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ABSTRACT

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Captain, USAF
Ph.D., Economics, 1980, University of Colorado
97 pages

A MONTE CARLO INVESTIGATION OF ECONOMETRIC MODELS WITH FIXED AND STOCHASTIC REGRESSORS WHERE THE ERROR TERMS ARE AR(1) AND MA(1)

A Monte Carlo study of four specialized regression procedures is reported. Two of the procedures are designed for a simple linear econometric model while the other two procedures are designed for a single period lagged endogenous variable and single exogenous variable econometric model. For the simple linear model, the small sample properties of the Pesaran procedure, designed for an MA(1) error term, and the Beach-MacKinnon procedure, designed for an AR(1) error term, are compared against the small sample properties of OLS and against those of the Prais-Winston procedure. For the lagged endogenous model, the small sample properties of the Zellner-Geisel procedure, designed for an MA(1) error term, and the Wallis procedure, designed for an AR(1) error term, are likewise compared against the small sample properties of OLS and of Prais-Winston. In addition, the power of the Durbin-Watson d test is analyzed for both models and the Durbin h and the McNown tests are analyzed for the lagged endogenous model. For the simple linear model, the Prais-Winston transformation is only performed if the Durbin-Watson d test indicates the hypothesis of no autocorrelation should be rejected. For the lagged endogenous model, the transformation is only performed if the McNown test

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indicates the hypothesis should be rejected. Finally, to analyze the effects of misspecification, the two specialized procedures for each model are applied to the wrong error structure.

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A MONTE CARLO INVESTIGATION OF ECONOMETRIC MODELS WITH FIXED AND STOCHASTIC REGRESSORS WHERE THE ERROR TERMS ARE AR(1) AND MA(1)

by

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A thesis submitted to the Faculty of the Graduate School of the University of Colorado in partial fulfillment of the requirements for the degree of

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A Monte Carlo Investigation of Econometric Models with Fixed and Stochastic Regressors Where the Error Terms are AR(1) and MA(1)

Thesis directed by Professor J. Malcolm Dowling

A Monte Carlo study of four specialized regression procedures is reported. Two of the procedures are designed for a simple linear econometric model while the other two procedures are designed for a single period lagged endogenous variable and single exogenous variable econometric model. For the simple linear model, the small sample properties of the Pesaran procedure, designed for an MA(1) error term, and the Beach-MacKinnon procedure, designed for an AR(1) error term, are compared against the small sample properties of OLS and against those of the Prais-Winston procedure. For the lagged endogenous model, the small sample properties of the Zellner-Geisel procedure, designed for an MA(1) error term, and the Wallis procedure, designed for an AR(1) error term, are likewise compared against the small sample properties of OLS and of Prais-Winston. In addition, the power of the Durbin-Watson d test is analyzed for both models and the Durbin h and the McNown tests are analyzed for the lagged endogenous model. For the simple linear model, the Prais-Winston transformation is only performed if the Durbin-Watson d test indicates the hypothesis of no autocorrelation should be rejected. For the lagged endogenous model, the transformation is only performed if the McNown test indicates the hypothesis should be rejected. Finally, to analyze the effects of misspecification, the two specialized procedures for each model are applied to the wrong error structure. The Pesaran procedure was superior to OLS and Prais-Winston in the estimation of the coefficient of the exogenous variable but inferior in the estimation of the coefficient of autocorrelation. It did remove the autocorrelation under both error structures. The Beach-MacKinnon procedure demonstrated results similar to those of Pesaran. For both MA(1) and AR(1) autocorrelation, the Zellner-Geisel procedure was far superior to Prais-Winston and better than OLS for large values of the coefficient of autocorrelation. It did appear to remove MA(1) autocorrelation from the residuals but was not very successful in removing AR(1) autocorrelation. The Wallis procedure was inferior to OLS for both error structures. In certain circumstances, the Wallis procedure provided better estimates than Prais-Winston. In terms of removing autocorrelation, the Wallis procedure did not do an acceptable job for either error structure. All three tests for autocorrelation proved to be nearly equal in power when the error term was AR(1). When the error structure was MA(1), the Durbin-Watson d test exhibited remarkable power. For the lagged endogenous model, the d test outperformed the Durbin h test which outperformed the McNown test when the error term was MA(1).

This abstract is approved as to form and content. I recommend its publication.

Signed J. Malcolm Dowling
Faculty member in charge of thesis

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CHAPTER I

INTRODUCTION

In numerous recent investigations in the literature, error structures in the linear regression model other than the first-order autoregressive or Markov model have appeared. In particular, a moving average (MA) error structure has been applied in many different areas: Trivedi (1970;1973) and Burrows and Godfrey (1973) have used an MA error structure in their analysis of inventory; in consumption dos Santos (1972) and Zellner and Geisel (1970) applied an MA error structure; Hess (1973) applied it to durable goods demand; Rowley and Wilton (1973) to wage determination; and Pesaran (1973) to investment.

Despite this, many textbooks and applied researchers continue to place emphasis on an autoregressive (AR) error structure as the only alternative to the usual assumption of residual independence. Of the many available econometrics textbooks, only a few devote any space to a discussion of autoregressive-moving average (ARMA) error structures[1] and there is almost no mention of how these structures may arise in applied econometric investigations. For example, in discussing the familiar Koyck model (1954), several textbooks derive a reduced

[1] See for example, Pindyck and Rubinfeld (1976).

form equation similar to the following:

$$Y_t = \lambda Y_{t-1} + \beta(1-\lambda)X_t + u_t \tag{1}$$

where

$$u_t = v_t - \lambda v_{t-1}. \tag{2}$$

If v_t is serially independent, u_t is autocorrelated and follows a first-order moving average (MA(1)) structure. Nevertheless, the autocorrelation function of the MA(1) structure is seldom derived or estimation methods explored.

There are, of course, good reasons for the popularity of the AR(1) error structure. The Durbin-Watson d test (1950;1951) and Cochrane-Orcutt (1949) procedures have been known for many years and are built into most canned regression packages while testing and correction procedures for the more general class of ARMA models have only recently been developed. Moreover, efficient estimation of these alternative error structure models typically requires the use of maximum likelihood or nonlinear least squares computer routines sufficiently complicated to disuade researchers who find it so easy to use the canned routines.

In addition to the limited discussion and use of alternative error structures, Nichols, Pagan and Terrell in a recent survey article (1975) report a ". . . paucity of small sample studies. . . ." Most of the Monte Carlo studies they found were in terms of a pure MA time series model with no independent variable. A conspicuous exception to this would be the work of Hendry and Trivedi (1972).

In an attempt to learn more about the small sample properties of models with an MA(1) error structure, I have analyzed via Monte Carlo techniques two simple econometric models using both AR(1) and MA(1) error structures.

Model I

Model I is a simple linear, two variable econometric model,

$$Y_t = \beta X_t + u_t. \quad (3)$$

If $u_t \sim NID(0,\sigma_u^2)$, the ordinary least squares (OLS) estimate of β is unbiased, consistent and efficient. If u_t is autocorrelated, the OLS estimate of β is still unbiased but asymptotically inefficient.

Model I with an AR(1) Error Structure

If u_t in (3) follows a first-order autoregressive structure,

$$u_t = \rho u_{t-1} + v_t \quad (4)$$

where $-1 < \rho < 1$ and $v_t \sim NID(0,\sigma_v^2)$, then a maximum likelihood (ML) procedure developed by Beach and MacKinnon (1978) will provide estimates for β and ρ that are asymptotically efficient.[2]

I compared the small sample results of the Beach and MacKinnon procedure to OLS; the Beach-MacKinnon procedure is described in detail in Chapter II and the results are presented in Chapter IV.

I will henceforth refer to this model cum error structure as Model I-AR, that is Model I with an AR(1) error structure. I will also refer to the Beach-MacKinnon procedure as the B-M procedure.

[2] Hildreth and Dent (1974) also have a procedure that provides efficient estimates but the Beach-MacKinnon procedure was more recent and it appears to use fewer computer resources.

Model I with an MA(1) Error Structure

If u_t in (3) follows a first-order moving average structure,

$$u_t = v_t - \lambda v_{t-1} \tag{5}$$

where $-1 < \lambda < 1$ and $v_t \sim NID(0,\sigma_v^2)$, then an ML procedure developed by Pesaran (1973) will provide estimates for β and λ that are asymptotically efficient.

I likewise compared the small sample results of the Pesaran procedure to OLS; the Pesaran procedure is described in detail in Chapter II and the results of my comparison are presented in Chapter IV.

Henceforth, I will refer to this model as Model I-MA and to the Pesaran procedure as PES.

Model II

Model II is a single-period lagged endogenous variable and single exogenous variable econometric model,

$$Y_t = \beta_1 Y_{t-1} + \beta_2 X_t + u_t. \tag{6}$$

If $u_t \sim NID(0,\sigma_u^2)$, OLS will provide consistent estimates for β_1 and β_2. If, however, u_t is autocorrelated, OLS will provide biased, inconsistent and inefficient estimates. Additionally, Griliches (1961) and others have shown that as long as β_1 is positive, OLS will contain an upward bias in the estimate of β_1.

Model II with an AR(1) Error Structure

If u_t in (6) follows the AR(1) error structure given by (4), then a generalized least squares (GLS) procedure developed by Wallis (1967) provides consistent but not fully efficient estimates of β_1 and β_2.

I compared the small sample results of the Wallis procedure to OLS; the Wallis procedure is described in detail in Chapter III and the results are presented in Chapter IV.

Henceforth, this model will be referred to as Model II-AR and the Wallis procedure will be referred to as the WAL procedure.

Model II with an MA(1) Error Structure

If u_t in (6) follows the MA(1) error structure given by (5), then an ML procedure developed by Zellner and Geisel (1970) provides consistent and efficient estimates of β_1 and β_2.

I compared the small sample results of the Zellner-Geisel procedure to OLS; like the WAL procedure, the Zellner-Geisel procedure is described in detail in Chapter III and the results are presented in Chapter IV.

Model II with an MA(1) error structure will be referred to as Model II-MA and I will refer to the Zellner-Geisel procedure as the Z-G procedure.

Table I summarizes the models, error structures and procedures as they are correctly applied to each other.

Testing for Autocorrelation

In conjunction with the comparisons of the four different procedures and OLS, statistics on three different tests for

TABLE I

ESTIMATION PROCEDURES CORRECTLY
APPLIED TO MODELS AND ERROR STRUCTURES

Error Structure	Model	
	I: $Y_t = \beta X_t + u_t$	II: $Y_t = \beta_1 Y_{t-1} + \beta_2 X_t + u_t$
AR(1) $u_t = \rho u_{t-1} + v_t$	Beach-MacKinnon	Wallis
MA(1) $u_t = v_t - \lambda v_{t-1}$	Pesaran	Zellner-Geisel

autocorrelation were collected. All three tests were designed to detect the presence of AR autocorrelation and their performance when the autocorrelation was MA(1) was monitored.

For Model I, a Durbin-Watson d test (1950;1951) was performed after both the OLS regression and either a PES or B-M regression. Since both PES and B-M were designed to remove autocorrelation, you would expect that the d test would indicate the presence of autocorrelation after OLS but not after PES or B-M. In addition, if the d test indicated the presence of autocorrelation after an OLS regression, I performed a Prais-Winston transformation and regression procedure (1954) after which I did another d test.[3] The Prais-Winston or P-W procedure results could then be compared to the OLS and either

[3]I chose to use the Prais-Winston transformation and regression procedure over the Cochrane-Orcutt procedure because Prais-Winston retains the first observation and Cochrane-Orcutt does not. In addition, both Rao and Griliches (1969) and Spitzer (1979) have found the Prais-Winston procedure to be one of the best two-stage procedures.

PES or B-M results. I present the outcome of these comparisons in Chapter IV.

Similarly for Model II, a Durbin-Watson d test was performed after both the OLS and either Z-G or WAL regressions. But, since the Durbin-Watson d test was not designed to detect autocorrelation in models with lagged dependent variables,[4] a Durbin h test (1970) and a McNown test (1977) were also performed after each OLS regression. Additionally, a Durbin h test was performed after a WAL regression. If the McNown test indicated the presence of autocorrelation after an OLS regression, a P-W type transformation was performed on the data and another OLS regression was performed on the transformed data. The outcome of the comparisons of the three tests for autocorrelation and of the comparisons of the small sample properties of the various regression procedures is presented in Chapter IV.

Effects of Misspecification

I was also interested in what the outcome might be if one of the four specialized procedures was applied to the wrong error structure. For example, how well would the PES procedure remove AR(1) autocorrelation when it was designed to handle MA(1) autocorrelation and how well would it do estimating ρ when it was designed to estimate λ? This might occur if an applied researcher assumed or specified that his error term was MA(1) and used PES when in actuality the error term was AR(1).

[4]See Durbin (1970).

Table II shows how all four specialized procedures were incorrectly applied to error structures. All of the properties and autocorrelation test results that were compared for the correctly applied procedures were also compared for the incorrectly applied ones. These results are also summarized in Chapter IV.

TABLE II

ESTIMATION PROCEDURES INCORRECTLY APPLIED TO MODELS AND ERROR STRUCTURES

Error Structure	Model	
	I: $Y_t = \beta X_t + u_t$	II: $Y_t = \beta_1 Y_{t-1} + \beta_2 X_t + u_t$
AR(1) $u_t = \rho u_{t-1} + v_t$	Pesaran	Zellner-Geisel
MA(1) $u_t = v_t - \lambda v_{t-1}$	Beach-MacKinnon	Wallis

CHAPTER II

MODEL I ESTIMATION

Model I is a simple linear, two variable econometric model,

$$Y_t = \beta X_t + u_t. \tag{1}$$

The Beach-MacKinnon (1978) or B-M procedure is used to estimate this model when u_t follows an AR(1) error structure and the Pesaran (1973) or PES procedure is used to estimate this model when u_t follows an MA(1) error structure.

In this chapter, I will explain each procedure in detail and I will discuss the Monte Carlo procedure I followed in evaluating these two procedures against OLS and Prais-Winston or P-W. The results of the evaluation are presented in Chapter IV.

The Beach-MacKinnon Procedure for Model I-AR

The B-M procedure is an iterative technique which alternates between the estimation of β and ρ until the estimates of each become arbitrarily close to the previous iteration's estimates.

In matrix terms, the estimate of β, b, is obtained as follows:

$$b = (Z'Z)^{-1}Z'w \tag{2}$$

where

$$Z = QX \tag{3}$$

$$w = Qy \tag{4}$$

and

$$Q = \begin{bmatrix} (1-r^2)^{\frac{1}{2}} & 0 & \cdots & \cdots & \cdots & 0 \\ -r & 1 & 0 & \cdots & \cdots & 0 \\ 0 & -r & 1 & 0 & \cdots & 0 \\ \vdots & & & \vdots & & \\ 0 & \cdots & \cdots & 0 & -r & 1 \end{bmatrix}. \qquad (5)$$

For the first iteration, the value of r, the estimate of ρ, is assumed to be zero.

To estimate ρ, first calculate the residuals using the previous iteration's estimate of β and the original X and Y data, that is,

$$e_t = Y_t - bX_t. \qquad (6)$$

Then calculate

$$r = -2\cdot\left(\frac{a^2}{9} - \frac{d}{3}\right)^{\frac{1}{2}}\cdot\cos\left(\frac{\phi + \pi}{3}\right) - \frac{a}{3} \qquad (7)$$

where

$$\phi = \cos^{-1}\left[\frac{27^{\frac{1}{2}}\cdot\left(c - \frac{a\cdot d}{3} + \frac{2\cdot a^3}{27}\right)}{2\cdot\left(\frac{a^2}{3} - d\right)^{\frac{1}{2}}\cdot\left(d - \frac{a^2}{3}\right)}\right], \qquad (8)$$

$$a = -\frac{(T - 2)\cdot\Sigma e_t\cdot e_{t-1}}{(T - 1)\cdot(\Sigma e_{t-1}^2 - e_1^2)}, \qquad (9)$$

$$d = \frac{(T - 1)\cdot e_1^2 - T\cdot\Sigma e_{t-1}^2 - \Sigma e_t^2}{(T - 1)\cdot(\Sigma e_{t-1}^2 - e_1^2)}, \qquad (10)$$

$$c = \frac{T\cdot\Sigma e_t\cdot e_{t-1}}{(T - 1)\cdot(\Sigma e_{t-1}^2 - e_1^2)}. \qquad (11)$$

T represents the number of observations and the summations run from t = 2 to t = T.

The B-M procedure was programmed in FORTRAN to run on a Control Data Corporation (CDC) 6400 computer. This program is available from the author upon request. The maximum number of iterations was set at ten as Beach and MacKinnon (1978,p.53) suggested the average number of iterations should run between four and seven to achieve five-digit accuracy.

The Pesaran Procedure for Model I-MA

The PES procedure applies the simple and well-known iterative method of False Position[1] to the first-order condition of the concentrated log likelihood function

$$\lambda \cdot \Sigma w_t \cdot e_t^2 - T \cdot (1 - \lambda^2) \cdot \Sigma(\lambda + \cos(\frac{t \cdot \pi}{T + 1})) \cdot w_t^2 \cdot e_t^2 = 0 \qquad (12)$$

where

$$b = (Z'WZ)^{-1} Z'WFy, \qquad (13)$$

$$e = Fy - Zb, \qquad (14)$$

$$Z = FX, \qquad (15)$$

$$F = (\frac{2}{T + 1})^{\frac{1}{2}} \cdot \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1T} \\ f_{21} & f_{22} & \cdots & f_{2T} \\ \vdots & \vdots & & \vdots \\ f_{T1} & f_{T2} & \cdots & f_{TT} \end{bmatrix}, \qquad (16)$$

$$f_{ij} = \sin(\frac{i \cdot j \cdot \pi}{T + 1}), \qquad (17)$$

$$w_t = (\lambda^2 + 2 \cdot \lambda \cdot \cos(\frac{t \cdot \pi}{T + 1}) + 1)^{-1} \qquad (18)$$

and W is the inverse of the diagonal matrix with $w_1^{-1}, w_2^{-1}, \ldots, w_T^{-1}$

[1]See Hamming (1971,pp.45-48).

as its diagonal elements. T represents the number of observations and the summations run from $t = 1$ to $t = T$.

Dr. Pesaran graciously provided a copy of his own FORTRAN program which was modified slightly in order to incorporate his logic into my Monte Carlo program.[2] Pesaran's own cut-offs were used, that is, the program iterates up to a maximum of thirty times unless the difference between successive estimates of β and λ is less than 10^{-4}.

The Monte Carlo Procedure

The Procedure in General

After calculating an independent data series of the appropriate length using

$$X_t = \theta X_{t-1} + \mu_t \tag{19}$$

where $\theta = 0.8$, $X_0 = 0.0$ and $\mu_t \sim NID(0,10)$, an error series, u_t, was calculated under either an AR(1) or an MA(1) error structure. I used the internal pseudo uniform random number generator provided by the FORTRAN compiler on the CDC 6400 computer[3] and a normal approximation

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[2]Pesaran is planning to publish his programs under the title Dynamic Regression: Theory and Algorithms. See Pesaran (1976).

[3]To validate the series of random numbers generated by the CDC random number generator, twenty-five of the random number seeds were chosen at random from the 280 seeds required to complete this Monte Carlo investigation. These twenty-five seeds were then used to initiate a uniform random number series utilizing the pseudo uniform random number generator provided by the International Mathematical and Statistical Library (IMSL). A chi-square goodness-of-fit test was run on each of the series initiated by the twenty-five seeds. Fourteen times out of the twenty-five, the IMSL series had a better fit than CDC and eleven times out of twenty-five, CDC had a better series. Additionally, the Monte Carlo runs were re-run using the IMSL generator and the results compared against those obtained when

routine obtained from H. M. Wagner (1975,p.934) to generate the normal random numbers. A different random number seed drawn from a table of random digits was used for each run to insure different random number series.

Using these X_t and u_t series, the dependent variable, Y_t, series was calculated using (1). The X_t and Y_t series then became the data to be regressed. First an OLS regression was calculated, the estimate of β saved, an estimate of ρ was calculated and saved and a Durbin-Watson d test was performed using an α of 0.05. If the hypothesis of no autocorrelation was rejected, a P-W transformation and estimation procedure was performed, the new estimates of β and ρ saved and a new Durbin-Watson d test performed. If, following the OLS regression, the hypothesis of no autocorrelation was not rejected, the P-W estimates for this replication were taken to be the same as those of the OLS regression. Following this, either B-M or PES estimates were calculated and saved and another Durbin-Watson d test performed.

At first, the computer runs were made for the correctly specified error structure, that is, B-M estimates were obtained for Model I-AR and PES estimates were obtained for Model I-MA. Then to check the effects of misspecification, different computer runs were made for the misspecified models: B-M estimates were obtained for Model I-MA and PES estimates for Model I-AR.

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the CDC generator was used. No major change in the results was observed; the differences in the results were about the same as could be expected if a different random number seed was used with the same random number generator.

This general Monte Carlo procedure was replicated 100 times for each set of input parameter values. This provided for each model and for each set of input parameter values, 100 OLS estimates, 100 B-M or PES estimates and 100 P-W estimates as well as the results of the three Durbin-Watson d tests. The number of times the Durbin-Watson d test proved inconclusive was collected along with the number of times the hypothesis of no autocorrelation was accepted and rejected. The comparison statistics, discussed later in this chapter, were calculated on the 100 estimates collected on each run.

Input Parameter Values

The input parameter values were determined after examining recent Monte Carlo studies by Beach and MacKinnon (1978), Rao and Griliches (1969), Maddala and Rao (1973), Spitzer (1979), Kenkel (1975) and Hendry and Trivedi (1972).

Sample sizes of 20 and 50 were selected. The independent variable coefficient, β, was set at 1.0 for all trials. The standard deviation of v_t, σ_v, was set at 20 when T = 20 and at 40 when T = 50. Ten different values of λ and ρ were tried: -.99, -.8, -.6, -.3, -.1, .1, .3, .6, .8 and .99. There were then twenty different sets of input parameter values for both B-M and PES runs.

Comparison Statistics Collected and Analyzed

The following statistics for the OLS, B-M or PES and P-W estimates were collected: the sample mean, the sample variance, the average absolute bias, the largest and smallest absolute biases, the mean squared error (MSE) and the Euclidian distance ala Hendry and

Trivedi (1972,p.122), that is

$$E.D. = (\Sigma(\hat{p}_i - p_i)^2)^{\frac{1}{2}} \qquad (20)$$

where p_i represents the true value of the ith parameter to be estimated, $\hat{p}_i$ represents its estimate and i runs from i = 1 to i = the number of parameters to be estimated--two in the case of Model I. The Euclidian distance gives a measure of "aggregate" bias.

These statistics as well as the results of the Durbin-Watson d tests were then output at the completion of a computer run on a particular set of input parameter values and a particular model. The consolidated results for all runs are presented in Chapter IV along with a comparison of my results with the outcome of other Monte Carlo studies in the literature.

CHAPTER III

MODEL II ESTIMATION

Model II includes a single-period lagged endogenous variable and a single exogenous variable

$$Y_t = \beta_1 Y_{t-1} + \beta_2 X_t + u_t. \quad (1)$$

This model was originally derived by Koyck (1954) from an infinite geometric lag model which arises when the adaptive expectations or partial adjustment models are used. The Zellner-Geisel (1970) or Z-G procedure was developed to estimate this model when the error term, u_t, follows an MA(1) structure. Wallis (1967) developed an estimation procedure to handle the AR(1) error structure; I will use WAL when referring to this procedure.

As in the last chapter, first I will describe each estimation procedure separately and then I will outline the Monte Carlo procedure I used to analyze the small sample properties of these two procedures compared to those of OLS and Prais-Winston (P-W). The results of this analysis are in Chapter IV

The Wallis Three-Step Procedure for Model II-AR

The Wallis procedure is basically a generalized least squares (GLS) technique that Wallis himself separated into three steps.[1]

[1]This procedure is not to be confused with three-pass least

First, estimate the coefficients of Model II via OLS but substitute X_{t-1} as an instrument for Y_{t-1}. Second, using the residuals from this regression, that is,

$$e_t = Y_t - b_1 Y_{t-1} - b_2 X_t, \tag{2}$$

calculate an estimate of ρ making a correction for bias[2]

$$r = \frac{\dfrac{\Sigma e_t \cdot e_{t-1}}{T-1}}{\dfrac{\Sigma e_t^2}{T}} + \frac{2}{T} \tag{3}$$

where T represents the number of observations, the summation in the numerator runs from t = 2 to t = T and the summation in the denominator runs from t = 1 to t = T. Third, use this estimate of ρ to calculate the matrix

$$Q = \begin{bmatrix} 1 & r & r^2 & \cdots & r^{T-1} \\ r & 1 & r & \cdots & r^{T-2} \\ \cdot & & \cdot & & \cdot \\ \cdot & & & \cdot & \cdot \\ \cdot & & & \cdot & \cdot \\ r^{T-1} & r^{T-2} & \cdots & \cdots & 1 \end{bmatrix} \tag{4}$$

which is then used to obtain the GLS estimates of β_1 and β_2

$$b = (X'Q^{-1}X)^{-1}X'Q^{-1}y. \tag{5}$$

squares. In fact, Wallis wrote his article introducing his procedure in response to a previous paper by Taylor and Wilson (1964) on three-pass least squares.

[2]In general, the correction for bias is k/T, where k is the number of parameters to be estimated.

The B-M procedure requires the least amount of computer resources as it does not iterate nor search; only two least squares matrix inversions are required for each replication.

The Zellner-Geisel Procedure for Model II-MA

The Zellner-Geisel procedure is a maximum likelihood (ML) technique that requires that Model II first be transformed. After recognizing that in this model β_1 is really λ and after defining

$$w_t = Y_t - v_t, \tag{6}$$

you can obtain the transformed model[3]

$$Y_t = w_0\lambda^t + \beta_2 \cdot (X_t + \lambda X_{t-1} + \lambda^2 X_{t-2} + \cdots + \lambda^{t-1} X_1) + v_t. \tag{7}$$

Using OLS on (7), search over various values of λ from zero to one looking for the minimum residual sum of squares. The program which implements the Z-G procedure performs a grid search of λ for values between zero and one and finds to five-digit accuracy the set of estimates that yield the minimum residual sum of squares.

Both procedures, WAL and Z-G, were programmed in FORTRAN to run on a Control Data Corporation (CDC) 6400 computer. Both programs are available from the author upon request.

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[3]See Johnston (1972,pp.313-315) for the derivation.

The Monte Carlo Procedure

The Procedure in General

The data generation for Model II is exactly the same as for Model I except that after the calculation of the X_t series and the appropriate u_t series, Model II was used to generate the Y_t series,

$$Y_t = \beta_1 Y_{t-1} + \beta_2 X_t + u_t, \tag{8}$$

where $Y_0 = 200$ for all trials.

As with Model I, an OLS regression was performed first on the generated data and the estimates were saved. Using the residuals from this regression, a Durbin-Watson d test was performed as well as a Durbin h test and a McNown test.

Durbin (1970) and others recognized that the Durbin-Watson d test is not applicable when there are lagged endogenous variables as regressors in the model. In fact, Griliches (1961) notes that the d statistic is biased toward 2.0 or biased toward the acceptance of the hypothesis of no autocorrelation. Both Durbin (1970) and McNown (1977) have developed alternate tests to be used in place of the d test.

Durbin suggests the use of his h test, that is calculate

$$h = r\circ\left(\frac{T}{1 - T\cdot\hat{\sigma}^2_{b_1}}\right)^{\frac{1}{2}} \tag{9}$$

where T is the sample size and r is an estimate of ρ based on the OLS regression residuals. The h statistic is used as a standard normal deviate to test the hypothesis of $\rho = 0$. If $T\cdot\hat{\sigma}^2_{b_1} > 1$, the h test is not applicable and Durbin suggests an alternate test for this situation.[4]

If the h test is inapplicable, the following regression should be performed on the sample residuals using OLS:

$$e_t = \alpha_1 e_{t-1} + \alpha_2 Y_{t-1} + \alpha_3 X_t + \gamma_t \tag{10}$$

where

$$e_t = Y_t - b_1 Y_{t-1} - b_2 X_t \tag{11}$$

and t runs from t = 2 to t = T. The test for autocorrelation of u_t in (1) consists in testing the significance of the estimate of α_1 in (10).[5]

McNown proposed a similar test to be used in place of the Durbin-Watson d for lagged endogenous variable models. First perform an OLS regression of the following model:

$$Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \alpha_3 X_t + \alpha_4 X_{t-1} + \delta_t \tag{12}$$

where t runs from t = 3 to t = T. To test the hypothesis of no autocorrelation of u_t in (1), perform a significance test on the estimate of α_4 in (12).

If, based on the outcome of the McNown test, the hypothesis of no autocorrelation of u_t in (1) was rejected, a Prais-Winston (P-W) transformation was performed on the data and new estimates of β_1, β_2 and λ or ρ were calculated and saved.

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[4]See Durbin (1970).

[5]Out of 200,000 sets of generated data for Model II, the Durbin h test was inapplicable only twelve times.

Finally, either a Z-G or WAL procedure regression was performed, the estimates saved and a Durbin-Watson d test was performed using the residuals from this regression. If the WAL procedure was used, a Durbin h test was performed in addition to the d test.

As with Model I, the Monte Carlo procedure just outlined was replicated 100 times for each set of input parameters and for each error structure. Also each procedure, Z-G and WAL, was applied not only to the error structure for which it was developed, but also to the incorrect error structure.

Input Parameter Values

As stated in Chapter II, the values of the input parameters were determined after a review of the recent literature. Sample sizes of 20 and 50 were tried as with Model I. The coefficient of the exogenous variable, β_2, was set at 1.0 for all trials. The coefficient of the lagged endogenous variable, β_1, was set at either 0.4 or 0.8 if the WAL procedure was being run; if a Z-G procedure was being run, β_1 was set equal to the input value of λ or ρ.

The standard deviation of v_t, σ_v, was calculated based on signal-to-noise ratios of either 10 or 100. Maddala and Rao (1973,p.769) derived the white noise variance, σ_v^2, from the signal-to-noise ratio, G, when the error structure was AR(1) obtaining the following:

$$\sigma_v^2 = \frac{1 + \theta\cdot\beta_1}{1 - \theta\cdot\beta_1} \cdot \frac{1 - \rho\cdot\beta_1}{1 + \rho\cdot\beta_1} \cdot \frac{1 - \rho^2}{1 - \theta^2} \cdot \frac{\beta_2^2\cdot\sigma_\mu^2}{G} \qquad (13)$$

where $\theta = 0.8$ and $\sigma_\mu^2 = 10.0$ throughout all trials. The corresponding formula for an MA(1) error structure is as follows:

$$\sigma_v^2 = \frac{1 + \theta \cdot \beta_1}{1 - \theta \cdot \beta_1} \cdot \frac{1}{1 - \theta^2} \cdot \frac{\beta_2^2 \cdot \sigma_\mu^2}{(1 + \lambda^2 - 2 \cdot \lambda \cdot \rho_1)} \cdot \frac{1}{G} \tag{14}$$

where $\theta = 0.8$ and $\sigma_\mu^2 = 10.0$ throughout all trials.

Ten different values of λ and ρ were tried: -.99, -.8, -.6, -.3, -.1, .1, .3, .6, .8 and .99. However, because the Z-G procedure searches only between zero and one for the value of the autocorrelation parameter, only positive values of λ and ρ were attempted for the Z-G runs.

The combination of all these input parameter values represents twenty different sets for Z-G runs and eighty different sets for WAL runs.

Comparison Statistics Collected and Analyzed

The same comparison statistics were collected and analyzed for Model II as were collected and analyzed for Model I. The results of my analysis are presented and discussed in the next chapter along with comparisons of my results to those found in the literature.

CHAPTER IV

RESULTS AND CONCLUSIONS

In this chapter, the estimated parameter comparison statistics results are presented before the results of the autocorrelation detection tests. Within each section of results, Model I will be discussed before Model II. But before proceeding to the results an explanation of Table III through Table XVIII is required.

Table III throught Table XVIII contain the percentage differences between the estimated parameter comparison statistics of two regression procedures for two or three parameters. For each parameter that was estimated, the percentage differences for bias, variance and mean squared error (MSE) are displayed along with the percentage difference for the Euclidian distance (E.D.).[1] Each row of a table represents a different set of input parameter values.

The percentage difference was calculated using this formula:

$$\text{Percentage Difference} = \frac{|p_b| - |p_a|}{|p_b|} \cdot 100 \qquad (1)$$

where p_b represents the estimated parameter comparison statistic for the second procedure listed in the title of the table and p_a

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[1]Although the largest absolute bias and the smallest absolute bias statistics were collected and analyzed, they added little or nothing to the understanding of the problem. Consequently, these results are not included in the tables.

represents the estimated parameter comparison statistic for the first procedure listed. For example, the first procedure listed in Table III is Pesaran and OLS is the second.

The sign of the percentage difference gives a qualitative comparison between the two procedures and the absolute value of the percentage difference gives a quantitative comparison between the two. If the percentage difference is negative, the estimated parameter comparison statistic for the second procedure was less than that for the first procedure and the larger the absolute value of the percentage difference, the greater the difference between the two procedures. On the other hand, if the percentage difference is positive, the first procedure was better than the second, but a word of caution is in order in analyzing the quantitative difference because the percentage difference is not symmetric about zero. When the percentage difference is positive, the largest value possible is 100 due to the way in which it is calculated. A percentage difference of 50 is comparable to a negative percentage difference of -100; a percentage difference of 75 is comparable to a negative percentage difference of -300; 88 is comparable to -700; 90 to -900; 95 to -1800 through -2100; 98 to -3900 through -5900; and a percentage difference of 100 is comparable to any negative percentage difference less than -19,900.

Comparison Statistic Results for Model I

Since Model I is a simple linear regression model, OLS estimates will be unbiased but not asymptotically efficient when the error term is autocorrelated. We are therefore most interested in the small sample variance but we cannot overlook the bias in these small samples. The results for PES and B-M applied to their correct error structure will be discussed before the results of the incorrectly applied error structures.

Pesaran Procedure on MA(1)

The results on the Pesaran procedure are mixed but in general both OLS and P-W seemed to be slightly better. Looking at Table III and Table IV, more negative percentage differences can be seen than positive ones. The percentage differences for λ are nearly all negative meaning that OLS and P-W were almost always better than PES; this is quite surprising considering that PES is truly estimating λ while OLS and P-W both estimated ρ as a proxy for λ. If PES had any edge over OLS and P-W on the estimation of λ, it would be in the area of λ's variance when λ was large, either negative or positive.

PES showed up better in the estimation of β where for both large positive and negative values of λ, PES had some rather large positive percentage differences.

The most disturbing result of the PES runs on Model I-MA was that all three procedures estimated the wrong sign on λ for all twenty sets of input parameter values.[2] OLS and P-W were really estimating ρ and that may well be the reason for these two procedures obtaining the wrong sign, but the PES procedure is designed to estimate λ and the fact that it estimated the wrong sign makes this procedure suspect.

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[2] This result cannot be seen from the tables.

Since the PES procedure uses the False Position algorithm as mentioned in Chapter II and this algorithm approaches the root of the function from both sides of zero, it is possible that the algorithm may not work and therefore the PES procedure cannot be performed. The program that performed the PES procedure kept track of the number of times it was impossible to perform the PES procedure because of the failure of the algorithm. In no case on the PES runs on Model I-MA did the algorithm experience a failure.

Likewise, the P-W procedure requires the taking of a square root and applying it to the first observation. Therefore, it is quite possible that the value under the square root radical could be negative making it impossible to perform P-W. All four procedure programs kept track of the number of times it was impossible to perform P-W due to a negative value under the square root radical. During the PES runs on Model I-MA, this problem never occurred.

As mentioned in Chapter II, Pesaran's own cut-offs of thirty iterations or parameter differences of less than 10^{-4} were used. The PES procedure reached the thirty iteration cut-off rarely when T was 50 but when T was 20, the thirty iteration cut-off was reached frequently with low values of λ and almost every time with values of λ near $\pm$ 1.

Some reluctance should accompany the use of the PES procedure to estimate λ and β for Model I-MA. A better alternative appears to be that of P-W since on all comparison statistics it was better than CLS. The P-W estimate of ρ would have to be used as the estimate for λ but as can be seen from the tables, the P-W estimate of ρ does not appear to be a poor proxy for λ.

Beach-MacKinnon Procedure on AR(1)

Rao and Griliches (1969) found that non-linear maximum likelihood procedures like Beach-MacKinnon are no improvement over simpler two-stage procedures like Prais-Winston in samples of the same size. But Spitzer (1979) in trying to duplicate the work of Rao and Griliches came to the opposite conclusion. My results tend to favor Spitzer.

Looking at Table V, the percentage differences for ρ are rather small and that for large positive and negative values of ρ, the B-M variance is less than that for OLS. Bias favors OLS when ρ is negative but B-M had the lower bias for positive values of ρ. The results for MSE are very close to those for variance.

As for β, the percentage differences are larger than for ρ and all three comparison statistics seem to indicate that B-M is better than OLS when ρ is large. The Euclidian distance also tends to favor B-M when ρ is near ± 1, especially for positive values.

Table VI compares B-M to P-W and the results are generally the same as for OLS except that the percentage differences tend to be larger, especially for the estimation of ρ. For negative ρ, there is no clear winner on the bias of β.

A surprising outcome of the B-M runs on Model I-AR was that OLS tended to do a better job in terms of Euclidian distance than P-W. In terms of the other comparison statistics, P-W did do a better job than OLS on the estimation of β; OLS came out better on the estimation of ρ. OLS had some very large sample variances on the estimate of ρ especially when $|\rho|$ was large and this accounted for the P-W showing.

Due to negative values under the square root radical, P-W estimates could not be calculated when $|\rho| = .99$ on several sets of data although for far less than half of the number of sets of data generated and for far fewer times when T was 50.

Since there are two different square roots to be taken in the B-M procedure--see (5) and (7) in Chapter II--and there is the chance that the procedure might try to take the square root of a negative number, it is possible that the B-M procedure cannot be performed. The B-M procedure program kept track of the number of times it was impossible to perform a B-M procedure due to negative values under the square root radical. In no case was it impossible to calculate B-M estimates on Model I-AR.

The ten iteration cut-off was reached only rarely but when it was, it was more likely that the input value of ρ was near zero.

In general, the B-M procedure appears to be quite reliable for the estimation of Model I-AR.

Beach-MacKinnon Procedure on MA(1)

The Beach-MacKinnon procedure does a job nearly comparable to OLS on the estimation of $\bar{\lambda}$ but it is inferior to P-W on the estimation of λ. The estimation of β tends to favor B-M over both OLS and P-W.

Table VII[3] presents the results of B-M versus OLS and although there are many negative percentage differences for the three comparison statistics for λ, only a few are in double digits and many are zero. So technically OLS is the winner but not by much. As for

[3]Since B-M is really trying to estimate ρ, all three procedures are estimating ρ as a proxy for λ; hence the ρ/λ label in Table VII and Table VIII.

the estimation of β, the percentage differences are larger and many of them are positive indicating that B-M was better than OLS. The bias column seems to be sprinkled with negative values in a random fashion but for positive and large negative values of λ, B-M had the edge over OLS. The Euclidian distance, which is an "aggregate" bias, indicates that there was little difference between B-M and OLS.

Table VIII has far more negative percentage differences and the values are much larger especially for λ and the Euclidian distance. The results on β are roughly the same as for B-M versus OLS.

At no time was it impossible to do a B-M procedure or a P-W procedure because of a negative value under the square root radical. The average number of iterations required for a B-M regression was slightly higher with the smaller sample size and the average fell as the value of λ grew. The ten iteration cut-off was reached more often with a negative λ than with a positive one.

As with the PES runs on Model I-MA, P-W came out the clear winner against OLS; all comparison statistics favored P-W.

Again, however, all three procedures estimated the wrong sign on λ for all possible sets of data. I believe the reason for the wrong sign estimate is that the form of an MA(1) error structure--(5) in Chapter I--has a $-\lambda$ whereas the form of an AR(1) error structure--(4) in Chapter I--has a positive ρ. In other words, the regression procedures are trying to estimate $-\lambda$.

Pesaran Procedure on AR(1)

The Pesaran procedure turns out to be clearly inferior to OLS in terms of the estimation of ρ; as for the comparison of PES and OLS on β and for PES versus P-W, the results are mixed. These results are displayed in Table IX and in Table X.

On the estimation of β, the Pesaran procedure appears to have an edge over OLS in terms of variance and MSE when ρ is near one; in the cases of bias and Euclidian distance, PES seemed better than OLS when ρ was positive.

Comparing PES to P-W, you can see almost the opposite results to PES versus OLS. PES was better than P-W in the estimation of ρ for large values of ρ; this was also true for Euclidian distance. In terms of the estimation of β, P-W appeared to be better than PES when $\rho > 0.6$.

In results not tabulated, PES and OLS almost consistently overestimated β when T was set at 50. At no time was it impossible to perform a PES procedure but when $|\rho| = .99$, the P-W procedure couldn't be performed 10-20 times out of 100 due to negative values under the square root radical. The thirty iteration cut-off on the PES procedure was reached more often for large values of ρ and for $T = 20$.

Comparing OLS and P-W, P-W was only slightly better than OLS on the variance of both ρ and β. On bias and MSE, P-W was generally better than OLS on the estimation of β, while OLS was better on ρ. In addition, OLS was generally better than P-W in terms of Euclidian distance.

The fact that P-W did not prove superior to OLS on Model I-AR still concerns me and I am unable to account for it. Both Rao and Griliches (1969) and Spitzer (1979) found P-W to be one of the best two-stage procedures but I am disappointed in its performance when the error structure was AR(1). However, P-W did seem to remove the AR(1) autocorrelation as will be shown later in this chapter and it did seem to do a better job than OLS when the error structure was MA(1).

Before ending this section on Model I, I think it would be instructive to repeat the results concerning whether it was possible to perform a P-W procedure remembering that if $(1 - r^2) < 0$, a P-W transformation cannot be performed. In no case under an MA(1) error structure was it impossible to perform P-W and under an AR(1) error structure only large values of ρ caused the value under the square root radical to become negative and thereby make it impossible to perform P-W. This suggests that if a P-W procedure can't be performed, it is quite likely that the error structure is not MA(1).

Comparison Statistics Results for Model II

Model II is a single-period lagged endogenous variable and single exogenous variable econometric model. If the error term is autocorrelated, OLS will provide biased, inconsistent and inefficient estimates. The small sample bias, therefore, is the comparison statistic of most interest but the other comparison statistics provide noteworthy information as well. The results for Z-G and WAL applied to their correct error structures will be discussed first, then the results of the incorrectly applied error structures will be presented.

Zellner-Geisel Procedure on MA(1)

The Zellner-Geisel procedure would appear to be the procedure of choice when the value of λ is near one. Table XI displays mostly positive percentage differences when $\lambda > 0.6$ and Table XII is nearly all positive percentage differences. In addition, the percentage differences arrayed in Table XII, which compares Z-G to P-W, are almost all 90 or above indicating that Z-G was clearly better than P-W based on the outcome of the McNown test.

The large negative percentage differences for the estimation of λ in Table XI for low values of λ is quite consistent with Morrison (1970). He found that OLS was good for small λ and small signal-to-noise ratios but that it degenerated rapidly as λ and the signal-to-noise ratio got larger. He also felt that maximum likelihood leaning techniques gave the best estimates.

Morrison reported that the degeneration of the OLS estimates as λ and the signal-to-noise ratio increased was due to the fact that the OLS estimates displayed a strongly negative bias. OLS did provide estimates of λ that almost consistently underestimated the true value of λ. However, OLS did not consistently underestimate β_2. P-W did underestimate λ more often than not and P-W far underestimated β_2 in all cases although the bias was less as λ and the signal-to-noise increased. Morrison's results and mine do conflict with Griliches (1961) who concluded that as long as β_1 in Model II is positive,[4] OLS will overestimate it. Under an AR(1) error structure, OLS overestimated β_1 during the Z-G runs eighteen times out of twenty but during the WAL runs on both MA(1) and AR(1) error structures, OLS more often than not underestimated β_1.

As could be discerned from the above discussion, OLS was clearly superior to P-W; this superiority was evident in all comparison statistics. In other non-tabulated results, the bias,

[4]Recall that for Model II-MA, β_1 and λ are the same.

variance, MSE and the Euclidian distance statistics tended to fall for both parameter estimates and for all procedures as the signal-to-noise ratio increased. This last result is not unexpected.

In his analysis of distributed lag estimators, Sargent (1968) concluded that there was not much difference between special procedures and OLS. My results tend to point to a different conclusion: Z-G is a useful procedure especially when λ is large.

Wallis Procedure on AR(1)

OLS proved to be better than WAL for all three parameter estimates for all values of ρ and β_1 except when $\rho > 0.3$ and $\beta_1 = 0.8$. WAL proved better than P-W for positive values of ρ.

The results of the comparison between WAL and OLS are provided in Table XIII which had to be continued on two additional pages because of the eighty possible sets of input parameter values. The results for WAL versus P-W can be found in Table XIV which is also three pages long.

As can be seen in Table XIII, the large negative percentage differences for the comparison statistics for the estimate of ρ and for the Euclidian distance when the value of ρ is negative indicate that OLS was better than WAL. Although not all the comparison statistics for the estimates of β_1 and β_2 have negative percentage differences nor are the differences as great as those for the estimate of ρ, most of the percentage differences are negative. For negative values of ρ, OLS is the choice over WAL.

The OLS superiority continues through small positive values of ρ when for values of $\rho > 0.3$, more and more of the percentage differences are positive indicating that WAL was better than OLS. But notice that even for large positive values of ρ, when $\beta_1 = 0.4$, the percentage differences for the estimate of ρ are negative or favoring OLS over WAL.

As for WAL versus P-W, WAL is favored on the estimate of β_1 for nearly every set of input parameter values. WAL is also favored on the estimate of β_2 for values of $\rho > -0.6$ but WAL is favored over OLS on the estimate of ρ only for $\rho > 0.3$.

In non-tabulated results, WAL overestimated ρ when $\rho < 0.6$; WAL underestimated β_1 sixty times out of eighty and nearly every time that $\beta_1 = 0.4$. Additionally, WAL estimated a positive ρ in twenty-six times out of forty when ρ was negative but every time the true ρ was positive, WAL estimated it as positive. P-W underestimated β_2 in nearly every case but both OLS and P-W always obtained the correct sign on the estimate of ρ.

Concerning OLS versus P-W, in all but the variance of the estimate of ρ, OLS was better than P-W. The variance of the estimate of ρ favored P-W slightly over OLS for mid-range values of ρ, but for large positive and negative values of ρ, OLS was better than P-W even for the variance of the estimate of ρ.

Although the signal-to-noise ratio had no appreciable effect on the estimate of ρ, the bias, variance and MSE for the estimates of β_1 and β_2 tended to fall for all procedures when the value of the signal-to-noise ratio went from 10 to 100.

Wallis Procedure on MA(1)

The results for this misspecified model are not very clear-cut. Both the bias on the estimate of λ and the Euclidian distance favor OLS over WAL for negative values of λ but they favor WAL over OLS for positive λ. Otherwise, the results are mixed.

Table XV and Table XVI provide the results on the WAL runs on Model II-MA. The value of β_1 had an important effect on the results. When $\beta_1 = 0.4$, WAL is favored over OLS either by an outright positive percentage difference or by a reduction in the size of the negative percentage difference when $\beta_1 = 0.8$. This result is most marked when λ is negative and can be seen in the comparison statistics for all three parameter estimates as well as for the Euclidian distance.

Comparing WAL and P-W, WAL comes out the clear choice in terms of the estimates of β_1 and β_2 as nearly every percentage difference for these two parameter estimates is 95 or above. As for the estimate of λ, the variance tended to favor P-W through all values of λ but both the bias and the MSE favored P-W for negative values of λ while WAL was better for positive values of λ. The Euclidian distance statistic favored P-W for $\lambda < -0.3$ but favored WAL for $\lambda > -0.6$.

As was the case with Model I-MA, the OLS and P-W procedures estimated the wrong sign on λ in all cases for the WAL runs on Model II-MA. The WAL procedure in all but nine cases estimated a positive λ; the nine cases where WAL estimated a negative λ occurred when the true value of $\lambda > 0.3$ and when T was 50.

The OLS versus P-W comparison yeilded mixed results. The bias, variance and MSE on the estimate of λ favored P-W but OLS was almost consistently better than P-W on the estimation of β_1 and β_2. As far as the Euclidian distance, OLS tended to be better than P-W for mid-range values of λ but for large positive and negative values of λ, P-W was generally better than OLS.

The signal-to-noise ratio had an effect on the β's once again. The bias, variance and MSE on the estimates of the β's tended to become smaller as the signal-to-noise ratio increased.

Zellner-Geisel Procedure on AR(1)

This misspecified error structure model yielded quite clear results. OLS did a better job than Z-G and Z-G was generally much better than P-W.

Table XVII provides the results of the comparison between Z-G and OLS and there are far more negative percentage differences than positive ones. The verdict is not quite unanimous but I would choose OLS over Z-G.

Table XVIII provides the results of the comparison between Z-G and P-W. There are some very large positive percentage differences in this table but the largest negative percentage differences I found in the eight different sets of runs I made can be seen under the variance and MSE columns for β_2 when $\rho = .99$. The Z-G procedure calculated estimates for β_2 when ρ was large that yielded enormous variances; for example, when T was 50, the signal-to-noise ratio was 10 and ρ was .99, the Z-G procedure obtained a sample variance for the estimate of β_2 that was equal to 3145.33 as compared to OLS's 44.29 and P-W's 1.96. The exact reason for this is unknown but it may well be that the interaction between the values of the input parameters and the grid search on λ yielded some local instead of global minimums.

In non-tabulated results, both OLS and P-W almost consistently overestimated ρ while P-W almost consistently overestimated β_2 as well. OLS was generally better than P-W in all comparison statistics for both parameter estimates. Once again, as the signal-to-noise ratio increased, the bias, variance and MSE for both parameter estimates tended to fall.

Autocorrelation Test Results for Model I

MA(1) Error Structure

The hypothesis tested by the Durbin-Watson d test, namely H_o: $\rho = 0$, does not strictly apply to the case where the error structure is MA(1) but since the d statistic is calculated and printed by most canned regression programs, the outcome of the use of this test under the MA(1) error structure is quite remarkable. Table XIX arrays the percentage of time the hypothesis of no AR(1) autocorrelation was accepted and rejected for the various input parameter value sets for both the PES and B-M runs on Model I-MA.[5]

Even though the d test is not applicable to an MA(1) error structure, Table XIX exhibits a typical power function. At values of λ near 1.0 and -1.0, the hypothesis was accepted after an OLS regression only a few times especially when T = 50. At values of λ near zero, the hypothesis was accepted the majority of the time.

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[5]The number of times the Durbin-Watson d test proved to be inconclusive was collected but was not tabulated. The inconclusive percentage can be obtained by adding together the percentages of acceptances and rejections and subtracting the total from 100.

This power of the d test to detect MA(1) autocorrelation has been reported before. Smith (1976) found the d test was satisfactory and uniformly better than Durbin's periodogram (1969), Geary's sign test (1970) and Schmidt's $d_1 + d_2$ test (1972). Also Blattberg (1973) found the power of the Durbin-Watson d test quite satisfactory for MA(1) autocorrelation.

Even though both Fitts (1973) and Godfrey (1978) have developed tests for MA(1) autocorrelation, it is not poor policy to rely on the d test. Fomby and Guilkey (1978) suggested that for AR(1) autocorrelation detection an α level of 0.50 or better should be used. If a higher α level were used for testing for MA(1) autocorrelation, the d test would likely be quite adequate.

The Pesaran procedure was developed to handle Model I-MA and looking at Table XIX, this procedure has apparently removed the MA(1) autocorrelation from the residuals as can be seen by the acceptance percentages being at least 88. But there is hardly any difference between the PES and B-M columns of the table, that is the B-M procedure seemed to also remove the MA(1) autocorrelation. In addition, both of these procedures appeared to do a better job than Prais-Winston at removing the autocorrelation.

AR(1) Error Structure

The results for the Durbin-Watson d test for Model I-AR are given in Table XX which was arrayed exactly like Table XIX to facilitate comparison of the two tables.

As can be seen by looking at the Beach-MacKinnon or right hand side of Table XX, a typical power function was obtained when the d test was applied after an OLS regression: low acceptance/high rejection for values of ρ near 1.0 and -1.0 and high acceptance/low rejection percentages for ρ values near zero. As for the B-M and P-W columns, the expected result is also displayed. Since both B-M and P-W are designed to handle AR(1) autocorrelation, the d test acceptance rate should be quite high regardless of the value of ρ. This is what can be seen but B-M seemed to do a better job than P-W especially when ρ = .99.

As is obvious from the acceptance and rejection percentages under the PES column, it is evident that with high negative and positive values of ρ, the PES procedure did not do an acceptable job of removing AR(1) autocorrelation.[6]

Autocorrelation Test Results for Model II

MA(1) Error Structure

Again with the understanding that these tests were not designed to detect MA(1) autocorrelation, Tables XXI and XXII show the results of using the Durbin-Watson d, the McNown and the Durbin h tests on MA(1) autocorrelation. Table XXI shows the percentage of acceptances and rejections for the Z-G runs on Model II-MA; Table XXII shows the same for the WAL runs.

The McNown test administered after an OLS regression appears to be unreliable for small samples. It did a better job when T = 50 and

[6]The zero acceptance/zero rejection for P-W under the Pesaran runs for T = 20 and ρ = -0.1 and the triple dashes under the Beach-MacKinnon runs is due to the fact that a P-W procedure was performed only if there was a rejection by the Durbin-Watson d test.

for the larger signal-to-noise ratio--this result is especially clear in Table XXII--but both the h and d tests appear to have been more powerful. The McNown test also exhibits an interesting anomaly when λ nears the value of one in Table XXI. The percentage of rejections tends to show an increasing trend and the percentage of acceptances, a decreasing trend as λ increases from a value of 0.1 but these trends are markedly broken when the value of λ = .99. This anomaly shows up for the Z-G runs but it is absent in the WAL runs. It appears again, interestingly enough, in the Z-G runs on Model II-AR to be discussed later in this chapter. Why it appears in the Z-G runs and not in the WAL runs is unclear to me; the McNown test was administered only after an OLS regression and since the data generation was the same for either the Z-G or WAL runs for a given error structure, the anomaly should have appeared under both runs. Neither the Z-G nor the WAL procedure should have had any effect on the outcome of the McNown test.

The Durbin h test administered after an OLS regression appears to be reliable; it is more powerful for the larger sample size, this being especially evident for $|\lambda| > 0.3$ in both tables.

The Durbin-Watson d test again appears reasonably powerful in detecting MA(1) autocorrelation. If you consider the percentage of inconclusives--not arrayed in the tables--as rejections, the d test would be more powerful than Durbin's h.

Looking at the d test results after a Z-G regression, the Z-G procedure seemed to do a passable job at removing the MA(1) autocorrelation. Most of the rejection percentages are below five and all are below ten. And in all cases the acceptance percentages are higher after a Z-G procedure regression than after an OLS regression. The d test results after a WAL procedure regression indicate that the WAL procedure did not do an acceptable job of removing MA(1) autocorrelation. In fact, the results seem to parallel rather closely the outcome of the d test following an OLS regression and indicate, if anything, that the WAL procedure tended to create autocorrelation rather than remove it.

The h test administered after a WAL procedure regression also indicates not only that the WAL procedure did not remove the MA(1) autocorrelation but also increased the chance of rejecting the hypothesis of no autocorrelation when $\lambda < 0$.

The value of β_1 did not appear to affect the outcome of the tests for autocorrelation and other than the effect mentioned on the McNown test, the signal-to-noise ratio did not seem to play a part in the outcome of the tests either.

AR(1) Error Structure

The results of the autocorrelation tests for Model II-AR are arrayed in Tables XXIII and XXIV; Table XXIII contains the results for the Z-G runs and Table XXIV, the results for the WAL runs.

The McNown test and the Durbin h test were designed specifically to detect AR autocorrelation in a lagged endogenous model and therefore they should be more powerful than the Durbin-Watson d test which Durbin himself (1970) said is not applicable to the lagged endogenous case. Yet, the Durbin-Watson d test exhibited generally fewer acceptances than either the McNown or the h test especially for the smaller sample size. For $|\rho| > 0.3$, the percentages of acceptance and rejection for the d test and the h test are very nearly the same indicating that both were equally powerful.

The fact that my results indicate that the Durbin-Watson d test and Durbin's h test are about equal in power conflicts with previous results of Kenkel (1974;1975;1976), Park (1975;1976) and Spencer (1975). Kenkel and Park battled each other in the literature over the power of the h and d tests; Kenkel found that d was better than h and Park countered that h was better than d. Spencer sided with Kenkel; he found evidence of a serious small sample bias in the h test in that it tended to detect serial correlation when none existed. My results, as pointed out above, indicate that if there is a bias, the h test tended toward a higher level of acceptance than the d test when T = 20.

The anomaly mentioned earlier with respect to the McNown test can be seen in Table XXIII. For values of $\rho < 0.8$, the McNown test results paralleled those of the d and h tests but when the value of $\rho = .99$, there was a sharp reversal of the trend of acceptances and rejections. As you can see by looking at Table XXIV, the McNown test does not exhibit this behavior during the WAL runs. Again I am at a loss to explain this. However, with a ρ value so close to 1.0, it is entirely possible that unexpected things might happen during the OLS regression of (12) in Chapter III.

Neither the Z-G procedure nor the WAL procedure was very successful at removing the AR(1) autocorrelation even though the WAL procedure was specifically designed for it. The Durbin-Watson d test exhibits rather high levels of rejection after a Z-G run and both the Durbin-Watson d test and the Durbin h test show high levels of rejection after a WAL procedure especially when ρ is close to one.

Even though the signal-to-noise ratio did not seem to appreciably affect the results, the value of β_1 did have an interesting effect. For $|\rho| > 0.3$, when β_1 went from 0.4 to 0.8, the level of acceptances for the d test rose and the level of rejections fell.

Conclusions and Recommendations

As is true of any Monte Carlo investigation, the results should not be generalized to any great extent. Strictly speaking, the results are only valid for the exact input parameter values tried and for the exact error structures used. The reader is warned that applying the results of this investigation to values of parameters or error structures not actually tried should be done cautiously. That said, I will now summarize the results of this Monte Carlo investigation.

Pesaran Procedure

The Pesaran procedure was developed to handle Model I-MA but in general both OLS and P-W were better than PES on the estimation of λ but worse on the estimation of β. The Durbin-Watson d test seemed to indicate that this procedure removed the MA(1) autocorrelation. On AR(1) autocorrelation, this procedure displayed the same properties except that with high values of ρ, it did not remove the AR(1) autocorrelation.

Use of P-W is recommended over PES; the estimate of ρ would be used as a proxy for λ.

Beach-MacKinnon Procedure

The Beach-MacKinnon procedure was developed to handle Model I-AR and the data seemed to point toward its superiority over both OLS and P-W. Under an MA(1) error structure, the results are not as clear, however. None of the procedures, OLS, P-W or B-M, was able to estimate the correct sign on λ so caution is advised here. B-M did slightly better on the estimate of β in terms of its variance and MSE but both OLS and P-W were better in terms of the absolute bias of the estimate of λ. B-M also appeared to remove both MA(1) and AR(1) autocorrelation.

The use of B-M is recommended over both OLS and P-W unless theoretically the sign on the estimate of ρ is doubted. In that case, analyze the autocovariances of the disturbances of an OLS regression to determine if the error structure might be MA.[7] If the disturbance appears to be MA(1), use of P-W is recommended.

Zellner-Geisel Procedure

The Zellner-Geisel procedure was designed for Model II-MA and the results indicated that it was far superior to P-W and better than OLS for large values of λ. Furthermore, it seemed to do a passable job at removing the MA(1) autocorrelation. On AR(1) autocorrelation, this procedure holds its own against OLS especially for large values of ρ in terms of its bias. The Z-G procedure was clearly better than

[7]See Box and Jenkins (1976) or Pindyck and Rubinfeld (1976) for information on how to analyze autocovariance functions.

P-W based on the outcome of the McNown test. However, the Z-G procedure did not appear to remove AR(1) autocorrelation.

It is recommended that the Z-G procedure be performed and a *Durbin-Watson* d test on the residuals be accomplished. If the hypothesis of no autocorrelation is rejected, then look at the autocovariance function of the residuals. If an MA(1) error structure seems appropriate and the value of $\lambda > 0.6$, use the Z-G procedure estimates with some confidence. If, however, an AR(1) error structure seems more appropriate, or an MA(1) error structure with a small value for λ, use of OLS on the data is recommended.

Wallis Three-Step Procedure

The Wallis procedure was designed for Model II-AR. The results were not favorable. OLS was better than WAL in terms of bias, variance, MSE and Euclidian distance. This was true even when the error structure was MA(1). Additionally, based on the results of the Durbin-Watson d test, the WAL procedure did not do an acceptable job removing either MA(1) or AR(1) autocorrelation.

In certain circumstances WAL performed better than P-W based on the outcome of the McNown test but use of OLS is recommended when an AR(1) error structure has been specified. Try, also, either the Iteration on a Serial Correlation Parameter procedure discussed by Sargent (1968) or Klein's Nonlinear Maximum Likelihood procedure (1958). Sargent found these two methods were the best in his study.

Durbin-Watson d Test

The Durbin-Watson d test proved to be quite powerful at detecting the presence of not only an AR(1) error structure but also an MA(1) error structure. It was more powerful than the Durbin h test when the error structure was MA(1) and the model was Model II-MA. And it was at least as good if not better than Durbin's h for Model II with an AR(1) error structure.

It is indeed fortuitous that most canned regression packages calculate and output the Durbin-Watson d statistic and its continued use is recommended.

McNown Test

In small samples, the McNown test appeared to be roughly as powerful as the Durbin-Watson d test when the error structure was AR(1). It was not very reliable when the error structure was MA(1). Additionally, the P-W estimates for Model II--calculated only if the McNown test indicated rejection of the no autocorrelation hypothesis--tended to be inferior to the OLS, Z-G and WAL estimates. Re-running the Model II computer runs basing the P-W estimates on the outcome of the Durbin-Watson d test or the Durbin h test is suggested as a possible extension of this investigation.

Use of the McNown test on small samples is not recommended; use the Durbin-Watson d test instead.

Durbin h Test

The Durbin h test seemed to be adequate in detecting both AR(1) and MA(1) autocorrelation. But the Durbin-Watson d test, even though theoretically it should not be applied when lagged endogenous variables are used as regressors, performed at least as well if not better than the h test on AR(1) data and outperformed the h test on MA(1) data.

Because of the questionable nature of Durbin's h test in recent studies and because the Durbin-Watson d test could detect both AR(1) and MA(1) autocorrelation in small samples, use of the d test over the h test is recommended.

TABLE III

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL I-MA, PESARAN VERSUS OLS

	Lambda				Beta				
T	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	-.99	-28	-47	-65	1.0	27	57	57	-28
50	-.99	-34	87	-78	1.0	94	76	76	-33
20	-.80	-26	-153	-61	1.0	-706	45	45	-26
50	-.80	-28	-7	-64	1.0	-4178	35	35	-28
20	-.60	-24	-126	-56	1.0	38	33	33	-22
50	-.60	-21	-54	-47	1.0	25	12	13	-19
20	-.30	-11	-100	-34	1.0	-32	-8	-8	-12
50	-.30	-7	-37	-16	1.0	-86	6	6	-10
20	-.10	-8	-112	-86	1.0	-33	-6	-6	-16
50	-.10	-2	-20	-10	1.0	35	1	1	-2
20	.10	-23	-152	-96	1.0	-48	-3	-4	-29
50	.10	-8	-33	-21	1.0	77	5	5	-7
20	.30	-18	-143	-48	1.0	-4	-5	-5	-16
50	.30	-9	-15	-19	1.0	99	6	6	-9
20	.60	-24	-101	-55	1.0	65	34	34	-24
50	.60	-22	-184	-50	1.0	74	58	58	-22
20	.80	-30	21	-67	1.0	59	73	73	-30
50	.80	-29	-20	-66	1.0	94	74	74	-29
20	.99	-28	71	-63	1.0	51	79	79	-28
50	.99	-33	89	-76	1.0	89	94	94	-32

TABLE IV

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL I-MA, PESARAN VERSUS PRAIS-WINSTON

	Lambda				Beta				
T	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	-.99	-40	-112	-97	1.0	-73	55	55	-40
50	-.99	-66	63	-175	1.0	96	70	70	-64
20	-.80	-43	-334	-107	1.0	91	23	23	-42
50	-.80	-67	-209	-180	1.0	-61	32	32	-67
20	-.60	-39	-166	-94	1.0	24	25	25	-36
50	-.60	-65	-467	-176	1.0	25	10	11	-57
20	-.30	-20	-144	-56	1.0	-54	-8	-8	-21
50	-.30	-40	-122	-97	1.0	-93	6	5	-42
20	-.10	-12	-127	-100	1.0	-32	-6	-6	-18
50	-.10	-6	-35	-20	1.0	56	1	1	-6
20	.10	-25	-165	-104	1.0	-32	3	1	-27
50	.10	-10	-42	-27	1.0	78	5	5	-9
20	.30	-26	-189	-70	1.0	-7	-7	-7	-23
50	.30	-40	-50	-94	1.0	95	4	4	-40
20	.60	-42	-111	-101	1.0	64	33	34	-42
50	.60	-66	-305	-177	1.0	-754	36	36	-66
20	.80	-43	12	-101	1.0	26	70	70	-43
50	.80	-70	-189	-190	1.0	77	53	53	-70
20	.99	-43	66	-102	1.0	59	73	73	-43
50	.99	-65	75	-172	1.0	65	83	83	-65

TABLE V

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL I-AR, BEACH-MACKINNON VERSUS OLS

	Rho				Beta				
T	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	-.99	-25	22	3	1.0	30	81	81	-21
50	-.99	-26	14	-12	1.0	56	86	86	48
20	-.80	-12	11	5	1.0	31	49	49	9
50	-.80	-7	4	3	1.0	10	43	42	10
20	-.60	20	1	3	1.0	-153	28	28	-2
50	-.60	-3	2	2	1.0	46	17	17	45
20	-.30	-97	-8	-9	1.0	31	-4	-3	30
50	-.30	-32	2	2	1.0	27	6	6	26
20	-.10	-12	-11	-11	1.0	-11	3	2	-11
50	-.10	-6	-3	-3	1.0	-7	-4	-5	-7
20	.10	12	-11	-10	1.0	21	-3	-3	14
50	.10	8	-3	-3	1.0	-287	-4	-4	-25
20	.30	34	-13	-9	1.0	-62	4	4	-10
50	.30	18	-6	-3	1.0	2	12	12	3
20	.60	28	-13	-3	1.0	51	7	7	33
50	.60	18	2	8	1.0	40	20	21	39
20	.80	29	6	29	1.0	36	70	70	35
50	.80	39	13	25	1.0	45	82	82	45
20	.99	21	29	32	1.0	89	93	94	83
50	.99	30	41	46	1.0	62	98	98	33

TABLE VI

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL I-AR, BEACH-MACKINNON VERSUS PRAIS-WINSTON

	Rho				Beta				
T	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	-.99	82	88	94	1.0	-17	48	48	81
50	-.99	93	98	99	1.0	7	53	53	88
20	-.80	86	60	93	1.0	-18	4	4	84
50	-.80	96	35	98	1.0	0	0	0	84
20	-.60	89	23	78	1.0	-201	21	21	85
50	-.60	98	-54	97	1.0	0	0	0	91
20	-.30	32	-14	-13	1.0	32	-5	-4	32
50	-.30	98	-1	61	1.0	1	4	4	70
20	-.10	-12	-11	-11	1.0	-11	3	2	-11
50	-.10	-516	-30	-32	1.0	-6	-5	-5	-8
20	.10	50	-37	-30	1.0	-804	0	0	43
50	.10	28	-14	-10	1.0	-722	-2	-2	0
20	.30	75	-61	-6	1.0	6	13	13	54
50	.30	82	-31	55	1.0	16	5	5	47
20	.60	82	-93	68	1.0	-9	-7	-7	81
50	.60	91	-87	94	1.0	10	-1	0	62
20	.80	81	53	91	1.0	31	32	33	57
50	.80	95	16	98	1.0	9	7	8	55
20	.99	80	77	92	1.0	15	63	63	75
50	.99	93	94	99	1.0	96	53	54	93

TABLE VII

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL I-MA, BEACH-MACKINNON VERSUS OLS

	Rho/Lambda				Beta				
T	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	-.99	-2	-10	-4	1.0	-167	27	27	-2
50	-.99	0	-2	-1	1.0	-53	19	19	-1
20	-.80	-2	-14	-5	1.0	48	6	8	-1
50	-.80	-1	-8	-1	1.0	11	-1	0	0
20	-.60	-3	-19	-7	1.0	97	0	0	-3
50	-.60	-1	-5	-2	1.0	38	1	3	2
20	-.30	-3	-18	-9	1.0	-56	-15	-15	-4
50	-.30	-1	-8	-3	1.0	7	12	12	-1
20	-.10	-3	-7	-7	1.0	14	-10	-10	-3
50	-.10	-1	-6	-3	1.0	-50	-3	-4	-7
20	.10	-4	-13	-11	1.0	19	2	3	4
50	.10	-1	-1	-1	1.0	-116	3	3	-4
20	.30	-1	-5	-3	1.0	66	4	4	-1
50	.30	0	0	0	1.0	42	4	5	0
20	.60	0	1	-1	1.0	46	24	24	0
50	.60	0	5	0	1.0	15	45	45	0
20	.80	0	-4	-1	1.0	-453	39	37	-1
50	.80	0	-3	0	1.0	75	53	54	0
20	.99	0	4	0	1.0	47	41	41	0
50	.99	0	3	0	1.0	-29	52	52	0

TABLE VIII

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL I-MA, BEACH-MACKINNON VERSUS PRAIS-WINSTON

		Rho/Lambda				Beta			
T	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	-.99	-15	-98	-34	1.0	-84	8	8	-16
50	-.99	-24	-162	-55	1.0	-10	-1	-2	-24
20	-.80	-15	-114	-34	1.0	40	2	3	-14
50	-.80	-30	-216	-69	1.0	2	-3	-2	-27
20	-.60	-13	-100	-30	1.0	93	1	1	-13
50	-.60	-37	-89	-87	1.0	13	1	1	-33
20	-.30	-16	-64	-39	1.0	19	-10	-10	-16
50	-.30	-34	-109	-80	1.0	20	7	8	-28
20	-.10	-17	-43	-41	1.0	19	-11	-11	-17
50	-.10	-8	-34	-23	1.0	-27	-4	-4	-11
20	.10	-7	-20	-16	1.0	19	2	3	3
50	.10	-4	-15	-10	1.0	-101	3	3	-7
20	.30	-6	-13	-12	1.0	38	3	3	-6
50	.30	-32	-16	-71	1.0	41	1	1	-31
20	.60	-7	-6	-15	1.0	52	20	20	-7
50	.60	-38	-113	-90	1.0	13	12	13	-37
20	.80	-10	-5	-20	1.0	-29	22	21	-10
50	.80	-36	-93	-84	1.0	4	0	0	-36
20	.99	-10	-21	-21	1.0	17	26	26	-10
50	.99	-25	-196	-57	1.0	-306	3	3	-25

TABLE IX

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL I-AR, PESARAN VERSUS OLS

	Lambda/Rho				Beta				
T	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	-.99	-68	10	-40	1.0	38	70	70	-11
50	-.99	-142	-99	-197	1.0	-19	87	87	-68
20	-.80	49	-35	-21	1.0	-1285	49	49	-15
50	-.80	-336	-61	-167	1.0	35	17	17	5
20	-.60	63	-65	-49	1.0	-215	13	11	-36
50	-.60	-214	-58	-82	1.0	0	6	6	-20
20	-.30	-247	-83	-104	1.0	-15	18	18	-96
50	-.30	63	-37	-33	1.0	13	17	17	15
20	-.10	-95	-126	-128	1.0	-167	-10	-11	-145
50	-.10	-128	-53	-61	1.0	-38	-3	-3	-49
20	.10	-42	-127	-126	1.0	22	3	3	1
50	.10	2	-15	-14	1.0	11	1	1	9
20	.30	31	-50	-30	1.0	20	-18	-17	23
50	.30	54	-46	-39	1.0	14	-10	-8	14
20	.60	39	-37	-6	1.0	38	17	18	38
50	.60	-51	-1	-34	1.0	83	35	35	36
20	.80	6	-6	3	1.0	38	45	45	22
50	.80	-131	-68	-172	1.0	86	46	46	-24
20	.99	-14	4	-13	1.0	17	69	68	16
50	.99	-120	-74	-211	1.0	32	72	72	31

TABLE X

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL I-AR. PESARAN VERSUS PRIAS-WINSTON

	Lambda/R[illegible]				Beta				
T	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	-.99	81	92	95	1.0	-104	28	28	79
50	-.99	86	94	97	1.0	-882	74	74	83
20	-.80	95	57	94	1.0	-201	4	3	90
50	-.80	86	-60	95	1.0	-5	-42	-42	82
20	-.60	93	-43	62	1.0	-58	-6	-8	72
50	-.60	90	-99	93	1.0	-22	-10	-10	82
20	-.30	-119	-106	-121	1.0	-22	13	13	-74
50	-.30	94	-88	33	1.0	-1	15	15	50
20	-.10	-79	-135	-137	1.0	-157	-10	-11	-132
50	-.10	-162	-58	-67	1.0	-38	-3	-3	-50
20	.10	-2	-168	-153	1.0	21	6	6	11
50	.10	38	-59	-39	1.0	3	2	2	19
20	.30	45	-95	-40	1.0	4	-16	-15	19
50	.30	92	-193	39	1.0	24	2	4	35
20	.60	78	-180	61	1.0	24	7	7	58
50	.60	80	-127	91	1.0	-93	-23	-23	79
20	.80	73	-9	86	1.0	-559	-14	-14	66
50	.80	81	-62	93	1.0	74	-72	-72	81
20	.99	67	69	84	1.0	-66	-32	-37	-9
50	.99	80	87	95	1.0	-109	-285	-285	17

TABLE XI

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-MA, ZELLNER-GEISEL VERSUS OLS

		Lambda				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	10	.10	-2096	-6172	-6249	1.0	-464	-34	-35	-997
50	10	.10	-17	-3732	-3596	1.0	28	-48	-45	26
20	100	.10	-2310	-9216	-9588	1.0	-264	-69	-70	-610
50	100	.10	-6901	-3248	-3392	1.0	-85086	-104	-108	-8821
20	10	.30	15	-886	-855	1.0	-154	-20	-20	-57
50	10	.30	-80	-662	-649	1.0	-13	6	6	-38
20	100	.30	-407	-1119	-1124	1.0	-8	-9	-9	-21
50	100	.30	-84	-836	-821	1.0	18	-24	-24	-6
20	10	.60	55	-186	-146	1.0	-261	35	34	-160
50	10	.60	63	-104	-64	1.0	8	35	35	26
20	100	.60	-450	-120	-121	1.0	91	42	42	90
50	100	.60	18	-157	-141	1.0	88	33	35	82
20	10	.80	93	8	19	1.0	11	70	70	12
50	10	.80	95	-2	72	1.0	70	67	69	72
20	100	.80	87	-90	-79	1.0	29	33	33	34
50	100	.80	59	-31	-11	1.0	-3	75	74	7
20	10	.99	91	83	91	1.0	-63	88	88	-36
50	10	.99	99	98	99	1.0	70	92	92	73
20	100	.99	91	54	65	1.0	-119	72	71	-116
50	100	.99	98	96	98	1.0	91	92	92	92

TABLE XII

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-MA. ZELLNER-GEISEL VERSUS PRAIS-WINSTON

		Lambda				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	10	.10	94	90	92	1.0	100	91	99	99
50	10	.10	97	77	84	1.0	99	98	99	99
20	100	.10	94	98	98	1.0	100	99	100	99
50	100	.10	94	97	98	1.0	100	100	100	99
20	10	.30	99	98	99	1.0	100	87	98	100
50	10	.30	98	96	98	1.0	100	98	99	99
20	100	.30	99	100	100	1.0	100	99	100	100
50	100	.30	98	99	99	1.0	100	100	100	100
20	10	.60	99	100	100	1.0	97	92	97	97
50	10	.60	98	99	100	1.0	98	98	98	98
20	100	.60	100	100	100	1.0	100	99	99	100
50	100	.60	98	100	100	1.0	99	99	100	99
20	10	.80	100	100	100	1.0	94	37	85	95
50	10	.80	100	100	100	1.0	98	95	98	98
20	100	.80	100	100	100	1.0	100	97	99	100
50	100	.80	99	100	100	1.0	98	99	99	98
20	10	.99	99	99	100	1.0	70	-276	-88	79
50	10	.99	100	100	100	1.0	92	-41	58	95
20	100	.99	100	100	100	1.0	86	-17	63	90
50	100	.99	100	100	100	1.0	100	84	96	100

TABLE XIII

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-AR. WALLIS VERSUS OLS

		Rho				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	10	-.99	-1072	-1033	-4884	.4	-24	-126	-114	1.0	-347	-566	-574	-1070
20	10	-.99	-1093	-1751	-6415	.8	-707	-10809	-9805	1.0	-956	-1607	-1609	-1093
50	10	-.99	-1489	-6036	-13113	.4	28	-71	-15	1.0	16	-216	-214	-1475
50	10	-.99	-1080	-6120	-9803	.8	29	-119	-52	1.0	-16	-249	-227	-860
20	100	-.99	-835	-848	-3333	.4	-216	-119	-125	1.0	-611	-294	-294	-835
20	100	-.99	-1080	-1535	-5796	.8	-1896	-1669	-1747	1.0	-670	-936	-953	-1080
50	100	-.99	-1295	-6289	-11539	.4	30	-42	-28	1.0	51	-191	-190	-1295
50	100	-.99	-1151	-3797	-7776	.8	-23	-706	-577	1.0	-66	-449	-443	-1147
20	10	-.80	-843	-477	-2470	.4	-92	-73	-82	1.0	-12220	-240	-241	-843
20	10	-.80	-1321	-1462	-5924	.8	-827	-3616	-4502	1.0	87	-961	-952	-1273
50	10	-.80	-1693	-2028	-5218	.4	39	-34	6	1.0	12	-72	-65	-1456
50	10	-.80	-878	-2039	-4189	.8	-21	-1013	-512	1.0	87	-475	-461	-814
20	100	-.80	-1102	-693	-2770	.4	-25	-46	-46	1.0	-70	-299	-299	-1102
20	100	-.80	-1386	-1206	-4564	.8	-1365	-708	-763	1.0	-508	-1023	-1032	-1383
50	100	-.80	-2014	-1629	-4442	.4	58	-20	-13	1.0	-613	-41	-41	-2014
50	100	-.80	-1624	-1458	-3613	.8	41	-72	-57	1.0	-53	-212	-212	-1611
20	10	-.60	-1898	-210	-1506	.4	-35	-77	-78	1.0	-67	-185	-185	-1840
20	10	-.60	-1765	-464	-2332	.8	-933	-1720	-2229	1.0	92	-417	-413	-1609
50	10	-.60	-3614	-759	-2300	.4	3	-25	-18	1.0	-221	-175	-176	-3251
50	10	-.60	-1654	-1005	-3297	.8	-174	-798	-772	1.0	-99	-297	-297	-1563
20	100	-.60	-11143	-192	-1675	.4	96	-24	-24	1.0	-182	-187	-189	-10540
20	100	-.60	-2761	-429	-2698	.8	-265	-207	-226	1.0	-129	-663	-663	-2757
50	100	-.60	-5192	-1072	-3438	.4	-5	-9	-9	1.0	-60	-87	-87	-5151
50	100	-.60	-1797	-705	-1892	.8	-24	-79	-77	1.0	-645	-222	-223	-1795
20	10	-.30	-6036	-82	-735	.4	-74	-28	-31	1.0	-251	-77	-77	-5867
20	10	-.30	-2464	-456	-2083	.8	-1934	-760	-939	1.0	-131	-187	-189	-1692
50	10	-.30	-3877	-221	-856	.4	-37	-9	-12	1.0	34	-36	-36	-3604
50	10	-.30	-1499	-409	-1200	.8	-100	-77	-111	1.0	-62	-153	-153	-1098
20	100	-.30	-81805	-111	-739	.4	-96	-20	-20	1.0	-154	-67	-67	-41879
20	100	-.30	-7709	-287	-1521	.8	-558	-294	-321	1.0	-90	-390	-390	-7662

TABLE XIII (CONTINUED)

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-AR. WALLIS VERSUS OLS

		Rho				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
50	100	-.30	-4569	-246	-802	.4	5	-4	-4	1.0	-15	-69	-68	-4232
50	100	-.30	-2719	-517	-1274	.8	-129	-14	-14	1.0	74	-146	-146	-2713
20	10	-.10	-562	-32	-283	.4	-61	-24	-24	1.0	43	-97	-94	-524
20	10	-.10	-1261	-114	-633	.8	-631	-126	-201	1.0	-307	-211	-213	-1235
50	10	-.10	-383	-95	-250	.4	34	-14	-13	1.0	-76	-34	-34	-383
50	10	-.10	-1356	-353	-781	.8	-154	-127	-168	1.0	-147	-112	-112	-1303
20	100	-.10	-638	-36	-302	.4	-16	-30	-30	1.0	-1741	-42	-42	-638
20	100	-.10	-1211	-85	-623	.8	-598	-125	-131	1.0	22	-247	-239	-1182
50	100	-.10	-3046	-81	-378	.4	94	-11	-11	1.0	55	-47	-45	-2820
50	100	-.10	-973	-417	-1018	.8	91	-63	-54	1.0	-194	-103	-104	-972
20	10	.10	-318	31	-125	.4	98	-19	-19	1.0	-267	-36	-41	-317
20	10	.10	-419	-69	-447	.8	-660	-93	-122	1.0	-308	-82	-82	-419
50	10	.10	-239	-38	-148	.4	-29	-9	-10	1.0	-30	0	-1	-234
50	10	.10	-1372	-113	-441	.8	-215	-39	-54	1.0	-287	-53	-53	-1367
20	100	.10	-400	33	-93	.4	-2564	-14	-15	1.0	5	-47	-47	-400
20	100	.10	-400	-101	-461	.8	-243	-215	-216	1.0	69	-63	-60	-398
50	100	.10	-700	-13	-111	.4	-305	-14	-14	1.0	28	-7	-6	-699
50	100	.10	-1918	-140	-414	.8	-44	-34	-34	1.0	-2	-52	-51	-1759
20	10	.30	-24	47	25	.4	-112	3	1	1.0	36	24	25	-23
20	10	.30	-146	-50	-199	.8	-3616	-163	-206	1.0	90	-73	-72	-146
50	10	.30	-157	31	2	.4	39	-10	-9	1.0	86	12	12	-155
50	10	.30	-111	-84	-138	.8	-112	-45	-50	1.0	56	-28	-28	-110
20	100	.30	8	28	26	.4	16	-15	-14	1.0	-55	-16	-16	8
20	100	.30	-113	-17	-137	.8	-332	-32	-35	1.0	-352	-81	-82	-113
50	100	.30	-31	26	16	.4	95	16	17	1.0	-175	7	7	-31
50	100	.30	-447	-56	-190	.8	-1088	-16	-27	1.0	-224	-12	-12	-447
20	10	.60	51	65	69	.4	61	20	28	1.0	57	34	35	51
20	10	.60	40	30	48	.8	91	6	7	1.0	63	43	43	40
50	10	.60	-58	6	-7	.4	97	25	29	1.0	60	51	51	-50
50	10	.60	17	6	12	.8	-182	16	14	1.0	64	35	38	22

TABLE XIII (CONTINUED)

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-AR. WALLIS VERSUS OLS

		Rho				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	100	.60	55	56	65	.4	-45	11	10	1.0	71	43	44	55
20	100	.60	47	11	41	.8	-684	8	7	1.0	-47	30	30	47
50	100	.60	-10	27	16	.4	-87	29	29	1.0	60	46	46	-10
50	100	.60	43	-10	12	.8	-297	-14	-17	1.0	81	27	31	43
20	10	.80	-23	53	14	.4	-101	38	37	1.0	79	67	67	-23
20	10	.80	96	44	78	.8	-1010	26	26	1.0	-3534	64	63	94
50	10	.80	-107	-50	-160	.4	96	49	51	1.0	11	67	67	-107
50	10	.80	77	19	56	.8	96	47	48	1.0	80	75	76	77
20	100	.80	-40	15	-35	.4	-603	27	26	1.0	55	61	61	-40
20	100	.80	99	59	82	.8	-118	43	43	1.0	24	69	69	98
50	100	.80	-147	-106	-208	.4	-59	43	42	1.0	1	66	66	-147
50	100	.80	85	25	54	.8	-121	53	51	1.0	-697	72	72	85
20	10	.99	-59	40	-61	.4	65	66	68	1.0	51	76	76	-59
20	10	.99	57	77	79	.8	-8767	-6	-7	1.0	62	93	93	57
50	10	.99	-203	-283	-534	.4	80	79	82	1.0	30	78	78	-203
50	10	.99	18	4	20	.8	76	65	67	1.0	94	98	98	18
20	100	.99	-75	25	-97	.4	2	52	51	1.0	76	69	69	-75
20	100	.99	50	55	67	.8	10	50	50	1.0	82	96	96	50
50	100	.99	-199	-298	-551	.4	69	73	73	1.0	-9	80	80	-199
50	100	.99	20	12	26	.8	87	61	63	1.0	73	97	97	20

TABLE XIV

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-AR, WALLIS VERSUS PRAIS-WINSTON

		Rho				Beta 1				Beta 2			
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	10	-.99	-45	-66	-102	.4	99	100	100	1.0	82	63	68	-41
20	10	-.99	-60	-188	-160	.8	80	98	97	1.0	24	-3877	-3524	-58
50	10	-.99	24	-68	28	.4	97	100	100	1.0	95	83	85	24
50	10	-.99	33	-243	36	.8	83	99	99	1.0	-354	-2022	-2019	33
20	100	-.99	-48	-17	-87	.4	100	100	100	1.0	99	96	97	-34
20	100	-.99	-79	-74	-178	.8	100	100	100	1.0	52	-234	-168	-67
50	100	-.99	26	-74	29	.4	100	100	100	1.0	100	99	100	27
50	100	-.99	25	-41	31	.8	99	100	100	1.0	78	24	35	27
20	10	-.80	-41	-240	-115	.4	94	100	100	1.0	89	49	56	-39
20	10	-.80	-174	-207	-484	.8	87	97	98	1.0	99	-614	-336	-91
50	10	-.80	32	-834	31	.4	-807	-128	-172	1.0	-117	-261	-264	32
50	10	-.80	26	-434	20	.8	60	94	94	1.0	89	-271	-262	26
20	100	-.80	-14	-446	-59	.4	99	100	100	1.0	95	85	86	-14
20	100	-.80	-61	-630	-206	.8	93	99	99	1.0	47	-78	-68	-61
50	100	-.80	34	-902	33	.4	40	-46	-42	1.0	63	-216	-213	34
50	100	-.80	36	-991	34	.8	-121	-118	-121	1.0	-560	-644	-647	36
20	10	-.60	-77	-163	-204	.4	97	100	100	1.0	95	77	85	-39
20	10	-.60	-254	-261	-714	.8	92	98	99	1.0	100	-157	-10	-59
50	10	-.60	15	-757	-8	.4	73	98	98	1.0	78	66	68	15
50	10	-.60	-34	-150	-97	.8	91	98	98	1.0	89	28	46	-18
20	100	-.60	-64	-321	-187	.4	100	100	100	1.0	96	98	98	-52
20	100	-.60	-141	-522	-487	.8	98	100	100	1.0	98	69	77	-110
50	100	-.60	15	-1500	-5	.4	-556	-45	-50	1.0	-8511	-172	-173	15
50	100	-.60	13	-1825	-21	.8	83	99	99	1.0	83	72	73	13
20	10	-.30	-458	-105	-660	.4	99	100	100	1.0	99	83	96	29
20	10	-.30	-1239	-410	-1788	.8	94	97	99	1.0	89	-69	53	-11
50	10	-.30	-95	-241	-267	.4	97	99	100	1.0	100	97	99	39
50	10	-.30	-178	-303	-473	.8	93	99	99	1.0	92	80	90	15
20	100	-.30	-311	-215	-708	.4	100	100	100	1.0	100	99	100	26
20	100	-.30	-479	-488	-1481	.8	99	100	100	1.0	100	86	96	-24

TABLE XIV (CONTINUED)

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-AR. WALLIS VERSUS PRAIS-WINSTON

		Rho				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
50	100	-.30	-31	-866	-152	.4	100	100	100	1.0	99	100	100	10
50	100	-.30	-82	-921	-372	.8	100	100	100	1.0	100	98	99	-2
20	10	-.10	-1299	-72	-421	.4	100	100	100	1.0	99	53	96	58
20	10	-.10	-9388	-155	-800	.8	90	99	99	1.0	95	-33	75	23
50	10	-.10	-921	-246	-549	.4	99	99	99	1.0	100	96	99	74
50	10	-.10	-1547	-500	-1066	.8	90	98	99	1.0	99	80	96	64
20	100	-.10	-15838	-121	-589	.4	100	100	100	1.0	100	98	100	58
20	100	-.10	-15320	-181	-1036	.8	99	100	100	1.0	99	90	98	23
50	100	-.10	-397	-256	-663	.4	100	100	100	1.0	100	100	100	68
50	100	-.10	-3046	-568	-1416	.8	100	100	100	1.0	100	98	100	58
20	10	.10	-319	14	-176	.4	100	100	100	1.0	97	71	98	71
20	10	.10	-380	-87	-478	.8	-96	99	99	1.0	98	-10	92	52
50	10	.10	-142	-154	-254	.4	98	99	99	1.0	99	95	99	82
50	10	.10	-578	-171	-541	.8	92	99	99	1.0	100	81	98	74
20	100	.10	-295	-4	-178	.4	99	100	100	1.0	100	97	100	70
20	100	.10	-425	-166	-621	.8	92	100	100	1.0	100	95	99	46
50	100	.10	-168	-148	-259	.4	100	100	100	1.0	100	100	100	83
50	100	.10	-743	-320	-748	.8	100	100	100	1.0	99	99	100	74
20	10	.30	8	35	28	.4	99	100	100	1.0	99	88	98	87
20	10	.30	-115	-64	-187	.8	96	99	100	1.0	100	56	95	67
50	10	.30	59	24	66	.4	99	99	100	1.0	100	98	99	89
50	10	.30	16	-182	-31	.8	98	99	99	1.0	100	95	98	81
20	100	.30	42	-31	24	.4	100	100	100	1.0	100	99	100	87
20	100	.30	-73	-66	-138	.8	99	100	100	1.0	99	96	99	65
50	100	.30	73	-83	68	.4	100	100	100	1.0	100	100	100	89
50	100	.30	19	-272	-13	.8	98	100	100	1.0	99	100	100	66
20	10	.60	78	49	87	.4	99	100	100	1.0	99	96	98	88
20	10	.60	67	-8	76	.8	100	100	100	1.0	100	96	98	84
50	10	.60	90	-41	95	.4	99	98	98	1.0	87	90	90	90
50	10	.60	89	-74	94	.8	90	98	98	1.0	84	92	92	89

TABLE XIV (CONTINUED)

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-AR, WALLIS VERSUS PRAIS-WINSTON

		Rho				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	100	.60	84	28	89	.4	100	100	100	1.0	99	100	100	89
20	100	.60	72	-47	71	.8	100	100	100	1.0	99	99	100	85
50	100	.60	87	-87	94	.4	94	99	99	1.0	97	98	98	87
50	100	.60	91	-170	93	.8	88	99	99	1.0	95	98	98	91
20	10	.80	64	23	82	.4	98	100	100	1.0	100	93	94	65
20	10	.80	98	1	94	.8	99	100	100	1.0	96	98	98	98
50	10	.80	75	-128	90	.4	55	-15	-15	1.0	-295	-29	-30	75
50	10	.80	97	5	98	.8	88	-3	-2	1.0	26	5	5	97
20	100	.80	66	-14	83	.4	99	100	100	1.0	96	99	99	66
20	100	.80	100	22	95	.8	100	100	100	1.0	98	100	100	99
50	100	.80	80	-102	92	.4	-5	-7	-7	1.0	-12	-32	-32	80
50	100	.80	98	22	98	.8	-7	-12	-12	1.0	47	7	7	98
20	10	.99	43	76	70	.4	100	100	100	1.0	98	100	100	47
20	10	.99	84	86	95	.8	100	100	100	1.0	100	100	100	85
50	10	.99	67	67	86	.4	100	100	100	1.0	98	99	100	68
50	10	.99	91	91	99	.8	100	100	100	1.0	100	100	100	91
20	100	.99	47	65	71	.4	100	100	100	1.0	100	100	100	48
20	100	.99	82	81	94	.8	100	100	100	1.0	100	100	100	82
50	100	.99	64	62	84	.4	100	100	100	1.0	100	100	100	64
50	100	.99	91	87	98	.8	100	100	100	1.0	99	100	100	91

TABLE XV

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-MA. WALLIS VERSUS OLS

		Rho/Lambda				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	10	-.99	-6	61	-10	.4	36	34	34	1.0	34	20	20	-6
20	10	-.99	-24	-17	-54	.8	-222	-39	-50	1.0	-651	-3	-3	-24
50	10	-.99	-2	27	-3	.4	38	41	41	1.0	87	29	29	-2
50	10	-.99	-12	-17	-25	.8	-991	3	-7	1.0	-50	-16	-17	-12
20	100	-.99	-8	54	-15	.4	-223	24	23	1.0	53	18	18	-8
20	100	-.99	-28	-3	-62	.8	94	-19	-19	1.0	-12	-32	-32	-28
50	100	-.99	-1	29	-2	.4	-194	46	46	1.0	-264	20	20	-1
50	100	-.99	-11	-77	-23	.8	-68	31	29	1.0	99	26	26	-11
20	10	-.80	-11	60	-20	.4	68	18	23	1.0	82	22	24	-11
20	10	-.80	-29	-6	-66	.8	-158	-27	-45	1.0	-4	-9	-9	-29
50	10	-.80	-3	18	-7	.4	30	23	24	1.0	90	17	20	-3
50	10	-.80	-14	-49	-31	.8	-461	-6	-49	1.0	-833	-13	-14	-14
20	100	-.80	-6	46	-10	.4	1	30	30	1.0	-6	22	22	-6
20	100	-.80	-30	-7	-69	.8	-1087	-5	-11	1.0	-86	3	2	-30
50	100	-.80	-1	38	-3	.4	-285	18	17	1.0	44	12	12	-1
50	100	-.80	-11	-16	-23	.8	-918	13	11	1.0	-326	1	-1	-11
20	10	-.60	-15	46	-29	.4	-469	28	27	1.0	25	2	3	-15
20	10	-.60	-43	-12	-101	.8	-385	-66	-82	1.0	73	1	3	-43
50	10	-.60	-4	34	-8	.4	92	12	16	1.0	43	26	27	-4
50	10	-.60	-18	-74	-39	.8	-230	-19	-44	1.0	-49	5	4	-18
20	100	-.60	-14	54	-28	.4	35	4	4	1.0	-145	11	9	-14
20	100	-.60	-47	-13	-111	.8	-876	-71	-78	1.0	-784	9	5	-47
50	100	-.60	-4	20	-8	.4	28	33	34	1.0	-20	11	10	-4
50	100	-.60	-16	-57	-35	.8	52	-7	-5	1.0	6	-10	-9	-16
20	10	-.30	-42	52	-79	.4	83	-28	-24	1.0	-104	14	14	-42
20	10	-.30	-97	-66	-256	.8	-342	-96	-190	1.0	-174	-25	-26	-97
50	10	-.30	-22	7	-45	.4	74	2	8	1.0	-63	8	5	-22
50	10	-.30	-40	-129	-96	.8	-1139	-19	-34	1.0	-101	-13	-19	-40
20	100	-.30	-49	45	-95	.4	-76	10	10	1.0	-215	-1	-3	-49
20	100	-.30	-111	-15	-293	.8	-36	-66	-66	1.0	-220	-30	-32	-111

TABLE XV (CONTINUED)

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-MA. WALLIS VERSUS OLS

		Rho/Lambda				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
50	100	-.30	-19	18	-38	.4	50	-4	-3	1.0	59	2	2	-19
50	100	-.30	-46	-81	-112	.8	-211	-20	-27	1.0	-35	-55	-55	-46
20	10	-.10	-308	48	-282	.4	-130	-13	-13	1.0	11	-29	-24	-286
20	10	-.10	-707	-67	-736	.8	-879	-103	-156	1.0	-61	-78	-79	-692
50	10	-.10	-146	-14	-275	.4	-433	-14	-15	1.0	-847	-10	-11	-146
50	10	-.10	-182	-130	-435	.8	-3515	-39	-60	1.0	-102	-24	-26	-181
20	100	-.10	-261	38	-240	.4	20	11	11	1.0	-104	-37	-38	-261
20	100	-.10	-734	-82	-791	.8	-984	-97	-102	1.0	-695	-126	-126	-734
50	100	-.10	-100	-13	-186	.4	12	-14	-13	1.0	-54	-9	-9	-100
50	100	-.10	-166	-255	-480	.8	24	-39	-38	1.0	-11	-33	-32	-166
20	10	.10	21	-2	19	.4	-145	-34	-34	1.0	100	-67	-67	21
20	10	.10	-51	-300	-186	.8	-457	-227	-264	1.0	-18	-147	-146	-51
50	10	.10	77	-78	28	.4	-108	-18	-23	1.0	-131	-32	-32	77
50	10	.10	75	-259	9	.8	-54	-45	-46	1.0	-11	-147	-146	75
20	100	.10	30	-21	23	.4	3	-19	-19	1.0	55	-67	-64	30
20	100	.10	-43	-152	-120	.8	-64	-145	-146	1.0	53	-124	-117	-43
50	100	.10	98	-156	34	.4	-71	-13	-13	1.0	-55	-19	-19	98
50	100	.10	50	-234	-19	.8	-120	-39	-42	1.0	67	-40	-40	50
20	10	.30	91	-127	79	.4	66	-24	-24	1.0	92	-126	-125	91
20	10	.30	75	-243	57	.8	-579	-290	-376	1.0	44	-369	-365	75
50	10	.30	56	-263	64	.4	-63	-18	-21	1.0	-67	-28	-28	56
50	10	.30	59	-500	61	.8	-88	-87	-105	1.0	-52	-139	-138	59
20	100	.30	92	-66	84	.4	64	-37	-36	1.0	-1515	-187	-188	92
20	100	.30	88	-468	59	.8	-2324	-235	-247	1.0	0	-230	-227	88
50	100	.30	53	-254	65	.4	-107	-23	-25	1.0	-113	-70	-71	53
50	100	.30	71	-601	60	.8	-795	-98	-108	1.0	-235	-134	-135	71
20	10	.60	60	-224	75	.4	-14	-96	-93	1.0	24	-195	-187	60
20	10	.60	79	-659	79	.8	-11250	-525	-607	1.0	-3501	-441	-444	79
50	10	.60	30	-531	45	.4	35	-12	-10	1.0	-111	-60	-62	30
50	10	.60	44	-925	56	.8	-170	-220	-237	1.0	-314	-371	-381	44

TABLE XV (CONTINUED)

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-MA. WALLIS VERSUS OLS

		Rho/Lambda				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	100	.60	58	-312	72	.4	60	-74	-71	1.0	-345	-208	-208	58
20	100	.60	74	-863	73	.8	70	-404	-402	1.0	-93	-509	-504	74
50	100	.60	37	-456	53	.4	24	-21	-18	1.0	9	-85	-83	37
50	100	.60	43	-1009	54	.8	-36	-107	-104	1.0	-296	-520	-525	43
20	10	.80	50	-277	69	.4	41	-101	-97	1.0	-14548	-242	-243	50
20	10	.80	69	-800	77	.8	-12737	-640	-705	1.0	-248	-749	-752	69
50	10	.80	31	-656	48	.4	52	-26	-22	1.0	-315	-125	-129	31
50	10	.80	31	-1013	47	.8	-93	-132	-144	1.0	54	-184	-183	31
20	100	.80	52	-276	72	.4	-397	-84	-85	1.0	-29	-165	-165	52
20	100	.80	69	-472	79	.8	-1625	-556	-604	1.0	-20	-536	-534	69
50	100	.80	34	-916	50	.4	12	-14	-13	1.0	78	-129	-124	34
50	100	.80	36	-1009	52	.8	-294	-100	-108	1.0	-1508	-337	-343	36
20	10	.99	45	-580	65	.4	92	-218	-215	1.0	62	-319	-306	45
20	10	.99	62	-598	77	.8	-765	-1381	-1385	1.0	-134	-465	-465	62
50	10	.99	28	-732	45	.4	-36	-41	-44	1.0	-348	-88	-88	28
50	10	.99	30	-1042	46	.8	-20	-438	-433	1.0	-127	-440	-440	30
20	100	.99	41	-489	60	.4	-74	-81	-81	1.0	-9	-185	-184	41
20	100	.99	53	-668	69	.8	87	-522	-513	1.0	-965	-406	-409	53
50	100	.99	24	-1010	39	.4	22	-20	-20	1.0	-359	-173	-176	24
50	100	.99	37	-1598	55	.8	57	-425	-415	1.0	-274	-568	-569	37

TABLE XVI

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-MA, WALLIS VERSUS PRAIS-WINSTON

		Rho/Lambda				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	10	-.99	-20	23	-44	.4	100	100	100	1.0	100	99	100	-12
20	10	-.99	-36	-100	-84	.8	98	100	100	1.0	99	95	98	-15
50	10	-.99	-26	-115	-60	.4	97	99	99	1.0	99	97	97	-26
50	10	-.99	-37	-171	-87	.8	93	99	100	1.0	92	96	97	-35
20	100	-.99	-20	9	-44	.4	100	100	100	1.0	100	100	100	-8
20	100	-.99	-40	-146	-97	.8	100	100	100	1.0	100	99	100	-20
50	100	-.99	-25	-128	-57	.4	100	100	100	1.0	99	100	100	-25
50	100	-.99	-36	-589	-87	.8	97	100	100	1.0	100	99	99	-36
20	10	-.80	-24	41	-50	.4	100	100	100	1.0	99	92	97	-2
20	10	-.80	-36	-12	-83	.8	96	99	99	1.0	97	57	90	1
50	10	-.80	-29	-5	-67	.4	95	99	99	1.0	98	93	94	-28
50	10	-.80	-32	34	-72	.8	93	99	99	1.0	97	89	94	-13
20	100	-.80	-24	-37	-54	.4	100	100	100	1.0	99	99	100	-10
20	100	-.80	-41	-53	-97	.8	99	100	100	1.0	99	96	99	-10
50	100	-.80	-30	-70	-70	.4	98	100	100	1.0	100	99	99	-30
50	100	-.80	-42	-134	-103	.8	97	100	100	1.0	93	97	97	-41
20	10	-.60	-24	28	-52	.4	100	100	100	1.0	97	90	97	11
20	10	-.60	-51	-34	-123	.8	96	99	99	1.0	98	45	88	3
50	10	-.60	-34	22	-79	.4	100	99	100	1.0	97	96	98	-22
50	10	-.60	-39	3	-92	.8	94	99	99	1.0	95	93	96	-9
20	100	-.60	-36	12	-82	.4	100	100	100	1.0	99	99	100	-7
20	100	-.60	-61	-113	-159	.8	99	100	100	1.0	97	95	99	-9
50	100	-.60	-42	-168	-101	.4	98	100	100	1.0	97	99	99	-39
50	100	-.60	-55	-142	-140	.8	99	100	100	1.0	95	98	98	-49
20	10	-.30	-57	29	-125	.4	100	99	100	1.0	99	86	98	29
20	10	-.30	-103	-71	-277	.8	89	99	99	1.0	96	37	92	17
50	10	-.30	-53	-31	-127	.4	99	99	99	1.0	97	97	99	19
50	10	-.30	-65	-120	-168	.8	95	98	99	1.0	94	91	97	19
20	100	-.30	-76	-3	-186	.4	100	100	100	1.0	99	98	100	21
20	100	-.30	-129	-60	-381	.8	99	100	100	1.0	98	92	99	7

TABLE XVI (CONTINUED)

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-MA, WALLIS VERSUS PRAIS-WINSTON

		Rho/Lambda				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
50	100	-.30	-58	-105	-147	.4	100	100	100	1.0	100	100	100	7
50	100	-.30	-88	-196	-251	.8	98	100	100	1.0	99	99	99	2
20	10	-.10	-311	25	-409	.4	87	100	100	1.0	96	76	97	47
20	10	-.10	-844	-115	-981	.8	73	99	99	1.0	97	-22	86	23
50	10	-.10	-188	-65	-429	.4	94	99	99	1.0	99	96	99	58
50	10	-.10	-194	-173	-506	.8	88	99	99	1.0	98	77	98	55
20	100	-.10	-345	3	-426	.4	94	100	100	1.0	99	97	100	50
20	100	-.10	-840	-136	-1055	.8	97	100	100	1.0	99	88	99	27
50	100	-.10	-159	-142	-424	.4	99	100	100	1.0	100	100	100	58
50	100	-.10	-195	-417	-655	.8	99	100	100	1.0	99	97	100	54
20	10	.10	1	-35	-17	.4	93	100	100	1.0	100	82	97	76
20	10	.10	-61	-322	-216	.8	95	99	99	1.0	97	-23	89	55
50	10	.10	73	-139	2	.4	96	99	99	1.0	99	96	99	95
50	10	.10	70	-335	-27	.8	98	99	100	1.0	99	84	97	92
20	100	.10	8	-122	-36	.4	99	100	100	1.0	100	98	100	77
20	100	.10	-76	-256	-227	.8	99	100	100	1.0	99	95	99	47
50	100	.10	97	-342	-3	.4	100	100	100	1.0	100	100	100	99
50	100	.10	37	-517	-100	.8	93	100	100	1.0	100	99	100	87
20	10	.30	89	-186	72	.4	100	100	100	1.0	100	88	97	94
20	10	.30	69	-432	33	.8	96	100	100	1.0	99	38	78	79
50	10	.30	37	-592	27	.4	97	99	100	1.0	99	98	99	55
50	10	.30	46	-342	35	.8	97	100	100	1.0	92	94	97	62
20	100	.30	90	-220	75	.4	100	100	100	1.0	100	99	100	94
20	100	.30	63	-720	28	.8	100	100	100	1.0	99	94	98	88
50	100	.30	30	-622	22	.4	93	100	100	1.0	99	100	100	47
50	100	.30	57	-1932	8	.8	99	100	100	1.0	99	99	99	67
20	10	.60	53	-429	65	.4	99	100	100	1.0	98	93	97	60
20	10	.60	74	-762	68	.8	98	100	100	1.0	95	57	75	76
50	10	.60	2	-1089	-10	.4	98	100	100	1.0	94	97	97	3
50	10	.60	19	-1970	11	.8	94	100	100	1.0	85	92	92	20

TABLE XVI (CONTINUED)

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-MA, WALLIS VERSUS PRAIS-WINSTON

		Rho/Lambda				Beta 1				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	100	.60	47	-438	57	.4	100	100	100	1.0	100	99	100	54
20	100	.60	66	-1692	56	.8	100	100	100	1.0	98	98	99	69
50	100	.60	9	-3247	0	.4	95	100	100	1.0	95	99	99	9
50	100	.60	19	-2782	8	.8	96	100	100	1.0	93	98	98	19
20	10	.80	40	-485	55	.4	100	100	100	1.0	99	97	98	44
20	10	.80	61	-1344	65	.8	99	100	100	1.0	94	85	90	62
50	10	.80	9	-1789	8	.4	86	97	97	1.0	49	85	85	9
50	10	.80	10	-2229	8	.8	94	100	100	1.0	99	97	97	10
20	100	.80	40	-628	56	.4	100	100	100	1.0	100	100	100	42
20	100	.80	61	-1628	66	.8	100	100	100	1.0	100	99	99	62
50	100	.80	10	-2083	9	.4	96	100	100	1.0	98	99	99	10
50	100	.80	15	-3705	15	.8	97	100	100	1.0	90	99	99	15
20	10	.99	32	-811	45	.4	100	100	100	1.0	100	100	100	32
20	10	.99	54	-1690	66	.8	100	100	100	1.0	99	100	100	55
50	10	.99	9	-2417	11	.4	92	100	100	1.0	96	99	99	9
50	10	.99	11	-2370	13	.8	100	100	100	1.0	98	99	99	11
20	100	.99	27	-807	39	.4	100	100	100	1.0	100	100	100	28
20	100	.99	44	-1450	55	.8	100	100	100	1.0	100	100	100	45
50	100	.99	4	-2114	1	.4	-168	-106	-107	1.0	-17819	-465	-471	4
50	100	.99	19	-3771	25	.8	26	-498	-494	1.0	-181	-1428	-1425	19

TABLE XVII

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-AR, ZELLNER-GEISEL VERSUS OLS

		Lambda/Rho				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	10	.10	-1150	-6094	-6100	1.0	-10	-33	-33	-20
50	10	.10	-3890	-4433	-4455	1.0	63	-45	-44	15
20	100	.10	-36	-9282	-9129	1.0	29	-42	-40	29
50	100	.10	-880	-4238	-4420	1.0	-6990	-98	-103	-1085
20	10	.30	-7841	-1381	-1387	1.0	-22	-52	-52	-24
50	10	.30	79	-1335	-1219	1.0	25	-44	-42	26
20	100	.30	-5875	-1266	-1270	1.0	-16	-33	-33	-19
50	100	.30	-660	-1531	-1582	1.0	-193	-24	-27	-227
20	10	.60	-88	-637	-606	1.0	-37	-97	-97	-48
50	10	.60	63	-715	-592	1.0	21	-102	-95	22
20	100	.60	-18	-504	-484	1.0	-70	-88	-91	-69
50	100	.60	-97	-613	-602	1.0	64	-110	-109	36
20	10	.80	19	-544	-448	1.0	-3901	-376	-382	-1010
50	10	.80	54	-910	-222	1.0	-47	-426	-416	-27
20	100	.80	23	-434	-432	1.0	-72	-429	-423	-72
50	100	.80	17	-486	-397	1.0	-120	-250	-251	-110
20	10	.99	42	-202	-72	1.0	-3	-2194	-2185	-2
50	10	.99	-87	-7401	-2046	1.0	-203	-7003	-6927	-202
20	100	.99	-14	-120	-101	1.0	-352	-1721	-1723	-347
50	100	.99	-186	-7645	-3039	1.0	-227	-10728	-10483	-227

TABLE XVIII

PERCENTAGE DIFFERENCES FOR SELECTED COMPARISON STATISTICS
FOR MODEL II-AR, ZELLNER-GEISEL VERSUS PRAIS-WINSTON

		Lambda/Rho				Beta 2				
T	S/N	Value	Bias	Var	MSE	Value	Bias	Var	MSE	E.D.
20	10	.10	93	89	89	1.0	99	77	99	99
50	10	.10	93	73	79	1.0	100	95	99	99
20	100	.10	99	98	98	1.0	100	96	100	100
50	100	.10	90	97	97	1.0	100	100	100	99
20	10	.30	97	96	97	1.0	98	78	95	98
50	10	.30	99	91	94	1.0	98	95	98	98
20	100	.30	99	99	100	1.0	100	98	100	100
50	100	.30	95	97	98	1.0	99	100	100	99
20	10	.60	95	96	97	1.0	98	36	72	97
50	10	.60	95	86	88	1.0	81	65	70	82
20	100	.60	98	99	99	1.0	94	93	96	94
50	100	.60	79	90	90	1.0	96	86	87	94
20	10	.80	96	90	95	1.0	77	-390	-134	78
50	10	.80	86	82	87	1.0	65	-152	-97	68
20	100	.80	99	97	98	1.0	81	-6	22	82
50	100	.80	-138	-1476	-1411	1.0	-304	-1295	-1298	-298
20	10	.99	95	89	97	1.0	69	-44265	-23146	71
50	10	.99	89	54	92	1.0	-59	-160153	-78807	-39
20	100	.99	94	94	98	1.0	28	-11661	-4607	34
50	100	.99	77	72	84	1.0	-40	-47396	-29308	-23

TABLE XIX

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED BY THE DURBIN-WATSON D TEST FOR MODEL I-MA

		Pesaran Runs						Beach-MacKinnon Runs					
		OLS		PES		P-W		OLS		B-M		P-W	
T	Lambda	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
20	-.99	17	32	89	1	66	0	17	44	87	0	70	0
50	-.99	1	93	90	4	72	3	1	93	76	1	72	1
20	-.80	14	39	88	0	56	0	18	39	85	0	62	0
50	-.80	0	95	90	3	78	2	6	89	91	2	85	2
20	-.60	20	24	96	0	79	0	29	21	94	0	76	0
50	-.60	5	85	97	3	94	0	8	83	97	1	96	1
20	-.30	56	7	100	0	100	0	50	13	100	0	100	0
50	-.30	36	37	100	0	100	0	41	40	100	0	100	0
20	-.10	83	1	99	0	100	0	81	4	100	0	100	0
50	-.10	88	2	100	0	100	0	79	6	100	0	100	0
20	.10	82	1	95	1	100	0	85	1	100	0	100	0
50	.10	84	1	100	0	100	0	90	2	100	0	100	0
20	.30	62	8	97	1	100	0	60	5	97	0	100	0
50	.30	44	33	99	0	100	0	38	40	100	0	100	0
20	.60	33	28	95	1	93	0	33	17	98	0	16	0
50	.60	4	82	94	3	98	0	7	84	97	0	80	0
20	.80	31	25	92	0	80	0	18	27	97	0	85	0
50	.80	2	95	92	7	89	0	1	99	95	0	95	0
20	.99	28	37	90	0	84	0	16	34	90	0	79	0
50	.99	5	91	94	2	81	0	2	89	91	0	91	0

TABLE XX

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED BY THE DURBIN-WATSON D TEST FOR MODEL I-AR

		Pesaran Runs						Beach-MacKinnon Runs					
		OLS		PES		P-W		OLS		B-M		P-W	
T	Rho	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
20	-.99	1	96	26	40	87	2	3	91	89	0	91	0
50	-.99	0	100	9	84	86	4	0	100	93	4	95	1
20	-.80	3	84	67	10	90	0	4	81	95	1	94	1
50	-.80	0	100	36	38	98	0	0	100	97	1	97	1
20	-.60	21	49	95	0	94	0	15	50	99	0	100	0
50	-.60	0	98	95	1	100	0	1	99	100	0	100	0
20	-.30	53	13	95	0	92	0	55	6	98	0	100	0
50	-.30	45	34	100	0	97	0	38	40	100	0	100	0
20	-.10	84	1	97	1	0	0	82	0	100	0	---	---
50	-.10	85	1	100	0	100	0	84	5	100	0	100	0
20	.10	72	4	99	0	100	0	81	4	100	0	100	0
50	.10	88	6	100	0	100	0	85	2	100	0	100	0
20	.30	58	6	99	0	83	0	50	16	100	0	100	0
50	.30	37	45	100	0	100	0	33	36	100	0	100	0
20	.60	18	50	89	1	92	0	18	59	95	1	86	0
50	.60	3	95	91	1	97	0	2	96	99	0	99	0
20	.80	4	79	69	4	87	1	1	81	90	3	83	5
50	.80	0	100	31	41	94	1	0	100	98	1	94	2
20	.99	2	92	28	42	59	13	3	91	81	1	61	6
50	.99	0	100	2	94	80	12	0	100	92	2	79	13

TABLE XXI

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED FOR THE ZELLNER-GEISEL RUNS ON MODEL II-MA

			Durbin-Watson d				McNown		Durbin h	
			OLS		Z-G		OLS		OLS	
T	S/N	Lambda	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
20	10	.10	67	1	69	4	87	13	81	19
20	100	.10	82	2	86	2	89	11	87	13
50	10	.10	78	7	83	9	77	23	74	26
50	100	.10	84	7	92	1	85	15	81	19
20	10	.30	61	6	87	1	86	14	73	27
20	100	.30	54	6	81	1	70	30	63	37
50	10	.30	43	30	89	2	57	43	36	64
50	100	.30	27	43	95	1	33	67	26	74
20	10	.60	26	28	79	4	66	34	31	69
20	100	.60	28	28	79	4	42	58	33	67
50	10	.60	5	65	88	2	32	68	4	96
50	100	.60	5	83	88	4	10	90	7	93
20	10	.80	25	23	77	3	82	18	36	64
20	100	.80	26	27	86	2	58	42	32	68
50	10	.80	1	91	90	5	60	40	2	98
50	100	.80	1	94	93	3	11	89	1	99
20	10	.99	21	19	77	2	91	9	27	73
20	100	.99	28	29	82	0	87	13	42	58
50	10	.99	5	62	91	3	87	13	10	90
50	100	.99	2	90	75	8	81	19	13	87

TABLE XXII

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED FOR THE WALLIS RUNS ON MODEL II-MA

				Durbin-Watson d				McNown		Durbin h			
				OLS		WAL		OLS		OLS		WAL	
T	S/N	Lambda	Beta 1	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
20	10	-.99	.4	21	43	11	54	45	55	34	66	11	89
20	10	-.99	.8	25	23	13	52	61	39	43	57	5	95
20	100	-.99	.4	18	32	11	49	52	48	41	59	10	90
20	100	-.99	.8	30	22	17	44	61	39	56	44	5	95
50	10	-.99	.4	2	96	1	97	2	98	2	98	0	100
50	10	-.99	.8	1	90	1	94	12	88	3	97	0	100
50	100	-.99	.4	2	92	2	94	5	95	3	97	1	99
50	100	-.99	.8	1	90	1	91	5	95	3	97	0	100
20	10	-.80	.4	24	30	13	46	62	38	40	60	13	87
20	10	-.80	.8	28	27	11	56	79	21	44	56	4	96
20	100	-.80	.4	25	31	17	46	47	53	36	64	19	81
20	100	-.80	.8	19	22	6	53	68	32	41	59	4	96
50	10	-.80	.4	2	93	1	96	10	90	2	98	1	99
50	10	-.80	.8	2	93	1	99	48	52	2	98	0	100
50	100	-.80	.4	3	89	2	92	7	93	3	97	1	99
50	100	-.80	.8	3	89	2	92	11	89	6	94	0	100
20	10	-.60	.4	34	19	26	34	75	25	52	48	19	81
20	10	-.60	.8	38	18	21	39	81	19	63	37	8	92
20	100	-.60	.4	30	24	22	31	57	43	50	50	13	87
20	100	-.60	.8	47	16	28	39	75	25	64	36	6	94
50	10	-.60	.4	4	79	2	81	30	70	4	96	0	100
50	10	-.60	.8	4	87	2	95	52	48	5	95	1	99
50	100	-.60	.4	9	80	8	84	13	87	11	89	3	97
50	100	-.60	.8	4	78	3	82	17	83	6	94	0	100
20	10	-.30	.4	63	12	57	19	87	13	74	26	26	74
20	10	-.30	.8	60	4	38	27	91	9	82	18	14	86
20	100	-.30	.4	66	6	47	15	72	28	73	27	24	76
20	100	-.30	.8	68	7	46	21	87	13	82	18	11	89
50	10	-.30	.4	47	31	39	39	63	37	50	50	19	81
50	10	-.30	.8	45	27	36	39	69	31	52	48	12	88

TABLE XXII (CONTINUED)

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED FOR THE WALLIS RUNS ON MODEL II-MA

				Durbin-Watson d				McNown		Durbin h			
				OLS		WAL		OLS		OLS		WAL	
T	S/N	Lambda	Beta 1	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
50	100	-.30	.4	47	28	42	34	52	48	49	51	18	82
50	100	-.30	.8	49	27	41	33	59	41	52	48	8	92
20	10	-.10	.4	82	4	75	8	91	9	92	8	42	58
20	10	-.10	.8	76	5	55	16	91	9	83	17	24	76
20	100	-.10	.4	82	4	78	4	89	11	94	6	43	57
20	100	-.10	.8	81	1	61	12	92	8	88	12	26	74
50	10	-.10	.4	89	3	85	4	90	10	89	11	39	61
50	10	-.10	.8	86	6	80	11	88	12	89	11	37	63
50	100	-.10	.4	84	4	82	7	84	16	85	15	39	61
50	100	-.10	.8	87	2	79	8	89	11	91	9	33	67
20	10	.10	.4	74	4	76	2	84	16	80	20	50	50
20	10	.10	.8	85	0	72	3	94	6	87	13	32	68
20	100	.10	.4	77	3	78	4	82	18	79	21	50	50
20	100	.10	.8	67	3	65	4	84	16	83	17	33	67
50	10	.10	.4	83	3	83	3	86	14	83	17	66	34
50	10	.10	.8	82	7	84	5	85	15	71	29	62	38
50	100	.10	.4	89	6	88	6	85	15	86	14	72	28
50	100	.10	.8	84	5	88	3	81	19	80	20	54	46
20	10	.30	.4	55	11	67	8	76	24	63	37	53	47
20	10	.30	.8	56	12	58	11	68	32	57	43	41	59
20	100	.30	.4	59	8	67	4	71	29	69	31	58	42
20	100	.30	.8	45	9	53	6	60	40	45	55	47	53
50	10	.30	.4	30	37	40	34	43	57	33	67	74	26
50	10	.30	.8	35	40	43	36	56	44	27	73	74	26
50	100	.30	.4	36	37	41	34	36	64	32	68	78	22
50	100	.30	.8	41	41	53	35	37	63	35	65	63	37
20	10	.60	.4	37	21	50	16	55	45	41	59	56	44
20	10	.60	.8	25	34	42	18	44	56	24	76	43	57
20	100	.60	.4	34	19	45	18	47	53	37	63	60	40
20	100	.60	.8	30	18	40	14	37	63	33	67	45	55

TABLE XXII (CONTINUED)

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED FOR THE WALLIS RUNS ON MODEL II-MA

				Durbin-Watson d				McNown		Durbin h			
				OLS		WAL		OLS		OLS		WAL	
T	S/N	Lambda	Beta 1	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
50	10	.60	.4	4	80	5	78	10	90	3	97	86	14
50	10	.60	.8	6	86	12	80	10	90	3	97	73	27
50	100	.60	.4	4	82	5	79	3	97	4	96	78	22
50	100	.60	.8	8	76	18	68	6	94	7	93	67	33
20	10	.80	.4	27	30	40	25	40	60	30	70	60	40
20	10	.80	.8	20	28	38	20	33	67	24	76	39	61
20	100	.80	.4	21	37	35	26	26	74	21	79	63	37
20	100	.80	.8	25	41	38	26	32	68	28	72	44	56
50	10	.80	.4	5	68	6	84	1	99	3	97	78	22
50	10	.80	.8	2	89	5	89	5	95	2	98	81	19
50	100	.80	.4	1	95	1	94	1	99	1	99	78	22
50	100	.80	.8	4	88	8	83	2	98	1	94	74	26
20	10	.99	.4	12	43	23	32	18	82	11	89	61	39
20	10	.99	.8	29	31	45	14	34	66	30	70	36	64
20	100	.99	.4	16	39	31	34	25	75	19	81	64	36
20	100	.99	.8	21	36	35	29	28	72	21	79	51	49
50	10	.99	.4	2	91	3	89	1	99	1	99	77	23
50	10	.99	.8	2	93	7	86	2	98	1	99	75	25
50	100	.99	.4	0	95	1	91	0	100	0	100	83	17
50	100	.99	.8	0	99	5	89	0	100	0	100	68	32

TABLE XXIII

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED FOR THE ZELLNER-GEISEL RUNS ON MODEL II-AR

			Durbin-Watson d OLS		Durbin-Watson d Z-G		McNown OLS		Durbin h OLS	
T	S/N	Rho	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
20	10	.10	78	4	65	10	95	5	90	10
20	100	.10	88	1	77	2	96	4	97	3
50	10	.10	81	6	64	21	87	13	85	15
50	100	.10	83	4	65	15	84	16	86	14
20	10	.30	65	9	34	29	82	18	78	22
20	100	.30	60	8	24	35	82	18	76	24
50	10	.30	37	37	3	90	51	49	40	60
50	100	.30	36	38	0	92	43	57	38	62
20	10	.60	23	45	1	91	59	41	37	63
20	100	.60	25	43	0	94	43	57	35	65
50	10	.60	1	98	0	100	14	86	1	99
50	100	.60	2	96	0	100	5	95	2	98
20	10	.80	11	61	0	95	63	37	23	77
20	100	.80	9	63	1	88	27	73	23	77
50	10	.80	0	100	0	100	24	76	0	100
50	100	.80	0	100	0	100	0	100	0	100
20	10	.99	9	76	0	99	86	14	13	87
20	100	.99	10	75	0	100	81	19	16	84
50	10	.99	0	100	0	100	85	15	0	100
50	100	.99	0	100	0	100	51	49	0	100

TABLE XXIV

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED FOR THE WALLIS RUNS ON MODEL II-AR

				Durbin-Watson d				McNown		Durbin h			
				OLS		WAL		OLS		OLS		WAL	
T	S/N	Rho	Beta 1	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
20	10	-.99	.4	1	93	10	78	2	98	2	98	63	37
20	10	-.99	.8	0	92	17	62	1	99	1	99	47	53
20	100	-.99	.4	1	96	4	80	1	99	1	99	71	29
20	100	-.99	.8	0	97	13	76	0	100	0	100	56	44
50	10	-.99	.4	0	100	0	100	0	100	0	100	89	11
50	10	-.99	.8	0	100	3	97	0	100	0	100	90	10
50	100	-.99	.4	0	100	0	100	0	100	0	100	86	14
50	100	-.99	.8	0	100	0	100	0	100	0	100	91	9
20	10	-.80	.4	4	77	9	64	12	88	3	97	64	36
20	10	-.80	.8	3	81	24	56	51	49	1	99	43	57
20	100	-.80	.4	3	85	5	74	3	97	2	98	76	24
20	100	-.80	.8	3	81	23	56	8	92	3	97	50	50
50	10	-.80	.4	0	100	0	99	0	100	0	100	85	15
50	10	-.80	.8	0	100	4	95	5	95	0	100	85	15
50	100	-.80	.4	0	100	0	100	0	100	0	100	90	10
50	100	-.80	.8	0	100	1	99	0	100	0	100	89	11
20	10	-.60	.4	17	56	26	42	35	65	17	83	62	38
20	10	-.60	.8	15	50	30	37	65	35	17	33	51	49
20	100	-.60	.4	12	61	23	52	20	80	15	85	63	37
20	100	-.60	.8	19	54	38	32	28	72	18	82	40	60
50	10	-.60	.4	1	96	2	96	4	96	0	100	84	16
50	10	-.60	.8	2	96	10	84	30	70	2	98	77	23
50	100	-.60	.4	0	99	0	98	0	100	0	100	80	20
50	100	-.60	.8	2	96	8	89	3	97	2	98	81	19
20	10	-.30	.4	55	12	66	7	78	22	60	40	60	40
20	10	-.30	.8	54	8	60	16	80	20	61	39	41	59
20	100	-.30	.4	56	13	67	10	71	29	61	39	57	43
20	100	-.30	.8	55	9	56	11	70	30	57	43	37	63
50	10	-.30	.4	36	43	38	40	55	45	33	67	77	23
50	10	-.30	.8	35	49	41	43	55	45	26	74	63	37

TABLE XXIV (CONTINUED)

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED FOR THE WALLIS RUNS ON MODEL II-AR

				Durbin-Watson d				McNown		Durbin h			
				OLS		WAL		OLS		OLS		WAL	
T	S/N	Rho	Beta 1	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
50	100	-.30	.4	30	45	33	45	27	73	27	73	73	27
50	100	-.30	.8	32	44	39	39	36	64	28	72	68	32
20	10	-.10	.4	80	6	78	5	92	8	85	15	54	46
20	10	-.10	.8	69	8	64	12	85	15	75	25	28	72
20	100	-.10	.4	80	2	77	2	88	12	86	14	56	44
20	100	-.10	.8	71	8	60	16	86	14	74	26	32	68
50	10	-.10	.4	78	12	78	12	78	22	74	26	67	33
50	10	-.10	.8	84	4	80	6	84	16	79	21	64	36
50	100	-.10	.4	83	5	83	5	80	20	85	15	60	40
50	100	-.10	.8	84	5	83	5	84	16	77	23	54	46
20	10	.10	.4	85	1	77	3	90	10	94	6	46	54
20	10	.10	.8	83	0	65	12	96	4	96	4	23	77
20	100	.10	.4	76	5	70	5	87	13	92	8	35	65
20	100	.10	.8	83	2	60	11	89	11	95	5	23	77
50	10	.10	.4	90	2	89	5	90	10	93	7	40	60
50	10	.10	.8	82	5	73	10	85	15	87	13	33	67
50	100	.10	.4	82	8	79	11	81	19	84	16	44	56
50	100	.10	.8	80	6	75	11	83	17	85	15	37	63
20	10	.30	.4	66	6	53	11	88	12	79	21	26	74
20	10	.30	.8	71	5	40	25	92	8	84	16	17	83
20	100	.30	.4	62	8	55	14	83	17	79	21	30	70
20	100	.30	.8	69	5	48	26	88	12	84	16	13	87
50	10	.30	.4	33	40	29	43	54	46	37	63	7	93
50	10	.30	.8	47	29	39	36	67	33	56	44	13	87
50	100	.30	.4	45	37	39	42	49	51	47	53	14	86
50	100	.30	.8	33	43	28	52	39	61	38	62	9	91
20	10	.60	.4	23	37	15	57	37	63	38	62	13	87
20	10	.60	.8	27	34	12	62	56	44	45	55	7	93
20	100	.60	.4	20	45	6	62	39	61	29	71	8	92
20	100	.60	.8	20	31	12	59	51	49	45	55	9	91

TABLE XXIV (CONTINUED)

PERCENTAGE OF TIME THE HYPOTHESIS OF NO AUTOCORRELATION WAS ACCEPTED AND REJECTED FOR THE WALLIS RUNS ON MODEL II-AR

				Durbin-Watson d				McNown		Durbin h			
				OLS		WAL		OLS		OLS		WAL	
T	S/N	Rho	Beta 1	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej	Acc	Rej
50	10	.60	.4	1	98	1	98	3	97	1	99	0	100
50	10	.60	.8	2	93	2	96	6	94	3	97	1	99
50	100	.60	.4	3	96	1	97	2	98	3	97	0	100
50	100	.60	.8	0	93	0	96	2	98	1	99	0	100
20	10	.80	.4	9	73	5	88	13	87	12	88	6	94
20	10	.80	.8	11	65	4	83	26	74	19	81	4	96
20	100	.80	.4	3	83	0	93	6	94	8	92	7	93
20	100	.80	.8	7	59	2	84	22	78	19	81	1	99
50	10	.80	.4	0	100	0	100	0	100	0	100	0	100
50	10	.80	.8	0	100	0	100	0	100	0	100	0	100
50	100	.80	.4	0	100	0	100	0	100	0	100	0	100
50	100	.80	.8	0	100	0	100	0	100	0	100	0	100
20	10	.99	.4	2	81	0	95	3	97	8	92	3	97
20	10	.99	.8	6	86	0	98	7	93	11	89	0	100
20	100	.99	.4	3	89	3	95	3	97	4	96	6	94
20	100	.99	.8	2	86	1	97	3	97	5	95	1	99
50	10	.99	.4	0	100	0	100	0	100	0	100	0	100
50	10	.99	.8	0	100	0	100	0	100	0	100	0	100
50	100	.99	.4	0	100	0	100	0	100	0	100	0	100
50	100	.99	.8	0	100	0	100	0	100	0	100	0	100

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