IMPACT: International Journal of Research in Applied, Natural and Social Sciences (IMPACT: IJRANSS)
ISSN(P): 2347-4580;ISSN(E): 2321-8851
Vol. 4, Issue 7, Jul 2016, 9-16

COMPARISM OF THE POWER OF SOME SPECIFICATION ERROR TESTS

CHOJI NIRI MARTHA[1] & DATONG, GODWIN MONDAY[2]

[1]Department of Mathematics, Plateau State University, Bokkos, Nigeria

[2]Department of Mathematics, University of Jos, Jos, Nigeria

ABSTRACT

Because there are a number of tests for specification error in detecting the errors of omitted variables or incorrect functional form, one rarely knows the best test to use. This paper compares the power of the test RESET (regression specification error test) to that of Durbin-Watson in detecting the errors of omitted variables or incorrect functional form in a regression analysis using the Bootstrap method of simulation to see which test is better. The overall results show that the RESET is more powerful at all sample sizes in detecting a non zero disturbance mean (i.e in detecting specification error) as a result of incorrect functional forms or omitted variables in a regression model.

KEYWORDS: Bootstrapping, Durbin Watson, Power, RESET, Specification Error

INTRODUCTION

The Encarta English Dictionary (2007) defined specification as a detailed description of something, especially one that provides information needed to make, build, or produce something.

In regression analysis and related fields such as econometrics, specification is the process of converting a theory into a regression model. This process consists of selecting an appropriate functional form for the model and choosing which variables to include. Model specification is one of the first steps in regression analysis.

One of the assumptions of the classical linear regression model is that the regression model used in the analysis is correctly specified. If this fails to happen, then we encounter the problem of specification error.

Specification errors as the name implies are errors associated with the specification of the model. These can take many forms such as omission of a relevant variable(s), inclusion of an unnecessary variable(s), adopting the wrong functional form, errors of measurement and incorrect specification of the stochastic error term.

In the inclusion of an irrelevant variable, the presence of such an error in the specification of the model does not affect the properties of OLS estimators however; the estimates will generally be inefficient. It may be, however, that the included irrelevant variable correlates with another variable in the model, and this will cause a fairly serious problem of multicollinearity which could result in an unnecessary increase in the standard error of the coefficients, and so the usual t-tests would become unreliable.

Of unquestionable importance is the exclusion of a relevant variable. This specification error will affect the properties of the OLS estimators. In the presence of such an error, OLS estimators will be biased and inconsistent, that is the bias will not go away as the sample size increases, since inconsistency is an asymptotic property.

As mentioned earlier, specification errors can also be errors in the specification of the functional form that the equation should take in describing the relationship between the variables in which we are interested. If we estimate a non-linear population relation with a linear regression of sample data, then we cannot expect the OLS estimators to be either unbiased or consistent.

The practical question is not why specification errors are made for they generally are but how to detect them. Because there are a number of tests for specification error in detecting the errors of omitted variables or incorrect functional form, one rarely knows the best test to use.

This project work compares the power of the test RESET (regression specification error test) to that of Durbin-Watson in detecting the errors of omitted variables or incorrect functional form using the Bootstrap method of simulation to see which test is better.

LITERATURE REVIEW

An economic investigation begins with the specification of the econometric model underlying the phenomenon of interest. Some important questions that arise in the specification of the model include the following;

- What variable(s) should be included in the model?
- What is the functional form of the model? Is it linear in the parameters, the variables, or both?
- What are the probabilistic assumptions made about the Y_i, the X_i and the U_i entering the model?

These are very important questions. By omitting important variables of the model, or by choosing the wrong functional form, or by making wrong stochastic assumptions about the variables of the model, the validity of interpreting the estimated regression will be highly questionable.

As earlier stated, we are comparing the power of the test RESET to that of the Durbin-Watson in detecting the errors of omitted variables or incorrect functional form in regression analysis.

In a comparison between the power of the Durbin-Watson and the power of the BLUS (best linear unbiased scalar). Abramhamse & koerts (1968) powers of both tests were computed and compared. It appears that, for the cases considered, the power of the Durbin-Watson exceeds that of the BLUS.

Thursby and Schmidt (1977) in an article titled; "Some properties of tests for specification error in a linear regression model" considered the power of a number of variants to the test RESET, a test suggested by Ramsey (1969), which is intended to detect a nonzero mean of the disturbance in a linear regression. In the test, they considered the specification error test with various choices of test variables in addition to those originally suggested by Ramsey (1969). Analysis of an approximation to the test statistic's distribution and the Monte Carlo experiments reveal that the power of the test may decline as the size of the disturbance mean increases. However, the possibility is remote and declines with increasing sample size. Alternative sets of test variables are considered, and their effects on the power of the test are studied in the Monte Carlo experiments. The best set seems to be composed of powers of the explanatory variables.

In a paper, a Monte Carlo study of some small sample properties of tests for specification error, by Ramsey and Gilbert (1972) where some tests for specification errors of omitted variables, incorrect functional form, simultaneous equation problems and heteroskedasticity previously developed by other author are further considered. Some tests were considered; RESET, BAMSET (Barlett's M specification error test) and RASET (rank specification error test). In comparing the relative sensitivities of the test statistic to various misspecifications, one concludes that RESET is the powerful of the three tests against alternative H_1.

Several tests for specification error in a regression model have been proposed, and efforts have been made to show the relationship between the tests. For example, Thursby (1985) in a paper, "The Relationship among the Specification Test of Hausman, Ramsey and Chow" says that the three tests are related. The Monte Carlo study of Thursby and Schmidt (1977) indicates that the power of RESET generally rises only slightly as a number of testvariables increases and, therefore, should be similar to that of Hausman's tests.

Furthermore, Olubusoye O. E. et el (2004) in a paper titled "A Comparative Study of Some Specification Error Tests" compared the power of RESET, White test and the Q-test in detecting specification errors arising from omitted variables, functional misspecification and contemporaneous correlation residuals. They concluded that RESET is the most powerful test for detecting incorrect functional form and that the test is robust to autocorrelation and heteroscedastic disturbances. The Q-test is most powerful in detecting autocorrelation while White test is used in detecting heteroscedasticity.

Finally, Sapra (2005) motivated by specification tests for testing for functional and omitted variables in linear regression model, has developed two versions of the regression specification error test (RESET) for GLMs (generalized linear models). The tests when applied

METHODOLOGY

Consider the standard linear regression model

$$Y = X\beta + U \tag{3.1}$$

Where,

Y is an n x 1 vector of dependent variables

X is an n x k matrix of regressors

B is a k x 1 vector of parameters

U is an n x 1 vector of disturbances

The null hypothesis to be tested is that $E[U / X] = 0$

Where, U is normally distributed with covariance matrix proportional to the identity matrix. The alternative hypothesis is that a specification error has occurred which results in $E[U / X] = \epsilon \neq 0$

This project used the bootstrap method of simulation to generate data for the comparison of RESET and the Durbin-Watson test.

The table below lists 3 models investigated in this paper. The models were selected from the models considered by Thursby (1979)

Since we are looking at specification errors as a result of omitted variables or incorrect functional forms, we consider model 1 which is correctly specified, model 2 is the case of incorrect functional form and model 3 is the case of omitted variable. Observations on the dependent variable are generated according to one of the specification labelled True. The model labelled Null is then tested for specification error at the 5 percent level of significance.

Table 1: The Models Considered

Model	Specification	Problem
1	True: $Y_t = 10.0 + 5.0X_{1t} -2.0X_{2t} + U_t$ Null : $Y_t = \beta_0 + \beta_1X_{1t} + \beta_2X_{2t} + U_t$	None (correct specification)
2	True: $Y_t = 1.0 + 2.0X_{1t} -0.8X_{2t} + U_t$ Null : $Y_t = \beta_0 + \beta_1 e^{X_{1t}/3} + \beta_2 e^{X_{2t}/5} + U_t$	Incorrect functional form (additive effects)
3	True: $Y_t = 0.8 – 0.6X_{6t} + X_{7t} + 1.5X_{8t} + U_t$ Null : $Y_t = \beta_0 + \beta_1X_{6t} + \beta_2X_{7t} + U_t$	Omitted variable (R^2= 0.96)

The Bootstrap Experiment

Using the typical bootstrap, let's consider the specification labelled true in model 1.

$$Y_t = 10.0 + 5.0X_{1t} -2.0X_{2t} + U_t \quad (3.2)$$

Where, U~ N (0, σ^2) and also satisfies other classical assumptions of the least squares estimation. Numerical values were assigned to all the parameters (β_0 = 10.0, β_1 =5.0, β_2 = -2.0) in the model. The variance σ^2 was also assigned a numerical value, and on the basis of the assumed σ^2, the disturbance term U is generated. A random sample n of X was selected from a pool of uniformly distributed random numbers with interval (0, 1) and the numerical values of 10.0 + $5.0X_{1t}$ $-2.0X_{2t}$ are computed. The vector Y was then obtained by computing $10.0 + 5.0X_{1t} -2.0X_{2t} + U_t$. We set sample sizes n = 20, 30 and 50 for the purpose of the study. The Microsoft excel software was used to generate the data.

Using a bootstrap software package (in this work, STATA was used), the X's and the Y's generated were copied from Excel into STATA then bootstrapped and replicated 1000 times using a STATA command. Each replicate produces a bootstrap sample which gave distinct values of Y. This leads to having different estimates $\hat{\beta}$'s of β's for each bootstrapped sample from several regression of Y on fixed X's. The procedure described above is then repeated for different sample sizes n.

The above procedure was performed on each of the three models on the tables above. The outcome of the bootstrap experiment was then subject to analyses to compare the power of RESET and Durbin-Watson.

RESET (Regression Specification Error Test)

Ramsey (1969) has argued that various specification errors (omitted variables, incorrect functional form, correlation between X and U) give rise to a nonzero U vector. Thus, the null and alternative hypotheses are restated as follows.

H_0: U~ N (0, σ^2I)

H_1: U~ N (U, σ^2 I) where, U ≠ 0

The test of H_0 is based on the augmented regression

$Y = X\beta + Z\alpha + U$

The RESET procedure amounts to using the standard F-test to test whether α = 0. Ramsey's suggestion is that Z should contain powers of the predicted values of the dependent variable. Using the second, third and fourth powers give

$Z = [\hat{Y}^2\ \hat{Y}^3\ \hat{Y}^4]$

Where $\hat{Y} = X\beta$, and $\hat{Y}^2 = [\hat{Y}_1^{\,2}\ \hat{Y}_2^{\,2} \ldots \hat{Y}_n^{\,2}]$. In the experiments we used the square and cube powers of the predicted variable following Thursby (1989).

Using the STATA package, we subject the result of the Bootstrap to analysis of the test RESET using the command ovtest which computes the Ramsey RESET test using the powers of the fitted values of X. The idea behind the ovtest is that it creates new variables based on the predictors and refits the model using those new variables to see if any of them would be significant.

Durbin-Watson Test

To use the Durbin-Watson test for detecting model specification error(s), we proceed as follows;

- From the assumed model, obtain the OLS residual
- If it is believed that the assumed model is misspecified because it excludes a relevant explanatory variable, say, Z from the model, order the residuals obtained in step 1 according to increasing values of Z.

Note: The Z variable could be one of the X variables included in the assumed model or it could be some function of that variable such as $X^2$and X^3

- Compute the d statistic from the residuals thus ordered by the usual d formula, namely;

$$d = \frac{\sum_{t=2}^{t=n} (\hat{U}_t - \hat{U}_{t-1})^2}{\sum_{t=1}^{t=n} \hat{U}_t^2}$$

Note: That the subscript t is the index of observation here and does not necessarily mean that the data are time series.

From the Durbin-Watson tables, if the estimated d value is significant, then one can accept the hypothesis of model misspecification. If that turns out to be the case, the remedial measures will naturally suggest themselves.

Here, we also used the STATA to order the residual using the command esset var1 and subsequently compute the Dubin Watson d statistic using the command estat dwatson.

The Durbin Watson statistic ranges in value from 0-4. A value near 2 indicates non-autocorrelation, a value towards 0 indicates positive autocorrelation and a value towards 4 indicates negative autocorrelation.

The Power of a Test

The power of a statistical test is the probability that it will correctly lead to the rejection of a false null hypothesis. The statistical power is the ability of a test to detect an effect, if the effect actually exists. The power may also be defined as 1-β, where β is the probability of accepting a false null hypothesis. Recall that accepting a false null hypothesis is referred to as a type II error. High power is always a desirable characteristic of a test. In this work, power is simply the number of times we rejected the null hypothesis.

RESULTS

The experimental results are given in the table below. The entries in the table are the percentage rejections of the null hypothesis of no misspecification (i.e. the percentage power) of the test RESET and the Durbin Watson.

Table 2: Percentage Rejections of the Tests

TESTS						
n	RESET	DW	RESET	DW	RESET	DW
	MODEL 1		MODEL 2		MODEL 3	
20	4.76	0.0	61.90	0.0	66.67	4.76
30	9.52	0.0	85.71	0.0	71.43	0.0
50	4.79	0.0	80.95	0.0	42.86	14.28

The table above represents the percentage rejections of the models showing the two tests considered in the analysis at different sample sizes. Model 1 represents the result of the model with correct specification, Model 2 represents the result of the model with incorrect functional form while Model 3 represents the result of the model with omitted variable.

Based on the results, model1, the case of correct specification, it is obvious that the RESET is more powerful than the Durbin Watson even though the power of the RESET is not strong because it is a case of correct specification. Considering model 2, the case of incorrect functional form, we see that the RESET exhibit substantial power while the Durbin Watson shows no power at all. Finally, looking at model 3 the case of omitted variables, the RESET once again performs better than the Durbin Watson which shows little power.

CONCLUSIONS

The overall results show that the RESET is more powerful at all sample sizes in detecting a non zero disturbance mean (i. e in detecting specification error) as a result of incorrect functional forms or omitted variables in a regression model.

REFERENCES

1. J. Johnston, “Econometric methods.” 2nd ed. New York: McGraw-Hill. 1960.
2. D. N. Gujarati, “Basic Econometrics.” 4th ed. New York: McGraw-Hill. 2004.
3. Koutsoyiannis, “Theory of Econometrics.” 2nd ed. New York: Palgrave. 1977.
4. J. Johnston, & J. Dinardo, “Econometric methods.” 4th ed. New york. McGraw-Hill. 1997.

5. O. E. Olubusoye, O. E. Olaomi, & O. O. O. Detunde, "Bootstrap Approach to Comparison of Alternative Methods of Parameter Estimation of a Simultaneous Equation Model". An International Multidisciplinary Journal (African Research Review) Vol. 2(3) August 2008, Pg. 51-61.

6. O. E. Olubusoye, S. O. Olofin, & D. Buari, "A Comparative Study of the Power of Some Specification Error Tests". The Nigerian Journals of Economic and Social Studies. Vol.46, No.1, March 2004. Pg. 84-92.

7. A. P. J. Abrahamse, & J. Koerts, "A Comparison Between the Power of the Durbin-Watson Test and the Power of the BLUES Test". Journal of the American Statistical Association. 64, 938-948, 1969.

8. J. G. Thursby, & P. Schmidt, "Some Properties of Test for Specification in a Linear Regression Model". Journal of the American Statistical Association. 72, 635-641. 1977.

9. J. Ramsey, & R. Gilbert, "A Monte Carlo Study of Some Small Sample Properties of Tests for Specification Error". Journal of the American Statistical Association. 64, 180-186. 1972.

10. J. G. Thursby, "The relationship among the specification Test of Hausman, Ramsey and Chow". Journal of the American statistical Association, Vol. 80, No. 392 (Dec., 1985), pp. 926-928. 2288555 80,926-928

11. J. G. Thursby, "Alternative specification error test: A comparative study". Journal of the American statistical Association. 74, 222 – 225, 1979.

12. J. L. Horouritz, "Bootstrap methods in Econometrics: Theory and numerical performance". (Econometric Society) Department of Economics University of Iowa. 1995.

13. K. Yuan, & K. Hayashi, 2003. Bootstrap approach to inference and power analysis based on three test statistics for covariance structure models. British journal of mathematical and statistical psychology, 56, 93 – 110

14. T. Hesterberg, D. S. Moore, S. Monaghan, A. Clipson, & R. Epstein. Bootstrap methods and permutation tests

15. H. M. Park, 2008 – 2010. Hypothesis Testing and Statistical Power of a Test. University Information Technology Services Centre for Statistical and Mathematical computing Indiana University.