.30846	0.49098	0.45026	2.4812
		FGLS	0.17205	0.25913	0.22939	0.15842	0.25608	0.24145	1.3165
		Huber	0.28395	0.45822	0.47347	0.3031	0.49372	0.4281	2.4406
		Bi-Square	0.28399	0.48309	0.46601	0.30561	0.51449	0.42145	2.4746
	N=50	OLS	0.21103	0.34602	0.34017	0.22012	0.35744	0.33407	1.8089
		FGLS	0.11629	0.19029	0.17287	0.12157	0.19766	0.19582	0.9945
		Huber	0.19627	0.35642	0.3248	0.20039	0.31806	0.33409	1.7300
		Bi-Square	0.20422	0.3771	0.33211	0.20161	0.31326	0.34795	1.7763
	N=100	OLS	0.14047	0.23165	0.21966	0.14701	0.23215	0.23708	1.2080
		FGLS	0.08993	0.12064	0.1212	0.07606	0.12896	0.11649	0.6533
		Huber	0.12977	0.2283	0.2034	0.13724	0.23046	0.22543	1.1546
		Bi-Square	0.1347	0.23536	0.21058	0.1403	0.2424	0.22851	1.1919
	N=250	OLS	0.08872	0.13786	0.15246	0.10278	0.14456	0.16994	0.7963
		FGLS	0.05469	0.09192	0.08411	0.05926	0.08431	0.08279	0.4571
		Huber	0.08262	0.13507	0.14488	0.09722	0.1485	0.16407	0.7724
		Bi-Square	0.08648	0.14291	0.14767	0.09841	0.14373	0.16795	0.7872
	N=500	OLS	0.0679	0.10677	0.10499	0.07066	0.10924	0.10668	0.5662
		FGLS	0.04264	0.05781	0.05473	0.03695	0.06166	0.05031	0.3041
		Huber	0.06267	0.09913	0.10069	0.07089	0.10914	0.10667	0.5492
		Bi-Square	0.06351	0.10131	0.10232	0.07316	0.11284	0.10803	0.5612

TABLE 4.2.24C: Root Mean Squares Error: When Errors are Normal ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.44895	0.67886	0.62121	0.51138	0.748	0.58959	3.5980
		FGLS	0.22159	0.33661	0.27557	0.25135	0.3549	0.30993	1.7500
		Huber	0.48728	0.69643	0.65375	0.534	0.76367	0.59774	3.7329
		Bi-Square	0.49773	0.70561	0.66387	0.54937	0.76791	0.63379	3.8183
	N=30	OLS	0.3705	0.52134	0.57076	0.38706	0.56276	0.53037	2.9428
		FGLS	0.1927	0.23227	0.22187	0.17108	0.22687	0.22451	1.2693
		Huber	0.36874	0.53941	0.57846	0.40124	0.5871	0.52523	3.0002
		Bi-Square	0.37106	0.54193	0.58048	0.40149	0.5897	0.52748	3.0121
	N=50	OLS	0.25646	0.39211	0.39759	0.26892	0.40493	0.39744	2.1174
		FGLS	0.12703	0.15919	0.16575	0.12443	0.1732	0.18189	0.9315
		Huber	0.25261	0.40877	0.39928	0.26438	0.38126	0.41594	2.1222
		Bi-Square	0.25421	0.41764	0.40201	0.26143	0.37446	0.418	2.1277
	N=100	OLS	0.1645	0.2628	0.25381	0.18154	0.26458	0.27929	1.4065
		FGLS	0.09117	0.10345	0.10901	0.08117	0.11517	0.10492	0.6049
		Huber	0.16583	0.26442	0.2508	0.18089	0.26838	0.28034	1.4107
		Bi-Square	0.16639	0.2648	0.25365	0.18142	0.27546	0.28053	1.4222
	N=250	OLS	0.10976	0.154	0.17647	0.12414	0.16372	0.19918	0.9273
		FGLS	0.05456	0.07972	0.07043	0.06081	0.06887	0.07478	0.4092
		Huber	0.10918	0.15581	0.17537	0.125	0.17272	0.20126	0.9393
		Bi-Square	0.11037	0.15664	0.17797	0.12418	0.17199	0.20231	0.9435
	N=500	OLS	0.08259	0.12137	0.12074	0.08995	0.12347	0.1293	0.6674
		FGLS	0.04164	0.05196	0.04627	0.0367	0.04986	0.04236	0.2688
		Huber	0.08237	0.11784	0.12409	0.09319	0.1267	0.13262	0.6768
		Bi-Square	0.08321	0.11803	0.12555	0.09439	0.12844	0.13317	0.6828

TABLE 4.2.25C: Root Mean Squares Error: When Errors are Normal ,Square Root Heteroscedastic (g= 0.5) and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	<i>OLS</i>	0.51052	0.73012	0.68992	0.59887	0.83311	0.65461	4.0172
		<i>FGLS</i>	0.24957	0.3231	0.27289	0.28767	0.35544	0.31567	1.8043
		<i>Huber</i>	0.55527	0.76005	0.72007	0.62583	0.85693	0.67274	4.1909
		<i>Bi-Square</i>	0.56847	0.77313	0.73232	0.64337	0.8704	0.68845	4.2761
	N=30	<i>OLS</i>	0.42899	0.57165	0.6331	0.44964	0.61771	0.58772	3.2888
		<i>FGLS</i>	0.22131	0.22823	0.23058	0.19803	0.22223	0.22195	1.3223
		<i>Huber</i>	0.43278	0.59575	0.64811	0.47492	0.65108	0.59082	3.3935
		<i>Bi-Square</i>	0.43775	0.59585	0.65406	0.47282	0.64763	0.59437	3.4025
	N=50	<i>OLS</i>	0.29379	0.42755	0.43788	0.3082	0.44055	0.44225	2.3502
		<i>FGLS</i>	0.14777	0.14983	0.16903	0.13999	0.16768	0.18084	0.9551
		<i>Huber</i>	0.29634	0.44895	0.44753	0.30837	0.42401	0.46627	2.3915
		<i>Bi-Square</i>	0.29603	0.45211	0.4488	0.30657	0.41826	0.4657	2.3875
	N=100	<i>OLS</i>	0.1857	0.28651	0.27867	0.20991	0.28952	0.30914	1.5594
		<i>FGLS</i>	0.09981	0.10041	0.10747	0.09279	0.11147	0.10578	0.6177
		<i>Huber</i>	0.19359	0.2908	0.28141	0.21349	0.29692	0.31478	1.5910
		<i>Bi-Square</i>	0.19141	0.28806	0.28158	0.21299	0.30144	0.31297	1.5885
	N=250	<i>OLS</i>	0.1288	0.16804	0.19414	0.14185	0.17933	0.17933	0.9915
		<i>FGLS</i>	0.06437	0.07653	0.06615	0.06768	0.06298	0.07333	0.4110
		<i>Huber</i>	0.12994	0.17024	0.19576	0.1452	0.18996	0.22392	1.0550
		<i>Bi-Square</i>	0.13058	0.17031	0.19805	0.14431	0.1879	0.22468	1.0558
	N=500	<i>OLS</i>	0.09484	0.13246	0.13233	0.10519	0.13469	0.1451	0.7446
		<i>FGLS</i>	0.04523	0.05106	0.04364	0.04207	0.04631	0.03945	0.2677
		<i>Huber</i>	0.09649	0.13064	0.13836	0.10993	0.13985	0.14937	0.7647
		<i>Bi-Square</i>	0.09696	0.12986	0.13973	0.11038	0.14016	0.1494	0.7665

TABLE 4.3.1 A: VARIANCE: When Errors are Log-Normal , Homoscedastic and No contemporal correlation under varving sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	2.654	3.295	3.60936	1.854	3.5104	3.1582	18.0813
		FGLS	2.442	3.027	3.74337	1.8886	3.655	3.2611	18.0177
		Huber	0.565	0.782	1.1225	0.5825	1.18	0.8444	5.0762
		Bi-Square	0.46	0.672	0.90264	0.5578	1.0592	0.6215	4.2727
	N=30	OLS	1.035	1.784	1.84376	1.111	1.4904	2.8418	10.1060
		FGLS	1.066	1.976	2.03144	1.2209	1.5735	2.8369	10.7043
		Huber	0.426	0.641	0.5901	0.3653	0.6139	0.6527	3.2896
		Bi-Square	0.261	0.441	0.30416	0.2445	0.4664	0.4764	2.1937
	N=50	OLS	0.595	1.342	0.81338	1.0676	1.6273	1.3194	6.7655
		FGLS	0.612	1.359	0.82653	1.069	1.7065	1.3267	6.8994
		Huber	0.168	0.241	0.26855	0.1951	0.2985	0.31	1.4815
		Bi-Square	0.14	0.217	0.22437	0.1761	0.239	0.2612	1.2584
	N=100	OLS	0.24	0.462	0.47175	0.4138	0.5559	0.7722	2.9164
		FGLS	0.239	0.465	0.46424	0.4148	0.5454	0.7542	2.8833
		Huber	0.091	0.154	0.14139	0.109	0.1508	0.1601	0.8068
		Bi-Square	0.068	0.107	0.11615	0.0779	0.1258	0.1017	0.5965
	N=250	OLS	0.108	0.235	0.2249	0.1354	0.2438	0.245	1.1923
		FGLS	0.108	0.234	0.23092	0.1368	0.2482	0.2477	1.2056
		Huber	0.036	0.044	0.05282	0.0383	0.0544	0.057	0.2821
		Bi-Square	0.023	0.027	0.03633	0.0262	0.0381	0.0318	0.1818
	N=500	OLS	0.059	0.121	0.09146	0.0658	0.1052	0.1228	0.5653
		FGLS	0.059	0.122	0.09038	0.0657	0.1049	0.1222	0.5641
		Huber	0.017	0.029	0.02297	0.0178	0.024	0.0317	0.1432
		Bi-Square	0.014	0.017	0.01891	0.0137	0.0189	0.0226	0.1050

TABLE 4.3.2 A: VARIANCE: When Errors are Log-Normal, Exponential Heteroscedastic and No contemporal correlation under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	10.55	14.96	16.86813	8.0759	17.812	15.99	84.2573
		FGLS	9.64	13.79	17.56383	8.2567	18.306	16.866	84.4240
		Huber	2.371	3.662	5.7762	2.3729	5.4366	4.1173	23.7355
		Bi-Square	2.086	3.684	4.78291	2.2251	4.6428	2.9339	20.3542
	N=30	OLS	4.667	9.317	9.79575	4.7965	7.502	14.22	50.2977
		FGLS	4.897	10.31	10.78498	5.2346	7.8436	14.271	53.3380
		Huber	1.963	3.331	3.05867	1.5953	3.1655	3.3541	16.4678
		Bi-Square	1.219	2.375	1.57431	1.1472	2.5219	2.5419	11.3795
	N=50	OLS	2.685	6.739	4.29155	5.2283	9.2067	7.0204	35.1708
		FGLS	2.787	6.916	4.38128	5.2202	9.589	7.0777	35.9710
		Huber	0.741	1.213	1.39918	0.8574	1.6474	1.593	7.4513
		Bi-Square	0.583	1.094	1.114	0.7427	1.3025	1.3419	6.1785
	N=100	OLS	1.045	2.355	2.42015	1.8913	2.9424	4.0749	14.7288
		FGLS	1.045	2.37	2.39484	1.893	2.8876	3.9762	14.5664
		Huber	0.418	0.787	0.74235	0.4768	0.7605	0.8092	3.9938
		Bi-Square	0.3	0.554	0.57518	0.3307	0.6521	0.5101	2.9220
	N=250	OLS	0.48	1.225	1.17293	0.5708	1.2773	1.2016	5.9279
		FGLS	0.483	1.214	1.20353	0.5762	1.3016	1.2151	5.9933
		Huber	0.154	0.204	0.26072	0.1647	0.2713	0.2806	1.3352
		Bi-Square	0.097	0.142	0.18044	0.1098	0.1863	0.1562	0.8713
	500	OLS	0.265	0.641	0.480747	0.2929	0.5505	0.6247	2.8548
		FGLS	0.266	0.644	0.474809	0.291	0.5491	0.6203	2.8455
		Huber	0.074	0.148	0.112366	0.0789	0.1267	0.1552	0.6952
		Bi-Square	0.055	0.086	0.096262	0.0575	0.0941	0.109	0.4972

TABLE 4.3.3 A: VARIANCE: When Errors are Log-Normal , Quadratic Heteroscedastic(g=2) and No contemporal correlation(P=0) under varying sample sizes

Contemporall Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	<i>OLS</i>	0.689	1.249	1.39471	0.6329	1.7054	1.4372	7.1082
		<i>FGLS</i>	0.616	1.136	1.43934	0.6721	1.7581	1.5635	7.1851
		<i>Huber</i>	0.172	0.324	0.54106	0.1521	0.4438	0.3407	1.9739
		<i>Bi-Square</i>	0.155	0.317	0.39588	0.1432	0.3557	0.2653	1.6319
	N=30	<i>OLS</i>	0.378	0.912	0.94864	0.3559	0.7095	1.2404	4.5449
		<i>FGLS</i>	0.406	1.003	1.04513	0.3847	0.7336	1.2492	4.8209
		<i>Huber</i>	0.148	0.303	0.26572	0.115	0.2963	0.3015	1.4295
		<i>Bi-Square</i>	0.094	0.223	0.13596	0.0822	0.2164	0.2165	0.9678
	N=50	<i>OLS</i>	0.216	0.613	0.42071	0.4755	0.9834	0.698	3.4076
		<i>FGLS</i>	0.228	0.645	0.42936	0.4744	1.014	0.7094	3.4998
		<i>Huber</i>	0.051	0.11	0.11956	0.0662	0.1749	0.1435	0.6648
		<i>Bi-Square</i>	0.033	0.093	0.08457	0.0474	0.1202	0.1104	0.4893
	N=100	<i>OLS</i>	0.08	0.221	0.22413	0.1576	0.298	0.3917	1.3723
		<i>FGLS</i>	0.08	0.224	0.2225	0.1578	0.2934	0.3845	1.3621
		<i>Huber</i>	0.03	0.07	0.06607	0.0311	0.0669	0.0684	0.3331
		<i>Bi-Square</i>	0.021	0.049	0.0492	0.0197	0.0537	0.0428	0.2354
	N=250	<i>OLS</i>	0.038	0.118	0.11081	0.0407	0.1235	0.1044	0.5358
		<i>FGLS</i>	0.038	0.117	0.11342	0.0412	0.1261	0.1055	0.5421
		<i>Huber</i>	0.01	0.017	0.02137	0.0108	0.0241	0.0226	0.1054
		<i>Bi-Square</i>	0.006	0.013	0.01429	0.0066	0.0161	0.0126	0.0684
	N=500	<i>OLS</i>	0.022	0.064	0.0469	0.0229	0.0537	0.0569	0.2658
		<i>FGLS</i>	0.022	0.064	0.04643	0.0227	0.0537	0.0564	0.2650
		<i>Huber</i>	0.005	0.014	0.00986	0.0056	0.0117	0.013	0.0589
		<i>Bi-Square</i>	0.003	0.008	0.00815	0.0037	0.0077	0.0083	0.0392

TABLE 4.3.4 A: VARIANCE: When Errors are Log- Normal , Linear Heteroscedastic (g=1) and No contemporal correlation (P=0) under varying sample sizes

Contemporall Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	<i>OLS</i>	1.241	1.848	2.09555	0.9902	2.2709	2.068	10.5140
		<i>FGLS</i>	1.131	1.708	2.17959	1.0173	2.3351	2.1925	10.5637
		<i>Huber</i>	0.286	0.464	0.7412	0.2842	0.6745	0.5231	2.9723
		<i>Bi-Square</i>	0.258	0.477	0.61389	0.2602	0.5738	0.3698	2.5528
	N=30	<i>OLS</i>	0.574	1.198	1.26388	0.5757	0.9495	1.815	6.3757
		<i>FGLS</i>	0.605	1.324	1.39002	0.6259	0.9894	1.8217	6.7563
		<i>Huber</i>	0.246	0.427	0.3901	0.1913	0.403	0.4264	2.0840
		<i>Bi-Square</i>	0.156	0.31	0.20568	0.1403	0.3223	0.3272	1.4607
	N=50	<i>OLS</i>	0.33	0.857	0.55636	0.6564	1.1959	0.905	4.5014
		<i>FGLS</i>	0.344	0.883	0.56871	0.6547	1.2437	0.913	4.6072
		<i>Huber</i>	0.09	0.153	0.17837	0.1049	0.2168	0.202	0.9444
		<i>Bi-Square</i>	0.069	0.137	0.13968	0.0873	0.1667	0.1669	0.7670
	N=100	<i>OLS</i>	0.126	0.299	0.31077	0.2305	0.375	0.5207	1.8614
		<i>FGLS</i>	0.126	0.301	0.30729	0.2307	0.3679	0.5078	1.8407
		<i>Huber</i>	0.052	0.101	0.09479	0.058	0.0959	0.1034	0.5047
		<i>Bi-Square</i>	0.037	0.071	0.07302	0.0397	0.0821	0.065	0.3676
	N=250	<i>OLS</i>	0.058	0.157	0.15126	0.0682	0.1639	0.1522	0.7503
		<i>FGLS</i>	0.059	0.155	0.15517	0.0688	0.1671	0.1538	0.7585
		<i>Huber</i>	0.019	0.026	0.03287	0.0199	0.0342	0.035	0.1661
		<i>Bi-Square</i>	0.012	0.018	0.02275	0.0131	0.0235	0.0196	0.1089
	N=500	<i>OLS</i>	0.032	0.082	0.0622	0.0357	0.0704	0.0799	0.3626
		<i>FGLS</i>	0.033	0.082	0.06148	0.0354	0.0703	0.0794	0.3614
		<i>Huber</i>	0.009	0.019	0.01419	0.0097	0.0162	0.0195	0.0873
		<i>Bi-Square</i>	0.006	0.011	0.01221	0.0069	0.0119	0.0136	0.0619

TABLE 4.3.5 A: VARIANCE: When Errors are Log-Normal , Square Root Heteroscedastic(g=0.5) and No contemporaneous correlation under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	<i>OLS</i>	1.782	2.411	2.70273	1.3262	2.7649	2.5368	13.5231
		<i>FGLS</i>	1.635	2.231	2.81246	1.3527	2.8556	2.6533	13.5402
		<i>Huber</i>	0.393	0.586	0.90031	0.405	0.8793	0.6549	3.8178
		<i>Bi-Square</i>	0.339	0.56	0.74855	0.3786	0.7505	0.4618	3.2385
	N=30	<i>OLS</i>	0.755	1.437	1.50737	0.7825	1.1622	2.2505	7.8943
		<i>FGLS</i>	0.787	1.59	1.65865	0.8549	1.2183	2.2521	8.3608
		<i>Huber</i>	0.32	0.518	0.47787	0.2615	0.4902	0.5272	2.5953
		<i>Bi-Square</i>	0.197	0.363	0.24772	0.1811	0.3867	0.392	1.7680
	N=50	<i>OLS</i>	0.435	1.057	0.66336	0.8201	1.3732	1.0756	5.4774
		<i>FGLS</i>	0.45	1.079	0.67673	0.8192	1.4341	1.0827	5.5348
		<i>Huber</i>	0.123	0.191	0.21931	0.1406	0.2489	0.2499	3.5014
		<i>Bi-Square</i>	0.099	0.172	0.17708	0.1238	0.1991	0.2092	3.0772
	N=100	<i>OLS</i>	0.17	0.365	0.37826	0.3015	0.4462	0.6251	2.2858
		<i>FGLS</i>	0.17	0.367	0.37316	0.3019	0.4377	0.6092	2.2592
		<i>Huber</i>	0.068	0.124	0.11584	0.0791	0.1192	0.1278	0.6340
		<i>Bi-Square</i>	0.05	0.087	0.09137	0.0559	0.102	0.0807	0.4666
	N=250	<i>OLS</i>	0.078	0.189	0.18225	0.0942	0.1966	0.1906	0.9296
		<i>FGLS</i>	0.078	0.187	0.18708	0.0951	0.2002	0.1926	0.9397
		<i>Huber</i>	0.026	0.034	0.04162	0.0276	0.0429	0.0448	0.2162
		<i>Bi-Square</i>	0.016	0.022	0.02868	0.0187	0.0297	0.0251	0.1403
	N=500	<i>OLS</i>	0.043	0.098	0.07434	0.0475	0.0845	0.0979	0.4445
		<i>FGLS</i>	0.043	0.098	0.07344	0.0473	0.0843	0.0973	0.4433
		<i>Huber</i>	0.012	0.023	0.01787	0.0129	0.0196	0.0248	0.1109
		<i>Bi-Square</i>	0.009	0.013	0.01521	0.0096	0.0149	0.0175	0.0801

TABLE 4.3.6 A: VARIANCE: When Errors are Log-Normal , Homoscedastic and contemporaneous correlation (P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	<i>OLS</i>	2.72	4.095	4.239	1.8167	3.7886	3.5763	20.2352
		<i>FGLS</i>	2.167	3.002	3.87137	1.7367	4.221	3.5579	18.5561
		<i>Huber</i>	0.617	0.986	1.30151	0.5598	0.6954	1.0052	5.1648
		<i>Bi-Square</i>	0.55	0.749	1.13621	0.4596	0.7487	0.7644	4.4085
	N=30	<i>OLS</i>	0.927	1.505	1.53857	1.4593	3.5491	2.4333	11.4119
		<i>FGLS</i>	0.881	1.491	1.42644	1.5936	3.238	2.3114	10.9414
		<i>Huber</i>	0.414	0.541	0.66128	0.4176	0.7379	0.7628	3.5340
		<i>Bi-Square</i>	0.322	0.374	0.5238	0.3144	0.6081	0.5492	2.6917
	N=50	<i>OLS</i>	0.672	1.178	2.08677	0.6455	1.0314	0.9585	6.5727
		<i>FGLS</i>	0.675	1.121	1.24518	0.6582	0.9382	1.0305	5.6688
		<i>Huber</i>	0.222	0.273	0.32116	0.1904	0.3527	0.3371	1.6968
		<i>Bi-Square</i>	0.172	0.223	0.22201	0.1549	0.2868	0.2774	1.3359
	N=100	<i>OLS</i>	0.359	0.565	0.5681	0.3396	0.5046	0.5896	2.9258
		<i>FGLS</i>	0.341	0.506	0.58663	0.3364	0.5145	0.5827	2.8673
		<i>Huber</i>	0.108	0.171	0.14734	0.1038	0.1383	0.1326	0.8009
		<i>Bi-Square</i>	0.086	0.122	0.11113	0.0875	0.1239	0.1275	0.6582
	N=250	<i>OLS</i>	0.09	0.264	0.20148	0.1075	0.2184	0.2636	1.1457
		<i>FGLS</i>	0.08	0.208	0.18298	0.0983	0.2167	0.2565	1.0427
		<i>Huber</i>	0.029	0.057	0.05218	0.0373	0.0507	0.0638	0.2897
		<i>Bi-Square</i>	0.026	0.038	0.04551	0.0271	0.0444	0.0464	0.2277
	N=500	<i>OLS</i>	0.059	0.116	0.11046	0.0808	0.1356	0.1187	0.6212
		<i>FGLS</i>	0.058	0.114	0.10605	0.078	0.1308	0.1089	0.5958
		<i>Huber</i>	0.015	0.028	0.02293	0.0205	0.0282	0.0339	0.1485
		<i>Bi-Square</i>	0.011	0.023	0.01366	0.0167	0.0237	0.0283	0.1166

TABLE 4.3.7A: VARIANCE: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	10.09	17.51	20.52957	8.0862	17.977	18.786	92.9754
		FGLS	7.868	13.58	17.87051	7.9635	19.665	19.04	85.9887
		Huber	2.682	5.005	6.37561	2.3573	3.6221	5.22	25.2619
		Bi-Square	2.271	3.755	5.53393	2.0813	3.7116	4.131	21.4838
	N=30	OLS	4.574	8.044	8.51934	5.8855	18.772	11.956	57.7503
		FGLS	4.277	7.829	7.67365	6.5373	17.486	10.779	54.5819
		Huber	1.86	2.783	3.37517	1.7482	3.6906	3.5167	16.9731
		Bi-Square	1.409	1.918	2.73758	1.2246	2.9826	2.5297	12.8013
	N=50	OLS	3.071	5.902	11.1446	2.811	5.2314	4.8806	33.0413
		FGLS	3.058	5.499	6.61084	2.8919	4.7758	5.2252	28.0605
		Huber	0.99	1.499	1.58703	0.8552	1.8371	1.6928	8.4615
		Bi-Square	0.774	1.275	1.14372	0.6293	1.3779	1.3605	6.5601
	N=100	OLS	1.587	2.839	3.00018	1.5086	2.6623	3.0799	14.6764
		FGLS	1.495	2.508	3.12122	1.4431	2.6762	2.9889	14.2324
		Huber	0.482	0.873	0.7525	0.4305	0.6448	0.6913	3.8739
		Bi-Square	0.359	0.591	0.52967	0.3649	0.6134	0.6267	3.0852
	N=250	OLS	0.4	1.353	1.0579	0.4664	1.1794	1.3774	5.8339
		FGLS	0.354	1.09	0.95526	0.4328	1.1828	1.3507	5.3656
		Huber	0.119	0.299	0.25799	0.1592	0.2528	0.3226	1.4108
		Bi-Square	0.107	0.194	0.22106	0.1071	0.2287	0.2249	1.0830
	N=500	OLS	0.259	0.567	0.58795	0.3525	0.6725	0.6067	3.0455
		FGLS	0.259	0.568	0.57183	0.3365	0.6432	0.5605	2.9388
		Huber	0.066	0.143	0.11757	0.0892	0.1404	0.1684	0.7249
		Bi-Square	0.049	0.121	0.07265	0.0673	0.1221	0.1373	0.5699

TABLE 4.3.8A: VARIANCE: When Errors are Log-Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.642	1.402	1.8256	0.6519	1.5423	1.7876	7.8517
		FGLS	0.5	1.177	1.5602	0.6731	1.6587	1.8504	7.4189
		Huber	0.198	0.469	0.5157	0.1694	0.3685	0.4791	2.1990
		Bi-Square	0.132	0.279	0.41486	0.1459	0.3519	0.3653	1.6890
	N=30	OLS	0.417	0.8	0.8754	0.3864	1.8428	1.0304	5.3522
		FGLS	0.385	0.764	0.7685	0.4444	1.793	0.877	5.0323
		Huber	0.146	0.268	0.3016	0.1121	0.3173	0.2722	1.4173
		Bi-Square	0.104	0.198	0.2455	0.075	0.2421	0.1916	1.0570
	N=50	OLS	0.244	0.535	1.0493	0.2183	0.4921	0.4619	3.0009
		FGLS	0.24	0.496	0.6243	0.2275	0.456	0.4886	2.5319
		Huber	0.068	0.15	0.1309	0.0617	0.1756	0.1425	0.7283
		Bi-Square	0.051	0.133	0.0933	0.0449	0.1232	0.115	0.5597
	N=100	OLS	0.124	0.265	0.2908	0.1208	0.2708	0.2924	1.3637
		FGLS	0.117	0.234	0.305	0.1136	0.2702	0.2819	1.3215
		Huber	0.033	0.076	0.0639	0.0288	0.0558	0.0641	0.3212
		Bi-Square	0.021	0.046	0.0406	0.0223	0.0494	0.0532	0.2327
	N=250	OLS	0.035	0.131	0.1031	0.0376	0.1224	0.1302	0.5589
		FGLS	0.031	0.11	0.0936	0.0366	0.1239	0.1291	0.5237
		Huber	0.008	0.028	0.0218	0.0105	0.0232	0.027	0.1175
		Bi-Square	0.007	0.017	0.0179	0.0066	0.0215	0.0182	0.0879
	N=500	OLS	0.02	0.05	0.0568	0.0268	0.0616	0.0558	0.2716
		FGLS	0.021	0.052	0.0561	0.0253	0.0586	0.0524	0.2658
		Huber	0.005	0.013	0.0104	0.0059	0.0134	0.0138	0.0612
		Bi-Square	0.004	0.011	0.007	0.0041	0.0119	0.0107	0.0479

TABLE 4.3.9A: VARIANCE: When Errors are Log- Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.125	2.093	2.5518	0.9904	2.2506	2.4251	11.4355
		FGLS	0.875	1.671	2.1971	0.9835	2.4621	2.4624	10.6510
		Huber	0.329	0.642	0.8075	0.2837	0.4651	0.6658	3.1929
		Bi-Square	0.272	0.477	0.6913	0.2529	0.4775	0.5257	2.6962
	N=30	OLS	0.569	1.025	1.1019	0.6976	2.4129	1.5151	7.3216
		FGLS	0.53	0.995	0.9891	0.7833	2.265	1.3484	6.9107
		Huber	0.228	0.356	0.4297	0.2089	0.467	0.4345	2.1231
		Bi-Square	0.169	0.243	0.3532	0.144	0.3729	0.3139	1.5958
	N=50	OLS	0.38	0.749	1.4553	0.341	0.6644	0.6223	4.2114
		FGLS	0.377	0.694	0.8613	0.3529	0.608	0.6658	3.5591
		Huber	0.119	0.192	0.1983	0.1059	0.2359	0.2159	1.0669
		Bi-Square	0.093	0.168	0.1439	0.0784	0.1757	0.1744	0.8332
	N=100	OLS	0.193	0.358	0.3869	0.1855	0.3438	0.3972	1.8639
		FGLS	0.182	0.316	0.4036	0.1761	0.3451	0.384	1.8061
		Huber	0.059	0.11	0.0962	0.0516	0.0799	0.0884	0.4853
		Bi-Square	0.043	0.073	0.0666	0.043	0.0761	0.0788	0.3803
	N=250	OLS	0.049	0.173	0.1364	0.0565	0.1517	0.1783	0.7443
		FGLS	0.043	0.14	0.1231	0.0529	0.1528	0.1753	0.6874
		Huber	0.014	0.038	0.0326	0.019	0.032	0.0409	0.1770
		Bi-Square	0.013	0.025	0.0277	0.0124	0.029	0.0282	0.1346
	N=500	OLS	0.031	0.071	0.0761	0.0422	0.0842	0.0773	0.3822
		FGLS	0.032	0.072	0.0741	0.0401	0.0804	0.0715	0.3692
		Huber	0.008	0.018	0.015	0.0108	0.0179	0.0212	0.0909
		Bi-Square	0.006	0.015	0.0094	0.008	0.0156	0.0172	0.0714

TABLE 4.3.10A: VARIANCE: When Errors are Log- Normal , Square Root Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.687	2.819	3.2088	1.3107	2.8663	2.9116	14.8036
		FGLS	1.324	2.161	2.8278	1.2749	3.164	2.9276	13.6798
		Huber	0.441	0.774	1.0199	0.3913	0.5548	0.8109	3.9915
		Bi-Square	0.391	0.619	0.8941	0.3309	0.57	0.6267	3.4315
	N=30	OLS	0.71	1.22	1.2838	0.994	2.8774	1.8984	8.9827
		FGLS	0.668	1.195	1.1703	1.1002	2.6575	1.743	8.5337
		Huber	0.299	0.428	0.5255	0.2961	0.5838	0.5743	2.7068
		Bi-Square	0.228	0.293	0.4187	0.213	0.4739	0.4179	2.0441
	N=50	OLS	0.497	0.925	1.7347	0.459	0.8126	0.7584	5.1870
		FGLS	0.497	0.866	1.0291	0.4718	0.7405	0.8143	4.4182
		Huber	0.163	0.227	0.2525	0.1413	0.2862	0.2678	1.3369
		Bi-Square	0.127	0.19	0.1786	0.106	0.22	0.2163	1.0386
	N=100	OLS	0.258	0.441	0.4623	0.2457	0.408	0.4779	2.2920
		FGLS	0.243	0.391	0.4799	0.2375	0.4121	0.4657	2.2292
		Huber	0.08	0.137	0.1187	0.0725	0.1037	0.1072	0.6189
		Bi-Square	0.061	0.095	0.086	0.0612	0.097	0.0992	0.4993
	N=250	OLS	0.064	0.209	0.1633	0.0758	0.1781	0.2145	0.9052
		FGLS	0.057	0.167	0.1477	0.0699	0.1782	0.2098	0.8297
		Huber	0.02	0.047	0.041	0.0265	0.0395	0.0508	0.2243
		Bi-Square	0.018	0.03	0.0354	0.0182	0.0353	0.036	0.1734
	N=500	OLS	0.042	0.089	0.0907	0.0571	0.1045	0.0945	0.4781
		FGLS	0.042	0.089	0.0877	0.0546	0.1003	0.0869	0.4597
		Huber	0.011	0.022	0.0185	0.0148	0.0221	0.0268	0.1153
		Bi-Square	0.008	0.019	0.0112	0.0115	0.0188	0.0221	0.0904

TABLE 4.3.11A: VARIANCE: When Errors are Log-Normal , Homoscedastic and contemporal correlation (P=0.5) under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g ; g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	2.72	4.095	4.239	1.7529	3.2669	3.2699	19.3432
		FGLS	1.545	2.244	2.68905	1.5122	3.4888	2.9867	14.4659
		Huber	0.617	0.986	1.30151	0.6363	0.8654	1.2428	5.6490
		Bi-Square	0.55	0.749	1.13621	0.5746	0.9964	1.0276	5.0345
	N=30	OLS	0.927	1.505	1.53857	1.2127	3.2366	2.2003	10.6199
		FGLS	0.825	1.374	1.17904	1.318	2.7893	1.8917	9.3770
		Huber	0.414	0.541	0.66128	0.4389	1.0167	0.9453	4.0167
		Bi-Square	0.322	0.374	0.5238	0.4015	0.9003	0.7845	3.3062
	N=50	OLS	0.672	1.178	2.08677	0.6546	1.0741	0.907	6.5730
		FGLS	0.634	0.913	1.02472	0.6113	0.7968	0.9095	4.8894
		Huber	0.222	0.273	0.32116	0.2631	0.4584	0.3892	1.9273
		Bi-Square	0.172	0.223	0.22201	0.1933	0.3554	0.3557	1.5212
	N=100	OLS	0.359	0.565	0.5681	0.3179	0.4703	0.5649	2.8452
		FGLS	0.301	0.432	0.50475	0.2845	0.4404	0.5011	2.4635
		Huber	0.108	0.171	0.14734	0.1131	0.1804	0.182	0.9016
		Bi-Square	0.086	0.122	0.11113	0.1023	0.1632	0.1806	0.7654
	N=250	OLS	0.09	0.264	0.20148	0.1288	0.2181	0.2651	1.1682
		FGLS	0.08	0.179	0.15854	0.1033	0.1809	0.23	0.9318
		Huber	0.029	0.057	0.05218	0.0517	0.0663	0.0951	0.3511
		Bi-Square	0.026	0.038	0.04551	0.044	0.06	0.0821	0.2960
	N=500	OLS	0.059	0.116	0.11046	0.078	0.1351	0.1226	0.6218
		FGLS	0.05	0.095	0.0841	0.0662	0.1191	0.0949	0.5088
		Huber	0.015	0.028	0.02293	0.0264	0.0369	0.0461	0.1753
		Bi-Square	0.011	0.023	0.01366	0.0246	0.0347	0.0394	0.1466

TABLE 4.3.12A: VARIANCE: When Errors are Log-Normal , Exponential Heteroscedastic and Contemporal Correlation(P=0.5) under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	10.09	17.51	20.52957	7.7243	15.424	16.941	88.2160
		FGLS	5.8	10.47	12.85342	6.8833	16.165	16.015	68.1827
		Huber	2.682	5.005	6.37561	2.6606	4.4907	6.2997	27.5134
		Bi-Square	2.271	3.755	5.53393	2.4906	5.0091	5.5436	24.6031
	N=30	OLS	4.574	8.044	8.51934	4.9833	17.464	11.037	54.6221
		FGLS	3.964	7.128	6.05792	5.4652	15.469	8.7941	46.8779
		Huber	1.86	2.783	3.37517	1.8495	5.2072	4.6502	19.7244
		Bi-Square	1.409	1.918	2.73758	1.7433	4.7082	3.8834	16.3992
	N=50	OLS	3.071	5.902	11.1446	2.7523	5.3684	4.5419	32.7809
		FGLS	2.835	4.521	5.50402	2.6111	3.9653	4.5508	23.9878
		Huber	0.99	1.499	1.58703	1.167	2.3668	1.9317	9.5419
		Bi-Square	0.774	1.275	1.14372	0.8794	1.8898	1.8754	7.8371
	N=100	OLS	1.587	2.839	3.00018	1.4012	2.4844	2.9306	14.2419
		FGLS	1.329	2.122	2.71514	1.1973	2.2942	2.5596	12.2168
		Huber	0.482	0.873	0.7525	0.4869	0.9011	0.9341	4.4294
		Bi-Square	0.359	0.591	0.52967	0.425	0.8302	0.894	3.6295
	N=250	OLS	0.4	1.353	1.0579	0.5551	1.1528	1.3698	5.8884
		FGLS	0.346	0.937	0.82381	0.4484	0.9752	1.1978	4.7288
		Huber	0.119	0.299	0.25799	0.2238	0.3368	0.4726	1.7094
		Bi-Square	0.107	0.194	0.22106	0.1765	0.2846	0.4088	1.3923
	N=500	OLS	0.259	0.567	0.58795	0.3474	0.6835	0.631	3.0756
		FGLS	0.229	0.487	0.46897	0.2874	0.5929	0.4954	2.5605
		Huber	0.066	0.143	0.11757	0.1159	0.1933	0.2317	0.8679
		Bi-Square	0.049	0.121	0.07265	0.1003	0.1833	0.1938	0.7206

TABLE 4.3.13A: VARIANCE: When Errors are Log- Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	0.642	1.402	1.8256	0.612	1.3301	1.5824	7.3944
		FGLS	0.399	0.959	1.20281	0.5845	1.3744	1.5724	6.0929
		Huber	0.198	0.469	0.5157	0.194	0.4475	0.5809	2.4044
		Bi-Square	0.132	0.279	0.41486	0.1821	0.4893	0.5224	2.0197
	N=30	OLS	0.417	0.8	0.87538	0.3457	1.7586	0.9813	5.1782
		FGLS	0.352	0.694	0.58667	0.3855	1.6482	0.7215	4.3877
		Huber	0.146	0.268	0.30162	0.1283	0.4777	0.3796	1.7014
		Bi-Square	0.104	0.198	0.24546	0.1074	0.381	0.3012	1.3379
	N=50	OLS	0.244	0.535	1.04931	0.2021	0.4978	0.4228	2.9512
		FGLS	0.219	0.411	0.53497	0.1988	0.3796	0.4221	2.1653
		Huber	0.068	0.15	0.13086	0.0794	0.2245	0.1613	0.8136
		Bi-Square	0.051	0.133	0.09333	0.064	0.1937	0.1586	0.6930
	N=100	OLS	0.124	0.265	0.29081	0.1128	0.2553	0.2778	1.3257
		FGLS	0.108	0.2	0.27418	0.0962	0.2375	0.2464	1.1621
		Huber	0.033	0.076	0.06391	0.0342	0.0819	0.083	0.3717
		Bi-Square	0.021	0.046	0.04064	0.0261	0.0752	0.0707	0.2800
	N=250	OLS	0.035	0.131	0.10308	0.043	0.117	0.1275	0.5561
		FGLS	0.029	0.096	0.0817	0.0368	0.1027	0.1138	0.4604
		Huber	0.008	0.028	0.0218	0.0157	0.0314	0.0403	0.1442
		Bi-Square	0.007	0.017	0.01791	0.0109	0.0253	0.0331	0.1108
	N=500	OLS	0.02	0.05	0.05681	0.0275	0.0643	0.0586	0.2778
		FGLS	0.02	0.048	0.04896	0.0224	0.0557	0.0479	0.2430
		Huber	0.005	0.013	0.01045	0.0079	0.0189	0.0191	0.0740
		Bi-Square	0.003	0.011	0.00698	0.006	0.0177	0.0155	0.0604

TABLE 4.3.14A: VARIANCE: When Errors are Log- Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	1.125	2.093	2.55181	0.9431	1.9253	2.1766	10.8144
		FGLS	0.658	1.301	1.60547	0.8487	2.0202	2.0687	8.5020
		Huber	0.329	0.642	0.80745	0.3181	0.5766	0.7983	3.4713
		Bi-Square	0.272	0.477	0.69134	0.3044	0.641	0.7106	3.0962
	N=30	OLS	0.569	1.025	1.10187	0.5936	2.2525	1.4041	6.9462
		FGLS	0.492	0.904	0.77717	0.6591	2.0156	1.1006	5.9493
		Huber	0.228	0.356	0.42972	0.2244	0.666	0.5867	2.4899
		Bi-Square	0.169	0.243	0.35324	0.2134	0.6049	0.4898	2.0732
	N=50	OLS	0.379	0.749	1.45532	0.331	0.6804	0.5774	4.1726
		FGLS	0.349	0.571	0.72066	0.3182	0.5046	0.5796	3.0422
		Huber	0.119	0.192	0.1983	0.142	0.3032	0.244	1.1983
		Bi-Square	0.093	0.168	0.14394	0.1105	0.246	0.2417	1.0029
	N=100	OLS	0.193	0.358	0.38694	0.1724	0.3215	0.3774	1.8087
		FGLS	0.162	0.268	0.35271	0.1463	0.2975	0.3292	1.5562
		Huber	0.059	0.11	0.09619	0.0601	0.1154	0.1191	0.5600
		Bi-Square	0.043	0.073	0.06657	0.0511	0.1061	0.1126	0.4522
	N=250	OLS	0.049	0.172	0.13639	0.0667	0.1469	0.1765	0.7478
		FGLS	0.042	0.121	0.10614	0.0544	0.1253	0.1551	0.6039
		Huber	0.014	0.038	0.0326	0.0269	0.0426	0.0602	0.2148
		Bi-Square	0.013	0.025	0.02767	0.0207	0.0354	0.0518	0.1729
	N=500	OLS	0.031	0.071	0.07607	0.0418	0.086	0.0806	0.3869
		FGLS	0.028	0.062	0.06136	0.0343	0.0744	0.0635	0.3239
		Huber	0.008	0.018	0.01498	0.0142	0.0249	0.0292	0.1093
		Bi-Square	0.006	0.015	0.00936	0.0119	0.0234	0.0242	0.0901

TABLE 4.3.15A: VARIANCE: When Errors are Log- Normal , Square Root Heteroscedastic($g=0.5$) and Contemporaneous Correlation($P=0.5$) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	<i>OLS</i>	1.687	2.819	3.20884	1.2573	2.4569	2.6368	14.0660
		<i>FGLS</i>	0.969	1.647	2.01495	1.1034	2.6002	2.4559	10.7902
		<i>Huber</i>	0.441	0.774	1.01986	0.4409	0.6873	0.9741	4.3367
		<i>Bi-Square</i>	0.391	0.618	0.89412	0.4065	0.7767	0.8498	3.9370
	N=30	<i>OLS</i>	0.71	1.22	1.28382	0.8337	2.6552	1.7374	8.4391
		<i>FGLS</i>	0.623	1.093	0.94151	0.9168	2.3254	1.4236	7.3233
		<i>Huber</i>	0.299	0.428	0.52553	0.3113	0.812	0.7403	3.1162
		<i>Bi-Square</i>	0.228	0.293	0.41868	0.2959	0.7404	0.6263	2.6018
	N=50	<i>OLS</i>	0.497	0.925	1.73469	0.4562	0.8389	0.7103	5.1624
		<i>FGLS</i>	0.463	0.709	0.85266	0.4322	0.6196	0.7134	3.7894
		<i>Huber</i>	0.163	0.227	0.25245	0.194	0.3684	0.3064	1.5104
		<i>Bi-Square</i>	0.127	0.19	0.17865	0.146	0.2904	0.2946	1.2273
	N=100	<i>OLS</i>	0.258	0.44	0.46229	0.2289	0.3806	0.4555	2.2254
		<i>FGLS</i>	0.215	0.332	0.41491	0.1983	0.3533	0.3986	1.9125
		<i>Huber</i>	0.08	0.137	0.11874	0.0812	0.1424	0.1466	0.7057
		<i>Bi-Square</i>	0.061	0.095	0.08604	0.0714	0.1289	0.1426	0.5849
	N=250	<i>OLS</i>	0.064	0.209	0.1633	0.0903	0.1747	0.2139	0.9157
		<i>FGLS</i>	0.056	0.144	0.12736	0.0727	0.1469	0.1867	0.7336
		<i>Huber</i>	0.02	0.047	0.04102	0.0368	0.0521	0.0751	0.2716
		<i>Bi-Square</i>	0.018	0.03	0.03544	0.03	0.0456	0.0651	0.2246
	N=500	<i>OLS</i>	0.042	0.089	0.09066	0.0558	0.1055	0.0981	0.4813
		<i>FGLS</i>	0.036	0.075	0.07088	0.0465	0.092	0.0764	0.3969
		<i>Huber</i>	0.011	0.022	0.0185	0.0191	0.0297	0.0366	0.1370
		<i>Bi-Square</i>	0.008	0.019	0.0112	0.0171	0.0281	0.0307	0.1140

TABLE 4.3.16A: VARIANCE: When Errors are Log-Normal , Homoscedastic and contemporaneous correlation ($P=0.7$) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	<i>OLS</i>	2.72	4.095	4.239	1.7283	3.4568	2.3405	18.5791
		<i>FGLS</i>	1.391	2.079	2.39551	1.4612	3.1824	1.9302	12.4396
		<i>Huber</i>	0.617	0.986	1.30151	1.2258	2.0584	1.5235	7.7122
		<i>Bi-Square</i>	0.55	0.749	1.13621	1.0464	1.6361	1.2749	6.3934
	N=30	<i>OLS</i>	0.927	1.505	1.53857	0.7305	1.2819	1.1382	7.1208
		<i>FGLS</i>	0.784	1.326	1.18177	0.625	1.0208	0.8233	5.7612
		<i>Huber</i>	0.414	0.541	0.66128	0.6147	0.8541	1.0459	4.1304
		<i>Bi-Square</i>	0.322	0.374	0.5238	0.6555	0.793	1.1381	3.8066
	N=50	<i>OLS</i>	0.672	1.178	2.08677	0.6313	1.3523	0.99	6.9109
		<i>FGLS</i>	0.44	0.696	0.81586	0.5617	0.9671	0.7517	4.2326
		<i>Huber</i>	0.222	0.273	0.32116	0.2818	0.6162	0.5068	2.2213
		<i>Bi-Square</i>	0.172	0.223	0.22201	0.2561	0.5088	0.4564	1.8382
	N=100	<i>OLS</i>	0.359	0.565	0.5681	0.2594	0.5145	0.4767	2.7426
		<i>FGLS</i>	0.252	0.349	0.43942	0.2165	0.3826	0.34	1.9788
		<i>Huber</i>	0.108	0.171	0.14734	0.1568	0.2798	0.292	1.1547
		<i>Bi-Square</i>	0.086	0.122	0.11113	0.1578	0.2608	0.2825	1.0204
	N=250	<i>OLS</i>	0.09	0.264	0.20148	0.1347	0.2153	0.1964	1.1026
		<i>FGLS</i>	0.08	0.155	0.11569	0.1069	0.1714	0.1393	0.7684
		<i>Huber</i>	0.029	0.057	0.05218	0.067	0.1173	0.1046	0.4268
		<i>Bi-Square</i>	0.026	0.038	0.04551	0.0661	0.114	0.11	0.4000
	N=500	<i>OLS</i>	0.059	0.116	0.11046	0.0708	0.1105	0.111	0.5784
		<i>FGLS</i>	0.044	0.076	0.08316	0.0431	0.0806	0.0692	0.3965
		<i>Huber</i>	0.015	0.028	0.02293	0.0297	0.0495	0.0475	0.1926
		<i>Bi-Square</i>	0.011	0.023	0.01366	0.025	0.0462	0.0438	0.1629

TABLE 4.3.17A: VARIANCE: When Errors are Log-Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	10.09	17.51	20.52957	8.5208	18.155	12.731	87.5328
		FGLS	5.818	10.45	12.12684	7.2912	16.869	10.777	63.3310
		Huber	2.682	5.005	6.37561	5.7622	10.606	8.0113	38.4415
		Bi-Square	2.271	3.755	5.53393	4.8089	8.2823	8.2445	32.8956
	N=30	OLS	4.574	8.044	8.51934	3.1838	6.5026	5.8474	36.6712
		FGLS	3.726	6.846	6.4268	2.5639	4.9466	4.15	28.6594
		Huber	1.86	2.783	3.37517	2.6467	4.3369	5.1481	20.1493
		Bi-Square	1.409	1.918	2.73758	2.7721	4.0736	5.5107	18.4208
	N=50	OLS	3.071	5.902	11.1446	2.7167	7.0145	4.7649	34.6143
		FGLS	1.977	3.515	4.33381	2.4031	4.8607	3.6981	20.7875
		Huber	0.99	1.499	1.58703	1.2491	3.1775	2.5217	11.0247
		Bi-Square	0.774	1.275	1.14372	1.1472	2.6772	2.3855	9.4024
	N=100	OLS	1.587	2.839	3.00018	1.1954	2.7538	2.4994	13.8743
		FGLS	1.123	1.715	2.52162	0.911	2.0061	1.7031	9.9797
		Huber	0.482	0.873	0.7525	0.728	1.4786	1.4763	5.7900
		Bi-Square	0.359	0.591	0.52967	0.7184	1.4211	1.4107	5.0304
	N=250	OLS	0.4	1.353	1.0579	0.5926	1.1066	1.0183	5.5283
		FGLS	0.335	0.804	0.61229	0.4501	0.8613	0.7137	3.7759
		Huber	0.119	0.299	0.25799	0.2979	0.5955	0.5343	2.1039
		Bi-Square	0.107	0.194	0.22106	0.2823	0.5677	0.552	1.9244
	N=500	OLS	0.259	0.567	0.58795	0.3223	0.579	0.5735	2.8885
		FGLS	0.205	0.399	0.4642	0.1892	0.4235	0.3633	2.0450
		Huber	0.066	0.143	0.11757	0.1345	0.2542	0.2357	0.9514
		Bi-Square	0.049	0.121	0.07265	0.1108	0.2425	0.2149	0.8115

TABLE 4.3.18A: VARIANCE: When Errors are Log- Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.642	1.402	1.8256	0.7837	1.7682	1.2838	7.7055
		FGLS	0.441	1.001	1.17182	0.6975	1.6743	1.1499	6.1359
		Huber	0.198	0.469	0.5157	0.439	0.9096	0.7181	3.2487
		Bi-Square	0.132	0.279	0.41486	0.307	0.6052	0.7347	2.4728
	N=30	OLS	0.417	0.8	0.87538	0.2566	0.6282	0.5594	3.5368
		FGLS	0.325	0.658	0.66202	0.1958	0.4763	0.4073	2.7241
		Huber	0.146	0.268	0.30162	0.1652	0.3708	0.4088	1.6606
		Bi-Square	0.104	0.198	0.24546	0.1707	0.3454	0.439	1.5033
	N=50	OLS	0.244	0.535	1.04931	0.2004	0.6638	0.4051	3.0978
		FGLS	0.158	0.344	0.42854	0.178	0.459	0.3286	1.8955
		Huber	0.068	0.15	0.13086	0.0849	0.2851	0.2081	0.9267
		Bi-Square	0.051	0.133	0.09333	0.0772	0.2352	0.2059	0.7950
	N=100	OLS	0.124	0.265	0.29081	0.1042	0.2753	0.245	1.3042
		FGLS	0.098	0.165	0.27785	0.0739	0.2053	0.1735	0.9931
		Huber	0.033	0.076	0.06391	0.0527	0.1372	0.1229	0.4852
		Bi-Square	0.021	0.046	0.04064	0.0523	0.1328	0.1149	0.4078
	N=250	OLS	0.035	0.131	0.10308	0.0468	0.1084	0.097	0.5209
		FGLS	0.028	0.082	0.06527	0.0356	0.0857	0.0708	0.3667
		Huber	0.008	0.028	0.0218	0.0211	0.0532	0.0468	0.1779
		Bi-Square	0.007	0.017	0.01791	0.0183	0.0514	0.0441	0.1554
	N=500	OLS	0.02	0.05	0.05681	0.0268	0.0578	0.0543	0.2663
		FGLS	0.018	0.041	0.04887	0.0162	0.0441	0.0364	0.2047
		Huber	0.005	0.013	0.01045	0.0094	0.0229	0.0193	0.0798
		Bi-Square	0.003	0.011	0.00698	0.0075	0.0207	0.0176	0.0669

TABLE 4.3.19A: VARIANCE: When Errors are Log-Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	1.125	2.093	2.55181	1.0557	2.2932	1.6487	10.7669
		FGLS	0.689	1.323	1.54032	0.9049	2.1373	1.4005	7.9946
		Huber	0.329	0.642	0.80745	0.6998	1.3288	1.0102	4.8170
		Bi-Square	0.272	0.477	0.69134	0.5859	1.0528	1.0682	4.1471
	N=30	OLS	0.569	1.025	1.10187	0.3877	0.8273	0.7471	4.6581
		FGLS	0.461	0.869	0.83474	0.3097	0.625	0.5312	3.6312
		Huber	0.228	0.356	0.42972	0.314	0.5445	0.6419	2.5131
		Bi-Square	0.169	0.243	0.35324	0.3271	0.5097	0.6922	2.2941
	N=50	OLS	0.379	0.749	1.45532	0.3242	0.8889	0.6011	4.3979
		FGLS	0.244	0.45	0.56756	0.2879	0.6114	0.4701	2.6309
		Huber	0.119	0.192	0.1983	0.1514	0.4032	0.3216	1.3854
		Bi-Square	0.093	0.168	0.14394	0.1406	0.3411	0.3062	1.1927
	N=100	OLS	0.193	0.358	0.38694	0.1474	0.3532	0.3228	1.7608
		FGLS	0.138	0.216	0.33411	0.1105	0.2576	0.2194	1.2758
		Huber	0.059	0.11	0.09619	0.088	0.1883	0.1857	0.7273
		Bi-Square	0.043	0.073	0.06657	0.0872	0.1827	0.1773	0.6296
	N=250	OLS	0.049	0.172	0.13639	0.0713	0.14	0.1304	0.6995
		FGLS	0.041	0.103	0.07995	0.0542	0.1093	0.0918	0.4788
		Huber	0.014	0.038	0.0326	0.0358	0.075	0.0681	0.2640
		Bi-Square	0.013	0.025	0.02767	0.0336	0.0715	0.0699	0.2399
	N=500	OLS	0.031	0.071	0.07607	0.0394	0.0736	0.0736	0.3650
		FGLS	0.025	0.051	0.06099	0.023	0.0539	0.0471	0.2617
		Huber	0.008	0.018	0.01498	0.0165	0.0322	0.0301	0.1197
		Bi-Square	0.006	0.015	0.00936	0.0135	0.0308	0.0273	0.1022

TABLE 4.3.20A: VARIANCE: When Errors are Log-Normal , Square Root Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	1.687	2.819	3.20884	1.3155	2.7576	1.9372	13.7253
		FGLS	0.946	1.614	1.87649	1.1159	2.554	1.6164	9.7231
		Huber	0.441	0.774	1.01986	0.921	1.6423	1.2443	6.0420
		Bi-Square	0.391	0.618	0.89412	0.793	1.3408	1.3226	5.3604
	N=30	OLS	0.71	1.22	1.28382	0.5184	1.0067	0.9059	5.6439
		FGLS	0.588	1.054	0.9772	0.4285	0.7752	0.6462	4.4691
		Huber	0.299	0.428	0.52553	0.4412	0.6783	0.8205	3.1926
		Bi-Square	0.228	0.293	0.41868	0.4608	0.6372	0.8775	2.9148
	N=50	OLS	0.497	0.925	1.73469	0.4428	1.0769	0.761	5.4376
		FGLS	0.321	0.547	0.67197	0.3934	0.7508	0.5854	3.2697
		Huber	0.163	0.227	0.25245	0.2035	0.4937	0.4007	1.7394
		Bi-Square	0.127	0.19	0.17865	0.1881	0.4144	0.3713	1.4702
	N=100	OLS	0.258	0.44	0.46229	0.1903	0.4187	0.3862	2.1556
		FGLS	0.181	0.267	0.37763	0.1501	0.3064	0.2655	1.5470
		Huber	0.08	0.137	0.11874	0.1173	0.2278	0.2317	0.9123
		Bi-Square	0.061	0.095	0.08604	0.1157	0.2159	0.2218	0.7953
	N=250	OLS	0.064	0.209	0.1633	0.0955	0.1694	0.1575	0.8592
		FGLS	0.055	0.123	0.09395	0.0738	0.1329	0.1106	0.5897
		Huber	0.02	0.047	0.04102	0.0485	0.0926	0.0836	0.3322
		Bi-Square	0.018	0.03	0.03544	0.0468	0.0892	0.0876	0.3074
	N=500	OLS	0.042	0.089	0.09066	0.0515	0.0881	0.089	0.4506
		FGLS	0.033	0.061	0.07027	0.0304	0.0641	0.0561	0.3142
		Huber	0.011	0.022	0.0185	0.022	0.0394	0.0376	0.1506
		Bi-Square	0.008	0.019	0.0112	0.0183	0.0375	0.0344	0.1283

TABLE 4.3.21A: VARIANCE: When Errors are Log- Normal , Homoscedastic and contemporal correlation (P=0.95) under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g ; g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	1.818	2.865	3.70954	1.7529	3.2669	3.2699	16.6827
		FGLS	0.356	0.246	0.35995	0.3919	0.3698	0.4127	2.1366
		Huber	0.558	0.847	0.97266	0.6363	0.8654	1.2428	5.1216
		Bi-Square	0.547	0.768	0.88135	0.5746	0.9964	1.0276	4.7948
	N=30	OLS	0.779	1.684	2.0165	1.2127	3.2366	2.2003	11.1283
		FGLS	0.239	0.186	0.18391	0.266	0.3094	0.2777	1.4619
		Huber	0.313	0.665	0.66107	0.4389	1.0167	0.9453	4.0400
		Bi-Square	0.296	0.522	0.62315	0.4015	0.9003	0.7845	3.5267
	N=50	OLS	0.5	1.068	0.69805	0.6546	1.0741	0.907	4.9016
		FGLS	0.201	0.111	0.09286	0.1983	0.1144	0.1403	0.8578
		Huber	0.182	0.323	0.27	0.2631	0.4584	0.3892	1.8856
		Bi-Square	0.156	0.267	0.24991	0.1933	0.3554	0.3557	1.5772
	N=100	OLS	0.492	0.678	0.58292	0.3179	0.4703	0.5649	3.1065
		FGLS	0.081	0.044	0.05153	0.0681	0.0468	0.0548	0.3466
		Huber	0.121	0.165	0.20194	0.1131	0.1804	0.182	0.9635
		Bi-Square	0.095	0.128	0.16222	0.1023	0.1632	0.1806	0.8309
	N=250	OLS	0.178	0.254	0.26327	0.1288	0.2181	0.2651	1.3071
		FGLS	0.031	0.015	0.01542	0.0383	0.024	0.0217	0.1454
		Huber	0.048	0.07	0.07471	0.0517	0.0663	0.0951	0.4056
		Bi-Square	0.038	0.061	0.06388	0.044	0.06	0.0821	0.3489
	N=500	OLS	0.061	0.093	0.11463	0.078	0.1351	0.1226	0.6042
		FGLS	0.015	0.012	0.01273	0.0142	0.0114	0.0105	0.0757
		Huber	0.018	0.027	0.03246	0.0264	0.0369	0.0461	0.1865
		Bi-Square	0.015	0.021	0.02652	0.0246	0.0347	0.0394	0.1614

TABLE 4.3.22A: VARIANCE: When Errors are Log- Normal , Exponential Heteroscedastic and Contemporal Correlation(P=0.95) under varying sample sizes

Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}[E(Y_i)]$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	7.935	15.3	18.06716	7.7243	15.424	16.941	81.3880
		FGLS	1.455	1.842	2.14263	1.5708	2.0003	2.3461	11.3566
		Huber	2.428	4.643	4.86261	2.6606	4.4907	6.2997	25.3840
		Bi-Square	2.294	3.82	4.53232	2.4906	5.0091	5.5436	23.6895
	N=30	OLS	3.746	8.58	10.65193	4.9833	17.464	11.037	56.4632
		FGLS	1.035	1.244	1.26214	1.0655	2.2214	1.4759	8.3039
		Huber	1.345	3.315	3.3303	1.8495	5.2072	4.6502	19.6970
		Bi-Square	1.126	2.465	2.99228	1.7433	4.7082	3.8834	16.9177
	N=50	OLS	2.105	5.686	3.70596	2.7523	5.3684	4.5419	24.1593
		FGLS	0.846	0.893	0.70042	0.7381	0.7457	0.7974	4.7207
		Huber	0.808	1.655	1.38114	1.167	2.3668	1.9317	9.3092
		Bi-Square	0.764	1.517	1.30175	0.8794	1.8898	1.8754	8.2277
	N=100	OLS	2.102	3.369	2.88411	1.4012	2.4844	2.9306	15.1720
		FGLS	0.302	0.324	0.32357	0.24	0.3167	0.3471	1.8534
		Huber	0.537	0.836	0.99904	0.4869	0.9011	0.9341	4.6939
		Bi-Square	0.384	0.627	0.75341	0.425	0.8302	0.894	3.9136
	N=250	OLS	0.792	1.315	1.36988	0.5551	1.1528	1.3698	6.5550
		FGLS	0.118	0.113	0.11687	0.1485	0.1626	0.1393	0.7987
		Huber	0.224	0.375	0.39025	0.2238	0.3368	0.4726	2.0226
		Bi-Square	0.168	0.328	0.31344	0.1765	0.2846	0.4088	1.6799
	N=500	OLS	0.272	0.482	0.59593	0.3474	0.6835	0.631	3.0117
		FGLS	0.06	0.094	0.08898	0.0589	0.0859	0.0665	0.4541
		Huber	0.081	0.139	0.166	0.1159	0.1933	0.2317	0.9269
		Bi-Square	0.067	0.113	0.13776	0.1003	0.1833	0.1938	0.7959

TABLE 4.3.23A: VARIANCE: When Errors are Log- Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.625	1.577	1.55896	0.612	1.3301	1.5824	7.2857
		FGLS	0.157	0.347	0.34038	0.1637	0.3123	0.3276	1.6486
		Huber	0.168	0.443	0.41517	0.194	0.4475	0.5809	2.2492
		Bi-Square	0.147	0.335	0.39144	0.1821	0.4893	0.5224	2.0670
	N=30	OLS	0.343	0.818	1.0254	0.3457	1.7586	0.9813	5.2727
		FGLS	0.117	0.231	0.25265	0.1049	0.3937	0.1986	1.2977
		Huber	0.092	0.287	0.27088	0.1283	0.4777	0.3796	1.6355
		Bi-Square	0.062	0.204	0.21778	0.1074	0.381	0.3012	1.2731
	N=50	OLS	0.166	0.578	0.38492	0.2021	0.4978	0.4228	2.2519
		FGLS	0.093	0.192	0.14574	0.0795	0.1655	0.1366	0.8129
		Huber	0.056	0.151	0.12244	0.0794	0.2245	0.1613	0.7941
		Bi-Square	0.053	0.138	0.10891	0.064	0.1937	0.1586	0.7164
	N=100	OLS	0.15	0.307	0.25521	0.1128	0.2553	0.2778	1.3582
		FGLS	0.029	0.067	0.05734	0.027	0.0711	0.0634	0.3151
		Huber	0.038	0.078	0.08146	0.0342	0.0819	0.083	0.3961
		Bi-Square	0.024	0.057	0.05628	0.0261	0.0752	0.0707	0.3094
	N=250	OLS	0.063	0.129	0.13024	0.043	0.117	0.1275	0.6097
		FGLS	0.013	0.028	0.02715	0.016	0.0343	0.0259	0.1440
		Huber	0.017	0.036	0.03494	0.0157	0.0314	0.0403	0.1749
		Bi-Square	0.011	0.03	0.02615	0.0109	0.0253	0.0331	0.1363
	N=500	OLS	0.022	0.048	0.05602	0.0275	0.0643	0.0586	0.2761
		FGLS	0.008	0.02	0.01731	0.0079	0.0191	0.0134	0.0854
		Huber	0.006	0.013	0.01449	0.0079	0.0189	0.0191	0.0791
		Bi-Square	0.005	0.01	0.01163	0.006	0.0177	0.0155	0.0660

TABLE 4.3.24A: VARIANCE: When Errors are Log-Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.967	1.97	2.30092	0.9431	1.9253	2.1766	10.2836
		FGLS	0.185	0.267	0.29729	0.1976	0.2698	0.3217	1.5386
		Huber	0.293	0.599	0.61457	0.3181	0.5766	0.7983	3.1996
		Bi-Square	0.271	0.483	0.57534	0.3044	0.641	0.7106	2.9851
	N=30	OLS	0.469	1.093	1.38704	0.5936	2.2525	1.4041	7.1993
		FGLS	0.131	0.183	0.18345	0.131	0.3126	0.1955	1.1362
		Huber	0.163	0.419	0.41914	0.2244	0.666	0.5867	2.4780
		Bi-Square	0.129	0.31	0.37047	0.2134	0.6049	0.4898	2.1175
	N=50	OLS	0.254	0.736	0.47777	0.331	0.6804	0.5774	3.0566
		FGLS	0.107	0.133	0.10266	0.0924	0.1116	0.112	0.6590
		Huber	0.096	0.21	0.17405	0.142	0.3032	0.244	1.1688
		Bi-Square	0.094	0.194	0.16587	0.1105	0.246	0.2417	1.0518
	N=100	OLS	0.252	0.422	0.36399	0.1724	0.3215	0.3774	1.9094
		FGLS	0.037	0.046	0.0449	0.0297	0.0472	0.0496	0.2537
		Huber	0.066	0.106	0.12647	0.0601	0.1154	0.1191	0.5930
		Bi-Square	0.046	0.078	0.09393	0.0511	0.1061	0.1126	0.4880
	N=250	OLS	0.097	0.167	0.17556	0.0667	0.1469	0.1765	0.8288
		FGLS	0.015	0.017	0.01721	0.0184	0.0235	0.0198	0.1103
		Huber	0.028	0.048	0.0502	0.0269	0.0426	0.0602	0.2556
		Bi-Square	0.021	0.042	0.03991	0.0207	0.0354	0.0518	0.2107
	N=500	OLS	0.033	0.062	0.07687	0.0418	0.086	0.0806	0.3801
		FGLS	0.008	0.014	0.01286	0.0076	0.0127	0.0096	0.0642
		Huber	0.01	0.018	0.02115	0.0142	0.0249	0.0292	0.1172
		Bi-Square	0.008	0.015	0.01751	0.0119	0.0234	0.0242	0.0999

**TABLE 4.3.25A: VARIANCE: When Errors are Log- Normal , Square Root
Heteroscedastic(g=0.5) and Contemporaneous Correlation(P=0.95) under varying sample sizes**

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	<i>OLS</i>	1.294	2.322	2.88781	1.2573	2.4569	2.6368	12.8553
		<i>FGLS</i>	0.24	0.241	0.30402	0.2601	0.2886	0.3448	1.6781
		<i>Huber</i>	0.399	0.709	0.76467	0.4409	0.6873	0.9741	3.9752
		<i>Bi-Square</i>	0.385	0.591	0.71165	0.4065	0.7767	0.8498	3.7208
	N=30	<i>OLS</i>	0.59	1.331	1.65645	0.8337	2.6552	1.7374	8.8036
		<i>FGLS</i>	0.166	0.168	0.16834	0.1766	0.2939	0.2186	1.1914
		<i>Huber</i>	0.224	0.521	0.52781	0.3113	0.812	0.7403	3.1366
		<i>Bi-Square</i>	0.194	0.394	0.48485	0.2959	0.7404	0.6263	2.7355
	N=50	<i>OLS</i>	0.346	0.869	0.56412	0.4562	0.8389	0.7103	3.7849
		<i>FGLS</i>	0.136	0.11	0.08826	0.1261	0.0981	0.1136	0.6722
		<i>Huber</i>	0.131	0.255	0.21401	0.194	0.3684	0.3064	1.4688
		<i>Bi-Square</i>	0.121	0.228	0.20307	0.146	0.2904	0.2946	1.2831
	N=100	<i>OLS</i>	0.346	0.524	0.45358	0.2289	0.3806	0.4555	2.3889
		<i>FGLS</i>	0.051	0.04	0.04359	0.0413	0.0412	0.0476	0.2651
		<i>Huber</i>	0.089	0.131	0.15855	0.0812	0.1424	0.1466	0.7481
		<i>Bi-Square</i>	0.066	0.099	0.12411	0.0714	0.1289	0.1426	0.6322
	N=250	<i>OLS</i>	0.128	0.201	0.21194	0.0903	0.1747	0.2139	1.0202
		<i>FGLS</i>	0.02	0.014	0.01432	0.0245	0.021	0.0186	0.1120
		<i>Huber</i>	0.037	0.057	0.0611	0.0368	0.0521	0.0751	0.3191
		<i>Bi-Square</i>	0.028	0.051	0.05066	0.03	0.0456	0.0651	0.2703
	N=500	<i>OLS</i>	0.044	0.074	0.09283	0.0558	0.1055	0.0981	0.4702
		<i>FGLS</i>	0.01	0.012	0.01172	0.0094	0.0108	0.009	0.0624
		<i>Huber</i>	0.013	0.022	0.02607	0.0191	0.0297	0.0366	0.1463
		<i>Bi-Square</i>	0.011	0.017	0.0215	0.0171	0.0281	0.0307	0.1260

TABLE 4.3.1 B :Absolute Bias: When Errors are Log-Normal , Homoscedastic and No contemporal correlation under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.8927	1.2872	1.351	1.7681	1.3668	1.3119	8.9777
		FGLS	1.8613	1.2713	1.4216	1.7532	1.404	1.3495	9.0610
		Huber	1.2347	0.6599	0.7701	1.3509	0.7898	0.6874	5.4928
		Bi-Square	1.0478	0.6353	0.6663	1.1455	0.7025	0.5872	4.7845
	N=30	OLS	1.6407	1.0143	1.054	1.6515	0.9455	1.1941	7.5001
		FGLS	1.6399	1.0635	1.0888	1.6823	0.9826	1.2037	7.6608
		Huber	1.3107	0.6102	0.592	1.2445	0.5991	0.5996	4.9560
		Bi-Square	1.1647	0.5189	0.4533	1.0485	0.5343	0.4924	4.2121
	N=50	OLS	1.5008	0.8339	0.6663	1.6949	0.8654	0.8541	6.4155
		FGLS	1.5107	0.8293	0.6697	1.706	0.9023	0.8603	6.4783
		Huber	1.1614	0.3924	0.4079	1.282	0.4316	0.4661	4.1415
		Bi-Square	0.9713	0.3689	0.3873	1.0943	0.3901	0.4068	3.6185
	N=100	OLS	1.587	0.543	0.5349	1.6279	0.5737	0.6557	5.5222
		FGLS	1.579	0.5476	0.5315	1.6296	0.5693	0.6511	5.5081
		Huber	1.2359	0.3165	0.3007	1.2853	0.3057	0.3226	3.7666
		Bi-Square	1.0341	0.2584	0.2823	1.1097	0.2863	0.2555	3.2263
	N=250	OLS	1.6465	0.3846	0.3675	1.6206	0.3626	0.4021	4.7839
		FGLS	1.6444	0.3825	0.3725	1.6208	0.3632	0.4056	4.7890
		Huber	1.2638	0.1677	0.1796	1.2589	0.1817	0.1942	3.2461
		Bi-Square	1.0584	0.137	0.15	1.0485	0.1537	0.1384	2.6860
	N=500	OLS	1.5963	0.2853	0.253	1.6793	0.2489	0.2833	4.3461
		FGLS	1.5961	0.2864	0.2518	1.6787	0.2483	0.2809	4.3422
		Huber	1.2312	0.1474	0.118	1.2635	0.1201	0.1361	3.0162
		Bi-Square	1.024	0.1112	0.1097	1.0261	0.1123	0.116	2.4993

TABLE 4.3.2 B: Absolute Bias: When Errors are Log-Normal , Exponential Heteroscedastic and No contemporal correlation under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}(E(Y_i))$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	3.3663	2.9315	3.018	3.0306	3.3634	3.0312	18.7411
		FGLS	3.2705	2.8488	3.1668	2.9946	3.4375	3.1653	18.8835
		Huber	2.1182	1.7371	1.7547	2.3219	1.9415	1.6079	11.4813
		Bi-Square	1.8609	1.6972	1.5093	2.0779	1.7263	1.3511	10.2228
	N=30	OLS	2.833	2.5463	2.431	2.7289	2.5455	2.7013	15.7860
		FGLS	2.8634	2.6045	2.5247	2.7937	2.5668	2.7163	16.0693
		Huber	2.2655	1.6377	1.3612	2.1026	1.6185	1.3915	10.3771
		Bi-Square	2.1284	1.3607	1.0242	1.8621	1.3246	1.1817	8.8815
	N=50	OLS	2.3921	2.3485	1.712	2.8063	2.4174	2.1074	13.7837
		FGLS	2.4105	2.3298	1.7383	2.8422	2.4581	2.1161	13.8951
		Huber	1.9641	1.1981	1.0585	2.1649	1.2349	1.1279	8.7484
		Bi-Square	1.7429	0.9942	0.9206	1.9154	1.048	1.0017	7.6228
	N=100	OLS	2.4875	1.8139	1.33	2.5941	1.9208	1.5189	11.6652
		FGLS	2.4713	1.8227	1.3323	2.5933	1.9176	1.5163	11.6534
		Huber	2.1099	1.0921	0.8039	2.1965	1.0304	0.7974	8.0302
		Bi-Square	1.8487	0.8117	0.7106	1.997	0.7673	0.6372	6.7725
	N=250	OLS	2.6031	1.603	0.9538	2.5453	1.6323	1.0527	10.3902
		FGLS	2.5984	1.6075	0.9673	2.5444	1.6326	1.0527	10.4029
		Huber	2.163	0.8549	0.5272	2.1533	0.8755	0.5794	7.1533
		Bi-Square	1.8899	0.6191	0.3845	1.8713	0.6277	0.4115	5.8041
	N=500	OLS	2.4964	1.6014	0.8431	2.6599	1.3791	0.8304	9.8102
		FGLS	2.4953	1.6031	0.8406	2.6584	1.3802	0.8305	9.8081
		Huber	2.0949	0.9686	0.4783	2.1711	0.8113	0.4985	7.0226
		Bi-Square	1.8256	0.6749	0.3747	1.8332	0.6031	0.3795	5.6911

TABLE 4.3.3 B: Absolute Bias: When Errors are Log-Normal , Quadratic Heteroscedastic(g=2) and No contemporaneous correlation(P=0) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.6861	1.0956	0.9205	0.6256	1.2775	0.9723	5.5776
		FGLS	0.6556	1.1043	0.9598	0.6326	1.3035	1.0137	5.6695
		Huber	0.3907	0.7564	0.5726	0.4052	0.7872	0.533	3.4450
		Bi-Square	0.3813	0.6602	0.4633	0.4031	0.6523	0.4502	3.0103
	N=30	OLS	0.5478	1.1311	0.7745	0.4868	1.201	0.8812	5.0224
		FGLS	0.5658	1.1331	0.7987	0.5162	1.1873	0.8884	5.0895
		Huber	0.421	0.7425	0.4451	0.3693	0.7317	0.4738	3.1833
		Bi-Square	0.4093	0.5462	0.3193	0.3593	0.5261	0.3816	2.5418
	N=50	OLS	0.4016	1.1387	0.6963	0.5106	1.1489	0.7803	4.6763
		FGLS	0.408	1.1302	0.6999	0.5109	1.1382	0.7748	4.6619
		Huber	0.3068	0.6315	0.4007	0.3421	0.6488	0.4258	2.7556
		Bi-Square	0.3112	0.4634	0.3147	0.3426	0.4913	0.3496	2.2727
	N=100	OLS	0.3299	1.0896	0.5737	0.3815	1.1175	0.6149	4.1070
		FGLS	0.3296	1.0982	0.5701	0.3809	1.1165	0.6129	4.1082
		Huber	0.3295	0.6514	0.3404	0.3418	0.625	0.3384	2.6264
		Bi-Square	0.3336	0.4552	0.2664	0.3564	0.4286	0.2441	2.0842
	N=250	OLS	0.3183	1.0634	0.5112	0.2961	1.0772	0.538	3.8042
		FGLS	0.3171	1.0645	0.5125	0.2962	1.0788	0.5384	3.8075
		Huber	0.3384	0.6133	0.303	0.3356	0.6163	0.3244	2.5310
		Bi-Square	0.3367	0.4398	0.2097	0.3333	0.4367	0.2262	1.9824
	N=500	OLS	0.2766	1.081	0.5307	0.3159	1.019	0.5171	3.7402
		FGLS	0.2764	1.0819	0.5306	0.3155	1.0194	0.5178	3.7416
		Huber	0.3222	0.642	0.3085	0.343	0.5934	0.31	2.5191
		Bi-Square	0.3222	0.453	0.2196	0.3281	0.4308	0.2207	1.9744

TABLE 4.3.4 B: Absolute Bias: When Errors are Log-Normal , Linear Heteroscedastic(g=1) and No contemporaneous correlation(P=0) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=1							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.1227	1.071	1.0726	1.0025	1.2388	1.0981	6.6057
		FGLS	1.091	1.0491	1.1293	0.9925	1.2642	1.1494	6.6755
		Huber	0.7006	0.6596	0.6295	0.7633	0.7239	0.5841	4.0610
		Bi-Square	0.6266	0.6398	0.5406	0.6928	0.6453	0.4885	3.6336
	N=30	OLS	0.9407	0.965	0.8761	0.887	0.99	0.9777	5.6365
		FGLS	0.9555	0.9783	0.9097	0.9081	0.9836	0.9828	5.7180
		Huber	0.7536	0.6293	0.494	0.6851	0.6172	0.5047	3.6840
		Bi-Square	0.7146	0.5126	0.3721	0.6147	0.4967	0.4316	3.1423
	N=50	OLS	0.777	0.9067	0.6393	0.9121	0.9379	0.776	4.9490
		FGLS	0.7823	0.8984	0.6522	0.9244	0.9448	0.78	4.9820
		Huber	0.6416	0.4735	0.3928	0.7039	0.4964	0.4169	3.1250
		Bi-Square	0.5775	0.3831	0.3365	0.6323	0.4056	0.364	2.6990
	N=100	OLS	0.7917	0.7454	0.5032	0.8313	0.7849	0.5598	4.2163
		FGLS	0.7862	0.753	0.5049	0.8312	0.7852	0.5579	4.2184
		Huber	0.6907	0.4493	0.3023	0.7161	0.4266	0.3013	2.8862
		Bi-Square	0.6149	0.332	0.2628	0.6615	0.3085	0.2349	2.4146
	N=250	OLS	0.8304	0.6884	0.3765	0.8098	0.701	0.4065	3.8125
		FGLS	0.8288	0.6896	0.3808	0.8093	0.7014	0.4067	3.8165
		Huber	0.707	0.3835	0.215	0.7038	0.3882	0.2336	2.6311
		Bi-Square	0.6257	0.2777	0.1515	0.6201	0.2762	0.1675	2.1186
	N=500	OLS	0.7923	0.7009	0.354	0.8483	0.6216	0.3455	3.6626
		FGLS	0.7919	0.7018	0.3528	0.8477	0.622	0.3459	3.6621
		Huber	0.6832	0.4248	0.2032	0.7103	0.3662	0.2084	2.5961
		Bi-Square	0.6039	0.2988	0.1541	0.6075	0.2726	0.1558	2.0927

TABLE 4.3.5 B: Absolute Bias: When Errors are Log-Normal , Square Root Heteroscedastic(g=0.5) and No contemporaneous correlation under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0.5							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.4548	1.1323	1.1909	1.3358	1.2714	1.1927	7.5778
		FGLS	1.4195	1.1045	1.2501	1.3192	1.2983	1.2389	7.6306
		Huber	0.9315	0.6384	0.6885	1.0247	0.73	0.6252	4.6383
		Bi-Square	0.8036	0.6238	0.5977	0.8948	0.6515	0.5224	4.0938
	N=30	OLS	1.2453	0.9377	0.9506	1.2154	0.909	1.0669	6.3250
		FGLS	1.2501	0.9737	0.9869	1.2419	0.9307	1.0685	6.4518
		Huber	0.9948	0.5929	0.532	0.9318	0.5899	0.5429	4.1841
		Bi-Square	0.9152	0.5048	0.4035	0.806	0.4973	0.4579	3.5847
	N=50	OLS	1.0809	0.8352	0.6394	1.2564	0.8675	0.798	5.4774
		FGLS	1.0891	0.8349	0.6484	1.2698	0.8896	0.8031	5.5348
		Huber	0.8731	0.4125	0.3956	0.9643	0.4254	0.4305	3.5014
		Bi-Square	0.7573	0.3625	0.3562	0.8373	0.3794	0.3843	3.0772
	N=100	OLS	1.1427	0.5975	0.4915	1.1794	0.6194	0.5846	4.6150
		FGLS	1.1362	0.605	0.4905	1.1799	0.6156	0.5809	4.6082
		Huber	0.9345	0.3547	0.2978	0.9722	0.3323	0.2996	3.1911
		Bi-Square	0.8035	0.2717	0.2691	0.8655	0.2695	0.2431	2.7224
	N=250	OLS	1.1939	0.4587	0.3404	1.1708	0.4785	0.3826	4.0248
		FGLS	1.192	0.4614	0.3477	1.1707	0.4791	0.3838	4.0347
		Huber	0.9582	0.2314	0.1766	0.9541	0.2462	0.199	2.7655
		Bi-Square	0.8212	0.171	0.1381	0.8137	0.1837	0.1415	2.2691
	N=500	OLS	1.1501	0.4443	0.2727	1.2181	0.3586	0.2782	3.7220
		FGLS	1.1497	0.4455	0.272	1.2175	0.3593	0.276	3.7200
		Huber	0.9295	0.2624	0.1479	0.959	0.2082	0.1572	2.6642
		Bi-Square	0.7937	0.1854	0.1229	0.7963	0.1575	0.1264	2.1822

TABLE 4.3.6 B: Absolute Bias: When Errors are Log-Normal , Homoscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.8858	1.3384	1.4784	2.1441	1.2675	1.3143	9.4284
		FGLS	1.8453	1.2872	1.4058	2.1731	1.3562	1.3093	9.3768
		Huber	1.4007	0.7751	0.8713	1.658	0.6798	0.73	6.1148
		Bi-Square	1.2008	0.6433	0.7754	1.4637	0.6957	0.6435	5.4223
	N=30	OLS	1.5896	0.9768	0.945	2.1011	1.2068	1.0856	7.9050
		FGLS	1.5867	0.9811	0.9032	2.1116	1.1962	1.1159	7.8947
		Huber	1.2665	0.5852	0.6314	1.6621	0.7065	0.6481	5.4998
		Bi-Square	1.0761	0.4753	0.5121	1.4564	0.6163	0.5723	4.7084
	N=50	OLS	1.5968	0.8157	0.9013	1.9566	0.8267	0.7813	6.8785
		FGLS	1.5994	0.8292	0.8264	1.9706	0.7906	0.8277	6.8439
		Huber	1.2695	0.4122	0.4492	1.5514	0.4639	0.4624	4.6087
		Bi-Square	1.1135	0.3719	0.3675	1.3523	0.4334	0.4192	4.0579
	N=100	OLS	1.6402	0.6112	0.5922	2.022	0.5374	0.5587	5.9617
		FGLS	1.6358	0.5683	0.5906	2.0125	0.5329	0.5702	5.9102
		Huber	1.2833	0.3218	0.3028	1.6096	0.2925	0.2703	4.0802
		Bi-Square	1.0911	0.2681	0.2584	1.4106	0.2783	0.2808	3.5872
	N=250	OLS	1.6538	0.4018	0.3456	1.8724	0.3631	0.3981	5.0348
		FGLS	1.6442	0.3706	0.3279	1.8838	0.3371	0.3975	4.9612
		Huber	1.2475	0.1908	0.1867	1.5659	0.1805	0.2008	3.5722
		Bi-Square	1.0272	0.1489	0.172	1.3912	0.1647	0.1609	3.0649
	N=500	OLS	1.6503	0.2664	0.2661	1.9435	0.284	0.2732	4.6836
		FGLS	1.6461	0.266	0.2612	1.9488	0.2755	0.2605	4.6580
		Huber	1.2568	0.1357	0.1219	1.569	0.1318	0.1533	3.3686
		Bi-Square	1.0289	0.1229	0.0983	1.3764	0.1256	0.1378	2.8900

TABLE 4.3.7B: Absolute Bias: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}(E(Y_i))$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	3.2513	3.1947	3.3613	3.6867	2.8583	2.9677	19.3200
		FGLS	3.128	3.0627	3.1374	3.7527	2.9338	2.9885	19.0031
		Huber	2.4624	1.8249	1.9851	2.7891	1.5659	1.753	12.3803
		Bi-Square	2.1804	1.543	1.7531	2.5417	1.5992	1.5863	11.2036
	N=30	OLS	2.673	2.5578	2.2324	3.4034	2.9038	2.5518	16.3222
		FGLS	2.6556	2.5285	2.1174	3.4524	2.8143	2.5599	16.1281
		Huber	2.1755	1.5794	1.4349	2.7935	1.7748	1.4378	11.1960
		Bi-Square	1.9672	1.2007	1.1767	2.5661	1.5458	1.2354	9.6918
	N=50	OLS	2.5996	2.3415	2.142	3.1349	2.5064	1.7773	14.5016
		FGLS	2.5503	2.2968	2.0289	3.1833	2.4196	1.8773	14.3561
		Huber	2.1733	1.2979	1.0374	2.587	1.6178	1.0824	9.7958
		Bi-Square	1.9682	1.0744	0.8172	2.3304	1.3699	1.0004	8.5605
	N=100	OLS	2.5654	1.8147	1.4758	3.239	1.7988	1.4938	12.3874
		FGLS	2.5499	1.765	1.5015	3.2212	1.8296	1.4823	12.3495
		Huber	2.2014	1.0297	0.734	2.732	1.1415	0.8092	8.6478
		Bi-Square	1.9446	0.7967	0.5985	2.4613	0.9541	0.7079	7.4630
	N=250	OLS	2.5951	1.6891	0.9887	2.9159	2.095	1.1154	11.3992
		FGLS	2.5767	1.6635	0.9621	2.9464	2.0266	1.108	11.2833
		Huber	2.1318	0.923	0.5815	2.6303	1.2596	0.6001	8.1263
		Bi-Square	1.8354	0.662	0.4872	2.4187	0.9499	0.4746	6.8278
	N=500	OLS	2.6042	1.4322	0.9014	3.0525	1.9046	0.8934	10.7883
		FGLS	2.5916	1.4387	0.8938	3.0688	1.88	0.8849	10.7579
		Huber	2.1463	0.8635	0.4875	2.6402	1.2129	0.5583	7.9086
		Bi-Square	1.8325	0.6534	0.3596	2.3866	0.9634	0.4926	6.6881

TABLE 4.3.8B: Absolute Bias: When Errors are Log- Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.6807	1.2201	1.0794	0.6983	1.2439	1.0249	5.9473
		FGLS	0.6242	1.201	1.0237	0.7058	1.2402	1.023	5.8179
		Huber	0.4635	0.7335	0.6175	0.4704	0.8378	0.621	3.7437
		Bi-Square	0.4321	0.5252	0.5247	0.4458	0.7364	0.5464	3.2105
	N=30	OLS	0.5665	1.1146	0.7826	0.5677	1.2852	0.8921	5.2087
		FGLS	0.5484	1.1119	0.7644	0.609	1.2335	0.8946	5.1618
		Huber	0.4055	0.7006	0.475	0.4449	0.8579	0.5079	3.3918
		Bi-Square	0.3978	0.5085	0.3775	0.4614	0.6846	0.4043	2.8341
	N=50	OLS	0.4295	1.1292	0.7655	0.477	1.3078	0.6582	4.7672
		FGLS	0.4248	1.1384	0.7525	0.4979	1.2854	0.6703	4.7693
		Huber	0.3578	0.667	0.3704	0.3822	0.9077	0.4532	3.1383
		Bi-Square	0.3564	0.4984	0.2776	0.3709	0.7341	0.3968	2.6342
	N=100	OLS	0.3727	1.077	0.63	0.4493	1.1984	0.6712	4.3986
		FGLS	0.3613	1.0708	0.6447	0.444	1.2126	0.6605	4.3939
		Huber	0.3483	0.6494	0.3235	0.4142	0.8111	0.4239	2.9704
		Bi-Square	0.3545	0.4614	0.2316	0.4138	0.6289	0.3321	2.4223
	N=250	OLS	0.2994	1.1005	0.5391	0.3252	1.3363	0.6289	4.2294
		FGLS	0.2958	1.1005	0.5406	0.3348	1.3165	0.6271	4.2153
		Huber	0.3314	0.6261	0.3194	0.3858	0.8495	0.3975	2.9097
		Bi-Square	0.3244	0.4479	0.2365	0.4001	0.654	0.3109	2.3738
	N=500	OLS	0.3022	1.0342	0.5385	0.3442	1.2956	0.5914	4.1061
		FGLS	0.2994	1.0387	0.5433	0.3498	1.2865	0.5872	4.1049
		Huber	0.3321	0.6178	0.3206	0.3886	0.8395	0.4025	2.9011
		Bi-Square	0.3235	0.4495	0.2282	0.3933	0.6598	0.3227	2.3770

TABLE 4.3.9B: Absolute Bias: When Errors are Log-Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.0773	1.1691	1.2011	1.2121	1.0687	1.0829	6.8112
		FGLS	1.0343	1.1259	1.1153	1.2301	1.0778	1.0828	6.6662
		Huber	0.8165	0.6798	0.7151	0.9093	0.6073	0.6364	4.3644
		Bi-Square	0.7305	0.5603	0.6288	0.8343	0.6046	0.5757	3.9342
	N=30	OLS	0.8838	0.9607	0.8096	1.093	1.0814	0.9313	5.7598
		FGLS	0.8788	0.949	0.7715	1.1197	1.0463	0.9318	5.6971
		Huber	0.7171	0.6016	0.5164	0.9071	0.6778	0.5222	3.9422
		Bi-Square	0.6604	0.4505	0.4291	0.8506	0.5826	0.4444	3.4176
	N=50	OLS	0.8443	0.9161	0.7858	1.0083	0.9914	0.6503	5.1962
		FGLS	0.8236	0.8981	0.7498	1.0266	0.9586	0.6836	5.1403
		Huber	0.7102	0.5146	0.3745	0.8381	0.656	0.4032	3.4966
		Bi-Square	0.6498	0.4141	0.2907	0.763	0.5519	0.3721	3.0416
	N=100	OLS	0.8181	0.7367	0.5579	1.0408	0.7682	0.5693	4.4910
		FGLS	0.8112	0.7248	0.5694	1.0346	0.7817	0.5648	4.4865
		Huber	0.721	0.433	0.2769	0.8896	0.5022	0.3205	3.1432
		Bi-Square	0.6449	0.3269	0.223	0.8087	0.4077	0.2757	2.6869
	N=250	OLS	0.8259	0.7185	0.3906	0.9249	0.8976	0.4438	4.2013
		FGLS	0.8198	0.7159	0.3844	0.9361	0.8743	0.4441	4.1746
		Huber	0.6967	0.4039	0.2346	0.8544	0.5518	0.253	2.9944
		Bi-Square	0.6075	0.29	0.1921	0.794	0.4222	0.2007	2.5065
	N=500	OLS	0.8294	0.639	0.3685	0.9704	0.8335	0.3722	4.0130
		FGLS	0.8247	0.6432	0.3709	0.9766	0.825	0.3722	4.0126
		Huber	0.7005	0.3883	0.2104	0.8578	0.5392	0.2486	2.9448
		Bi-Square	0.6062	0.2899	0.1537	0.783	0.4293	0.2109	2.4730

TABLE 4.3.10B: Absolute Bias: When Errors are Log-Normal , Square Root Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.2) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.4142	1.1997	1.3158	1.6173	1.0967	1.1646	7.8083
		FGLS	1.3674	1.1566	1.235	1.6445	1.1508	1.1675	7.7218
		Huber	1.072	0.696	0.7783	1.237	0.5837	0.677	5.0440
		Bi-Square	0.9369	0.6027	0.6971	1.1117	0.611	0.6057	4.5651
	N=30	OLS	1.1769	0.9321	0.8615	1.537	1.1003	0.9909	6.5987
		FGLS	1.174	0.9323	0.8166	1.5477	1.0685	0.9978	6.5369
		Huber	0.9564	0.5696	0.5615	1.2449	0.656	0.5653	4.5537
		Bi-Square	0.8428	0.446	0.4533	1.1171	0.5809	0.4953	3.9354
	N=50	OLS	1.1709	0.8162	0.8278	1.4247	0.869	0.6878	5.7964
		FGLS	1.1564	0.8131	0.7751	1.4404	0.8332	0.7323	5.7505
		Huber	0.9593	0.4471	0.4061	1.1572	0.5381	0.4148	3.9226
		Bi-Square	0.8587	0.3788	0.3231	1.0265	0.4635	0.3834	3.4340
	N=100	OLS	1.1804	0.6149	0.5431	1.4748	0.5668	0.5452	4.9252
		FGLS	1.1758	0.583	0.5563	1.4667	0.5772	0.5427	4.9017
		Huber	0.9734	0.3251	0.2764	1.2123	0.3375	0.2795	3.4042
		Bi-Square	0.8451	0.2637	0.2299	1.0787	0.2957	0.2559	2.9690
	N=250	OLS	1.1948	0.5098	0.3438	1.3468	0.5941	0.3859	4.3752
		FGLS	1.1871	0.4854	0.3255	1.3582	0.5677	0.3811	4.3050
		Huber	0.9447	0.2611	0.196	1.1736	0.3409	0.1974	3.1137
		Bi-Square	0.7977	0.1957	0.1735	1.063	0.256	0.1562	2.6421
	N=500	OLS	1.1947	0.3913	0.2922	1.4033	0.518	0.2821	4.0816
		FGLS	1.1902	0.3885	0.291	1.4092	0.5077	0.2718	4.0584
		Huber	0.951	0.2212	0.1483	1.1772	0.3182	0.1661	2.9820
		Bi-Square	0.7975	0.1777	0.1141	1.0497	0.2584	0.1513	2.5487

TABLE 4.3.11B: Absolute Bias: When Errors are Log- Normal , Homoscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; g=0							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.5	N=20	OLS	1.8858	1.3384	1.4784	2.6206	1.223	1.2443	9.7905
		FGLS	1.7918	1.1597	1.2319	2.6411	1.2425	1.2053	9.2724
		Huber	1.4007	0.7751	0.8713	2.1858	0.7245	0.7977	6.7550
		Bi-Square	1.2008	0.6433	0.7754	1.9986	0.7981	0.7692	6.1854
	N=30	OLS	1.5896	0.9768	0.945	2.6045	1.1974	1.0733	8.3866
		FGLS	1.6003	0.9427	0.8368	2.6406	1.1364	1.0127	8.1694
		Huber	1.2665	0.5852	0.6314	2.254	0.8281	0.7752	6.3405
		Bi-Square	1.0761	0.4753	0.5121	2.1433	0.7506	0.7162	5.6736
	N=50	OLS	1.5968	0.8157	0.9013	2.5186	0.8394	0.7468	7.4186
		FGLS	1.615	0.7598	0.7643	2.5318	0.7277	0.7747	7.1733
		Huber	1.2695	0.4122	0.4492	2.1394	0.5438	0.486	5.3002
		Bi-Square	1.1135	0.3719	0.3675	1.9575	0.4923	0.459	4.7618
	N=100	OLS	1.6402	0.6112	0.5922	2.583	0.5382	0.5504	6.5153
		FGLS	1.6298	0.5185	0.5596	2.5671	0.5002	0.5254	6.3007
		Huber	1.2833	0.3218	0.3028	2.2164	0.3393	0.3186	4.7823
		Bi-Square	1.0911	0.2681	0.2584	2.0519	0.3312	0.3251	4.3257
	N=250	OLS	1.6538	0.4018	0.3456	2.4298	0.3776	0.3948	5.6034
		FGLS	1.6363	0.336	0.3118	2.4529	0.311	0.3773	5.4251
		Huber	1.2475	0.1908	0.1867	2.1457	0.2016	0.2484	4.2208
		Bi-Square	1.0272	0.1489	0.172	1.9976	0.1929	0.2196	3.7582
	N=500	OLS	1.6503	0.2664	0.2661	2.4874	0.2918	0.2811	5.2432
		FGLS	1.6481	0.246	0.2313	2.4973	0.2661	0.2382	5.1270
		Huber	1.2568	0.1357	0.1219	2.1448	0.1528	0.1804	3.9924
		Bi-Square	1.0289	0.1229	0.0983	1.984	0.1521	0.1624	3.5486

TABLE 4.3.12B: Absolute Bias: When Errors are Log- Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}(E(Y_i))$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	3.2513	3.1947	3.3613	4.2774	3.0449	2.9831	20.1127
		FGLS	2.9689	2.8371	2.791	4.3818	2.9151	2.8533	18.7471
		Huber	2.4624	1.8249	1.9851	3.5676	1.9857	2.0504	13.8760
		Bi-Square	2.1804	1.543	1.7531	3.2873	2.0621	1.9508	12.7766
	N=30	OLS	2.673	2.5578	2.2324	4.1051	3.2347	2.5294	17.3324
		FGLS	2.6453	2.4047	1.9753	4.2062	2.9393	2.4196	16.5902
		Huber	2.1755	1.5794	1.4349	3.7398	2.3068	1.7608	12.9973
		Bi-Square	1.9672	1.2007	1.1767	3.6396	2.102	1.6221	11.7082
	N=50	OLS	2.5996	2.3415	2.142	3.9973	2.7848	1.8062	15.6714
		FGLS	2.5671	2.1416	1.9099	4.0424	2.628	1.8271	15.1160
		Huber	2.1733	1.2979	1.0374	3.4996	2.085	1.282	11.3752
		Bi-Square	1.9682	1.0744	0.8172	3.2934	1.8337	1.2918	10.2787
	N=100	OLS	2.5654	1.8147	1.4758	4.1299	2.1385	1.5325	13.6567
		FGLS	2.5404	1.7422	1.4173	4.1018	2.2093	1.4805	13.4915
		Huber	2.2014	1.0297	0.734	3.7085	1.6072	0.9873	10.2682
		Bi-Square	1.9446	0.7967	0.5985	3.5203	1.375	0.8939	9.1289
	N=250	OLS	2.5951	1.6891	0.9887	3.7856	2.5888	1.2939	12.9411
		FGLS	2.5609	1.659	0.9356	3.8463	2.4638	1.2685	12.7342
		Huber	2.1318	0.923	0.5815	3.5498	1.7755	0.8613	9.8229
		Bi-Square	1.8354	0.662	0.4872	3.4017	1.454	0.7554	8.5957
	N=500	OLS	2.6042	1.4322	0.9014	3.8968	2.4145	1.0974	12.3466
		FGLS	2.5952	1.4389	0.8585	3.9289	2.3694	1.0841	12.2751
		Huber	2.1463	0.8635	0.4875	3.5519	1.7589	0.8023	9.6104
		Bi-Square	1.8325	0.6534	0.3596	3.3615	1.5094	0.7103	8.4267

TABLE 4.3.13B: Absolute Bias: When Errors are Log-Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	0.6807	1.2201	1.0794	0.7216	1.5632	1.1203	6.3853
		FGLS	0.572	1.1424	0.9369	0.7211	1.5206	1.0718	5.9648
		Huber	0.4635	0.7335	0.6175	0.5477	1.2043	0.8096	4.3761
		Bi-Square	0.4321	0.5252	0.5247	0.5314	1.0978	0.734	3.8451
	N=30	OLS	0.5665	1.1146	0.7826	0.5976	1.6704	0.9562	5.6877
		FGLS	0.5314	1.0709	0.7204	0.6456	1.5609	0.9197	5.4489
		Huber	0.4056	0.7006	0.475	0.5327	1.2893	0.6337	4.0369
		Bi-Square	0.3978	0.5085	0.3775	0.5695	1.1121	0.5499	3.5154
	N=50	OLS	0.4295	1.1292	0.7655	0.5319	1.6552	0.7859	5.2970
		FGLS	0.4154	1.1016	0.7329	0.5547	1.6295	0.763	5.1971
		Huber	0.3578	0.667	0.3705	0.4796	1.2828	0.6255	3.7831
		Bi-Square	0.3564	0.4984	0.2776	0.4913	1.1	0.566	3.2896
	N=100	OLS	0.3727	1.077	0.63	0.5346	1.5431	0.8022	4.9595
		FGLS	0.3555	1.0728	0.6339	0.5276	1.5579	0.7892	4.9369
		Huber	0.3483	0.6494	0.3235	0.5388	1.1753	0.5793	3.6144
		Bi-Square	0.3545	0.4614	0.2316	0.559	0.9907	0.4786	3.0758
	N=250	OLS	0.2994	1.1005	0.5391	0.4067	1.6981	0.8156	4.8594
		FGLS	0.2948	1.0989	0.5414	0.4271	1.6594	0.812	4.8335
		Huber	0.3314	0.6262	0.3194	0.4918	1.2238	0.588	3.5806
		Bi-Square	0.3244	0.4479	0.2365	0.5272	1.0143	0.4969	3.0471
	N=500	OLS	0.3022	1.0342	0.5385	0.4294	1.6601	0.7803	4.7448
		FGLS	0.2995	1.0397	0.5404	0.4426	1.6419	0.7717	4.7358
		Huber	0.3321	0.6178	0.3206	0.4937	1.2185	0.5844	3.5670
		Bi-Square	0.3235	0.4495	0.2282	0.5175	1.0291	0.4987	3.0465

TABLE 4.3.14B: Absolute Bias: When Errors are Log-Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	1.0773	1.1691	1.2011	1.3872	1.1906	1.107	7.1323
		FGLS	0.9702	1.0472	1.0023	1.4239	1.1445	1.0578	6.6458
		Huber	0.8165	0.6798	0.7151	1.145	0.8121	0.7667	4.9353
		Bi-Square	0.7305	0.5603	0.6288	1.0597	0.8115	0.7256	4.5163
	N=30	OLS	0.8839	0.9607	0.8096	1.3054	1.2565	0.9332	6.1493
		FGLS	0.869	0.9033	0.7224	1.3481	1.1544	0.8978	5.8949
		Huber	0.7171	0.6016	0.5164	1.207	0.9145	0.6439	4.6005
		Bi-Square	0.6604	0.4505	0.4291	1.184	0.8315	0.5872	4.1427
	N=50	OLS	0.8443	0.9161	0.7858	1.2766	1.1346	0.6802	5.6376
		FGLS	0.8285	0.8456	0.7074	1.2946	1.0923	0.6777	5.4460
		Huber	0.7102	0.5146	0.3745	1.1256	0.8781	0.4957	4.0987
		Bi-Square	0.6498	0.4141	0.2907	1.069	0.7685	0.4944	3.6865
	N=100	OLS	0.8181	0.7367	0.5579	1.322	0.9456	0.6028	4.9831
		FGLS	0.805	0.7279	0.544	1.3125	0.9725	0.5843	4.9463
		Huber	0.721	0.433	0.2769	1.2028	0.7249	0.4039	3.7625
		Bi-Square	0.6449	0.327	0.223	1.1495	0.6188	0.3574	3.3206
	N=250	OLS	0.826	0.7185	0.3906	1.2006	1.1201	0.5373	4.7931
		FGLS	0.8144	0.7157	0.3772	1.2229	1.0752	0.5346	4.7400
		Huber	0.6967	0.4039	0.2346	1.1466	0.7864	0.3745	3.6427
		Bi-Square	0.6075	0.29	0.1921	1.1091	0.6505	0.3257	3.1749
	N=500	OLS	0.8294	0.639	0.3685	1.2377	1.0621	0.4833	4.6199
		FGLS	0.8259	0.6455	0.364	1.25	1.0442	0.4765	4.6060
		Huber	0.7005	0.3883	0.2104	1.1475	0.7814	0.3622	3.5903
		Bi-Square	0.6062	0.29	0.1537	1.0942	0.6716	0.3171	3.1327

TABLE 4.3.15B: Absolute Bias: When Errors are Log- Normal , Square Root Heteroscedastic($g=0.5$) and Contemporaneous Correlation($P=0.5$) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	$\text{Sum}(\beta_{ij})$
P= 0.5	N=20	<i>OLS</i>	1.4142	1.1997	1.3158	1.9164	1.1045	1.1368	8.0874
		<i>FGLS</i>	1.3197	1.0664	1.0885	1.948	1.067	1.0861	7.5758
		<i>Huber</i>	1.072	0.696	0.7783	1.6083	0.6687	0.7603	5.5834
		<i>Bi-Square</i>	0.9369	0.6027	0.6971	1.4741	0.7521	0.729	5.1919
	N=30	<i>OLS</i>	1.1769	0.9321	0.8615	1.8807	1.1413	0.9714	6.9639
		<i>FGLS</i>	1.1776	0.8846	0.7612	1.9161	1.0507	0.9242	6.7145
		<i>Huber</i>	0.9564	0.5696	0.5615	1.6778	0.8048	0.6858	5.2559
		<i>Bi-Square</i>	0.8428	0.446	0.4533	1.617	0.7489	0.6408	4.7488
	N=50	<i>OLS</i>	1.1709	0.8162	0.8278	1.8259	0.9181	0.6748	6.2336
		<i>FGLS</i>	1.1669	0.7455	0.7269	1.8427	0.839	0.6999	6.0207
		<i>Huber</i>	0.9593	0.4472	0.4061	1.5802	0.6594	0.4681	4.5203
		<i>Bi-Square</i>	0.8587	0.3788	0.3231	1.469	0.5877	0.4692	4.0866
	N=100	<i>OLS</i>	1.1804	0.6149	0.5431	1.8833	0.6114	0.5365	5.3697
		<i>FGLS</i>	1.171	0.5541	0.522	1.8706	0.6162	0.5183	5.2522
		<i>Huber</i>	0.9734	0.3251	0.2764	1.6561	0.4314	0.3305	3.9928
		<i>Bi-Square</i>	0.8451	0.2637	0.2299	1.5545	0.3868	0.3109	3.5908
	N=250	<i>OLS</i>	1.1948	0.5098	0.3438	1.7479	0.7145	0.4141	4.9249
		<i>FGLS</i>	1.1805	0.4766	0.318	1.7707	0.6615	0.3989	4.8062
		<i>Huber</i>	0.9447	0.2611	0.196	1.5952	0.4686	0.2656	3.7312
		<i>Bi-Square</i>	0.7977	0.1957	0.1735	1.5079	0.3775	0.235	3.2873
	N=500	<i>OLS</i>	1.1947	0.3913	0.2922	1.7937	0.6389	0.3216	4.6324
		<i>FGLS</i>	1.1918	0.3772	0.2678	1.8051	0.6204	0.3067	4.5689
		<i>Huber</i>	0.951	0.2212	0.1483	1.5948	0.4578	0.2217	3.5947
		<i>Bi-Square</i>	0.7975	0.1777	0.1141	1.4929	0.3953	0.2033	3.1808

TABLE 4.3.16B: Absolute Bias: When Errors are Log-Normal , Homoscedastic and Contemporaneous Correlation($P=0.7$) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	$\text{Sum}(\beta_{ij})$
P=0.7	N=20	<i>OLS</i>	1.8858	1.3384	1.4784	2.0195	1.4022	1.1373	9.2616
		<i>FGLS</i>	1.8066	1.0991	1.21	2.0068	1.3343	1.0978	8.5545
		<i>Huber</i>	1.4007	0.7751	0.8713	1.7656	1.0266	0.9551	6.7943
		<i>Bi-Square</i>	1.2008	0.6433	0.7754	1.6796	0.9472	0.8989	6.1451
	N=30	<i>OLS</i>	1.5896	0.9768	0.945	1.7234	0.931	0.881	7.0469
		<i>FGLS</i>	1.5517	0.9272	0.7751	1.7734	0.7947	0.7426	6.5647
		<i>Huber</i>	1.2665	0.5852	0.6314	1.5526	0.7369	0.8131	5.5857
		<i>Bi-Square</i>	1.0761	0.4753	0.5121	1.4868	0.7105	0.8507	5.1115
	N=50	<i>OLS</i>	1.5968	0.8157	0.9013	1.7995	0.883	0.793	6.7894
		<i>FGLS</i>	1.5401	0.6728	0.6867	1.8009	0.74	0.6599	6.1004
		<i>Huber</i>	1.2695	0.4122	0.4492	1.5244	0.6167	0.5674	4.8395
		<i>Bi-Square</i>	1.1135	0.3719	0.3675	1.4425	0.5724	0.5419	4.4097
	N=100	<i>OLS</i>	1.6402	0.6112	0.5922	1.8405	0.5816	0.5563	5.8220
		<i>FGLS</i>	1.6157	0.487	0.5314	1.8231	0.4712	0.4875	5.4158
		<i>Huber</i>	1.2833	0.3218	0.3028	1.5765	0.4236	0.417	4.3250
		<i>Bi-Square</i>	1.0911	0.2681	0.2584	1.4888	0.4109	0.4241	3.9414
	N=250	<i>OLS</i>	1.6538	0.4018	0.3456	1.756	0.3778	0.3509	4.8859
		<i>FGLS</i>	1.677	0.307	0.2756	1.7825	0.3264	0.301	4.6695
		<i>Huber</i>	1.2475	0.1908	0.1867	1.5428	0.2781	0.2631	3.7090
		<i>Bi-Square</i>	1.0272	0.1489	0.172	1.4678	0.2692	0.2577	3.3428
	N=500	<i>OLS</i>	1.6503	0.2664	0.2661	1.8068	0.2608	0.2615	4.5120
		<i>FGLS</i>	1.6335	0.2169	0.227	1.8189	0.2136	0.2073	4.3173
		<i>Huber</i>	1.2568	0.1357	0.1219	1.5679	0.1791	0.1699	3.4313
		<i>Bi-Square</i>	1.0289	0.1229	0.0983	1.4784	0.1747	0.1686	3.0719

TABLE 4.3.17B: Absolute Bias: When Errors are Log- Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}(E(Y_i))$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	3.2513	3.1947	3.3613	3.5674	3.4277	2.6456	19.4480
		FGLS	3.0785	2.7006	2.7704	3.5433	3.194	2.5233	17.8100
		Huber	2.4624	1.8249	1.9851	3.1278	2.5996	2.1533	14.1530
		Bi-Square	2.1804	1.543	1.7531	3.0611	2.3505	2.1434	13.0315
	N=30	OLS	2.673	2.5578	2.2324	2.7437	2.4553	2.0118	14.6739
		FGLS	2.6068	2.4222	1.9617	2.8839	2.1549	1.6991	13.7285
		Huber	2.1755	1.5794	1.4349	2.5891	2.0621	1.7832	11.6242
		Bi-Square	1.9672	1.2007	1.1767	2.5209	1.9588	1.8634	10.6875
	N=50	OLS	2.5996	2.3415	2.142	2.8804	2.3589	1.8775	14.1998
		FGLS	2.4233	2.0578	1.7804	2.8889	2.1649	1.6099	12.9251
		Huber	2.1733	1.2979	1.0374	2.5342	1.6488	1.4246	10.1162
		Bi-Square	1.9682	1.0744	0.8172	2.4797	1.4494	1.3706	9.1596
	N=100	OLS	2.5654	1.8147	1.4758	2.9161	1.7946	1.4182	11.9848
		FGLS	2.5117	1.6966	1.361	2.8915	1.7424	1.2342	11.4373
		Huber	2.2014	1.0297	0.734	2.6079	1.4137	1.0644	9.0511
		Bi-Square	1.9446	0.7967	0.5985	2.5402	1.2482	1.0153	8.1434
	N=250	OLS	2.5951	1.6891	0.9887	2.7152	1.9662	1.0925	11.0468
		FGLS	2.6541	1.5352	0.871	2.7852	1.8164	1.0212	10.6832
		Huber	2.1318	0.923	0.5815	2.5401	1.411	0.7697	8.3571
		Bi-Square	1.8354	0.662	0.4872	2.5157	1.1832	0.7054	7.3889
	N=500	OLS	2.6042	1.4322	0.9014	2.8286	1.6886	0.949	10.4041
		FGLS	2.5728	1.4748	0.8727	2.8692	1.6153	0.8797	10.2845
		Huber	2.1463	0.8635	0.4875	2.5959	1.3031	0.592	7.9882
		Bi-Square	1.8325	0.6534	0.3596	2.5169	1.149	0.497	7.0084

TABLE 4.3.18 B: Absolute Bias: When Errors are Log-Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.6807	1.2201	1.0794	0.7369	1.3781	0.9047	6.0000
		FGLS	0.6093	1.1257	0.9169	0.7348	1.294	0.861	5.5417
		Huber	0.4635	0.7335	0.6175	0.6063	1.0349	0.7061	4.1618
		Bi-Square	0.4321	0.5252	0.5247	0.5782	0.8604	0.6627	3.5832
	N=30	OLS	0.5665	1.1146	0.7826	0.4856	1.1697	0.7055	4.8244
		FGLS	0.5149	1.1154	0.7282	0.4699	1.075	0.6612	4.5646
		Huber	0.4056	0.7006	0.475	0.4352	0.9621	0.5913	3.5697
		Bi-Square	0.3978	0.5085	0.3775	0.4487	0.8397	0.5788	3.1511
	N=50	OLS	0.4295	1.1292	0.7655	0.4371	1.1958	0.6808	4.6378
		FGLS	0.3681	1.0817	0.6894	0.4411	1.1528	0.6444	4.3776
		Huber	0.3578	0.667	0.3705	0.3847	0.9011	0.5482	3.2292
		Bi-Square	0.3564	0.4984	0.2776	0.3982	0.7848	0.5111	2.8265
	N=100	OLS	0.3727	1.077	0.63	0.4008	1.108	0.6494	4.2378
		FGLS	0.3381	1.0795	0.6223	0.3728	1.1135	0.6083	4.1344
		Huber	0.3483	0.6494	0.3235	0.3813	0.8548	0.4738	3.0310
		Bi-Square	0.3545	0.4614	0.2316	0.4082	0.724	0.4092	2.5890
	N=250	OLS	0.2994	1.1005	0.5391	0.2914	1.2646	0.6118	4.1068
		FGLS	0.3104	1.0557	0.5331	0.3079	1.2195	0.5988	4.0253
		Huber	0.3314	0.6262	0.3194	0.3485	0.9174	0.4323	2.9752
		Bi-Square	0.3244	0.4479	0.2365	0.3941	0.7609	0.3574	2.5211
	N=500	OLS	0.3022	1.0342	0.5385	0.3158	1.1821	0.5968	3.9696
		FGLS	0.2961	1.0477	0.5362	0.3273	1.1579	0.5867	3.9519
		Huber	0.3321	0.6178	0.3206	0.3637	0.8944	0.4121	2.9408
		Bi-Square	0.3235	0.4495	0.2282	0.3918	0.7688	0.3377	2.4996

TABLE 4.3.19B: Absolute Bias: When Errors are Log- Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	1.0773	1.1691	1.2011	1.1878	1.2702	0.9618	6.8672
		FGLS	1.0151	1.0014	0.9925	1.1791	1.1757	0.9116	6.2754
		Huber	0.8165	0.6798	0.7151	1.033	0.972	0.773	4.9894
		Bi-Square	0.7305	0.5603	0.6288	1.0172	0.8757	0.7697	4.5822
	N=30	OLS	0.8839	0.9607	0.8096	0.888	0.9439	0.7261	5.2122
		FGLS	0.8561	0.9225	0.7251	0.9314	0.8357	0.6223	4.8929
		Huber	0.7171	0.6016	0.5164	0.8407	0.8002	0.6376	4.1136
		Bi-Square	0.6604	0.4505	0.4291	0.8222	0.7494	0.6676	3.7792
	N=50	OLS	0.8443	0.9161	0.7858	0.9271	0.9267	0.6839	5.0838
		FGLS	0.7754	0.8169	0.664	0.9294	0.8612	0.6048	4.6516
		Huber	0.7102	0.5146	0.3745	0.8227	0.659	0.5328	3.6138
		Bi-Square	0.6498	0.4141	0.2907	0.8104	0.5808	0.5112	3.2570
	N=100	OLS	0.8181	0.7367	0.5579	0.932	0.744	0.544	4.3326
		FGLS	0.7961	0.7082	0.5223	0.9225	0.7343	0.4779	4.1613
		Huber	0.721	0.433	0.2769	0.8427	0.579	0.4083	3.2608
		Bi-Square	0.6449	0.327	0.223	0.828	0.5129	0.3785	2.9143
	N=250	OLS	0.826	0.7185	0.3906	0.8586	0.8446	0.4432	4.0815
		FGLS	0.8475	0.6678	0.3579	0.8843	0.7919	0.4181	3.9675
		Huber	0.6967	0.4039	0.2346	0.8195	0.6101	0.3137	3.0785
		Bi-Square	0.6075	0.29	0.1921	0.8206	0.5107	0.2794	2.7002
	N=500	OLS	0.8294	0.639	0.3685	0.8983	0.7469	0.3969	3.8790
		FGLS	0.8187	0.658	0.3658	0.9139	0.7224	0.3776	3.8563
		Huber	0.7005	0.3883	0.2104	0.8385	0.5774	0.2549	2.9700
		Bi-Square	0.6062	0.29	0.1537	0.8196	0.5073	0.2114	2.5881

TABLE 4.3.20 B: Absolute Bias: When Errors are Log-Normal , Square Root Heteroscedastic(P=0.5) and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	1.4142	1.1997	1.3158	1.5448	1.2903	1.0274	7.7922
		FGLS	1.3526	1.0127	1.0799	1.5309	1.2151	0.9836	7.1748
		Huber	1.072	0.696	0.7783	1.3546	0.9691	0.8516	5.7215
		Bi-Square	0.9369	0.6027	0.6971	1.3242	0.9008	0.8547	5.3164
	N=30	OLS	1.1769	0.9321	0.8615	1.2501	0.8868	0.7878	5.8951
		FGLS	1.1484	0.8762	0.7327	1.2992	0.7709	0.6565	5.4838
		Huber	0.9564	0.5696	0.5615	1.1555	0.7413	0.7078	4.6920
		Bi-Square	0.8428	0.446	0.4533	1.1147	0.7074	0.741	4.3052
	N=50	OLS	1.1709	0.8162	0.8278	1.311	0.829	0.7257	5.6805
		FGLS	1.1107	0.7036	0.6651	1.3153	0.7363	0.6043	5.1353
		Huber	0.9593	0.4472	0.4061	1.1327	0.5754	0.5414	4.0621
		Bi-Square	0.8587	0.3788	0.3231	1.0961	0.5151	0.5155	3.6873
	N=100	OLS	1.1804	0.6149	0.5431	1.3354	0.5912	0.5177	4.7827
		FGLS	1.1595	0.5378	0.4965	1.3231	0.5479	0.4567	4.5214
		Huber	0.9734	0.3251	0.2764	1.171	0.4564	0.3902	3.5924
		Bi-Square	0.8451	0.2637	0.2299	1.1242	0.4182	0.3848	3.2658
	N=250	OLS	1.1948	0.5098	0.3438	1.2581	0.573	0.3653	4.2449
		FGLS	1.2173	0.4352	0.2837	1.2843	0.5024	0.3308	4.0537
		Huber	0.9447	0.2611	0.196	1.1431	0.4021	0.2579	3.2050
		Bi-Square	0.7977	0.1957	0.1735	1.1118	0.3521	0.2484	2.8792
	N=500	OLS	1.1947	0.3913	0.2922	1.3026	0.4614	0.2932	3.9354
		FGLS	1.1811	0.3784	0.2717	1.3168	0.4238	0.2577	3.8295
		Huber	0.951	0.2212	0.1483	1.1648	0.3503	0.1852	3.0208
		Bi-Square	0.7975	0.1777	0.1141	1.1148	0.3136	0.1607	2.6784

TABLE 4.3.21 B: Absolute Bias: When Errors are Log- Normal , Homoscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	2.0576	1.289	1.3198	2.6206	1.223	1.2443	9.7542
		FGLS	1.9298	0.3853	0.4553	2.4455	0.4452	0.4446	6.1058
		Huber	1.6652	0.7362	0.7905	2.1858	0.7245	0.7977	6.8999
		Bi-Square	1.5336	0.7095	0.7435	1.9986	0.7981	0.7692	6.5525
	N=30	OLS	1.9113	0.9869	1.0422	2.6045	1.1974	1.0733	8.8156
		FGLS	1.979	0.3212	0.3107	2.5311	0.3772	0.4047	5.9239
		Huber	1.6025	0.6117	0.6474	2.254	0.8281	0.7752	6.7189
		Bi-Square	1.4699	0.5546	0.6133	2.1433	0.7506	0.7162	6.2478
	N=50	OLS	1.9885	0.7952	0.6612	2.5186	0.8394	0.7468	7.5497
		FGLS	1.9992	0.2669	0.2427	2.5155	0.2643	0.2959	5.5844
		Huber	1.5903	0.4609	0.4157	2.1394	0.5438	0.486	5.6361
		Bi-Square	1.4109	0.4261	0.3943	1.9575	0.4923	0.459	5.1401
	N=100	OLS	2.056	0.6367	0.5997	2.583	0.5382	0.5504	6.9639
		FGLS	1.9962	0.1679	0.1815	2.5468	0.1703	0.1873	5.2500
		Huber	1.6366	0.3208	0.3497	2.2164	0.3393	0.3186	5.1814
		Bi-Square	1.4351	0.295	0.2992	2.0519	0.3312	0.3251	4.7373
	N=250	OLS	1.9918	0.386	0.3965	2.4298	0.3776	0.3948	5.9764
		FGLS	1.9461	0.1002	0.0994	2.4982	0.1271	0.1147	4.8857
		Huber	1.5795	0.2071	0.2179	2.1457	0.2016	0.2484	4.6002
		Bi-Square	1.3718	0.2	0.2016	1.9976	0.1929	0.2196	4.1835
	N=500	OLS	1.9527	0.2405	0.2816	2.4874	0.2918	0.2811	5.5352
		FGLS	1.9587	0.0885	0.0923	2.4965	0.0807	0.0826	4.7994
		Huber	1.5812	0.1334	0.1436	2.1448	0.1528	0.1804	4.3363
		Bi-Square	1.3937	0.1162	0.1302	1.984	0.1521	0.1624	3.9386

TABLE 4.3.22B: Absolute Bias: When Errors are Log- Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	3.4668	3.1792	3.0443	4.2774	3.0449	2.9831	19.9955
		FGLS	3.1312	1.6478	1.3692	3.8876	2.2528	1.5278	13.8164
		Huber	2.8112	1.8536	1.8179	3.5676	1.9857	2.0504	14.0864
		Bi-Square	2.6781	1.6146	1.7599	3.2873	2.0621	1.9508	13.3527
	N=30	OLS	3.0618	2.7778	2.5719	4.1051	3.2347	2.5294	18.2807
		FGLS	3.1831	1.7573	1.1175	4.0191	2.4524	1.1176	13.6469
		Huber	2.6734	1.7482	1.4862	3.7398	2.3068	1.7608	13.7152
		Bi-Square	2.5735	1.4783	1.3688	3.6396	2.102	1.6221	12.7842
	N=50	OLS	3.1256	2.2211	1.5327	3.9973	2.7848	1.8062	15.4676
		FGLS	3.1472	1.6938	0.9383	3.9963	2.1858	1.1703	13.1317
		Huber	2.6549	1.4284	1.0695	3.4996	2.085	1.282	12.0194
		Bi-Square	2.4509	1.2656	1.0291	3.2934	1.8337	1.2918	11.1644
	N=100	OLS	3.27	2.1196	1.4124	4.1299	2.1385	1.5325	14.6029
		FGLS	3.1726	1.7678	0.8144	4.0979	2.1469	1.0386	13.0382
		Huber	2.7766	1.2105	0.8791	3.7085	1.6072	0.9873	11.1692
		Bi-Square	2.5248	0.9056	0.7547	3.5203	1.375	0.8939	9.9742
	N=250	OLS	3.1499	1.7315	1.1481	3.7856	2.5888	1.2939	13.6977
		FGLS	3.0733	1.6853	0.8902	3.9495	2.2363	1.1422	12.9767
		Huber	2.6776	1.1366	0.6861	3.5498	1.7755	0.8613	10.6868
		Bi-Square	2.3997	0.9829	0.5893	3.4017	1.454	0.7554	9.5830
	N=500	OLS	3.0774	1.7047	0.9694	3.8968	2.4145	1.0974	13.1602
		FGLS	3.0849	1.7261	0.868	3.9218	2.2942	1.1256	13.0206
		Huber	2.6612	1.1069	0.6443	3.5519	1.7589	0.8023	10.5255
		Bi-Square	2.422	0.8666	0.5261	3.3615	1.5094	0.7103	9.3958

TABLE 4.3.23B: Absolute Bias: When Errors are Log- Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.6866	1.3659	1.0031	0.7216	1.5632	1.1203	6.4607
		FGLS	0.4714	1.1261	0.6855	0.4952	1.5154	0.8641	5.1577
		Huber	0.4879	0.8748	0.5918	0.5477	1.2043	0.8096	4.5161
		Bi-Square	0.4924	0.6912	0.5712	0.5314	1.0978	0.734	4.1179
	N=30	OLS	0.5383	1.2716	0.9474	0.5976	1.6704	0.9562	5.9814
		FGLS	0.4424	1.208	0.662	0.5071	1.6391	0.7197	5.1783
		Huber	0.412	0.8888	0.5271	0.5327	1.2893	0.6337	4.2837
		Bi-Square	0.4337	0.7107	0.4282	0.5695	1.1121	0.5499	3.8043
	N=50	OLS	0.4452	1.2619	0.6919	0.5319	1.6552	0.7859	5.3719
		FGLS	0.3907	1.2135	0.6387	0.4852	1.5572	0.7856	5.0709
		Huber	0.3828	0.8434	0.4657	0.4796	1.2828	0.6255	4.0797
		Bi-Square	0.3949	0.6753	0.4074	0.4913	1.1	0.566	3.6348
	N=100	OLS	0.4457	1.298	0.6128	0.5346	1.5431	0.8022	5.2364
		FGLS	0.3785	1.2523	0.5926	0.5164	1.5418	0.744	5.0255
		Huber	0.4208	0.8326	0.4041	0.5388	1.1753	0.5793	3.9508
		Bi-Square	0.4273	0.6199	0.3319	0.559	0.9907	0.4786	3.4073
	N=250	OLS	0.3764	1.2163	0.6175	0.4067	1.6981	0.8156	5.1306
		FGLS	0.3538	1.2139	0.6261	0.4546	1.5986	0.8008	5.0477
		Huber	0.4018	0.8151	0.4037	0.4918	1.2238	0.588	3.9243
		Bi-Square	0.405	0.6558	0.3109	0.5272	1.0143	0.4969	3.4100
	N=500	OLS	0.3522	1.2336	0.6291	0.4294	1.6601	0.7803	5.0848
		FGLS	0.3503	1.2353	0.6278	0.4384	1.6283	0.7939	5.0739
		Huber	0.395	0.8074	0.4142	0.4937	1.2185	0.5844	3.9131
		Bi-Square	0.4011	0.633	0.3313	0.5175	1.0291	0.4987	3.4107

TABLE 4.3.24B: Absolute Bias: When Errors are Log- Normal , Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	1.1472	1.1852	1.1073	1.3872	1.1906	1.107	7.1245
		FGLS	1.0134	0.7133	0.5343	1.2393	0.9835	0.6291	5.1129
		Huber	0.9197	0.7084	0.6555	1.145	0.8121	0.7667	5.0074
		Bi-Square	0.8889	0.5928	0.6377	1.0597	0.8115	0.7256	4.7161
	N=30	OLS	0.9996	1.0579	0.9525	1.3054	1.2565	0.9332	6.5051
		FGLS	1.0248	0.7658	0.4578	1.2808	1.072	0.4634	5.0646
		Huber	0.8676	0.6876	0.5391	1.207	0.9145	0.6439	4.8596
		Bi-Square	0.8473	0.5777	0.4925	1.184	0.8315	0.5872	4.5202
	N=50	OLS	0.9975	0.893	0.5745	1.2766	1.1346	0.6802	5.5563
		FGLS	1.0013	0.7585	0.4031	1.2766	0.9756	0.5062	4.9213
		Huber	0.8594	0.5739	0.4044	1.1256	0.8781	0.4957	4.3371
		Bi-Square	0.8032	0.5006	0.3875	1.069	0.7685	0.4944	4.0232
	N=100	OLS	1.0455	0.8744	0.5276	1.322	0.9456	0.6028	5.3179
		FGLS	1.0118	0.7884	0.3614	1.3146	0.9626	0.459	4.8978
		Huber	0.9048	0.5228	0.3368	1.2028	0.7249	0.4039	4.0959
		Bi-Square	0.8315	0.3865	0.2879	1.1495	0.6188	0.3574	3.6316
	N=250	OLS	1.0045	0.7631	0.4548	1.2006	1.1201	0.5373	5.0804
		FGLS	0.9795	0.7541	0.3944	1.26	0.9979	0.5051	4.8911
		Huber	0.8727	0.5075	0.2794	1.1466	0.7864	0.3745	3.9671
		Bi-Square	0.7901	0.4282	0.2339	1.1091	0.6505	0.3257	3.5376
	N=500	OLS	0.9792	0.7653	0.4099	1.2377	1.0621	0.4833	4.9375
		FGLS	0.9817	0.772	0.3889	1.2471	1.0225	0.4993	4.9115
		Huber	0.8647	0.5012	0.2746	1.1475	0.7814	0.3622	3.9315
		Bi-Square	0.7947	0.3939	0.2245	1.0942	0.6716	0.3171	3.4961

**TABLE 4.3.25B: Absolute Bias: When Errors are Log-Normal , Square Root Heteroscedastic(
g=0.5) and Contemporaneous Correlation(P=0.95) under varying sample sizes**

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=0.5							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	<i>OLS</i>	1.5335	1.1835	1.1863	1.9164	1.1045	1.1368	8.0610
		<i>FGLS</i>	1.4226	0.4811	0.4728	1.7745	0.6352	0.4942	5.2803
		<i>Huber</i>	1.2515	0.6808	0.7081	1.6083	0.6687	0.7603	5.6776
		<i>Bi-Square</i>	1.1745	0.6205	0.6889	1.4741	0.7521	0.729	5.4391
	N=30	<i>OLS</i>	1.3865	0.9969	0.971	1.8807	1.1413	0.9714	7.3478
		<i>FGLS</i>	1.4513	0.4866	0.3473	1.8359	0.6782	0.3739	5.1732
		<i>Huber</i>	1.1975	0.6077	0.5804	1.6778	0.8048	0.6858	5.5540
		<i>Bi-Square</i>	1.1291	0.5258	0.54	1.617	0.7489	0.6408	5.2016
	N=50	<i>OLS</i>	1.4362	0.7629	0.5746	1.8259	0.9181	0.6748	6.1925
		<i>FGLS</i>	1.445	0.4432	0.2761	1.8277	0.5672	0.345	4.9042
		<i>Huber</i>	1.1884	0.4804	0.3937	1.5802	0.6594	0.4681	4.7703
		<i>Bi-Square</i>	1.0803	0.4329	0.3802	1.469	0.5877	0.4692	4.4193
	N=100	<i>OLS</i>	1.4919	0.6817	0.5328	1.8833	0.6114	0.5365	5.7376
		<i>FGLS</i>	1.4493	0.4524	0.2212	1.863	0.5401	0.2825	4.8085
		<i>Huber</i>	1.2337	0.3623	0.3207	1.6561	0.4314	0.3305	4.3345
		<i>Bi-Square</i>	1.1037	0.2848	0.2833	1.5545	0.3868	0.3109	3.9239
	N=250	<i>OLS</i>	1.444	0.4831	0.3937	1.7479	0.7145	0.4141	5.1973
		<i>FGLS</i>	1.4097	0.4204	0.2281	1.8118	0.5625	0.2928	4.7253
		<i>Huber</i>	1.1914	0.3177	0.2291	1.5952	0.4686	0.2656	4.0676
		<i>Bi-Square</i>	1.0524	0.2903	0.2054	1.5079	0.3775	0.235	3.6685
	N=500	<i>OLS</i>	1.4123	0.4364	0.3068	1.7937	0.6389	0.3216	4.9097
		<i>FGLS</i>	1.4165	0.4337	0.2188	1.8032	0.5812	0.2858	4.7391
		<i>Huber</i>	1.1861	0.275	0.189	1.5948	0.4578	0.2217	3.9243
		<i>Bi-Square</i>	1.064	0.2163	0.1603	1.4929	0.3953	0.2033	3.5321

TABLE 4.3.1C: Root Mean Squares Error: When Errors are Log-Normal , Homoscedastic and No contemporaneous correlation under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	2.45829	1.81429	1.90676	2.19891	1.86528	1.76909	12.0126
		FGLS	2.40234	1.73642	1.94184	2.19586	1.90399	1.79717	11.9776
		Huber	1.44139	0.88366	1.05426	1.54732	1.08151	0.91485	6.9230
		Bi-Square	1.24198	0.82751	0.94584	1.35618	1.02418	0.78449	6.1802
	N=30	OLS	1.91197	1.33105	1.35162	1.93281	1.23437	1.68446	9.4463
		FGLS	1.91443	1.4001	1.41826	1.98529	1.26067	1.68506	9.6638
		Huber	1.46292	0.79826	0.76628	1.37708	0.78338	0.80402	5.9919
		Bi-Square	1.27079	0.66117	0.55336	1.14712	0.68133	0.68674	5.0005
	N=50	OLS	1.68582	1.15349	0.91064	1.91674	1.2698	1.14531	8.0818
		FGLS	1.69936	1.16001	0.91814	1.923	1.29996	1.14861	8.1491
		Huber	1.23107	0.48901	0.52082	1.35529	0.54477	0.55473	4.6957
		Bi-Square	1.04044	0.46489	0.47378	1.17122	0.4884	0.51082	4.1496
	N=100	OLS	1.66028	0.67937	0.68473	1.74796	0.74557	0.87465	6.3926
		FGLS	1.65232	0.68305	0.67939	1.74972	0.73838	0.86444	6.3673
		Huber	1.2719	0.39269	0.37421	1.3266	0.38673	0.39841	4.1505
		Bi-Square	1.06596	0.32689	0.33992	1.14386	0.35829	0.31755	3.5525
	N=250	OLS	1.67866	0.48344	0.47323	1.66144	0.49365	0.49273	5.2832
		FGLS	1.67667	0.48203	0.47935	1.6621	0.49794	0.49542	5.2935
		Huber	1.27772	0.20896	0.22872	1.2739	0.23205	0.23829	3.4596
		Bi-Square	1.06886	0.16341	0.19026	1.06082	0.19437	0.17755	2.8553
	N=500	OLS	1.61459	0.35197	0.30109	1.69859	0.32557	0.34954	4.6414
		FGLS	1.61443	0.35327	0.2993	1.69797	0.32503	0.34868	4.6387
		Huber	1.23822	0.17665	0.15084	1.27043	0.15641	0.17721	3.1698
		Bi-Square	1.03056	0.13368	0.13682	1.03269	0.13683	0.14973	2.6203

TABLE 4.3.2 C: Root Mean Squares Error: When Errors are Log-Normal , Exponential Heteroscedastic and No contemporaneous correlation under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	4.42221	4.00639	4.09052	3.96804	4.50886	4.01824	25.0143
		FGLS	4.2989	3.88151	4.1729	3.96532	4.58435	4.12956	25.0325
		Huber	2.56425	2.20673	2.4409	2.76512	2.48549	2.08476	14.5473
		Bi-Square	2.28474	2.19732	2.22066	2.51399	2.24868	1.75963	13.2250
	N=30	OLS	3.37489	3.43251	3.16262	3.33798	3.34604	3.77731	20.4314
		FGLS	3.40282	3.56978	3.31869	3.44073	3.35484	3.77992	20.8668
		Huber	2.62907	2.0982	1.77253	2.41175	2.085	1.87329	12.8698
		Bi-Square	2.38736	1.65314	1.25715	2.09737	1.7512	1.62412	10.7703
	N=50	OLS	2.81727	3.01502	2.31023	3.36323	3.40851	2.8119	17.7262
		FGLS	2.85217	3.0221	2.33021	3.37899	3.44833	2.81887	17.8507
		Huber	2.13723	1.4261	1.31649	2.35278	1.53314	1.36488	10.1306
		Bi-Square	1.90073	1.23153	1.11797	2.09318	1.29213	1.24686	8.8824
	N=100	OLS	2.67818	2.21495	1.74502	2.86859	2.38239	2.13455	14.0237
		FGLS	2.66399	2.2419	1.73747	2.87037	2.36734	2.11197	13.9930
		Huber	2.20591	1.31061	0.96715	2.30142	1.21503	0.98653	8.9867
		Bi-Square	1.92728	1.00108	0.83169	2.07734	0.94499	0.76109	7.5435
	N=250	OLS	2.69281	1.88415	1.25592	2.65402	1.93129	1.33039	11.7486
		FGLS	2.68882	1.885	1.2702	2.65411	1.93845	1.33609	11.7727
		Huber	2.19794	0.96024	0.66232	2.19081	1.00649	0.71379	7.7316
		Bi-Square	1.91517	0.71107	0.50313	1.90017	0.74377	0.51266	6.2860
	N=500	OLS	2.5485	1.78591	1.02061	2.71387	1.55476	1.04354	10.6672
		FGLS	2.54763	1.78887	1.01757	2.71203	1.55572	1.04242	10.6642
		Huber	2.11226	1.04154	0.55204	2.18897	0.87758	0.58954	7.3619
		Bi-Square	1.84034	0.73503	0.43584	1.84871	0.67538	0.45861	5.9939

TABLE 4.3.3 C: Root Mean Squares Error: When Errors are Log-Normal ,Quadratic Heteroscedastic(g=2) and No contemporal correlation (P=0) under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	0.9202	1.46905	1.23072	0.8651	1.71155	1.27615	7.4728
		FGLS	0.87738	1.44315	1.24536	0.88169	1.74288	1.32725	7.5177
		Huber	0.5113	0.91458	0.80621	0.5266	0.94895	0.67127	4.3789
		Bi-Square	0.49218	0.8221	0.67798	0.52539	0.77489	0.57711	3.8697
	N=30	OLS	0.69124	1.43605	1.06088	0.65242	1.44574	1.19867	6.4850
		FGLS	0.71175	1.46633	1.10473	0.67779	1.44297	1.19962	6.6032
		Huber	0.51722	0.89163	0.5864	0.44636	0.89141	0.63609	3.9691
		Bi-Square	0.49074	0.66717	0.40821	0.41763	0.66792	0.52085	3.1725
	N=50	OLS	0.51253	1.32698	0.88033	0.72614	1.47526	1.04204	5.9633
		FGLS	0.52565	1.33129	0.88488	0.72847	1.47776	1.04279	5.9908
		Huber	0.36825	0.709	0.48619	0.41269	0.76014	0.51916	3.2554
		Bi-Square	0.35444	0.54325	0.37067	0.38977	0.58547	0.43283	2.6764
	N=100	OLS	0.38804	1.18511	0.71251	0.47384	1.24249	0.82202	4.8240
		FGLS	0.3862	1.19447	0.71021	0.47388	1.23977	0.81861	4.8231
		Huber	0.37113	0.70196	0.40254	0.38193	0.67596	0.40577	2.9393
		Bi-Square	0.36406	0.50216	0.31412	0.38269	0.47994	0.29581	2.3388
	N=250	OLS	0.35795	1.11721	0.59542	0.34788	1.13254	0.61879	4.1698
		FGLS	0.35756	1.11775	0.59882	0.34758	1.13523	0.62034	4.1773
		Huber	0.35236	0.62667	0.33539	0.3512	0.63536	0.35559	2.6566
		Bi-Square	0.34554	0.45404	0.23932	0.34294	0.45456	0.25062	2.0870
	N=500	OLS	0.30947	1.10968	0.5692	0.34525	1.04477	0.56594	3.9443
		FGLS	0.3093	1.11078	0.56882	0.34441	1.04513	0.56611	3.9446
		Huber	0.32974	0.65254	0.32395	0.35097	0.60304	0.33013	2.5904
		Bi-Square	0.32705	0.46174	0.23706	0.33371	0.43952	0.23849	2.0376

TABLE 4.3.4 C: Root Mean Squares Error: When Errors are Log-Normal ,Linear Heteroscedastic(g=1) and No contemporal correlation(P=0) under varying sample sizes									
Contemporal Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g; g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.47645	1.45343	1.44617	1.33372	1.66428	1.45452	8.8286
		FGLS	1.43221	1.41531	1.47384	1.33414	1.69348	1.49854	8.8475
		Huber	0.85579	0.83087	0.88322	0.91978	0.9145	0.75416	5.1583
		Bi-Square	0.77373	0.82366	0.80166	0.8415	0.81569	0.63399	4.6902
	N=30	OLS	1.12683	1.29302	1.14652	1.09842	1.27475	1.35987	7.2994
		FGLS	1.13997	1.33905	1.20129	1.13317	1.27451	1.36022	7.4482
		Huber	0.88257	0.79687	0.64132	0.79405	0.79403	0.6799	4.5887
		Bi-Square	0.81074	0.61982	0.45767	0.70005	0.65459	0.59044	3.8333
	N=50	OLS	0.92293	1.1484	0.85907	1.12186	1.29322	1.03573	6.3812
		FGLS	0.93598	1.15074	0.86639	1.12708	1.30497	1.03796	6.4231
		Huber	0.70372	0.5606	0.48776	0.77417	0.60476	0.50514	3.6362
		Bi-Square	0.63296	0.47082	0.40633	0.69385	0.49674	0.45421	3.1549
	N=100	OLS	0.86177	0.88906	0.65624	0.92928	0.94904	0.78853	5.0739
		FGLS	0.8571	0.89945	0.65332	0.92966	0.94404	0.78074	5.0643
		Huber	0.72688	0.52908	0.3648	0.75516	0.49479	0.3727	3.2434
		Bi-Square	0.64368	0.3978	0.30876	0.69053	0.37259	0.28425	2.6976
	N=250	OLS	0.86441	0.78308	0.48575	0.85043	0.80025	0.51358	4.2975
		FGLS	0.86307	0.78353	0.49069	0.85031	0.80275	0.51547	4.3058
		Huber	0.71979	0.4152	0.26295	0.71767	0.42889	0.28182	2.8263
		Bi-Square	0.63495	0.30642	0.19644	0.63044	0.31463	0.20266	2.2855
	N=500	OLS	0.81231	0.75659	0.41563	0.86886	0.67433	0.41946	3.9472
		FGLS	0.81197	0.75768	0.41472	0.86817	0.67473	0.41919	3.9465
		Huber	0.68952	0.44622	0.22986	0.71707	0.38693	0.2413	2.7109
		Bi-Square	0.60913	0.31638	0.17783	0.61306	0.29334	0.18447	2.1942

TABLE 4.3.5 C: Root Mean Squares Error: When Errors are Log- Normal ,Linear Heteroscedastic(g= 0.5) and No contemporaneous correlation under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.0	N=20	OLS	1.90414	1.56087	1.63618	1.70837	1.71056	1.58951	10.1096
		FGLS	1.85636	1.50771	1.66925	1.70556	1.74219	1.62661	10.1077
		Huber	1.11237	0.82087	0.95241	1.20038	0.95665	0.81781	5.8605
		Bi-Square	0.97926	0.80979	0.86935	1.07272	0.87905	0.6868	5.2970
	N=30	OLS	1.46958	1.2655	1.22785	1.45934	1.21206	1.49391	8.1282
		FGLS	1.47765	1.32273	1.28875	1.50159	1.2203	1.49388	8.3049
		Huber	1.1383	0.76964	0.69108	1.05235	0.76073	0.73028	5.1424
		Bi-Square	1.01477	0.61899	0.49554	0.89633	0.65381	0.62958	4.3090
	N=50	OLS	1.25548	1.09969	0.86827	1.46341	1.23567	1.06649	6.9890
		FGLS	1.26867	1.10287	0.87628	1.46935	1.25559	1.06952	7.0423
		Huber	0.93997	0.49565	0.4972	1.03398	0.53637	0.51799	4.0212
		Bi-Square	0.81932	0.4492	0.43338	0.90757	0.46632	0.4755	3.5513
	N=100	OLS	1.21412	0.73475	0.64915	1.28757	0.79846	0.80568	5.4897
		FGLS	1.20796	0.744	0.64539	1.28852	0.79212	0.79588	5.4739
		Huber	0.97002	0.43412	0.35791	1.01163	0.40264	0.36975	3.5461
		Bi-Square	0.83345	0.34281	0.31601	0.89692	0.33501	0.29011	3.0143
	N=250	OLS	1.22557	0.58516	0.45025	1.20998	0.60238	0.47677	4.5501
		FGLS	1.22389	0.58506	0.45612	1.21022	0.60537	0.47906	4.5597
		Huber	0.97143	0.27863	0.2291	0.96836	0.29901	0.24672	2.9933
		Bi-Square	0.83089	0.21017	0.18053	0.82492	0.22882	0.17985	2.4552
	N=500	OLS	1.16831	0.52518	0.33275	1.23725	0.43903	0.35193	4.0545
		FGLS	1.16802	0.52633	0.33135	1.2366	0.43928	0.3513	4.0529
		Huber	0.93603	0.30172	0.17462	0.96568	0.23917	0.193	2.8102
		Bi-Square	0.79958	0.21474	0.14591	0.80227	0.19438	0.15607	2.3130

TABLE 4.3.6.C:Root Mean Square Error: When Errors are Log-Normal , Homoscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	2.44874	2.02528	2.05141	2.4992	1.96302	1.88178	12.8694
		FGLS	2.32498	1.73313	1.96108	2.49767	2.07465	1.87688	12.4684
		Huber	1.58669	0.99761	1.13512	1.81745	0.83727	0.99777	7.3719
		Bi-Square	1.39602	0.86284	1.06197	1.61166	0.86132	0.87145	6.6653
	N=30	OLS	1.8288	1.2207	1.2342	2.41832	1.8794	1.55524	10.1367
		FGLS	1.82763	1.21506	1.18836	2.45693	1.80356	1.51346	10.0050
		Huber	1.41605	0.73179	0.81047	1.78211	0.85482	0.87587	6.4711
		Bi-Square	1.20664	0.60873	0.72161	1.55957	0.77787	0.74128	5.6157
	N=50	OLS	1.76827	1.08012	1.4491	2.10801	1.01515	0.97888	8.3995
		FGLS	1.77241	1.05387	1.12156	2.12511	0.96727	1.01601	8.0562
		Huber	1.35342	0.52067	0.56483	1.61096	0.59688	0.57789	5.2247
		Bi-Square	1.18755	0.46954	0.47641	1.40789	0.54117	0.5246	4.6072
	N=100	OLS	1.74517	0.74842	0.74998	2.10348	0.71022	0.76401	6.8213
		FGLS	1.73584	0.70856	0.76224	2.09359	0.71505	0.75958	6.7749
		Huber	1.32429	0.41157	0.3834	1.64117	0.37101	0.36235	4.4938
		Bi-Square	1.12948	0.34785	0.33432	1.44094	0.35178	0.35535	3.9597
	N=250	OLS	1.68062	0.51365	0.44677	1.90064	0.48923	0.51093	5.5418
		FGLS	1.66821	0.45766	0.42568	1.90939	0.48055	0.50397	5.4455
		Huber	1.25888	0.23774	0.22805	1.57758	0.22855	0.25295	3.7838
		Bi-Square	1.03969	0.19463	0.21349	1.40078	0.20988	0.216	3.2745
	N=500	OLS	1.66798	0.3402	0.33159	1.96394	0.37021	0.34439	5.0183
		FGLS	1.66342	0.33671	0.32521	1.96847	0.3626	0.33022	4.9866
		Huber	1.2627	0.16671	0.15118	1.57546	0.16883	0.18373	3.5086
		Bi-Square	1.03416	0.15224	0.117	1.38241	0.15477	0.16737	3.0080

TABLE 4.3.7C: Root Mean Squares Error: When Errors are Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	4.25559	4.30717	4.54703	4.40461	4.34404	4.4195	26.2779
		FGLS	3.98568	3.85664	4.2398	4.43139	4.51211	4.44415	25.4698
		Huber	2.85093	2.33862	2.55638	3.1574	2.13887	2.37814	15.4203
		Bi-Square	2.60365	2.00806	2.35442	2.88635	2.14986	2.12019	14.1225
	N=30	OLS	3.21158	3.18472	3.00229	4.11801	4.56027	3.51228	21.5892
		FGLS	3.18136	3.13894	2.8537	4.21795	4.35592	3.37276	21.1206
		Huber	2.52079	1.88773	1.86738	3.08778	2.23943	1.90523	13.5083
		Bi-Square	2.23236	1.51798	1.66414	2.79232	1.99808	1.60701	11.8119
	N=50	OLS	2.98233	2.84084	3.51242	3.50542	2.99914	2.2906	18.1308
		FGLS	2.97897	2.7971	2.78144	3.55657	2.8917	2.35325	17.3590
		Huber	2.38185	1.54691	1.30548	2.74577	1.92682	1.40963	11.3165
		Bi-Square	2.14984	1.31683	1.07614	2.46044	1.64303	1.26709	9.9134
	N=100	OLS	2.85027	2.27883	1.89516	3.45775	2.268	1.94078	14.6908
		FGLS	2.82517	2.19968	1.9385	3.43078	2.30724	1.91181	14.6132
		Huber	2.30731	1.31053	0.94025	2.80887	1.35477	1.00944	9.7312
		Bi-Square	2.03402	1.01729	0.75791	2.53358	1.14777	0.91104	8.4016
	N=250	OLS	2.67039	1.97544	1.24808	2.99403	2.33546	1.44104	12.6644
		FGLS	2.64383	1.92382	1.21667	3.01818	2.28179	1.43183	12.5161
		Huber	2.15922	1.04931	0.69294	2.66005	1.34722	0.76556	8.6743
		Bi-Square	1.86415	0.77216	0.58868	2.44054	1.04986	0.61854	7.3339
	N=500	OLS	2.65302	1.60354	1.09404	3.10912	2.05198	1.10369	11.6154
		FGLS	2.64061	1.61648	1.09529	3.12263	2.02225	1.0764	11.5737
		Huber	2.1615	0.94162	0.57868	2.65685	1.2689	0.68125	8.2888
		Bi-Square	1.84574	0.73423	0.43074	2.40052	1.02421	0.58424	7.0197

TABLE 4.3.8C: Root Mean Squares Error: When Errors are Log- Normal ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	0.85805	1.54096	1.443	0.90495	1.61683	1.4878	7.8516
		FGLS	0.77515	1.48247	1.33632	0.92679	1.63	1.50469	7.6554
		Huber	0.5621	0.93856	0.79236	0.57414	1.02042	0.83146	4.7190
		Bi-Square	0.53198	0.68553	0.67819	0.54453	0.9322	0.72715	4.0996
	N=30	OLS	0.6874	1.3687	1.0745	0.7358	1.8008	1.1731	6.8403
		FGLS	0.6643	1.3518	1.0231	0.7782	1.747	1.1283	6.6927
		Huber	0.4887	0.8373	0.6355	0.5362	1.0063	0.6429	4.1469
		Bi-Square	0.4596	0.6336	0.5406	0.5284	0.8109	0.5168	3.4899
	N=50	OLS	0.5483	1.2875	1.2036	0.5857	1.479	0.8721	5.9762
		FGLS	0.5431	1.2864	1.006	0.6038	1.4504	0.8777	5.7674
		Huber	0.4215	0.7601	0.4671	0.4441	0.9988	0.5571	3.6487
		Bi-Square	0.4063	0.5993	0.3619	0.4251	0.8129	0.4836	3.0891
	N=100	OLS	0.4464	1.1924	0.7725	0.5264	1.3054	0.8112	5.0543
		FGLS	0.4371	1.1737	0.7894	0.5171	1.3162	0.8011	5.0346
		Huber	0.3893	0.7024	0.3894	0.4472	0.8445	0.4835	3.2563
		Bi-Square	0.3833	0.5046	0.2786	0.4397	0.6666	0.393	2.6658
	N=250	OLS	0.3425	1.1579	0.6117	0.3653	1.3809	0.7086	4.5669
		FGLS	0.3335	1.1488	0.6103	0.373	1.3623	0.7065	4.5344
		Huber	0.3425	0.6475	0.3513	0.3991	0.8629	0.4271	3.0304
		Bi-Square	0.3344	0.4663	0.2697	0.4082	0.6701	0.3355	2.4842
	N=500	OLS	0.3302	1.058	0.5863	0.378	1.319	0.6364	4.3079
		FGLS	0.3274	1.0633	0.5901	0.382	1.3089	0.6298	4.3015
		Huber	0.3392	0.6281	0.3363	0.396	0.8474	0.4191	2.9661
		Bi-Square	0.3288	0.4611	0.2429	0.3984	0.6686	0.3386	2.4384

TABLE 4.3.9C: Root Mean Squares Error: When Errors are Log-Normal ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.3887	1.5376	1.615	1.4638	1.5847	1.6078	9.1976
		FGLS	1.2973	1.408	1.4976	1.4758	1.6389	1.6176	8.9352
		Huber	0.9535	0.8698	0.9184	1.0397	0.8263	0.8692	5.4769
		Bi-Square	0.8763	0.7377	0.8366	0.9548	0.8197	0.7743	4.9994
	N=30	OLS	1.0686	1.202	1.0971	1.3487	1.6949	1.2708	7.6821
		FGLS	1.0551	1.1847	1.043	1.3869	1.6224	1.2189	7.5110
		Huber	0.8386	0.7183	0.6769	1.0148	0.8605	0.6851	4.7942
		Bi-Square	0.7499	0.5661	0.6035	0.9307	0.7511	0.576	4.1773
	N=50	OLS	0.9787	1.0886	1.2904	1.1413	1.178	0.8428	6.5198
		FGLS	0.9764	1.0758	1.0297	1.1612	1.1407	0.8626	6.2464
		Huber	0.7853	0.6083	0.4752	0.8985	0.7716	0.5278	4.0667
		Bi-Square	0.7142	0.5114	0.3888	0.8123	0.6514	0.4725	3.5506
	N=100	OLS	0.922	0.906	0.711	1.1209	0.9279	0.7329	5.3207
		FGLS	0.9121	0.8803	0.7284	1.1107	0.9426	0.7216	5.2957
		Huber	0.7603	0.5282	0.3546	0.9179	0.5713	0.3944	3.5267
		Bi-Square	0.6768	0.4029	0.2793	0.8346	0.4747	0.3478	3.0161
	N=250	OLS	0.8548	0.8174	0.4867	0.9546	0.9741	0.5646	4.6522
		FGLS	0.8455	0.8018	0.4775	0.9636	0.9542	0.5618	4.6044
		Huber	0.7067	0.4446	0.2754	0.8654	0.5798	0.3113	3.1832
		Bi-Square	0.6178	0.3258	0.2285	0.8017	0.4526	0.2507	2.6771
	N=500	OLS	0.8478	0.691	0.4409	0.9917	0.8796	0.4512	4.3022
		FGLS	0.8434	0.6962	0.4422	0.9967	0.8689	0.4419	4.2893
		Huber	0.7062	0.4107	0.2408	0.8641	0.5554	0.2873	3.0645
		Bi-Square	0.611	0.315	0.1785	0.788	0.447	0.2435	2.5830

TABLE 4.3.10C: Root Mean Squares Error: When Errors are Log-Normal , Square Root Heteroscedastic(P= 0.5) and Contemporaneous Correlation(P=0.2) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.2	N=20	OLS	1.8391	1.6837	1.786	1.9121	1.6921	1.7166	10.6296
		FGLS	1.7353	1.4832	1.6759	1.9175	1.7744	1.7205	10.3068
		Huber	1.2324	0.8855	1.0119	1.3818	0.7722	0.915	6.1988
		Bi-Square	1.1152	0.7923	0.942	1.2453	0.7889	0.8079	5.6916
	N=30	OLS	1.3955	1.1613	1.1437	1.8169	1.7202	1.379	8.6166
		FGLS	1.388	1.1473	1.0918	1.8544	1.6421	1.3289	8.4525
		Huber	1.0947	0.688	0.7256	1.3576	0.8138	0.7567	5.4364
		Bi-Square	0.9515	0.5641	0.6455	1.2078	0.7417	0.6452	4.7558
	N=50	OLS	1.3227	1.0287	1.3561	1.5657	1.0388	0.8763	7.1883
		FGLS	1.3231	1.0071	1.0611	1.5847	0.9952	0.9053	6.8765
		Huber	1.0396	0.5359	0.5068	1.2162	0.6516	0.533	4.4831
		Bi-Square	0.9292	0.4683	0.4207	1.0764	0.5688	0.4831	3.9465
	N=100	OLS	1.2839	0.7704	0.7056	1.5551	0.7381	0.72	5.7731
		FGLS	1.274	0.7371	0.721	1.5447	0.7519	0.7102	5.7389
		Huber	1.0132	0.4389	0.3531	1.2415	0.4181	0.3575	3.8223
		Bi-Square	0.8802	0.3518	0.2952	1.1065	0.3707	0.3349	3.3393
	N=250	OLS	1.2212	0.6174	0.4382	1.3744	0.7078	0.5058	4.8648
		FGLS	1.2106	0.589	0.4226	1.3834	0.6893	0.5014	4.7963
		Huber	0.9551	0.3152	0.2381	1.1847	0.3855	0.2548	3.3334
		Bi-Square	0.8089	0.2382	0.2115	1.0714	0.3045	0.2105	2.8450
	N=500	OLS	1.212	0.4588	0.3633	1.4233	0.5871	0.3583	4.4028
		FGLS	1.2073	0.4622	0.3616	1.4283	0.576	0.3461	4.3815
		Huber	0.9566	0.2622	0.1829	1.1834	0.3474	0.2102	3.1427
		Bi-Square	0.8025	0.2155	0.1384	1.0552	0.2864	0.1868	2.6848

TABLE 4.3.11C:Root Mean Squares Error: When Errors are Log- Normal , Homoscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.5	N=20	OLS	2.44874	2.02528	2.05141	2.92378	1.81576	1.79956	13.0645
		FGLS	2.16322	1.49872	1.63281	2.90061	1.88398	1.72035	11.7997
		Huber	1.58669	0.99761	1.13512	2.32539	0.93077	1.11299	8.0886
		Bi-Square	1.39602	0.86284	1.06197	2.1362	0.99331	1.01653	7.4669
	N=30	OLS	1.8288	1.2207	1.2342	2.82557	1.79004	1.4847	10.3840
		FGLS	1.82468	1.16665	1.08041	2.87705	1.66704	1.37237	9.9882
		Huber	1.41605	0.73179	0.81047	2.34841	1.00447	0.98296	7.2942
		Bi-Square	1.20664	0.60873	0.72161	2.23411	0.94485	0.90077	6.6167
	N=50	OLS	1.76827	1.08012	1.4491	2.64413	1.03571	0.95555	8.9329
		FGLS	1.77685	0.951	1.01482	2.64863	0.89224	0.9582	8.2417
		Huber	1.35342	0.52067	0.56483	2.19942	0.67918	0.62101	5.9385
		Bi-Square	1.18755	0.46954	0.47641	2.00581	0.6004	0.59395	5.3337
	N=100	OLS	1.74517	0.74842	0.74998	2.64327	0.68605	0.74817	7.3211
		FGLS	1.71887	0.65498	0.70707	2.62141	0.66117	0.70482	7.0683
		Huber	1.32429	0.41157	0.3834	2.24153	0.4237	0.42522	5.2097
		Bi-Square	1.12948	0.34785	0.33432	2.07638	0.4033	0.42371	4.7150
	N=250	OLS	1.68062	0.51365	0.44677	2.45593	0.48793	0.51231	6.0972
		FGLS	1.66031	0.42655	0.39618	2.4736	0.43547	0.47723	5.8693
		Huber	1.25888	0.23774	0.22805	2.15764	0.26077	0.30714	4.4502
		Bi-Square	1.03969	0.19463	0.21349	2.00846	0.24452	0.28521	3.9860
	N=500	OLS	1.66798	0.3402	0.33159	2.5029	0.37096	0.34901	5.5626
		FGLS	1.66297	0.30643	0.2892	2.5104	0.34639	0.30749	5.4229
		Huber	1.2627	0.16671	0.15118	2.15091	0.19566	0.21421	4.1414
		Bi-Square	1.03416	0.15224	0.117	1.99015	0.18884	0.1979	3.6803

TABLE 4.3.12C: Root Mean Squares Error: When Errors are Log-Normal, Exponential Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	4.25559	4.30717	4.54703	4.97322	4.25604	4.27975	26.6188
		FGLS	3.68503	3.43458	3.62607	4.95897	4.27816	4.17191	24.1547
		Huber	2.85093	2.33862	2.55638	3.91942	2.61576	2.73232	17.0134
		Bi-Square	2.60365	2.00806	2.35442	3.64308	2.70906	2.59051	15.9088
	N=30	OLS	3.21158	3.18472	3.00229	4.66747	4.74761	3.40443	22.2181
		FGLS	3.16394	2.98782	2.56323	4.80392	4.3751	3.09863	20.9926
		Huber	2.52079	1.88773	1.86738	3.9771	2.92406	2.20382	15.3809
		Bi-Square	2.23236	1.51798	1.66414	3.86942	2.69191	1.99675	13.9726
	N=50	OLS	2.98233	2.84084	3.51242	4.31178	3.35995	2.28005	19.2874
		FGLS	2.97862	2.59449	2.55172	4.34336	3.10596	2.26705	17.8412
		Huber	2.38185	1.54691	1.30548	3.66095	2.45182	1.61181	12.9588
		Bi-Square	2.14984	1.31683	1.07614	3.42302	2.16272	1.57562	11.7042
	N=100	OLS	2.85027	2.27883	1.89516	4.29459	2.59258	1.99965	15.9111
		FGLS	2.78733	2.12694	1.83166	4.24385	2.61433	1.89869	15.5028
		Huber	2.30731	1.31053	0.94025	3.7729	1.85448	1.22821	11.4137
		Bi-Square	2.03402	1.01729	0.75791	3.57955	1.62226	1.13679	10.1478
	N=250	OLS	2.67039	1.97544	1.24808	3.85746	2.78511	1.62344	14.1599
		FGLS	2.62702	1.89212	1.17478	3.90359	2.64252	1.56712	13.8072
		Huber	2.15922	1.04931	0.69294	3.58084	1.8654	1.05525	10.4030
		Bi-Square	1.86415	0.77216	0.58868	3.42726	1.54783	0.93513	9.1352
	N=500	OLS	2.65302	1.60354	1.09404	3.9407	2.54148	1.32734	13.1601
		FGLS	2.63842	1.59776	1.03697	3.96496	2.4773	1.26182	12.9772
		Huber	2.1615	0.94162	0.57868	3.56805	1.81246	0.93157	9.9939
		Bi-Square	1.84574	0.73423	0.43074	3.37622	1.56834	0.82408	8.7794

TABLE 4.3.13C: Root Mean Squares Error: When Errors are Log-Normal ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	0.85805	1.54096	1.443	0.91625	1.84215	1.51441	8.1148
		FGLS	0.7069	1.39261	1.21197	0.92383	1.80367	1.50225	7.5412
		Huber	0.5621	0.93856	0.79236	0.64355	1.36762	1.03468	5.3389
		Bi-Square	0.53198	0.68553	0.67819	0.62934	1.29471	0.97182	4.7916
	N=30	OLS	0.68735	1.36872	1.0745	0.74973	2.10299	1.22774	7.2110
		FGLS	0.64552	1.30356	0.9309	0.79757	1.99209	1.14037	6.8100
		Huber	0.48866	0.83727	0.63554	0.63112	1.45337	0.80686	4.8528
		Bi-Square	0.45964	0.63364	0.54065	0.64972	1.25179	0.69449	4.2299
	N=50	OLS	0.54833	1.28747	1.20358	0.64284	1.79787	0.96343	6.4435
		FGLS	0.53074	1.23598	0.95355	0.65727	1.74095	0.94919	6.0677
		Huber	0.42145	0.76012	0.46706	0.54722	1.36669	0.72213	4.2847
		Bi-Square	0.40628	0.59929	0.36187	0.55069	1.17993	0.6635	3.7616
	N=100	OLS	0.44635	1.19242	0.77247	0.60592	1.62291	0.92959	5.5697
		FGLS	0.42582	1.16148	0.76964	0.5893	1.63162	0.90697	5.4848
		Huber	0.38926	0.70244	0.38936	0.56936	1.20926	0.64038	3.9001
		Bi-Square	0.38327	0.50455	0.27859	0.58163	1.02759	0.54492	3.3206
	N=250	OLS	0.3425	1.15787	0.61166	0.45349	1.73182	0.87677	5.1741
		FGLS	0.32843	1.14128	0.60773	0.46562	1.68973	0.866	5.0988
		Huber	0.34246	0.64755	0.35129	0.50737	1.23641	0.62022	3.7053
		Bi-Square	0.33445	0.46631	0.26971	0.53726	1.02653	0.52726	3.1615
	N=500	OLS	0.33019	1.05803	0.58635	0.45996	1.67921	0.81668	4.9304
		FGLS	0.32605	1.06236	0.58252	0.46694	1.65857	0.80182	4.8983
		Huber	0.33919	0.62808	0.33634	0.50151	1.22612	0.60032	3.6316
		Bi-Square	0.32878	0.46107	0.2429	0.52324	1.03761	0.51383	3.1074

TABLE 4.3.14 C: Root Mean Squares Error: When Errors are Log-Normal ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.5) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	1.38872	1.53762	1.61495	1.63205	1.60023	1.5675	9.3411
		FGLS	1.20221	1.26939	1.29598	1.62924	1.59917	1.5325	8.5285
		Huber	0.95349	0.86977	0.91837	1.27453	1.04116	1.01123	6.0686
		Bi-Square	0.87632	0.73769	0.83663	1.19209	1.05841	0.96295	5.6641
	N=30	OLS	1.06855	1.20201	1.09713	1.51174	1.81296	1.24486	7.9373
		FGLS	1.04884	1.12919	0.93897	1.56311	1.67845	1.13581	7.4944
		Huber	0.83859	0.71835	0.67689	1.29574	1.15452	0.80649	5.4906
		Bi-Square	0.74987	0.56613	0.6035	1.27012	1.05629	0.7275	4.9734
	N=50	OLS	0.97866	1.08862	1.29041	1.39242	1.35193	0.85488	6.9569
		FGLS	0.9747	1.00673	0.95012	1.40651	1.26847	0.84848	6.4550
		Huber	0.78528	0.60828	0.47519	1.18637	1.00466	0.61896	4.6787
		Bi-Square	0.71419	0.51137	0.38876	1.11896	0.8848	0.60243	4.2205
	N=100	OLS	0.922	0.90604	0.71105	1.38507	1.09373	0.77249	5.7904
		FGLS	0.89855	0.85906	0.69309	1.36655	1.10425	0.73813	5.6596
		Huber	0.76027	0.52823	0.35462	1.22728	0.79969	0.4902	4.1603
		Bi-Square	0.67682	0.40288	0.27933	1.17133	0.69497	0.445	3.6703
	N=250	OLS	0.85476	0.81736	0.48669	1.22783	1.18169	0.65324	5.2216
		FGLS	0.83964	0.79175	0.46534	1.24474	1.13135	0.63545	5.1083
		Huber	0.70668	0.44465	0.27541	1.15814	0.81276	0.43813	3.8358
		Bi-Square	0.61776	0.32581	0.22855	1.11831	0.67693	0.38524	3.3526
	N=500	OLS	0.84785	0.691	0.44093	1.25429	1.10142	0.55604	4.8915
		FGLS	0.84265	0.69151	0.42382	1.26352	1.07856	0.53445	4.8345
		Huber	0.70616	0.41066	0.2408	1.15355	0.79706	0.4001	3.7083
		Bi-Square	0.61098	0.31499	0.1785	1.09959	0.68865	0.35283	3.2455

TABLE 4.3.15C: Root Mean Squares Error: When Errors are Log- Normal ,Square Root Heteroscedastic($g = 0.5$) and Contemporaneous Correlation($P=0.5$) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P= 0.5	N=20	OLS	1.83908	1.68371	1.78599	2.19512	1.59766	1.64834	10.7499
		FGLS	1.61433	1.30191	1.41939	2.1831	1.62966	1.59457	9.7430
		Huber	1.23238	0.8855	1.01193	1.73872	0.90111	1.03058	6.8002
		Bi-Square	1.11523	0.7923	0.94201	1.60483	0.95982	0.97333	6.3875
	N=30	OLS	1.39548	1.16134	1.14365	2.08864	1.72176	1.32069	8.8316
		FGLS	1.38455	1.09227	0.98422	2.13991	1.58335	1.2056	8.3899
		Huber	1.09467	0.68796	0.72563	1.76726	1.01726	0.85907	6.1519
		Bi-Square	0.9515	0.5641	0.64552	1.70517	0.95366	0.78829	5.6082
	N=50	OLS	1.32273	1.02868	1.35611	1.94494	1.11817	0.85583	7.6265
		FGLS	1.32494	0.92156	0.96665	1.9553	1.00574	0.85494	7.0291
		Huber	1.03962	0.53591	0.50677	1.63988	0.79142	0.58705	5.1007
		Bi-Square	0.92922	0.46826	0.42073	1.5174	0.70224	0.57888	4.6167
	N=100	OLS	1.2839	0.77045	0.70563	1.94258	0.78926	0.71914	6.2110
		FGLS	1.25873	0.7023	0.67498	1.92232	0.7919	0.67726	6.0275
		Huber	1.01319	0.43886	0.35309	1.68016	0.5448	0.42367	4.4538
		Bi-Square	0.88021	0.3518	0.2952	1.57708	0.48732	0.40628	3.9979
	N=250	OLS	1.22116	0.61739	0.43818	1.77332	0.80984	0.54156	5.4015
		FGLS	1.20388	0.57268	0.40159	1.79092	0.7534	0.51548	5.2380
		Huber	0.95513	0.31518	0.23813	1.60657	0.51604	0.33741	3.9685
		Bi-Square	0.80892	0.23822	0.21146	1.51774	0.43075	0.30647	3.5136
	N=500	OLS	1.21197	0.45884	0.36334	1.80906	0.70383	0.40649	4.9535
		FGLS	1.2068	0.44977	0.3338	1.81777	0.67832	0.37537	4.8618
		Huber	0.95662	0.26221	0.18289	1.60071	0.48891	0.27399	3.7653
		Bi-Square	0.8025	0.21554	0.13844	1.49853	0.42907	0.24671	3.3308

TABLE 4.3.16C:Root Mean Squares Error: When Errors are Log- Normal , Homoscedastic and Contemporaneous Correlation($P=0.7$) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	2.44874	2.02528	2.05141	2.32202	1.85035	1.52302	12.2208
		FGLS	2.09587	1.43625	1.54277	2.27181	1.778	1.38234	10.5070
		Huber	1.58669	0.99761	1.13512	2.02507	1.43125	1.22814	8.4039
		Bi-Square	1.39602	0.86284	1.06197	1.91926	1.27676	1.1238	7.6407
	N=30	OLS	1.8288	1.2207	1.2342	1.92086	1.13005	1.06283	8.3974
		FGLS	1.76444	1.14846	1.08172	1.93148	1.0054	0.90339	7.8349
		Huber	1.41605	0.73179	0.81047	1.73246	0.9238	1.02399	6.6386
		Bi-Square	1.20664	0.60873	0.72161	1.67479	0.88864	1.06511	6.1655
	N=50	OLS	1.76827	1.08012	1.4491	1.95846	1.15718	0.99001	8.4031
		FGLS	1.67554	0.83356	0.91453	1.94917	0.97916	0.8634	7.2154
		Huber	1.35342	0.52067	0.56483	1.61331	0.78182	0.71137	5.5454
		Bi-Square	1.18755	0.46954	0.47641	1.52712	0.71012	0.67678	5.0475
	N=100	OLS	1.74517	0.74842	0.74998	1.90901	0.71744	0.68715	6.5572
		FGLS	1.69101	0.58929	0.66082	1.88092	0.61641	0.58035	6.0188
		Huber	1.32429	0.41157	0.3834	1.62501	0.52708	0.53874	4.8101
		Bi-Square	1.12948	0.34785	0.33432	1.54032	0.50854	0.5301	4.3906
	N=250	OLS	1.68062	0.51365	0.44677	1.79354	0.48061	0.44127	5.3565
		FGLS	1.70047	0.39194	0.33885	1.8119	0.41963	0.37162	5.0344
		Huber	1.25888	0.23774	0.22805	1.56412	0.34983	0.32219	3.9608
		Bi-Square	1.03969	0.19463	0.21349	1.48989	0.34121	0.33194	3.6109
	N=500	OLS	1.66798	0.3402	0.33159	1.82608	0.33144	0.33186	4.8292
		FGLS	1.64682	0.27477	0.28859	1.83061	0.28246	0.26206	4.5853
		Huber	1.2627	0.16671	0.15118	1.57723	0.22413	0.21929	3.6012
		Bi-Square	1.03416	0.15224	0.117	1.48677	0.21785	0.2135	3.2215

TABLE 4.3.17 C: Root Mean Squares Error: When Errors are Log- Normal , Exponential Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	4.25559	4.30717	4.54703	4.22004	4.53463	3.61289	25.4774
		FGLS	3.64578	3.48809	3.51067	4.11795	4.32994	3.34657	22.4390
		Huber	2.85093	2.33862	2.55638	3.6829	3.41685	2.90373	17.7494
		Bi-Square	2.60365	2.00806	2.35442	3.55474	2.96566	2.9277	16.4142
	N=30	OLS	3.21158	3.18472	3.00229	3.24486	3.05852	2.50138	18.2034
		FGLS	3.04418	3.05673	2.6281	3.2521	2.63164	2.15257	16.7653
		Huber	2.52079	1.88773	1.86738	2.99983	2.51129	2.29046	14.0775
		Bi-Square	2.23236	1.51798	1.66414	2.93528	2.36264	2.37097	13.0834
	N=50	OLS	2.98233	2.84084	3.51242	3.27513	3.10047	2.30415	18.0153
		FGLS	2.78173	2.44435	2.33471	3.27243	2.72816	2.03402	15.5954
		Huber	2.38185	1.54691	1.30548	2.74886	2.19622	1.74552	11.9248
		Bi-Square	2.14984	1.31683	1.07614	2.67718	1.98027	1.67727	10.8775
	N=100	OLS	2.85027	2.27883	1.89516	3.11243	2.19552	1.78594	14.1182
		FGLS	2.72404	2.04162	1.79891	3.04342	2.06612	1.5439	13.2180
		Huber	2.30731	1.31053	0.94025	2.74257	1.67418	1.39118	10.3660
		Bi-Square	2.03402	1.01729	0.75791	2.67649	1.55214	1.32303	9.3609
	N=250	OLS	2.67039	1.97544	1.24808	2.82113	2.20936	1.32143	12.2458
		FGLS	2.71589	1.72829	1.0563	2.86404	2.03051	1.19871	11.5937
		Huber	2.15922	1.04931	0.69294	2.59751	1.59095	0.92803	9.0180
		Bi-Square	1.86415	0.77216	0.58868	2.57068	1.37183	0.8545	8.0220
	N=500	OLS	2.65302	1.60354	1.09404	2.88444	1.84368	1.14118	11.2199
		FGLS	2.61203	1.60326	1.04195	2.90163	1.74019	1.03234	10.9314
		Huber	2.1615	0.94162	0.57868	2.62146	1.39433	0.72182	8.4194
		Bi-Square	1.84574	0.73423	0.43074	2.53863	1.24412	0.62173	7.4152

TABLE 4.3.18 C: Root Mean Squares Error: When Errors are Log-Normal ,Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; g=2							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	0.85805	1.54096	1.443	0.95616	1.77693	1.24362	7.8187
		FGLS	0.7331	1.42942	1.18513	0.92577	1.70772	1.18585	7.1670
		Huber	0.5621	0.93856	0.79236	0.75919	1.29827	0.97872	5.3292
		Bi-Square	0.53198	0.68553	0.67819	0.70183	1.04484	0.95542	4.5978
	N=30	OLS	0.68735	1.36872	1.0745	0.59174	1.38279	0.91865	6.0238
		FGLS	0.61719	1.33775	0.95851	0.56491	1.24298	0.83857	5.5599
		Huber	0.48866	0.83727	0.63554	0.52923	1.10542	0.74174	4.3379
		Bi-Square	0.45964	0.63364	0.54065	0.54403	0.98554	0.74342	3.9069
	N=50	OLS	0.54833	1.28747	1.20358	0.55374	1.40744	0.84055	5.8411
		FGLS	0.47291	1.21022	0.89051	0.55009	1.31222	0.777	5.2130
		Huber	0.42145	0.76012	0.46706	0.45155	1.04588	0.64845	3.7945
		Bi-Square	0.40628	0.59929	0.36187	0.46575	0.91594	0.6072	3.3563
	N=100	OLS	0.44635	1.19242	0.77247	0.46848	1.22101	0.7672	4.8679
		FGLS	0.40874	1.15263	0.77886	0.4346	1.20095	0.7147	4.6905
		Huber	0.38926	0.70244	0.38936	0.43264	0.92973	0.57211	3.4155
		Bi-Square	0.38327	0.50455	0.27859	0.45934	0.80949	0.51214	2.9474
	N=250	OLS	0.3425	1.15787	0.61166	0.35088	1.30632	0.67408	4.4433
		FGLS	0.34871	1.09344	0.58523	0.35484	1.25374	0.65148	4.2874
		Huber	0.34246	0.64755	0.35129	0.37709	0.94566	0.47847	3.1425
		Bi-Square	0.33445	0.46631	0.26971	0.41637	0.79361	0.39917	2.6796
	N=500	OLS	0.33019	1.05803	0.58635	0.3506	1.20605	0.64026	4.1715
		FGLS	0.32159	1.06677	0.57905	0.35096	1.17657	0.61669	4.1116
		Huber	0.33919	0.62808	0.33634	0.37626	0.90699	0.43471	3.0216
		Bi-Square	0.32878	0.46107	0.2429	0.40122	0.78196	0.36266	2.5786

TABLE 4.3.19C: Root Mean Squares Error: When Errors are Log- Normal ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	1.38872	1.53762	1.61495	1.41431	1.67441	1.3148	8.9448
		FGLS	1.20287	1.30011	1.26369	1.37796	1.59935	1.22208	7.9661
		Huber	0.95349	0.86977	0.91837	1.22424	1.25854	1.04963	6.2740
		Bi-Square	0.87632	0.73769	0.83663	1.18723	1.09018	1.06932	5.7974
	N=30	OLS	1.06855	1.20201	1.09713	1.06372	1.17301	0.9162	6.5206
		FGLS	1.0074	1.16165	0.96534	1.06412	1.01533	0.79672	6.0106
		Huber	0.83859	0.71835	0.67689	0.98413	0.96082	0.82182	5.0006
		Bi-Square	0.74987	0.56613	0.6035	0.96515	0.89618	0.85227	4.6331
	N=50	OLS	0.97866	1.08862	1.29041	1.06689	1.18675	0.84467	6.4560
		FGLS	0.9065	0.96209	0.87261	1.06799	1.05881	0.7514	5.6194
		Huber	0.78528	0.60828	0.47519	0.89973	0.85436	0.64844	4.2713
		Bi-Square	0.71419	0.51137	0.38876	0.88311	0.76857	0.62105	3.8871
	N=100	OLS	0.922	0.90604	0.71105	1.00562	0.88695	0.67787	5.1095
		FGLS	0.8765	0.83337	0.68706	0.97998	0.84871	0.59515	4.8208
		Huber	0.76027	0.52823	0.35462	0.89285	0.68091	0.52461	3.7415
		Bi-Square	0.67682	0.40288	0.27933	0.87858	0.62344	0.49398	3.3550
	N=250	OLS	0.85476	0.81736	0.48669	0.89881	0.92061	0.52189	4.5001
		FGLS	0.87089	0.73278	0.42653	0.91411	0.85747	0.48249	4.2843
		Huber	0.70668	0.44465	0.27541	0.84087	0.66669	0.369	3.3033
		Bi-Square	0.61776	0.32581	0.22855	0.84056	0.57223	0.33232	2.9172
	N=500	OLS	0.84785	0.691	0.44093	0.9197	0.79416	0.46495	4.1586
		FGLS	0.8339	0.69542	0.4252	0.92629	0.75842	0.42957	4.0688
		Huber	0.70616	0.41066	0.2408	0.84816	0.60434	0.30226	3.1124
		Bi-Square	0.61098	0.31499	0.1785	0.82777	0.53657	0.25799	2.7268

TABLE 4.3.20 C: Root Mean Squares Error: When Errors are Log-Normal ,Square Root Heteroscedastic(P= 0.5) and Contemporaneous Correlation(P=0.7) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
P=0.7	N=20	OLS	1.83908	1.68371	1.78599	1.80267	1.69885	1.39337	10.2037
		FGLS	1.58718	1.30364	1.36737	1.76062	1.62388	1.27839	8.9211
		Huber	1.23238	0.8855	1.01193	1.57747	1.29821	1.12567	7.1312
		Bi-Square	1.11523	0.7923	0.94201	1.52902	1.16106	1.15689	6.6965
	N=30	OLS	1.39548	1.16134	1.14365	1.43754	1.09912	0.95955	7.1967
		FGLS	1.3343	1.10765	1.00153	1.44468	0.94497	0.81812	6.6513
		Huber	1.09467	0.68796	0.72563	1.31773	0.90716	0.90327	5.6364
		Bi-Square	0.9515	0.5641	0.64552	1.27818	0.86429	0.93534	5.2389
	N=50	OLS	1.32273	1.02868	1.35611	1.45822	1.11366	0.88903	7.1684
		FGLS	1.24297	0.84892	0.87875	1.45583	0.95919	0.77826	6.1639
		Huber	1.03962	0.53591	0.50677	1.21598	0.77672	0.66418	4.7392
		Bi-Square	0.92922	0.46826	0.42073	1.17263	0.70362	0.63741	4.3319
	N=100	OLS	1.2839	0.77045	0.70563	1.40412	0.728	0.65572	5.5478
		FGLS	1.23421	0.65765	0.65325	1.37813	0.66282	0.556	5.1421
		Huber	1.01319	0.43886	0.35309	1.21958	0.5531	0.51361	4.0914
		Bi-Square	0.88021	0.3518	0.2952	1.17399	0.5248	0.4963	3.7223
	N=250	OLS	1.22116	0.61739	0.43818	1.29515	0.67189	0.452	4.6958
		FGLS	1.23954	0.51057	0.35052	1.31248	0.60222	0.39666	4.4120
		Huber	0.95513	0.31518	0.23813	1.16389	0.48415	0.32041	3.4769
		Bi-Square	0.80892	0.23822	0.21146	1.13243	0.43049	0.31052	3.1320
	N=500	OLS	1.21197	0.45884	0.36334	1.32199	0.52125	0.36975	4.2471
		FGLS	1.19471	0.44666	0.33682	1.3282	0.47736	0.31922	4.1030
		Huber	0.95662	0.26221	0.18289	1.17413	0.39426	0.23037	3.2005
		Bi-Square	0.8025	0.21554	0.13844	1.12293	0.36069	0.20612	2.8462

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \{E(Y_i)\}^g$; $g=0$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	2.40161	1.68424	1.91876	2.92378	1.81576	1.79956	12.5437
		FGLS	2.01901	0.49396	0.59972	2.52361	0.6073	0.64107	6.8847
		Huber	1.8204	0.91668	0.98659	2.32539	0.93077	1.11299	8.0928
		Bi-Square	1.70103	0.87793	0.93605	2.1362	0.99331	1.01653	7.6611
	N=30	OLS	2.10328	1.29121	1.41761	2.82557	1.79004	1.4847	10.9124
		FGLS	2.03802	0.42876	0.42707	2.58262	0.56477	0.53798	6.5792
		Huber	1.69638	0.81154	0.80904	2.34841	1.00447	0.98296	7.6528
		Bi-Square	1.56634	0.71861	0.78818	2.23411	0.94485	0.90077	7.1529
	N=50	OLS	2.10935	1.02815	0.83683	2.64413	1.03571	0.95555	8.6097
		FGLS	2.04821	0.33242	0.31507	2.55418	0.33657	0.37306	5.9595
		Huber	1.64587	0.56563	0.51705	2.19942	0.67918	0.62101	6.2282
		Bi-Square	1.46458	0.51446	0.49767	2.00581	0.6004	0.59395	5.6769
	N=100	OLS	2.17118	0.81963	0.77569	2.64327	0.68605	0.74817	7.8440
		FGLS	2.01629	0.2094	0.22961	2.55997	0.21549	0.23353	5.4643
		Huber	1.67284	0.40414	0.45135	2.24153	0.4237	0.42522	5.6188
		Bi-Square	1.46734	0.35943	0.4015	2.07638	0.4033	0.42371	5.1317
	N=250	OLS	2.03549	0.50399	0.51195	2.45593	0.48793	0.51231	6.5076
		FGLS	1.95401	0.12183	0.12373	2.50572	0.15421	0.14735	5.0069
		Huber	1.59443	0.26313	0.27204	2.15764	0.26077	0.30714	4.8552
		Bi-Square	1.38554	0.24642	0.25149	2.00846	0.24452	0.28521	4.4216
	N=500	OLS	1.96814	0.30353	0.33726	2.5029	0.37096	0.34901	5.8318
		FGLS	1.96246	0.10893	0.11263	2.49934	0.10715	0.10248	4.8930
		Huber	1.58677	0.16406	0.17935	2.15091	0.19566	0.21421	4.4910
		Bi-Square	1.39905	0.14638	0.16212	1.99015	0.18884	0.1979	4.0844

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 \text{Exp}\{E(Y_i)\}$;							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	4.20268	4.29123	4.28082	4.97322	4.25604	4.27975	26.2837
		FGLS	3.3533	2.0672	1.73074	4.08271	2.60514	1.94511	15.7842
		Huber	3.19136	2.42755	2.22612	3.91942	2.61576	2.73232	17.1125
		Bi-Square	3.05821	2.09645	2.148	3.64308	2.70906	2.59051	16.2453
	N=30	OLS	3.56912	3.39707	3.43945	4.66747	4.74761	3.40443	23.2252
		FGLS	3.3402	2.02751	1.42499	4.14825	2.86011	1.47533	15.2764
		Huber	2.9118	2.16924	1.91088	3.9771	2.92406	2.20382	16.0969
		Bi-Square	2.78163	1.8173	1.75087	3.86942	2.69191	1.99675	14.9079
	N=50	OLS	3.44105	2.96554	2.04503	4.31178	3.35995	2.28005	18.4034
		FGLS	3.27758	1.92295	1.13433	4.08665	2.34419	1.39965	14.1654
		Huber	2.80146	1.72815	1.31552	3.66095	2.45182	1.61181	13.5697
		Bi-Square	2.60069	1.51409	1.24911	3.42302	2.16272	1.57562	12.5253
	N=100	OLS	3.56321	2.58768	1.77576	4.29459	2.59258	1.99965	16.8135
		FGLS	3.21942	1.85626	0.96272	4.12681	2.21867	1.17489	13.5588
		Huber	2.87073	1.45633	1.08968	3.7729	1.85448	1.22821	12.2723
		Bi-Square	2.59895	1.12113	0.94745	3.57955	1.62226	1.13679	11.0061
	N=250	OLS	3.272	1.99144	1.41081	3.85746	2.78511	1.62344	14.9403
		FGLS	3.09233	1.71822	0.95087	3.96802	2.27198	1.201	13.2024
		Huber	2.71872	1.28162	0.834	3.58084	1.8654	1.05525	11.3358
		Bi-Square	2.43414	1.11701	0.7044	3.42726	1.54783	0.93513	10.1658
	N=500	OLS	3.12082	1.83932	1.18599	3.9407	2.54148	1.32734	13.9557
		FGLS	3.09448	1.75284	0.91718	3.92924	2.31266	1.15451	13.1609
		Huber	2.67624	1.1673	0.71632	3.56805	1.81246	0.93157	10.8719
		Bi-Square	2.43572	0.92529	0.60594	3.37622	1.56834	0.82408	9.7356

TABLE 4.3.23 C: Root Mean Squares Error: When Errors are Log- Normal , Quadratic Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=2$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	0.86172	1.7927	1.36435	0.91625	1.84215	1.51441	8.2916
		FGLS	0.56863	1.26767	0.84507	0.61503	1.6142	0.99385	5.9045
		Huber	0.58092	1.07844	0.73726	0.64355	1.36762	1.03468	5.4425
		Bi-Square	0.58701	0.85996	0.69793	0.62934	1.29471	0.97182	5.0408
	N=30	OLS	0.67268	1.5246	1.22765	0.74973	2.10299	1.22774	7.5054
		FGLS	0.52264	1.29925	0.79183	0.57644	1.75399	0.84093	5.7851
		Huber	0.48968	1.01061	0.67199	0.63112	1.45337	0.80686	5.0636
		Bi-Square	0.49449	0.81437	0.55107	0.64972	1.25179	0.69449	4.4559
	N=50	OLS	0.53524	1.46796	0.86244	0.64284	1.79787	0.96343	6.2698
		FGLS	0.46997	1.28954	0.73295	0.55309	1.60895	0.86739	5.5219
		Huber	0.44389	0.92767	0.55999	0.54722	1.36669	0.72213	4.5676
		Bi-Square	0.44833	0.76945	0.49166	0.55069	1.17993	0.6635	4.1036
	N=100	OLS	0.54269	1.41015	0.73594	0.60592	1.62291	0.92959	5.8472
		FGLS	0.41358	1.27845	0.63867	0.54166	1.56439	0.78508	5.2218
		Huber	0.46266	0.87749	0.47281	0.56936	1.20926	0.64038	4.2320
		Bi-Square	0.4547	0.66355	0.38426	0.58163	1.02759	0.54492	3.6567
	N=250	OLS	0.44175	1.2678	0.70312	0.45349	1.73182	0.87677	5.4748
		FGLS	0.37171	1.22508	0.64716	0.47168	1.60917	0.81659	5.1414
		Huber	0.42187	0.83664	0.44451	0.50737	1.23641	0.62022	4.0670
		Bi-Square	0.41859	0.67784	0.34694	0.53726	1.02653	0.52726	3.5344
	N=500	OLS	0.3799	1.25261	0.67175	0.45996	1.67921	0.81668	5.2601
		FGLS	0.36154	1.24309	0.64126	0.44719	1.63404	0.80224	5.1294
		Huber	0.40212	0.81533	0.43118	0.50151	1.22612	0.60032	3.9766
		Bi-Square	0.40679	0.6411	0.34825	0.52324	1.03761	0.51383	3.4708

TABLE 4.3.24 C: Root Mean Squares Error: When Errors are Log-Normal ,Linear Heteroscedastic and Contemporaneous Correlation(P=0.95) under varying sample sizes									
Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=1$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	Sum(β_{ij})
0.95	N=20	OLS	1.39718	1.61238	1.54137	1.63205	1.60023	1.5675	9.3507
		FGLS	1.09985	0.86707	0.67293	1.31583	1.10152	0.77555	5.8328
		Huber	1.05498	0.92951	0.80272	1.27453	1.04116	1.01123	6.1141
		Bi-Square	1.01802	0.78377	0.77459	1.19209	1.05841	0.96295	5.7898
	N=30	OLS	1.17734	1.29623	1.26582	1.51174	1.81296	1.24486	8.3090
		FGLS	1.08616	0.86858	0.57487	1.33045	1.20778	0.59738	5.6652
		Huber	0.95601	0.838	0.69801	1.29574	1.15452	0.80649	5.7488
		Bi-Square	0.91962	0.69548	0.62624	1.27012	1.05629	0.7275	5.2953
	N=50	OLS	1.11248	1.16525	0.76626	1.39242	1.35193	0.85488	6.6432
		FGLS	1.05299	0.83828	0.47978	1.31191	1.03068	0.58889	5.3025
		Huber	0.91297	0.69517	0.49707	1.18637	1.00466	0.61896	4.9152
		Bi-Square	0.85891	0.59852	0.46722	1.11896	0.8848	0.60243	4.5308
	N=100	OLS	1.1528	1.04167	0.66017	1.38507	1.09373	0.77249	6.1059
		FGLS	1.02955	0.81664	0.41406	1.32568	0.98654	0.50849	5.0810
		Huber	0.94014	0.60742	0.4137	1.22728	0.79969	0.4902	4.4784
		Bi-Square	0.85841	0.46326	0.35586	1.17133	0.69497	0.445	3.9888
	N=250	OLS	1.05101	0.84387	0.55214	1.22783	1.18169	0.65324	5.5098
		FGLS	0.987	0.76501	0.41547	1.26717	1.00949	0.52414	4.9683
		Huber	0.88833	0.55224	0.33535	1.15814	0.81276	0.43813	4.1850
		Bi-Square	0.80295	0.47379	0.27831	1.11831	0.67693	0.38524	3.7355
	N=500	OLS	0.9959	0.80415	0.48613	1.25429	1.10142	0.55604	5.1979
		FGLS	0.98563	0.78078	0.40492	1.25007	1.02867	0.50869	4.9588
		Huber	0.87034	0.51855	0.30163	1.15355	0.79706	0.4001	4.0412
		Bi-Square	0.79986	0.41192	0.25318	1.09959	0.68865	0.35283	3.6060

TABLE 4.3. 25 C: Root Mean Squares Error: When Errors are Log-Normal , Square Root Heteroscedastic($g=0.5$) and Contemporaneous Correlation($P=0.95$) under varying sample sizes

Contemporaneous Correlation	Sample size	Forms of Heteroscedasticity: $\text{Var}(Y_i) = \sigma^2 [E(Y_i)]^g$; $g=0.5$							
		Estimators	β_{10}	β_{11}	β_{12}	β_{20}	β_{21}	β_{22}	$\text{Sum}(\beta_{ij})$
0.95	N=20	<i>OLS</i>	1.83199	1.58349	1.69612	2.19512	1.59766	1.64834	10.5527
		<i>FGLS</i>	1.50374	0.62492	0.60214	1.84562	0.7832	0.66758	6.0272
		<i>Huber</i>	1.39586	0.88055	0.87225	1.73872	0.90111	1.03058	6.8191
		<i>Bi-Square</i>	1.32455	0.7824	0.84218	1.60483	0.95982	0.97333	6.4871
	N=30	<i>OLS</i>	1.58178	1.2305	1.31981	2.08864	1.72176	1.32069	9.2632
		<i>FGLS</i>	1.50677	0.5933	0.46572	1.88294	0.84817	0.49737	5.7943
		<i>Huber</i>	1.28674	0.77756	0.73775	1.76726	1.01726	0.85907	6.4456
		<i>Bi-Square</i>	1.21131	0.66561	0.69546	1.70517	0.95366	0.78829	6.0195
	N=50	<i>OLS</i>	1.55082	1.03243	0.76183	1.94494	1.11817	0.85583	7.2640
		<i>FGLS</i>	1.49095	0.53357	0.3381	1.8615	0.6318	0.42821	5.2841
		<i>Huber</i>	1.24178	0.58016	0.48375	1.63988	0.79142	0.58705	5.3240
		<i>Bi-Square</i>	1.13457	0.52175	0.46851	1.5174	0.70224	0.57888	4.9234
	N=100	<i>OLS</i>	1.60207	0.85785	0.6756	1.94258	0.78926	0.71914	6.5865
		<i>FGLS</i>	1.46665	0.49285	0.27731	1.87389	0.57542	0.33167	5.0178
		<i>Huber</i>	1.26876	0.45671	0.40699	1.68016	0.5448	0.42367	4.7811
		<i>Bi-Square</i>	1.13301	0.36371	0.36262	1.57708	0.48732	0.40628	4.3300
	N=250	<i>OLS</i>	1.48737	0.59463	0.49483	1.77332	0.80984	0.54156	5.7016
		<i>FGLS</i>	1.41666	0.4362	0.25502	1.81849	0.58062	0.32153	4.8285
		<i>Huber</i>	1.20644	0.36905	0.28227	1.60657	0.51604	0.33741	4.3178
		<i>Bi-Square</i>	1.06559	0.33708	0.24882	1.51774	0.43075	0.30647	3.9065
	N=500	<i>OLS</i>	1.42767	0.50287	0.38249	1.80906	0.70383	0.40649	5.2324
		<i>FGLS</i>	1.41984	0.44693	0.24069	1.80573	0.59029	0.30093	4.8044
		<i>Huber</i>	1.19159	0.31027	0.22116	1.60071	0.48891	0.27399	4.0866
		<i>Bi-Square</i>	1.06913	0.24908	0.19208	1.49853	0.42907	0.24671	3.6846

APPENDIX III

R-CODES USED FOR SIMULATION

```
library(lattice) #splom
library(car) #Vif
#library(sn)
library(systemfit)
library(MASS)
library(corpcor)
library(gmm)
library(sem)
set.seed(123456)
MRAF=function(n,itrr)
{
  set.seed(1234567)
  ## OLS ##
  VARbeta1 <- BIASbeta1<- ABSBbeta1 <- RMSEbeta1 <- BIASbeta1 <- c()
  VARbeta2 <- BIASbeta2 <-ABSBbeta2 <- RMSEbeta2 <- BIASbeta2 <- c()
  VARbeta3 <- BIASbeta3 <-ABSBbeta3 <- RMSEbeta3 <- BIASbeta3 <- c()
  VARbeta4 <- BIASbeta4 <-ABSBbeta4 <- RMSEbeta4 <- BIASbeta4 <- c()
  VARbeta5 <- BIASbeta5 <-ABSBbeta5 <- RMSEbeta5 <- BIASbeta5 <- c()
  VARbeta6 <- BIASbeta6 <-ABSBbeta6 <- RMSEbeta6 <- BIASbeta6 <- c()
  beta1Estim <- beta2Estim <- beta3Estim <- beta4Estim <- beta5Estim <- beta6Estim <- c()

  ## SUR ##
  VARbeta1S <- BIASbeta1S <- ABSBbeta1S <- RMSEbeta1S <- BIASbeta1S <- c()
  VARbeta2S <- BIASbeta2S <-ABSBbeta2S <- RMSEbeta2S <- BIASbeta2S <- c()
  VARbeta3S <- BIASbeta3S <-ABSBbeta3S <- RMSEbeta3S <- BIASbeta3S <- c()
  VARbeta4S <- BIASbeta4S <-ABSBbeta4S <- RMSEbeta4S <- BIASbeta4S <- c()
  VARbeta5S <- BIASbeta5S <-ABSBbeta5S <- RMSEbeta5S <- BIASbeta5S <- c()
  VARbeta6S <- BIASbeta6S <-ABSBbeta6S <- RMSEbeta6S <- BIASbeta6S <- c()
  beta1EstimS <- beta2EstimS <- beta3EstimS <- beta4EstimS <- beta5EstimS <- beta6EstimS <- c()

  ## Huber ##
```

```

VARbeta1H <- BIASbeta1H <- ABSBbeta1H <- RMSEbeta1H <- BIASbeta1H <- c()
VARbeta2H <- BIASbeta2H <- ABSBbeta2H <- RMSEbeta2H <- BIASbeta2H <- c()
VARbeta3H <- BIASbeta3H <- ABSBbeta3H <- RMSEbeta3H <- BIASbeta3H <- c()
VARbeta4H <- BIASbeta4H <- ABSBbeta4H <- RMSEbeta4H <- BIASbeta4H <- c()
VARbeta5H <- BIASbeta5H <- ABSBbeta5H <- RMSEbeta5H <- BIASbeta5H <- c()
VARbeta6H <- BIASbeta6H <- ABSBbeta6H <- RMSEbeta6H <- BIASbeta6H <- c()
beta1EstimH <- beta2EstimH <- beta3EstimH <- beta4EstimH <- beta5EstimH <- beta6EstimH <- c()

## Bi square ##
VARbeta1bsq<- BIASbeta1bsq <- ABSBbeta1bsq <- RMSEbeta1bsq <- BIASbeta1bsq<- c()
VARbeta2bsq <- BIASbeta2bsq <- ABSBbeta2bsq <- RMSEbeta2bsq <- BIASbeta2bsq <- c()
VARbeta3bsq <- BIASbeta3bsq <- ABSBbeta3bsq <- RMSEbeta3bsq <- BIASbeta3bsq<- c()
VARbeta4bsq<- BIASbeta4bsq <- ABSBbeta4bsq <- RMSEbeta4bsq <- BIASbeta4bsq <- c()
VARbeta5bsq <- BIASbeta5bsq <- ABSBbeta5bsq <- RMSEbeta5bsq <- BIASbeta5bsq <- c()
VARbeta6bsq <- BIASbeta6bsq <- ABSBbeta6bsq <- RMSEbeta6bsq <- BIASbeta6bsq <- c()
beta1Estimbsq <- beta2Estimbsq <- beta3Estimbsq <- beta4Estimbsq <- beta5Estimbsq <- beta6Estimbsq <- c()

mat7 = matrix(NA, ncol = 42, nrow = itr)
colnames(mat7)<-c("OLS_Beta1","OLS_Beta2","OLS_Beta3","OLS_Beta4","OLS_Beta5","OLS_Beta6",
  "WLS_Beta1", WLS_Beta2", "WLS_Beta3", "WLS_Beta4", "WLS_Beta5", "WLS_Beta6",
  "SUR_Beta1", SUR_Beta2", "SUR_Beta3", "SUR_Beta4", "SUR_Beta5", "SUR_Beta6",
  "MM bi-square_Beta1", "MM bi-square_Beta2", "MM bi-square_Beta3", "MM bi-square_Beta4", "MM
bi-square_Beta5", "MM bi-square_Beta6",
  "HUBER-M_Beta1", "HUBER-M_Beta2", "HUBER-M_Beta3", "HUBER-M_Beta4", "HUBER-
M_Beta5", "HUBER-M_Beta6",
  "W2SLS_Beta1",
"W2SLS_Beta2", "W2SLS_Beta3", "W2SLS_Beta4", "W2SLS_Beta5", "W2SLS_Beta6",
  "GMM_Beta1", "GMM_Beta2", "GMM_Beta3", "GMM_Beta4", "GMM_Beta5", "GMM_Beta6")

for(i in 1:itr)
{
#Using a correlation Matrix M(assume unit variances)
M= matrix(c(1, 0.2, 0.4, 0.5,
  0.2, 1, 0.95, 0.3,
  0.4, 0.95, 1, 0.3,
  0.5, 0.3, 0.3, 1), nrow=4, ncol=4)

L =chol(M)

```

```

nvars = dim(L)[ 1 ]

R = t(L)                # transpose of L (upper triangular Matrix)

# Generate a random variable that follow an m correlation matrix

## generate a gamma(4,1) variates that follow an M correlation matrix

data<-matrix(rgamma(nvars*n, scale = 4, shape = 1),nrow = nvars, ncol= n) #GAMMA distributions

G<-t(L) %*% data

GM<-t(G)

datum= as.data.frame(GM)

G1<-datum[,1] ; G2<-datum[,2] ; G3<-datum[,3] ;G4<-datum[,4]

#generate a normal variates that follow an M correlation matrix

N = t(L) %*% matrix(rnorm(nvars*n), nrow = nvars, ncol = n)

T = t(N)

data2 = as.data.frame(T)

N1<-data2[,1] ; N2<-data2[,2] ; N3<-data2[,3] ;N4<-data2[,4]

#generate a LOG-Normal variates that follow an M correlation matrix

LP = t(L) %*% matrix(rlnorm(nvars*n), nrow = nvars, ncol = n)

LT = t(LP)

data4 = as.data.frame(LT)

LN1<-data4[,1] ; LN2<-data4[,2] ; LN3<-data4[,3] ;LN4<-data4[,4]


#create random variables x, independent variables

xP= matrix(c(1, 0.0, 0.0, 0.0,
             0.0, 1, 0.0, 0.0,
             0.0, 0.0, 1, 0.0,
             0.0, 0.0, 0.0, 1 ), nrow=4, ncol=4)


# Cholesky decomposition

xK = chol(xP)

xpvars = dim(xK)[1]

# Uniform Random variables that follow an M correlation matrix

X = t(xK) %*% matrix(runif(xpvars*n), nrow=xpvars, ncol=n)

X = t(X)

```

```

framedata=as.data.frame(X)

e1<-framedata[,1] ; e2<-framedata[,2] ; e3<-framedata[,3] ;e4<-framedata[,4]

X1<-framedata[,1]; X12<-framedata[,2] ;X21<-framedata[,3]; X22<-framedata[,4]

# create random variables error terms that follows Gamma distribution
GT= t(xK) %*% matrix(rgamma(xpvars*n, scale = 4, shape = 1),nrow = xpvars, ncol= n)
GT= t(GT)

framedataG=as.data.frame(GT)

GT1<-framedataG[,1] ; GT2<-framedataG[,2] ; GT3<-framedataG[,3] ;GT4<-framedataG[,4]

# LOG NORMAL Distribution

LNT= t(xK) %*% matrix(rlnorm(xpvars*n), nrow = xpvars, ncol = n)

LNT= t(LNT)

framedataLN=as.data.frame(LNT)

LNT1<-framedataLN[,1] ; LNT2<-framedataLN[,2] ; LNT3<-framedataLN[,3] ;LNT4<-framedataLN[,4]

# NORMAL ERRORS with no contemporaneous correlation

norvars = dim(xK)[1]

# Random variables that follow an M correlation matrix

nore = t(xK) %*% matrix(rnorm(norvars*n), nrow=norvars, ncol=n)

nore = t(nore)

framedata2=as.data.frame(nore)

e1<-framedata2[,1] ; e2<-framedata2[,2] ; e3<-framedata2[,3] ;e4<-framedata2[,4]

# FORM OF HETEROSCEDASTICITY

g11<- (0.5 +0.4*X1 +0.2*X12) #LINEAR FORM

g12<-exp(0.5 +0.4*X1 +0.2*X12) # EXPONENTIAL FORM

g21<-(0.5 +0.4*X21 + 0.2*X22) #LINEAR FORM

g22<-exp(0.5 +0.4*X21 + 0.2*X22) # EXPONENTIAL FORM

# models SPECIFICATIONS)

Y1 = -20 + 15*X1 + 13*X12 + LN2*g11

Y2 = 11.5 + 10*X21 + 6.5*X22 + LN3*g21

model1<-data.frame(Y1,Y2,X1,X12,X21,X22,N1,N2,N3,N4,g21,g11,g12,g22,LN2,LN3)

# GMM model specifications

g<-Y1~X1 + X12

g3<-Y2~X21 + X22

```

```

h<- cbind(X22, X12)

# Estimators

ols2=(systemfit(list(Y1~X1 + X12 ,Y2~X21 + X22 ),method="OLS"))
sur2=(systemfit(list(Y1~X1 + X12 ,Y2~X21 + X22 ),method="SUR"))

GMM = gmm(g,x=h,type='iterative',crit=1e-8,itermax=200)
GMM1 = gmm(g=g3,x=h,type='iterative',crit=1e-8,itermax=200)
TRUEVALUE=c(-20,15,13,11.5,10,6.5)

olsr=round(coef(summary(ols2)),digits=4) #round(coef(summary(theilOls)), digits = 3)

olscoef=olsr[,1]

sur2r=round(coef(summary(sur2)),digits=4)

sur2coef=sur2r[,1]

GMMf=summary(GMM)
GMMf1=summary(GMM1)
GMMc=c(GMMf$par[,1],GMMf1$par[,1])
gmm2r= rbind(GMMc)

#HUBER M-ESTIMATOR
HUBER1=rlm(Y1~X1+X12)
HUBER2=rlm(Y2~X21+X22)
Hub1coef=round(coef(summary(HUBER1)),digits=4)
Hub2coef=round(coef(summary(HUBER2)),digits=4)
HUBER= c(Hub1coef[,1],Hub2coef[,1])

# Bi-SQUARE MM estimator#
bis1=rlm(Y1~X1+X12,data=model1,method="MM")
bis2=rlm(Y2~X21+X22,data=model1, method="MM")
bisq1=round(coef(bis1),digit=4)
bisq2=round(coef(bis2),digit=4)
bisq=c(bisq1,bisq2)
True=rbind(TRUEVALUE)

# OLS and RANDOM

beta1B = olsr[1,1]          # Estimated intercept
beta1ABS = abs(olsr[1,1] - True[1])  # To estimate bias alone for beta1
beta1BIAS = (olsr[1,1] - True[1])

```

```

beta1RMSE = (olsr[1,1]-True[1])^2
beta1Estim <- c(beta1Estim, olsr[1,1])
beta2B = olsr[2,1]          # Estimated intercept
beta2ABS = abs(olsr[2,1] - True[2])  # To estimate bias alone for beta2
beta2BIAS = (olsr[2,1] - True[2])
beta2RMSE = (olsr[2,1]-True[2])^2
beta2Estim <- c(beta2Estim, olsr[2,1])
beta3B = olsr[3,1]          # Estimated intercept
beta3ABS = abs(olsr[3,1] - True[3])  # To estimate bias alone for beta3
beta3BIAS = (olsr[3,1] - True[3])
beta3RMSE = (olsr[3,1]-True[3])^2
beta3Estim <- c(beta3Estim, olsr[3,1])
beta4B = olsr[4,1]          # Estimated intercept
beta4ABS = abs(olsr[4,1] - True[4])  # To estimate bias alone for beta4
beta4BIAS = (olsr[4,1] - True[4])
beta4RMSE = (olsr[4,1]-True[4])^2
beta4Estim <- c(beta4Estim, olsr[4,1])
beta5B = olsr[5,1]          # Estimated intercept
beta5ABS = abs(olsr[5,1] - True[5])  # To estimate bias alone for beta5
beta5BIAS = (olsr[5,1] - True[5])
beta5RMSE = (olsr[5,1]-True[5])^2
beta5Estim <- c(beta5Estim, olsr[5,1])
beta6B = olsr[6,1]          # Estimated intercept
beta6ABS = abs(olsr[6,1] - True[6])  # To estimate bias alone for beta6
beta6BIAS = (olsr[6,1] - True[6])
beta6RMSE = (olsr[6,1]-True[6])^2
beta6Estim <- c(beta6Estim, olsr[6,1])
VARbeta1 = c(VARbeta1, beta1B); ABSBbeta1 = c(ABSBbeta1, beta1ABS)
BIASbeta1 = c(BIASbeta1, beta1BIAS); RMSEbeta1 = c(RMSEbeta1, beta1RMSE)
VARbeta2 = c(VARbeta2, beta2B); ABSBbeta2 = c(ABSBbeta2, beta2ABS)
BIASbeta2 = c(BIASbeta2, beta2BIAS); RMSEbeta2 = c(RMSEbeta2, beta2RMSE)
VARbeta3 = c(VARbeta3, beta3B); ABSBbeta3 = c(ABSBbeta3, beta3ABS)

```

```

BIASbeta3 = c(BIASbeta3, beta3BIAS) ; RMSEbeta3 = c(RMSEbeta3, beta3RMSE)
VARbeta4 = c(VARbeta4, beta4B); ABSBbeta4 = c(ABSBbeta4, beta4ABS)
BIASbeta4 = c(BIASbeta4, beta4BIAS) ; RMSEbeta4 = c(RMSEbeta4, beta4RMSE)
VARbeta5 = c(VARbeta5, beta5B); ABSBbeta5 = c(ABSBbeta5, beta5ABS)
BIASbeta5 = c(BIASbeta5, beta5BIAS) ; RMSEbeta5 = c(RMSEbeta5, beta5RMSE)

VARbeta6 = c(VARbeta6, beta6B); ABSBbeta6 = c(ABSBbeta6, beta6ABS)
BIASbeta6 = c(BIASbeta6, beta6BIAS) ; RMSEbeta6 = c(RMSEbeta6, beta6RMSE)

## WLS##

beta1Bw = wls2r[1,1]          # Estimated intercept
beta1ABSw = abs(wls2r[1,1] - True[1])  # To estimate bias alone for beta1
beta1BIASw = (wls2r[1,1] - True[1])
beta1RMSEw = (wls2r[1,1]-True[1])^2
beta1Estimw <- c(beta1Estimw, wls2r[1,1])

beta2Bw = wls2r[2,1]          # Estimated intercept
beta2ABSw = abs(wls2r[2,1] - True[2])  # To estimate bias alone for beta2
beta2BIASw = (wls2r[2,1] - True[2])
beta2RMSEw = (wls2r[2,1]-True[2])^2
beta2Estimw <- c(beta2Estimw, wls2r[2,1])

beta3Bw = wls2r[3,1]          # Estimated intercept
beta3ABSw = abs(wls2r[3,1] - True[3])  # To estimate bias alone for beta3
beta3BIASw = (wls2r[3,1] - True[3])
beta3RMSEw = (wls2r[3,1]-True[3])^2
beta3Estimw <- c(beta3Estimw, wls2r[3,1])

beta4Bw = wls2r[4,1]          # Estimated intercept
beta4ABSw = abs(wls2r[4,1] - True[4])  # To estimate bias alone for beta4
beta4BIASw = (wls2r[4,1] - True[4])
beta4RMSEw = (wls2r[4,1]-True[4])^2
beta4Estimw <- c(beta4Estimw, wls2r[4,1])

beta5Bw = wls2r[5,1]          # Estimated intercept
beta5ABSw = abs(wls2r[5,1] - True[5])  # To estimate bias alone for beta5
beta5BIASw = (wls2r[5,1] - True[5])

```

```

beta5RMSEw = (wls2r[5,1]-True[5])^2
beta5Estimw <- c(beta5Estimw, wls2r[5,1])
beta6Bw = wls2r[6,1]          # Estimated intercept
beta6ABSw = abs(wls2r[6,1] - True[6])  # To estimate bias alone for beta6
beta6BIASw = (wls2r[6,1] - True[6])
beta6RMSEw = (wls2r[6,1]-True[6])^2
beta6Estimw <- c(beta6Estimw, wls2r[6,1])

VARbeta1w = c(VARbeta1w, beta1Bw) ; ABSBbeta1w = c(ABSBbeta1w, beta1ABSw)
BIASbeta1w = c(BIASbeta1w, beta1BIASw) ; RMSEbeta1w = c(RMSEbeta1w, beta1RMSEw)
VARbeta2w = c(VARbeta2w, beta2Bw); ABSBbeta2w = c(ABSBbeta2w, beta2ABSw)
BIASbeta2w = c(BIASbeta2w, beta2BIASw) ; RMSEbeta2w = c(RMSEbeta2w, beta2RMSEw)
VARbeta3w = c(VARbeta3w, beta3Bw); ABSBbeta3w = c(ABSBbeta3w, beta3ABSw)
BIASbeta3w = c(BIASbeta3w, beta3BIASw) ; RMSEbeta3w = c(RMSEbeta3w, beta3RMSEw)

VARbeta4w = c(VARbeta4w, beta4Bw); ABSBbeta4w = c(ABSBbeta4w, beta4ABSw)
BIASbeta4w = c(BIASbeta4w, beta4BIASw) ; RMSEbeta4w = c(RMSEbeta4w, beta4RMSEw)
VARbeta5w = c(VARbeta5w, beta5Bw); ABSBbeta5w = c(ABSBbeta5w, beta5ABSw)
BIASbeta5w = c(BIASbeta5w, beta5BIASw) ; RMSEbeta5w = c(RMSEbeta5w, beta5RMSEw)
VARbeta6w = c(VARbeta6w, beta6Bw); ABSBbeta6w = c(ABSBbeta6w, beta6ABSw)
BIASbeta6w = c(BIASbeta6w, beta6BIASw) ; RMSEbeta6w = c(RMSEbeta6w, beta6RMSEw)

###SUR###

beta1BS = sur2r[1,1]          # Estimated intercept
beta1ABSS = abs(sur2r[1,1] - True[1])  # To estimate bias alone for beta1
beta1BIASS = (sur2r[1,1] - True[1])
beta1RMSES = (sur2r[1,1]-True[1])^2
beta1EstimS <- c(beta1EstimS, sur2r[1,1])

beta2BS = sur2r[2,1]          # Estimated intercept
beta2ABSS = abs(sur2r[2,1] - True[2])  # To estimate bias alone for beta2
beta2BIASS = (sur2r[2,1] - True[2])
beta2RMSES = (sur2r[2,1]-True[2])^2
beta2EstimS <- c(beta2EstimS, sur2r[2,1])

```

```

beta3BS = sur2r[3,1]          # Estimated intercept
beta3ABSS = abs(sur2r[3,1] - True[3])  # To estimate bias alone for beta3
beta3BIASS = (sur2r[3,1] - True[3])
beta3RMSES = (sur2r[3,1]-True[3])^2
beta3EstimS <- c(beta3EstimS, sur2r[3,1])

beta4BS = sur2r[4,1]          # Estimated intercept
beta4ABSS = abs(sur2r[4,1] - True[4])  # To estimate bias alone for beta4
beta4BIASS = (sur2r[4,1] - True[4])
beta4RMSES = (sur2r[4,1]-True[4])^2
beta4EstimS <- c(beta4EstimS, sur2r[4,1])

beta5BS = sur2r[5,1]          # Estimated intercept
beta5ABSS = abs(sur2r[5,1] - True[5])  # To estimate bias alone for beta5
beta5BIASS = (sur2r[5,1] - True[5])
beta5RMSES = (sur2r[5,1]-True[5])^2
beta5EstimS <- c(beta5EstimS, sur2r[5,1])

beta6BS = sur2r[6,1]          # Estimated intercept
beta6ABSS = abs(sur2r[6,1] - True[6])  # To estimate bias alone for beta6
beta6BIASS = (sur2r[6,1] - True[6])
beta6RMSES = (sur2r[6,1] -True[6])^2
beta6EstimS <- c(beta6EstimS, sur2r[6,1] )

VARbeta1S = c(VARbeta1S, beta1BS); ABSBbeta1S = c(ABSBbeta1S, beta1ABSS)
BIASbeta1S = c(BIASbeta1S, beta1BIASS) ; RMSEbeta1S = c(RMSEbeta1S, beta1RMSES)

VARbeta2S = c(VARbeta2S, beta2BS); ABSBbeta2S = c(ABSBbeta2S, beta2ABSS)
BIASbeta2S = c(BIASbeta2S, beta2BIASS) ; RMSEbeta2S = c(RMSEbeta2S, beta2RMSES)
VARbeta3S = c(VARbeta3S, beta3BS); ABSBbeta3S = c(ABSBbeta3S, beta3ABSS)
BIASbeta3S = c(BIASbeta3S, beta3BIASS) ; RMSEbeta3S = c(RMSEbeta3S, beta3RMSES)
VARbeta4S = c(VARbeta4S, beta4BS); ABSBbeta4S = c(ABSBbeta4S, beta4ABSS)
BIASbeta4S = c(BIASbeta4S, beta4BIASS) ; RMSEbeta4S = c(RMSEbeta4S, beta4RMSES)
VARbeta5S = c(VARbeta5S, beta5BS); ABSBbeta5S = c(ABSBbeta5S, beta5ABSS)
BIASbeta5S = c(BIASbeta5S, beta5BIASS) ; RMSEbeta5S = c(RMSEbeta5S, beta5RMSES)
VARbeta6S = c(VARbeta6S, beta6BS); ABSBbeta6S = c(ABSBbeta6S, beta6ABSS)

```

```
BIASbeta6S = c(BIASbeta6S, beta6BIASS) ; RMSEbeta6S = c(RMSEbeta6S, beta6RMSES)
```

```
## W2sls##
```

```
beta1Bw2 = w2sls2r[1,1]          # Estimated intercept
```

```
beta1ABSw2 = abs(w2sls2r[1,1] - True[1])  # To estimate bias a lone for beta1
```

```
beta1BIASw2 = (w2sls2r[1,1] - True[1])
```

```
beta1RMSEw2 = (w2sls2r[1,1]-True[1])^2
```

```
beta1Estimw2 <- c(beta1Estimw2, w2sls2r[1,1])
```

```
beta2Bw2 = w2sls2r[2,1]          # Estimated intercept
```

```
beta2ABSw2 = abs(w2sls2r[2,1] - True[2])  # To estimate bias a lone for beta2
```

```
beta2BIASw2 = (w2sls2r[2,1] - True[2])
```

```
beta2RMSEw2 = (w2sls2r[2,1]-True[2])^2
```

```
beta2Estimw2 <- c(beta2Estimw2, w2sls2r[2,1])
```

```
beta3Bw2 = w2sls2r[3,1]          # Estimated intercept
```

```
beta3ABSw2 = abs(w2sls2r[3,1] - True[3])  # To estimate bias a lone for beta3
```

```
beta3BIASw2 = (w2sls2r[3,1] - True[3])
```

```
beta3RMSEw2 = (w2sls2r[3,1]-True[3])^2
```

```
beta3Estimw2 <- c(beta3Estimw2, w2sls2r[3,1])
```

```
beta4Bw2 = w2sls2r[4,1]          # Estimated intercept
```

```
beta4ABSw2 = abs(w2sls2r[4,1] - True[4])  # To estimate bias a lone for beta4
```

```
beta4BIASw2 = (w2sls2r[4,1] - True[4])
```

```
beta4RMSEw2 = (w2sls2r[4,1]-True[4])^2
```

```
beta4Estimw2 <- c(beta4Estimw2, w2sls2r[4,1])
```

```
beta5Bw2 = w2sls2r[5,1]          # Estimated intercept
```

```
beta5ABSw2 = abs(w2sls2r[5,1] - True[5])  # To estimate bias a lone for beta5
```

```
beta5BIASw2 = (w2sls2r[5,1] - True[5])
```

```
beta5RMSEw2 = (w2sls2r[5,1]-True[5])^2
```

```
beta5Estimw2 <- c(beta5Estimw2, w2sls2r[5,1])
```

```
beta6Bw2 = w2sls2r[6,1]          # Estimated intercept
```

```
beta6ABSw2 = abs(w2sls2r[6,1] - True[6])  # To estimate bias a lone for beta6
```

```
beta6BIASw2 = (w2sls2r[6,1] - True[6])
```

```
beta6RMSEw2 = (w2sls2r[6,1]-True[6])^2
```

```
beta6Estimw2 <- c(beta6Estimw2, w2sls2r[6,1])
```

```

VARbeta1w2 = c(VARbeta1w2, beta1Bw2) ; ABSBbeta1w2 = c(ABSBbeta1w2, beta1ABSw2)
BIASbeta1w2 = c(BIASbeta1w2, beta1BIASw2) ; RMSEbeta1w2 = c(RMSEbeta1w2, beta1RMSEw2)
VARbeta2w2 = c(VARbeta2w2, beta2Bw2); ABSBbeta2w2 = c(ABSBbeta2w2, beta2ABSw2)
BIASbeta2w2 = c(BIASbeta2w2, beta2BIASw2) ; RMSEbeta2w2 = c(RMSEbeta2w2, beta2RMSEw2)
VARbeta3w2 = c(VARbeta3w2, beta3Bw2); ABSBbeta3w2 = c(ABSBbeta3w2, beta3ABSw2)
BIASbeta3w2 = c(BIASbeta3w2, beta3BIASw2) ; RMSEbeta3w2 = c(RMSEbeta3w2, beta3RMSEw2)
VARbeta4w2 = c(VARbeta4w2, beta4Bw2); ABSBbeta4w2 = c(ABSBbeta4w2, beta4ABSw2)
BIASbeta4w2 = c(BIASbeta4w2, beta4BIASw2) ; RMSEbeta4w2 = c(RMSEbeta4w2, beta4RMSEw2)
VARbeta5w2 = c(VARbeta5w2, beta5Bw2); ABSBbeta5w2 = c(ABSBbeta5w2, beta5ABSw2)
BIASbeta5w2 = c(BIASbeta5w2, beta5BIASw2) ; RMSEbeta5w2 = c(RMSEbeta5w2, beta5RMSEw2)
VARbeta6w2 = c(VARbeta6w2, beta6Bw2); ABSBbeta6w2 = c(ABSBbeta6w2, beta6ABSw2)
BIASbeta6w2 = c(BIASbeta6w2, beta6BIASw2) ; RMSEbeta6w2 = c(RMSEbeta6w2, beta6RMSEw2)

```

```
## Bi-SQUARE MM ESTIMATOR ##
```

```

beta1Bbsq = bisq[1]          # Estimated intercept
beta1ABSbsq = abs(bisq[1] - True[1]) # To estimate bias a lone for beta1
beta1BIASbsq = (bisq[1] - True[1])
beta1RMSEbsq = (bisq[1]-True[1])^2
beta1Estimbsq <- c(beta1Estimbsq, bisq[1])
beta2Bbsq = bisq[2]          # Estimated intercept
beta2ABSbsq = abs(bisq[2] - True[2]) # To estimate bias a lone for beta2
beta2BIASbsq = (bisq[2] - True[2])
beta2RMSEbsq = (bisq[2]-True[2])^2
beta2Estimbsq <- c(beta2Estimbsq, bisq[2])
beta3Bbsq = bisq[3]          # Estimated intercept
beta3ABSbsq = abs(bisq[3] - True[3]) # To estimate bias a lone for beta3
beta3BIASbsq = (bisq[3] - True[3])
beta3RMSEbsq = (bisq[3]-True[3])^2
beta3Estimbsq <- c(beta3Estimbsq, bisq[3])
beta4Bbsq = bisq[4]          # Estimated intercept
beta4ABSbsq = abs(bisq[4] - True[4]) # To estimate bias a lone for beta4
beta4BIASbsq = (bisq[4] - True[4])

```

```

beta4RMSEbsq = (bisq[4]-True[4])^2
beta4Estimbsq <- c(beta4Estimbsq, bisq[4])
beta5Bbsq = bisq[5]          # Estimated intercept
beta5ABSbsq = abs(bisq[5] - True[5])  # To estimate bias alone for beta5
beta5BIASbsq = (bisq[5] - True[5])
beta5RMSEbsq = (bisq[5]-True[5])^2
beta5Estimbsq <- c(beta5Estimbsq, bisq[5])
beta6Bbsq = bisq[6]          # Estimated intercept
beta6ABSbsq = abs(bisq[6] - True[6])  # To estimate bias alone for beta6
beta6BIASbsq = (bisq[6] - True[6])
beta6RMSEbsq = (bisq[6]-True[6])^2
beta6Estimbsq <- c(beta6Estimbsq, bisq[6])

VARbeta1bsq = c(VARbeta1bsq, beta1Bbsq) ; ABSBbeta1bsq = c(ABSBbeta1bsq, beta1ABSbsq)
BIASbeta1bsq = c(BIASbeta1bsq, beta1BIASbsq) ; RMSEbeta1bsq = c(RMSEbeta1bsq, beta1RMSEbsq)
VARbeta2bsq = c(VARbeta2bsq, beta2Bbsq); ABSBbeta2bsq = c(ABSBbeta2bsq, beta2ABSbsq)
BIASbeta2bsq = c(BIASbeta2bsq, beta2BIASbsq) ; RMSEbeta2bsq = c(RMSEbeta2bsq, beta2RMSEbsq)
VARbeta3bsq = c(VARbeta3bsq, beta3Bbsq); ABSBbeta3bsq = c(ABSBbeta3bsq, beta3ABSbsq)
BIASbeta3bsq = c(BIASbeta3bsq, beta3BIASbsq) ; RMSEbeta3bsq = c(RMSEbeta3bsq, beta3RMSEbsq)
VARbeta4bsq = c(VARbeta4bsq, beta4Bbsq); ABSBbeta4bsq = c(ABSBbeta4bsq, beta4ABSbsq)
BIASbeta4bsq = c(BIASbeta4bsq, beta4BIASbsq) ; RMSEbeta4bsq = c(RMSEbeta4bsq, beta4RMSEbsq)

VARbeta5bsq = c(VARbeta5bsq, beta5Bbsq); ABSBbeta5bsq = c(ABSBbeta5bsq, beta5ABSbsq)
BIASbeta5bsq = c(BIASbeta5bsq, beta5BIASbsq) ; RMSEbeta5bsq = c(RMSEbeta5bsq, beta5RMSEbsq)
VARbeta6bsq = c(VARbeta6bsq, beta6Bbsq); ABSBbeta6bsq = c(ABSBbeta6bsq, beta6ABSbsq)
BIASbeta6bsq = c(BIASbeta6bsq, beta6BIASbsq) ; RMSEbeta6bsq = c(RMSEbeta6bsq, beta6RMSEbsq)

## HUBER- M ESTIMATOR###

beta1BH = HUBER[1]          # Estimated intercept
beta1ABSH = abs(HUBER[1] - True[1])  # To estimate bias alone for beta1
beta1BIASH = (HUBER[1] - True[1])
beta1RMSEH = (HUBER[1]-True[1])^2
beta1EstimH <- c(beta1EstimH, HUBER[1])
beta2BH = HUBER[2]          # Estimated intercept

```

```

beta2ABSH = abs(HUBER[2] - True[2]) # To esimate bias a lone for beta2
beta2BIASH = (HUBER[2] - True[2])
beta2RMSEH = (HUBER[2]-True[2])^2
beta2EstimH <- c(beta2EstimH, HUBER[2])
beta3BH = HUBER[3] # Estimated intercept
beta3ABSH = abs(HUBER[3] - True[3]) # To esimate bias a lone for beta3
beta3BIASH = (HUBER[3] - True[3])
beta3RMSEH = (HUBER[3]-True[3])^2
beta3EstimH <- c(beta3EstimH, HUBER[3])
beta4BH = HUBER[4] # Estimated intercept
beta4ABSH = abs(HUBER[4] - True[4]) # To esimate bias a lone for beta4
beta4BIASH = (HUBER[4] - True[4])
beta4RMSEH = (HUBER[4]-True[4])^2
beta4EstimH <- c(beta4EstimH, HUBER[4])
beta5BH = HUBER[5] # Estimated intercept
beta5ABSH = abs(HUBER[5] - True[5]) # To esimate bias a lone for beta5
beta5BIASH = (HUBER[5] - True[5])
beta5RMSEH = (HUBER[5] -True[5])^2
beta5EstimH <- c(beta5EstimH, HUBER[5] )
beta6BH = HUBER[6] # Estimated intercept
beta6ABSH = abs(HUBER[6] - True[6]) # To esimate bias a lone for beta6
beta6BIASH = (HUBER[6] - True[6])
beta6RMSEH = (HUBER[6]-True[6])^2
beta6EstimH <- c(beta6EstimH, HUBER[6])

VARbeta1H = c(VARbeta1H, beta1BH) ; ABSBbeta1H = c(ABSBbeta1H, beta1ABSH)
BIASbeta1H = c(BIASbeta1H, beta1BIASH) ; RMSEbeta1H = c(RMSEbeta1H, beta1RMSEH)
VARbeta2H = c(VARbeta2H, beta2BH); ABSBbeta2H = c(ABSBbeta2H, beta2ABSH)
BIASbeta2H = c(BIASbeta2H, beta2BIASH) ; RMSEbeta2H = c(RMSEbeta2H, beta2RMSEH)

VARbeta3H = c(VARbeta3H, beta3BH); ABSBbeta3H = c(ABSBbeta3H, beta3ABSH)
BIASbeta3H = c(BIASbeta3H, beta3BIASH) ; RMSEbeta3H = c(RMSEbeta3H, beta3RMSEH)
VARbeta4H = c(VARbeta4H, beta4BH); ABSBbeta4H = c(ABSBbeta4H, beta4ABSH)

```

```

BIASbeta4H = c(BIASbeta4H, beta4BIASH) ; RMSEbeta4H = c(RMSEbeta4H, beta4RMSEH)
VARbeta5H = c(VARbeta5H, beta5BH); ABSBbeta5H = c(ABSBbeta5H, beta5ABSH)
BIASbeta5H = c(BIASbeta5H, beta5BIASH) ; RMSEbeta5H = c(RMSEbeta5H, beta5RMSEH)
VARbeta6H = c(VARbeta6H, beta6BH); ABSBbeta6H = c(ABSBbeta6H, beta6ABSH)
BIASbeta6H = c(BIASbeta6H, beta6BIASH) ; RMSEbeta6H = c(RMSEbeta6H, beta6RMSEH)

## GMM##

beta1Bgm = gmm2r[1,1]          # Estimated intercept
beta1ABSGm = abs(gmm2r[1,1] - True[1])  # To estimate bias alone for beta1
beta1BIASgm = (gmm2r[1,1] - True[1])
beta1RMSEgm = (gmm2r[1,1]-True[1])^2
beta1Estimgm <- c(beta1Estimgm, gmm2r[1,1])

beta2Bgm = gmm2r[1,2]          # Estimated intercept
beta2ABSGm = abs(gmm2r[1,2] - True[2])  # To estimate bias alone for beta2
beta2BIASgm = (gmm2r[1,2] - True[2])
beta2RMSEgm = (gmm2r[1,2]-True[2])^2
beta2Estimgm <- c(beta2Estimgm, gmm2r[1,2])

beta3Bgm = gmm2r[1,3]          # Estimated intercept
beta3ABSGm = abs(gmm2r[1,3] - True[3])  # To estimate bias alone for beta3
beta3BIASgm = (gmm2r[1,3] - True[3])
beta3RMSEgm = (gmm2r[1,3] -True[3])^2
beta3Estimgm <- c(beta3Estimgm, gmm2r[1,3] )

beta4Bgm = gmm2r[1,4]          # Estimated intercept
beta4ABSGm = abs(gmm2r[1,4] - True[4])  # To estimate bias alone for beta4
beta4BIASgm = (gmm2r[1,4] - True[4])
beta4RMSEgm = (gmm2r[1,4]-True[4])^2
beta4Estimgm <- c(beta4Estimgm, gmm2r[1,4])

beta5Bgm = gmm2r[1,5]          # Estimated intercept
beta5ABSGm = abs(gmm2r[1,5] - True[5])  # To estimate bias alone for beta5
beta5BIASgm = (gmm2r[1,5] - True[5])
beta5RMSEgm = (gmm2r[1,5] -True[5])^2
beta5Estimgm <- c(beta5Estimgm, gmm2r[1,5] )

beta6Bgm = gmm2r[1,6]          # Estimated intercept

```

```

beta6ABSgm = abs(gmm2r[1,6] - True[6]) # To estimate bias alone for beta6
beta6BIASgm = (gmm2r[1,6] - True[6])
beta6RMSEgm = (gmm2r[1,6] - True[6])^2
beta6Estimgm <- c(beta6Estimgm, gmm2r[1,6] )

VARbeta1gm = c(VARbeta1gm, beta1Bgm) ; ABSBbeta1gm = c(ABSBbeta1gm, beta1ABSgm)
BIASbeta1gm = c(BIASbeta1gm, beta1BIASgm) ; RMSEbeta1gm = c(RMSEbeta1gm, beta1RMSEgm)
VARbeta2gm = c(VARbeta2gm, beta2Bgm); ABSBbeta2gm = c(ABSBbeta2gm, beta2ABSgm)
BIASbeta2gm = c(BIASbeta2gm, beta2BIASgm) ; RMSEbeta2gm = c(RMSEbeta2gm, beta2RMSEgm)
VARbeta3gm = c(VARbeta3gm, beta3Bgm); ABSBbeta3gm = c(ABSBbeta3gm, beta3ABSgm)
BIASbeta3gm = c(BIASbeta3gm, beta3BIASgm) ; RMSEbeta3gm = c(RMSEbeta3gm, beta3RMSEgm)
VARbeta4gm = c(VARbeta4gm, beta4Bgm); ABSBbeta4gm = c(ABSBbeta4gm, beta4ABSgm)
BIASbeta4gm = c(BIASbeta4gm, beta4BIASgm) ; RMSEbeta4gm = c(RMSEbeta4gm, beta4RMSEgm)
VARbeta5gm = c(VARbeta5gm, beta5Bgm); ABSBbeta5gm = c(ABSBbeta5gm, beta5ABSgm)
BIASbeta5gm = c(BIASbeta5gm, beta5BIASgm) ; RMSEbeta5gm = c(RMSEbeta5gm, beta5RMSEgm)
VARbeta6gm = c(VARbeta6gm, beta6Bgm); ABSBbeta6gm = c(ABSBbeta6gm, beta6ABSgm)
BIASbeta6gm = c(BIASbeta6gm, beta6BIASgm) ; RMSEbeta6gm = c(RMSEbeta6gm, beta6RMSEgm)

# To estimate BIASES

#OLS#
BIASbeta1 = c(BIASbeta1, beta1BIAS) # For OLS
BIASbeta2 = c(BIASbeta2, beta2BIAS) # For OLS
BIASbeta3= c(BIASbeta3, beta3BIAS) # For OLS
BIASbeta4 = c(BIASbeta4, beta4BIAS) # For OLS
BIASbeta5 = c(BIASbeta5, beta5BIAS) # For OLS
BIASbeta6= c(BIASbeta6, beta6BIAS) # For OLS

## WLS##
BIASbeta1w = c(BIASbeta1w, beta1BIASw)
BIASbeta2w = c(BIASbeta2w, beta2BIASw)
BIASbeta3w = c(BIASbeta3w, beta3BIASw)
BIASbeta4w = c(BIASbeta4w, beta4BIASw)
BIASbeta5w = c(BIASbeta5w, beta5BIASw)
BIASbeta6w = c(BIASbeta6w, beta6BIASw)

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SUR

BIASbeta1S = c(BIASbeta1S, beta1BIASS)

BIASbeta2S = c(BIASbeta2S, beta2BIASS)

BIASbeta3S = c(BIASbeta3S, beta3BIASS)

BIASbeta4S = c(BIASbeta4S, beta4BIASS)

BIASbeta5S = c(BIASbeta5S, beta5BIASS)

BIASbeta6S = c(BIASbeta6S, beta6BIASS)

MM-Bisq

BIASbeta1bsq = c(BIASbeta1bsq, beta1BIASbsq)

BIASbeta2bsq = c(BIASbeta2bsq, beta2BIASbsq)

BIASbeta3bsq = c(BIASbeta3bsq, beta3BIASbsq)

BIASbeta4bsq = c(BIASbeta4bsq, beta4BIASbsq)

BIASbeta5bsq = c(BIASbeta5bsq, beta5BIASbsq)

BIASbeta6bsq = c(BIASbeta6bsq, beta6BIASbsq)

Huber

BIASbeta1H = c(BIASbeta1H, beta1BIASH)

BIASbeta2H = c(BIASbeta2H, beta2BIASH)

BIASbeta3H = c(BIASbeta3H, beta3BIASH)

BIASbeta4H = c(BIASbeta4H, beta4BIASH)

BIASbeta5H = c(BIASbeta5H, beta5BIASH)

BIASbeta6H = c(BIASbeta6H, beta6BIASH)

W2SLS##

BIASbeta1w2 = c(BIASbeta1w2, beta1BIASw2)

BIASbeta2w2 = c(BIASbeta2w2, beta2BIASw2)

BIASbeta3w2 = c(BIASbeta3w2, beta3BIASw2)

BIASbeta4w2 = c(BIASbeta4w2, beta4BIASw2)

BIASbeta5w2 = c(BIASbeta5w2, beta5BIASw2)

BIASbeta6w2 = c(BIASbeta6w2, beta6BIASw2)

GMM

BIASbeta1gm = c(BIASbeta1gm, beta1BIASgm)

BIASbeta2gm = c(BIASbeta2gm, beta2BIASgm)

```

BIASbeta3gm = c(BIASbeta3gm, beta3BIASgm)
BIASbeta4gm = c(BIASbeta4gm, beta4BIASgm)
BIASbeta5gm = c(BIASbeta5gm, beta5BIASgm)
BIASbeta6gm = c(BIASbeta6gm, beta6BIASgm)
All.BIAS = cbind(beta1BIAS, beta2BIAS, beta3BIAS,beta4BIAS, beta5BIAS, beta6BIAS,
  beta1BIASw, beta2BIASw, beta3BIASw,beta4BIASw, beta5BIASw, beta6BIASw,
  beta1BIASS, beta2BIASS, beta3BIASS,beta4BIASS, beta5BIASS, beta6BIASS,
  beta1BIASbsq, beta2BIASbsq, beta3BIASbsq,beta4BIASbsq, beta5BIASbsq,beta6BIASbsq,
  beta1BIASH, beta2BIASH, beta3BIASH,beta4BIASH, beta5BIASH,beta6BIASH,
  beta1BIASw2, beta2BIASw2, beta3BIASw2,beta4BIASw2, beta5BIASw2, beta6BIASw2,
  beta1BIASgm, beta2BIASgm, beta3BIASgm,beta4BIASgm, beta5BIASgm, beta6BIASgm)
#All.BIAS = cbind(BIASbeta1, BIASbeta2, BIASbeta3,BIASbeta4, BIASbeta5, BIASbeta6,
  # BIASbeta1w, BIASbeta2w, BIASbeta3w,BIASbeta4w, BIASbeta5w, BIASbeta6w,
  # BIASbeta1S, BIASbeta2S, BIASbeta3S,BIASbeta4S, BIASbeta5S, BIASbeta6S,
  #BIASbeta1tw, BIASbeta2tw, BIASbeta3tw,BIASbeta4tw, BIASbeta5tw,BIASbeta6tw,
  #BIASbeta1tr, BIASbeta2tr, BIASbeta3tr,BIASbeta4tr, BIASbeta5tr,BIASbeta6tr,
  #BIASbeta1w2, BIASbeta2w2, BIASbeta3w2,BIASbeta4w2, BIASbeta5w2, BIASbeta6w2,
  #BIASbeta1gm, BIASbeta2gm, BIASbeta3gm,BIASbeta4gm, BIASbeta5gm, BIASbeta6gm)
  mat7[i,] = All.BIAS
}
criteria = c(var(VARbeta1),mean(BIASbeta1), mean(ABSBbeta1), sqrt(mean(RMSEbeta1)),
  mean(beta1Estim), True[1], var(VARbeta2),mean(BIASbeta2), mean(ABSBbeta2),
  sqrt(mean(RMSEbeta2)), mean(beta2Estim), True[2], var(VARbeta3),mean(BIASbeta3),
  mean(ABSBbeta3), sqrt(mean(RMSEbeta3)), mean(beta3Estim), True[3],
  var(VARbeta4),mean(BIASbeta4), mean(ABSBbeta4), sqrt(mean(RMSEbeta4)),
  mean(beta4Estim), True[4], var(VARbeta5),mean(BIASbeta5), mean(ABSBbeta5),
  sqrt(mean(RMSEbeta5)), mean(beta5Estim), True[5],
  var(VARbeta6),mean(BIASbeta6),
  mean(ABSBbeta6), sqrt(mean(RMSEbeta6)), mean(beta6Estim), True[6])
criteria1 = c(var(VARbeta1w),mean(BIASbeta1w), mean(ABSBbeta1w), sqrt(mean(RMSEbeta1w)),
  mean(beta1Estimw), True[1], var(VARbeta2w),mean(BIASbeta2w), mean(ABSBbeta2w),
  sqrt(mean(RMSEbeta2w)), mean(beta2Estimw), True[2], var(VARbeta3w),mean(BIASbeta3w),
  mean(ABSBbeta3w), sqrt(mean(RMSEbeta3w)), mean(beta3Estimw), True[3],

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```

var(VARbeta4w),mean(BIASbeta4w), mean(ABSBbeta4w), sqrt(mean(RMSEbeta4w)),
mean(beta4Estimw), True[4], var(VARbeta5w),mean(BIASbeta5w), mean(ABSBbeta5w),
sqrt(mean(RMSEbeta5w)), mean(beta5Estimw), True[5], var(VARbeta6w),mean(BIASbeta6w),
mean(ABSBbeta6w), sqrt(mean(RMSEbeta6w)), mean(beta6Estimw), True[6])
criteria2 = c(var(VARbeta1S),mean(BIASbeta1S), mean(ABSBbeta1S), sqrt(mean(RMSEbeta1S)),
mean(beta1EstimS), True[1], var(VARbeta2S),mean(BIASbeta2S), mean(ABSBbeta2S),
sqrt(mean(RMSEbeta2S)), mean(beta2EstimS), True[2], var(VARbeta3S),mean(BIASbeta3S),
mean(ABSBbeta3S), sqrt(mean(RMSEbeta3S)), mean(beta3EstimS), True[3],
var(VARbeta4S),mean(BIASbeta4S), mean(ABSBbeta4S), sqrt(mean(RMSEbeta4S)),
mean(beta4EstimS), True[4], var(VARbeta5S),mean(BIASbeta5S), mean(ABSBbeta5S),
sqrt(mean(RMSEbeta5S)), mean(beta5EstimS), True[5], var(VARbeta6S),mean(BIASbeta6S),
mean(ABSBbeta6S), sqrt(mean(RMSEbeta6S)), mean(beta6EstimS), True[6])
criteria3 = c(var(VARbeta1w2),mean(BIASbeta1w2), mean(ABSBbeta1w2), sqrt(mean(RMSEbeta1w2)),
mean(beta1Estimw2), True[1], var(VARbeta2w2),mean(BIASbeta2w2), mean(ABSBbeta2w2),
sqrt(mean(RMSEbeta2w2)), mean(beta2Estimw2), True[2], var(VARbeta3w2),mean(BIASbeta3w2),
mean(ABSBbeta3w2), sqrt(mean(RMSEbeta3w2)), mean(beta3Estimw2), True[3],
var(VARbeta4w2),mean(BIASbeta4w2), mean(ABSBbeta4w2), sqrt(mean(RMSEbeta4w2)),
mean(beta4Estimw2), True[4], var(VARbeta5w2),mean(BIASbeta5w2), mean(ABSBbeta5w2),
sqrt(mean(RMSEbeta5w2)), mean(beta5Estimw2), True[5], var(VARbeta6w2),mean(BIASbeta6w2),
mean(ABSBbeta6w2), sqrt(mean(RMSEbeta6w2)), mean(beta6Estimw2), True[6])
criteria4 = c(var(VARbeta1bsq),mean(BIASbeta1bsq), mean(ABSBbeta1bsq), sqrt(mean(RMSEbeta1bsq)),
mean(beta1Estimbsq), True[1], var(VARbeta2bsq),mean(BIASbeta2bsq), mean(ABSBbeta2bsq),
sqrt(mean(RMSEbeta2bsq)), mean(beta2Estimbsq), True[2], var(VARbeta3bsq),mean(BIASbeta3bsq),
mean(ABSBbeta3bsq), sqrt(mean(RMSEbeta3bsq)), mean(beta3Estimbsq), True[3],
var(VARbeta4bsq),mean(BIASbeta4bsq), mean(ABSBbeta4bsq), sqrt(mean(RMSEbeta4bsq)),
mean(beta4Estimbsq), True[4], var(VARbeta5bsq),mean(BIASbeta5bsq), mean(ABSBbeta5bsq),
sqrt(mean(RMSEbeta5bsq)), mean(beta5Estimbsq), True[5], var(VARbeta6bsq),mean(BIASbeta6bsq),
mean(ABSBbeta6bsq), sqrt(mean(RMSEbeta6bsq)), mean(beta6Estimbsq), True[6])
criteria5 = c(var(VARbeta1H),mean(BIASbeta1H), mean(ABSBbeta1H), sqrt(mean(RMSEbeta1H)),
mean(beta1EstimH), True[1], var(VARbeta2H),mean(BIASbeta2H), mean(ABSBbeta2H),
sqrt(mean(RMSEbeta2H)), mean(beta2EstimH), True[2], var(VARbeta3H),mean(BIASbeta3H),
mean(ABSBbeta3H), sqrt(mean(RMSEbeta3H)), mean(beta3EstimH), True[3],

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var(VARbeta4H),mean(BIASbeta4H), mean(ABSBbeta4H), sqrt(mean(RMSEbeta4H)),
mean(beta4EstimH), True[4], var(VARbeta5H),mean(BIASbeta5H), mean(ABSBbeta5H),
sqrt(mean(RMSEbeta5H)), mean(beta5EstimH), True[5], var(VARbeta6H),mean(BIASbeta6H),
mean(ABSBbeta6H), sqrt(mean(RMSEbeta6H)), mean(beta6EstimH), True[6])
criteria6 = c(var(VARbeta1gm),mean(BIASbeta1gm), mean(ABSBbeta1gm), sqrt(mean(RMSEbeta1gm)),
mean(beta1Estimgm), True[1], var(VARbeta2gm),mean(BIASbeta2gm), mean(ABSBbeta2gm),
sqrt(mean(RMSEbeta2gm)), mean(beta2Estimgm), True[2], var(VARbeta3gm),mean(BIASbeta3gm),
mean(ABSBbeta3gm), sqrt(mean(RMSEbeta3gm)), mean(beta3Estimgm), True[3],
var(VARbeta4gm),mean(BIASbeta4gm), mean(ABSBbeta4gm), sqrt(mean(RMSEbeta4gm)),
mean(beta4Estimgm), True[4], var(VARbeta5gm),mean(BIASbeta5gm), mean(ABSBbeta5gm),
sqrt(mean(RMSEbeta5gm)), mean(beta5Estimgm), True[5], var(VARbeta6gm),mean(BIASbeta6gm),
mean(ABSBbeta6gm), sqrt(mean(RMSEbeta6gm)), mean(beta6Estimgm), True[6])

mat = matrix(criteria, ncol = 6, nrow = 6,byrow=T)

rownames(mat) <- c("OLS_Beta1", "OLS_Beta2","OLS_Beta3","OLS_Beta4","OLS_Beta5","OLS_Beta6")

colnames(mat) <- c("VARIANCE"," BIAS","ABSOLUTE_BIAS", "RMSE", "Parameter Estimates", "True
Values")

mat1 = matrix(criteria1, ncol = 6, nrow = 6,byrow=T)

rownames(mat1) <- c("WLS_Beta1",
"WLS_Beta2","WLS_Beta3","WLS_Beta4","WLS_Beta5","WLS_Beta6")

colnames(mat1) <- c("VARIANCE"," BIAS","ABSOLUTE_BIAS", "RMSE", "Parameter Estimates", "True
Values")

mat2 = matrix(criteria2, ncol = 6, nrow = 6,byrow=T)

rownames(mat2) <- c("SUR_Beta1", "SUR_Beta2","SUR_Beta3","SUR_Beta4","SUR_Beta5","SUR_Beta6")

colnames(mat2) <- c("VARIANCE"," BIAS","ABSOLUTE_BIAS", "RMSE", "Parameter Estimates", "True
Values")

mat3 = matrix(criteria3, ncol = 6, nrow = 6,byrow=T)

rownames(mat3) <- c("W2SLS_Beta1",
"W2SLS_Beta2","W2SLS_Beta3","W2SLS_Beta4","W2SLS_Beta5","W2SLS_Beta6")

colnames(mat3) <- c("VARIANCE"," BIAS","ABSOLUTE_BIAS", "RMSE", "Parameter Estimates", "True
Values")

mat4 = matrix(criteria4, ncol = 6, nrow = 6,byrow=T)

rownames(mat4) <- c("MM bi-square_Beta1", "MM bi-square_Beta2","MM bi-square_Beta3","MM bi-
square_Beta4","MM bi-square_Beta5","MM bi-square_Beta6")

colnames(mat4) <- c("VARIANCE"," BIAS","ABSOLUTE_BIAS", "RMSE", "Parameter Estimates", "True
Values")

mat5 = matrix(criteria5, ncol = 6, nrow = 6,byrow=T)

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rownames(mat5) <- c("HUBER-M_Beta1", "HUBER-M_Beta2", "HUBER-M_Beta3", "HUBER-
M_Beta4", "HUBER-M_Beta5", "HUBER-M_Beta6")

colnames(mat5) <- c("VARIANCE", "BIAS", "ABSOLUTE_BIAS", "RMSE", "Parameter Estimates", "True
Values")

mat6 = matrix(criteria6, ncol = 6, nrow = 6, byrow=T)

rownames(mat6) <- c("GMM_Beta1",
"GMM_Beta2", "GMM_Beta3", "GMM_Beta4", "GMM_Beta5", "GMM_Beta6")

colnames(mat6) <- c("VARIANCE", "BIAS", "ABSOLUTE_BIAS", "RMSE", "Parameter Estimates", "True
Values")

return(list("OLS_RESULTS" = mat, "SUR_RESULTS" = mat2, "HUBER-M_RESULTS" = mat5, "MM bi-
square_RESULTS" = mat4, "GMM_RESULTS" = mat6))

#,"WLS_RESULTS" = mat1, "W2SLS_RESULTS" = mat3)) #, "ALL_BIASES" = mat7))

}

MRAF(20,1000)

```