



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.

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

CANTER

9/13 ✓

Department of Economics
UNIVERSITY OF CANTERBURY
CHRISTCHURCH, NEW ZEALAND

ISSN 1171-0705

GIANNINI FOUNDATION
AGRICULTURAL ECONOMICS
LIBRARY



JAN 29 1992

GIANNINI FOUNDATION OF
AGRICULTURAL ECONOMICS
LIBRARY

JAN 29 1992

WITHDRAWN

THE EXACT DISTRIBUTION OF R^2 WHEN THE
REGRESSION DISTURBANCES ARE AUTOCORRELATED

Mark L. Carrodus and David E. A. Giles

Discussion Paper
11

No. 9113

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. 9113

October 1991

**THE EXACT DISTRIBUTION OF R^2 WHEN THE
REGRESSION DISTURBANCES ARE AUTOCORRELATED**

Mark L. Carrodus and David E. A. Giles

THE EXACT DISTRIBUTION OF R^2

WHEN THE REGRESSION DISTURBANCES

ARE AUTOCORRELATED*

Mark L. Carrodus

and

David E.A. Giles

Department of Economics
University of Canterbury

October, 1991

Abstract

This paper provides exact evaluations of the distribution of the usual coefficient of determination when the regression model's errors follow an AR(1) or MA(1) process. This provides insights into the extent to which this measure of goodness of fit is distorted by such model mis-specification.

Address for Correspondence : Professor David E.A. Giles, Department of Economics, University of Canterbury, Christchurch, NEW ZEALAND.

1. Introduction

This paper provides some preliminary results concerning the exact distribution of the coefficient of determination in a regression model which is mis-specified by virtue of the errors being autocorrelated. Both AR(1) and MA(1) disturbances are considered. These results are obtained for a range of data sets, and are compared with their counterparts under serially independent errors.

This type of model mis-specification induces a shift in the distribution of R^2 , which in turn alters the probability of observing values of R^2 in any given range. Information of this type is useful to applied researchers, as it assists in the interpretation of a calculated R^2 value when the presence of serial correlation is suspected.

2. Notation and Theory

Consider the model

$$y = X\beta + u \quad ; \quad u \sim N(0, \Omega) \quad (1)$$

where y and u are $(nx1)$; X is (nxk) , non-stochastic and of rank k ; and β is $(kx1)$. Generally, it is further assumed that $\Omega = \sigma^2 I_n$, so that Ordinary Least Squares (OLS) provides the best linear unbiased estimator of β .

Then, if the model includes an intercept¹, the coefficient of determination can be written unambiguously as

$$R^2 = 1 - \left(\sum_{i=1}^n v_i^2 \right) / \left(\sum_{i=1}^n (y_i - \bar{y})^2 \right), \quad (2)$$

where v_i is the i 'th element of the OLS residual vector, $v = y - X(X'X)^{-1}X'y$; y_i is the i 'th element of y ; and $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$. More compactly,

$$R^2 = y' (E - M) y / y' E y, \quad (3)$$

where $M = I_n - X(X'X)^{-1}X'$, $E = I_n - \frac{1}{n} \iota \iota'$, and ι is $(n \times 1)$ with each element unity.

As Koerts and Abrahamse (1971) show, writing R^2 as a ratio of quadratic forms in the Normal random vector y (as in (3)) facilitates the calculation of its cumulative distribution function (cdf). They calculate the cdf of R^2 for two data sets, assuming $\Omega = \sigma^2 I_n$, and for one data set when Ω corresponds to AR(1) errors.²

The c.d.f. of R^2 is

$$\begin{aligned} F(R^2) &= \Pr(R^2 \leq r^2) \\ &= \Pr[y'(qE-M)y \leq 0], \end{aligned} \quad (4)$$

where $q = 1 - r^2$. As is well known, after some simple manipulations, we have

$$F(R^2) = \Pr \left[\sum_{j=1}^n \lambda_j Z_j^2 \leq 0 \right], \quad (5)$$

where the λ_j 's are the eigenvalues of $\Omega^{1/2}(qE-M)\Omega^{1/2}$ and the Z_j^2 are independent non-central χ^2 variates, each with one degree of freedom, and with non-centrality parameters given by the squared elements of $P'\Omega^{-1/2}X\beta$, where the columns of P are the eigenvectors corresponding to the λ_j 's.

Probabilities of the form (5) can be computed efficiently in various ways. We have used Davies' (1980) algorithm in the SHAZAM package (White et al. (1990)). Having computed $F(R^2)$, numerical differentiation³ yields the probability density function (pdf) of R^2 .

3. Design of the Study

Clearly, the distribution of R^2 depends on X and Ω . We have considered six data sets, $n = 20, 60$; and AR(1) and MA(1) disturbances. With AR(1) errors $u_t = \rho u_{t-1} + \varepsilon_t$, $|\rho| < 1$, $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. With MA(1) errors, $u_t = \varepsilon_t + \theta \varepsilon_{t-1}$, $|\theta| < 1$. The X matrices used are⁴: the annual "spirits" income and price data of Durbin and Watson (1951); the quarterly

Australian Consumers Price Index and its lag; a Normal (30,4) variable and a linear trend; a log-Normal (2.23, 19.58) variable and a linear trend; and the orthogonal regressors $(a_2 + a_n)/\sqrt{2}$, $(a_3 + a_{n-1})/\sqrt{2}$, where the a_i 's are the eigenvectors of the usual "differencing" matrix,⁵ A.

Similar data sets have been used in other studies associated with autocorrelation (e.g., Evans (1991)), and a range of characteristics is covered. The last X matrix above is due to Watson (1955) - it produces the least efficient least squares parameter estimates in the class of orthogonal regressor matrices.⁶

Values of $\sigma_e^2 = 0.1, 1.0$ and various values of ρ and θ were considered, and the elements of β were controlled to preclude degenerate distributions. The SHAZAM code was checked by replicating the results given by Koerts and Abrahamse (1971, pp.139-140).

4. Results

We concur with previous findings that decreasing σ_e^2 shifts the cdf (and hence the pdf) of R^2 to the right with serially independent errors. That is, the probability of a low R^2 is decreased. As expected, increasing n concentrates the pdf of R^2 . These effects are illustrated in Figures 1 and 2, with $\beta' = (0.001, 0.002, 0.001)$. Both of these results continue to hold with AR(1) or MA(1) errors.

Except for Watsons X matrix, negative AR(1) errors shift the cdf of R^2 increasingly to the left, for any n or σ_e^2 , reflecting a higher probability of underestimating the proportion of total variation explained by the model. Depending on the data, positive AR(1) errors have a mixed effect, contrary to the very limited evidence given by Koerts and Abrahamse (1971, pp.151-152). In particular, the cdf of R^2 does not necessarily shift to the right in this case, though there is a tendency for it to do so.

Contrary to certain econometric folk-lore, positive AR(1) errors do not necessarily introduce a downward bias in the estimation of the error variance.⁷ With Watson's X matrix the cdf of R^2 shifts increasingly to the right as the absolute value of ρ increases.

The results with MA(1) errors are even more mixed. With few exceptions, negative autocorrelation of this type shifts the cdf of R^2 to the left. There is no clear pattern regarding such shifts under positive MA(1) autocorrelation. This highlights the importance of having considered a range of data sets. Generally, in this case, the shifts in the cdf of R^2 are less pronounced than in the corresponding positive AR(1) cases, especially with positive autocorrelation. These results are illustrated in Figures 3 and 4, with $\beta' = (0.01, 0.02, 0.02)$, $n = 20$ and $\sigma_{\epsilon}^2 = 0.1$.

5. Conclusions

These results have some interesting implications for diligent reporters of R^2 . A reasonably large R^2 value is especially encouraging if there is evidence of negative autocorrelation in the errors - such autocorrelation increases the probability of a low R^2 . On the other hand, caution is needed in the (likely) presence of positively autocorrelated errors as the likelihood of a high R^2 value is then dependent heavily on the form of the regressor matrix, in an apparently non-systematic way. Work in progress seeks to identify these dependencies, and to determine any possible effects due to multicollinear data.

FIGURE 1
CPI DATA
SERIALLY INDEPENDENT ERRORS

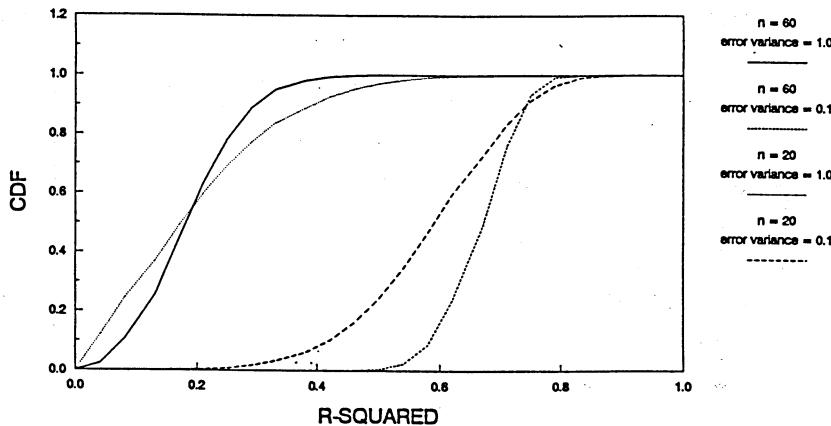


FIGURE 2
CPI DATA
SERIALLY INDEPENDENT ERRORS

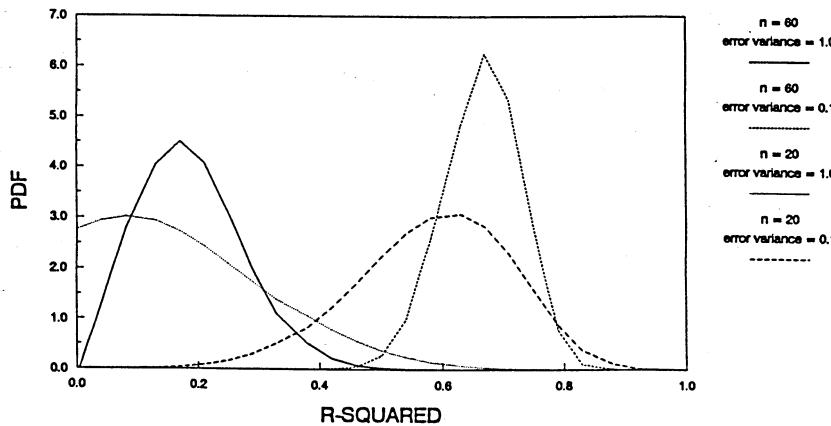


FIGURE 3
LOG-NORMAL & TREND DATA
AR(1) ERRORS

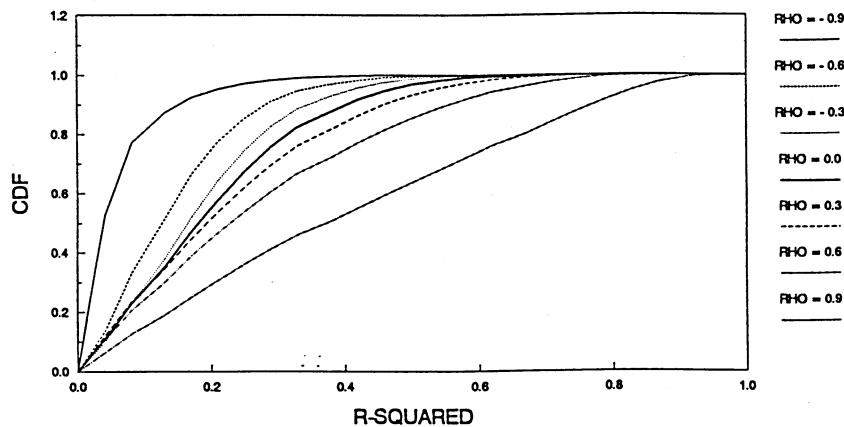
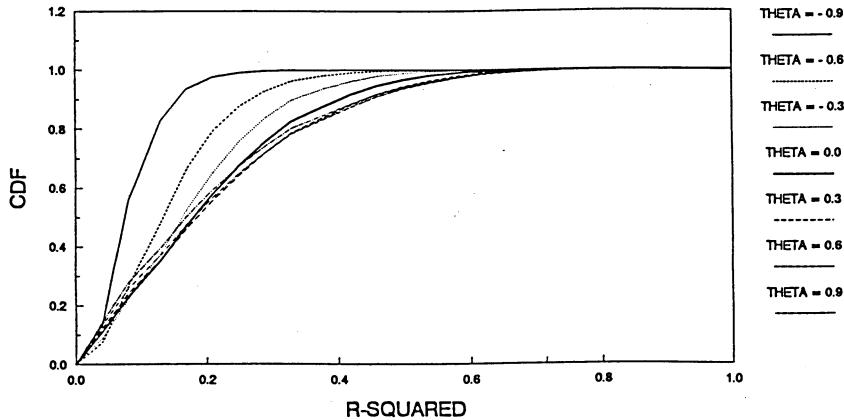


FIGURE 4
LOG-NORMAL & TREND DATA
MA(1) ERRORS



References

Battese, G.E. and W.E. Griffiths, 1980, On R^2 -statistics for the general linear model with non-scalar covariance matrix, *Australian Economic Papers* 19, 343-348.

Cramer, J.S., 1987, Mean and variance of R^2 in small and moderate samples, *Journal of Econometrics* 35, 253-266.

Davies, R.B., 1980, The distribution of a linear combination of χ^2 random variables: Algorithm AS 155, *Applied Statistics* 29, 323-333.

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

Evans, M.A., 1991, Robustness and size of tests of autocorrelation and heteroscedasticity to non-normality, *Journal of Econometrics*, forthcoming.

Koerts, J. and A.P.J. Abrahamse, 1971, On the theory and application of the general linear model (Rotterdam University Press, Rotterdam).

Nicholls, D.F. and A.R. Pagan, 1977, Specification of the disturbance for efficient estimation - an extended analysis, *Econometrica* 45, 211-217.

Watson, G.S., 1955, Serial correlation in regression analysis I, *Biometrika* 42, 327-341.

White, K.J., S.D. Wong, D. Whistler and S.A. Haun, 1990, *SHAZAM user's reference manual: Version 6.2* (McGraw-Hill, New York).

Footnotes

- * We are grateful to Judith Giles, Murray Scott, John Small and Jason Wong for their helpful comments.
- 1. If no intercept is included, the value of R^2 depends on whether it is defined as the proportion of "explained" variation, or one minus the proportion of "unexplained" variation in the sample.
- 2. Cramer (1987) derives expressions for the first two moments of R^2 under certain conditions, and Battese and Griffiths (1980) develop alternative goodness-of-fit measures for the case of a non-scalar error covariance matrix.
- 3. We have used the method of central differences, with end-point adjustments.
- 4. Each model also includes an intercept, so $k = 3$ in each case.
- 5. The matrix A is tri-diagonal, with 2 on the leading diagonal, except for the top left and bottom right elements (which are 1), and -1 on the two leading off-diagonals. The eigenvalues of A are placed in increasing order to number the eigenvectors. The first eigenvector has constant elements.
- 6. Watson's X matrix is also known to generate extreme situations for the distributions of other statistics (such as the Durbin-Watson statistic) which can be written as ratios of quadratic forms in a Normal vector.
- 7. Many text book discussions suggest that this is unambiguously the case, but Nicholls and Pagan (1977) provide contrary evidence.

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. 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 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 R² when the Disturbances are Autocorrelated, by Mark L. Carrodus and David E. A. Giles.

* 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.