PREDICTIVE RESIDUAL SUM OF SQUARES COMPARED WITH J AND JA IN NONNESTED HYPOTHESIS TESTING

A THESIS PRESENTED BY

YENER KANDOĞAN

TO

THE INSTITUTE OF ECONOMICS

AND

SOCIAL SCIENCES

IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS

FOR THE DEGREE OF

MASTER OF ECONOMICS

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I certify that I have read this thesis and in my opinion it is fully adequate in scope and in quality, as a thesis for the degree of Master of Economics.

Prof. Dr. Asad Zaman

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ABSTRACT

PREDICTIVE RESIDUAL SUM OF SQUARES
COMPARED WITH J AND JA
IN NONNESTED HYPOTHESIS TESTING

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MASTER OF ECONOMICS
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May 1996

In nonnested hypothesis testing, J test suggested by Davidson and MacKinnon (1981) and JA test suggested by Fisher and McAleer (1981) are two common tests used to evaluate hypotheses. In this thesis, we first give the necessary background for J and JA tests in nonnested hypothesis testing and the literature survey on these issues. We then compare the performances of J and JA tests with Predictive Residual Sum of Squares method. Monte Carlo experiments are carried out to compare these tests in testing Quadratic versus Leontieff models and also Linear versus Log-Linear models, where we find that Predictive Residual Sum of Squares method has superiority over the other tests mentioned in terms of power. In the end, a real case study testing different consumption function theories for 1987-1995 period in Turkey is presented.

Key Words: Predictive Residual Sum of Squares, J test, JA test, nonnested hypothesis testing

ÖZET

İÇİÇE GEÇMEMİŞ HİPOTEZ TESTİNDE TAHMİNİ HATA KARELERİNİN TOPLAMI METODUNUN J VE JA TESTLERİ İLE KARŞILAŞTIRILMASI

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İçiçe geçmemiş hipotez testinde Davidson ve MacKinnon (1981) tarafından önerilen J testi ve Fisher ve McAleer (1981) tarafından önerilen JA testi sık kullanılan iki testtir. Bu tezde ilk önce içiçe geçmemiş hipotez testinde kullanılan J ve JA testi için genel bilgi ve bu konularda yapmış olduğumuz yayın araştırması veriliyor. Sonra J ve JA testlerinin performansını tahmini hata karelerinin toplamı metodunkiyle karşılaştırılıyor. İkinci dereceden modellerin Leontieff modeliyle, Logaritmik modellerin Lineer modellerle test edilmesinde Monte Carlo deneylerini kullanarak bu test teknikleri karşılaştırıldı. Bu deneyler sonucunda tahmini hata karelerinin toplamı metodunun diğer testler karşısında güç bakımından üstün olduğu bulundu. Son olarak gerçek verileri kullanarak 1987-1995 dönemi Türkiyesi için değişik tüketim fonksiyonları teorileri test edildi.

Anahtar Sözcükler: Tahmini Hata Karelerinin Toplamı, J testi, JA testi, İçiçe Geçmemiş Hipotez Testi

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CONTENTS

1. Why Comparing Models ?

Econometricians build models for two main purposes: estimation and inference. In such practices, a linear statistical model with parameters is generally assumed. This approach is consistent with the sampling process, by which the observations are drawn. Every applied econometrician has had the experience of estimating a regression model which at first glance, seemed to be satisfactory, but later turned out to be invalid. In practice, true statistical models are very rare. The nature of economic data makes this situation inevitable. The right-hand side variables, that is, the explanatory variables are usually collinear. This is because of time-series data exhibiting the same trends, the same business cycles.

Then, a reasonable judgment is that most of the statistical models used by economists so far are invalid. This fact casts doubt upon the estimations and inferences that are being built on them. But, first the roots of the problem must be identified. What are the sources of misspecification yielding such judgment? How can they be detected? What are the ways of avoiding them? Actually, there are many reasons causing model misspecification. Omission of a relevant explanatory variable or misinclusion of some explanatory variables are two most likely reasons for model misspecification. To detect and avoid such defects, some variable selection procedures that includes both discrimination among nested alternative models and testing of separate (nonnested) models are developed to solve model misspecification problems.

At this point, a differentiation between nested and nonnested models needs to be done. Two statistical models are nested when one of them is a special case of the other, with some parameter restrictions. For example, Cobb-Douglas production function is nested within Constant Elasticity of Substitution (C.E.S.) production function. Cobb-Douglas production function is a special case of Constant Elasticity of Substitution production function, obtained with some parameter restrictions. C.E.S. production function with unity elasticity of substitution reduces to a Cobb-Douglas production function. Two models are said to be nonnested when one of them can not be expressed as a special case of the other. Linear versus log-linear statistical models constitutes an example of two nonnested models. Here, log-linear statistical models are actually multiplicative models or exponential models, linearized by taking logarithm of both sides. Clearly, linear models can not be obtained from log-linear models merely by some parameter restrictions.

Model misspecification, or rather, selection of a statistical model and nonexperimental model building are very old problems in econometrics. Many research efforts have been devoted in this area. As a result of these researches many criteria, testing mechanisms, search processes and empirical rules came out to help the economists in selecting appropriate statistical models. These procedures and rules are discussed in recent articles or books of Gaver and Geisel (1974), Hocking (1976), Thompson (1978), Leamer (1978), Amemiya (1980), Maddala (1981), White (1982,1983), MacKinnon (1983), Sawyer (1980), McAleer (1984) and Doran (1993) among others.

In this literature, some criteria and rules are suggested in adjusting a design matrix, more explicitly, in deleting or adding explanatory variables. In this framework, it is usual to appeal to economic theory for guidance in specifying econometric models. So, in all of these studies main emphasis is made on the importance of economic theory in forming explanatory variables matrix.

Economic theory helps a lot in narrowing the range of explanatory variables as well as in determining possible functional forms. It has much to offer the researcher in describing which economic variables should be considered and the direction of possible relationships between the variables. But theory rarely suggests one model to explain a particular phenomenon. Often there are rival theories, and even when there are not, a single theory may be compatible with several functional forms, or some handful of stochastic specifications. Besides, unfortunately, economic theory, treating most variables symmetrically, is of little help when the researcher is at the stage of quantitative analysis, where the appropriate functional form should be specified. When faced with several competing regression models, it is simply necessary to choose the model which is best. In order to do this an applied econometrician would use a model selection criterion. Of course, the econometrician usually does not know whether any of the competing models could conceivably be true. So, specification of each of the available models should be tested. Tests for heteroskedasticity, serial correlation, parameter stability and other criteria play important roles in this context. But, it should be noted that the tests mentioned above do not make use of the information that the model tested is only one of the several models to explain a certain phenomenon. Some of the rules or criteria in selecting between nested statistical models are:

-Orthodox (Classical) Hypothesis Testing Framework: F test, Mean Square Error Norm test,

-Residual Sum of Squares Rules: Coefficient of Determination: R^2, Adjusted Coefficient of Determination: $\bar{R}^2$, Amemiya's Unconditional Mean Square Error Criterion: PC, Mallows Conditional Mean Square Error Prediction Criterion C_p,

-Information Criteria: Akaike Information Criterion AIC, Sawa's Criterion BIC, Schwarz Criterion SC, Chow Criterion are some examples. The fundamental notion in this approach is the following. The information criterion seeks to incorporate in model selection the divergent considerations of accuracy of estimation and the best approximation to reality. Thus, use of this criterion involves a statistic that incorporates a measure of the precision of the estimated a measure of the rule of parsimony in the parametrization of an econometric model. In this context, the adequacy of an approximation to the true distribution of a random variable is measured by the distance between model of reality and the true distribution.

-Bayes Criteria: Jeffreys-Bayes Posterior Odds Ratio is an example for this approach. Gaver and Geisel (1974) developed a framework for using the posterior odds ratio and a basis for discriminating among models. Fundamentally, the posterior odds ratio depends on the prior odds ratio, the compatibility of the prior distributions and the maximum likelihood estimates. This criterion makes use of a ratio of the determinants of the two design matrices and a ratio of likelihoods. Consequently, a goodness of fit consideration results.

-Stein Rules: Basically, including some extraneous variables in the design matrix or excluding any of the important explanatory variables from the design matrix conditions the precision and the bias, with which the coefficients of explanatory variables are estimated. In bias-variance choice within Stein rule context, the data are used to determine the compromise between bias and variance and the appropriate dimension of the design matrix.

2. Comparing Nonnested Statistical Models

The primary concern of this thesis is the comparison of nonnested models. Cox, Atkinson, Quandt, Pesaran and Deaton, Davidson and MacKinnon, Fisher and McAleer worked on this area and they developed some tests, which are variants of likelihood ratio test. The initial work in this subject is done by Cox (1961). Then, Pesaran (1974) extended the researches by Cox to include the regression model and concentrated on the autocorrelated disturbance case. Thereafter, Pesaran with Deaton (1978) extended his early results so that there is no need for the assumption of linearity in the models. So, testing of competing nonlinear models can also be done. Afterwards, Atkinson (1970) suggested a procedure that combines the nonnested models into a general model, which constituted an important pace in nonnested hypothesis testing. Dastoor (1983) noted an inequality between Cox and Atkinson statistics. Fisher and McAleer (1981) modified the Cox test for linear regressions. In the mean time, Davidson and MacKinnon (1981) suggested processes for model specification testing, known as J test, which are linearized versions of Cox test. These are closely related to the nonnested model testing of Pesaran and Deaton (1978), named as JA test.

There are many cases in applied econometrics, where there is a need for testing nonnested hypotheses. At this point, let's clarify a point. Since to each hypothesis, there corresponds a unique model, the terms hypothesis and model will be used synonymously. In nonnested hypothesis situations, one model can not be obtained from the other model by simply imposing some restrictions or by making some approximations. But what are the situations that nonnested hypothesis testing will be needed? The following are some instances faced in applied econometrics, where nonnested models are appropriate:

-Functional Form Differences: In general, models with different functional forms can not be nested. Quadratic and Leontieff production functions provide an example to this case.

-Variable Definition Differences: For example, models may use different definitions for expected price or interest rate.

-Different Theories: In consumption function, models of different theories are examples for this case. Absolute Income Hypothesis, Relative Income Hypothesis, Permanent Income Hypothesis, Life-Cycle Hypothesis can be tested using nonnested hypothesis tests.

-Linear and Log-linear Models: Testing Cobb-Douglas production functions with additive or multiplicative error terms is an example for this case.

Despite many possible situations as above, Is nonnested hypothesis testing widely used in practical applications? In agricultural economics literature, for instance there are many applications, where one should include nonnested hypothesis testing as part of the general specification testing program, but it is not usually considered. American Journal of Agricultural Economics (1990-1991 issues) state out some important observations from applied research:

-Without any theoretical justification models are usually used in log-linear form,

-A comparison between models with same dependent variables and different explanatory variables is usually made,

-Hypotheses with different functional forms are compared in an ad-hoc way.

Until recently, a misleading approach was subject to nonnested models. In this approach the primary emphasis was on discrimination rather than testing. That is a very deceptive point of view. Basically, model selection criteria are appropriate when one wishes to choose one out of a group of competing models. Here, the objective is to choose the best model, by explicitly trading of fit and parsimony in parametrization. Within that framework a best model was chosen depending on its performance or sample explanation. R^2, $\bar{R}^2$ and Akaike Information Criterion were mainly used for this purpose.

But, actually there are two fundamental differences between discrimination and testing. Since one best model is sought, the discrimination process will always lead to choosing a model. In testing framework, however, all of the models can be rejected as inadequate to explain the variations in the dependent variable. Also, in testing framework probabilities are attached to the misrejection of null hypothesis, whereas, in discrimination process, even though such probabilities exist, they are difficult to obtain.

On the other hand, nonnested hypothesis tests are tests of model specification. The only important difference between nonnested hypothesis tests and more classical procedures is that they rely on the existence of nonnested alternative models. Orthodox tests, in this respect ignore the availability of a nonnested alternative hypothesis. The results of applying such tests to two competing models may be that one model can be rejected while the other can not, but it may just, as well, be that both of the models , or neither model can be rejected. Thus testing each model against the evidence provided by the other can not allow the researcher to choose one of the competing models. What it can do is to provide evidence that one of the models or both of the models are misspecified.

It must again be stressed that, nonnested model tests are specification tests. They make use of alternative models. Using the information about the alternative, they test whether the null can correctly predict the performance of the alternative. In nonnested hypothesis case, there is a data system and a system of alternative models. Since alternative models are nonnested, they are unranked as to generality, in contrast to nested models. Nested models can be ranked among themselves, by the number of additional explanatory variables added to a core model. In nonnested case, each of the models is considered equally likely. Separate tests of each pair of hypotheses is made. In each case, a check is made to see whether the performance of one model is consistent with the truth of the other model. This process is repeated for the truth of each available model. It is clear that in comparing two nonnested models, four outcomes are possible:

-Both of the hypotheses are rejected as inadequate,

-The first model is accepted and the second is rejected as inadequate,

-The second model is accepted and the first is rejected as inadequate,

-Both models are accepted.

Note that, the Discrimination Criteria should be used only with the last outcome, where both models are considered as adequate.

3. Preliminaries for J and JA tests

Suppose that we have two competing hypotheses H0 and H1 about a dependent variable y. Suppose further that the true data generating process of y is also known. For clarity, lets assume data generating process to be:

H_0: $y=X_0B_0 + u_0$ where $u_0 \sim N(0,\sigma_0^2 I_t)$

Let the alternative model be of the form:

H_1: $y=X_1B_1 + u_1$ where $u_1 \sim N(0,\sigma_1^2 I_t)$

The parameters B_0 and σ_0^2 are known and the parameters B_1 and, σ_1^2 have to be estimated. Here, the estimated, σ_1^2 is taken as a measure of model performance. The ability to predict model performance according to the data generating process of the dependent variable is a major concept in nonnested model testing, which is first used by Cox (1961). In the test for nonnested models implemented by Cox, a variant of Neyman-Pearson likelihood ratio test which compares the value of this test statistic with its expected value is used. The basic idea of this procedure is that one may test the validity of a null hypothesis about how a data set was generated, by comparing the observed ratio of the values of the likelihood functions for the null hypothesis and for some nonnested alternative hypothesis with an estimate of the expected value of this likelihood ratio if null hypothesis were true. If alternative hypothesis fits either better or worse than it should if null hypothesis were true, then null hypothesis must be false. Cox considered the asymptotic distribution of a function of the generalized log likelihood ratio, in his procedure.

For the case where the data generating function of y is not known, the method is similar, but with slight differences. In short, this procedure for this case works as follows: First one of the models is assumed to be the data generating process and the performance of the other model is predicted on the basis of first model. If the actual performance of the estimated, σ_1^2 is close to its predicted performance, a confirmation of the first model can be made. In contrast, if the actual performance of the estimated, σ_1^2 is not close to its predicted performance, the first model will be rejected as inadequate. In determining the closeness of estimated performance to its predicted performance, significance level method is applied. A significant value for the test statistic suggests rejecting the first model. Here, it is crucial to note that rejecting the first hypothesis has no implications whatsoever on the adequacy of the other model.

So, in summary, two tests will be performed, where each model will have a chance of being assumed to be the data generating process. The outcome of these tests will determine whether the data is:

-consistent with the first model,

-consistent with the second model,

-consistent with neither models,

-consistent with both models.

As previously noted, when two models are tested against each other, there are four (even nine) possible outcomes (nine outcomes if one distinguishes between rejection in the direction of alternative model and rejection in the opposite direction). Therefore, interpreting the results of such a pair of tests may seem complicated. For a detailed discussion on this matter see Fisher and McAleer (1979). However, for practical purposes interpretation of results is not particularly difficult. If none of the models is rejected, the data does not allow us to say that either is false. If one model is rejected and the other is not, then the set of models that are worth further examination has been reduced in size. This is a quite useful outcome for practical purposes. At this point, it should be remembered that there may be many nonnested alternative models. Furthermore, if both models are rejected , then the set of models has been reduced in size even more. Indeed, if there are no models around, the applied econometrician should presumably invent some. In this particular situation, the signs of the test statistics may be useful. This is because, in such a case, the sign of tests statistics will tell us whether one should look for a model that combines features of both models rejected, or for a model that moves away from one of the models.

Furthermore, there is also another important remark that should be made. One should note that in the case of nonnested models, there are many alternative hypotheses. Therefore, rejecting one of the models as null hypothesis does not necessarily imply that the other model is acceptable.

Now, it is time to set out an important preliminary concept in J and JA tests: A convenient way of comparing nonnested models is to add another explanatory variable to the model being tested and examine the associated t-statistic. As noted earlier, the rejection of the first model does not imply anything about the adequacy of the other model, even if the added variable is derived from the other model. Then, the only implication of this is that the augmenting variable is correlated with the variable(s), which are incorrectly omitted from the first model. In this testing procedure the model is tested against a nonnested alternative. Since each of the models is drawn from the economic theory, there is good reason to believe that the augmenting variable is highly correlated with the incorrectly omitted variables in the first model.

4. J and JA tests

J test is a linear version of the test proposed by Cox. It has been suggested by Davidson and MacKinnon (1981). Lets assume two competing hypotheses:

H_0: $y=X_0B_0 + u_0$ where $u_0 \sim N(0,\sigma_0^2 I_t)$

H_1: $y=X_1B_1 + u_1$ where $u_1 \sim N(0,\sigma_1^2 I_t)$

Assume that X_0 and X_1 are independent. An immediate way of testing these models is to combine them in a composite form given as:

H_c: $y=X_0B_0 + X_1B_1 + u$

Then, an F test carried out to test whether $B_0=0$ or $B_1=0$ will imply H_1 or H_0 respectively. However, problems arise when power of these test is considered: If both X_0 and X_1 have large number of columns, that is, both models use numerous explanatory variables, then the degrees of freedom in the numerator of the F-statistic will be large, consequently the power will be diminished. Furthermore, if the assumption of linearly independent X_0 and X_1 is relaxed in such a way that, X_0 and X_1 are highly collinear, then multicollinearity problem will arise. Then, the power of this test will be further reduced. With such a low power this test may fail to reject none of the models even if they are both inadequate.

Davidson and MacKinnon (1981) solved these problems by considering embedding the models by a more general way: by taking the weighted average of the models using a fixing parameter L:

$y=(1-L)X_0B_0 + LX_1B_1 + u$

Davidson and MacKinnon replaced the X_1B_1 by its estimate $\tilde{y}=(I-M_1)y$, where $M_1=X_1(X_1^tX_1)^{-1} X_1^t$. Therefore, the above equation can be written as:

$y=(1-L)X_0B_0 + L\tilde{y} + u$

Since the estimate of y is asymptotically independent of the error term, Davidson and MacKinnon proposed to test if L equals to 0 to see if H_0 is true by using a likelihood ratio or even a conventional t test. They named this process as J test.

An exponential type and constant elasticity of substitution type combination of deterministic components of the regression models could also be considered. For competing linear regression models, Davidson and MacKinnon (1980) conjecture that the various combinations yield similar results, but they recommend the linear combination for its simplicity. Therefore, a choice between the numerous ways of combination of models is a topic for further research.

JA test suggested by Fisher and McAleer (1981) is in principle very similar to J test. Both J and JA tests use an artificial regression, which is obtained by augmenting the null hypothesis by a variable. This variable is obtained by some regressions using the alternative hypothesis as well. Since both of the tests are one degree of freedom tests, their power is higher than the direct composition approach considered at the beginning. Pesaran justified this case in his studies (1982).

The difference between the J test and the JA test is that the augmenting variables added to the null hypothesis are different. In J test, X_1B_1 is replaced by $(I-M_1)y$. Thus, J test requires only two regressions. However, in JA test, X_1B_1 is replaced by $(I-M_1)(I-M_0)y$. Therefore, three regressions must be carried out for JA test. But, the advantage of JA test is that when the models in consideration are linear and the disturbances are normal, this test is exact. Even with small samples, this test produces tests of correct size. However, J test is not exact in this sense. With small samples, J test may reject a true model too often. In spite of this disadvantage of J test, Monte Carlo evidence proves that J test is a more powerful procedure compared to JA test.

Let's at this point, state a deficiency of using J and JA tests. Of course, a statistical outcome could be the acceptance of the composite model. This is at the one hand and at the same time an advantage and a disadvantage of using J and JA tests. In J and JA tests, the acceptance of the composite model is not possible. Thus, on the one hand, using J and JA tests has an advantage in that the composite model itself may not be conceiveable, whence one is not forced by the data to accept an inconceivalbe proposition. On the other hand, it has a disadvantage in the case where the composite model may have some hidden meaning. For example Cox (1961) points out that the combined model may lead to an adequate representation of the data when both component hypotheses are false. That is, if the artificial model is in some sense closer to reality than either of the component models, the fact that we can not accept it is an obvious drawback of using J and JA tests as numerical methods of identification.

Although the exponential weighting of likelihood functions is naturally appealing, there are certainly other methods available for nesting alternative models within a more generally framework. This raises the interesting question of whether the concept of nonnested hypotheses is itself more than a thoroughly practical artifact. It could be argued, for example, that the reasonable competing hypotheses are just special cases of some more general system, special components of which are the individual null and alternative hypotheses. Therefore, consideration of the form of nesting of the competing hypotheses may then be as important as the actual testing procedures themselves.

We are now in a position to spell out the simple steps in J and JA tests in testing two competing linear models:

Model 0: $y=X_0B_0 + u_0$

Model 1: $y=X_1B_1 + u_1$

J test:

Null hypothesis is Model 0.

-Regress y on X_1, and get the predictions $\tilde{y}1$,

-Regress y on X_0 and $\tilde{y}1$,

-J-statistic is the t-value of the coefficient of $\tilde{y}1$.

Null hypothesis is Model 1.

-Regress y on X_0, and get the predictions $\tilde{y}0$,

-Regress y on X_1 and $\tilde{y}0$,

-J-statistic is the t-value of the coefficient of $\tilde{y}0$.

JA test:

Null hypothesis is Model 0.

-Regress y on X_0 to obtain predictions $\tilde{y}0$,

-Regress $\tilde{y}0$ on X_1 to obtain predictions $\tilde{y}o1$,

-Regress y on X_0 and $\tilde{y}o1$,

-JA-statistic is the t-value of the coefficient of $\tilde{y}o1$.

Null hypothesis is Model 1.

-Regress y on X_1 to obtain predictions $\tilde{y}1$,

-Regress $\tilde{y}1$ on X_0 to obtain predictions $\tilde{y}10$,

-Regress y on X_1 and $\tilde{y}10$,

-JA-statistic is the t-value of the coefficient of $\tilde{y}10$.

The below are the steps that must be carried out for J and JA tests in testing competing linear versus log-linear regression models, which is suggested by Bera and McAleer:

Model 0: $\log y = X_0 B0 + u_0$

Model 1: $y = X_1 B1 + u_1$

J test:

Null hypothesis is Model 0.

-Regress y on X_1, and get the predictions $\tilde{y}1$,

-Take the logarithm of $\tilde{y}1$, and get log $\tilde{y}1$,

-Regress log y on X_0 and log $\tilde{y}1$,

-J-statistic is the t-value of the coefficient of log $\tilde{y}1$.

Null hypothesis is Model 1.

-Regress log y on X_0, and get the predictions log $\tilde{y}0$,

-Take the exponential of log $\tilde{y}0$, and get $\tilde{y}0$,

- Regress y on X_1 and $\tilde{y}0$,

-J-statistic is the t-value of the coefficient of $\tilde{y}0$.

JA test:

Null hypothesis is Model 0.

-Regress log y on X_0 to obtain predictions log $\tilde{y}0$,

-Take the exponential of log $\tilde{y}0$ to get $\tilde{y}0$,

-Regress $\tilde{y}0$ on X_1 to obtain predictions $\tilde{y}01$,

-Take the logarithm of $\tilde{y}01$ to get log $\tilde{y}01$,

-Regress log y on X_0 and log $\tilde{y}01$,

-JA-statistic is the t-value of the coefficient of log $\tilde{y}01$.

Null hypothesis is Model 1.

-Regress y on X_1 to obtain predictions $\tilde{y}1$,

-Take the logarithm of $\tilde{y}1$ to get log $\tilde{y}1$,

-Regress log $\tilde{y}1$ on X_0 to obtain predictions log $\tilde{y}10$,

-Take the exponential of log $\tilde{y}10$ to get $\tilde{y}10$,

-Regress y on X_1 and $\tilde{y}10$,

-JA-statistic is the t-value of the coefficient of $\tilde{y}10$.

5. Predictive Residual Sum of Squares Method

The primary purpose of this thesis is to compare the performances of Predictive Residual Sum of Squares method with J and JA tests, in nonnested hypotheses testing. All three methods will be compared according to their power. More explicitly, they will be judged in their ability to detect the inadequacies of the models tested.

Predictive Residual Sum of Squares test, abbreviated as PRESS calculates the predictive performances of models. It has a simple procedure, but requires many regressions, as many as the number of observations. In each regression, one of the observations is omitted and regression is carried out using the remaining observations then, a linear model is fitted accordingly. Using the parameters and the coefficients of the resulting regression model, an estimate of the dependent variable is calculated. Since the actual value of the dependent variable for the omitted observation is known, using the regression results, the residual for this observation is calculated. This process is repeated for all of the observations. The squares of each residual are summed, thus, predictive residual sum of squares is obtained.

There are some problems arising in J and JA testing, which are solved with Predictive Residual Sum of Squares method. Turning now to several problems with these tests, first note that no complete ranking of the models being considered will be obtained with J and JA tests. For example, these tests may tell us to reject neither the null nor the alternative hypothesis. In this case, it is argued that the data do not reveal which model is false. However, the data can only tell us which model is in some sense more likely to be true. In this example, we would like to know which model is better and these tests, J and JA tests, do not answer this question. However, ranking is possible when predictive residual sum of squares method is used in nonnested hypothesis testing.

At the other extreme, J and JA tests might tell us to reject both the null and the alternative hypotheses. It certainly is desirable to know that both models are wrong. Yet, since all models are simplified abstractions from reality, we already know that both models are likely to be incorrect. Again, we want first to know which model is best. Second, if the best model is inadequate for our purposes, then we want to know in which direction to seek improvement. The J and JA tests do not provide such guidance, which predictive residual sum of squares method provides.

Moreover, note that J and JA tests are derived by nesting the nonnested models in some larger alternative. Since there are an infinite number of such alternative composite models, how can we be sure that they would all give the same ranking in finite samples? Is there any reason to suppose that the particular composite model advocated here is in some sense optimal or more feasible? Consequently, at best these tests may tell us that something is wrong, but not in which direction to seek improvement.

In this research, a number of models will be tested differing in functional form (Quadratic versus Leontieff). Linear versus Log-Linear formulations will also be tested. In these tests, each time, one model will be the data generating process, that is, the true model. Afterwards, the power of each testing procedure will be computed. In the end, real data will be used in comparing different theories about the consumption function. By using the Predictive Residual Sum of Squares method, J and JA tests, all theories will be tested. Thus, the most appropriate model for the time period being considered in the real data will be chosen accordingly.

6. Previous Researches on Power Comparison of Nonnested Tests

Lets at this point give a brief summary of the previous researches carried on comparison of nonnested tests regarding of their powers. Here, there is some practical ambiguity.

Pesaran (1982) made a comparison of local power of alternative tests of nonnested regression models. In this paper, he compared orthodox F test, Cox's nonnested test and Davidson and MacKinnon's J test. It is true that the Cox test will reject the null hypothesis with probability one asymptotically if the alternative hypothesis is true. Thus, the test may be said to be consistent. For proof see Pereira (1977). It is also easily established that all three procedures provide tests that have the correct size asymptotically and are consistent in the sense that the probability of rejecting the null hypothesis when a fixed alternative is true tends to unity as the sample size increases. Pesaran (1981) has shown that the F test and J test statistics will tend asymptotically to the same random variable with a non central Chi-squared distribution. However, all tests having similar asymptotic properties does not mean that these tests can be regarded as asymptotically equivalent as they may possess different asymptotic powers for local alternatives. In order to compare the asymptotic efficiency of these three tests, an examination of the local behavior of their power curve as the sample size increases is needed as pointed out by Pesaran (1982).

In Pesaran (1982), he shows that the asymptotic power of orthodox F test against local alternatives is strictly less than that of Cox's nonnested test or J test, unless the number of nonoverlapping variables of the alternative hypothesis over the null hypothesis is unity. In that case, all three test are asymptotically equivalent. The larger the number of nonoverlapping variables the more powerful the nonnested tests would be as compared to the orthodox F test, in large samples.

As previously stated, the orthodox F test and the nonnested tests (Cox and J tests) are asymptotically distributed as a non central Chi-square with the same noncentrality parameter, but with different degrees of freedom. It is this difference in the degrees of freedom of the orthodox F test on the one hand and the nonnested tests on the other that establishes the higher local power of the nonnested tests compared to F test. This result immediately follows from the property of noncentral chi-square distribution. It is shown by Das Gupta and Pearlman that the power function of noncentral chi-square test is strictly decreasing in its degrees of freedom. It is this property of non-central Chi-square distribution, with the help of which it can be concluded that nonnested hypothesis tests have higher local power compared to F test.

Complications arising from the nonnested, non linear regression case naturally lead to the use of test statistics which are large sample approximations. A difficulty with such approximations is that there usually exist many corresponding test statistics which are asymptotically equivalent. In a practical situation though, the actual calculated test statistics will differ numerically, yet all will have the same asymptotic distribution. For this reason, there is room for conflict in the inferences to be drawn from the results of the tests. In some of the nonnested cases examined by Fisher and McAleer (1981) it turns out that differences in numerical values of asymptotically equivalent tests may serve to guide the interpretation underlying the rejection of the hypothesis under test. Therefore , faced with a practical case, a careful researcher needs to carry out more than one nonnested test. Thus, he will be able to correctly interpret the results of tests.

Because of numerous alternative hypotheses, there will be practical problems in power measurements. Whether one would want to test a model against several alternative hypotheses simultaneously, in practice, is not clear. If one of the alternatives is true, then highest power will be surely achieved by testing against that hypothesis alone. On the other hand, if none of the alternatives is true, testing against several of them jointly may have higher power than testing against each of them individually.

Now comes the comparison of F test and J test in small samples. In the case of small sample sizes the Monte Carlo results of Pesaran (1928) indicate that the Cox test tend to reject the true model far more frequently than it should and that this overrejection of true model becomes increasingly more serious as the number of nonoverlapping variables is increased relative to sample size. However, as the sample size is allowed to rise it is demonstrated that the estimates of both the size and the power of Cox type nonnested tests rapidly tend towards their values predicted by the asymptotic theory. In the case of medium and large sample sizes the Cox type nonnested tests are preferable to the orthodox F test and that the superiority of Cox tests steadily increases with the number of nonoverlapping variables as predicted by the asymptotic theory.

The F test will involve as many degrees of freedom as there are columns in the design matrix of the alternative hypothesis excluding the common parameters with the null hypothesis. In contrast, the J test will involve only one degree of freedom. This difference in degrees of freedom between F and J tests suggests that the J test will have higher power compared to F test. Since the critical value of the F test statistic will be larger than that of J test statistic because there are more degrees of freedom, J test must have higher power against the alternative hypothesis. On the other hand, if both the null and the alternative hypotheses are false, the F test might well have more power than the J test.

At this point, the possibility of somewhat pathological special case should be mentioned. Let X be the design matrix consisting of the data of variables of null hypothesis excluding the common variables with the alternative hypothesis. Similarly, let Z be the design matrix consisting of the data of variables of alternative hypothesis excluding the common variables with the null hypothesis. Consequently, W will be the design matrix consisting of the data of common variables for the null and the alternative hypotheses. Suppose further that X and Z are orthogonal to each other and to W. Then it follows that the residual sum of squares will be identical, so that one degree of freedom test will not be valid, even asymptotically. In this situation, the Cox test as implemented by Pesaran and Deaton (1978) will de undefined. Thus, it can be concluded that nonnested hypothesis tests are not valid in the case of orthogonal models. All authors will have to make some regularity assumptions which rule out such possible situations. For an example, see Pesaran (1974). Of course, even in such a case, the Classical F test remains both valid and powerful.

Some research on power comparison of J and JA test is also done. Davidson, for example, carried out a Monte-Carlo study on this subject. He made his comparisons in different cases, varying the true model, alternative or null hypothesis. For the case where the null hypothesis is a linear regression model with nonstochastic regressors and normally distributed error terms, the JA test provides an exact nonnested hypothesis test as stated in MacKinnon (1983). Unfortunately, this does not mean that the other tests discussed above, which are valid only asymptotically, are obsolete. Preliminary Monte Carlo work by Davidson suggests that the JA test can be very much less powerful than the J test when neither null nor alternative hypotheses are true. Actually, in practice this situation is quite likely to occur. This is because every model is basically wrong. Models are reflections of reality. Each model usually suits to a particular case, reflecting only a part of the reality. Therefore, every model is wrong in some sense. Consequently, J test is more powerful than JA test in many situations. On the other hand, when the alternative hypothesis is true, the J and JA tests of the null hypothesis seem to be equally powerful.

The results of Fisher and McAleer (1981) and Godfrey (1982) for the JA test are also disappointing. The estimated probabilities of a Type 1 error are satisfactory but power considerations indicate that JA test is inferior to other tests when the number of nonoverlapping variables for the null hypothesis, the X matrix mentioned above, is larger than that for the alternative hypothesis, the Z matrix. Since the identity of the true model is not known in practice, this result suggests that the JA test should only be used if both models under consideration have the same number of nonoverlapping variables.

The J test of Davidson and MacKinnon (1981), although it is simple to implement, has some sort of deficiency as well. Often it has too high a significance level with very large values, for example 20% being observed. The problem of finding adjusted J test which combine the ease of calculation with good small sample performance is clearly an interesting topic for further research.

7. Data Set

The models tested are as follows: Sample size is 20.

Quadratic:

$$y = 1 + x + x^2 + e \qquad e \sim N(0,s^2);$$

Leontieff:

$$y = 1 + x + x^{1/2} + e \qquad e \sim N(0,s^2);$$

Linear:

$$y = 1 + x + e \qquad e \sim N(0,s^2);$$

Logarithmic:

$$y = 1 + \ln(x) + e \qquad e \sim N(0,s^2);$$

In testing of Quadratic versus Leontieff models, the x variable is the square of a normal random variable. This is to prevent complex numbers that will come out of square root operation in Leontieff model.

In testing of Linear versus Logarithmic models, the x variable is the exponential of a normal random variable. This is again to prevent complex numbers that will come out of natural logarithm operation in Logarithmic model.

In power calculations, after generating the data according to the above description, they are estimated by Ordinary Least Square method, and these estimated values for the coefficients and the standard errors are used in generating the true and the alternative models' data.

8. Power Comparisons

In comparing the power of each test, the following strategy will be applied.

-Using Monte-Carlo experiments, fix the probability of type 1 error at 5%. Actually for each hypothesis assumed in turn, the level of significance is a subjective decision. The optimal level of significance for such test procedures requires further research. But, for simplicity 5% significance level is adopted here.

For Predictive Residual Sum of Squares method, the PRESS values for the competing models are first computed. The ratio of PRESS for data generating process model to alternative model is taken. This ratio is compared with 1/k, where the constant k is set using Monte-Carlo experiments such that the probability of rejecting the null hypothesis, which is true, is 5%. Here, null hypothesis is accepted if k times the PRESS for it is less than the PRESS for the alternative hypothesis.

For J and JA tests, fixing the probability of type 1 error is much simpler. Since J and JA tests are actually t-statistics, 5% critical t-values is easily found by looking at statistical tables. Of course, these critical values are asymptotically exact, but the true levels are also calculated during the Monte-Carlo experiments and they are found to be close to 5%. Therefore, this approach is satisfactory.

-After fixing the probability of type 1 error at the same significance level, the power of each test become comparable. In measuring the power, the alternative hypothesis will be the true model. But in generating the dependent variable data, the alternative hypothesis is made closest to the null hypothesis. So, in order to achieve this, first, the dependent variable values are calculated according to the null hypothesis without adding any error terms. Then, a regression of the calculated dependent variable on the alternative model is carried out. Dependent variable data are generated using this regression results, i.e. using the coefficients found and by adding the error terms. As a result of this approach, the probability of accepting the null hypothesis with 5% significance level, when the alternative hypothesis is true will have the highest possible value. Thus, the power of the test will be minimized. These minimized power of tests will be compared.

By swapping the status of null and alternative hypotheses, probabilities of tests leading to a Type 2 error can be estimated by calculating the proportions of times that the tests did not reject the false model. But, it must be stressed that when models are nested this approach to find the probability of Type 2 error will yield a satisfactory indicator of power. However, for nonnested hypothesis testing a more useful concept of power is the probability of making correct decision. More explicitly by the correct decision, the probability of accepting the true model and the probability of rejecting a false model is meant. This approach is used in measuring the power of J and JA tests.

9. The Results

In the power plots, we see a clear superiority of predictive residual sum of squares method over J and JA tests.

When the standard error of the X variable is reduced, the performance of all tests become closer. But when the standard error of the x variable is increased the power of PRESS increases significantly, while the power of J and JA tests are not as high as the power of PRESS.

In Quadratic versus Leontieff hypothesis testing, at high standard error of x variable, the power of JA is higher than J, where both are lower than that of PRESS. In Linear versus Logarithmic hypothesis testing, the power of PRESS is overwhelmingly higher than those for J and JA.

Figure 1: The Power of PRESS, J and JA, when true model is Quadratic

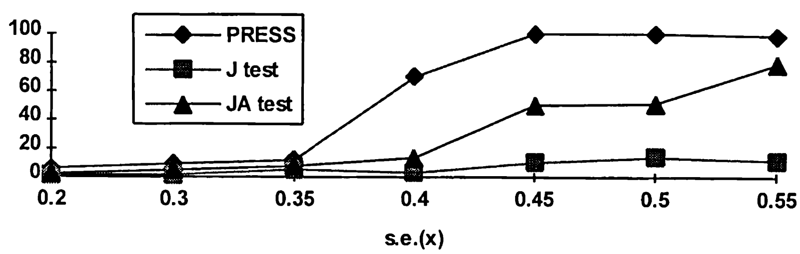


Figure 2: The Power of PRESS, J and JA, when true model is Leontieff

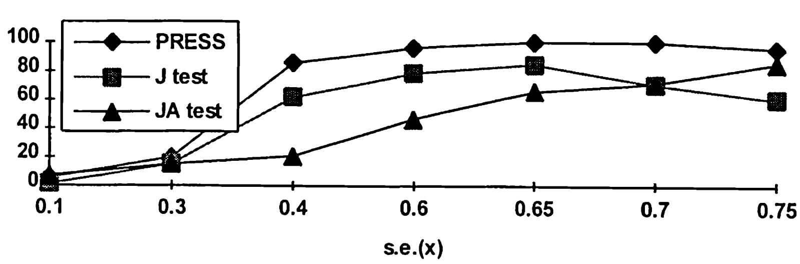


Figure 3: The Power of PRESS, J and JA, when true model is Linear

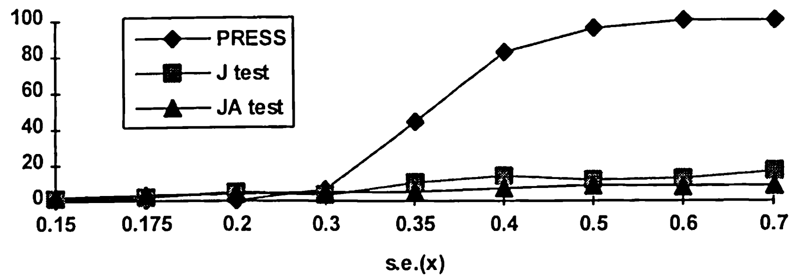
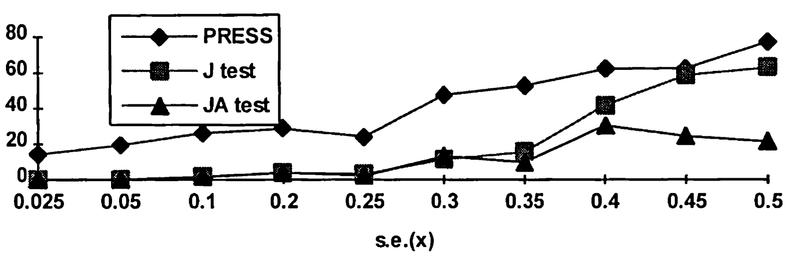


Figure 4: The Power of PRESS, J and JA, when true model is Logarithmic



The following four figures show the effect of increases in sample size on the power of tests. As the sample size increases the dominance of the PRESS test over J and JA tests is preserved; PRESS still gives the highest power in each different standard error of the X variable. It can also be observed that as the sample size increases the powers of all tests increase as each standard error of X.

Figure 5: The Power of PRESS, J and JA, when true model is Quadratic, Sample Size:20

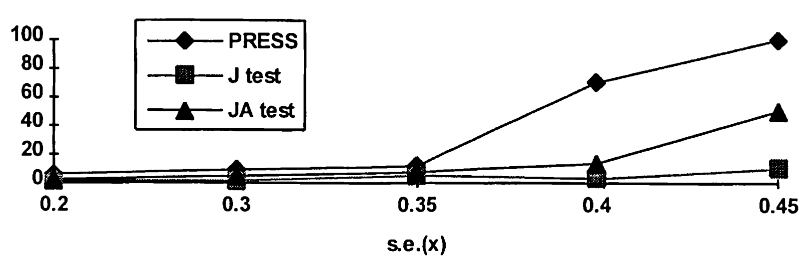


Figure 6: The Power of PRESS, J and JA, when true model is Quadratic, Sample Size:40

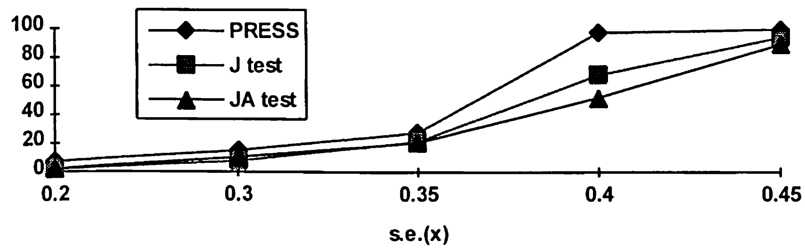


Figure 7: The Power of PRESS, J and JA, when true model is Quadratic, Sample Size:80

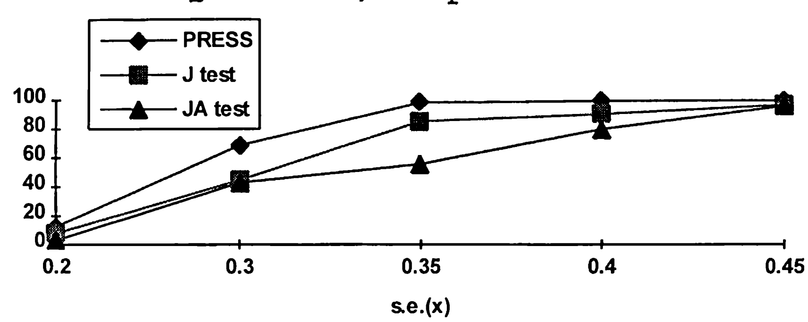
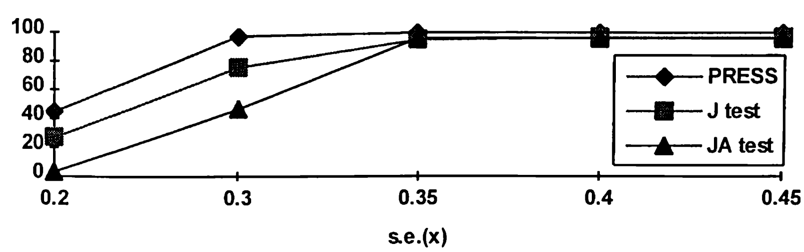


Figure 8: The Power of PRESS, J and JA, when true model is Quadratic, Sample Size:160



10. Nonnested Tests in Empirical Works

Empirical tests on nonnested hypothesis tests are very rare. Basically, nonnested hypothesis tests can be used in identifying model misspecifications. But first, let's define what a useful model is.

The followings are some conditions set by Hendry and Anderson (1977), Davidson (1978) and Hendry and Ungern-Sternberg (1981) which should be present in a useful model:

-data coherency,

-data admissibility,

-theory consistency,

-parameter constancy,

-valid conditioning,

-interpretable, parsimonious, orthogonal parameters of interest,

-encompassing contending explanations of the same phenomena.

In order to satisfy the first five conditions, the orthodox tests for autocorrelation, heteroskedasticity, parameter constancy become model selection criteria. This is because, if a model fails these tests, they are discarded immediately. There is no need for further subjecting the models to nonnested tests to detect a misspecification. Encompassing tests relieves information on how the model approximates the data mechanism. This is because, it may seem difficult to design sensible models to account for all results obtained in previous researches, whereas good approximations should be able to explain contending findings. If all contenders are nested special cases, encompassing is automatic, but if some are separate hypotheses, indirect inference is required, perhaps based on nonnested tests.

Actually, in many practical cases, a specification error that can be detected by a nonnested hypothesis test could also be detected by applying one of the many orthodox tests available for different types of model misspecification. Misspecification usually causes heteroskedasticity, serial correlation, failure of linear or nonlinear restrictions to hold, unstable parameter estimates, correlation between error terms or some other observable misbehavior of the model in consideration. These defects can be detected by classical tests. So in principle, applied econometricians may rarely need nonnested hypothesis tests to detect the above mentioned misspecified models.

However, in practice, researchers are very inclined to test their models. Every applied researcher wants to form the best model in order to explain a certain phenomenon. Anything that forces them to tests their model a bit more rigorously is therefore highly desirable. So, when a researcher decides to make use of nonnested hypothesis tests, he is forced to recognize that there are usually many models around to explain the same phenomenon and that most of these models must be false. Consequently, he is obliged to estimate several nonnested alternative models, and to give each of them several chances to show that it is not true by confronting it with the evidence provided by the available data and the other models. Doing this must increase greatly the probability that the model finally selected will not be thoroughly false. If this is the only contribution of nonnested tests, it will be a very valuable one.

An empirical work in this area is the one done by Pesaran and Deaton (1978). They estimated five models of consumption behavior and tested them against each other. In this work, the models were deliberately kept very simple for illustrative purposes. Therefore, they can not be taken seriously. They all suffer from numerous econometric problems such that they could easily be rejected by orthodox tests without any further need for nonnested hypothesis tests. One of the serious papers published in this context is the one of Deaton (1978). In this paper, two competing demand theories were tested against each other. Both models were rejected. Before 1978, some unpublished work exists, but by and large it is fair to say that the literature on nonnested hypothesis testing had no impact whatsoever on empirical works in economics. But since then, this literature is improved by the researches done in Agricultural Economics.

11. Empirical Work: Turkish Consumption Function

A. Abstract

The aim of this section is to examine the consumption behavior in Turkey, by estimating three simple forms of consumption model: Absolute Income Hypothesis model, Relative Income Hypothesis model and Permanent Income Hypothesis model.

Consumption pattern for the period 1987-1995(2) is considered. Yearly data is taken. During this period, Turkey experienced an unusual pattern of growth. The growth rate of GDP were very small in years 1988,1989,1991 very large in 1990, 1992, 1993 and 1995 and negative very large in 1994. The high growth rate in population also critically affect the consumption pattern in Turkey. The growth in private consumption over this period was always less than the growth in disposable income, but followed the pattern closely at each year. These suggest that Turkish consumers' behavior fits better to absolute income hypothesis or relative income hypothesis, but Turkish consumers do not have a lifetime pattern of consumption as suggested by Permanent Income hypothesis.

B. Theoretical Framework

Absolute Income Hypothesis

This hypothesis is Keynes' contribution to consumption theory. It is a simple observation that consumption increases with income and that marginal propensity to consume is less than 1. At low levels of income individuals tend to consume a large fraction of their incomes and at higher income levels, a smaller fraction of it is consumed cross sectional data is used in this model. The implied model is as follows.

$C_t = a + bY_{dt}$, where b is the marginal propensity to consume.

Here, the emphasis is on current disposable income as the principal determinant of consumption. This function reflects the observation that as income increases people tend to spend a decreasing percentage of income or conversely tend to save an increasing percentage of income. The behavior of consumer expenditure in the short-run over the duration of business cycle. Reasoning is that as income falls relative to recent levels, people will protect consumption standards by not cutting consumption proportionally to the drop in income and conversely, as income increases consumption will not rise proportionally.

This is usually taken to mean that the proportion of income consumed, average propensity to consume will tend to fall as income increases.

Any theory of consumption has to be able to explain the short-run behavior of consumption. In other words, it has to show the average propensity to consume behaving in a contra cyclical manner over time, cross-sectional data, which shows that at any point in time higher income earners have a lower average propensity to consume than low-income earners and finally, the long-run constancy of the average propensity to consume. It has been felt by economists as early as 1950's that simple Keynesian function had been tested against the available evidence and had been found wanting. Therefore, the search for new theories began and it is to those we now turn.

Relative Income Hypothesis

Duesenberry's relative income hypothesis assumes that consumption is influenced by the consumer's relative income; both current income relative to previous income and current income relative other people's income. So, Duesenberry suggests that consumers' preferences are interdependent. The utility a consumer derives from a given bundle of consumer goods depends to some extent on what others around him are consuming. In this theory consumption is influenced by the "demonstration effect" of other people's consumption. This assumption leads to the result that the individual's average propensity to consume will depend on his position in income distribution.

A person with income below the average will tend to have a high average propensity to consume, because, essentially, he is trying to keep up to the national average consumption standard with a below-average income. On the other hand, an individual with an above-average income will have a lower average propensity to consume, because it takes a smaller proportion of his income to buy the standard basket of consumer goods.

This provides an explanation to the short-run behavior consumption and the long-run constancy of average propensity to consume. As people learn more about the trend, they can increase their consumption proportionately to maintain the same ratio between their consumption and the national average

This hypothesis suggests that consumption behavior depends on the ratio of current income to the previous peak level of income, over the business cycle, along with the current level of disposable income.

It is more difficult, he argues, for a family to reduce a level of consumption once attained than to reduce the portion of its income saved in any period. Actually, the shortcoming of this hypothesis arises from this assumption. It is the asymmetry suggesting that a current increase in income if it exceeds a previous peak, induces a new consumption standard immediately. Algebraically, Duesenberry's formulation is as follows:

$$C_t = a + bY_{dt} + dY_{dt-1}$$

Permanent Income Hypothesis

Another approach to the consumption function is the permanent income hypothesis, developed by Friedman in mid 1950's. This hypothesis is similar to Duesenberry's hypothesis in that both of them provides the basis for a consumption function which is not based merely on current income.

The basic notion underlying this hypothesis is permanent income, which is the income generated by the individual's total wealth. Moreover, it is the level of income that can be expected to persist in the long-run. Over the long-run, there are episodes of positive transitory income and episodes of negative transitory income, which average out to zero. This hypothesis suggests that the consumption is proportional to permanent income. Friedman further assumes that there is no relationship between the transitory consumption and transitory income.

So,

$$C_p = kY_p$$

$$Y = Y_p + Y_{tr}$$

$$C = C_p + C_{tr}$$

$$Cov(Y_p, Y_{tr}) = 0$$

$$Cov(C_p, C_{tr}) = 0$$

$$Cov(C_{tr}, Y_{tr}) = 0$$

According to Friedman, in booms more people will think that they are better than normal than will think they are doing worse than normal. For the economy as a whole, therefore, there will be positive transitory income. Unexpectedly, high income will have little impact on consumer views of their permanent income unless it lasts for several years. So, unexpected increases in income are therefore largely saved with the result that in boom, the average propensity to consume falls.

It can be seen Friedman is able to explain why the short-run consumption function is flatter with a variable average propensity to consume, while the long-run consumption function is steeper with a constant average propensity to consume. Booms usually cause average propensity to consume to fall.

To be operational, the permanent income hypothesis consumption function requires some means of measuring permanent income. A common procedure for this is to assume that permanent income is an average of past income with the most recent past weighted most heavily.

This simplification of Friedman's consumption function is made by Koyck. His methodology is as follows:

$Y_p=Y_{dt}+eY_{dt-1}+e^2Y_{dt-2}+..+e^nY_{dt-n}$

$C_t=kY_p$, so,

$C_t=kde^nY_{t-n}$

$eC_{t-1}=kde^nY_{t-n+1}$, then

$C_t-eC_{t-1}=kY_t$ $\qquad$ $C_t=kY_t+eC_{t-1}$

C. Empirical Estimation

Each of the models considered are first subjected to a series of tests. These include tests for outliers, normality of errors, non linearity of regressors, structural stability and heteroskedasticity. Lets briefly discuss the results of these tests for each model.

Keynes' Model

The regression result is as follows:

Variable	Estimate	t-value	R^2	RSS	F
Const.	561.836	17.607	0.988	972.697	3629.681
Y_{dt}	0.57	60.246			

No outliers is found in this model. So, we do not need to revise our observations. Skewness and Kurtosis are found to be -3258 and 177190 respectively. Both are smaller than 5% critical values, which are 11823 and 1155699 respectively. The model is then tested for possible non linearity. DW statistic is 2.956, but this statistic just tests for first order serial correlation, so another test is implemented. An F test is conducted on the coefficients of non-linear terms added to the model (Y_{dt}^2). F statistic of this test is extremely small, 0.000276. this test yields that the data do not have any non-linear characteristic. Besides the t-statistic of Y_{dt}^2 is very small, leading to the same conclusion.

Structural stability is tested using Chow test. F-statistic associated with this test is 0.119, which leads to the conclusion that the structure of this model is stable. Then the model is tested for the presence of heteroskedasticity. White test is used in order to do that. The F-statistic of this test is 2.718 with p-value 0.143. So, it can be concluded that asymptotically no heteroskedasticity is present. At least, OLS standard errors and the statistics are valid.

The above regression results show that the constant term is significant. The short-run marginal propensity to consume, which equals to long-run marginal propensity to consume in this model is 0.57.

Duesenberry's Model

The regression results are as follows:

Variable	Estimate	t-value	R^2	RSS	F
Const.	559.976	16.538	0.998	928.748	1629.331
Y_{dt}	0.56	24.460			
Y_{dt-1}	0.012	0.532			

No outliers are present for this model as well. Skewness and Kurtosis associated with this model are both smaller than the 5% critical values (1877<11997; 197700<1070896 respectively). So, the errors in this model are normal as well. The OLS statistics are valid. DW statistic is 3.006. When the model is tested for non linearity, the data do not show any evidence of non linearity. The t-statistics associated with the nonlinear terms (Y_{dt}^2,Y_{dt-1}^2,$Y_{dt}Y_{dt-1}$) added to the model are all insignificant. Besides the related F-statistic is 0.0522, which is not significant at all. So, we can conclude that data show no non linearity.

Structural stability is tested again by Chow test. The associated F-statistic is 0.575. So, the structure of this model is stable as well. Then, using White test, this model is tested for heteroskedasticity. The t-statistics of all terms in this test are very small. Besides, the over all F-statistic is 1.119. All of these findings suggest that heteroskedasticity is not present in the data. With this result of White test, one can conclude that OLS standard errors and test statistics are valid and can be safely used.

The above regression results show that the constant term is significant. The short-run marginal propensity to consume is 0.56, and the long-run marginal propensity to consume is 0.57, which perfectly suits to the Keynesian model of consumption.

Friedman's model

The regression results are as follows:

Variable	Estimate	t-value	R^2	RSS	F
Y_{dt}	0.506	5.092	0.951	1117.307	361.028
C_{t-1}	0.322	2.314			

When subjected to least mean square method, we find some outliers present with this model. This is largely due to the omitted constant term in this formulation. The test for normality of errors yields that errors in this model are normal with both Skewness and Kurtosis smaller than 5% critical values (92529<1637065;

1.43318e8<7.31189e8 respectively). DW statistic is 2.398. In testing non linearity for this model,we observe that t-statistics for non linear terms ($Y_{dt}^2, C_{t-1}^2, Y_{dt}C_{t-1}$) are very small. Besides, the f-statistic associated with this test is 0.045, which suggests that the data do not yield any evidence of non linearity.

Structural stability of this model is also tested using Chow test. F-statistic of this test is 2.74, which is small to reject the null hypothesis. So this test has structural stability. The model is tested for heteroskedasticity using the White test. F-statistic of White test is 0.513, which rejects null hypothesis heteroskedasticity. White test yields the result that OLS standard errors are valid. No heteroskedasticity is present asymptotically in the model.

The above regression results show that, this model yields the short-run marginal propensity to consume as 0.506 and the long-run marginal propensity to consume as 0.746, which is very different from the findings of other models. This may due to bad outliers found present in the model.

D. Conclusion and Results

In all of the regressions, except for the Friedman's model, short-run marginal propensity to consume were very close to long-run marginal propensity to consume. In fact, there is not a significant difference between these. Only in Friedman's model, the difference between long-run marginal propensity to consume and short-run marginal propensity to consume. is very large. And also the constant part of the regressions is very large and significant in each of the regressions, which contradicts to Friedman's argument about the consumption function.

So, we can say that Turkish consumption behavior is not in agreement with Friedman's argument. Besides, the predictive residual sum of squares method of evaluating the forecasting performance of models yields that the Turkish data for the period considered is not in much consistence with the Friedman's model.

Rather, the two other models by Keynes and Duesenberry are more appropriate for Turkish case. The results of regressions which are significant constant term and very close long-run and short-run marginal propensity to consume suggests that Absolute Income hypothesis model is the most appropriate model among models considered for Turkish data during 1987-1995.

PRESS for Keynesian Model	1730.87
PRESS for Duesenberry's Model	2150.30
PRESS for Friedman's Model	47549.25

The results of predictive residual sum of squares method is in accordance with the above result. Turkish consumption behavior for period 1987-1995 is best explained by Keynes' absolute income hypothesis.

To carry out J and JA tests to compare these three models, models should be taken two by two. That is, Keynesian model is compared with Duesenberry's model, then it is compared with Friedman's model, afterwards Duesenberry's model is compared with Friedman's model.

Keynesian vs.	J k	D.of Fr.	J d	D. of Fr.
Duesenberry	0.5328	6	$1.06\text{x}10^{-5}$	5
Keynesian vs.	J k	D. of Fr.	J f	D. of Fr.
Friedman	0.4829	6	12.4056	6
Duesenberry vs.	J d	D. of Fr.	J f	D. of Fr.
Friedman	-0.299	5	12.46	6

From the above table we see that, J test does not differentiate between Keynesian and Duesenberry's models. Both models are accepted. However, when Keynesian model and Duesenberry's model are compared with Friedman's model, Friedman's model is rejected in both tests.

Similar to J test, Ja test also requires two by two comparisons. The results are listed in the below table.

Keynesian vs.	Ja k	D.of Fr.	Ja d	D. of Fr.
Duesenberry	0.5328	6	1.06×10^{-5}	5
Keynesian vs.	Ja k	D. of Fr.	Ja f	D. of Fr.
Friedman	0.4829	6	12.4056	6
Duesenberry vs.	Ja d	D. of Fr.	Ja f	D. of Fr.
Friedman	-0.299	5	12.46	6

Note that the J and Ja statistics are the same. So, similar conclusions can be drawn for this test as well.

12. Appendices

Appendix 1A

```
/*  This program segment takes four inputs              */
/*  y1,x1, and y2, x2 and calculates the                */
/*  PRESS for the model of y1 explained by x1           */
/*  and the PRESS for the model of y2 explained         */
/*  by x2                                               */

/*  This procedure calculates PRESS                     */
/*  for the model of y explained by x                   */
proc (1) = findrss(y,x);
local ReSS,i,del,ya,xa,yi,xi,yfit,res,rs;
local vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat;
ReSS=0;
i=1;
do while i <= rows(y);
        /* Omit 1 sample from the data set    */
        del=zeros(1,rows(y));
        del[i]=1;
        del=del';
        ya=delif(y,del);
        xa=delif(x,del);
        /* Make OLS regression for the remaining observations      */
        {vnam, m,b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",ya,xa);
        /* Calculate the residual sum of squares for the omitted observation         */
                yi=y[i];
                xi=x[i,.];
                yfit=xi*b;
                res=yi-yfit;
                rs=res*res;
                ReSS=ReSS+rs;
        i=i+1;
endo;
retp(ReSS);
endp;

/* This procedure calculates the              */
/* logarithmic scale PRESS for                */
/* linear models for comparison reasons       */
proc(1) = lfindrss(y,x);
local ReSS,i,del,ya,xa,lnxi,lnyi,lnyfit,res,rs;
local vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat;
ReSS=0;
i=1;
do while i<= rows(y);
        /* Omit 1 sample from the data set    */
        del=zeros(1,rows(y));
        del[i]=1;
```

```
        del=del';
        ya=delif(y,del);
        xa=delif(x,del);
        /* Make OLS regression for the remaining observations      */
        {vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",ya,xa);
        /* Calculate the residual sum of squares for the omitted observation         */
        /* Convert the observed values into logarithmic scale                  */
                lnyi=ln(y[i]);
                lnxi=ln(x[i,.]);
                lnyfit=lnxi*b;
                res=lnyi-lnyfit;
                rs=res*res;
                ReSS=ReSS+rs;
        i=i+1;
endo;
retp(ReSS);
endp;

/* Calculate the PRESS for both models */
proc(3) = press(y1,x1,y2,x2,k);
local PReSS1, PReSS2,Ratio,accept;
PReSS1=findrss(y1,x1);
PReSS2=findrss(y2,x2);

/* Print the results */
print "The PRESS for model 1 : " PReSS1;
print "The PRESS for model 2 : " PReSS2;
print "";

/* Decide on the acceptance */
Ratio=PReSS1/PReSS2;
if Ratio < K;
        accept=1;
else;
        accept=0;
endif;
retp(accept,PReSS1,PReSS2);
endp;
```

Appendix 1B

```
/* This program segment takes four inputs          */
/* y1,x1, and y2, x2 and performs the J            */
/* test, first by taking the model y1 against      */
/* x1 as the null hypothesis and then by taking    */
/* the model y2 against x2 as the null hypothesis  */
/* and by comparing the t-statistics of both       */
/* models                                          */

/* Since, this program compares linear versus      */
/* linear models, the dependent variables y1,      */
/* and y2 are the same.                            */

/* First null hypothesis is the first model        */
/* so, first regress y1 against x2 and get y1fit   */
/* then regress y1 against x1 and y1fit            */
/* J-statistic is the t value of the coef. of y1fit */
proc (4) = J(y1,x1,y2,x2);
local vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat;
local y1fit,xa,tstat1,y2fit,tstat2,DF1,DF2;
{vnam, m, b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",y1,x2);
y1fit=x2*b;
xa= x1 ~ y1fit;
{vnam, m, b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",y1,xa);
tstat1=b[cols(xa)]/stderr[cols(xa)];
DF1=rows(y1)-rows(b);

/* Second, null hypothesis is the second model     */
/* so, first regress y2 (y2=y1) against x1 and get */
/* y2fit then regress y2 against x2 and y2fit      */
/* J-statistic is the t value of the coef. of y2fit */
{vnam, m, b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",y2,x1);
y2fit=x1*b;
xa= x2 ~ y2fit;
{vnam, m, b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",y2,xa);
tstat2=b[cols(xa)]/stderr[cols(xa)];
DF2=rows(y2)-rows(b);

/* print the J-statistics for both null hypotheses */
print "the J-statistic for null hypothesis of true model 1:" tstat1;
print "the J-statistic for null hypothesis of true model 2:" tstat2;
print "";
retp(tstat1,DF1,tstat2,DF2);
endp;
```

Appendix 1C

```
/* This program segment takes four inputs            */
/* y1,x1, and y2, x2 and performs the J              */
/* test, first by taking the model y1 against        */
/* x1 as the null hypothesis and then by taking      */
/* the model y2 against x2 as the null hypothesis    */
/* and by comparing the t-statistics of both         */
/* models                                            */

/* Since, this program compares log-linear versus    */
/* linear models, the dependent variable y1 is       */
/* log of  y2. That is the model y1,x1 is in log-linear */
/* form and the model y2,x2 is in linear form.       */

/* First, null hypothesis is the first model         */
/* so, first regress exp. of y1 against x2 and get y1fit*/
/* then regress y1 against x1 and log. of y1fit      */
/* J-statistic is the t value of the coef. of log. of y1fit*/
proc (4) = LJ(y1,x1,y2,x2);
local vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat;
local ey1,ly2,y1fit,ly1fit,xa,tstat1,y2fit,ey2fit,tstat2,DF1,DF2;
ey1=exp(y1);
{vnam, m, b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",ey1,x2);
y1fit=x2*b;
ly1fit=ln(y1fit);
xa= x1 ~ ly1fit;
{vnam, m, b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",y1,xa);
tstat1=b[cols(xa)]/stderr[cols(xa)];
DF1=rows(y1)-rows(b);
/* Second, null hypothesis is the second model             */
/* so, first regress log. of y2 against x1 and get         */
/* y2fit then regress y2 against x2 and exp. of  y2fit     */
/* J-statistic is the t value of the coef of exp. of  y2fit */
ly2=ln(y2);
{vnam, m, b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",ly2,x1);
y2fit=x1*b;
ey2fit=exp(y2fit);
xa= x2 ~ ey2fit;
{vnam, m, b,stb,vc,stderr,sigma, cx, rsq, resid, dwstat }=ols("",y2,xa);
tstat2=b[cols(xa)]/stderr[cols(xa)];
DF2=rows(y2)-rows(b);
/* Print the J-statistics for both null hypotheses */
print "the J-statistic for null hypothesis of true model 1:" tstat1;
print "the J-statistic for null hypothesis of true model 2:" tstat2;
print "";
```

```
retp(tstat1,DF1,tstat2,DF2);
endp;
```

Appendix 1D

```
/* This program segment takes four inputs          */
/* y1,x1 and y2, x2 and performs the JA test,      */
/* first by taking the the model y1 against        */
/* x1 as the null hypothesis and then by taking    */
/* the model y2 against x2 as the null hypothesis  */
/* and then by comparing the t-statistics of the   */
/* related variables.                              */

/* First, null hypothesis is the first model       */
/* so, first regress  y1 against x1 and get y1fit  */
/* then regress y1fit against x2 and get y12fit    */
/* finally, regress y1 against x1 and y12fit       */
/* JA-statistic is the t value of the coef. y12fit */
proc (4) =JA(y1,x1,y2,x2);
local vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat;
local y1fit,y12fit,xa,JA1,y2fit,y21fit,JA2,DF1,DF2;
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y1,x1);
y1fit=x1*b;
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y1fit,x2);
y12fit=x2*b;
xa=x1 ~ y12fit;
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y1,xa);
JA1=b[cols(xa)]/stderr[cols(xa)];
DF1=rows(y1)-rows(b);

/* Second, null hypothesis is the second  model    */
/* so, first regress  y2 against x2 and get y2fit  */
/* then regress y2fit against x1 and get y21fit    */
/* finally, regress y2 against x2 and y21fit       */
/* JA-statistic is the t value of the coef. y21fit */
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y2,x2);
y2fit=x2*b;
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y2fit,x1);
y21fit=x1*b;
xa=x2 ~ y21fit;
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y2,xa);
JA2=b[cols(xa)]/stderr[cols(xa)];
DF2=rows(y2)-rows(b);
/* print the JA-statistics for both null hypotheses */
print "JA-statistic for null hypothesis of model 1 :" JA1;
print "JA-statistic for null hypothesis if model 2 :" JA2;
retp(JA1,DF1,JA2,DF2);
endp;
```

Appendix 1E

```
/* This program segment takes four inputs           */
/* y1,x1 and y2, x2 and performs the JA test,       */
/* first by taking the the model y1 against         */
/* x1 as the null hypothesis and then by taking     */
/* the model y2 against x2 as the null hypothesis   */
/* and then by comparing the t-statistics of the    */
/* related variables.                               */
/* Since, this program compares log-linear versus   */
/* linear models, the dependent variable y1 is      */
/* log of y2. That is the model y1,x1 is in log-linear */
/* form and the model y2,x2 is in linear form.      */

/* First, null hypothesis is the first model        */
/* so, first regress y1 against x1 and get y1fit    */
/* then regress exp. of y1fit against x2 and get    */
/* y12fit finally, regress y1 against x1 and        */
/* log. of y12fit. JA-statistic is the t value of the */
/* coef. of log. of y12fit                          */
proc (4) =LJA(y1,x1,y2,x2);
local vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat;
local y1fit,ey1fit,y12fit,ly12fit,xa,JA1,y2fit,ly2fit,y21fit;
local ey21fit,JA2,DF1,DF2;
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y1,x1);
y1fit=x1*b;
ey1fit=exp(y1fit);
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",ey1fit,x2);
y12fit=x2*b;
ly12fit=ln(y12fit);
xa=x1 ~ ly12fit;
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y1,xa);
JA1=b[cols(xa)]/stderr[cols(xa)];
DF1=rows(y1)-rows(b);

/* Second, null hypothesis is the second model      */
/* so, first regress y2 against x2 and get y2fit    */
/* then regress log. of y2fit against x1 and get    */
/* y21fit finally, regress y2 against x2 and        */
/* exp. of y21fit. JA-statistic is the t value of the */
/* coef. of exp. of y21fit                          */
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y2,x2);
y2fit=x2*b;
ly2fit=ln(ly2fit);
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",ly2fit,x1);
```

```
y21fit=x1*b;
ey21fit=exp(y21fit);
xa=x2 ~ ey21fit;
{vnam, m,b, stb, vc,stderr,sigma,cx,rsq,resid,dwstat }=ols("",y2,xa);
JA2=b[cols(xa)]/stderr[cols(xa)];
DF2=rows(y2)-rows(b);

/* Print the JA-statistics for both null hypotheses */
print "JA-statistic for null hypothesis of model 1 :" JA1;
print "JA-statistic for null hypothesis if model 2 :" JA2;
retp(JA1,DF1,JA2,DF2);
endp;
```

Appendix 2A

```
/* This program sets the probability of type 1          */
/* error to 5% and measures the power of                */
/* PRESS test                                           */

/*The data set is as follows                            */
/*The first model, y1,x1 is a Quadratic model           */
/*The second model, y2,x2 is a Leontieff model          */
 /* For this case, both models are linear.              */


x10=ones(20,1);
/* Repeat the same procedure for different variances of x */
h={ 0.2 0.3 0.35 0.4 0.45 0.5 0.55 };
n=1;
do while n <= 7;
/* Generate the data set */
random=rndn(20,1)*h[n];
x11=random.*random;
x12=x11.*x11;
x1=x10~x11~x12;
x13=sqrt(x11);
x2=x10~x11~x13;
b1={1 1 1};
y=x1*b1'+rndn(20,1)*0.05;
{vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",y,x1);
b1=b;
sigma1=sigma;
{vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",y,x2);
b2=b;
sigma2=sigma;
library;
screen off;
```

```
/* calculate the prob. of type 1 error */
k=1.4474753;
sumap=0;
z=1;
screen off;
boot=zeros(2000,1);
do while z <= 2000;

/* create y according to the null hypothesis */
 i=1;
 y1=zeros(rows(x1),1);
 do while i<=rows(x1);
  e=rndn(1,1)*sigma1;
  y1[i]=x1[i,.]*b1 + e;
  i=i+1;
 endo;
  y2=y1;

  {A,press1,press2}=press(y1,x1,y2,x2,k);
  boot[z,1]=press1/press2;
  sumap=sumap+A;

 z=z+1;
 endo;
 screen on;
 boot=sortc(boot,1);
 print "";
/* Find the 95% critical value */
 k= boot[1900,1];
 screen off;
/* calculate the power of the PRESS */
 z=1;
 suma2p=0;

 /* choose the b coefs of model 2, such that Ho is closest to H1 */
 /* so generate Y first using Ho, then regress it wrt H2 and get */
 /* b coefs for H1   */
  do while z <= 2000;
  i=1;
  y1=zeros(rows(x1),1);
  do while i<= rows(x1);
   y1[i]=x1[i,.]*b1;
   i=i+1;
  endo;
  {vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",y1,x2);
  i=1;
  do while i <= rows(x2);
```

```
    e=rndn(1,1)*sigma2;
    y2[i]=x2[i,.]*b+e;
    i=i+1;
  endo;

  y1=y2;
  {A,press1,press2}=press(y1,x1,y2,x2,k);
  suma2p=suma2p+A;


z=z+1;
 endo;
 screen on;
 screen off;
 ptype2p=suma2p/2000;
 powerp=1-ptype2p;
/* Print out the results */
output file = outq on;
print " the standard error is: ";;h[n];
print " the power of press is : ";;powerp;
output off;
n=n+1;
endo;
```

Appendix 2B

```
/* This program sets the probability of type 1       */
/* error to 5% and measures the power of             */
/* J-test                                            */

/*The data set is as follows                         */
/*The first model, y1,x1 is a Linear   model         */
/*The second model, y2,x2 is a Log-Linear model      */


x10=ones(20,1);
/* Repeat the same procedure for different variances of x */
h= {  0.15 0.175 0.2 0.3 0.4  0.5 0.6 0.7 };
n=1;
do while n <= 8;
/* Generate the data set */
random=rndn(20,1)*h[n];
x11=exp(random);
x1=x10~x11;
x12=ln(x11);
x2=x10~x12;
b1={1 1 };
```

```
y=x1*b1'+rndn(20,1)*0.05;
{vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",y,x1);
b1=b;
sigma1=sigma;
{vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",y,x2);
b2=b;
sigma2=sigma;

 library;
 screen off;

 /* calculate the prob. of type 1 error */
sumaj=0;
 z=1;
 do while z <= 2000;
/* create y according to the null hypothesis */
  i=1;
  y1=zeros(rows(x1),1);
  do while i<=rows(x1);
   e=rndn(1,1)*sigma1;
   y1[i]=x1[i,.]*b1 + e;
   i=i+1;
  endo;
   y2=ln(y1);

   {tstat1,df1,tstat2,df2}=LJ(y2,x2,y1,x1);
   if abs(tstat2) >2.11;
     accnullj=0;
   else;
     accnullj=1;
   endif;
   sumaj=sumaj+accnullj;
z=z+1;
endo;
screen on;
ptype1j=(2000-sumaj)/2000;

 screen off;
 /* calculate the power of  J test */
 z=1;
 suma2j=0;

 /* choose the b coefs of model 2, such that Ho is closest to H1 */
 /* so generate Y first using Ho, then regress it wrt H2 and get */
 /* b coefs for H1   */
   do while z <= 2000;
   i=1;
   y1=zeros(rows(x1),1);
```

```
  do while i<= rows(x1);
   y1[i]=x1[i,.]*b1;
   i=i+1;
  endo;
  {vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",ln(y1),x2);
  i=1;
  do while i <= rows(x2);
    e=rndn(1,1)*sigma2;
    y2[i]=x2[i,.]*b+e;
    i=i+1;
  endo;

  y1=exp(y2);
  {tstat1,df1,tstat2,df2}=LJ(y2,x2,y1,x1);
  if (abs(tstat2) >2.11) and (abs(tstat1)<2.11);
    accnullj=1;
  else;
    accnullj=0;
  endif;
  suma2j=suma2j+accnullj;

  z=z+1;
 endo;

powerj=suma2j/2000;
/* Print out the results */
output file= outli on;
print " the standard error is : ";;h[n];
print " the ptype1 for j is : ";;ptype1j;
print " the power for j is : ";;powerj;
output off;
n=n+1;
endo;
```

Appendix 2C

```
/* This program sets the probability of type 1         */
/* error to 5% and measures the power of               */
/* JA-test                                             */

/*The data set is as follows                           */
/*The first model, y1,x1 is a Linear   model           */
/*The second model, y2,x2 is a Log-Linear model        */

x10=ones(20,1);
/* Repeat the same procedure for different variances of x */
h= { 0.05 0.075 0.1 0.2 0.25 0.3 0.35 0.4 0.45 0.5  };
n=1;
```

```
do while n <=10;
/* Generate the data set */
random=rndn(20,1)*h[n];
x11=exp(random);
x12=ln(x11);
x1=x10~x11;
x2=x10~x12;
b2={1 1};
y=x2*b2'+rndn(20,1)*0.005;
{vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",y,x1);
b1=b;
sigma1=sigma;
{vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",y,x2);
b2=b;
sigma2=sigma;

 library;
 screen off;

 /* calculate the prob. of type 1 error */

 suma1=0;
 suma2=0;
 z=1;
  do while z <= 2000;
   y2=zeros(rows(x2),1);
   i=1;
   do while i<= rows(x2);
   y2[i]=x2[i,.]*b2+rndn(1,1)*sigma2;
   i=i+1;
   endo;

   y1=exp(y2);
   {JA1,DF1,JA2,DF2}=LJA(y2,x2,y1,x1);
   if abs(JA1) > 2.11;    /* tcrit for deg. of freedom under null */
     accnull=0;
   else;
     accnull=1;
   endif;
   suma1=suma1+ accnull;
   z=z+1;
 endo;
 ptype1=(2000-suma1)/2000;

/* choose the b coefs of model 2, such that Ho is closest to H1 */
 /* so generate Y first using Ho, then regress it wrt H2 and get */
 /* b coefs for H1    */
z=1;
```

```
 do while z<=2000;
 i=1;
 y1=zeros(rows(x1),1);
 y2=zeros(rows(x2),1);
 do while i <= rows(x2);
  y2[i]=x2[i,.]*b2;
  i=i+1;
 endo;
 {vnam,m,b,stb,vc,stderr,sigma,cx,rsq,resid,dwstat}=ols("",exp(y2),x1);
 i=1;
 do while i <= rows(x1);
  y1[i]=x1[i,.]*b+rndn(1,1)*sigma1;
  i=i+1;
 endo;

 y2=ln(y1);
 {JA1,DF1,JA2,DF2}=LJA(y2,x2,y1,x1);
 if (abs(JA1)> 2.11) and (abs(JA2)< 2.11);
   accnull2=1;
 else;
   accnull2=0;
 endif;
 suma2=suma2+ accnull2;
 z=z+1;
endo;
power=suma2/2000;
/* Print out the results */
output file= out3lo on;
print " the standard error is : ";;h[n];
print " the ptype1 error is :";;ptype1;
print " the power is :";;power;
output off;
n=n+1;
endo;
```

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