THE BAYESIAN APPROACH TO ESTIMATION OF MULTI-EQUATION ECONOMETRIC MODELS IN THE PRESENCE OF MULTICOLLINEARITY

BY

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ABSTRACT

The Bayesian approach conveys information not available in the data but on prior knowledge of the subject matter, which enables one to make probability statements about the parameters of interest, while the classical approaches deals solely with the data. Several researches on the classical approaches have shown them to be sensitive to multicollinearity, a violation of one of the assumptions of multi-equation models which often plagues economic variables. Studies on the performance of the Bayesian method in this context are however limited. This study was aimed at investigating the performance of the Bayesian approach in estimating multi-equation models in the presence of multicollinearity.

The purely just- and over-identified multi-equation models were considered. In both cases, the normal distribution with zero mean and large variance served as locally-uniform prior for the regression coefficients. Three Bayesian Method Prior Variances (BMPV) were specified as 10, 100 and 1000 in a Monte Carlo prior variance sensitivity analysis. The Wishart distribution with zero degree of freedom served as prior distribution for inverse of error variance-covariance matrix, being its conjugate. The posterior distributions for the two models were then derived from the prior distributions and the likelihood functions as a bivariate Student-t and generalized Student-t distributions respectively. The estimates were then compared with those from the classical estimators; Ordinary Least Squares (OLS), Two stage Least Squares (2SLS), Three stage Least Squares (3SLS) and Limited Information Maximum Likelihood (LIML). Samples of sizes T=20, 40, 60, and 100 in 5000 replicates were generated based on eight specified research scenario. The Mean Squared Error (MSE) of the estimates were computed and used as evaluation criteria.

The BMPV 10 produced the least MSE in the prior variance sensitivity analysis for the over-identified model, whereas for the just-identified model without multicollinearity, BMPV 100 was the smallest. The Bayesian method was better in the small sample cases $T \leq 40$ than the classical estimators for β (the coefficient of the exogenous variable in the just-identified model); when T=20, MSE for BMPV 10, 100 and 1000 were 0.169, 0.168 and 0.171 respectively, whereas OLS, 2SLS, 3SLS and LIML yielded same results; 0.244, when T=40, BMPV 10, 100 and 1000 were 0.1220, 0.1272, 0.1361 respectively and 0.1262 for the classical methods. The 2SLS and 3SLS estimates of γ (coefficient of the endogenous explanatory variable) which were the same in the over-identified model had smaller MSE than the Bayesian method; when T=20, MSE for 2SLS/3SLS =0.0280, whereas BMPV 10=0.0286, BMPV 100 = 0.0300, and BMPV 1000 = 0.033. The Bayesian method was less sensitive to multicollinearity in estimating coefficients of the correlated exogenous variables; MSE (T=20) for BMPV 10, 100, and 1000 were 0.4529, 0.5220, 0.5290 respectively, while it was 0.7492 for the classical estimators. The MSE of LIML (0.0036) was similar to that of BMPV 100 (0.0036) and BMPV 1000 (0.0036) in large sample case $T = 100$ for γ.

Bayesian approach was suitable for estimating the parameters of exogenous variables in the small sample cases when the model is purely just-identified, and in over-identified model in the presence of multicollinearity.

Keywords: Bayesian approach, Prior distribution, Multicollinearity, Mean squared error

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DEDICATION

To God Almighty.

To My husband and my son

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CERTIFICATION

This is to certify that this research work was carried out by Dorcas Modupe Oyebisi OKEWOLE matriculation number 86624, under my supervision.

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CHAPTER ONE

GENERAL BACKGROUND

1.0 Introduction

In investigating and analyzing relationships amongst variables, it is often necessary to use equations, some of which could be single linear and non-linear, while others are multiple, also linear and non-linear, depending on the variables involved and the type of relationship connecting them. The simple linear model describes a direct relationship between a dependent variable, Y, and only one independent variable, X, where the independent variable is believed to be able to predict the values of the dependent variable. It can be represented as follows;

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \qquad (1.1)$$

Where:

Y_i is the i^{th} observation on the dependent variable

β_0 *and* β_1 are parameters, the regression coefficients

X_i is the i^{th} observation on the independent or predictor variable, whose values are assumed to be fixed.

ε_i is the random error term, with the assumption that the mean $E(\varepsilon_i) = 0$, constant variance $\sigma^2(\varepsilon_i) = \sigma^2$ and covariance of ε_i and ε_j equals zero (i.e., $\sigma(\varepsilon_i, \varepsilon_j) = 0$ for all $i, j; i \neq j$), $i = 1, 2, ..., T$. The assumption of fixed values for X_i also implies that they are uncorrelated with the random error term ε_i

The linear relationship implies that X_i is in the first power and no parameter $(\beta_0$ *and* $\beta_1)$ appears as exponent, neither is it divided by or multiplied by another parameter.

Multiple linear regression involves the case where two or more predictors jointly explain the variation in the dependent variable. It deals with the situation where only one predictor X will be inadequate for predicting the dependent variable Y. The general form of a multiple linear regression model can be written as;

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \varepsilon_i \qquad (1.2)$$

Where the terms are as defined for simple linear model with an extension of the predictor variables to k. There is an additional assumption that the predictors are not strongly correlated among themselves, i.e., no multicollinearity.

The non-linear model is however non-linear in the parameters of the model, they include but not limited to; exponential functions, logistic functions, trigonometric functions, power functions, and Gaussian functions. An important feature of the non linear regression is that the number of parameters is not necessarily directly linked with the number of independent (X) variables in the model. If only one independent variable is involved, then it is a simple non- linear model while the multiple non-linear models extend to more than one independent variable.

The nature of some economic variables however requires multi-equation systems. These include general linear models, Vector Auto-Regressive (VAR) models, Seemingly Unrelated Regression (SUR) models, and Simultaneous Equations Econometric Models (SEM). Haavelmo (1943) presented some important statistical implications of a linear simultaneous equation model, such as estimation of the stochastic equations which should not be done separately; the restrictions imposed upon the same variables by other equations ought to be taken into consideration. The SEM are multi-equation systems that are most commonly applied to economic variables due to their nature. It allows an “explanatory” variable (exogenous or predetermined) in one equation to be treated as “dependent” variable (endogenous) in another equation. A general form of M structural equations at time t, containing M endogenous (jointly dependent) variables $y_1, y_2, \cdots, y_M$ and K predetermined variables $X_1, X_2, \cdots, X_K$ may be written as;

$$\gamma_{i1} y_{1t} + \gamma_{i2} y_{2t} + \cdots + \gamma_{iM} y_{Mt} + \beta_{i1} X_{1t} + \beta_{i2} X_{2t} \cdots + \beta_{iK} X_{Kt} = U_{it} \qquad (1.3)$$

$i = 1, 2, \cdots, M \quad t = 1, 2, \cdots, T$

In matrix form, (1.3) can be written as;

$$\Gamma y_t + \beta X_t = U_t \qquad (1.4)$$

Where Γ is an M x M matrix of coefficients of endogenous variables, β is an M x K matrix of coefficients of predetermined variables, y_t, X_t and U_t are column vectors of M, K and M elements respectively. The parameters and variables of the model (1.4) are written in detail below;

$$\Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1M} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2M} \\ \vdots & \vdots & & \vdots \\ \gamma_{M1} & \gamma_{M2} & \cdots & \gamma_{MM} \end{bmatrix}, \qquad \beta = \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1K} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{21} \\ \vdots & \vdots & & \vdots \\ \beta_{M1} & \beta_{M2} & \cdots & \beta_{MK} \end{bmatrix}$$

$$y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{Mt} \end{bmatrix}, \quad X_t = \begin{bmatrix} X_{1t} \\ X_{2t} \\ \vdots \\ X_{Kt} \end{bmatrix}, \quad U_t = \begin{bmatrix} U_{1t} \\ U_{2t} \\ \vdots \\ U_{Mt} \end{bmatrix}$$

The system of equations (1.3) represents the structural specification of a model containing systems of equations that jointly determine the M endogenous variables at time t, in terms of the predetermined variables X_{it} and the values of the random disturbance terms U_{it} $i = 1, 2, ..., k$. Identification of each equation requires that some of the $M + K$ parameters

$(\gamma_{i1}, \gamma_{i2}, \cdots, \gamma_{iM}, \beta_{i1}, \beta_{i2}, \cdots, \beta_{iK})$ of model (1.3) be specified to be zero.

One of the basic assumptions of the model is that the regressors (exogenous or explanatory variables) should be non-correlated among themselves. The violation of this assumption is referred to as Multicollinearity. The cause, effect, diagnostics and possible remedies are discussed in chapter three.

Various estimation approaches are used in the literature for multi-equation models, such as; the Ordinary Least Squares (OLS), Indirect Least Squares (ILS), Two-Stage Least Squares (2SLS), Three-Stage Least Squares (3SLS)], Limited Information Maximum Likelihood (LIML) and Full Information Maximum Likelihood (FIML)], and the Bayesian estimation approach. The OLS, ILS, 2SLS, 3SLS, LIML, and FIML are referred to as classical estimators. Dreze (1962) argued that such classical inferences have shortcomings in that; the available information on parameters is ignored. This classical estimation method has gained a lot of attention in literature and has been so much applied in research activities; while research on the Bayesian method as well as its applications, particularly in multi-equation systems has only of recent being on the increase. The Bayesian inference combines the prior information on the parameter of interest with the likelihood function to give the posterior value. The Posterior distribution thus provides updated information on the parameter(s) under study.

Generally, econometric models are often expressed in terms of an unknown vector of parameters $\underline{\theta} \in \Theta \subseteq R^k$ which fully specifies the joint probability distribution of the observations $X = (\underline{x}_1, \underline{x}_2 \cdots, \underline{x}_t)$. Given the probability density function $f(X / \underline{\theta})$, the classical estimation often proceeds by making use of the likelihood function $L(\underline{\theta}) = f(X / \underline{\theta})$, while the Bayesian estimation technique combines the likelihood function with the prior information which is usually expressed as probability density function of the parameters, $\pi(\underline{\theta})$. This gives the posterior distribution, which is proportional to $p(\underline{\theta}) = \pi(\underline{\theta}) L(\underline{\theta})$. Most Bayesian inference problems, according to Geweke (1989), can be seen as evaluation of the expectation of a function $u(\underline{\theta})$ of interest under the posterior,

$$E[u(\underline{\theta})] = \int_{\Re} u(\underline{\theta}) p(\underline{\theta}) d(\underline{\theta}) / \int_{\Re} p(\underline{\theta}) d(\underline{\theta}) \qquad (1.5)$$

Methods of solving this problem (1.5) are not as systematic, methodical or general as are those of classical inference problems because classical inference is carried out routinely using likelihood functions for which the evaluation of (1.5) is difficult and for most practical purposes impossible. The problem with the analytical integration of (1.5) is that the range of likelihood functions of interest that can be considered is small, and the class of priors and functions of interest that can be considered is severely restricted. Also, many numerical approaches like quadrature methods require special adaptation for each u, π or L and become unworkable for large number of parameters (k > 3).

However, with the advent of powerful and cheap computing, numerically intensive methods for solving (1.5) have become more interesting. This is where Monte Carlo integration comes in as a way out, particularly the Markov Chain Monte Carlo (MCMC), which involves Gibbs sampling. It provides a systematic approach that, in principle, can be applied in any situation in which $E[u(\underline{\theta})]$ exists, and is practical for large values of k. In this regard, the works of Geweke (1989), Gilks, Richardson and Spiegelhalter (1996), Gao and Lahiri (2001) among others are of note. WinBUGS (Bayesian Analysis using Gibbs sampling) used for the Bayesian analysis in this project is a software developed on this principle by a group of researchers from the Biostatistics Unit at the Medical Research council (MRC) Cambridge, and Imperial College School of medicine, London. A comparative study of the classical and the Bayesian approaches is necessary so as to take advantage of their strength and research more on possible ways of improving on their weaknesses. This work is a follow up on some of the studies that have been carried out in this regard; Zellner (1971) presented a Monte Carlo study of both Classical and Bayesian methods of a just-identified simultaneous equations model estimation. 50 replications were carried out in the experiment by Zellner and the results indicated that the Bayesian method performs better than the classical method mostly in the small sample case. Gao and Lahiri (2001) carried out a Monte Carlo study of limited information simultaneous equations with weak instruments. They compare the Classical and the Bayesian methods and found that no estimator was superior in cases with very weak instruments. Kleibergen and Zivot (2003) presented a detailed analytical study on the Bayesian and Classical approaches to instrumental variable regression, with focus also on weak instruments. They showed the form of priors that lead to posteriors for structural parameters having similar properties as classical 2SLS and LIML. This research work involves the use of Monte Carlo studies to investigate the performance of the Bayesian estimation method particularly in the presence of multicollinearity. The essence of a Monte Carlo study is that various sets of parameter values are specified for postulated distributions underlying a model, repeated numerical selection from the resultant distributions yield a large number of finite samples; various estimating techniques are applied to these sample values and the sampling distributions of the estimates are studied in relation to the true parameter values and to theoretical expectations (Olubusoye, 2001). A locally uniform prior (represented by a normal distribution with zero mean and large variance) was used for the regression coefficients of the model and the Wishart distribution with zero degree of freedom for the variance-covariance matrix of the residual terms which reflects the state of little or no prior information assumed in this research work. The results were then compared with those from some classical methods: OLS, 2SLS, 3SLS and LIML, in the presence of multicollinearity and different level of identification (considering a just-identified and an over-identified model). The classical estimation methods are restricted to OLS, 2SLS, 3SLS and LIML because the focus of the research is particularly on the Bayesian approach.

1.1 Statement of Problem

The need for modelling issues with multi-equation models will always arise, with varying research scenarios. It is the usual practice to gather data and use any convenient applicable estimation method on it. However, this could lead eventually to wrong inferences if not properly handled. For instance, most classical methods are known to be sensitive to violations of basic assumptions underlying the model they estimate, such as multicollinearity which leads to large variances making estimates of the regression coefficients to be unstable. Also, while the classical method is easily applied with little mathematical rigours and has received much attention over the years, studies on the Bayesian approach when this assumption of orthogonality of regressors is violated are limited. A researcher then needs to be furnished with the information on the behaviour of the Bayesian method in this scenario. Two sets of two-equation models; the first model contains two structural equations that are both just-identified and the second contains one just-identified structural equation and one over-identified structural equation. Some research scenarios were then specified as follows:

The first model;

- Run (1) represents negatively correlated residual terms
- Runs (2) and (3) represent positively correlated residual terms with different distribution for X, the instrumental variable in the model

The second model

- Runs (1) and (2) representing high and low levels of multicollinearity respectively for two exogenous terms in the second equation with negative correlations between the residual terms of the two equations
- Runs (3) and (4) representing high and low levels of multicollinearity respectively for two exogenous terms in the second equation with positive correlations between the residual terms of the two equations

- Run (5) representing a higher level (than runs (1) and (3)) of multicollinearity for two exogenous terms in the second equation with positive correlations between the residual terms of the two equations

Three different prior variances, designated as Bayesian Method Prior Variance (BMPV) were also specified as follows for a Monte Carlo prior variance sensitivity analysis;

(1).Normally distributed with mean zero and precision 0.001 (variance 1000)

(2).Normally distributed with mean zero and precision 0.01(variance 100)

(3).Normally distributed with mean zero and precision 0.1 (variance 10)

The following research questions were then raised and treated:

(1) What is the form of the posterior distribution for the Bayesian estimator of the models?

(2) In which Research Scenario does the Bayesian estimator perform well?

(3) Is there any difference in the Bayesian estimates for different prior variance specifications?

(4) In which Research Scenario does each of the classical estimators perform well?

1.2 Justification

Multi-equation econometric models have wide range of applications in modelling various concepts of life. There are situations where modelling with multi-equation models describe the relationship between the variables of interest more appropriately than single equation. For instance, a study on birth inputs and outputs by Li and Poirier (2003) where some variables previously considered strictly exogenous were reconsidered as endogenous, thus yielding better results than the previous single equation analysis. In recent times, attention is being given also to the Bayesian estimation of multi-equation econometric models, but studies on the performance in the presence of violations of the basic assumptions of the model, particularly in the event of multicollinearity, are limited. We therefore consider it necessary to study the performance of Bayesian estimation of multi-equation econometric models in the presence of multicollinearity. The rationale for the prior variance sensitivity analysis is that the interpretation of "large variance" in the prior distribution for the regression coefficients might differ from one researcher to another. Also, the sample size and covariance of the residual terms were varied in other to give enough room for evaluating the performance of the estimators.

1.3 Aim and Objectives

This research is aimed at evaluating and presenting the performance of Bayesian approach to estimating the parameters of multi-equation econometric models in the presence of multicollinearity, for better understanding of its theory and use by applied users.

The specific objectives are:

(1) To derive the Bayesian estimator for the parameters of the multi-equations models

(2) To estimate the multi-equation models using the Bayesian method and the Classical methods.

(3) To assess the performance of the Bayesian approach as compared with the classical approach.

(4) To carry out a Monte Carlo prior variance sensitivity analysis

1.4 Organisation of the thesis

This thesis is presented in six chapters. The review of literature on multi-equation models, estimation methods; classical and Bayesian, as well as comparative studies on the two methods, follows this introductory chapter. The next chapter after the literature review is the theoretical framework for this research work. This chapter presents the specification of the models, the underlying assumptions and the Statistical theories of the various concepts involved

Chapter four contains the methodology, which is the step by step details of how the whole experiments was carried out, the tools used for analysis, how the results were obtained and other explanations on the Monte Carlo studies. Discussion of results follows in chapter five, where the results are presented, interpreted and discussed.

The last chapter, chapter six, is the summary and conclusion while the simulated data for the Monte Carlo experiment are contained in the appendix. Sub-programs written for the analysis are also in the appendix.

CHAPTER TWO

REVIEW OF LITERATURE

2.0 Introduction

This chapter contains a review of literature on developments of various types of multi-equation systems, Monte Carlo studies, Classical and Bayesian estimation of the multi-equation models, as well as studies on comparison of the two methods.

2.1 Multi-equation Systems

There are various types of models that combine multiple equations in a system. These systems of equations all point to the fact that some variables are better studied simultaneously for adequate and proper inference about them. Some of these models such as; general linear models, seemingly unrelated regression, vector auto-regressive models, and the simultaneous equations econometric models are discussed briefly in this section.

2.1.1 General linear models

The general linear model is an extension of the multiple linear regressions to the case of more than one dependent variable. The general linear model also has a wider scope than the multivariate regression model by allowing for linear transformations or linear combinations of multiple dependent variables. One advantage of this is that multivariate tests of significance can be employed when responses on multiple dependent variables are correlated. It allows for analysis such as; analysis of variance (ANOVA), analysis of covariance (ANCOVA), multivariate analysis of variance (MANOVA), as well as multivariate analysis of covariance (MANCOVA).

Its origin dates back to the 1800's at the emergence of the theory of algebraic invariants which has a lot of contributions to developments of Statistical theory. In the late 19th century, the development of linear regression model came up, and was followed shortly after by the correlation methods. These two, linear regression model and correlation methods, both form the basis for the general linear model. The general linear model has since then been researched into, although with more focus on the single dependent variable linear model. Specification and Classical Inference issues have been extensively discussed over the past few decades. Wallace (1964) presented a study on misspecification problem in linear models based on some related articles presented earlier; Freund et. al. (1961), Goldberger and Jochems (1961), Goldberger (1961) and Kabe (1961). It was shown that under certain conditions, the stepwise estimators were better than the direct least squares estimators for the two-explanatory variable case. Other issues bordering on inference have also being discussed in; Tarone (1976), Hilmar (1976), Hammerstrom (1981), Dietrich (1995), Elian (2000), and Graham (2008).

For n observations on m dependent variables each containing k independent/explanatory variables, the mathematical form of the general linear model can be written as;

$$Y_{ij} = \alpha_j + \sum \beta_{tj} X_{tj} + U_{ij} \qquad (2.1)$$

$i = 1, 2, ..., n,\ j = 1, 2, ..., m,\ t = 1, 2, ..., k,$

Where,

Y_{ij} is the i^{th} observation of the j^{th} dependent variable

X_{tj} is the t independent variable in the j^{th} dependent variable

α_j is the intercept of the j^{th} regression line on the corresponding Y-axis

β_{tj} is the regression coefficient of the t independent variable in the j^{th} dependent variable equation

U_{ij} is the random disturbance term associated with the j^{th} dependent variable equation.

The assumptions of the model are that the independent variables are fixed and also that the random disturbance terms are independently and normally distributed with zero mean vector and constant variance i.e., $U_{ij} \sim NIID(0, \Sigma)$

2.1.2 Vector Auto-regressive models (VAR)

Research work on vector autoregressive models started around 1980, an aftermath of a paper by Sim (1980). The objections earlier raised by various researchers to previously existing strategies for econometric analysis related to macroeconomics were discussed in this paper by Sims, where it was argued that those objections indicated that large macroeconomics models were not over identified as claimed by the builders of such models. He maintained that most of the restrictions on the models were false, the models were nominally over-identified and the spurious identification results in restrictions on the reduced form. He presented the implications of this; that on one hand, such restrictions on the reduced form need not distort the results of forecasting and policy analysis, and on the other hand, "the reduced form would be infected by false restrictions and may thereby become useless as a framework within which to do formal statistical tests of competing macroeconomics theories" Sims (1980). He then made a suggestion by using an example of a simple model where past values of a variable were used to predict its present value. After the work of Sims, more researches and discussions came up which started interests in vector autoregressive models. Tiao and Box (1981) made contributions by introducing vector autoregressive moving average. Litterman (1986) in his own contribution discussed the use of Bayesian approach in forecasting with Vector Autoregressive models, a model which places some restrictions on the parameters of the VAR models and very useful for prediction. A study on the maximum likelihood estimates of cointegrated systems was carried out by Phillips (1991), presenting a solution for problems of specification and inference. The VAR model is widely discussed and applied till date. Lutkepohl (1991), Watson (1994), Waggoner and Zha (1999) and Maddala and Lahiri (2009) are some of the texts containing a comprehensive discussion of Vector Auto-regressive models and issue associated with it. Applications of VAR models, for example, to financial data are given in Hamilton (1994), Cuthbertson (1996), and Tsay (2001).

Auto-regressive models can be described as models designed to specify the relationship between the present value of random variable and its past values. In other words, they attempt to predict an output of a system based on the previous outputs. Vector autoregressive model, as the word "vector" connotes, is then the extension of the univariate case to the multiple equations system. The design of a VAR model makes it natural tool for forecasting. It is used for the analysis of multivariate time series.

For m endogenous variables and p lags, the following represents the m equations of a VAR model in matrix form:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \varepsilon_t \qquad (2.2)$$

Where;

Y_t is an m x 1 vector of variables at time t,

$\alpha_i, i = 1, 2, \ldots, p,$ is a p x p matrix of coefficients, α_0 an m x 1 vector of the intercept

ε_t is an m x 1 vector of residuals

For better understanding of the structure of the model (2.2), a special case with two equations (m=2) and two lags (p=2) in each variable and without the intercept is given as;

$$\begin{aligned} Y_{1t} &= \alpha_{11} Y_{1,t-1} + \alpha_{12} Y_{1,t-2} + \varepsilon_{1t} \\ Y_{2t} &= \alpha_{21} Y_{2,t-1} + \alpha_{22} Y_{2,t-2} + \varepsilon_{2t} \end{aligned} \qquad (2.3)$$

2.1.3 Seemingly Unrelated Regression [SUR]

This model was proposed by Arnold Zellner (1962). More research works have been carried out on it since then such as; Kakwani (1967), Kamenta and Gilbert (1968), Phillips (1977), Baltagi (1980), Moon (1999), Moon and Perron (2004).

Seemingly unrelated regression model is a system of regression equations whereby, each equation is allowed to have different set of exogenous explanatory variables, such that it can be regarded as a generalization of the multivariate regression model. The name seemingly unrelated regression was given to this type of model because each equation is a valid linear regression that could be estimated separately. However, the relationship which brings the equations together in a system is from the assumption that the residual terms are correlated across the equations. The general form of a SUR model containing m equations each containing k_i exogenous variables, can be written as;

$$y_{it} = X_{it}'\beta_i + \varepsilon_{it},\ i = 1, 2, \ldots, m \tag{2.4}$$

Where i represents number of equation and $t = 1, 2, \ldots, T$ represents observation number, y_{it} is the response (dependent) variable for observation t in equation i, X_{it} is the set of k_i exogenous variables for equation i, β_i is the corresponding set of regression coefficients for equation i and ε_{it} is the residual term for equation i. For better clarification, equation (2.4) can also be written as;

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix} = \begin{pmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_m \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_m \end{pmatrix} \Rightarrow y = X\beta + \varepsilon \tag{2.5}$$

The assumptions of the model are;

(1) For each equation i, X_{it} is of full rank

(2) The residual terms ε_{it} are independently and identically distributed over time with mean zero and constant variance $\sum$ that is,

$$E(\varepsilon_{it}\varepsilon_{js} / X) = 0 \ when\ t \neq s$$
$$= \sigma_{ij} \ \text{otherwise}$$

Where σ_{ij} is the $(i, j)^{th}$ element of $\sum$.

The covariance matrix of the entire vector of disturbances $\varepsilon = (\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_m)$ is given as;

$$E(\varepsilon\varepsilon' / X) = \sum \otimes I_T$$

Where $\sum$ is of dimension mxm, $\otimes$ is kronecker product and I_T is identity matrix of dimension T

2.1.4 Simultaneous Equations Econometric models

Simultaneous equations model is a system of equations which describes the joint dependence of variables. If there is a two-way causation in a function, then the function cannot be treated in isolation as a single equation model, rather, it belongs to a wider system of equations describing the relationships among all the relevant variables. For instance, if $Y = f(X)$, and also $X = f(Y)$, a single equation is not appropriate to describe the relationship between Y and X, it requires the use of a multi-equation system. This multi-equation model includes separate equations in which Y and X appears as endogenous variables, and may also appear as explanatory variables in other equations of the model. Since most economic phenomena involve interactions among several variables, it is only appropriate to apply simultaneous equations model for such purposes. The term "simultaneous equations econometric model" is thus taken to mean a stochastic model that permits an investigator to make probabilistic statements about a set of random variables, that is, the endogenous variables (Zellner, 1971). A system of G simultaneous equations, has been given earlier in equation (1.3) of chapter one.

A general form of G structural equations at time t, containing G endogenous (jointly dependent) variables $y_1, y_2, \cdots, y_G$ and K predetermined variables $X_1, X_2, \cdots, X_K$ may be written as;

$$\sum_{j=1}^{G} y_{tj}\gamma_{ji} + \sum_{j=1}^{K} X_{tj}\beta_{ji} + \varepsilon_{ti} = 0, \quad i = 1,2,\ldots,G, \quad t = 1,2,\ldots,T \tag{2.6}$$

This is written in details as;

$$\begin{array}{l}
Y_{t1}\gamma_{11} + Y_{t2}\gamma_{21} + \ldots + Y_{tG}\gamma_{G1} + X_{t1}\beta_{11} + X_{t2}\beta_{21} + \ldots + X_{tK}\beta_{K1} + u_{t1} = 0 \\
Y_{t1}\gamma_{12} + Y_{t2}\gamma_{22} + \ldots + Y_{tG}\gamma_{G2} + X_{t1}\beta_{12} + X_{t2}\beta_{22} + \ldots + X_{tK}\beta_{K2} + u_{t2} = 0 \\
\qquad\qquad\qquad\qquad \vdots \\
\qquad\qquad\qquad\qquad \vdots \\
Y_{t1}\gamma_{1G} + Y_{t2}\gamma_{2G} + \ldots + Y_{tG}\gamma_{GG} + X_{t1}\beta_{1G} + X_{t2}\beta_{2G} + \ldots + X_{tK}\beta_{KG} + u_{tG} = 0
\end{array} \tag{2.7}$$

The equations as written in (2.7) indicate that there are G equations determining the G endogenous variables $y_{t1}, y_{t2}, \cdots, y_{tG}$, K predetermined variables $X_{t1}, X_{t2}, \cdots, X_{tK}$ and a random disturbance for each equation $\varepsilon_{t1}, \varepsilon_{t2}, \cdots, \varepsilon_{tG}$. There are a total of T observations on each variable. The γ_{ji}'s and β_{ji}'s are the structural coefficients. Equation (2.7) can be written in matrix form as follows;

$$Y\Gamma + XB + U = 0 \tag{2.8}$$

Y is a TxG matrix given as; $\begin{pmatrix} y_{11} & y_{12} & \cdots & y_{1G} \\ y_{21} & y_{22} & \cdots & y_{2G} \\ \vdots & \vdots & & \vdots \\ y_{T1} & y_{T2} & \cdots & y_{TG} \end{pmatrix}$ Γ a GxG matrix; $\begin{pmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1G} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2G} \\ \vdots & \vdots & & \vdots \\ \gamma_{G1} & \gamma_{G2} & \cdots & \gamma_{GG} \end{pmatrix}$,

X is a (TxK) matrix; $\begin{pmatrix} X_{11} & X_{12} & \cdots & X_{1K} \\ X_{21} & X_{22} & \cdots & X_{2k} \\ \vdots & \vdots & & \vdots \\ X_{T1} & X_{T2} & \cdots & X_{TK} \end{pmatrix}$, β a (KxG) matrix; $\begin{pmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1G} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2G} \\ \vdots & \vdots & & \vdots \\ \beta_{K1} & \beta_{K2} & \cdots & \beta_{KG} \end{pmatrix}$ and

U a (TxG) matrix; $\begin{pmatrix} u_{11} & u_{12} & \cdots & u_{1G} \\ u_{21} & u_{22} & \cdots & u_{2G} \\ \vdots & \vdots & & \vdots \\ u_{T1} & u_{T1} & \cdots & u_{TG} \end{pmatrix}$

(2.9)

Model (2.7) represents the structural specification of a model containing systems of equations that jointly determines the G endogenous variables at time t, in terms of the predetermined variables and the values of the random disturbance terms. Identification of each equation requires that some of the $G+K$ parameters

($\gamma_{i1}, \gamma_{i2}, \cdots, \gamma_{iG}, \beta_{i1}, \beta_{i2}, \cdots, \beta_{iK}$) of model (2.7) be specified to be zero.

The assumptions of the simultaneous equations model are:

(1) The assumption about the exogenous regressors or predetermined variable: it is assumed that the matrix of the exogenous regressors is of full rank, i.e., the number of independent columns of the matrix X is K

(2) The second assumption is the major one which is about the residual term U, the summary of this assumption is;

$$U \sim NIID(0, \Sigma) \tag{2.10}$$

The assumption as stated in (2.10) is made up of the following;

(i). $E(U)=0$. The expected value of the disturbance terms for any period t is equal to zero.

(ii).The variance-covariance matrix $\sum$ is given as;

$$\sum = E\left[UU'\right] = E\left[U_{it}U_{i^*t^*}\right]$$

$$= \begin{pmatrix}
\sigma_1^2 & 0 & \cdots & 0 & \sigma_{12} & 0 & \cdots & 0 & & \sigma_{1G} & 0 & \cdots & 0 \\
0 & \sigma_1^2 & \cdots & 0 & 0 & \sigma_{12} & \cdots & 0 & & 0 & \sigma_{1G} & \cdots & 0 \\
\vdots & & \ddots & \vdots & \vdots & & \ddots & \vdots & \cdots & \vdots & & \ddots & \\
0 & 0 & \cdots & \sigma_1^2 & 0 & 0 & \cdots & \sigma_{12} & & 0 & 0 & \cdots & \sigma_{1G} \\
\sigma_{21} & 0 & \cdots & 0 & \sigma_2^2 & 0 & \cdots & 0 & & \sigma_{2G} & 0 & \cdots & 0 \\
0 & \sigma_{21} & \cdots & 0 & 0 & \sigma_2^2 & & 0 & \cdots & 0 & \sigma_{2G} & & 0 \\
\vdots & & \ddots & & \vdots & & \ddots & & & \vdots & & \ddots & \\
0 & 0 & \cdots & \sigma_{21} & 0 & 0 & \cdots & \sigma_2^2 & & 0 & 0 & \cdots & \sigma_{2G} \\
 & \vdots & & & & \vdots & & & \cdots & & \vdots & & \\
\sigma_{G1} & 0 & \cdots & 0 & \sigma_{G1} & 0 & \cdots & 0 & & \sigma_G^2 & 0 & \cdots & 0 \\
0 & \sigma_{G1} & & 0 & 0 & \sigma_{G1} & & 0 & \cdots & 0 & \sigma_G^2 & & 0 \\
\vdots & & \ddots & \vdots & \vdots & & \ddots & & & \vdots & & \ddots & \\
0 & 0 & \cdots & \sigma_{G1} & 0 & 0 & \cdots & \sigma_{G1} & & 0 & 0 & \cdots & \sigma_G^2
\end{pmatrix}, \quad (2.11)$$

where $t = 1, 2, \ldots, T$, the sample size in each equation and $i =$ 1, 2,...,G

The interpretations of the variance-covariance matrix (2.11) are as follows;

(a). The variance of the residual term within an equation $i = i^*, t = t^*$ is constant, equal to σ_i^2 i. e., there is homoscedasticity.

(b).The covariance for different periods $t \neq t^*$ within an equation $i = i^*$ is zero, i. e., no autocorrelation

(c) The covariances of the same period $t = t^*$ but different equations $i \neq i^*$ are equal to σ_{ii^*} That is, contemporaneous covariances in different equations are independent of time periods, t)

(d).The covariances at different times $t \neq t^*$ for different equations $i \neq i^*$ are zero.

An important special case of the simultaneous equations econometric model is the fully recursive model defined as follows;

Fully recursive models: The matrix of coefficients for the endogenous variables, Γ, as given in equation (1.4), is triangular and the variance-covariance matrix of the disturbance term, $\sum$, is diagonal. The model is represented as;

$$
\begin{aligned}
y_1 &= X_1\beta_1 + u_1 \\
y_2 &= y_1\gamma_{21} + X_2\beta_2 + u_2 \\
y_3 &= y_1\gamma_{31} + y_2\gamma_{32} + X_3\beta_3 + u_3 \\
\vdots \quad & \vdots \quad \vdots \qquad \vdots \qquad \vdots \qquad \vdots \\
y_m &= y_1\gamma_{m1} + y_2\gamma_{m2} + \cdots + y_{m\text{-}1}\gamma_{m,m-1} + X_m\beta_m + u_m
\end{aligned}
\qquad (2.11)
$$

where y_j is an n x 1 vector of observations on the jth endogenous variable, X_j is an n x k_j matrix of rank k_j for the observations on k_j predetermined variables appearing in the jth equation, β_j is the k_j x 1 column vector of coefficients of the predetermined variables, the γ_{jl} are the scalar coefficients of the endogenous variables appearing as explanatory variables and u_j, j= 1, 2, . . . , m, are normally and independently distributed random disturbances with zero means. Also, the variance- covariance matrix is assumed in this model to be;

$$E(uu') = D(\sigma_j^2) \otimes I_n \qquad (2.12)$$

where $u' = (u_1^{'}, \ldots, u_m^{'})$ and $D(\sigma_j^2)$ is a diagonal matrix with σ_1^2, σ_2^2, . . . , σ_m^2 on the main diagonal. This, in addition to assumption of normality and independence, also means that disturbance terms in different equations have different variances.

The literature on simultaneous equations models is vast and keeps expanding. Haavelmo, T. (1943) was one of the earliest researchers. Various issues have been the subject of discourse over the decades; specification, identification, estimation and forecasting. Fisher (1961), Zellner et. al. (1966) and Nelson and Olson (1978) discussed issues of specification and estimation of the simultaneous equations models. Some other authors have presented research works on various estimators for the simultaneous equations model. For limited information maximum likelihood we have; Marino and Sawa (1972), Anderson (1974), Hendry (1976), Dent (1976), and Jennings (1980). Derivation of the exact distribution of the ordinary least squares and two-stage least squares estimators in a two-endogenous-variable equation were presented by Richardson (1968), and Sawa (1969). Further works on the two stage least squares as well as Ordinary least squares were also carried out by Anderson and Sawa (1973), Marino (1973a), Marino and McDonald (1979), Holly and Phillips (1979). Anderson and

Sawa (1979) compare the two-stage least squares and limited information maximum likelihood estimators and note major differences in small sample properties. Sargan and Mikhail (1971), Carter (1976), and Marino (1977) considered the distribution of instrumental variable estimators. Exact distributions of k-class estimators are derived by Anderson and Sawa (1973) and also provide an approximation. Marino (1973b) and Holly and Phillips (1979) provided alternative approximations. Moments of the k-class estimators were derived by Sawa (1972) and commented on by Mehta and Swamy (1978). Necessary and sufficient conditions for the existence of moments of k-class estimators were provided by Kinal (1980). Nagar (1959) and Kadane (1971) examine the moments of k-class estimators where error variances are small. Identification has also received a lot of attention, for example; Liu (1960), Fisher (1966), Rothenberg (1971), Richmond (1974), Kelly (1975), Fomby et. al.(1985). Stock and Wright (2000) developed asymptotic distribution theory for generalised method of moment (GMM) estimators and test Statistics when some or all the parameters are weakly identified. Some of these literatures are discussed in details later in this chapter.

2.2 Literature Review on Developments of the Bayesian theory

The origin of Bayesian theory could be traced to the source of the name: Reverend Thomas Bayes, an 18th century Mathematician and theologian. He wrote a paper titled "An Essay towards Solving a Problem in the Doctrine of chances", published in 1761, two years after his death. He presented a particular case of what is now known as of Bayes' theorem. However the Bayesian probability as it is known today was pioneered by Pierre-Simon Laplace. The developments of Bayesian theory was however slow for the first 200 years. Gradually, Bayesian researchers started increasing, more books were written and more articles published. For instance, discussing the development of the Bayesian theory in terms of books and articles published, Berger (2000) provided a very detailed record; possibly 15 books were written between 1769 and 1969, a guess of about 30 books from 1970-1989, and about 60 Bayesian books between 1990 and 1999. There were also more Bayesian conference proceedings, papers and Bayesian organisations from 1990 till date.

The application of the Bayesian theory cuts across several fields of research. Some references were made in Berger (2000) in terms of books and articles published in each field of application. Some of them are mentioned here; in the field of archaeology see Buck, Cavanaugh, and Litton (1996) ; in atmospheric sciences, there is Berliner, et. al. (1999); for application in education, see Johnson (1997); epidemiology, see Greenland (1998);

engineering, see Godsill and Rayner (1998); hydrology, see Parent, Hubert, Bobée and Miquel (1998); law, see DeGroot, Fienberg, and Kadane (1986). Application in medicine could be found in Berry and Stangl (1996); for physical sciences, see Bretthorst (1988). In Econometrics, some of the available books and journal articles on Bayesian theory are; Dreze (1962), Zellner (1965), Cyert and DeGroot (1987), Poirier (1995), Perlman and Blaug (1997), Kim, Shephard and Chib (1998), Kleibergen, F.& van Dijk, H.K., (1998), Geweke (1999, 2005), Lancaster (2004), Greenberg (2007), and, Koop, Poirier and Tobias (2007).

There are many approaches to Bayesian analysis. The most common ones are the objective, subjective, robust, frequentist-Bayes and quasi-Bayes approaches. Beginning with the first set of Bayesians, Bayes (1783) and Laplace (1812), who carried out Bayesian analysis using constant prior distribution for unknown parameters, Bayesian analysis has been taken as an objective theory. The use of uniform or flat prior, more generally known as noninformative, is a common objective Bayesian approach, Jeffrey's prior as presented in Jeffrey (1961) is the most popular in this school of thought. Although these priors are often referred to as noninformative prior, they also reflect certain informative features of the system being analysed, in fact, some Bayesians have argued that it rather be referred to as "weakly informative" prior for example, German et. al (2008). Another prior in the objective Bayesian approach is the maximum entropy priors. More recently, we also have the reference priors, these could be seen in Bernardo (1979) and Yang and Berger (1997). A review of ways of selecting noninformative priors could be found in Kass and Wasserman (1996). The fact that the objective Bayesian procedure involves the use of improper prior distributions which do not automatically have desirable Bayesian properties is a major concern. Moreover, the choice of improper priors can lead to improper posteriors requiring difficult evaluation techniques. Thus, proposed objective Bayesian procedures are typically studied to ensure that such problems do not arise.

The subjective Bayesian School is new on the Bayesian theory compared with other approaches. It is regarded by many Statisticians as appealing because the needed inputs (models and subjective prior distributions) can be fully and accurately specified. Although the difficulty in the specification often limits application of the approach (Kahneman, Slovic, and Tversky 1986), there has been a considerable research effort to further develop elicitation techniques for subjective Bayesian analysis (Lad, 1996). The situation with the subjective Bayesian approach is such that the subjective prior is essential in some problems, while in others it is readily available in which case it will bring about much gain. The Robust Bayesian analysis takes into consideration the fact that complete subjective specification of the model is impossible since it requires infinite number of assessments even in the simplest situation. Robust Bayesian approach thus involves the use of classes of models and classes of prior distributions, whereby the classes reflect the uncertainty remaining after the efforts at discovering and specifying the priors. Walley (1991) and Berger (1985, 1994) presented the foundational basis, history and developments of Robust Bayesian analysis. The robust Bayesian approach as reviewed in Berger (2000) is an attractive tool for implementing a general subjective Bayesian elicitation program. It is also useful in directing the elicitation effort for the subjective Bayesian analysis, by first assessing if the current information is sufficient for solving the problem and then, if not, determining which additional elicitations would be most valuable (Berger, 2000).

Another Bayesian approach school of thought is what one can refer to as the frequentist (classical) Bayes Analysis. This approach was presented in Berger (2000) as unification in Statistical theory and methods involving both Bayesian and frequentist approaches. Berger (2000) was of the opinion that Statistics will be discussed in the Bayesian sense since research activities over the years have proved that the only coherent language for discussing uncertainty, which Statistics seeks to measure, is the Bayesian language. In terms of methodology, both approaches are important in this unification. For instance, the Bayesian approach is considered to have an edge in terms of methodology for parametric problems while the frequentist approach can be useful in determining good objective Bayesian procedures. Also, in nonparametric studies, studies have shown the Bayesian approach to behave poorly by frequentist's standard (Diaconis and Freedman 1986). This should draw attention to the fact that something might be wrong somewhere especially when the information contained in the prior distribution is small compared to that which is "hidden" Another unification issue suggested by Berger (2000) was that there are many cases where frequentist arguments yield satisfactory answers easily, whereas Bayesian analysis requires more vigorous work. For example, in Markov Chain Monte Carlo (MCMC) where one evaluates an integral by a sample average rather than a formal Bayesian estimate. Berger (2000) suggested that frequentist answer be accepted by the Bayesians as an approximate Bayesian answer, although the appropriateness of this still needs to be verified. The need for unification from the frequentist perspective was also raised by Berger; that optimal unconditional frequentist procedures must be Bayesian even from a frequentist perspective (Berger, Boukai and Wang 1997).

The last of the Bayesian approaches discussed here is the Quasi-Bayesian approach. It is a type of Bayesian analysis where priors are chosen in various ad hoc methods, such as; choosing vague proper priors, choosing priors to span the range of likelihood, and choosing priors with tuning parameters that are adjusted until the answer "looks nice". Berger referred to such analyses as quasi-Bayes because, according to him, although they make use of Bayesian methods, they do not reflect the assurance of good performance that comes with either true subjective analysis or well studied objective Bayesian analysis. However, if handled by an expert Bayesian analyst, the quasi-Bayesian procedures can be quite reasonable, in that the expert may have the experience and skill to know when the procedures are likely to be successful. Also, there are many instances when results from the quasi-Bayes analysis could be trusted more than any other alternative.

Another important area in the development of the Bayesian Statistics is computation and software. The most serious challenge with the use of Bayesian method before now (about 20 years ago) was computational difficulties. This is because, Bayesian methods often involve calculation of posterior expectations that are complex or intractable numerical integration, to which analytical solution is not available. However, events have since overtaken this, because today, there are a number of numerical intensive softwares that can take care of the computational or even mathematical difficulties. In fact, presently, truly complex models in most cases can only be taken care of by the use of Bayesian techniques (Berger 2000). The usual methods for computing these posterior expectations have been the numerical integration, Laplace approximation and Monte Carlo importance sampling. Numerical integration can be carried out more effectively in problems with few dimensions, not more than 10 since the complexity increases with the dimension up to the point when it becomes impracticable. In the past years, computation of posterior expectations was traditionally carried out mostly by the use of Monte Carlo importance sampling. The method works well even for large dimensions and also has a good advantage of producing reliable measures of the accuracy of the computation. Specifically, there are methods that have been used to obtain Bayesian posterior estimates. The Maximum aposteriori approach is used to obtain the mode of the posterior distribution. It is most easily applicable to cases with conjugate prior where the posterior distributions are of the form that can be solved analytically. The maximum aposteriori estimate could also be obtained by; numerical optimization such as conjugate gradiant method or Newton's method; modification of an expectation-maximization algorithm which does not require derivatives of the posterior density; and also by Monte Carlo method. The Kalman filter is an algorithm that operates recursively on streams of input data containing random variations to produce a statistically optimal estimate of the parameter of interest. It was named after Rudolf E. Kalman, one of the developers of its theory. It is applicable to linear models having Gaussian distribution. Particle filter is another method of obtaining Bayesian posterior estimates. It is a sequential Monte Carlo method based on point mass (or filters) representations of probability densities which can be applied a model whether linear or non linear. It is a generalization of the kalman filter in that it can be applied to non-Gaussian models (Arulampalam, et. al., 2002).

In recent years (less than 20 years) the Markov Chain Monte Carlo (MCMC) method has become the most popular in carrying out the integration for obtaining the posterior point estimates. This is because of its ability to handle complex situations and the ease of programming compared to other methods. The approach usually employed by the MCMC method is to simulate draws of samples from the complex posterior distribution of interest.It has its roots in Metropolis Hastings algorithm (Metropolis and Ulam, 1949, Metropolis et. al. 1953) and also involves the use of Gibbs sampling as one of the ways of carrying out the simulation, discussions on this are presented in Gilks, et.al. (1996) and Chen, et. al.(2000). Softwares that make use of the MCMC approach are now available for carrying out Bayesian analysis more conveniently. Examples of such softwares are; the OpenBUGS consisting of WinBUGS and ClassicBUGS for Windows and Linux operating systems respectively (available at http://www.mrc-bsu.cam.ac.uk); BayesX (available at http://www.bayesx.org). A list of Bayesian software available before 1990 was provided by Press (1989), while those available from 1990 are presented in Berger (2000).

2.3 Monte Carlo Studies

This is a method used to draw parameter values from a distribution defined on the structural parameter space of an equation system. It is also used extensively in econometric studies; the experimental or researcher artificially sets up a system and specifies values for all exogenous variables and for the parameters using clearly defined assumptions. Sample sizes are specified for the experiment and values are generated for the random error term. Values are then calculated for the endogenous variables. With all the values on ground, the parameters are then treated as unknown and estimators are applied to estimate them. The whole experiment is replicated for a sufficiently large number of times. Estimates of each parameter from the various estimators used are then compared with their known values to evaluate their performance, using comparison criteria such as mean, bias, mean squared error, root mean squared error.

Monte Carlo could also be used when it is difficult to compute an exact result with a deterministic algorithm. It is one of the ways of determining how random variation, lack of knowledge or mis-specification affects the sensitivity, reliability or performance of the system being modelled. For instance, in Bayesian inference, an important advantage of the Monte Carlo is that a large number of posterior moments can be estimated at a reasonable computational effort. Also, estimates of the numerical accuracy of these results are obtained in a simple way (Kloek and Van Dijk ,1978).

Several Monte Carlo studies in Statistical inference have been and are still being carried out. This is because most studies on Statistical model estimation, if not analytical, will use the Monte Carlo approach. These Studies covers various fields of application of Statistical theory and methods. Some of such fields and corresponding articles on Monte Carlo studies are; **Bioinformatics:** Lin (2005); **Econometrics:** Zellner (1965, 1971), Olson, et. al. (1980), Banerjee, et. al. (1986), Andersen, et. al. (1999), Olubusoye (2001), Muthen and Muthen (2002), Oduntan (2004) and Adejumobi (2005); **Psychology:** Harwell et. al. (1996) and Chih-Ping et. al. (1991)

2.4 Review of Studies on Classical Estimation method For Multi-equation Models

Research on the analysis of simultaneous equations Econometric models has received a lot attention since its early proposal and suggestion by researchers such as Haavelmo (1943) who in his paper titled “The Statistical implications of a System of Simultaneous Equations” presented the need for simultaneous equations for model some variables. Majority of these studies have been on the classical estimation methods. Various issues have been raised, among which we have; problems and solutions to violation of the model assumptions, and performance of the different estimators under various conditions or research scenario. Some of these past works on studies of multi-equation models using the classical estimation techniques are highlighted and briefly discussed next.

(1) **Blomquist and Matz (1999)**

This study was focused on the performance of the 2SLS, LIML and four other new Jacknife IV estimators (Split sample Instrumental variable, unbiased split instrumental variable, jacknife instrumental variable and unbiased Jacknife instrumental variable) when the instruments are weak. Their results showed that LIML and the new estimators had smaller bias than the 2SLS but the variance for 2SLS was smaller. Their conclusion was that when instruments are weak, there was no easy way to obtain reliable estimates in small samples; the only way to increase precision was to make use of better instruments and also use large samples.

(2) **Olubusoye (2001)**

He analyzed a just-identified model. It was a study of the extent of the effect of inadvertent use of non-mutually independent normal deviates in earlier studies on the performance of the estimators of the simultaneous equations models. The estimators he considered were; the ordinary least squares (OLS), indirect least squares (ILS), two stage least squares (2SLS), three stage least squares (3SLS), Limited information maximum likelihood (LIML), and the full information maximum likelihood (FIML). Three arbitrarily fixed levels of correlation of the normal deviates were used; the negatively highly correlated, the feebly (positively or negatively) correlated, and the positively highly correlated. His result showed that the FIML estimator is more robust to extreme levels of inherent correlations between normal deviates than the least squares and the LIML estimators. He suggested that in simultaneous equations based comparison of the performance of estimators; only feebly correlated pairs of normal deviates should be used.

(3) **Oduntan (2004)**

This was a study on the performance of six estimators in the presence of multicollinearity in the explanatory variables of a just identified simultaneous equations Econometric model. The Ordinary least squares, indirect least squares, two stage least squares, three stage least squares, limited information maximum likelihood and full information maximum likelihood estimators were considered in his study. He used two levels of positive correlation among the three predetermined variables of his model; low multicollinearity (insignificant at the 5% level), and high multicollinearity (significant at the 1% level). His result also showed that when multicollinearity exists, whether low or high, indirect least squares and ordinary least squares had better performance, while others performed poorly. Also that the estimators were not sensitive to changing sample sizes and number of replications as levels of multicollinearity changes from low to high.

(4).Adejumobi (2005)

This work which is continuation of the work of Olubusoye (2001), was focused on the over-identified model estimation by the OLS, ILS, LIML, 2SLS, 3SLS and FIML. The study revealed that only the random disturbances obtained from the feebly negatively or positively correlated returned the specified variance-covariance matrix values. As expected, results from 2SLS and 3SLS were identical for the just-identified equation while 2SLS and LIML were identical for the over-identical equation. This result also showed that the magnitude of the OLS and 3SLS estimates exhibited fairly consistent reaction to changes in magnitude and direction of correlations of error terms.

(5). Agunbiade (2008)

It was an extension of the research by Oduntan (2004). A 3-equation just identified model was analysed with the OLS, ILS, LIML, 2SLS, 3SLS and FIML. The problem of Multicollinearity was also the focus, using three levels; the relatively highly negative correlation level of multicollinearity, relatively highly positive correlation level, and feebly negatively or positively correlation level. This work suggested that LIML, 2SLS and ILS were best for estimating parameters of a model having the relatively highly negative correlation level of multicollinearity while OLS performed poorly under this scenario but performed best in the relatively highly positive correlation level of multicollinearity. Compared with some earlier research, his work showed smaller biases and suggests that the higher number of equations and parameters may likely reduce the adverse effects of multicollinearity.

2.5 Review of Studies on Bayesian Estimation method For Multi-Equation models

The Bayesian inference area in Econometrics, which is more recent than the classical methods, is now being researched into extensively; prominent researchers in this area are Arnold zellner and J. Dreze. In the particular area of simultaneous equations models, the earliest of these papers is Dreze (1962). This and some of the other research works in the

Bayesian estimation of multi-equation models are highlighted and also briefly discussed in this section.

(1). Dreze (1962)

Dreze's argument was that the available information on an Economic variable is not supposed to be ignored but should be used for inference on it. It was an introduction into the use of the Bayesian method in Simultaneous equations estimation.

(2). Zellner (1965)

This is another one of the earliest papers advocating the use of Bayesian inference in Econometric model. Here, Zeller gave several reasons for the use of Bayesian inference in Econometrics. Some of these reasons are that; (1) the Bayesian approach yields finite sample results in estimating parameters of models, (2) It provides a systematic and flexible means of combining prior information and sample data, (3) The approach is convenient in the analysis of effects of departures from model assumptions. The posterior distributions of the parameters of the general simultaneous equations model were presented as well as results of some Monte Carlo experiments. Using a just-identified two equation model, he was able to show that in small samples, the Bayesian estimates are more highly concentrated about the true value of the coefficient being estimated.

(3). Chao and Phillips (1998)

These authors presented the use of Jeffreys prior in the Bayesian analysis of Simultaneous Equation Model (SEM) in their paper, focusing on the consequences of the use of this prior in Bayesian limited information analysis of the SEM. They derived the exact and asymtoptically approximate representations for the posterior density of the parameter of a limited information formulation of m-equation simultaneous equations model.

They obtained exact calculations for some special cases which have been extensively studied in classical literature on the exact finite-sample distributions of the LIML estimators. Their results showed that the use of a Jeffreys prior brings Bayesian inference closer to classical inference because, according to them, the posterior obtained through the use of this prior exhibit Cauchy-like tail behavior just like the LIML estimator. In particular, for a just-identified case which they analyzed, they showed that the posterior density derived under the

Jeffreys prior had the same functional form as the density of the exact finite sample distribution of the corresponding LIML estimator given in earlier studies.

(4). Kleibergen and Dijk (1998)

They based this paper on the problem of local non-identification leading to pathological behaviour of the posteriors when the diffuse prior is used in Bayesian analysis of SEM. Details of this behaviour were presented as well as a way of obtaining consistent Bayesian estimation for SEM that does not suffer from those pathologies. Their suggestion was the specification of the reduced form of SEM as a multivariate linear model with nonlinear (reduced rank) restrictions on its parameters. They used singular value decomposition to specify the restrictions such that a one-to-one correspondence is obtained when the restriction does not hold and the reduced form of the SEM is obtained when they hold. They applied this framework to examples of one, two, and three structural equations in SEM, for which expressions of the priors and posteriors were derived jointly with simulators for the posterior values.

2.6 Review of comparative Studies of the Classical and Bayesian Estimation

The increase in research works on the Bayesian approach to simultaneous equations estimation brought about the need to compare it with the classical estimators. Discovery of new methods and concepts might not necessarily mean outright condemnation of previous methods; it could be that different estimators have certain conditions or research scenarios where they perform "best". Some of these research works are given below.

(1).**Zellner (1971)**

In his book, Arnold Zellner carried out Monte Carlo studies on the classical and Bayesian estimators of a just -identified two-equation Simultaneous equations model. He considered three different research scenarios representing negatively and positively correlated residual terms as well as different variances of the exogenous variable. He used flat or locally-uniform prior which he referred to as "uninformative" on the parameters of the model. The result showed that the Bayesian estimator performs better mostly for small samples, as the sample size increases, the performance gets more alike.

(2).**Gao and Lahiri (2001)**

Their results showed that in cases with very weak instruments, there is no single estimator that is superior to others in all cases. In the case of weak endogeneity, they showed that Zellner's MELO performs best. However, when endogeneity is not weak and $\rho w_{12} > 0$, where ρ is the correlation coefficient between the structural and reduced form errors, and w_{12} is the co-variance between the unrestricted reduced form errors, BMOM (Bayesian method of moments) performed far more than other estimators.

(3). Kleibergen and Zivot (2003)

They focused on cases with weak instruments and determined the form of priors that lead to posteriors for structural parameters having similar properties as classical 2SLS and LIML. Their work provided more insight into the small sample behaviour of the Bayesian and classical procedures. They were able to show the class of priors that give rise to posteriors having identical functional form to the sampling densities of the 2SLS and LIML estimators.

Various issues have been addressed in the papers reviewed. Some of the literatures focused on the performance of classical estimators under various conditions such as weak instruements and non-mutually independent normal deviates in models containing only just-identified structural equations as well as models with over-identification constraints. Also, some of the literatures considered the performance of the classical estimators in the presence of multicollinearity. Theories and developments in the Bayesian approach to inferences on multi-equation models as well as advocacy for its use have also been discussed while other literature involved comparison of classical and Bayesian estimators in different research scenarios such as weak instruments, correlated residual terms, and their asymptotic properties. Having gone through the various literatures on both Bayesian and classical inferences on multi-equation Econometric models, literatures on the Bayesian approach particularly in the presence of multicollinearity were scarce, hence, the area of contribution of this project is the performance of the Bayesian method when the assumption of "no serial correlation of exogenous variables" is violated as well as the prior variance sensitivity analysis.

CHAPTER THREE

THEORETICAL FRAMEWORK

3.0 Introduction

This chapter contains specification of the model and its basic assumptions. Statistical methods underlying the classical and the Bayesian approaches were discussed as well as causes, effect, detection and remedies of multicollinearity. It is a presentation of the various theories on which the whole research work is based.

3.1 Model Specification

Given that; number of observations is represented by T, number of endogenous variables in other equations apart from the first is represented as n, total number of endogenous variables in the model is represented as $m = n+1$, number of exogenous variables in the first equation is represented as k_1, and number of exogenous variables included in other equations apart from the first is represented as k_2, we first state a two-structural-equation model as follows;

$$\begin{aligned} Y_1 &= \gamma Y_2 + \beta X_1 + u \\ Y_2 &= \alpha X_2 + V \end{aligned} \qquad (3.1)$$

Where;

Y_1 is a $(T\text{x}1)$ observation vector of the endogenous variables in the first equation

Y_2 is a $(T\text{x}n)$ observation matrix on the n endogenous variables in other equations of the model;

Y is a $(T\text{x}1)$ vector of endogenous explanatory variables in the first equation.

X_1 is a $(T\text{x}k_1)$ observation matrix of exogenous variables included in the first equation;

X_2 is a $(T\text{x}k_2)$ observation matrix of exogenous variables in other equations of the model;

γ is a scalar parameter, coefficient of the endogenous explanatory variable in the first equation

β is a $(k_1 \text{x} 1)$ vector of coefficients of the exogenous variables included in the first equation

α is a $(k_2 \text{x} 1)$ vector of coefficients of the exogenous variables in other equations of the model

u and V are a $(T\text{x}1)$ vector and a $(T\text{x}n)$ matrix of random disturbances to the system;

The two models considered in this research work are special cases of the general form (3.1), each consisting of 2 equations given as;

(1). A just-identified model;

$$\begin{aligned} y_{1t} &= \gamma y_{2t} + u_{1t} \\ y_{2t} &= \beta X_t + u_{2t} \end{aligned} \qquad (3.2)$$

which in reduced form is given as;

$$\begin{aligned} y_{1t} &= \pi_1 X_t + v_{1t} \\ y_{2t} &= \pi_2 X_t + v_{2t} \end{aligned} \qquad (3.3)$$

with the parameters given as; $\pi_1 = \gamma\beta, \pi_2 = \beta, v_{1t} = \gamma u_{2t} + u_{1t} \text{ and } v_{2t} = u_{2t}$

(2).An over-identified model;

$$\begin{aligned} y_{1t} &= \gamma y_{2t} + \beta_{11} X_{1t} + u_{1t} \\ y_{2t} &= \beta_{21} X_{1t} + \beta_{22} X_{2t} + \beta_{23} X_{3t} + u_{2t} \end{aligned} \qquad (3.4)$$

where, for the 2 models (3.2) and (3.4), y_{1t} and y_{2t} are each $(T\text{x}1)$ vectors containing observations on the endogenous variables

$X_t, X_{1t}, X_{2t}, X_{3t}$ are each $(T\text{x}1)$ vectors of observations on the exogenous variables

γ is the scalar coefficient of the endogenous explanatory variable

$\beta, \beta_{11}, \beta_{21}, \beta_{22}, \beta_{23}$ are the scalar coefficients of the predetermined explanatory variables.

u_{1t} and u_{2t} are each $(T\text{x}1)$ random disturbance terms.

The reduced form of model (3.4) is also given as;

$$y_{1t} = \pi_{11}X_{1t} + \pi_{12}X_{2t} + \pi_{13}X_{3t} + v_{1t}$$
$$y_{2t} = \pi_{21}X_{1t} + \pi_{22}X_{2t} + \pi_{23}X_{3t} + v_{2t} \qquad (3.5)$$

$\pi_{11} = (\beta_{11} + \beta_{21})\gamma,\ \pi_{12} = \gamma\beta_{22}, \pi_{13} = \gamma\beta_{23}, \pi_{21} = \beta_{21}, \pi_{22} = \beta_{22}, \pi_{23} = \beta_{23}, v_{1t} = \gamma u_{2t} + u_{1t}$ and $v_{2t} = u_{2t}$

3.2 Model Assumptions

In order to state the assumptions, we first represent the variables and parameters of the two models in matrix form;

$$y = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} y_{11} \\ y_{12} \\ \vdots \\ y_{1T} \\ y_{21} \\ y_{22} \\ \vdots \\ y_{2T} \end{bmatrix},\ X = \left[X_{1t} X_{2t} X_{3t}\right] = \begin{bmatrix} X_{11} & X_{12} & X_{13} \\ X_{21} & X_{22} & X_{23} \\ \vdots & \vdots & \vdots \\ X_{1T} & X_{2T} & X_{3T} \end{bmatrix},\ U = \begin{bmatrix} U_{11} \\ U_{12} \\ \vdots \\ U_{1T} \\ U_{21} \\ U_{22} \\ \vdots \\ U_{2T} \end{bmatrix}$$

The assumptions about the models are as follows;

(1) The assumption about the exogenous regressors or predetermined variables: it is assumed that the matrix of the exogenous regressors is of full rank, i.e., the number of independent columns of the matrix X, which in the case of model (3.4) is three.

(2). The second assumption is the major one, which is about the residual term U, the summary of this assumption is;

$$U \sim NIID(0, \Sigma) \qquad (3.6)$$

the assumption as stated in (3.6) is made up of the following;

(i). $E(U) = 0$. The expected value of the disturbance terms for any period t is equal to zero.

(ii).The variance-covariance matrix Σ is given as;

$$\Sigma = E[UU'] = E\left[U_{it}U_{i^*t^*}\right]$$

$$= \begin{pmatrix} \sigma_1^2 & 0 & \cdots & 0 & \sigma_{12} & 0 & \cdots & 0 \\ 0 & \sigma_1^2 & \cdots & 0 & 0 & \sigma_{12} & \cdots & 0 \\ \vdots & & \ddots & \vdots & \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_1^2 & 0 & 0 & \cdots & \sigma_{12} \\ \sigma_{21} & 0 & \cdots & 0 & \sigma_2^2 & 0 & \cdots & 0 \\ 0 & \sigma_{21} & \cdots & 0 & 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & & \ddots & \vdots & \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{21} & 0 & 0 & \cdots & \sigma_2^2 \end{pmatrix}, \qquad (3.7)$$

where $t = 1, 2, \ldots, T$ (the sample size) and $i = 1, 2$

The interpretations of the variance-covariance matrix (3.7) are as follows;

(a). The variance of the residual term within an equation $i = i^*, t = t^*$ is constant, equal to σ_i^2 i. e., there is homoscedasticity.

(b).The covariance for different periods $t \neq t^*$ within an equation $i = i^*$ is zero, i. e., no autocorrelation

(c) The covariances of the same period $t = t^*$ but different equations $i \neq i^*$ are equal to σ_{ii^*} That is, contemporaneous covariances in different equations are independent of time periods, (t)

(d).The covariances at different times $t \neq t^*$ for different equations $i \neq i^*$ are zero.

3.3 Identification

Identification in Simultaneous equations Econometric models

This section will not be complete without some discussion on the concept of identification as it relates to estimation of simultaneous equations models specifically. Identification in this sense refers to the uniqueness of the parameters of a function or model, if a model has a unique statistical form; it enables the estimation of its parameters. A system of simultaneous equations is identified if all the equations in the system are identified. There are basically two ways of checking the identification status of a model; they are discussed as follows;

(i)Order condition: Order condition for identification states that; for an equation to be identified, the number of variables excluded from that equation must be greater than or equal to the number of endogenous variables in the model less one.

That is, if;

G = number of equations which is also number of endogenous variables in the model

K = total number of variables in the model (endogenous and predetermined)

M = number of variables (endogenous and predetermined), in a particular equation,

Then, the order condition is; $K - M \geq G - 1$

The order condition is necessary but not sufficient for identification

(ii) The rank condition for identification;

In a system of G equations, an equation is identified if and only if it is possible to construct a non-zero determinant of order $(G-1)$ from the coefficients of the variables excluded from the equation but included in other equations of the model. This is a sufficient condition for identification. An equation is just identified if only 1 non-zero determinant of order $(G-1)$ is constructed from these coefficients while it is over identified if it is possible to have more than one non-zero determinant. In terms of levels of identification, there are three types of models; under-identified (No identification), just-identified, and over-identified. A model is under-identified if at least one of its equations is not identified. If all the equations of a model are just-identified, then the model is just-identified. However, if at least one of the equations of a model is over-identified, then the model can be regarded as an over-identified model.

Applying the two conditions to our models in (3.2) and (3.4) above, we proceed as follows:

Model (3.2)

$Y_{1t} = \gamma Y_{2t} + u_{1t}$ (1)

$Y_{2t} = \beta X_t + u_{2t}$ (2)

Order condition :

$K - M \geq G - 1$

Equation	K	M	G	$K-M$	$G-1$	Identification Status
(1)	3	2	2	1	1	Just-identified
(2)	3	2	2	1	1	Just-identified

Rank condition

Coefficients of all variables in the model:

Equations	Variables		
	y_{1t}	y_{2t}	X_t
(1)	-1	γ	0
(2)	0	-1	β

As shown in the table, We can form a non-zero determinant of order $G-1$ =1 from the coefficients of variables excluded from equation (1) but included in equation (2), i. e., β Thus, equation (1) is identified. Also, from equation (2), we could form a non-zero determinant of order G – 1 =1 from the coefficients of variables excluded from that equation but included in equation (1), i. e., -1. Equation (2) is also identified. We can then conclude that model (3.2) is identified.

Model (3.4)

$Y_{1t} = \gamma Y_{2t} + \beta_{11} X_{1t} + u_{1t}$ (1)

$Y_{2t} = \beta_{21} X_{1t} + \beta_{22} X_{2t} + \beta_{23} X_{3t} + u_{2t}$ (2)

Order condition:

$K - M \geq G - 1$

Equation	K	M	G	$K-M$	$G-1$	Identification Status
(1)	5	3	2	2	1	over-identified

(2)	5	4	2	1	1	Just-identified

Rank condition:

Coefficients of all variables in the model:

Equations	Variables				
	Y_{1t}	Y_{2t}	X_{1t}	X_{2t}	X_{3t}
(1)	-1	γ	β_{11}	0	0
(2)	0	-1	β_{21}	β_{22}	β_{23}

As shown in the table, We can form two non-zero determinants of order $G-1=1$ from the coefficients of variables excluded from equation (1) but included in equation (2), i. e., β_{22} *and* β_{23}. Thus, equation (1) is identified. While, from equation (2), we could form a non-zero determinant of order $G-1=1$ from the coefficients of variables excluded from that equation but included in equation (1), i. e., -1. Equation (2) is also identified. Thus model (3.4) is also identified.

3.4 Model Estimation

3.4.1 The Classical Approach

Various classical estimation techniques have been used in literature on multi-equation models generally. Of all these estimation techniques, we shall discuss only the ones used in this research work; the Ordinary least squares (OLS), Two-stage least squares (2SLS), Limited information maximum likelihood (LIML), and Three-stage least squares (3SLS)

Ordinary Least Squares (OLS)

As a method that seeks the estimates (of the parameters) that minimizes the unexplained variation of a model, it is applied to one equation at a time. Given a system of two equations such as model (3.4);

$$y_{1t} = \gamma y_{2t} + \beta_{11} X_{1t} + u_{1t}$$
$$y_{2t} = \beta_{21} X_{1t} + \beta_{22} X_{2t} + \beta_{23} X_{3t} + u_{2t}$$

the OLS estimates of the parameters of the model are;

$$\left(\hat{\gamma}\,\hat{\beta}_{11}\right)' = (Z'Z)^{-1} Z'Y_1 \text{ where } Z = (y_2 X_1) \quad (3.8)$$

and

$$\left(\hat{\beta}_{21}\hat{\beta}_{22}\hat{\beta}_{23}\right)' = (X'X)^{-1} X'Y_2 \text{ where } X = (X_1 X_2 X_3) \quad (3.9)$$

OLS is known to be biased and inconsistent when endogenous variable appears as regressor in an equation but it is still efficient.

Two-Stage least squares

As the name implies, this method involves two stages. In the first stage, each endogenous covariate in the equation of interest is regressed on all the exogenous variables in the model, exogenous covariates in the equation and excluded instruments. The two stages are described below;

Suppose that the equation of interest is $Y = \beta X + \Sigma$ where X is correlated with the error term thereby requiring instrumental variable C so that we have another equation simultaneously as;

$$X = C\gamma + U \quad (3.10)$$

We can generalize this to multivariate case and use matrix notation so that we have the stages as;

<u>First stage:</u>

Regress each column of X on C, that is, $X = C\gamma + U$

Where $\gamma = (C'C)^{-1} C'X \quad (3.11)$

The predicted values, $\hat{X} = C(C'C)^{-1} C'X \quad (3.12)$

<u>Second stage</u>

Replace each endogenous covariate with the corresponding predicted value, then regress Y on these values, that is, $Y = \hat{X}\beta + V$. The 2SLS estimates of the parameters γ and β are then given as;

$$\hat{\gamma} = (C'C)^{-1}C'X \text{ and } \hat{\beta} = (\hat{X}'\hat{X})^{-1}\hat{X}'Y$$

$$= [X'C(C'C)^{-1}C'C(C'C)^{-1}X'C(C'C)^{-1}C'Y$$

$$= [X'C(C'C)^{-1}C'X]^{-1}C'Y \qquad (3.13)$$

Koutsoyiannis (1977) reported 2SLS to be is biased in small samples because the simultaneous-equation bias is not eliminated in small samples despite the transformation in the second stage. However, in large samples (as $n \to \infty$) the bias tends to zero, which implies that 2SLS estimates are asymptotically unbiased just as in the asymptotic unbiasedness of the instrumental variables method. 2SLS is identical to an instrumental variable estimation if the estimated endogenous variables are used for their corresponding original values in 2SLS. Also, 2SLS estimates are consistent even under conditions in which the OLS method fails (that is with overidentification constraints). As $n \to \infty$their distribution becomes the true parameter, the identity of the two-stage least squares with instrumental-variables estimation establishes this consistency. When an equation contains no endogenous variable as regressor, 2SLS is identical with OLS. Lastly, the two-stage least squares estimates are asymptotically efficient

Limited Information Maximum Likelihood (LIML)

It is an estimation method for obtaining consistent estimates of the coefficients of an over-identified structural equation. It is based on the idea of purging the endogenous variables, which appear as explanatory variables in the particular equation, from their random component, making them non-stochastic thereby becoming independent of the disturbance term of the particular structural equation. LIML makes use of all the predetermined variables in the entire model in order to estimate the structural parameters of a single equation; this is a point of similarity of LIML and 2SLS. Another point of similarity is that neither of them requires a detailed knowledge of the structure of all other equations of the model, only the knowledge of all the predetermined variables of the model irrespective of the equation where it appears, is required.

Given a structural equation;

$$y_1 = \gamma_2 y_2 + \beta_1 x_1 + \beta_2 x_2 + u_1 \tag{3.14}$$

where,
the y's are the endogenous variables
the x's are the predetermined variables
the γ's are the parameters of the endogenous variables
the β's are the parameters of predetermined variables
and u_1 is the random disturbance term

The least-variance ratio method as a way of obtaining the LIML estimate is described in the following steps;

(i).Rewrite the structural equation (3.14) as;

$$\gamma_1 y_1 + \gamma_2 y_2 = \beta_1 x_1 + \beta_2 x_2 + u_1 \tag{3.15}$$

where $\gamma_1 = 1$ such that if $y_2 = f(y_1, y_3, ..., y_{m;} x_1, x_2, ..., x_k)$ then we set $\gamma_2 = 1$, and so on.

(ii)Estimate the reduced form equations of the endogenous variables appearing in the particular structural equation on all the predetermined variables of the entire model, i. e.

$$y_1 = \pi_{11} x_1 + \pi_{12} x_2 + \pi_{13} x_3 + \pi_{14} x_4 + v_1 \tag{3.16}$$

$$y_2 = \pi_{21} x_1 + \pi_{22} x_2 + \pi_{23} x_3 + \pi_{24} x_4 + v_2 \tag{3.17}$$

which can be estimated by OLS.

multiplying equation (3.16) by γ_1 and (3.17) by γ_2 and summing the resulting equations we have;

$$\gamma_1 y_1 + \gamma_2 y_2 = \gamma_1(\pi_{11} x_1 + \pi_{12} x_2 + \pi_{13} x_3 + \pi_{14} x_4) + \gamma_2(\pi_{21} x_1 + \pi_{22} x_2 + \pi_{23} x_3 + \pi_{24} x_4) + (\gamma_1 v_1 + \gamma_2 v_2)$$

The unexplained variation in y_{1t} and y_{2t} after eliminating the influence of all the exogenous variables is

$$\sum_{t=1}^{T}(\gamma_1 v_1 + \gamma_2 v_2)^2 = \sum\left(\gamma_1^2 v_1^2 + \gamma_2^2 v_2^2 + 2\gamma_1\gamma_2 v_1 v_2\right) \quad (3.17)$$

This unexplained variation in y_1 and y_2 (using all the predetermined variables) is reprersented by Q, so that,

$$Q = \gamma_1^2\sum v_1^2 + \gamma_2^2\sum v_2^2 + 2\gamma_1\gamma_2\sum v_1 v_2 \quad (3.18)$$

the residuals v_1 and v_2 are estimated from the reduced form equations (3.16) and (3.17), so that when substituted in Q, we have an expression for the unknown $\gamma's$;

$$Q = \gamma_1^2\sum \hat{v}_1^2 + \gamma_2^2\sum \hat{v}_2^2 + 2\gamma_1\gamma_2\sum \hat{v}_1 \hat{v}_2 \quad (3.19)$$

(iii)The next step is to estimate the reduced form equations of the $y's$ on those $x's$ appearing explicitly in the original structural equation, using OLS method

$$y_1 = \pi_{11}^* x_1 + \pi_{12}^* x_2 + \mathrm{w}_1 \quad (3.20)$$

$$y_2 = \pi_{21}^* x_1 + \pi_{22}^* x_2 + \mathrm{w}_2 \quad (3.21)$$

Multiplying through these equations by γ_1 and γ_2 respectively and summing the two resulting forms, we have;

$$\gamma_1 y_1 + \gamma_2 y_2 = \gamma_1(\pi_{11}^* x_1 + \pi_{12}^* x_2) + \gamma_2(\pi_{21}^* x_1 + \pi_{22}^* x_2) + \left(\gamma_1 w_1 + \gamma_2 w_2\right)$$

The unexplained variation in y_1 and y_2, after eliminating the influence of the explicit exogenous variables is

$$\sum\left(\gamma_1 w_1 + \gamma_2 w_2\right)^2 = \gamma_1^2\sum w_1^2 + \gamma_2^2\sum w_2^2 + 2\gamma_1\gamma_2\sum w_1\sum w_2$$

The unexplained variance terms w_1 and w_2 can be substituted for by their reduced form estimates $\hat{w}_1$ and $\hat{\mathrm{w}}_2$ to give;

$$S = \gamma_1^2\sum \hat{w}_1^2 + \gamma_2^2\sum \hat{w}_2^2 + 2\gamma_1\gamma_2\sum \hat{w}_1\sum \hat{w}_2 \quad (3.22)$$

where S is used to represent the unexplained variation using only the explicit exogenous $x's$

(iv).We form the ratio of the two unexplained variances (3.19) and (3.22), setting the larger in the numerator, which is called the 'unexplained-variance ratio' denoted by L, i. e.,

$$L = \frac{\text{residual variance using the explicit exogenous } x's}{\text{residual variance using all exogenous } x's}$$

$$= \frac{\gamma_1^2 \sum \hat{w}_1^2 + \gamma_2^2 \sum \hat{w}_2^2 + 2\gamma_1\gamma_2 \sum \hat{w}_1\hat{w}_2}{\gamma_1^2 \sum \hat{v}_1^2 + \gamma_2^2 \sum \hat{v}_2^2 + 2\gamma_1\gamma_2 \sum \hat{v}_1\hat{v}_2} \quad (3.23)$$

$$= \frac{S}{Q} = \text{unexplained-variance ratio} \quad (3.24)$$

(v)We minimize the unexplained-variance ratio with respect to the $\gamma's$ which implies choosing the values $\gamma's$ which make the value of L minimum. These estimates of the $\gamma's$ are called Least-Variance Ratio (LVR) estimates of the structural parameters. Taking partial derivatives of L with respect to the $\gamma's$ and equating to zero we have the simultaneous equations in which the unknowns are the $\gamma's$ and L.

$$\frac{\partial L}{\partial \gamma_1} = \frac{1}{Q^2}\left[\left(2\gamma_1 \sum \hat{w}_1^2 + 2\gamma_2 \sum \hat{w}_1\hat{w}_2\right)Q - S\left(2\gamma_1 \sum \hat{v}_1^2 + 2\gamma_2 \sum \hat{v}_1\hat{v}_2\right)\right] = 0 \quad (3.25)$$

$$\frac{\partial L}{\partial \gamma_2} = \frac{1}{Q^2}\left[\left(2\gamma_2 \sum \hat{w}_2^2 + 2\gamma_1 \sum \hat{w}_1\hat{w}_2\right)Q - S\left(2\gamma_2 \sum \hat{v}_2^2 + 2\gamma_1 \sum \hat{v}_1\hat{v}_2\right)\right] = 0 \quad (3.26)$$

Since $\frac{\partial L}{\partial \gamma_1} = \frac{\partial L}{\partial \gamma_2} = 0$, we remove the common terms $2/Q^2$ and have the following two equations simultaneously;

$$\gamma_1\left(\sum \hat{w}_1^2 Q - \sum \hat{v}_1^2 S\right) + \gamma_2\left(\sum \hat{w}_1\hat{w}_2 Q - \sum \hat{v}_1\hat{v}_2 S\right) = 0 \quad (3.27)$$

$$\gamma_2\left(\sum \hat{w}_2^2 Q - \sum \hat{v}_2^2 S\right) + \gamma_1\left(\sum \hat{w}_1\hat{w}_2 Q - \sum \hat{v}_1\hat{v}_2 S\right) = 0 \quad (3.28)$$

dividing both equations by Q and rearranging, we have;

$$\gamma_1\left(\sum \hat{w}_1^2 - L\sum \hat{v}_1^2\right) + \gamma_2\left(\sum \hat{w}_1\hat{w}_2 - L\sum \hat{v}_1\hat{v}_2\right) = 0 \quad (3.29)$$

$$\gamma_1\left(\sum \hat{w}_1\hat{w}_2 - L\sum \hat{v}_1\hat{v}_2\right) + \gamma_2\left(\sum \hat{w}_2^2 - L\sum \hat{v}_2^2\right) = 0 \quad (3.30)$$

These two equations are satisfied either if $\gamma_1 = \gamma_2 = 0$, or if the determinant of the terms in parenthesis is zero, that is,

$$\begin{vmatrix} \left(\sum \hat{w}_1^2 - L\sum \hat{v}_1^2\right) & \left(\sum \hat{w}_1\hat{w}_2 - L\sum \hat{v}_1\hat{v}_2\right) \\ \left(\sum \hat{w}_1\hat{w}_2 - L\sum \hat{v}_1\hat{v}_2\right) & \left(\sum \hat{w}_2^2 - L\sum \hat{v}_2^2\right) \end{vmatrix} = 0 \qquad (3.31)$$

equating the determinant to zero gives;

$$\left(\sum \hat{w}_1^2 - L\sum \hat{v}_1^2\right)\left(\sum \hat{w}_2^2 - L\sum \hat{v}_2^2\right) - \left(\sum \hat{w}_1\hat{w}_2 - L\sum \hat{v}_1\hat{v}_2\right)^2 = 0 \qquad (3.32)$$

which after expanding yields,

$$AL^2 + BL + C = 0 \qquad (3.33)$$

where,

$$\begin{aligned} A &= \sum \hat{v}_1^2 \sum \hat{v}_2^2 - \left(\sum \hat{v}_1\hat{v}_2\right)^2 \\ B &= 2\sum \hat{w}_1\hat{w}_2 \sum \hat{v}_1\hat{v}_2 - \sum \hat{w}_2^2 \sum \hat{v}_1^2 - \sum \hat{w}_1^2 \sum \hat{v}_2^2 \\ C &= \sum \hat{w}_1^2\hat{w}_2^2 - \left(\sum \hat{w}_1\hat{w}_2\right)^2 \end{aligned} \qquad (3.34)$$

We then solve the quadratic equation for L, then substitute in (3.29) with $\gamma_1 = 1$ to obtain

$$\hat{\gamma}_2 = \frac{L\sum \hat{v}_1^2 - \sum \hat{w}_1^2}{L\sum \hat{v}_1\hat{v}_2 - \sum \hat{w}_1\hat{w}_2} \qquad (3.35)$$

L is the minimum of the two solutions of the quadratic equation (3.33) given as

$$L = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A}$$

It has been shown in literature, for example, J.Johnston (1963), koutsoyiannis (1977) that estimates from LIML are biased for small samples but consistent, that is, the bias tends to zero and their distribution collapses on the true value of the parameters as the sample size tends to infinity. Also, if the distribution of the residual terms of the structural equations is normal, the LIML estimates are asymptotically efficient

Three-stage least squares

This method was first developed by Zellner and Theil (1962). It involves the applications of the least squares method in three stages, with the first two stages being similar to the two-stage least squares method. However, while the two stages of the two-stage least squares method are applied to the structural equations of the model, the first two stages of the three-stage least squares method are applied to the reduced form of the model. The generalised least squares technique is then applied in the third stage of the 3SLS method, to correct for any problem of heteroscedasticity that may arise in the model. The method is described as follows;

Given the general linear system of equations containing G endogenous variables and k predetermined variables, each equation could be written as

$$y_i = Y_i\gamma + \beta_i X_i + u_i \qquad i = 1, 2, \ldots, G \tag{3.36}$$

where y_i is the column vector of observations on the dependent variable of the i^{th} equation, Y_i is the T x g_i matrix of observations on the endogenous explanatory variables of that equation (g_i is the number of such endogenous explanatory variables in that equation); γ is the corresponding coefficient vector;

X_i is the T x k_i matrix of observations on the k_i predetermined variables in that equation i ;

β_i is the coefficient of the predetermined variables

and u_i is the column vector of n disturbance terms of the structural equation.

We can write (3.36) as;

$$y_i = Z_i\theta_i + u_i \tag{3.37}$$

where $Z_i = [Y_i \; X_i] \; and \; \theta_i = \begin{bmatrix} \gamma_i \\ \beta_i \end{bmatrix}$

Pre-multiplying (3.37) by X , we have;

$$X' y_i = X' Z_i \theta_i + X' u_i \qquad i = 1, 2, \ldots, G \tag{3.38}$$

the variance-covariance matrix of the disturbance term in equation (3.38) is ;

$$E(X'u_i u_i' X) = \sigma_{ii} X'X \tag{3.39}$$

Which is based on the assumption that $E(u_i u_i) = \sigma_{ii} I$, the variance of each of the T disturbances of the i^{th} structural equation.

Equation (3.38) can be seen as a relationship between a dependent variable $X'y_i$ and explanatory variables $X'Z_i$ so that the generalised least squares method can be used to estimate its parameters since the disturbance matrix in equation (3.39) is nonspherical. The estimator of θ_i by the GLS method is then given as;

$$\hat{\theta}_i = \left[Z_i' X \left(X'X \right)^{-1} X'Z_i \right]^{-1} Z_i' X \left(X'X \right)^{-1} X'y_i \tag{3.40}$$

(3.40) is just like the 2SLS estimator (3.13)

the variance –covariance matrix is given as;

$$V(\hat{\theta}_i) = \sigma_{ii} \left[Z_i' X \left(X'X \right)^{1} X'Z_i \right]^{-1} \tag{3.41}$$

Equation (3.38) can be expressed in matrix form for all the G equations of the model combined thus:

$$\begin{bmatrix} X'y_1 \\ X'y_2 \\ \vdots \\ X'y_m \end{bmatrix} = \begin{bmatrix} X'Z_1 & 0 & \cdots & 0 \\ 0 & X'Z_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & X'Z_m \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_m \end{bmatrix} + \begin{bmatrix} X'u_1 \\ X'u_2 \\ \vdots \\ X'u_m \end{bmatrix}, \tag{3.42}$$

which is a system of m equations involving $n = \sum_{i=1}^{m} n_i$ parameters, n_i is the number of parameters and θ_i is the coefficient vector in the i^{th} equation. Then, writing θ for the n element column vector for all the parameters of the system, we can apply the Generalised least squares to (3.42) to estimate all the elements of θ simultaneously. For this purpose, we need the variance-covariance matrix for the disturbance term of (3.42) given as;

$$V\begin{bmatrix} X'u \\ X'u_2 \\ \vdots \\ X'u_m \end{bmatrix} = \begin{bmatrix} \sigma_{11}X'X & \sigma_{12}X'X & \cdots & \sigma_{1m}X'X \\ \sigma_{21}X'X & \sigma_{22}X'X & \cdots & \sigma_{2m}X'X \\ \vdots & \vdots & & \vdots \\ \sigma_{m1}X'X & \sigma_{m1}X'X & \cdots & \sigma_{mm}X'X \end{bmatrix}, \qquad (3.43)$$

where σ_{ij} is the contemporaneous covariance of the structural disturbances of the i^{th} and the j^{th} equation:

$$E\left(u_i u_j\right) = \begin{bmatrix} \sigma_{ij} & 0 & \cdots & 0 \\ 0 & \sigma_{ij} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \sigma_{ij} \end{bmatrix} = \sigma_{ij} I \qquad (3.44)$$

we also need the inverse of variance-covariance matrix (3.43);

$$V^{-1}\begin{bmatrix} X'u_1 \\ X'u_2 \\ \vdots \\ X'u_m \end{bmatrix} = \begin{bmatrix} \sigma^{11}(X'X)^{-1} & \sigma^{12}(X'X)^{-1} & \sigma^{1m}(X'X)^{-1} \\ \sigma^{21}(X'X)^{-1} & \sigma^{22}(X'X)^{-1} & \sigma^{2m}(X'X)^{-1} \\ & & \\ \sigma^{m1}(X'X)^{-1} & \sigma^{m2}(X'X)^{-1} & \sigma^{mm}(X'X)^{-1} \end{bmatrix}, \qquad (3.45)$$

where σ^{ij} is an element of the inverse of the contemporaneous variance-covariance matrix for the disturbance terms.

$$\sigma^{ij} = (\sigma_{ij})^{-1}$$

Applying the generalised least squares on (3.42) then gives the following result;

$$\hat{\theta} = \begin{bmatrix} \sigma^{11}Z_1'X\left(X'X\right)^{-1}X'Z_1 & \cdots & \sigma^{1m}Z_1'X\left(X'X\right)^{-1}X'Z_m \\ \vdots & & \\ \sigma^{m1}Z_m'X\left(X'X\right)^{-1}X'Z_1 & \cdots & \sigma^{mm}Z_m'X\left(X'X\right)^{-1}X'Z_m \end{bmatrix}^{-1} \text{x} \begin{bmatrix} \sum\sigma^{1i}Z_1'X\left(X'X\right)^{-1}X'y_i \\ \vdots \\ \sum\sigma^{mi}Z_m'X\left(X'X\right)^{-1}X'y_i \end{bmatrix}$$

(3.46)

However, there is a problem with the estimator as presented in (3.46) in that σ is unknown. The suggestion by Zellner and Theil (1962) is that σ be replaced with the two-stage least squares estimate, which we can represent as S^{ij}. If the residuals from the 2SLS is given as

$\hat{u}_i = y_i - Z_i\lambda_i, i = 1, 2, ..., G$

then $S^{ij} = \left(\frac{\hat{u}_i\hat{u}_j}{n}\right)^{-1}$ for all i, j

The 3SLS estimator is thus given as;

$$\hat{\theta} = \begin{bmatrix} S^{11}Z_1'X(X'X)^{-1}X'Z_1 & \cdots & S^{1m}Z_1'X(X'X)^{-1}X'Z_m \\ \vdots & & \\ S^{m1}Z_m'X(X'X)^{-1}X'Z_1 & \cdots & S^{mm}Z_m'X(X'X)^{-1}X'Z_m \end{bmatrix}^{-1} \text{x} \begin{bmatrix} \sum S^{1i}Z_1'X(X'X)^{-1}X'y_i \\ \vdots \\ \sum S^{mi}Z_m'X(X'X)^{-1}X'y_i \end{bmatrix} \quad (3.47)$$

Where the summations in the right side of (3.47) covers $i = 1, 2, ..., m$

The 3SLS estimator (3.47) will be equal to the 2SLS estimator if the contemporaneous covariances of disturbance terms in different structural equations are all zero, also when all equations are just identified.

The summary of the 3SLS method is as follows;

Stage 1: obtain the estimate of Z_i (equation 3.37) from other exogenous variables of the model

Stage 2: obtain the generalised least squares estimate of θ, which will be equivalent to the 2SLS estimate and compute the 2SLS residual variance-covariance matrix

Stage 3: Use the generalised least squares method to compute the 3SLS estimate of θ by combining the variance-covariance matrix obtained in the second stage with other terms of equation (3.47). Some properties of three-stage least squares are as follows. 3SLS estimates are biased but consistent. They are more efficient than 2SLS, since in their estimation we use more information than in 2SLS

Based on the methods described above for the estimators OLS, 2SLS, LIML and 3SLS, these estimators for our models (3.2) and (3.4) are as follows:

(a). The first model (equation 3.2)

Ordinary Least Squares (OLS)

The OLS estimators for the parameters of equation 3.2 are:

$$.\hat{\gamma} = (y_2'y_2)^{-1}y_2'y_1 = \frac{\sum y_{1t}y_{2t}}{\sum y_{2t}^2} \tag{3.48}$$

$$\hat{\beta} = (X'X)^{-1}X'y_2 = \frac{\sum X_t y_{2t}}{\sum X_t^2} \tag{3.49}$$

Two stage least squares (2SLS)

$$\hat{\gamma} = (\hat{y}_2'\hat{y}_2)^{-1}\hat{y}_2'y_1 = \frac{\sum \hat{y}_{2t}y_{1t}}{\sum \hat{y}_{2t}^2} \tag{3.50}$$

$$\hat{\beta} = (X'X)^{-1}X'y_2 = \frac{\sum X_t y_{2t}}{\sum X_t^2} \tag{3.51}$$

Limited Information Maximum Likelihood (LIML)

As given earlier in equation (3.35), the LIML estimator γ is given as

$$\hat{\gamma}_2 = \frac{L\sum \hat{v}_{1t}^2 - \sum \hat{w}_{1t}^2}{L\sum \hat{v}_{1t}\hat{v}_{2t} - \sum \hat{w}_{1t}\hat{w}_{2t}}$$

, Since there is no exogenous variable in equation (1) of model (3.2), w_{1t} and w_{2t} are zero each, so that we have;

$$\hat{\gamma}_2 = \frac{\sum v_{1t}^2}{\sum \hat{v}_{1t}\hat{v}_{2t}} \tag{3.52}$$

$$\hat{\beta} = \left(X_t'X_t\right)^{-1} X_t'y_{2t} = \frac{\sum X_t y_{2t}}{\sum X_t^2} \tag{3.53}$$

Three-stage least squares (3SLS)

The 3SLS estimator is given as;

$$\hat{\theta} = (X_*'X_*\Sigma^{-1})^{-1}X_*'y\Sigma^{-1} \tag{3.54}$$

$$where\ \hat{\theta} = (\gamma, \beta),\ X_* = (Z, X),\ Z = (\hat{y}_{2t}),\ X = (X_{1t}),\ X_* = (y_{2t}, X_t),\ y = (y_{1t}, y_{2t})$$

$$\Sigma^{-1} = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}^{-1} \text{ and } \sigma_{ij} = \frac{e_i'e_j}{n}, \text{ obtained from the 2SLS estimate.}$$

Since this is a just-identified model, in which both equations are just identified, then the 3SLS estimate reduces to the 2SLS, as shown in Zellner and Theil (1962), expanding the matrices in (3.54), the $\sum^{-1}$ cancels out leaving the 3rd stage of the 3SLS estimator as the 2SLS estimator (3.50) and (3.51). That is,

$$\hat{\gamma} = \left(X_*^{'}X_*\right)^{-1} \sum X_*^{'} y \Sigma^{-1} = \left(\hat{y}_{2t}{'}\hat{y}_{2t}\right)^{-1} \hat{y}_{2t}^{'} y_{1t} = \frac{\sum \hat{y}_{2t} y_{1t}}{\sum \hat{y}_{2t}^2}, \quad (3.55)$$

and

$$\hat{\beta} = (X_*^{'}X_*)^{-1} X_*^{'} y_2 = (X_t^{'}X_t)^{-1} X_t^{'} y_{2t} = \frac{\sum X_t y_{2t}}{\sum X_t^2} \quad (3.56)$$

(b). The over-identified model (3.4)

Ordinary Least Squares (OLS)

The OLS estimators for the parameters of model (3.4) are:

$$(\hat{\gamma}, \hat{\beta}_{11}) = (Z'Z)^{-1} Z' y_1) \quad (3.57)$$

where, $Z = (y_{2t}, X_{1t})$

$$\hat{\beta} = (X'X)^{-1} X' y_{2t} \quad (3.58)$$

where, $\hat{\beta} = (\hat{\beta}_{21}, \hat{\beta}_{22}, \hat{\beta}_{23})$ and $X = (X_{1t}, X_{2t}, X_{3t})$

Two stage least squares (2SLS)

$$(\hat{\gamma}, \hat{\beta}_{11}) = (C'C)^{-1} C' y_{1t} \quad (3.60)$$

where $C = (\hat{y}_{2t}, X_{1t})$

$$\hat{\beta} = (X'X)^{-1} X' y_{2t} \quad (3.61)$$

where, $\hat{\beta} = (\hat{\beta}_{21}, \hat{\beta}_{22}, \hat{\beta}_{23})$ and $X = (X_{1t}, X_{2t}, X_{3t})$

Limited Information Maximum Likelihood (LIML)

As given earlier in equation (3.35), the LIML estimator γ is given as

$$\hat{\gamma} = \frac{\sum \hat{w}_{1t}^2 - l \sum \hat{v}_{1t}^2}{l \sum \hat{v}_{1t} \hat{v}_{2t} - \sum \hat{w}_{1t} \hat{w}_{2t}} \quad (3.62)$$

$$\hat{\beta}_{11} = (X_{1t}{'}X_{1t})^{-1} X_{1t}{'}\hat{y}_{1t} \quad (3.63)$$

where, $\hat{y}_{1t} = y_{1t} - \hat{\gamma} y_{2t}$

$$\hat{\beta} = \left(X'X\right)^{-1} X' y_{2t} \quad (3.64)$$

where,

$\hat{\beta} = (\hat{\beta}_{21}, \hat{\beta}_{22}, \hat{\beta}_{23})$ and $X = (X_{1t}, X_{2t}, X_{3t})$

Three-stage least squares (3SLS)

The 3SLS estimator is given as;

$$\hat{\theta} = (X_*^{'} X_* \Sigma^{-1})^{-1} X_*^{'} y \Sigma^{-1} \tag{3.65}$$

$where\, \hat{\theta} = (\gamma, \beta_{11}, \beta_{21}, \beta_{22}, \beta_{23},)$, $X_* = (Z, X)$, $Z = (\hat{y}_{2t}, X_{1t})$, $X = (X_{1t}, X_{2t}, X_{3t})$, $y = (y_{1t}, y_{2t})$

$\Sigma^{-1} = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}^{-1}$ and $\sigma_{ij} = \dfrac{e_i' e_j}{n}$, obtained from the 2SLS estimate.

This is an over-identified model, in which one equation is over-identified and the other is just-identified, the 3SLS estimate still reduces to the 2SLS as given in (3.60). That is,

$(\hat{\gamma}, \hat{\beta}_{11}) = \left(X_*^{'} X_* \right)^{-1} \Sigma X_*^{'} y \Sigma^{-1} = \left(Z^{'} Z \right)^{-1} Z^{'} y_{1t}$,

and

$\hat{\beta} = (\hat{\beta}_{21}\ \hat{\beta}_{22}\ \hat{\beta}_{23}) = (X_*^{'} X_*)^{-1} X_*^{'} y_{2t} = (X_t^{'} X_t)^{-1} X_t^{'} y_{2t}$, where $X_t = (X_{1t}, X_{2t}, X_{3t})$

3.4.2 The Bayesian Appproach

(A). The Just-identified model (equation 3.2)

Prior Probability density function

The diffuse prior is assumed for the parameters of our models. The idea behind the use of this prior (also known as flat or locally-uniform prior) is to make inferences that are not greatly affected by external information or when external information is not available. Two rules were suggested by Jeffrey (1961) to serve as guide in choosing a prior distribution. The first one states as, "If the parameter may have any value in a finite range, or from $-\infty$ to $+\infty$, it's prior probability should be taken as uniformly distributed". While the second is that if the parameter, by nature, can take any value from 0 to ∞, the prior probability of its logarithm should be taken as uniformly distributed.

Using the reduced form of the just-identified model (3.2), we assume little is known, a priori, about the parameters, π, and the three distinct elements of Σ. As the prior pdf, we assume that the elements of π and those of Σ are independently distributed; that is,

$$P(\pi, \Sigma) = P(\pi) P(\Sigma) \tag{3.66}$$

Using the Jeffrey's invariance theory (Zellner 1971), we take

$$P(\pi) = \text{constant} \tag{3.67}$$

and

$$P(\Sigma) \propto |\Sigma|^{-\frac{3}{2}} \tag{3.68}$$

Next we denote $\sigma^{\mu\mu'}$ as the $(\mu, \mu')th$ element of the inverse of Σ, while the Jacobian of the transformation of the three variances, $(\sigma_{11}, \sigma_{12}, \sigma_{22})$ to $(\sigma^{11}, \sigma^{12}, \sigma^{22})$ is

$$J = \left| \frac{\partial(\sigma_{11}, \sigma_{12}, \sigma_{22})}{\partial(\sigma^{11}, \sigma^{12}, \sigma^{22})} \right| = |\Sigma|^{3} \tag{3.69}$$

So that the prior pdf in (3.68) implies the following prior pdf on the three distinct elements of Σ^{-1}

$$P(\Sigma^{-1}) \propto |\Sigma^{-1}|^{-\frac{3}{2}} \tag{3.70}$$

This is as a result of taking an informative prior pdf on Σ^{-1} in the Wishart pdf form and allowing the "degrees of freedom" in the prior pdf to be zero. With zero degrees of freedom, there is a "spread out" Wishart pdf which then serve as a diffuse prior pdf since it is diffuse enough to be substantially modified by a small number of observations. The Wishart distribution is the conjugate for the multivariate normal distribution, which is the distribution of the variance-covariance matrix (Σ)

Hence, our prior p.d.f 's are (3.67), (3.68), and (3.70)

These prior p.d.f's were arrived at by Zellner (1971), Geisser (1965) and others.

Likelihood function

Based on the assumption from our model that rows of V are normally and independently distributed, each with zero mean vector and 2x2 covariance matrix Σ, the likelihood function for π and Σ is;

$$L(\pi, \Sigma / Y, X) \propto \exp[-\tfrac{1}{2} tr(Y - X\pi)'(Y - X\pi)\Sigma^{-1}] \tag{3.71}$$

This is the same as;

$$L(\pi,\Sigma/Y,X)\propto|\Sigma|^{-n/2}\exp[-\tfrac{1}{2}trS\Sigma^{-1}-\tfrac{1}{2}tr(\pi-\hat{\pi})'X'X(\pi-\hat{\pi})\Sigma^{-1}] \qquad (3.72)$$

where $(Y-X\pi)'((Y-X\pi)=(Y-X\hat{\pi})'(Y-X\hat{\pi})+(\pi-\hat{\pi})'X'X(\pi-\hat{\pi})$

$$=S+(\pi-\hat{\pi})'X'X(\pi-\hat{\pi})$$

S = (Y-X $\hat{\pi}$)'(Y-X $\hat{\pi}$) and $\hat{\pi}$ is the estimate of π

Thus, the likelihood function for the parameters is as given in (3.72)

The Posterior Pdf

Combining the Prior pdf (3.67) and (3.70) with the likelihood function (3.72), we have for the just-identified model (3.2), a posterior distribution that is in the bivariate student-t form. This is given as:

$$P(\pi_1,\pi_2/y_1,y_2)\propto\left[1+(\pi_1-\hat{\pi}_1\vdots\pi_2-\hat{\pi}_2)\begin{pmatrix}s^{11} & s^{12}\\ s^{21} & s^{22}\end{pmatrix}(\pi_1-\hat{\pi}_1\vdots\pi_2-\hat{\pi}_2)'\right]^{-N/2} \qquad (3.72)$$

Where $\hat{\pi}_1$ and $\hat{\pi}_2$ are the least squares estimates, $s^{ij}=\hat{w}^{ij}\sum_{n=1}^{N}x_n{}^2$, and $\hat{w}^{ij}$ the i,j^{th} element of $\left[\sum_{n=1}^{N}(y_{in}-\hat{\pi}_i x_n)(y_{jn}-\hat{\pi}_j x_n)\right]$ $i,j=1,2$. To obtain the posterior distribution in terms of γ and β, we carry out the following transformation:

$\gamma=\dfrac{\pi_1}{\pi_2}$, $\beta=\pi_2$ with the Jacobian of transformation $|\beta|$. This gives us:

$$p(\gamma,\beta/y_1y_2)\propto|\beta|\left[1+(\beta\gamma-\hat{\pi}_1)^2s^{11}+(\beta-\hat{\pi}_2)^2s^{22}+2(\beta\gamma-\hat{\pi}_1)(\beta-\hat{\pi}_2)s^{12}\right]^{-N/2}. \qquad (3.73)$$

(B). The second model (with one over-identified equation)

For the over-identified model, we carried out the Bayesian analysis by working directly on the structural model (3.4) which we write in matrix form as

$$Y=Z\delta+U \qquad (3.74)$$

Where $Y=\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix}$, $Z=\begin{pmatrix} y_{2t} & X_{1t} & 0 & 0 \\ 0 & X_{1t} & X_{2t} & X_{3t} \end{pmatrix}$, $\delta=\begin{pmatrix} \gamma & 0 \\ \beta_{11} & \beta_{21} \\ 0 & \beta_{22} \\ 0 & \beta_{23} \end{pmatrix}$ and $U=\begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$

Prior Probability density function

The procedure here is the same as in the case of the just-identified model, we assume little is known, a priori, about the parameters, δ, and the three distinct elements of Σ. As our locally uniform prior pdf, we assume that the elements of δ and those of Σ are independently distributed; that is,

$$P(\delta,\Sigma)=P(\delta)P(\Sigma) \tag{3.74}$$

$$P(\delta)=\text{constant} \tag{3.75}$$

$$P(\Sigma)\propto|\Sigma|^{-3/2} \tag{3.76}$$

and

$$P(\Sigma^{-1})\propto\left|\Sigma^{-1}\right|^{-3/2} \tag{3.77}$$

the same as for the just-identified model such that our prior pdf's are (3.75) and (3.77)

Likelihood function

Also, as it is with the just-identified model, based on the assumption from our model that rows of U are normally and independently distributed, each with zero mean vector and 2x2 covariance matrix Σ, the likelihood function for δ and Σ is;

$$L(\delta,\Sigma/Y,X)\propto|\Sigma|^{-n/2}\exp[-\tfrac{1}{2}tr(Y-X\delta)'(Y-X\delta)\Sigma^{-1} \tag{3.78}$$

This is the same as;

$$L(\delta,\Sigma/Y,X)\propto|\Sigma|^{-n/2}\exp[-\tfrac{1}{2}trS\,\Sigma^{-1}-\tfrac{1}{2}tr(\delta-\hat{\delta})'X'X(\delta-\hat{\delta})\Sigma^{-1}] \qquad (3.79)$$

Where $(Y-X\delta)'(Y-X\delta)=(Y-X\hat{\delta})'(Y-X\hat{\delta})+(\delta-\hat{\delta})'X'X(\delta-\hat{\delta})$,

$$=S+(\delta-\hat{\delta})'X'X(\delta-\hat{\delta})$$

$S=(Y-X\hat{\delta})'(Y-X\hat{\delta})$ and $\hat{\delta}$ is the estimate of δ

Thus, the likelihood function for the parameters is as given in (3.79)

The Posterior Pdf

Combining the diffuse Prior pdf (3.75) and (3.77) with the likelihood function (3.79), we have the joint posterior distribution for δ and Σ^{-1} given as;

$$P(\delta,\Sigma^{-1}/Y,X)\propto|\Sigma|^{-(n+3/2)}EXP\{-\tfrac{1}{2}tr\left[S+\left(\delta-\hat{\delta}\right)'Z'Z\left(\delta-\hat{\delta}\right)\right]\Sigma^{-1}\} \qquad (3.80)$$

Integrating (3.80) with respect to Σ^{-1}, we have the marginal posterior pdf for δ given as:

$$P(\delta/Y,X)\propto\left[S+(\delta-\hat{\delta})'Z'Z(\delta-\hat{\delta})\right]^{-T/2} \qquad (3.81)$$

A pdf in the generalized student-t form.

3.5 Multicollinearity: Causes, effect, detection and Remedies

3.5.1 Causes

Multicollinearity occurs when two or more predictors or explanatory variables of a model are highly correlated and thereby providing redundant information about the response (dependent) variable. In the multi-equation systems it implies that two or more exogenous variables are correlated. Inclusion of highly correlated variables in a model usually arises by mistake or lack of understanding by the researcher. For example, if variables X_1 and X_2 are already in a model, the researcher might ignorantly include $X_3=X_1+X_2$ which has no additional information thereby implying a case of perfect multicollinearity in the model. By this, contents of X_1, X_2 and X_3 cannot be obtained by OLS. An over defined model could also lead to the problem of multicollinearity. Such models usually have more regressors than number of observations. For example, in the medical sciences and the behavioural sciences where there may be more regressors than the available subjects on which the information is collected.

3.5.2 Effect

In this section, we describe the effect of multicollinearity using the second equation of our over-identified model (3.3) which contains two correlated variables X_2 and X_3. The equation is given as:

$$Y_{2t} = \beta_{21}X_{1t} + \beta_{22}X_{2t} + \beta_{23}X_{3t} + \varepsilon_{2t} \quad (3.82)$$

Estimation of this equation reduces to the Ordinary least squares for most classical estimators; hence we present the least-squares estimators of $\beta's$ as;

$$\hat{\beta} = (X'X)^{-1}X'Y$$

$$= \begin{pmatrix} \hat{\beta}_{21} \\ \hat{\beta}_{22} \\ \hat{\beta}_{23} \end{pmatrix} = \begin{pmatrix} 1 & r_{12} & r_{13} \\ r_{21} & 1 & r_{23} \\ r_{31} & r_{32} & 1 \end{pmatrix}^{-1} \begin{pmatrix} r_{1y} \\ r_{2y} \\ r_{3y} \end{pmatrix} \quad (3.83)$$

where r_{ij} is the simple correlation between regressors X_{it} and X_{jt}, and r_{jy} is the simple correlation between X_{jt} and Y_{2t}, $i, j =$ 1, 2, 3. The inverse of $X^{'}X$ is given as;

$$(X'X)^{-1} = \frac{1}{d}\begin{pmatrix} (1-r_{23}^2) & -(r_{13}r_{23}+r_{12}) & (r_{12}r_{23}-r_{13}) \\ -(r_{13}r_{23}+r_{12}) & (1-r_{13}^2) & -(r_{23}+r_{12}r_{13}) \\ (r_{12}r_{23}-r_{13}) & -(r_{23}+r_{12}r_{13}) & (1-r_{12}^2) \end{pmatrix} \quad (3.84)$$

where $d = 1 - r_{12}^2 - r_{13}^2 - r_{23}^2 + 2r_{12}r_{13}r_{23}$

Strong multicollinearity between X_{2t} and X_{3t} implies that the correlation coefficient r_{23} will be large. From equation (3.84) we see that as $|r_{23}| \to 1$, $\text{var}(\hat{\beta}_j) = (X'X)_{ij}^{-1}\sigma_{jj}^2 \to \propto$ and $\text{cov}(\hat{\beta}_i \hat{\beta}_j) = (X'X)_{ij}^{-1}\sigma^2 \to \pm\propto$, $i \neq j$, depending on whether $r_{23} \to +1$ or $r_{23} \to -1$. Hence, we can conclude that strong multicolinearity between X_{2t} and X_{3t} will result in large variances and covariances for the least-squares estimators of the regression coefficients. In a multi-equation system such as model (3.3), the large variances will in turn have adverse effect on the estimates of the parameters of the first equation where the endogenous variable Y_{2t} is a regressor.

The effects of multicollinearity can be summarised as follows;

(i) When there is a perfect correlation between the regressors, it implies exact multicollinearity and the least squares estimator is undefined. This is because $X'X$ matrix is singular which makes estimation of coefficients and standard errors impossible.

(ii) In the case of the presence of highly correlated (but not perfectly correlated) regressors in the model, the variance and covariances are large leading to difficulty in making precise estimation.

(iii) The Confidence intervals tend to be much wider, leading to the acceptance of null hypothesis more readily as a result of relatively large standard error which is based partly on the correlation between the regressors of the model

3.5.3 Detection

The problem of multicollinearity is more of the degree than the presence or absence. The disturbing consequences of multicollinearity increase as its degree increases. There are many techniques in literature for detecting multicollinearity. Some of them are discussed in this section.

(1)By observing the correlation matrix

A very simple way of detecting multicollinearity is to compute the correlation matrix and look for those pairs of regressors with high coefficients. This could also be done by inspecting the off-diagonal elements r_{ij} in $X'X$. If regressors X_i and X_j are nearly linearly dependent, then $|r_{ij}|$ will be close to unity. We make use of the first sample (T=20) from run 1 and run 2 of our simulated samples (with correlation already built in) to illustrate this technique. The samples are contained in Appendix B.

Table 3.1: Correlation matrix for exogenous variables of the second model (3.4)

	RUN 1			RUN 2		
	X_1	X_2	X_3	X_1	X_2	X_3
X_1	1	-0.4545	-0.4507	1	0.5018	-0.0303
X_2	-0.4545	1	0.779	0.5018	1	-0.0644
X_3	-0.4507	0.779	1	-0.0303	-0.0644	1

Going through table 3.1, for run 1, correlation between X_{2t} and X_{3t} is high which could be taken as an indication of multicollinearity. For run 2 however, none of the correlations is high which could be taken as no serious level of multicollinearity.

(2)The use of Variance Inflation Factor (VIF)

We can also make use of the diagonal elements of $(X'X)^{-1}$ matrix in correlation form to detect multicollinearity. The j^{th} diagonal element of $(X'X)^{-1}$ matrix can also be written as $(1-R_j^2)^{-1}$ where R_j^2 is the coefficient of determination obtained when X_j is regressed on the remaining $k-1$ regressors. If X_j is close to being orthogonal to the remaining $k-1$ regressors, then R_j^2 will be small and $(X'X)^{-1}$ is close to one, while if X_j is close to being linearly dependent on some subset of the remaining regressors, R_j^2 is close to one and $(X'X)^{-1}$ is large. Since the variance of the j^{th} regression coeficient is $(X'X)^{-1}_{jj}\sigma^2$, $(X'X)^{-1}_{jj}$ can be viewed as the factor by which the variance of $\hat{\beta}_j$ is increased due to linear dependences among the regressors. This is referred to variance inflation factor (VIF) given as;

$$\begin{aligned} \text{VIF}_j &= (\text{X'X})^{-1}_{\text{j}} \\ &= (1-R_j^2)^{-1} \end{aligned}$$

The VIF for each regressor in the model thus measures the combined effect of the dependencies among regressors on the variance of that term. Large VIF is an indication of multicollinearity. It has been suggested that a VIF 5 is high enough to indicate multicollinearity. Detecting multicollinearity using VIF is illustrated with our data on model (3.3) in table 3.2;

Table 3.2: Variance Inflation factor (VIF) for Data from the over-identified model

RUN I	X_1	X_2	X_3
T=20	1.299207	2.632965	2.621919
T=40	1.051967	3.479471	3.485535
T=60	1.019576	2.658161	2.629503
T=100	1.0004	2.493144	2.492522
RUN II			
T=20	1.344267	1.34971	1.010816
T=40	1.011839	1.091346	1.078981
T=60	1.003009	1.011531	1.008878
T=100	1.037129	1.053519	1.017294
RUN III			
T=20	1.053741	3.133814	3.050641
T=40	1.062135	1.941748	1.988467
T=60	1.054074	2.800336	2.777006
T=100	1.007963	2.923122	2.933412
RUN IV			
T=20	1.009082	1.036162	1.033271
T=40	1.023646	0.1167	1.15714
T=60	1.064963	1.053186	1.019264
T=100	1.018745	1.030609	1.017294
RUN V			
T=20	1.061233	12.78772	12.62626
T=40	1.007151	7.8125	7.830854
T=60	1.01968	5.194805	5.235602
T=100	1.037452	5.173306	5.09165

From table 3.2, we could see that multicollinearity reflected to some extent in runs I and III where the VIF for X_{2t} and X_{3t} are fairly large although not high enough to give serious problem. In run V, the VIF are really high enough (with values ranging from 5 to 12) to give serious multicollinearity problem

(3)Eigenvalues of $X'X$ matrix

The eigenvalues of $X'X$, say, $e_1, e_2, ..., e_p$ where p is the number of elements in $X'X$ can be used to detect the severity of multicollinearity in a given data set. One approach to the use of this method is to obtain the ratio $E = \frac{e_{\max}}{e_{\min}}$ which is a measure of the spread in the eigenvalues spectrum of $X'X$. If E is less than 100, there is no serious problem with multicollinearity. Any values of E between 100 and 1000 imply moderate to strong multicollinearity while a value greater than 1000 is an indication of severe multicollinearity.

There are several other ways of detecting multicollinearity such as observing the determinant of $X'X$ matrix when expressed in correlation form. The possible range of values of the determinant is $0 \le |X'X| \le 1$. If $|X'X| = 1$, the regressors are orthogonal, while in the situation where $|X'X| = 0$, it implies that there is perfect linear dependence among the regressors. Multicollinearity becomes more severe as $|X'X|$ approaches zero. However, this method does not provide information on the source of the multicollinearity. The sign and magnitude of the regression coefficients can also sometimes provide a means of detecting multicollinearity. Specifically, large changes in the estimates of the regression coefficients as a result of adding or removing a regressor, indicates multicollinearity. If deletion of part of the data points results in large changes in the regression coefficients, multicollinearity may be present. Also, if the signs or magnitude of the regression coefficients in the regression model are different from expectation, one should be alert to possible multicollinearity.

3.5.4 Remedies of Multicollinearity

In a situation where multicollinearity is detected, there are a number of ways in literature for dealing with it.Three of such approaches are discussed in this section.

(1)Respecification of the model

Multicollinearity is mostly caused by the choice of model, which is essentially the way the model is specified, such as the inclusion of two highly correlated regressors in the model. In such situations, respecifying the regression equation may reduce the impact of multicollinearity. The regressor may be redefined, for example, if X_1, X_2, and X_3 are linearly correlated, it may be possible to find some function such as $X = (X_1 + X_2)/X_3$ or $X = X_1X_2X_3$ that preserves the information content in the original regressors while reducing the severity of the multicollinearity problem, but the problem with this is that of interpretation. Another widely used approach to model respecification is elimination of some of the variables involved. If X_1, X_2, and X_3 are linearly dependent, elimination one of them is often very effective in removing the multicollinearity. However, this approach might bring a more serious problem if the regressor dropped from the model has significant explanatory power relative to the dependent variable. In other words, eliminating regressors to reduce multicollinearity may negatively affect the predictive power of the model. Variable selection must thus be carried out with care because some of the selection procedures are seriously distorted by the multicollinearity, and there is no assurance that the severity of the multicollinearity will reduce in the final model compared with the original data.

(2)Use of Additional or New Data

Another way of dealing with the problem of multicollinearity is to use another set of data on the variables. Since the problem of multicollinearity is with the sample, it is possible that a new sample on the same variables may not be so serious as in the first sample. At times, increasing the sample size may reduce the effect of multicollinearity. Increase in sample size makes the effect of multicollinearity on the standard error to decrease, since the larger the sample size, the smaller the standard error.

However, collecting additional data is not always possible because of economic constraints as well as if the process being studied is no longer available for sampling. Another constraint to the use of additional data is that it may be inappropriate to use if the new data extend the range of the regressor far beyond the analyst's region of interest. Also, in a situation where multicollinearity is due to constraints on the model or in the population, collecting additional data is obviously not a viable solution

(3)Ridge Regression

The Ridge regression proposed by Hoerl and Kennard (1970) can be used to obtain a biased estimator of the regression coefficients but with reduced mean squared error. Given that the mean squared error (MSE) of estimator of β, the regession coefficient is given as

$$\text{MSE}(\hat{\beta}^*) = \text{V}(\hat{\beta}^*) + (\text{bias in } \hat{\beta}^*)^2 \qquad (3.85)$$

If a small amount of bias is allowed in $\hat{\beta}^*$, then its variance can be made small such that the MSE of $\hat{\beta}^*$ is less than the variance of the unbiased estimator β. Ridge regression is defined as the procedure that seeks solution to $\hat{\beta}_R = (X'X + kI)^{-1} X'y$ where $k \geq 0$ is a constant selected by the analyst, I is an identity matrix of the same order as $X'X$ and $\hat{\beta}_R$ is the rigde estimator. When $k = 0$ then the ridge estimator becomes the least-square estimator. The variance-covariance matrix of $\hat{\beta}_R$ is

$$\mathrm{V}(\hat{\beta}_\mathrm{R}) = \sigma^2 (X'X + kI)^{-1} X'X (X'X + kI)^{-1} \tag{3.86}$$

such that the mean squared error of $\hat{\beta}_R$ is

$$\begin{aligned} MSE(\hat{\beta}_R) &= V(\hat{\beta}_R) + (\text{bias in } \hat{\beta}_R)^2 \\ &= \sigma^2 \mathrm{Tr}[(X'X + kI)^{-1} X'X (X'X + kI)^{-1}] + k^2 \beta'(X'X + kI)^{-2} \beta \\ &= \sigma^2 \sum_{j=1}^{p} \frac{\lambda_j}{(\lambda_j + k)^2} + k^2 \beta'(X'X + kI)^{-2} \beta \end{aligned} \tag{3.87}$$

Where $\lambda_1, \lambda_2, ..., \lambda_p$ are the eigenvalues of $X'X$. If $k > 0$, it is obvious in (3.87) that the bias in $\hat{\beta}_R$ increases with k while the variance decreases. It is thus important to choose k such that reduction in the variance term is greater than the increase in the squared bias so that the MSE of the ridge estimator $\hat{\beta}_R$ will be less than that of the least-square estimator $\hat{\beta}$. Hoerl et. al. (1975) suggested that an appropriate choice of k is $k = \frac{p\hat{\sigma}^2}{\hat{\beta}'\hat{\beta}}$ where p is the order of the $X'X$ matrix and $\hat{\beta}$ and $\hat{\sigma}^2$ are least squares estimates. It is however important to note that ridge estimate will not necessarily provide the best fit to the data. This fact is proved as follows;

The residual sum of squares for $\hat{\beta}_R$ is

$$\begin{aligned} \mathrm{SS_R} &= (y - X\hat{\beta}_R)'(y - X\hat{\beta}_R) \\ &= (y - X\hat{\beta})'(y - X\hat{\beta}) + (\hat{\beta}_R - \hat{\beta})' X'X (\hat{\beta}_R - \hat{\beta}) \end{aligned} \tag{3.88}$$

Note that;

(i) the first term in the right hand side of equation (3.88) is the residual sum of squares for the least squares estimates $\hat{\beta}$

(ii) as k increases the second term of equation (3.88) increases for the same reason that bias in $\hat{\beta}_R$ increases with k

(iii) the residual sum of squares for $\hat{\beta}_R$ increases as a result of (i) and (ii)

(iv) Consequently, because the total sum of squares is fixed, R^2 decreases as k increases.

Hence, the ridge estimate may not necessarily provide the best fit to the data.

(4)Principal Component Analysis

The principal components regression is another method of obtaining biased estimators of regression coefficient. It deals with multicollinearity by using fewer set of principal component than the full set of principal components in the model. To obtain the principal components, the regressors are first arranged in order of decreasing eigenvalues $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_p > 0$. Suppose that the last set of these values are approximately equal to zero, in principal component regression, the principal components corresponding to those zero eigenvalues are removed from the analysis while least squares is applied to the remaining components. Thus, the principal components estimator reduces the effect of multicollinearity by using a subset of the principal components in the model. However, the use of a subset of the principal components could reduce the fit of the model.

CHAPTER FOUR

METHODOLOGY

4.0 Introduction

The various steps leading to the conclusions reached in this study are presented in this chapter. They include the design of the Monte Carlo experiment, the method for generating data for the experiment, procedures for obtaining estimates from both classical and Bayesian approaches. The use of WinBUGS for obtaining Bayesian posterior point estimates is also discussed in this section. Finally, evaluations of criteria for the experiment are also provided

4.1 The design of the Monte Carlo experiment

The experiment involved generating data according to some specified research scenario, carrying out the estimation of the already stated parameters of the model using the Bayesian approach as well as the classical approach, and summarizing the results. The whole procedure and design are highlighted below;

Step One: Describe research scenario under study and state conditions under which data were generated

Step Two: Generate data for the experiment

Step Three: Using the data generated, obtain estimates of the parameters from the two approaches

Step Four: Collate and summarize the results for clear conclusions and interpretations.

These steps are described in the following sections.

4.2 Simulating Data for the experiment

The data were generated by arbitrarily fixing values for the parameters (the same for all the three runs of the first model (equation 3.2) and also for the five runs of the second model(equation 3.4) of the model and stating specific distributions for the predetermined variables and the error terms. These values are put together in three runs for model (3.2) and five runs for model (3.4) respectively to depict some possible research scenario that a researcher could encounter. They are stated as follows.

(a). The first model (equation 3.2): $\gamma = 2.0, \beta = 0.5$. These values are arbitrarily fixed.

RUN ONE

$X_t : NID(0,1), (U_{1t}, U_{2t}) : NID(0,0; \sigma_{11}, \sigma_{12}, \sigma_{22}), \sigma_{11} = 1.0, \sigma_{12} = -1.0, \sigma_{22} = 4.0,$
i. e. $\rho(u_1 u_2) = -0.5$

RUN TWO

$X_t : NID(0,2), (U_{1t}, U_{2t}) : NID(0,0; \sigma_{11}, \sigma_{12}, \sigma_{22}), \sigma_{11} = 1.0, \sigma_{12} = 1.0, \sigma_{22} = 4.0$
i. e. $\rho(u_1 u_2) = 0.5$

RUN THREE

$X_t : NID(0,9), (U_{1t}, U_{2t}) : NID(0,0; \sigma_{11}, \sigma_{12}, \sigma_{22}), \sigma_{11} = 1.0, \sigma_{12} = 1.0, \sigma_{22} = 4.0$
i. e. $\rho(u_1 u_2) = 0.5$

Multicollinearity was not included in the just-identified model (3.2) as reflected in runs 1 to 3 above because we want to first evaluate the performance of the Bayesian approach in analyzing a simple multi-equation model without any possibility of multicollinearity.

(b). The second model (equation 3.4): $\gamma = 3.0, \beta_{11} = 1.0, \beta_{21} = 2.0, \beta_{22} = 0.5, \beta_{23} = 1.5$. These values too are arbritrarily fixed

RUN ONE: Depicting a high level of multicollinearity of two exogenous terms in the second equation with negative correlations between the residual terms of the two equations

$X_{1t} : NID(0,1), X_{2t} : NID(0,1), X_{3t} : NID(0,1), \rho(X_{2t} X_{3t}) = 0.8, (u_{1t} u_{2t}) : NID(0,0; \sigma_{11}, \sigma_{12}, \sigma_{22}),$
$\sigma_{11} = 1.0, \sigma_{12} = -1.0, \sigma_{22} = 4.0,$ i. e. $\rho(u_1 u_2) = -0.5$

RUN TWO: Depicting a low level of multicollinearity of two exogenous terms in the second equation with negative correlations between the residual terms of the two equations

$X_{1t} : NID(0,1), X_{2t} : NID(0,1), X_{3t} : NID(0,1), \rho(X_{2t}X_{3t}) = 0.2, (u_{1t}u_{2t}) : NID(0,0;\sigma_{11},\sigma_{12},\sigma_{22}),$
$\sigma_{11} = 1.0, \sigma_{12} = -1.0, \sigma_{22} = 4.0,$ i. e. $\rho(u_1u_2) = -0.5$

RUN THREE: Depicting a high level of multicollinearity of two exogenous terms in the second equation with positive correlations between the residual terms of the two equations

$X_{1t} : NID(0,1), X_{2t} : NID(0,1), X_{3t} : NID(0,1), \rho(X_{2t}X_{3t}) = 0.8, (u_{1t}u_{2t}) : NID(0,0;\sigma_{11},\sigma_{12},\sigma_{22}),$
$\sigma_{11} = 1.0, \sigma_{12} = 1.0, \sigma_{22} = 4.0,$ i. e. $\rho(u_1u_2) = 0.5$

RUN FOUR: Depicting low level of multicollinearity of two exogenous terms in the second equation with positive correlations between the residual terms of the two equations

$X_{1t} : NID(0,1), X_{2t} : NID(0,1), X_{3t} : NID(0,1), \rho(X_{2t}X_{3t}) = 0.2, (u_{1t}u_{2t}) : NID(0,0;\sigma_{11},\sigma_{12},\sigma_{22}),$
$\sigma_{11} = 1.0, \sigma_{12} = 1.0, \sigma_{22} = 4.0,$ i. e. $\rho(u_1u_2) = 0.5$

RUN FIVE: Depicting a very high level of multicollinearity of two exogenous terms in the second equation with positive correlations between the residual terms of the two equations

$X_{1t} : NID(0,1), X_{2t} : NID(0,1), X_{3t} : NID(0,1), \rho(X_{2t}X_{3t}) = 0.9, (u_{1t}u_{2t}) : NID(0,0;\sigma_{11},\sigma_{12},\sigma_{22}),$
$\sigma_{11} = 1.0, \sigma_{12} = 1.0, \sigma_{22} = 4.0,$ i. e. $\rho(u_1u_2) = 0.5$

In each of these runs, $N = 5000$ samples of size $T = 20, 40, 60,$ and 100 were generated. That is, the number of replicates is 5000, making a total of 20,000 samples in one run, and 160,000 samples altogether. We represent number of replicates with N and sample size with T.

Generating the residual terms of the Model

The residual terms of the two equations of the models are correlated as indicated in (a) and (b) above. In other to generate values of the endogenous variables having this property, we made use of the cholesky transformation approach as described by Gentle (1998), whereby the variance-covariance matrix of the residuals is given as:

$$\Sigma = pp' = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$$

p is the lower triangular matrix $\begin{pmatrix} p_{11} & 0 \\ p_{21} & p_{22} \end{pmatrix}$. This decomposition, which is like "taking the square root" of the matrix, is possible because Σ is a positive-definite symmetric matrix. The following steps describe the approach:

*State the matrix to be factorized in terms of the product of the lower triangular matrix p and its transpose, i.e.

$$\Sigma = \begin{pmatrix} p_{11} & 0 \\ p_{21} & p_{22} \end{pmatrix} \begin{pmatrix} p_{11} & p_{12} \\ 0 & p_{22} \end{pmatrix} = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$$

*Express each term of Σ in terms of the corresponding row by column multiplication of pp' i.e.

$$p_{11}^2 = \sigma_{11} \tag{4.1}$$

$$p_{11}p_{12} = \sigma_{12} \tag{4.2}$$

$$p_{11}p_{21} = \sigma_{21} \tag{4.3}$$

$$p_{21}^2 + p_{22}^2 = \sigma_{22} \tag{4.4}$$

Essentially, the required equations are (4.1), (4.2) or (4.3), and (4.4), since $\sigma_{12} = \sigma_{21}$

*Obtain expressions for P_{11}, P_{21} and P_{22} from equations (4.1), (4.3) and (4.4) above, i.e.

$$p_{11} = \sqrt{\sigma_{11}} \tag{4.5}$$

$$p_{21} = \frac{\sigma_{21}}{\sqrt{\sigma_{11}}} \tag{4.6}$$

$$p_{22} = \sqrt{\sigma_{22} - \left(p_{21}^2\right)} \tag{4.7}$$

*The residual terms are then generated as;

$$u_{1t} = p_{11}\varepsilon_{1t}$$
$$u_{2t} = p_{21}\varepsilon_{1t} + p_{22}\varepsilon_{2t} \quad (4.8)$$

where ε_{it} are independent series of normal deviates

With variance-covariance matrix Σ for our model given as $\Sigma = \begin{pmatrix} 1.0 & -1 \\ -1 & 4.0 \end{pmatrix}$ for runs one in the just-identified model (3.2), and one and two in the over-identified model (3.4), and $\Sigma = \begin{pmatrix} 1.0 & 1 \\ 1 & 4.0 \end{pmatrix}$ for runs two and three in the just-identified model (3.2) and three, four and five in the over-identified model (3.4), using equations (4.5), (4.6) and (4.7), we have the following for P_{11}, P_{21}, and P_{22}

$$P_{11} = \sqrt{1} = 1$$

$$P_{21} = \frac{-1}{1} = -1 \text{ when } \sigma_{21} = -1, \text{ and } P_{21} = 1 \text{ when } \sigma_{21} = 1$$

$$P_{22} = \sqrt{4-(-1)^2} = 1.732051$$

We then substitute in (4.8) so that we have the equations for generating values for the residual terms as;

Run 1 in model (3.2) and runs 1 and 2 in model (3.4)

$$u_{1t} = \varepsilon_{1t}$$
$$u_{2t} = -\varepsilon_{1t} + 1.732051\varepsilon_{2t} \quad (4.9)$$

and

Runs 2 and 3 in equation 3.2 and runs 3 and 4 in equation 3.4

$$u_{1t} = \varepsilon_{1t}$$
$$u_{2t} = \varepsilon_{1t} + 1.732051\varepsilon_{2t} \quad (4.10)$$

Samples from the first replicate for sample size 20 in run one for equation 3.4 (with over-identified constraint are presented in Tables (4.1) and (4.2)

Table 4.1: Random deviates ε_{1t} , ε_{2t} and disturbance terms u_{1t}, u_{2t} for the first replicate in run one of equation 3.4

t	ε_{1t}	ε_{2t}	u_{1t}	u_{2t}
1	1.255616	1.983905	1.255616	2.180609
2	-0.03648	-0.8525	-0.03648	-1.4401
3	-0.74768	-0.57332	-0.74768	-0.24534
4	1.534772	-0.75509	1.534772	-2.84263
5	1.252978	0.284272	1.252978	-0.76061
6	1.081464	-1.4369	1.081464	-3.57025
7	-0.87427	0.14282	-0.87427	1.121643
8	0.323186	0.568853	0.323186	0.662096
9	0.640722	-0.66067	0.640722	-1.78503
10	0.104382	-0.79597	0.104382	-1.48304
11	-1.35853	-0.05725	-1.35853	1.25936
12	-0.29497	0.314656	-0.29497	0.839975
13	-1.68437	-0.88687	-1.68437	0.148267
14	0.874658	1.144658	0.874658	1.107948
15	-0.22197	0.548267	-0.22197	1.171597
16	0.012484	-0.35068	0.012484	-0.61987
17	-0.33318	-0.32262	-0.33318	-0.22562
18	-0.5509	-0.58522	-0.5509	-0.46272
19	-0.21509	0.960135	-0.21509	1.878097
20	-0.8536	1.897852	-0.8536	4.140776

Table 4.2: $X_{1t}, X_{2t}, X_{3t}, Y_{1t}, Y_{2t}$ for the first replicate in run one of equation 3.4

t	X_{1t}	X_{2t}	X_{3t}	y_{1t}	y_{2t}
1	-1.09397	-0.59203	0.698365	2.394248	0.744201
2	0.367081	-1.18496	-1.41895	-9.94992	-3.42684
3	0.145398	-0.23277	-0.57024	-3.38113	-0.92628
4	0.265778	0.588642	-0.1135	-4.76049	-2.18701
5	0.479409	1.134421	1.332485	10.02484	2.76415
6	-1.23364	-0.09755	-0.27496	-19.6485	-6.49876
7	0.301434	-0.19762	-0.34211	2.764796	1.112545
8	-1.54591	1.250681	2.110797	2.862747	1.361822
9	0.138909	-1.57122	-1.13226	-11.194	-3.99121
10	1.133268	0.4564	0.86009	8.143142	2.301831
11	-0.65837	0.568878	-0.34641	-2.89457	-0.29256

12	-1.7005	0.521725	0.958801	-4.58133	-0.86195
13	-0.19127	-0.7314	-0.96094	-7.99982	-2.04139
14	1.272184	-1.29195	-1.10465	6.194941	1.349366
15	0.054985	0.240014	-0.4807	1.874606	0.680531
16	1.000267	-0.37619	-0.75308	1.201579	0.062943
17	-0.80293	0.867518	-0.37849	-7.03248	-1.96546
18	0.162158	-1.26779	-1.58247	-9.82676	-3.146
19	-0.62861	0.195217	-0.17518	0.523419	0.455708
20	1.62335	-1.23091	-0.78819	17.53894	5.589731

Where the endogenous variables y_{1t} and y_{2t} in table 4.2, which is for the over-identified model (equation 3.4), were generated as follows:

$$y_{1t} = 3 * y_{2t} + X_{1t} + u_{1t}$$

$$y_{2t} = 2.0 * X_{1t} + 0.5 * X_{2t} + 1.5 * X_{3t} + u_{2t}$$

while for the just identified model (equation 3.2) we have;

$$y_{1t} = 2 * y_{2t} + u_{1t}$$

$$y_{2t} = 0.5 * X_t + u_{2t}$$

For instance, the first set of for values for y_{1t} and y_{2t} in table 4.2 were obtained thus;

$$y_{21} = 2.0 * X_{1t} + 0.5 * X_{2t} + 1.5 * X_{3t} + u_{2t} = (2 \text{ x } -1.09397) + (1.5 \text{ x } 0.698365) + 2.180609$$

$$= 0.744202$$

$$y_{11} = (3 \text{ x } 0.744202) - 1.09397 + 1.255616$$

$$= 2.39425$$

The data for the whole experiment generated in STATA as well as the subprogram are presented in the appendix.

4.3 Procedure for obtaining the classical estimators

The data was imported into mathlab where a sub program was written to carry out the estimation using the classical methods; OLS, 2SLS, 3SLS, and LIML. The mathlab sub-programs are contained in appendix A for each of the methods for both models (equation 3.2 and 3.4).

4.4 The Bayesian estimator: Relevance and Use of WinBUGS

BUGS is the acronym for Bayesian analysis using Gibbs sampling, while WinBUGS is the Windows version. It is a free software developed jointly by teams of researchers from; (1)the medical research council (MRC) Biostatistics Unit, Institute of public health, Cambridge, (2) Department of Mathematics and Statistics, University of Helsinki and (3)Department of Epidemiology & Public health, imperial School of Medicine, London.

Numerical integration methods, one of which is used in Markov Chain Monte Carlo approach of WinBUGS, are usually employed when analytical solution of the posterior p.d.f is complex, difficult or not possible. In WinBUGS, sub-programs are written by the researcher to solve problems of interest. The sub-program, usually referred to as model or simply WinBUGS' codes, contains the specification of the model, the prior distribution, the data to be used in the analysis and the initial values for the parameters that were given prior distributions and are to be updated. WinBUGS then carry out Markov chain Monte Carlo (MCMC) simulation to draw samples from the resulting posterior distribution of the parameter of interest. An appropriate measure of central tendency is then applied on the samples to serve as the desired Bayesian estimate. The following are the description of the steps involved as used in this research work.

(1). Write the WinBUGS codes for solving the problem at hand using the rules and guidelines stated in the user manual. Examples are provided by the authors in the package, to serve as guide. The program should be in a new file in the software and labeled as desired. The WinBUGS code we wrote for this project is contained in appendix A

(2). The next step is to check the program, to know if it is syntactically correct, this is done by clicking on the check model icon contained in the specification tool box as shown in figure 4.1. If the model is syntactically correct, the message will show at the bottom of the WinBUGS window

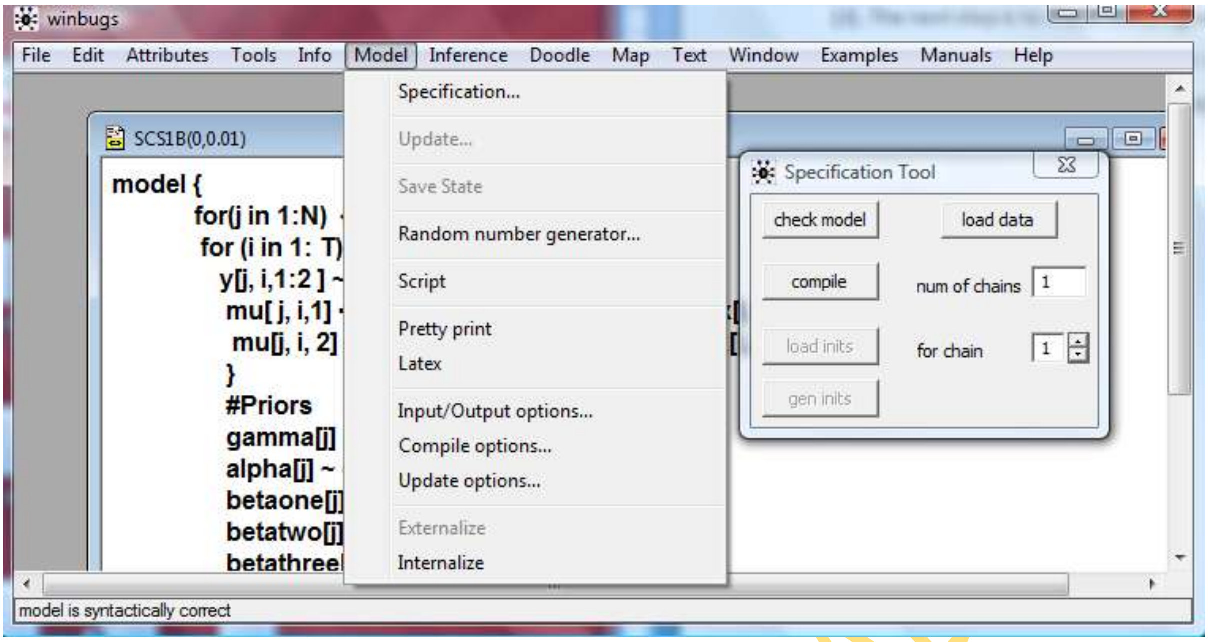

Figure 4.1: Illustration on how to check the WinBUGS model whether it is syntactically correct or not

(3). If the model is correct, then the next thing to do is to load the data that has been entered into the program or on a text file (notepad) according to the WinBUGS' specified format, by clicking on the word "list" as shown in figure 4.2 below, then "load data" as shown in figure 4.1. If the data is in the right format and complete as specified in the program, the message; "data loaded" will show at the bottom of the Window. The first iteration for T=20 in run I are shown in figure 4.2 as illustration of the WinBUGS' data format

list(T=20, N=5,

y=structure(.Data=c(6.264537, 3.428283,-1.167131, 0.0089164,-1.838982, -0.8031065,-3.697005, -2.142823,1.798427, 0.3320026,-2.273004, -1.087725,-0.5633444,-0.182864,3.613456, 1.181388,2.430152, 2.000684,3.534578, 1.539089,-5.854781, -3.211829,0.9036765, 0.1909758,-1.629707, -0.4491555,2.15367, 1.722808,-4.068905, -2.154459,-1.23392, -0.4288644,-7.862575,-4.365047,-1.850781, -0.291497,-2.736923, -1.46607,3.988953, 2.609931),.Dim=c(3, 20, 2)),

x= structure (.Data= c(-1.09397,-0.5920295, 0.6983646,0.3670809,-1.184964,-1.418946, 0.145398,-0.2327694, -0.570237,0.2657781, 0.5886417,-0.1135049,0.4794085,1.134421, 1.332485,-1.233643, -0.0975549,-0.2749635,0.3014338, -0.1976163, -0.3421052,

-1.545905,1.250681, 2.110797,0.1389086, -1.571217,-1.132261, 1.133268, 0.4563997, 0.8600896,-0.658371, 0.5688778,-0.3464097,-1.700496,0.5217248,0.9588012,-0.1912733, -0.7313956,-0.9609418,1.272184,-1.291947,-1.104651,0.0549849, 0.2400143, -0.4806955, 1.000267,-0.3761912, -0.7530838,-0.8029298,0.8675182,-0.3784932,0.1621577,-1.267787,-1.582468,-0.6286104,0.1952169,-0.1751844,1.62335,-1.23091,-0.788193),.Dim=c(20,3)))

Figure 4.2: Data in WinBUGS format from run 1 of the over-identified model, T=20.

(4).The number of parallel chains of iteration to be run is specified in the space provide as shown in figure 4.1. It is usually necessary to run more than one chain in other to have an easy judgment of the convergence of the iteration. The compile option is selected after choosing the number of chains. The message “model compiled” appears in the usual place if the model has no error, otherwise, message indicating the error in the program appears.

(5). Initial values are stated for the parameters of the model that were given prior distributions and are to be updated. Each chain of iteration should be given initial values. This should also follow the specified format in the user manual. It could also be generated by the software, but it might require larger amount of iterations before convergence is reached otherwise the results will be misleading. Initial values for 5 iterations of model 3.4 are shown in figure 4.3 as illustration. Two parallel chains were used in the experiment.

Initial values for chain 1

list(gamma= c(2, 2, 2, 2, 2), alpha =c(0.5, 0.5, 0.5, 0.5, 0.5), betaone= c(1.6, 1.6, 1.6, 1.6, 1.6), betatwo= c(0.2, 0.2, 0.2, 0.2, 0.2), betathree = c(1.2, 1.2, 1.2, 1.2, 1.2), tau= structure(.Data =c(1.0,-1.0,-1.0,0.25),.Dim=c(2,2)))

Initial values for chain 2

list(gamma= c(2.5, 2.5, 2.5, 2.5, 2.5), alpha= c(0.8, 0.8, 0.8, 0.8, 0.8),betaone= c(1.8, 1.8, 1.8, 1.8, 1.8), betatwo= c(0.3, 0.3, 0.3, 0.3, 0.3), betathree=c(1.4, 1.4, 1.4, 1.4, 1.4), tau= structure(.Data =c(0.5, -0.5, -0.5, 0.3),.Dim=c(2,2)))

Figure 4.3: Initial values for the WinBUGS sub-program

(6) The next step after loading the initial values is to set the parameters to be updated. This will make it possible to have some summary statistics such as mean, median, standard

deviation, Monte Carlo error, e.t.c. after the iterations are completed. This is done by selecting the inference tool on the menu bar and selecting samples as shown in figure 4.4. Each of the parameters to be updated are then entered and “set” one after the other.

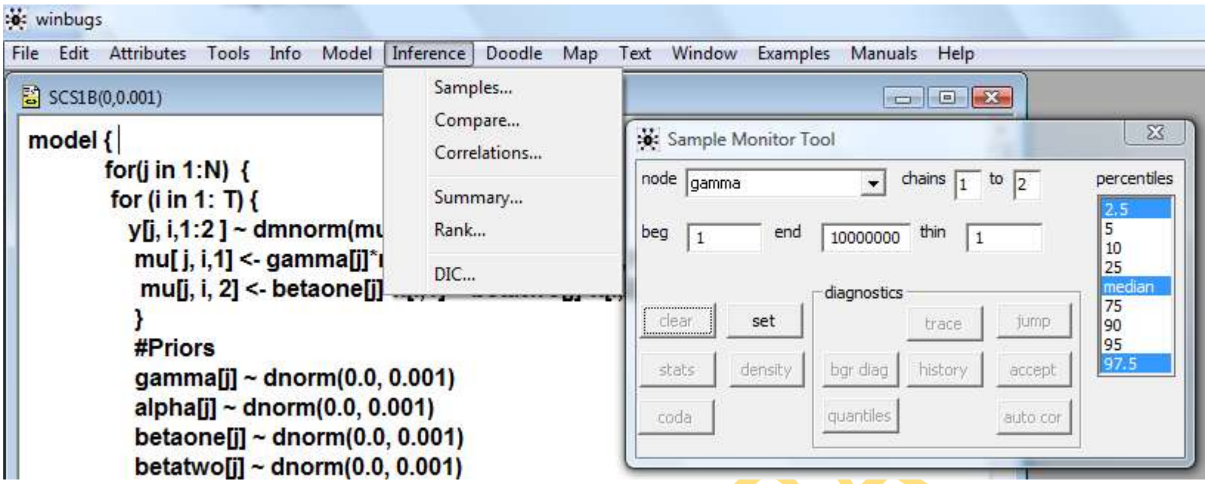

Figure 4.4: Illustration on how to set parameters to be updated

(7) The final stage is to start the update. The update tool is selected from the model option on the menu bar. When the tool box appears, a number of iterations are run first to check convergence, after which further iterations are run. Figure 4.5 shows a sample of iterations having signs of convergence because the two chains are thoroughly mixed. Other ways of checking convergence are presented by Gilks, et al (1996).

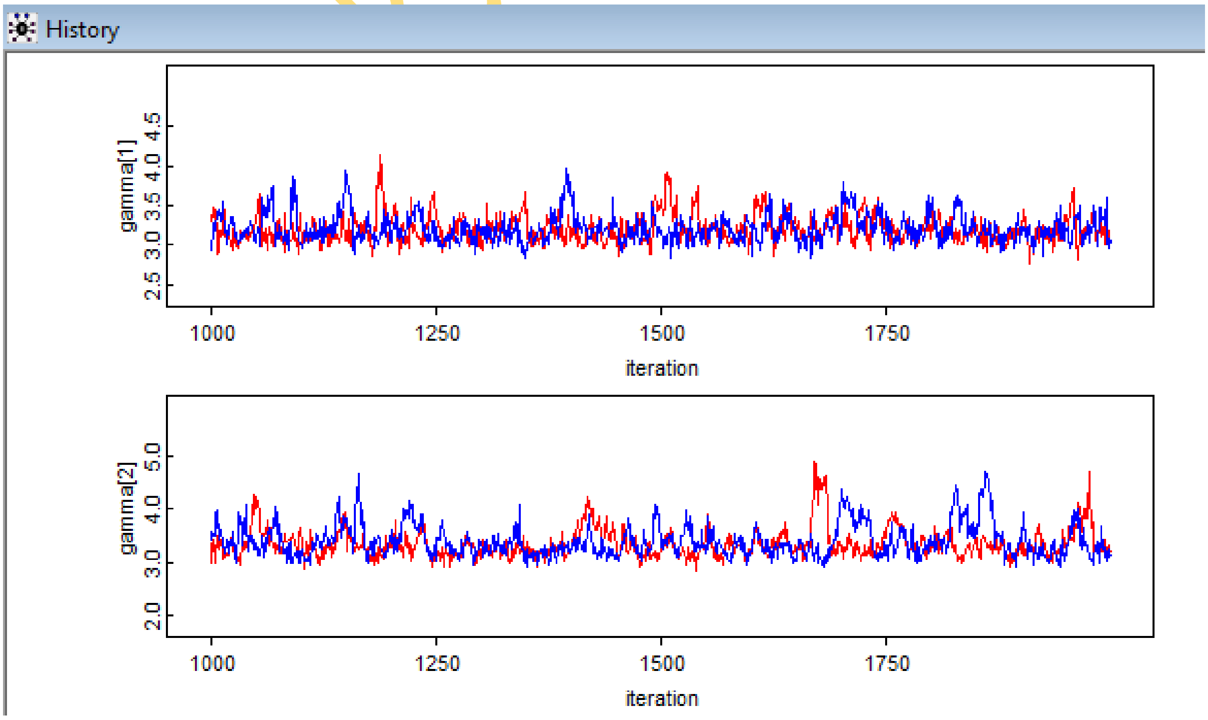

Figure 4.5: History plots

The first sets of iterations before convergence are taken as “burn-in” and should not be used in computing the estimates after all the iterations. Once the number of iterations is fixed, the update field in the update tool box is clicked for the update to start. In our experiment, we first ran 1000 iterations within which convergence was reached. A further 5000 iterations were run. 1000 iterations were then taken as burn-in. Once the update is complete, summary Statistics can be obtained from the inference tool box. The number of iterations to begin from (the next iteration after the “burn-in”) is first indicated in the “beg” field, this is 1001 in our experiment. The “stats” field is then selected to bring out the summary statistics which contains mean, standard deviation, Monte Carlo error, median and the number of MCMC samples from which the estimates were computed

Prior variance Sensitivity Analysis: The behavior of the Bayesian estimates under different specification of variance of the prior distribution for parameters of the models was also studied. In WinBUGS, the usual practice is to state the precision of a parameter rather than the variance, hence, in terms of the precision of the parameters, three prior distributions were considered as follows;

(1).Normally distributed with mean zero and precision 0.001 (variance 1000)

(2).Normally distributed with mean zero and precision 0.01(variance 100)

(3).Normally distributed with mean zero and precision 0.1 (variance 10)

These are the ones earlier referred to as BMPV 10, 100 and 1000 in section (1.2) of chapter one

4.5 Criteria for Assessing the performance of the Estimators

There are a number of comparison criteria used in the literature are, however, we made use of the mean, the bias, and the Mean Squared Error (MSE).

There are 5000 replicates so the mean of the estimates i. e. $\bar{\hat{\theta}} = \frac{1}{5000}\sum_{i=1}^{N=5000}\hat{\theta}_i$

Estimated bias $= \frac{1}{5000}\sum_{i=1}^{N=5000}\hat{\theta}_i - \theta$ i. e. $\bar{\hat{\theta}} - \theta$

The mean squared error, for an estimator of a parameter θ, is given as;

$$MSE(\hat{\theta}) = E(\hat{\theta} - \theta)^2$$

$$= \text{Var}(\hat{\theta}) + (\text{Estimated bias})^2$$

where $Var(\hat{\theta}) = \frac{1}{N_r}\sum_{1}^{N_r}\hat{\theta}^2 - (\frac{1}{N_r}\sum_{1}^{N_r}\hat{\theta})^2$ and N_r is number of replications and therefore number of estimates ($\hat{\theta}$).

θ is the true value of the parameter, which in this case is the value used to generate the sample values.

It is important to note that in Bayesian estimation method, the convergence process of the estimates to the expected value, in the Monte Carlo integration takes time. As a result of this, posterior estimates obtained early in the convergence process might make the estimator appear to be biased. Also, the effect of multicollinearity is increase in variance of estimates as mentioned in section (3.5.2) of chapter three. Hence, we made use of MSE which also has a component that represents variance of the estimates. This is expected to serve the purpose of appropriate comparison of the Bayesian estimates with those from the classical approaches. We therefore emphasise more on the MSE of the estimates.

CHAPTER FIVE

DISCUSSION OF RESULTS

5.0 Introduction

This chapter contains presentation and discussion of results from the experiment as described in chapter 4. The results of the first model were first presented followed by the second model. Estimates from the Bayesian method prior variances BMPV 10, 100, and 1000 were included in each table alongside the classical estimators.

5.1 Results from the first model (equation 3.2)

Results of the Monte Carlo studies on the just-identified model (equation 3.2) are presented in Tables 5.1 to 5.6. As mentioned in chapter 4, the Mean, Bias and Mean Squared Error are the comparison criteria, with more focus on the Mean squared error. For this model, 2SLS, 3SLS and LIML are equal for the coefficient of the endogenous explanatory variable in the first equation while all the classical estimators are the same as OLS for the second equation which contains no endogenous variable. The three runs on the just-identified model are again as follows;

(1). RUN ONE γ = 2.0, β = 0.5, X_t : NID(0,1), negatively correlated residual terms

(2). RUN TWO γ = 2.0, β = 0.5, X_t : NID(0,2), positively correlated residual terms

(3). RUN THREE γ = 2.0, β = 0.5, X_t : NID(0,9), positively correlated residual terms

Table 5.1: The mean, absolute bias and mean squared error for γ and β in run 1

T	Estimator		γ			β		
			Mean	Bias	MSE	Mean	Bias	MSE
20	Classical	OLS	1.763	0.237	0.0664	0.506	0.006	0.243
		2/3SLS/LI	1.633	0.367	202.662	0.506	0.006	0.243
	Bayesian	BMPV 10	1.625	0.374	0.2695	0.294	0.205	0.168
		BMPV 100	1.799	0.201	0.1672	0.268	0.231	0.167
		BMPV1000	1.851	0.148	0.1678	0.238	0.261	0.171
40	Classical	OLS	1.763	0.237	0.0611	0.501	0.001	0.126
		2/3SLS/LI	1.849	0.151	75.4489	0.501	0.001	0.126
	Bayesian	BMPV 10	1.731	0.268	0.2083	0.318	0.181	0.122
		BMPV 100	1.889	0.110	0.1437	0.290	0.209	0.127
		BMPV1000	1.936	0.063	0.1698	0.262	0.237	0.136
60	Classical	OLS	1.763	0.237	0.0594	0.497	0.003	0.078
		2/3SLS/LI	3.085	1.085	3185.14	0.497	0.003	0.078
	Bayesian	BMPV 10	1.838	0.161	0.1455	0.318	0.181	0.122
		BMPV 100	1.966	0.033	0.1150	0.318	0.181	0.102
		BMPV1000	2.005	0.005	0.1643	0.293	0.206	0.112
100	Classical	OLS	1.762	0.238	0.0583	0.502	0.002	0.047
		2/3SLS/LI	2.078	0.078	2.1172	0.502	0.002	0.047
	Bayesian	BMPV 10	1.953	0.046	0.1420	0.387	0.112	0.065
		BMPV 100	2.037	0.037	0.0997	0.363	0.153	0.073
		BMPV1000	2.064	0.064	0.0837	0.342	0.157	0.083

In run 1 as shown in Tables 5.1 - 5.6, the Bayesian estimation method for γ with the three stated prior variances performed better than 2SLS both in terms of bias (except for $T \leq 40$ where 2SLS/3SLS/LIML slightly perform better than BMPV 10) and MSE in all sample size cases. It was also better than OLS in terms of bias except for $T \leq 40$ where OLS was better than BMPV 10 only. This is consistent with results from literature, for example; Zellner

(1971), Gao and Lahiri (2001), Okewole, Olubusoye and Shangodoyin (2011). The 2SLS estimates were characterized with large variance while OLS estimates had the least variance as expected, though biased. The bias of OLS estimator is not affected by sample size. They are the same at all the levels of sample size. Estimates obtained through BMPV 100 are the best among the three prior variance levels for γ. The iterations in WinBUGS for the Bayesian estimates converged faster for γ in the just-identified model because it is a simple case involving only two endogenous variables and one exogenous regressor.

The situation is somehow different for parameter β of the instrumental variable in the model as observed from Table 5.1 and 5.2. First, OLS, 2SLS, 3SLS and LIML are the same. This is due to absence of endogenous variable in the equation. The Bayesian estimates were better than those from the classical methods only in terms of MSE and in small sample sizes $T \leq 20$ The classical estimators had better performance than the Bayesian method in the large sample cases, being less biased and having lower MSE.

Table 5.2: Cases in which each estimator has minimum MSE in Run 1 for equation 3.2

T	Estimator		γ	β	Total
20	Classical	OLS	1	0	1
		2/3SLS/LIML	0	0	0
	Bayesian	BMPV 10	0	0	0
		BMPV 100	0	1	1
		BMPV 1000	0	0	0
40	Classical	OLS	1	0	1
		2/3SLS/LIML	0	0	0
	Bayesian	BMPV 10	0	0	0
		BMPV 100	0	0	0
		BMPV 1000	0	1	1
60	Classical	OLS	1	1	2
		2/3SLS/LIML	0	1	1
	Bayesian	BMPV 10	0	0	0
		BMPV 100	0	0	0
		BMPV 1000	0	0	0
100	Classical	OLS	1	1	2
		2/3SLS/LIML	0	1	1
	Bayesian	BMPV 10	0	0	0
		BMPV 100	0	0	0
		BMPV 1000	0	0	0

The Bayesian estimator of β was slower in convergence than the estimates of γ. Varying the Bayesian Prior precision appears not to have much effect on the estimates obtained; BMPV

100 only performed a little better than other prior variance levels but could not bring the Bayesian estimates close to estimates from the classical methods. Most likely explanation for this is that for this parameter (β), a lot more iterations are required to obtain estimates closer to the true value.

Table 5.3: The mean, absolute bias and mean squared error for γ and β in run 2

T	Estimator		γ			β		
			Mean	Bias	MSE	Mean	Bias	MSE
20	Classical	OLS	2.225	0.225	0.0602	0.498	0.002	0.120
		2/3SLS/LI	2.210	0.210	179.595	0.498	0.002	0.120
	Bayesian	BMPV 10	1.793	0.206	0.1927	0.325	0.175	0.107
		BMPV 100	1.952	0.047	0.1384	0.292	0.207	0.121
		BMPV1000	1.999	0.000	0.1559	0.263	0.236	0.131
40	Classical	OLS	2.227	0.227	0.0562	0.503	0.003	0.063
		2/3SLS/LI	1.947	0.053	7.6169	0.503	0.003	0.063
	Bayesian	BMPV 10	1.808	0.192	0.1841	0.362	0.137	0.075
		BMPV 100	1.902	0.098	0.1418	0.338	0.161	0.088
		BMPV1000	1.928	0.071	0.1556	0.314	0.185	0.098
60	Classical	OLS	2.225	0.225	0.0536	0.500	0.000	0.039
		2/3SLS/LI	1.976	0.024	15.2951	0.500	0.000	0.039
	Bayesian	BMPV 10	1.838	0.161	0.1467	0.394	0.105	0.054
		BMPV 100	1.888	0.112	0.1213	0.380	0.119	0.063
		BMPV1000	1.899	0.100	0.1328	0.363	0.136	0.071
100	Classical	OLS	2.226	0.226	0.0528	0.502	0.002	0.024
		2/3SLS/LI	1.964	0.036	0.0593	0.502	0.002	0.024
	Bayesian	BMPV 10	1.889	0.110	0.0894	0.430	0.069	0.035
		BMPV 100	1.906	0.093	0.0828	0.426	0.074	0.038
		BMPV1000	1.911	0.088	0.1139	0.417	0.082	0.043

Going through tables 5.3 and 5.4 containing results from run 2, we could see that the same pattern of result as in run 1 (Tables 5.1 and5. 2) was recorded for both parameters of the model, γ and β, except that MSE reduced for all the estimators. OLS performed better than the Bayesian approach

Table 5.4: Cases in which each estimator has minimum MSE in Run 2 for equation 3.2

Sample Size	Estimator		γ	β	Total
	Classical	OLS	1	0	1
		2/3SLS/LIML	0	0	0
	Bayesian	BMPV 10	0	1	1
20		BMPV 100	0	0	0
		BMPV 1000	0	0	0
	Classical	OLS	1	1	2
		2/3SLS/LIML	0	1	1
	Bayesian	BMPV 10	0	0	0
40		BMPV 100	0	0	0
		BMPV 1000	0	0	0
	Classical	OLS	1	1	2
		2/3SLS/LIML	0	1	1
	Bayesian	BMPV 10	0	0	0
60		BMPV 100	0	0	0
		BMPV 1000	0	0	0
	Classical	OLS	1	1	2
		2/3SLS/LIML	0	1	1
	Bayesian	BMPV 10	0	0	0
100		BMPV 100	0	0	0
		BMPV 1000	0	0	0

In run 3, where the variance of the exogenous variable X_t was increased to 9, the MSE for all the estimators was smaller than the other 2 runs. Also, the bias of 2SLS became smaller than that of the Bayesian. In all the three runs, BMPV 100 produced the smallest MSE among the three prior variances specified

Table 5.5: The mean, absolute bias and mean squared error for γ and β in run 3

T	Estimator		γ			β		
			Mean	Bias	MSE	Mean	Bias	MSE
20	Classical	OLS	2.167	0.167	0.0354	0.499	0.001	0.0267
		2/3SLS/LIML	1.945	0.055	2.5607	0.499	0.001	0.0267
	Bayesian	BMPV 10	1.8724	0.1276	0.1066	0.4195	0.0805	0.0391
		BMPV 100	1.8973	0.1027	0.0956	0.4122	0.0878	0.0441
		BMPV 1000	1.8999	0.1001	0.1136	0.4009	0.0991	0.0495
40	Classical	OLS	2.172	0.172	0.0334	0.501	0.001	0.0140
		2/3SLS/LIML	1.983	0.017	0.0219	0.501	0.001	0.0140
	Bayesian	BMPV 10	1.9452	0.0548	0.0378	0.4622	0.0378	0.0188
		BMPV 100	1.9511	0.0489	0.0371	0.4633	0.0367	0.0193
		BMPV 1000	1.9505	0.0495	0.0415	0.4601	0.0399	0.0203
60	Classical	OLS	2.168	0.168	0.0304	0.500	0.000	0.0087
		2/3SLS/LIML	1.991	0.009	0.0102	0.500	0.000	0.0087
	Bayesian	BMPV 10	1.9750	0.0250	0.0135	0.4788	0.0212	0.0102
		BMPV 100	1.9777	0.0223	0.0130	0.4802	0.0198	0.0101
		BMPV 1000	1.9779	0.0221	0.0130	0.4796	0.0204	0.0103
100	Classical	OLS	2.169	0.169	0.0301	0.501	0.001	0.0054
		2/3SLS/LIML	1.994	0.006	0.0059	0.501	0.001	0.0054
	Bayesian	BMPV 10	1.9860	0.0140	0.0066	0.4788	0.0212	0.0102
		BMPV 100	1.9874	0.0126	0.0066	0.4894	0.0106	0.0058
		BMPV 1000	1.9875	0.0125	0.0067	0.4893	0.0107	0.0058

For γ, Tables 5.5 and 5.6 show that estimates from the Bayesian approach have smaller MSE than those from 2/3SLS/LIML while OLS has the least MSE. The bias from OLS estimator is however more than that of the Bayesian as it is in runs 1 and 2.

Table 5.6: Cases in which each estimator has minimum MSE in Run 3 for equation 3.2

Sample size	Estimator		γ	β	Total
20	Classical	OLS	1	1	2
		2/3SLS/LIML	0	1	1
	Bayesian	BMPV 10	0	0	0
		BMPV 100	0	0	0
		BMPV 1000	0	0	0
	Classical	OLS	0	1	1
		2/3SLS/LIML	1	1	2

40	Bayesian	BMPV 10	0	0	0
		BMPV 100	0	0	0
		BMPV 1000	0	0	0
60	Classical	OLS	0	1	1
		2/3SLS/LIML	1	1	2
	Bayesian	BMPV 10	0	0	0
		BMPV 100	0	0	0
		BMPV 1000	0	0	0
100	Classical	OLS	0	1	1
		2/3SLS/LIML	1	1	2
	Bayesian	BMPV 10	0	0	0
		BMPV 100	0	0	0
		BMPV 1000	0	0	0

5.2 Results from the second model (equation 3.4)

Tables 5.7 to 5.25 contain results from the second model (equation 3.4). Summaries of number of cases in which each estimator has minimum MSE in each run are presented as well as the values of MSE and absolute bias for run 1, 2 and 3. Tables containing mean, absolute bias and MSE for all the runs are presented in the appendix.

There were 5 runs as mentioned in chapter 4;

RUN ONE: Depicting a high level of multicollinearity of two exogenous terms in the second equation with negative correlations between the residual terms of the two equations

RUN TWO: Depicting a low level of multicollinearity of two exogenous terms in the second equation with negative correlations between the residual terms of the two equations

RUN THREE: Depicting a high level of multicollinearity of two exogenous terms in the second equation with positive correlations between the residual terms of the two equations

RUN FOUR: Depicting a low level of multicollinearity of two exogenous terms in the second equation with positive correlations between the residual terms of the two equations

RUN FIVE: Depicting a higher level of multicollinearity of two exogenous terms in the second equation with positive correlations between the residual terms of the two equations

(a).Results of the Coefficients of the endogenous variable and the exogenous variable in the first equation of model (3.4), γ *and* β_{11} **for run one**

The classical methods 2SLS and 3SLS are the same for our model (3.4), while others have different values. As reflected in Tables 5.7 and 5.8, among the three specified prior variances, BMPV 10 has the smallest MSE throughout, it also has the smallest bias for β_{11}

sample size 20 and for γ in sample size 60 (Table 5.8). Number of cases in which each estimation approach has the least MSE (presented in Table 5.9) shows that 2SLS has the least MSE in most cases although MSE from the Bayesian methods were either close to it in some cases or better in few other cases.

Table 5.7: MSE from run 1 for all sample sizes.

Parameter	T	MSE					
		OLS	2/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	20	0.0286	0.0280	2.1277	0.0330	0.0300	0.0286
	40	0.0176	0.0070	0.0076	0.0173	0.0125	0.0089
	60	0.0193	0.0051	0.0054	0.0049	0.0098	0.0051
	100	0.0205	0.0035	0.0036	0.0036	0.0036	0.0058
$\beta_{11}(1.0)$	20	0.0837	0.1031	1.2347	0.1493	0.1050	0.0950
	40	0.1057	0.0636	0.0670	0.7046	0.2722	0.0943
	60	0.1032	0.0271	0.0434	0.0387	0.4723	0.1197
	100	0.0937	0.0271	0.0278	0.9571	0.0312	0.1758
$\beta_{21}(2.0)$	20	0.3094	0.3094	0.3094	0.3190	0.3162	0.3052
	40	0.1323	0.1323	0.1323	0.1309	0.1306	0.1276
	60	0.0795	0.0795	0.0795	0.0858	0.0791	0.0783
	100	0.0471	0.0471	0.0471	0.0471	0.0471	0.0468
$\beta_{22}(0.5)$	20	0.7492	0.7492	0.7492	0.5290	0.5220	0.4529
	40	0.3888	0.3888	0.3888	0.2886	0.2859	0.2650
	60	0.1974	0.1974	0.1974	0.1071	0.1502	0.1431
	100	0.0973	0.0973	0.0973	0.0764	0.0751	0.0744
$\beta_{23}(1.5)$	20	0.5807	0.5807	0.5807	0.5163	0.5045	0.4335
	40	0.3147	0.3147	0.3147	0.2971	0.2894	0.2358
	60	0.1853	0.1853	0.1853	0.1285	0.1878	0.1565
	100	0.1231	0.1231	0.1231	0.1153	0.1017	0.1120

OLS has large bias as expected (referred to as simultaneity bias) for both γ *and* β_{11} because of its high sensitivity to over-identification constraint. In large sample size 100, LIML estimator for γ was similar to BMPV 100 and 1000 both in terms of MSE (Table 5.7) and bias (Table 5.8)

Table 5.8: Absolute bias (ABS bias) from run 1 for all sample sizes

Parameter	T	Absolute bias					
		OLS	2/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	20	0.1469	0.0052	0.0448	0.0071	0.0077	0.0063
	40	0.1220	0.0013	0.0082	0.0022	0.0010	0.0046
	60	0.1323	0.0012	0.0038	0.0075	0.0037	0.0004
	100	0.1389	0.0018	0.0052	0.0052	0.0051	0.0013
$\beta_{11}(1.0)$	20	0.1621	0.0054	0.039	0.0023	0.0058	0.0020
	40	0.2599	0.0011	0.0157	0.1014	0.0572	0.0078
	60	0.2817	0.0037	0.0065	0.0056	0.0949	0.0346
	100	0.2812	0.0037	0.0105	0.1186	0.0094	0.0411
$\beta_{21}(2.0)$	20	0.0084	0.0084	0.0084	0.0551	0.0594	0.1133
	40	0.0012	0.0012	0.0012	0.0047	0.0018	0.0179
	60	0.0043	0.0043	0.0043	0.1345	0.0029	0.0169
	100	0.0022	0.0022	0.0022	0.0024	0.0016	0.0070
$\beta_{22}(0.5)$	20	0.0089	0.0089	0.0089	0.0375	0.0350	0.0248
	40	0.0026	0.0026	0.0026	0.0216	0.0197	0.0010
	60	0.0166	0.0166	0.0166	0.0840	0.0073	0.0069
	100	0.0067	0.0067	0.0067	0.0053	0.0004	0.0007
$\beta_{23}(1.5)$	20	0.0019	0.0019	0.0019	0.1275	0.1284	0.1554
	40	0.0069	0.0069	0.0069	0.0757	0.0738	0.0606
	60	0.0053	0.0053	0.0053	0.1657	0.0547	0.0503
	100	0.0083	0.0083	0.0083	0.0341	0.0218	0.0438

(b) Results of the coefficients of the regressors in the second equation of model (3.4), $\beta_{21}, \beta_{22}, \beta_{23}$ in run one: The classical estimation methods all reduce to OLS for the coefficients of the instrumental variables in any equation such as equation 2 of model (3.4) since it doesn't contain any endogenous variable.

The Bayesian estimation method performed better than the classical method in terms of MSE as shown in Tables 5.7 to 5.11, suggesting that it is less sensitive to multicollinearity. Specifically, the Bayesian method with prior variance 10 (BMPV 10) had the least variance throughout for β_{21}, β_{22} and β_{23} as reflected in Tables 5.7 and 5.9.

Table 5.9: Cases in which each estimator has minimum MSE in Run 1 for equation 3.4

T	Estimator		γ	β_{11}	β_{21}	β_{22}	β_{23}	Total
20	Classical	OLS	0	1	0	0	0	1
		2SLS/3SLS	1	0	0	0	0	1
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
40	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
60	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	0	1	0	0	0	1
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	0	0	1
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	1	0	0	1	1	3
100	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	0	2
		BMPV 100	0	0	0	0	1	1
		BMPV 1000	0	0	0	0	0	0

The Relative Efficiency (RE) of BMPV 10 to the least-squares estimators ($\frac{MSE_{least-squares}}{MSE_{BMPV10}}$) also provides a clearer view of this result. RE for β_{22} and β_{23} are presented in Table 5.10. This also shows that as the sample size increases, estimates of β_{21}, β_{22} and β_{23} from the classical approaches gets closer to those from the Bayesian approach. Estimates from the Bayesian method also has less bias in some cases than estimates from the classical approaches.

In terms of all the parameters of the model, Table 5.9 shows that BMPV 10 has the least MSE for sample sizes 20 and 40, BMPV 1000 for sample size 60 and 2SLS/3SLS and BMPV 10 for sample size 100 in run 1.

Table 5.10: Relative efficiency of BMPV 10 to the classical estimators for β_{22} and β_{23} in run1

Parameter \ Sample Size	**20**	**40**	**60**	**100**
β_{22}	1.6542	1.4672	1.3795	1.3078
β_{23}	1.3396	1.3346	1.1840	1.0991

Results from run 2 are presented in Tables 5.11 to 5.19. In terms of the overall performance of the estimators considering all the parameters of the model, results from Table 5.11 show that BMPV 10 has the minimum MSE in run 2 for sample sizes 20 and 40 and is therefore the most efficient for such cases, while 2SLS/3SLS shows more efficiency for sample sizes 60 and 100.

Table 5.11: Cases in which each estimator has minimum MSE in Run 2 for equation 3.4

Sample size	Estimator		γ	β_{11}	β_{21}	β_{22}	β_{23}	Total
	Classical	OLS	0	0	0	0	1	1
		2SLS/3SLS	1	0	0	0	1	2
		LIML	0	0	0	0	1	1
20	Bayesian	BMPV 10	0	1	1	1	0	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
40		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
	Classical	OLS	0	0	0	0	1	1
		2SLS/3SLS	1	1	0	0	1	3
		LIML	0	0	0	0	1	1
	Bayesian	BMPV 10	0	0	1	1	0	2
60		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
	Classical	OLS	0	0	0	0	1	1
		2SLS/3SLS	1	1	0	0	1	3
		LIML	0	0	0	0	1	1
	Bayesian	BMPV 10	0	0	1	1	0	2
100		BMPV 100	0	0	1	0	0	1
		BMPV 1000	0	0	1	0	0	1

Results of the second run indicates similar pattern as in run one in that estimates of β_{21}, β_{22}, and β_{23} from the Bayesian approach have smaller MSE than other estimators, while estimates of γ *and* β_{11} from 2SLS estimator had the least MSE as well as smaller bias than estimates from the Bayesian approach. The actual values of MSE and bias are contained in Tables 5.12 and 5.14

Table 5.12: MSE from run 2 for all sample sizes

Parameter	T	MSE					
		OLS	2/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	20	0.0295	0.0265	0.0872	0.0522	0.0339	0.0269
	40	0.0210	0.0080	0.0089	0.0328	0.0212	0.0091
	60	0.0291	0.0094	0.0106	0.0571	0.0361	0.0163
	100	0.0110	0.0034	0.0035	0.0036	0.0036	0.0036
$\beta_{11}(1.0)$	20	0.2205	0.2364	0.5816	0.5814	0.2734	0.2133
	40	0.1139	0.0650	0.0694	0.8094	0.3035	0.1240
	60	0.1373	0.0594	0.0654	1.3421	0.5870	0.1306
	100	0.0816	0.0222	0.0228	0.7578	0.5939	0.1644
$\beta_{21}(2.0)$	20	0.5047	0.5047	0.5047	0.4698	0.4641	0.4267
	40	0.1202	0.1202	0.1202	0.1199	0.1196	0.1175
	60	0.0750	0.0750	0.0750	0.0750	0.0749	0.0740
	100	0.0382	0.0382	0.0382	0.0379	0.0380	0.0380
$\beta_{22}(0.5)$	20	0.2346	0.2346	0.2346	0.1740	0.1728	0.1654
	40	0.0837	0.0837	0.0837	0.0661	0.0689	0.0642
	60	0.0517	0.0517	0.0517	0.0479	0.0470	0.0406
	100	0.0540	0.0540	0.0540	0.0442	0.0441	0.0414
$\beta_{23}(1.5)$	20	0.2185	0.2185	0.2185	0.2598	0.2521	0.2213
	40	0.0990	0.0990	0.0990	0.1154	0.1280	0.0985
	60	0.0999	0.0999	0.0999	0.1502	0.1447	0.1068
	100	0.0325	0.0325	0.0325	0.0445	0.0443	0.0445

It is important to note that MSE for all the estimates reduced in run two where the exogenous variables has no significant correlations. This reduction in MSE of the classical estimators reflected in the relative efficiency of the Bayesian approach to the classical approach contained in Table 5.13. The MSE obviously reduced enough for the RE to reduce in this run compared with run 1. This supports the fact that the classical approaches of the regression coefficients are sensitive to presence of multicollinearity as shown in section (3.5.2) of chapter three. It also suggests that the Bayesian approach as well is sensitive to this problem of multicollinearity although in a lesser degree compared with the classical approaches. This is because MSE of the Bayesian is smaller than that of the classical.

Table 5.13: Relative efficiency of BMPV10 to the classical methods for β_{22} and β_{23} in run2

Parameter \ Sample size	20	40	60	100
β_{22}	1.4184	1.3037	1.2734	1.3043
β_{23}	0.9873	1.0051	0.9354	0.7303

Table 5.14: Absolute bias (ABS bias) from run 2 for all sample sizes

Parameter	T	Absolute bias					
		OLS	2/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	20	0.1505	0.0028	0.0285	0.0050	0.0084	0.0067
	40	0.1344	0.0016	0.0071	0.0075	0.0045	0.0034
	60	0.16349	0.0014	0.0111	0.0118	0.0082	0.0017
	100	0.1372	0.0012	0.0044	0.0003	0.0004	0.0012
$\beta_{11}(1.0)$	20	0.3328	0.0003	0.0703	0.0042	0.0195	0.0092
	40	0.2778	0.0023	0.0160	0.1124	0.0594	0.0009
	60	0.3348	0.0036	0.0236	0.1798	0.1139	0.0198
	100	0.2648	0.0040	0.0103	0.1036	0.0903	0.0405
$\beta_{21}(2.0)$	20	0.0004	0.0004	0.0004	0.0166	0.0058	0.0742
	40	0.0011	0.0011	0.0011	0.0037	0.0009	0.0193
	60	0.0028	0.0028	0.0028	0.0051	0.0031	0.0101
	100	0.0010	0.0010	0.0010	0.0000	0.0010	0.0075
$\beta_{22}(0.5)$	20	0.0011	0.0011	0.0011	0.0450	0.0406	0.0083
	40	0.0016	0.0016	0.0016	0.0189	0.0264	0.0132
	60	0.0083	0.0083	0.0083	0.0283	0.0269	0.0123
	100	0.0023	0.0023	0.0023	0.0153	0.0153	0.0126
$\beta_{23}(1.5)$	20	0.0025	0.0025	0.0025	0.1255	0.1241	0.1285
	40	0.0054	0.0054	0.0054	0.0479	0.0566	0.0459
	60	0.0999	0.0999	0.0999	0.1502	0.1447	0.1068
	100	0.0023	0.0023	0.0023	0.0295	0.0296	0.0323

Also, rates of change in the MSE of β_{22} and β_{23} from run one to run two ($\frac{MSE_{run\ one}}{MSE_{run\ two}}$) is higher with the classical approach than the Bayesian. The values of β_{22} are 3.1941 and 2.6579 for $T = 20$, 4.6440 and 2.3934 for $T = 40$, 3.8210 and 1.8717 for $T = 60$, and 1.8003 and 3.7918 for $T = 100$ for the classical estimators compared with Bayesian; while those of β_{23} are 2.7388 and 1.9587 for $T = 20$, 4.1263 and 2.3934 for $T = 40$, 2.227 and 1.5892 for $T = 60$, and 1.7971 and 2.519 for $T = 100$. These values are shown in table 5.15

Table 5.15: Rate of change in MSE of β_{22} and β_{23} from run 1 to run 2

Sample size	β_{22}		β_{23}	
	Classical	Bayesian	Classical	Bayesian
20	3.1941	2.7388	2.6579	1.9587
40	4.6440	4.1263	2.3934	2.3934
60	3.8210	2.227	1.8717	1.5892
100	1.8003	1.7971	3.7918	2.519

NOTE: Rate of change = $\frac{\text{MSE of Estimator in RUN 1}}{\text{MSE of Estimator in RUN 2}}$

The overall performance of the estimators in terms of minimum MSE in run 3 are also presented in Table 5. 16. BMPV 10 has the overall best performance in terms of efficiency as it has the minimum MSE in all the sample sizes. However, the details of this result are that 2SLS/3SLS is best for γ *and* β_{11} while BMPV 10 is best for β_{21}, β_{22}, and β_{23}. This is the same pattern of result as in run 1 and 2.

Table 5.16: Cases in which each estimator has minimum MSE in Run 3 for equation 3.4

Sample size	Estimator		γ	β_{11}	β_{21}	β_{22}	β_{23}	Total
20	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
40	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
60	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
100	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0

Table 5.17: MSE from run 3 for all sample sizes

Parameter	T	MSE					
		OLS	2/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	20	0.0127	0.0089	0.0103	0.0101	0.0101	0.0103
	40	0.0216	0.0087	0.0099	0.0098	0.0098	0.0096
	60	0.0173	0.0045	0.0048	0.0048	0.0048	0.0048
	100	0.0146	0.0023	0.0023	0.0023	0.0023	0.0024
$\beta_{11}(1.0)$	20	0.0819	0.0746	0.0803	0.0799	0.0796	0.0768
	40	0.1357	0.0676	0.0751	0.0746	0.0742	0.0712
	60	0.1078	0.0379	0.0397	0.0397	0.0397	0.0391
	100	0.0607	0.0171	0.0174	0.0174	0.0174	0.0173
$\beta_{21}(2.0)$	20	0.1845	0.1845	0.1845	0.1817	0.1811	0.1762
	40	0.0840	0.0840	0.0840	0.0842	0.0840	0.0823
	60	0.0480	0.0480	0.0480	0.0480	0.0480	0.0474
	100	0.0354	0.0354	0.0354	0.0353	0.0353	0.0352
$\beta_{22}(0.5)$	20	0.4230	0.4230	0.4230	0.3096	0.3066	0.2825
	40	0.1583	0.1583	0.1583	0.1167	0.1162	0.1128
	60	0.1498	0.1498	0.1498	0.1118	0.1114	0.1079
	100	0.0897	0.0897	0.0897	0.0663	0.0661	0.0649
$\beta_{23}(1.5)$	20	0.3502	0.3502	0.3502	0.2764	0.2740	0.2502
	40	0.2284	0.2284	0.2284	0.1908	0.1900	0.1799
	60	0.1614	0.1614	0.1614	0.1333	0.1329	0.1280
	100	0.1019	0.1019	0.1019	0.0817	0.0815	0.0797

The 2SLS estimator for γ *and* β_{11} performed better that the Bayesian not only in terms of MSE (Table 5.17) but also in terms of bias (Table 5.18) in the small sample cases $T \leq 40$. However, in terms of all the parameters of the model combined, the Bayesian approach has the highest number of cases in which its MSE is minimum.The results also show that for both Classical and Bayesian methods, MSE reduces as the sample size increases.

Table 5.18: Absolute bias (ABS bias) from run 3 for all sample sizes

Parameter	T	Absolute bias					
		OLS	2/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	20	0.0906	0.0000	0.0097	0.0095	0.0099	0.0133
	40	0.1366	0.0000	0.0095	0.0093	0.0095	0.0109
	60	0.1244	0.0016	0.0063	0.0063	0.0064	0.0073
	100	0.1168	0.0005	0.0028	0.0028	0.0029	0.0037
$\beta_{11}(1.0)$	20	0.1685	0.0000	0.0181	0.0177	0.0171	0.0110
	40	0.3227	0.0011	0.0236	0.0233	0.0230	0.0206
	60	0.2967	0.0046	0.0157	0.0158	0.0156	0.0145
	100	0.2235	0.003	0.0058	0.0058	0.0058	0.0049
$\beta_{21}(2.0)$	20	0.0062	0.0062	0.0062	0.0011	0.0024	0.0370
	40	0.0018	0.0018	0.0018	0.0111	0.0096	0.0045
	60	0.0019	0.0019	0.0019	0.0070	0.0061	0.0027
	100	0.0013	0.0013	0.0013	0.0021	0.0028	0.0105
$\beta_{22}(0.5)$	20	0.0118	0.0118	0.0118	0.0142	0.0133	0.0008
	40	0.0060	0.0060	0.0060	0.0106	0.0098	0.0019
	60	0.0050	0.0050	0.0050	0.0006	0.0002	0.0074
	100	0.0080	0.0080	0.0080	0.0098	0.0093	0.0033
$\beta_{23}(1.5)$	20	0.0011	0.0011	0.0011	0.0419	0.0443	0.0589
	40	0.0047	0.0047	0.0047	0.0503	0.0520	0.0617
	60	0.0061	0.0061	0.0061	0.0338	0.0351	0.0427
	100	0.0054	0.0054	0.0054	0.0100	0.0109	0.0180

The relative efficiency of the Bayesian to the classical (Table 5.19) also shows that the Bayesian approach is less sensitive to multicollinearity than all the Classical approach.

Table 5.19: Relative efficiency of BMPV 10 to the classical methods for β_{22} and β_{23} in run3

Sample size / Parameter	**20**	**40**	**60**	**100**
β_{22}	1.4973	1.4034	1.3883	1.3821
β_{23}	1.3997	1.2696	1.2609	1.2785

Run four was also a case of low correlation between the exogenous variables. The results here, as shown in tables 5.20 to 5.22, are also the same with others in terms of performance of the estimators. Table 5.20 contains the summary of number of cases each estimator has the minimum MSE

Table 5.20: Cases in which each estimator has minimum MSE in Run 4 for equation 3.4

T	Estimator		γ	β_{11}	β_{21}	β_{22}	β_{23}	Total
20	Classical	OLS	0	0	0	0	1	1
		2SLS/3SLS	1	0	0	0	1	2
		LIML	0	0	0	0	1	1
	Bayesian	BMPV 10	0	0	1	0	0	1
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	1	0	1	0	2
40	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
60	Classical	OLS	0	0	0	0	1	1
		2SLS/3SLS	1	1	0	0	1	3
		LIML	0	0	0	0	1	1
	Bayesian	BMPV 10	0	0	1	1	0	2
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
100	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0

Results from Table 5.20 shows that 2SLS/3SLS and BMPV 1000 has the least MSE for sample size 20, BMPV 10 for sample sizes 40 and 100, and 2SLS/3SLS for sample size 60. This suggests that the classical estimators performs better in the absence of multicollinearity as represented by run 4, than in the presence of multicollinearity (as represented by run 3) and gets closer to the Bayesian approaches

Table 5.21: MSE from run 4 for all sample sizes

Parameter	T	MSE					
		OLS	2/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10

$\gamma(3.0)$	20	0.0315	0.0292	0.2249	0.1947	0.0309	0.0293
	40	0.0267	0.0118	0.0136	0.0141	0.0133	0.0134
	60	0.0257	0.0075	0.0081	0.0081	0.0081	0.0082
	100	0.0253	0.0043	0.0046	0.0046	0.0046	0.0046
$\beta_{11}(1.0)$	20	0.1756	0.1870	1.0188	0.0884	0.1884	0.1623
	40	0.1069	0.07361	0.0804	0.1101	0.0787	0.0754
	60	0.0897	0.0441	0.0464	0.0463	0.0462	0.0455
	100	0.0957	0.0274	0.0285	0.0286	0.0285	0.0283
$\beta_{21}(2.0)$	20	0.2581	0.2581	0.2581	0.5847	0.2567	0.2497
	40	0.1565	0.1565	0.1565	0.1565	0.1562	0.1542
	60	0.0974	0.0974	0.0974	0.0967	0.0966	0.0958
	100	0.0541	0.0541	0.0541	0.0541	0.0540	0.0536
$\beta_{22}(0.5)$	20	0.3639	0.3639	0.3639	0.1510	0.2604	0.2503
	40	0.1327	0.1327	0.1327	0.0997	0.0993	0.0972
	60	0.0935	0.0935	0.0935	0.0705	0.0703	0.0694
	100	0.0424	0.0424	0.0424	0.0329	0.0329	0.0327
$\beta_{23}(1.5)$	20	0.2331	0.2331	0.2331	0.3995	0.2630	0.2361
	40	0.1463	0.1463	0.1463	0.1423	0.1416	0.1370
	60	0.0626	0.0626	0.0626	0.0646	0.0645	0.0645
	100	0.0459	0.0459	0.0459	0.0446	0.0446	0.0444

The relative efficiency of the Bayesian approach over the classical approaches for β_{22} and β_{23} is contained in Table 5.22. The pattern of sensitivity of the estimators to multicollinearity was also the same in this case as reflected in the rate of change of the MSE of β_{22} and β_{23} from run 3 to run 4. They are given as 1.1626 and 1.5023 for the classical compared with 1.1286 and 1.05972 for the Bayesian when $N = 20$, 1.1931 and 1.5607 for classical compared with 1.1605 and 1.3131 for the Bayesian when $N = 40$, 1.6011 and 2.5775 for the classical compared with 1.5535 and 1.9851 for the Bayesian when $N = 60$, and 2.1159 and 2.2211 for the classical compared with 1.9838 and 1.7939 for the Bayesian when $N = 100$. This, as was the case with rate of change from run 1 to 2 shows that the Bayesian approach is less sensitive to multicollinearity than the classical approaches.

Table 5.22: Relative efficiency of BMPV 10 to the classical methods for β_{22} and β_{23} in run 4

Sample size / Parameter	**20**	**40**	**60**	**100**
β_{22}	1.4539	1.3652	1.3473	1.2966
β_{23}	0.9873	1.0679	0.9705	1.0338

The degree of multicollinearity was increased by increasing the correlation between X_{2t} *and* X_{3t} from 0.8 in runs 1 and 3 to 0.9 in run 5. The results as shown in tables 5.23 to 5.25 follow the same pattern as in the case of runs 1 and 3 although the performance of the Bayesian approach is more pronounced in this run since multicollinearity is higher than the other runs. Specifically, BMPV 10 is best in all sample sizes for β_{21}, β_{22}, and β_{23} while 2SLS is best for γ *and* β_{11}.

Table 5.23: Cases in which each estimator has minimum MSE in Run 5 for equation 3.4

T	Estimator		γ	β_{11}	β_{21}	β_{22}	β_{23}	Total
	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
20	Bayesian	BMPV 10	0	0	1	1	1	3
		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
40		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
60		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0
	Classical	OLS	0	0	0	0	0	0
		2SLS/3SLS	1	1	0	0	0	2
		LIML	0	0	0	0	0	0
	Bayesian	BMPV 10	0	0	1	1	1	3
100		BMPV 100	0	0	0	0	0	0
		BMPV 1000	0	0	0	0	0	0

The increase in the degree of multicollinearity reflected in the MSE of the coefficients of the exogenous variables involved, i.e. β_{22} and β_{23}: there is an increase in the MSE for all the estimators.

Table 5.24: MSE from run 5 for all sample sizes

Parameter	T	MSE

		OLS	2/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	20	0.0113	0.0079	0.0088	0.0302	0.0182	0.0114
	40	0.0180	0.0067	0.0073	0.0139	0.0116	0.0084
	60	0.0180	0.0047	0.0050	0.0052	0.1420	0.0049
	100	0.0169	0.0028	0.0029	0.0029	0.0029	0.0029
$\beta_{11}(1.0)$	20	0.1213	0.1084	0.1150	1.1331	0.7577	0.1373
	40	0.0967	0.0487	0.0514	0.8846	0.5033	0.1147
	60	0.0956	0.0359	0.0372	1.1935	0.4355	0.1722
	100	0.0882	0.0226	0.0232	0.7759	0.4299	0.1550
$\beta_{21}(2.0)$	20	0.2188	0.2188	0.2188	0.2190	0.2177	0.2087
	40	0.0764	0.0764	0.0764	0.0765	0.0763	0.0753
	60	0.0560	0.0560	0.0560	0.0559	0.4573	0.0551
	100	0.0369	0.0369	0.0369	0.0369	0.0369	0.0366
$\beta_{22}(0.5)$	20	1.5317	1.5317	1.5317	1.0990	1.0732	0.7695
	40	0.7150	0.7150	0.7150	0.5069	0.4971	0.4188
	60	0.3936	0.3936	0.3936	0.3108	0.5155	0.2595
	100	0.2160	0.2160	0.2160	0.1622	0.1613	0.1535
$\beta_{23}(1.5)$	20	1.3442	1.3442	1.3442	1.0223	0.9630	0.7025
	40	0.7928	0.7928	0.7928	0.6461	0.5985	0.5131
	60	0.3422	0.3422	0.3422	0.3108	0.4942	0.2688
	100	0.1976	0.1976	0.1976	0.1598	0.1590	0.1511

The effect of multicollinearity could also be seen more in the relative efficiency of the Bayesian method to the classical in run five as presented in table 5.25, compared with runs one to four (Tables 5.10, 5.13, 5.19 and 5.22), it is obvious that as the degree of multicollinearity increases, the relative efficiency of the Bayesian approach over the classical approach increases. In all the five runs of the experiment, estimates from the BMPV 100 and 1000 are either the same or close to LIML estimates mostly in the large sample cases 60 and 100, this property of the Bayesian and the LIML was obtained analytically in Chao and Phillips (1998).

Table 5.25: Relative efficiency of BMPV 10 to the classical methods for β_{22} and β_{23} in run 5

Parameter \ Sample size	20	40	60	100
β_{22}	1.9905	1.7073	1.5168	1.3542
β_{23}	1.9135	1.5451	1.2731	1.3280

5.3 Interpretations

The results presented in section [5.1] in terms of MSE supports results in literature that Bayesian posterior estimates are better than classical estimates of γ, the coefficient of the endogenous explanatory variable for the purely just-identified model of the type in equation 3.2, having no possibility of multicollinearity. The Bayesian estimator was also more efficient than the classical estimators for the coefficient of the exogenous (instrumental) variable β in the small sample case $T \leq 40$ when the variance of the exogenous variable X_t was 1 and 2 respectively. As the sample increased the asymptotic consistency property of the classical estimators made the estimates better than those from the Bayesian approach. This Monte Carlo experiment also suggest that variance 100, for the prior distribution could lead to smaller MSE than other prior variances for the posterior estimates of γ in the purely just-identified model (equation 3.2) when little information is available on the prior distribution or we want to proceed as if the available information is little, i.e., being objective. A smaller Prior variance (10) however produced the least MSE of the posterior estimates for β, the coefficient of the exogenous instrumental variable of the second equation of the model. These two results might be a suggestion that a mixture prior will produce better results for the Bayesian estimation of the parameters of the purely just-identified model (equation 3.2). Posterior estimates of the over-identified model obtained from the three different prior variances didn't show difference in a particular direction in terms of bias. This is so for all the parameters of the model. In terms of MSE, the Bayesian estimates from prior variance 10 gave the least MSE out of the 3 prior variance levels. This implies that, for the model with one over-identified equation (equation 3.4), the prior variance 10 can be used in the Bayesian analysis in order to have posterior estimates with minimum variance.

One of the assumptions on the random disturbance term of a regression model is that the values of the disturbance term are independent of the values of the regressors, that is,

$$Cov(u_i X_j) = 0 \quad \begin{matrix} \text{for } i = 1, 2, \ldots, n \\ j = 1, 2, \ldots, k \end{matrix} \tag{5.1}$$

Hence, for the OLS estimates to possess the optimal properties of unbiasedness and consistency, the u's and the X's should be independent. The breakdown of this assumption in simultaneous equations models (referred to as simultaneous equations bias), strengthened by the contemporaneous correlation of the disturbance terms u_{1t} and $u_{2t,}$ could be the reason for the bias and inconsistencies of the OLS estimates of γ and β_{11} in run 1 to 4 of model (3.4) as reflected in tables 5.7 to 5.22. However, other estimators in our experiment (2SLS/3SLS, LIML and the Bayesian) were less sensitive to this simultaneous relationship but became consistent as the sample size increased, that is they are asymptotically consistent as stated in the properties of the classical estimators in section 3.4.1 of chapter 3.

In the presence of over-identification constraints as represented by the second model (equation 3.4), the 2SLS/3SLS performed best for γ and β_{11} in terms of bias, the poor performance of 2SLS in the purely just-identified model might hence be attributed to the level of identification caused by shortage of instrumental variable, that is only one (X_t). In addition, since 2SLS gets better as the variance of the exogenous variable increased from 1 to 2 and 9 in the just-identified model, it could also be an indication that 2SLS performs better in a purely just-identified model as the variance of the exogenous instrumental variable increases

In the case of correlated explanatory variables (multicollinearity), the Bayesian estimates of their coefficients; $\beta_{21}, \beta_{22}, \beta_{23}$ were less sensitive and less affected than the classical methods, since the later reduced to OLS. This is a strong point for the Bayesian method. The Bayesian estimation approach has smaller MSE and in some cases smaller bias than the classical estimators in all the sample sizes considered. Athough, the Bayesian approach produced bigger MSE than the classical methods for γ in the over-identified equation, it is mostly in the smaller sample cases $T \leq 60$. When $T \geq 100$, estimates from the Bayesian approach are either close in some cases or similar in other cases to the estimates from the classical approaches. The estimates actually got better in terms of bias and efficiency as the sample increased from 20 to 100. We could conclude here that in estimating coefficients of correlated regressors in a multi-equation system with over-identification constraints, the performance of the Bayesian approach is better than that of the classical approaches considered here. The Bayesian approach to the estimation of coefficients of the endogenous explanatory variable in the model is also asymptotically consistent.

CHAPTER SIX

SUMMARY AND CONCLUSIONS

6.0 Introduction

This chapter consists of summary of the whole research work and conclusions made from results obtained. Contributions to knowledge, recommendations, area of further studies are as well as limitations of the study also given.

6.1 Summary

This research was focused on evaluating the performance of the Bayesian approach to estimation of multi-equation econometric models, particularly in the presence of multicollinearity to which most classical estimators are known to be sensitive. The Bayesian approach treats parameters of a model as random variables, makes use of prior information as well as information conveys by the data and enables one to make probabilitistic statements about such parameters. Studies on the Bayesian approach are not as much as the classical approach which is widely researched into. This is mostly due to the fact that the Bayesian approach often involves difficult and sometimes intractable mathematical analysis making it unattractive to some researchers. Recent availability of varieties of software for such Bayesian analysis has however brought a change to this. Analysis of high dimensional numerical integration can now be carried out with the use of these software. Two different multi-equation models were considered in this research work; a purely just-identified model and another one with over-identification constraints, each with two structural equations. The models were estimated using the Bayesian approach as well as some classical approaches; Ordinary Least Squares (OLS), Two Stage Least Squares (2SLS), Three Stage Least Squares (3SLS) and Limited Information Maximum Likelihood (LIML).

The objectives of the work as stated in chapter one consist of; deriving the Bayesian estimator for the parameters of the multi-equation models, estimating the model using the Bayesian method and the Classical methods, assessing the performance of the Bayesian approach as compared with the classical approach, and caring out Monte Carlo prior variance sensitivity analysis. Literatures on both Bayesian and the classical approaches were reviewed from where we discovered a gap: the Bayesian approach in the presence of multicollinearity. The theoretical framework for the research was discussed consisting of both classical and the Bayesian approach. To achieve the stated objectives, 3 research scenarios are stated for the purely just-identified model. It consists of a case of negatively correlated residual terms and 2 cases of positively correlated residual terms with different variances for the exogenous variable in the model. Five research scenarios are stated for the over-identified model representing presence and absence of multicollinearity. The locally-uniform prior was used for the parameters of the models and Wishart distribution with zero degree of freedom for inverse of the variance-covariance matrix of the residual terms. Values were arbitrarily fixed for parameters of the structural equations to simulate values for the endogenous variables. These values were then used to estimate the parameters of the structural equations using the Bayesian and classical approaches. For the Bayesian approach, 3 Bayesian Method Prior Variances (BMPV) were stated as 10, 100, and 1000. Mean, absolute bias and Mean Squared Error (MSE) were then computed with more emphaisis on MSE as evaluation criterion

The results show that BMPV 100 is the best among the 3 BMPV's for the purely just-identified model while BMPV 10 is the best for the over-identified model. 2SLS, 3SLS and LIML are the same for the coefficient of the endogenous variable of the just-identified model while OLS is different. For the two models, all the classical estimators are the same for the coefficient of the exogenous variable in the second equation because it contains no endogenous variable. OLS is better than the Bayesian method in terms of MSE while the Bayesian is better in terms of bias (except small sample sizes $T \leq 40$) for coefficient of the endogenous explanatory variable in the purely just-identified model which is the model without multicollinearity. The Bayesian method is better than 2SLS/3SLS/LIML both in terms of MSE and bias. The Bayesian method is less sensitive to multicollinearity in estimating coefficients of the exogenous variables of the over-identified model. Details of these results are presented in chapter five.

6.2 Conclusion

Based on the results presented in chapter 5, we make the following Conclusions;

(1) The Bayesian estimation method is good for estimating a just-identified model with correlated residual terms across equations, especially in the small sample cases less than or equal to 40.

(2) The Bayesian method to a very large extent is less sensitive to multicollinearity in estimating the coefficient of the correlated exogenous variables of an over-identified model. As the degree of multicollinearity increases, the relative efficiency of the Bayesian approach over the classical approaches increases.

(3) In stating an uninformative prior for the Bayesian estimation of the regression coefficients in a just-identified model, the use of a large variance such as 100 produces less MSE in the posterior estimate; for the over-identified model, prior variance 10 yield the smallest MSE..

(4) The Bayesian uninformative prior produce posterior estimates that are more biased than the classical methods (OLS, 2SLS) for the coefficient of the exogenous variable of a just-identified model

(5) The performance of the LIML is similar to that of the Bayesian method with prior variance 100 and 1000 respectively, mostly in large sample cases greater than 60.

(6) As the sample size increases, MSE of the estimators reduces and the estimators gets closer.

6.3 Contributions

The contributions of this research work to knowledge are as follows

(i) The Bayesian approach is less sensitive to multicollinearity than the classical approaches in estimating the coefficients of the non orthorgonal exogenous variables of a multi-equation Econometric model

(ii) The Bayesian approach is asymptotically consistent in estimating the coefficient of endogenous regressor in an over-identified equation of a multi-equation Econometric model

(iii) Bayesian posterior point estimates are sensitive to the choice of prior variance for the locally-uniform prior for parameters in a multi-equation model. The use of prior variance 10 is more efficient than other prior variances.

6.4 Recommendation:

In order to make the best possible conclusion from research on multi-equations Econometric models and associated research, careful attention should be paid to the choice of estimation method based on the research scenario. We make few recommendations as follows:

(1) In the presence of multicollinearity, if the option of finding solution to it is not taken for whatever reason, the Bayesian method is recommended for estimating the coefficients of the correlated exogenous variables irrespective of the sample size and also for other parameters when the sample size is at least 100.

(2).When there is no multicollinearity, but the residual terms across equations are correlated, the Bayesian method is best for estimating the just-identified equation

6.5 Suggestion for area of further Research

Areas that can still be researched into are;

(1) The effect of the degree of over-identification on the performance of various estimation method for the simultaneous equations models

(2) The use of mixture prior in the Bayesian approach for simultaneous equations model estimation.

(3) Evaluation of the performance of the Classical and Bayesian methods for models containing more equations (at least four) in which:

(a) The first equation will contain endogenous variable without multicollinearity in exogenous variables
(b) The second will contain endogenous variable with multicollinearity in exogenous variables
(c) The third will contain exogenous variables alone without multicollinearity
(d) The fourth will contain exogenous variables alone with multicollinearity

6.6 Limitation of the study

A general limitation of Monte Carlo studies is that the scope of generalization is not as wide as when analytical approach is used.

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APPENDIX A

Subprograms for the Experiments

(1). WinBUGS codes for the Bayesian analysis of model (3.4).

```
model {
	for(j in 1:N)  {
	 for (i in 1: T) {
	   y[j, i,1:2 ] ~ dmnorm(mu[ j, i,1:2], tau[,])
	    mu[ j, i,1] <- gamma[j]*mu[j, i, 2] + alpha[j]*x[i,1]
	     mu[j, i, 2] <- betaone[j]*x[i,1] + betatwo[j]*x[i,2] + betathree[j]*x[i,3]
	    }
	    #Priors
	    gamma[j] ~ dnorm(0.0, 0.001)
	    alpha[j] ~ dnorm(0.0, 0.001)
	    betaone[j] ~ dnorm(0.0, 0.001)
	    betatwo[j] ~ dnorm(0.0, 0.001)
	    betathree[j] ~ dnorm(0.0, 0.001)
```

```
          }
          tau[1:2,1:2] ~dwish(R[ ,], 2)
          R[1,1] <- 0.01
          R[1,2] <- 0
          R[2,1] <- 0
          R[2,2] <- 0.01
          sigma[1:2,1:2] <- inverse(tau[1:2,1:2 ])
        }
```

Where alpha = β_{11}, betaone = β_{21}, betatwo = β_{22}, betathree = β_{23}. The data and the initial values were stored in separate text files because of their large sizes.

(2) Sub-program in STATA for generating the data.

```
******Begining of the programme*******

 set more off

 set obs 20
  set seed 123456789
drawnorm x1,  n(20)
 mat sigma1 = (1, .8 \ .8, 1)
 drawnorm x2 x3, n(20) corr(sigma1)
 pwcorr x2 x3, sig
 gen eta2 = 2.0*x1+0.5*x2+1.5*x3
gen eta1 = 3*eta2 + x1
 matrix aveCoeffs=(0,0,0)
 matrix aveCoeffy1=(0,0)
 matrix aveCoeffy2=(0)
local  i = 1
while `i' < 5001 {
drawnorm e1_`i', n(20)
drawnorm e2_`i', n(20)
gen u1_`i' = e1_`i'
```

```
gen u2_`i' = 1.732051*e2_`i' - e1_`i'
gen y1_`i' = eta1 + u1_`i' + 3* u2_`i'

 gen y2_`i' = eta2 + u2_`i'

drop e1 e2 u1 u2
 local i = `i' + 1
}
```

The sample size, the correlation between the exogenous variables, as well as the command for generating the residual terms, are changed according to the conditions corresponding to each data set.

(3) Mathlab subprogram for Ordinary Least Squares estimates in model (3.2)

```
function f=Olsmodel2(A)
% The program estimates the parameters of the model
% y(1,t) = g*y(2,t) + u(1,t);
% y(2,t) = b21*x(1,t) + u(2,t)
% using ordinary least squares OLS.

% The Sample A contains 3 variables arranged as
% x1,y1 and y2 underneath each other
% i.e for sample size n and 5000 replicates
% sample A will have 3n rows and 5000 columns.

[a,b]=size(A);
n=int32(a/3);
for k=1:b;
   x1=A(1:n,k);
   y1=A((n+1):(2*n),k);
   y2=A((2*n+1):(3*n),k);

   f1(k)=((y2'*y2)^-1)*(y2'*y1);
   f2(k)=((x1'*x1)^-1)*(x1'*y2);
   % f1 is a row matrix containing the parameter of
```

```
   % the 1st model, f2 a row matrix containing the
   % parameter of the 2nd model

end
   f =[f1' f2'];
   %The parameters of the models appears in the result; arranged in the
   %order g b21 (where the parameter are as defined
   % in equations that appeared in lines 3 and 4 above).
end
```

(4)Mathlab subprogram for Two-stage Least Squares estimates in model (3.2)

```
function f = a2slsmodel2(A)
% The program estimates the parameters of the model
% y(1,t) = g*y(2,t) + u(1,t);
% y(2,t) = b21*x(t) + u(2,t)
% using 2sls.

% The Sample A contains 3 variables arranged as
% x,y1 and y2 underneath each other
% i.e for sample size n and 5000 replicates
% sample A will have 3n rows and 5000 columns.

[a,b]=size(A);
n=int32(a/3);
for k=1:b;
   x=A(1:n,k);
   y1=A((n+1):(2*n),k);
   y2=A((2*n+1):(3*n),k);

   % The Stage one regression using all the exogenous variables.
   p = (inv(x'*x))*(x'*y2);
   % Obtaining the new endogenous variable for stage 2 regression.
   y = p*x;
```

% y is used as instrument for y2 in the 2sls

% Performing the stage 2 regression.

f1(k) = (inv(y'*y))*(y'*y1);

f2(k) = (inv(x'*x))*(x'*y2);

% f1 is a row vector containing the parameter of

% the 1st model, f2 a row vector containing the

% parameter of the 2nd model

end

f =[f1' f2'];

%The parameters of the models appears in the result; arranged in the

%order g b21(where the parameter are as defined

% in equations that appeared in lines 3 and 4 above).

end

(1) Mathlab sub-program for OLS in model (3.4)

```
function f=OkewoleOls(A)
% The program estimates the parameters of the model
% y(1,t) = g*y(2,t) + b11*x(1,t) + u(1,t);
% y(2,t) = b21*x(1,t) + b22*x(2,t) + b23*x(3,t) + u(2,t)
% using ordinary least squares OLS.

% The Sample A contains 5 variables arranged as
% x1,x2,x3,y1 and y2 underneath each other
% i.e for sample size n and 5000 replicates
% sample A will have 5n rows and 5000 columns.

[a,b]=size(A);
n=int32(a/5);
for k=1:b;
x1=A(1:n,k);
x2=A((n+1):(2*n),k);
x3=A((2*n+1):(3*n),k);
y1=A((3*n+1):(4*n),k);
y2=A((4*n+1):(5*n),k);

X1=[y2 x1];
X2=[x1 x2 x3];

f1(k,:)=((X1'*X1)^-1)*(X1'*y1);
f2(k,:)=((X2'*X2)^-1)*(X2'*y2);
% f1 is a 2Xb matrix containing the parameter of
% the 1st model, f2 a 3Xb matrix containing the
% parameter of the 2nd model
```

```
end
f =[f1 f2];
%The parameters of the models appears in the result; arranged in the
%order g b11 b21 b22 b23(where the parameter are as defined
% in equations that appeared in lines 3 and 4 above).
end
```

(2) Mathlab sub-program for 2SLS in model (3.4)

```
function f=Okewole2sls(A)
% The program estimates the parameters of the model
% y(1,t) = g*y(2,t) + b11*x(1,t) + u(1,t);
% y(2,t) = b21*x(1,t) + b22*x(2,t) + b23*x(3,t) + u(2,t)
% using ordinary least squares OLS.

% The Sample A contains 5 variables arranged as
% x1,x2,x3,y1 and y2 underneath each other
% i.e for sample size n and 5000 replicates
% sample A will have 5n rows and 5000 columns.

[a,b]=size(A);
n=int32(a/5);
for k=1:b;
x1=A(1:n,k);
x2=A((n+1):(2*n),k);
x3=A((2*n+1):(3*n),k);
y1=A((3*n+1):(4*n),k);
y2=A((4*n+1):(5*n),k);

%%x1=A(1:n,k);
%x2=A((n+1):(2*n),k);
%y1=A((2*n+1):(3*n),k);
%y2=A((3*n+1):(4*n),k);

% The Stage one regression using all the exogenous variables.

X=[x1 x2 x3];
P = (inv(X'*X))*(X'*y2);

% Obtaining the new endogenous variable for stage 2 regression.

Y2 = X*P;

% Replacing the endogenous variable that appeared as explanatory
% with the estimated endogenous variable Y2.

X1=[Y2 x1];

% Performing the stage 2 regression.

 f1(k,:) = (inv(X1'*X1))*(X1'*y1);
 f2(k,:)=(inv(X'*X))*(X'*y2);

% f1 is a 2Xb matrix containing the parameter of
% the 1st model, f2 a 3Xb matrix containing the
% parameter of the 2nd model
```

```
end
f =[f1 f2];
%The parameters of the models appears in the result; arranged in the
%order g b11 b21 b22 b23(where the parameter are as defined
% in equations that appeared in lines 3 and 4 above).
end
```

(3) Mathlab sub-program for 3SLS in model (3.4)

```
function f=Okewole3sls(A)
% The program estimates the parameters of the model
% y(1,t) = g*y(2,t) + b11*x(1,t) + u(1,t);
% y(2,t) = b21*x(1,t) + b22*x(2,t) + b23*x(3,t) + u(2,t)
% using ordinary least squares OLS.

% The Sample A contains 5 variables arranged as
% x1,x2,x3,y1 and y2 underneath each other
% i.e for sample size n and 5000 replicates
% sample A will have 5n rows and 5000 columns.

[a,b]=size(A);
n=int32(a/5);
for k=1:b;
x1=A(1:n,k);
x2=A((n+1):(2*n),k);
x3=A((2*n+1):(3*n),k);
y1=A((3*n+1):(4*n),k);
y2=A((4*n+1):(5*n),k);

% The Stage one regression using all the exogenous variables.
X=[x1 x2 x3];
P = (inv(X'*X))*(X'*y2);

% Obtaining the new endogenous variable for stage 2 regression.
Y2 = X*P;

X1=[Y2 x1];
% Performing the stage 2 regression.
Q1 =(inv(X1'*X1))*(X1'*y1);
Q2 =(inv(X'*X))*(X'*y2);

% Obtaining the new endogenous variable for stage 2 regression.
Yy1 = X1*Q1;
Yy2 = X*Q2;

%Obtaining the residuals
e1 = y1 - Yy1;
e2 = y2 - Yy2;

% The third stage regression using SUR model
% stacking the error residuals
e(1:n,1) = e1;
e((n+1):(2*n),1) = e2;

% Stacking the vector of regressors
Xs(1:n,1:2) = X1;
```

```
Xs((n+1):(2*n),3:5) = X;
% Stacking the regressand
y(1:n,1) = y1;
y((n+1):(2*n),1) = y2;
% forming the variance covariance matrix
zigma = (e*e')/double(n);
% Performing generalised least square.
f(k,:)= (Xs'*(zigma\Xs))\(Xs'*(zigma\y));

% inv(A)*b = A\b and b*inv(A)=b/A
%The parameters of the models appears in the result; arranged in the
%order g b11 b21 b22 b23(where the parameter are as defined
% in equations that appeared in lines 3 and 4 above).
end
end
```

(4) Mathlab sub-program for LIML in model (3.4)

```
function f=Okewoleliml(A)
% The program estimates the parameters of the model
% y(1,t) = g*y(2,t) + b11*x(1,t) + u(1,t);
% y(2,t) = b21*x(1,t) + b22*x(2,t) + b23*x(3,t) + u(2,t)
% using ordinary least squares OLS.

% The Sample A contains 5 variables arranged as
% x1,x2,x3,y1 and y2 underneath each other
% i.e for sample size n and 5000 replicates
% sample A will have 5n rows and 5000 columns.

[a,b]=size(A);
n=int32(a/5);
for k=1:b;
  x1=A(1:n,k);
  x2=A((n+1):(2*n),k);
  x3=A((2*n+1):(3*n),k);
  y1=A((3*n+1):(4*n),k);
  y2=A((4*n+1):(5*n),k);

  X=[x1 x2 x3];
  %regressing endogenous variables on all the exogenous variables
 b1 =inv(X'*X)*X'*y1;
 b2 =inv(X'*X)*X'*y2;
 %fitting the regression to obtain ycap
 y1cap = X*b1;
 y2cap = X*b2;
 %estimating the residuals
 v1 = y1 - y1cap;
 v2 = y2 - y2cap;
 % This part is for equation 1 only.
 %regressing the endogenous variables on exogenous variables present in
 %equation 1
 P11 = (x1'*x1)\(x1'*y1); % a^-1*b = inv(a)*b =a\b
 P12 = (x1'*x1)\(x1'*y2);
 %fitting the regression to obtain ycap
 y1capeq1 = P11 * x1;
 y2capeq1 = P12 * x1;
 %estimating the residuals
 w1 = y1 - y1capeq1;
```

```
w2 = y2 - y2capeq1;
%computing the coeffiecients of L in the resulting Quadratic equation
aqd = (v1' *v1)*(v2' *v2) - ((v1' *v2)^2);
bqd = 2*(w1' *w2)*(v1' *v2) - (w1' *w1)*(v2' *v2)- (w2' *w2)*(v1' *v1);
cqd = (w1' *w1)*(w2' *w2)- ((w1' *w2)^2);

l1 = (-bqd + sqrt(bqd^2 - 4 *aqd *cqd) )/(2* aqd);
l2 = (-bqd - sqrt(bqd^2 - 4 *aqd *cqd) )/(2* aqd);
%chosing the least variance ratio(LVR).
if(l1 < l2)
l = l1;
else
l = l2;
end
%obtaining the coefficient of the endogenous variable
beq1(k,1) = ((w1' *w1)- l *(v1' *v1))/((w1' *w2)- l *(v1' *v2));
%obtaining the new dependent variables via collection of the endogenous
%variables into the LHS
y = y1 - beq1(k,1) * y2;
%obtaining the coefficient of the exogenous variable
beq1(k,2) = (x1'*x1)\(x1'*y);

% This part is for equation 2 only.
X2 = [x1 x2 x3];
%%%%%%%%%%% Since there is no endogenous variable present in equation 2
%%%%%%%%%%% LIML-LVR reduces to OLS
P(k,:)= (X2'*X2)\(X2'*y2);
end
f = [beq1 P];
%The parameters of the models appears in the result; arranged in the
%order g b11 b21 b22 b23(where the parameter are as defined
% in equations that appeared in lines 3 and 4 above).
end.
```

APPENDIX B

Tables containing Mean, ABS bias and MSE

Table 1: Results from run 1 Sample Size T= 20

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV 1000	BMPV 100	BMPV 10
$\gamma(3.0)$	Mean	2.853	2.9948	3.0448	3.0071	3.0077	3.0063
	ABS Bias	0.1469	0.0052	0.0448	0.0071	0.0077	0.0063
	MSE	0.0286	0.0280	2.1277	0.0330	0.0300	0.0286
$\beta_{11}(1.0)$	Mean	1.1621	1.0054	0.961	0.9977	0.9942	0.9980
	ABS Bias	0.1621	0.0054	0.039	0.0023	0.0058	0.0020
	MSE	0.0837	0.1031	1.2347	0.1493	0.1050	0.0950
$\beta_{21}(2.0)$	Mean	2.0084	2.0084	2.0084	1.9449	1.9406	1.8867
	ABS Bias	0.0084	0.0084	0.0084	0.0551	0.0594	0.1133
	MSE	0.3094	0.3094	0.3094	0.3190	0.3162	0.3052
$\beta_{22}(0.5)$	Mean	0.5089	0.5089	0.5089	0.4625	0.4650	0.4752
	ABS Bias	0.0089	0.0089	0.0089	0.0375	0.0350	0.0248
	MSE	0.7492	0.7492	0.7492	0.5290	0.5220	0.4529
$\beta_{23}(1.5)$	Mean	1.4981	1.4981	1.4981	1.3725	1.3716	1.3446
	ABS Bias	0.0019	0.0019	0.0019	0.1275	0.1284	0.1554
	MSE	0.5807	0.5807	0.5807	0.5163	0.5045	0.4335

Table 2: Results from run 1 Sample Size T= 40

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV 1000	BMPV 100	BMPV 10
$\gamma(3.0)$	Mean	2.8780	3.0013	3.0082	2.9978	2.9990	3.0046
	ABS Bias	0.1220	0.0013	0.0082	0.0022	0.0010	0.0046
	MSE	0.0176	0.0070	0.0076	0.0173	0.0125	0.0089

$\beta_{11}(1.0)$	Mean	1.2599	0.9989	0.9843	1.1014	1.0572	1.0078
	ABS Bias	0.2599	0.0011	0.0157	0.1014	0.0572	0.0078
	MSE	0.1057	0.0636	0.0670	0.7046	0.2722	0.0943
$\beta_{21}(2.0)$	Mean	2.0012	2.0012	2.0012	2.0047	2.0018	1.9821
	ABS Bias	0.0012	0.0012	0.0012	0.0047	0.0018	0.0179
	MSE	0.1323	0.1323	0.1323	0.1309	0.1306	0.1276
$\beta_{22}(0.5)$	Mean	0.5026	0.5026	0.5026	0.4784	0.4803	0.5010
	ABS Bias	0.0026	0.0026	0.0026	0.0216	0.0197	0.0010
	MSE	0.3888	0.3888	0.3888	0.2886	0.2859	0.2650
$\beta_{23}(1.5)$	Mean	1.4931	1.4931	1.4931	1.4243	1.4262	1.4394
	ABS Bias	0.0069	0.0069	0.0069	0.0757	0.0738	0.0606
	MSE	0.3147	0.3147	0.3147	0.2971	0.2894	0.2358

Table 3:Results from run 1 Sample Size T= 60

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	2.8677	2.9988	3.0038	3.0075	2.9963	2.9996
	ABS Bias	0.1323	0.0012	0.0038	0.0075	0.0037	0.0004
	MSE	0.0193	0.0051	0.0054	0.0049	0.0098	0.0051
$\beta_{11}(1.0)$	Mean	1.2817	0.9963	0.9935	1.0056	1.0949	1.0346
	ABS Bias	0.2817	0.0037	0.0065	0.0056	0.0949	0.0346
	MSE	0.1032	0.0271	0.0434	0.0387	0.4723	0.1197
$\beta_{21}(2.0)$	Mean	1.9957	2.0022	1.9957	1.8655	1.9971	1.9831
	ABS Bias	0.0043	0.0022	0.0043	0.1345	0.0029	0.0169
	MSE	0.0795	0.0795	0.0795	0.0858	0.0791	0.0783
$\beta_{22}(0.5)$	Mean	0.5166	0.5067	0.5166	0.5840	0.4927	0.5069
	ABS Bias	0.0166	0.0166	0.0166	0.0840	0.0073	0.0069
	MSE	0.1974	0.1974	0.1974	0.1071	0.1502	0.1431
$\beta_{23}(1.5)$	Mean	1.4947	1.4947	1.4947	1.3343	1.4453	1.4497
	ABS Bias	0.0053	0.0053	0.0053	0.1657	0.0547	0.0503
	MSE	0.1853	0.1853	0.1853	0.1285	0.1878	0.1565

Table 4: Results from run 1 Sample size T=100

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV 1000	BMPV100	BMPV 10
$\gamma(3.0)$	Mean	2.8611	3.0018	3.0052	3.0052	3.0051	3.0013
	ABS Bias	0.1389	0.0018	0.0052	0.0052	0.0051	0.0013
	MSE	0.0205	0.0035	0.0036	0.0036	0.0036	0.0058
$\beta_{11}(1.0)$	Mean	1.2812	0.9963	0.9895	1.1186	0.9906	1.0411
	ABS Bias	0.2812	0.0037	0.0105	0.1186	0.0094	0.0411
	MSE	0.0937	0.0271	0.0278	0.9571	0.0312	0.1758
$\beta_{21}(2.0)$	Mean	2.0022	2.0022	2.0022	2.0024	2.0016	1.9930
	ABS Bias	0.0022	0.0022	0.0022	0.0024	0.0016	0.0070
	MSE	0.0471	0.0471	0.0471	0.0471	0.0471	0.0468
$\beta_{22}(0.5)$	Mean	0.5067	0.5067	0.5067	0.4947	0.4996	0.5007

	ABS Bias	0.0067	0.0067	0.0067	0.0053	0.0004	0.0007
	MSE	0.0973	0.0973	0.0973	0.0764	0.0751	0.0744
$\beta_{23}(1.5)$	Mean	1.4917	1.4917	1.4917	1.4659	1.4782	1.4562
	ABS Bias	0.0083	0.0083	0.0083	0.0341	0.0218	0.0438
	MSE	0.1231	0.1231	0.1231	0.1153	0.1017	0.1120

Table 5: Results from run 2 Sample Size T= 20

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV 100	BMPV10
$\gamma(3.0)$	Mean	2.8495	2.9972	3.0285	3.0050	3.0084	3.0067
	ABS Bias	0.1505	0.0028	0.0285	0.0050	0.0084	0.0067
	MSE	0.0295	0.0265	0.0872	0.0522	0.0339	0.0269
$\beta_{11}(1.0)$	Mean	1.3328	0.9997	0.9297	1.0042	0.9805	0.9908
	ABS Bias	0.3328	0.0003	0.0703	0.0042	0.0195	0.0092
	MSE	0.2205	0.2364	0.5816	0.5814	0.2734	0.2133
$\beta_{21}(2.0)$	Mean	2.0004	2.0004	2.0004	2.0166	2.0058	1.9258
	ABS Bias	0.0004	0.0004	0.0004	0.0166	0.0058	0.0742
	MSE	0.5047	0.5047	0.5047	0.4698	0.4641	0.4267
$\beta_{22}(0.5)$	Mean	0.5011	0.5011	0.5011	0.4550	0.4594	0.4917
	ABS Bias	0.0011	0.0011	0.0011	0.0450	0.0406	0.0083
	MSE	0.2346	0.2346	0.2346	0.1740	0.1728	0.1654
$\beta_{23}(1.5)$	Mean	1.4975	1.4975	1.4975	1.3745	1.3759	1.3715
	ABS Bias	0.0025	0.0025	0.0025	0.1255	0.1241	0.1285
	MSE	0.2185	0.2185	0.2185	0.2598	0.2521	0.2213

Table 6: Results from run 2 Sample Size T= 40

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV 1000	BMPV 100	BMPV 10
$\gamma(3.0)$	Mean	2.8656	2.9983	3.0071	2.9925	2.9955	3.0034
	ABS Bias	0.1344	0.0016	0.0071	0.0075	0.0045	0.0034
	MSE	0.0210	0.0080	0.0089	0.0328	0.0212	0.0091
$\beta_{11}(1.0)$	Mean	1.2778	1.0023	0.9840	1.1124	1.0594	0.9991

	ABS Bias	0.2778	0.0023	0.0160	0.1124	0.0594	0.0009
	MSE	0.1139	0.0650	0.0694	0.8094	0.3035	0.1240
$\beta_{21}(2.0)$	Mean	2.0011	2.0011	2.0011	2.0037	2.0009	1.9807
	ABS Bias	0.0011	0.0011	0.0011	0.0037	0.0009	0.0193
	MSE	0.1202	0.1202	0.1202	0.1199	0.1196	0.1175
$\beta_{22}(0.5)$	Mean	0.5016	0.5016	0.5016	0.4811	0.4736	0.4868
	ABS Bias	0.0016	0.0016	0.0016	0.0189	0.0264	0.0132
	MSE	0.0837	0.0837	0.0837	0.0661	0.0689	0.0642
$\beta_{23}(1.5)$	Mean	1.5054	1.5054	1.5054	1.4521	1.4434	1.4541
	ABS Bias	0.0054	0.0054	0.0054	0.0479	0.0566	0.0459
	MSE	0.0990	0.0990	0.0990	0.1154	0.1280	0.0985

Table 7: Results from run 2 Sample Size T= 60

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV 1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	2.8365	3.0014	3.0111	2.9882	2.9918	3.0017
	ABS Bias	0.16349	0.0014	0.0111	0.0118	0.0082	0.0017
	MSE	0.0291	0.0094	0.0106	0.0571	0.0361	0.0163
$\beta_{11}(1.0)$	Mean	1.3348	0.9964	0.9764	1.1798	1.1139	1.0198
	ABS Bias	0.3348	0.0036	0.0236	0.1798	0.1139	0.0198
	MSE	0.1373	0.0594	0.0654	1.3421	0.5870	0.1306
$\beta_{21}(2.0)$	Mean	2.0028	2.0028	2.0028	2.0051	2.0031	1.9899
	ABS Bias	0.0028	0.0028	0.0028	0.0051	0.0031	0.0101
	MSE	0.0750	0.0750	0.0750	0.0750	0.0749	0.0740
$\beta_{22}(0.5)$	Mean	0.5083	0.5083	0.5083	0.4717	0.4731	0.4877
	ABS Bias	0.0083	0.0083	0.0083	0.0283	0.0269	0.0123
	MSE	0.0517	0.0517	0.0517	0.0479	0.0470	0.0406
$\beta_{23}(1.5)$	Mean	1.5013	1.5013	1.5013	1.4238	1.4264	1.4437
	ABS Bias	0.0013	0.0013	0.0013	0.0762	0.0736	0.0563
	MSE	0.0999	0.0999	0.0999	0.1502	0.1447	0.1068

Table 8: Results from run 2 Sample Size T= 100

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV 10
$\gamma(3.0)$	Mean	2.8628	3.0012	3.0044	3.0003	3.0004	3.0012
	ABS Bias	0.1372	0.0012	0.0044	0.0003	0.0004	0.0012
	MSE	0.0110	0.0034	0.0035	0.0036	0.0036	0.0036
$\beta_{11}(1.0)$	Mean	1.2648	0.9960	0.9897	1.1036	1.0903	1.0405
	ABS Bias	0.2648	0.0040	0.0103	0.1036	0.0903	0.0405
	MSE	0.0816	0.0222	0.0228	0.7578	0.5939	0.1644
$\beta_{21}(2.0)$	Mean	2.0010	2.0010	2.0010	2.0000	1.9990	1.9925
	ABS Bias	0.0010	0.0010	0.0010	0.0000	0.0010	0.0075
	MSE	0.0382	0.0382	0.0382	0.0379	0.0380	0.0380

$\beta_{22}(0.5)$	Mean	0.4977	0.4977	0.4977	0.4847	0.4847	0.4874
	ABS Bias	0.0023	0.0023	0.0023	0.0153	0.0153	0.0126
	MSE	0.0540	0.0540	0.0540	0.0442	0.0441	0.0414
$\beta_{23}(1.5)$	Mean	1.4977	1.4977	1.4977	1.4705	1.4704	1.4677
	ABS Bias	0.0023	0.0023	0.0023	0.0295	0.0296	0.0323
	MSE	0.0325	0.0325	0.0325	0.0445	0.0443	0.0445

Table 9: Results from run 3 Sample Size T= 20

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV 1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	3.0906	3.0000	2.9903	2.9905	2.9901	2.9867
	ABS Bias	0.0906	0.0000	0.0097	0.0095	0.0099	0.0133
	MSE	0.0127	0.0089	0.0103	0.0101	0.0101	0.0103
$\beta_{11}(1.0)$	Mean	0.8315	1.0000	1.0181	1.0177	1.0171	1.0110
	ABS Bias	0.1685	0.0000	0.0181	0.0177	0.0171	0.0110
	MSE	0.0819	0.0746	0.0803	0.0799	0.0796	0.0768
$\beta_{21}(2.0)$	Mean	2.0062	2.0062	2.0062	2.0011	1.9976	1.9630
	ABS Bias	0.0062	0.0062	0.0062	0.0011	0.0024	0.0370
	MSE	0.1845	0.1845	0.1845	0.1817	0.1811	0.1762
$\beta_{22}(0.5)$	Mean	0.5118	0.5118	0.5118	0.4858	0.4867	0.4992
	ABS Bias	0.0118	0.0118	0.0118	0.0142	0.0133	0.0008
	MSE	0.4230	0.4230	0.4230	0.3096	0.3066	0.2825
$\beta_{23}(1.5)$	Mean	1.4989	1.4989	1.4989	1.4581	1.4557	1.4411
	ABS Bias	0.0011	0.0011	0.0011	0.0419	0.0443	0.0589
	MSE	0.3502	0.3502	0.3502	0.2764	0.2740	0.2502

Table 10: Results from run 3 Sample Size T= 40

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	3.1366	3.0000	2.9905	2.9907	2.9905	2.9891
	ABS Bias	0.1366	0.0000	0.0095	0.0093	0.0095	0.0109
	MSE	0.0216	0.0087	0.0099	0.0098	0.0098	0.0096
$\beta_{11}(1.0)$	Mean	0.6773	1.0011	1.0236	1.0233	1.0230	1.0206
	ABS Bias	0.3227	0.0011	0.0236	0.0233	0.0230	0.0206
	MSE	0.1357	0.0676	0.0751	0.0746	0.0742	0.0712
$\beta_{21}(2.0)$	Mean	2.0018	2.0018	2.0018	2.0111	2.0096	1.9955
	ABS Bias	0.0018	0.0018	0.0018	0.0111	0.0096	0.0045

	MSE	0.0840	0.0840	0.0840	0.0842	0.0840	0.0823
$\beta_{22}(0.5)$	Mean	0.5060	0.5060	0.5060	0.4894	0.4902	0.5019
	ABS Bias	0.0060	0.0060	0.0060	0.0106	0.0098	0.0019
	MSE	0.1583	0.1583	0.1583	0.1167	0.1162	0.1128
$\beta_{23}(1.5)$	Mean	1.4953	1.4953	1.4953	1.4497	1.4480	1.4383
	ABS Bias	0.0047	0.0047	0.0047	0.0503	0.0520	0.0617
	MSE	0.2284	0.2284	0.2284	0.1908	0.1900	0.1799

Table 11: Results from run 3 Sample Size T= 60

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	3.1244	2.9984	2.9937	2.9937	2.9936	2.9927
	ABS Bias	0.1244	0.0016	0.0063	0.0063	0.0064	0.0073
	MSE	0.0173	0.0045	0.0048	0.0048	0.0048	0.0048
$\beta_{11}(1.0)$	Mean	0.7033	1.0046	1.0157	1.0158	1.0156	1.0145
	ABS Bias	0.2967	0.0046	0.0157	0.0158	0.0156	0.0145
	MSE	0.1078	0.0379	0.0397	0.0397	0.0397	0.0391
$\beta_{21}(2.0)$	Mean	2.0019	2.0019	2.0019	2.0070	2.0061	1.9973
	ABS Bias	0.0019	0.0019	0.0019	0.0070	0.0061	0.0027
	MSE	0.0480	0.0480	0.0480	0.0480	0.0480	0.0474
$\beta_{22}(0.5)$	Mean	0.5050	0.5050	0.5050	0.4994	0.5002	0.5074
	ABS Bias	0.0050	0.0050	0.0050	0.0006	0.0002	0.0074
	MSE	0.1498	0.1498	0.1498	0.1118	0.1114	0.1079
$\beta_{23}(1.5)$	Mean	1.4939	1.4939	1.4939	1.4662	1.4649	1.4573
	ABS Bias	0.0061	0.0061	0.0061	0.0338	0.0351	0.0427
	MSE	0.1614	0.1614	0.1614	0.1333	0.1329	0.1280

Table 12: Results from run 3 Sample Size T= 100

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	3.1168	2.9995	2.9972	2.9972	2.9971	2.9963
	ABS Bias	0.1168	0.0005	0.0028	0.0028	0.0029	0.0037
	MSE	0.0146	0.0023	0.0023	0.0023	0.0023	0.0024
$\beta_{11}(1.0)$	Mean	0.7765	1.0013	1.0058	1.0058	1.0058	1.0049
	ABS Bias	0.2235	0.003	0.0058	0.0058	0.0058	0.0049
	MSE	0.0607	0.0171	0.0174	0.0174	0.0174	0.0173
$\beta_{21}(2.0)$	Mean	1.9987	1.9987	1.9987	1.9979	1.9972	1.9895
	ABS Bias	0.0013	0.0013	0.0013	0.0021	0.0028	0.0105
	MSE	0.0354	0.0354	0.0354	0.0353	0.0353	0.0352

$\beta_{22}(0.5)$	Mean	0.4920	0.4920	0.4920	0.4902	0.4907	0.4967
	ABS Bias	0.0080	0.0080	0.0080	0.0098	0.0093	0.0033
	MSE	0.0897	0.0897	0.0897	0.0663	0.0661	0.0649
$\beta_{23}(1.5)$	Mean	1.5054	1.5054	1.5054	1.4900	1.4891	1.4820
	ABS Bias	0.0054	0.0054	0.0054	0.0100	0.0109	0.0180
	MSE	0.1019	0.1019	0.1019	0.0817	0.0815	0.0797

Table 13: Results from run 4 Sample Size T= 20

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	3.1552	3.0013	2.9706	2.6942	2.9841	2.9781
	ABS Bias	0.1552	0.0013	0.0294	0.3058	0.0159	0.0219
	MSE	0.0315	0.0292	0.2249	0.1947	0.0309	0.0293
$\beta_{11}(1.0)$	Mean	0.6959	0.9967	1.0499	0.9968	1.0239	1.0122
	ABS Bias	0.3041	0.0033	0.0499	0.0032	0.0239	0.0122
	MSE	0.1756	0.1870	1.0188	0.0884	0.1884	0.1623
$\beta_{21}(2.0)$	Mean	1.9959	1.9959	1.9959	1.3654	1.9845	1.9264
	ABS Bias	0.0041	0.0041	0.0041	0.6346	0.0155	0.0736
	MSE	0.2581	0.2581	0.2581	0.5847	0.2567	0.2497
$\beta_{22}(0.5)$	Mean	0.5033	0.5033	0.5033	0.3187	0.4537	0.4570
	ABS Bias	0.0033	0.0033	0.0033	0.1813	0.0463	0.0430
	MSE	0.3639	0.3639	0.3639	0.1510	0.2604	0.2503
$\beta_{23}(1.5)$	Mean	1.5099	1.5099	1.5099	1.0059	1.3859	1.3720
	ABS Bias	0.0099	0.0099	0.0099	0.4941	0.1141	0.1280
	MSE	0.2331	0.2331	0.2331	0.3995	0.2630	0.2361

Table 14: RUN 4 Sample Size T= 40

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	3.1529	3.0010	2.9891	2.9890	2.9890	2.9851
	ABS Bias	0.1529	0.0009	0.0109	0.0110	0.0110	0.0149
	MSE	0.0267	0.0118	0.0136	0.0141	0.0133	0.0134
$\beta_{11}(1.0)$	Mean	0.7415	0.9988	1.0191	1.0210	1.0178	1.0129
	ABS Bias	0.2585	0.0012	0.0191	0.0210	0.0178	0.0129
	MSE	0.1069	0.07361	0.0804	0.1101	0.0787	0.0754
$\beta_{21}(2.0)$	Mean	1.9997	1.9997	1.9997	1.9893	1.9856	1.9501
	ABS Bias	0.0003	0.0003	0.0003	0.0107	0.0144	0.0499

	MSE	0.1565	0.1565	0.1565	0.1565	0.1562	0.1542
$\beta_{22}(0.5)$	Mean	0.5106	0.5106	0.5106	0.4869	0.4867	0.4905
	ABS Bias	0.0106	0.0106	0.0106	0.0131	0.0133	0.0095
	MSE	0.1327	0.1327	0.1327	0.0997	0.0993	0.0972
$\beta_{23}(1.5)$	Mean	1.4937	1.4937	1.4937	1.4405	1.4386	1.4224
	ABS Bias	0.0063	0.0063	0.0063	0.0595	0.0614	0.0776
	MSE	0.1463	0.1463	0.1463	0.1423	0.1416	0.1370

Table 15: Results from run 4 Sample Size T= 60

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	3.1531	2.9999	2.9927	2.9926	2.9924	2.9895
	ABS Bias	0.1531	0.0001	0.0073	0.0074	0.0077	0.0105
	MSE	0.0257	0.0075	0.0081	0.0081	0.0081	0.0082
$\beta_{11}(1.0)$	Mean	0.7447	1.0008	1.0130	1.0130	1.0129	1.0111
	ABS Bias	0.2553	0.0008	0.0130	0.0130	0.0129	0.0111
	MSE	0.0897	0.0441	0.0464	0.0463	0.0462	0.0455
$\beta_{21}(2.0)$	Mean	1.9998	1.9998	1.9998	1.9921	1.9899	1.9681
	ABS Bias	0.0002	0.0002	0.0002	0.0079	0.0101	0.0319
	MSE	0.0974	0.0974	0.0974	0.0967	0.0966	0.0958
$\beta_{22}(0.5)$	Mean	0.5050	0.5050	0.5050	0.4882	0.4875	0.4833
	ABS Bias	0.0050	0.0050	0.0050	0.0118	0.0125	0.0167
	MSE	0.0935	0.0935	0.0935	0.0705	0.0703	0.0694
$\beta_{23}(1.5)$	Mean	1.4989	1.4989	1.4989	1.4676	1.4664	1.4549
	ABS Bias	0.0011	0.0011	0.0011	0.0324	0.0336	0.0451
	MSE	0.0626	0.0626	0.0626	0.0646	0.0645	0.0645

Table 16: Results from run 4 Sample Size T= 100

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	3.1549	2.9986	2.9942	2.9942	2.9940	2.9925
	ABS Bias	0.1549	0.0014	0.0058	0.0058	0.0060	0.0075
	MSE	0.0253	0.0043	0.0046	0.0046	0.0046	0.0046
$\beta_{11}(1.0)$	Mean	0.7151	1.0034	1.0116	1.0117	1.0116	1.0106
	ABS Bias	0.2849	0.0034	0.0116	0.0117	0.0116	0.0106
	MSE	0.0957	0.0274	0.0285	0.0286	0.0285	0.0283
$\beta_{21}(2.0)$	Mean	2.0017	2.0017	2.0017	1.9997	1.9985	1.9871
	ABS Bias	0.0017	0.0017	0.0017	0.0003	0.0015	0.0129
	MSE	0.0541	0.0541	0.0541	0.0541	0.0540	0.0536

$\beta_{22}(0.5)$	Mean	0.5001	0.5001	0.5001	0.4926	0.4925	0.4920
	ABS Bias	0.0001	0.0001	0.0001	0.0074	0.0075	0.0080
	MSE	0.0424	0.0424	0.0424	0.0329	0.0329	0.0327
$\beta_{23}(1.5)$	Mean	1.4972	1.4972	1.4972	1.4767	1.4760	1.4700
	ABS Bias	0.0028	0.0028	0.0028	0.0233	0.0240	0.0300
	MSE	0.0459	0.0459	0.0459	0.0446	0.0446	0.0444

Table 17: Results from run 5 Sample Size T= 20

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV 1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	2.9161	3.0015	3.0096	2.9979	3.0014	3.0080
	ABS Bias	0.0839	0.0015	0.0096	0.0021	0.0014	0.0080
	MSE	0.0113	0.0079	0.0088	0.0302	0.0182	0.0114
$\beta_{11}(1.0)$	Mean	1.2145	0.9969	0.9762	1.1091	1.0743	0.9941
	ABS Bias	0.2145	0.0031	0.0238	0.1091	0.0743	0.0059
	MSE	0.1213	0.1084	0.1150	1.1331	0.7577	0.1373
$\beta_{21}(2.0)$	Mean	2.0032	2.0032	2.0032	2.0220	2.0161	1.9798
	ABS Bias	0.0032	0.0032	0.0032	0.0220	0.0161	0.0202
	MSE	0.2188	0.2188	0.2188	0.2190	0.2177	0.2087
$\beta_{22}(0.5)$	Mean	0.4957	0.4957	0.4957	0.4700	0.4884	0.5591
	ABS Bias	0.0043	0.0043	0.0043	0.0300	0.0116	0.0591
	MSE	1.5317	1.5317	1.5317	1.0990	1.0732	0.7695
$\beta_{23}(1.5)$	Mean	1.5081	1.5081	1.5081	1.4306	1.4482	1.3718
	ABS Bias	0.0081	0.0081	0.0081	0.0694	0.0518	0.1282
	MSE	1.3442	1.3442	1.3442	1.0223	0.9630	0.7025

Table 18: Results from run 5 Sample Size T= 40

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	2.8767	2.9997	3.0068	2.9949	2.9961	3.0028
	ABS Bias	0.1233	0.0003	0.0068	0.0051	0.0039	0.0028
	MSE	0.0180	0.0067	0.0073	0.0139	0.0116	0.0084
$\beta_{11}(1.0)$	Mean	1.2618	1.0044	0.9897	1.1466	1.1052	1.0251
	ABS Bias	0.2618	0.0044	0.0103	0.1466	0.1052	0.0251
	MSE	0.0967	0.0487	0.0514	0.8846	0.5033	0.1147
$\beta_{21}(2.0)$	Mean	1.9961	1.9961	1.9961	1.9994	1.9976	1.9856
	ABS Bias	0.0039	0.0039	0.0039	0.0006	0.0024	0.0144
	MSE	0.0764	0.0764	0.0764	0.0765	0.0763	0.0753

$\beta_{22}(0.5)$	Mean	0.4999	0.4999	0.4999	0.4741	0.4795	0.5239
	ABS Bias	0.0001	0.0001	0.0001	0.0259	0.0205	0.0239
	MSE	0.7150	0.7150	0.7150	0.5069	0.4971	0.4188
$\beta_{23}(1.5)$	Mean	1.4967	1.4967	1.4967	1.4130	1.4350	1.3822
	ABS Bias	0.0033	0.0033	0.0033	0.0870	0.0650	0.1178
	MSE	0.7928	0.7928	0.7928	0.6461	0.5985	0.5131

Table 19: Results from run 5 Sample Size T= 60

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	2.8726	2.9994	3.0041	2.9963	2.9997	2.9997
	ABS Bias	0.1274	0.0006	0.0041	0.0037	0.0363	0.0003
	MSE	0.0180	0.0047	0.0050	0.0052	0.1420	0.0049
$\beta_{11}(1.0)$	Mean	1.2753	1.0006	0.9904	1.1654	1.0462	1.0462
	ABS Bias	0.2753	0.0006	0.0096	0.1654	0.0462	0.0462
	MSE	0.0956	0.0359	0.0372	1.1935	0.4355	0.1722
$\beta_{21}(2.0)$	Mean	2.0037	2.0037	2.0037	2.0081	1.9977	1.9977
	ABS Bias	0.0037	0.0037	0.0037	0.0081	0.0023	0.0023
	MSE	0.0560	0.0560	0.0560	0.0559	0.4573	0.0551
$\beta_{22}(0.5)$	Mean	0.4881	0.4881	0.4881	0.4748	0.4979	0.4979
	ABS Bias	0.0119	0.0119	0.0119	0.0634	0.0021	0.0021
	MSE	0.3936	0.3936	0.3936	0.3108	0.5155	0.2595
$\beta_{23}(1.5)$	Mean	1.5059	1.5059	1.5059	1.4366	1.4259	1.4259
	ABS Bias	0.0059	0.0059	0.0059	0.0634	0.0741	0.0741
	MSE	0.3422	0.3422	0.3422	0.3108	0.4942	0.2688

Table 20: Results from run 5 Sample Size T= 100

		OLS	2SLS/3SLS	LIML	BAYESIAN		
					BMPV1000	BMPV100	BMPV10
$\gamma(3.0)$	Mean	2.8741	2.9993	3.0020	2.9995	2.9996	3.0004
	ABS Bias	0.1259	0.0007	0.0020	0.0005	0.0004	0.0004
	MSE	0.0169	0.0028	0.0029	0.0029	0.0029	0.0029
$\beta_{11}(1.0)$	Mean	1.2759	1.0009	0.9950	1.0899	1.0614	1.0275
	ABS Bias	0.2759	0.0009	0.0050	0.0899	0.0614	0.0275
	MSE	0.0882	0.0226	0.0231	0.7759	0.4299	0.1550
$\beta_{21}(2.0)$	Mean	2.0062	2.0062	2.0062	2.0085	2.0077	2.0010
	ABS Bias	0.0062	0.0062	0.0062	0.0085	0.0077	0.0010
	MSE	0.0369	0.0369	0.0369	0.0369	0.0369	0.0366

$\beta_{22}(0.5)$	Mean	0.4872	0.4872	0.4872	0.4818	0.4831	0.4962
	ABS Bias	0.0128	0.0128	0.0128	0.0182	0.0169	0.0038
	MSE	0.2160	0.2160	0.2160	0.1622	0.1613	0.1535
$\beta_{23}(1.5)$	Mean	1.5136	1.5136	1.5136	1.4919	1.4905	1.4766
	ABS Bias	0.0136	0.0136	0.0136	0.0081	0.0095	0.0234
	MSE	0.1976	0.1976	0.1976	0.1598	0.1590	0.1511

APPENDIX C

Samples of Data Simulated and used in the Experiment.

As a result of the large volume of the data in this research work which would require thousands of pages for its presentation, only data from a few number of replicates are presented here

RUN 1 SAMPLE SIZE 20.

REPLICATE 1

y_{1t}	y_{2t}	X_{1t}	X_{2t}	X_{3t}
2.394248	0.744201	-1.09397	-0.59203	0.698365
-9.94992	-3.42684	0.367081	-1.18496	-1.41895
-3.38113	-0.92628	0.145398	-0.23277	-0.57024
-4.76049	-2.18701	0.265778	0.588642	-0.1135
10.02484	2.76415	0.479409	1.134421	1.332485
-19.6485	-6.49876	-1.23364	-0.09755	-0.27496
2.764796	1.112545	0.301434	-0.19762	-0.34211
2.862747	1.361822	-1.54591	1.250681	2.110797
-11.194	-3.99121	0.138909	-1.57122	-1.13226
8.143142	2.301831	1.133268	0.4564	0.86009
-2.89457	-0.29256	-0.65837	0.568878	-0.34641
-4.58133	-0.86195	-1.7005	0.521725	0.958801
-7.99982	-2.04139	-0.19127	-0.7314	-0.96094

6.194941	1.349366	1.272184	-1.29195	-1.10465
1.874606	0.680531	0.054985	0.240014	-0.4807
1.201579	0.062943	1.000267	-0.37619	-0.75308
-7.03248	-1.96546	-0.80293	0.867518	-0.37849
-9.82676	-3.146	0.162158	-1.26779	-1.58247
0.523419	0.455708	-0.62861	0.195217	-0.17518
17.53894	5.589731	1.62335	-1.23091	-0.78819

REPLICATE 2		**REPLICATE 3**		**REPLICATE 4**		**REPLICATE 5**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-5.46466	-1.7107	-11.8727	-3.47128	-3.02136	-0.29495	0.097597	0.092699
-4.40693	-1.7136	1.36918	0.313314	-5.94475	-1.46484	-14.2553	-5.18312
-1.91702	-0.58856	-1.65668	-0.70962	0.336073	0.319417	-5.1927	-1.93777
1.76347	1.34215	-3.22347	-1.25147	8.071803	2.420133	-0.5674	-0.55364
9.257936	2.539103	5.922835	1.752102	6.766427	1.893654	13.34953	4.49186
-3.01294	-0.72392	-4.62042	-1.07128	-11.8225	-3.5917	-10.3035	-2.65176
7.568464	2.698971	-10.442	-4.29938	-11.4489	-4.35101	-0.25197	-0.48313
2.045098	1.080781	-6.45771	-2.20047	1.229482	1.204834	-5.62941	-1.24332
-12.589	-4.12851	-5.70571	-2.40818	-4.06975	-1.249	-0.47669	-0.13795
10.89026	2.8866	12.27526	3.114067	10.09495	2.584947	12.23647	4.013348
-2.65849	-0.74347	-0.34734	0.361214	-7.72969	-2.69902	-8.71958	-2.79798
-3.51231	-0.71502	-6.56603	-1.47584	-1.54239	0.138027	-14.2597	-4.42937
-4.54365	-1.13939	-12.5468	-4.19883	-16.091	-5.72555	-9.85248	-3.532
1.93231	0.630567	-3.80906	-1.26794	11.70178	3.539586	-1.23815	-1.04973
-7.33126	-2.58344	1.634584	0.392931	5.206044	1.814313	-8.91742	-3.39672
3.522341	0.829226	7.989657	3.054762	8.509723	2.069683	13.73786	4.673139
-20.6636	-7.00301	-6.08668	-1.65904	-8.64965	-2.86664	-3.58147	-1.33361
-5.53598	-1.07121	-8.61242	-2.49797	-14.2816	-5.05864	-14.7462	-5.05149
-4.87972	-1.40836	2.876652	1.791805	-1.66714	-0.38176	1.233561	0.39257
10.49089	2.613474	-5.46754	-2.68169	3.513219	0.251445	11.96767	4.05587

REPLICATE 6		**REPLICATE 7**		**REPLICATE 8**		**REPLICATE 9**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
4.628544	1.919143	-3.12053	-0.23712	-22.3077	-7.12543	-2.84515	-0.42129
-7.08001	-2.37524	-6.78799	-2.17852	4.95006	1.531031	-4.3524	-1.54801
-2.14865	-0.76843	4.143965	1.726249	2.078357	0.772861	-10.1071	-3.31243
13.72136	5.18832	3.473955	1.168089	-1.23748	-0.89231	9.238173	3.472848
10.65128	3.234463	7.389711	2.152283	13.93629	4.681722	11.72497	3.76381
-14.7656	-4.98392	-3.96386	-0.73362	-8.21238	-1.91009	-23.0968	-7.73907

-5.61588	-1.56261	-3.2251	-0.90725	-5.59809	-2.14936	-1.22957	-0.53967
-2.24099	-0.41836	0.056863	0.238756	0.097944	0.329635	-3.26667	-0.8128
-12.6655	-4.50981	-0.75077	-0.13715	-8.79852	-3.54968	-3.95422	-1.4815
16.05841	5.642626	6.145422	1.013145	10.70786	3.527273	7.649861	2.038773
-9.01396	-3.3469	0.636239	0.554945	-1.91045	-0.27994	-0.24372	0.228615
-5.77469	-1.15243	-11.3634	-3.63087	-0.65008	0.589533	-16.9423	-5.51583
-13.2118	-5.16225	-1.61148	-0.38471	-14.3618	-4.59224	-5.24336	-1.37513
3.839103	1.039448	2.676618	0.63885	-1.82476	-0.76856	1.832612	-0.14918
5.549183	2.218073	-4.85898	-1.40608	-6.2825	-1.92506	0.240564	0.028435
3.636098	1.107084	14.20774	4.22643	-1.0327	-0.25195	-1.55086	-0.6998
-14.8472	-4.7618	-9.96504	-3.27804	-4.03078	-0.77396	-11.7713	-4.10184
1.432528	0.514404	-10.9426	-3.65857	-6.38008	-2.0417	-11.5922	-3.83119
-7.97857	-2.63562	-4.32904	-1.41183	-1.65457	-0.16867	-6.09893	-2.4096
0.097952	-0.9266	1.673472	0.169845	20.38078	6.536279	13.07561	4.027218

REPLICATE 10		**REPLICATE 11**		**REPLICATE 12**		**REPLICATE 13**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-4.30063	-1.15678	-20.6489	-6.65528	-10.8744	-3.17739	-2.75111	-0.76956
-13.1177	-4.51463	-12.2511	-4.55113	-10.2235	-3.56553	-13.8583	-4.47901
1.030163	0.04443	6.799644	2.197064	7.029297	1.940452	7.150711	2.584899
-1.85828	-1.23338	7.335218	2.608395	-1.15429	-0.4787	-4.78442	-1.95986
2.964943	0.183533	11.44718	3.96744	9.379056	2.924047	8.114307	2.476185
-5.01993	-1.50769	-8.77877	-2.97869	-13.1774	-3.5854	-11.4907	-3.64118
-0.7825	-0.7948	-2.63081	-1.18974	11.23881	3.359668	-2.93697	-1.02326
4.619421	2.588174	-0.18792	0.673394	3.170043	1.736947	0.799783	0.896327
-0.25399	0.581218	-2.41057	-0.88702	-3.8705	-1.11512	-2.62143	-1.33509
16.59677	5.175677	25.90132	9.121394	5.578045	1.170842	15.74614	5.287196
-2.1088	-0.73211	-12.9824	-4.49467	-0.46415	0.298375	-1.67408	-0.56014
-13.3479	-3.90241	3.818433	1.638186	0.362266	0.713974	-9.4408	-2.41306
-6.82376	-2.50412	-3.59673	-0.97005	-6.48984	-2.51018	1.748699	0.734344
0.968278	-0.33575	-2.72235	-1.44549	-0.59887	0.158791	12.14382	3.648396
-2.77417	-1.74479	-16.5617	-5.81963	6.826987	2.778994	-2.90265	-1.01034
8.661231	2.078629	-1.66717	-0.9818	-2.11967	-0.68779	8.995651	2.701907
-7.34172	-2.45287	-4.40572	-1.10318	2.580084	1.917177	-3.5997	-1.30642
-17.8625	-6.25523	-17.9751	-6.05406	-11.6253	-3.09994	-12.9422	-4.48246
-14.2569	-4.80843	-1.86897	-0.2121	9.203471	3.537168	-8.67008	-2.53194
10.25642	2.789147	9.222298	2.793522	9.357317	2.920909	-5.90798	-2.69569

REPLICATE 14 **REPLICATE 15** **REPLICATE 16** **REPLICATE 17**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
0.696653	1.330596	-0.08902	-0.19044	-0.10049	1.01978	-2.18779	-0.30544
-0.47533	-0.01204	-11.0998	-4.00769	3.12635	0.901032	-15.5038	-5.35663
0.017203	-0.24788	6.138163	2.18677	-7.41742	-2.96108	-3.31721	-0.85321
11.35576	4.133013	5.929544	2.581614	4.595528	1.592027	8.058728	2.895022
6.990269	2.271646	1.53331	0.291428	9.797123	3.009829	2.362503	0.363533
-15.5358	-5.06148	-14.9716	-4.85004	-9.72742	-3.00005	-15.9975	-5.1444
8.113965	2.848754	2.970979	1.179631	2.976396	0.598369	-5.49667	-1.7946
4.664248	1.671989	-7.59781	-2.29115	5.968016	2.94511	0.549953	1.183373
-0.24128	0.118168	-2.45995	-0.48829	-10.6206	-4.03975	-7.72925	-1.82633
5.613919	1.012777	10.81444	2.669564	16.67503	5.725653	5.812179	1.315689
2.835883	1.119869	-12.3286	-3.48915	-3.86996	-0.99766	-2.24879	-0.27298
-5.52527	-1.19757	-4.73591	-1.12548	-5.3858	-0.38369	-10.4318	-2.74221
-0.20967	-0.11499	-12.7283	-4.58871	-10.4538	-3.50586	-7.74375	-2.93654
-7.05909	-2.47585	1.922021	0.047084	3.937308	1.105026	-4.46071	-1.88717
-6.4716	-2.05138	-0.46048	-0.37418	2.978581	1.180804	-8.54119	-3.06569
10.07742	2.361015	6.363235	1.992816	2.385192	0.639855	4.942845	1.149387
-1.72486	0.020921	-8.88621	-2.05001	-22.4843	-7.40839	-5.71314	-1.86789
-20.0755	-7.20992	-5.63896	-2.13851	-2.39949	-0.90169	-13.3574	-4.5987
-2.94096	-0.96994	-9.54719	-3.47492	-5.62545	-1.57247	-2.56554	-0.71368
5.325778	0.888627	2.791186	0.39743	1.073053	0.184925	1.452666	-1.01917

REPLICATE 18		**REPLICATE 19**		**REPLICATE 20**		**REPLICATE 21**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
0.614465	0.44731	-11.5747	-3.78006	5.733811	2.428153	-0.06482	0.002141
-7.45191	-3.27548	2.139548	0.841122	6.583017	1.877941	-4.44518	-1.19484
-1.48201	-0.0689	5.956491	2.314161	-2.33764	-0.87472	8.83113	3.268599
-5.1851	-2.19725	9.776127	3.301603	4.804719	1.379401	0.51161	-0.34352
15.36707	4.913711	10.90598	3.843451	15.68905	5.130938	8.328306	2.282566
1.253165	0.640871	-4.49919	-1.42956	-13.1792	-4.04477	0.658974	0.555029
-0.40843	0.004996	-2.25737	-0.44751	-0.23495	-0.22018	-4.5667	-1.78593
1.933906	1.286328	4.522446	1.848342	-2.58402	-0.37779	3.140077	1.57328
-0.7404	-0.1657	-6.83668	-2.37771	-12.2533	-4.21469	-3.54551	-1.27989
3.382633	0.712142	16.87334	5.273677	11.39029	3.670589	18.98918	6.168249
-1.65656	-0.51016	2.075524	0.532384	-4.66822	-1.46723	-11.685	-4.23782
-1.95534	0.063958	1.120552	1.141781	-11.9856	-3.0043	-6.54819	-2.138
-7.40691	-2.49307	-7.32682	-2.42706	-3.55869	-1.38951	-16.3952	-5.4957
1.518987	0.196809	-9.39494	-3.90581	2.984964	0.491861	3.866727	0.635399

4.151649	1.759528	3.176318	1.232506	-9.56981	-3.56405	-8.39681	-3.35477
1.985464	-0.03917	3.667869	1.198955	5.266155	1.002324	-4.74764	-1.73702
-13.8574	-4.77924	-15.7092	-4.94809	-14.045	-4.18498	-18.6266	-6.60721
-10.0528	-3.06779	-2.03059	-0.42332	-3.8909	-0.74348	-5.96015	-2.31775
-10.2099	-3.57252	-8.53728	-2.80397	-8.78911	-3.16388	-6.00024	-1.71694
9.977954	3.041643	11.48549	3.279464	6.109549	1.433809	10.772	3.552899

REPLICATE 22		**REPLICATE 23**		**REPLICATE 24**		**REPLICATE 25**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-9.80224	-3.0198	-10.7185	-3.3684	1.224844	0.844698	-18.6745	-6.24012
-14.8177	-5.41823	3.735946	1.331827	-10.2427	-4.17076	-0.39204	-0.44501
-6.09266	-1.81501	4.890957	1.786106	8.756263	2.844633	1.70186	1.183986
-1.28142	-0.18696	11.17444	3.907353	15.25146	4.923494	-4.8922	-1.96651
7.380549	2.096219	17.75104	6.095025	14.01602	4.773945	9.875817	3.010073
-3.53366	-0.8091	-7.88923	-2.34245	-9.3203	-2.50911	-5.60194	-1.24145
-3.18104	-0.93894	-7.10406	-2.78528	-7.1198	-2.69641	3.752739	1.052616
8.970837	3.725207	5.041293	2.082589	-2.7519	-0.21953	6.528794	2.998825
-12.5128	-4.25716	-12.4682	-4.013	-11.8008	-3.86149	-3.92567	-1.41675
20.42253	6.752576	8.770404	2.49085	12.01875	3.531647	16.97707	4.705274
5.089326	1.354566	-9.86614	-3.69034	-5.14718	-1.54799	-8.14481	-2.76777
-3.92644	-0.04836	0.044063	1.083512	-15.2613	-4.43349	-13.4742	-4.00338
4.644878	2.026681	-5.94743	-1.50244	-4.77288	-1.51876	-9.98767	-3.54444
20.76952	7.26406	3.301407	0.991378	10.64205	3.778043	1.199995	0.23986
3.476003	1.401076	-3.79165	-1.1472	-1.59819	-0.81211	-3.80599	-1.89936
7.362739	1.9262	-3.47132	-1.23571	-1.76709	-0.15226	6.008099	1.47736
-4.65247	-1.5498	-5.5452	-1.23636	-14.5222	-4.97492	-5.21714	-1.44981
-3.75436	-0.65155	-5.03002	-1.39782	-13.2348	-4.84249	-15.247	-5.68925
2.09868	0.762161	2.245575	1.088315	-1.75521	-0.49426	-9.27673	-3.10613
3.274963	0.53448	12.54687	3.665694	6.548669	1.323174	-5.62906	-2.46088

REPLICATE 26		**REPLICATE 27**		**REPLICATE 28**		**REPLICATE 29**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-4.96669	-1.19921	-10.8042	-2.87603	-10.528	-3.50783	-6.97513	-2.1287
-11.8043	-4.06762	0.16494	0.174019	-8.04231	-3.05724	-4.74687	-2.19847
2.562603	0.669437	-10.973	-3.81987	-1.41226	-0.06401	8.755718	3.04029
-3.6018	-1.74058	15.28572	5.417118	9.225576	3.420118	1.424969	0.367966
-2.54835	-0.85891	5.486934	1.885388	7.883392	1.793848	12.40086	3.837842

-27.5212	-8.92009	-13.9232	-4.26204	-2.22281	-0.17924	-16.0446	-5.16513
-3.61256	-1.61041	6.522743	1.846223	-4.28526	-1.53886	3.422557	0.989132
2.825012	1.933613	5.394414	2.4048	3.230631	2.072127	5.363113	2.391631
-11.6218	-4.14914	-11.4889	-3.85646	-7.95131	-3.00831	-9.85605	-3.23792
12.08267	3.29268	14.27992	4.378077	19.51287	5.595231	14.9807	4.879576
-1.90449	-0.24329	-13.0668	-4.31898	-6.21314	-1.8559	-2.32301	-0.14513
-3.39352	-0.34874	-20.1939	-6.0538	-12.3625	-3.65707	-7.40277	-2.11271
-8.36343	-2.324	-5.10646	-1.36143	-2.47375	-0.24364	-20.0099	-6.82606
2.789423	0.377779	10.21674	3.457916	8.650843	2.695085	4.782969	1.022552
-1.80525	-0.69083	-7.09536	-2.67389	3.365242	1.184696	-5.57247	-1.90759
13.29622	4.959105	9.144983	2.395297	10.37105	3.804699	-0.01076	0.116611
-14.4393	-4.95368	-12.0501	-3.41582	-6.0854	-1.82623	-7.77708	-2.12572
-6.97398	-2.07164	-4.68556	-2.09788	-12.9853	-4.43844	-7.7573	-2.575
-1.85169	-0.67603	-12.6828	-3.91238	-3.67232	-1.04959	-8.94626	-2.88629
2.977828	0.873911	5.913771	1.21603	2.879727	0.164914	4.025578	0.960099

REPLICATE 30		**REPLICATE 31**		**REPLICATE 32**		**REPLICATE 33**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
8.280239	3.440827	-3.81955	-0.8036	-7.75318	-2.35692	-10.7862	-3.52953
-12.8798	-4.30831	-2.85817	-1.98961	0.54834	0.226842	-2.32655	-0.88602
-5.14631	-2.60021	-6.32576	-2.19509	-3.86802	-1.64235	-0.34718	-0.05052
-9.5157	-3.61665	1.747774	0.780767	8.047769	2.702271	-2.34209	-0.7782
14.61535	4.728518	-1.55313	-1.37367	10.17236	3.158455	20.53548	6.680593
-8.63931	-2.42344	-11.2852	-3.31949	-12.9184	-4.1108	-17.5182	-5.80686
4.106309	1.349506	-0.15483	-0.32266	-4.13411	-2.28224	6.613931	2.356379
4.830663	2.744424	4.516812	1.688777	-0.14954	0.830997	6.957524	3.159686
-6.27057	-1.73005	-7.84761	-2.5047	-10.1308	-3.44579	-2.46051	-1.376
16.95281	6.015502	15.50824	4.896115	19.53511	6.101092	6.628693	1.908726
-12.489	-4.27329	5.124085	1.888595	-6.9274	-1.34904	-3.27224	-0.93671
-1.58423	0.551312	-11.1445	-3.20596	-4.9913	-0.60287	-11.7346	-2.90485
-4.47698	-0.9452	-5.95232	-2.46106	-12.2079	-4.38342	-12.8521	-4.20471
7.009687	2.512507	2.775463	0.831729	0.215514	-0.18246	-9.11587	-3.39402
0.902825	0.428196	9.205642	3.073997	-0.61208	-0.83985	-7.61904	-3.23517
10.28951	3.157635	15.53582	4.720747	10.9501	3.467406	0.310397	-0.36618
-5.43674	-1.43298	-8.58641	-2.52711	-7.42688	-2.43731	-12.1617	-4.0655
-6.70546	-2.15703	-5.85697	-2.16229	-0.85433	-0.19963	-17.1022	-5.76166
-14.3848	-4.80628	-0.31488	0.152101	5.12187	1.831803	-4.15685	-1.62865
9.188357	2.42254	3.406931	0.889963	6.754099	1.812485	5.688344	1.098213

REPLICATE 34 **REPLICATE 35** **REPLICATE 36** **REPLICATE 37**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-0.28476	0.477135	-3.80934	-1.18492	-4.14577	-0.98055	4.741202	2.727903
0.716297	0.07229	-2.86	-1.12899	-11.9969	-4.07005	-3.1357	-1.15121
-0.32069	-0.25002	-8.57409	-3.12621	-2.63554	-1.30151	-9.70765	-3.41295
2.829377	1.038643	2.595291	0.815124	5.012801	1.681019	-10.0366	-4.25027
9.551679	2.856757	7.397594	1.741447	8.437109	2.17076	9.961848	2.954479
-11.5443	-3.66051	-5.89899	-1.85923	-6.48292	-1.29364	-16.3886	-5.42848
-2.33366	-0.2568	4.989682	1.539371	5.230648	1.783639	-8.47661	-3.67879
10.47803	3.862567	-2.74609	-0.48914	4.216578	1.913211	-6.2681	-1.43886
-6.59737	-2.47758	-1.50597	-0.47303	-10.4228	-3.28098	2.305351	0.858546
19.18923	6.322492	-0.40456	-1.16132	16.1734	5.2873	14.05805	4.511456
-12.7368	-4.21065	-4.147	-1.32966	-14.9387	-5.65181	-11.4845	-4.15569
5.311724	2.584668	0.150857	0.470117	-4.13339	-0.16845	-4.2007	-0.19567
-0.58964	0.529683	-14.0845	-4.90571	-3.67181	-1.59475	-9.84285	-3.36654
2.765861	0.423942	9.268312	2.901482	5.656998	2.018596	7.498097	2.042228
3.47396	1.606583	-0.2149	-0.26734	-8.54507	-2.94322	1.180057	0.574278
1.983667	0.293551	8.485684	2.552223	11.28478	3.479721	3.056323	1.101187
-2.14874	-0.09267	-19.7389	-6.58096	-2.51922	-0.73161	-6.93467	-2.84299
-7.25543	-2.32857	-8.7375	-3.12485	-17.1053	-6.41958	-9.10242	-3.42162
-2.27582	-0.91804	-8.78825	-2.77903	-9.08634	-3.07648	2.181777	1.002942
1.735115	-0.00508	-4.68394	-2.63176	4.103885	0.626134	5.295613	1.329268

REPLICATE 38		**REPLICATE 39**		**REPLICATE 40**		**REPLICATE 41**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-6.96363	-1.55003	-3.93563	-0.24871	-6.33477	-1.5895	1.32164	0.643288
-7.15197	-2.99263	3.212437	0.977854	-14.7419	-5.41939	1.500273	0.709787
-8.23644	-3.02509	-7.37757	-2.79693	-6.09953	-2.53197	-15.48	-5.59081
1.135031	0.449107	7.256173	2.366029	2.68759	0.063677	7.597088	2.259254
14.78688	4.922728	11.83717	3.360822	15.09421	4.862028	2.715661	0.509184
-8.36245	-1.6945	-15.4634	-5.22988	-0.50801	0.289906	-17.3617	-5.21793
-6.81389	-2.49053	4.628697	0.978804	5.985776	2.24426	0.813692	-0.0375
-3.19551	-0.23315	-0.82346	0.150637	0.846431	0.664504	13.65202	5.61442
-6.24104	-2.046	-5.75434	-1.84229	-5.33078	-1.51911	-8.64475	-3.09408
18.35217	6.039474	17.9259	5.866552	6.901294	1.550665	12.66351	3.661453
-1.04932	-0.18522	-7.53248	-2.53151	-7.92866	-2.59045	-18.9876	-6.54581
-11.9756	-3.53874	-0.49572	0.847565	-5.3167	-0.89636	-9.65902	-2.28153
-4.09777	-1.43409	-11.0939	-3.68743	5.372838	2.048814	6.636922	1.76652

-3.77443	-1.43233	4.027523	0.799493	-0.9477	-0.93303	0.650616	-0.3818
-3.88922	-1.11926	-6.04648	-1.80243	5.900894	2.022768	-9.57604	-3.54823
5.496436	1.797634	-5.41878	-2.03224	12.87633	4.187525	7.966939	2.534961
-4.26105	-1.27173	-4.13507	-1.04854	0.068692	0.476859	-6.14035	-2.25603
-8.82306	-3.02176	-4.12375	-1.39217	-10.3815	-4.01535	-4.58944	-1.19134
-6.03663	-1.77339	-9.64469	-2.44105	-15.5014	-4.45035	-1.69792	-0.25778
13.27481	3.883321	17.75259	5.480099	3.014561	0.236908	4.37746	0.810544

REPLICATE 42		**REPLICATE 43**		**REPLICATE 44**		**REPLICATE 45**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-11.7451	-3.05068	-12.0776	-3.54767	-1.09688	-0.26738	-5.11013	-1.85619
-14.698	-5.37483	-1.38916	-1.14249	-12.2185	-4.66003	0.601432	-0.11675
4.029689	1.419122	-0.26627	-0.59962	-7.70126	-2.49229	5.629956	1.93563
1.71936	0.484934	-1.49266	-0.53992	-5.0495	-2.00662	6.934277	2.274115
3.00557	0.811613	6.083745	1.886867	3.488482	1.373528	3.911105	0.82706
-11.9554	-3.9146	-12.8555	-3.88856	-9.05632	-2.62935	-16.361	-5.5533
-4.29528	-1.18958	-0.89682	-0.79943	-2.87409	-1.52774	-1.03376	-0.20273
-0.1522	0.610702	-8.20704	-2.47775	-2.93815	-0.0491	-2.01744	-0.04738
-14.6765	-4.42415	-5.69153	-1.96886	-10.0603	-3.9314	1.450847	0.479358
18.59522	6.539165	16.39543	5.009273	19.11242	6.020715	17.61563	5.664638
2.393252	1.360861	-9.64669	-3.31322	-0.19332	-0.18758	-13.152	-4.05199
-6.35077	-1.77029	-2.19274	0.152153	-1.88977	-0.30051	-4.72493	-1.4223
-7.01334	-2.31012	-6.24763	-2.21711	-5.26572	-1.88881	-22.6468	-7.66326
4.975986	1.197729	-2.50908	-1.58259	5.315911	1.57174	-1.51296	-1.26484
-10.9456	-3.65377	1.146712	1.02404	-3.36917	-0.96829	-9.66259	-3.57945
2.496597	0.675872	-3.63771	-1.23792	7.639375	2.232928	6.721701	1.901697
6.644846	3.169433	-10.6052	-3.23574	-11.8461	-3.64406	-3.98075	-0.45451
-6.8553	-2.15427	-14.5726	-5.0963	-7.53014	-2.30157	-7.41867	-2.89573
-0.19786	0.340729	-7.12684	-2.14395	-10.1338	-3.07501	-2.65926	-0.48707
9.502474	3.169071	10.40446	3.372386	7.156559	2.047258	0.645646	-0.13199

REPLICATE 46		**REPLICATE 47**		**REPLICATE 48**		**REPLICATE 49**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-6.65827	-2.16248	-9.29517	-3.27557	-13.9657	-3.89588	-3.50733	-0.95965
-8.41021	-3.72207	1.35716	0.61347	-7.47036	-2.66912	-10.8593	-3.44244
-7.155	-2.58798	-1.37277	-0.35338	-1.42045	-0.45364	-13.6509	-4.83279
-1.54634	-0.89269	0.232555	0.168531	-2.44291	-1.05776	-0.87086	-0.42297
16.56672	5.349508	12.62677	4.80382	15.24735	5.26095	12.51318	3.673577
-14.1551	-4.17247	-8.72878	-2.55087	-19.1441	-6.67156	-16.9347	-5.09055

-1.97504	-0.58603	1.239398	0.533017	6.607694	2.325156	5.853571	1.742325
7.519341	2.863638	-1.35276	-0.28519	0.478014	0.41736	2.556405	1.48379
-10.3965	-3.5431	-15.1618	-5.67123	-7.03361	-2.6021	-1.47525	-0.44953
14.94885	4.000427	10.04953	2.358796	20.66674	6.331927	18.42216	5.825046
-12.6964	-4.17611	-2.20069	-0.29615	-8.79133	-2.58639	-8.58862	-2.71218
-10.161	-2.67966	-5.62564	-1.08175	-12.4005	-3.19406	-8.68695	-2.03457
-8.25278	-2.63548	-10.4153	-3.59979	-15.1106	-5.19653	-5.36364	-2.17398
5.884356	1.692647	-8.11568	-2.78598	-1.27975	-1.26535	-4.22329	-1.90281
1.259781	0.123694	1.632176	0.614759	6.089591	2.006556	-0.35361	-0.23333
5.158321	1.972473	11.16127	3.087746	-7.55829	-3.35404	-3.72397	-1.94536
5.981009	2.851537	-3.26554	-1.14986	-12.7406	-4.24085	-8.06969	-2.08124
-6.12636	-2.54713	-18.3006	-6.42794	-5.26474	-1.90408	-9.17515	-2.83669
-5.73678	-1.73998	-11.2164	-3.77531	-6.48195	-2.28445	4.898413	1.887383
8.837129	2.511348	6.567529	1.770731	5.801945	0.873752	3.407315	0.46203

REPLICATE 50 **REPLICATE 51** **REPLICATE 52** **REPLICATE 53**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-2.6975	-0.83958	-7.55531	-2.16064	-4.73755	-1.15232	-4.88861	-1.08976
-9.15589	-3.18699	-5.43627	-2.0772	-12.816	-4.02202	-6.54893	-1.73134
-2.22984	-0.50369	-0.74253	-0.37954	-2.6647	-0.32563	-2.15447	-0.64588
3.171938	0.883817	2.779721	0.92337	8.041169	3.302591	-1.68112	-0.85473
-1.20485	-1.24801	15.75328	5.525854	0.917217	-0.29926	11.87182	3.797143
-7.24646	-1.65256	-25.7329	-8.85566	-8.80644	-2.40547	-7.95251	-2.95274
-11.6701	-4.33249	-8.08119	-2.73647	-3.43898	-1.57841	-2.36178	-1.41387
4.924965	2.120579	-3.2517	-0.88273	8.638957	3.531914	-3.74802	-0.8251
-4.71613	-1.23555	-13.4409	-4.39434	1.280838	0.512581	-5.67631	-2.0804
16.77989	5.659601	14.40238	4.814391	11.22138	3.151931	10.95702	3.149484
-9.87256	-3.13742	-5.6439	-1.86796	-9.46221	-3.28122	-0.71026	0.754507
-7.28183	-1.74692	2.923356	2.057125	-8.42593	-1.94743	-4.34055	-0.66873
-9.54003	-2.9448	3.547491	1.808371	-6.64152	-2.38877	-7.19166	-2.30974
4.2966	1.278708	15.11592	5.139881	0.497096	-0.4195	2.063759	0.012446
7.211838	2.805438	4.196723	1.79388	-0.4333	0.522782	-3.97684	-1.62936
1.13181	-0.00874	4.281436	1.430076	6.278719	2.070787	7.04879	1.709045
-9.98482	-3.80614	-3.45334	-0.33331	-0.85704	0.212725	-1.32139	-0.07404
-8.25891	-2.97479	3.884959	1.51944	-2.36038	-0.43735	-4.59677	-1.48663
-10.184	-2.81354	-3.08089	-0.94477	-12.6727	-3.95726	-4.10948	-0.94862
11.54583	3.761933	10.38182	2.824385	3.11541	0.394471	4.387405	0.514968

REPLICATE 54 **REPLICATE 55** **REPLICATE 56** **REPLICATE 57**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-13.7602	-4.06841	-2.83475	-0.6301	-0.85459	0.083814	0.746625	0.509231
-3.65479	-1.23273	-14.6728	-4.90434	5.209622	2.071397	0.573257	0.510395
-3.06178	-1.79183	-4.7744	-1.75112	-1.54029	0.174775	-5.3121	-2.44365
4.198646	2.001361	1.484029	0.508806	-1.15519	-0.83331	1.536021	0.803471
13.78242	4.632678	21.74593	7.335371	9.461711	2.769332	18.99813	6.54749
-6.70321	-1.64625	-18.0955	-5.79553	-10.1984	-3.18248	-16.9181	-5.65021
-2.1837	-1.49531	-12.3835	-4.41142	2.401415	0.588027	-0.45877	-0.23928
1.645284	1.54037	3.504451	1.363086	-3.47172	-0.77654	12.54962	5.508301
-17.2908	-5.67914	-11.2335	-4.53394	-5.50806	-1.76266	-14.8479	-5.17702
2.459656	-0.21241	12.71834	3.65529	13.85451	3.763291	15.235	4.328691
-10.0459	-3.67029	-7.75357	-2.21411	1.112631	0.826341	-2.07508	-0.82186
-10.4879	-3.08148	-15.7381	-4.62937	-13.4354	-3.92128	-4.26703	-1.00376
-17.6854	-6.17975	-11.744	-4.55481	-6.87233	-2.76544	-10.6986	-3.58238
5.443008	1.873402	7.872094	2.265757	9.226311	2.957766	1.509421	-0.21477
-3.79178	-1.83119	-0.32689	0.079495	-6.96395	-2.62182	-1.07811	0.327565
-1.97603	-1.56652	14.24643	4.57698	-8.73239	-3.51661	9.563787	2.440526
1.512281	1.155351	-13.5992	-4.16475	-8.88123	-2.34667	-7.65841	-2.58741
-9.64489	-2.72318	-12.3643	-3.92834	-6.27092	-1.87935	-13.7051	-4.83005
-7.9857	-2.30627	-3.87013	-1.65152	-5.23688	-1.7475	-14.8745	-5.03271
1.665459	-0.31623	13.69711	4.416317	-1.2185	-1.41275	5.91356	1.202722

REPLICATE 58		**REPLICATE 59**		**REPLICATE 60**		**REPLICATE 61**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
11.42943	4.268287	3.907469	1.684045	-3.14495	-0.72516	-10.7218	-2.79819
-3.42476	-1.2672	-6.19005	-2.38587	-8.76719	-3.36564	-12.0843	-3.97023
3.230696	1.212511	-3.3586	-1.70553	-7.06293	-2.59015	-2.68166	-1.12028
-2.07685	-1.01615	0.905518	0.554571	1.293733	0.353024	9.008986	3.345348
11.05534	3.058891	15.81123	5.110144	6.322992	1.689748	10.08514	3.069786
-1.42273	0.096484	-10.9564	-3.16026	-4.36024	-0.82552	-16.0303	-4.68587
-6.11327	-2.41477	6.242601	2.079958	-8.14667	-3.31318	-1.98299	-0.54626
18.27143	7.492851	-0.92141	0.148274	9.605513	3.719648	2.748449	1.088714
-7.29192	-2.55258	-4.65618	-1.84374	-3.65914	-1.07334	-2.89014	-0.24515
21.42436	6.75568	10.97823	3.660686	17.237	5.387473	15.20782	4.637567
-10.6551	-3.58183	-10.416	-2.98307	-5.32595	-1.7273	-12.7875	-4.47899
0.828	1.411869	-3.22004	-0.51234	-7.19186	-1.80736	-3.13718	-0.56828
-4.57179	-1.08997	0.152663	0.186061	-17.5671	-6.2003	-5.17921	-1.7865
2.507153	-0.55955	4.098219	0.887073	5.447332	1.415224	8.514271	2.783458

-7.52885	-3.35837	2.526831	1.024537	-5.7884	-2.73648	-9.85109	-3.14268
1.206644	0.050581	11.42778	3.404853	1.549126	-0.36362	0.932058	-0.15741
-11.0375	-3.31402	-1.40999	-0.0747	-10.1149	-3.24568	-20.9234	-7.40583
1.390907	0.473564	-5.37463	-2.17144	-0.37539	0.26968	-3.00269	-1.3354
1.63262	1.106682	-7.38381	-1.8224	-8.87573	-2.91076	-7.041	-2.1341
7.050891	1.85519	-3.18799	-1.84188	0.25019	-0.53453	8.694368	2.570096

REPLICATE 62		REPLICATE 63		REPLICATE 64		REPLICATE 65	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-5.65928	-1.94838	0.756497	0.702639	0.071474	0.16003	-10.6795	-3.50102
-12.6476	-4.48599	1.274515	0.485515	-10.607	-3.91566	4.433444	1.442001
4.904799	1.504634	-8.68986	-3.15066	1.850029	-0.29648	-2.33278	-0.92912
-2.76032	-1.28571	-0.75687	-0.53505	2.045094	0.188323	6.004451	2.098892
20.01816	6.905442	18.41966	6.323312	5.333333	1.807654	7.008259	1.483708
-9.6562	-2.71484	-14.4831	-4.07764	-15.7139	-4.84294	-14.1118	-4.03298
3.874625	0.577796	2.586928	0.723391	3.266487	1.236438	-7.97636	-3.23589
-0.24765	0.220366	3.283907	1.254662	0.227764	-0.08316	2.956965	1.447935
-14.3168	-4.47381	-9.50043	-3.3261	-8.55291	-2.69532	-0.83757	-0.55567
13.14194	3.851381	6.674817	1.535618	19.12794	6.172983	10.9834	3.334739
-1.10156	-0.30447	-8.70165	-2.801	-3.18843	-0.66337	-2.70169	-0.91743
-8.59424	-2.03216	-2.59477	0.256389	-16.0307	-4.53415	-8.92251	-2.60175
-12.2495	-3.98363	-6.59138	-2.24212	-10.007	-3.20362	-1.84088	-0.73259
-5.42356	-1.85578	9.730709	3.033692	7.43235	2.059198	1.810439	-0.08292
-2.69271	-0.5187	-1.86685	-1.19685	0.709204	0.220924	-11.1107	-3.64202
-1.54275	-1.25589	-4.56321	-1.65515	-4.28273	-1.87736	-1.6464	-0.9529
-10.8982	-3.74736	0.966796	0.472167	-1.60152	-0.58012	-9.73721	-2.46624
-6.99863	-2.0478	-9.42597	-3.13806	-8.18368	-2.9668	-7.52098	-2.36552
2.499488	0.906774	-3.43736	-0.65752	-5.0896	-1.28399	1.524588	0.775181
14.16326	4.093847	7.620402	1.871602	8.680679	2.180678	3.094645	0.380671

REPLICATE 66		REPLICATE 67		REPLICATE 68		REPLICATE 69	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-1.89776	-0.51394	-8.16365	-2.96865	-9.19185	-3.42714	-6.99454	-2.10173
-9.24702	-2.6857	-5.48611	-1.7562	2.85704	1.163927	-13.2887	-4.04387
-3.83184	-0.96279	8.302185	3.09548	-2.79385	-1.30724	-10.3773	-3.64545
-8.42905	-3.16882	16.21604	6.055914	4.343318	1.236464	-6.72159	-2.34863
13.76447	4.950153	9.258249	2.811383	3.432566	1.169142	22.37568	7.161532
-4.5448	-0.69619	-12.6646	-4.35396	-11.2792	-3.80729	-13.171	-4.08027

-9.12442	-3.1967	-2.74616	-1.34203	-0.72061	-0.2074	5.199173	1.446152
1.662588	1.259637	-2.64069	-0.73735	-2.32906	-0.24926	10.20676	4.573442
1.785687	0.452616	-5.59549	-2.30068	-4.54012	-2.02133	-8.09493	-2.98435
5.835316	1.152939	6.985129	2.276154	20.60676	7.065905	10.17408	3.113557
-6.47377	-2.31802	-9.4218	-2.72457	-16.8104	-5.58979	-4.99744	-1.17095
1.334068	1.394858	-4.48619	-0.81375	-13.3823	-4.2244	-12.2352	-3.48455
-5.63396	-2.22719	-8.61964	-2.9662	-9.01916	-2.57346	-5.47631	-1.64944
10.9579	3.482447	5.243571	1.068444	-1.08523	-0.60849	8.244658	2.78407
1.733776	0.539736	-7.54725	-2.25861	-1.77189	-0.60641	-0.98748	-0.42005
7.562887	2.106116	4.005099	0.487314	8.914055	2.324917	9.59652	2.9828
-0.11455	-0.05918	-14.9071	-5.14538	-9.26094	-2.77956	-5.72783	-1.4018
-3.01204	-0.91138	-12.2947	-4.40434	1.205817	0.230333	-3.21876	-1.30511
-6.56118	-1.43102	-2.03159	-0.43797	-6.8953	-2.10487	4.588786	1.981464
4.491827	0.880909	6.528733	1.692333	11.14347	3.257649	12.74416	3.492249

REPLICATE 70		**REPLICATE 71**		**REPLICATE 72**		**REPLICATE 73**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-1.2576	0.474844	-7.76863	-2.11303	-4.32617	-0.86092	-5.47354	-1.23457
-11.0778	-4.33115	-1.39987	-0.40177	-9.62478	-3.47527	-8.1695	-2.91501
0.964005	0.361026	-1.54522	-1.02417	3.163049	1.137531	1.495042	0.753626
-6.93952	-2.94372	2.897823	0.948324	-1.308	-0.60909	4.609518	1.290578
3.730539	1.465539	6.348793	2.014002	4.421569	1.354047	8.991053	2.406358
-4.09701	-1.27035	-18.5488	-6.40154	-12.7401	-3.7613	-17.082	-5.44226
-4.53046	-2.05371	3.543115	0.951161	3.937886	1.648981	7.186337	2.604755
3.324944	1.423104	5.064902	2.652875	2.526173	1.679647	6.122657	2.286949
-4.17193	-2.22498	-6.65907	-2.90157	-0.86617	-0.35938	-14.3011	-5.41754
20.17625	6.498494	16.43597	4.862462	8.562321	2.641475	15.95232	5.058312
-15.8897	-4.85372	2.755966	1.364538	6.279001	2.758532	0.225146	0.165565
3.000039	1.890358	-0.89685	0.750083	-7.94579	-2.01603	-10.5207	-3.09073
-3.19527	-0.97688	-15.8044	-4.80179	9.189674	2.959093	-13.1846	-4.42027
7.48257	2.000315	8.894398	2.273733	4.879814	1.430982	2.358718	0.529444
-1.09055	-0.41999	7.04917	2.625252	0.190341	0.19766	8.141526	3.27033
5.030235	1.527255	3.787929	0.886939	5.390879	1.463157	-6.49246	-2.94127
-5.98739	-1.14555	-14.1301	-4.68361	-4.66684	-0.75093	-6.30769	-1.61567
-4.0584	-1.69992	-2.31732	-0.52367	-8.99643	-3.41939	-13.1175	-4.61961
-10.0513	-3.52865	-2.40942	-0.40241	-0.03492	0.551617	-7.49176	-2.62265
11.35967	3.995526	9.156515	2.530548	2.191377	0.199235	3.304054	-0.12833

REPLICATE 74 **REPLICATE 75** **REPLICATE 76** **REPLICATE 77**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-1.68277	-0.32297	-6.64916	-1.70572	-6.34262	-1.94783	-2.03353	-0.4295
-4.05407	-1.57656	-2.24765	-0.55561	3.794736	1.600959	-16.6538	-5.89606
-2.66756	-1.17431	3.401551	1.609712	-0.511	-0.64134	-1.69453	-0.42247
7.048738	2.566764	5.777945	2.021868	10.73561	3.92258	7.386843	2.505322
6.05689	1.597606	10.22797	3.215709	12.11369	4.043964	9.645452	2.603499
-3.02522	-0.5164	-15.665	-4.60127	-15.8038	-5.006	-4.3781	-0.74028
-3.84633	-1.50094	2.161009	0.728241	-8.38135	-3.08035	3.268933	0.267154
-6.19501	-1.79064	1.490123	0.695199	1.584424	1.399993	3.457383	1.577745
-3.66059	-1.41877	-9.20656	-3.36416	-3.33567	-0.93851	-8.01822	-2.58238
6.78794	1.830307	14.43311	4.700417	1.824534	0.185881	10.81497	2.673689
4.727365	1.708364	1.533253	0.605483	-12.6661	-4.17639	-4.75027	-1.41504
-7.83965	-2.16706	-22.0532	-6.89442	-2.55347	-0.27492	-11.0655	-2.9083
-13.3711	-4.53826	-18.3951	-6.7056	-5.0279	-1.34707	-6.91374	-2.11153
0.727218	-0.39278	-6.58464	-2.67108	0.444886	-0.30273	1.000252	0.018126
1.038504	0.412203	-7.75279	-2.33238	1.914283	1.211381	-3.83087	-1.41227
2.689056	0.397738	-2.60755	-0.86054	2.297159	0.113801	-5.37662	-2.0063
-5.20372	-1.51146	0.639034	0.649041	-12.085	-3.82234	-8.47584	-2.50094
-9.08055	-3.04255	-3.34987	-0.95135	-13.7424	-5.1979	-3.3112	-0.91411
-11.0412	-3.54269	-13.6111	-4.41878	-7.60109	-2.28804	-6.67913	-2.60068
7.794864	2.678939	2.399251	0.026878	14.15263	4.736644	4.130164	1.027118

REPLICATE 78		**REPLICATE 79**		**REPLICATE 80**		**REPLICATE 81**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-1.63402	-0.06798	-3.82462	-0.42686	-17.6605	-5.97459	-11.2769	-3.38936
-6.33063	-2.07581	-11.904	-4.43263	-8.63488	-3.22754	-3.82996	-1.25225
-1.29283	-0.61528	-7.70305	-2.81386	-2.88028	-1.15219	4.505649	1.463701
12.64839	4.151055	-2.96049	-1.06351	-4.42293	-1.67196	-1.30882	-0.5936
10.48303	3.667606	8.228266	2.420645	6.613581	1.838277	9.502501	2.841042
-6.50582	-1.41382	-4.85289	-1.25777	-11.6399	-3.59696	-0.52093	0.694297
5.138376	1.128621	-2.51618	-0.60782	4.613383	1.681143	4.443665	1.537566
2.019048	1.054986	5.764545	2.271907	6.606117	3.284981	3.831186	1.618793
-9.93588	-2.712	-9.49274	-3.72817	-5.24915	-2.22605	-3.30494	-0.83459
17.15771	5.423048	13.32877	4.155685	10.08099	3.255115	13.85813	4.633944
-12.8656	-4.45181	-4.14244	-1.68626	-4.03204	-1.179	-5.9793	-2.01253
-3.71186	-0.49559	-2.7647	0.024668	-8.89335	-2.27993	-13.3002	-3.39838
-6.53967	-2.14583	0.835877	0.190737	-7.0365	-2.55983	0.236315	-0.0951
7.584504	1.781207	-0.9537	-0.44187	-4.83146	-2.06549	-1.92476	-1.83971

-0.90687	-0.14892	-4.10811	-1.34354	10.06376	3.447007	3.019253	1.150319
-0.78279	-0.86307	6.384588	1.79277	6.425994	1.827748	2.361891	-0.1049
2.963754	1.239551	-14.4506	-4.2415	-7.70696	-2.66702	-2.22816	-0.29729
-5.6308	-1.106	-9.09074	-2.80028	-8.2836	-2.26819	-16.7524	-6.09166
-5.46469	-1.0552	-5.55328	-1.54604	2.732981	1.137693	1.720276	1.116828
7.962541	1.988611	12.13141	3.596819	-1.03609	-1.50371	9.273092	2.867832

REPLICATE 82		REPLICATE 83		REPLICATE 84		REPLICATE 85	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-5.71193	-0.84518	-9.19775	-2.85963	-5.43441	-1.61087	-5.45807	-1.22892
-11.7076	-4.4363	-0.16244	-0.24251	-10.8139	-4.20053	-22.0546	-8.50456
-4.25625	-1.98362	-3.0242	-1.03714	2.685872	0.744423	4.456856	1.308323
-0.56302	-0.31722	-6.99687	-2.6117	-0.88047	-0.62502	3.390177	1.236755
12.52478	3.911516	14.47052	4.465007	6.537602	1.733879	17.34878	5.016055
-7.94229	-2.62268	-3.12925	-0.42752	-6.39435	-1.4168	-7.73409	-2.10235
4.736373	1.665383	6.203743	2.144806	5.618462	1.569625	-10.9394	-4.04837
1.570804	1.409979	-4.66791	-0.56595	-2.86942	-0.60002	6.71382	3.196923
-4.75964	-1.7483	-16.1112	-5.86071	-8.84037	-3.37094	-3.81646	-1.57061
6.636811	1.65657	19.44697	6.220637	13.12828	3.901564	11.09071	3.22022
-5.86192	-2.07798	-4.23967	-0.67971	-3.66051	-0.97394	-15.5906	-4.93842
-18.7852	-6.15562	-7.18403	-2.12363	-13.0681	-3.33247	-6.87184	-1.47005
-2.23688	-0.5354	-6.59561	-2.17208	-10.1272	-3.17951	-9.04574	-3.19765
1.530533	0.352904	3.684677	1.153789	6.930075	2.277935	9.126137	2.708437
-3.16314	-0.90028	2.073227	1.050238	-3.75616	-1.1531	-3.20492	-0.99507
9.834858	3.230745	5.010964	1.228384	6.036391	1.570612	-3.69942	-1.27267
-10.813	-4.15881	-10.894	-3.67634	-6.26137	-1.85459	-11.7582	-4.49805
-5.86482	-1.46992	-2.17787	-0.37615	-14.1472	-4.98578	-1.85192	-0.2649
-2.08935	-0.46948	-8.80249	-2.91477	-18.5292	-5.78583	-8.32287	-2.56462
17.20071	5.695914	2.136387	-0.23631	10.77078	2.627176	14.66887	5.021008

REPLICATE 86		REPLICATE 87		REPLICATE 88		REPLICATE 89	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-9.50532	-2.93786	-2.2938	-0.0121	0.536497	1.083908	-4.18208	-0.62448
0.022904	0.0118	-13.8986	-4.91852	-1.56053	-0.57125	1.476057	0.619927
-10.6839	-3.92122	0.077155	0.148089	-1.64761	-0.86194	1.969927	1.197767
14.5352	5.320689	2.884125	1.044107	2.603278	0.423629	5.679167	1.726221
2.399115	0.686606	9.208229	2.697343	17.54228	5.584504	15.48839	5.15036
-4.31483	-0.75676	-10.2518	-3.14147	-4.70111	-0.78313	-8.15577	-2.63842

-3.45831	-1.18435	5.563884	1.938553	-0.51838	-0.17265	-2.57164	-1.31261
4.205911	2.264669	-1.47441	-0.11598	1.323757	1.190599	-0.23798	0.777864
-13.1924	-4.76769	-5.70856	-2.19882	0.666664	0.827145	-1.1343	0.031557
9.77566	2.548347	12.24086	2.938556	13.36179	4.034413	7.07478	1.812905
7.057384	3.087229	-9.01837	-2.80155	5.153711	2.309151	-6.33412	-1.80988
-4.74213	-0.93563	-9.2294	-2.37399	-0.30719	0.885203	-8.17477	-2.28924
-10.8201	-3.68006	-12.01	-4.5022	2.920576	1.361436	-1.41153	-0.5723
-0.70533	-0.55093	-8.27887	-3.36233	-3.36569	-1.81987	-5.68787	-2.25764
3.601523	1.448345	-4.8656	-1.85641	-5.04132	-1.54512	-2.37469	-1.03756
0.779335	-0.33119	-1.77861	-0.96054	-2.93713	-1.67408	5.061443	1.378323
-1.60527	0.170728	-10.9873	-3.19365	-2.18114	-0.40335	-7.74106	-2.17339
-9.69184	-3.00594	-6.65943	-2.1451	-5.96643	-2.16806	-4.80174	-1.03247
-3.40305	-0.98196	-1.26998	-0.29003	-12.038	-4.49589	-0.42299	-0.22651
8.005838	2.784513	16.34674	5.00836	13.92239	4.009381	16.55835	5.477294

REPLICATE 90		**REPLICATE 91**		**REPLICATE 92**		**REPLICATE 93**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-6.58947	-1.59179	-10.6062	-3.65516	-14.9497	-4.80142	-11.0773	-3.30595
-7.42814	-2.33353	-11.1735	-3.70075	-5.71383	-2.07008	-6.59772	-2.73962
-2.10928	-0.52054	-4.7489	-1.29575	-2.08211	-1.2687	-8.06683	-3.05072
-7.57857	-3.37908	4.953458	1.889185	8.809635	3.091911	0.831917	0.283287
6.424411	2.095267	8.660925	3.239319	14.5259	4.635687	15.40097	4.862769
-1.73168	0.443516	-5.86437	-1.68584	-9.46585	-3.16083	-6.4846	-1.75241
2.003907	0.229316	-7.52382	-2.90187	1.291481	0.5589	7.159574	2.341418
8.696411	3.552197	-1.48932	0.12217	-9.00451	-2.71349	13.78645	5.666064
-6.59987	-2.28318	0.293817	-0.052	4.296219	2.183121	-8.69504	-3.06656
7.808822	1.925953	17.57941	5.656284	20.09786	6.607698	6.973727	2.19209
-11.0055	-3.98226	2.242046	1.196506	-6.11149	-1.55343	-13.2676	-4.24274
-14.4524	-4.08187	-7.4008	-2.06755	-6.36786	-1.43592	-6.95239	-1.32419
-5.63726	-1.28924	-2.79551	-0.24966	-14.8581	-5.47778	-3.56581	-1.35329
11.30005	3.04132	8.128319	2.936936	-0.09663	-0.22547	3.978094	1.395168
5.239736	1.766176	-3.51204	-1.21268	-3.1577	-0.77772	9.176859	3.215852
4.117705	1.363579	3.123046	0.936828	4.745324	1.37714	1.853148	-0.07425
-13.2809	-4.76448	-11.4168	-3.65587	-17.4253	-5.62954	-7.97709	-2.54021
-16.2341	-5.7786	-5.06676	-2.37563	-18.2688	-6.59486	-2.78996	-0.63561
-10.6817	-2.95016	-1.82918	-0.26121	-0.73232	0.604512	-5.91347	-1.95803
7.501733	1.53222	-1.4159	-1.09461	15.03991	4.38728	-0.93751	-1.05502

REPLICATE 94 **REPLICATE 95** **REPLICATE 96** **REPLICATE 97**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-7.44609	-2.10709	-10.3415	-3.71373	-0.384	0.423072	1.767062	1.41436
-4.81972	-1.88964	-14.5162	-4.99658	-8.85099	-3.29302	-2.60475	-0.90909
-2.66848	-0.69716	3.185571	1.470258	-6.46509	-2.21121	-6.81738	-2.00542
-5.14066	-1.82912	2.404711	0.826226	4.379642	1.170808	5.339535	2.214584
18.7372	5.863004	2.826751	0.671143	7.977612	2.94958	5.391173	1.083261
-11.9091	-3.72067	-8.07559	-2.14473	-1.94161	0.049632	-8.13026	-1.95627
3.389212	1.207337	-2.39958	-0.30474	10.83071	4.657834	-6.42906	-2.32514
-5.60977	-1.16349	-0.63681	0.094483	-6.7702	-1.56999	1.798576	1.143242
-20.2356	-7.59944	-3.99641	-1.15306	-4.07815	-1.27544	-1.40288	-0.50779
7.98348	2.42221	19.12107	6.310842	13.64451	4.108163	2.193874	0.589669
1.044653	0.667174	0.764135	0.512781	0.294896	1.003178	-5.24421	-1.44048
-4.06121	-0.93958	-9.83939	-2.76505	-12.4385	-3.06378	-1.93676	0.172142
7.166832	3.260898	-9.79203	-3.42811	-8.33871	-3.32735	-5.45931	-1.44601
-2.20256	-1.55669	7.408248	2.056462	2.548322	-0.0349	-4.67503	-1.62317
0.623202	0.334784	-3.06695	-1.5416	-0.48507	0.025469	-8.92508	-2.32654
-0.2601	-0.26186	4.112069	1.14181	5.521334	1.837267	-1.80442	-1.40565
-6.59342	-1.47566	-2.48936	-0.46402	4.455853	1.808749	-10.8137	-3.32317
-2.77668	-0.43783	-9.83806	-2.80136	-2.52871	-0.62099	-7.5352	-2.45387
-9.44969	-3.33456	-2.50639	-0.34706	-7.39695	-2.13338	-2.94044	-1.09813
11.0204	2.781601	7.730478	2.337506	3.983055	1.288574	-1.25544	-1.18491

REPLICATE 98		**REPLICATE 99**		**REPLICATE 100**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-5.61266	-1.19914	-1.00399	0.040393	-1.46927	-0.37639
-5.31213	-2.05505	-17.9978	-6.20476	0.316014	-0.29489
0.55239	0.329428	-12.1079	-4.39164	0.396173	0.654957
1.244472	0.094847	-3.07096	-1.84735	-0.06752	0.598856
16.10572	5.14306	16.89607	5.760568	5.144881	0.887883
-22.2841	-7.98536	-6.8938	-2.35223	-11.5538	-3.08144
7.926015	2.474504	4.215848	1.458324	2.3925	1.230271
-2.91906	-0.3888	0.445344	0.164031	4.398334	2.045454
-7.0603	-2.09704	2.594504	0.82046	-10.9179	-3.83976
17.06596	5.28166	24.0662	7.729185	11.87352	3.836871
-9.39506	-2.71523	-7.1134	-1.93944	-5.99559	-1.70383
-8.01408	-1.70773	-6.66623	-1.70055	-2.6402	-0.43658
-9.5467	-3.3605	-3.61539	-1.7229	-7.29317	-1.71177
0.392831	-0.04855	10.48975	2.845936	-0.81223	-0.9421

4.943157	1.223186	-7.09018	-2.21316	-2.36798	-0.53336
16.08497	5.018407	-4.50408	-1.84168	1.849516	0.205474
-7.08192	-2.54552	-7.93386	-2.3678	1.19791	1.448315
-2.6361	-0.99578	-11.3137	-4.34561	-10.1577	-3.73696
-10.7166	-3.30106	-0.40933	0.367729	-5.08885	-0.9655
1.106961	-0.44937	2.432592	0.331318	16.48164	5.185143

RUN 1 SAMPLE SIZE 40 REPLICATE 1

y_{1t}	y_{2t}	X_{1t}	X_{2t}	X_{3t}
-0.10117	0.237186	-1.09397	1.953314	2.752994
2.612223	0.625226	0.367081	-0.78496	-1.13947
-2.66408	-0.89716	0.145398	-0.64004	-0.85602
-7.94445	-2.3822	0.265778	-0.97403	-1.23228
2.776129	0.731786	0.479409	0.708247	0.73716
-12.1349	-4.13355	-1.23364	-0.3282	-1.1247
-7.64396	-3.00992	0.301434	-0.30669	-0.15966
-4.32263	-1.06601	-1.54591	1.85042	1.821647
6.397435	2.52202	0.138909	0.207854	-0.23012
13.14828	3.966722	1.133268	0.82495	0.182379
-9.35391	-3.09842	-0.65837	-1.33585	-1.10304
-8.61197	-2.55789	-1.7005	0.902369	0.910689
-12.3665	-4.08074	-0.19127	-0.62638	-1.03322
4.003972	1.072721	1.272184	-0.11849	0.592003
1.997284	0.980044	0.054985	-1.12118	-0.56798
2.594316	0.496553	1.000267	-0.75355	-0.81325
-11.534	-2.78512	-0.80293	-1.78751	-1.62358
-7.55371	-2.40406	0.162158	-0.94706	-1.10878
-0.57847	0.019023	-0.62861	-0.55226	0.13427
6.098111	1.069807	1.62335	0.327558	1.400757
-0.37217	0.19492	-0.59203	1.255616	1.461345
-17.5775	-5.48489	-1.18496	-0.03648	0.190895
-10.8858	-3.65993	-0.23277	-0.74768	-0.7762
7.425043	2.190417	0.588642	1.534772	-0.28944
20.24134	6.306599	1.134421	1.252978	1.699113
7.206009	2.492165	-0.09755	1.081464	1.100646
-5.62313	-2.52673	-0.19762	-0.87427	-1.19735
3.60499	0.221563	1.250681	0.323186	0.467745
-13.814	-4.54091	-1.57122	0.640722	0.307141
9.360936	2.368247	0.4564	0.104382	0.741823

4.550556	1.584764	0.568878	-1.35853	-0.94865
2.59344	0.836574	0.521725	-0.29497	-0.03602
-10.0794	-3.19635	-0.7314	-1.68437	-1.90802
-6.33621	-1.25561	-1.29195	0.874658	-0.03922
-0.78721	-0.47601	0.240014	-0.22197	0.040869
8.630101	3.727062	-0.37619	0.012484	0.030625
12.00089	3.813336	0.867518	-0.33318	0.422457
-12.0264	-3.15932	-1.26779	-0.5509	-1.93143
4.494356	2.05643	0.195217	-0.21509	-0.18769
-6.20445	-1.97591	-1.23091	-0.8536	-0.06661

REPLICATE 2		**REPLICATE 3**		**REPLICATE 4**		**REPLICATE 5**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
14.87417	5.303678	3.4786	0.885133	15.62546	6.636704	-7.39048	-2.2034
-8.93238	-2.83127	-5.34969	-1.76897	-6.69593	-3.02939	-5.47232	-1.47136
-6.40803	-2.22928	-0.02529	-0.04222	-13.8679	-4.87666	3.323499	0.775147
-8.95793	-3.51916	-7.29494	-2.98661	-0.60045	-0.21672	-1.19345	-0.42619
10.00401	3.372138	4.772631	1.39678	7.658359	2.283541	7.88369	2.738734
-16.1517	-4.88092	-8.45839	-2.28592	-24.2928	-7.6421	-12.6581	-4.22337
5.706808	2.386687	-0.96372	0.113869	1.441752	0.686429	-1.29386	-0.63083
-6.35239	-1.53788	2.072725	1.313614	-2.56188	-0.39348	-2.24787	-0.28965
5.275904	1.616969	6.843889	2.5388	3.051709	0.900091	3.789289	1.091538
7.857908	2.240215	7.761393	2.237276	7.414032	2.337003	16.67956	4.926663
-14.1759	-4.48248	-6.23926	-1.83915	-8.04075	-2.62625	-18.7324	-6.32599
-14.2765	-4.49684	-8.47171	-2.2441	-15.7931	-5.00031	7.853421	3.596603
-5.54218	-1.34889	-1.72668	-0.41435	-4.03554	-0.74326	-5.40795	-1.84771
5.844755	0.925863	10.76276	3.116066	15.32359	5.030451	7.210937	1.955302
-11.2415	-4.15299	-10.4738	-3.80772	0.311653	0.469743	-18.6414	-6.45372
7.23444	1.560891	14.72888	4.626462	-0.737	-0.15341	-5.20534	-2.61142
-10.2909	-3.09075	-14.9955	-4.19567	-18.7516	-5.99441	-14.701	-4.65323
-9.74398	-2.98582	-11.9654	-4.60539	-9.76013	-3.35062	-12.0436	-3.52377
1.548915	0.505026	-2.22974	-0.4074	-3.15792	-0.98432	0.183809	0.769065
20.58064	6.331025	14.23722	4.420392	19.11358	5.014876	17.9928	5.147442
2.306909	0.661823	7.790554	3.232591	6.659938	2.579755	2.203401	0.794828
-11.0144	-3.58547	-6.30394	-1.49982	-7.03214	-1.92391	-9.00995	-2.95341
-7.13579	-2.45941	-5.8872	-1.49142	-1.70859	-0.38687	-0.84877	-0.22635
-7.49593	-2.97077	11.81086	3.839434	16.20207	5.686526	6.715002	2.294035
21.11167	6.860903	13.50269	3.971607	27.61238	8.841274	19.99807	6.599401
15.49882	5.570318	0.463762	0.363556	7.01253	1.918667	-3.0604	-1.45127

-16.2634	-5.65393	-3.6228	-0.87347	-1.50137	-0.46391	-4.89646	-1.7786
14.96132	4.688064	12.97459	3.612471	1.599466	-0.12295	10.09724	3.169585
-4.48459	-0.90388	1.194898	1.081444	-20.4599	-6.41335	-12.3289	-3.62308
-1.84324	-0.45427	-2.48957	-1.63956	5.558925	1.567416	16.72597	6.288568
5.766052	1.621478	-3.7263	-1.30832	2.093545	0.598622	-8.28645	-3.33842
-1.61588	-0.9555	-3.14365	-1.63169	0.747142	-0.36009	1.427437	0.100447
-5.28715	-1.83018	-17.7464	-5.58297	-9.80705	-2.71632	-8.84027	-2.53786
-12.0511	-3.79936	-10.9955	-3.0638	-6.26939	-1.99514	-20.7896	-6.61319
-6.93209	-2.79662	0.000744	0.152153	13.82838	4.496029	-8.28532	-3.12253
-3.4747	-0.60556	-10.1693	-3.44044	5.831545	2.219818	-8.52283	-2.80819
6.28238	1.397518	1.422293	-0.03908	9.059545	2.284956	-4.24679	-1.60702
-20.3022	-6.42683	-20.3018	-6.30165	-14.0205	-4.16398	-31.3681	-10.0418
1.724165	0.281496	-3.57259	-1.43429	0.823691	-0.37667	-2.64262	-0.7446
-0.03188	1.007437	-13.7017	-4.0038	-7.55746	-1.89905	-13.9789	-3.98878

REPLICATE 6		**REPLICATE 7**		**REPLICATE 8**		**REPLICATE 9**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
13.91277	5.385076	15.47403	5.41377	10.07034	3.646317	0.609682	0.134829
-11.8769	-3.79789	-9.47895	-3.50687	-16.6474	-6.23805	1.665524	0.294501
-0.49884	-0.92372	1.89542	0.381555	-5.91189	-1.8344	2.730556	1.017348
-9.21288	-2.94434	-8.11488	-3.21085	-1.6699	-0.73954	3.585561	1.436069
5.755176	1.849657	0.372408	0.264014	0.89104	0.180839	3.607156	0.747079
-12.1979	-3.29977	-16.0729	-4.70572	-19.3307	-6.11604	-11.3958	-4.18288
-7.49789	-3.41329	-0.56303	-0.69694	-7.38527	-2.84847	-3.21182	-1.0343
-0.9146	0.106065	-8.85787	-2.85425	-3.82705	-0.9382	4.928012	2.118052
6.103611	1.906054	0.164726	-0.29732	-5.23217	-1.69917	-1.70818	-0.93483
12.69379	4.177166	13.19803	4.277502	4.426126	1.038808	17.63223	6.069266
-7.93378	-2.64634	-24.2365	-8.39949	-10.4413	-3.32556	-3.73046	-1.32696
-12.7868	-4.14514	-4.01381	-0.82351	-9.68258	-2.42668	-1.25682	-0.10598
0.002388	-0.11086	-13.2105	-4.80186	-4.17193	-1.12267	-7.15728	-2.31434
24.19783	8.109548	16.51548	5.777959	4.54496	1.049808	2.549083	0.500349
-7.15933	-2.73292	0.550866	0.537253	-10.99	-3.88431	-1.64463	-0.77221
10.74087	3.713977	0.055085	-1.0218	5.761859	1.698356	0.532956	-0.22904
-12.428	-4.123	-23.2343	-7.62646	-7.99406	-1.41078	-23.3908	-7.19133
-6.28993	-1.59177	1.821993	1.156518	-12.4146	-4.56272	0.3486	0.330824

-14.1169	-5.30056	-7.47583	-2.48446	-1.39007	-0.17116	-6.08875	-1.62493
6.879735	1.666836	14.38036	4.16069	22.14989	7.298113	22.77138	6.891078
-8.42538	-2.8283	-9.57183	-3.5187	6.574693	2.448075	0.22342	-0.01466
-10.1033	-2.70998	-8.31091	-2.56071	2.542432	1.176117	-2.9639	-0.34268
-1.54707	-0.1883	1.752423	0.850913	-11.8201	-3.56147	-3.24779	-0.62788
-3.34064	-1.58622	6.963132	2.818523	12.83251	4.378664	7.991393	2.59907
15.4737	4.710978	18.60486	5.763607	16.64281	4.905298	18.7222	6.230523
9.143875	2.858328	6.899067	2.061484	7.485175	2.304463	4.826859	1.300429
-11.5581	-3.73062	-1.77222	-0.23509	-11.0206	-3.46957	-5.00511	-1.19707
18.23616	5.776259	2.835047	0.25427	12.28268	4.162087	10.79273	3.006243
-14.9628	-4.87882	0.677924	1.127713	-5.86299	-0.6342	-7.66182	-2.08271
16.68152	5.824612	-5.1521	-2.42699	5.812734	1.541497	2.92973	0.851428
-2.95434	-1.39598	-1.05496	-0.14036	1.98429	0.728966	-2.562	-1.42254
2.843969	0.94112	-10.8028	-3.88852	1.735648	0.572866	-2.35431	-0.75725
-14.0093	-4.3383	-17.3653	-5.95435	-17.3771	-5.96762	-12.361	-3.92506
-12.4569	-3.69713	-12.3026	-3.83973	-9.5509	-2.72919	-8.77621	-2.84485
-0.55098	-0.28812	-2.89857	-1.24856	-5.81216	-2.21769	8.229564	2.855245
8.105569	2.864032	-4.02391	-1.01075	2.264175	0.715317	5.92325	2.409568
0.112358	-0.62588	14.16596	5.077225	12.75503	3.731346	4.02761	1.074028
-11.8447	-3.63999	-18.8759	-6.07417	-24.2016	-7.73675	-26.0173	-7.94226
4.195123	1.481857	-4.26502	-1.98881	5.695284	1.765323	6.109643	1.803726
-5.92194	-1.74893	-15.8897	-4.87812	-19.9729	-7.20959	-9.28389	-2.69224

REPLICATE 10		**REPLICATE 11**		**REPLICATE 12**		**REPLICATE 13**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
11.10939	3.41194	4.729729	2.178382	-5.71647	-1.9384	0.139051	0.418299
-10.1778	-4.37073	7.067264	2.687877	2.942555	0.912673	2.940684	1.252282
4.754873	1.546626	3.99374	1.653653	-8.34592	-3.52375	-14.2189	-5.12669
-5.61261	-2.17588	4.281005	1.690383	-15.9642	-6.27277	6.647654	2.327833
5.369329	1.356116	13.34822	4.446653	6.754231	2.002317	6.454051	2.921984
-1.98478	-0.07188	-13.9098	-4.65775	-10.898	-3.19453	-11.5273	-2.36912
-2.82958	-1.02694	-2.70367	-0.69465	7.328763	2.73106	9.335325	3.142946
3.805007	1.972672	2.585872	0.921807	5.97722	2.789965	4.67105	2.110045
5.521669	2.132326	-4.64603	-1.22331	5.495448	2.172432	-3.42706	-0.9469
16.1981	5.188853	4.294177	0.668882	17.89308	5.579421	11.13913	3.223825
-15.1235	-4.91341	-17.7022	-6.56471	-12.9567	-4.13005	-19.1465	-6.31522
-0.08827	1.03288	-2.12003	-0.05761	-9.1922	-1.92144	-21.3192	-6.6755
-17.8454	-6.19288	-12.0452	-4.52334	-9.22702	-3.13616	-5.39505	-1.47777
14.07547	4.173917	5.347522	0.44858	7.195976	1.671996	16.15275	4.860063

-5.29049	-1.39584	-8.31794	-3.00458	-3.1	-1.14059	-7.80168	-2.62129
-8.4807	-3.46409	-7.94695	-3.33406	9.955113	3.590329	8.268727	2.09663
-20.5994	-5.99601	-18.3401	-6.03622	-12.5886	-3.53798	-21.338	-6.46223
-1.82089	-0.68357	-4.49544	-1.56598	-8.12944	-2.5659	1.176429	0.397667
-5.6967	-1.61039	-1.29612	-0.72775	-9.14785	-3.08691	-14.837	-5.03468
19.74403	6.007582	25.58805	8.154955	5.860959	1.2528	21.51371	6.984672
4.094324	1.22121	2.235194	0.782167	0.606247	0.019489	12.14078	4.604991
0.524574	0.979098	3.648387	1.819989	-8.47894	-2.6233	-2.08085	-0.05723
-8.12446	-2.25721	-4.61836	-1.25761	-0.12813	0.700046	-14.0222	-4.7102
-2.55773	-1.47425	7.865165	2.696638	10.67352	3.114447	0.825113	0.489293
18.6466	5.503659	15.41317	5.097398	14.39045	4.296613	29.27261	9.59561
6.098598	1.989541	2.242358	0.656052	9.636513	3.459335	3.353418	1.118146
-12.521	-4.271	-6.5124	-2.4217	-3.90355	-1.33313	-9.29273	-3.25925
7.988473	2.257217	7.821201	2.07703	5.757849	1.809648	4.410909	1.14477
-8.34367	-2.30923	-9.36473	-2.40848	-5.45824	-1.35757	-3.68156	-0.68396
2.954961	1.049132	7.870085	2.416367	8.80057	2.205396	14.9469	4.826025
3.052068	0.26545	-5.24489	-2.55901	-6.64073	-2.67549	-3.35442	-1.49062
-10.8977	-4.32857	4.706546	1.896933	-0.78628	-0.5148	5.318137	1.709481
-23.2623	-7.60472	-13.8664	-3.96204	-24.1425	-8.08266	-22.6328	-7.02351
-21.2092	-6.86852	-16.2249	-4.66268	-4.32977	-0.74868	-8.72132	-2.00006
-5.75843	-2.53698	6.410549	2.191857	-1.04025	-1.03912	-1.47861	-0.86332
1.630775	0.847936	-12.954	-3.93777	-17.0414	-5.747	-15.0118	-5.19815
7.634244	1.589595	15.80435	5.323339	13.96729	4.388189	10.49288	3.541682
-30.2483	-9.93717	-10.5204	-2.75131	-26.4961	-8.9623	-20.4121	-6.86341
2.931388	0.985659	2.831495	1.009012	3.041701	0.725405	1.379382	0.500409
-6.9261	-1.39505	-5.08292	-1.25948	-17.0418	-5.31371	-7.52358	-2.31167

REPLICATE 14		**REPLICATE 15**		**REPLICATE 16**		**REPLICATE 17**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
8.232417	3.297768	4.077975	0.967853	4.658123	2.015314	9.44217	3.263526
0.429542	0.080128	7.53916	2.899441	-2.51957	-1.29214	-3.21295	-1.61507
6.702188	2.32968	-8.67537	-3.05374	-2.87099	-0.99627	-9.97823	-3.51213
-7.53336	-2.88145	-3.65191	-0.68933	-12.2553	-4.50506	-4.81942	-1.66248
9.561852	2.971375	-2.02712	-1.05763	17.41755	5.674667	7.658739	2.425057
-21.4988	-7.19729	-16.0681	-5.01596	-18.7987	-5.75214	-8.17352	-2.30153
6.119322	2.227947	0.238557	-0.23553	5.598672	1.739181	8.226541	3.048233
4.507677	2.03084	5.89094	2.442769	5.719392	2.607547	-6.76906	-2.43369
-3.84326	-1.3529	-1.20602	-0.30528	8.678155	3.071957	4.279897	1.298527
6.970338	1.290539	12.38037	3.748329	0.881963	-0.54849	-0.88685	-0.98632

-10.7073	-3.29364	1.09562	0.918015	-6.81026	-1.66207	-6.97734	-1.70118
-3.87601	-0.40841	-11.2687	-3.32711	-13.5769	-3.88506	-2.70587	-1.01732
-19.314	-6.45016	-2.63833	-0.77611	-11.8892	-3.69527	-13.4496	-4.56029
13.04701	3.588719	9.642831	2.699558	0.944772	0.07045	16.77988	5.091409
-9.46984	-3.45052	6.071236	1.912557	-7.72698	-2.88338	-2.38987	-0.94907
-4.81469	-2.14589	12.80008	3.492337	-2.40205	-1.58294	7.637251	2.267468
-18.6833	-5.98127	-18.5438	-5.90823	-20.0608	-6.41746	-28.3794	-9.30365
-3.70063	-0.98212	-2.45862	-0.89856	-16.8338	-6.06295	-5.08593	-1.73451
-8.54429	-2.73053	2.813521	1.671078	-5.22228	-2.20658	-10.0225	-3.44139
15.86064	4.846301	12.3547	3.332518	19.35142	5.89842	12.2123	3.785038
-1.62197	-0.51162	7.083315	2.663373	-0.7105	-0.33828	2.064067	0.605568
-12.1263	-4.14093	-15.5719	-5.71017	-6.7316	-1.83702	-8.60941	-2.52811
7.81411	2.852477	-1.72459	-0.53531	-4.08612	-1.17078	-1.72379	-0.71672
10.56157	3.305878	5.152968	1.808211	2.796707	0.827107	3.81365	1.113622
16.39275	4.950136	14.42013	3.732415	20.0463	6.299198	21.58936	6.253698
3.820101	1.077743	9.443892	3.21151	7.106307	2.022622	-3.04274	-1.28585
-9.65624	-3.20412	3.422638	1.036181	-16.2587	-5.10149	-10.4143	-3.42893
2.228424	0.414539	3.653423	0.468786	15.56238	5.095774	10.92869	3.136929
-14.4288	-4.19212	-7.35891	-1.77176	-8.0936	-2.68366	-11.9388	-3.3806
-3.29948	-0.9882	7.828475	2.561817	2.414734	0.729695	-1.47273	-1.29175
5.274073	1.978142	-14.1033	-4.92962	0.159171	-0.20199	10.57489	3.168554
-6.21417	-2.45725	-5.00183	-1.89913	1.832198	0.876677	-7.85023	-2.93765
-25.0865	-8.33821	-13.5861	-4.8256	-26.4659	-8.56261	-11.106	-3.73282
-18.1476	-5.76625	-8.57062	-2.09559	-6.34334	-1.61513	-15.1741	-4.39129
-0.92902	-0.42145	11.29955	3.71029	-9.81054	-4.02735	1.659846	0.295896
-0.7094	0.342551	-5.57409	-1.85707	-2.76025	-0.93091	-2.93788	-0.79681
6.927871	2.219112	11.45308	3.595899	0.250114	-0.48504	8.346501	2.224005
-20.0638	-6.20053	-21.4976	-6.89919	-20.6777	-6.47685	-8.99505	-2.73406
2.960121	0.807895	1.809798	0.585717	3.235532	0.560872	3.854283	1.160537
-7.69509	-1.99537	-10.0176	-2.63345	-11.0773	-3.5389	-10.2437	-3.53358

REPLICATE 18		**REPLICATE 19**		**REPLICATE 20**		**REPLICATE 21**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
12.70879	4.534391	6.476601	2.780095	16.07913	5.844724	3.900168	2.263883
1.20687	0.710462	4.370656	1.247355	4.002275	1.651179	6.499907	2.492431
-11.4138	-3.94988	-5.63276	-1.60837	-14.5053	-4.78734	-1.38297	-0.84182
-13.3604	-4.68243	0.452781	0.194082	-0.56668	-0.59288	-8.94999	-3.03884
7.776064	2.414624	9.987273	2.988912	-0.76247	-0.67684	5.680406	2.238235
-18.6053	-5.84184	-15.7767	-4.69156	-26.0301	-8.85714	-16.979	-5.25537

-4.88569	-1.9929	10.52173	3.81575	1.329316	0.110741	4.71075	1.894789
-8.90847	-2.69212	1.490379	1.374482	9.539931	3.625304	-6.45539	-1.53499
10.28629	3.72764	0.335589	0.081297	-0.65917	-0.22267	5.531769	2.521416
9.55605	2.676601	12.25025	3.444876	12.54955	4.02062	13.67587	4.065638
-12.8192	-3.77942	-14.1219	-4.78256	-22.0125	-7.01461	-16.1789	-5.53565
-7.21763	-1.76321	-1.09005	0.491324	-11.3921	-3.20713	-4.41955	-1.02033
-11.3068	-4.07057	-12.2719	-4.24844	5.304714	1.128371	-5.21138	-1.67102
16.96905	5.21185	16.93464	5.687199	11.78074	3.617405	7.587066	1.89963
0.116327	0.448176	-8.46689	-2.60687	-12.6292	-4.66906	-1.55129	0.080803
-3.32648	-1.95075	-7.15201	-2.7594	2.599572	-0.00926	-5.70143	-2.13032
-13.4424	-4.49929	-15.0464	-4.90663	-14.7787	-4.97761	-23.6702	-8.17065
-2.47419	-0.54295	-1.43143	-0.48146	-4.52853	-1.59634	-10.8222	-3.65651
3.075112	1.404388	-12.2525	-3.79017	3.235076	2.163495	-8.34121	-2.79636
17.10733	5.2038	26.50575	7.825353	17.82419	5.502579	19.81409	6.045868
2.675315	1.871961	6.052112	2.913222	-4.44581	-1.44651	9.1493	3.360635
0.188203	0.474102	-1.34255	-0.02313	0.006702	0.729278	-3.58669	-1.35766
-3.41219	-1.1884	-0.9596	-0.53155	-10.4765	-3.79694	-10.9396	-4.03134
-2.26081	-1.76597	16.92704	5.482029	4.006752	0.954854	9.058643	2.869556
13.8345	4.027025	15.06505	4.218445	16.52356	4.893478	11.80338	3.575076
-6.99637	-2.67642	2.223862	0.287193	12.15142	4.241097	6.144139	2.065947
-10.7481	-4.26961	-16.3123	-5.83519	-14.6738	-5.03365	-3.16817	-1.3902
7.218519	2.124482	12.87568	3.78482	12.35708	4.250577	3.331347	0.436188
-9.09417	-2.37125	-12.6633	-3.57522	-17.6701	-5.5325	-0.51981	0.32509
3.234696	1.129294	14.10271	4.817778	-5.60272	-2.20167	5.789639	1.699631
-4.75071	-2.32019	-1.16176	-0.81702	-10.298	-4.05836	1.113356	-0.13562
8.646542	3.346005	0.905935	0.574043	8.70794	3.100046	8.645957	3.024312
-15.072	-4.92956	-19.5776	-6.33526	-18.7271	-6.5081	-14.3463	-4.73663
-12.0018	-3.60302	-5.61217	-1.55903	-8.38102	-2.53764	-13.3303	-4.33495
-0.32055	0.012399	1.763793	0.739317	-0.70056	-0.65141	2.79356	1.511313
-4.64136	-1.00589	-5.39938	-1.56696	-3.96103	-0.98221	-0.93843	0.12066
4.534791	0.423344	4.942571	1.420529	-6.09421	-2.79747	7.087089	2.104868
-19.9769	-6.56982	-10.367	-2.9966	-18.9191	-5.49126	-23.593	-7.62643
0.139634	0.047619	-4.32232	-0.94153	-2.28201	-0.72709	-1.12386	-0.41757
-9.55765	-2.6704	-6.03847	-1.49883	-19.3013	-6.13095	-10.6866	-2.70655

REPLICATE 22 **REPLICATE 23** **REPLICATE 24** **REPLICATE 25**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
8.785803	2.914467	6.792148	2.590779	14.69492	5.964167	3.803737	1.341576
5.104851	1.825353	0.75945	0.005005	-10.2081	-3.42642	-1.38004	-0.3587
5.606906	2.24026	-2.51898	-0.61033	-14.1695	-4.77594	-1.34493	-0.36458
1.508592	0.791022	-7.43566	-2.43583	-6.54289	-2.02923	-5.66872	-2.0711
6.261401	2.555245	2.628512	0.35773	10.38817	3.16411	12.96037	4.682436
-17.8865	-5.6211	-10.6807	-2.83186	-20.071	-5.96372	-26.0222	-8.30533
-1.70224	-0.64654	1.83939	0.723445	5.238676	1.325309	-3.96267	-0.78678
-0.77561	0.640463	-2.70324	-0.89351	0.891525	0.718278	-3.53516	-0.95753
8.077212	2.671165	-3.57226	-0.99784	4.447213	1.390323	-7.30084	-2.44571
11.60976	3.077848	8.88852	2.194438	11.99083	3.025526	8.930903	2.494799
-22.8514	-7.85803	-7.30633	-1.80533	-12.8118	-3.78013	-9.06705	-2.53588
-4.32621	-1.28202	-5.01527	-0.83564	-7.08425	-1.29229	0.627981	0.850361
-22.777	-7.7004	-8.73849	-2.73343	-0.13416	0.468719	1.472938	0.799051
9.140183	2.495875	-1.91833	-1.25316	5.901015	1.593493	21.09876	6.565445
-8.90493	-2.79486	-3.00913	-1.30013	-5.10662	-2.20408	-3.06983	-1.43364
4.196605	0.778611	12.6624	3.977772	0.588148	0.350158	2.042905	0.450272
-14.8678	-4.30046	-14.1341	-4.98657	-17.7197	-5.30865	-16.5363	-5.27722
-2.12463	-0.68415	-15.7653	-5.59571	-9.44617	-3.40765	4.582042	1.432536
-1.295	0.149838	-9.23119	-2.82792	4.740202	1.763056	0.848054	0.974479
11.68201	3.354863	17.16254	5.036909	15.25697	4.355529	22.04385	6.624073
6.00728	1.682299	-5.08847	-2.04065	8.139693	2.755378	3.304342	1.29193
3.753624	1.451332	-4.90684	-0.95718	-5.49488	-1.13695	-14.1514	-4.46489
-3.19042	-0.87844	-6.39259	-1.9006	-12.1383	-4.20252	-16.2708	-5.42957
9.927501	3.164235	8.611983	2.854052	6.179178	1.819428	-5.44766	-1.92671
15.76692	4.560659	16.72102	5.950233	26.14326	7.9986	27.01369	9.060985
0.727651	-0.23579	16.51117	5.483753	1.268411	0.598462	-0.0951	-0.68843
-9.32238	-2.79926	-10.2379	-3.1264	-3.40193	-1.17649	-2.56719	-0.73212
14.4679	4.515538	13.25753	3.652706	12.60958	3.902654	7.324619	1.710517
-7.91515	-2.0726	-8.788	-2.97659	-14.0914	-4.08487	-9.91851	-2.65018
17.14004	5.731731	5.803768	1.169166	0.139834	-0.04344	12.32333	4.346996
0.898538	0.222432	-2.95908	-0.95804	-1.70796	-0.82771	1.841741	0.218173
-1.6276	-1.1306	-1.40137	-0.4144	3.043363	1.134801	1.553592	0.859797
-18.1067	-5.96984	-13.9003	-4.58143	-21.6042	-7.40745	-9.13897	-2.24041
-12.3471	-4.02151	0.616294	0.979392	-12.5518	-3.82425	-2.24437	0.207827
3.82159	0.853598	2.142847	0.723306	-5.59612	-2.04252	-6.6757	-1.89194
-11.6514	-3.76386	3.540429	1.006285	-3.88067	-1.53878	-5.31142	-1.30872
1.901835	0.949539	9.578609	2.574704	21.14126	7.098926	7.177669	2.653545
-13.5754	-4.4713	-18.5517	-6.03497	-14.1226	-4.0092	-23.0112	-6.96929

1.918922	0.764383	3.919225	0.995298	-5.32285	-1.79431	-1.46023	-0.67916
-10.6972	-2.96152	-1.36829	0.076877	-18.0763	-5.74774	-9.16336	-2.73925

REPLICATE 26		**REPLICATE 27**		**REPLICATE 28**		**REPLICATE 29**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
7.011959	2.68322	14.09969	5.65981	12.69481	4.306014	10.60771	2.856857
-4.49527	-1.01412	-13.9658	-4.86045	-3.32119	-1.74644	-3.97355	-1.58723
-3.06933	-0.78716	-7.22523	-2.66038	-1.89829	-0.42059	-3.57905	-1.4996
-8.41923	-2.99404	-5.6731	-1.84001	-7.64943	-2.5595	-7.40554	-2.37121
11.42897	4.128751	16.35628	5.193582	13.52608	4.364501	11.418	3.466564
-8.03603	-2.29954	-22.0834	-7.09454	-18.935	-5.96369	-18.5507	-6.2624
2.115757	0.715337	-11.2217	-3.94009	-0.96344	-0.60119	8.122486	2.910332
-6.39909	-2.08371	5.705523	2.530549	8.527656	3.564248	-5.73475	-2.19147
-0.77841	-0.75282	4.416631	2.169772	-7.12885	-2.43886	3.682323	1.204133
9.211476	2.692856	13.80813	4.616333	13.34157	3.798121	2.749007	-0.03778
-10.8069	-3.25013	-14.3496	-4.46847	-8.16787	-2.82461	-16.8153	-5.13907
-3.95054	-0.53281	-14.6175	-4.12812	-0.49383	0.823766	-4.45495	-1.18887
-8.09867	-2.73529	-4.2878	-0.79875	-11.5869	-3.99859	-0.43095	-0.07779
13.17232	4.000872	16.66165	5.094681	10.59245	2.760889	11.3835	2.96386
-3.4948	-0.98258	-4.3563	-1.52945	-6.26136	-1.8583	-0.67708	-0.17165
7.530485	2.089355	13.04755	4.117004	15.11638	5.356285	11.68388	3.672364
-12.9548	-4.29316	-25.803	-8.66904	-13.5308	-3.92601	-9.60595	-2.5751
-3.77779	-1.51259	-9.2976	-2.83044	-9.85685	-3.34138	-4.23049	-2.03481
-1.98217	0.069814	1.353958	0.915307	-13.2558	-4.26854	-11.3862	-3.86882
19.8749	6.227388	24.42888	7.750875	21.15762	6.793422	10.1189	2.780235
2.970355	1.362585	3.95353	1.465345	2.226977	0.835368	5.063671	1.902132
-5.72838	-0.94047	-13.964	-4.15071	-4.78965	-0.75989	-3.68933	-1.03495
5.747613	2.114203	-18.3945	-6.1651	-12.8602	-4.83364	-6.54816	-2.64266
-6.87676	-2.69423	11.34296	3.687495	11.06803	3.873188	7.006436	2.480589
14.37263	4.412406	22.44941	7.351527	26.98469	8.991341	21.48723	6.783807
-1.14462	-1.06214	7.87018	2.48099	0.87324	-0.09847	2.998617	1.112729
-0.84318	-0.74131	-7.43596	-2.59588	-3.68735	-1.14912	0.264423	0.253582
3.367939	0.61469	11.52045	3.10289	2.375078	1.184593	10.94595	3.171868
-11.5456	-3.46678	-14.9794	-5.21253	-8.56468	-2.51256	-13.1311	-4.09868
16.14225	5.103517	12.88879	3.937729	4.583236	1.003724	8.658818	3.11317
10.7413	4.162612	-5.09783	-1.73795	-0.53185	-0.71653	1.964634	0.734718
6.690141	2.267423	3.496966	1.041582	-6.7124	-2.55962	2.652541	0.70445
-10.6595	-3.28564	-12.0627	-4.48099	-22.4831	-7.33051	-9.4382	-2.83085
-16.9478	-5.47003	-12.2896	-3.60008	5.468388	1.959594	-8.60421	-2.49236

8.375513	2.426413	7.17043	2.516924	18.70766	6.861146	15.02893	5.130228
4.634799	1.363201	2.738962	1.199977	-4.67679	-1.84752	5.617554	1.926929
2.08666	0.505162	2.682884	0.705801	4.140763	0.788836	10.44849	3.321311
-26.303	-8.2454	-21.0405	-6.34375	-20.6355	-6.66354	-27.3444	-9.01805
-0.80811	-0.12277	0.068849	-0.61313	-7.0069	-2.68477	5.296289	2.129694
-7.48648	-2.49158	-0.59024	0.605289	-12.2778	-3.90965	-10.4278	-3.30373

REPLICATE 30		**REPLICATE 31**		**REPLICATE 32**		**REPLICATE 33**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-1.08963	-0.15939	12.4188	4.356482	1.584572	0.453716	6.655385	2.263556
-10.8273	-3.65134	4.4079	1.742598	7.106698	2.469019	-2.19267	-0.41909
-1.95555	-0.44107	-12.1605	-4.56983	-7.05068	-2.97191	5.728698	2.124892
-0.56984	-0.21432	-5.68828	-1.77101	-3.35267	-1.34992	7.881473	3.118381
8.784429	2.972466	10.49815	2.915591	10.48529	3.775263	6.791066	2.130829
-23.3558	-7.65366	-20.6116	-6.44693	-17.6855	-5.12487	-14.7386	-4.69596
-0.52384	0.07375	0.672869	-0.34321	-5.03804	-1.8763	3.359309	1.601136
0.924891	0.243863	4.831786	2.095529	1.441389	0.757075	-0.79559	0.252129
-1.38976	-0.61633	1.718442	1.16196	8.53614	3.009809	0.064305	-0.59216
11.25189	3.075747	5.445683	1.337197	6.026203	1.272284	4.138586	1.269028
-16.8252	-5.45416	-16.2275	-5.52028	-7.9482	-2.49703	-17.2933	-5.61668
-2.04466	-0.0811	-4.26526	-0.63794	-3.29085	0.155	-7.06856	-2.16401
-1.38734	0.137391	-3.91115	-0.87405	0.495019	0.463319	-9.23413	-3.24549
14.41886	4.1699	21.56535	7.385156	10.70074	2.796376	13.30785	3.534726
-13.3811	-4.5019	0.443868	0.364268	-14.8367	-5.09927	-12.8937	-4.52607
0.218275	-0.37484	-5.77155	-2.11985	0.494074	0.256795	4.328558	0.788506
-25.0668	-7.87997	-6.91828	-1.8728	-24.8204	-8.41026	-24.7692	-8.47884
-0.5622	-0.5506	-6.7202	-2.22062	-6.3944	-2.23768	-9.70758	-3.54623
-5.63147	-1.47455	-7.99878	-2.98345	1.994645	0.964988	-0.03527	0.514965
21.62807	7.005616	17.22048	4.640312	14.50126	4.052648	18.76873	5.781001
13.43204	5.085788	8.391381	3.080287	6.31515	1.996556	11.98866	3.58147
-4.10542	-0.79327	-2.37623	-0.21405	-15.0615	-4.53897	-11.5269	-3.25245
-6.0357	-2.11224	6.001891	1.872647	-12.52	-4.1988	1.120626	0.827683
12.02407	4.242755	10.26508	3.031306	10.45351	3.474291	11.46809	4.365645
10.5548	3.008001	16.56897	5.488077	5.176931	0.654928	13.89698	4.139289
5.925502	2.254016	8.17774	3.097272	1.097904	0.658223	9.781694	2.749451
2.768431	1.203901	-12.1807	-4.03281	-10.089	-3.77377	-12.1175	-4.29945
12.59874	3.43995	19.72539	5.80296	8.062284	2.217513	8.926095	2.186049
-9.44224	-1.85914	-12.4814	-3.7497	-8.53505	-2.55146	-3.79414	-1.13019
8.727701	2.70315	2.095931	0.234945	13.45776	4.385148	-0.31653	0.06789

-2.49691	-1.45787	-5.84968	-2.25942	2.17413	0.298764	2.06268	0.694504
-1.63151	-0.80713	2.59282	1.244844	-4.09461	-1.73319	8.888134	2.903618
-17.5332	-5.72447	-17.9492	-5.84803	-10.8912	-3.56933	-22.9276	-7.55548
-11.5549	-3.05157	-6.71358	-1.59303	-13.4397	-4.31159	-12.2042	-3.89277
-3.70454	-1.1555	-1.85084	-1.25319	2.319844	0.77314	3.144183	1.243522
3.078575	1.016912	0.533106	0.502447	-1.63162	-0.48915	-0.6832	-0.61663
9.238614	2.091361	11.66104	3.4801	15.04455	5.237537	4.189984	0.663505
-25.3614	-8.31167	-15.1629	-4.57371	-19.5057	-5.88379	-18.0721	-5.8535
2.338338	0.71774	-1.29283	-0.21728	-7.97524	-2.66604	0.626376	0.173408
-7.57546	-1.90176	-8.28345	-2.47826	-9.68204	-2.9268	-11.167	-3.25483

REPLICATE 34		**REPLICATE 35**		**REPLICATE 36**		**REPLICATE 37**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
6.655904	2.546187	4.251013	1.719483	6.323997	2.486889	3.813986	1.34855
-16.9607	-6.18947	0.253482	0.115298	-4.6772	-1.47847	-3.1157	-1.29924
-11.8581	-4.0697	-1.57618	-0.72349	-3.86811	-1.6118	-1.89148	-0.72065
-15.0789	-5.29751	-2.62774	-0.58471	-0.65733	-0.11309	-3.85498	-1.56485
23.24085	8.147153	6.385798	2.585542	10.90303	3.915384	8.431835	2.870681
-17.3083	-5.45396	-21.9485	-7.40645	-19.0764	-5.7445	-23.5952	-7.87142
7.665833	2.569914	5.802961	1.971516	5.583663	1.69385	3.480781	1.278559
7.006499	3.04024	0.437824	0.406263	7.321446	2.95327	5.030403	2.532266
-1.74092	-0.92872	1.174492	-0.10616	-6.1645	-2.47061	-2.42097	-1.09274
5.279848	1.082584	12.75881	3.440028	14.63595	4.816276	12.40128	4.100646
-8.96211	-2.10963	-0.27806	0.891175	-8.69515	-3.25093	-8.04392	-3.13945
-10.2749	-2.5635	-6.46292	-2.09203	-8.6718	-2.22537	-20.9186	-6.38619
-4.59548	-1.18107	-19.7032	-6.72326	-19.3441	-7.47209	-12.5273	-3.74373
16.47592	5.333846	17.61872	5.070037	10.168	2.868228	3.124268	0.61752
-2.84467	-0.94289	2.637218	0.82504	1.991198	0.600929	-12.5594	-4.32993
5.075008	0.861506	2.86693	0.565901	-5.56945	-2.3403	-5.73976	-2.28719
-15.4139	-4.64727	-20.9362	-6.48909	-16.4902	-5.10933	-10.3747	-3.26025
-3.30881	-1.78559	-3.67226	-1.63659	-9.76605	-3.37935	-1.50542	-0.46458
4.138853	1.711276	-2.19633	-0.34109	-6.26488	-2.05443	-10.5926	-2.95475
24.42369	7.300689	20.88539	6.363654	21.10077	6.738693	16.71137	5.151607
-4.7463	-1.51963	1.611755	0.846451	7.642163	2.970017	8.282261	3.104112
3.604374	2.104507	-4.11227	-0.78855	-6.30412	-1.77587	-12.7405	-3.53588
-8.44545	-2.87546	-11.0597	-4.06962	-0.73213	0.13729	3.488886	1.76488
13.45132	4.268055	6.863282	2.162522	-0.59043	-0.55036	-0.51705	-0.18408
10.69095	3.048284	17.18823	5.408811	18.95852	5.510508	14.67789	4.480678
10.2097	3.334599	0.956999	-0.27832	3.675941	1.098364	9.474564	3.399882

-2.29442	-0.88536	-15.6687	-5.28642	-4.37921	-1.08408	-4.53164	-1.33629
18.4054	6.374128	9.016064	3.037733	13.48488	3.808828	3.885476	0.561455
2.190559	1.014188	-12.0891	-4.14154	-9.90695	-3.38278	-13.5739	-4.24988
4.938054	1.593836	2.684913	0.504398	8.252234	2.71724	8.986706	3.11057
-4.15446	-1.29904	-7.91963	-2.60308	-1.74387	-0.89986	-0.36543	-0.4365
-1.83349	-0.75806	4.915998	1.946958	4.024658	1.016977	2.239782	0.462502
-15.9402	-4.95737	-11.1999	-3.08691	-14.5074	-4.68116	-24.1914	-8.45764
-4.06036	-0.46289	-13.0712	-4.19341	-3.6134	-0.60655	-7.80064	-2.2217
1.690397	0.410898	0.916308	0.519289	3.664864	1.716433	-6.07004	-1.83314
-4.63972	-1.30379	-2.72456	-0.82507	-2.56389	-1.17293	4.540453	1.980945
-0.16896	-0.10566	-2.34504	-1.31208	9.48355	3.091259	9.44522	3.027621
-14.8927	-4.71978	-10.8618	-2.89518	-20.1486	-6.48669	-8.2995	-2.12458
7.697474	2.743084	-4.16751	-1.26305	-0.69044	-0.63015	-0.91158	-0.46022
-23.1773	-7.53015	-10.2338	-2.98146	-24.0203	-8.28504	-20.3199	-6.59477

REPLICATE 38		**REPLICATE 39**		**REPLICATE 40**		**REPLICATE 41**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
11.63189	4.225899	5.147052	1.88167	5.430142	2.786877	6.538158	2.831022
-16.0164	-5.88694	-7.34689	-2.46368	-2.20609	-0.74993	3.494645	1.27642
-6.24596	-2.38203	-8.96019	-3.12628	2.593594	0.823829	-5.32217	-1.86997
-3.05512	-1.48591	-14.3652	-5.5361	-5.96504	-1.69196	-12.249	-4.00802
9.013386	2.840503	6.872703	2.295901	8.416437	2.851047	11.53897	3.552271
-8.5134	-2.11297	-9.27337	-2.77305	-7.10339	-1.90197	-10.217	-3.27644
11.16016	4.103199	-6.83636	-2.87748	3.053056	0.732694	4.511438	1.189086
4.02245	1.927206	5.480347	2.196735	3.452213	1.496234	-7.45248	-1.89131
-2.81272	-1.10101	3.163994	1.478827	0.076433	-0.26528	-7.64757	-2.75026
15.64081	5.502759	8.679738	2.247316	10.56313	3.40259	18.09481	5.960704
-8.27735	-2.13493	-5.23219	-1.18749	-11.4271	-3.69277	-14.1682	-4.60035
-13.6065	-4.23788	-5.47386	-1.38899	-14.6798	-4.14724	-1.50819	0.65521
-7.91168	-2.58255	1.424549	0.513029	0.958488	0.293939	-7.94236	-2.8175
10.27768	3.090987	3.744333	0.341291	14.67132	4.892478	11.7775	3.634348
-5.47993	-1.83104	-6.60792	-2.18768	-4.55236	-2.22972	-1.55647	-0.35884
-7.37563	-2.86634	6.414012	1.946944	3.622107	0.664673	2.873505	0.299117
-16.2103	-4.77061	-29.3783	-10.1078	-13.0764	-4.12385	-18.6583	-5.96091
-1.20733	-0.29763	-7.14565	-2.26318	-10.0033	-3.15251	-1.52203	-0.48367
-1.7801	-0.19638	-4.35015	-0.9897	-2.90827	-1.24267	-8.43027	-2.77388
13.31341	3.587413	22.70033	6.849951	20.82485	6.61238	13.60835	3.468345
1.870956	0.704679	14.26783	5.436645	-6.47547	-1.95618	5.922562	2.013166
-11.2687	-3.58366	-6.00719	-1.94967	-0.19682	0.476145	-0.50485	0.160699

-2.98071	-0.72514	-5.19103	-1.85047	1.867864	0.710496	-4.53115	-1.4134
5.543353	1.783203	6.891732	2.112944	5.346114	1.517089	7.762231	2.200383
9.563377	2.357803	19.71078	6.029812	18.08158	5.482396	20.72504	6.33151
2.383758	1.134977	7.582853	2.508778	14.6569	5.374879	2.388153	1.03292
-4.87483	-2.28108	-9.89537	-2.9012	-10.058	-3.12997	-3.85851	-1.04293
12.88274	3.787334	1.506302	-0.0797	4.51847	0.915693	16.66899	5.614158
-17.9096	-5.30947	-5.05746	-1.6797	-4.97556	-0.82142	-5.42929	-1.73003
2.096797	-0.00674	2.984227	0.933128	11.81739	4.179318	8.894537	2.928782
3.335042	0.870978	-4.62534	-2.25631	1.596154	0.103535	0.342416	0.438564
1.60194	0.573451	3.489363	1.368614	13.03876	4.640532	-5.84709	-2.41873
-14.9938	-4.62485	-12.8073	-4.17695	-19.9414	-6.64097	-18.5211	-5.96721
-2.222	-0.20125	-5.6252	-1.14433	-16.7113	-5.91384	-11.9206	-3.19326
-1.84745	-0.81281	0.069592	-0.01265	-0.1835	0.021059	1.967727	0.953395
2.428014	1.054064	-2.78769	-0.80583	-10.2859	-3.862	-1.44283	-0.46406
8.063664	2.455409	15.02066	5.025455	21.35614	7.007323	6.145283	1.446612
-29.7905	-9.26391	-25.2161	-7.69874	-29.5163	-9.86962	-12.6023	-3.37431
-11.9838	-4.64352	0.504843	0.198728	1.930775	0.912385	-3.7637	-1.50978
-7.10739	-1.76731	-0.00997	0.501114	-16.1372	-4.65083	-6.06262	-2.01789

REPLICATE 42		**REPLICATE 43**		**REPLICATE 44**		**REPLICATE 45**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
5.884264	2.264933	9.712215	3.813605	5.4143	1.996399	6.375075	2.658174
-13.0971	-4.33539	-12.9306	-4.74411	0.444592	-0.20541	-8.87449	-2.86086
1.332301	0.062201	-0.1821	0.334616	-4.17102	-1.55655	-8.0449	-2.62759
-4.52285	-1.49001	-8.95458	-3.6455	-2.19362	-0.98042	-2.37352	-0.54455
18.75184	6.270621	10.60259	3.947559	8.550352	2.23438	4.313972	1.61888
-12.9851	-4.03288	-15.1803	-4.91077	-11.5256	-3.62834	-10.9628	-3.54009
-10.9986	-4.18754	6.710615	2.402351	0.752696	0.239992	-6.55246	-2.52576
4.600706	2.207294	-1.64072	-0.13221	-2.44692	-0.25968	-5.32612	-1.7293
4.460735	1.446617	4.35344	1.7108	1.611519	0.283092	7.604901	2.482165
8.717432	2.449725	14.604	4.536273	5.150685	1.267003	15.14703	4.856242
-22.661	-7.42998	-18.7627	-6.63008	-16.2587	-5.72851	-4.43884	-1.10029
-4.57479	-0.3806	-10.3026	-2.96967	-8.5632	-2.54253	-2.70891	0.219322
-6.13464	-1.71415	-7.55599	-2.24725	-3.56352	-1.62034	-5.89104	-1.76947
16.98481	5.071919	3.478031	0.950264	4.764331	1.402601	9.337317	1.97558
-5.01815	-1.49592	-7.32033	-2.67801	-1.69392	-0.29141	-8.27965	-3.19072
-7.69912	-3.13306	-2.13119	-0.99737	5.545928	1.760027	1.248657	0.139095
-16.2549	-5.14885	-22.4679	-7.33638	-19.5115	-6.46104	-18.8985	-5.79917
0.232502	0.341866	-3.48125	-0.99145	-6.95064	-2.54237	3.831093	1.63785

-2.38671	0.358234	-1.24777	-0.32414	2.767783	1.323661	0.761084	0.988696
19.99963	5.655056	28.66514	9.13623	22.48323	6.408408	9.685091	2.424555
7.760023	3.009792	-1.78194	-0.00879	3.00269	1.603127	4.259027	1.132606
-15.6468	-5.85127	-9.58156	-2.96216	-10.1179	-2.72737	-5.94173	-1.43948
-2.16196	-0.77189	-1.09921	-0.11798	-6.30747	-1.43531	3.972893	1.737575
-2.50331	-0.83536	11.69042	3.871917	16.56493	5.247189	3.276995	1.222743
13.09596	3.380108	17.80033	5.343038	16.57978	5.295819	21.2638	7.221938
2.065348	0.78543	-0.73006	-0.34627	-5.59558	-2.16371	11.53527	3.735347
-10.9654	-3.8907	-8.54495	-2.59804	-4.94066	-1.93593	-13.4115	-4.69807
8.591102	2.890489	6.857113	1.728998	11.24309	3.672689	15.50725	4.855497
-5.11907	-1.43477	-20.3049	-6.49424	-5.34397	-0.80162	-21.7066	-6.81543
11.2784	3.508406	2.756741	0.002806	10.34854	3.129781	3.27409	1.113468
-10.1236	-3.52518	-8.20949	-2.941	6.47956	2.052259	-5.06613	-1.64864
3.350103	1.196522	-2.69774	-0.93751	-0.37025	-0.42847	0.174346	-0.28324
-15.5719	-5.19299	-24.6612	-8.53924	-25.4267	-8.39732	-3.34299	-0.25211
-9.05277	-2.49649	-4.71015	-1.31805	-2.83706	-0.45266	-7.5966	-1.44999
-2.06867	-0.678	-2.16131	-1.01665	-0.42614	-0.44972	-3.18118	-1.16407
3.301202	1.519686	2.95471	1.076054	-7.38663	-2.31222	-3.109	-0.6817
-4.43433	-2.61358	7.807022	2.514319	17.74353	5.764659	8.149652	2.309458
-20.2984	-5.93706	-15.6681	-4.67133	-9.77711	-2.21428	-15.1548	-5.26168
1.09097	0.298714	10.54092	3.37233	-7.82002	-2.96679	-8.9292	-2.9025
-16.4034	-4.38499	-8.18553	-2.21764	-0.54271	0.728363	-9.36213	-2.79193

REPLICATE 46		**REPLICATE 47**		**REPLICATE 48**		**REPLICATE 49**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
5.107782	2.609283	7.319702	2.939567	10.56543	3.636235	12.78727	4.758718
-2.28504	-0.89289	-13.1145	-4.60532	-0.49109	-0.16187	-16.1237	-5.5773
-9.22804	-3.31516	-0.59969	-0.10622	-8.86705	-2.7141	-12.657	-4.35005
-9.08211	-3.44398	-2.87759	-0.58517	-6.46832	-2.4596	-6.19287	-2.17855
11.30547	3.368056	-3.29586	-1.83713	7.620531	2.750977	9.751478	2.741308
-11.8173	-3.72378	-12.708	-3.76598	-16.8051	-5.59872	-5.78648	-1.10361
7.621766	2.462946	-6.10348	-2.26626	-6.69368	-2.56701	0.852153	-0.33309
13.20712	5.443326	3.026472	1.993051	4.441242	2.531503	4.537751	2.277162
-3.54155	-1.61119	4.808363	2.127951	4.665035	1.404785	10.23373	3.518699
0.737026	-0.51012	16.78906	5.56098	-2.30876	-1.2455	19.23045	5.727456
-18.3743	-5.75244	-7.94716	-2.79921	-12.6109	-4.08019	-12.623	-3.6506
-9.0485	-2.43132	-10.5816	-3.19523	0.270836	1.216863	-4.65869	-0.75586
-0.60582	0.154657	-12.0867	-4.5475	-8.29181	-2.8343	0.219624	0.222561
11.75267	3.716599	17.43277	5.50287	1.289281	-0.20687	22.42643	7.248421

7.037512	2.551942	-2.9458	-1.07526	-15.2452	-5.08083	-13.9227	-5.22366
2.812017	0.544649	4.287094	1.368784	-0.00572	-0.36684	-10.3398	-4.62009
-12.4856	-3.19687	-11.3942	-3.31885	-24.3858	-8.51166	-18.2116	-5.90911
0.685843	0.666849	-11.1337	-3.88462	-7.01941	-2.63141	-7.74598	-2.9972
-4.59033	-1.34167	-3.06584	-0.67201	0.542174	0.597952	0.476886	0.765615
8.771842	1.76833	15.35385	4.117862	14.20862	4.51579	15.48276	4.825075
4.285945	1.647819	-2.37795	-1.22652	2.292316	1.422132	8.294856	2.972695
-7.49339	-2.52083	-4.26873	-1.06341	-4.47634	-1.01561	-3.6576	-0.90733
-11.8773	-4.19482	-3.38238	-0.593	-7.37125	-2.06399	-16.9938	-5.89421
6.1081	1.934393	8.924851	2.891985	11.86709	4.282815	-10.3575	-4.38382
20.27499	6.269103	9.781012	2.770893	15.16682	4.123472	29.5983	9.776304
8.408031	2.833104	2.255343	0.920216	23.04582	8.057057	-2.49123	-1.2634
-10.5265	-3.38759	-22.406	-6.80719	-7.52783	-2.52504	-15.4742	-4.93868
11.69664	4.037264	7.420656	1.84811	10.44058	3.091714	7.347776	1.532646
3.207819	1.471102	-9.33337	-2.362	-13.3371	-3.91583	-6.24077	-1.55459
5.997429	2.09228	9.549436	3.345919	8.562133	2.938045	3.195942	0.998056
-4.11357	-1.60048	-12.7776	-4.41021	-4.86662	-1.7237	-2.22409	-0.71876
7.986139	2.914576	-5.30191	-1.9933	-1.63261	-0.46722	4.6984	1.346921
-30.2016	-10.0519	-8.06665	-2.67294	-10.5996	-2.97939	-29.9402	-10.3178
1.262107	1.34455	-0.66638	0.219629	-9.56512	-2.39849	-5.41276	-1.60019
0.316202	0.200624	-4.67789	-2.14026	11.86409	4.541512	-1.73339	-0.48924
-7.09508	-2.59817	-6.99756	-2.10258	-5.14813	-2.0614	-1.30838	-0.31763
-0.50394	-0.60597	7.192489	2.206446	14.61049	4.594743	-4.65135	-1.83045
-24.7473	-7.47807	-19.5019	-5.546	-16.7382	-5.04487	-16.8841	-5.72577
5.165827	1.460464	-0.04074	0.200218	-2.72615	-1.30131	-6.15837	-1.82323
-5.93727	-1.77018	-16.2112	-4.69164	-7.22671	-2.22392	-13.4495	-4.01129

REPLICATE 50		**REPLICATE 51**		**REPLICATE 52**		**REPLICATE 53**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
4.349709	1.465477	22.87817	8.475767	4.371257	1.820144	7.935307	2.763556
-3.04096	-1.62204	-6.2039	-1.92116	-11.1955	-3.87753	-17.0819	-5.77635
-3.32515	-1.08407	-10.5533	-3.91933	-6.50859	-2.66144	-4.86908	-1.94541
7.399391	2.798688	-13.3244	-4.97057	-3.75482	-1.33251	-14.2486	-5.55078
7.337794	2.408344	11.33432	3.789392	15.23527	4.998441	11.50436	3.593022
-18.6018	-5.55291	-22.3502	-7.44776	-26.2307	-8.99384	-14.6363	-4.45091
3.496036	1.134222	0.377669	0.327391	5.791954	1.948086	4.479568	1.306378
6.568781	2.482884	5.016225	2.517356	0.380689	0.431275	5.983957	2.916293
3.708864	1.415369	13.09544	4.862346	-3.2292	-1.09491	-9.46965	-3.83417
16.8131	5.364857	5.984777	1.57498	8.205449	1.900235	7.310474	2.032981

-6.09016	-1.73792	-10.4081	-3.8418	-1.9213	0.461348	-22.7903	-7.71504
-2.8131	-0.6856	-4.92818	-0.98362	-8.09724	-2.39077	-10.6818	-2.82644
-5.01473	-1.32132	-7.37819	-2.49875	-6.14523	-1.89988	-10.6858	-4.33622
11.47356	3.485452	12.10128	3.844291	18.59433	5.658512	0.849743	-0.13148
-4.86951	-1.475	-10.4045	-3.22724	-6.03585	-1.63526	-1.7914	-0.53784
5.905853	1.682252	7.204555	1.925287	12.66626	4.174124	-2.82163	-0.80726
-23.1342	-7.6062	-15.4605	-4.77442	-20.3106	-6.43338	-26.0362	-8.21078
8.251951	2.727892	1.078797	0.222552	-15.7702	-5.29978	-6.7629	-2.65743
1.400058	0.889237	-6.2498	-1.66529	2.444283	0.837908	3.570424	1.337653
5.502564	0.708206	25.90663	8.484242	23.41348	6.945407	12.33626	3.348786
4.545994	1.999004	20.24453	7.192218	3.038068	1.481241	-5.23118	-1.16047
-17.2767	-5.27852	-14.5336	-4.64671	-7.70008	-2.03946	-2.21448	-0.1246
-9.71103	-3.63301	-2.32379	-0.47233	-1.82856	-0.52614	-3.47822	-0.94134
11.12526	3.439599	-0.7282	-0.6936	3.988526	0.951137	12.02786	3.947241
30.59978	10.15945	12.32141	3.919369	12.62315	4.095726	19.55401	6.201712
7.639117	2.768167	5.325285	1.476616	8.015179	2.789622	6.727217	2.307399
-14.6969	-4.55919	-1.47258	-0.41148	-14.4093	-4.3487	-4.24024	-1.55623
10.98192	3.44385	19.81641	6.401934	17.97586	5.3495	10.27271	2.875731
-4.79751	-0.66057	-12.8904	-3.67606	-4.74534	-0.63362	-6.3024	-1.61209
3.744047	1.226648	9.578495	3.173913	3.071908	0.733134	-3.55574	-2.01875
-1.58182	-0.71145	-11.1699	-3.49834	-2.82462	-1.3847	-2.48633	-0.68278
10.58752	3.493937	4.975301	1.312246	2.011807	0.600226	6.937647	2.796418
-15.2825	-4.7964	-20.7521	-6.28058	-31.1113	-10.1253	-15.2065	-4.52744
-7.6656	-2.05382	-3.89237	-0.54795	6.89559	3.135476	0.709128	0.805624
0.490966	0.378232	-3.74666	-1.31226	-0.44104	-0.56796	-1.8034	-0.91109
0.77529	0.21592	-7.98336	-3.08936	-0.2	-0.12119	-5.99405	-2.16556
5.577252	2.01128	18.14925	6.361504	3.791391	0.875444	12.77246	3.506171
-22.4279	-7.25769	-15.1242	-4.44205	-29.7458	-9.94522	-15.6418	-4.13336
3.084786	1.569712	1.282101	0.256799	-1.38214	-0.40553	-1.54227	-0.46489
12.7243	5.318163	-16.9104	-5.22212	-11.7036	-3.03576	4.081925	1.784214

REPLICATE 54		**REPLICATE 55**		**REPLICATE 56**		**REPLICATE 57**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
8.337263	2.42647	7.516047	2.35986	5.628601	2.472047	9.293771	3.661929
-4.4622	-1.8317	-11.9533	-4.61254	-9.28678	-3.1891	-0.35006	-0.14778
-2.13616	-0.90465	-2.62286	-1.20539	1.762653	0.09786	-7.87324	-3.21587
-0.50257	-0.17015	-14.0074	-4.67487	3.550644	1.134782	4.568027	1.713758
4.114294	1.48957	13.76565	4.365493	7.19709	1.62751	2.906902	1.152452
-20.9055	-6.97086	-15.3065	-4.91367	-3.55418	-0.26508	-7.45745	-1.87484

-3.8077	-1.58449	-4.15528	-1.748	-1.67332	-0.84728	1.854069	0.571569
5.384589	2.37553	-10.6917	-2.70656	3.297301	1.512569	2.183659	1.318589
6.471579	2.320261	8.493615	2.565277	-5.77595	-2.07838	-4.21004	-1.68387
12.6755	3.871919	20.1785	6.530471	10.75549	4.479587	12.50063	3.752961
-0.18455	0.715432	-7.15443	-1.96241	-4.82256	-1.35466	-14.0091	-4.63488
-1.82049	-0.20157	-9.79358	-3.20911	-2.22948	0.194463	-5.17492	-1.28914
-4.36541	-1.08216	2.994874	1.875559	-3.50717	-1.4853	-17.4951	-6.49447
16.89177	5.835888	3.47975	0.885466	9.616947	2.459247	12.66767	3.870795
-8.31577	-2.4834	-11.6986	-3.80705	-5.01959	-2.03462	-0.86278	-0.23678
2.278023	0.318125	0.46987	-0.50652	2.882818	1.14124	-0.43029	-1.06899
-21.1164	-7.5894	-22.6333	-7.4591	-20.2619	-6.51799	-7.87983	-1.63653
-22.1982	-8.61069	-3.78506	-1.24964	-6.47225	-1.95947	-2.1052	-0.83171
-5.49231	-1.62648	-11.5884	-3.54377	-13.2373	-4.27073	0.021248	0.590173
26.32227	8.782236	25.05307	7.8583	20.04307	6.680909	27.05566	9.050568
-0.98045	-0.74115	-2.83504	-1.11588	2.15738	1.010518	9.487774	3.188068
-6.58724	-1.9724	-17.2745	-5.50803	-10.6485	-3.15566	-7.21275	-2.05689
-7.56018	-2.68046	-7.92636	-3.30277	-1.72088	-0.84335	-7.50464	-2.44829
5.004847	1.586321	-5.03276	-2.17103	4.908111	1.740338	4.730671	1.275783
16.2217	5.753802	11.5022	3.686753	23.27489	7.669646	18.7474	5.778981
5.393412	1.601936	5.558838	1.623865	15.65683	5.611469	1.642972	0.700685
-12.2837	-4.07344	-10.2725	-3.83026	-10.9338	-3.17608	-5.09903	-1.6436
19.2225	6.34086	8.396743	2.703763	14.15462	4.307649	11.39837	3.666354
-1.39699	0.583186	-8.80782	-2.23911	-1.3622	0.470595	-14.4165	-4.6468
9.603545	3.350415	1.339976	-0.23023	11.37214	3.891193	6.486733	1.83065
-5.32659	-1.96283	-0.5143	-0.26527	-7.71528	-3.26218	-4.39597	-1.53921
-0.92642	-0.71931	1.553082	0.121285	13.96492	4.390111	3.231308	0.783523
-12.3842	-4.00006	-34.0474	-11.8942	-8.95262	-2.49319	-26.2105	-9.63208
-7.17331	-1.16905	-6.62182	-1.64813	-8.82597	-3.14046	-11.4991	-3.54228
4.250024	1.323021	-2.9445	-1.28231	-7.6578	-2.74811	3.807299	1.074246
-3.83575	-1.88457	5.987906	2.400234	-4.3865	-1.48791	-3.82937	-1.40796
11.19034	3.869698	6.61412	2.247025	18.00771	6.497211	1.050366	-0.06162
-20.7746	-7.15073	-21.0483	-6.37189	-15.6895	-4.5337	-9.17972	-2.80898
8.644422	3.403389	0.353214	0.119374	-1.82611	-1.04203	0.794349	0.179748
-24.9276	-7.85733	-0.46309	0.622375	-6.65386	-1.54712	-15.1309	-4.704

REPLICATE 58		**REPLICATE 59**		**REPLICATE 60**		**REPLICATE 61**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
9.899793	3.899289	7.112386	2.567315	5.648212	2.464056	4.27886	1.701041
-4.10063	-1.71541	-1.45179	-0.31153	-11.0903	-3.55087	4.658811	1.694327

2.083018	1.089504	7.299959	3.034825	-5.12254	-1.91597	-1.81808	-0.98575
0.380411	-0.13459	-9.19021	-3.03312	-1.9999	-0.49491	-2.41862	-0.97318
13.89631	4.782261	5.982565	1.636289	3.267294	0.799047	5.472968	1.793135
-17.7409	-5.95734	-16.5534	-5.37581	-15.1921	-4.99938	-8.34289	-2.6735
2.27264	0.539527	7.918546	2.574843	-8.19271	-3.24741	-5.14073	-2.31193
-3.78116	-0.41137	9.923845	3.197656	-5.67026	-1.24285	-1.09898	-0.18293
6.498284	2.150354	-1.61654	-0.18451	-0.37007	-0.60284	2.102196	0.834693
11.16687	2.989504	11.90583	3.971613	10.58688	2.862196	5.054077	1.0866
-13.7778	-4.59785	-7.0423	-2.06677	-13.0472	-4.46013	-12.4932	-4.12388
6.174343	2.969856	1.946317	1.846897	1.919713	1.739032	-16.7939	-5.10192
-1.57079	-0.46563	-13.6611	-4.87819	-3.26827	-0.99128	-6.87777	-2.6283
8.403445	2.35634	7.692798	1.630887	10.7573	2.550436	10.85008	3.567067
-1.75262	-0.45811	-2.79299	-0.91395	-4.32496	-1.48089	6.312721	1.862874
-2.56491	-1.46431	2.806584	0.992313	4.626824	1.199049	9.99146	3.629428
-12.1902	-3.53272	-18.4095	-5.90976	-14.9491	-4.8059	-9.00576	-2.06393
-4.73011	-1.76763	-11.1939	-3.93288	-9.90179	-2.85175	3.373233	1.20929
-5.18224	-1.74187	-6.40173	-1.98368	1.266779	0.823876	-2.21364	-0.80133
18.54082	5.68905	27.04441	8.385436	18.05713	5.327333	17.67025	5.187505
6.608504	2.616684	8.296766	2.916729	7.818133	2.245836	6.049922	1.870905
-13.813	-4.30304	-14.6448	-4.45632	4.161343	2.515808	-9.01883	-2.76609
-7.02185	-1.77532	-7.44655	-2.36355	-14.4008	-4.43482	-4.06288	-1.46598
14.03467	4.477935	3.578389	0.544978	12.16521	3.465631	7.264584	2.156169
8.873339	2.270623	17.32342	5.549084	9.486991	2.875262	14.23361	4.758673
20.11112	6.864276	3.362591	1.062455	1.655141	0.487143	-0.02476	0.12915
-10.1989	-3.15286	-7.26251	-2.42296	-9.92602	-2.91358	-12.4946	-4.09561
10.09363	2.959383	23.33228	7.423215	6.816402	1.918415	19.24905	6.437608
0.143906	0.371962	-14.8027	-3.69382	-7.82085	-2.40074	-6.05698	-1.58563
7.453508	1.793688	10.06	3.366788	4.515695	1.826753	9.650982	2.746149
3.662476	0.866657	6.56003	1.915592	-8.05169	-2.45396	-4.97435	-2.11615
-2.22487	-0.97606	2.623302	1.016106	4.581593	1.544827	-1.0899	-0.37326
-17.6288	-5.72708	-18.53	-6.1715	-10.5608	-2.95474	-20.6492	-6.65498
-8.46823	-2.2406	-20.1866	-6.54387	1.058316	0.883109	3.149798	1.623499
-1.11779	-0.69818	-4.04355	-1.23992	2.642517	1.073339	-2.98361	-1.3894
-6.83594	-2.09234	7.863597	2.808651	-7.21636	-2.6565	-4.92917	-1.62407
3.5688	1.206722	9.085495	2.647902	6.543448	1.368254	7.845131	2.327654
-15.4841	-5.10021	-22.879	-7.32041	-13.212	-3.94987	-21.5373	-6.88223
13.6111	4.429117	1.123275	0.139451	0.834423	0.220513	-3.6117	-1.64699
-11.2419	-3.41326	-13.912	-4.17966	-12.8938	-4.55107	-16.4246	-5.89318

EPLICATE 62 **REPLICATE 63** **REPLICATE 64** **REPLICATE 65**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
12.71215	4.938902	14.00632	5.413825	11.51122	4.81058	7.131423	2.621157
-7.29344	-2.93765	-3.64672	-2.09554	-4.97376	-1.2692	-4.77193	-1.81435
-5.92196	-2.95858	-6.11004	-2.46963	-8.53238	-2.29074	-2.04751	-0.49569
2.172862	1.094969	-4.56674	-1.55052	-16.7263	-5.98988	-9.42638	-3.46951
10.12606	3.573464	3.156873	0.600695	14.90193	5.395097	6.8903	2.24242
-17.591	-5.51156	-24.951	-8.08623	-15.0371	-5.07014	-4.50803	-0.67455
8.021165	2.540035	5.472247	1.153689	2.561399	0.512271	7.241748	2.132955
-3.96353	-1.04272	1.051379	1.067666	2.898938	1.474421	-6.48598	-2.00344
-2.44954	-0.43086	-4.94052	-1.87852	-7.48504	-2.85738	-1.04529	-0.83362
21.23011	6.859423	8.690617	2.552138	7.967682	1.902783	7.034435	1.263119
-22.5807	-7.76755	-11.2814	-3.63445	-6.62288	-1.47913	-13.7701	-4.02804
-12.8198	-3.55571	0.909568	0.611356	-5.29006	-1.12912	-2.35363	0.330406
3.897538	1.529794	-5.35779	-1.57905	-17.1513	-5.52312	-19.2807	-7.02863
3.939017	0.697428	4.012208	0.946303	9.748032	2.769203	6.384713	1.428845
-7.25444	-2.88877	-7.96826	-2.61015	-9.36586	-3.27001	-4.49848	-1.21591
0.12891	-0.08132	7.894433	2.556548	-8.5737	-3.80122	-1.39479	-1.12074
-20.2626	-5.771	-14.6044	-4.20801	-12.1741	-3.81109	-19.0009	-5.72206
-6.55629	-1.78424	-6.73126	-2.3001	-0.59596	0.41217	-1.12066	-0.37268
-0.47251	0.697619	-2.08343	-0.4399	-4.00775	-1.04331	-1.56455	-0.01219
18.45833	5.651847	16.27123	4.217453	5.219392	0.781661	25.27356	8.209414
1.947113	0.253656	4.189521	1.358774	-5.40236	-1.73085	7.075026	2.33174
1.352411	0.953068	-4.56823	-1.07425	1.266987	0.77874	-8.5091	-2.56687
-4.09234	-0.87884	-11.5764	-4.12229	-8.33526	-2.68717	-2.39807	-1.0277
13.14583	4.175076	-3.1143	-1.91542	5.797107	1.860225	-3.97622	-1.80864
26.19248	8.398215	23.97204	8.014362	19.32209	6.216204	21.24895	6.40985
7.332337	2.764098	13.8132	5.387763	0.956742	0.295513	4.992265	0.728058
-1.00759	-0.13764	-8.02023	-2.43282	0.488254	0.071999	4.072621	1.621817
4.936536	0.998966	10.91443	4.212728	10.19385	3.376563	18.35922	6.124465
-6.52124	-1.45351	-8.76658	-2.62601	-13.2992	-4.36922	-5.98551	-1.3764
13.93422	4.799065	13.07605	3.718125	4.308738	1.222172	12.68026	4.224108
9.799046	2.870763	0.233682	0.047323	-7.98241	-2.97794	9.231934	3.266259
5.777191	1.66708	7.124116	2.34713	1.374626	0.340434	4.983406	1.140868
-13.6832	-4.13338	-15.8476	-4.33556	-11.3786	-3.89577	-23.2613	-7.16225
-15.1574	-5.30024	-16.7505	-5.5586	-6.16183	-1.91938	-13.6866	-3.37986
5.380645	1.577292	0.644114	-0.08117	6.483199	1.711249	5.394113	1.714034
-12.4423	-4.37377	-7.23459	-2.16701	-1.30584	0.386159	-6.1803	-2.56712
16.21778	5.854067	12.10264	3.88727	22.47967	7.649914	5.650053	1.012908
-17.6669	-5.43523	-20.7383	-6.24198	-16.9551	-5.12974	-23.2135	-7.99532

-1.16168	0.081344	7.106318	2.69665	-3.41983	-1.3093	3.744438	1.709305
-7.44477	-1.77339	-16.6136	-5.23758	-8.72865	-2.72065	-15.3872	-5.11759

REPLICATE 66		**REPLICATE 67**		**REPLICATE 68**		**REPLICATE 69**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
5.219157	2.387801	-0.22646	-0.54205	-1.28316	-0.38874	1.941235	0.291011
7.185609	2.878482	-5.27435	-1.75321	4.448811	1.284309	-0.55765	-0.55427
2.962684	0.863433	-4.00649	-1.34378	-9.48092	-3.22268	-2.51786	-1.02507
-11.3602	-3.80186	1.022306	0.181517	-1.54341	-0.22493	-6.76391	-2.29321
5.280106	1.401774	7.099498	2.601218	-1.86893	-1.16291	10.12408	3.371867
-18.1237	-5.72382	-11.9408	-3.98335	-15.5118	-4.55182	-24.2075	-7.52744
-0.53491	-0.51613	0.624558	0.46368	7.231909	2.457343	7.149714	2.604071
3.360417	1.237281	-3.00764	-0.85315	1.647574	1.174866	-2.36716	-0.85461
5.908713	2.933199	0.558634	0.075056	-7.6539	-2.11726	2.491822	0.898651
8.83289	2.041374	10.1302	3.011207	8.828207	2.130852	6.807683	2.181609
-7.77473	-1.98236	-8.13482	-2.0218	-19.949	-6.70888	-16.5812	-5.44358
-11.9313	-3.505	-3.86391	-0.7786	-7.73197	-2.72886	-3.47579	-0.26628
-6.53058	-2.49823	-7.50946	-2.52773	-4.68798	-2.15727	-3.06776	-0.73989
8.844048	2.804317	7.299555	1.444909	16.96072	5.028348	12.07514	3.748809
-7.42188	-2.76564	-6.82415	-2.73766	8.712983	2.961508	0.524099	0.352579
10.81965	3.578695	4.778578	1.651701	6.778082	2.111909	-2.56448	-1.22276
-20.0224	-6.5338	-17.4291	-5.5696	-16.0128	-5.10452	-20.684	-6.72087
-4.82302	-2.15261	-0.01984	-0.21069	-2.22764	-0.8544	-1.24437	-0.25958
-11.2265	-3.98612	-0.42282	0.786769	-6.65686	-2.2044	3.940326	1.804801
21.14793	7.317941	13.13221	3.685768	14.28201	4.147646	16.92075	4.771895
4.819787	1.617141	-3.26292	-1.08355	13.9323	5.036174	0.593891	-0.22692
-0.80206	0.258451	-5.70779	-1.49064	3.95344	2.33091	-25.4796	-8.0153
-4.57629	-1.25104	-9.40601	-3.38371	-9.11064	-3.29184	-0.61561	0.393828
9.676	3.465874	2.941107	0.500531	7.050756	2.599769	4.935637	1.135861
6.028817	1.408857	12.97706	3.692624	13.03826	4.232521	24.04013	7.86922
10.65757	4.027012	4.449656	1.734939	-15.2638	-5.18751	4.757379	1.639329
3.911089	1.5178	-11.6794	-4.38957	-8.8088	-2.49761	-5.45297	-1.51628
2.166868	-0.34511	16.44993	5.064885	7.261303	1.823671	10.46987	3.142401
-0.9368	0.540236	-0.47202	0.685767	-2.38907	-0.17675	-5.4652	-1.10079
5.611586	1.567457	17.53287	5.608515	16.16976	5.571274	11.16555	3.656958
-4.3844	-1.95069	-13.135	-4.72429	-1.68014	-0.15015	-2.92681	-1.26185
7.635828	2.48723	8.735839	2.814692	-0.56986	-0.59359	4.318511	1.213659
-14.0539	-4.35524	-25.1723	-8.3524	-17.1908	-4.92718	-7.95335	-2.65191
-5.8377	-1.11321	-8.37303	-1.81329	-9.45783	-2.98594	-15.5876	-5.42576

2.602857	0.474822	-7.27976	-2.88631	7.193411	2.502421	4.621048	1.831675
-1.54387	-0.33377	-1.76589	-0.7056	1.105937	0.229715	-4.76436	-1.53344
7.814983	2.571808	3.88647	0.982726	1.315122	0.411351	13.16062	3.826341
-7.46318	-1.57525	-25.1367	-7.98635	-16.7192	-5.08379	-22.5157	-6.49298
0.365156	0.28517	9.062038	2.906631	-5.40035	-1.47477	-4.42672	-1.71032
-19.6788	-6.79329	-13.4168	-4.44788	-20.33	-6.0442	-17.5414	-5.09801

REPLICATE 70		**REPLICATE 71**		**REPLICATE 72**		**REPLICATE 73**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
11.95576	4.798326	6.956712	1.98615	6.191963	2.854725	-1.76586	-0.21966
-9.26149	-3.3377	-12.9164	-5.07849	-6.72194	-2.08161	-2.36184	-0.98801
-5.60158	-1.49865	-6.8566	-2.0561	-8.65083	-2.75033	2.587892	0.778555
-9.13568	-3.50637	0.525314	0.551147	0.735009	0.189521	8.844259	2.653671
6.488485	2.165836	6.77989	2.133104	14.87661	4.50418	15.11008	5.245308
-15.0619	-4.94066	-8.58629	-2.42875	-8.53896	-2.37428	-15.4973	-4.70264
0.586809	0.284958	-4.25115	-1.456	-13.3255	-4.97421	-1.39935	-0.8578
6.320602	2.74022	-4.10998	-0.60008	-7.18317	-1.9367	-12.0558	-3.76167
-0.15035	0.202584	-8.7925	-2.84835	-10.6127	-3.94978	4.130677	1.700783
7.828253	2.081633	8.63191	2.853256	11.5124	3.422631	7.424329	1.851168
-13.6761	-4.63616	-24.9709	-8.46936	-13.4588	-4.55421	-12.0988	-4.13104
0.785534	0.564307	-6.48576	-1.4192	-5.62934	-1.74356	-0.8357	0.538114
-7.69503	-2.54641	0.848647	0.534636	-12.3755	-4.03929	3.734723	1.008979
11.16307	3.006366	7.650943	1.620088	10.39562	3.153385	7.41263	1.856939
-5.69996	-2.40427	-11.9636	-3.68143	6.863085	2.415773	-6.35919	-1.73964
0.824957	0.429525	5.274548	1.600378	10.78259	3.558938	-0.29478	-0.39509
-14.1983	-4.35405	-10.8832	-3.08843	-6.59452	-1.77247	-5.95171	-1.58418
-0.85261	-0.13956	-3.9772	-1.43764	-2.11775	-0.89254	-0.92219	-0.90496
-3.77822	-0.96163	-6.27727	-1.5784	-2.03326	-0.61832	-1.68618	-0.03856
22.0011	6.789907	15.91573	4.721145	17.30292	6.117749	10.24333	2.361683
8.351563	3.075995	9.497681	3.771409	5.624163	2.548526	1.097497	0.557862
-5.93582	-1.22245	-7.35435	-2.09574	4.992983	2.336863	-9.69219	-2.93245
-9.99405	-3.43439	-5.86775	-1.40915	-5.69502	-1.32462	-8.98495	-2.27274
-4.85856	-2.16922	1.01722	0.044174	-0.65925	-0.97356	3.902687	1.411612
19.85317	6.212909	20.4144	6.17607	18.18917	5.466492	8.574995	2.681962
7.880906	3.213836	15.7621	5.923751	3.71325	1.164365	16.16047	5.708076
-6.00389	-1.46568	-10.2765	-2.82534	-22.3218	-7.53756	-18.5921	-6.54042
13.02433	3.615225	8.06575	2.145765	13.94903	4.41332	9.783056	2.396416
-8.02917	-1.90673	-9.31615	-2.55773	-4.22678	-1.34712	-11.0811	-3.27473
2.548229	0.832024	3.215411	0.860396	9.857294	3.551873	10.96066	3.365592

-1.52204	-0.64163	-3.05261	-1.363	-7.09361	-2.50286	5.871144	1.648275
-3.45486	-1.60603	-1.61995	-0.92745	6.086102	2.078659	5.728492	2.341996
-11.3086	-3.26178	-11.179	-2.98913	-10.7482	-3.50098	-8.44812	-2.11421
-6.41618	-1.05343	-7.44998	-2.0017	-16.3731	-5.34379	-16.3324	-5.31088
5.144822	1.906214	0.972993	0.099264	-2.75613	-1.08947	-4.79988	-2.02534
4.875462	2.331292	-5.17121	-1.6026	-8.21733	-2.5145	-7.72267	-2.74335
4.340406	1.144445	7.597797	1.584225	-6.218	-2.90118	17.62765	6.091857
-23.3522	-7.86772	-22.8376	-7.51323	-29.8109	-9.91086	-13.6363	-4.10512
-9.72232	-3.1486	-3.38015	-0.92894	4.974472	1.316694	2.0045	0.46049
-24.2816	-8.54413	-12.1587	-3.43957	4.202754	1.59008	-10.5067	-2.89541

REPLICATE 74		**REPLICATE 75**		**REPLICATE 76**		**REPLICATE 77**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
8.669521	3.016878	-1.69031	-0.63624	8.154414	3.486814	13.00724	4.963414
-9.14318	-4.1379	4.20306	1.504254	1.129466	0.235959	-1.44084	-0.98057
-12.1517	-3.62676	-14.0445	-5.24704	-6.86098	-2.65843	-8.21585	-2.76947
1.764848	0.75728	-2.46412	-0.45271	-6.3907	-1.97059	-16.8012	-5.98487
12.58275	3.976147	6.540414	1.786845	0.156788	0.240241	4.665071	1.115271
-12.1204	-3.31748	-13.8165	-4.37628	-15.4149	-4.65804	0.037443	0.646951
11.17784	3.383899	-4.9783	-2.1498	1.096807	0.306515	0.336103	0.072077
1.277795	1.27212	7.12498	3.094531	-6.676	-1.85013	5.135354	2.510325
0.903593	-0.14629	-1.30731	-0.3855	-9.91221	-3.6117	6.022768	1.984217
0.296211	-0.58345	15.52333	5.054408	4.646247	0.832829	6.990252	2.146843
-10.2732	-2.80816	-10.3262	-3.08361	-6.09854	-1.68247	-13.3027	-4.33125
-7.28259	-2.02392	-21.3196	-6.76163	2.619618	2.297285	-4.20577	-0.46077
-1.87334	-0.19572	-8.74092	-3.1413	-6.5486	-2.17506	-8.47194	-2.90339
12.83345	3.519662	6.045973	1.373809	11.65925	3.706679	10.72075	3.463691
-0.93003	-0.00929	2.587844	1.721051	-2.67901	-0.93534	-4.0957	-0.97286
-3.87793	-1.71477	7.208927	1.87428	-1.44075	-0.28057	-3.05533	-1.70472
-16.4131	-4.77242	-15.5378	-4.97779	-22.8555	-7.46907	-20.1861	-6.7501
-13.4065	-4.3598	-1.23967	-0.25594	-15.0928	-4.96365	0.527373	0.247151
-10.288	-3.57056	-7.75928	-2.57115	-21.4353	-6.87963	0.932025	0.196629
6.54009	1.893216	20.79359	6.864649	10.84933	2.903211	25.36938	8.029974
10.6642	3.899568	-0.8408	-0.03626	-1.34244	-0.0973	0.74759	0.41048
-10.8867	-3.16515	-16.3347	-5.55452	-10.7562	-3.09038	-11.331	-3.47677
-3.21062	-0.79521	-1.14986	-0.07765	-11.5553	-3.75574	-3.71858	-0.7541
16.30162	5.611745	6.616898	1.861682	2.7528	0.154207	18.15667	6.139224
14.00308	4.59501	11.48158	3.724747	19.84965	6.147634	17.37825	5.243627

5.62973	1.475673	6.630552	1.95084	-3.25797	-1.78978	8.994712	2.94817
-7.516	-1.9183	-10.4313	-3.90647	-10.8225	-3.35735	-3.02011	-1.02963
12.07845	4.042894	7.419664	1.408492	18.50801	5.224998	14.72163	4.918542
-9.65976	-2.47815	-9.98493	-2.33823	-5.27977	-1.40905	-8.73659	-2.72668
5.612309	2.131053	-1.75716	-1.20537	9.438096	2.42513	13.10707	4.993585
3.237649	0.82397	5.873357	1.959884	0.675583	-0.21184	-2.53116	-1.21615
7.202775	2.444142	5.922259	1.193443	3.936746	0.80039	0.496854	-0.0493
-18.0501	-5.406	-10.0435	-3.11354	-13.3119	-4.24469	-6.70333	-2.35275
-2.11823	-0.33825	-7.79299	-1.97269	-4.73862	-1.22338	-7.7551	-2.23094
3.57946	1.02047	4.442841	1.791568	12.39152	4.442082	-2.12672	-1.05569
0.808904	0.39364	10.98451	4.522416	-4.49493	-1.51786	7.62708	3.297585
8.293808	2.455013	8.10957	2.610095	8.511819	2.759809	7.778399	2.145128
-21.0111	-7.01034	-11.0007	-3.527	-21.1389	-6.61999	-15.4205	-4.69191
-6.51893	-2.47894	-4.58258	-1.85781	1.712459	0.776919	3.14796	0.921914
-4.02441	-0.73452	-5.0834	-1.35631	-14.0414	-4.13208	-16.6085	-5.42806

REPLICATE 78		**REPLICATE 79**		**REPLICATE 80**		**REPLICATE 81**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
5.003284	1.441296	-1.2527	-0.12251	5.749964	2.563822	6.696514	2.640179
-2.97041	-0.63527	-8.37645	-2.90244	4.721375	1.54948	-9.24282	-3.48024
-5.05627	-1.77213	-2.15345	-0.72899	11.89548	4.081553	-3.66846	-0.96599
-6.53471	-2.58854	-7.0336	-2.2993	-5.26586	-1.35984	8.80903	3.674496
9.684	2.951536	10.37747	3.172428	5.285715	2.222095	5.380713	1.454328
-9.49324	-3.06191	-18.0854	-5.43586	-9.75579	-2.46507	-17.3734	-5.34355
-1.02972	-1.02779	-3.7388	-1.72837	3.069061	0.702648	2.953297	0.581987
15.95407	6.284509	0.492654	0.779261	-2.62519	-0.52075	-9.95	-3.16362
-5.53936	-2.01086	7.273846	2.652189	-9.0421	-3.32018	3.623683	1.413735
20.37552	6.516012	7.278105	1.390731	7.377678	1.56454	9.839334	2.55504
-4.64965	-1.44843	-12.284	-4.12164	-2.35148	-0.03939	-8.49916	-2.3386
0.736888	0.578849	-3.06845	-0.29271	-3.374	-0.94264	-18.7885	-6.04359
-9.62557	-2.94002	-7.32593	-2.86009	-5.45664	-1.77366	-3.60254	-0.5381
11.98301	3.36492	13.95735	4.568714	13.93889	4.528786	12.7006	3.759993
-9.03273	-3.40925	-2.9616	-0.95475	-0.70429	-0.56304	-0.38392	-0.04015
-9.88899	-4.60053	-2.85097	-0.62386	2.559653	0.821972	-0.71132	-0.7546
-11.7383	-4.2	-17.98	-5.75681	-5.02666	-0.69469	-18.2819	-6.02958
-7.70809	-2.6965	-1.11845	-0.14438	-2.5161	-0.22777	-8.69758	-2.86794
-2.55313	-0.76544	-23.1923	-7.41663	-10.8553	-3.6691	-4.18164	-1.2972
12.78354	3.494973	16.26667	5.16984	28.63691	9.716627	13.30638	4.133029
6.496463	2.246406	0.715101	0.499022	-0.65561	-0.06369	-3.25643	-1.31095

-5.15139	-1.42167	-9.598	-2.61991	-8.48337	-2.37307	-9.80603	-2.85653
-1.62864	-0.42817	-1.3734	-0.33488	-7.71649	-2.44146	10.29839	3.659763
6.953815	2.378894	0.683208	-0.11196	17.12943	5.377912	10.87729	3.292127
17.9349	5.17471	22.00028	7.190186	21.71828	6.849044	28.48296	9.644825
3.219411	1.256988	8.111142	2.63881	-1.6126	-0.64889	3.553654	0.881815
-6.90251	-2.36015	-4.72048	-2.15598	-15.7021	-5.31444	-11.6172	-4.00391
5.037572	0.635646	5.945535	1.431302	9.942587	2.675307	6.930391	2.074387
0.103888	0.486486	-9.80327	-2.83175	-13.4442	-4.39974	-8.07407	-2.74389
11.03013	3.631172	0.743319	-0.22342	-1.30329	-0.86904	13.95709	4.603985
2.808352	0.703556	-9.61033	-3.27537	9.166003	3.39519	-2.731	-0.86558
-1.14081	-0.62383	-0.74189	-0.49435	8.733893	2.950501	3.600526	1.322306
-5.48466	-1.36591	-10.4812	-3.50241	-6.9086	-2.28631	-12.1134	-3.50456
-5.90398	-1.63523	-8.83474	-2.1244	-10.7824	-3.39546	-10.6542	-2.96389
-4.52376	-2.18465	-15.6781	-5.75787	-1.39174	-0.88455	-2.5072	-0.85585
-13.1294	-4.45042	-7.29331	-2.55632	-11.0656	-3.60854	-0.95752	-0.19622
4.17155	1.465289	9.696565	2.723492	8.536298	2.376343	10.91392	3.582008
-14.9594	-4.61917	-12.6953	-3.54734	-19.4601	-5.66665	-11.6123	-3.12142
-3.60642	-1.06521	6.366569	2.501765	7.678741	2.785866	1.440054	0.477965
-15.112	-4.88721	-17.4653	-5.54117	-9.56259	-3.16385	-15.8218	-5.24589

REPLICATE 82		**REPLICATE 83**		**REPLICATE 84**		**REPLICATE 85**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
13.88724	5.293118	7.153351	3.144994	2.55774	0.722103	13.87181	4.335449
-4.89991	-2.21161	-12.6813	-4.64418	-9.30822	-3.21244	-3.75095	-1.49899
-4.93931	-1.92844	3.091687	1.693053	-6.92009	-2.56538	-2.59845	-0.4366
-10.1189	-3.18847	-7.28193	-2.4722	-13.636	-4.63885	-6.84404	-2.86252
7.833571	2.728983	10.75247	3.887766	5.036808	1.232969	1.45716	0.432229
-16.0176	-5.1535	-17.1038	-5.06693	1.467158	1.317997	-19.854	-5.94453
3.464811	1.455462	-3.61048	-1.46323	6.996271	2.727888	6.883915	2.283244
-3.39779	-0.74483	7.108706	3.22312	3.262235	1.919853	-9.13036	-2.55699
-0.03863	0.015423	0.922496	0.096852	-6.53482	-2.51138	-1.77162	-0.95603
11.6109	3.42085	21.06602	7.309963	3.319916	0.431343	14.14451	4.419466
-6.52852	-1.85005	-9.53237	-2.56352	-9.54418	-2.99622	0.177407	1.260389
-3.23815	-0.83493	-7.42847	-1.86077	-2.47223	0.116618	-2.68392	-0.13677
-12.5619	-4.111	-15.6749	-5.42144	-12.2317	-4.55979	-4.46304	-1.60425
15.72315	5.232023	13.65969	3.967946	6.405461	1.594128	5.100866	1.497337
-5.08162	-1.61315	-8.27296	-2.58872	-7.85097	-2.64122	-3.27283	-1.21611
7.921408	2.121417	0.557443	-0.53153	-4.90479	-1.52243	7.089339	2.031256
-18.9047	-5.94305	-15.2308	-4.46165	-12.4025	-3.77587	-7.15111	-2.00842

-2.62951	-1.3027	-16.8895	-6.33643	-8.24375	-2.26853	-1.83164	-0.71697
-2.18084	-0.33091	-0.45659	0.755944	-3.00689	-0.79175	0.900277	0.576584
14.70673	4.862971	23.01525	7.431388	11.86754	3.904135	16.31188	4.400458
6.490852	2.652364	10.22643	4.232497	9.259786	3.509309	0.623861	0.187216
-9.655	-3.10822	-4.67888	-1.76976	-8.29343	-2.22946	-14.0804	-4.54246
-1.284	0.145204	0.304916	0.453112	1.177594	0.523622	-7.96435	-2.6049
2.684306	0.836023	12.49827	3.8725	-0.92731	-0.72415	1.864118	0.347036
16.41589	4.109255	9.227272	2.612992	25.05302	8.152281	15.8596	4.868219
-3.48487	-1.3303	-0.351	-0.40074	2.040873	0.184355	0.834838	0.00695
-11.0843	-4.05138	-4.78374	-1.45692	-11.1137	-3.24637	-14.5076	-4.14603
16.37554	5.124324	6.514489	1.54257	17.21028	5.555158	5.056463	1.095004
-5.5328	-1.37024	-5.52544	-1.74754	-20.8419	-6.59558	-4.17105	-1.00311
2.640858	0.538533	-4.37263	-1.72318	-0.64824	-0.61757	-3.82025	-1.76262
-2.56659	-1.51874	-3.09914	-1.47813	0.061291	0.422729	0.988011	0.162822
0.017194	-0.27337	4.146552	1.039819	-5.89391	-1.99117	1.053204	0.172483
-14.0795	-4.3204	-5.19357	-1.14022	-15.8501	-4.66571	-27.2747	-9.12134
-4.93143	-0.21262	-9.69425	-3.01428	-6.7746	-1.65443	-3.44527	-0.44125
13.75445	5.05597	2.015432	0.228704	4.316532	1.576482	11.46477	3.784838
-5.25605	-2.35841	5.403635	2.022338	-7.56082	-2.63137	5.051207	1.72329
12.59023	4.476584	5.216809	0.934789	15.32179	4.515697	4.836955	0.635223
-13.6884	-4.12039	-14.5766	-4.04083	-16.3609	-4.87597	-21.2948	-6.48845
-5.93701	-1.92934	-0.17284	-0.32616	-4.21347	-1.58921	-0.84345	-0.10793
-13.1029	-4.11955	-20.1778	-6.26183	-21.6163	-7.41479	-5.9676	-1.44431

REPLICATE 86		**REPLICATE 87**		**REPLICATE 88**		**REPLICATE 89**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
11.16787	4.468004	8.771911	2.585201	12.321	5.121968	2.581621	0.677268
-5.77099	-2.22191	0.629973	0.243057	-3.38065	-1.52142	-2.01345	-1.06532
-3.88572	-1.14198	1.384957	0.530909	4.076347	1.386014	-4.00789	-1.59076
-2.46244	-0.82744	-4.8974	-1.33965	-10.9267	-4.2016	6.537916	1.912236
4.714385	1.366438	7.826759	2.444901	9.523884	2.95924	16.7699	5.835315
-15.7533	-5.09801	-4.34375	-0.85511	-16.3874	-4.99987	-5.67301	-1.80668
3.143727	0.489655	1.165347	0.457034	-9.8687	-3.82681	5.736718	2.056483
4.251132	2.582599	4.879459	2.716704	-9.63135	-2.78649	-1.03069	0.274711
0.357154	0.142925	-3.42277	-1.20833	12.79844	4.663449	-1.89193	-0.45377
20.85069	7.023753	2.954455	0.642311	9.660784	2.694425	11.00092	3.317027
-10.2944	-3.26394	-18.8775	-6.36678	-11.0347	-3.48393	-18.8803	-6.42149
1.884916	0.681038	-4.57958	-1.17563	-0.31466	0.749821	2.657197	2.00978
-2.27535	-1.22771	-19.1852	-7.09093	-0.72841	-0.27405	-12.9828	-4.70011

13.58082	4.224205	5.194594	1.198755	6.204285	1.901599	11.27365	3.386128
-2.97042	-1.42455	-4.44988	-1.29367	-1.38135	-0.51887	-5.91621	-2.3526
-1.00378	-0.41359	2.972799	0.545847	0.566837	-0.0191	-5.99953	-2.84153
-20.0267	-6.42343	-15.1803	-5.14846	-16.3873	-4.94719	-24.3698	-8.48438
-2.42969	-0.91869	0.503249	0.122682	3.244954	0.076652	-16.1303	-5.83428
-7.57262	-2.00558	-15.914	-6.0571	-0.07925	0.510876	-7.24423	-2.87922
23.48263	7.420653	26.1591	8.096167	21.98806	7.033595	25.54203	8.545067
4.597246	1.749804	6.166172	2.292279	-3.36864	-1.31725	4.433958	1.266551
-10.4633	-3.06995	-4.39171	-0.59811	-5.69329	-1.19413	-9.32004	-2.59322
0.300945	0.86346	-4.20729	-1.45063	-16.5756	-5.61593	-12.6824	-4.20414
-0.85595	-0.36768	2.349299	0.227359	5.104275	1.531624	12.39779	3.985408
15.76526	4.817636	17.50631	4.9613	16.83766	5.518399	16.59205	5.604406
11.42263	4.43148	2.85876	0.4928	9.724607	3.313621	10.90179	3.727805
-11.2696	-3.80915	0.22974	0.230406	-6.37745	-2.20894	-10.1065	-2.95933
1.954178	0.287647	13.82452	4.754251	6.129937	1.634279	11.90285	3.79482
-16.1883	-4.59179	-13.2242	-3.9822	-12.6106	-3.60964	-13.2099	-4.21619
14.54999	4.775297	5.883779	1.621038	8.446508	2.889467	6.883867	1.993348
4.318532	1.655376	-4.79424	-2.05307	-12.5732	-4.74509	-12.4742	-5.24957
0.278573	-0.06754	5.387132	1.724052	-0.40679	-0.01952	0.683802	-0.25144
-16.2939	-4.81271	-17.6261	-5.60855	-16.1768	-5.19249	-28.9706	-9.73274
-15.0902	-4.6719	-8.75677	-2.61182	6.282942	2.715144	-0.12887	0.451218
1.21176	0.189415	-5.40085	-2.06356	9.327818	3.132894	-5.01923	-1.61129
-7.80302	-2.78637	-10.327	-3.72244	-18.4591	-6.23356	-14.6764	-5.10309
11.54179	3.334243	11.99669	4.070028	2.613655	0.297292	2.041896	0.303788
-15.6762	-4.44598	-13.2551	-3.7986	-17.0003	-4.4385	-7.80949	-1.95176
-5.62505	-2.42425	6.128088	1.996872	0.679708	0.060695	1.306488	0.453023
-7.86131	-1.94799	-4.1886	-0.61701	-11.632	-3.17109	-3.38782	-0.48358

REPLICATE 90		**REPLICATE 91**		**REPLICATE 92**		**REPLICATE 93**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
18.69218	6.532418	-0.0905	-0.27592	9.974592	3.498247	4.704661	1.770425
8.359056	2.928051	-8.76175	-3.75585	-10.9674	-3.69582	-3.37292	-0.60816
-7.07671	-2.24403	3.495992	1.139868	2.799714	0.971949	-11.6646	-4.90976
-15.9782	-5.73628	-8.11078	-2.75885	-1.64734	-0.59806	-7.11671	-1.96715
9.635637	2.934673	14.87568	4.829006	4.473618	0.6445	5.566695	1.51464
-22.7431	-7.28865	-15.107	-4.60544	-10.321	-2.90449	-13.0647	-3.69632
-6.18538	-2.27998	-11.7939	-4.87947	-10.4075	-3.88017	-5.18196	-1.8676
0.816657	0.366908	-4.99551	-1.18987	3.552358	1.45968	10.34459	4.662567
5.568189	1.7859	-2.2039	-0.7863	3.742519	1.396817	4.53636	2.04837

5.765799	2.014869	16.75283	5.351422	16.85972	5.365047	11.21849	3.183858
-6.87199	-1.80445	-0.9872	0.005898	-13.4015	-3.9378	-21.4267	-7.01641
-8.43775	-2.48163	-4.11596	-0.45811	-13.5016	-4.05551	-6.56385	-1.79183
-9.16202	-3.33466	-3.66195	-0.84012	-19.1372	-6.06055	-5.09394	-1.30703
13.03527	3.921176	21.95134	6.64994	0.926421	-0.39408	5.719609	0.667965
-6.23043	-1.71693	-6.15247	-1.82038	-1.05826	-0.43478	-9.40305	-3.13598
1.29967	-0.0423	-5.0001	-2.36501	5.342996	0.796423	2.861435	0.649487
-18.1355	-6.65153	-19.8254	-5.70757	-15.8154	-4.7055	-6.346	-2.14134
2.403134	1.125591	-17.9023	-6.26677	-3.95754	-1.88761	2.217401	0.584388
-4.4721	-1.05989	-5.65887	-1.37897	-0.27166	-0.10503	-1.72782	-0.03826
18.60736	5.259088	19.57759	5.679458	21.73227	6.7119	22.86914	7.065179
5.896566	2.018054	5.639875	2.115428	5.839401	2.370523	7.184602	2.640196
-3.52912	-0.48935	-15.1342	-4.16226	-4.15117	-0.98909	-5.74412	-1.45847
-2.98772	-0.22801	0.015923	0.518883	-1.45249	-0.35014	-0.73702	-0.30121
11.90665	3.753513	8.780152	2.715366	3.606215	1.332478	-7.58062	-3.19343
12.37473	3.57969	19.89507	6.142353	18.55903	5.437173	14.55547	4.181273
-0.91599	-0.5976	1.685436	1.20166	15.65668	5.720931	12.67778	4.571322
-8.63365	-2.53503	-10.2151	-2.82541	-15.0505	-5.10526	0.017056	0.492532
18.92216	6.441302	7.531576	1.984571	13.94776	4.235834	4.074409	0.641722
-13.4529	-4.4127	-23.4004	-8.01677	-15.277	-4.32174	-11.0422	-2.90437
-4.47892	-1.79083	8.9203	3.389862	6.517832	1.756196	3.894626	1.309237
-3.6806	-1.54577	0.078934	-0.2631	5.471477	1.401472	-11.7157	-4.50384
2.49523	-0.12076	5.411828	1.730167	5.076239	1.535014	6.409983	2.75233
-20.8343	-7.24226	-16.7586	-4.85091	-11.3805	-3.70439	-12.365	-3.77822
-5.01662	-0.85829	-10.2882	-2.50732	0.953141	0.726376	-15.305	-5.04094
1.06534	-0.15445	-4.25004	-1.6205	3.953939	1.739134	9.855976	3.327392
-2.20654	-0.71752	-5.32018	-1.5549	4.512578	1.518862	14.72544	6.091339
1.068326	-0.46515	11.9801	4.157466	8.062359	2.412889	3.324657	0.726292
-11.1325	-3.36426	-22.4814	-7.13846	-7.99915	-2.20739	-8.84529	-2.34602
-6.16153	-2.39808	-1.63678	-1.09619	0.034042	-0.04071	3.604376	1.227279
-12.4224	-3.92204	-7.87995	-2.28181	-18.345	-5.73389	-18.1506	-5.38609

REPLICATE 94		**REPLICATE 95**		**REPLICATE 96**		**REPLICATE 97**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
13.35779	5.047265	13.18428	4.522708	5.75494	2.161484	4.498041	1.881664
-1.70692	-1.04168	-5.72829	-2.12114	-0.64683	-0.22095	-4.93902	-1.03019
1.455758	0.576547	-8.70982	-3.09824	-10.0268	-3.29891	-0.8403	-0.36422
-7.20231	-2.53625	-4.50255	-1.66798	-4.65007	-1.72719	4.779359	2.052031
10.05594	3.755507	14.28653	5.16678	4.858778	1.282138	8.328795	2.791231

-17.1764	-4.98925	-9.09629	-2.04259	-3.85007	-0.66502	-9.18931	-2.4852
10.56109	4.038505	-2.82464	-1.71695	-12.0083	-4.72871	1.274224	0.297441
-1.41527	-0.54586	-6.92291	-1.95047	11.64631	4.607992	0.85718	0.142344
-13.5423	-4.51132	-4.68575	-1.2406	1.74283	0.777276	3.004436	1.071302
18.08011	5.967045	0.175196	-0.58341	16.67974	5.039793	6.607738	1.772362
-4.7433	-1.32221	-10.0809	-2.89796	-6.68066	-2.2341	-22.2771	-7.62276
-5.15231	-0.71433	-6.00617	-1.23664	-11.4714	-2.82484	-9.69726	-2.79144
-12.9828	-4.49062	-6.0105	-1.89201	-9.41553	-3.31239	-1.45672	-0.4818
12.39004	4.012524	5.469914	1.341875	6.587804	1.664367	9.54955	2.936848
-2.39413	0.171301	-2.25831	-0.56328	-4.08107	-1.85884	-5.47727	-2.01515
4.798644	1.249322	3.626471	0.712997	12.59329	3.505889	8.593549	2.563502
-21.3985	-7.10439	-19.6405	-6.15746	-17.9762	-6.75337	-25.6423	-8.85325
-22.9716	-8.17124	-15.7507	-5.27569	-19.8932	-7.15106	-2.78017	-0.86651
-10.5714	-3.51999	-8.46155	-3.0027	-7.22602	-2.67655	-8.65251	-2.20338
20.45804	6.405835	20.20157	6.099062	20.75364	6.638732	16.59911	4.789611
-1.92204	-0.44519	10.63543	3.329828	-3.89835	-1.05331	4.947991	2.119378
-13.8735	-4.53029	-5.31723	-1.59689	8.532327	3.672168	-9.43069	-2.95071
-10.1986	-3.70845	-1.05556	0.083473	-1.71792	-0.76407	-3.67883	-0.88646
6.645887	2.009656	8.777152	2.66188	1.415574	0.403069	11.81062	3.855534
23.60033	6.931858	17.20672	5.560451	17.30302	5.402721	24.11936	8.110536
10.6162	3.414256	9.119893	2.512139	1.938096	0.582103	8.608158	2.931124
-3.22997	-0.44835	-14.9707	-5.23083	-4.88997	-1.32776	-20.4322	-6.75672
13.76471	4.241999	9.538877	2.71216	9.828021	2.478415	3.750714	0.299955
-2.34973	0.219664	-6.50576	-1.79524	-12.5341	-4.133	-11.1749	-2.96552
9.107385	2.940161	0.325344	-0.21019	7.227728	2.322912	-4.83496	-1.60474
-1.62216	-0.53988	-5.22502	-1.99117	1.686064	0.616949	-7.11436	-2.48782
5.818152	1.907694	5.519222	2.347671	-3.88732	-1.6729	-1.38982	-0.93622
-20.2469	-6.09959	-14.5136	-4.92778	-16.9261	-5.16842	-17.8683	-5.31102
-7.84835	-2.19959	-6.73104	-1.97233	-5.76692	-1.00595	-12.2916	-4.05158
-2.53821	-1.32669	-0.7811	-0.19306	0.776633	0.167129	1.256997	0.727286
-7.1766	-1.79872	-0.90426	-0.22197	-10.101	-3.37996	1.583581	0.612071
3.166556	0.60613	4.550745	0.913994	5.18144	1.061766	8.57334	2.905248
-22.6384	-7.21849	-15.5259	-4.34397	-9.67564	-2.87408	-25.5242	-8.13643
-0.02832	-0.71456	-9.60846	-3.91163	1.302201	-0.01033	-0.02499	-0.05701
-10.5481	-3.36322	-0.99579	0.659992	-6.09119	-1.39371	-11.8246	-3.45586

REPLICATE 98		**REPLICATE 99**		**REPLICATE 100**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
7.583056	2.640851	9.225235	3.289206	11.07539	4.164744

2.338435	0.275764	-7.01673	-2.4117	-2.71951	-0.91798
-9.91286	-2.78017	-2.60773	-1.37257	-6.20456	-1.81499
-0.15495	-0.42825	-2.56089	-0.48178	-3.35573	-0.54965
5.086212	1.744543	12.45826	4.273499	4.946542	2.117436
-18.5266	-6.05339	-19.2982	-5.55415	-13.6141	-3.61007
2.198996	0.19236	3.094725	1.473997	6.065406	1.884207
2.544395	1.562363	1.569921	1.444644	-2.2827	-0.06768
-1.12847	-0.76426	-4.74137	-1.55111	-0.62084	0.209349
4.841335	1.069916	13.12355	3.780476	4.383892	0.997954
-5.78983	-1.58213	-12.9348	-3.954	-19.9593	-7.49653
-12.0861	-3.19004	1.868865	1.534374	-9.69522	-2.39217
2.732225	1.661878	-6.77015	-2.20538	-5.88052	-1.80244
17.12625	5.567005	24.78927	7.538151	9.13214	2.967916
3.344939	1.251367	-0.90671	-0.19208	-1.43093	-0.39706
0.938026	-0.23345	5.266824	1.257933	8.962448	2.344949
-16.4678	-4.95764	-17.2809	-5.31031	-20.0035	-6.59578
-4.20875	-1.69976	0.145508	-0.54169	-3.04855	-1.18172
-13.369	-3.98499	-1.49352	-0.06347	-16.8554	-5.29192
16.01902	4.554058	17.26316	5.273515	12.35098	2.881958
-0.61601	0.099438	2.851512	1.140851	3.784357	1.228484
-2.5999	-0.47487	-11.7849	-3.57415	1.161501	1.089639
-10.449	-3.39075	-4.78818	-1.60545	0.070999	0.008022
14.99987	5.029518	1.603	0.519175	6.234693	1.974814
9.64444	2.685562	23.51194	7.573156	15.47408	4.756368
3.797612	1.054789	8.294179	2.636871	7.367059	2.612903
-10.1919	-3.31638	-13.9434	-4.64177	1.51944	0.855156
10.20752	2.75021	12.97734	3.702813	12.00083	4.053366
-13.5801	-4.26369	-4.90335	-0.6993	-13.4228	-3.77871
5.440989	1.644074	10.56058	3.39022	4.711764	1.19042
5.067444	1.2364	5.824399	1.92292	0.366639	-0.38585
2.627522	1.191364	-4.54763	-1.914	8.761024	2.494863
-19.2711	-6.34747	-17.9384	-5.75166	-10.2354	-3.32806
-8.54048	-2.47982	-8.46377	-2.60889	-3.17702	-0.14701
16.68013	5.992292	0.665253	0.089965	-0.99573	-0.60449
-4.53095	-1.32533	-0.34019	0.349247	-13.6354	-4.88788
-2.33101	-1.41967	9.403424	3.182937	16.98655	5.241749
-27.3127	-8.7567	-23.4798	-7.84745	-17.7035	-5.8363
15.59454	5.747979	-7.29498	-2.8377	-4.85847	-1.36577
-13.6633	-4.358	1.197721	1.442007	-15.3106	-4.61058

RUN 1 SAMPLE SIZE 60.

REPLICATE 1

y_{1t}	y_{2t}	X_{1t}	X_{2t}	X_{3t}
8.918032	3.684851	-1.09397	1.255616	1.173238
0.40755	0.652599	0.367081	-0.03648	0.192496
-3.92369	-1.1005	0.145398	-0.74768	-0.66894
4.580231	1.256275	0.265778	1.534772	0.589651
9.892559	2.935698	0.479409	1.252978	1.0632
-1.95767	-0.30343	-1.23364	1.081464	1.764816
-0.76046	-0.7882	0.301434	-0.87427	-0.04879
-13.2471	-3.6207	-1.54591	0.323186	0.511329
7.232502	2.51842	0.138909	0.640722	-0.27194
4.236525	0.632137	1.133268	0.104382	0.152416
-14.7093	-5.02556	-0.65837	-1.35853	-0.72699
-16.8336	-4.95905	-1.7005	-0.29497	0.221339
-13.5248	-4.87013	-0.19127	-1.68437	-1.30729
10.47432	3.130434	1.272184	0.874658	0.407902
-7.92125	-2.56145	0.054985	-0.22197	-0.77628
12.87208	3.523802	1.000267	0.012484	0.072621
-10.3549	-3.43504	-0.80293	-0.33318	-1.69196
-10.8652	-3.91985	0.162158	-0.5509	-0.74294
1.768765	0.763536	-0.62861	-0.21509	-0.17623
10.50633	2.582483	1.62335	-0.8536	0.076326
4.692835	1.742586	-0.59203	1.983905	1.368182
-12.5334	-3.51425	-1.18496	-0.8525	-0.64471
-3.88142	-1.26102	-0.23277	-0.57332	-0.26259
-12.6427	-4.85504	0.588642	-0.75509	-0.44498
13.51391	4.323767	1.134421	0.284272	0.33969
-0.54985	-0.05898	-0.09755	-1.4369	-1.25328
2.283489	1.41193	-0.19762	0.14282	1.40707
19.5134	6.151853	1.250681	0.568853	1.468855
-7.4471	-2.05399	-1.57122	-0.66067	0.299413
-6.41969	-2.29336	0.4564	-0.79597	0.443103
10.50033	3.333839	0.568878	-0.05725	-0.50937
-0.96041	-0.79888	0.521725	0.314656	-0.01108
6.431214	2.822279	-0.7314	-0.88687	-0.56489
-13.1102	-4.53773	-1.29195	1.144658	0.149272
-2.79419	-1.3989	0.240014	0.548267	0.679098
-16.9585	-6.04462	-0.37619	-0.35068	-1.58548

5.283818	1.544	0.867518	-0.32262	-0.44208
-14.8373	-4.20694	-1.26779	-0.58522	-1.23658
2.782725	0.641687	0.195217	0.960135	-0.35398
10.22857	3.831753	-1.23091	1.897852	2.090788
21.95053	6.361248	1.953314	0.761421	-0.22217
-3.92535	-1.35579	-0.78496	0.366795	1.11173
-6.7081	-2.18109	-0.64004	-0.29675	-0.13413
-16.6599	-5.50454	-0.97403	-2.52876	-2.59179
10.15384	3.350349	0.708247	1.161218	0.37973
2.651988	1.364922	-0.3282	0.392458	0.897424
-19.8493	-6.81286	-0.30669	-0.82988	-1.4037
11.87683	3.459986	1.85042	0.348661	-0.14043
-2.78745	-0.93119	0.207854	-0.34239	0.134127
14.56903	4.893643	0.82495	1.097196	1.268851
-7.3937	-2.1302	-1.33585	0.230288	0.579317
6.025815	1.464851	0.902369	0.333258	0.193195
-15.2941	-5.20083	-0.62638	-0.93421	-1.35988
-11.9925	-4.17097	-0.11849	-1.23157	-1.95063
-1.77679	-0.62445	-1.12118	0.364075	0.736329
-3.01206	-0.32556	-0.75355	0.034397	0.095779
-17.7952	-5.74333	-1.78751	1.148329	0.840432
-12.7256	-4.0082	-0.94706	-2.48451	-2.36705
-5.2413	-1.79117	-0.55226	-0.02603	0.444769
2.862701	1.45281	0.327558	1.027119	-0.27866

REPLICATE 2		**REPLICATE 3**		**REPLICATE 4**		**REPLICATE 5**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-14.4437	-4.01151	-15.4459	-4.87187	-0.10035	0.114031	6.497322	3.219051
15.1431	5.13185	-1.32472	-0.58365	8.463086	2.961466	-6.24379	-2.22235
2.450929	1.161904	4.206258	1.103128	1.530331	0.711439	-8.98053	-3.48212
6.285406	2.105239	7.254956	1.804363	11.66228	3.522376	11.75056	3.977036
10.81886	3.295334	4.674256	0.753304	4.935479	1.416576	2.337094	0.523153
1.296955	1.019983	3.477075	1.324643	-4.15654	-1.19645	-4.72405	-1.33226
-2.58648	-0.69438	-3.65288	-1.75159	7.288669	2.385286	-7.78006	-2.98712
-8.95401	-2.76487	-6.90276	-1.25255	-0.84964	0.346521	-8.3046	-1.81243
2.770459	1.036589	9.275014	3.757553	2.988803	0.534987	-8.03767	-3.17876
1.035406	-0.69019	17.12354	5.351268	7.283427	2.466291	6.833689	2.445204
-6.59826	-1.85655	-16.7581	-5.61519	-2.82798	-0.94477	-7.9583	-2.36044
-9.08945	-2.87288	0.363831	0.668156	-9.53077	-2.44305	-10.9163	-2.2272

-17.6052	-5.71595	-9.33513	-3.34125	-2.01843	-0.52137	-8.72767	-2.93049
7.673323	2.304418	6.611211	1.545228	1.336969	0.046113	6.752842	2.043538
-8.03872	-2.46599	-21.7107	-8.05696	-9.38634	-3.17157	-8.12487	-2.52035
-0.34463	-0.62436	0.337251	-0.69603	18.585	5.898355	11.29964	3.611337
-14.8984	-4.9225	-14.3435	-4.78679	-13.6508	-4.6568	-13.1254	-4.28875
-2.1031	-0.71207	-14.554	-5.15238	-13.1241	-4.54311	-8.23812	-2.8479
-4.38477	-1.43041	-5.29128	-1.81989	-1.47487	-0.13353	-2.21869	-0.43689
24.05308	7.629715	11.5841	3.231708	10.74368	2.854859	13.89275	4.458158
2.590226	1.083058	3.071144	1.116499	11.65675	3.829205	6.442176	2.269617
-11.9299	-3.42551	-9.07311	-2.15427	-5.79652	-0.90582	-5.44311	-1.98594
-6.72576	-2.40047	0.14478	-0.15837	-9.52585	-3.58199	-9.94512	-3.05275
-6.77885	-2.49747	1.430075	0.340698	-7.76577	-2.44107	6.347629	1.825347
10.71882	3.371666	12.18234	3.95328	11.8018	3.71788	10.91911	3.30519
-3.36516	-1.40974	-17.1401	-6.09608	-4.20445	-1.36007	-6.04846	-2.06732
7.586316	2.922374	9.028589	2.976336	2.01123	0.963909	-0.32111	-0.3274
19.45548	5.986372	13.31235	3.96489	20.65621	6.49674	13.18074	3.798867
-10.6533	-3.33352	-14.8441	-4.54956	-18.978	-6.20948	-12.081	-3.41207
6.997313	2.334073	7.306323	2.027873	12.39245	3.929875	4.228787	1.198651
-1.8104	-1.12731	-3.84582	-1.77289	-6.5583	-2.69452	3.982391	1.073241
11.66622	3.849403	6.13467	2.282945	7.246048	2.474738	3.157108	1.112478
-15.5843	-5.24712	-3.24342	-0.94616	-5.67796	-2.16095	-6.39723	-1.68439
-1.28491	0.024416	-18.9982	-5.92637	-7.86133	-2.83131	-8.68715	-2.50619
7.939404	2.876451	-3.90306	-1.60263	9.227822	3.081748	-1.79896	-0.88232
-17.3429	-6.43919	-19.0414	-6.76462	-15.6962	-5.474	-3.89724	-1.06252
11.54761	3.726729	-8.83116	-3.25344	-8.24265	-3.33616	16.18497	6.09208
-15.3967	-4.49709	-24.974	-7.35725	-10.4429	-2.77815	-22.7961	-7.54656
9.721129	3.070299	0.15336	0.484306	10.83597	3.846219	7.613959	2.555573
2.375997	1.536881	-3.56087	-1.0857	7.655995	3.652986	2.371838	1.65685
15.0738	4.319294	7.025954	1.553898	26.68463	8.977494	20.92123	6.381807
1.168345	0.654473	-6.43046	-2.22691	-2.72345	-0.3774	1.816283	0.800733
-13.5978	-4.19071	5.396739	1.991241	0.140637	0.055075	-6.14905	-1.53535
-20.5085	-6.9027	-24.1178	-7.46266	-20.1215	-5.94615	-25.6262	-7.92001
10.16447	3.348171	8.857835	3.028046	-0.14463	-0.18293	11.42979	3.309684
-5.54283	-1.32206	-5.98553	-2.34943	-2.76298	-1.10569	13.39174	4.3502
-12.1331	-4.125	1.699234	0.456319	-7.28266	-2.08075	-11.0119	-3.43032
9.149442	2.214692	15.79537	4.869048	3.947657	0.301017	16.37481	5.326219
1.349896	-0.18985	2.602873	0.76115	4.766033	1.764291	11.29812	4.493148
11.10726	3.76318	13.27721	5.016133	11.91717	3.216632	2.787217	0.410141
-1.04609	0.23401	-5.27032	-1.69814	-16.0878	-4.96221	-0.13349	0.657951

1.597597	0.471135	13.48733	3.993531	10.90239	3.410689	12.65271	4.085004
-11.4543	-3.47806	-8.1804	-2.35291	-16.0683	-5.25617	-14.5392	-5.05664
-8.01996	-2.37007	-19.4287	-6.5507	-8.70442	-2.56074	-12.4766	-4.09557
-1.00474	0.226246	-0.55791	-0.09299	-1.07186	0.140587	-1.98441	-0.48804
-7.741	-1.90344	-12.6297	-4.05136	-6.69691	-2.64582	-4.63893	-1.45993
-8.27071	-1.85907	-2.55618	-0.15848	-11.769	-2.99893	-13.6635	-4.18982
-24.3996	-7.67846	-29.7706	-9.61616	-20.3146	-6.91988	-25.7492	-8.35953
1.45029	0.840833	11.84508	4.333798	-4.73739	-1.5942	-5.35321	-1.66835
10.12902	3.550956	5.472414	1.975492	-2.72144	-1.36185	-0.72696	-1.31378

REPLICATE 6		**REPLICATE 7**		**REPLICATE 8**		**REPLICATE 9**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
8.009973	2.748167	-5.55087	-1.60267	-2.88809	-0.97798	-3.23585	-1.07713
18.22326	6.202357	9.31708	2.626691	-3.91908	-1.6207	5.665601	1.512063
-1.00918	-0.00773	4.034995	1.560881	6.154844	2.668314	9.2493	3.489838
10.97851	3.702398	16.10373	5.608096	2.206845	0.399844	8.720065	3.251614
16.49633	5.706903	13.46523	4.124446	-5.21672	-2.02077	8.137882	1.878678
-3.90035	-1.22995	3.547225	1.551191	-14.3403	-4.15424	-2.82535	-0.38009
2.750838	1.221896	-3.56718	-1.06765	-2.06007	-0.88499	3.975141	1.214604
-12.029	-3.6688	-1.55094	0.21795	-6.78013	-1.43748	-0.87779	0.702652
-4.8754	-1.72395	-6.65442	-2.30435	-3.43031	-1.25163	-5.09848	-2.05736
6.330157	1.759281	7.323944	2.38638	7.056869	1.39854	6.497749	1.256859
-10.7618	-3.74671	-14.1114	-5.04567	-9.17443	-3.11098	-9.4111	-2.92189
-17.865	-5.18672	-3.34977	0.143865	-9.70359	-2.7465	-11.2931	-3.30058
-5.23577	-1.73004	-8.94539	-2.50341	-15.4256	-5.35708	-18.5757	-5.61096
11.41516	3.030891	16.05766	5.69344	15.19716	4.905582	17.13881	5.524408
-8.30582	-2.59487	-5.06039	-1.44439	-7.07803	-2.99004	-6.91723	-2.2428
13.9412	4.623398	-1.86931	-1.15115	11.28068	3.234888	5.652813	2.231952
-23.0069	-7.38064	-16.9229	-5.63996	-19.5719	-6.23472	-17.0751	-5.48947
-0.8374	-0.02559	1.74948	1.183062	-7.28031	-3.03368	-3.62867	-1.31955
-7.75348	-2.54271	-0.03774	0.05002	-2.20238	-0.74801	-9.09415	-2.85687
10.8879	3.080268	16.75971	5.029396	4.639155	0.961858	6.002469	1.205828
12.01653	4.488488	5.292734	2.198737	3.596092	2.101159	1.194932	0.784626
-21.2526	-7.08892	0.137798	0.895404	-18.683	-6.24022	-13.7918	-4.14297
-11.6431	-4.16212	-1.04589	0.099834	-1.74726	-0.4797	10.23028	3.631766
5.017865	1.043102	4.215463	1.560914	-3.24165	-0.91484	4.846976	1.137709
16.00488	5.107912	6.75811	2.031612	6.696994	1.882768	9.301502	2.666255
-10.208	-3.85551	-13.9786	-5.05939	-9.18086	-3.22852	-11.8346	-4.35455
9.617783	3.590245	10.4761	3.864957	7.145014	2.186741	5.628634	2.230734

14.11137	3.96513	10.64084	2.6746	13.20333	3.71915	6.648046	1.812101
-9.81931	-2.74667	-10.2577	-2.52383	-12.0719	-3.68789	-17.1311	-5.21213
-1.00229	-0.75717	3.195964	0.528434	1.001276	-0.32806	-11.5077	-4.6432
6.649818	1.40709	-2.89037	-2.03652	4.915149	1.525541	7.080334	2.226496
9.627172	2.604173	3.214701	0.979893	4.733432	1.801322	-2.01516	-0.52887
-7.41444	-2.21002	-12.556	-4.51358	-12.7116	-3.89374	-16.9825	-5.49296
0.49786	1.192606	-22.3207	-7.91945	-13.1652	-3.80506	-18.0254	-5.91405
12.61234	3.903295	8.346226	2.488464	9.590906	3.034441	1.635574	0.189611
-12.6065	-3.99726	-24.41	-8.36294	-6.89407	-2.43634	-12.4938	-4.24676
17.75711	6.259223	8.720345	2.427102	-1.85527	-0.95094	1.732502	0.267191
-12.5433	-4.01583	-9.5232	-2.76525	-6.24785	-1.40071	-15.5445	-4.45343
1.080677	0.464189	0.033007	-0.55932	0.736551	0.375487	4.105294	1.211393
-6.34857	-2.06274	9.605748	3.778939	11.34092	4.917994	5.787456	2.439992
22.11274	6.872033	19.05159	5.539185	6.800378	1.707385	24.59258	7.37811
-2.41351	-0.73689	0.466902	0.626159	4.305075	1.686199	-10.8352	-3.84391
2.67724	1.058722	6.504171	2.585655	-14.7399	-4.83625	-2.73887	-0.52943
-22.2441	-7.22362	-7.19841	-1.80366	-14.3925	-4.92419	-31.9964	-10.3592
8.051712	2.508879	11.82712	4.044107	2.44637	0.729716	11.05492	3.312918
13.08536	4.40826	1.166399	0.374281	-2.32675	-0.82376	2.070014	0.571263
-13.8181	-4.54517	-17.6669	-6.1035	-3.92887	-1.51314	-6.67083	-2.17262
15.17257	4.408964	7.765188	1.858446	19.99683	6.525444	13.93973	4.118396
4.285915	1.275411	-3.35038	-0.99672	-4.95475	-1.94978	-0.12226	-0.01631
19.84339	6.59106	12.91305	3.974504	12.80444	3.636044	14.72387	4.896737
-10.1795	-3.07849	-9.64787	-3.39175	-12.0217	-3.38987	-9.13658	-2.1905
13.62091	4.663572	1.722018	0.775209	-5.07222	-1.77592	8.560854	2.340876
-22.5761	-7.58361	-7.47098	-1.86525	-9.51307	-2.56218	-13.8414	-4.62486
-8.68203	-2.93358	-4.8477	-1.26143	-6.8605	-2.3753	-10.9277	-3.75077
-9.87696	-3.27438	-1.79223	-0.08867	-8.34762	-2.47956	-2.73177	-0.56864
-16.1801	-5.56183	-12.7003	-3.72742	8.384391	3.906434	4.80295	2.305789
-14.2422	-3.92254	-11.0305	-2.73659	-17.4846	-5.64058	-5.8982	-1.17124
-13.7733	-3.66786	-22.0965	-6.71692	-13.0715	-3.73442	-20.2299	-6.36278
-6.1118	-2.2969	2.731002	1.224674	-11.9346	-4.06245	-10.7496	-3.51284
3.991754	1.159808	5.216761	1.654254	6.342322	2.42734	7.348649	2.499719

REPLICATE 10		**REPLICATE 11**		**REPLICATE 12**		**REPLICATE 13**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-1.39213	0.005539	4.022229	1.912797	0.202723	1.215077	8.146152	3.237478
3.036842	-0.02461	6.169309	1.889961	4.838212	1.506757	6.183735	1.555815
-3.48549	-1.24833	-9.0403	-3.15656	-8.8377	-3.12296	-17.1043	-6.20022
13.70214	4.765554	8.051634	2.779395	-0.13459	-0.9496	8.826023	2.109822

5.396673	0.942935	8.747341	2.588645	11.59351	3.498366	3.041683	0.84452
-0.48927	0.279153	5.531447	2.031398	-3.76639	-1.22106	-7.07467	-1.89898
-0.03026	-0.28114	9.164249	3.575836	-10.3131	-4.29094	4.465022	1.737342
-12.9244	-4.12496	-11.673	-3.52109	-12.8734	-3.64064	0.974854	0.707311
-1.86132	-0.50927	3.838892	1.001178	1.282766	0.517685	1.366482	0.713307
16.64643	5.275511	1.59815	0.458798	14.05974	4.512018	7.810645	1.853782
-16.2083	-5.2222	-8.85711	-2.91743	-8.6056	-3.19607	-21.9771	-7.27326
-12.847	-3.77343	-2.0272	0.138361	-12.0105	-2.79894	-14.5763	-3.98289
-16.1729	-5.86791	-11.4499	-3.0904	-7.19036	-2.48238	7.870815	2.881474
11.23716	3.652294	17.46437	5.323446	4.584249	1.070946	10.59626	2.914954
1.212479	0.409609	1.627846	0.991211	-5.88963	-1.78228	-9.12701	-2.98653
13.59739	4.074601	12.23637	3.71112	10.49666	3.5813	12.36223	4.016157
-13.3583	-4.11774	-23.701	-7.27675	-16.0531	-5.88245	-9.87274	-2.83695
2.228219	0.532777	-2.07077	-0.60035	-5.81037	-2.32428	-5.09611	-2.25355
5.29697	2.022717	-11.2673	-3.91521	-6.43565	-1.86953	0.133557	0.761321
12.3696	3.877521	2.694288	0.314643	18.36518	5.685791	8.117746	1.93797
9.278959	3.229124	2.924931	0.9238	-7.99687	-2.81773	-2.07897	-0.37529
-15.8243	-5.40722	-15.8043	-5.29483	-13.8411	-4.37004	-4.3332	-0.60997
-3.82639	-0.92844	1.341769	0.387262	3.54752	1.711625	-5.03219	-1.50357
0.414436	0.083413	-0.35733	-0.28274	3.263462	1.364543	-0.91328	-0.81603
13.21487	4.567594	17.59826	5.519894	16.46631	5.101254	8.793184	2.290036
-2.01623	-0.5464	-15.5177	-5.12829	0.688954	0.525737	-6.71735	-2.79825
1.002312	0.361842	5.410678	2.275962	14.01952	5.010664	-1.57008	-0.68937
8.855795	2.152941	12.18078	2.950725	20.56142	6.926545	13.52005	4.019814
-1.80921	0.069034	-14.868	-4.51408	-15.6122	-5.1914	-18.3996	-5.56612
1.874489	0.319146	-2.15291	-1.18272	-0.33374	-0.2859	-5.91457	-1.90847
-1.4836	-1.36874	17.93513	6.193894	6.459207	2.148735	-3.13233	-1.1303
-1.24644	-0.33339	-10.0347	-4.20101	-2.40793	-0.89824	7.647146	2.398532
-10.7945	-3.61431	-3.06297	-0.91805	-7.32108	-2.0563	-12.6512	-4.67689
-7.26163	-1.91261	-15.8045	-4.91534	-6.9946	-2.26655	-5.39282	-1.2524
12.08012	3.274333	5.946835	1.76816	1.4115	0.300509	2.70823	0.381751
-13.2642	-5.14494	-10.7667	-3.40838	-11.0114	-3.38551	-16.3088	-5.85324
9.094651	2.932791	5.416853	1.404944	1.135808	-0.15962	-9.02165	-3.61542
-16.3513	-5.21812	-4.88084	-1.1895	-16.1878	-5.02375	-18.3956	-5.74204
6.615169	1.864411	3.363205	0.745909	-10.1544	-3.87844	3.39419	1.941924
9.310726	3.792027	8.300055	3.432374	2.525198	1.335795	-4.20706	-0.88975
9.402224	2.345785	13.17387	3.460387	13.5312	4.265816	3.503918	0.354953
4.252239	1.845488	-6.97284	-2.11592	5.769746	1.698621	-4.93545	-1.05144
-6.48804	-2.25388	-5.33821	-1.78578	-10.6603	-3.57124	-2.64214	-1.04973

-26.746	-8.48238	-19.8546	-6.2549	-16.5101	-5.01934	-23.8972	-7.82558
17.48354	5.519236	5.294924	0.964278	12.66384	4.138766	-0.87452	-0.76382
-4.19276	-1.50408	1.304506	0.240119	3.895726	2.089744	3.386106	1.396207
-9.7041	-3.9362	-5.73542	-1.83296	-3.28456	-1.11139	-17.5832	-5.96708
19.49024	6.24548	16.01856	4.63364	13.90864	4.33612	14.5524	4.78244
8.48593	2.736807	-3.3843	-1.12212	2.021426	0.685177	-10.7351	-3.81385
6.612459	1.896316	11.28	2.836307	18.75328	6.27595	13.83476	4.154644
0.479611	1.345793	-11.6737	-3.61275	-7.50555	-2.11147	-3.36956	-1.11397
3.082773	1.220864	5.621678	1.426102	10.63828	3.131589	11.69041	3.967323
-20.358	-6.95507	-7.85733	-2.68495	-16.7114	-5.49359	-14.9992	-5.30048
-21.9604	-7.11087	-9.71937	-2.96419	-7.21055	-2.11414	-9.30151	-3.23562
-9.83149	-3.52094	-11.7206	-3.71051	-8.83242	-2.37494	-15.622	-5.1715
-5.80847	-1.53418	3.477018	1.467274	-12.1109	-3.48688	-5.13052	-1.24625
-12.848	-3.91615	-4.1618	-1.06042	-6.20796	-1.5925	-1.32325	-0.32213
-29.3459	-9.32708	-27.1928	-8.90687	-17.6229	-5.58528	-18.7297	-5.53502
1.040753	0.445981	-4.90548	-1.51022	-9.86251	-3.07413	2.203543	1.017257
4.451845	1.476998	-1.25842	-1.05798	13.73685	4.469267	2.210712	0.520225

REPLICATE 14		**REPLICATE 15**		**REPLICATE 16**		**REPLICATE 17**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
6.091111	2.508552	-2.98204	-0.93707	3.110154	1.246178	-0.65769	0.207638
-3.79766	-1.94533	3.852862	0.365617	1.692457	0.741482	1.215405	0.655127
-12.4317	-4.65478	-4.43249	-1.68048	-6.57884	-2.47544	-0.42905	0.419587
1.220403	0.364431	2.006417	0.291562	8.000248	2.534072	8.401628	3.422744
0.344049	-0.02636	6.987049	2.156286	-0.14532	-0.54592	8.168687	2.117899
1.934229	1.041339	3.341744	1.659806	2.449639	1.370901	7.986492	3.192175
-2.15382	-1.21843	1.2589	0.491948	-9.96349	-3.53003	-0.88973	-0.72866
-15.5611	-4.92909	-8.79281	-2.57375	-2.7475	-0.28418	-10.9687	-3.00398
0.166725	-0.01611	-4.73429	-1.6557	0.707555	0.278069	3.156615	1.13784
14.76518	4.465857	6.388112	1.146849	10.77545	3.276144	6.730435	1.65495
-4.64413	-1.6457	-9.0928	-2.97492	-14.4928	-4.68023	-12.0244	-4.13529
-3.11146	-0.15409	-10.6861	-2.85469	-10.7411	-2.71927	-8.38559	-1.93398
-8.25972	-2.8878	-11.9425	-3.86539	-16.2559	-5.80473	-11.7542	-4.09299
12.09632	3.28588	0.81238	0.001988	12.3037	3.606191	12.66178	3.635392
-2.47005	-0.18155	-2.59251	-1.1604	2.087004	0.580203	-0.17416	0.609163
13.66715	4.53037	20.77421	7.177771	3.522346	0.470077	15.05807	4.997236
-19.5897	-6.23059	-5.46188	-0.96276	-11.1774	-3.11714	-8.24115	-2.24865
-5.36035	-2.02554	-14.5111	-5.34204	-0.74466	-0.02653	2.079334	1.042557
-11.1816	-3.49554	-10.5839	-3.35569	-12.7634	-3.99988	-5.65504	-1.61803
13.06782	4.260173	10.92833	3.208415	12.47975	3.486173	10.66471	2.910906

15.88618	5.964594	-1.3918	-0.30452	4.007283	1.351749	2.480274	1.005345
-12.3417	-4.20301	-12.3465	-3.84628	-7.53035	-1.66195	-10.5166	-2.50389
-7.04162	-2.55223	-3.0691	-0.66765	1.61501	1.279835	9.302448	3.462826
1.726624	0.636096	4.18751	1.330943	0.747071	0.234931	-10.3711	-3.75229
16.79123	5.544978	2.47052	0.086728	1.780197	-0.00834	9.677526	3.326601
0.543475	0.389999	4.358827	1.802617	5.258628	2.284121	-11.4286	-3.80908
0.912092	0.291056	2.95019	1.260062	1.864913	0.28787	16.22247	5.583923
17.28376	5.807274	17.1821	4.802744	20.61238	6.370184	5.991922	1.114433
-11.6595	-3.42309	-5.91357	-1.20823	-14.4255	-4.57171	-15.3628	-5.04424
-0.34769	-0.54877	4.444868	0.938844	-4.24653	-1.92443	14.19881	4.580924
0.784936	0.227897	2.125843	0.929651	5.918646	1.966847	10.83529	3.554829
9.484803	2.813453	-0.11876	0.055788	-2.56354	-0.79452	7.752388	2.627429
-6.87137	-2.15587	-4.81545	-1.24571	-19.3311	-6.46264	-4.15843	-1.24183
-0.41984	0.455729	-1.32829	-0.20177	-12.6135	-3.40218	-13.9812	-4.19558
11.39986	3.809492	3.963507	0.962405	-1.51837	-0.69181	15.31952	5.227184
-6.92401	-1.63509	-1.93887	-0.4305	-13.7863	-4.17823	-1.86393	-0.5833
-3.99098	-1.31332	4.420916	0.641621	-3.40131	-1.16036	-3.83586	-1.81033
-7.4217	-1.69356	-15.5537	-5.04852	-18.5261	-5.56404	-25.0214	-8.11714
-0.83528	-0.19186	6.647649	2.190421	-0.46686	-0.83165	2.062401	1.143396
-0.06205	0.276578	10.87421	3.892215	5.801675	2.457557	9.648501	3.770007
15.615	4.287489	-0.36617	-1.315	9.874166	2.335212	5.587167	1.386408
4.63295	1.341124	0.221552	0.618946	0.995669	0.580878	4.793234	2.433397
2.093308	1.034373	-4.54578	-1.14924	-2.14438	-0.21339	-1.63221	-0.20998
-19.2896	-6.34006	-24.9431	-7.81009	-22.7491	-7.34325	-25.6854	-8.44289
5.389822	1.931028	15.1004	5.552086	6.381013	1.204329	9.945065	3.078611
-1.07766	-0.27161	-2.90172	-0.91033	-7.13827	-1.91831	0.305353	-0.50193
-15.2856	-5.46219	-3.39094	-0.80772	-20.462	-7.06042	-11.3213	-4.19766
12.10435	3.832952	12.21496	3.10527	10.70555	2.915332	10.5298	2.802064
6.033215	1.410128	-1.1674	-1.02941	-3.91297	-0.99081	-10.9027	-3.84552
17.40092	5.552987	18.70478	5.346653	15.36102	5.289418	6.27869	1.692812
-16.9674	-5.5531	-9.31568	-2.44199	-5.88784	-1.58335	-3.25292	0.132783
10.82759	3.070986	1.215618	0.331046	15.00158	4.813262	6.186055	1.972513
-27.9074	-9.291	-20.0659	-6.67162	-3.94164	-0.93364	-20.5979	-6.63347
-11.6023	-3.60409	-10.1827	-3.01143	0.136472	0.355557	-12.4153	-4.35035
-9.15289	-2.50414	4.0832	1.823821	1.665406	1.348682	-4.78115	-1.50541
-0.96723	-0.05133	-14.1877	-4.77729	-5.8932	-1.76581	-8.21323	-2.79369
-8.373	-2.15815	-14.1303	-4.44327	-12.213	-4.22068	-1.18242	0.30048
-16.751	-5.00545	-19.4563	-6.44343	-11.9129	-3.82305	-25.4421	-8.06533
-0.24542	0.195678	-2.96581	-1.05056	2.905015	1.524006	-4.59989	-1.13754

-2.6913	-0.80343	6.262034	2.10083	10.28846	3.77474	-2.18187	-1.24286

REPLICATE 18		**REPLICATE 19**		**REPLICATE 20**		**REPLICATE 21**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
3.730626	1.558357	9.27739	3.550938	4.27536	2.200875	-5.3068	-1.63273
12.09431	4.018038	3.965611	1.196253	-1.70533	-0.51059	11.34263	3.40089
-7.844	-2.77432	-0.24548	0.053786	3.111703	0.810843	-8.1191	-3.61952
6.202469	2.081619	2.029346	0.352585	6.070832	2.365963	7.043152	1.854343
11.25556	3.838582	11.98155	3.367625	15.8363	4.986839	11.26784	3.785824
0.864857	0.524578	0.464135	0.725439	2.213251	1.395295	-4.81985	-1.2116
2.279564	0.476283	4.290909	1.053293	9.150459	3.164894	-3.32319	-0.96012
-13.1752	-4.19678	-3.82848	0.126212	-9.61861	-3.03364	-9.36007	-3.27911
-3.49545	-1.95458	3.551618	1.061933	-4.60875	-0.81801	8.944545	3.137164
11.76629	3.337939	4.943384	1.262021	10.01475	2.906543	8.011249	2.467421
-4.00142	-0.96339	-18.134	-6.07477	-7.38051	-2.67665	-4.8076	-1.20309
-17.6221	-5.25737	-4.31451	-0.3023	-15.2687	-4.61212	-10.8441	-2.8053
-10.8532	-4.25789	-1.04264	0.086419	-16.1953	-5.45854	-3.32298	-0.97563
17.83909	5.588088	8.657011	1.490403	4.592591	1.476231	13.47574	4.07366
-6.05328	-1.8293	-5.68233	-2.74286	-6.14289	-1.90661	-13.5958	-4.54742
-1.82979	-0.78176	16.04311	4.996071	4.397163	0.997622	2.378231	0.342965
-18.0654	-5.65347	-9.30263	-2.73575	-20.5104	-7.26816	-22.4035	-7.51413
-1.5249	-0.3152	1.817484	0.615757	-5.86289	-2.2888	-4.95003	-1.88892
-8.01462	-3.03301	-8.46238	-2.25832	2.71506	1.117924	1.777738	1.005119
8.380982	2.644276	2.972981	0.495887	20.41483	6.476915	7.178922	1.680093
5.510659	1.850279	-0.62673	-1.05527	6.647248	2.912515	6.188586	1.821074
-15.6132	-4.18503	-8.31474	-2.51695	-12.4133	-3.25702	-19.2302	-5.79259
6.914346	2.524133	-2.29891	-0.94683	-0.57552	-0.13243	-12.7682	-4.75169
-4.41371	-1.57989	1.939115	0.636056	2.399275	0.334712	4.340126	1.106725
0.510682	-0.79893	12.84176	3.722813	4.613238	1.170882	4.401722	1.529068
0.806032	0.751962	-14.796	-5.38955	-10.8775	-3.11287	-12.6762	-3.83381
9.39173	3.937966	14.73241	5.279991	7.127755	2.669423	5.437384	1.781863
1.718688	-0.15662	11.40767	2.590478	20.11965	6.016915	11.82177	3.285006
-7.70071	-2.02423	-13.5077	-3.95584	-8.49681	-2.24453	-7.87644	-1.89101
9.226601	2.829173	0.231697	-0.65126	7.680129	2.21266	8.302667	2.256728
8.341737	2.805546	5.755891	1.97557	5.342961	1.902987	7.118187	2.116016
9.93811	3.730955	2.08988	0.252001	-6.18793	-2.50633	2.209291	1.247642
-7.45312	-2.1918	-2.61375	-0.62535	-8.19133	-2.63574	-1.14727	0.095931
-4.18386	-1.31557	-9.46085	-3.12955	-11.6493	-3.72836	-12.6913	-4.14627
-5.37802	-1.8631	18.28699	6.088026	17.84321	6.470035	5.055789	1.469881

-7.7775	-3.12324	-1.10678	-0.13237	-12.8978	-4.08994	-6.47157	-1.60627
11.4597	4.055529	7.963405	2.724531	9.555845	3.582958	5.67223	1.197139
-9.78637	-2.45722	-25.7376	-8.72721	-18.7487	-6.24829	-17.9165	-5.60174
3.928504	0.958852	2.037097	0.331009	-2.29776	-0.69208	-6.76198	-2.2285
5.11355	1.769917	4.526578	1.867546	5.068758	2.007153	3.372059	1.294334
20.61531	6.224687	16.42423	4.840537	16.90069	4.55585	16.96202	4.697065
6.317943	2.82485	-2.39146	-0.73566	4.940998	1.760869	-6.19031	-1.71524
-0.77667	0.691128	-12.7954	-4.58933	-11.579	-3.72814	-10.2594	-3.30952
-27.4093	-9.1714	-21.2276	-6.40987	-25.761	-8.53932	-30.1968	-9.55493
12.75669	3.791378	5.223553	1.504639	16.07012	5.51315	3.832888	0.348972
-3.20207	-1.15217	7.172614	2.580943	-3.61119	-1.00165	6.917316	2.674909
-11.1977	-3.7423	-14.5488	-4.64779	-10.8444	-4.12585	-21.6381	-7.58708
19.17397	5.639913	21.52185	6.497253	16.43197	4.648133	12.49435	3.494956
-5.01691	-1.62192	1.737111	0.264372	1.270609	0.699004	9.007069	2.702893
15.24599	4.32989	20.03621	6.782783	8.277534	2.332684	9.272338	2.867157
0.354214	0.799363	-3.76504	-0.54026	-10.0071	-3.04717	-6.69888	-2.024
11.05668	3.375118	7.12676	2.068974	10.16501	3.353301	12.3597	3.624697
-18.5945	-6.5278	-19.8335	-6.33097	-10.8693	-3.37854	-9.3976	-3.10646
-8.34019	-2.43418	-8.4744	-2.84024	-2.74862	-0.50057	-5.59045	-2.08633
-9.57317	-3.0995	-2.42321	-0.23342	1.283349	1.198706	-0.23831	0.374152
2.572339	0.836236	-3.4383	-0.9659	-16.0496	-5.50688	-0.21362	0.109297
-4.75406	-0.64275	-9.48459	-2.43804	-1.60597	-0.32174	3.702749	2.341946
-23.9894	-7.41578	-18.1439	-6.0581	-20.8593	-6.2983	-15.8393	-4.76854
-11.4463	-3.84275	-2.33702	-0.16558	-2.93296	-0.92949	-6.50318	-1.92619
1.094242	-0.2099	-4.1082	-1.71669	4.477546	1.297207	0.894141	0.0791

REPLICATE 22		**REPLICATE 23**		**REPLICATE 24**		**REPLICATE 25**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-3.58895	-1.44375	-0.35504	0.775699	5.337589	2.369139	2.383076	0.960734
10.99679	3.738098	3.353982	0.479454	5.120324	1.514928	-3.5946	-0.86215
0.21388	0.399378	0.53094	0.216671	-0.64165	0.041394	-6.59135	-2.66812
14.09798	5.349894	3.80367	0.637348	8.853464	2.705227	13.77625	4.936126
0.600701	-0.07447	7.260578	2.642219	4.00713	0.74505	12.31783	4.11201
-0.84097	-0.41274	-5.71761	-1.81055	6.480734	2.411991	3.826432	1.537396
-3.17239	-1.48411	1.965948	0.111759	-0.97261	-0.11489	6.789387	1.976562
-13.2232	-4.26484	-7.42265	-2.15943	-14.9536	-4.73848	-2.45206	0.054498
3.083846	0.592432	-0.38452	-0.96251	0.817111	-0.37814	-0.33076	0.063129
15.39896	5.080766	15.05904	4.792757	4.114659	1.112426	10.15642	2.963178
-19	-5.91731	-1.86598	-0.17915	-0.12873	0.047606	-10.0904	-3.31783

-15.2541	-4.40305	-6.3926	-1.24052	-12.5632	-3.77158	-16.833	-5.03477
-15.1627	-5.1472	-21.0611	-6.93215	-16.0243	-5.36684	-9.0867	-2.7
6.375206	1.445655	20.13394	6.217438	13.05396	4.094525	10.24225	2.963057
-2.15745	-0.46201	3.034025	0.954862	1.958133	1.209199	-1.60235	0.03917
12.00504	3.15396	9.443893	2.998474	5.316724	0.995125	-3.70489	-1.88688
-19.8751	-6.80139	-16.8987	-4.78266	-11.3327	-3.29068	-16.8975	-5.42651
5.252009	1.444564	-1.03944	-0.6936	-5.61593	-2.1191	-3.29824	-1.7165
-7.24152	-2.17461	-6.5032	-2.34593	-13.2399	-4.5387	-3.57957	-0.94753
15.43734	4.661869	17.99638	6.207763	4.389142	0.233362	10.79868	3.61866
6.73983	2.385442	1.240751	0.548749	3.259676	1.375127	3.145727	1.229865
-19.9858	-6.1988	-9.30083	-2.55213	-16.5689	-4.98946	-17.4731	-5.85518
-4.57758	-1.95764	-6.62099	-2.27904	-12.4488	-4.17273	-3.06245	-1.1948
-2.38573	-1.60399	4.581453	1.710735	-3.16853	-1.46543	-1.65488	-1.12679
12.4608	3.846413	12.973	4.562937	10.2219	2.995639	4.679068	1.177393
-7.13843	-2.3865	-12.6432	-4.68337	-9.38851	-2.70528	-11.952	-3.63786
8.478122	2.960124	-0.82073	-0.07003	1.528131	0.251069	15.6045	5.750998
6.362891	1.765618	9.664044	2.549475	18.39104	5.252546	18.72286	5.895148
-8.14418	-2.39751	-12.9707	-4.25117	-5.14544	-0.92222	-21.4192	-6.73313
5.306515	2.095004	-1.19014	-0.984	-1.22892	-0.73836	6.72475	2.75636
-0.65407	-0.06848	-0.76309	0.320416	1.123712	-0.22003	9.998529	3.547945
3.025263	0.729871	0.022169	-0.67107	6.873527	2.297554	-0.26682	-0.53205
-10.388	-3.15993	-7.69063	-2.53903	3.214632	1.69314	-8.5837	-2.62651
-15.6638	-5.0972	-12.4888	-4.11108	-5.59531	-1.39331	-1.08649	0.157639
9.684816	3.647472	2.966321	0.873065	-1.00584	-0.8073	2.965449	0.922411
-13.6797	-4.69379	-10.626	-3.47292	-12.9785	-3.75949	-6.55142	-2.13279
2.25508	0.861582	-3.44028	-1.21394	1.590571	0.343704	6.04004	2.08936
-11.4259	-3.20033	-11.7541	-3.85388	-17.1688	-5.03917	-27.224	-8.49321
-3.59764	-1.4366	-3.21121	-0.95399	2.862573	0.926734	-6.34159	-1.99149
6.902727	2.697402	3.142596	1.40081	6.687694	2.545538	3.723341	1.342142
8.666377	1.509845	14.26481	4.215688	10.93326	2.866606	16.21464	4.637458
-8.68203	-2.29842	-1.98218	-0.21186	0.890877	0.455764	-2.95435	-0.94556
-15.1463	-5.16293	-4.02213	-1.58799	-4.79593	-1.62196	-2.96407	-0.58384
-31.8479	-10.414	-24.8822	-7.89841	-18.0013	-5.36998	-11.21	-3.28035
21.66223	7.169416	1.881514	0.44863	6.216166	1.574419	3.128219	0.354809
-2.96773	-1.3386	-4.61523	-2.05884	-4.0864	-1.17194	5.628876	2.293564
-2.86495	-0.71947	-9.44189	-3.17447	-9.18177	-3.07671	-6.27394	-2.7111
18.63289	5.605947	15.57881	5.025403	14.23606	3.887606	14.56967	4.149731
-1.40182	-0.99821	3.491097	0.458841	-0.60152	-0.42206	-4.96891	-1.58893
13.66521	4.854827	6.783334	1.747688	13.14519	4.052164	13.98943	3.834618

-8.96906	-2.75019	3.876617	1.963916	0.677824	0.584344	-11.9603	-3.59254
0.111958	-0.59395	9.045127	3.196453	-7.62404	-2.96281	11.01137	3.583046
-9.07988	-2.44867	7.467317	3.10047	-20.5843	-6.79763	-10.7309	-3.23889
-6.90202	-2.08387	-11.5439	-4.07548	-20.9896	-7.16817	-3.27654	-0.94391
-3.10727	-0.65949	-1.5322	0.156849	-11.4383	-3.35469	-5.20944	-1.47974
-0.82682	-0.33743	-2.70149	-0.6916	-13.492	-4.41136	-6.29549	-1.72799
-7.91388	-2.00235	-10.3221	-3.0861	-1.62416	0.009921	2.414274	1.457289
-15.9755	-5.12703	-18.1006	-5.41502	-17.5559	-5.49793	-22.2389	-6.85362
6.031318	2.178555	1.982288	1.036046	-10.502	-3.38843	-9.31632	-3.50519
11.14731	3.690861	-1.14165	-0.47024	4.129772	1.889173	6.467718	2.238233

REPLICATE 26		**REPLICATE 27**		**REPLICATE 28**		**REPLICATE 29**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-7.13748	-1.53115	0.825661	1.334015	-2.43779	-0.22217	1.539509	1.418245
-0.35291	-0.58226	6.739442	1.712724	2.053971	-0.46837	9.376416	3.074403
-4.42129	-1.71994	-7.45552	-3.05005	-10.8048	-3.77891	-4.36978	-1.76933
0.886309	0.218757	-1.51429	-0.63431	16.90505	5.741714	8.59879	2.422132
5.844475	1.626048	14.0071	4.405623	-2.55748	-1.61937	12.95152	4.054251
-0.23114	0.282809	4.273417	1.449226	5.397641	2.27489	7.014127	3.121947
5.443637	2.045451	6.56686	2.275546	-5.37537	-2.1937	0.466529	0.155657
-6.37803	-1.77562	-13.8786	-3.73983	-3.80523	-0.30943	-9.47387	-2.40861
1.414679	-0.09236	-6.95051	-2.47859	-5.57259	-2.15598	7.226633	3.013802
5.276314	1.471534	13.97033	4.101077	7.464235	2.011395	4.117241	0.952895
-11.4586	-4.12497	-13.9885	-4.78684	-0.40434	0.123658	-9.19931	-2.47519
-11.8667	-3.00933	-12.7173	-4.13302	-8.23287	-1.92373	-9.4069	-2.14803
-9.26588	-3.17652	-8.48108	-2.6168	-14.4624	-5.0032	-1.46136	-0.09921
7.211153	2.279747	13.24405	4.257409	9.244317	2.74783	2.350818	0.085633
7.641118	2.572868	-1.18022	-0.23931	0.530824	0.250177	-2.10992	-0.56799
10.59762	3.197115	11.67602	3.844467	8.386598	2.755999	7.042866	1.652587
-11.3781	-3.21732	-21.6625	-7.7753	-17.0238	-6.25324	-15.9523	-4.99374
-5.00868	-1.43959	3.486578	1.647209	-4.07221	-1.00499	-4.43269	-1.65681
2.582938	1.166035	-8.17726	-2.49879	-3.67953	-1.01685	-3.42947	-1.62638
7.688419	2.115823	12.05736	3.981464	12.55504	4.316396	17.4791	5.194952
5.419722	2.088696	9.267824	3.573597	-0.51497	0.116108	0.208423	0.093794
-13.1239	-3.70653	-3.68967	-0.601	-5.97331	-0.93681	-17.9913	-5.83335
-2.05338	-0.31054	-2.35943	-0.75633	-9.0774	-3.40542	-7.97872	-2.69973
4.083249	1.502594	5.75383	1.885309	-1.6798	-0.75524	11.93588	3.62179
13.20654	4.142817	13.54125	4.00136	9.379865	2.110988	5.389501	0.962425
-17.7048	-6.22026	-14.9	-5.21614	-7.09741	-2.45506	-19.1658	-6.55379

4.557401	1.891554	7.037289	2.197386	5.908135	2.638578	10.97178	3.812703
16.53693	4.697639	19.15948	6.047152	17.0508	5.04228	14.3092	4.393497
-15.5626	-4.66972	-5.68075	-1.52462	-8.35759	-2.53002	-11.3133	-3.45513
-2.23551	-0.91641	7.344485	2.602884	16.21329	5.303849	8.226551	2.517914
3.664813	0.754778	0.604421	-0.08521	5.881455	2.445096	6.745567	1.530487
-3.90354	-1.58832	0.500996	0.584199	2.570865	0.784913	-0.08644	-0.45768
-8.56172	-3.15577	-12.4598	-4.14327	0.089607	0.325534	-20.1706	-6.976
7.240005	3.14874	-11.9697	-3.42668	-6.40543	-2.12705	-0.52679	0.493606
4.166845	1.498497	4.800001	1.698301	9.828002	3.345856	6.716597	2.450422
-2.87222	-1.04678	-10.5607	-3.72014	-6.48409	-1.48996	-13.8826	-4.25732
4.782676	1.964171	4.091846	1.065658	0.716951	-0.00798	11.68394	3.380628
-7.12932	-1.76735	-11.4838	-3.32761	-18.7087	-6.04438	-11.4634	-3.56997
-3.51699	-1.15846	-2.64828	-1.12116	3.721612	1.395363	-3.88604	-1.16889
-3.47095	-1.10569	7.056825	2.235923	0.276284	0.203224	7.029664	2.208637
5.197534	0.628994	13.81853	3.796708	13.79338	3.812607	13.61834	4.293231
-0.42046	-0.10539	-2.71736	-0.71014	-6.50822	-1.78123	-1.86439	-0.10954
-0.04941	0.053242	-0.21489	0.161108	-6.44802	-2.24743	-3.58938	-0.39352
-26.0578	-8.47032	-25.0748	-8.22441	-19.2656	-5.53297	-27.9693	-9.07666
6.618417	1.763609	4.413198	1.036287	8.116698	2.516188	3.981675	1.238509
8.318239	2.753924	5.359975	2.100409	4.531569	1.890228	4.973808	1.436298
-5.01671	-1.32618	-2.08341	-0.41487	-5.11152	-1.53271	-8.07894	-2.94567
20.56918	6.807227	13.22275	4.265498	13.73958	4.31045	22.20992	7.128386
0.259314	-0.41288	-1.21272	-0.91753	1.870633	0.230358	4.382021	1.847349
13.78182	4.591497	15.04773	4.856996	15.47239	4.550031	9.241012	2.637755
-5.95711	-1.59486	-1.82132	0.352228	-6.92172	-1.34665	-8.39856	-2.2722
-0.91109	-0.4868	-3.09114	-1.62696	4.918337	1.416905	-1.75978	-1.01853
-5.15155	-1.78648	-16.2909	-5.2588	-14.6021	-4.79569	-14.9322	-4.93417
-10.9171	-3.63049	-6.77506	-1.86923	-20.0086	-6.52179	0.03104	0.112217
0.139929	0.531118	-4.76535	-0.83723	-4.54178	-0.87403	1.075755	0.504647
-2.01141	-0.40012	-1.80708	-0.45969	-10.9594	-3.65947	-5.52228	-1.56498
-6.4746	-1.92804	-8.91231	-2.68758	-10.5509	-2.48295	-9.7996	-2.53137
-23.8696	-7.09377	-23.5484	-7.12993	-18.8799	-5.6989	-23.7422	-6.97622
2.812408	1.13872	-17.7639	-5.92737	1.836885	0.73923	-11.8649	-4.06591
0.271556	-0.6359	7.468037	1.972841	16.29483	5.979442	9.668327	3.612551

REPLICATE 30		**REPLICATE 31**		**REPLICATE 32**		**REPLICATE 33**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-11.8507	-4.07	-1.58411	-0.1531	0.217298	0.897772	-3.21897	-0.95962
4.395716	1.488988	-6.29331	-2.38084	5.123071	1.666847	5.324538	1.374616

1.872641	0.911435	0.672617	0.416538	0.066294	0.289136	0.346731	0.638476
13.88903	4.86771	6.14678	1.93336	10.35616	3.886794	21.09612	7.653401
16.84369	5.966907	1.123074	-0.00837	12.14209	3.333567	4.885132	0.8013
3.128666	1.311843	1.083277	0.610112	-3.46975	-0.40277	-2.75167	-0.14738
-1.53763	-0.90647	-4.59977	-1.45566	8.143239	2.532297	5.926909	2.408408
-15.6098	-4.58466	-6.82758	-1.56943	-11.7509	-3.37326	0.097816	0.611949
6.079626	1.876602	-3.00701	-1.85658	-1.65035	-0.59029	1.892744	0.430462
15.71372	5.034389	14.3519	4.545017	14.94562	4.840252	16.30864	5.315242
-10.9227	-3.19175	-3.47428	-0.83914	-14.652	-4.57639	-4.41659	-1.1775
-12.6353	-3.8124	-14.9866	-4.58137	-13.4331	-3.65998	-6.56288	-1.74414
-10.6027	-2.85206	-6.56378	-1.31597	-9.22256	-2.70042	-5.62089	-1.15435
12.4843	4.388931	15.00737	4.179958	11.13725	3.647591	10.14112	2.709021
-7.0819	-2.40263	-1.21204	-0.27696	9.358222	3.7679	-3.81128	-1.01446
9.646688	3.111375	8.733062	2.735859	17.6181	5.068524	10.29331	3.020073
-25.3121	-8.28764	-8.06274	-1.96544	-11.9959	-3.71725	-15.5976	-4.15018
-14.5044	-5.52153	-4.92643	-1.15441	3.26682	1.146808	8.52256	2.489777
-4.35315	-1.10254	-7.165	-2.573	-13.6715	-4.67517	2.357954	1.516769
19.51647	5.882846	8.27152	1.86531	5.874783	1.191828	2.674351	0.582712
5.532154	2.188717	2.892607	1.296555	3.13042	0.958162	1.406727	0.31717
-3.47307	-0.34849	-9.7089	-2.95278	-12.141	-3.81233	-25.6895	-8.65421
3.085694	1.418282	-2.69795	-0.67958	3.740227	1.761384	-3.86002	-1.1363
-0.78177	-0.50563	6.886292	2.561832	12.45723	3.95832	9.951029	3.541612
13.73133	4.549592	-0.59384	-1.15479	6.301184	1.872272	21.73663	6.989619
-10.3731	-3.74647	-12.5775	-4.10118	-1.15725	-0.34254	-6.44785	-1.88028
6.623312	2.660932	-13.5218	-4.57267	5.161136	2.184839	-2.67859	-0.75764
8.586729	2.616145	16.359	5.505031	23.59404	7.378839	13.32271	3.801999
-11.5882	-3.81341	-9.2437	-1.98603	-12.6121	-4.00361	-7.92126	-1.8913
-1.38592	-0.87366	7.019526	2.530092	7.179218	2.992188	1.09417	0.350838
-0.15557	-0.6378	-11.2983	-4.32534	-1.52768	-0.66941	2.750219	0.799791
-2.73118	-1.11061	-5.37188	-2.1994	3.485565	0.772137	8.893808	2.475965
-5.5288	-1.61544	-2.95328	-1.32298	0.288257	0.375751	-6.64699	-1.68536
-15.1986	-4.77812	1.21622	0.952062	0.274687	1.088456	-6.32684	-1.5933
3.578158	1.237922	1.905218	0.480067	7.360156	3.111606	3.749887	1.336461
-4.20412	-1.19251	-13.803	-4.20242	-9.40565	-2.87969	-5.75213	-1.74492
7.723172	2.585878	3.998561	1.255245	5.332185	1.800873	-1.92017	-1.09167
-23.2953	-7.76698	-20.3349	-6.47504	-7.08307	-1.91796	-17.939	-5.52576
3.416078	0.930389	0.143013	0.123004	-4.8881	-1.94594	1.738265	0.727363
9.433051	3.997093	-6.94037	-2.36213	4.939982	2.433766	19.05201	6.176107
6.913439	1.470533	13.92897	3.360668	19.9949	6.320951	7.972293	2.292655

1.303148	0.652924	-2.09051	-0.47067	-12.8196	-4.17352	-3.62529	-0.86138
-12.9757	-4.63808	-7.30916	-1.76617	-12.7336	-3.83742	-2.86641	-1.21572
-22.7788	-7.0243	-18.245	-5.64375	-24.5557	-8.09194	-15.8432	-5.02901
13.14329	4.098539	1.963379	0.307073	12.12638	3.740333	7.767312	2.690683
3.376266	0.818064	9.509039	3.414995	2.436907	-0.04683	9.839533	3.57852
-1.78174	-0.2628	-2.46658	-0.12437	-7.0898	-2.32806	-12.7723	-3.88131
21.38181	6.28318	3.240613	0.254849	16.14789	4.834741	8.900762	2.550219
4.845125	2.343108	4.517243	1.661843	12.42371	4.374651	-4.4382	-1.13382
7.861507	2.631687	16.54987	5.556546	24.02392	7.703753	14.57254	4.713295
-12.5285	-3.46658	-4.67046	-1.07292	-8.28931	-2.12082	2.86092	1.404371
5.700283	1.719167	-1.35233	-0.80365	10.47852	3.58885	7.0794	2.197684
-10.8732	-4.00444	-11.1817	-3.74631	-6.7235	-2.2744	-9.97423	-3.06199
-11.0474	-3.41215	-8.07439	-2.64086	-0.13438	0.239269	-14.6871	-4.78547
7.314131	3.104949	-7.29416	-2.55861	-13.1092	-4.40222	-6.26245	-1.41918
-3.06385	-0.64131	-3.67385	-0.86889	-12.3626	-3.87952	-3.57353	-1.1079
-8.60229	-2.36033	3.723957	1.935279	-11.6897	-3.75326	-6.09716	-0.99518
-20.708	-7.03816	-14.1125	-3.85643	-21.6902	-6.97741	-20.9401	-6.86865
2.091813	1.520442	-3.46778	-0.69297	1.184824	0.640631	-1.5136	0.286079
-3.62918	-1.40382	-0.60883	-0.01033	-2.99087	-1.38338	0.501515	0.724412

REPLICATE 34		**REPLICATE 35**		**REPLICATE 36**		**REPLICATE 37**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
1.010302	0.948121	2.374996	1.342643	3.787531	1.015492	-2.01218	0.0109
2.561871	0.534424	-9.81897	-3.331	10.2353	3.117764	1.088071	0.812228
5.146697	1.891771	-4.23124	-1.73989	-0.13607	-0.33182	4.033138	1.119703
5.168183	1.379478	2.004239	0.58197	6.209991	2.095657	18.49503	6.613327
9.917699	3.336469	16.75922	5.83974	15.354	5.682905	15.98037	5.63844
9.253822	3.164825	-0.23884	0.228274	3.03002	1.192835	8.036752	3.010828
-1.17797	-0.47963	7.977389	3.114038	4.401529	1.321964	-1.13883	-0.52129
-3.46746	-0.42716	-7.71472	-2.5685	-11.2657	-2.88968	-2.4014	0.027766
0.85838	0.336805	-5.74548	-2.04893	7.283964	2.906793	-4.21586	-1.37518
16.70101	5.322462	7.323435	2.242076	7.745474	2.505435	2.75391	0.681413
-21.1846	-6.4275	-19.4988	-6.34566	-13.0674	-4.13402	-3.84037	-1.13992
-8.3536	-2.38998	-15.9461	-4.64226	-4.7974	-1.2689	-9.29096	-2.51993
-8.71192	-2.44724	-2.74795	0.102759	-23.1245	-7.76021	0.987735	1.232201
15.76701	5.150466	-3.30466	-2.31889	14.46904	5.190355	12.01391	3.547516
-9.49922	-3.16811	-1.87392	-0.64769	-5.25064	-1.78219	-1.33683	-0.26182
-0.42431	-1.0285	-1.77826	-1.14149	8.098915	1.634828	2.321884	0.004864
-11.2068	-2.86702	-24.1757	-7.59287	-8.31958	-2.07679	-17.1015	-5.25009

-2.14567	-0.59251	0.896897	0.799047	-7.95568	-3.3544	-4.20968	-1.2016
-3.24341	-0.97709	3.937476	1.669764	-3.70087	-0.4371	-13.6269	-4.31696
15.40944	4.599744	7.568825	2.25368	9.921505	2.807612	6.165228	1.030602
-3.9763	-1.9176	-8.35068	-2.83242	8.811384	2.814988	3.653433	1.646344
-12.9645	-3.66454	-8.27036	-2.32184	-10.4496	-3.12702	-15.4528	-4.72708
-1.97521	-0.28313	-3.39181	-1.32693	6.86579	2.204334	0.288381	-0.26751
5.955616	2.144097	2.812082	0.028481	4.030056	0.882361	-0.79078	-0.41998
4.757024	1.042518	11.1207	3.246797	8.333371	2.738927	10.29717	2.442534
-7.61194	-2.13864	-7.73795	-2.53015	-2.77001	-0.61914	2.177152	1.266664
0.016904	0.22327	9.739408	3.226009	13.84833	4.903336	-1.23822	-0.5359
18.62372	5.605963	18.3739	6.11408	9.339244	2.385658	18.37911	5.607644
-20.9478	-7.07379	-11.867	-4.06324	-15.2521	-4.87892	-6.39513	-1.71473
7.601526	2.622469	-2.31878	-0.95115	11.19829	3.417852	14.79479	6.051643
3.739839	0.754238	-2.59778	-1.39328	-2.98632	-1.70125	-0.58144	-0.35003
2.08696	0.459522	5.021664	1.667309	5.386923	1.262446	17.76211	6.117587
-9.07739	-2.79281	-14.78	-5.52092	3.032888	1.20939	-5.47562	-1.96141
-12.7199	-3.76454	1.186758	0.835571	-9.32155	-2.78713	-5.73213	-1.8024
13.99356	5.10459	4.069406	1.354083	11.4269	4.133368	-4.99594	-2.08841
-9.74074	-3.49676	-9.25338	-2.49236	-14.9155	-4.89216	-8.21454	-2.09906
5.34604	1.52628	12.87248	4.201946	-1.33755	-0.6966	9.24014	2.759189
-10.8994	-3.65009	-18.6087	-6.12938	-14.9302	-3.91393	-12.7433	-3.57316
0.446127	0.268132	-1.58551	-0.6556	0.495829	0.153856	0.99085	0.197367
-5.53787	-1.78268	16.50466	5.689672	-3.94709	-1.21771	8.864416	3.906111
4.974298	0.080086	27.31225	8.838893	17.35754	5.23903	11.27231	3.200381
-5.00614	-1.03114	4.829319	2.089993	-5.86895	-1.81867	-1.37134	-0.19661
-6.57247	-2.14247	-2.43924	-0.45926	-2.70459	-0.69534	0.851534	0.149882
-19.2666	-5.82036	-22.8095	-7.14433	-31.3248	-10.0656	-24.831	-7.65181
17.84921	6.11698	4.446743	1.308013	16.97079	5.779637	4.793962	1.651396
-6.28939	-2.07809	8.971681	3.132435	2.213089	0.791189	1.37566	0.92796
-8.0684	-3.00608	-7.61225	-2.64388	-11.7069	-3.54779	-8.13461	-2.20668
11.57037	2.778626	11.03538	2.930043	-2.27492	-1.74568	11.70663	3.291737
-0.24556	0.157869	-1.92898	-0.7473	9.526668	2.842764	7.601526	2.865479
13.28337	4.018758	8.659966	1.930297	21.7998	6.92068	15.20964	5.04751
2.324114	1.94698	-13.0753	-3.57752	-2.0338	-0.03917	-6.52531	-2.23061
6.451695	1.659797	14.15109	5.074017	8.395714	2.661642	9.182129	2.668964
-8.98411	-2.34472	-14.94	-4.4736	-8.61222	-2.95339	0.903259	0.757096
-4.36793	-1.55136	-20.4338	-6.63316	-18.7193	-5.94279	-16.3563	-6.04172
-6.47201	-1.43865	-10.1516	-3.2401	-13.5774	-4.33175	-5.75942	-1.66159
4.790217	1.988073	-4.86956	-1.66494	-5.722	-1.85049	3.531346	1.277161

-14.847	-4.80669	2.974262	1.125115	-13.3799	-3.93752	-13.567	-3.14268
-32.4189	-10.6322	0.97923	1.300059	-20.4952	-6.6128	-18.1832	-5.47186
5.623234	1.94843	-1.13594	-0.08029	-11.4193	-3.93816	-9.93604	-3.49618
12.33699	4.435526	-5.90293	-2.06356	14.95009	5.835172	-4.79143	-1.4458

REPLICATE 38		**REPLICATE 39**		**REPLICATE 40**		**REPLICATE 41**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-5.18463	-1.53542	-0.41691	0.16191	-2.43867	-1.00578	1.075548	0.479844
6.621009	2.037017	6.11332	2.284933	3.671852	1.835296	2.358768	0.702358
-10.1755	-3.46462	5.506315	2.024604	3.7769	1.498347	-0.90131	-0.56166
8.880377	2.766639	-1.38216	-1.12275	5.678617	1.411055	10.39405	3.211913
4.635855	1.29347	12.04926	4.288924	8.561238	2.785015	12.41311	4.336272
8.743032	3.446068	-4.99795	-2.11763	5.080848	2.007741	0.400623	0.964701
2.352567	0.673914	8.583447	2.966043	10.3155	3.667238	9.573892	3.375147
-11.5349	-3.04587	5.998646	2.599603	-2.48263	-0.24907	-12.7604	-4.07659
-1.95697	-1.06367	-7.40741	-3.15679	-4.00553	-1.69901	-5.789	-2.17744
13.23291	3.853754	6.867527	1.655075	15.05195	5.113215	17.1757	5.03483
-5.72073	-1.57172	-8.43578	-3.03987	-4.61126	-0.89807	-17.7619	-5.63449
-17.4446	-5.36769	-4.84996	-0.73489	-9.09735	-2.27408	-16.6511	-4.65503
-16.4922	-6.5727	-13.833	-4.49407	-1.59096	-0.14485	1.739779	0.920966
11.53685	3.281656	11.97542	3.661988	6.814107	1.946996	1.823241	-0.47067
-6.38177	-2.26044	-2.14134	-0.65671	1.670545	0.811024	-3.11863	-0.88945
10.10709	2.778704	7.419286	2.442755	-4.76886	-2.29949	4.707762	1.352195
-18.5697	-6.04484	-14.0797	-4.05719	-27.3262	-9.3648	-22.821	-7.36247
-1.93083	-0.86933	-10.0224	-3.72055	-5.01097	-1.69283	-6.12709	-1.94306
-2.14401	-0.5251	-12.1985	-4.7335	-1.21582	-0.18829	-4.64368	-1.23938
9.224783	2.463149	20.06848	6.186086	8.962811	1.783043	10.96906	3.195829
1.445258	0.651061	8.238358	2.775326	11.6115	4.280333	8.197838	3.266818
-12.1061	-3.82244	-18.0423	-5.32434	-6.61121	-1.23369	-6.58036	-2.18261
-10.9577	-3.52231	-1.22024	0.320815	-0.57881	-0.09173	-9.5825	-4.05271
-2.04407	-1.39307	2.866508	0.878165	1.453583	0.186696	11.83064	4.206607
17.36434	5.851854	7.647856	1.973049	5.199956	1.591678	20.49633	6.811881
-12.6037	-4.52366	-12.0773	-4.26248	-10.5273	-3.54561	-9.11731	-3.06569
2.1126	0.731686	6.605767	2.3036	7.660902	3.044697	11.2446	3.780863
15.42704	4.624124	24.07612	6.982884	11.93336	3.985155	9.766863	2.60188
-6.35318	-1.39812	-18.6856	-5.30416	-9.99557	-2.93516	-7.09535	-1.40942
11.34255	3.453805	8.656246	3.114041	8.066248	2.387152	10.36356	3.462862
4.679176	1.45512	11.34469	3.653143	5.591086	1.641225	12.20282	3.417875
4.223669	1.101647	5.544273	2.305475	-0.4745	-0.66423	8.216711	2.715722

-5.12781	-1.06723	-12.1872	-4.20686	-10.0762	-3.33647	-6.54495	-1.771
-9.34074	-2.73697	-20.5154	-6.91712	-10.0503	-3.11405	-10.9827	-3.42177
8.395432	2.553274	-0.93155	-0.35515	10.60005	3.475585	7.511779	1.971628
-11.5939	-3.79766	2.015314	1.187376	-9.58741	-3.2291	-16.8944	-5.29695
-2.48146	-1.33402	5.513973	1.507904	3.108938	0.670038	12.2127	4.497293
-11.0779	-3.50261	-19.9889	-6.38788	-10.4147	-2.55859	-12.0469	-3.13778
0.956206	0.099422	2.80136	0.809405	5.28251	1.391773	0.52451	0.75535
2.726728	0.969038	-0.89021	0.025314	16.24713	5.774533	4.844459	2.065311
12.25868	3.037155	10.1609	2.689662	8.337315	1.68869	4.329431	0.199314
0.833289	0.503271	-3.94153	-1.0219	4.079707	1.156497	12.51188	4.539557
-1.88426	-0.34322	-2.78867	-0.67516	2.239229	1.593817	2.910643	1.591247
-15.8037	-4.95859	-29.0419	-9.80757	-22.6966	-7.84414	-23.2786	-7.44551
12.0039	3.647626	11.35523	3.701746	8.655766	3.196108	13.23011	4.219481
3.421182	1.568767	7.186504	2.413975	11.4049	4.145473	6.867396	2.685999
-8.83299	-3.03728	-3.63093	-1.17607	-11.3235	-3.42732	-0.03008	0.224548
7.543476	2.003455	11.16338	3.167002	15.47347	4.855803	8.318706	1.926442
8.985707	3.155026	12.59746	4.846531	1.262468	0.175791	5.613676	1.99844
16.09994	5.035601	18.62898	6.100266	11.44595	3.862098	14.45426	4.849563
-6.18764	-1.43984	-1.73498	-0.2145	-3.06893	-0.04881	-6.17772	-1.81992
17.89544	5.606503	1.281663	0.442012	-2.37972	-1.11872	11.20959	3.350998
-5.30337	-1.35732	-13.8733	-4.65427	-10.8984	-3.66403	-13.0332	-3.95172
-13.2592	-4.20371	-3.3998	-1.33943	-17.4637	-6.31856	-16.039	-5.98527
-3.89639	-1.1153	-2.53503	-0.28335	7.716612	2.979517	-5.80803	-1.69853
-7.9863	-2.42303	-4.26712	-1.10913	0.147977	0.459659	-10.9321	-3.74457
-2.97923	-0.03235	-6.1457	-1.54415	-5.27946	-1.30587	-8.70244	-1.56766
-23.5841	-8.20275	-29.5474	-9.6501	-15.1143	-5.04259	-20.7854	-6.58164
-1.3924	-0.3259	-5.91706	-1.95817	1.91804	0.785554	0.596315	0.916502
4.398929	1.646468	5.211281	1.675273	2.566461	0.663972	14.73599	5.100703

REPLICATE 42		**REPLICATE 43**		**REPLICATE 44**		**REPLICATE 45**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-11.3963	-3.66918	3.145903	1.987638	11.34183	3.95847	-5.014	-0.89492
-4.26484	-1.49046	-0.5071	-0.86803	2.182157	0.735843	11.37602	3.561821
-14.5424	-5.237	-1.94223	-0.55645	-2.55956	-0.70485	-8.25272	-2.72198
7.808892	1.833262	3.994219	1.247143	10.53802	3.860836	8.333416	2.719833
3.271036	1.332366	8.182432	2.507773	2.534095	0.462287	3.835341	1.308518
12.74442	5.410198	9.878311	3.999073	10.03852	4.199358	-0.5783	0.395359
5.384987	1.869237	4.311452	0.726556	-4.08062	-1.31245	6.081995	1.941135
-1.97457	0.848592	-11.1766	-2.98418	-6.23466	-2.21342	-9.1706	-2.86967

4.271344	1.14992	2.774477	0.999416	3.693239	1.513542	-12.4871	-4.6107
11.69598	3.03248	10.81571	3.356369	7.67902	2.030979	5.850543	0.844634
-16.8987	-5.25438	-12.2838	-3.56127	-19.0475	-6.42932	-12.8189	-3.4202
-11.5226	-3.1277	-9.76689	-2.55988	-9.759	-2.57031	-10.3323	-3.21267
-7.55941	-1.75288	-20.7769	-7.30672	-7.85773	-2.4699	-0.59154	0.361007
10.49253	2.667699	7.34205	1.797302	23.26034	7.73143	20.27134	6.573443
-2.71428	-1.13896	-8.65861	-3.36455	1.612724	0.206454	11.1858	4.129333
17.5695	5.6422	6.831766	2.136623	1.565347	0.243817	9.964365	2.849141
-12.5583	-3.77623	-23.9367	-8.50226	-11.7687	-3.39927	-12.6054	-3.71312
-11.9098	-3.7758	0.466532	0.047503	2.243492	1.183662	2.886243	1.329123
-4.45313	-0.88189	-3.10265	-0.63265	-15.34	-4.67528	-9.90285	-3.67881
16.26712	4.771243	14.50954	4.116016	8.908944	1.784539	7.329996	1.960253
5.410585	1.740211	8.368051	2.866053	9.595293	3.661487	11.48304	3.699345
-13.6571	-4.45468	-13.3485	-4.15586	-15.544	-5.25384	-5.19707	-1.41364
-3.88057	-1.21537	3.421971	1.453525	-1.36523	-0.84007	-4.62603	-1.47833
-1.03224	-0.55423	-7.82162	-3.04221	7.96826	2.886802	2.510412	1.018724
8.589242	2.666345	16.08119	5.087713	14.35654	4.488496	1.599601	-0.22507
-3.88071	-0.64012	-1.06515	0.094385	-10.5972	-3.28355	-27.596	-8.95861
4.540394	1.068691	15.04481	4.900325	13.94482	4.716866	3.083124	1.240765
10.17253	2.993949	18.56252	5.413866	14.08722	3.919755	13.87625	4.318896
-1.90397	0.150614	-11.1759	-3.64044	-15.4669	-4.60625	-2.06905	0.314403
5.537148	1.789713	4.864937	0.765576	4.531582	1.230551	8.869299	2.370172
3.262517	0.843012	12.94429	4.467664	3.478346	0.875988	-3.02069	-1.4752
-0.23159	-0.8229	11.37697	4.16653	4.769556	1.730988	-2.47495	-1.71725
-3.86112	-1.08888	-22.1004	-7.78851	-6.83222	-2.20734	-17.2565	-6.16673
0.87698	1.209049	-18.5954	-6.04315	-13.5549	-3.81633	-7.82774	-2.37976
13.05572	4.560647	11.25698	3.974236	12.22004	4.117085	10.56611	3.517541
-22.7345	-7.7178	-12.1374	-4.24279	-9.12332	-3.35028	-4.00947	-1.02512
-2.83082	-1.14609	7.326649	2.496969	5.372173	1.735731	-4.33962	-1.77026
-16.3106	-4.92173	-15.728	-4.76513	-16.1564	-5.1808	-14.3907	-4.4321
1.965479	0.444417	3.40031	1.368153	3.471059	1.340915	-7.89825	-2.89281
6.280422	2.3688	2.797369	1.668769	10.37422	3.988256	-8.85899	-2.6146
13.51854	3.77266	8.053717	1.809523	10.29017	2.67469	26.21892	8.283266
-5.24768	-1.65444	-10.1357	-3.2424	-4.51642	-1.62253	7.602076	3.413787
-12.6133	-3.78026	-6.18512	-2.1543	-6.16952	-1.87438	-5.38365	-1.91375
-30.3033	-9.51032	-25.1418	-8.34293	-16.4272	-5.2752	-20.3798	-6.02286
10.47323	2.992321	9.732036	2.712935	9.293501	3.509792	7.548768	2.544748
2.980806	0.883871	-2.01938	-1.53228	6.250168	2.057207	-0.49715	-0.18842
-6.25268	-1.91876	-4.81796	-1.30535	-16.4252	-6.08519	-12.4803	-3.68509

18.08961	5.822267	21.58043	6.998289	13.91027	4.358308	20.81957	6.143181
-4.77499	-1.7414	-13.6281	-4.51697	0.032492	-0.42705	0.337663	0.139137
9.772959	2.384983	22.21374	7.279085	13.26242	4.15688	10.60841	3.594641
-5.11705	-1.36329	-10.203	-2.57713	-5.67859	-1.43076	-0.68195	0.817493
7.212058	1.898038	7.084469	1.714341	9.12005	2.489481	1.2337	-0.11929
-21.4343	-6.69003	-3.81552	-0.71531	-12.5977	-4.09725	-11.9625	-3.21941
-10.2953	-2.9812	-11.315	-2.98049	-12.0298	-3.9485	-15.3429	-5.33877
-8.8805	-2.61263	0.248532	0.452572	-5.42725	-1.62451	-5.9395	-1.42148
-9.81213	-2.66846	-13.3501	-4.83125	-4.81021	-1.39072	-5.84023	-1.95989
-4.90343	-1.28083	-8.51094	-2.82241	-8.20414	-2.06223	-3.97238	-0.46614
-18.842	-5.71896	-17.4364	-6.17654	-17.9279	-6.17282	-23.87	-7.5743
-3.53617	-1.28648	8.323326	3.484761	-1.54692	-0.25424	-3.95408	-0.74352
-5.64122	-1.62028	-12.4361	-4.6534	0.619242	0.457645	9.613762	3.417567

REPLICATE 46		**REPLICATE 47**		**REPLICATE 48**		**REPLICATE 49**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-11.2183	-3.997	1.651085	0.692578	2.296836	1.60673	3.166042	1.624379
5.876548	1.919397	-1.66006	-0.63643	6.267987	2.244516	4.404386	1.449788
-6.48587	-1.68898	-6.81726	-2.14983	0.417884	0.586955	-11.7612	-3.5449
10.74473	3.179846	12.72388	4.656783	6.678925	1.580119	13.35864	4.560529
8.885664	3.036068	7.886246	2.305569	2.966097	0.610471	19.10511	6.856613
6.218193	2.504963	6.913015	2.801348	-0.51642	0.133171	-2.15725	-0.85544
-0.96709	-0.18733	-4.68816	-1.61576	4.136319	1.115453	15.37545	5.541454
-9.45978	-2.56862	-15.1859	-4.77349	-2.92484	-0.27911	-9.32779	-2.66612
-2.76806	-0.77178	-8.77721	-2.91755	-7.83264	-3.11911	4.4635	1.556821
11.63749	3.58865	7.199165	2.339498	15.11724	5.079565	-1.05052	-1.0542
-5.86907	-1.83352	-21.3026	-6.91158	-4.65977	-1.2825	-14.4253	-5.16057
-7.54041	-1.99857	-10.5842	-2.65207	-13.9015	-3.84313	-10.8328	-2.98269
-10.5119	-3.68479	-4.38521	-1.61224	-6.04892	-2.1146	-8.82187	-3.19993
12.61946	3.121872	12.28679	3.827798	13.11219	3.629916	18.05496	6.020209
6.362	2.473669	-14.2652	-4.9008	-10.1966	-3.50794	-0.79366	-0.00969
-0.68349	-0.63197	7.867571	2.040981	7.372145	2.223167	3.128692	0.932635
-17.0937	-5.70161	-9.46357	-2.69094	-19.029	-6.61471	-19.8666	-6.81149
-2.59396	-0.32906	-0.64968	-0.14729	3.059053	0.569143	-13.9341	-4.99702
-7.90953	-2.59665	-4.81374	-0.69805	-12.0685	-4.08968	-10.099	-3.32749
12.50109	3.964717	11.87588	3.989829	17.07541	4.929547	-2.14414	-1.16029
4.047677	1.636063	3.537385	0.679061	6.620583	2.662419	9.026749	2.96864
-19.8961	-6.53559	-16.007	-5.59134	-9.16782	-2.36106	-22.0904	-7.9363
-1.6638	-0.61175	-4.44265	-1.1254	-11.4313	-3.35133	1.011396	0.887007

7.234008	2.338174	0.262386	0.355883	-5.98623	-2.55614	11.46788	3.884002
9.75491	2.780685	14.54514	4.503182	3.321022	0.157259	4.250085	0.980255
-12.962	-3.59522	-2.29852	-0.71152	-15.0131	-5.31089	-4.27125	-1.07978
-3.81119	-1.47975	0.132473	0.17156	16.02721	6.156622	1.153104	0.20867
20.66787	6.410407	15.22245	4.911866	25.88713	8.660504	16.33544	5.359139
-15.075	-4.60116	-10.6738	-2.90539	-5.67353	-0.81153	-15.3619	-4.99808
3.789608	1.426953	2.998541	1.201088	5.440926	1.549639	-1.38353	-0.91774
2.353917	0.863761	-0.38013	-0.68153	3.522342	0.994643	9.940614	3.520675
8.053039	2.444803	1.743384	0.583103	-6.69747	-2.62619	5.947379	1.645326
-14.087	-4.61525	-5.77109	-1.4919	-13.9843	-4.05969	-10.8214	-2.99838
-16.7816	-5.15016	-9.5396	-3.25538	-1.37645	0.078923	-2.49262	-0.73432
0.098094	-0.25256	7.819354	2.851213	7.155882	1.674217	10.0772	3.59811
-17.5881	-5.44419	-11.9091	-3.6687	-8.31309	-3.08068	-7.53215	-2.47402
5.541936	1.847652	9.308275	3.085228	-7.37937	-3.26633	7.127477	2.517612
-8.49333	-2.58654	-18.1697	-5.69181	-17.1144	-5.53577	-14.3819	-4.20829
-3.88322	-1.80044	-2.11576	-0.46584	2.092784	0.408523	-6.16373	-2.47042
16.77462	5.95527	0.200542	0.434167	2.962801	1.795801	10.15699	4.050269
15.41556	4.486644	9.622641	2.964614	4.95975	1.10157	21.51973	6.669629
2.416786	2.253163	-4.564	-1.29896	-2.26179	-1.18626	-3.0458	-0.68485
-10.8003	-3.54711	-5.5471	-1.16651	2.001476	1.036259	3.715823	1.649363
-24.681	-8.01102	-23.3827	-7.56823	-6.11256	-1.55671	-27.1578	-8.35385
4.19465	0.830491	11.50166	3.347213	12.78983	3.89676	13.88082	4.696313
3.92964	1.50017	5.204649	2.481481	1.303923	0.643059	2.566384	0.53144
-11.6603	-3.8626	0.230259	0.713268	-5.18937	-0.77681	-0.5035	0.45556
18.80133	5.733092	12.9866	3.586135	1.601079	-0.18071	12.2621	3.904197
-1.42047	-0.67151	7.392447	2.418777	0.434535	-0.38633	1.347799	0.598017
10.34637	2.920253	13.35263	4.116619	11.78535	3.611238	11.58732	3.999875
-6.7085	-1.78944	-2.85343	-0.6617	-3.06196	-0.24969	-8.95917	-2.60673
15.90027	4.897774	13.16905	3.875341	11.1503	3.307219	12.44813	4.065714
-16.1529	-5.80077	-9.2895	-2.39431	-1.92967	-0.84862	-5.16118	-1.14469
-8.5092	-2.55851	-12.8984	-4.20901	-11.7677	-3.46195	-8.4418	-2.83726
-3.25186	-0.76553	-7.14128	-2.15176	-7.445	-1.86785	-18.2121	-5.78967
-8.38984	-2.4259	-9.46571	-2.90831	-5.07992	-1.03568	-1.7566	-0.33574
-9.08046	-2.90023	-13.4272	-4.53911	5.880035	3.226595	-6.09947	-1.45774
-14.8289	-4.1358	-20.8811	-6.96798	-9.91467	-2.40931	-26.8779	-9.07284
-0.19793	0.349559	2.013513	1.118105	-3.3252	-1.33703	-0.32047	-0.16362
10.04805	3.841741	-10.0949	-3.27112	-8.31838	-3.89081	-3.63836	-1.12533

REPLICATE 50 **REPLICATE 51** **REPLICATE 52** **REPLICATE 53**

y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-6.51285	-1.75963	5.804337	2.721203	-0.10843	0.21209	-2.56863	-0.23623
0.636746	-0.41471	9.431249	3.269381	2.595833	0.643391	12.48679	4.246096
3.288942	1.275893	-5.55412	-1.552	-3.47251	-1.16885	9.816803	2.928814
2.060081	0.450365	-3.46274	-1.30928	6.272974	2.259568	5.168261	1.863568
6.252516	2.200062	7.50211	2.153077	9.445617	2.563287	2.647433	0.522241
-1.89907	-0.51367	15.63671	5.927032	-0.99106	0.232195	2.028598	0.907572
-3.03772	-1.60831	1.100538	0.513042	5.776925	1.699977	1.244466	-0.1509
-9.73859	-3.37873	-8.72672	-3.05617	-13.3503	-4.56145	-8.07715	-1.88219
7.581379	2.947162	4.647821	1.219896	-3.99091	-1.44849	-6.78267	-2.26732
11.24166	2.901947	2.236055	-0.02764	19.66506	6.283862	10.81545	3.486041
-10.8084	-3.19161	-12.6719	-4.29221	-6.3339	-1.93478	-0.7671	0.476441
-28.3535	-9.49106	-12.4725	-3.77779	-14.3129	-4.2738	-4.67363	-0.77611
-8.9331	-2.92345	-11.6756	-4.03515	-0.92549	-0.02622	-10.9624	-4.05647
9.410137	2.906976	8.105036	2.045622	6.160363	1.531502	14.01787	4.458065
-0.7233	0.131197	-9.42428	-3.70573	-7.81317	-3.21944	7.147196	3.294127
3.450189	1.552157	4.639275	1.286673	-4.13531	-1.91121	7.157153	2.264813
-10.7151	-3.10796	-16.4884	-5.2136	-11.0654	-3.05686	-8.79466	-2.89099
-6.62194	-2.54407	3.081105	1.150598	-7.76977	-2.69927	-5.85365	-2.26996
-7.97899	-2.71534	2.025826	0.892115	-5.9345	-1.56663	-11.5326	-3.85913
12.67663	3.612281	18.74876	6.008279	4.364464	0.653514	19.13075	6.25216
5.194969	2.360488	3.215208	1.532089	3.659215	1.360029	1.9676	1.135721
-16.5683	-5.55022	-18.0143	-5.98771	-14.5422	-4.3178	-13.2378	-3.91955
-1.20749	0.133617	-3.48715	-1.06718	-3.98033	-1.18295	-4.47322	-1.24863
9.850663	3.091306	10.5474	3.023716	3.01364	0.773603	16.713	5.858821
11.23175	3.352569	9.153968	2.393232	5.214814	1.190228	17.94123	6.222261
2.436183	0.750629	-3.54045	-0.92438	-9.47964	-3.54741	-12.8657	-3.88039
3.664627	1.516463	11.1213	3.833492	14.67568	4.858773	-2.89835	-1.12014
22.22762	6.623589	18.72519	6.108076	13.26091	3.16335	15.18211	4.482818
-7.12562	-1.71449	-8.55652	-2.3055	-7.31954	-1.59027	-14.3378	-4.51537
11.32683	3.367773	6.919239	2.348795	5.206855	0.95655	-5.40478	-2.47066
5.300758	1.550618	1.795535	0.292425	-3.16912	-1.73575	13.06767	4.691246
14.55242	5.545245	4.015544	1.538924	1.908046	-0.08897	6.173074	1.498974
-8.16932	-2.47517	1.85061	0.717499	-3.54545	-0.68616	1.583939	0.753234
-3.93841	-0.62293	-4.15756	-0.64103	-13.4343	-4.16442	-6.29803	-1.36214
-0.99989	-0.489	5.965489	2.319189	13.718	4.67869	2.819805	0.549987
-10.4087	-3.73989	-6.08622	-2.2562	-3.97158	-0.79584	-16.7972	-5.17148
0.119391	-0.27933	3.120434	0.46191	4.250498	0.665846	10.02055	3.764235
-16.4397	-5.23483	-11.7466	-3.36752	-18.6305	-5.65964	-14.7795	-3.83891

-2.25538	-0.69054	2.595003	0.476346	-6.80105	-2.51267	5.383939	1.469376
1.567796	0.946503	-0.2722	0.434199	7.210038	3.071795	10.86523	4.744155
13.97754	4.356798	22.81388	6.917463	4.211377	0.567952	12.88483	3.601348
7.27109	3.058492	-7.94943	-2.48291	-5.78524	-1.85512	4.733715	1.899294
-8.09176	-2.72291	-2.48585	-0.20744	-5.80243	-2.00257	-9.96942	-3.05669
-25.9259	-8.47017	-15.5602	-4.57885	-25.0769	-8.05294	-35.9762	-11.8031
1.683241	0.81504	9.201022	2.659944	10.64907	3.119798	11.13208	3.462368
-0.2687	-0.13987	6.646505	2.242316	-1.27674	-0.08647	0.899693	0.265418
-10.0312	-3.28147	-1.13633	-0.36534	-12.8322	-4.29908	-5.87868	-2.0036
6.871441	1.676094	8.380088	2.604783	13.56681	4.068849	17.15901	4.880867
-5.45919	-1.62422	1.356752	0.044742	3.389513	0.470984	-5.03798	-2.19068
11.98596	4.082248	16.20154	5.902223	12.93816	3.800319	16.84434	5.057321
-4.41926	-1.47991	-5.656	-1.62285	-7.70277	-2.46811	-7.50855	-1.52808
9.106119	2.316635	11.08143	3.352008	11.54083	3.788027	14.38292	4.706629
-13.5943	-4.72333	-17.2697	-5.90988	-13.0442	-4.74465	-22.6062	-7.55385
-12.2484	-3.9759	-8.71278	-2.94132	-11.9282	-4.10283	-12.0752	-4.21753
-2.88945	-0.62586	0.334444	0.218434	-2.44969	-0.2841	-7.68713	-2.52929
-15.1262	-5.37134	14.11966	5.587566	-10.1747	-2.53374	-2.19541	-0.52604
-13.3384	-3.81561	0.690688	0.667568	-7.08199	-1.4129	-4.91923	-1.22382
-35.0515	-11.9511	-19.7147	-6.23023	-19.9953	-6.59091	-19.9531	-5.9379
-17.8217	-5.55182	-0.34542	0.006613	-19.1676	-5.88322	1.604048	1.010128
-5.83123	-2.40871	4.275337	1.013745	0.246745	0.188241	-3.46088	-1.64943

REPLICATE 54		**REPLICATE 55**		**REPLICATE 56**		**REPLICATE 57**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-7.69861	-2.62437	-3.54183	-0.84336	11.03896	4.269681	1.645273	1.065946
10.59159	3.425333	-3.621	-1.30015	6.190193	2.081062	4.373939	1.664459
1.422683	0.575139	-1.25812	-0.59525	-10.2444	-3.40978	-3.81744	-1.22124
1.734197	0.352052	5.672787	2.011509	13.18167	4.086467	10.08049	3.450376
8.864314	3.323613	8.386871	2.324252	9.438983	3.165939	7.795674	2.52637
2.432012	0.886631	-0.18064	0.875102	-6.3308	-2.22751	2.157714	1.337933
-6.85616	-2.58323	-2.82777	-1.01313	1.544382	0.806649	9.451826	3.702454
-4.9605	-0.95705	-4.85357	-1.39347	-6.17436	-1.30753	-5.81833	-1.08759
-3.91089	-1.92621	1.052989	0.085252	4.653201	1.332734	-1.64404	-0.93452
10.51543	3.231142	16.97649	5.467815	5.994932	1.371198	20.19413	6.898091
-10.1743	-2.9376	-11.2416	-3.69451	-21.671	-6.41229	-9.54635	-3.16627
-4.54827	-0.65322	-11.6944	-3.17741	-13.4436	-3.767	0.828228	0.969042
-8.20696	-2.38245	-17.4646	-5.84626	-4.69408	-1.12707	1.720765	1.240399
6.524212	1.907533	16.45321	5.254494	9.644805	2.963996	12.43499	3.541077

-4.62613	-1.50049	-12.417	-4.72932	-0.46996	0.042662	-3.78603	-1.90094
10.22645	3.072956	7.376152	2.021916	5.904042	1.398101	-0.49064	-1.01293
-13.7512	-4.08287	-16.098	-5.20754	-17.2265	-5.7769	-18.6337	-6.03921
4.727245	1.848452	-12.4985	-4.51436	-1.28778	-0.32825	1.688728	0.767103
-8.0451	-2.40915	-2.9129	-0.32363	-7.27759	-2.33598	-9.367	-2.75419
0.310041	-0.82001	14.22312	4.323935	14.43612	3.651272	13.6287	3.782305
0.917144	0.581593	9.516887	3.765526	9.208664	3.403673	7.434513	3.056237
-6.55369	-1.54287	-7.80084	-2.50003	-6.49724	-1.40839	-16.6399	-5.32754
-10.7403	-3.39308	5.500115	2.621918	-2.52151	-0.64331	-0.02925	0.269568
-4.61945	-2.31302	9.209999	2.917489	5.459693	2.166427	-5.182	-1.84158
25.7358	8.28245	4.945021	1.733611	10.90006	3.318186	8.27932	2.336412
-4.03202	-1.09322	-11.4849	-3.57265	-8.80281	-3.74531	-8.0449	-2.90725
10.27296	3.244269	7.075457	2.265096	-5.75231	-2.0496	-0.05981	-0.41184
17.98023	6.085109	14.68968	4.817916	18.45905	5.658651	10.4103	3.703461
-10.584	-3.12373	-5.92155	-1.61446	-6.56579	-1.34009	-19.4375	-5.88526
6.207739	1.793289	-2.39207	-0.28378	11.12969	3.871192	14.09831	4.998583
8.437273	2.531264	4.729131	1.781234	0.382577	-0.20564	5.502709	1.592688
9.659709	3.703604	6.475298	2.033074	3.478756	0.874285	-1.86039	-1.30814
-10.8991	-3.372	-1.59769	-0.549	-3.94745	-0.94206	-14.5003	-5.12267
-22.87	-7.29569	-8.1273	-2.43967	-9.3165	-2.40001	-12.6742	-3.67277
-4.12329	-1.63611	9.344999	3.222257	6.40946	2.310695	3.549652	0.68713
1.813611	0.846612	-5.29147	-2.02235	-5.18681	-0.97537	-12.2292	-3.69657
-4.7109	-1.76617	6.517862	2.23108	13.2986	3.972961	8.917342	2.667783
-14.1112	-4.02873	-17.7892	-6.1597	-15.8605	-4.46847	-15.0703	-4.65557
-1.00578	-0.47218	6.254161	2.718251	-3.12109	-1.20882	0.14898	0.293676
8.586267	3.675506	-4.86063	-0.90915	5.092402	2.699688	5.206679	2.28009
20.18374	6.399789	25.292	8.405907	22.56292	6.639423	24.90116	7.669326
2.560434	1.270282	-3.7698	-1.60007	1.4331	0.84476	-2.22755	-0.45803
-11.2949	-4.55529	-0.60873	0.284319	-9.93406	-3.5535	-3.25075	-0.18468
-31.4194	-10.5707	-22.7818	-7.36663	-19.1948	-5.76986	-27.5369	-8.74043
3.821473	0.534507	12.36145	3.799776	-1.01356	-0.99156	8.118204	2.410677
1.979876	0.790338	-6.07964	-2.23341	-4.64706	-1.39596	3.047427	1.716629
-8.6764	-2.63913	-17.0137	-5.49721	-2.21773	-0.29157	-13.0546	-4.3678
12.17706	3.795096	6.628084	1.380522	2.020535	-0.22903	4.20084	0.836622
-0.74447	-0.57653	3.439014	0.647586	5.733191	2.557334	3.557398	1.397087
12.62267	3.506297	17.08742	5.307317	19.03794	6.445739	13.04539	4.150914
-1.29338	0.130443	-7.3969	-2.2758	-0.08728	0.490969	0.613448	1.055259
13.30461	4.212548	0.847192	-0.18685	14.08943	5.026003	11.13296	3.423709
-18.5314	-6.12117	-1.30612	0.120595	-7.64222	-2.21924	2.184543	1.311754

-8.19404	-2.45532	-10.9124	-3.81148	-19.1085	-6.33607	-10.1948	-3.43123
-4.11919	-0.71723	-6.07533	-2.01448	-3.33715	-0.83357	-8.03727	-2.43986
1.440594	0.632981	-11.1691	-3.37612	1.486438	0.981778	-4.91612	-1.69828
-11.6355	-3.41359	-11.5112	-3.7562	-2.91622	-0.99607	-2.80181	-0.56195
-17.9846	-5.98833	-26.9508	-8.27246	-17.6741	-5.64632	-19.007	-5.66317
-0.91086	-0.17487	-3.14	-1.06605	4.641717	1.96835	10.18723	3.095672
-2.60052	-0.76229	-4.72668	-1.63094	6.672072	2.608916	5.437199	1.965353

REPLICATE 58		**REPLICATE 59**		**REPLICATE 60**		**REPLICATE 61**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-10.3949	-3.06076	-0.23334	0.62903	8.151685	2.937074	2.544998	1.142691
10.44872	3.83135	6.755044	2.132833	16.24642	5.585148	-0.27707	0.463253
-5.04869	-1.85715	1.498417	1.049	0.669251	0.864919	1.554541	0.235964
11.99728	3.550972	19.63779	6.468526	6.181389	1.952715	8.633016	2.548465
7.910228	1.980943	17.52111	5.830209	8.545695	2.521681	9.687738	2.870847
-2.8283	-1.02419	10.02193	3.52124	-1.31669	-0.35247	7.070464	3.271662
7.915196	2.625875	2.915418	0.704581	15.45504	5.32818	-6.88967	-2.0625
-3.23388	0.000315	-7.81061	-1.7507	-4.10719	-0.30295	-1.98079	0.057655
-6.7926	-2.40837	-1.08558	-0.12744	-1.91965	-1.13833	6.995515	2.946468
9.955135	2.752534	9.46429	2.751325	5.642168	1.357241	15.36109	4.818346
-11.1176	-3.75177	-12.0338	-3.2746	-12.4941	-4.07453	-14.7582	-4.89254
-15.2239	-4.40557	-3.58494	-0.29494	-21.4314	-7.35555	-18.3476	-5.66218
-8.12916	-2.62293	-13.3085	-4.39293	-17.9341	-6.45557	-22.1485	-7.09616
7.296526	1.884569	6.598135	0.938161	18.14217	6.006592	5.311703	1.688347
-3.91589	-1.5069	-6.09319	-2.50967	-9.89663	-3.74676	1.674626	0.863082
2.960008	0.247756	7.861619	3.23313	12.39094	3.689486	15.69477	5.116404
-15.4321	-4.5161	-17.5103	-5.36693	-26.7979	-9.19707	-16.4213	-5.32072
12.97225	4.467189	-10.1444	-3.2147	0.3328	-0.01915	2.787773	1.111626
-10.5097	-3.27443	-4.50936	-1.3632	-11.8329	-4.01394	-0.23367	0.062552
8.815104	2.766138	15.61333	4.86933	14.03631	3.946128	12.90421	3.586483
9.042456	2.869459	4.272253	1.073498	0.00269	-0.53367	4.004675	1.340961
-18.6074	-6.02769	-16.646	-5.42548	-24.119	-8.3189	-8.63923	-2.40241
-2.76871	-1.13226	-11.022	-3.80274	-8.8268	-2.59125	1.304738	0.59968
1.358871	0.387608	6.898022	1.92465	4.648019	1.924231	-2.2504	-0.9067
5.424173	1.422437	8.741317	2.940784	10.62681	2.997045	9.093328	1.966066
-12.4648	-4.6841	-5.7979	-2.227	-14.9273	-4.44024	-0.78297	-0.10386
7.785828	2.711222	2.545435	1.159072	-0.37852	0.350944	-2.74224	-1.15873
15.60336	4.702226	15.92961	4.995951	16.69067	4.942113	17.36197	5.130688
-10.3711	-2.70589	-11.8378	-3.19903	-1.20358	-0.22789	-17.5714	-5.13777

3.260062	1.399516	5.2508	1.625942	-2.1549	-0.41822	6.146127	2.019472
9.416273	3.304454	-5.21944	-2.27697	1.965112	0.26632	12.65587	4.338892
-1.66549	-0.93229	6.8866	2.678841	2.732928	0.773675	5.271057	1.461305
-5.34196	-1.04293	-22.4299	-7.66912	-16.5891	-5.27514	-1.68335	-0.06256
-7.48541	-1.7088	1.057021	0.835296	-14.9481	-4.65744	0.665299	0.373587
4.653125	1.58938	-4.01576	-1.78079	9.277102	3.310462	4.592175	1.387021
-7.63491	-2.51136	-23.5251	-8.22458	-11.7222	-3.77818	-6.54717	-2.70815
7.051507	1.896879	-5.07926	-2.61103	-4.51208	-1.96746	5.892115	1.973531
-30.0793	-9.97107	-8.52769	-2.82341	-16.3493	-5.37399	-8.2285	-2.83462
4.908934	1.925202	-2.21867	-1.47865	9.234689	3.088551	-0.37357	-0.41361
-4.24445	-1.5495	12.46834	5.138589	3.557594	1.412529	-4.28087	-1.00773
13.95294	3.896362	12.3444	3.054919	8.783797	2.11965	17.70821	5.478346
1.940741	0.890995	-3.34717	-0.7356	-1.54084	-0.39368	-9.89726	-3.03779
0.813219	0.305361	-8.40068	-2.64115	1.964285	0.924926	9.978824	3.596054
-24.9945	-7.96746	-16.9667	-5.28188	-28.0957	-9.48329	-28.0104	-8.68551
9.369472	2.693607	12.94965	4.532331	16.941	5.673241	9.005574	2.394745
-0.14709	0.065351	4.550407	1.687559	3.16802	1.477143	1.290795	1.009183
-20.8843	-7.3586	-5.81152	-1.4913	-16.4959	-5.25446	-10.0137	-3.38997
3.954521	0.758956	20.86529	6.582385	6.292134	1.206463	1.967465	0.042489
12.96572	4.508051	-0.10291	-0.44022	-0.07301	0.04011	-6.05498	-1.84075
13.56431	4.225752	4.898066	1.208565	22.9849	8.047021	14.31751	4.23324
-5.36843	-1.2879	-15.9681	-5.7793	3.720547	1.722697	-6.33565	-1.89933
11.43137	3.398935	9.530029	2.57042	6.353914	1.55293	10.44802	3.198725
-4.54617	-1.20833	-8.45456	-2.92907	-10.0188	-3.04395	-17.934	-5.92391
-18.146	-6.00227	-11.0758	-3.5889	0.336	0.113525	1.110421	0.38765
0.968221	1.070607	-9.03369	-2.49572	-8.59373	-2.62631	-1.24205	0.460868
-5.10451	-1.1028	-4.59527	-1.61692	-10.1671	-3.19651	-5.91021	-1.82961
-10.182	-2.94961	6.090336	2.538278	-13.7884	-3.79416	-2.34292	-0.17053
-8.30429	-2.70608	-25.5369	-7.96779	-35.1335	-11.8905	-19.2199	-6.05453
-1.5623	-0.7096	-4.85709	-1.35234	-2.92098	-0.48898	-6.94057	-2.11642
3.476791	0.806322	10.26236	3.546989	6.245163	2.04161	2.66561	0.750165

REPLICATE 62		**REPLICATE 63**		**REPLICATE 64**		**REPLICATE 65**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-3.7924	-0.85149	8.845538	3.712579	-0.47732	0.254346	1.322805	0.869967
9.20997	3.008883	3.686659	1.40024	-5.53271	-1.53353	12.02313	3.932017
-6.09138	-2.21205	-6.52077	-2.11712	-4.17233	-1.70827	-13.0496	-4.46195
4.724941	1.016043	7.321563	2.250426	-0.95416	-0.27922	11.22515	3.268146
-0.51616	-0.62427	9.537602	2.411604	7.374476	2.311543	4.592791	1.117119

-2.26077	-0.0295	0.370416	0.171214	-2.24876	-0.43482	-2.65274	-0.63601
-6.53843	-1.85898	0.303462	-0.09415	2.415287	0.94097	9.213411	3.758317
-0.64482	0.000842	-14.9298	-4.58937	-0.05189	0.117308	-5.14546	-0.91802
1.460204	0.693068	-7.7508	-2.84997	-3.97273	-1.84925	2.897497	1.171877
4.795627	1.383948	-0.25632	-0.59655	9.987918	3.017352	9.425388	3.564557
-12.9865	-4.51836	-9.71052	-2.98913	-1.95781	-0.18859	-2.88902	-0.40809
-13.4133	-3.1147	-12.8338	-3.83408	-10.6075	-3.1722	-17.5979	-5.12957
-5.61513	-1.70831	-6.6354	-1.73441	-7.43427	-2.18451	-2.65602	-0.56219
5.054337	0.890804	6.419777	1.706595	12.19663	4.127191	16.89168	5.339511
-18.1052	-5.93132	-2.45264	-0.72903	-0.84516	-0.31179	3.83034	1.425486
13.95411	5.375411	12.6263	4.357002	6.011991	1.532206	5.691749	1.287501
-10.5621	-3.3458	-17.2092	-5.2541	-7.05202	-2.45924	-15.8236	-4.94784
5.214739	1.864002	-12.2666	-3.90707	-5.24453	-1.8737	2.11591	1.089151
-1.76357	-0.28743	-8.39329	-2.81998	-15.138	-5.2158	-15.7071	-5.00545
9.960295	3.032802	12.57264	3.573211	14.9385	4.664768	10.55503	3.110676
5.779974	2.251101	12.36433	4.082079	1.190371	0.669625	-2.09634	-0.75293
-6.45129	-1.53294	-9.52076	-2.86795	-10.2424	-3.17224	-9.85294	-3.27068
3.135838	1.253195	-1.50824	-0.57166	-5.1479	-1.20323	-4.52877	-0.85941
3.031044	1.130582	4.576905	1.250883	-1.20068	-0.66234	7.782394	2.109909
18.99173	6.021849	11.80457	4.121124	3.595421	0.936494	4.234288	1.242231
-5.89212	-1.90843	1.581524	1.13799	-12.4346	-4.69587	-10.8454	-3.8717
-1.34354	-0.00511	-3.93591	-1.92103	8.883473	3.616371	0.322271	-0.26686
12.80764	3.467516	13.76702	4.013984	20.59466	5.791669	17.68702	5.677709
-18.4167	-5.66598	-5.38457	-0.9035	-14.331	-4.25574	-16.0535	-5.16923
2.230816	0.444261	-2.9547	-1.40109	-1.38777	-1.0986	1.854316	0.299866
2.210296	1.143029	0.520148	0.226639	-1.94555	-1.23943	11.34496	3.720382
1.50612	0.269612	3.646398	1.240141	11.66562	4.202954	2.348647	0.880808
-15.2647	-4.83614	-4.9847	-1.37004	-14.8387	-4.63431	-6.90117	-1.36921
-6.13272	-1.56324	-4.86628	-1.24881	0.947546	1.01328	-5.21153	-1.02421
13.97822	4.941881	3.609283	1.330908	-1.51543	-0.75531	18.5623	6.262145
-17.7735	-5.82958	-9.42018	-3.17707	-14.4756	-5.50372	-13.9819	-4.74794
1.8538	-0.37842	3.289053	0.928911	-3.1131	-1.57099	-2.50074	-0.85877
-16.9533	-5.74791	-14.7315	-4.45934	-9.97212	-2.14302	-25.2437	-8.23476
10.83409	3.486775	-7.08182	-2.8174	0.857089	0.203758	14.49059	5.026917
5.800861	2.035268	8.787901	3.245926	2.070129	1.03468	-0.01165	0.161922
17.13904	4.896311	13.23339	3.347368	13.82109	4.501612	16.80666	5.058547
3.658215	1.392608	-3.08264	-0.98536	-10.7434	-4.18064	-0.7338	0.013832
-3.54441	-1.37263	-4.81382	-1.03352	-4.72428	-1.7553	1.649611	0.777885
-20.2472	-5.79066	-21.2995	-6.84276	-13.914	-4.02664	-28.0973	-8.81533

7.793987	2.436102	12.39577	4.09886	8.046418	2.461616	3.128358	0.655593
-4.49703	-1.70448	-4.26104	-1.87129	7.628402	2.868735	-6.41748	-2.27336
-5.93587	-2.23397	-1.7968	-0.80317	-9.88773	-3.30753	-18.0809	-5.90967
16.91995	5.374259	9.257841	2.418568	17.20605	5.069288	5.102107	0.848491
-11.0384	-3.49839	-3.1397	-1.26624	3.991466	1.325778	-1.19861	-0.72953
20.76337	6.888237	14.35046	4.341999	10.0066	3.051355	16.3971	5.173261
2.867645	1.846184	-3.22443	-0.6894	-15.5796	-4.91106	-10.1309	-3.1948
6.896925	2.08639	5.040964	2.06137	7.395391	2.530991	5.250862	1.938929
-17.8579	-5.95359	-10.2031	-3.52595	-5.27644	-1.41707	-12.7171	-4.1978
-10.3028	-3.06264	-10.7345	-3.69798	-14.0654	-4.59939	-7.14625	-2.40623
-11.3784	-3.90613	4.380121	1.981084	-4.3235	-1.02356	-2.91806	-0.08671
-6.28377	-2.53991	0.51973	0.378476	4.009902	2.02365	-1.87427	-0.31398
-9.98082	-2.50063	7.149242	2.66517	-13.5883	-3.93132	-11.9717	-3.74822
-39.2041	-13.2956	-11.2924	-3.0397	-22.7188	-7.84392	-13.1007	-4.12628
-7.71669	-2.5716	1.676316	0.099124	-10.0595	-3.38585	-1.71896	0.225972
7.761547	3.08595	1.985626	1.134307	1.177037	0.106939	0.357288	-0.20396

REPLICATE 66		**REPLICATE 67**		**REPLICATE 68**		**REPLICATE 69**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-2.22484	-0.38395	-2.93199	-0.66726	-7.05234	-1.98028	-6.84186	-2.09823
1.407633	0.306015	-2.2281	-1.30173	-0.23205	0.145483	-2.25225	-1.32998
-8.33834	-2.91489	-1.56447	-1.01094	-6.77156	-1.99892	3.967352	1.196397
-2.34738	-0.69	3.752256	1.126381	20.44654	7.364587	4.353883	1.532158
0.90798	0.256841	13.70156	4.526141	6.912444	2.071531	13.77337	4.220626
-8.08923	-2.44557	1.441342	0.845047	-1.69239	-0.61351	-1.92347	-0.91937
0.798625	0.105893	-11.0067	-4.27651	-2.00843	-1.13927	-6.52378	-2.51335
-12.0455	-3.70595	-4.77104	-0.93626	-5.44405	-0.71221	-8.75899	-2.0148
-4.03304	-0.97924	15.0436	5.340207	-2.33616	-0.92336	12.08488	4.186425
10.24246	3.058556	15.56692	4.850325	10.33398	3.131727	2.742477	0.71086
7.677344	2.949652	-8.55431	-2.92719	-10.4854	-2.44551	-10.6307	-3.10174
-16.9467	-5.30627	-9.71939	-3.13632	-6.21785	-1.54106	-17.6905	-5.19281
-11.309	-3.72189	-5.33661	-2.16143	-25.4025	-9.18515	-2.94718	-0.34501
5.319452	1.130809	19.17795	5.850358	6.960477	2.14689	9.73493	2.949343
-5.2835	-1.83128	-2.19753	-0.66287	5.057806	1.707145	3.418856	1.841943
14.18945	4.73364	8.881392	3.162687	-2.27475	-0.95597	3.935449	0.78835
-8.65927	-2.28114	-15.8693	-5.68288	-11.7078	-3.24254	-5.25193	-1.83165
-3.95735	-1.81662	2.94904	0.747094	-3.85631	-1.60298	-0.15927	-0.06995
-9.38549	-3.25993	-1.57619	0.131299	-5.58515	-1.88426	1.813735	0.550507
25.03843	8.437489	17.03726	5.497854	14.18208	4.298675	11.1907	3.213227

7.628823	2.581977	2.417515	0.844944	12.03483	4.284202	6.006869	2.018574
-15.8905	-4.67226	-8.15663	-2.1542	-15.7831	-5.48587	-22.1137	-7.15773
-3.72486	-1.41523	0.165306	0.39907	-2.38069	-0.8706	-3.10039	-0.40757
-0.39276	-0.31573	6.064904	1.292716	-5.82513	-1.85967	-8.14215	-3.28818
9.092667	2.457763	0.688404	-0.30411	7.415386	1.8185	13.73012	4.856707
-7.37595	-1.91848	-9.88344	-3.55068	3.267019	1.080594	-7.15627	-2.56102
1.175421	0.527874	8.958278	3.150484	-3.78272	-1.52689	10.79481	4.199062
9.283402	2.742879	9.950768	2.692495	10.13036	2.122107	14.90853	4.764552
-11.2254	-2.86885	5.599346	2.915399	-12.1625	-3.63687	-16.4706	-5.06568
5.844308	1.511768	7.018657	2.152397	8.598193	2.912636	10.98466	3.576886
7.410103	2.420748	5.671796	1.947635	7.542755	2.679526	-6.94723	-2.86475
5.588949	1.287934	-5.06628	-2.02137	9.969691	3.265468	9.491211	3.902225
-6.58629	-1.96654	-5.68731	-1.19204	-11.3347	-3.50694	-16.6435	-5.32582
-20.0099	-7.2146	-6.67355	-1.79196	-4.82265	-1.0322	-9.34794	-3.06205
7.72318	2.354852	12.70354	4.040581	2.352791	0.952523	-5.9702	-2.42444
-4.55177	-1.65105	-10.5255	-3.89501	-11.8183	-3.67381	1.181936	0.873346
6.710557	2.12519	4.994735	1.888389	2.589445	0.454916	0.518706	0.170114
-13.0653	-4.4866	-12.6537	-4.27484	-8.76955	-1.89034	-16.6543	-5.58607
-4.44155	-1.6599	5.321524	1.52158	-3.74862	-1.10889	7.155149	2.714172
2.834131	1.435617	9.33676	4.150465	-5.25691	-1.89603	-0.84425	-0.22285
17.12781	5.149371	21.42318	6.343953	18.50698	5.571798	11.03841	3.082139
1.967601	1.177292	1.716797	0.891712	-0.96385	0.89245	-6.2865	-1.69152
-10.5103	-3.41694	4.557181	1.923498	-3.34214	-0.85487	-7.36796	-2.21954
-22.6575	-6.93251	-26.4101	-8.29299	-15.8341	-4.90687	-12.9555	-3.1043
-0.2146	-0.65156	3.298045	0.817891	13.35456	3.886365	2.936404	0.715635
-1.49085	-0.60337	5.289917	1.956206	1.602545	1.0232	0.937252	0.733443
-2.23413	-0.28955	-10.0629	-3.27579	-13.1275	-4.90962	-17.5538	-6.04642
8.237639	1.945002	17.40907	5.117062	9.044266	2.424694	13.76094	3.932259
-2.59411	-1.01632	7.08399	2.481846	7.25579	2.748787	-5.02964	-1.92301
6.597912	1.684525	9.462537	2.918931	14.11244	3.889615	19.38611	6.753306
-11.146	-3.72697	-9.71353	-3.12712	-1.62999	-0.04718	-11.2137	-3.13944
5.211616	1.837345	9.57335	3.079718	10.06825	3.287004	-0.07147	-0.58
-10.802	-3.28858	-21.424	-7.20299	-19.9959	-6.89756	-5.68572	-1.16454
-16.0919	-5.37283	-8.23321	-2.90591	-6.69554	-2.25644	-14.5563	-5.08829
-1.9426	-0.2382	-2.39772	0.114212	-14.6378	-4.66801	5.38789	2.172256
3.76938	1.500387	-11.6262	-3.7161	0.559161	0.465054	-12.6442	-4.08168
-10.1931	-2.79569	-3.63469	-0.82373	-11.7997	-3.03936	-4.82831	-0.71383
-17.1785	-5.25481	-22.415	-7.69181	-21.7169	-6.68622	-23.5991	-7.86783
-12.7392	-3.71279	0.964665	0.402959	-2.82795	-0.74114	2.95144	1.094209

-1.98913	-1.25973	3.51263	0.907376	5.740581	1.997681	-1.4947	-1.24093

REPLICATE 70		**REPLICATE 71**		**REPLICATE 72**		**REPLICATE 73**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-6.34554	-1.64656	-9.46676	-2.52794	-0.24947	0.649916	6.15801	2.063898
12.53366	4.632026	10.66786	3.789268	15.33046	5.121243	4.653465	1.545267
5.326969	1.990684	-0.20438	0.645964	-0.29146	-0.43694	-7.59562	-2.70515
17.15538	6.110863	8.665779	2.272623	7.186576	2.407238	4.735987	1.474362
0.548917	-0.84601	9.220367	2.547029	12.9838	4.04185	17.00418	5.773117
-9.07284	-3.32367	1.933641	0.826327	1.865049	1.06294	0.028804	0.334317
-4.57552	-1.44255	0.002865	0.192665	9.114661	2.94437	-5.16416	-2.23697
-4.69844	-0.40524	-6.63196	-1.20979	-6.26453	-1.46258	-6.42839	-2.0838
-6.48173	-2.36094	0.173975	-0.17098	2.644401	1.226489	-1.74423	-0.38657
5.640622	1.305079	2.245422	0.446035	-6.24439	-2.68457	17.59824	5.604873
-6.20379	-1.87122	-16.4835	-5.23607	-6.63745	-1.63481	-6.3438	-1.94422
-16.0629	-5.33945	-13.6486	-4.56636	-14.9843	-4.63664	-4.23101	-0.20777
-8.43901	-2.54467	-4.92606	-1.00486	-8.45812	-2.68028	-8.94112	-3.40283
16.56164	5.192675	13.31629	4.197752	10.06179	2.924247	15.27476	5.102523
-13.0625	-4.91145	-8.24401	-3.23788	-7.63128	-2.20654	-13.2493	-4.21245
-2.57435	-1.62302	10.9599	3.844535	8.536787	2.086945	2.298274	0.475214
-11.5542	-3.92306	-13.2527	-4.3607	-7.31916	-1.64693	-17.8519	-5.98108
-7.88143	-3.03886	-10.1399	-3.04939	-3.59772	-1.63979	-8.93141	-3.29758
-6.23673	-1.74707	0.760303	0.697138	-8.3494	-2.13832	-7.45923	-2.24074
7.232873	1.957189	8.191503	1.416867	2.28312	0.441086	8.28581	2.294846
6.40624	2.502555	10.49511	3.647319	-4.6047	-1.92644	12.77444	4.474326
-15.634	-4.96532	-8.65123	-1.96276	-5.11616	-0.60777	-18.4704	-5.83312
-2.91752	-0.58431	-5.61282	-2.27184	4.664349	2.434731	8.432338	3.368484
-0.29966	-0.30619	-4.69659	-1.66804	2.516316	0.496054	-2.95736	-1.16217
5.737012	1.725502	5.903061	1.321401	10.27603	2.607324	1.16007	-0.99271
-14.3441	-4.67163	-11.6269	-4.22234	-9.4833	-3.47354	-11.4916	-3.87093
-0.19462	-0.05609	-1.01221	-0.61445	3.070474	1.246841	6.687839	2.446399
21.86745	6.924561	17.30285	5.161793	18.12657	5.534624	16.81985	5.079306
-8.12868	-2.46464	-6.44934	-0.97736	-0.18874	0.655657	-1.80466	0.54255
0.413578	-0.27295	-8.43932	-3.04051	8.955587	2.945144	3.181956	0.890734
1.940114	0.375961	3.198034	0.668759	-1.6538	-0.42604	-0.87828	-0.82388
-5.81817	-2.7677	4.612576	1.217723	7.004656	2.118043	9.45993	3.286008
-2.59843	0.166124	-0.24839	0.68742	-12.5563	-4.59368	-8.23532	-2.24417
-15.6182	-5.37734	-3.01478	-0.72928	-10.475	-2.79365	-14.0687	-4.19803
8.1403	2.76389	2.551084	0.519614	-6.49426	-2.51153	1.782819	0.143526

-10.7271	-3.85807	-3.57271	-0.86494	-8.35397	-2.65957	-13.4895	-4.68982
8.835973	2.49107	-4.34919	-1.91577	-0.81093	-0.94589	-1.74563	-0.77459
-14.527	-4.17388	-25.3818	-8.61661	-21.4003	-6.99228	-11.6823	-4.28611
-2.72298	-0.93515	11.74168	3.86182	-0.17319	-0.23185	-0.61487	0.248063
11.4707	4.35774	3.805261	2.021511	2.851839	1.305246	-0.53324	0.262058
8.779902	2.69328	8.879187	2.40752	15.1645	4.091339	7.897037	1.864433
-10.0568	-3.23942	-3.01435	-0.71039	-3.45896	-0.505	5.55154	2.289956
-0.68398	0.061392	-13.089	-4.33967	-4.68423	-1.74603	-12.3725	-4.49892
-23.5944	-7.31335	-19.9976	-6.46351	-21.7319	-6.69036	-14.9237	-4.89825
-1.67363	-1.41551	0.463994	-0.35583	6.631982	1.924958	9.27566	2.800896
11.55207	4.367926	10.09796	3.725368	-3.35082	-1.87463	1.206963	0.341289
-2.82878	-0.066	0.333139	1.09946	-14.75	-4.66954	-9.45156	-2.95536
9.378868	2.259264	19.77361	6.238176	19.05087	5.638202	16.62645	4.840723
3.658306	1.822511	8.73779	2.672173	2.46644	0.480697	7.5116	2.698237
16.82142	5.518259	6.383271	2.636617	13.17171	3.941907	21.1436	7.158444
-1.43019	-0.1855	-11.3249	-2.90961	-12.2623	-4.14852	-8.5977	-2.89078
11.17591	3.554496	8.992083	2.864665	16.29785	5.68886	10.27225	2.958708
-1.7043	0.117987	-7.7236	-2.96291	-11.9586	-3.55208	-25.6942	-8.37661
-17.8605	-5.78254	-0.86579	0.182027	-12.2119	-4.06507	-8.31966	-2.68621
2.083557	0.867104	2.773361	1.630549	-7.30077	-1.97418	-0.97408	-0.14866
-9.39827	-3.02847	6.331987	2.314715	-12.2272	-3.4459	3.305569	1.516155
1.929587	1.222095	-8.52832	-2.35413	-10.4105	-2.95096	1.387939	2.237083
-14.4421	-4.12668	-12.8596	-3.61403	-20.8492	-6.77506	-20.5369	-6.57986
-3.29682	-0.82829	7.546366	3.263367	7.556848	2.626963	-7.61994	-2.91869
4.751244	1.770205	0.921834	0.623804	-5.04989	-1.87594	3.081837	1.233896

REPLICATE 74		**REPLICATE 75**		**REPLICATE 76**		**REPLICATE 77**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-3.48444	-0.75871	6.023255	2.897547	0.34042	0.254376	3.165256	0.915507
3.414004	1.150538	1.784905	0.618988	5.579199	1.622659	7.074298	2.47754
-12.5099	-3.95041	8.906887	3.384727	0.070284	-0.21554	-7.14237	-2.30924
8.077906	2.641771	12.59894	3.744982	7.410249	2.237164	8.028829	2.336947
9.707515	3.316048	15.94927	5.13271	3.184484	0.741013	4.691401	0.91826
-9.64793	-2.75914	1.534651	0.376079	4.148649	2.155106	0.605125	0.274963
-11.751	-4.24925	1.339337	-0.32933	-0.7599	-0.02589	6.355605	1.762234
-17.3962	-4.81653	-5.50267	-0.6896	-13.8728	-4.72171	-10.6281	-3.30412
-1.79359	-1.43581	-1.81118	-0.76505	-3.55297	-1.2092	7.241832	1.607021
6.543931	1.920006	5.600959	1.538929	10.0402	3.186857	5.762105	1.278386
-7.19211	-2.38033	-15.7024	-4.91366	-8.84642	-2.29082	-7.62468	-1.75485

-13.4011	-4.08789	-19.1387	-5.93306	-22.3557	-6.65651	-2.50139	-1.18514
-1.35782	-0.77612	-8.88214	-2.81023	-14.3112	-5.05842	-10.6436	-3.27893
13.91612	4.116414	1.36241	-0.55379	15.95054	4.834302	9.355699	3.002593
-12.8178	-4.61177	-14.1578	-5.13629	-9.4047	-3.21741	1.388521	0.380256
18.07737	5.66169	9.466624	3.155275	13.15724	4.895776	10.55565	2.902885
-22.0226	-7.16595	-17.9297	-5.63539	-12.6889	-3.48003	-8.94295	-2.82193
-2.46721	-0.68031	3.438554	1.150426	-3.88433	-1.40577	-6.46628	-2.50538
-4.33013	-0.88261	-4.58714	-0.55411	-12.65	-4.47073	2.242831	1.077525
6.443379	1.418121	16.6765	5.060883	10.2573	2.463923	18.45501	5.813847
-9.01736	-3.30542	15.57393	5.337376	1.229917	0.650417	5.811255	1.698976
-17.0224	-5.07669	-12.4393	-4.12259	-15.1987	-4.64471	-5.07312	-1.08132
5.983774	2.168927	-5.4112	-1.4025	-7.92793	-2.68865	-3.05773	-0.6203
0.854924	-0.25552	3.953007	1.939836	-3.39294	-1.82169	5.437237	1.901031
16.72278	5.074375	20.54888	6.424783	9.855584	3.056231	15.18916	5.308485
-1.05117	-0.53296	-7.79246	-3.0828	-8.85268	-3.28209	-12.8597	-4.28197
2.22918	0.317129	4.48211	1.758601	17.99892	6.336014	9.771271	3.489709
12.65764	3.737439	18.5264	6.380564	19.64432	5.963537	18.27905	5.43949
-11.436	-3.08135	-21.9658	-7.47496	-16.3378	-4.91917	-2.01507	-0.36571
0.70095	0.311742	3.160555	0.531652	14.22881	4.589079	4.765295	1.468934
0.062538	0.318453	-2.256	-0.83334	-8.28273	-3.08325	9.231345	2.623225
5.18809	2.053994	6.007136	1.896248	-2.16616	-0.92659	-2.0303	-0.78066
-13.2766	-4.24455	-19.2128	-6.5683	-11.9763	-3.95577	-7.46312	-2.55779
-3.5254	-0.78894	-1.95782	-0.41791	-10.7655	-3.39261	5.668382	2.975849
0.303993	0.093225	14.7057	4.892472	10.13751	3.355763	4.764251	1.828789
-14.6783	-4.74804	-5.46589	-1.52429	-6.75772	-2.40515	-15.7777	-5.04322
3.188869	0.767757	6.068994	1.706837	0.716136	0.132713	1.182366	0.206163
-18.0606	-5.51094	-11.4946	-3.04161	-13.0731	-4.04579	-19.138	-5.25673
1.801922	0.201868	-2.35223	-1.17616	-4.04424	-1.68981	2.273609	0.859548
11.25679	4.553955	3.141542	1.016111	2.113123	0.969966	15.93493	6.194517
13.7698	3.659137	18.28969	5.87279	9.889108	2.853925	14.37857	4.142466
-0.01709	-0.08614	-2.48134	-0.05468	-8.89776	-2.8747	-1.02729	0.017071
-15.9243	-5.23389	-3.37459	-0.62887	-7.73407	-1.73944	-14.0784	-4.72081
-16.3927	-4.25266	-24.2462	-7.94228	-22.3206	-7.12974	-16.5043	-5.12763
15.96762	5.580801	13.46433	4.748825	11.0479	3.556963	8.548849	2.151193
-10.1343	-4.00326	7.945322	3.18095	2.773424	1.222017	1.488729	0.643244
-15.2998	-4.83229	-3.43593	-0.98454	-13.1861	-4.51194	-3.21781	-0.91287
14.86584	4.057364	3.769423	0.641649	5.487096	0.331121	8.131688	1.830809
-1.0038	-0.2695	2.967886	0.83397	-8.71007	-3.372	2.221714	0.796313
21.20741	6.811738	16.73378	4.964388	9.544325	3.082819	22.26381	7.140849

-5.23883	-1.23328	-7.1687	-2.32028	-5.67242	-1.33289	-0.47682	0.553189
-2.18586	-0.98342	-0.08317	-0.2774	8.381229	2.899866	11.36597	3.285908
-4.8338	-1.49932	-17.3312	-5.92073	-9.30028	-2.42574	-16.8953	-5.99794
-6.83522	-1.85428	-8.84206	-3.09015	-3.8271	-0.72808	-12.5795	-4.42951
-9.57121	-3.25165	-7.5077	-2.03384	-7.16762	-1.62338	-1.70991	-0.54344
1.419948	0.376122	-11.4182	-3.64234	-11.5153	-2.84639	-9.03404	-2.77868
-3.73435	-0.16382	-4.90897	-0.97421	3.23682	1.943503	-14.8852	-5.09827
-25.1708	-8.75919	-16.8182	-5.09326	-20.1032	-6.28581	-28.3688	-9.3375
-1.42952	-0.63341	0.03623	0.141661	11.68395	4.431029	1.070323	0.834098
9.564171	3.815363	-2.26304	-0.4716	-1.62717	-1.21555	-3.9455	-1.39413

REPLICATE 78		**REPLICATE 79**		**REPLICATE 80**		**REPLICATE 81**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
0.342791	0.682541	-0.96132	-0.23629	2.163207	1.58554	-12.6558	-3.83252
2.15645	0.763205	2.451905	0.783794	6.853416	2.470757	5.303166	1.93889
2.57487	0.780109	-5.93674	-2.37386	-7.03005	-2.77857	-7.59416	-2.99406
3.495051	1.287336	9.371026	2.969568	8.26442	2.631375	9.533831	3.45718
1.521212	0.304843	8.772433	2.617631	3.359284	0.491059	4.760611	0.873673
6.206096	2.747399	-10.6292	-2.64452	-8.36283	-2.28275	-12.4118	-3.77314
4.623576	1.973268	4.579894	1.419164	-1.76645	-1.23949	4.431294	1.751769
-0.01844	0.566279	-14.1059	-4.48343	-3.60988	-0.52034	-16.9696	-5.09623
10.56805	3.058418	-12.9806	-4.8326	8.513867	3.283123	-0.84822	-0.4335
9.348257	2.363447	11.12083	3.26335	14.98133	4.355906	10.94406	2.95167
-1.81264	-0.6349	-12.2174	-3.65305	-0.77996	0.396484	-8.70615	-2.22197
-5.0629	-1.09621	-10.9052	-2.95157	-19.7898	-6.14824	-16.5028	-5.40724
-6.5059	-1.95634	-9.32178	-2.743	-4.41694	-1.52544	-16.4471	-5.70546
18.89959	5.903378	1.296346	-0.5736	6.63304	1.750751	18.76623	6.271935
-4.22933	-1.55188	-1.34399	-0.40971	-5.34929	-2.66207	-12.2579	-4.05968
10.66308	3.88425	9.018674	2.880309	7.697256	2.148743	1.320474	-0.09434
-8.53225	-2.68471	-16.2444	-5.48448	-14.0581	-4.64635	-11.6699	-3.55303
1.892137	0.289875	-1.59525	-0.6708	5.729311	2.092372	-8.93176	-3.45305
-1.30879	0.075942	1.71066	0.75672	-10.8699	-4.14209	-6.08454	-1.67625
0.987226	-0.40188	11.99042	3.488289	4.623804	0.589956	12.84175	3.742438
5.576615	1.606787	5.27987	1.88129	-1.09643	-0.08013	13.72635	5.498855
-6.36166	-1.34436	-15.1553	-4.87652	-17.5383	-4.97944	-9.07923	-2.75893
-10.6135	-4.14729	-6.5715	-2.11285	1.932932	0.23866	-3.38042	-0.85939
3.818537	1.327929	1.299361	0.328944	-2.93626	-1.77178	2.608675	1.172926
8.296208	2.454266	5.004661	1.168241	17.6229	5.922116	11.6048	3.727668
-8.99987	-3.00293	-12.9121	-4.20393	-9.42883	-3.12846	-10.8479	-3.29642

11.18673	3.342767	-0.34737	0.165175	6.989377	2.202974	-2.69588	-0.98734
12.87276	4.119054	15.71944	4.794312	15.40414	4.766443	17.85644	5.797262
-9.37354	-2.41209	-10.8167	-2.43666	-1.67917	0.568251	-15.6731	-4.88093
3.600372	0.948138	6.224949	2.143302	3.519796	0.587686	0.476115	-0.22283
3.586843	1.096453	3.216262	1.311607	9.53356	3.350888	-3.25411	-1.98675
-1.96911	-0.95885	2.469172	0.553814	4.241361	1.699956	8.479612	2.519102
-6.39389	-1.92855	-13.1537	-4.06935	-7.32969	-2.02852	-16.1807	-6.06757
-1.26091	0.764455	-8.01453	-2.32676	-8.41748	-2.21055	-11.1214	-3.45981
1.980876	0.062808	13.62028	4.691253	10.27846	3.84236	7.560694	2.472615
-3.41707	-1.16938	-3.69838	-1.03169	-9.33695	-2.83902	-7.66683	-1.85691
2.415267	0.359398	-5.58313	-2.2377	1.827384	-0.1032	2.911587	0.684746
-12.0039	-3.66562	-17.6027	-5.78304	-16.0466	-4.94457	-8.69556	-2.1218
6.813355	1.830057	-4.44543	-1.61454	3.80904	1.395519	-0.5249	0.070297
1.541223	0.85466	7.619188	3.248472	2.951748	1.374432	12.67359	4.757202
20.54584	6.135996	13.00862	3.934334	15.65914	5.025797	13.88722	3.909538
-4.92713	-1.38777	-2.12883	-0.7445	6.169755	1.851395	1.414609	1.263943
-6.43846	-1.78394	-15.9785	-5.39992	-7.36065	-2.25533	-2.25967	-0.70343
-20.6929	-6.35869	-21.6918	-6.96655	-19.7611	-5.56153	-19.7229	-6.33321
14.27538	4.537999	20.23296	6.507402	6.5311	2.031988	13.21767	4.556789
-2.55359	-0.96133	-0.5349	0.328384	10.18745	4.007628	-6.76191	-2.63897
-20.0324	-7.32957	-20.4761	-6.7648	-15.918	-5.28247	1.335074	0.737814
9.716152	2.377552	7.62346	1.531505	10.53964	3.008543	26.32845	8.329747
7.363443	2.693524	11.53195	4.018771	11.87742	4.370484	-10.4688	-3.57512
12.86783	3.795856	13.74339	3.949092	11.84469	3.30492	9.15907	3.088819
-8.46991	-2.40642	-5.16377	-1.50998	-7.1586	-1.80442	-6.02759	-0.76074
11.72949	3.807083	-3.36159	-1.89804	1.391038	-0.10696	12.75988	4.000049
-13.5479	-4.11309	-0.49385	-0.03975	-19.6978	-6.5355	-7.62826	-2.56134
-11.5531	-3.8196	-6.87476	-2.09113	-8.54912	-2.92389	-13.6178	-4.49178
-3.8072	-1.16446	-3.72876	-0.93512	2.529311	1.168332	-7.73496	-1.50368
-6.70292	-1.76447	0.601582	0.288476	-3.87565	-1.00772	-10.0124	-3.41558
-1.18918	0.382556	-18.2114	-5.73566	-9.58622	-2.69667	-10.7713	-3.18521
-29.5369	-9.72662	-24.8779	-7.45959	-9.20862	-2.75125	-14.8706	-4.43263
0.948388	0.727838	0.080658	0.383544	-8.21041	-3.54903	2.287436	0.78095
-1.2171	-0.24205	7.465693	2.806067	1.971913	0.371037	-4.21057	-1.66155

REPLICATE 82		**REPLICATE 83**		**REPLICATE 84**		**REPLICATE 85**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-2.71604	-0.30612	-7.47224	-2.5147	-0.87666	0.449208	0.992456	0.851348
0.071276	0.015075	4.684203	1.586809	10.7283	3.73282	-3.69982	-1.67122

-16.5842	-6.09981	-5.2181	-2.00275	-9.61024	-3.58346	-2.17006	-0.82496
11.78627	3.909873	1.699933	0.674248	-9.11129	-3.1027	1.476878	0.682517
16.87728	5.488084	10.83058	3.518812	7.291644	2.264134	3.782065	0.942277
0.786847	0.778131	-2.46303	-0.45197	-1.60428	-0.4884	-8.33549	-2.36498
-0.38953	-0.1057	-3.08912	-1.13491	2.843749	1.16392	-3.80001	-1.46761
-8.44368	-2.08767	-9.54096	-2.37362	-5.40761	-1.01863	-14.622	-4.44566
2.566285	1.049797	-3.06964	-1.85511	5.120043	1.50086	-0.56572	-0.15938
10.20952	2.884574	11.91933	3.925899	4.636833	0.391468	6.88787	2.260402
-6.00705	-1.41988	-18.4515	-6.21722	-18.4116	-6.20313	-0.43628	0.435292
-14.2657	-4.2871	-3.65598	-0.45484	-14.3575	-4.41896	-12.7164	-4.21807
1.632935	0.890775	-9.33464	-2.68505	-18.4753	-5.97577	-12.0923	-4.03761
7.349102	2.323511	3.07894	0.641408	8.347551	2.40817	10.79236	2.618486
2.808652	1.163159	1.077893	0.456531	-6.0323	-2.14045	-14.6937	-5.19215
7.888059	1.879384	1.668249	-0.1964	6.580937	1.804439	1.948983	0.470364
-9.95831	-2.35469	-22.8289	-7.97331	-22.6047	-7.04566	-17.4688	-5.77027
-4.46049	-1.0443	-4.45619	-1.38385	-2.14293	-0.83039	-5.04149	-1.49737
-5.34203	-1.1693	1.506292	1.092219	-9.33128	-2.75841	-0.32863	0.296504
17.56318	5.380816	1.430681	-0.0385	11.44519	2.912531	7.016451	1.908965
7.275517	2.341238	6.103719	2.424283	7.2431	2.540634	2.912914	1.407467
-16.4445	-5.19275	-6.65987	-1.81092	-6.15384	-1.60194	-8.17537	-2.0858
-2.79705	-0.67634	-10.3042	-3.51421	8.820844	3.100687	5.161837	1.856356
2.506911	1.234888	2.197471	1.104813	3.011637	1.186483	0.670718	0.63379
17.7962	5.519317	5.313609	1.504541	5.277874	1.058488	6.183865	1.454172
-8.24779	-3.08227	-5.41515	-1.55727	-10.6058	-3.59017	-2.28476	-0.73382
4.59163	1.080245	3.773569	1.027866	2.310063	1.342113	5.102664	2.210411
28.54627	9.393951	18.81414	6.342208	19.47948	6.452559	18.70065	5.600174
-18.5498	-6.04528	-3.5562	-1.11908	-15.4167	-4.43285	-0.53273	0.609211
1.201754	-0.21612	-3.55134	-1.22307	4.227984	1.410735	11.97581	4.011742
3.736263	0.786243	12.29534	4.130028	0.714728	-0.05219	2.065268	0.436767
-0.40265	-0.14326	2.479859	0.714387	0.729136	-0.30947	5.302339	1.620477
-10.8626	-2.97427	-9.34604	-2.55742	-7.40423	-1.91525	-5.78517	-1.37062
0.711014	1.051764	-7.35029	-2.23067	-7.18894	-1.98872	1.397734	1.073487
-0.1937	0.015319	10.96481	3.723482	7.230043	1.960709	-2.4661	-1.39633
-17.8247	-6.42737	-8.35961	-3.18424	-16.3837	-6.05051	-4.57658	-1.63813
5.281371	1.586748	10.98428	3.246849	5.919191	2.218893	0.017958	-0.39865
-20.248	-6.26671	-19.033	-5.55382	-22.9451	-7.58441	-19.0788	-5.95729
13.24216	5.061415	0.200306	-0.00692	-3.4421	-0.85188	1.343801	0.678986
8.697285	3.944506	3.614509	1.698067	0.145436	0.362423	10.78199	3.680316
26.27284	8.532075	19.6742	5.930622	13.73847	4.210565	16.98491	4.51813

-0.26623	-0.28117	-8.17676	-2.07299	-8.06348	-2.56242	4.198315	1.28064
-9.99941	-2.7266	-9.31958	-2.87944	6.122576	2.501689	-1.02184	-0.33831
-26.9413	-8.43729	-19.1119	-5.94108	-19.2431	-6.40971	-20.8621	-7.23317
11.04389	3.733768	5.151989	1.285429	3.582174	1.476948	13.1412	4.840095
-0.52727	-0.00243	3.67136	1.664572	14.96083	5.67692	11.091	3.901696
-5.28701	-1.05563	-12.5523	-4.03259	-12.1503	-4.1911	-4.80898	-1.85281
18.62703	5.519185	3.796134	0.407582	10.53382	3.07416	20.11947	6.036847
1.835275	0.205893	-7.85407	-3.08564	-1.35014	-0.65914	6.607833	2.227528
20.18576	6.296076	12.89832	4.108308	1.982314	0.438857	19.20013	6.056215
-6.4511	-1.62832	-4.50987	-0.78812	-12.3808	-4.19216	3.655146	1.574394
8.899875	2.794193	16.91291	5.308029	11.90278	3.700529	12.26529	3.774449
-11.3429	-4.13506	-15.6975	-5.20112	-19.9373	-6.39693	-7.52341	-2.38454
-8.18448	-2.70846	-10.4287	-3.3963	-14.7504	-4.6784	-13.3901	-4.45103
-2.06036	-0.37242	-3.15619	-0.73089	-7.10339	-1.86389	-2.44531	-0.40658
-15.8614	-5.46826	1.881852	1.445439	0.688562	0.592873	-4.2918	-1.18456
-7.04033	-1.92329	-3.96725	-0.634	-12.1223	-2.98416	-6.69247	-1.71894
-23.3316	-7.40339	-28.2292	-9.73957	-13.9105	-4.19265	-19.7571	-6.94059
-7.65335	-3.13365	1.365926	0.788041	-3.80266	-1.27129	2.325418	1.421535
4.230253	1.252024	13.79012	5.236093	-5.0761	-1.5924	1.144842	0.013571

REPLICATE 86		**REPLICATE 87**		**REPLICATE 88**		**REPLICATE 89**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-1.99425	-0.5815	2.358327	1.711042	-0.0483	0.29426	5.545359	2.144455
13.20131	4.086788	3.621618	0.676724	-4.44366	-1.90292	6.651078	2.271787
-9.73802	-3.19395	-1.27086	-0.20443	-9.45639	-3.61973	-1.64987	-0.8531
6.997747	2.303649	12.01756	4.179135	-0.12127	-0.60413	12.28257	3.961264
19.25152	6.899832	11.59123	3.767034	16.7361	5.560672	18.19053	6.195304
-3.94869	-1.31287	1.88555	0.809753	-5.38704	-1.02661	5.702888	1.974235
-1.19264	-0.3075	-5.67322	-1.95589	6.438682	2.114229	12.29489	3.84328
0.116409	0.819937	0.486537	0.615409	-8.59265	-2.28435	-1.28117	1.207388
4.183654	1.360595	3.815167	1.127461	1.736051	0.987337	0.929225	0.659188
8.115247	0.968502	6.190073	0.944895	7.667514	2.135185	17.7049	5.839593
-5.77862	-1.25889	-15.2649	-4.64054	-11.897	-3.32865	-15.1105	-5.20411
-11.8431	-3.24131	-6.34553	-1.40435	-11.44	-3.05244	-2.75586	-0.27641
-11.9701	-4.13493	-11.6449	-3.61822	3.469631	1.54592	-18.1362	-6.44782
11.15272	3.931137	11.15743	3.010538	6.944379	2.078279	23.44468	8.309246
-3.34821	-0.7327	-1	0.021544	-4.88713	-1.4167	-10.1167	-3.94035
2.821413	0.207104	-0.12552	-0.5226	-1.3068	-1.17429	1.183035	-0.21927
-10.5987	-3.03781	-15.9815	-4.74021	-1.08307	0.408157	-14.1662	-4.24606

-0.60132	0.159647	3.529683	1.233706	-1.19828	-0.59413	4.814807	2.015791
-3.19485	-1.24237	-14.0266	-4.67093	-6.67965	-2.13438	-16.3135	-5.5305
23.42787	7.576213	16.7751	5.451794	9.194555	2.624207	8.100082	1.802089
4.572522	1.829425	4.46637	1.603972	11.21484	4.174641	8.741889	3.405268
-17.3267	-4.9974	-10.958	-3.19875	-13.5624	-3.79119	-11.6114	-3.6041
-2.09791	-0.65326	-2.17012	-0.15717	1.042054	0.023332	1.635863	0.728325
1.746847	-0.09585	2.479779	0.326826	-5.01434	-1.88419	5.553886	1.507779
13.15405	4.064425	17.03922	5.270282	7.548768	2.131055	5.552763	1.7353
-10.7555	-3.69018	-13.6262	-4.88677	-9.18518	-3.23536	-10.9467	-3.46578
8.092393	2.442987	5.872441	2.171305	2.599778	0.610485	3.638463	1.301145
4.511926	1.094289	20.45836	7.039465	23.69	7.935215	18.14926	6.596869
-15.3315	-4.13995	-8.31982	-2.4249	-12.2704	-3.56811	-15.0094	-4.40321
11.05364	4.584476	9.426749	2.826015	1.110131	0.335467	-3.85844	-1.31874
10.12912	3.856868	6.954684	2.269939	5.176324	1.563332	-2.42298	-0.93925
3.891175	0.612308	4.352745	1.258947	2.043002	-0.15153	13.04418	4.2705
-4.50344	-1.10938	-3.90802	-0.5326	-15.5388	-4.98087	-12.5674	-3.99492
-10.361	-2.73622	-13.6923	-4.694	-7.71026	-1.96332	-8.22584	-2.07129
9.793574	3.034687	-4.32354	-1.91616	17.22738	5.533371	2.48527	0.420841
-8.90623	-3.03074	-6.37574	-2.12549	-4.70731	-1.68469	-11.4888	-3.65154
-2.23793	-1.30471	-4.57735	-2.23668	-1.94864	-0.86889	3.567295	0.777555
-6.94929	-1.24789	-21.1552	-6.93704	-19.1849	-6.17121	-16.5939	-4.67447
6.502036	2.313039	-7.51152	-2.14041	1.669609	0.414432	5.990111	2.014597
-5.94471	-1.78815	5.875361	2.543079	-1.40771	0.159049	2.018122	0.850765
13.67794	3.944363	13.58343	3.628571	13.34933	4.017321	10.45823	3.257309
8.575792	2.854791	-1.97481	-0.41211	2.409814	1.159936	-5.09869	-1.61429
-13.0391	-3.59591	-1.33808	-0.45886	-6.12639	-1.92042	-7.0695	-1.95695
-23.6639	-7.15966	-28.7015	-9.65834	-26.67	-8.59195	-24.2659	-7.97393
-0.30888	-0.41599	14.28234	4.453413	3.263719	0.93522	3.114264	0.880523
4.727246	2.121377	10.86663	4.236168	-6.44945	-2.5353	-1.89073	-0.12341
-9.75078	-3.06023	-13.5977	-5.06338	-8.79624	-2.96931	-9.27442	-3.14066
15.16187	3.914424	9.065134	2.247058	-4.4005	-2.97846	14.22196	3.84951
-7.70359	-2.3721	-0.45853	-0.07605	9.539497	3.33239	-3.061	-0.43795
13.53948	4.299858	8.347275	2.521844	22.65531	7.436484	17.07508	5.475537
-6.48938	-1.6827	0.381574	0.654719	-11.4029	-3.2071	-0.26639	0.34022
-2.00614	-1.60206	7.36125	1.908678	15.19268	4.964711	-1.7108	-1.27974
-8.12822	-2.7378	-4.9581	-1.12072	-11.7339	-3.26572	-2.12404	-0.60088
-4.53875	-1.81939	-7.64357	-2.31109	-10.3658	-3.1667	-25.9926	-8.695
-5.84831	-1.66927	-3.0701	-0.65119	-4.29737	-1.26535	5.587812	2.382258
-0.35296	0.10655	2.941525	0.681336	-9.93041	-3.17311	-10.5269	-3.34872

-6.90366	-1.76436	-8.38934	-2.60785	-5.87216	-1.7622	-1.30999	0.06451
-17.6239	-5.49364	-18.8935	-6.77386	-14.4835	-4.41885	-18.4523	-5.95296
-3.7084	-0.95135	3.011502	1.627835	0.572978	0.33189	-0.31775	0.306228
9.441359	3.514258	4.725058	1.649372	2.873658	1.02214	3.654762	1.173771

REPLICATE 90		**REPLICATE 91**		**REPLICATE 92**		**REPLICATE 93**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
7.511129	2.890622	0.883534	0.583122	3.818158	1.548701	10.36067	4.084454
-0.18207	0.205411	4.548832	1.621142	8.610706	2.533639	11.40358	3.861825
2.401179	1.124655	2.578421	0.593457	-3.90524	-1.07198	-2.11883	-0.99979
0.408218	0.255251	7.297079	3.01561	-5.04176	-1.81284	7.929615	3.217873
9.151859	2.719487	5.247164	1.34246	1.753345	0.374136	7.908089	2.426492
8.632581	2.974361	5.706476	2.648705	2.861071	1.034457	-3.50419	-0.65913
9.006544	3.383674	7.170968	2.610343	6.591702	2.386876	-3.36095	-0.96839
-7.85228	-2.22689	-15.7815	-4.51219	-10.7785	-3.10033	-20.0511	-6.36036
-6.34337	-2.25285	7.657851	2.478464	1.63564	0.610555	-9.32116	-3.4772
3.937532	0.699852	11.43706	4.140699	10.46661	3.192413	10.76345	3.331731
-7.33834	-2.43283	-11.8993	-3.92551	-11.0187	-4.07591	-6.32591	-1.82359
-10.1422	-3.65796	-11.2207	-3.10031	-18.2002	-5.87106	-12.4626	-3.51569
-15.5201	-5.22258	-6.42312	-2.18214	-5.35597	-1.63701	-15.6424	-5.39201
19.50886	6.191939	12.54894	3.620821	13.99615	4.489547	5.645027	1.360958
-2.19211	-0.71002	-7.93805	-2.94677	-13.1165	-5.16307	-9.51788	-3.11274
14.83785	4.643904	-1.9304	-1.58195	4.594043	0.743296	8.78056	2.821762
-19.994	-6.71972	-4.90695	-1.39671	-10.3156	-3.20174	-12.2696	-3.3522
-5.71077	-2.37907	-2.86938	-1.09802	-0.24565	0.080044	-1.47065	-0.67188
-7.95411	-2.3436	-10.5803	-3.29532	-7.37551	-2.27116	-7.75473	-3.02189
9.869023	2.993327	-0.11564	-0.73602	16.12566	5.411786	6.261977	1.330116
4.082613	1.031626	-2.49191	-0.20516	-3.27161	-1.12579	5.990351	2.259133
-12.4693	-3.40325	-13.9689	-4.46365	-15.121	-4.80116	-12.0051	-4.32059
-4.49361	-1.5227	5.289477	1.857187	0.379341	1.206404	-4.86401	-1.63542
-0.61682	-0.57985	7.49685	2.530929	-8.45533	-3.83272	-4.97524	-1.88169
10.55474	3.288551	10.07364	3.218083	12.9172	3.924144	12.31746	3.991827
-5.05618	-1.50532	-8.06735	-2.60547	-9.34902	-3.41714	-15.2946	-5.26174
6.786459	2.663321	-5.45543	-1.68166	6.442273	2.478759	0.223525	-0.14833
16.32105	5.679866	22.70079	7.124584	18.79281	5.91138	17.95283	4.937742
-8.94098	-2.25979	-11.7596	-3.35076	-11.4439	-2.62518	-16.941	-5.46554
0.67645	-0.13296	4.305974	1.234049	1.373276	0.332651	-4.78802	-1.74834
-0.15301	-0.65243	0.822167	-0.14317	9.382915	3.117053	11.01032	4.041326
8.82393	3.220345	-0.53591	-0.42515	5.298466	1.567163	6.272919	1.372531

-14.6367	-4.52553	-12.0932	-3.88838	-12.9294	-4.216	-14.4533	-4.96271
-11.7411	-3.83123	-3.2404	-0.73515	-3.18929	-0.36108	-6.27443	-2.20167
10.2128	3.333333	8.796453	2.732858	7.027127	2.204259	6.368386	2.263766
-5.92362	-1.8059	-15.1349	-5.3519	-9.7031	-2.90215	-11.824	-4.29774
2.079603	0.663876	6.003316	1.726481	-3.4654	-1.08866	14.42047	4.37909
-11.8646	-3.22948	-4.90685	-0.71432	-17.3641	-5.25174	-27.3156	-8.82641
11.67204	3.954383	13.44637	5.123703	12.10588	4.362721	-1.45553	-0.21127
6.145992	2.414826	6.816483	2.823909	-0.98398	0.072658	7.666641	2.897091
12.51478	3.302147	9.367074	2.645739	14.22424	4.553151	12.59222	3.443667
0.569651	0.691502	8.760392	3.246157	-5.05493	-1.6657	3.251075	1.561788
1.559197	0.9163	-2.84815	-1.17751	3.255184	1.864129	-7.7108	-2.12298
-26.1785	-8.56901	-23.972	-7.87222	-32.639	-10.4327	-17.3805	-5.51921
14.47157	4.837213	5.925468	1.891831	20.42325	6.584594	2.68418	0.403241
-1.46816	-0.7743	0.158579	0.176243	6.275002	2.782154	12.29137	4.703012
0.006819	0.24923	-5.15432	-1.7906	-6.31433	-2.00816	-11.0652	-3.62403
4.457819	0.513428	12.68886	3.543565	11.25218	3.082558	10.68446	3.228878
3.843177	0.617582	5.215448	1.432127	14.67347	4.961699	-1.5504	-1.11852
12.47024	4.507314	19.16216	6.088895	18.8834	5.541708	13.30752	4.274573
-9.30835	-2.5264	-0.76651	0.436015	-9.82976	-2.8709	-9.13897	-2.76795
1.174424	0.495656	14.34017	4.569475	6.397743	1.960862	2.609907	0.375592
-4.95051	-1.08894	-8.48655	-2.79951	-13.7532	-4.2518	-6.70912	-1.86654
-10.3982	-3.41386	1.545681	1.111168	-11.2671	-3.90215	-15.3396	-5.40298
3.350601	2.000147	-4.98593	-1.29377	1.771167	0.768657	-5.76629	-1.41722
-10.2721	-3.6148	-8.14578	-2.31509	1.954036	1.132686	-10.591	-3.23531
-2.08271	-0.3346	6.742529	3.108086	-4.90251	-0.72148	-14.8237	-4.284
-23.4767	-7.33994	-25.7385	-8.21207	-20.2851	-6.77788	-28.8986	-9.35498
5.904037	2.479456	-7.82309	-2.71187	2.035938	0.87288	1.936343	0.703768
5.497316	1.677003	0.391794	-0.33981	8.338948	2.393227	1.884568	0.496687

REPLICATE 94		**REPLICATE 95**		**REPLICATE 96**		**REPLICATE 97**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-3.51878	-1.7092	7.540123	2.920335	-0.65758	-0.03517	6.227271	2.245492
3.706079	0.768001	-3.20181	-1.68777	1.051548	0.082012	-2.043	-0.84635
-1.71878	-0.53974	-12.8366	-4.60931	-7.99292	-3.07617	1.269036	0.610658
4.233174	0.957396	3.393165	0.745451	9.44898	3.445173	20.76532	6.896666
15.28809	5.127404	18.65726	6.615555	16.70973	5.311595	11.84194	3.989233
-0.30908	0.513997	8.413289	4.150602	3.378572	1.864929	-0.60383	0.509462
-3.52802	-1.17103	4.298135	1.222453	5.231811	2.236156	11.44643	3.641098
-5.70129	-0.89315	2.065694	0.752249	-7.80355	-2.24098	-12.598	-3.86537
-12.3964	-4.38424	3.406362	1.109	0.413003	0.722171	-2.414	-0.93671

9.024817	2.607669	16.82482	5.357079	4.67235	1.538064	10.4727	2.987863
-5.48655	-2.04554	-1.48904	0.544895	-3.61213	-0.66821	-2.78712	-0.49692
-3.52424	0.013686	-18.4335	-5.40447	-13.1889	-3.23007	-10.6049	-2.99796
-21.5312	-7.27504	-8.90417	-2.58044	-9.58299	-3.24497	-10.9456	-3.70584
14.93767	4.86826	8.623988	2.300223	5.470583	1.192556	10.02929	2.531722
-3.78405	-1.18299	-1.08746	-0.46231	-4.47648	-1.59564	-10.772	-4.30569
-2.72651	-1.52688	-1.28362	-1.28058	7.114335	1.404129	1.886446	0.402811
-18.4764	-6.27407	-4.86896	-0.94602	-9.52162	-3.53699	-21.6981	-6.64942
-1.02562	-0.19861	0.926845	0.621936	-3.74561	-1.17349	4.559714	1.761103
0.928805	0.268806	-7.89944	-3.02741	-4.92131	-2.08716	-0.94889	-0.19978
10.88133	3.061104	6.684997	1.653021	8.915961	2.051418	19.49206	6.242045
5.795479	2.136279	1.648677	0.524907	6.880339	2.117948	11.17331	4.298421
-14.9314	-4.74541	-10.2503	-2.39866	-3.89606	0.173246	-23.2792	-7.47235
-8.99545	-3.02978	-9.03148	-3.04807	5.805234	2.090091	-4.72487	-1.51536
5.276018	1.960208	-5.57348	-2.12881	2.275188	0.934034	0.12667	-0.17722
14.12312	4.338714	14.6924	4.885914	15.31797	4.665728	4.338793	0.981769
-7.26352	-2.13893	-8.03742	-2.96653	-2.82719	-1.11136	0.051552	0.110632
8.210829	2.92516	4.064813	1.457203	-1.80512	-0.31972	4.664034	1.322546
15.26727	4.700949	20.54859	6.5045	8.882931	2.15378	1.546913	-0.32919
-12.6839	-3.38451	-3.43615	-0.49726	-16.086	-5.52335	-10.5819	-2.85683
12.6653	4.593904	-1.97235	-1.13311	3.595658	0.846719	-3.25837	-0.96853
9.008686	2.866184	-6.54807	-3.19647	-3.49324	-0.93799	-3.61414	-1.71915
15.65079	5.430573	3.545065	1.040632	-3.51248	-1.14866	-1.44426	-1.40696
-12.494	-3.68519	-12.5649	-3.7093	-8.22016	-2.67236	-3.08879	-0.46178
-2.90857	-0.70348	-15.5861	-4.87302	-19.7578	-5.86111	-14.8711	-4.34945
2.33434	1.027764	1.340536	0.181528	0.171196	-0.03478	13.14811	4.540857
-10.0779	-3.22669	-12.8202	-3.6681	-12.0198	-4.38938	-10.362	-3.38249
-9.06414	-3.56641	-3.04638	-2.2277	-0.02239	0.010207	2.756497	0.615386
-20.1784	-6.68851	-18.8798	-6.32973	-6.24706	-2.13902	-12.7442	-4.53441
-13.9939	-4.75898	6.351231	2.50684	7.183834	2.599533	-5.83245	-2.71273
7.053668	2.334684	7.115099	3.110968	4.546493	1.699962	5.50849	2.27449
18.77683	6.064966	26.35645	9.061441	9.904587	2.47453	9.526946	2.908592
-3.39901	-0.64255	-6.93088	-1.85331	5.7539	1.947483	-4.2465	-1.75765
-9.38982	-3.41556	-11.3666	-3.80676	-10.6794	-3.28362	-8.38218	-2.33939
-24.4767	-7.17633	-32.3108	-10.7232	-15.3345	-4.71135	-15.0332	-4.06496
0.888318	0.068669	24.33486	8.725295	10.70928	3.411733	7.50261	2.51103
-0.73171	0.224217	2.221823	1.280572	-0.87775	-0.18701	2.988205	1.09934
-5.6189	-1.55411	-16.9894	-5.72523	-14.7549	-4.91311	-20.312	-6.38058
14.0107	3.916572	19.05647	6.173076	13.18662	4.354576	6.616006	1.465298

2.178653	0.855045	5.052003	2.010433	5.32339	1.603885	-1.38422	-0.73079
24.73911	7.723171	25.89473	8.731989	15.13773	4.557923	10.36163	2.918392
-3.06117	0.062267	-12.587	-3.69968	-16.2831	-4.75855	-4.2223	-1.42097
12.71223	3.793966	2.582073	0.441705	-0.42251	-0.4752	5.592705	1.544854
-13.8767	-4.00054	-13.0692	-3.65694	-14.2718	-4.94446	-5.33114	-1.66584
-14.6197	-4.73708	-9.64395	-2.91223	-16.4604	-6.06702	-13.4231	-4.17262
-0.21977	0.605989	-10.5908	-3.26536	-10.2889	-2.96784	-1.61422	-0.3611
-3.85172	-0.98184	-9.44288	-3.24982	-4.98885	-1.76436	-8.06157	-2.50317
-8.71282	-2.05757	-5.61031	-1.059	2.942894	1.419409	-3.82546	-0.82518
-23.4979	-7.30215	-10.5929	-3.44391	-15.8228	-5.03703	-18.5217	-5.94317
0.775081	0.771871	-0.09852	-0.41203	-6.04271	-1.88122	-5.22131	-1.50933
3.039489	1.403169	3.739619	1.815074	7.229489	2.448623	1.807467	0.880209

REPLICATE 98		**REPLICATE 99**		**REPLICATE 100**	
y_{1t}	y_{2t}	y_{1t}	y_{2t}	y_{1t}	y_{2t}
-0.50805	0.20349	-2.03847	0.020428	-1.06821	0.059038
0.772883	-0.27796	0.02024	0.030272	-3.51557	-1.21127
-2.60972	-1.63492	-12.24	-4.09343	6.202579	2.159983
2.581246	0.710638	0.904008	-0.30537	-2.83359	-1.31559
12.70218	4.326224	1.67078	0.605657	11.06985	2.615117
7.351294	2.729836	9.393927	3.834925	8.820083	3.694818
-2.66218	-1.34891	2.56964	0.542045	-0.10433	0.362546
2.903933	1.653158	-0.59415	0.323827	-6.20376	-1.75768
-1.35461	-0.94498	6.15481	2.677198	1.772298	0.944829
9.885331	2.543599	8.595676	3.051474	13.82482	4.282564
-19.7802	-5.83504	-3.18178	-1.29121	-7.22481	-2.24974
-19.2114	-6.0356	-12.0914	-3.92954	-18.6402	-6.17795
-5.23198	-1.17059	-7.23315	-2.3872	-8.34482	-3.47478
8.060489	2.092371	16.11687	5.601238	16.28388	4.96999
2.227974	0.805881	-9.08733	-3.07661	-2.10253	-0.34716
12.93586	3.751829	4.040287	1.572574	12.32746	3.804197
-25.3002	-8.44073	-4.53193	-1.18232	-7.4281	-2.25266
2.17132	0.816299	0.361049	0.151223	-0.01548	0.410396
-5.38608	-1.27822	-6.34973	-1.73068	-6.11395	-1.73968
12.2416	3.827999	10.1116	2.549138	7.83989	1.705058
7.197763	2.882485	13.45769	4.605661	9.858459	3.252948
-15.0367	-4.72232	-8.86239	-3.04487	-14.6567	-4.32206
-0.40321	-0.03972	-4.71128	-1.40318	-2.06509	-0.63634
3.819685	0.600182	-2.2815	-1.3036	4.979334	2.054808

10.11043	2.459592	12.05434	3.457646	7.234989	2.337983
-9.82416	-3.05622	-11.3055	-3.94488	-11.5176	-3.81828
0.361681	-0.6783	11.53566	3.678575	10.36043	3.205916
11.72627	2.957811	13.7415	3.922418	19.09784	6.209108
-13.1997	-3.22481	-13.7406	-3.73578	-11.3835	-3.6532
-0.94049	-0.57341	3.186493	0.058454	-0.44092	-0.4727
1.725049	0.898695	-3.83727	-1.57558	-3.9313	-1.55896
10.06002	3.204678	4.07133	0.610172	1.815365	0.501865
-15.9121	-5.22628	6.172325	2.465383	-15.3709	-5.05222
-0.41905	0.168143	0.482034	1.033332	-7.76674	-2.13094
9.368164	3.276074	-2.36084	-1.00108	5.505266	1.289278
-9.10556	-3.10316	-11.108	-3.24676	-15.9126	-5.38182
-1.51013	-0.72325	3.208817	1.208154	0.077503	-0.64461
-21.9234	-7.34199	-12.6632	-4.18362	-16.8749	-5.95034
3.40595	1.728147	8.066305	3.192921	-1.08296	-0.22443
2.398637	1.285489	13.78568	4.9735	6.524252	2.304902
13.07522	3.636644	9.1291	2.406462	15.98681	4.943395
1.426455	1.008133	10.12582	3.45834	-13.5911	-4.18452
-4.58242	-1.46831	-4.68307	-1.68918	-4.09383	-1.39783
-21.6994	-7.62226	-16.4425	-5.26418	-18.5727	-5.90893
10.59862	2.957947	13.63914	4.139042	14.14923	4.669134
4.093912	0.819043	-0.13971	0.629849	-6.82813	-2.53435
-13.3209	-4.55606	-8.43742	-2.48434	-1.13408	0.240975
15.26353	3.958715	5.587029	1.211938	12.86846	3.569125
-2.57672	-0.80647	3.709898	1.62142	-1.24708	-1.0264
21.44065	6.854172	12.61054	3.981974	16.74475	5.074691
-13.7827	-4.43026	-7.86994	-2.08733	-1.02737	0.600906
6.620574	0.969359	10.06783	3.7588	5.702986	1.686364
-15.7291	-5.0807	-9.87327	-3.56396	-2.69637	-0.29586
-13.3997	-4.61253	-8.4876	-2.14605	-15.8258	-5.61201
8.111368	3.208517	-4.6367	-1.33997	1.585888	0.709291
-13.3403	-5.04265	-9.06988	-2.59926	-6.33385	-1.75193
1.851842	1.396047	-15.4374	-4.29254	-7.2329	-1.62642
-18.551	-5.65269	-21.8014	-6.19433	-32.1516	-10.7994
-5.20537	-1.75763	3.111089	1.254186	-4.03871	-1.30531
-2.83609	-0.94382	-1.66013	-0.33867	-3.37677	-1.2562