Department of Economics
UNIVERSITY OF CANTERBURY
CHRISTCHURCH, NEW ZEALAND

ISSN 1171-0705

TESTING AND ESTIMATION WITH SEASONAL AUTOREGRESSIVE MIS-SPECIFICATION

John P. Small

Discussion Paper

No. 9208

Department of Economics, University of Canterbury
Christchurch, New Zealand

Discussion Paper No. 9208

October 1992

TESTING AND ESTIMATION WITH SEASONAL AUTOREGRESSIVE MIS-SPECIFICATION

John P. Small

TESTING AND ESTIMATION WITH SEASONAL AUTOREGRESSIVE MIS-SPECIFICATION*

John P. Small

Department of Economics

University of Canterbury

October 1992

Abstract

The problem of testing for AR(1) disturbances is considered using a model in which fourth order autocorrelation is also present. The effect of this mis-specification of the model on the power of some popular AR(1) tests is shown. Effects at the unit root boundaries of the parameter space are incorporated into the analysis. The efficiency of OLS estimation in this model is considered using spectral analysis of the disturbances.

Address for Correspondence: Department of Economics, University of Canterbury, Private Bag 4800, Christchurch, New Zealand, 8001.

1. Introduction

Several authors have suggested that time series regressions using quarterly data could produce residual autocorrelation which has both first and fourth order components (see Harvey (1990, p.205), for example). This is entirely consistent with the standard rationale for the existence of a random disturbance term in a regression model. The possibility of simple AR(4) disturbances has been considered as a separate issue by Wallis (1972) and Vinod (1973) who proposed a fourth order generalisation of the Durbin-Watson (1950,1951) test, and by King (1984) who constructed the associated point optimal invariant test. In addition, King (1989) presented a test designed to detect a simple AR(4) process when it is already known that AR(1) errors exist.

The aim of this paper is to take a step back from the analysis of King (1989) and seek the answers to two questions. First, how does the joint presence of AR(1) and simple AR(4) error processes affect the probability of detecting the AR(1) component? This will be answered be evaluating the power functions of several popular AR(1) tests under this form of mis-specification. The second question concerns the estimation efficiency of OLS relative to a feasible GLS estimator which might be used for final estimation, depending on the outcome of the AR(1) test. This issue could be addressed as a pre-testing problem by considering the risk, under some loss function, of the pre-test estimator and its components. The approach taken here, however, will focus on the spectral density of the error process.

The paper is organised in the following way. The next section introduces the AR(1) tests and discusses some issues associated with computing their powers. Section 3 presents the results of the numerical evaluations. This motivates the analysis, in Section 4, of the efficiency of OLS for the model used. Section 5 offers some concluding comments.

2. Test Power

Consider the standard linear regression model

$$y = X\beta + u \tag{1}$$

where y is T×1, X is T×k, independent of u and of rank $k < T$, β is a k×1 parameter vector and u is a T×1 vector of disturbances. Assuming that the data are observed quarterly, the following model is considered for u:

$$(1-\phi_1 L)(1-\phi_4 L^4)u_t = \varepsilon_t \qquad t = 1,2,\dots,T \tag{2}$$

where $\varepsilon_t \sim N(0,\sigma_\varepsilon^2)$ and L is the usual lag operator, such that $u_t(1-\phi_1 L) = u_t - \phi_1 u_{t-1}$. Stationarity of (2) requires that $|\phi_1|$, $|\phi_4| < 1$ and these conditions will generally be imposed. This process can be seen as a restricted AR(5) scheme by writing (2) as

$$u_t = \phi_1 u_{t-1} + \phi_4 u_{t-4} - \phi_1\phi_4 u_{t-5} + \varepsilon_t \quad . \tag{3}$$

To study the effect of seasonal autoregressive mis-specification, the power of five tests of H_0: $\phi_1 = 0$ vs H_a: $\phi_1 > 0$ will be considered, ignoring the possibility that ϕ_4 is non-zero. The tests used are the Durbin-Watson (DW) test, King's (1981) alternative DW test (ADW), the Berenblut and Webb (1973) test (BW) and two versions of King's (1985) point optimal test, which will be denoted S(0.5) and S(0.75) to indicate the value of ϕ_1 at which each is most powerful invariant. Both the BW and the point optimal test are special cases of a more general test due to Kadiyala (1970). Each of these tests has optimality properties in particular regions of the ϕ_1 space which are well established for correctly specified models.[1]

The statistic for each test can be written as a ratio of quadratic forms in u, the general form of which is

$$r = \frac{u'Qu}{u'Mu} \tag{4}$$

where $M = I_T - X(X'X)^{-1}X'$ and Q is some non-stochastic T×T matrix defining the individual test statistic.

The exact versions of the tests reject H_0 if $r < r^*$ where r^* is the exact critical value for some 100α% size (α = 0.05 throughout this study). To compute the exact power of each test the manipulations of Koerts and Abrahamse (1969) are used to write

$$pr(r<r^*|V) = pr\left\{\sum_{j=1}^{T} \lambda_j Z_j^2 < 0\right\} \tag{5}$$

where V is the true covariance matrix of u (up to a scalar multiple), the Z_j^2 are $\chi^2_{(1)}$ and independent, and the λ_j are the eigenvalues of $(Q-r^*M)V$. Several algorithms are available for computing the probabilities in (5) such as the procedures of Imhof (1961) and Shively, Ansley and Kohn (1990).[2] In this study the probabilities were evaluated using the FORTRAN version of Davies (1980) algorithm contained in the SHAZAM (White et.al (1990)) computer package running on a Vax 6340 under VMS 5.5.

To implement the procedure outlined above, the form of V is required. The covariance matrix used by King (1989) does not truly reflect (2) but the correct form can be derived from the Yule-Walker equations for this process.[3] Denoting the autocovariance function by $\gamma_k = \gamma_{-k} = cov(u_t u_{t-k})$ gives

$$\gamma_0 = \phi_1\gamma_1 + \phi_4\gamma_4 - \phi_1\phi_4\gamma_5 + \sigma^2_\varepsilon$$
$$\gamma_1 = \phi_1\gamma_0 + \phi_4\gamma_3 - \phi_1\phi_4\gamma_4$$
$$\gamma_2 = \phi_1\gamma_1 + \phi_4\gamma_2 - \phi_1\phi_4\gamma_3$$
$$\gamma_3 = \phi_1\gamma_2 + \phi_4\gamma_1 - \phi_1\phi_4\gamma_2$$
$$\gamma_4 = \phi_1\gamma_3 + \phi_4\gamma_0 - \phi_1\phi_4\gamma_1$$

and $$\gamma_k = \phi_1\gamma_{k-1} + \phi_4\gamma_{k-4} - \phi_1\phi_4\gamma_{k-5} \qquad \text{for all } k > 4.$$

The simultaneous solution of these equations provides the autocovariance function and subsequent division by γ_0 gives the following autocorrelation function, where ρ_k represents the correlation between u_t and u_{t-k}:

$$
\begin{aligned}
\rho_0 &= 1 \\
\rho_1 &= \phi_1(1+\phi_1^2\phi_4)/(1+\phi_1^4\phi_4) \\
\rho_2 &= \phi_1^2(1+\phi_4)/(1+\phi_1^4\phi_4) \\
\rho_3 &= \phi_1(\phi_1^2+\phi_4)/(1+\phi_1^4\phi_4) \\
\rho_4 &= (\phi_1^4+\phi_4)/(1+\phi_1^4\phi_4) \\
\rho_k &= \phi_1\rho_{k-1} + \phi_4\rho_{k-4} - \phi_1\phi_4\rho_{k-5} , \qquad \text{for } k > 4 .
\end{aligned}
$$

The scale factor was found by this method to be

$$\gamma_0 = \sigma_u^2 = \frac{\sigma_\varepsilon^2(1+\phi_1^4\phi_4)}{(1-\phi_1^2)(1+\phi_1^4\phi_4^3-\phi_1^4\phi_4-\phi_4^2)} .$$

It is immediately apparent that these expressions collapse to those for the well known AR(1) case when $\phi_4 = 0$.

By routinely testing data for unit roots, econometricians explicitly acknowledge the fact that many economic time series are non-stationary. Also widely accepted, is the virtual inevitability that relevant variables are omitted from many regression models. The clear implication of these two facts is that we may often encounter non-stationary residuals. Consequently, it was considered desirable to explore the power properties of these tests along the unit root boundaries of the stationary parameter space. For this problem these boundaries are the closed curve defined by $\phi_1,\phi_4 = \pm 1$. The power of each test was computed numerically along these line segments using a modification of the techniques suggested by Krämer and Zeisel (1989). When $\phi_1 = 1$, for example, $V = \iota\iota'$ where $\iota = (1,1,\ldots,1)'$ and $MV = 0$ for regressions with an intercept. Thus all the λ_j of (5) are zero and the power of the test is undefined. The limiting power as $\phi_1 \to 1$ can, however, be computated by replacing V with a transformation matrix W such that

$$W = \lim_{\phi_1 \to 1} \; (1-\phi_1)^{-1}(V-\iota\iota') \; .$$

This matrix W can be shown to be a Toeplitz matrix with first column equal to

$$W_1 = \frac{\phi_4 - 1}{\phi_4 + 1} \begin{bmatrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 + 2\phi_4^4 \\ 6 + 4\phi_4^4 \\ 7 + 6\phi_4^4 \\ 8 + 8\phi_4^4 \\ 9 + 10\phi_4^4 + 2\phi_4^2 \\ \vdots \end{bmatrix} .$$

It can also be easily seen by inspection of the autocorrelation function that $V(\pm1, -1) = I_T$, where the arguments of V are the values of ϕ_1, ϕ_4. This means that the power of each test at these points is equal to the true size of the test. It can further be shown that at all points on the $\phi_4 = -1$ boundary, except the endpoints, the power of each test is either zero or one. This result draws on the findings of Krämer (1985) and Small (1991) and the proof is omitted here in the interests of brevity.

To conclude this section we consider the seasonal unit root case defined by $\phi_4 = 1$. From the general form of the autocorrelation function it can be seen that setting $\phi_4 = 1$ gives:

$$\rho_0 = 1$$

$$\rho_1 = \phi_1(1+\phi_1^2)/(1+\phi_1^4)$$

$$\rho_2 = 2\phi_1^2/(1+\phi_1^4)$$

$$\rho_3 = \rho_1$$

$$\rho_4 = 1.$$

This pattern repeats indefinitely so that the individual autocorrelations must take one of only three values. The rank of V, and the number of non-zero eigenvalues in (5), is therefore three.

The power of each test was computed under these conditions for the entire range of data outlined in Section 3 below. ϕ_1 took values ranging from zero to 0.9. In every case, each of the three non-zero eigenvalues of (5) were found to be positive so that test power was always zero.

3. Numerical Results

The well known dependence of the powers of these tests on the regressor data was allowed for by examining a range of data conditions. The design matrices used were:

X1 The income and price series from Durbin and Watson's (1951) spirits example.

X2 The quarterly Australian consumers price index commencing 1959(1) and the same series lagged one period.

X3 A linear time trend and observations drawn from the Normal (30,4) distribution.

X4 A linear time trend and a Uniform [0,10] series.

X5 A linear time trend and a lognormal (2.23, 19.58) series.

X6 $(a_2+a_T)/\sqrt{2}$ and $(a_3+a_{T-1})/\sqrt{2}$ where $a_1,\ldots,a_T$ are the eigenvectors corresponding to the eigenvalues of the DW first differencing matrix, A, arranged in increasing order.[4]

X7 A linear time trend and the logarithm of quarterly registered unemployed in New Zealand, commencing 1952(2).

Each design matrix also included an intercept. The first six data sets have been used in several related studies and are discussed by Evans (1992). X6 is often referred to as Watson's X-matrix, and was shown by Watson (1955) to produce the most inefficient OLS estimates within the class of orthogonal matrices. The X7 matrix was chosen for its strong seasonality, which is an important data characteristic in this study.

Using a sample size of 20, a thorough investigation was conducted across all tests and design matrices along 20 lines in the parameter space. A selection of the resulting power curves is presented in the Figures 1 to 3 to support the general conclusions outlined below, while Table 1 shows the lowest and highest power obtained across the tests for a variety of cases. A further more limited, study used a sample size of 60. This latter work confirmed the findings of previous studies (e.g., King (1985)) that a larger sample increases the power of each test and reduces the power, differences between the tests.

The following features were observed with all seven data sets and each test and are stated relative to power against pure AR(1) disturbances. First, the true sizes of the tests are decreased (increased) by the introduction of a positive (negative) fourth order component. The only exceptions to this were for S(0.75) and BW when using X6, where slight size increases were registered as $\phi_4 \to 1$. On average, sizes were 29.5% as $\phi_4 \to -1$ and 0.87% as $\phi_4 \to 1$.

Second, serious losses of power were found when ϕ_4 fell in the interval (0.4,1.0) for all $\phi_1 > 0$. This is not unexpected in view of the size effect noted above when $\phi_4 > 0$. No size corrections were made to the power functions, since $\phi_4 \neq 0$ is assumed to be a mis-specification. Table 1 provides power values which show that when $\phi_1 = 0.4$, the introduction of a fourth order component with $\phi_4 = 0.4$ reduces power from around 40% to 25%. Increasing ϕ_4 to 0.6 further reduces power to around 15% while when $\phi_4 = 0.8$ power was generally about 7%. It is apparent from Table 1 that some data cause large spreads in power across tests. This feature is well known for X6 (see King (1985), for example).

The third feature of the numerical results is that the power of all tests is reduced when ϕ_4 falls in the interval (-1,-0.4) for all $\phi_1 > 0$. In this region the power reduction is somewhat less serious, being offset by increased size.

4. Estimation Efficiency

The power effects summarised above suggest that an applied researcher has a greatly reduced chance of detecting an AR(1) process in the regression residuals if the true process is given by (2) and ϕ_4 is moderately large. Under these circumstances it would be useful to know something of the likely effect of failing to detect autocorrelation on the efficiency of OLS estimation.

Grenander (1954) and Grenander and Rosenblatt (1957) showed that if the spectral density function of the true disturbances is flat at all frequencies where the exogenous variables have spectral weight, then OLS is asymptotically fully efficient. Combining this with the finding of Granger (1966) that economic variables typically have their spectral weight at low frequencies, we follow Engle (1974) in concluding that OLS will be efficient if the disturbance spectrum is flat at low frequencies.

The spectrum of the covariance stationary process (2) is given by

$$f(\lambda) = \sigma_\varepsilon^2 \left\{2\pi|e^{5i\lambda} + \phi_1 e^{4i\lambda} + \phi_4 e^{i\lambda} - \phi_1\phi_4|^2\right\}^{-1}$$

$$= \sigma_\varepsilon^2 \left\{2\pi\left[(1+\phi_1^2)(1+\phi_4^2) + 2\phi_1\phi_4(\cos5\lambda+\cos3\lambda)\right.\right.$$

$$\left.\left. - 2\phi_4\cos4\lambda(1+\phi_1^2) - 2\phi_1\cos\lambda(1+\phi_4^2)\right]\right\}^{-1}.$$

Using a grid of frequencies in the range $-2\pi \le \lambda \le 2\pi$, $f(\lambda)$ was evaluated at 42 settings of ϕ_1, $\phi_4 \ge 0$ with σ_ε^2 arbitrarily set to 2π. A selection of the resulting spectra is presented in Figure 4. It is immediately apparent from these graphs that the spectra corresponding to the individual components of u reinforce each other at low frequencies. This suggests that, in general, the relative efficiency of OLS to GLS, which is known to decline with ϕ_1 is also decreasing in ϕ_4.[5] We can also see, however, that provided $\phi_4 \neq 0$, values of λ: $0 \le \lambda \le \pi$ exist for which the spectrum of u is flat. For design matrices whose spectral weight is concentrated on these frequencies we can conclude that OLS is (asymptotically) fully efficient.

The cause of these flat regions in $f(\lambda)$ can be seen by considering the log spectrum of u which has the same turning points as $f(\lambda)$. Apart from a constant this is given by

$$\ln f(\lambda) = \ln \frac{1}{|1-\phi_1 e^{i\lambda}|^2} + \ln \frac{1}{|1-\phi_4 e^{4i\lambda}|^2} \quad . \qquad (6)$$

The spectrum of u is therefore the sum of the spectra of simple AR(1) and simple AR(4) processes.[6] The first term in (6) has a unique maximum (over the $[0,\pi]$ interval) at $\lambda = 0$ while the second term has maxima at 0, $\pi/2$ and π. Comparing the spectrum of u with that of a simple AR(1) process, $f^1(\lambda)$ we can therefore conclude that $f(\lambda) > f^1(\lambda)$ when $\lambda \in (0, \pi/2 , \pi)$ and the integration constraint then requires that the inequality be reversed for some other λ between 0 and π.

5. Conclusion

This paper has considered the problem of detecting first order serial correlation when a fourth order component is also present. It has been shown that the power of several popular tests for AR(1) errors is considerably reduced by positive fourth order autocorrelation. It is suggested that this also reduces the chances of an applied researcher either adopting a suitable alternative estimator to OLS or investigating the residuals further to discover the true autocorrelation process. The possible consequences of this (lack of) action were revealed by a study of the disturbance spectrum, which showed that the relative efficiency of OLS is likely to be lower when u follows a joint first and fourth order autoregressive scheme rather than either of these as a simple process.

Footnotes

* Helpful comments from David Giles, Judith Giles, Howard Doran and Philip Franses are gratefully acknowledged. The author is solely responsible for any errors.

(1) For a good discussion of these, and related, issues see King (1987).

(2) A more general algorithm due to Lieberman (1992) uses a saddlepoint expansion to evaluate the p.d.f. of (4).

(3) The following autocorrelation function was also derived independently by Wu (1991).

(4) A is a tri-diagonal (TxT) matrix with (1,1) and (T,T) elements as unity, 2 elswhere on the leading diagonal and -1 for the leading off-diagonal elements.

(5) An obvious exception is when the columns of X are linear combinations of the eigenvectors of V (Anderson (1948)).

(6) I am grateful to Howard Doran for pointing this out.

References

Anderson, T.W., 1948, On the theory of testing for serial correlation, Skandinavisk Aktuarietidskrift, 31, 88-116.

Berenblut, I.I. and G.I. Webb, 1973, A new test for autocorrelated errors in the linear regression model Journal of the Royal Statistical Society B 35, 33-50.

Davies, R.B., 1980, The distribution of a linear combination of chi-square random variables (Algorithm AS155), Applied Statistics 29, 323-333.

Durbin, J. and G.S. Watson, 1950, Testing for serial correlation in least squares regression I, Biometrika 37, 409-428.

Durbin, J. and G.S. Watson, 1951, Testing for serial correlation in least squares regression II, Biometrika 38, 159-178.

Engle, R.F., 1974, Specification of the disturbance for efficient estimation, Econometrica 42, 135-146.

Evans, M., 1992, Robustness of size of tests of autocorrelation and heteroscedasticity to nonnormality, Journal of Econometrics 51, 7-24.

Granger, C.W., 1966, The typical spectral shape of an economic variable, Econometrica 34, 150.

Grenander, U., 1954, On the estimation of regression coefficients in the case of an autocorrelated disturbance, Annals of Mathematical Statistics 25, 252-272.

Grenander, U. and M. Rosenblatt, 1957, Problems in linear estimation Chapter 7 in Statistical Analysis of Stationary Time Series, New York, John Wiley.

Imhof, P.J., 1961, Computing the distribution of quadratic forms in normal variables, Biometrika 48, 419-426.

Kadiyala, K.R. 1970, Testing for the independence of regression disturbances, Econometrica 38, 97-117.

King, M.L., 1981, The alternative Durbin-Watson test: an assessment of Durbin and Watson's choice of test statistic, Journal of Econometrics 17, 51-66.

King, M.L. 1984, A new test for fourth-order autoregressive disturbances, Journal of Econometrics 24, 269-277.

King, M.L., 1985, A point optimal test for autoregressive disturbances, Journal of Econometrics, 27, 21-37.

King, M.L., 1987, Testing for autocorrelation in linear regression models: a survey, in M.L. King and D.E.A. Giles, eds, Specification Analysis in the Linear Model, Routledge and Kegan Paul, London.

King, M.L., 1989, Testing for fourth-order autocorrelation in regression disturbances when first-order autocorrelation is present, Journal of Econometrics 41, 285-301.

Krämer, W., 1985, The Power of the Durbin Watson Test for Regressions Without an Intercept, Journal of Econometrics, 43, 363-372.

Krämer, W. and H. Zeisel, 1990, Finite sample power of linear regression autocorrelation tests, Journal of Econometrics 43, 363-372.

Lieberman, O., 1992, Saddlepoint approximation for the distribution of a ratio of quadratic forms in normal variables, Working Paper 9/92, Dept. of Econometrics, Monash University.

Shively, T.S., C.F. Ansley and R. Kohn, 1990, Fast evaluation of the distribution of the Durbin-Watson and other invariant test statistics in time series regression, Journal of the American Statistical Association, 85, 676-685.

Small, J.P., 1991, The limiting power of point optimal autocorrelation tests, Discussion Paper 9110, Department of Economics, University of Canterbury.

Vinod, H.D., 1973, Generalisation of the Durbin-Watson statistic for higher order autoregressive processes, Communications in Statistics 2, 115-144.

Wallis, K.F. 1972, Testing for fourth order autocorrelation in quarterly regression equations, Econometrica 40, 617-636.

Watson, G.S., 1995, Serial correlation in regression analysis I, Biometrika 42, 327-341.

White, K.J., S.D. Wong, D. Whistler, and S.A. Haun, 1990, SHAZAM: Econometrics Computer Program (Version 6.2), Users Reference Manual, McGraw-Hill, New York.

Wu, P., 1991, One-sided and partially one-sided multiparameter hypothesis testing in econometrics, Unpublished Ph.D. Thesis, Monash University.

APPENDIX

Table 1

Power Range Across Tests

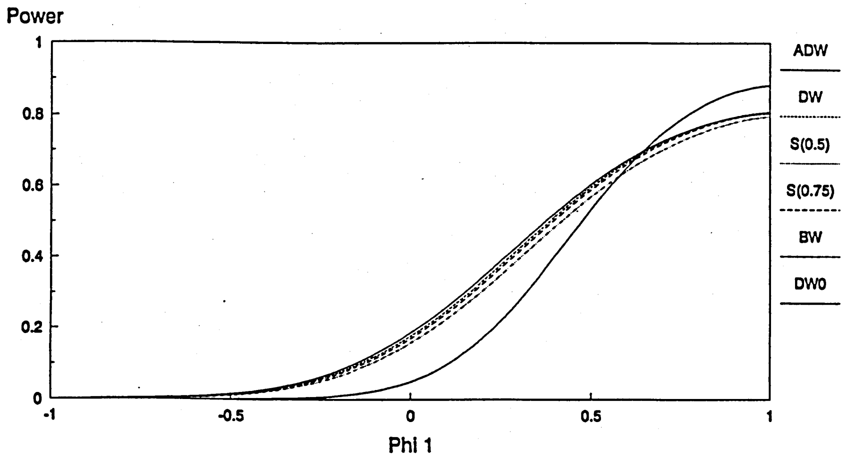
Selected Values

Data	ϕ_4	$\phi_1 = 0.4$		$\phi_1 = 0.6$		$\phi_1 = 0.8$	
X1	0	.40	.41	.65	.66	.81	.82
	.4	.25	.27	.50	.52	.72	.75
	.6	.15	.18	.37	.41	.62	.66
	.8	.06	.09	.19	.24	.43	.49
X2	0	.40	.40	.64	.65	.80	.81
	.4	.23	.23	.46	.47	.67	.69
	.6	.14	.14	.33	.34	.56	.58
	.8	.05	.06	.16	.17	.38	.39
X3	0	.40	.40	.65	.66	.81	.83
	.4	.24	.25	.49	.50	.71	.73
	.6	.14	.15	.35	.36	.60	.62
	.8	.05	.06	.17	.18	.39	.41
X4	0	.40	.40	.64	.66	.81	.83
	.4	.24	.25	.49	.50	.71	.73
	.6	.15	.16	.36	.37	.60	.62
	.8	.06	.06	.18	.19	.40	.42
X5	0	.38	.39	.61	.64	.77	.82
	.4	.21	.22	.43	.46	.64	.69
	.6	.12	.13	.30	.32	.53	.58
	.8	.04	.05	.14	.16	.33	.37
X6	0	.30	.34	.42	.60	.44	.83
	.4	.13	.26	.22	.52	.24	.79
	.6	.06	.22	.12	.46	.14	.75
	.8	.02	.15	.04	.32	.06	.63
X7	0	.38	.38	.60	.62	.75	.79
	.4	.21	.24	.42	.46	.62	.68
	.6	.13	.17	.29	.35	.50	.58
	.8	.05	.12	.15	.23	.32	.42

Figure 1a

Spirits Data; T = 20

Phi4 = -0.8

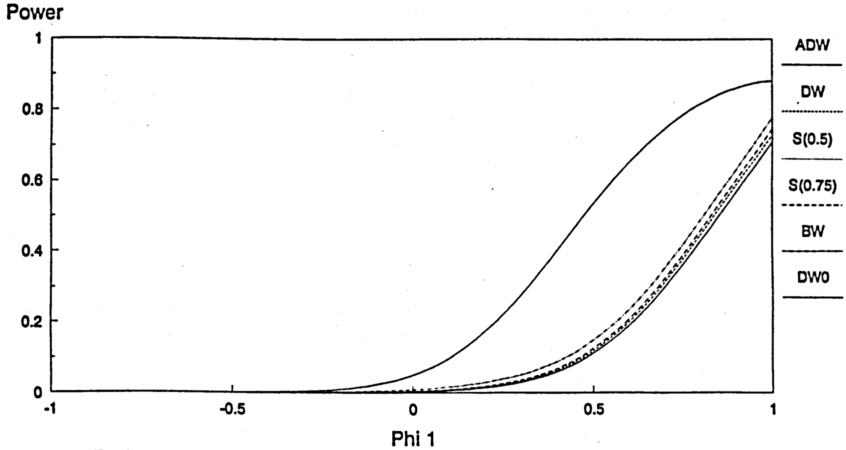


DW0 is DW Test When Phi4 = 0

Figure 1b

Spirits Data; T = 20

Phi4 = 0.8



DW0 is DW Test When Phi4 = 0

Figure 2a
Unemployed Data ; T=20
Phi4 = 0.6

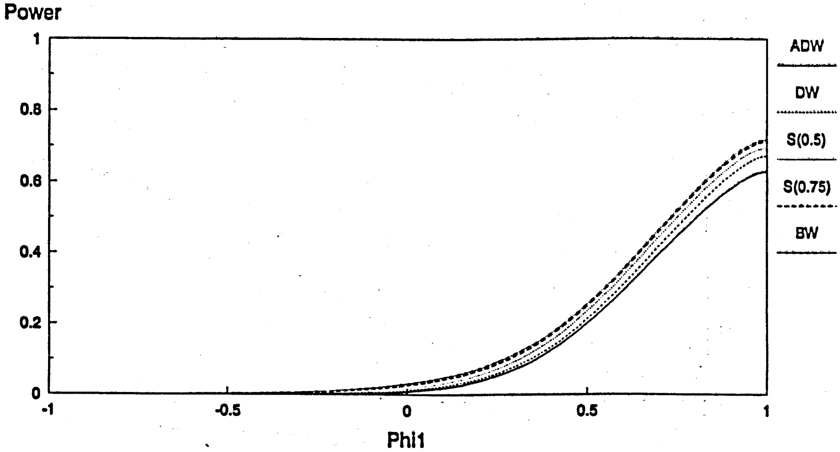


Figure 2b
Unemployed Data ; T=20
Phi4 = 0.8

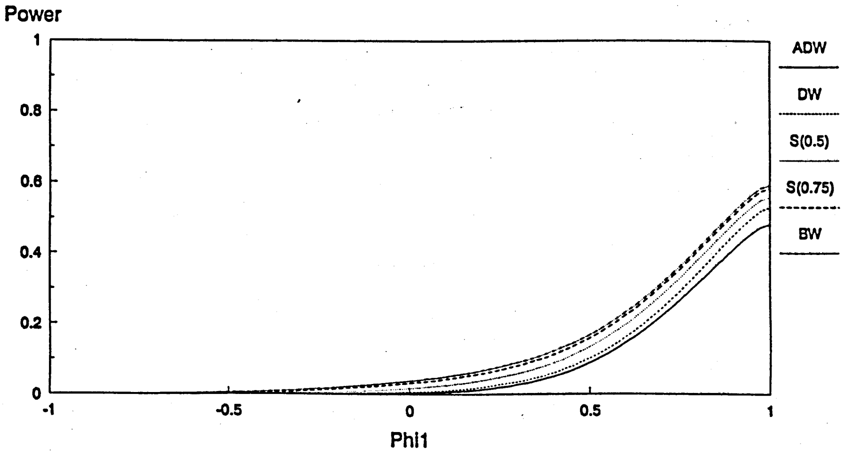


Figure 3a

Normal Data ; T=20

Phi4 = -1

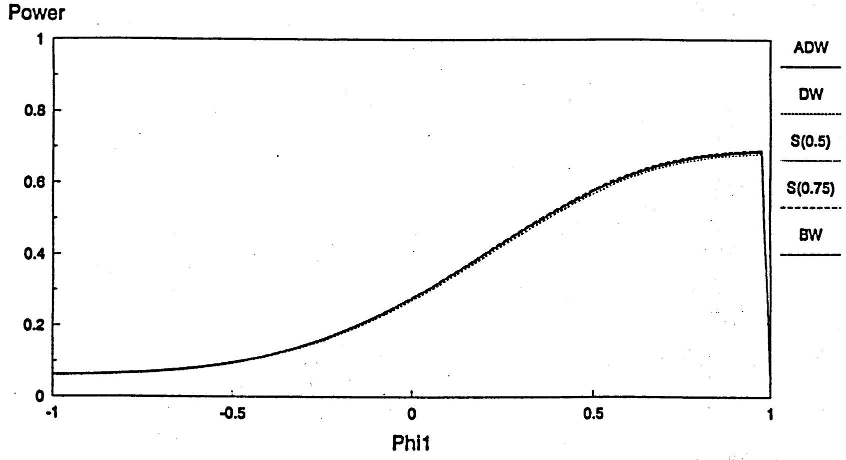


Figure 3b

Spirits Data ; T=20

Phi1 = 0.8

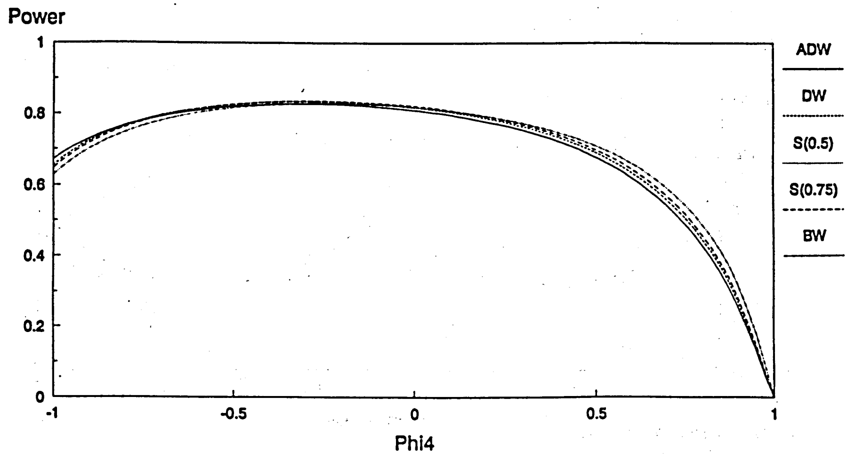
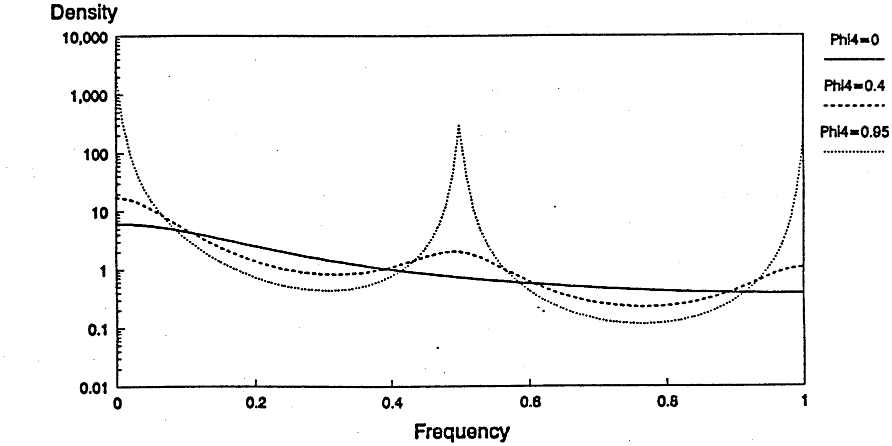


Figure 4a

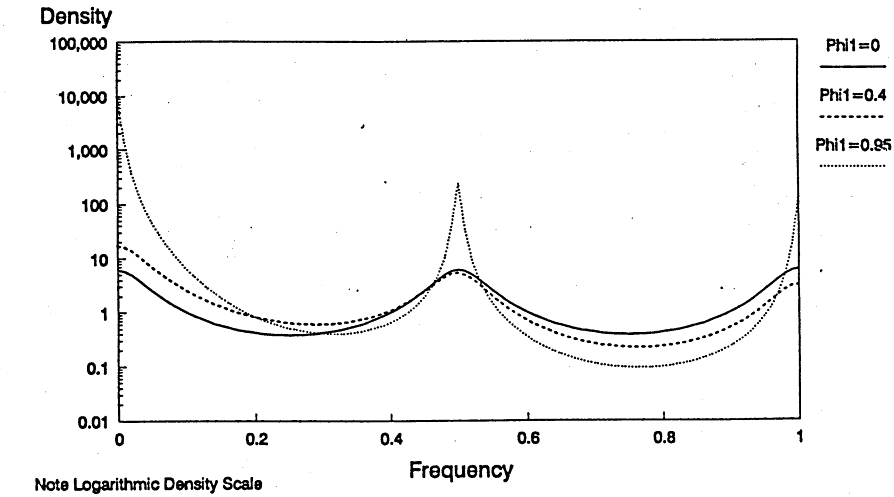
Spectral Density of u
Phi1=0.6



Note Logarithmic Density Scale

Figure 4b

Spectral Density of u
Phi4=0.6



Note Logarithmic Density Scale

LIST OF DISCUSSION PAPERS*

No. 8801 Workers' Compensation Rates and the Demand for Apprentices and Non-Apprentices in Victoria, by Pasquale M. Sgro and David E. A. Giles.

No. 8802 The Adventures of Sherlock Holmes, the 48% Solution, by Michael Carter.

No. 8803 The Exact Distribution of a Simple Pre-Test Estimator, by David E. A. Giles.

No. 8804 Pre-testing for Linear Restrictions in a Regression Model With Student-t Errors, by Judith A. Clarke.

No. 8805 Divisia Monetary Aggregates and the Real User Cost of Money, by Ewen McCann and David Giles.

No. 8806 The Management of New Zealand's Lobster Fishery, by Alan Woodfield and Pim Borren.

No. 8807 Poverty Measurement: A Generalization of Sen's Result, by Prasanta K. Pattanaik and Manimay Sen.

No. 8808 A Note on Sen's Normalization Axiom for a Poverty Measure, by Prasanta K. Pattanaik and Manimay Sen.

No. 8809 Budget Deficits and Asset Sales, by Ewen McCann.

No. 8810 Unorganized Money Markets and 'Unproductive' Assets in the New Structuralist Critique of Financial Liberalization, by P. Dorian Owen and Otton Solis-Fallas.

No. 8901 Testing for Financial Buffer Stocks in Sectoral Portfolio Models, by P. Dorian Owen.

No. 8902 Provisional Data and Unbiased Prediction of Economic Time Series by Karen Browning and David Giles.

No. 8903 Coefficient Sign Changes When Restricting Regression Models Under Instrumental Variables Estimation, by David E. A. Giles.

No. 8904 Economies of Scale in the New Zealand Electricity Distribution Industry, by David E. A. Giles and Nicolas S. Wyatt.

No. 8905 Some Recent Developments in Econometrics: Lessons for Applied Economists, by David E. A. Giles.

No. 8906 Asymptotic Properties of the Ordinary Least Squares Estimator in Simultaneous Equations Models, by V. K. Srivastava and D. E. A. Giles.

No. 8907 Unbiased Estimation of the Mean Squared Error of the Feasible Generalised Ridge Regression Estimator, by V. K. Srivasatva and D. E. A. Giles.

No. 8908 An Unbiased Estimator of the Covariance Matrix of the Mixed Regression Estimator, by D. E. A. Giles and V. K. Srivastava.

No. 8909 Pre-testing for Linear Restrictions in a Regression Model with Spherically Symmetric Disturbances, by Judith A. Giles.

No. 9001 The Durbin-Watson Test for Autocorrelation in Nonlinear Models, by Kenneth J. White.

No. 9002 Determinants of Aggregate Demand for Cigarettes in New Zealand, by Robin Harrison and Jane Chetwyd.

No. 9003 Unemployment Duration and the Measurement of Unemployment, by Manimay Sengupta.

No. 9004 Estimation of the Error Variance After a Preliminary-Test of Homogeneity in a Regression Model with Spherically Symmetric Disturbances, by Judith A. Giles.

No. 9005 An Expository Note on the Composite Commodity Theorem, by Michael Carter.

No. 9006 The Optimal Size of a Preliminary Test of Linear Restrictions in a Mis-specified Regression Model, by David E. A. Giles, Offer Lieberman, and Judith A. Giles.

No. 9007 Inflation, Unemployment and Macroeconomic Policy in New Zealand: A Public Choice Analysis, by David J. Smyth and Alan E. Woodfield.

No. 9008 Inflation — Unemployment Choices in New Zealand and the Median Voter Theorem, by David J. Smyth and Alan E. Woodfield.

No. 9009 The Power of the Durbin-Watson Test when the Errors are Heteroscedastic, by David E. A. Giles and John P. Small.

No. 9010 The Exact Distribution of a Least Squares Regression Coefficient Estimator After a Preliminary t-Test, by David E. A. Giles and Virendra K. Srivastava.

No. 9011 Testing Linear Restrictions on Coefficients in a Linear Regression Model with Proxy variables and Spherically Symmetric Disturbances, by Kazuhiro Ohtani and Judith A. Giles.

(Continued on next page)

No. 9012 Some Consequences of Applying the Goldfeld-Quandt Test to Mis-Specified Regression Models, by David E. A. Giles and Guy N. Saxton.

No. 9013 Pre-testing in a Mis-specified Regression Model, by Judith A. Giles.

No. 9014 Two Results in Balanced-Growth Educational Policy, by Alan E. Woodfield.

No. 9101 Bounds on the Effect of Heteroscedasticity on the Chow Test for Structural Change, by David Giles and Offer Lieberman.

No. 9102 The Optimal Size of a Preliminary Test for Linear Restrictions when Estimating the Regression Scale Parameter, by Judith A. Giles and Offer Lieberman.

No. 9103 Some Properties of the Durbin-Watson Test After a Preliminary t-Test, by David Giles and Offer Lieberman.

No. 9104 Preliminary-Test Estimation of the Regression Scale Parameter when the Loss Function is Asymmetric, by Judith A. Giles and David E. A. Giles.

No. 9105 On an Index of Poverty, by Manimay Sengupta and Prasanta K. Pattanaik.

No. 9106 Cartels May Be Good For You, by Michael Carter and Julian Wright.

No. 9107 L_p-Norm Consistencies of Nonparametric Estimates of Regression, Heteroskedasticity and Variance of Regression Estimate when Distribution of Regression is Known, by Radhey S. Singh.

No. 9108 Optimal Telecommunications Tariffs and the CCITT, by Michael Carter and Julian Wright.

No. 9109 Price Indices : Systems Estimation and Tests, by David Giles and Ewen McCann.

No. 9110 The Limiting Power of Point Optimal Autocorrelation Tests, by John P. Small.

No. 9111 The Exact Power of Some Autocorrelation Tests When the Disturbances are Heteroscedastic, by John P. Small.

No. 9112 Some Consequences of Using the Chow Test in the Context of Autocorrelated Disturbances, by David Giles and Murray Scott.

No. 9113 The Exact Distribution of R^2 when the Disturbances are Autocorrelated, by Mark L. Carrodus and David E. A. Giles.

No. 9114 Optimal Critical Values of a Preliminary Test for Linear Restrictions in a Regression Model with Multivariate Student-t Disturbances, by Jason K. Wong and Judith A. Giles.

No. 9115 Pre-Test Estimation in a Regression Model with a Misspecified Error Covariance Matrix, by K. V. Albertson.

No. 9116 Estimation of the Scale Parameter After a Pre-test for Homogeneity in a Mis-specified Regression Model, by Judith A. Giles.

No. 9201 Testing for Arch-Garch Errors in a Mis-specified Regression, by David E. A. Giles, Judith A. Giles, and Jason K. Wong.

No. 9202 Quasi Rational Consumer Demand — Some Positive and Normative Surprises, by John Fountain.

No. 9203 Pre-test Estimation and Testing in Econometrics: Recent Developments, by Judith A. Giles and David E. A. Giles.

No. 9204 Optimal Immigration in a Model of Education and Growth, by K-L. Shea and A. E. Woodfield.

No. 9205 Optimal Capital Requirements for Admission of Business Immigrants in the Long Run, by K-L. Shea and A. E. Woodfield.

No. 9206 Causality, Unit Roots and Export-Led Growth: The New Zealand Experience, by David E. A. Giles, Judith A. Giles and Ewen McCann.

No. 9207 The Sampling Performance of Inequality Restricted and Pre-Test Estimators in a Mis-specified Linear Model, by Alan T. K. Wan.

No. 9208 Testing and Estimation with Seasonal Autoregressive Mis-specification, by John P. Small.

* Copies of these Discussion Papers may be obtained for $4 (including postage, price changes occasionally) each by writing to the Secretary, Department of Economics, University of Canterbury, Christchurch, New Zealand. A list of the Discussion Papers prior to 1988 is available on request.