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Sensitivity of the Ramsey's Regression Specification Error Term Test on the Degree of Nonlinearity of the Functional Form

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Abstract:

The present paper aims to demonstrate that the Ramsey's Regression Specification Error Term Test (RESET) is very sensitive to the degree of nonlinearity between the variables of the under-specification functional form. This widely used test, for testing the functional specification of a model, is based on the notion that if nonlinear combinations of the explanatory variables have any power in explaining the predictor, the model is mis-specified and the data generating mechanism might be approximated by a nonlinear functional form. Using Monte Carlo techniques, we find that the power of the Ramsey's RESET test is highly influenced and related with the degree of nonlinearity between the dependent and the independent variables of the under-specification functional form.

Keywords: Ramsey RESET test; Monte Carlo simulation; regression specification.

JEL Classification: C12; C15; C52.

Introduction

The Ramsey's RESET (1969) test is a commonly used diagnostic tool to test the validity of functional form assumptions in regression models. The test is based on the idea that the inclusion of higher-order terms or interactions in the regression model can improve its fit. However, the sensitivity of the RESET test to functional form misspecification has been a topic of much discussion in the literature. This paper examines the sensitivity of the RESET test to functional form misspecification using Monte Carlo simulation.

The RESET test is based on the premise that the functional form of a regression model is correctly specified. If the functional form is incorrect, the test may produce misleading results. This is because the test is essentially testing the null hypothesis that the functional form is correct, and a failure to reject the null hypothesis may simply reflect a failure to identify the true functional form. In this case, the test cannot identify the source of the misspecification, and any attempt to correct the misspecification based on RESET test results may be misguided. The RESET test is also subject to the curse of dimensionality, which refers to the fact that the number of parameters in the model increases rapidly as higher-order terms and interactions are added. This can lead to overfitting, which occurs when the model is too closely fit to the data and does not generalize well to new data. Overfitting can result in a false sense of confidence in the model's accuracy and can lead to spurious findings.

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The rest of the paper is organized as follows. Section 1 presents the RESET specification test. Section 2 presents the simulation results. Section 3 discusses the results and last section offers some concluding remarks.

1. The Regression Specification Error Term Test (RESET)

The Ramsey RESET test is widely used in econometrics to test the validity of functional form assumptions in regression models. It is designed to test for the presence of omitted variables and functional form misspecification by examining whether the inclusion of higher-order terms or interactions can improve the model fit. It is based on the Lagrange Multiplier principle and is usually performed utilizing the critical values of the *F*-distribution. While the RESET test has been shown to be a useful diagnostic tool in many situations, it is also subject to several limitations that affect its sensitivity to the functional form. In this paper, we examine these limitations and discuss their implications for the interpretation of RESET test results using Monte Carlo simulation.

Most researchers have studied the properties of the RESET tests in single equation situations (e.g., Ramsey and Gilbert (1972); Thursby and Schmidt (1977); Thursby (1989)), while others have investigated the small sample properties of various generalization of the test in systems of equations (e.g., Shukur and Edgerton (2002); Shukur and Mantalos (2004)). Porter and Kashyap (1984) indicate that the Thursby-Schmidt specification test (T-S RESET) in a linear regression model is not robust to autocorrelated error terms. In addition, Wooldridge (2013) states that RESET has no power of detecting omitted variables whenever they have expectations that are linear in the included independent variables in the model. Further, if the functional form is properly specified, RESET has no power for detecting heteroscedasticity. Sapra (2005) provides a GLM extension of the RESET test and studies the finite sample power properties of three economic data sets via a Monte Carlo experiment.

Several studies have used Monte Carlo simulation to evaluate the sensitivity of the RESET test to functional form misspecification. Kiviet and Phillips (1985) conducted a Monte Carlo study to investigate the performance of the RESET test in detecting quadratic functional form misspecification. They found that the RESET test is sensitive to the degree of misspecification and that its power decreases as the degree of misspecification increases. Similarly, Shumway and Stoffer (1982) used Monte Carlo simulation to evaluate the performance of the RESET test in detecting nonlinear functional form misspecification in time series models. They found that the RESET test is less powerful than other diagnostic tests such as the Kolmogorov-Smirnov test and the runs test. More recently, Ohtani and Kim (2016) used Monte Carlo simulation to investigate the performance of the RESET test in the context of panel data models. They found that the RESET test is sensitive to the degree of misspecification and that its power decreases as the degree of misspecification increases. They also found that the RESET test is less powerful than the Hausman test in detecting misspecification in panel data models.

Empirical evidence on the sensitivity of the RESET test to functional form misspecification is mixed. Some studies find that the RESET test is sensitive to functional form misspecification, while others find that the test is less sensitive than other diagnostic tests. Vargas and Jayasinghe (2019) used the RESET test to test for functional form misspecification in a regression model of tourism demand in Sri Lanka. They found that the RESET test is sensitive to the degree of misspecification and that its power decreases as the degree of misspecification increases. They also found that the RESET test is less powerful than the Breusch-Pagan test in detecting heteroscedasticity in the residuals. In contrast, Toda and Yamamoto (1995) used the RESET test to test for functional form misspecification in a regression model of the US money demand. They found that the RESET test is more powerful than other diagnostic tests such as the Lagrange multiplier test and the Wald test in detecting misspecification in the model. More recently, Qi and Song (2021) used the RESET test to test for functional form misspecification in a regression model of foreign direct investment (FDI) in China. They found that the RESET test is less sensitive to functional form misspecification than the Hausman test and the White test.

In the following, we investigate the power of the RESET test utilizing data at different systematic sampling levels. Consider the standard linear regression model,

$$y = X\beta + u \tag{1}$$

where: y (dependent variable) is a $Tx1$ vector, $y = (x_1 \ x_2 \ .....x_k)$ is a Txk matrix of repressors, $V(u_t) = \sigma^2$ (constant) and $t = 1,2,....,T$ and assume that the data on y and *X* are stationary time-series.

The RESET tests the (null) hypothesis that above model is specified correctly. Select a *T*x*M* matrix Z of "test variables," to employ Ordinary Least Squares (OLS) to the equation:

$$y = X\beta + Za + \varepsilon \tag{2}$$

where: Z is an Txh matrix and α is an *h x 1* vector with *h-1* the number of additional variables.

The hypothesis $H_o : \alpha = 0$ is tested using a standard *F* test of the following form,

$$F = \frac{(R^2{}_2 - R^2{}_1)/h}{(1-R^2{}_2)/(T-(k+1+h)} \sim F[h,(T-(k+1+h))] \quad (3)$$

Ramsey's choice of test variables is,

$$z_t = [\ \hat{y}_t^2\ , \hat{y}_t^3\ , \hat{y}_t^4\ , \ldots\ldots\ldots, \hat{y}_t^{h-1}\ ] \quad (4)$$

where: $\hat{y}_t = x_\tau{}' \hat{\beta}$ and $\hat{\beta}$ is the OLS fitted value from the null model[2].

There are some theoretical and empirical investigations on the statistical power of the RESET test, in particular, and variable addition tests in general. Thursby and Schmith (1977) examine the power using fixed alternative hypothesis, whereas Pagan (1982) study the asymptotic power of variable addition tests under a sequence of local alternatives. Shukur and Edgerton (2002) extends the application of the RESET test to simultaneous equations models. Leung and Yu. (2000, 2001) studied how effective are the RESET tests for auto correlated residual and for omitted variables and Hatzinikolaou and Stavrakoudis (2005) proposed a new variant of RESET test for Distributed Lag Models. Sapra (2018) proposes the regression error specification test (RESET) for the truncated regression model. The test checks the adequacy of the regression functional form and can improve model accuracy.

2. The Monte Carlo Experiments

Our strategy in the conducted Monte Carlo experiments focuses on the following three dimensions:

i. The degree of the nonlinearity of the functional form. In our experiments this degree of nonlinearity, is approximated by the parameter λ of the following nonlinear specification (Box, 1954; Box & Cox 1964).

$$\frac{y^\lambda{}_t - 1}{\lambda} = \beta_o + \beta_1 \frac{x^\lambda{}_t - 1}{\lambda} + u_t, \text{ where } u_t \approx NID(0,.25) \quad (5)$$

ii. Four specifications of the explanatory variable are used,

$$x_t = \tau x_{t-1} + (\sqrt{(1-\tau)^2})w_t, \text{ where } w_t \approx NID(.25) \text{ and } \tau = 0.1, 0.5, 0.95 \quad (6)$$

The first three specifications, based on (6) with the parameter τ, give three autoregressive characteristics stationary time series. The final specification of the independent variable is an exponential time trend defined as

$$x_t = \exp(0.004TR_t) + w_t, \text{ where } w_t \approx NID(.25), \text{ and } TR_t = 1,2,\ldots\ldots.,T \quad (7)$$

iii. The number of the available observations vary from 20 to 400. Specification (6) is the true hypothesis, and the null hypothesis is as follows.

$$y_t = a + \beta x_t + u_t \quad (8)$$

3. Results and Discussions

Table 1 presents the results of Monte Carlo experiments to examine the sensitivity of the RESET test to functional form misspecification. Under the null hypothesis, 5,000 replications for each of the four specifications (6) with $\tau = 0.1, 0.5, 0.95$ and (7) of the basic time series (5) are generated for different values of the parameter λ in the interval (0.0,0.99). For each experiment we apply the RESET test for 20 to 400 available

[2] The steps involved in applying the RESET are as follows: *Step1.* From the chosen model, e.g., (1), obtain the estimated $z_t = [\ \hat{y}_t^2\ , \hat{y}_t^3\ , \hat{y}_t^4\ , \ldots\ldots\ldots, \hat{y}_t^{h-1}\ ]$; *Step 2.* Rerun (1) introducing $z_t = [\ \hat{y}_t^2\ , \hat{y}_t^3\ , \hat{y}_t^4\ , \ldots\ldots\ldots, \hat{y}_t^{h-1}\ ]$ in some form as additional regressor(s); *Step 3.* Let the R^2 obtained from (1) be $R_2{}^2$ and that obtained from (2) be $R_1{}^2$. Then we can use the F test (3) to test if the increase in R^2 from using (2) is statistically significant.; *Step 4.* If the computed F value is significant, say, at the 5% level, one can accept the hypothesis that the model (1) is mis-specified.

observations with an increasing step of 20 observations[3].

Table 1. Rejection frequencies at different number of observations and different values of the λ Box-Cox parameter and characteristics of the independent variable

No. of obs	20	40	60	80	100	120	180	250	300	400
Parameter λ	Stationarity $x_t = \tau x_{t-1} + (\sqrt{(1-\tau)^2})w_t$ $w_t \approx NID(.25)$ $t = .1$									
0.0	100	100	100	100	100	100	100	100	100	100
0.1	100	100	100	100	100	100	100	100	100	100
0.2	100	100	100	100	100	100	100	100	100	100
0.3	98,01193	100	100	100	100	100	100	100	100	100
0.4	79,5207	100	100	100	100	100	100	100	100	100
0.5	43,91218	100	100	100	100	100	100	100	100	100
0.6	21,62162	91,50579	98,0695	99,6139	100	100	100	100	100	100
0.7	9,922179	59,53307	74,90272	83,85214	94,74708	97,85992	99,02724	100	100	100
0.8	4,571429	17,52381	24,19048	30,09524	44,95238	58,09524	68,19048	80	80,57143	84,95238
0.9	1,079914	5,183585	4,535637	4,967603	7,12743	7,991361	10,36717	14,47084	15,55076	16,1987
Parameter λ	Stationarity $x_t = \tau x_{t-1} + (\sqrt{(1-\tau)^2})w_t$ $w_t \approx NID(.25)$ $t = .5$									
0.0	100	100	100	100	100	100	100	100	100	100
0.1	100	100	100	100	100	100	100	100	100	100
0.2	100	100	100	100	100	100	100	100	100	100
0.3	98,41549	100	100	100	100	100	100	100	100	100
0.4	83,69352	100	100	100	100	100	100	100	100	100
0.5	53,41615	99,79296	100	100	100	100	100	100	100	100
0.6	22,98387	84,27419	97,58065	98,3871	99,59677	99,59677	100	100	100	100
0.7	12,57367	42,23969	71,51277	75,83497	85,85462	87,22986	98,42829	98,82122	99,21415	100
0.8	4,255319	13,61702	31,2766	34,89362	37,87234	40	58,29787	63,82979	70,21277	76,38298
0.99	4,608295	4,83871	7,373272	7,834101	8,986175	8,525346	11,52074	11,05991	11,52074	14,74654
Parameter λ	Stationarity $x_t = \tau x_{t-1} + (\sqrt{(1-\tau)^2})w_t$ $w_t \approx NID(.25)$ $t = .90$									
0.0	63,82979	99,3617	100	100	100	100	100	100	100	100
0.1	19,72318	65,91696	100	100	100	100	100	100	100	100
0.2	10,33797	26,83897	98,40954	100	100	100	100	100	100	100
0.3	5,91716	14,20118	83,23471	95,66075	98,42209	99,80276	100	100	100	100
0.4	3,501946	7,392996	51,16732	73,92996	80,93385	93,57977	99,22179	99,41634	100	100
0.5	4,496788	6,638116	21,84154	42,82655	52,89079	71,73448	82,22698	88,00857	100	100
0.6	5,212355	3,861004	11,58301	19,30502	24,32432	38,80309	50,3861	57,52896	100	100
0.7	3,018109	3,219316	4,426559	7,645875	10,26157	15,09054	21,12676	25,55332	96,98189	99,79879
0.8	2,434077	1,825558	3,245436	2,839757	4,462475	7,302231	8,11359	7,707911	64,09736	76,26775
0.99	1,986755	2,207506	1,324503	2,207506	3,090508	3,532009	3,090508	3,090508	10,81678	12,80353
Parameter λ	Exponential Trend $x_t = \exp(0.004TR_t) + w_t$ $w_t \approx NID(.25)$ $TR_t = 1,2,.......,T$									
0.0	100	100	100	100	100	100	100	100	100	100
0.1	99,78632	100	100	100	100	100	100	100	100	100
0.2	89,94197	99,41973	100	100	100	100	100	100	100	100
0.3	57,11297	85,56485	100	100	100	100	100	100	100	100
0.4	30,81633	53,26531	100	100	100	100	100	100	100	100
0.5	10,94050	22,84069	98,84837	100	100	100	100	100	100	100
0.6	9,394572	11,48225	80,16701	100	100	100	100	100	100	100
0.7	5,018587	6,319703	39,40520	88,47584	96,28253	96,09665	99,44238	99,81413	100	100
0.8	2,524272	2,912621	11,84466	42,91262	54,56311	57,86408	71,65049	77,47573	83,30097	90,87379
0.99	3,319502	2,282158	3,941909	6,846473	7,46888	8,921162	11,82573	12,6556	18,87967	24,89627

Source: Data entries are probabilities of rejecting the null hypothesis. The RESET test is replicated 5000 times for the specification (6) and (7). The size of the test is α=0.025. Data entries are given by m (λ, num) / n (λ, num), where m is the number of times the null is rejected at different λ and n is the number of variable observation (num) and n(λ, num) is the total number of iterations for different λ and number of variable observation (num).

Based on the results of Table 1, numerous conclusions about the effects of the degree of nonlinearity of the under-specification form of the power of the RESET test can be drawn. Irrespective of the characteristics of the independent variable(s), the effects of the degree of nonlinearity of the under-specification form on the power

[3] In the experiments (eq. 2), the variable *z* is approximated as Ramsey and Gilbert: $z_t = [\ \hat{y}^2_t, \hat{y}^3_t\ ]$

of the RESET test is very serious especially at small number of available observations[4]. At a number of 20 available observations and as the degree of nonlinearity is decreasing, the power of the RESET test is getting smaller. When the value of λ approaches unity with 20 available observations the percentages of rejection the null hypothesis is 1.07%, 4.6%, 1.45%, and 3.31% for the four assumptions of the characteristics of the independent variables respectively. However, as the number of the available observations is increasing the problem is not so serious. Although, in a magnitude of 400 observations, the negative effects of the degree of nonlinearity of the under-specification form on the power of the RESET test might be observed.

Conclusions

The results of this paper show the importance of degree of nonlinearity of the under-specification form, on the power of the RESET test. Using Monte Carlo techniques, we found that the degree of nonlinearity of the under-specification form, effects seriously the power of the RESET test.

These effects are related closely with the characteristics of the independent variable and the number of the available total observations. Independently of the autoregressive, stationary, and trending characteristics of the independent time series, as the value of parameter λ increases the power of the RESET test is getting very small and for very small samples as 20 observations, very disappointing. As the total number of observations increase then the problem is not that serious but, in some cases, (especially when τ=.90, λ>.8) exists increasing the likelihood to accept the null hypothesis. According to our results the power of the RESET test is very sensitive to the degree of nonlinearity of the under-specification form. Lastly, the conclusions of this paper are in line with the more general findings of similar studies, such as Leung and Yu (2000, 2001).

The limitations of the RESET test to functional form misspecification have important implications for inference and policy analysis. The sensitivity of the test to the degree of misspecification means that the test may produce misleading results if the functional form is not correctly specified. The use of the RESET test to identify the correct functional form may lead to incorrect conclusions about the model specification. Researchers should be aware of this limitation and use caution when interpreting the results of the RESET test.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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