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SOME CONSEQUENCES OF APPLYING THE GOLDFELD-QUANDT TEST TO MIS-SPECIFIED REGRESSION MODELS

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Abstract

This paper considers regression models which are mis-specified through the omission of relevant regressors, and investigates some aspects of the power properties of the Goldfeld-Quandt test for homoscedasticity of the error variance in such cases. Attention focusses not on the full power function of the test, but on the locus of powers that emerges when, for a given departure from the null, different numbers of central observations are omitted in the construction of the test statistic. A well known rule of thumb regarding the optimal number of such observations is found to be questionable, whether the model is mis-specified or not. The form of the regressor data, and the sample size, are found to be important in governing these features of the test.

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1. INTRODUCTION

The inefficiency of the Ordinary Least Squares (OLS) estimator of the coefficients in a linear regression model when the disturbances are heteroscedastic is well known. Also of concern is the inconsistency of the estimated variance covariance matrix of this estimator, and hence of the usual "standard errors". Accordingly, various tests of the homoscedasticity of regression errors have been developed. Among the best known of these tests is that proposed by Goldfeld and Quandt (1965).

The Goldfeld-Quandt (GQ) test assumes some knowledge of the form of the potential heteroscedasticity, in that the user must order the sample according to the values of the variable inducing the non-constant error variance. Typically, this variable is one of the regressors. The sample is then split into two parts, and the test statistic is constructed from the least squares residuals associated with the two sub-sample regressions. Generally, it is suggested that the power of the test may be improved by deleting a central group of the ordered observations prior to fitting the regressions to the remaining two sub-samples. There is a trade-off effect associated with this refinement : omitting observations reduces the degrees of freedom, and this tends to reduce the test's power; but there is a tendency for power to be increased because of the greater discrimination between the variances of the two sub-samples.

One question which then arises, is "what is the optimal number of central observations to omit in order to maximise the power of the GQ test"? Harvey and Phillips (1974) suggest that this number should be chosen so that the remaining sub-sample degrees of freedom are approximately a third of the full available sample. This conclusion is reached on the basis of exact power calculations and a limited range of data types, and is consistent with the results of a very limited Monte Carlo study reported by Goldfeld and Quandt (1965).[1]

The validity of the GQ test depends on various assumptions, including the Normality[2] and independence of the model's errors, and the correct specification of the design matrix. Epps and Epps (1977) consider the effect on the GQ test of first-order autocorrelation in the errors. They find that the size and power of the test are quite sensitive to such a mis-specification of the model, but that this sensitivity can be virtually eliminated if the test is applied after a Cochrane-Orcutt correction for autocorrelation, where appropriate. Epps and Epps apply the GQ test according to the "one third" rule of thumb but their results reveal nothing about the robustness of the rule to this type of model mis-specification.[3]

In this paper we focus on the robustness of this rule of thumb in the face of a different form of model mis-specification. The omission of relevant regressors is one of the most important and inevitable forms of model mis-specification in econometrics. We present exact results based on a variety of data sets which show that this rule lacks robustness not only to the omission of relevant regressors from the model, but also to the form of the included regressors.

In the next section we set up the problem and discuss the theoretical underpinnings of our analysis. Section 3 describes the situations we have examined, and the results are presented in section 4. Some concluding remarks appear in the final section.

2. NOTATION AND BASIC RESULTS

Suppose that the data-generating process is

$$y = X_1\beta_1 + X_2\beta_2 + \varepsilon \; ; \qquad \varepsilon \sim N(0,V) \tag{1}$$

where y and ε are $(n\times 1)$; β_i is $(k_i\times 1)$; X_i is $(n\times k_i)$, non-stochastic and of rank k_i $(i=1,2)$; and V is $(n\times n)$, positive definite and diagonal. Specific hypothesised forms of V are discussed in the next section.

The model fitted to the data is

$$y = X_1\beta_1 + u \,, \tag{2}$$

so $u \sim N(X_2\beta_2, V)$. For a particular X_2, different degrees of model mis-specifiction arise as β_2 varies. When $\beta_2 = 0$ the fitted model is correctly specified.

In practice V is unknown. To apply the GQ test we omit c central observations after the data have been ordered according to hypothesised increasing values of the diagonal elements of V, leaving two sub-samples each comprising ℓ observations. The degrees of freedom associated with the OLS estimator of β_1 in (2) are then $m = \ell - k_1$, for each sub-sample. Let u_j denote the error vector in (2), and let X_{ij} denote the X_i matrix, each over the jth sub-sample (j=1,2). So, the OLS residual vectors associated with the estimation of (2) over each sub-sample separately are

$$e_j = \left[I - X_{1j}(X_{1j}'X_{1j})^{-1} X_{1j}'\right]u_j$$

$$= M_{1j}\, u_j \qquad ; \qquad j = 1,2.$$

The GQ test statistic is

$$R = (e_2'e_2/e_1'e_1). \tag{3}$$

Adapting the approach of Harvey and Phillips (1974, pp.314-315) to our situation, we have

$$R = \left(u_2'M_{12}u_2\right)/\left(u_1'M_{11}u_1\right)$$

$$= \left(u^{*\prime}M^*_{12}u^*\right)/\left(u^{*\prime}M^*_{11}u^*\right) \,, \tag{4}$$

where $u^{*\prime} = \left(u_1', u_2'\right)$ is $\left(2\ell \times 1\right)$, and

$$M_{11}^{*} = \begin{bmatrix} M_{11} & 0 \\ 0 & 0 \end{bmatrix}, \quad M_{12}^{*} = \begin{bmatrix} 0 & 0 \\ 0 & M_{12} \end{bmatrix}$$

are each $(2\ell \times 2\ell)$ and idempotent.

By writing R as in (4) it is then expressed as a ratio of quadratic forms in the <u>same</u> normal random vector, and its distribution is readily calculated by applying transformations of the type discussed by Koerts and Abrahamse (1971, pp.81-82), and then using an algorithm such as that of Imhof (1961) or Davies (1980). In particular, to evaluate the exact power of the GQ test we need to determine $\Pr.(R > f_\alpha | V)$, where f_α is the size-α critical F-value for m and m degrees of freedom. That is, we require

$$\text{Power (R)} = \Pr.\left[u_*'(M_{11}^* - M_{12}^*/f_\alpha)u_* \le 0 \middle| V\right].$$

V determines the covariance matrix of u_* through u_1 and u_2. If $E(u_* u_*') = V_*$, say,[4] and $z = V_*^{-1/2} u_*$, then

$$\text{Power (R)} = \Pr.\left[z' V_*^{1/2}(M_{11}^* - M_{12}^*/f_\alpha)V_*^{1/2} z \le 0 \mid V_*\right].$$

Applying an appropriate orthogonal transformation to z to diagonalise $V_*^{1/2}(M_{11}^* - M_{12}^*/f_\alpha)V_*^{1/2}$, we have

$$\text{Power(R)} = \Pr.\left(\sum_{i=1}^{2\ell} \lambda_i w_i^2 \le 0 \mid V_*\right), \tag{5}$$

where the λ_i's are the eigenvalues of $\left(M_{11}^* - M_{12}^*/f_\alpha\right)V_*$ and the w_i's are independent non-central chi-square random variables, each with one degree of freedom and non-centrality parameter equal to the square of the i'th diagonal element of $P' V_*^{-1/2} \begin{pmatrix} X_{21} \\ X_{22} \end{pmatrix} \beta_2$. P is the orthogonal matrix whose columns are the eigenvectors corresponding to the λ_i's, and it satisfies $w = P'z$. In this study we evaluate (5) using Davies' (1980) algorithm.

Note that the power of the GQ test depends not only on V (through V_*) but also on the included and omitted variables over both sub-samples, on the choice of c, and on the value (but not the sign) of β_2. The power is invariant to the scale[5] of the disturbances. Accordingly, in considering the optimal choice of c in this framework we need to take account of different regressor matrices and different degrees of misspecification (values of β_2).

3. DESIGN OF THE STUDY

For all data matrices considered, $k_1 = 2$ and $k_2 = 1$. In each case X_1 includes an intercept variable. We consider two forms of heteroscedasticity : $\sigma_j^2 \propto x_{j1}^2$, and $\sigma_j^2 \propto x_{j1}$ $(j = 1,\ldots,n)$, where σ_j^2 is the j'th diagonal element of V and x_{j1} is the j'th observation on the non-intercept variable in X_1. This implies two different forms of V (and V_*). It is assumed that the GQ test is applied at the 5% significance level in determining f_α, and sample sizes of n = 20 and n = 69 are investigated.[6]

Real and artificial data sets have been chosen to reflect a range of characteristics and to facilitate some comparisons with other studies which evaluate the power of the GQ test in correctly specified models. Goldfeld and Quandt (1965) consider uniformly distributed regressors and n = 30,60 in their Monte Carlo experiments, while Harvey and Phillips (1974) report[7] exact results based on uniform and lognormal data with n = 20. Griffiths and Surekha (1986) also use uniform and lognormal regressors with n = 20, 50 in their Monte Carlo study.

With x_1 defined as above and $x_2 = X_2$, our data sets are[8]:

<u>CPI</u>: x_2 is the weakly seasonal quarterly Australian Consumers Price Index, and x_1 is its one-period lag.

Spirits: The annual "spirits" income (x_1) and price (x_2) data of Durbin and Watson (1951).

Lognormal: x_1 is lognormal, generated from N(3,1) data, and x_2 is a linear time trend.

Uniform: x_1 is Uniform (0,20), and x_2 is a linear time trend.

Using the methods described in section 2, the exact finite-sample power of the GQ test is calculated for each data set, sample size and form of heteroscedasticity, and for various choices of c and β_2. Fixing all of these characteristics and varying the degree of heteroscedasticity[9], one could generate conventional exact power curves for the GQ test. However, to focus attention on the effect that the choice of c has on the test's power, we fix the degree of heteroscedasticity (through a choice of its form and of the data set) and generate power locii by varying c. One power locus corresponds to a "snapshot" across a sequence of conventional power curves (corresponding to different c values) for a given degree of departure from the null hypothesis of homoscedasticity. This is essentially the approach adopted by Harvey and Phillips (1974) for the properly specified model. Our results are discussed in the next section.

4. RESULTS

Our results for the case where $\sigma_j^2 \propto x_{j1}^2$ are summarised in Figures 1 to 5. The results associated with $\sigma_j^2 \propto x_{j1}$ are very similar to these, except as noted below. Several major points emerge.

First, we see that for the correctly specified models ($\beta_2 = 0$), as m increases (c decreases) the power of the GQ test generally rises steeply, reaches a plateau, then falls gradually, The only case in which the power fails to fall is when n = 69 with the Uniform data set. Harvey and Phillips (1974, p.312) also report a "flat" range for the optimum power. The "one third" rule of thumb seems appropriate when n = 20. Then m = 6 seems to maximize the power of the GQ test. In this sense the results in Figures 5b and 4b are consistent with those in Tables 1 and 2 of Harvey and Phillips (1974). Although the <u>values</u> of our maximum powers differ from theirs, we concur that there is a reduction in maximum power in moving from $\sigma_j^2 \propto x_{j1}^2$ to $\sigma_j^2 \propto x_{j1}$, though the location of this maximum is unaltered. However, the rule of thumb relating to the choice of c is <u>not</u> supported by the results when n = 69. Then maximum power occurs around m = 12 (m = 18 for the Spirits data), as opposed to m = 23 as this rule would suggest.

Second, whether the model is correctly specified or not, the performance of the GQ test is very sensitive to the regressor data. To some extent, of course, this reflects the different implied degrees of heteroscedasticity. As is shown in Table 1, ranking the x_1 data in terms of the coefficient of variation (cv) in the sample when n = 69 exactly matches the maximum power rankings for the GQ test. Given the construction of the test, this is expected if the model is correctly specified. However, it is interesting that this also holds if relevant regressors are omitted. Griffiths and Surekha (1986, p.225) provide results which accord with ours for a properly specified model, and also demonstrate that even for a fixed cv value, the power of the GQ test may vary with the type of regressor data, <u>ceteris paribus</u>.

<u>Table 1</u>

<u>Effect of Data Variability on Power</u>

x_1	cv	Power Ranking*
Lagged CPI	0.205	3
Spirits Income	0.049	5
Normal	0.423	2
Lognormal	0.192	4
Uniform	0.618	1

* 1 = Best

The literature on the power of this test rests heavily on artificial data sets. Looking at our range of results it is clear that for properly or mis-specified models, some of the previous results may be rather misleading in practice. In particular, the maximum powers achieved with the "Spirits" data set are very disappointing.

Third, when relevant regressors are omitted from the model the power of the GQ test may rise or fall relative to the properly specified case. Both the type of data and the sample size play a role in determining the direction of this shift, as may be seen in Figures 2 and 4. A transition situation is depicted in Figure 3. Referring back to Table 1, we see that such a transition is not simply a function of the degree of heteroscedasticity. We can conjecture that there exist sample sizes for which such transitions may occur for the other data sets considered. In each case, the more misspecified is the model, the greater is the shift in the power locus from that associated with $\beta_2 = 0$.

Finally, returning to the "one third" rule of thumb, we see that not only is it open to question when the model is properly specified, but when relevant regressors are omitted it may require adjustment in practice in either direction. Accordingly, it should be treated very cautiously, especially considering the likelihood of such a mis-specification of the model to an unknown degree and with respect to unknown variables.

5. CONCLUSIONS

Our study abstracts from the possible effects of varying degrees of multicollinearity among the (included or excluded) regressors. Harvey and Phillips (1974, p.311) report that such effects are insignificant with respect to the power properties of the GQ test in correctly specified models, but whether or not this extends to misspecified models remains to be investigated. The effects of other types of model misspecification and forms of heteroscedasticity on the power of the GQ and related tests are under investigation, as are the consequences of omitting central observations from the data in an asymmetric way when constructing the test statistic.

It seems clear that one should question the well known suggestion that, in applying the GQ test, one should omit central observations to the extent that the remaining sub-sample degrees of freedom equal a third of the original number of data points. Further, if the test is applied in the context of a model from which relevant regressors have been omitted, then this rule of thumb becomes even more suspect, as does the existing evidence on the power of the test per se. Standard econometric results rest in part on the folklore that the fitted model corresponds to the data-generating process. Once this myth is put to one side many such results need careful re-appraisal.

FIGURE 1a : POWER LOCII
CPI DATA : n=69

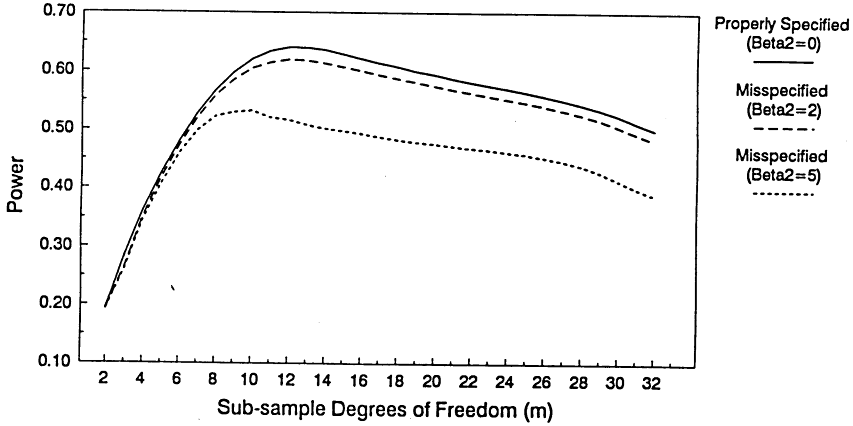


FIGURE 1b : POWER LOCII
CPI DATA : n=20

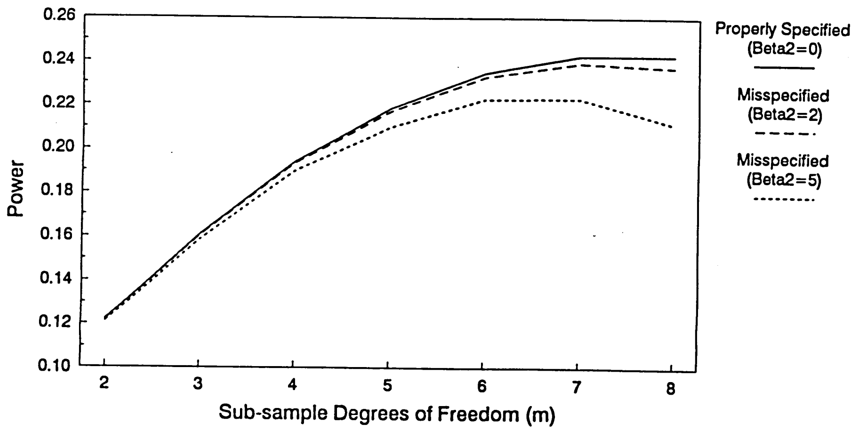


FIGURE 2a : POWER LOCII
SPIRITS DATA : n=69

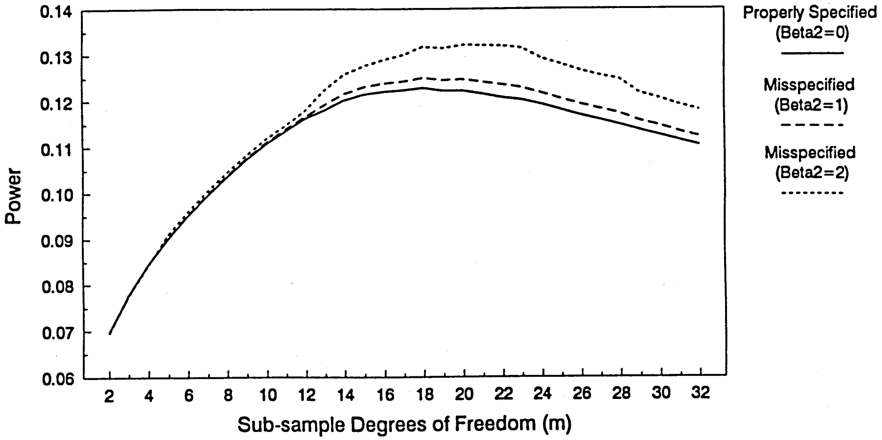


FIGURE 2b : POWER LOCII
SPIRITS DATA : n=20

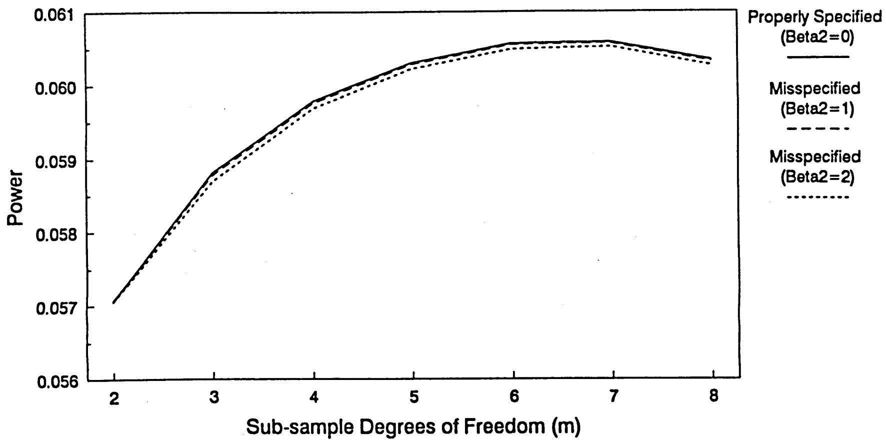


FIGURE 3a : POWER LOCII

NORMAL DATA : n=69

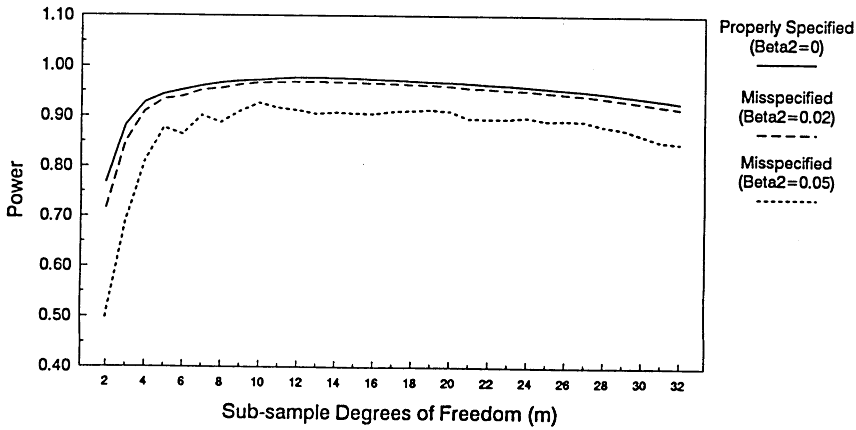


FIGURE 3b : POWER LOCII

NORMAL DATA : n=20

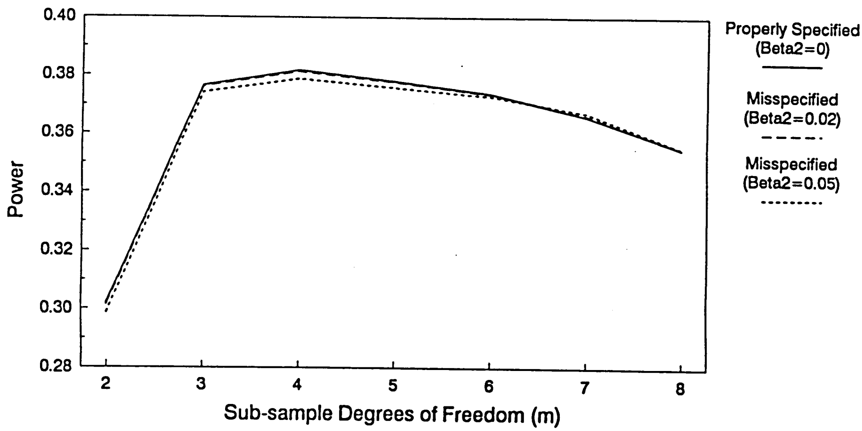


FIGURE 4a : POWER LOCII

LOGNORMAL DATA : n=69

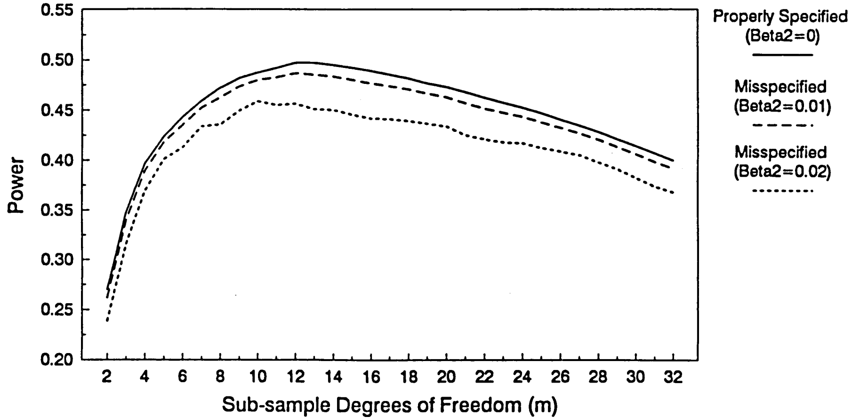


FIGURE 4b : POWER LOCII

LOGNORMAL DATA : n=20

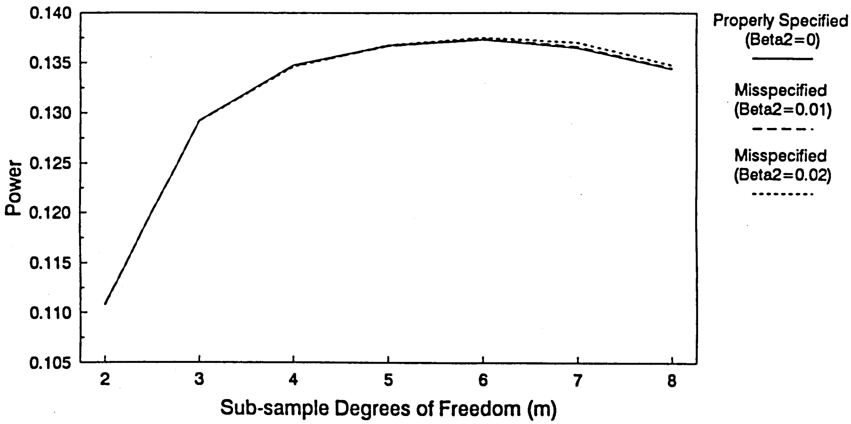


FIGURE 5a : POWER LOCII

UNIFORM DATA : n=69

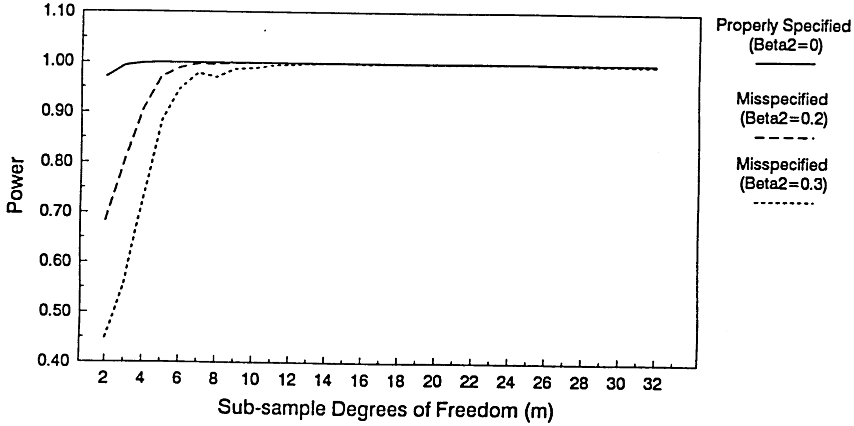
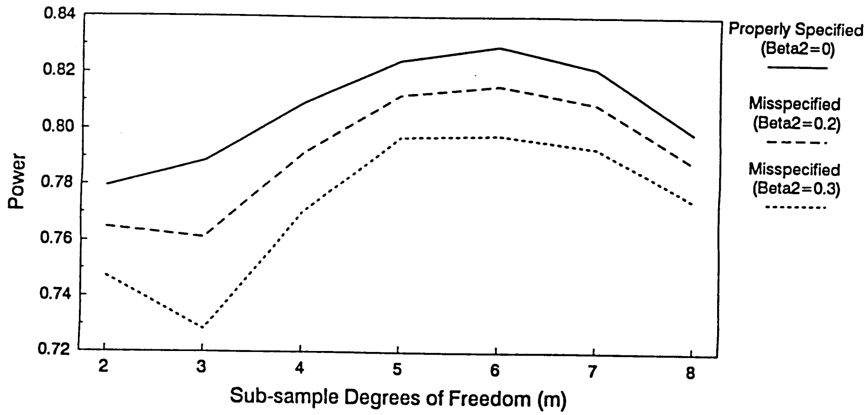


FIGURE 5b : POWER LOCII

UNIFORM DATA : n=20



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FOOTNOTES

* We are grateful to Merran Evans for supplying the data used in this study and to Robert Davies for providing FORTRAN code for his AS 155 algorithm. We also thank Judith Giles and John Small for their helpful comments and suggestions.

1. See also Goldfeld and Quandt (1972). It is worth noting that this result has been mis-quoted by some authors. For example, see Johnston (1984, p.301).

2. Strictly, only elliptical symmetry of the errors is required. See King (1979).

3. This point is under investigation in work in progress.

4. In this study powers are computed for specific forms of V. These dictate the forms of V_*.

5. That is, if $V = \sigma^2\Omega$, the power is invariant to σ^2.

6. The "Spirits" data set described below comprises 69 observations.

7. Their study also considers other data and sample sizes and various numbers of regressors, but they state that those results were similar to the ones they report.

8. These data sets are the same as, or derived from, the data used by Evans (1989).

9. This could be achieved by varying the coefficient of variation of σ_j^2, as suggested by Griffiths and Surekha (1986), for example.

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