CHANGING POINT AND PARAMETER INSTABILITY WITH HETEROSKEDASTIC MODELS

(Comparison of SupF test with SupMZ test)

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DECLARATION

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GULFAM HAIDER

In The Name of ALLAH the Most Beneficent and Merciful

APPROVAL SHEET

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(Comparison of SupF with SupMZ test)

By

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ABSTRACT

Structural breaks are an important issue in time series econometrics. Failure to take them into account can produce huge forecast errors. Existing literature is mainly concerned with structural breaks where the regression coefficients change, but variances remain unchanged. Our main contribution in this thesis is to utilize a newly developed test Massoumi et al (2010) which tests simultaneously for change in variance as well as regression coefficients. The original test is developed for case the known break point. In this thesis, we adapt the test for use when the breakpoint in unknown, and label it the SupMZ test. There is no directly comparable test available in the literature. The Andrews SupF test is similar, but tests only for change in regression coefficients under the maintained hypothesis of Homoskedasticity. We compare and evaluate these two tests in our thesis. The powers of Andrew's SupF test are compared with SupMZ test through Monte-Carlo simulations and empirically. Simulations show that SupMZ test incurs only a low cost in power in the case of Homoskedasticity, while having hugely better performance in the case of heteroskedasticity. Also the SupMZ test performed well in empirical analysis. In empirical analysis we conclude that with the presence of Heteroskedastic variance (break in variance with regime shifting) SupF test is misleading and sometimes fails to detect break in parameters. All above discussion shows that SupMZ test is better than SupF test so according to this study we suggest for researchers that SupMZ test should be used for testing parameters instability.

Key words: Structural Break, Heteroskedasticity, SupMZ test, SupF test.

DEDICATION

I feel highly proud to dedicate my research to my reverend supervisor

Prof. Dr. ASAD ZAMAN

Who with all his accomplishments of head and heart, guided me and encouraged me at every step.

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List of Contents

List of Table

List of Figure

CHAPTER 1

INTRODUCTION

Parameter Instability, SupF AND SupMZ Test

1.1 Introduction

A structural break is a shift in the parameters of the data generating process for time series observations. Failure to detect such shifts can lead to huge forecasting errors and unreliable estimates of model in general. Many natural phenomena such as Oil price shocks, Turning points of the Business cycle and natural disaster are the causes of breaks in economic series. The F test for structural change was developed early in the statistical literature. Chow (1960) generalized the test to the case where the structural change took place near the end of the observations, leaving insufficient observations to allow estimation of the parameters before and after the change separately. This became very popular, and the test became known as the Chow test in the econometrics literature.

Structural instability occurs when parameters of linear regression model are significantly different for different parts of same data set. If the parameters of linear regression model are statistically same for different parts of the same data set, this means that there is no detectable structural break in parameters.

A simultaneous shift in the coefficients .and variance of linear regression model will result in a structural change of the economic series. Mostly when we analyze economic time series data with linear regression model we face the problem of structural instability. The detection of such problem has a great importance for econometric modeling.

Various tests are available in literature for detection of structural break. Some of the famous tests are Chow test (1960) for known break point and CUSUM test (1975) and SupF test (1993) for unknown break point. Hansen (1997) provided a method to calculate P-values for SupF test. Hansen (2000) showed that Andrews' critical values are not robust to structural change in the marginal distribution of the regressors, which is undesirable in tests focusing on conditional relationships. He showed how to simulate robust critical values on a case-by-case basis.

The best known test in literature for detection of single known break is the Chow's (1960) test statistic which has F distribution under the null hypothesis of no break. Hence the tabulated critical values can be used. However the Chow has two assumptions, Break point must be known a priori and no shift in variance (Homoskedasticity).

1.2 Problem of Unknown Break

If the change point is unknown, this idea and solution for unknown break point go to Quandt (1960) who studied the problem of unknown break point and suggested Quandt LR test. He showed that the LR test for the unknown break point is just the maximum value of the interval of F is used as test statistics. But Quandt LR statistic had no practical application because the distribution of Quandt test under null hypothesis was unknown. Later Andrews (1993) and Andrews & Polberger (1994) provided tables of asymptotic critical values of Quandt LR test and thus this test became known as Andrew's SupF test. Now it is widely used for testing break in parameters.

Andrews showed that the SupF test is an optimal test for the detection of single unknown break point under the assumption of homoskedasticity (no break in variances). However, as we will show, the performance of this test is poor when there is a shift in variances.

1.3 The Problem of Shift in Variance

In literature the Goldfeld-Quandt test (1965) is a popular test and widely used for testing heteroskedasticity. This test statistic has an F distribution under null hypothesis. According to Zaman (1996, section 8.6) the GQ test is an optimal test for equality of variance in two subsets of data, when the regression coefficients are not assumed to be same and variance is constant within each of the two regimes. So the GQ test is optimal test to detect break in variance with the assumption of break in variance must be known priori. In this study, the idea is further extended for the detection of unknown break in variance.

1.4 Motivation

The Chow F test for known break assumes the equality of variances in both regimes. The SupF test by Andrew is considered an optimal test and widely used for the problem of testing single unknown break point with the assumption of homoskedastic variance. However, it is known that the performance of this test is poor if the variances change. This test is widely used, but homoskedasticity is not tested since there is no test available to detect unknown break in variance. The use of SupF test is misleading without testing the assumption of equality of variance. It is necessary to validate the SupF test by testing this background assumption.

1.4.1 Test Back Ground Assumption of SupF

The GQ test can be used to test the equality of variance as discussed in Zaman (1996). This can be extended to test the unknown break in variance by calculating GQ F statistic for all potential breaks in variance and use maximum value of the GQ test from the interval as a test statistics.

The problem of finding critical values can easily be solved by simulation. On the basis of the analogy with the SupF test, we will call this the SupGQ test. If SupGQ test detects no change in variance, this validates the background assumption for the SupF test. Only in this case would it be valid to use the SupF test to detect change in regression parameters at an unknown time.

1.4.2 Joint Testing Approach

Limitation of above mentioned criteria is that if SupGQ test rejects the hypothesis of equality of variance then there is no way forward to use SupF test to detect stability of mean. An alternate solution for this problem is joint testing approach discussed by Massoumi et al (2010). This is unified approach, where the equality of coefficients and variances are simultaneously tested under the null hypothesis that structure is same (mean and variance both are stable). This test has been developed recently and is not well known or utilized in the literature.

Although MZ test is quite powerful test but it can detect only known break point in mean and variance. In current study, we extend this idea and calculate MZ test for all potential break points in data. The supremum of the entire MZ statistic is taken as a test statistic. We will call this the SupMZ test for testing single unknown break in mean and variance simultaneously.

We have checked the performance of existing tests like SupF test by Andrews (1993) and AvgF test and ExpF test by Andrews and Ploberger (1994) for detection of unknown change point, and found these to be inferior. We also check the size and power of these tests to detect the break date point. We also checked the power of SupF and SupMZ by Monte-Carlo as well as on an empirical basis.

1.5 Outline of the Research

The remaining part of the thesis is arranged as follows:

Chapter 2 consists of review of literature related to this study, where we discussed all the literature of parameter constancy testing in econometric modeling. We also mention in this chapter that the gap of the existing studies is related to parameter stability testing, that indicate us to do this research.

Chapter 3 consists of the Monte-Carlo design according to this study where we mention all the procedure of parameter constancy testing on the base of the objective of the study. We analyzed by Monte Carlo simulation technique where we generate data on the basis of null hypothesis for getting critical value at 5% level of significance and check the performance of tests at different level.

Chapter 4 Discusses results of Monte Carlo simulation technique and empirical study where we show the table critical values that we conduct by Monte Carlo simulations technique and show the powers of SupF and SupMZ test by tables and graphical representations.

Chapter 5 Empirical design we take data from IFS data disk on household consumption and GDP and make consumption function and check break date points. When the break is detected at that point we apply GQ test to detect break in variance to check the performance of SupMZ test.

Chapter 6 discusses the results of Empirical analysis also mention graphical representation of the performance of test statistics.

In chapter 7 consists of all conclusion of this study also discusses the recommendations for future research.

OBJECTIVE OF THE STUDY

The objectives of the study are as follows:

1. Our first goal of this study is to evaluate the performance theoretically and empirically of joint SupMZ test to detect the unknown break points.

2. Our Second goal of this study is to compare the performance of existing methods with MZ test for heteroskedastic data.

SIGNIFICANCE OF THE STUDY

This study provides a new direction to practitioner for detection of unknown break in mean and variance simultaneously. Test statistics available in literature can either detect the breaks only in mean with homoskedastic variance or both mean and variance for known breaks.

In addition, this study provides a comprehensive comparison of available tests in term of power and size.

CHAPTER 2

REVIEW OF ITERATURE

In econometrics the testing of structural stability in linear regression model has a great importance in estimation and forecasting economic time series. Sometime structural breaks are known but mostly these breaks in economic time series are unknown. For this purpose the present study has been conducted and in this chapter we have been listed some literature on testing for known and unknown break in parameters of linear regression model.

2.1 Tests with Known Break Point (for testing break in mean)

For known break point Chow.C.G (1960) proposed a test for testing the parameters stability in the linear regression model. He followed maximum likelihood estimator that has F distribution under null hypothesis to detect the break in parameters keeping variance constant. It is known as Chow-F test for parameter stability testing for known break point in the data in literature. For testing known break in variance (homoskedasticity) in regression analyses. Zaman (1996, section 8.6) shows that the GQ test is an optimal test for equality of variance in two subsets of data, when the regression coefficients are not assumed to be same and variance is constant in each of the two regimes. The GQ test is optimal test to detect break in variance with the assumption that break in variance must be known priori. The GQ test has F distribution under Null hypothesis of homoskedasticity.

2.2 Tests with Known Break Point (mean and variance simultaneously)

There are vast amounts of literature which deal with testing structural break in parameters with the assumption of homoskedasticity. But Maasoumi et al. (2010) provided joint testing approach for the parameters constancy, when structural change simultaneously affects regression coefficients and variances. They developed a likelihood ratio test for testing multiple known regimes shifting that is known as MZ test. They followed the strategy of testing mean and variance shifting simultaneously.

2.3 Tests with Unknown Break Point

Timing of structural change is usually unknown in macroeconomic time series. To solve this problem, Quandt (1960) proposed the testing strategy of calculating the LR test for structural change with an unknown break point. Quandt could not provide the distribution of the LR test under the null hypothesis, so this test was not used. But this problem was solved by Andrews (1993). He proposed the SupLR test for single unknown break point in parameters and also presented the asymptotic critical values table of SupLR test of parameter constancy. His LR test asymptotically belongs to the F distribution under the null hypothesis of no change in parameters of linear regression model. Andrews test is known as SupF test for parameter stability with the assumption of homoskedastic variance.

Brown, et al (1975) introduced recursive residuals which are uncorrelated with zero means and constant variance. They developed tests on the cusum and cusum of squares of recursive residuals.

Further techniques based on moving regressions, in which the regression model is fitted from a segment of data which is moved along the series, and on regression models whose coefficients are polynomials in time are studied.

Andrews (1989c) compared CUSUM test and the Sup Wald test in nonlinear model using Monte Carlo simulation technique and came up with the conclusion that the Sup Wald test for known break point is superior to the CUSUM test of Brown in terms of closeness of true and nominal size and very much superior in term of power. The study of Bai (1994, 1997a) showed how to construct confidence intervals for break points by using asymptotic distribution of break point estimator. He claimed that the procedure of constructing confidence intervals is simple to calculate and useful in applications. Diebold and Chen (1995) provided the finite sample evaluation for structural change. They focused on a size comparison for testing of unknown break point by Andrews's SupF test for structural change in dynamic model with comparison of asymptotic critical values with bootstrap technique for finite sample size. They concluded that the results of bootstrap critical values are more accurate than asymptotic critical values in finite sample size in testing break point of SupF test. In empirical analysis of this study we also used bootstrap critical values rather than asymptotic critical values.

Banerjee, Lumsdaine and Stock (1992) and Perron, Vogelsang (1992) stated that it is unsuitable to specify the break point as known. They suggested that as suitable procedure is to select the break date in data that provided the maximum evidence against the random walk hypothesis. The critical values for the modified test are high and make it difficult to reject the null hypothesis of a random walk. They also showed that bootstrap critical values give better results than asymptotic critical values.

2.4 Contribution of the Study for Parameters Constancy According To Existing Literature

The Chow F test for known break requires the equality of variances. The SupF test by Andrew is considered an optimal test and widely used for the problem of testing single unknown break point with the assumption of no shift in variance (homoskedastic variance). This test is widely used in practice, but there is no test available to detect potential break in variance. The use of SupF test is misleading without testing the assumption of equality of variance. It is necessary to validate the SupF test by testing this background assumption.

The GQ test can be used to test the equality of variance as discussed in Zaman (1996). This can be extended to test the unknown break in variance by calculating GQ F statistic for all potential breaks in variance and use maximum value of the GQ test from the interval as a test statistics and simulated critical values will be used to make decision for break in variance that will be known as SupGQ test. If SupGQ test does not reject the null of equality of variances of two regimes then SupF test can be used to detect unknown break in parameters.

Limitation of above mentioned criteria is that if SupGQ test rejects the hypothesis of equality of variance then there is no way forward to use SupF test to detect stability of mean. An alternate solution for this problem is joint testing approach discussed by Massoumi et al (2010). This is unified approach, where the equality of coefficients and variances are simultaneously tested under the null hypothesis that structure is same (mean and variance both are stable). Proposed test statistic is called the MZ test statistic.this has been recently introduced and not been applied.

Although MZ test is quite powerful test but it can detect only known break point in mean and variance. In current study, we extend this idea and calculate MZ test for all potential break points in data and their supremum value is taken as a test statistic that will be called SupMZ test for testing single unknown break in mean and variance simultaneously.

CHAPTER 3

Monte-Carlo Simulation Design

Andrews (1993) showed that the SupF test is an optimal test. After this, it became widely used for detection of break with the assumption of no break in variance. This study has focused on testing the break in coefficient and variance simultaneously. According to our objectives of the study we want to evaluate and compare the power and size of SupF test and SupMZ test statistics in the presence of heteroskedasticity by Monte Carlo simulations technique and empirical analysis. There are two steps of Monte-Carlo study:

I. Overview of test for structural break.

II. Monte Carlo simulation design.

3.1 Overview of tests for structural break

There are several tests in literature to detect the break point but Andrew's (1993) SupF test established optimal test to detect break under the assumption that the variance is stable. The present study is focused the testing for change in coefficients and variance simultaneously for unknown timing of break point. The SupMZ test is a unified approach to detect break in coefficient and variance simultaneously. There are no other tests designed for this purpose available in the literature. Since there are no directly comparable tests, we have compared SupF test statistics with SupMZ test statistics for detection of potential break points.

Model: We used standard linear regression model

$$Y_t = X_t\beta + \epsilon_t \text{ for } t = 1,2,3\ldots T \text{ where } \epsilon_t \overset{iid}{\sim} N(0,\sigma^2)$$

The hypothesis is that the (k+1) parameters (β, σ^2) remain stable. If there is structural break in the data, one way to approach the problem is, we split data into two subgroups. Each subgroup of data has its own (k+1) parameters.

$$Y_{st} = X_{st}\beta_s + \epsilon_t \text{ for } t = T_{s-1} + 1, \ldots T_s \text{ where } \epsilon_t \overset{iid}{\sim} N(0, \sigma_s^2)$$

For s=1, 2 subgroup of the data as:

$$y_1 = X_1\beta_1 + \epsilon_1, \textit{ where } \epsilon_1 \overset{iid}{\sim} N(0, \sigma_1^2).$$

$$y_2 = X_2\beta_2 + \epsilon_2, \textit{ where } \epsilon_2 \overset{iid}{\sim} N(0, \sigma_2^2).$$

Here T_o= 0 and T_2=T, T_s is potential break point in the data. This study focuses on single break in parameters that is unknown. Now we set up some important notation and definition required for the calculation of test statistics. Here we will assume that $T_s > k$ in each regime/subgroup.

Define the vector $y_o' = (y_1', y_2')$, and similarly $\beta' = (\beta_1', \beta_2')$, and the vector $\sigma^2 = (\sigma_1^2, \sigma_2^2)'$. Let $N_s = T_s - T_{s-1}$, be the number of observations in each regime 's'. Let $N_0 = T$, and define $X_o$to be the T× k matrix obtained by stacking the X_1, X_2, and let β_o and σ_o^2 be the common values of the coefficients β_i and σ_i^2 respectively under null. Then the restricted model is:

$$y_o = X_o\beta_o + \epsilon, \textit{ where } \epsilon \sim N(0, \sigma_o^2 I_T).$$

3.1.1 The Test Statistics

There are the following test statistics as follow.

The Chow Test

As discussed earlier Chow test (1960) statistics has an F distribution under the null hypothesis of no break point. This F test statistic has been designed for single known break point with the assumption of constant variance.

The null and alternative hypothesis as:

H_0; $\beta_1 = \beta_2$ $\sigma_1^2 = \sigma_2^2$ No structural break

H_1; $\beta_1 \neq \beta_2$ $\sigma_1^2 = \sigma_2^2$ Structural break in regression coefficients

Where β_1, β_2 and σ_1^2, σ_2^2 are the parameters of regressions before and after break point and the Chow test has F distribution.

Notations for Unknown Break Point

When break point is unknown we calculate the F and MZ statistics for all potential change points or for all potential change points in an interval [a b] and to reject if any of those statistics get too large. Therefore the first step is to compute the F and MZ statistics F_j and MZ_j for all potential break point within the interval of $\{k < a \leq j \leq b < T\text{-}k\}$. The N_1 and N_2 are the numbers of observations in both subsets, for unknown break point these observations of both subsets are recursively change as $N_1 = j, j+1, \dots, T-j$ and $N_2 = T-j, T-j+1, \dots, j$, where j is a range of all potential break points.

The SupF Test

However if the break point is unknown then we can calculate F statistics for each potential break point and then find the maximum value of F in given statistics called SupF test statistics that has been suggested by Andrews (1993) here we also used AvgF and expF test statistics by Andrews and Ploberger (1994) get from the interval of F statistics. Andrews (1993) provided the table of asymptotic critical values of SupF test statistics to detect the unknown break points.

For unknown break point we calculate Chow F test for all potential break points and take supremum (maximum) value as a test statistic get from the interval that is known as SupF test statistics. The null hypothesis of SupF test statistics is

H_0; $\beta_1 = \beta_2$ $\sigma_1^2 = \sigma_2^2$ No structural break

H_1; $\beta_1 \neq \beta_2$ $\sigma_1^2 = \sigma_2^2$ Structural break in regression coefficients

$$\text{SupF} = \max_{a \leq j \leq b} F_j$$

Where {k < a ≤ j ≤ b < T-k}

F_j is usual F statistic calculated at the change point 'j' and 'j' notation is discussed above. Take maximum value as a test statistic from the interval of F statistics (a b) calculated for all potential break points that is known as SupF test. If the calculated value of SupF statistic is greater than some critical value we can reject the null hypothesis of no change point.

Andrews and Ploberger (1994) proposed avgF and expF test statistics for unknown break point which can be calculated as:

$$\text{avgF} = \frac{1}{b-a+1}\sum_{j=a}^{b} F_j$$

$$\text{expF} = \log\left(\frac{1}{b-a+1}\sum_{j=a}^{b} \exp(0.5 * F_j)\right)$$

Where {k < a ≤ j ≤ b < T-k}

The null hypothesis is rejected when the supremum value of F or the mean F statistics and expF statistics get too large. Here we are only focusing on SupF test and not considering avgF and expF test because their performance are not good as compared

SupF test. Stock and Watson (1996) discussed avgF and expF showed that they are not informative about location of break date.

The MZ Test

The F test is designed to detect the single break point in the parameters with the assumption of variance remain same throughout the process. However the MZ test detects break in regression coefficients and variances simultaneously.

H_0; $\beta_1 = \beta_2$ $\sigma_1^2 = \sigma_2^2$ there is no structural break

H_1; $\beta_1 \neq \beta_2$ $\sigma_1^2 \neq \sigma_2^2$ there is structural break

These β_s (s=1,2) are the parameters of regression before and after break. MZ test is known as joint testing of the structural break in linear regression model.

$$MZ = (N_o - k) * \log(\hat{\sigma}_0^2) - ((N_1 - k) * \log(\hat{\sigma}_1^2) + (N_2 - k) * \log(\hat{\sigma}_2^2))$$

Where $\hat{\sigma}_1^2$and $\hat{\sigma}_2^2$are estimated variance of regression before and after break respectively. All the notations are explained above.

RRSS = Restricted residuals sum of square regression under the null hypothesis

RSS_1 = residuals sum of square from the regression before regime shifting

RSS_2 = residuals sum of square from the regression after regime shifing

$$\hat{\sigma}_0^2 = variance\ from \text{ the regression under the null hypothesis} = \frac{RRSS}{N_O - k}$$

$$\hat{\sigma}_1^2 = variance\ from \text{ the regression before regime shifting} = \frac{RSS_1}{N_1 - k}$$

$$\hat{\sigma}_2^2 = variance\ from \text{ the regression after regime shifing} = \frac{RSS_2}{N_2 - k}$$

The SupMZ Test

A newly develop MZ test by Massoumi et al (2010) which tests simultaneously for change in variance as well as regression coefficients. Existing literature is mainly concerned with structural breaks where the regression coefficients change, but variances remain unchanged. Our main contribution in this thesis is to utilize MZ test which developed for case the known break point. In this thesis, we adapt the test for use when the breakpoint in unknown, and label it the SupMZ test. When break is unknown we calculate MZ test for all potential break points with the interval of (a b) and maximum value within the interval used as test statistic that is known SupMZ test.

$$MZ_j = (N_o - k) * log(\hat{\sigma}_0^2) - ((N_1 - k) * log(\hat{\sigma}_{1,j}^2) + (N_2 - k) * log(\hat{\sigma}_{2,T-j}^2)$$

$$\text{SupMZ} = \max_{a \leq j \leq b} MZ_j$$

$$\text{Where } \{k < a \leq j \leq b < T\text{-}k\}$$

MZ_j is usual MZ test calculated at the change point 'j'. Take maximum value as a test statistic from the interval of MZ statistics (a b) calculated for all potential break points that is known as SupMZ test statistic. If the calculated value of SupMZ statistic is greater than some critical value we can reject the null hypothesis of no break in variance dand regression coefficients.

3.2 Monte-Carlo Design

In this section we completely discussed our model and the procedure of Monte-Carlo simulation analysis.

3.2.1 Model under Null and Alternative Hypothesis

We used standard linear Regression model throughout the study

$$y_1 = X_1\beta_1 + \epsilon_1, \; where \; \epsilon_1 \sim N(0, \sigma_1^2).$$

$$y_2 = X_2\beta_2 + \epsilon_2,\ where\ \epsilon_2 \sim N(0, \sigma_2^2).$$

The conditional distribution of $Y_t$given X_t in the form of a linear regression and structural change in regression arises through the coefficients (β). The structural change appear in parameters as

H_0; $\beta_1 = \beta_2$ $\sigma_1^2 = \sigma_2^2$ there is no structural break

H_1; $\beta_1 \neq \beta_2$ $\sigma_1^2 \neq \sigma_2^2$ there is structural break

If there is no break the model will be same as above discussed

$$Y_o = X_o\beta_o + \epsilon$$

And if there is structural break in the model then regression will be as

$Y_1 = X_1\beta_1 + \epsilon_1$ Before break point where $\epsilon \sim N(0, \sigma_1^2 I_{T_1})$

$Y_2 = X_2\beta_2 + \epsilon_2$ After break point where $\epsilon \sim N(0, \sigma_2^2 I_{T_2})$

Where $Y_1$and Y_2 are explained variable before and after regime shifting respectively, similarly $X_1$and X_2 are explanatory variable and ϵ_1 and ϵ_2 are errors of regression before and after regime shifting. In econometric modeling we first test the model for possible break.

3.2.2 Data generating Process

We generate random data series and this kind of data set is used to check the power of these tests statistics by using the random data and throughout the process we take sample size '100 and perform simulation procedure. Tests depends only on the distribution of error ' ϵ '. The distribution of regressors does not affect so we use a univariate regression model.

First we check the size and power of these above mentioned test statistics by generating the series X_t and Y_t with following method.

These steps are followed in order to generate data under null Hypothesis.

i- We generate evenly space series as a regressor (X_t). Values of regressors vary from 1 to 50 with increment of 0.5 for each new value by arithmetic progression. Choice of range and increment is arbitrary as theoretically it will not affect the results.

ii- We assumed the initial values of parameters of regression 'a and b' as a=b=1. We generate a standard normal series of residuals $\mu_t \sim$ iid $N(0, I)$.

iii- We generate explained variable series (Y_t) under the null hypothesis according to values of parameters specified in step 'ii' using the following equation.

$$Y_o = X_o\beta_o + \mu \qquad \mu \sim \text{iid } N(0, \sigma_o^2 I_T) \qquad t = 1,2,3, \ldots, 100$$

These steps are followed in order to generate data under alternative Hypothesis.

i- We generate evenly space series as a regressor (X_t). Values of regressors vary from 1 to 50 with increment of 0.5 for each new value by arithmetic progression.

ii- We have used different combination of the values of parameters of regression and the values of standard error of two regressions before and after regime shifting according to alternative hypothesis.

iii- We generate explained variable series (Y_t) according to values of parameters specified in step 'ii' using the following equation.

Equation before regime shifting

$$Y_1 = X_1\beta_1 + \mu_1 \qquad \mu_1 \sim \text{iid } N\left(0, \sigma_1^2 I_{T_1}\right)$$

Equation after regime shifting

$$Y_2 = X_2\beta_2 + \mu_2 \qquad \mu_2 \sim \text{iid } N(0, \sigma_2^2 I_{T_2})$$

To measure of distance of parameters of two regimes following steps are followed

3.3 Heteroskedasticity (Break in variance with regime shifting)

To compute powers, we vary the standard errors to make them different for each regime with specific weights discussed below to measure the degree of heteroskedasticity with a systematic pattern as mentioned in Maasoumi et al (2010).

$$\sigma_1^2 \, and \, \sigma_2^2 \text{ are the } variance\ of \text{ first and } second\ regime\ respectively$$

$$H = log \sum W_s \sigma_s^2 - \sum W_s log \sigma_s^2$$

Where the W_s is the weight and σ_s^2 is the variance

$$W_s = {}^{N_s}/_{N_0} \quad s=1,2$$

In present study we design test statistic for single unknown structural break where 'T_1' shows that number of observations in regression before regime shifting and 'T_2' shows the number of observations in regression after regime shifting. '$W_1 = \frac{N_1}{N_0}$'is weight of variance before regime shifting and '$W_2 = \frac{N_2}{N_0}$'is weight of variance after regime shifting so we put single break date in the data that's why H can be calculated as:

$$H = log(W_1\sigma_1^2 + W_2\sigma_2^2) - (W_1 log\sigma_1^2 + W_2 log\sigma_2^2)$$

The value of heteroskedasticity in the model is computed by varying the value of the standard error to make different for each regime. The weight will be changed as the location of regime change.

3.4 Distance of Parameters for Different Regimes

The distance between coefficients of two regimes computed according to Massoumi et al (2010) discussed in their paper as:

$$D = \sum_{s=1}^{S}(\beta_s - \beta_0)^t (X_s{}'X_s)^{-1}(\beta_s - \beta_0)$$

This study is for single unknown break point so the D is:

$$D = (\beta_1 - \beta_0)^t \left(X_1{}'X_1\right)^{-1}(\beta_1 - \beta_0) + (\beta_2 - \beta_0)^t \left(X_2{}'X_2\right)^{-1}(\beta_2 - \beta_0)$$

β_0 *is the* common values of the *parameters of the restiricted regression*

β_1 *parameters of the regression befor regime change*

β_2*parameters of the regression after regime changes*

X_1 *matrix of regressors with constant of regression before regime changes*

X_2 *matrix of regressors with constant of regression after regime changes*

We will calculate the value of "D" by varying the values of parameters of second regression and keeping the values of the parameter of first regression constant and assume fix values of parameters of combine regression and for power comparison we calculate powers of test statistics by vary distance of parameters and heteroskedasticity.

3.5 Computation of tests statistics

The data are generated under the null/alternative hypothesis then following steps are followed to compute the tests statistics.

Regress Y_t on X_t.

I- Regression with no break point

$$Y_o = X_o\hat{\beta}_o + \mu \dots\dots\dots\dots (3.5.1) \quad t = 1,2,3, \dots T \text{ (Under null hypothesis)}$$

$$\hat{\mu}_t = Y_t - \hat{Y}_t \ldots\ldots\ldots\ldots (3.5.2)$$

$$RRSS = \hat{\mu}_t' * \hat{\mu}_t \text{ Restricted residuals sum of square } \ldots (3.5.3)$$

II- Regression before break point

$$Y_1 = X_1\hat{\beta}_1 + \mu_{t1} \ldots\ldots\ldots\ldots (3.5.4)\ t = 1,2,3,\ldots T_1$$

$$\hat{\mu}_{t1} = Y_t - \hat{Y}_t \ldots\ldots\ldots\ldots (3.5.5)$$

$$RSS_1 = \hat{\mu}_{t1}' * \hat{\mu}_{t1} \text{ residuals sum of square before break point } \ldots\ldots (3.5.6)$$

III- Regression after break point

$$Y_2 = X_2\hat{\beta}_2 + \mu_{t2} \ldots\ldots\ldots\ldots (3.5.7)\ t = T_1 + 1,2,3,\ldots T_2$$

$$\hat{\mu}_{t2} = Y_t - \hat{Y}_t \ldots\ldots\ldots\ldots (3.5.8)$$

$$RSS_2 = \hat{\mu}_{t2}' * \hat{\mu}_{t2} \text{ residuals sum of square before break point} \ldots\ldots (3.5.9)$$

The test statistics F and MZ can be calculated for all potential break date points within the interval (a b) as F_j and MZ_j where $\{k < a \leq j \leq b < T\text{-}k\}$. The maximum value of the interval F and MZ statistics is known as SupF and SupMZ respectively.

IV The F Test

$$F_j = \frac{\left(RRSS - (RSS_{1,j} + RSS_{2,T-j})\right)/k)}{(RSS_{1,j} + RSS_{2,T-j})/(N_1 + N_2 - 2k)}$$

$$\text{where}\ \{k < a \leq j \leq b < T - k\}$$

$$RRSS = \text{ Restricted residuals sum of square i.e.}$$

Residual sum of square from regression (3.5.3) under the null hypothesis

k= number of parameters i.e. '2'

2K= parameters in the unconstrained regression.

$URSS =$ Unrestricted residuals sum of square $= RSS_{1,j} + RSS_{2,T-j}$

$RSS_{1,j} =$ residuals sum of square from regression (3.5.6) before break point

$RSS_{2,T-j}$ = residuals sum of square from regression (3.5.9)after break point

N_1 number of observation in regression before break point

N_2 number of observation in regression after break point

We calculate F statistics for all potential break point and their maximum values will be SupF test as

$$\text{SupF} = \max_{a \le j \le b} F_j$$

Where {k < a ≤ j ≤ b < T-k}

IV- The MZ Test

$$MZ_j = (N_o - k) * log(\hat{\sigma}_0^2) - ((N_1 - k) * log(\hat{\sigma}_{1,j}^2) + (N_2 - k) * log(\hat{\sigma}_{2,T-j}^2)$$

$$\hat{\sigma}_0^2 = variance\ from\ (3.5.1)\ equation = \frac{RRSS}{N_O - k}$$

$$\hat{\sigma}_{1,j}^2 = variance\ from\ (3.5.5)\ equation = \frac{RSS_{1,j}}{N_1 - k}$$

$$\hat{\sigma}_{2,T-j}^2 = variance\ from\ (3.5.9)\ equation = \frac{RSS_{2,T-j}}{N_2 - k}$$

$$\text{SupMZ} = \max_{a \le j \le b} MZ_j$$

Where {k < a ≤ j ≤ b < T-k}

The test statistics 'SupF and SupMZ' are designed for detection of single unknown break date point in the model The SupF statistics have the assumption of constancy of variance but SupMZ statistics is designed for testing the break point in mean as well as the variance of the model.

3.6 Computation of Simulated Critical Value

The critical values of SupF and SupMZ under the null hypothesis of no break in mean and variance are computed by performing 30,000 simulations at 5% level of significance.

The level of significance may be 1% and 10% but we use 5% level of significance in present study.

3.7 Computation of size and Power

We have calculated the values of SupF and SupMZ according to alternate hypothesis we use different combination parameters for different regimes and calculated the power of test statistics at different values of distance of parameters. The power of test statistics means the probability of rejecting the null hypothesis (no break point) when the null hypothesis is false, the test statistics detect the break point when there is a break in the data. We put break at the level "π_j" break exist in the data (where j= 10%, 20%, 30%, 40%, 50%) in data.

We have also calculated the values of the tests statistics under null hypothesis and compute the size under critical values. The size of test statistics means the probability of rejecting the null hypothesis (no break point) when the null hypothesis is true. The test statistics detect the break point when there is no break.

CHAPTER 4

Monte-Carlo Simulations Analysis

Critical values for SupF and SupMZ tests have been calculated using Monte-Carlo simulation with 30,000 sample size. Further, power of both tests have been computed at different parameters and compared. Results of this comparison are given below:

4.1 Critical Values

The critical values for all the test statistics are found by using Monte Carlo simulation technique. We generate the data under the null hypothesis of (no break date point) keeping the values of parameters fix (intercept=.5 and slope =.5) and run 30,000 Monte Carlo simulations and get critical values at 5% level of significance are given in table below.

4.1.1 Critical Value by Monte-Carlo Analysis

These are critical values of F & MZ tests		
sup F	avg F	exp F
8.06	1.21	1.00
sup MZ	avg MZ	exp MZ
14.73	1.46	3.14

Critical values of tests statistics from Monte Carlo 30,000 simulations at 5% level of significance

To get critical values we have used 30,000 Monte Carlo sample size and for the rest of calculation we use 10,000 Monte Carlo sample size. There is a size distortion with asymptotic critical values of Andrews in a small sample size so we preferred simulated Critical values.

4.2 The Power Comparison

The power of test statistics means the probability of rejecting the null hypothesis (no break point) when the null hypothesis is false, the test statistics detect the break point when there is a break in the data. We check the performance of SupF and SupMZ with different level of heteroskedasticity (break in variance at regime shifting) and distance of parameters on different regimes as mentioned in Maasoumi et al (2010).

The tests statistics avgF, expF, avgMZ and expMZ are not giving us good results as we checked in Monte Carlo simulation technique. These tests have no good power to detect the correct break points so these tests may be misleading.

The Most Favorable case for SupF test is Homoskedasticity

The powers of SupF and SupMZ tests have computed in homoskedastic variance and heteroskedastic variance. The results have reported in table and their graphical representation also mentioned corresponding to distance of parameters of two regimes "D" and heteroskedasticity (break in variance at regime shifting)"H".

4.2.1 Power of tests with Heteroskedasticity (Break in variance)

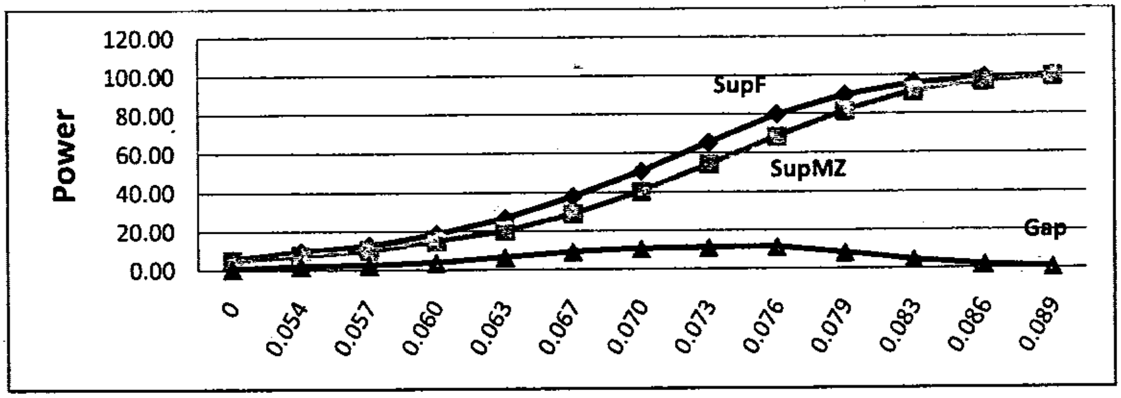
We have also computed powers of tests with the homoskedatic variance by varying coefficients (distance between parameters) of two regression. We have computed the powers of SupF and SupMZ, where supF performance is better than supMZ test because this most favourable case for SupF test.

4.2.1.1 Maximum Gap between SupF and SupMZ with Homoskedasticity

	10% Break	20% Break	30% Break	40% Break	50% Break
Power	12.32	12.93	11.38	10.27	12.52

The power of SupF test by Monte-Carlo simulation at different level

Figure # 4.2.1.Power and gap between SupF and SupMZ with Homoskedasticity



In case of Homoskedastic variance we have computed powers of SupF and SupMZ tests by varying the distance of parameters of two regimes. The maximum gap between both tests has been reported in table (4.2.1.1). This gap between SupF and SupMZ goes to zero when the distance of parameters between two regimes increases. In figure (4.2.1.1) showed that the power and gap between SupF and SupMZ, this gap go to zero when distance of two regimes increases. Further results on power of tests are discussed in appendix A.

The Most Favorable case for SupMZ test is Heteroskedasticity

4.2.2 Power of tests with Heteroskedasticity (Break in variance)

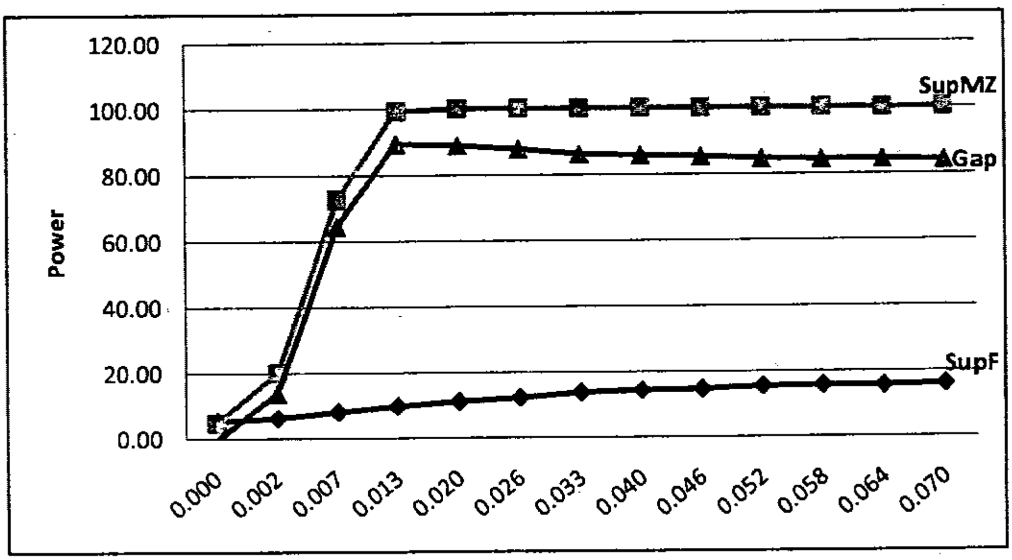
We have also computed powers of tests with the presence of heteroskedasticity (shift in variance at regime shifting) with same coefficients (no distance between parameters) of two regression only break in variance. We have computed the powers of SupF and SupMZ where supMZ performance is better than supF test.

4.2.2.1 Maximum Gap between SupF and SupMZ with Heteroskedastic Data

	10% Break	20% Break	30% Break	40% Break	50% BreaK
Power	94.10	92.68	89.41	84.35	84.48

The power of SupF test by Monte-Carlo simulation at different level

Figure# 4.2.2.1 power and Gap between SupF and SupMZ with Heteroskedastic Data

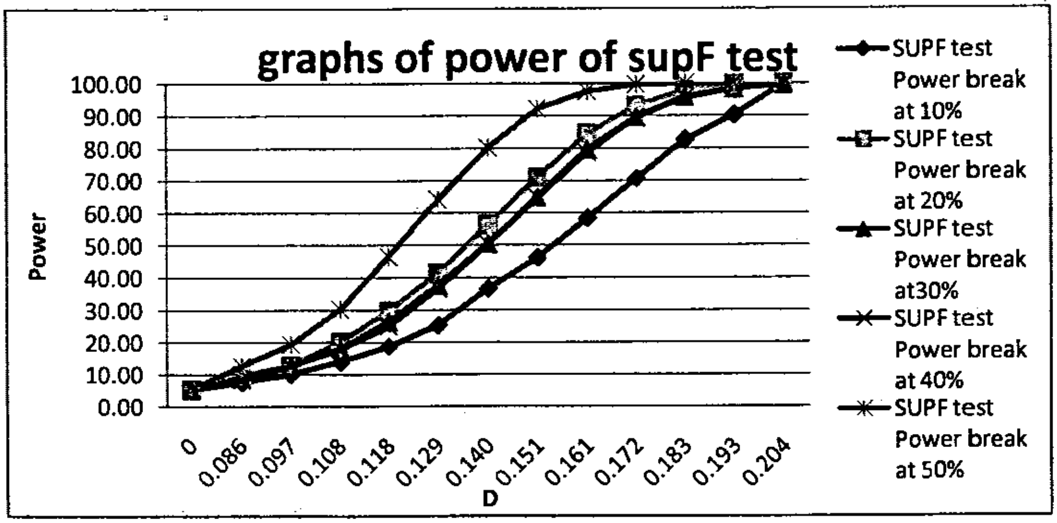


Here we have computed powers of SupF and SupMZ tests by putting break in variance of both regimes keeping distance constant. We conclude that the SupMZ test perform better than SupF test as shown in figure (4.2.2.1). The maximum gap between both tests has been reported in table (4.2.2.1). The SupMZ detects even a smaller break as shown by gap at 10% with 94.1% power. This gap decrease from 95% to 84% as we put break from 10% to 50% in data. The SupMZ test has advantages against SupF test when there apears break in variance at regime shifting. Further results of power of both tests are reported in appendix A.

4.3 Effect of Position of Break on Power Curves

We have computed powers of SupF and SupMZ with homoskedastic and heteroskedatic variance. When we used homokedastic variance then we computed powers by varying distance of coefficients of two regimes to check the performance of SupMZ test against SupF test. When we used heteroskedastic variance we kept distance constant to check the perforamce of SupF test against SupMZ test. But in this section we also checked the effects of posistions of break on powers of bith tests statistics so we put break in data at 10%, 20%,…,50% and their power curves are as:

4.3.1 Power of SupF Test Break at Different Positions With Homoskedasicity



Figure# 4.3.2 Power of SupMZ Test, Break at Different Positions With Homoskedasicity

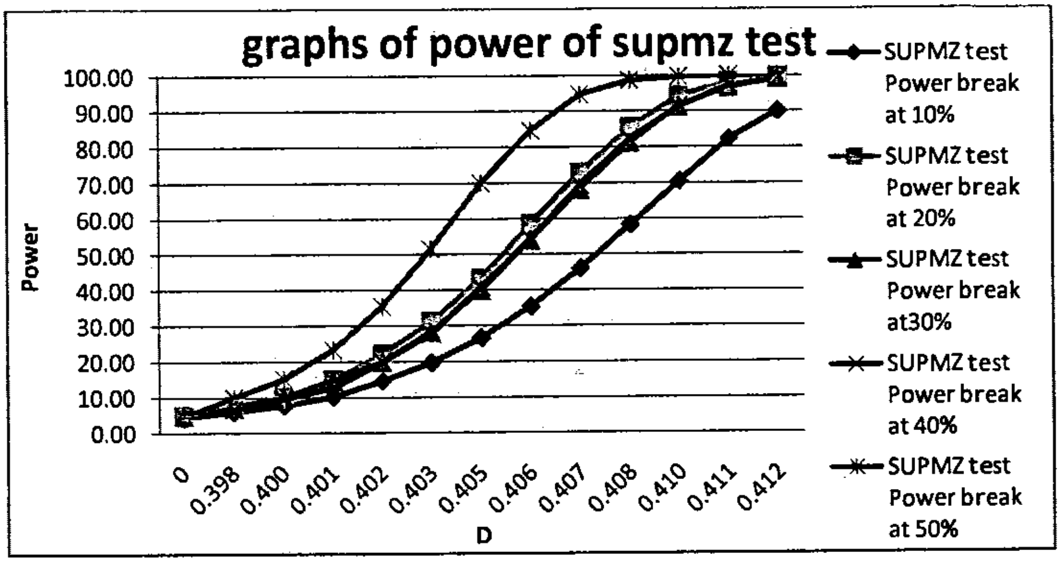


Figure (4.3.1) shows the power of SupF test at different level of break with homoskedasticity data. We put break from 10% to 20% SupF perfromnce increase rapidly but the performance of SupF test almost equale at 20%, 30% and 40% break level. When we put break at 50% in the data more perfromnce improve. Similarly in Figure (4.3.2) SupMZ performance increase by putting break from 10 % to 50% level. But power almost equal at break 20%, 30% and 40%.

Figure #4.3.3 Power of SupMZ Test at Different positions With Heteroskedasicity

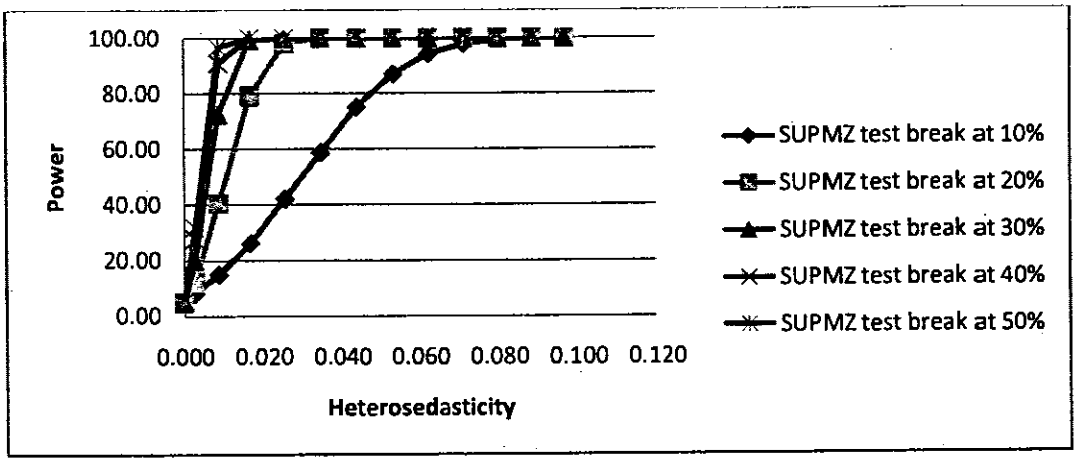
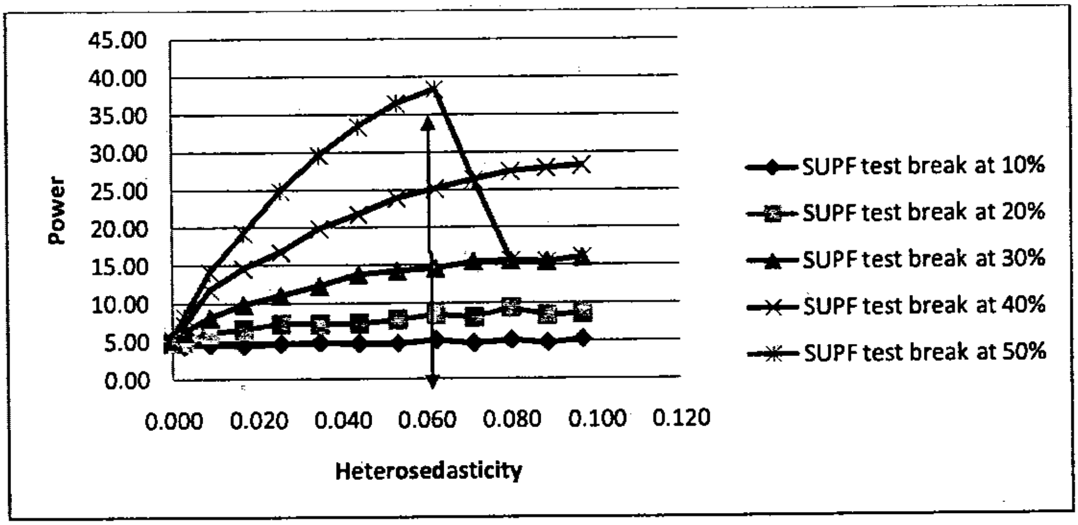


Figure # 4.3.4 Power of SupF Test at Different positions With Heteroskedasicity



In Figure (4.3.3) shows the power of SupMZ test at different level of break with heteroskedasticity data. As we put break from 10% to 50% performance and almost become 100%.. Similarly in Figure (4.3.4) SupF performance increase by putting break from 10 % to 50% level but as we increase heteroskydasicity power of SupF test go down at 50% break point shown by arow sign in start Power increase as random fluctuation.

4.4 Relative Powers of SupMZ against SupF Test

In this section we have computed powers by taking difference of the powers of SupF from SupMZ test statistics by varying distance between parameters of two regressions and different values of heteroskedasticity (shift in variance with regime shifting). We showed relative power by bar chat.

Table# 4.4.1 Difference, SupMZ minus SupF Test Break Located at 30% in the Data

0.390	-9.99	-8.50	-5.00	-0.80	**5.73**	**31.27**	**51.47**	**57.47**	**67.93**	**76.17**
0.386	-14.33	-5.80	-0.97	**14.53**	**28.80**	**40.97**	**58.30**	**66.37**	**71.90**	**79.57**
0.382	-18.34	-9.10	-0.17	**19.83**	**37.57**	**49.53**	**65.93**	**69.50**	**75.13**	**80.47**
0.378	-22.27	-9.10	**7.80**	**28.03**	**45.13**	**55.97**	**71.43**	**74.77**	**80.67**	**83.83**
0.374	-27.57	-10.57	**9.13**	**31.83**	**50.70**	**62.67**	**75.60**	**78.00**	**80.57**	**85.60**
0.370	-29.55	-7.17	**13.77**	**34.70**	**53.97**	**68.23**	**79.27**	**81.30**	**83.30**	**88.03**
0.366	-24.37	-2.73	**15.93**	**36.90**	**55.10**	**71.50**	**82.87**	**84.10**	**85.40**	**87.03**
0.363	-19.93	-0.63	**19.20**	**37.27**	**56.33**	**74.07**	**84.43**	**86.33**	**87.63**	**88.40**
0.359	-9.98	**0.33**	**14.67**	**34.43**	**56.77**	**74.87**	**86.37**	**88.40**	**88.50**	**89.47**
0.355	-7.53	**0.33**	**13.87**	**34.53**	**57.10**	**73.87**	**88.30**	**88.90**	**90.53**	**89.30**
0.351	-5.11	**0.93**	**14.13**	**32.50**	**54.03**	**74.87**	**90.00**	**89.97**	**89.77**	**89.40**
0.347	-2.85	**2.77**	**14.33**	**31.17**	**54.63**	**75.27**	**90.80**	**91.03**	**91.87**	**91.93**
0.343	-1.71	**2.57**	**12.43**	**28.13**	**53.00**	**72.77**	**91.73**	**92.13**	**91.90**	**92.27**
0.000	-0.38	**2.27**	**11.53**	**26.67**	**49.57**	**73.27**	**91.83**	**92.80**	**91.93**	**91.30**
D / H	0.0000	0.0007	0.0023	0.0044	0.0070	0.0097	0.0154	0.0183	0.0241	0.0333

In this table (4.4.1) shows the percentage point difference between the power of the SupMZ test and the SupF test. An entry of '7.8' means that SupMZ has 7.8% greater power than the SupF test, while an entry of -9.99 indicated 9.99% greater power for the SupF test over SupMZ. . At higher values of 'D', power of SupF test is high and power of

SupMZ is high at high value of 'H'. The bold face figures Shows that the best performances of SupMZ test against SupF test. Similar results computed at different locations in the data are reported in Appendix A and graphical representations are also reported in Appendix B.

CHAPTER 5

Empirical Design

The main purpose of this chapter is to check the performance of SupF and SupMZ test in real life data and compared empirical results with Monte-Carlo analysis. In this chapter we explained all the steps to conduct empirical analysis.

5.1 Empirical Data Series

For empirical analysis we take the annual data form IFS data base on household consumption and GDP for several countries. Regress household consumption on GDP and apply these statistics to detect the unknown break point. We use bootstrap critical value for finite sample to get more accurate results than simulated critical values of these tests statistics.

5.2 Consumption Function and Test Statistics

$$C_t = a + bY_t + \epsilon_t \dots\dots\dots\dots (5.2.1)$$

Take the residuals from consumption function and calculate the values of F and MZ statistics for all possible break point in an interval (a b). Therefore the first step is to compute the F and MZ statistics F_j and MZ_j for $\{k < a \leq j \leq b < T\text{-}k\}$. The maximum values from these intervals of test statistics known as SupF and SupMZ respectively and these values are calculated values of tests statistics for detection of break date points.

$$F = ((RRSS - URSS)/k)/((URSS)/(N_1 + N_2 - 2k))$$

$$MZ = (T - k) * log(\sigma_0^2) - ((t_1 - k) * log(\sigma_1^2) + (t_2 - k) * l0g(\sigma_2^2)$$

For unknown break F and MZ test statistics are calculated for all potential break point as:

$$F_j = \frac{\left(RRSS - (RSS_{1,j} + RSS_{2,T-j})\right)/k)}{(RSS_{1,j} + RSS_{2,T-j})/(N_1 + N_2 - 2k)}$$

$$SupF = \max_{a \le j \le b} F_j$$

$$MZ_j = (N_o - k) * log(\hat{\sigma}_0^2) - ((N_1 - k) * log(\hat{\sigma}_{1,j}^2) + (N_2 - k) * log(\hat{\sigma}_{2,T-j}^2)$$

$$SupMZ = \max_{a \le j \le b} MZ_j$$

$$\text{where}\{k < a \le j \le b < T - k\}$$

5.3 Bootstrapping procedure for Critical Values

We use estimated values of the parameters $\hat{a}$ and $\hat{b}$ and also calculate the value of the variance of residuals $\hat{\omega}$ from the regression equation 'D' $\epsilon_t \sim N(0, \hat{\omega})$'. For bootstrapping methodology we generate the residuals from normal distribution $\delta \sim N(o, \hat{\omega})$ and then generate consumption series by using the estimated values of parameters and residuals series as:

$$\bar{C}_t = \hat{a} + \hat{b}Y_t + \delta_t \quad \dots\dots\dots\dots (5.3.1)$$

Again regress $\bar{C}_t$ on Y_t for getting the bootstrap critical values of the test statistics.

$$\bar{C}_t = \gamma + \varphi Y_t + \Omega_t \dots\dots\dots\dots (5.3.2)$$

Take the residuals from (F) and calculate the values of the test statistics.

$$SupF = \max_{a \le j \le b} F_j$$

$$SupMZ = \max_{a \le j \le b} MZ_j$$

$$\text{where}\{k < a \le j \le b < T - k\}$$

If we simulate the values of SupF and SupMZ get from 'F' equation 30,000 times and sort them and calculate the values of these statistics at 5% level of significance these values are known as bootstrap critical values under the null hypothesis and we can take decision about switching the parameters in the main consumption functions.

5.4 Verification of Break in Variance

The SupMZ test detect break in coefficients and variance simultaneously at unknown point. After detection of break by SupMZ we also applied GQ test (test for detection of known break in variance) to verify the break in variance.

5.5 Computation of GQ test

In statistics, the Goldfeld-Quandt test (1965) checks for heteroskedasticity. In GQ test we split data into two parts, where we want to check the break in variance and run two separate regressions on two subset of original dataset. The GQ test also known as a two group test and it has an F distribution under the null hypothesis. According to Zaman (1996, 8.6) the GQ test is an optimal test for testing the equality of variance in two subsets of data, when the regression coefficients are not assumed to be same and variance is constant in each of the two regimes.

H_0; Homoskedastic variance

H_1; Heteroskedastic variance

$$GQ = \frac{RSS_1 / n_1 - k}{RSS_2 / n_2 - k} = F(n_1 - k, n_2 - k) \quad \text{where k is number of parameters i. e. 2}$$

RSS_1 and RSS_2 are residuals sum of square from first and second regression

n_1 and n_2 are the number of observations in first and second regression respectively

The GQ test is used to detect the break in variance and we apply this test in consumption function at where SupMZ test detect the break point as Maasoumi et al (2010) discussed.

CHAPTER 6

Empirical Analysis

In this chapter, we applied these tests to detect break in real life data. For that purpose, standard Keynesian consumption function is calculated for several countries. Choice of standard Keynesian function is just for ease and simplicity as this function is co-integrated in most of the cases. Results of this study can be generalized to all other models. Bootstrap critical values for small sample were taken to decide about break. Results of Monte-Carlo exercise were further verified by the empirical analysis. Results are also reported graphically.

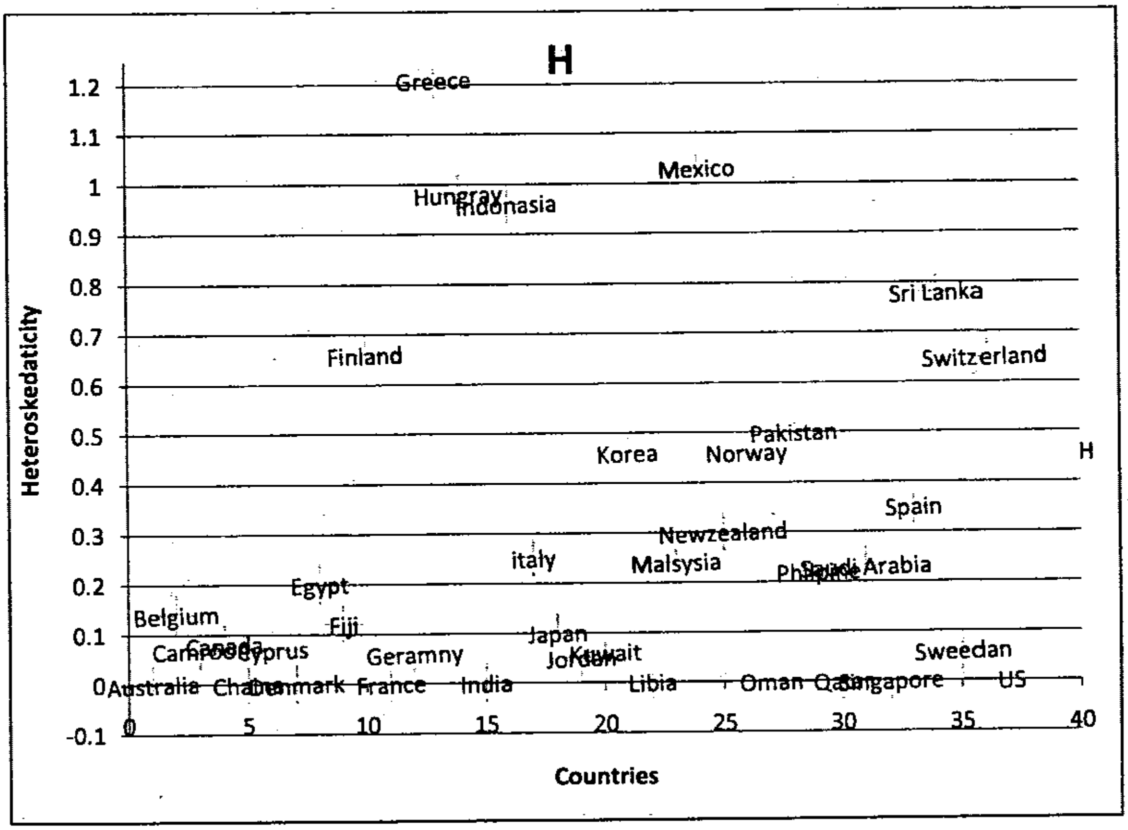
6.1 Detection of Single Unknown Break Point

As discussed above we take the households consumption expenditure and GDP from IFS data base and make consumption function for several countries. To check for possible unknown break point in the data we apply SupF and SupMZ test and use bootstrap critical values to make decision about break points. Where SupMZ detects the break in the data at that point we apply GQ test to detect break in variance, because GQ test is an optimal test to detect break in variance as discussed Zaman (1996).

The SupF test is an optimal test for homoskedastic data to detect the parameter instability. But the SupMZ test can detect break in parameter with the presence of heteroskedasticity. The main contribution of the present study is that SupMZ is optimal to the SupF test in the presence of heteroskedasticity.

We take data from IFS data base (May 2008) with '30' sample size and drop some countries from our analysis which have less than '30' observations. On remaining countries we apply test statistics to detect unknown break point and some important results are mentioned in table and some important results are also discussed graphically.

Figure#6.1.1 Countries and Heteroskedasticity



In this graph heteroskedasticity is presented on vertical axis and countries are on horizontal axis. The graph explicitly expressed that not all the countries have homoskedastic variance, but only a few countries have homoskedastic variance lies on horizontal axis so the use of SupF test on the basis of homoskedastic assumption lead to wrong conclusion. It is vital to detect stability in variance in line with the detection of mean, so use of SupMZ is most power full test and superior according to above scenario.

6.2 Countries and Detected Break Points

We have computed different results of tests for detection break for different countries we have discussed these results one by one. We apply GQ test where SupMZ test detect break. We also computed distance between parameters of two regimes and break in variance are shown in table as Distance 'D' and heteroskedasticity 'H' respectively. The results are reported as:

Table# 6.2.1 Tests Detected Break at Same Location

Country	SupF Test		SupMZ Test		D	GQ Test	H
	Year	Results	Year	Results		Results	
Belgium	1980	Yes	1980	Yes	58120.2	Yes	0.14
Cameroon	1992	Yes	1992	Yes	38040.47	Yes	0.07
Canada	1992	Yes	1992	Yes	5212.4208	Yes	0.08
Fiji	1988	Yes	1988	Yes	217537.45	Yes	0.12
Germany	1991	Yes	1991	Yes	-3508.335	Yes	0.06
Jordan	1994	Yes	1994	Yes	5160616.7	Yes	0.05
Kuwait	1998	Yes	1998	Yes	22049345	Yes	0.06
Saudi Arabia	1992	Yes	1992	Yes	6320.7856	Yes	0.23
Sweden	1991	Yes	1991	Yes	9466.2024	Yes	0.06

In table (6.2.1) we have computed results of tests countries (Belgium, Cambroon, Canada, Fiji, Germany, Jordan, Saudi Arabia, Kuwait and Sweden) where both tests detected break at same location because there is a large change in Distance of parameters of two regimes but low level of heteroskedasticity (break in variance) the significant value of Heteroskedasticity. We conclude that when there is a significantly large change distance in coefficient of two regimes but very small change in variance at regime shifting, SupF test and SupMZ test detected break at same location. It is not appropriate to use SupF test to detect structural break in the presence of variance break, so the SupMZ test optimal test for testing break in the presence of variance break

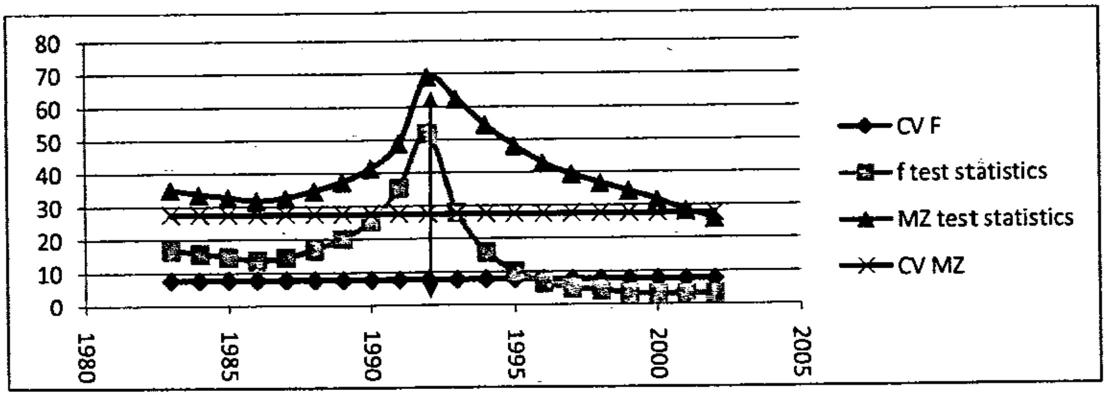
We discussed some results in graphical representation.

Table #6.2.1.1 Results of test statistics to detect break point for Saudi Arabia

	sup F	sup MZ	Distance
Calculated	51.8759	68.9253	6320.7856
Critical value	7.5834	27.5584	
Results of GQ test statistics to detect the variance break			
GQ calculated	p-value	Table value	Heteroskedasticity
9.225653246	0.00011	2.534243253	0.23

Calculated values of tests statistics critical values are taken from bootstrapping for Saudi Arabia

Figure #6.2.1.1 CDF of F and MZ Test Statistic for Saudi Arabia



CDF of F and MZ test statistics for monitoring unknown break point for Saudi Arabia

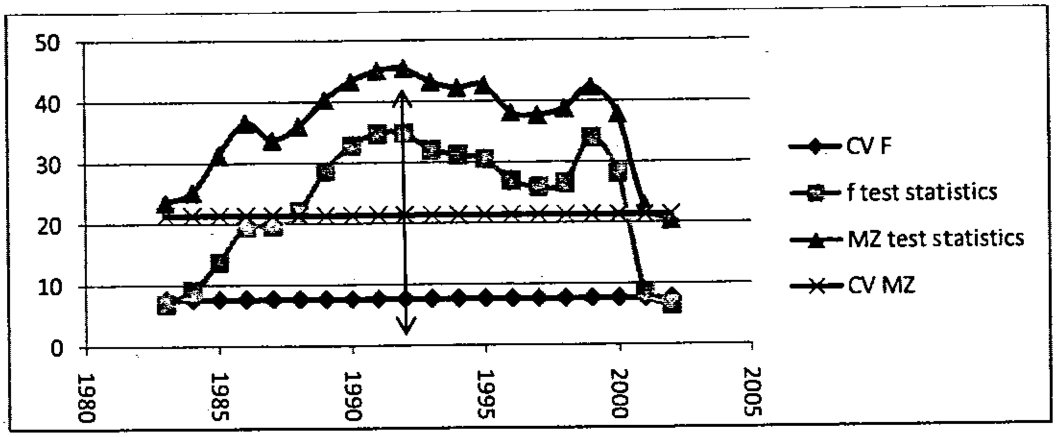
In the consumption function of Saudi Arabia Both tests statistics SupF and SupMZ showed that the break date point at 1992 figure (6.2.1.1) and at this point the value of GQ test statistic shows in table (6.2.1.1) that there is also break in variance that violate the assumption of SupF test. Saudi Arabian consumption function is heteroskedastic data so SupF test is not valid for this kind of data. The SupMZ test is most powerful test for Saudi Arabia consumption function to test the parameter break.

Table#6.2.1.2 Results of all Test Statistics to Detect Break Point for Canada

	SupF	SupMZ	Distance
Calculated	35.773	45.314	5212.4208
Critical value	7.6022	21.382	
Results of GQ test statistics to detect the variance break			
GQ calculated	p-value	Table value	Heteroskedasticity
3.429816	0.01938	2.637124	0.08

Calculated values of tests statistics critical values are taken from bootstrapping for Canada

Figure#6.2.1.2 CDF of F and MZ Test Statistic for Canada



CDF of F and MZ test statistics for monitoring unknown break point for Canada

In the consumption function of Canada both tests statistics SupF and SupMZ shows the break date point at 1992 figure (6.2.2) and at this point the value of GQ test statistic shows there is heteroskedasticity in consumption function of Canada as shown in table (6.2.2). In the presence of heteroskedasticity in the data SupF test is not appropriate but SupMZ test is optimal test to detect the break for Canadian consumption function.

Table# 6.2.2 The SupMZ Detected Break

Country	SupF Test		SupMZ Test		D	GQ Test	H
	Year	Results	Year	Results		Results	
Egypt	-	No	1996	Yes	79737374	Yes	0.20
Italy	-	No	1990	Yes	5139.3949	Yes	0.25
Newzealand	-	No	1985	Yes	97548.275	Yes	0.30
Sri Lanka	-	No	1995	Yes	606062339	Yes	0.78
Switzerland	-	No	1986	Yes	39679.165	Yes	0.65
Pakistan	-	No	1986	Yes	402.28023	Yes	0.50

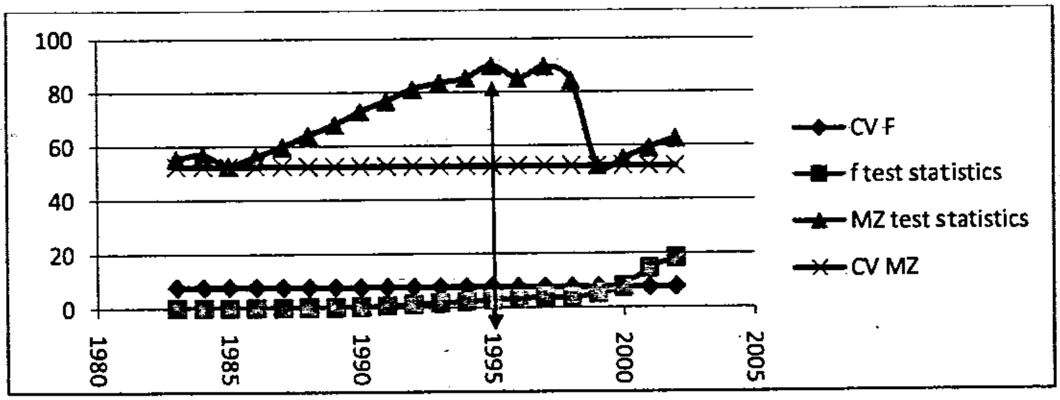
In table (6.2.2) we computed some results of these countries (Egypt, Sri Lanka, Italy, Newzeland, Pakistan and Switzerland) where SupF test fails to detect break in parameters because there is a large change in Heteroskedasticity (break in variance) as shown by the values of 'H' in table (6.2.2). In this case SupMZ detected break in data but SupF test fail to detect break because of large change in variance at regime shifting. So we conclude that SupMZ most powerful test against SupF test. Some graphical representations are shown the performance of SupMZ test as:

Table#6.2.2.1 Results of Test Statistics to Detect Break for Sri Lanka

	SupF	SupMZ	Distance
Calculated	18.2585	89.8724	606062339
Critical value	7.6818	52.467	
Results of GQ test statistics for testing variance break			
GQ calculated	p-value	critical value	Heteroskedasticity
100.5121145	0.00000	2.54371855	0.78

Calculated values of tests statistics critical values are taken from bootstrapping for Sri Lanka

Figure #6.2.2.1 CDF of F and MZ Test Statistic for Sri Lanka



CDF of F and MZ test statistics for monitoring unknown break point for Sri Lanka

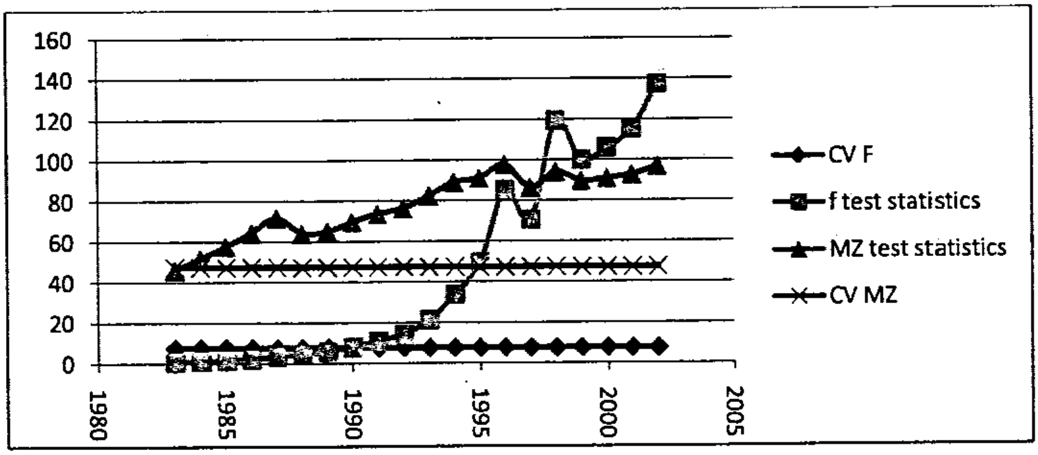
We have computed consumption function for Sri Lanka and applied both tests to detect break. The SupF and SupMZ tests statistic cross their critical boundary that is the evidence of possible break in parameters, but Supremum value of F test is at end point and fails to detect break. The SupMZ test showed that the break at 1995 in figure (6.2.2.1) at that point we also checked break in variance by GQ test statistic which showed that there is also break in variance at that point. The GQ test showed that Sri Lankan data is heteroskedastic so SupMZ is appropriate test to detect break in parameters for Sri Lankan consumption function. The use of SupF test leads us to wrong conclusion because of heteroskedastic data. So the SupMZ test is optimal test for testing structural break in Sri Lankan Consumption function.

Table#6.2.2.2 Results of all Test Statistics to Detect Break Point for Egypt

	sup F	sup MZ	Distance
calculated	136.94	97.539	79737374
Critical value	7.6089	47.454	
Results of GQ test statistics to detect the variance break			
GQ calculated	p-value	Table value	Heteroskedasticity
7.273852369	0.00028	2.493513221	0.20

These are the calculated values of tests statistics critical values are taken from bootstrapping for Egypt

Figure# 6.2.2.2 CDF of F and MZ Test Statistic for Egypt



CDF of F and MZ test statistics for monitoring unknown break point for Egypt

In the consumption function of Egypt we applied both test to check the structural break in parameters. Where SupMZ detected break in parameters at 1996 shows in figure (6.2.2.2) and at this point the value of GQ test statistic also showed that variance also shifted.

There is heteroskedasticity in Egypt consumption function so the SupMZ test is optimal to test the structural break for this consumption function. The use of SupF test gives wrong results in the presence of heteroskedasticity. The SupMZ test is most powerful test for Heteroskedastic data.

Table# 6.2.3 Detected Break with Homoskedastic data

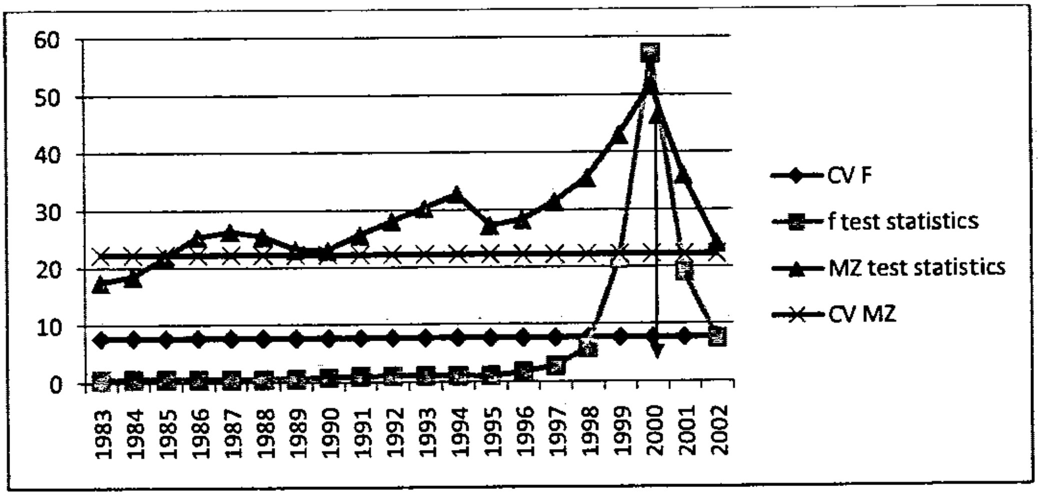
Country	SupF Test		SupMZ Test		D	GQ Test	H
	Year	Results	Year	Results		Results	
Denmark	2000	Yes	2000	Yes	12465.298	No*	-
India	2001	Yes	2001	Yes	35658178	No*	-
Libia	1991	Yes	1991	Yes	1397274	No*	-
Oman	1998	Yes	1998	Yes	7744195.8	No*	-
Qatar	2000	Yes	2003	Yes	128488581	No*	-

In table (6.2.3) there is no break in variance shown by results of GQ test as (NO*) in this case both tests detect break at same point in data of (Denmark, India, Libya, Oman, Qatar) countries. We conclude that SupMZ performance is same as SupF test when variances are Homoskedastic (no break in variance). This means SupMZ can cover SupF test so there is no need to apply SupF test to detect structural break.

6.2.3.1 Results of all Test Statistics to Detect Break Point for Denmark

	sup F	sup MZ	Distance
calculated	57.073	51.698	12465.298
Critical value	7.6808	22.246	
Results of GQ test statistics to detect the variance break			
GQ calculated	p-value	Table value	Heteroskedasticity
1.228177687	0.261422897	1.737057465	-

Figure# 6.2.3.1 CDF of F and MZ Test Statistic for Denmark



In the consumption function of Denmark we applied both tests to check the structural break. Where both tests detected break at (2000) showed in figure (6.2.3.1) and at this point the value of GQ test showed no break in variance. In homoskedastic data the both tests detect break at same location. We concluded that SupMZ can detect break with homoskedastic variances.

Table# 6.2.4 Tests Detected No Break

Country	SupF Test		SupMZ Test		D	GQ Test	H
	Year	Results	Year	Results		Results	
Australia	-	No	-	No	-	No	-
China	-	No	-	No	-	No	-
France	-	No	-	No	-	No	-
Singapore	-	No	-	No	-	No	-
US	-	No	-	No	-	No	-

In table (6.2.4) we computed that both the test detect there is no break in these countries (Australia, China, France, Singapore, and US). There is no structural break in these countries.

Table# 6.2.5 Both Tests detected Break at Different Locations

Country	SupF Test		SupMZ Test		D	GQ Test	H
	Year	Results	Year	Results		Results	
Cyprus	1995	Yes	1991	Yes	1631.558	Yes	0.07
Finland	1991	Yes	1988	Yes	3655.4651	Yes	0.66
Greece	1995	Yes	1987	Yes	296162.82	Yes	1.21
Hungary	1996	Yes	1988	Yes	711.86192	Yes	0.98
Indonesia	1998	Yes	1993	Yes	49609835	Yes	0.96
Japan	1997	Yes	1999	Yes	2.422E+12	Yes	0.10
Korea	2000	Yes	1998	Yes	778972741	Yes	0.46
Malaysia	1998	Yes	1996	Yes	187020346	Yes	0.24
Mexico	2001	Yes	1989	Yes	0.6786377	Yes	1.03
Norway	1997	Yes	1985	Yes	4132.1216	Yes	0.46
Philippine	2000	Yes	1992	Yes	5497.5617	Yes	0.22
Spain	1983	Yes	1982	Yes	211687.11	Yes	0.35

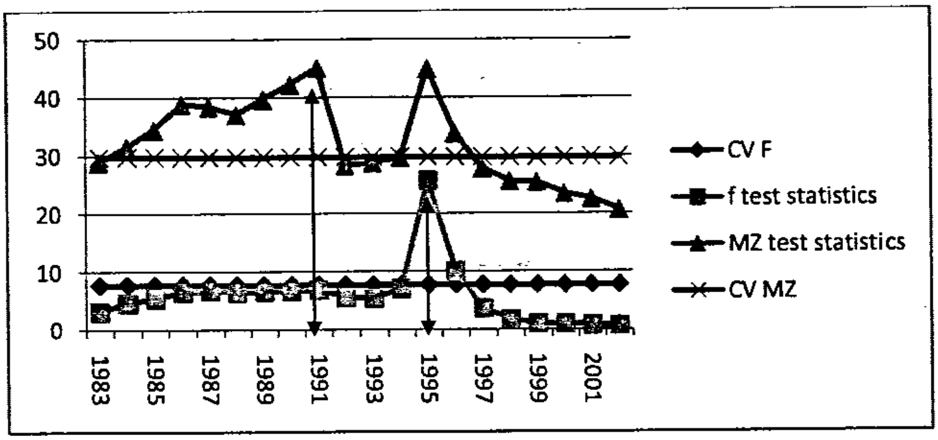
In table (6.2.5) we computed that both tests detected break in data but they locate break at different level this is because large value of Heteroskedasticity in the data in spite of it there is a large change in distance of parameters of two regimes. We conclude that when there is a large break in variance at regime shifting SupF tests will be misleading and detect break at wrong location. In all above discussion performance of SupMZ test is better than SupF test. Finally we conclude that SupMZ test is most powerful and optimal test to detect break in parameters. Now some graphical representation is discussed below.

Table# 6.2.5.1 Results of all Test Statistics to Detect Break Point for Cyprus

	sup F	sup MZ	Distance
calculated	25.627	45.022	1631.558
Critical value	7.7128	29.735	
Results of GQ test statistics to detect the variance break			
GQ calculated	p-value	Table value	Heteroskedasticity
3.123025438	0.02755	2.637124	0.07

These are the calculated values of tests statistics critical values are taken from bootstrapping for Cyprus

Figure#6.2.5.1 CDF of F and MZ Test Statistic for Cyprus



CDF of F and MZ test statistics for monitoring unknown break point for Cyprus

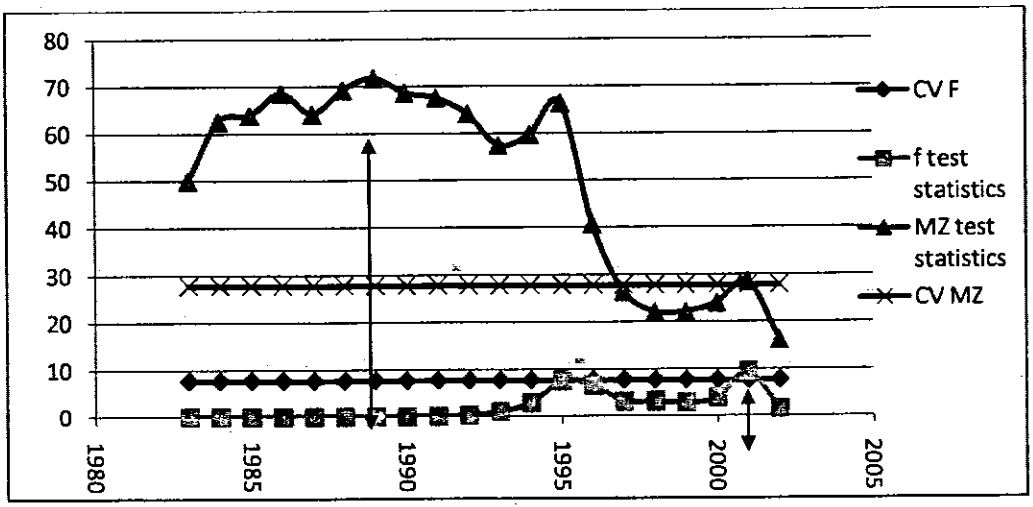
In this consumption function of Cyprus the calculated values of SupF and SupMZ exceed the critical limits shows in table (6.2.5.1) there is break in the data. But both tests showed break at different locations as SupMZ detected break at 1991 and SupF shows in figure (6.2.5.1) at 1995. The GQ test showed that there is also break in variance in 1995 where SupMZ test detect the break in parameter. This is heteroskedastic consumption function of Cyprus, the use of SupF test will be misleading.

Table #6.2.5.2 Results of all Test Statistics to Detect Break Point for Mexico

	sup F	sup MZ	Distance
calculated	9.3762	71.718	0.6786377
Critical value	7.6518	27.748	
Results of GQ test statistics to detect the variance break			
GQ calculated	p-value	Table value	Heteroskedasticity
2271.868501	0.00000	2.973695996	1.03

Calculated values of tests statistics critical values are taken from bootstrapping for Mexico

Figure#6.2.5.2 CDF of F and MZ Test Statistic for Mexico



CDF of F and MZ test statistics for monitoring unknown break point for Mexico

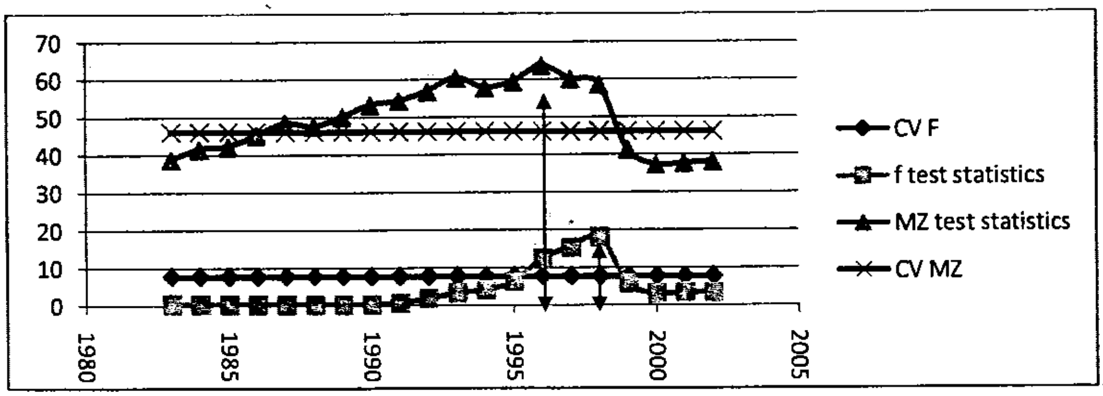
In the consumption function of Mexico the calculated values of both tests statistics SupF and SupMZ exceeded the critical limits, so there is break in the data as shown in table (6.2.5.2). Both tests showed break at different locations as SupMZ and SupF test showed break at 1989 and 2001 figure (6.2.5.2) respectively. The GQ test showed that there is break in variance in 1989. The use of SupF test in the presence of heteroskedastic data leads us to wrong conclusion. The SupMZ test is better to detect the break in parameters when there is heteroskedasticity in data.

Table#6.2.5.3 Results of Test Statistics to Detect Break Point for Malaysia

	sup F	sup MZ	Distance
Calculated	17.995	63.646	187020346
Critical value	7.6725	46.156	
Results of GQ test statistics to detect the variance break			
GQ calculated	p-value	Table value	Heteroskedasticity
8.902819895	0.00008	2.493513221	0.24

Calculated values of tests statistics critical values are taken from bootstrapping for Malaysia

Figure#6.2.5.3 CDF of F and MZ Test Statistic for Malaysia



CDF of F and MZ test statistics for monitoring unknown break point for Malaysia

We have computed consumption function of Malaysia and applied both tests to detect for possible structural break. Where both tests showed the break at different location as SupMZ and SupF test showed break at 1996 and at 1998 in figure (6.2.5.3). When we checked break in variance by GQ test, which showed that variance also shifted in 1996 that violate the assumption of SupF tests. This is heteroskedastic data set so SupMZ test is optimal to detect the break in the parameters for Malaysian consumption function.

CHAPTER 7

CONCLUSION, RECOMENDTAION AND DIRECTION FOR FUTURE RESEARCH

This study has been conducted for testing parameters constancy (break in coefficients and variance of two regimes simultaneously). We have compared SupF test and SupMZ test via simulation study and empirically. We have checked power by Monte Carlo simulation technique where we conclude that SupMZ test performs better against SupF test.

In chapter (4) we have analyzed both test statistics via Monte-Carlo simulation technique, where we apply both test statistics on homoskedastic and heteroskedastic data. In case of homoskedastic data with varying distance of the parameter in different regime, we have been applied both test statistics and concluded that SupF test has better power than SupMZ test. Maximum gain of SupF was 12.50% against SupMZ test that become zero when we have increase distance of parameters of different regimes. In case of heteroskedastic data where we conclude that the maximum gain of SupMZ test was 95% against SupF test by varying the value of heteroskedasticity. This gap decreases from 95% to 84% as we put break from 10% to 50% in the data. When the value of heteroskedasticity increases, performance of SupMZ also increases and powers of SupF test go on decreasing. We finally, concluded that in Monte Carlo simulation analysis SupMZ test has advantage over SupF test by Andrews.

In chapter (6) empirically we have computed the consumption function of several countries by getting annual data from IFS database and applied these test statistics on consumption function. We have been concluded that the performance of SupMZ test is better than the SupF test statistic to detect the unknown break point. We also concluded that GQ test performance good to detect break in variance, where the SupMZ test to detect the break in empirical analysis. As Zaman discussed (1996) the GQ test is an optimal test to detect break in variance when the coefficients are not same but the variances are same in both regimes.

In literature the SupF test is considered an optimal test to detect break in parameters with the assumption variances are stable. But no one tests the back ground assumption of SupF test and no available test in literature, which can test unknown break in variance. This study proved that most of cases the coefficients and variances are shifted simultaneously in real life so the SupF test is not an optimal test for testing break in parameters. The overall performance of SupF test is not good because in some cases it failed to detect the break and in some cases it detected break at wrong location with the presence of heteroskedasticity. All discussion in present study shows that the SupMZ test is an optimal test than the SupF test for the practitioners in testing of structural break. We have concluded the following points via simulation study as well as empirically.

- The SupF test statistics performs better than SupMZ test with homoskedastic data but this difference becomes zero (SupMZ cover its power) when the distance between parameters increases.

- The SupF test will be misleading to detect break point in the presence of heteroskedasticity (break in variance at regime shifting) as we see in empirical analysis.
- The SupF test some time detect break with heteroskedastic data when there is a huge distance between the coefficients of two regimes as we concluded that empirically as well as Monte Carlo simulation technique.
- The SupMZ test perform better in the presence of heteroskedasticity (break in variance at regime shifting) but SupF test worst off with heteroskedastic data.

All above discussion showed that SupMZ test is optimal test than SupF test so according to this study we suggest for researchers that SupMZ test should be used for testing structural instability. This study can be extended for multiple unknown breaks in future research.

APPENDIX A

Tables of Power of Tests Statistics

Section I: Table %Difference Power of SupMZ from SupF test

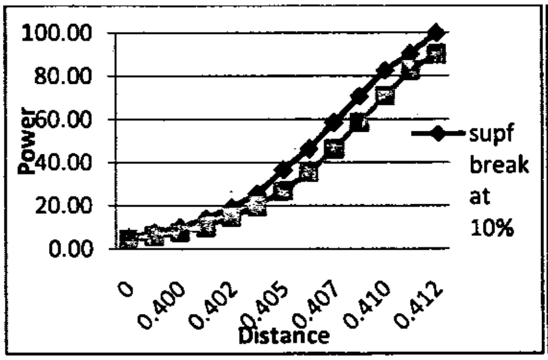
Gap 10%										
D \ H	0.0000	0.0004	0.0013	0.0024	0.0053	0.0068	0.0099	0.0114	0.0144	0.0177
0.0000	-0.85	3.17	6.03	8.63	22.93	29.50	50.97	59.80	76.90	89.60
0.5731	-1.50	1.43	4.63	9.93	22.17	33.73	50.77	61.80	78.03	89.70
0.5746	-2.25	1.07	4.77	10.77	24.43	32.57	51.17	61.67	77.43	88.70
0.5761	-3.89	0.67	8.07	10.00	24.13	32.40	52.70	63.93	78.57	89.33
0.5776	-7.27	0.33	5.70	10.07	24.67	35.33	53.60	62.10	78.67	89.33
0.5790	-10.65	0.63	6.87	11.93	26.80	35.50	54.60	64.70	79.33	88.87
0.5805	-16.84	-0.70	8.20	11.53	28.53	38.07	55.67	66.30	80.63	89.07
0.5820	-20.77	-0.93	11.60	16.83	29.77	38.83	57.80	65.50	79.93	89.30
0.5835	-26.19	-3.97	12.20	20.63	30.90	40.03	57.70	68.00	81.03	89.57
0.5850	-31.32	-5.83	5.80	17.73	32.07	43.23	59.50	68.50	81.30	89.83
0.5865	-41.90	-15.27	5.27	19.27	34.23	45.17	59.50	69.03	82.27	89.60
0.5880	-46.71	-23.17	1.23	16.10	37.47	47.07	62.63	71.53	82.50	89.37
0.5895	-54.75	-30.97	-1.43	16.57	39.20	46.77	63.43	70.60	81.33	89.63
0.5910	-44.63	-28.80	-6.77	-1.37	39.93	50.53	66.13	72.63	82.70	89.70
Gap 20%										
D \ H	0.0000	0.0007	0.0023	0.0044	0.0070	0.0097	0.0154	0.0183	0.0241	0.0333
0.0000	-0.38	2.27	11.53	26.67	49.57	73.27	91.83	92.80	91.93	91.30
0.3430	-1.71	2.57	12.43	28.13	53.00	72.77	91.73	92.13	91.90	92.27
0.3469	-2.85	2.77	14.33	31.17	54.63	75.27	90.80	91.03	91.87	91.93
0.3508	-5.11	0.93	14.13	32.50	54.03	74.87	90.00	89.97	89.77	89.40
0.3547	-7.53	0.33	13.87	34.53	57.10	73.87	88.30	88.90	90.53	89.30
0.3586	-9.98	0.33	14.67	34.43	56.77	74.87	86.37	88.40	88.50	89.47
0.3625	-19.93	-0.63	19.20	37.27	56.33	74.07	84.43	86.33	87.63	88.40
0.3665	-24.37	-2.73	15.93	36.90	55.10	71.50	82.87	84.10	85.40	87.03
0.3704	-29.55	-7.17	13.77	34.70	53.97	68.23	79.27	81.30	83.30	88.03
0.3743	-27.57	-10.57	9.13	31.83	50.70	62.67	75.60	78.00	80.57	85.60
0.3782	-22.27	-9.10	7.80	28.03	45.13	55.97	71.43	74.77	80.67	83.83
0.3821	-18.34	-9.10	-0.17	19.83	37.57	49.53	65.93	69.50	75.13	80.47
0.3861	-14.33	-5.80	-0.97	14.53	28.80	40.97	58.30	66.37	71.90	79.57
0.3900	-9.99	-8.50	-5.00	-0.80	5.73	31.27	51.47	57.47	67.93	76.17

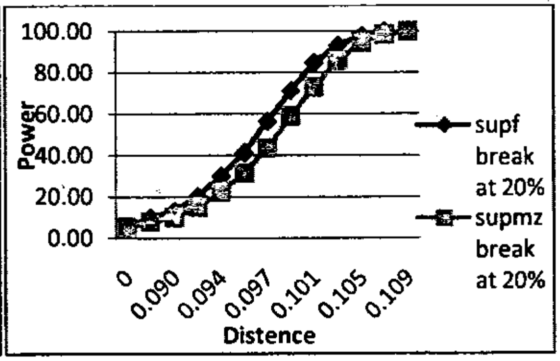
Gap 40%										
D H	0.0000	0.0003	0.0010	0.0035	0.0070	0.0155	0.0203	0.0301	0.0449	0.0561
0.0000	-0.59	1.60	7.00	31.57	71.07	84.50	83.63	80.37	77.53	75.20
0.0793	-1.52	-0.47	6.00	32.97	71.80	84.07	83.00	80.07	77.10	75.40
0.0861	-2.97	0.70	5.87	34.40	73.13	83.70	81.17	78.20	75.67	74.67
0.0929	-5.31	-1.30	6.03	35.60	72.23	81.07	79.27	77.13	73.43	74.17
0.0996	-5.07	-2.40	6.73	38.30	68.90	80.77	78.67	74.87	72.77	72.13
0.1064	-8.80	-4.73	6.30	37.07	67.23	75.27	74.50	74.53	73.00	70.80
0.1132	-9.48	-4.67	4.67	36.77	62.77	72.23	71.00	71.30	70.17	69.83
0.1199	-10.27	-4.47	6.33	34.97	61.23	67.97	68.47	69.30	69.37	68.63
0.1267	-9.09	-6.07	3.73	29.30	48.83	61.40	62.07	65.57	67.17	67.43
0.1335	-7.16	-6.13	0.20	23.77	39.03	53.37	56.80	59.77	61.83	64.70
0.1402	-4.28	-1.83	-0.07	16.00	29.93	46.83	50.73	66.90	61.57	62.43
0.1470	-1.03	-1.73	-0.97	9.00	20.33	37.67	42.20	50.87	57.30	60.53
0.1538	-0.48	-0.57	-0.60	5.13	11.53	28.07	36.20	45.37	52.90	57.60
0.1606	-0.40	-0.08	-0.13	1.67	7.27	20.20	27.77	39.87	49.67	54.67
Gap 50%										
D H	0.0000	0.0003	0.0011	0.0018	0.0037	0.0220	0.0274	0.0385	0.0552	0.0625
0.0000	-0.74	1.60	5.47	15.10	40.23	75.07	72.90	69.73	63.10	63.10
0.6466	-2.49	-0.37	8.17	17.30	40.30	75.37	74.07	68.63	62.27	61.80
0.6788	-4.29	-0.83	7.70	16.40	44.23	74.10	73.10	67.23	62.33	62.30
0.7110	-7.06	-2.37	7.00	17.43	46.10	73.33	71.17	67.33	62.47	59.90
0.7432	-11.00	-4.37	7.80	19.73	47.90	72.13	68.80	66.00	59.83	59.57
0.7754	-12.52	-6.00	8.20	19.83	44.80	67.17	65.43	63.10	60.13	58.43
0.8076	-10.01	-6.23	6.07	12.30	37.03	60.83	61.10	60.50	57.27	58.93
0.8398	-7.39	-4.83	3.70	9.53	25.77	56.60	55.50	58.17	55.27	56.10
0.8720	-2.85	-2.97	1.33	6.20	13.90	46.67	50.70	52.67	53.50	52.07
0.9042	-0.92	-1.07	0.77	2.80	6.17	38.50	43.70	48.33	51.43	50.37
0.9364	-0.15	-0.30	0.27	0.53	1.60	27.50	34.67	42.13	47.27	47.30
0.9686	0.00	-0.37	0.07	0.07	0.43	18.23	24.03	37.17	41.97	45.70
1.0008	0.00	-0.26	0.00	0.00	0.07	11.10	18.17	28.73	39.93	40.10
1.0330	0.00	0.00	0.00	0.00	0.00	5.70	10.47	22.07	33.57	36.60

APPENDIX B

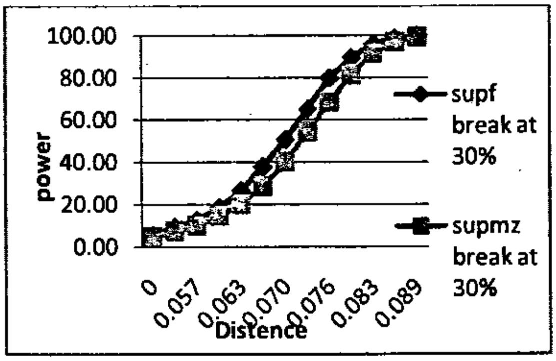
Contains All Graphs of Power of Tests Statistics

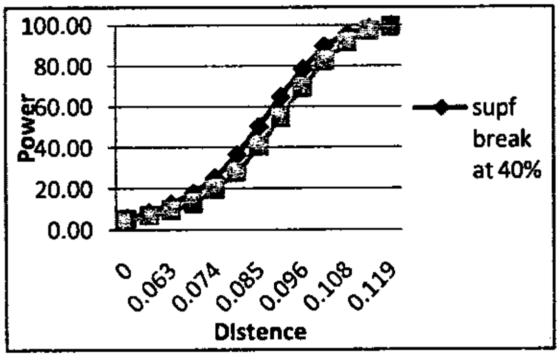
Section I: Power of SupF and SupMZ test with Homoskedasticity Break at 10% & 20%



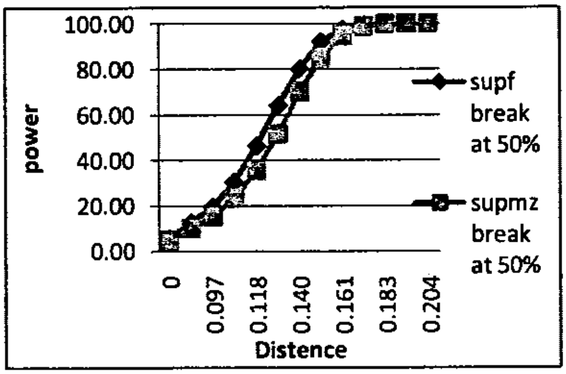


Power of SupF and SupMZ test with Homoskedasticity Break at 30% & 40%



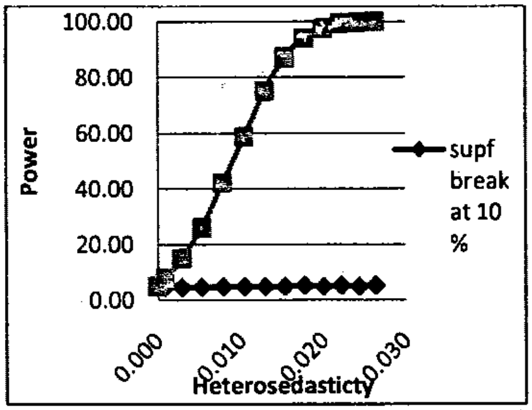


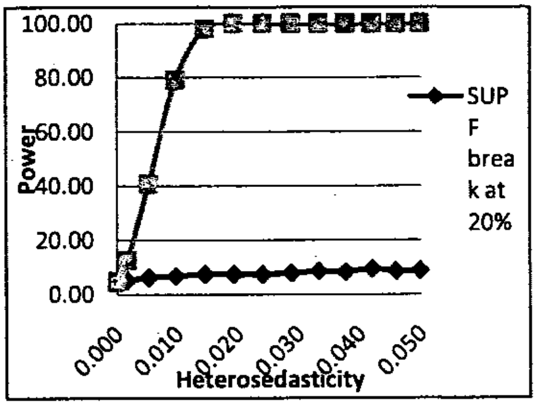
Power of SupF and SupMZ test with Homoskedasticity Break at 50%



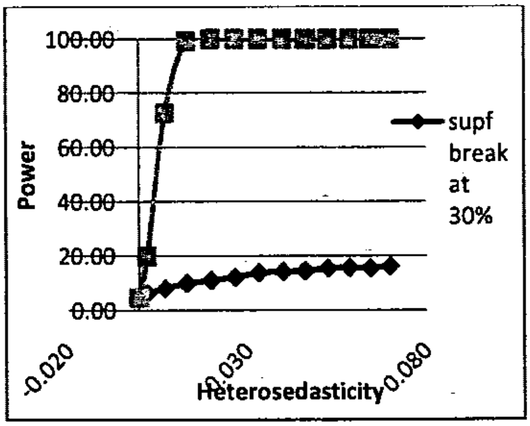
Section II:

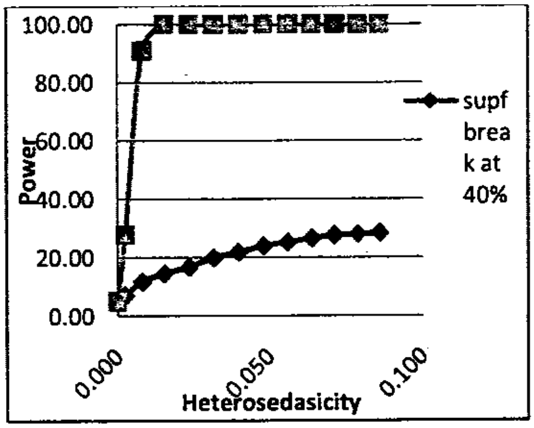
Power of SupF and SupMZ test with Heteroskedasticity Break at10% & 20%



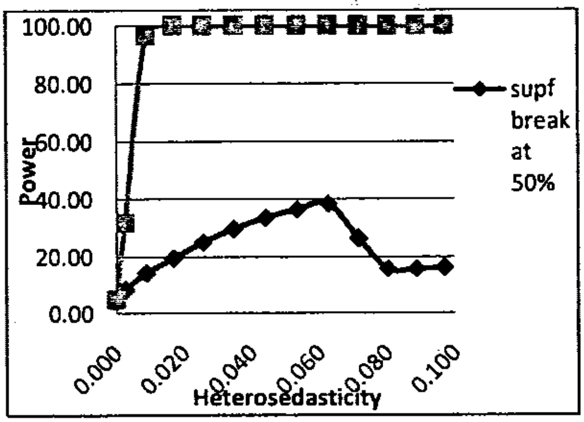


Power of SupF and SupMZ test with Heteroskedasticity Break at 30% & 40%

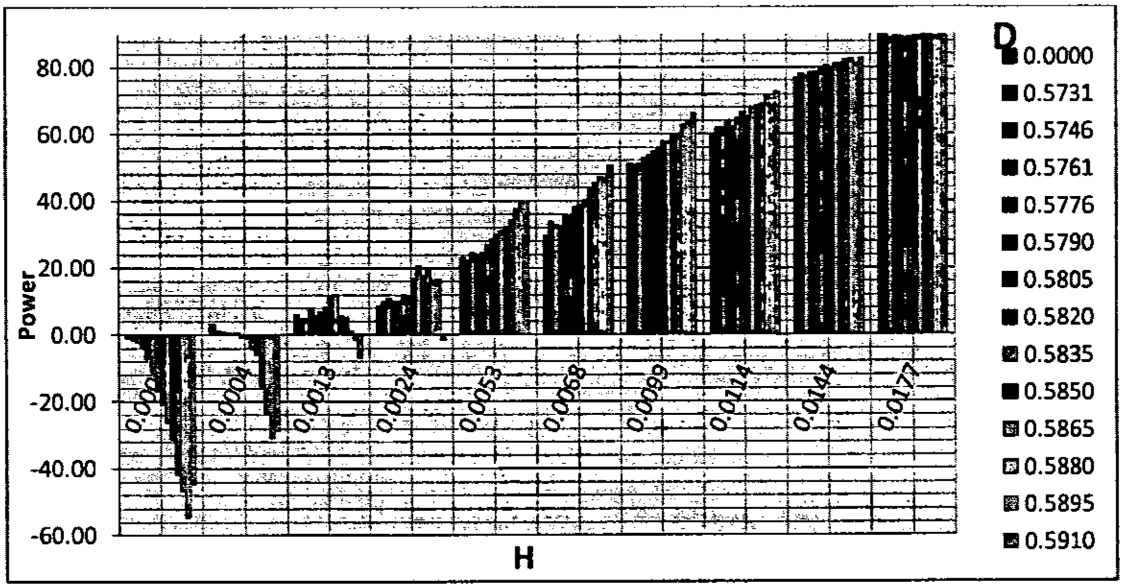




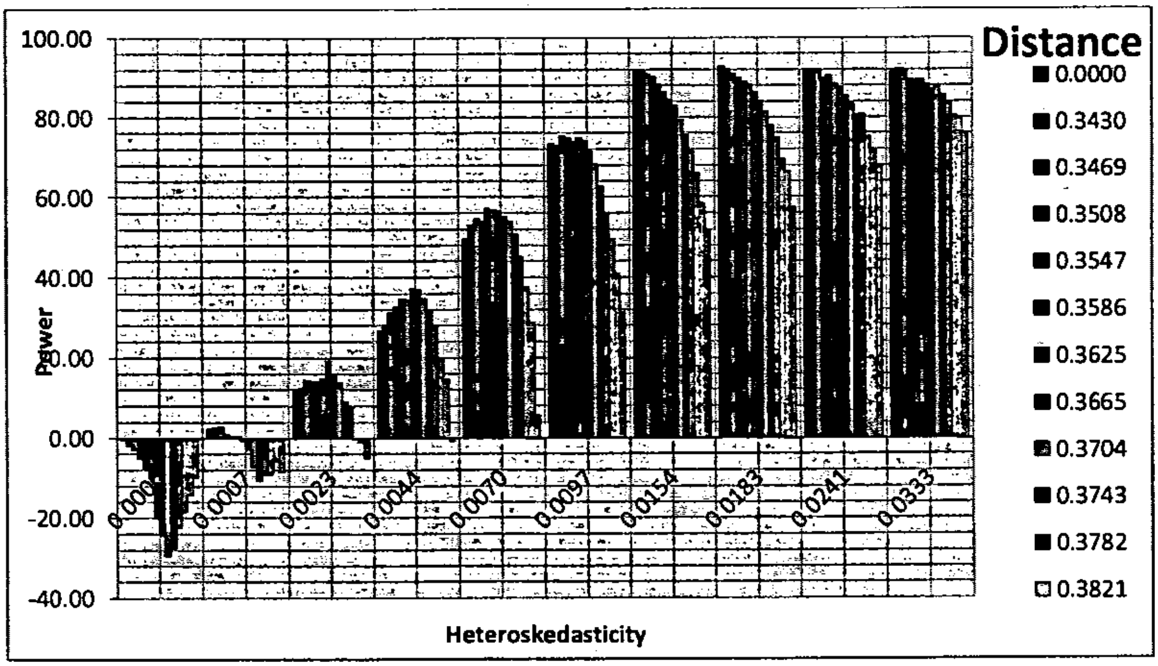
Power of SupF and SupMZ test with Heteroskedasticity Break at 50%



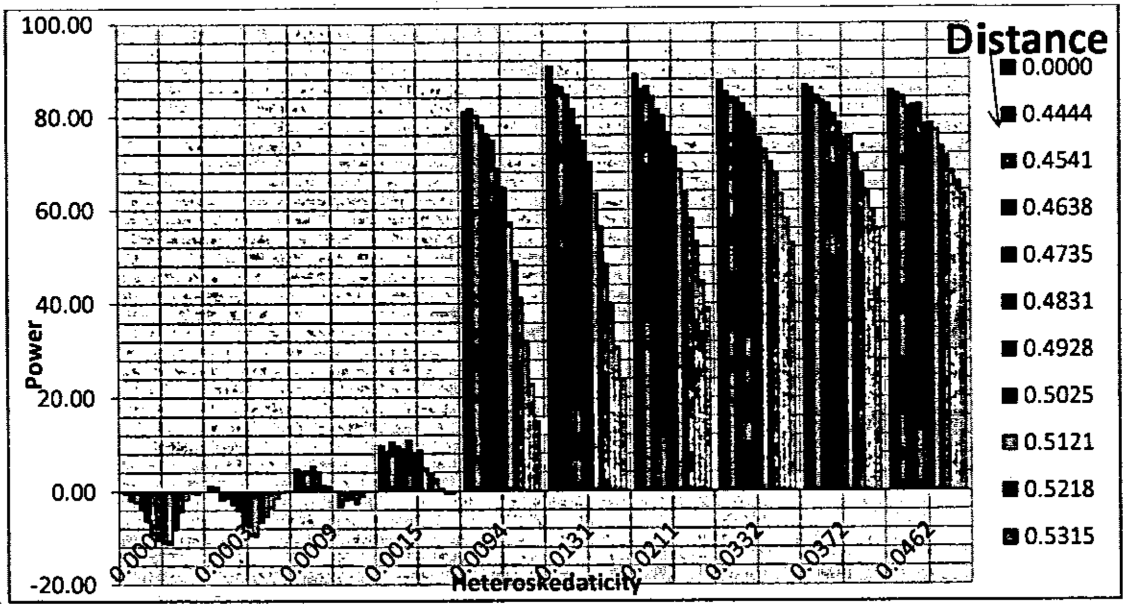
Section III: %Difference of SupMZ minus SupF test at different locations



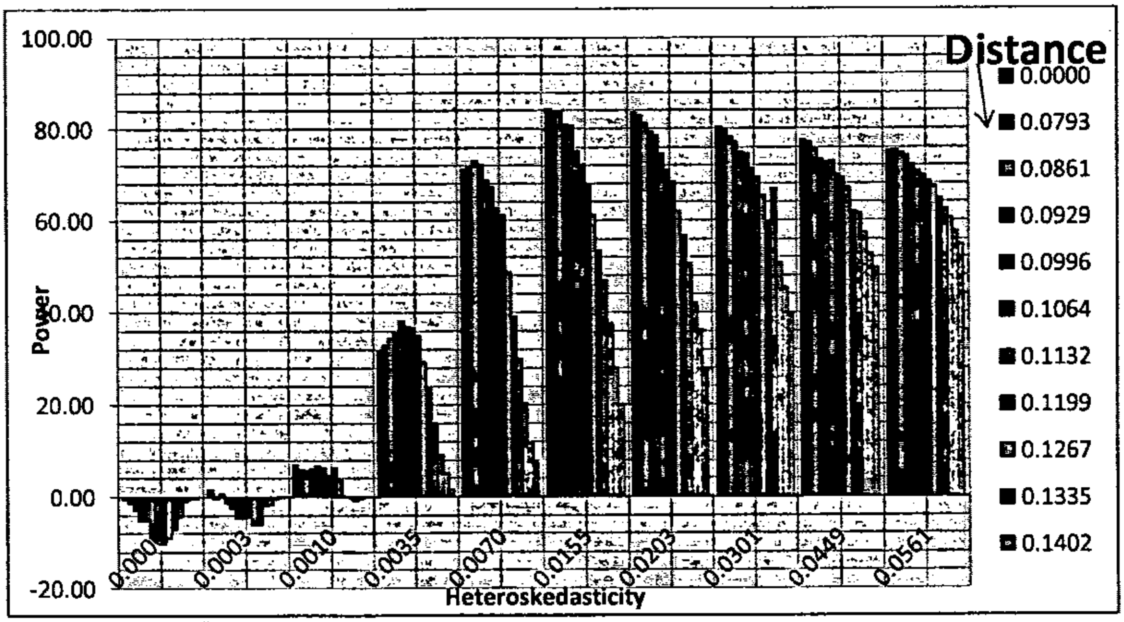
%Difference of SupF from SupMZ at 20% Break



%Difference of SupF from SupMZ at 30% Break



%Difference of SupF from SupMZ at 40% Break



REFERENCES

Andrews, D. W. K. (1993). "Test for Parameter Instability and Structural Change with Unknown Change Point." Econometrica. July, 61:4, pp. 821_56.

Andrews, D. W. K. (1989c): "Tests for Parameter Instability and Structural Change with Unknown Change Point," Cowles Foundation Discussion Paper No. 943, Yale University.

Bruce E, Hansen (2000). "Testing for Structural Change in Conditional Models" Journal of Econometrics.

Bai, Jushan. (1994). " Least Square Estimation of a Shift in Linear Processes." Journal of Time Series Analysis. 15:5, pp. 453-72.

Bai, Jushan. (1997a). "Esitmation of a Change Point in Multiple Regression Models." Review of Economics and Statistics. November, 79:4. Pp. 551-63.

Bai, Jushan. 1997b. "Esitmating Multiple Break one at Time." Econometric Theory. June, 13:3. pp. 315-52.

Banerjee, et al. (1992). "Recursive and Sequencial test of the Unit- Root and Trend-Break Hypothesis: Theory and International Evidence" Journal of Business and Economic Statistics. Jully, 10:3, pp. 271-87.

Brown, et al (1975) Techniques for Testing the Constancy of Regression Relationships Over Time, Journal of the Royal Statistical Society, Series B 37: 149-163.

Chow, Gregroy C. 1960. "Test of Equality between Sets of Coefficients in Two

Linear Regression." Econometrica. 28:3, pp. 591_605.

Chernoff,H and S. Zacks (1994) " Estimating the Current Mean of Normal Distribution which is Subjected to Change in Time," Annals of Mathematical Statistics, 35, 999-1018.

Hinkley, D. V. (1977), "Inference about the Change Point in a Sequence of Random Variable," Biometrika, 57, 1, 71-83.

Maasoumi, et al (2010)."Tests for Structural Change, Aggregation, and Homogeneity" Journal of Economic Modelling.

Quandt, Richard. 1960. "Tests of the Hypothesis that a Linear Regression Obeys Two Separate Regimes." Journal of the American Statistical Association. 55, pp. 324-30.

Stock, J. H., and M. W. Watson (1996): "Evidence on Structural Instability in Macroeconomic Time Series Relations," Journal of Business & Economic Statistics, 14(1), 11–30.

Zaman, Asad. (1996)."Statistical Foundations for Econometric Techniques". Academic Press.