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Relative Power of Glejser Test When Some Heteroscedasticity Structures Are Misspecified

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Abstract: This study uses Monte Carlo Experimentation to investigate the power of Glejser test when heteroscedasticity structures are mis-specified. The study considered four cases of functional misspecification. The result shows that Glejser test works as expected for all the four functional forms except for form $1/X$.

Key words: Monte corlo experimentation, Glejser, misspecification, functional forms

INTRODUCTION

Homoscedasticity is an important assumption in Ordinary Least Squares (OLS) regression. Although the estimator of the regression parameters in OLS regression is unbiased when the homoscedasticity assumption is violated, the estimator of the covariance matrix of the parameter estimates can be biased and inconsistent under heteroscedasticity, which can produce significance tests and confidence intervals that can be liberal or conservative.

Given that heteroscedasticity can affect the validity or power of statistical tests when using OLS regression, it behoves researchers to test the tenability of this assumption using one's data. The simplest test of the homoscedasticity assumption is the eyeball test, in which the residuals from the regression model are plotted against y (or alternatively, one or more of the predictor variables x) in a scatter plot. But as Darlington (1990), Weisberg (1980) discuss, a visual examination of residuals can be a useful means of detecting only blatant heteroscedasticity.

Alternatively, one could use one of the formal tests of homoscedasticity that exist, such as those introduced by Breusch and Pagan (1979), Cook Weisberg (1983), Goldfeld and Quandt (1965), White (1980), Glejser (1969).

The various tests for heteroscedasticity can be broken into two groups, those dealing with specific functional forms and those addressing unspecified functional forms. The Glejser test is an example of the former while the White test addresses the case where nothing is known about the structure of the heteroscedasticity. Both tests are employed in this study. Four different functional forms are used to plant heteroscedasticity in the data set, for each functional form so planted, seven functional forms are used to test for the presence of heteroscedasticity to enable us know if the true form could be recaptured by the test and which other functional forms could capture the true form. White test which is a general test is introduced as a control test. The powers of the tests are noted under various sample sizes.

MONTE CARLO DESIGN

We use the simple linear regression

$$\text{Model } Y = \alpha + \beta xi + ei \quad (1)$$

Where $e_i \sim N(0, \sigma_i^2)$

For what happen to ordinary least squares (OLS) estimators in the presence of heteroscedasticity see Fasoranbaku (2003).We set the null hypothesis

Ho: There is homoscedasticity, against the alternative
H_1: There is heteroscedasticity

At $\alpha = 0.05$ level of significance.
The test procedures are explained below:
(i)The Glejser test is conducted as follows:

- Specify $y = \alpha + \beta x$ (2)
- Find the residuals e_i from (2)
- Regress the absolute residuals $|ei|$ in (b) over g(x); where g(x) is any heteroscedasticity functional form.
- Test for the significance of the parameters of the auxiliary regression in (c).

In this study the functional forms g_s (x) used to pollute the data are (i) X (ii) X^2 (iii) 1/X (iv) $X^{1/2}$, each form is used at a time. For each form used to pollute,

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Glejser test is carried out using the said form and six other functional forms. This affords us the opportunity to see how well Glejser test of the form used to pollute could well capture the nature of heteroscedasticity planted.
White test is added as a control and it works thus:

- Specify $y = \alpha + \beta x$ (2)
- Find the squares of the residuals e^2i in (a)
- Regress e^2i on x x
- Obtain nR^2 from (c), where R^2 is the coefficient of determination.
- If nR^2>, reject H_0.

DATA GENERATION

Data are generated using (1), 0.5 and 2.0 are the values assumed for α and β, respectively in (1)

$X_I=\{1, 2, 3\ldots\ldots, 15\}$
$X_{II}=\{1, 2, 3\ldots\ldots, 30\}$
$X_{III}=\{1, 2, 3\ldots\ldots, 60\}$
$X_{IV}=\{1, 2, 3\ldots\ldots, 90\}$

are used in (1) and ei are generated using Microsoft Excel package. A new Eq.

$$= \alpha + \beta x_i + e_i(g(x_i)) \quad (3)$$

is used to generate new sets of endogeneous variable which really introduced the form of heteroscedasticity into the data.

Finally, and X_I, X_{II}, X_{III}, and X_{IV} are used accordingly for the various tests.

We use four different sample sizes; 15, 30, 60 and 90 as derived from X_I, X_{II}, X_{III}, and X_{IV} respectively for each of the forms used to pollute the data. Each combination of the sample size and the form is replicated 200 times in performing the Glejser test of the seven different forms and White test.

RESULTS AND DISCUSSION

Table 1-4 present the percentage of significant tests while Table 5-8 present the ranks of the power of the tests as shown on Table 1-4.

Table 1: The power of tests when the form of heteroscedasticity planted is X

n	X	X^2	InX	1/X	$1/\sqrt{X}$	$\sqrt{X}$	E^x	White
15	35	38	18	03	13	25	23	
30	93	83	80	0	23	88	38	78
60	100	98	100	73	98	100	80	95
90	100	100	100	0	100	100	88	100

Table 2: The power of tests when the form of heteroscedasticity planted is X^2

n	X	X^2	InX	1/X	$1/\sqrt{X}$	$\sqrt{X}$	e^X	White
15	54	66	16	0	06	32	34	58
30	98	98	72	0	06	98	26	98
60	12	16	0	0	0	04	30	98
90	100	100	100	0	96	100	100	100

Table 3 The Power of Tests when the form of heteroscedasticity planted is 1/X

n	X	X^2	InX	1/X	$1/\sqrt{X}$	$\sqrt{X}$	e^X	White
15	86	60	90	84	86	90	02	24
30	98	48	100	92	96	100	0	16
60	100	100	100	100	100	100	04	44
90	100	54	100	98	100	100	0	22

Table4: The power of tests when the form of heteroscedasticity planted is $1/\sqrt{X}$

n	X	X^2	InX	1/X	$1/\sqrt{X}$	$\sqrt{X}$	e^X	White
15	24	24	08	02	06	26	22	20
30	46	44	48	0	20	56	36	44
60	92	76	90	54	90	92	42	70
90	98	92	100	0	98	100	52	92

Table 5: The rank of the Power of tests when the form of heteroscedasticity is X

n	X	X^2	InX	1/X	$1/\sqrt{X}$	$\sqrt{X}$	e^X
15	6	7	3	1	2	5	4
30	7	5	4	1	2	6	3
60	7	4	7	1	4	7	2
90	7	7	7	1	7	7	2

Table 6: The rank of the power of tests when the form of heteroscedasticity is X^2

n	X	X^2	InX	1/X	$1/\sqrt{X}$	$\sqrt{X}$	e^X
15	6	7	3	1	2	4	5
30	7	7	4	1	2	7	3
60	5	6	1	1	1	4	7
90	7	7	7	1	2	7	7

Table 7: the rank of the power of tests when the form of heteroscedasticity is 1/X

n	X	X^2	InX	1/X	$1/\sqrt{X}$	$\sqrt{X}$	e^X
15	5	2	7	3	5	7	1
30	5	2	7	3	4	7	1
60	7	7	7	7	7	7	1
90	7	2	7	3	7	7	1

Table 8: The rank of the power of tests when the form of heteroscedasticity is $\sqrt{X}$

n	X	X^2	InX	1/X	$1/\sqrt{X}$	$\sqrt{X}$	e^X
15	6	6	3	1	2	7	4
30	5	4	6	1	2	7	3
60	7	3	5	2	5	7	1
90	5	3	7	1	5	7	2

To evaluate the degree with which the Glejser test of the functional form used to pollute the data detects the structure of heteroscedasticity, we rank Table 1-4 column-wise with the highest power being assigned the highest rank. The results of this exercise are displayed on Table 5-8.

CONCLUSION

For appropriate transformation of data infested with heteroscedasticity, it is important to know the nature (or structure) of the heteroscedasticity. For this study, Glejser works as expected for all the four functional forms used to pollute the data except for the form 1/X where InX $\sqrt{X}$ and even X do better than it.

Except for the fact that the assumption of the relationship between the disturbance term and the independent variable is incorrect, Glejser test could adequately capture the nature of heteroscedasticity in the data.

REFERENCES

Breuseh, T.S. and A.R. Pagan, 1979. A simple test for heteroscedasticity and random coefficient variation. Econometrica, 47: 1287 1294.

Cook, R.D. and S. Weisberg, 1983. Diagnostics for heteroscedasticity in regression. Biometrika, 70: 1-10.

Cook, R.D. and S. Weisberg, 1999. Applied regression including comprising and graphics. New York: Wiley.

Darlington, R.B., 1990. Regression and linear models. New York: McGraw-Hill

Fasoranbaku, O.A., 2003. The Relative Performance of Some Heteroscedatic Tests. J. Nigerian Statistician, pp: 104-108.

Glejser, H., 1969. A New Test for Heteroscedasticity. J. Am. Stat. Assoc., pp: 316-323.

Goldfield, S.M. and R.E. Quandt, 1965. Some tests for homoscedasticity. J. Am. Stat. Assoc., 60: 539-547.

Weisberg, S., 1980. Applied linear regression. New York. Wiley.

White, H., 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. Econometrica, 48: 817-838.