



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

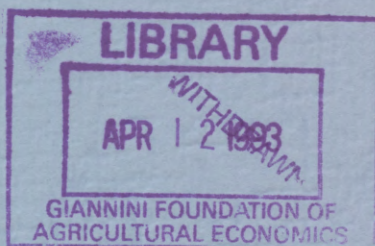
CANTER

9305 ✓

Department of Economics
UNIVERSITY OF CANTERBURY

CHRISTCHURCH, NEW ZEALAND

ISSN 1171-0705



THE EXACT POWERS OF SOME
AUTOCORRELATION TESTS WHEN
RELEVANT REGRESSORS ARE OMITTED

J. P. Small, D. E. Giles and K. J. White

Discussion Paper

No. 9305

This paper is circulated for discussion and comments. It should not be quoted without the prior approval of the author. It reflects the views of the author who is responsible for the facts and accuracy of the data presented. Responsibility for the application of material to specific cases, however, lies with any user of the paper and no responsibility in such cases will be attributed to the author or to the University of Canterbury.

Department of Economics, University of Canterbury
Christchurch, New Zealand

Discussion Paper No. 9305

March 1993

**THE EXACT POWERS OF SOME
AUTOCORRELATION TESTS WHEN
RELEVANT REGRESSORS ARE OMITTED**

J. P. Small, D. E. Giles and K. J. White

THE EXACT POWERS OF SOME
AUTOCORRELATION TESTS WHEN
RELEVANT REGRESSORS ARE OMITTED

J.P. SMALL, D.E.A. GILES
Department of Economics
University of Canterbury
Christchurch, New Zealand

and

K.J. WHITE
Department of Economics
University of British Columbia
Vancouver, B.C., Canada

March 1993

Abstract

We consider the power functions of five popular tests for AR(1) errors in a linear regression model from which relevant regressors have inadvertently been omitted. These functions are derived by numerically evaluating the finite-sample distributions of the test statistics. With this form of model mis-specification, it is found that the performances of the tests are not independent of the scale of the errors' distribution. The omission of seasonal effects or a linear trend component can have serious implications, especially if testing against positive autocorrelation, and some of the well known advantages of the "Alternative Durbin Watson test" (King (1981)) are found to still apply when the model is underspecified.

Keywords: Regression disturbances, serial independence, power, ratios of quadratic forms.

1. INTRODUCTION

When the residuals from a regression are found to be autocorrelated it is often concluded that one or more regressors may have been omitted from the fitted model. In particular, the typical time series characteristics of economic variables suggest that such an omission will induce or magnify an autoregressive error process. This argument is most convincing when both the true disturbances and the omitted variable(s) are positively autocorrelated, but it is questionable in other circumstances. More importantly, this argument takes no account of the effects of omitting variables on the probability of detecting autocorrelation. The purpose of this paper is to provide some exact finite sample numerical evidence of these effects on the power functions of several popular autocorrelation tests.

We consider five tests for first order autoregressive disturbances, all of which are well known and easily applied. These are the Durbin-Watson (DW) test of Durbin and Watson (1950), King's (1981) alternative DW (ADW) test, the Berenblut and Webb (1973) test (BW) and two versions of the point optimal test ($S(\rho_1)$) (Kadiyala (1970), King (1985)). These tests have well known power properties in correctly specified models, a thorough numerical evaluation of which is provided by King (1985).

The balance of the paper begins with an outline of the tests used in the next section. The distributions of the test statistics are discussed in Section 3, along with various computational considerations. Section 4 presents the models used in our evaluations and the results of these evaluations are given in Section 5. The final section offers some recommendations for applied workers.

2. THE TESTS

The statistic for each test studied here can be written in the form

$$r = \frac{w'Qw}{w'Mw}$$

where $w \sim N(0, \sigma_w^2 I)$ is an $n \times 1$ random vector, $M = I - X(X'X)^{-1}X'$, and Q is some non-stochastic $n \times n$ matrix.

The particular Q matrix for each test statistic is as follows. For the DW test, $Q = MAM$ where

$$A = \begin{bmatrix} 1 & -1 & 0 & \dots & 0 \\ -1 & 2 & -1 & 0 & \vdots \\ 0 & -1 & 2 & -1 & \vdots \\ \vdots & & & \ddots & 0 \\ \vdots & & & & 2 & -1 \\ 0 & \dots & & 0 & -1 & 1 \end{bmatrix}$$

The ADW test has $Q = MA_0M$ where A_0 is A with the top left and bottom right elements replaced by 2.

For the point optimal tests

$$Q = \Sigma(\rho_1)^{-1} - \Sigma(\rho_1)^{-1}X(X'\Sigma(\rho_1)^{-1}X)^{-1}X'\Sigma(\rho_1)^{-1}$$

where $\Sigma(\rho_1) = \sigma_w^2$

$$\begin{bmatrix} 1 & \rho_1 & \rho_1^2 & \dots & \rho_1^{T-1} \\ \rho_1 & 1 & \rho_1 & & \vdots \\ \rho_1^2 & \rho_1 & 1 & & \vdots \\ \vdots & & & \ddots & 1 & \rho_1 \\ \rho_1^{T-1} & \rho_1^{T-2} & \dots & \rho_1 & 1 \end{bmatrix}$$

and ρ_1 is chosen by the researcher. Following King (1985) we choose $\rho_1 = 0.5$ and 0.75 .

The BW test has $Q = B - BX(X'BX)^{-1}X'B$ where B is A with the top left element replaced by 2. This test can be seen as the limit of a sequence of point optimal tests as the autoregressive parameter, ρ , approaches unity.

For some purposes it is useful to write the $s(\rho_1)$ and BW test statistics in the form of a DW type test with a particular A matrix. This can be accomplished by noting, from Evans and King (1985), that as $Q = B - BX(X'BX)^{-1}X'B$, then $MQ = QM = Q$, and so $Q = MQM$.

3. THEORY

Suppose that the true data-generating process is in the form of the following multiple regression model with AR(1) errors:

$$y = X\beta + Z\gamma + u$$

$$u = \rho u_{-1} + \epsilon$$

$$\epsilon \sim N(0, \sigma^2 I)$$

where y and u are $n \times 1$ vectors of observations on the dependent variable and the random disturbances respectively, X and Z are non-stochastic regressor matrices of dimension $n \times k$ and $n \times p$, and β and γ are their associated parameter vectors. Note that $u \sim N(0, \Omega(\rho))$, where

$$\Omega(\rho) = \sigma_u^2 \begin{bmatrix} 1 & \rho_1 & \rho^2 & \dots & \rho^{T-1} \\ \rho_1 & 1 & & & \vdots \\ \rho_1^2 & & \cdot & & \vdots \\ \vdots & & & & 1 & \rho \\ \rho^{T-1} & \rho^{T-2} & \dots & \rho & 1 \end{bmatrix}$$

If the model fitted to the data is

$$y = X\beta + v$$

then the residuals from this regression are given by

$$\begin{aligned}\hat{v} &= y - X\hat{\beta} \\ &= My \\ &= Mw\end{aligned}$$

where $w = Z\gamma + u$
 $= \phi + u.$

and $M = I - X(X'X)^{-1}X'.$

We are interested in testing $H_0: \rho = 0$ vs $H_a^+: \rho > 0$, or $H_a^-: \rho < 0$, but we are constrained to using \hat{v} to do so, rather than being able to use the residuals associated with the fully specified model. This is because either it is not known that the fitted model is misspecified, or because the Z data are unavailable.

The distribution of the test statistic r is non-standard (since $E(w) = \phi \neq 0$) but we can follow the manipulations suggested by Koerts and Abrahamse (1969, pp.81-82) to compute the distribution function of r :

$$\Pr(r < r^*) = \Pr(w'(Q-r^*M)w < 0).$$

Let $z = \Omega^{-1/2}w$, such that $\Omega^{-1/2}\Omega^{-1/2} = \Omega^{-1}.$

$$\begin{aligned}\text{Now, } w'(Q-r^*M)w &= z'\Omega^{1/2}(Q-r^*M)^{1/2}\Omega z \\ &= z'Sz\end{aligned}$$

$$\text{and } z \sim N(\Omega^{-1/2}\phi, I_T).$$

Since S is symmetric, there exists an orthogonal matrix P

$$\text{such that } P'SP = \Lambda = \text{diag}(\lambda_j).$$

We can now make the orthogonal transformation $P'z = q$, so that $z'Sz = q'\Lambda q$

and $q \sim N(P'\Omega^{-1/2}\phi, I_T).$

$$\text{Then } \Pr(r < r^*) = \Pr(q'\Lambda q < 0)$$

$$= \Pr\left[\sum_{j=1}^T \lambda_j \chi_j^2 < 0\right] \quad (1)$$

where the λ_j 's are the eigenvalues of S and the χ_j^2 's are independent, non-central chi-square variates with 1 degree of freedom and non-centrality parameters given by

$$\theta_j = \left[(P' \Omega^{-1/2} \phi)_j \right]^2 . \quad (2)$$

When r^* is a $100\alpha\%$ critical value, the probability in (1) is the power of the test. The numerical evaluation of (1) is a fairly standard computational problem. Notice from (2) that the distribution of r depends on the scale of ϵ , through $\Omega^{-1/2}$. In particular $\frac{\partial \theta_j}{\partial \sigma^2} < 0$ so the effect of misspecification is reduced by more variable ϵ_t 's.

We can gain further insight into the effect of omitting variables on the tests considered by observing the following consequences of the diagonalisation of S.

$P'P = PP' = I$ implies that $S = P\Lambda P'$, and since $\Omega^{-1/2}\Omega^{1/2} = I$ we can write

$$\begin{aligned} \Omega^{-1/2} P \Lambda P' \Omega^{-1/2} &= Q - r^* M \\ \Lambda P' \Omega^{1/2} &= P' \Omega^{1/2} (Q - r^* M) \\ &= P' \Omega^{1/2} M (A - r^* I) M . \end{aligned}$$

The last step uses the fact that, for each test, Q can be written as a quadratic form in M. We can now exploit the diagonality of Λ to show that the j th non-centrality parameter is given by

$$\left(P' \Omega^{-1/2} \phi_j \right)^2 = \left(\frac{1}{\lambda_j} P' \Omega^{1/2} M (A - r^* I) M \phi_j \right)^2 . \quad (3)$$

If ϕ is linearly dependent on the included regressors, then $M\phi = 0$ and the non-centrality parameters are all zero. Alternatively, if ϕ is orthogonal

to all of the included regressors, then all of the non-centrality parameters are positive.

For the k eigenvalues satisfying $\lambda_j = 0$, the expression in (3) is undefined. Fortunately these cases are irrelevant for the determination of the tests' powers as the corresponding χ^2 variates receive zero weight in (1).

This result provides an interesting contrast with the well known dependence of the bias of the OLS estimator on the degree of linear dependence between X and Z . In testing for autocorrelation, an orthogonal regressor is the worst type of omission possible, notwithstanding the fact that the OLS estimator is unbiased. This is intuitively appealing in the case of OLS residuals, which are orthogonal to X and, by definition, contain all possible omitted variables.

We can also use (3) to see that $\theta_j \rightarrow 0$ as $\rho \rightarrow 1$ for all j , providing the regression has an intercept. This is because as $\rho \rightarrow 1$, $\Omega \rightarrow ii'$ where $i = (1,1,\dots,1)'$ so $\Omega^{1/2}$ is a matrix with all elements being $T^{-1/2}$. $\Omega^{1/2}$ is therefore linearly dependent on X when a constant is included in the regression, and so $\Omega^{1/2}M = 0$. This means that the mis-specified power functions must approach those for the true model as ρ approaches unity.

The distribution function of the non-central chi-square distribution with 1 degree of freedom lies to the right of that for the corresponding central distribution. Thus, drawings from a non-central distribution are likely to be smaller than their central counterparts. This does not allow a priori prediction of the direction of power shift however, as each chi-square variate in (1) will have a different θ_j (in general) and a weight (λ_j) which may be positive or negative. There is, therefore, a need to evaluate the power functions numerically to reveal both the direction and extent of shift in power under this form of model mis-specification.

The calculation of the power functions given by (1) and (2) is straightforward and was performed using the Davies (1980) algorithm option with the DISTRIB facility in the SHAZAM (1993) package. It is, however, worth noting that $\Omega^{-1/2}$ need not be computed unless non-centrality parameters are present, in which case it must be a symmetric matrix. All of the computations were undertaken on a VAX6340 computer under VMS 5.3.

4. MODELS

Recognising the data dependence of each test statistic's distribution, the numerical evaluations that we have undertaken involved a variety of data based on seven different design matrices, as characterised in Table 1. The numerical evaluations were conducted in two groups. For the first group, real variables were omitted which had varying degrees of linear dependence on the X matrix. To measure the degree of linear independence between the included and excluded variables, for this first group, we used the vector coefficient of alienation, defined by

$$\rho_A = \frac{\begin{vmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{vmatrix}}{\begin{vmatrix} \Sigma_{11} & \\ & \Sigma_{22} \end{vmatrix}}$$

where Σ_{11} is the sample covariance matrix of the included variables, X, $\Sigma_{22} = \text{cov}(Z)$ and $\Sigma_{12} = \text{cov}(X,Z)$ and all variables measured are in deviations from their sample means. When Z has only one non-constant variable, $(1-\rho_A)$ is equivalent to the uncentred R^2 from regressing Z on X.

Table 1 Regressors used in numerical evaluations

Model	$(1-\rho_A)$	R^2 (omitted/included)	Included	Omitted
1	0.79	.79	C INC	PRI
2	0.95	.95	C CPI	CPI(-1)
3	0.01	.01	C NOR	T
4	0.07	.07	C LNOR	T
5	0.00	.00	C X1	X2
6	0.17	.11	C LNOR T	S1 S2 S3
7	0.37	.25	C CPI CPIL	S1 S2 S3

In this table C is a constant, INC and PRI are the income and price variables from Durbin and Watson's (1950) "consumption of spirits" example, CPI is the quarterly Australian consumers' price index commencing 1951(1), NOR $\sim N(30,4)$, T is a linear time-trend, LNOR \sim lognormal (2.23, 19.58), S1-S3 are quarterly seasonal dummy variables, and X1-X5 are the first five vectors from the series $(a_2+a_n)/\sqrt{2}$, $(a_3+a_{n-1})/\sqrt{2}, \dots$, where a_1, \dots, a_n are the eigenvectors corresponding to the eigenvalues of A arranged in ascending order. These data have been used in previous studies of this type, such as Evans (1992).

Each model was fitted with 20 observations and some limited experimentation with 60 observations was performed. All tests were conducted at a nominal 5% size and no size corrections were made. The variance of ϵ was set to unity although limited experiments were conducted with higher values.

The second set of power functions was constructed using a single variable, which was orthonormal to X, as the omitted regressor. This variable was constructed by normalizing the OLS residual vector from a

regression of a standard normal random variable on the X matrix of the model concerned. The normal variable was generated via Brent's (1974) algorithm in the SHAZAM package.

The degree of mis-specification for both groups of power curves was controlled through γ , the values of which were chosen to reveal the degree of movement in the power curves. Notice that, from (1) and (2), the probability of rejection is independent of the sign of γ . When $\gamma = 0$ the Z matrix does not enter the true data generating process and $\theta = 0$. The reported results include the relevant values of γ .

5. RESULTS

The characteristics of all of the power functions in the correctly specified models ($\gamma = 0$) were in accord with those obtained in previous studies. With the exception of models using Watson's matrix (models 6 and 12) the power differences between the tests were relatively minor, particularly against H_a^+ . Where differences were apparent they revealed lower power for the ADW test against H_a^+ and higher power for this test against H_a^- . As noted by King (1985) the $S(\rho_1)$ and BW tests can have far greater power than the DW and ADW tests when used with Watson's matrix against H_a^+ , but this ranking is reversed against H_a^- .

The effect of omitting variables appears to depend mainly on the associated coefficient and the form of the omitted variable. The nature of the included regressors is generally of less importance, as is the particular test used.

The most serious power losses encountered in the first group of evaluations occurred when a seasonal shift in the intercept was not allowed for in testing against H_a^+ . In this case the true sizes of all tests fell dramatically from their nominal 5% level with an associated loss of power

for all $\rho > 0$. This effect occurred in model 6 and can be clearly seen in Figure 1. No single test emerged as being any more or less robust to this type of mis-specification across the relevant models.

[Figure 1 about here]

In models 3 and 4 the omission of a linear trend resulted in the true sizes of the tests against H_a^+ increasing to an average of 20.4% when the trend coefficient was 0.8. The ADW test was consistently the least distorted but still had an average size of 18.7% over the same three models. Testing against H_a^- in these models reduced the true sizes below 5% to a similar degree for all tests. These effects can be seen in Figure 2 which is based on model 3. While the size distortions in these models had predictable effects on the test powers in the neighbourhood of the null, the effects against high absolute values of ρ was less marked and the limiting powers were virtually identical. This effect was foreshadowed in the theoretical discussion above.

Models 1,2 and 7 involved the omission of real variables and produced broadly similar results, an example of which is given in Figure 3. Against H_a^+ there are power gains available by using the DW or BW tests rather than the other tests considered in these models. This conclusion is unambiguous in model 1 but is offset by size distortion, analogous to the case of an omitted linear trend discussed above, in models 2 and 7. Figure 3 also reveals a feature common to all models, though less discernable in others. This is the tendency for the power rankings of the tests to be reversed when moving from H_a^+ to H_a^- .

[Figures 2 and 3 about here]

For the second group of power functions, which examine the effect of the scale of an omitted orthogonal regressor on the powers of the tests, selected powers are presented in Tables 2 and 3. In each case considered

the true sizes of tests against H_a^+ are reduced by the omission of an orthogonal regressor, the degree of reduction increasing with $|\gamma|$. The size of the DW test in model 7, for example, is reduced from 5% to 0.3% by the omission of an orthogonal variable which would have had a coefficient of ± 5 . It is also clear from Tables 2 and 3 that the powers of the tests are correspondingly lower as $|\gamma|$ increases.

The sizes and powers of tests against H_a^- are considerably more robust than those against H_a^+ , as the tabulated values show. No general statement about the direction of size distortion is supported by the representative values in Tables 2 and 3.

[Tables 2 and 3 about here]

6. CONCLUSIONS

There are several results of interest emerging from this study. First, when relevant variables are omitted from a regression the distribution of all of the test statistics considered here is no longer independent of σ^2 . It has also been shown that a failure to allow for a seasonal shift in the intercept can seriously weaken all of these tests, particularly against H_a^+ . The dominance of the ADW test when testing against H_a^- is confirmed and extended to models mis-specified by the omission of variables. Furthermore the ADW test is the most robust to the effect of omitting a linear trend when testing for positive autocorrelation. The omission of an orthogonal regressor constitutes an informal bound on the degree of power function distortion. In all cases considered the true sizes and powers of tests against H_a^+ were reduced by this form of model mis-specification. The scale of the omitted variable has been shown to be important but the results are invariant to the sign of the associated coefficient.

In the light of these findings we make the following recommendations. First, the possibility of a seasonal shift in the regression intercept should be investigated before testing for AR(1) disturbances. This could be achieved by testing the significance of seasonal dummy variables prior to testing for autocorrelation. Of course, this involves a pre-test strategy, with commensurate implications for the size and power of the second test. Some evidence concerning the distortions associated with this type of strategy is provided by Giles and Lieberman (1992). Second, we recommend the use of the ADW test when negative autocorrelation is being investigated because it continues to have superior power against this alternative when relevant variables have been omitted. Finally, the rejection of H_a^+ using any of these tests should be regarded with suspicion unless one can be sure that a linear trend has not been omitted.

Acknowledgements

We are grateful to Judith Giles, and other participants at workshops at the University of Canterbury, for helpful comments on earlier versions of this work.

REFERENCES

- Berenblut, I.I. and Webb, G.I. (1973). A new test for autocorrelated errors in the linear regression model. Journal Of the Royal Statistical Society B, 35, 33-50.
- Brent, R.P., (1974). A Gaussian random number generator. Communications of the ACM 17, 704-706.
- Davies, R.B. (1980). The distribution of a linear combination of chi square random variables (algorithm AS 155). Applied Statistics, 29, 323-33.
- Durbin, J. and Watson, G.S. (1950). Testing for serial correlation in least squares regression I. Biometrika, 37, 409-28.
- Evans, M.A. (1992). Robustness and size of tests of autocorrelation and heteroscedasticity to non-normality. Journal of Econometrics 51, 7-24.
- Evans, M.A. and King, M.L. (1985). Critical value approximations for tests of linear regression disturbances. Australian Journal of Statistics, 27, 68-83.
- Giles, D.E.A. and Lieberman, O. (1992). Some properties of the Durbin-Watson test after a preliminary t-test. Journal of Statistical Computation and Simulation, 41, 219-227.
- 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. (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, 19-73.
- Koerts, J. and Abrahamse, A.P.J. (1969). On the Theory and Application of the General Linear Model, Rotterdam University Press, Rotterdam.
- SHAZAM Econometrics Computer Program (1993). Users Reference Manual, Version 7, McGraw-Hill, New York.
- Watson, G.S. (1955). Serial correlation in regression analysis I. Biometrika, 42, 327-41.

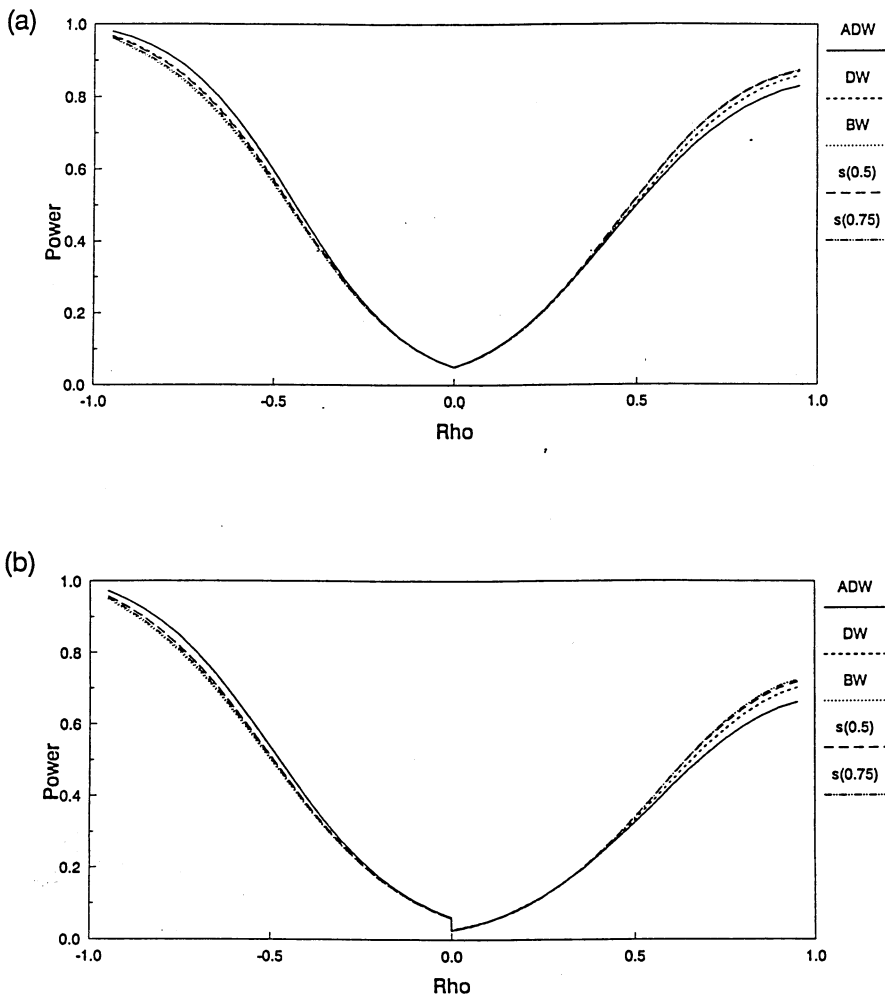


Figure 1 Power functions with lognormal data, seasonal dummies omitted.
 (a) $\gamma=(0,0,0)'$; (b) $\gamma=(1,1,1)'$.

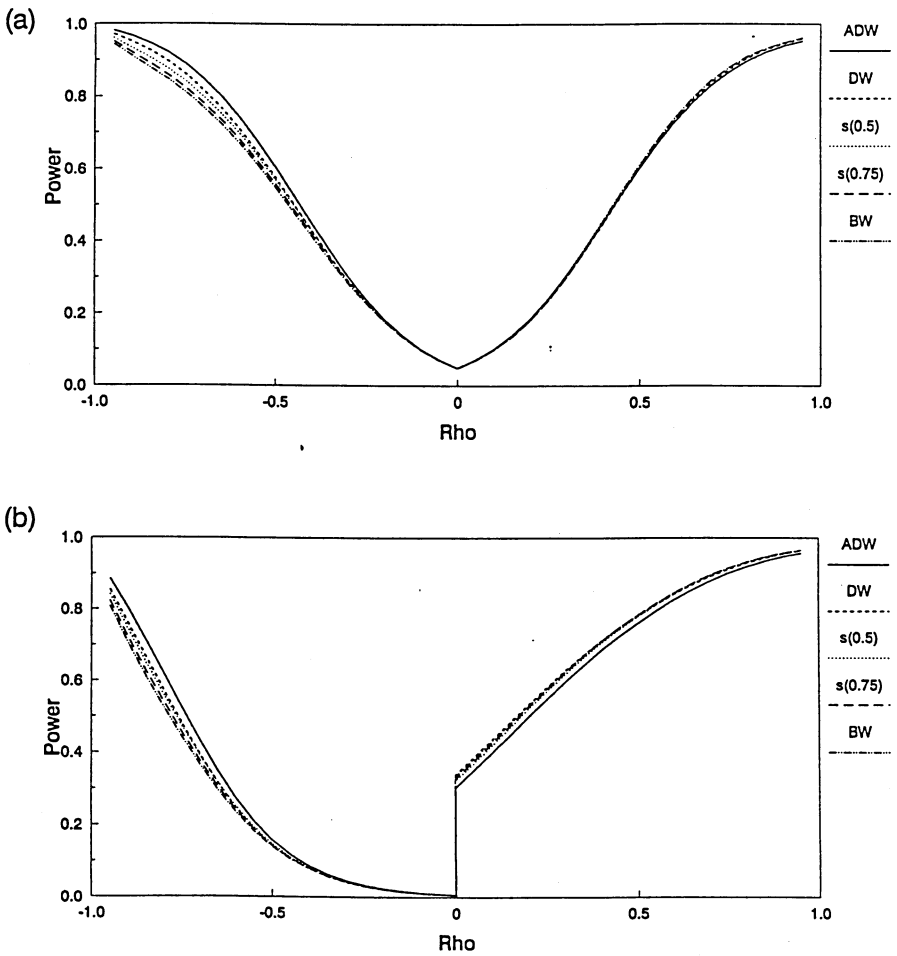


Figure 2 Power functions with normal data, linear trend omitted.
 (a) $\gamma=0$; (b) $\gamma=0.1$.

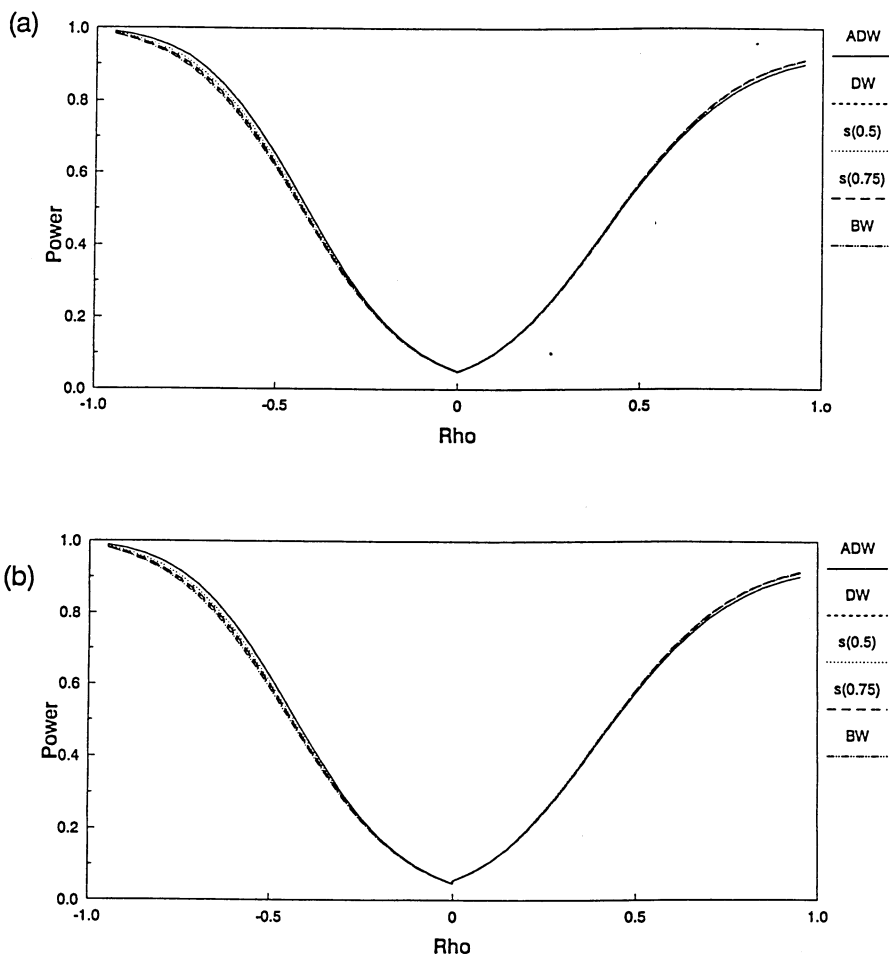


Figure 3 Power functions with spirits data, price omitted.
 (a) $\gamma=0$; (b) $\gamma=5$.

Table 2 Power of AR(1) tests with Omitted Orthogonal Variables (T=20)

ρ	DW			s(0.5)			BW		
	$\gamma=0$	$\gamma=1$	$\gamma=5$	$\gamma=0$	$\gamma=1$	$\gamma=5$	$\gamma=0$	$\gamma=1$	$\gamma=5$
Model 1									
-0.9	0.971	0.966	0.842	0.977	0.972	0.857	0.969	0.964	0.834
-0.6	0.759	0.740	0.477	0.773	0.754	0.485	0.751	0.731	0.454
-0.3	0.306	0.300	0.204	0.311	0.304	0.204	0.302	0.294	0.188
0.0	0.050	0.054	0.075	0.050	0.050	0.074	0.050	0.054	0.067
0.0	0.050	0.045	0.005	0.050	0.045	0.005	0.050	0.045	0.004
0.3	0.298	0.265	0.022	0.301	0.268	0.022	0.294	0.261	0.020
0.6	0.698	0.649	0.111	0.700	0.651	0.112	0.694	0.646	0.106
0.9	0.901	0.870	0.324	0.900	0.869	0.322	0.903	0.873	0.328
Model 2									
-0.9	0.969	0.962	0.818	0.976	0.971	0.834	0.969	0.962	0.815
-0.6	0.753	0.732	0.436	0.770	0.748	0.439	0.753	0.731	0.424
-0.3	0.304	0.295	0.174	0.309	0.300	0.170	0.303	0.294	0.164
0.0	0.050	0.054	0.061	0.050	0.053	0.058	0.050	0.053	0.057
0.0	0.050	0.047	0.008	0.050	0.047	0.008	0.050	0.047	0.009
0.3	0.291	0.262	0.032	0.296	0.267	0.033	0.291	0.263	0.034
0.6	0.681	0.633	0.124	0.683	0.636	0.127	0.680	0.634	0.131
0.9	0.880	0.846	0.296	0.878	0.844	0.296	0.880	0.846	0.305
Model 3									
-0.9	0.951	0.942	0.763	0.934	0.926	0.764	0.911	0.901	0.722
-0.6	0.710	0.686	0.391	0.698	0.676	0.402	0.670	0.649	0.386
-0.3	0.293	0.283	0.161	0.293	0.284	0.170	0.285	0.277	0.169
0.0	0.050	0.053	0.053	0.050	0.053	0.056	0.050	0.053	0.058
0.0	0.050	0.046	0.007	0.050	0.045	0.004	0.050	0.046	0.005
0.3	0.302	0.273	0.031	0.309	0.277	0.023	0.302	0.271	0.026
0.6	0.737	0.697	0.172	0.745	0.704	0.154	0.742	0.700	0.157
0.9	0.948	0.932	0.550	0.949	0.933	0.532	0.950	0.934	0.538
Model 4									
-0.9	0.954	0.948	0.796	0.946	0.940	0.795	0.939	0.933	0.784
-0.6	0.732	0.709	0.384	0.719	0.696	0.369	0.709	0.686	0.364
-0.3	0.302	0.289	0.134	0.298	0.285	0.124	0.295	0.282	0.124
0.0	0.050	0.052	0.041	0.050	0.051	0.037	0.050	0.051	0.037
0.0	0.050	0.047	0.010	0.050	0.047	0.009	0.050	0.047	0.009
0.3	0.294	0.268	0.041	0.297	0.270	0.038	0.292	0.265	0.037
0.6	0.716	0.676	0.184	0.732	0.693	0.183	0.729	0.689	0.179
0.9	0.936	0.918	0.540	0.946	0.930	0.551	0.947	0.931	0.551

Table 3 Power of AR(1) tests with Omitted Orthogonal Variables (T=20)

ρ	DW			s(0.5)			BW		
	$\gamma=0$	$\gamma=1$	$\gamma=5$	$\gamma=0$	$\gamma=1$	$\gamma=5$	b3=0	b3=1	b3=5
Model 5									
-0.9	0.669	0.658	0.484	0.488	0.482	0.367	0.448	0.441	0.330
-0.6	0.611	0.590	0.332	0.547	0.529	0.306	0.511	0.494	0.284
-0.3	0.268	0.260	0.148	0.260	0.252	0.141	0.250	0.242	0.132
0.0	0.050	0.053	0.053	0.050	0.052	0.049	0.050	0.053	0.047
0.0	0.050	0.047	0.009	0.050	0.046	0.007	0.050	0.048	0.015
0.3	0.266	0.241	0.034	0.277	0.250	0.029	0.263	0.240	0.040
0.6	0.602	0.561	0.124	0.695	0.650	0.132	0.689	0.646	0.156
0.9	0.680	0.652	0.248	0.928	0.905	0.408	0.933	0.912	0.463
Model 6									
-0.9	0.949	0.941	0.770	0.947	0.940	0.772	0.936	0.929	0.754
-0.6	0.707	0.681	0.328	0.705	0.678	0.310	0.689	0.663	0.303
-0.3	0.282	0.268	0.103	0.282	0.266	0.092	0.277	0.262	0.091
0.0	0.050	0.051	0.032	0.050	0.050	0.027	0.050	0.051	0.028
0.0	0.050	0.048	0.014	0.050	0.048	0.014	0.050	0.048	0.014
0.3	0.262	0.239	0.043	0.268	0.246	0.046	0.263	0.241	0.045
0.6	0.626	0.581	0.135	0.644	0.602	0.147	0.642	0.600	0.146
0.9	0.846	0.809	0.293	0.859	0.826	0.312	0.862	0.830	0.319
Model 7									
-0.9	0.965	0.961	0.852	0.963	0.958	0.834	0.950	0.943	0.788
-0.6	0.737	0.720	0.476	0.732	0.712	0.401	0.710	0.687	0.337
-0.3	0.290	0.285	0.199	0.289	0.279	0.134	0.283	0.269	0.099
0.0	0.050	0.054	0.073	0.050	0.051	0.040	0.050	0.050	0.026
0.0	0.050	0.044	0.003	0.050	0.045	0.004	0.050	0.046	0.006
0.3	0.274	0.240	0.014	0.277	0.246	0.019	0.273	0.246	0.027
0.6	0.638	0.583	0.072	0.647	0.597	0.091	0.645	0.600	0.115
0.9	0.844	0.800	0.215	0.851	0.812	0.244	0.854	0.819	0.282

LIST OF DISCUSSION PAPERS*

- 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. Srivastava 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 Mich-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.
- 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.

(Continued on next page)

- 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.
- No. 9209 A Bargaining Experiment, by Michael Carter and Mark Sunderland.
- No. 9210 Pre-Test Estimation in Regression Under Absolute Error Loss, by David E. A. Giles.
- No. 9211 Estimation of the Regression Scale After a Pre-Test for Homoscedasticity Under Linex Loss, by Judith A. Giles and David E. A. Giles.
- No. 9301 Assessing Starmer's Evidence for New Theories of Choice: A Subjectivist's Comment, by John Fountain.
- No. 9302 Preliminary-Test Estimation in a Dynamnic Linear Model, by David E. A. Giles and Matthew C. Cunneen.
- No. 9303 Fans, Frames and Risk Aversion: How Robust is the Common Consequence Effect? by John Fountain and Michael McCosker.
- No. 9304 Pre-test Estimation of the Regression Scale Parameter with Multivariate Student-t Errors and Independent Sub-Samples, by Juston Z. Anderson and Judith A. Giles
- No. 9305 The Exact Powers of Some Autocorrelation Tests When Relevant Regressors are Omitted, by J. P. Small, D. E. Giles and K. J. White.

* 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 1989 is available on request.