DATA MINING FOR DETECTION OF STRUCTURAL BREAKS IN ECONOMETRIC RELATIONSHIPS AT UNKNOWN LOCATIONS

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بسم الله الرحمن الرحيم

In the name of Allah,
the Most Beneficent,
the Most Merciful

This dissertation is dedicated to My Parents, who instilled in me the virtues of perseverance and commitment and relentlessly encouraged me to strive for excellence.

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(Muhammad Naoman Khan)

ABSTRACT

Structural change can be considered by breaking up a sample into subsets and asking if these can be aggregated or pooled. Literature on tests for structural breaks can be divided into three categories. First category consists of test for structural brakes at known location. Such as Chow, LR, Wald, MZ test. Second category consists of tests for structural breaks at unknown location such as sup F, sup W, supMZ tests. Third category borrows tests from the second category and then applies programming techniques to solve the problem of locations of multiple structural breaks. Our study is concerned with the third category.

We are providing a programming alternative to much more complex testing strategies currently being researched and developed in testing for structural change. We are using data mining techniques. Data Mining is a common field of Statistics and Software Engineering. Data Mining requires expertise in both statistical concepts and programming at the same time which is probably the reason which makes data mining a rare skill in the world. Use of programming skills in econometrics is still at preliminary level. Most of the econometrics softwares do not provide computation for structural breaks of unknown time. Eveiws-9 and Stata-14 have included options for computation of structural breaks at unknown locations. Procedure used by EView9 involves sequential tests for structural breaks where test for structural break is conducted in the full sample. If break is not found, full sample is split into two halves and each subsample is tested for structural break. Practice continues until a break is indicated. Stata14 does it by computing either Wald or LR test statistics at a set of possible break dates. The intuition behind these tests is to compare the maximum sample test with what could be expected under the null hypothesis of no break. We have developed algorithms, which thoroughly scan data by swapping window and so pinpoint all breaks.

If we are able to find each and every structural break in different time series, we can compare the locations of structural breaks in different time series. A lead and follow relationship may indicate cause and effect relationship just like the logic used in Granger causality. Granger causality checks for lead and follow relationship in actual data set and if found concludes it as cause and effect relationship. Discovering such a relationship among structural breaks of different time series may prove a second method for defining the causality. We have confirmed cause and effect with Granger causality test after observing such pattern in structural breaks in KSE 110 index, bullion price and Treasury Bill rates.

1-Introduction

A structural break is a concept in econometrics. A structural break appears when we see an unexpected shift in pattern of the data. This can lead to huge forecasting errors and unreliability of the model in general. Usually things change in economy as an evolutionary process but if a shock occurs, everything changes abruptly.

In economics, a structural break might occur when there is a war, or a major change in government policy, or some equally sudden event in financial sector. But that is not very often, and we know about the occurrence time of these events. We know that there was a structural break in world economy in 1945 due to World War II and we can easily test our hypothesis about structural break at this point. Things become trivial when we do not know if structural break has occurred or not. Even if we know that structural break has occurred, we do not know the exact location.

For a linear model with one known single break in mean, the Chow (1960) test is often used. This test needs information about the possible break point. Data is split in two groups and F statistics is used to test the hypothesis about structural change. Quandt (1960) proposed taking the largest Chow statistic over all possible break dates. Bai and Perron (1998) develop tests for multiple structural changes. Their method is sequential, starting by testing for a single structural break and then sequentially extending the search for structural break throughout the data set unless all possible breaks are indicated.

Various techniques have been developed in late 1990's for structural breaks of unknown timing by using complex algorithms and coding. In this study we have tried to present an improvement over the existing programming skills for computation of structural brakes at unknown locations. We are using Data Mining Techniques. Data Mining is a complex field of research which requires a combination of Statistics, Programming and Domain knowledge at the same time. When we apply data mining techniques on a field of specialization, we need domain knowledge in that specific field of specialization. In this thesis field of specialization is Economics. We are applying our technique to find structural breaks on real time series data sets, which are KSE 100 index, bullion price and treasury bill rates.

1.1 Research Objectives

Objective of this research is to find out the exact location of structural breaks within the data by analyzing intermediate result obtained from regression on data set along with the conventional F statistics. We want to present some improvement in contemporary techniques for computation of structural breaks at unknown locations.

In contemporary techniques, we first guess about the point where we suspect a structural break and then we go for testing our hypothesis of no structural break against the existence of structural break. If calculated F value is smaller than Critical Value, we don't reject the null hypothesis of no structural break meaning that there is no structural break in the data set at the suspected point. If calculated value is more than critical value then we reject the null hypothesis meaning that structural break is actually present and we cannot run a single equation on the whole of the data set. If structural break is known, things become simpler. Among other techniques, we may use quadratic or cubic spline functions. Spline functions are a simplification of polynomials. In spline functions we have knots at break points and distance between any two knots is a straight line. If structural breaks are unknown then we can neither define location of knots, nor can we use spline functions.

Techniques mentioned in this thesis do not require a priori information about the structural breaks. We have developed an efficient algorithm. Program written on the basis of this algorithm can do all the calculations about the structural breaks. We have tested our program on simulated data before applying it on real time series data sets. Data generated by DGP consists of 300 observations. We have swapped widows of different size over the data sets. A criterion for selection of window size is discussed in next chapter.

Our programs give the results from simulated data as expected, so we apply them to the real data sets. Three econometric time series are selected. These are Karachi Stock Index (KSE 100 index), Bullion Price and Treasury Bill rates. Data on KSE index and Bullion Price is originally obtained as daily data. This data is converted to fortnight data as data available on Treasury Bill rates is only fortnightly.

1.2 Usefulness of research:

Research is useful on different ground. Some of which are discussed below one by one.

1.2.1- Accuracy in Forecasting:

An important reason for estimating regression parameters is forecasting. Accuracy in forecasting depends on accuracy in estimating regression parameters. Intercept or slope or both may change causing it impossible to get valuable or useful forecast. Forecast for one sub sample of the data may be quite different than from the forecast from the other sub sample of the data. Due to structural breaks, inferences about economic relationships can go astray, forecasts can be inaccurate, and policy recommendations can be misleading or worse.

Clark and McCracken (2005) found that structural breaks can severely affect the out-of-sample predictive performance of econometric models. Researchers should be very careful in how they set up the out-of-sample forecasting experiment, paying close attention to any evidence of breaks. When interest lies in forecasting time-series with regression models that are subject to structural breaks, one might think that the parameters of the forecasting model should be estimated exclusively on data available after the most recent break. However, such an approach ignores two important facts. First, in choosing the estimation window, it is generally advantageous to include (some) pre-break information. Second, it can be difficult to precisely estimate the timing of one or multiple breaks, particularly when these are small and/or occur close to the boundaries of the data sample.

Our programming techniques compute structural break anywhere in data, be it in the beginning or at the end of the data set. For forecasting, we can give more (or sometimes all) of the weight to the data set after the structural break.

1.2.2- Simulation and Bootstrapping:

For the purpose of simulation and bootstrapping, we have to use the random numbers. These random numbers are generated by the computer according to some algorithm which is applied on a particular seed value. Seed value is a positive integer like 1, 2, 3 etc. This seed value gives the same set of random numbers from worksheet to worksheet for the purpose of analysis where same set of random number is required. Without seed value list of random number changes whenever we generate even a single random number. Even with seed value, the randomness of random numbers generated by any program like Excel, Oxmatrics, SPSS, Eviews etc. is questionable. Random numbers generated by a PC may not be purely random. It is quite possible that the numbers are having slight trend which may affect the conclusion and predictions obtained from the data set.

Programs written for this thesis can also be used to check the validity of random numbers generated by the computer. Suppose we generate a series of 500 random numbers which are uniformly distributed. We should expect the average of these numbers to be same anywhere in data set. If average of sample deviates too much from population average, then random numbers are not trust worthy. Output of the code can be helpful in deciding whether random numbers are reliable or not. What we need is to handover the data file containing random numbers to the program. If structural break points are discovered in the data then there is something wrong with the random numbers generation process. As a consequence randomness of random numbers may not be reliable. A small window size may help in this regard and random numbers can be checked for their consistency.

1.2.3- Dynamic View of change in Parameters:

The output of the codes is helpful in viewing the changes in intermediate results of regression analysis as we move the window over the entire data. We have swapped the window and so jumps are avoided as is the case in algorithms usually used in conventional tests for detecting structural breaks of unknown timing. So we can analyze regression parameters (intercept and slope) as new data is introduced. We can dynamically view changes in ESS and RSS and so can obtain important information about the changes in the data pattern. Use of simple statistics along with F value can provide additional help in predicting the starting point of structural break as well as the period of disturbance. The dynamic view can tell us if the data resumed original pattern after structural break or it adjusted to a new pattern.

1.2.4- Advantage over Contemporary Techniques:

EViews8 can estimate break points at unknown locations. Procedure used by EView8 is borrowed from Bai (1997), Bai and Perron (1998). Critical values for these tests are provided by Bai and Perron (2003).This procedure involves sequential tests for structural breaks. Test for structural break is conducted in the full sample. If break is not found, full sample is split into two halves. Each subsample is tested for structural break and practice continues until a break is indicated. Once structural breaks have been indicated by sequential procedure, refinement procedure is started. In refinement procedure, structural breaks are re-estimated if previously obtained structural breaks belong to a sample which has multiple structural breaks.

Stata14 too can estimate structural breaks at unknown locations. Stata14 does it by computing either Wald or LR test statistics at a set of possible break dates. Possible break dates can be predicted on the basis of change in regression parameters as Stata14 can compute recursive estimates of the regression parameters. A change in the consistency of parameters is a possibility of the candidate break date. After calculating test statistics at all the possible break dates, their Supremum can be taken. Specifically, the supremum Wald test uses the maximum of the sample Wald tests, and the supremum LR test uses the maximum of the sample LR tests. The intuition behind these tests is to compare the maximum sample test with what could be expected under the null hypothesis of no break (Quandt [1960], Kim and Siegmund [1989], and Andrews [1993]).

Another feature available in econometric softwares is rolling window methods. STATA has a command for rolling estimation. An example of this command is ".rolling, window (24) clear: regress XL(1/3).X." In this command: window (24) sets the window width w=24 . The number of observations for estimation will be 24. Clear command clears out the data in memory. The data will be replaced by the rolling estimates. The part regress XL(1/3).X is the command that STATA will implement using the rolling method. An AR(3) will be fit using 100 observations, rolling through the sample X. For example suppose we have fortnightly data, 2001-I through 2016-24 having total 384 observations. Using window size = 24, the first estimation window is 2001-1 to 2001-24. The second is 2001-2 to 2002-1, third is 2001-3 to 2002-2 and so on. There are 384-24+1 = 361 estimation windows. Now we can plot the estimated coefficients against time. We can use separate or joint plots.

As an alternative to rolling estimation, *sequential* or *recursive* estimation uses all the data up to the window width First window is [1,w]. Second window is [1,w+1]. Final window is [1,T]. With sequential estimation, *window* is the length of the first estimation window. We can use rolling and recursive estimation to investigate stability of estimated coefficients. We look for patterns and evidence of change and we try to identify potential *break dates*

Everything was fine up to this point. Now suppose that we want to find the break points. We can consider picking multiple possible break dates $t^*=[t1, t2, \ldots, tm]$. For each break date t^*, we can estimate the regression and compute the Chow statistic $F(t^*)$. Finding a break date is similar to searching for a big (significant) Chow statistic.

We have made an improvement over the algorithms and coding used by the contemporary softwares. These softwares can swap window for regression parameters but not for F statistics. So these softwares cannot give us a dynamic view of F statistics as we move towards or away from the break point. We have used Chow F statistics to judge about the structural break. Instead of taking Chow test only at possible break points, we have taken Chow test at all the points throughout the data set. We have devised a way to swap different windows on the data set and to get another type of data which is data of parameters and intermediate results. Then we swap next stage windows on the data of parameters. In other words we work on metadata. We generate data which depicts properties of the original data set. Various nested loops swap various windows over the data and so we can observe changes in Chow F statistics as we move towards the break point or away from break point. We get all the intermediate results too, which are regression coefficients (intercept, slope) and RSS.

Our algorithms and coding techniques will lessen the burden of econometricians to a large extend. Econometricians do not need to check the data manually for the existence of structural breaks. What is needed is merely hand over the data file to the program, set window size and run the program. For a data set of 300 observations and 40 window size, 542 (261+281) regression equations are run, results are obtained, compiled and conclusions displayed on screen only within 5 seconds. Detail about selection of window size is given in next chapter.

This study includes the comparison of results obtained by using different window sizes on the real econometrics time series. So that we get a fairly good idea of how results change when we swap a window of smaller or larger size over the data set.

2-Literature Review

Structural stability is of prime importance in applied time series econometrics. Estimates derived from unstable relationships erroneously considered as stable are not meaningful. Inferences can be severely biased, and forecasts lose accuracy in case of structural breaks.

By now classical approach to the detection of structural changes attempts to detect breaks ex post, see Hansen (2001) for a state of the art survey. Starting with the pioneering work of Chu, Stinchcombe and White (1996) a second line of research has emerged: given that in the real world new data arrive steadily it is frequently more natural to check whether incoming data are consistent with a previously established relationship, i.e., to employ a monitoring approach.

Tests for structural change can be divided into two classes which are F tests and Fluctuation Tests. F tests are designed for a single-shift (of unknown timing) alternative (Hansen 1992; Andrews 1993; Andrews and Ploberger 1994).

Fluctuation tests do not assume a particular pattern of structural change. Fluctuation tests can in turn either be based on estimates of the regression coefficients or on regression residuals (recursive or OLS), both from a widening data window or from a moving window of fixed size. The probably best-known test from the fluctuation test framework is the recursive (or standard) CUSUM test introduced by Brown, Durbin, and Evans (1975), later extended by Kr¨amer, Ploberger, and Alt (1988) to dynamic models. A unifying view on fluctuation-type tests in historical samples is provided by Kuan and Hornik (1995).

These tests are commonly used to detect structural change *ex post* (historical tests). The class of fluctuation tests can be extended to the monitoring of structural changes, i.e. for detecting shifts *online*. Chu et al. (1996) introduced the first fluctuation test for monitoring by extending the recursive estimates test of Ploberger, Kr¨amer, and Kontrus (1989). Leisch, Hornik, and Kuan (2000) generalized these results and established a class of estimates-based fluctuation tests for monitoring.

Consistency of population parameters like mean, variance and covariance is required for the accuracy of forecasting in applied time series. This consistency is what is called stationarity of data in technical term. In case of non stationary data, our analysis is redundant and same is the case of analysis in presence of structural breaks. In case of structural break, parameters change even if data is stationary before and after the structure break. In other words concentration on stationarity while ignoring presence of structural breaks can lead to the same situation of redundant results.

The econometrics of structural change means searching for methods and models which can detect and locate structural breaks. Various aspects of this narrow field of econometrics can be described as follows.

2.1 Structural Breaks at Known Locations

The history for detecting the structural breaks goes back to early 1960's. Chow (1960) suggested a procedure to test the structural break by splitting the data in two parts. Famous Chow F test uses the logic that RSS changes with additional data. This logic is briefly described as follows.

Logic behind Chow F Test: Chow F test takes its foundation from the changes in residual term with inclusion or exclusion of the data. If newly added data has the same pattern as the previous data then variance of residual term does not change. Variance of residual term is RSS divided by degree of freedom. Now if structural break has occurred, then new data causes the residual term to scatter at a larger distance from the fitted line. So variance of residual term increases. If such data is split in two parts, then we can run three regressions. First regression is run on first part of data, second regression on second part and third regression on whole of the data set. Here we will observe that sum of variances of individual data sets can never exceed variance of the overall data set. In other words we say that, RSS/df > RSS1/df + RSS2/df. Chow F statistics checks for the difference between RSS/df and RSS1/df + RSS2/df. This difference is divided by the sum of variances of individual data sets. The calculated value is now known as Chow F statistics. If this value is more than the tabulated (critical) value, then a structural break is indicated.

Chow test remained popular for detection of structural breaks. This test was extended to cover many of the econometrics models. Examples can be found in Andrews and Fair (1988).

Namba (2014) conducted double bootstrap methods on Wald test statistics to test for equality of regression coefficients between two linear regression models. This procedure can be used when disturbance variances are not equal as well as when there is structural break in the data set. Method is used for structural break of known timing. Wald statistics suffer size distortion in small samples. Namba has shown that his method can improve size distortion. He suggested for further research on the same lines to use the same method for multiple structural break at unknown locations.

In most of the tests including Chow test, equality of means and heteroscedasticity is pre-assumed. Thursby (1992) has presented a comparative study of this type of tests. Econometricians like Toyoda (1974), Schmidt and Sickles (1977) and Koschat and Weerahandi (1992) have shown that Chow type tests perform poorly in case of heteroscedasticity. In the fact Structural breaks may be indicated if there are changes in samples' means or variances over a given data sets. We can use two approaches here. In first approach known as MV strategy, we first test for equality of means and then for equality of variances. In second approach known as VM strategy, we first check for equality of variances and then for equality of means.

Maasoumi et al. (2010) developed MZ test by jointly testing restrictions on mean and variance. EM and EV are jointly (J) tested against UM and UV, which are unrestricted alternatives. This approach is uncommon. This approach resembles the tests for whole distribution changes which are represented by Li et al (2009).

Above mentioned tests assumes that break point is clearly known and task of the researcher is only to confirm if computed statistics at this point is significant or not. A researcher can use two approaches here. (1) Select a break date on his subjective judgment such as middle of the data or break after one third of the data. (2). Select a break point on the basis of some external event such as emergence of war or on the basis of technological revolution etc.

In the first case, test may mislead us as we can test the data at a point where it is quite stable. So an actual break point may be ignored. In second case, we may conclude a structural break while there might be none. It is possible if data changes sharply at the guessed break point and then stables again. So we actually had a few outliers at the break point. The result being that Structural break is indicated while actually there was none. Outlier is detected is window size around the outlier is small. When window size around outlier increases, indication of structural break vanishes. While a real structural break is indicated in case of both small and large window size around the structural break. In both cases different researcher can find conflicting results. So these choices of break points do not qualify for the sound scientific research.

The above mentioned two approaches lead us to a third approach. That is to think of structural break point as unknown.

2.2 Single Structural Break at Unknown Locations

The idea to detect structural break at an unknown location was given by Quandt (1960). He proposed to take the largest Chow F statistics out of all the possible calculated values. The necessary solution is to treat the break date as unknown. Quandt gave the solution and suggested to imagine all the possibilities of structural break in the data set. Then get all the Chow F statistics on these candidate break points. The worst case will have the largest F value and so this is the Quadt's statistics.

The simple method to estimate break date by selecting the date which can produce largest Chow F statistics can prove a good method in case of linear regression models only. Moreover these models must be homoscedastic as well. Another method is to split the sample at predicted break date. Now run regression on both the samples. Get estimates by ordinary least squares, calculate and store sum of squared errors. Now sum the stored values. Repeat procedure with different possible break dates. The break date is the one which minimizes the sum of squared errors for overall data set.

Another approach is to systematically plotting F statistics at all the suspected break point against the break dates. Chow F statistics is taken on Y axis and break dates on X axis. To compute Chow statistics, we split data in two parts around the suspected break date. We run regression on sub samples. If data is consistent, the estimates (intercept, slope) from both sub samples will almost be the same. If data is inconsistent then, regression estimates are different and this difference of regression estimates (in both the sub samples) is reflected in the Chow F statistics.

Next task is to use some critical value to judge about the significance of the Chow statistics. If we are sure about the break date, we can use chi square critical values. If calculated value lies below the critical chi square value then test is insignificant and we do not have structural break. If calculated value is high then test is significant meaning presence of structural break.

If break date is unknown, we do not use chi square value. In the early 1990's many authors suggested for critical values in case of unknown break dates. Andrews (1993) and Andrews and Ploberger (1994) prepared tables of critical values for Chow statistics in case of unknown break dates. Hansen (1997) suggested calculations for p values. The critical values suggested by these authors were larger than the corresponding chi square values. These values depended on many factors including number of parameters in the model.

Sup F test proposed by Quandt (1960) and many other like proposed by Kramer et al. (1988), Tran K. C. (1999) and Hayashi (2005) do not cover case of heteroscedasticity. To fill this gap in literature MZ test was further improved and extended for structural breaks of unknown timings by Ahmed et al. (2016) Supremum MZ test was introduced. MZ test statistics is calculated at different possible break point and then maximum of the MZ test is selected as an indicator of the unknown structural break.

The problem with this method is that we cannot have more than one break point in the data though in actual there may be multiple break points. In other words we have to switch over to another method if there can be more than one structural breaks in the data set.

2.3 Multiple Structural Breaks at Unknown Locations

Work on multiple structural breaks started in late 1990's. Bai and Perron (1998) suggested the methods in case of more than one structural break. They suggested to check for the structural break at the estimated break date of data set. It structural break is detected, split the data in two sets and apply the procedure on both the sets. This procedure is continued until all the sub samples do not reject the hypothesis of no structural breaks.

We can find a number of examples for detection of multiple structural breaks in the data. Stock and Watson (1996) have tested 76 time series for structural breaks. They used monthly data. Both univariate and bivariate regressions were run by them. More than half of the time series indicated for structural breaks at 10 percent level. Ben-David and Papell (1998) analyzed 74 time series, which were consisting of Summers-Heston GDP data of 74 countries. They tried to find if there is a decrease in the trend of the GDP data set over the time. They found that 46 countries have shown slowdowns or decrease in trends. Out of these 46 countries, 21 showed that trend actually became negative after the structural break. McConnell and Perez- Quiros (2000) tried to find if volatility of GDP growth rates in United States is stable or not. They found that volatility of GDP growth rate actually decreased after 1984 in United States.

Multiple break dates have been estimated by Chong (1995) and Bai (1997b) in a sequential manner. Here to fundamental principle is that in case of multiple break dates, sum of squared errors can have a local minimum near the predicted break date. The global minimum point is taken as an estimate of the break date. All the other local minimum points are taken as potential break dates. Now sample is split at the estimated break date and practice continues with the sub samples. Work of Bai (1997b) proves that improvements in estimation of break date can be obtained by iterative refinements. It means re-estimating the break dates from the refined samples.

2.4 Confidence Intervals for structural breaks

Sometimes it becomes necessary to know about the exact or nearly exact location of the structural break. We think of the date of structural break or break-date as an unknown parameter. Now our problem becomes how to estimate the exact break-date and how to make confidence interval for the estimated break date.

Efforts to construct such confidence intervals can be traced back to Hinkley (1970), Hawkins (1977), Worsley (1979, 1986) and Bhattacharya (1987). Work on constructing confidence intervals by using standard econometric methods can be found in Bai (1994). This work was further improved by Bai (1997a, 1997b), Bai et al (1998), Bai and Perron (1998) and Bai (1999).Methods proposed by them are suitable for structural breaks of moderate and large interval. Elliot and Muller (2007) found that previous work for constructing structural breaks is not suitable when applied on small samples for small or moderate structural breaks. They have used the technique to construct confidence sets by inverting the sequence of tests and thus obtained a valid confidence interval.

As long as confidence interval for break dates is concerned, Bai (1994, 1997a) has given the asymptotic distribution of the break date estimator. He has constructed confidence intervals for the break date. Method to calculate these confidence intervals is easy. These confidence intervals tell about degree of estimation accuracy and so they are useful in econometrics applications. Bai, Lumsdaine and Stock (1998) have used the same methodology for multiple time series. Whereas these time series have simultaneous structural breaks. It is proved by them that estimation accuracy is improved by using multiple time series. Similarly Bai and Perron (1998) have given simultaneous estimation for multiple break dates.

There are two methods to construct confidence interval. First method demands for expected value and standard deviation. According to level of significance we have lower and upper bounds of confidence interval as E(x)-t and E(x)+t. Second method is of simulation. We simulate possible values of x. Suppose we get 10,000 values by simulation. Now for 95% confidence interval, we select middle 9500 values. Minimum of these values is lower bound while maximum is upper bound.

Here in our case, we have relied more on software techniques as compared to econometric techniques. We have swapped the window over the data set due to which we get all possible values of Chow F statistics. We can observe that confidence sets exist when we move either toward or away from the break point. This is clear from all the graphs of computed F statistics. Somewhat similar intervals can be seen for the Residual Sum of Squares (RSS)..

2.5 Power of the Test

Power of a test is one minus type II error. Type II error occurs when we do not reject the null hypothesis which was actually false. So power of the test is our ability to reject the null hypothesis when it is actually false.

Maasoumi et al. (2010) have computed power of MZ test. MZ statistics is chi squared distributed. Powers of three tests are compared for the given structural break points in their study. They have taken a measure of heteroscedasticity 'H' and Departure of regression coefficients 'D'. By computing powers of the tests, they showed that VM test has high power at low and intermediate H. The MV test has high power at low and intermediate D. While J test has high power along the diagonal where both discrepancies are almost equal.

Hansen (2012) has described that Sup Wald tests are more powerful when conducted in the middle of data set. While sup Wald tests have less powers near the beginning and end of the samples It is difficult to measure structural break from the beginning or at the end of the data set. Data is trimmed by a factor λ, so that sample lies between λn and $(1-\lambda)n$. Hansen(2012) suggested $\lambda=0.15$. So that sample ϵ (0.15n, 0.85n).

Ahmed et al. (2016) have compared the size and power of Sup F test and Sup MZ test. They have proved that Sup MZ test is more powerful as compared to Sup F test when there is heteroscedasticity in the data.

Piehl et al. (2003) have pointed out that power of a structural break is not an issue at all if we are able to find a very clear evidence of the presence of structural break. In this thesis we have used Chow F statistics. Instead of using Sup F methodology, we have switched over to a software solution for the problem. We have swapped the window over data set and calculated all Chow F values along with all the intermediate results. We analyze the results and find out that Chow F test increases sharply when we move towards the break point. So in our case computing power is not an issue as break point is very sharply recognized. If even then someone is interested in computing power, algorithms and coding can be done for computing the power of the test as window is swapped. This exercise is beyond the scope of this thesis and is left for further research for those who are interested in the field of data mining.

2.6 Distinguishing Random Walk from Structural Change

A common characteristic of almost all of the time series is that they have a trend along the time. They may also include a cycle. Third possibility of no trend but only cycle can also be encountered. It was a common misperception that trend in time series is linear. Nelson and Plosser (1982) were the first ones to prove that any Macroeconomic time series have random walk. It means that time series do not have fixed trend during business cycles. The trend has random shocks. These random shocks create disturbance in the trend and time series may adjust at a new level unless disturbed by another random shock.

Discovery of movement of trend required its explanation. One plausible argument was presented by Perron (1989). According to him, movement of trend can be explained by a single structural break in the constant linear trend. Due to the trend break, serial correlation is produced and this serial correlation resembles the random walk.

Many authors like Christiano (1992), Zivot and Andrews (1992), Banerjee, Lumsdaine and Stock (1992) and Vogelsang (1992) criticized the argument of Perren (1989). These authors rejected the assumption that break date is already known. They argue that selection of break date is dependent on data and that it is not an appropriate selection. They offered an alternative procedure which was more appropriate. According to them we should select the break date which can give highest t value, so that we have maximum evidence against the random walk. The procedure proposed by them produced almost the same results as those of Perron's as break dates were again 1929 and 1973. Yet it is true that test was conducted using a different procedure. This test had different sampling distribution. In this case critical values were quite high due to which rejection of null hypothesis of no random walk was rarely rejected. So for the most of the time evidence of random walk was confirmed.

Perron (1997) revised the whole procedure by extending the data up to 1991:III. He wanted to check if longer data can give different results. Selection of lag order of autoregressive scheme was made with different methods. Although result became slightly more favorable for existence of structural break, but even then existence of random walk could not be ignored. If annual data is taken then there is over prediction for 1970 to 1990 period. If quarterly data is taken then there is under prediction for 1987 to 2000 period. This type of behavior is in favor of existence of random walk.

Lumsdaine and Papell (1997) conducted some more test for the same data set and tried to prove two break dates instead of one. This was evidence against random walk. But due to two break dates, distinction between trend break and random walk was narrowed.

The idea presented by Perron (1989) about structural break in time trend has changed the empirical analysis of time series. Now there is more focus on different properties of the trend. It is actually number of shocks which make trend breaks different from random walk hypothesis. If we have very few shocks, we may talk of trend breaks. If frequency of random shocks is high then we talk about random walk phenomenon. We may still discover methods which can narrow difference between trend break and random walk.

There are several applications of the idea presented by Perron (1989). Fernandez (1997) tried to find out if output can be predicted with the help of changes in money supply even when several lags of output are included. Earlier literature on the subject gives evidence that nature of results depend on inclusion of interest rest and detrending of time series. Time series is detrended by including a trend variable in the regression. Fernandez showed that output is a stationary process around the trend with a single trend break. He detrended the output by using estimated broken trend function. He was able to find robust results for the data before 1985 but not so for data after 1985.

Papell, Murray and Ghiblawi (2000) used Perron-Vogelsang (1992) tests to distinguish between time trend break and random walk. They checked hysteresis in unemployment rates. According to theory of hysteresis, any shock in unemployment can permanently change other macroeconomic variables. In other words, according to this theory, we may have either trend break or random walk in unemployment rate. They collected data of 16 OECD countries. Using the data, they showed that 10 out of 16 countries have one time trend break instead of random walk.

2.7 Programming for Structural Break at Unkown Locations

Programming for structural breaks is still very uncommon. A research work on these lines can be seen by Basci et al. (2000), where a program is written in Gauss to find structural break of unknown timing. A brief critical analysis of this algorithm is given here. The program is written in Gauss to find structural break of unknown timing. The algorithm is gives as follows.

```
10 Let START=1;
20 Let T=1;
30 If T-START>=51, test for the null of no structural break on the most recent 52 return data;
40 If rejected set START=Estimated change-point;
50 MEAN=Average of returns from START to T;
60 Obtain the following week's return;
70 Let T=T+1;
80 Go to 30;
```

Results were obtained for 5% level and 10% level. Let us quote here only results for 5% level and point out some shortcomings of the code written on the basis of this algorithm.

The estimated change points and their signaling times for the period
January 5, 1989 – October 29, 1998

At 5% significance Level		At 10% Significance Level	
Estimated Change Point	Signal Time	Estimated Change Point	Signal Time
58	99	58	98
149	151	149	151
153	201	153	201
---	---	165	213
212	216	212	217
264	265	264	265
265	316	265	316
268	319	268	319
278	320	278	320
329	330	329	330
420	421	420	421
421	472	421	472
---	---	500	504

Now let us have a look at the actual working of the code while producing results.

iteration	Start	T= Start+51	Estimated Break=Start	Signal Time	Unchecked points		
					From	To	Count
0	1	52					
1	48	99	58	99			
2	58	109	149	151	99	109	10
3	149	200	153	201	151	200	49
4	153	204	212	216	201	204	3
5	212	263	264	265	216	263	47
6	264	315	265	316	265	315	50
7	265	316	268	319	316	316	0
8	268	319	278	320	319	319	0
9	278	329	329	330	320	329	9
10	329	380	420	421	330	380	50
11	420	471	421	472	421	471	50
	Total						356

Different between above research and our thesis goes as follows,

1. It is impossible to get signal between unchecked points. The reason is that when our first window (consisting of 52 observations) is rebuild, observations below the upper bound of window and above the last signaled point are skipped. Total 356 points are skipped. These points cannot be checked for structural breaks and so these points are never shown as signaled point. We have overcome this shortcoming in our thesis by checking each point in our data above the upper bound of very first window and below the lower bound of last window. If we have 300 observations and window size is 20 then all the points from observation number 20 to 280 are checked for structural breaks.
2. First signal point is declared according to some critical value and then maximum F value is observed in previous points and it is declared as break point. In our thesis, we have just inverted the basic idea. We are first taking the maximum F value out of a predefined segment of F values and then we compare it with critical value. If maximum value is greater than critical value, only then it is declared as break point.
3. Algorithm takes an initial window of 52 observations and then goes on comparing it with date above the upper bound of this window. Algorithm expands the window unless signal is received. So in a sense it tries to calculate break point globally and not locally. In our thesis, instead of expanding the window, we are moving the window which gives us a break point with respect to the neighborhood of the data. This eliminates the chance of skipping closely situated breakpoint. Closely situated break point can be easily found out by reducing the window size.

We have tried to offer a way to calculate structural breaks of unknown time using traditional Chow Test statistics automatically (without manual interruption) and with accuracy. Accuracy is checked as we get exactly same structural break by out technique, which were generated by our data generating process (DGP). Our study can prove an improvement on conventional coding techniques.

Calculations of structural breaks of unknown timing are a new field and there is dearth of literature on the topic. This is because of the reason that a fair command on programming skills on some relevant higher level language (HLL) like C++, R, Python or Ox-Language is required for the purpose. This thesis is using Ox-Language for coding. Knowledge of structural breaks has implications in many areas. One is comparing structural breaks with stationarity of time series data. Again very few research papers can be found on the comparison of structural breaks with unit root or random walk. In our research, we have confined ourselves to the computations of break points. The codes written are fully commented in order to facilitate those who want to work in this field. We have tried to write code in such a way that minute changes in code can give us results according to our specification of data size and window size.

2.8 Selection of Optimal Window Size

Practically neither location of the structural break in data set, nor size of the disturbance is known. We have to use some techniques to resolve the issue of uncertainty about these structural breaks. Selection of size of the Windows in techniques used for detection of structural breaks of unknown locations is important. Practically smallest possible window size can be equal to number of regressors plus one. Pesaran et al (2006) suggest minimum size as 2 or 3 multiplied by number of unknown parameters. To decide about optimal window size, they use cross-validation technique for selecting window size. In this technique, they reserve last few observations for forecasting purpose and then selects the window size which gives least mean squared forecast error (MSFE) value. They select different combinations of pre break and post break window size at 25%, 50% and 75% of the data set.

Basci et al. (2000) tried different window sizes but faced the problem of indication of too many breaks when small window size was selected. They finally settled at window size of 52. It is worth noticing that they were using weekly data spread over about 10 years and there are 52 weeks per year.

A small window size causes indication of false structural breaks while a large window size may skip many important structural breaks. Selection of window size in case of swapping the window over the data is a matter of data type. If we are taking weekly data and we have information that break occurs on yearly basis, we can take a window size of 52 observations. If we are taking monthly data and breaks are suspected after an interval of one or two months, we can take a window size of 30 observations. In our case data is fortnightly. If we suspect a break each year, then window size may be selected around 26. If we are sure that interval between two structural breaks is never less than one and half year (18 months or 39 fortnights), we can select window size 40 (approximately 39) for fortnight data set. We have used different window sizes ranging from 20 to 76. The reason for selecting 38 or 76 window size is that we have 380 observations and window size must be an exact multiple of data size to run the code written by us. Selection of small window size indicates more structural breaks as compared to large window size.

Number of samples is defined as soon as we select the window size. Suppose we are using a window of 40 observations over a data of 300 observations will mean creating 261 windows/samples. We cannot go above observation 261 as our fixed window size will go below 40 after observation 261. Similarly using a window size of 20 observations on same data set of 300 observations will mean creating 281 windows/samples. So we are running regression lines on 261+281= 542 samples.

3-Methodology and Model

Different tests are available to test for structural breaks of unknown time in the literature. These models can be used to find out structural break point. Here we have prepared an algorithm which is able to depict changes in sample statistics as new data is introduced. Based on this algorithm a program is written in Higher Level Language (HLL), which is able to calculate the structural breaks in the data.

We are concerned with the calculation of structural breaks with the help of coding/programming constructs available in programming languages. For the purpose Ox Language is used. Three algorithms are prepared to find the structural breaks in different types of data. With the help of these algorithms, programs are written in Ox Editor and run in Ox Matrics. Results obtained confirm the working of the programs as these results match the visual inspection of the data.

As mentioned in previous chapter, a small window can trace structural breaks of small magnitude more readily as compared to a large window. Here initially a window size of 20 observations is be used. Coding is done in three independent stages. Each stage consists of several nested loops capable of calculating intermediate results and then finally Chow F statistics. We have repeated the procedure with changing the size of data set for windows of various sizes starting from size of 20 observations.

We have generated data for three types of data sets which are given as follows.

3.1 DGP for Structural Breaks with Constant Term only

DGP for structural break with constant tern only start with the equation,

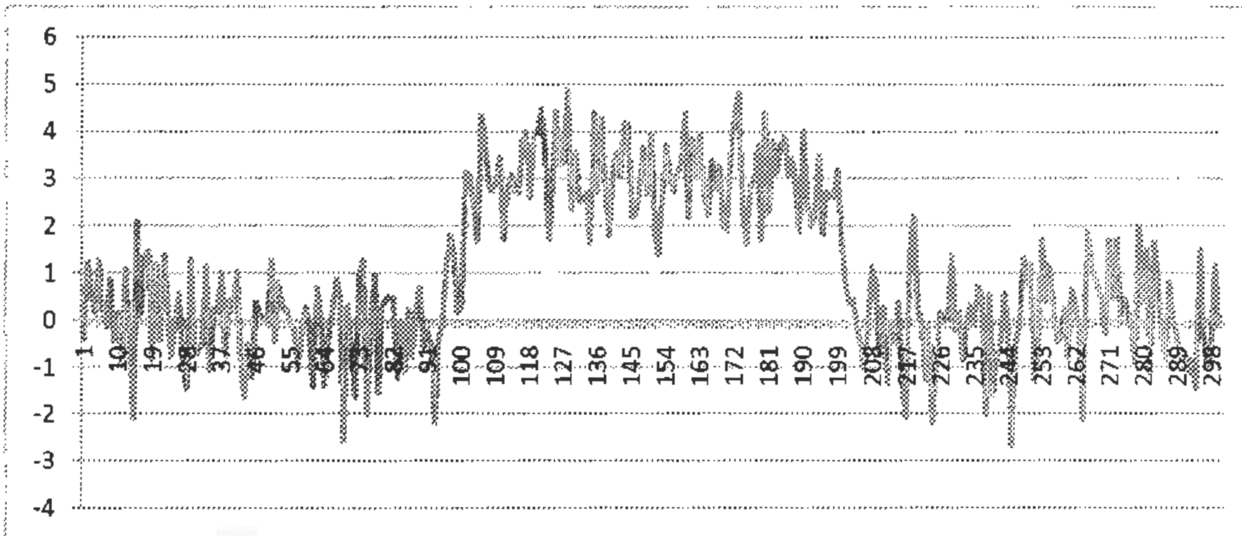
$Y_t = a + u_t$

So that $E(Y_t) = a$

We take 300 Y_t values. We introduce breaks from value Y_{101} to value Y_{200} by introducing a constant c in this range of values such that $Y_t = (a+c) + u_t$

Data is generated in MS Excel. First of all pseudo random numbers are generated in data analysis tool. The exact sequence of commands is Data > Data Analysis > Random Number Generation > normal. A seed value of 2 is used, so that same set of data is produced every time, but it is a matter of choice. If data is purely random then seed value does not matter.

After getting the data we have to introduce structural break in it. If date is saved in cells A1 to A300 and we introduce break from A101 to A200 equal to 3 units. In the regression, we have only beta1 (constant term) and no beta2 (coefficient). In other words our X matrix will be consisting of all ones. Data generated is depicted in the diagram as follows.

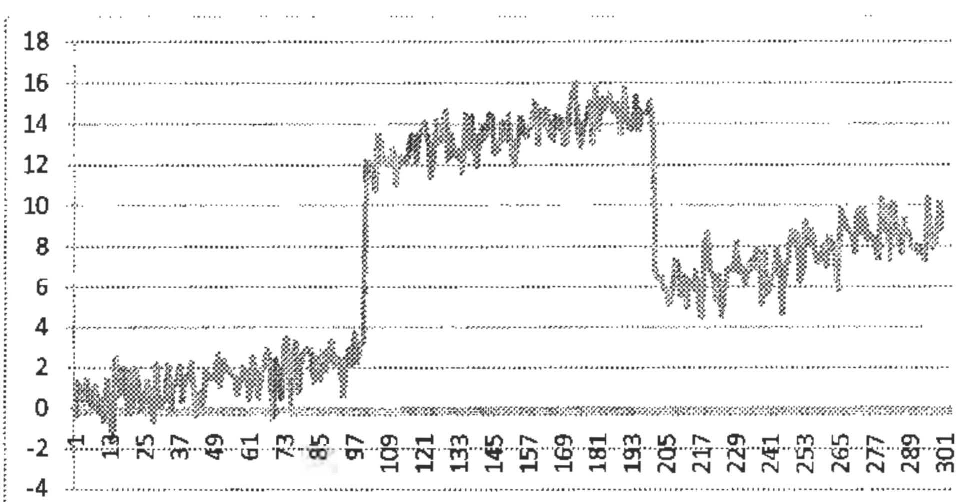


3.2 DGP for Structural Breaks with Time Trend

$Y_t = a + bT + u_t$

We take 300 Y_t values. We introduce breaks from value Y_{101} to value Y_{200} by introducing a constant c in this range of values such that $Y_t = (a+c) + bT + u_t$

Data generation process is same as explained in previous case. Here structural break is introduced equal to 6 units. As we want to introduce trend in data then we first of all write 1 to 300 in column C. Next we write D1=B1 +0.03C1. We drag it down up to D300. Now our D column has data with trend. Matrix X will be of 2 columns where first column is consisting of all ones and second column is consisting of numbers starting from 1 up to n. where n=sample size.



2.3 DGP for Breaks in Bivariate Time Series Data

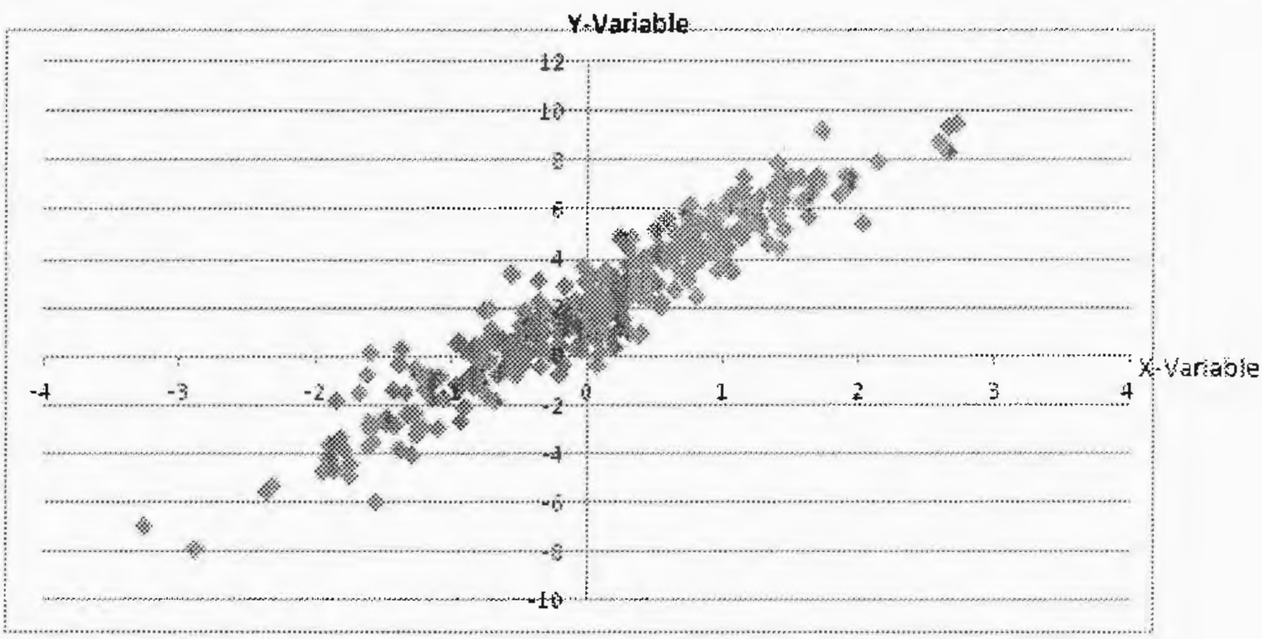
We have to generate artificial bivariate time series data for simple linear regression model. We assume that,

1- We have two variables X and Y
2- Both variables are random
3- Y is a function of X
4- Y has a stochastic relationship (PRF) with X such that $Y_t = a + bX_t + u_t$ Where $E(Y_t/X_t) = a + bX_t$
5- $\hat{Y}$ has a deterministic relationship such that $\hat{Y}_t = a + bX_t$
6- SRF is given as $Y_t = a + bX_t + \hat{u}$

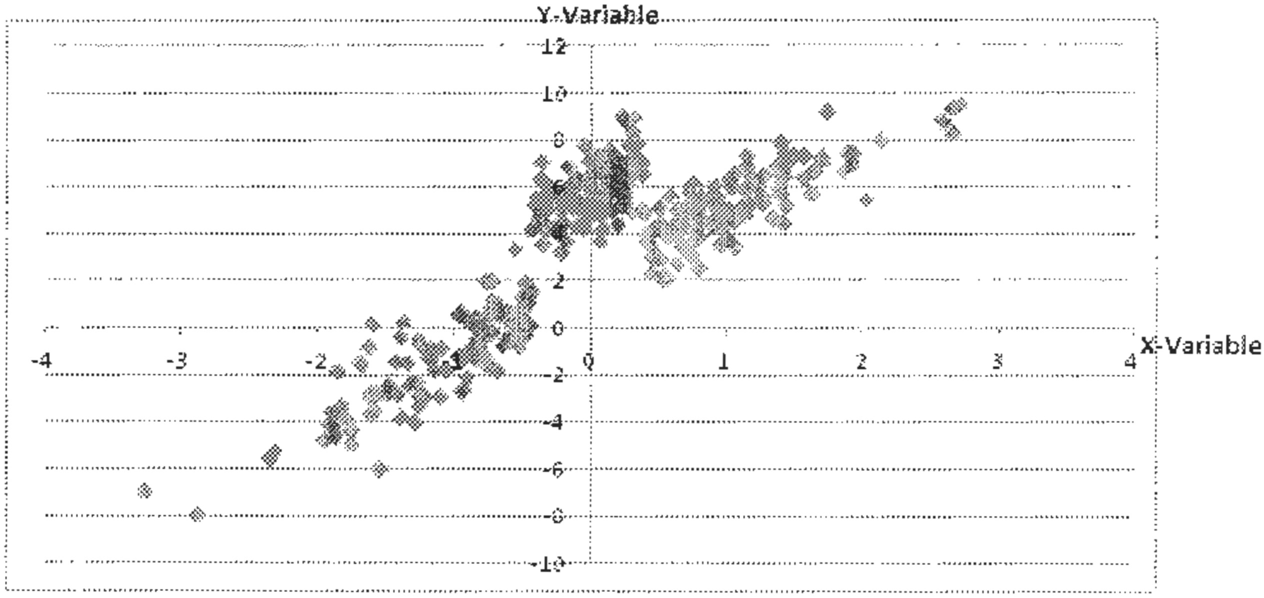
Now we can apply reverse engineering and start to generate data from a know deterministic relationship as follows,

1- We assume values of parameters say a=2 and b=3 , we get $\hat{Y}_t = a + bX_t$
2- We get $Y_t = a + bX_t + \hat{u}$
3- From above step. We sort X in such a way that no pair of X and Y value is disturbed. It means that after sorting X column, all the X value are still having their pre-sorting Y values.
4- Break is introduced from observation number 101 to 200. Break is equal to 4 units.

Data before introducing break depicts following scatter diagram.



Data after introducing break, depicts following diagram,



After getting data from DGP, we write our code according to our own algorithms. Results are obtained by running the programs on the data sets. Intermediate results and Chow F statistics can be obtained by swapping the windows on simulated data set. Finally whole process can be applied on real econometrics time series. We take three time series, which are KSE Index, T-Bill rate of interest and Gold prices. Data covering recent 16 years (2001 to 2016) is taken.

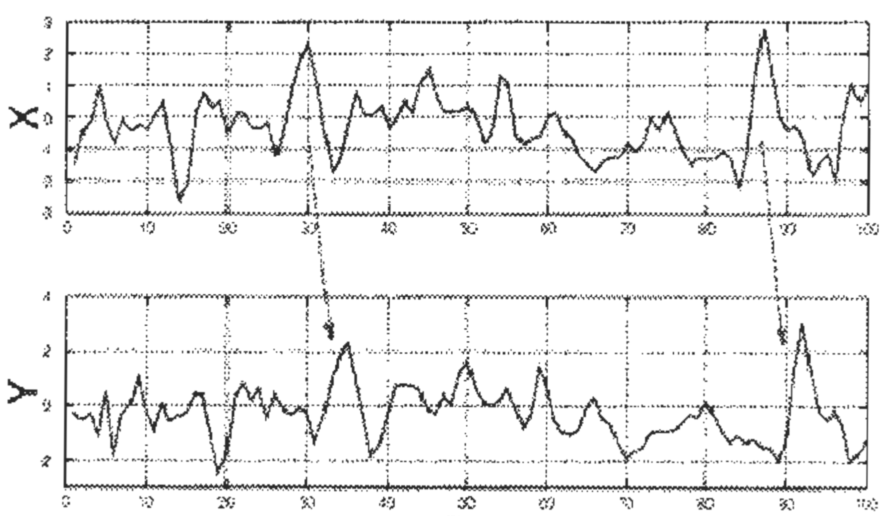
3.4 Cause and Effect Relationship

On the basis of our analysis of results, we try to make cause and effect relationship between econometrics time series. We know that Granger Causality is used to confirm Lead and Follow pattern among the data point of time series. If we are able to sharply pinpoint structural breaks in different time series, it is quite possible that Lead and Follow relationship exists among structural breaks of different time series. Structural break in one series can cause a similar structural break in another series and so on. We check if our established relationships are in accordance with Granger Causality or not. In either case (weather confirmed or not by Granger Causality), we can present the logic for harmony or contradiction of the results in two approaches. By establishing the relationship between structural breaks among different econometrics time series, we want to show that it is a second method to reveal the cause and effect relationship. Granger causality is briefly described as follows.

3.5 Granger Causality

The **Granger causality test** is a statistical hypothesis test for determining whether one time series is useful in forecasting another. This test was first proposed in 1969 by Clive Granger. He argued that causality in economics could be tested for by measuring the ability to predict the future values of a time series using prior values of another time series.

When time series *X* Granger-causes time series *Y*, the patterns in *X* are approximately repeated in *Y* after some time lag (two examples are indicated with arrows). Thus, past values of *X* can be used for the prediction of future values of *Y*.



We run Granger Causality for all of three possibilities. Which are as follows,

<u>Causality between TBill rate and KSE Index:</u>

$KSE_t = \sum_{i=1}^{n} \lambda i \; KSE_{t-I} + \sum_{i=1}^{n} \delta i \; TBill_{t-j} + \mu_{1t}$ 1

$Tbill_t = \sum_{i=1}^{n} \alpha i \; KSE_{t-I} + \sum_{i=1}^{n} \beta i \; TBill_{t-j} + \mu_{1t}$ 2

<u>Causality between KSE Index and Gold Price:</u>

$KSE_t = \sum_{i=1}^{n} \alpha i \; Gold_{t-I} + \sum_{i=1}^{n} \beta i \; KSE_{t-j} + \mu_{1t}$ 3

$Gold_t = \sum_{i=1}^{n} \lambda i \; Gold_{-I} + \sum_{i=1}^{n} \delta i \; KSE_{t-j} + \mu_{1t}$ 4

<u>Causality between Gold Price and TBillrate:</u>

$Gold_t = \sum_{i=1}^{n} \alpha i \; TBill_{t-I} + \sum_{i=1}^{n} \beta i \; Gold_{t-j} + \mu_{1t}$ 5

$Tbill_t = \sum_{i=1}^{n} \lambda i \; TBill_{t-I} + \sum_{i=1}^{n} \delta i \; Gold_{t-j} + \mu_{1t}$ 6

1. *Unidirectional causality from Tbill to KSE* is indicated if the estimated coefficients on the lagged Tbill in (1) are statistically different from zero as a group (i.e., $\Sigma \alpha i \neq 0$) and the set of estimated coefficients on the lagged KSE in (2) is not statistically different from zero (i.e., $\Sigma \delta j = 0$).

2. Conversely, *unidirectional causality from KSE to Tbill* exists if the set of _lagged Tbill coefficients in (1) is not statistically different from zero (i.e., $\Sigma \alpha i = 0$) and the set of the lagged KSE coefficients in (2) is statistically different from zero (i.e., $\Sigma \delta j \neq 0$).

3. *Feedback,* or *bilateral causality,* is suggested when the sets of Tbill and KSE coefficients are statistically significantly different from zero in both regressions.

4. Finally, *independence* is suggested when the sets of Tbill and KSE coefficients are not statistically significant in both the regressions.

All of the above mentioned equations from equation (1) to equation (6) represent unrestricted regression. These equations can provide us quick indication of Granger causality. A more technical way to assess Granger causality is to compute F statistics and compare it with critical F value. This method is described as follows.

1. Regress current Y on all lagged Y terms and other variables, if any, but *do not* include the lagged X variables in this regression. This is the restricted regression. From this regression obtain the restricted residual sum of squares, RSS*R*.

2. Now run the regression including the lagged X terms. This is the unrestricted regression. From this regression obtain the unrestricted residual sum of squares, RSSUR.

3. The null hypothesis is that is, lagged X terms do not belong in the regression.

4. To test this hypothesis, we apply the *F* test,

$$F = \frac{(RSSR - RSSUR)/m}{RSSUR/(n-k)}$$

This test follows the F distribution with m and $(n-k)$ df. In the present case m is equal to the number of lagged X terms and k is the number of parameters estimated in the unrestricted regression.

5. If the computed F value exceeds the critical F value at the chosen level of significance, we reject the null hypothesis; in which case the lagged X terms belong in the regression. This is another way of saying that X causes Y.

6. Steps 1 to 5 can be repeated to test the model, that is, whether Y causes X.

In EView, we can check for Gnager causality by using the "Granger Causality Test" option in value. Only F values calculated in this way are displayed on the screen. We have used E View to decide about Granger causality in chapter 5 of this study.

3.6 Idea behind Algorithms

Idea behind algorithm is to use several nested loops repeatedly in such a way that structural break is calculated at each and every point of data set. It does not matter how much large is the data. This is done in three stages. Each stage is independent of the other and starts only when previous stage has completely saved its data. So output of one stage is input of next stage.

In first stage, we first of all get estimated $\widehat{Y_i}$ of dependent variable Y_i. Calculation of regression estimates is not a problem. Almost in every language which is used in statistics, OLS function is given in library of the language from where it can be imported. We run several nested loops to calculate RSS which is sum of squares of $\hat{u} = Y_i - \widehat{Y_i}$. RSS tables are made twice, once for whole of the sample and then for sub sample. For example if window size is 40, then a table for all samples of window size 40 is prepared and then a second table of all samples of window size 20 is prepared.

In second stage, we run another pattern of nested loops to calculate ore test statistics, which in our case is Chow F statistics. A table of test statistic for all structural breaks is calculated and saved in a table. In third stage we are concerned with pinpointing the structural break point whereas there may be such multiple points. We define a window on the table of test statistic and use several loops as well as built-in functions from the library of the language for our purpose. These three algorithms are given as follows.

3.7 Algorithm for the Regression Coefficients and RSS:

```
StructuralBreak(int N, n, X, Y)
        maV ← dbase->GetAll();
                mX ← ones(2*n,2) ;
                for i ← 0 to N-2*n
                do      for j ← 0 to2*n
                        do      mY[j] ←maV[j+i][0];
                                mX[j][1] ←maV[j+i][1];
                        OLS(mY, mX, &b);
                        mB[i][0] ←b[0];
                        mB[i][1] ← b[1];
                        mYE ←mX*b ;
                        for h ← 0 to 2*n
                        do      me[h] ←mY[h] - mYE[h] ;
                        for h ← 0 to 2*n
                        do      RSS ←RSS + (me[h])^2
                                mRSS[i] ←RSS
                mX ← ones(2*n,2) ;
                for i ← 0 to N-n
                do      for j ← 0 to n
                        do      mYs[j] ←maV[j+i][0];
                                mXs[j][1] ←maV[j+i][1];
                        olsc(mYs, mXs, &b);
                        mBs[i][0] ←b[0];
                        mBs[i][1] ← b[1];
                        mYsE ←mXs*b ;
                        for h ← 0 to n
                        do      me[h] ←mYs[h] - mYsE[h]
                        for h ← 0 to n
                        do      RSSs ←RSSs + (me[h])^2
                                mRSSs[i] ←RSSs      ;
```

3.7.1 Explanation of the Algorithm:

1	Data size is N and Sample size is n. Matrix Y is to be regressed on matrix X.
2	A matrix maV is declared and it is assigned all the values of all the variables of database
3	In matrix mX first column will remain as it is. Independent variable will be introduced in second column of matrix mX.
4	Here for loop is used to create N-2n windows and statistical analysis of each window
5	Nested for loop is used to populate each window
6	Combined window mY is populated with data
7	Combined window mX is populated with data
8	OLS is run on each window
9	First column of mB matrix is populated with Beta (intercept) of respective sample
10	Second column of mB matrix is populated with Beta (slope) of respective sample
11	Matrix of Y Explained is populated.
12	Here for loop is used to populate matrix me of error terms where,
13	e = Y actual - Y explained
14	Here for loop is used to calculate RSS for given sample i.
15	RSS for each sample is calculated
16	Value of RSS is put at respective index in column matrix mRSS.
17	Matrix mX is defined and all entries initialized to ones. First column will remain as it is.
18	Data of variable X will be introduced in second column of matrix
19	Here for loop is used to create N-n windows and statistical analysis of each window
20	Nested for loop is used to populate each window
21	Sub Sample window mYs is populated with data
22	OLS is run on each window
23	Matrix mBs is populated with Beta of respective sample
24	Matrix mB is populated with Beta of respective sample
25	Matrix of Explained Y for sub samples is calculated
26	Here for loop is used for computations for Residual Sum of Squares
27	Matrix me of residual term is populated where, e = Y actual - Y explained
28	Here for loop is used to get RSS for given sub sample i.
29	RSS is calculated.
30	Value of RSS of sub sample is put at respective index in column matrix mRSSs..

3.7.2 Explanation of the Code for above Algorithm:

Codes are written for the above algorithm in Ox Language. These codes are given at the end in the appendix. There are some critical lines in the program/code. These lines can change the results. Here a brief explanation is given to change the values in these lines.

First of all data is loaded from hard disk drive like "dbase.Load("D:/data1.in7")". The file name may change to data2 or data3 for additional data sets. Then n and N are defined where n=20 and N=300 determines the data size and sample size for the Chow Test. Data size is 300 while Sub sample consists of 20 observations. Two sub samples are combined to give a sample of 40 observations.

Regression is run on combined data of two sub samples. Here declaration of X matrix is important. If program is meant to detect the structural breaks in data where there is no coefficient then X matrix consists of only one column all of the entries consisting of ones. This happens when we are concerned about change in the average value. For example if inflation rate is fluctuating around some mean value then this type of analysis is relevant. If program is meant to find structural break with trend in the data then X matrix consists of two columns. First column is of ones and second column consist of trend variable starting from 1 up to N in case of combined data of two sub samples. If we have two variables Y and X and X itself have different values then we need to load another database just like we did for Y variable. This makes program a little complex as X matrix may consists of more than two columns according to the econometric model.

We have to run regression on sub samples too along with combined data of sub samples. Data runs from 1 to n instead of from 1 to 2n in this case.

3.8 Algorithm for the Chow F Statistics:

```
            for i ← 0 to N-2*n+1
            do      mRSSss [i] ← mRSSs[i] + mRSSs[i+n];
                    mRSSd [i] ← mRSS[i] - mRSSss[i] ;
                    mF[i] ← mRSSd[i]/(mRSSss[i]/((2*n)-2));
      BrkPoint ← <20:300>';
     Return ← BrkPoint ~mRSSs~mB~mRSS~mF
```

3.8.1 Explanation of the Algorithm:

31	For loop is used to get F values for all samples
32	Matrix of RSS for sum of RSS of sub samples calculated
33	Matrix of difference of RSS (combined data) and summed RSS sub samples of previous step calculated
34	F value is calculated and put in respective index in matrix F. Matrix mF is populated.
35	An index is prepared to help in reading results stored in different matrices
36	Values of different matrices populated so far are displayed.

3.8.2 Explanation of the Code for above Algorithm:

In this stage, we calculate Chow F statistics from the matrices of RSS which were populated by running regression on N-n+1 samples and N-2n+1 sub samples. We are not sure about the exact location of break point, so we calculate and display all the F values.

An index is defined which makes it easy to read the results on the screen. The index starts from n where n is sub sample size. For example if n is 20 then first F value from Chow test indicates possibility of break point at observation number 20. We are going to display all the RSS values also, so that if someone tries to check for the correctness of computation of Chow test, he can do so at any level/observation by using a simple calculator.

Last value in our index is N which is data size. The index is declared by using library function of range so it is necessary to write numerical values of n and N like 20 and 300. If we want to use n and N instead of using numerical values, then we can make index by using "for" loop but it will increase number of lines in the program and will increase its complexity. In the last stage break point are indicated as is given in next algorithm.

3.9 Algorithm for the Break Points

```
for i ← 0 to 13
do      for j ← 0 to w
        do      mz[j][0] = (i*w)+j+21 ;
                mz[j][1] = mF[(i*w)+j];
        max = maxc( mz[][1] ) ;
        for j ← 0 to w
```

```
43                      if(max == mz[j][1])
44                              then    mF1[i][0]= mz[j][0] ;
45                                      mF1[i][1]=max       ;
46          for i ← 0 to 13
47          do      if(crt < mF1[i][1] )
48                      then    Return mF1[i][0]);
49                              Return mF1[i][1] , "\n");
```

3.9.1 Explanation of the Algorithm

37	For loop is used to make windows in the matrix of F values
38	Nested for loop is used to populate window with F values.
39	First column of matrix mz of respective window out of F matrix is populated with possible Break point
40	Second column of matrix mz of respective window out of F matrix is populated with respective F value
41	Maximum F value out of chunks of consecutive n F values is computed
42	Here for loop is used for matrix mF1 consisting of only max F values
43	If condition use to extract max values from matrix mz
44	First column is filled with break point where max F value occurs
45	Second column is filled with respective max F statistics
46	Here for loop is run on matrix F1.
47	Each F value in matrix F1 is compared with critical F value
48	Estimated break point is displayed
49	Chow F statistics at estimated break point is displayed.

3.9.2 Explanation of the Code for above Algorithm

Last stage is the most complex and important stage of the program. Here we analyze the matrix consisting of all the F values from previous stages. We have 261 F values and obviously a lot of them are above critical value. We use our logic. Our sub sample was of 20 observations. If structural break occurred between 100^{th} and 101^{st} observation, then F value starts accelerating as we move towards this point. It means that f value is less than critical until we are analyzing data below 100^{th} observation or our lower subsample is below 80^{th}

observation. As soon as observation number 101 is included in regression, F value starts rising. It keep on rising unless one subsample is below and one above this point. After this window of subsample keep on moving forward and as a consequence F value starts to decline. As soon as lower subsample has completely passed from observation number 101, F value again becomes less than the critical value. We do not need to display all the high F values. From the logic presented so far we select only highest F value from the neighborhood of the structural break.

Now the trivial part starts. We are working on structural breaks of unknown time. We are blank about the possible structural break and so have to use some trick. We set a segment or window on the all F values and select highest F out of each segment. Now question is about size of segment. Here we are using segment size equal to sub sample size. The logic behind it is that RSS values in one segment can be used only in one consecutive segment. If segment size is half of sub sample size then RSS values of one segment are overlapping with RSS values of three consecutive segments. If segment size is double of the sub ample then R in one segment cannot be used in another segment but it will make our analysis somewhat conservative.

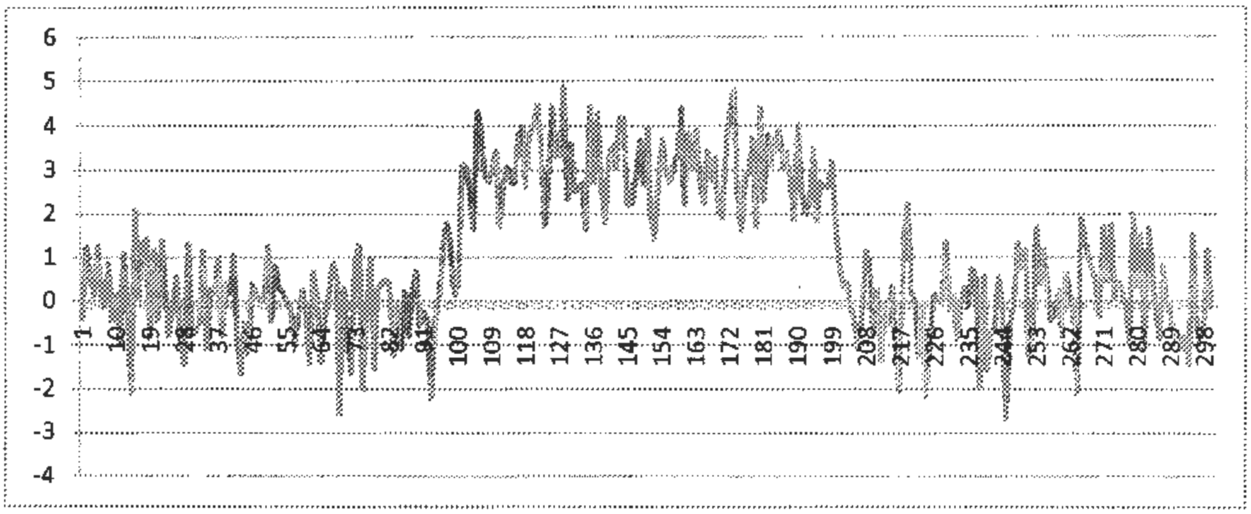
After selecting maximum F value from each of the segment we place all the maximum value in matrix mF1. Now we compare each maximum value against the critical value. If it is more than the critical value then break point is indicated and results are displayed on the screen.

4- Results for Simulated Data

Results obtained by running the programs on the data sets mentioned in previous chapter are explained here one by one.

4.1 CASE 1: Structural breaks for constant term only

As explained in previous chapter data is univaiate normal iid with mean value of zero and unit SD. Data set is given in Appendix section. This data can be graphically viewed as follows.



As we have 300 observation with sample size 40 and subsample size of 20, so we obtain 261 samples (281 sub samples) and same number of different parameter values obtained from 261 regression equations on samples and 281 on sub samples. We can see all the results in oxmatrix window. Here only results from observation number 80 to 120 are reported as rest of the results can easily be seen with the help of graphs given below. The thing worth noticing is the sharp rise in F value as we move towards 100th observation.

Point no.	RSS(20)	Intercept	RSS(40)	F-Chow
90	17.315	0.71626	108.67	16.242
91	17.052	0.77628	107.54	18.554
92	14.857	0.88525	104.93	22.530
93	17.638	0.93886	109.66	41.817
94	15.125	0.97504	112.71	61.551
95	12.306	1.0928	106.14	76.361
96	14.326	1.1905	111.52	75.436
97	16.926	1.2663	119.09	71.729
98	16.730	1.3701	112.66	71.079
99	16.680	1.4604	117.47	96.451
100	16.585	1.5480	122.24	**136.13**
101	25.866	1.6475	129.27	92.091

102	34 7	1.7244	131.15	70.298
103	36.310	1.7981	122.20	54.794
104	37.402	1.8640	119.51	54.443
105	47.698	2 20	116.58	36.280
106	56.371	2.0785	114.93	26.433
107	56.233	2.1816	107.93	22.668
108	57.335	2.2994	110.61	21.072
109	59.399	2.3402	107.98	17.451
110	58.818	2.4437	100.75	14.093

Maximum F values from each segment of 20 F values are given as follow.

observation	Max F
24	2.4891
53	1.5735
69	1.0879
100	96.451
101	136.13
138	1.5307
145	1.1839
171	1.4752
200	93.028
201	100.37
221	0.85524
253	3.8542
265	5.2184
281	3.3723

Conclusion after comparing each of above F value against critical F value is given as follows.

Structural break occurred at observation number100. F value at this point is 96.4508

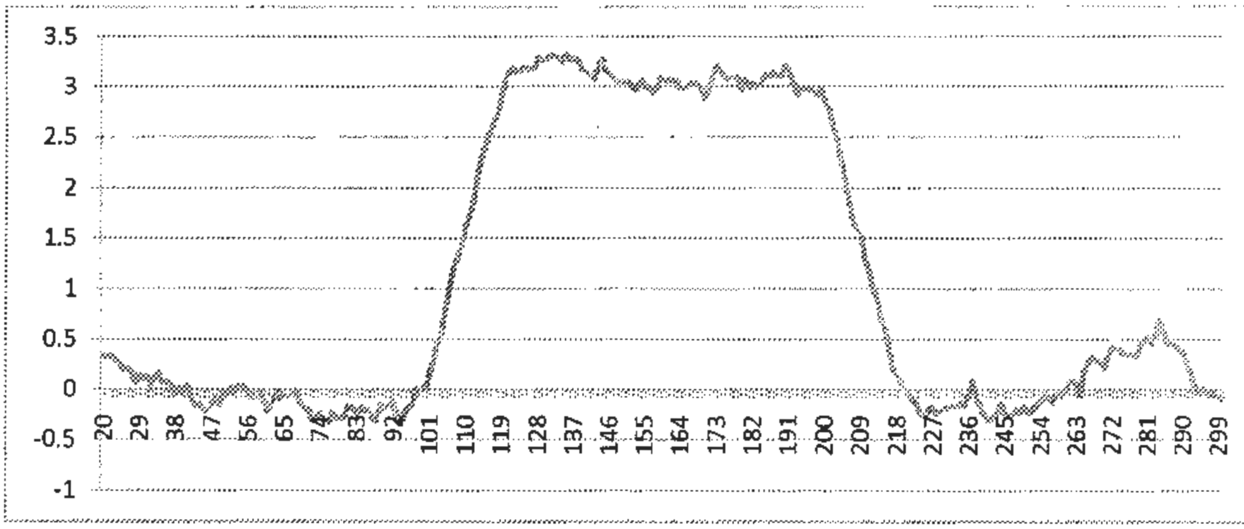
Structural break occurred at observation number101. F value at this point is 136.13

Structural break occurred at observation number200. F value at this point is 93.0276

Structural break occurred at observation number201. F value at this point is 100.366

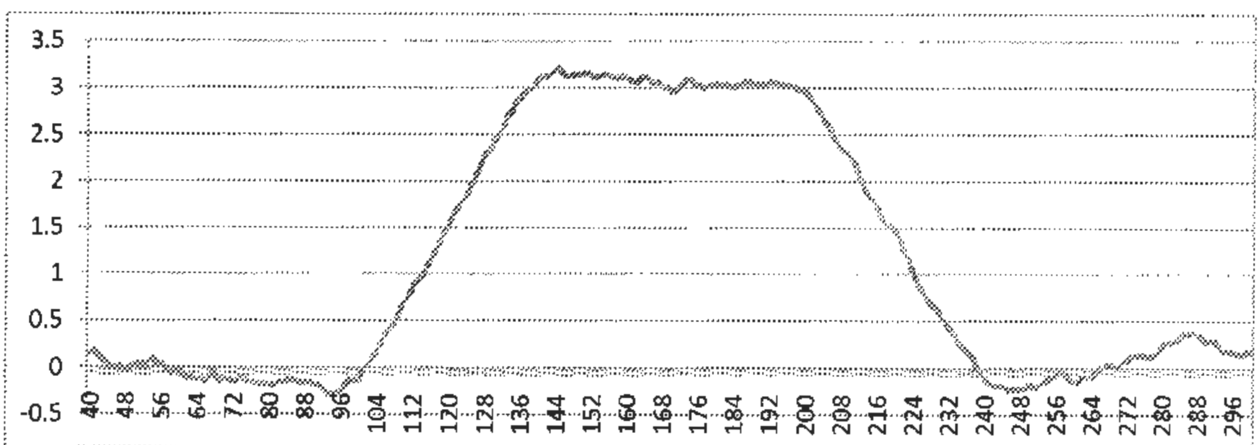
Change in Beta for sample size of 20:

Beta is fluctuating around average value of zero up to observation number 100. Then Beta starts rising and after observation 120 it becomes stable around average value of 3. After observation 200, beta starts to decline. After observation 120, beta again becomes stable around the average value of 220.



Change in Beta for sample size of 40:

Now let us observe change in value of Beta as sub sample window of size 40 swaps across the 300 observations. First value of Beta is obtained at observation number 40. First structural beak occurred at observation 100 and second at observation 200. Beta values are almost constant (near to zero) before 100 and after 240.

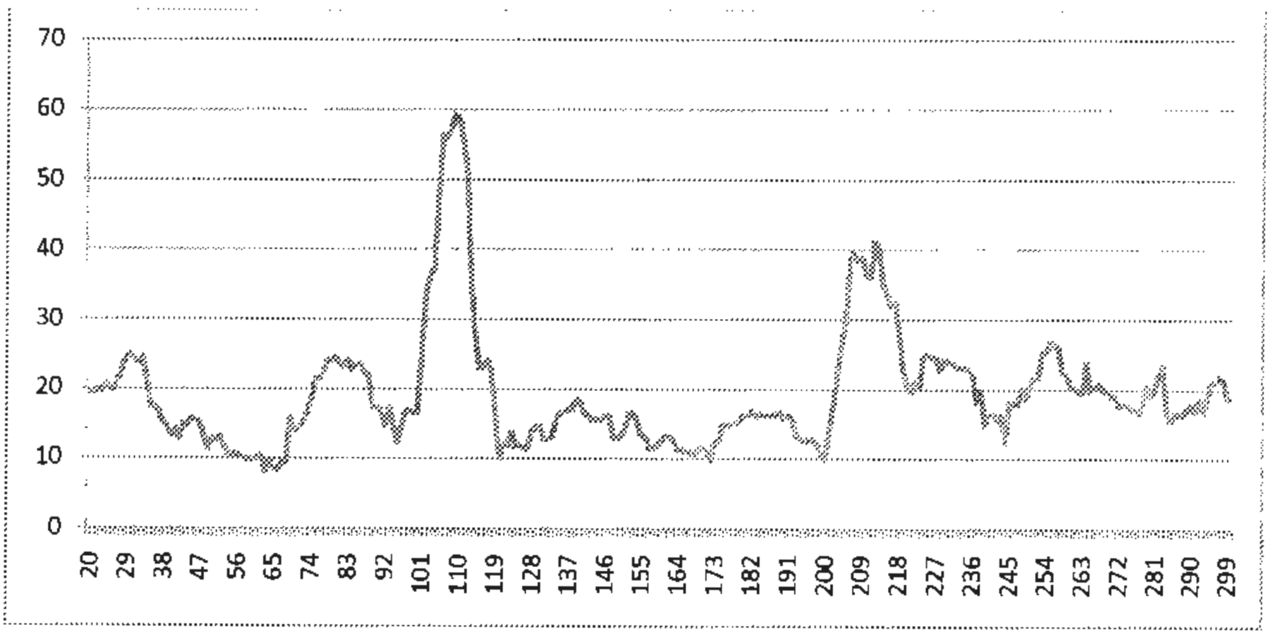


This is just in accordance with our data generating process. After observation 100, beta starts to rise due to inclusion of higher value in sample from observations above 100. Samples from observation 100 to 140 have a mix of two data sets, one having mean value of zero and other having mean value of three. Beta is constant from observation 140 to 200 at the value near to three. After observation 200, sample starts taking values from data set of mean value zero. So Beta goes on declining up to observation 240. After it Beta again assumes a constant value approximately equal to zero. We can see that after observation number 285 Beta moves upward steadily and then downwards , making a local maximum .

This is probably because of the non randomness of the random numbers produces by the computer.

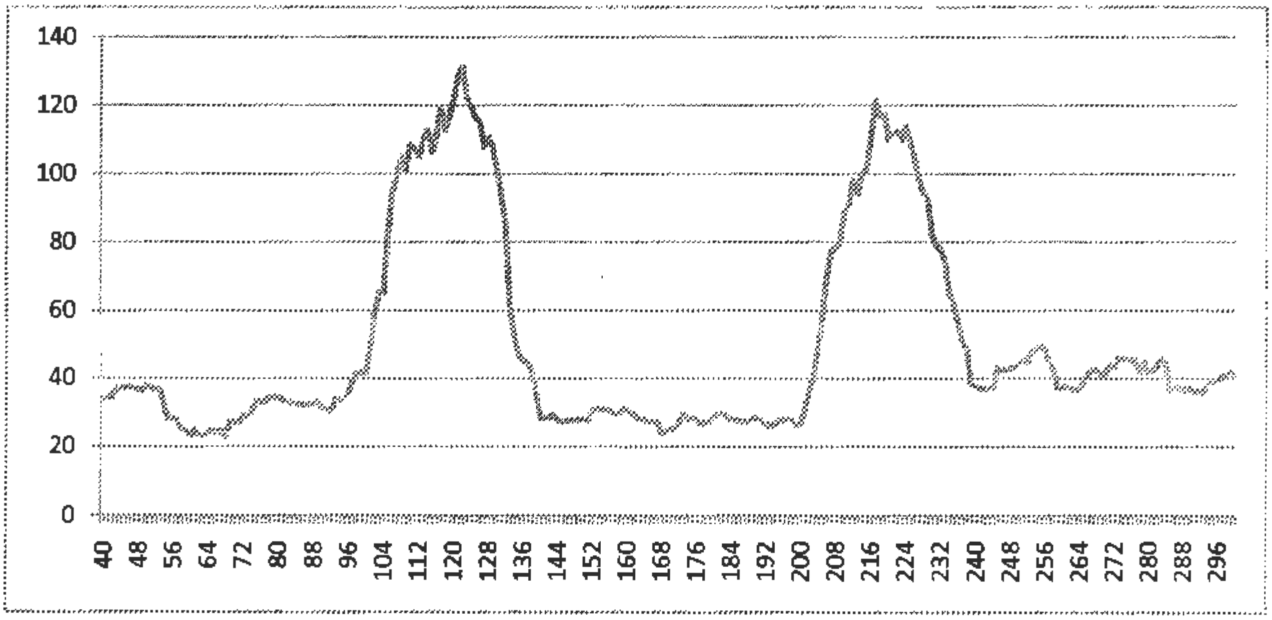
Change in RSS for sample size of 20:

It can be seen in the graph that RSS for sub samples take extra ordinarily high value twice over the whole range of RSS values. Fist time it occurs near observation 100 and secondly near observation 200. At upper limit of 110, we have a peak or maximum value. The reason is that as sample size is 20, so 10 observations 90-100 belong to one data set and other 10 observations 100-110 belong to second data set and so with upper limit 110, we observe maximum disturbance in the RSS. Same applies to second maximum or peak at the sample having upper limit 210. In other words plotting RSS against upper limit of selected sample can reveal important information about structural break. Extra ordinarily high value is an indication of the break in the middle of the sample.



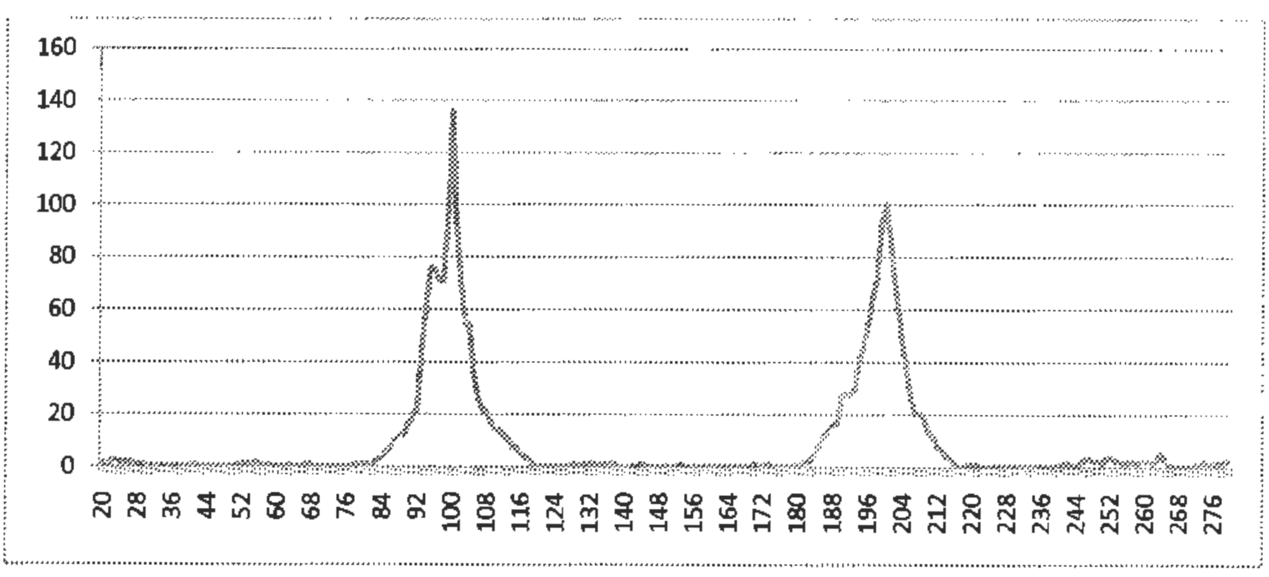
Change in RSS for sample size of 40:

Here RSS of the window size 40 is given. It can be seen that RSS changes its usual pattern after observation number 100 indicating a structural break at this point and same for observation 200. First extra ordinarily high value occurs at observation number 120 and second at 220 indicating structural break in the middle of the sample (of size 40). That is at observation number 100 and 200.



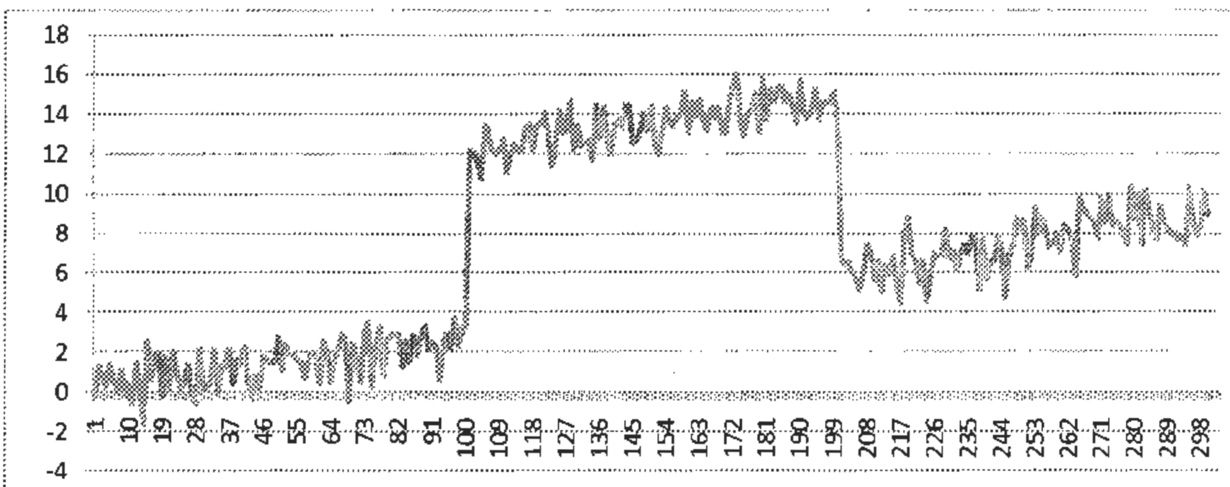
Change in F statistics:

F value proved very decisive in deciding about the structural beak. As compared to previous parameters, here we have very sharp peaks in case of the structural breaks. These two peaks occurred at observation number 100 and 200 as window size is 40.



4.2 CASE 2: Structural breaks for constant term and trend

This data can be graphically vied as follows. First of all normally distributed data of 300 observations with mean zero and unit SD is produces. Then trend having slope 0.03 is introduced and finally a beak is introduced at points 100 and 200, where data is shifted nine point high for each observation between 200 and 300.



All the results for 281 samples are given in appendix. When program is run all 281 rows are displayed on the screen. Only 40 results for sub samples having upper limit 180 and 220 are shown here. We can see how parameters change at value 200 and 201 when the structural beak occurs. This is explained graphically one by one.

Point	RSS(20)	Intercept	Slope	RSS(40)	F Value
190	15.765	17.293	-0.23537	242.84	48.261
191	16.017	17.359	-0.24841	237.29	44.161
192	15.842	17.391	-0.26271	238.09	46.211
193	13.209	17.260	-0.26811	236.72	42.135
194	13.181	17.363	-0.28244	223.86	33.947
195	11.723	17.466	-0.29485	205.70	23.042
196	11.468	17.493	-0.30705	195.54	20.874
197	11.237	17.514	-0.32002	186.04	22.307
198	11.138	17.231	-0.31475	194.04	27.287
199	8.6553	17.093	-0.31323	197.39	58.587
200	8.1429	16.752	-0.30750	202.67	**232.20**
201	50.713	16.605	-0.30900	200.58	70.491
202	82.106	16.332	-0.30771	201.43	36.274
203	96.356	16.025	-0.30247	207.29	29.380
204	105.86	15.727	-0.30100	207.83	22.626
205	109.75	15.304	-0.29206	213.18	22.368
206	107.06	14.870	-0.28028	225.05	27.455
207	101.94	14.371	-0.26589	235.54	33.233

208	98.185	13.900	-0.25218	245.72	39.248
209	90.889	13.425	-0.23546	265.57	50.083
210	91.210	12.780	-0.21501	265.44	49.815
211	93.730	12.236	-0.19718	270.77	50.019

Maximum F values from each segment of 20 F values are given as follow.

Observation	Max F
35	5.5102
46	3.6705
73	2.5440
100	73.717
101	388.79
129	5.3174
145	3.0142
180	3.1285
200	58.587
201	232.20
238	5.1213
247	6.0242
275	6.8196

Structural break occurred at observation number 100 F value at this point is 73.7173

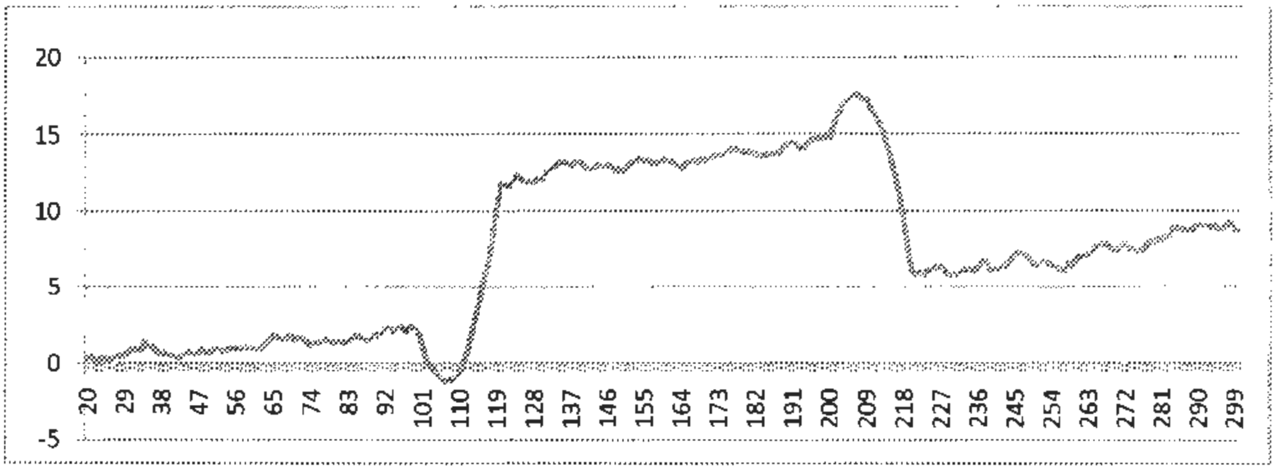
Structural break occurred at observation number 101 F value at this point is 388.79

Structural break occurred at observation number 200 F value at this point is 58.5869

Structural break occurred at observation number 201 F value at this point is 232.204

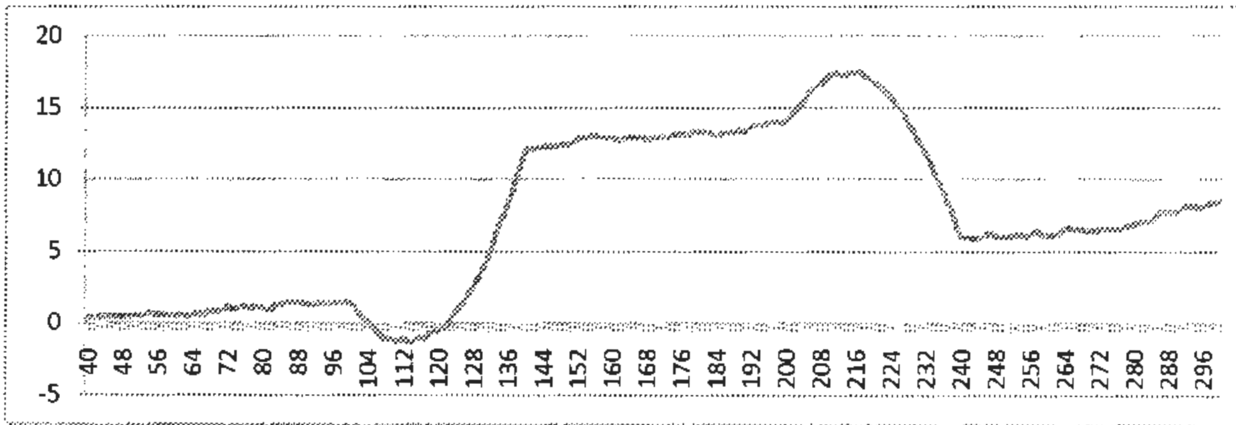
Change in intercept for sample size of 20:

First, we will analyze beta for sample size of 20, disturbance starts after observation number 100. Intercept declines due to sudden rise in data after observation 100. Intercept declines, reaches a minimum and starts to rise up to observation 120. After it intercept becomes stable up to observation 200. After observation 200, intercept rises initially, assumes a maximum value and then starts declining, after observation 220, intercept again becomes stable.



Change in intercept for sample size of 40:

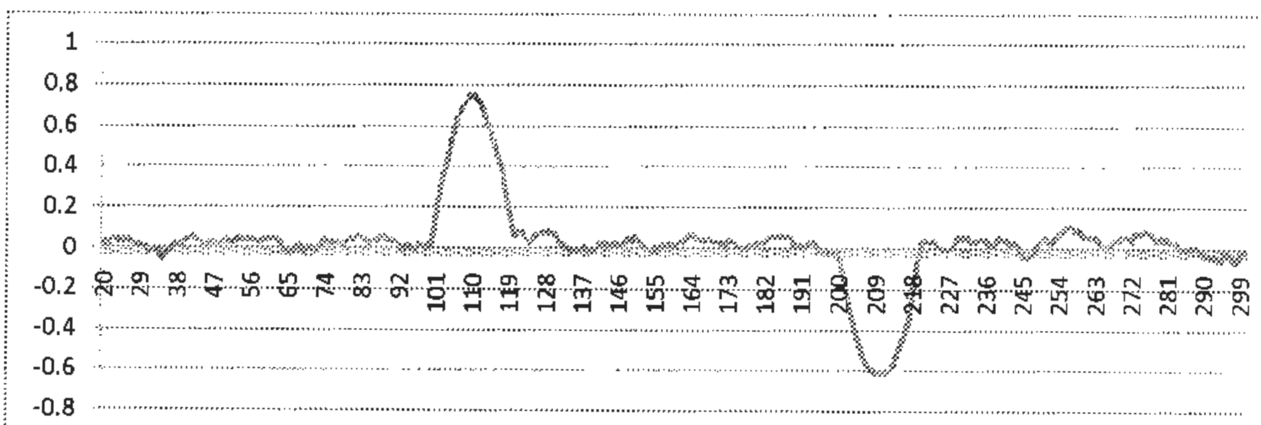
Intercept term takes an abrupt change near observation number 100 and 200 for the swapping window of sample size 40. Change in intercept for sample size 40 is depicted in graph below.



After observation number 100 intercept term starts to decline, the reason that some of the values to be included in sample data set belong to very high values. It causes intercept to decline. Intercept approaches to a minimum value up and then it starts to rise upto observation 140. Then intercept rises with almost constant rate of 0.03 upto observation 200. Then it starts rising after observation 200 due to inclusion of low values in the sample. It reaches to its maximum and then starts declining up to observation 240. After 240 it increases at almost constant rate of 0.03.

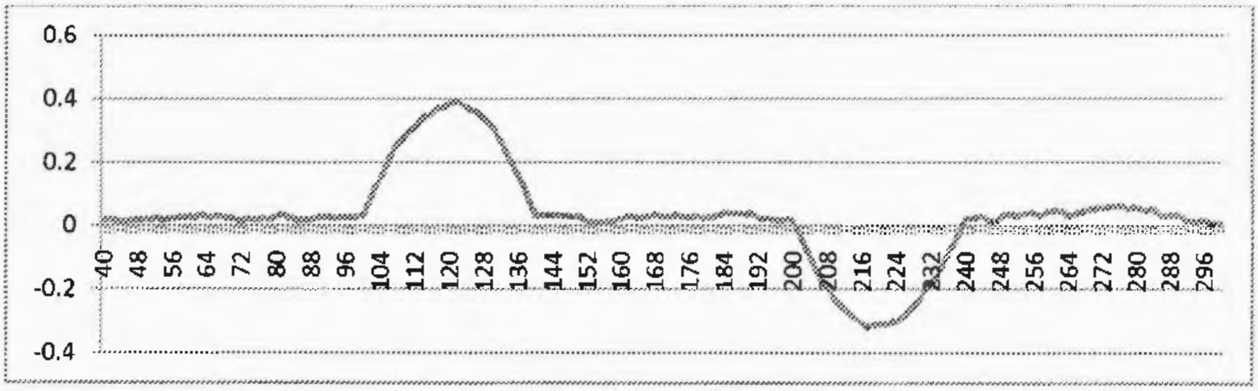
Change in slope for sample size of 20:

Slope fluctuates around a stable value of 0.03 upto observation number 100. After observation 100, slope starts to increase due to inclusion of data after sudden jump. At observation 110, it reaches to a maximum value and again starts to decline upto observation 120. After observation 120, slope again starts to fluctuate around a stable value of 0.03 upto observation 200. After observation 200, slope starts to decline due to inclusion of data from lower values after observation 200. Graph below depicts values of slope according to upper limit of the data sample of size 20. Slope reaches to a minimum at observation 210. Then it starts to rise and become stable again at observation 220. .



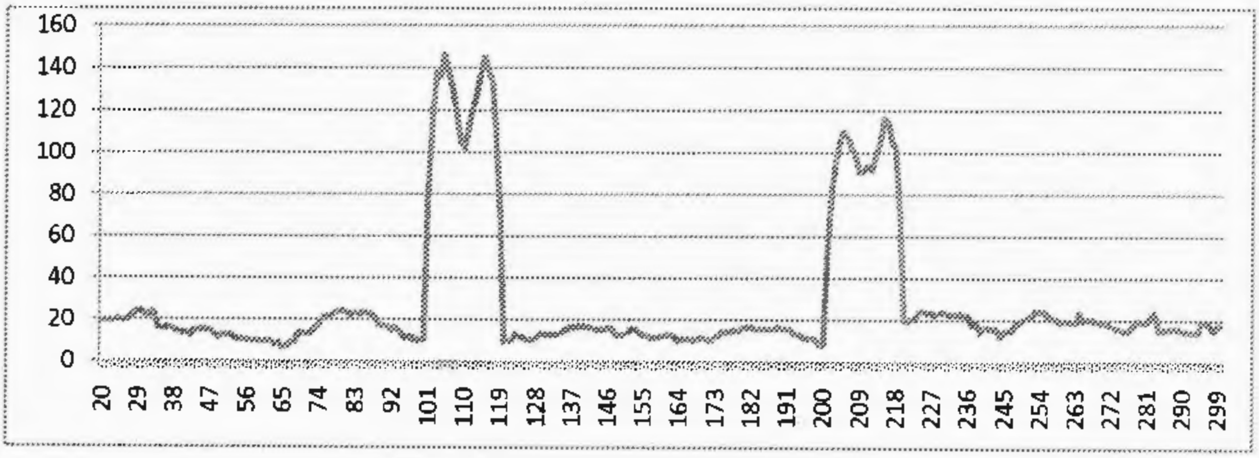
Change in slope for sample size of 40:

Change in Slope or Beta2 for sample size 40 is shown in the graph below. In DGP, we intentionally kept slope constant, so unlike intercept (Beta1), slope (Beta2) is constant when there is no structural break. From observation number 40 up to 100, slope is constant then a few higher values are included with many lower values so slope starts rising. At observation 120, the sample has half lower and half upper values. After 120, samples start taking more value from the data after beak and few values from data before break, so slope become starts declining due to inclusion of more values from a stable data part. After observation 140, slope becomes constant and remains constant up to observation 200. . After 120, slope becomes negative and its absolute quantity goes in increasing up to observation 220. Then slope starts to move towards its normal vale and after observation 140 it becomes 0.03 again.



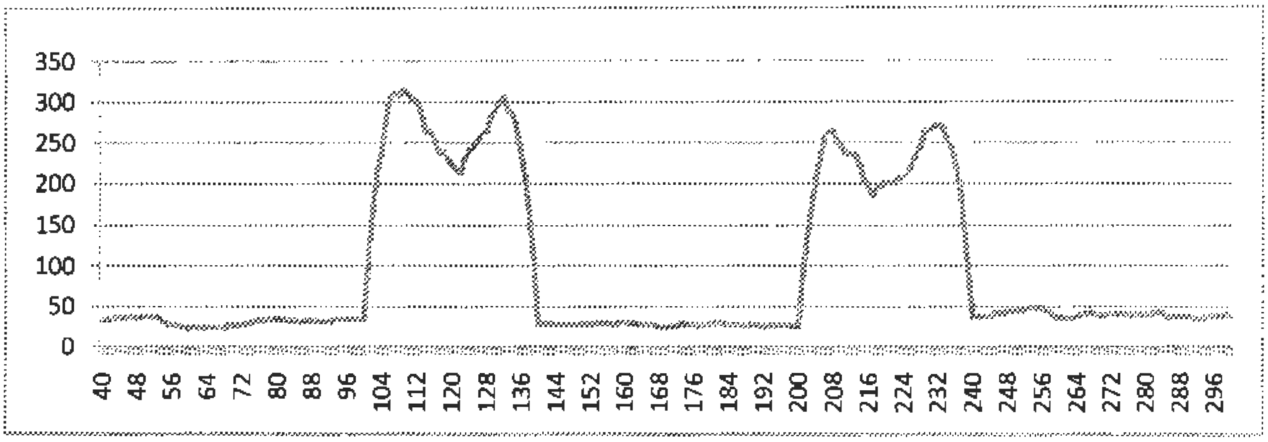
Change in RSS for sample size of 20:

Change in RSS of the samples each consisting of 20 observations is shown below. Disturbance in data occurs after observation 100 and 200 indication possibility for structural beak. RSS is quite stable below 100 and after 220 and same for 120 to 200. Data assumes values with constant mean and SD in these intervals.



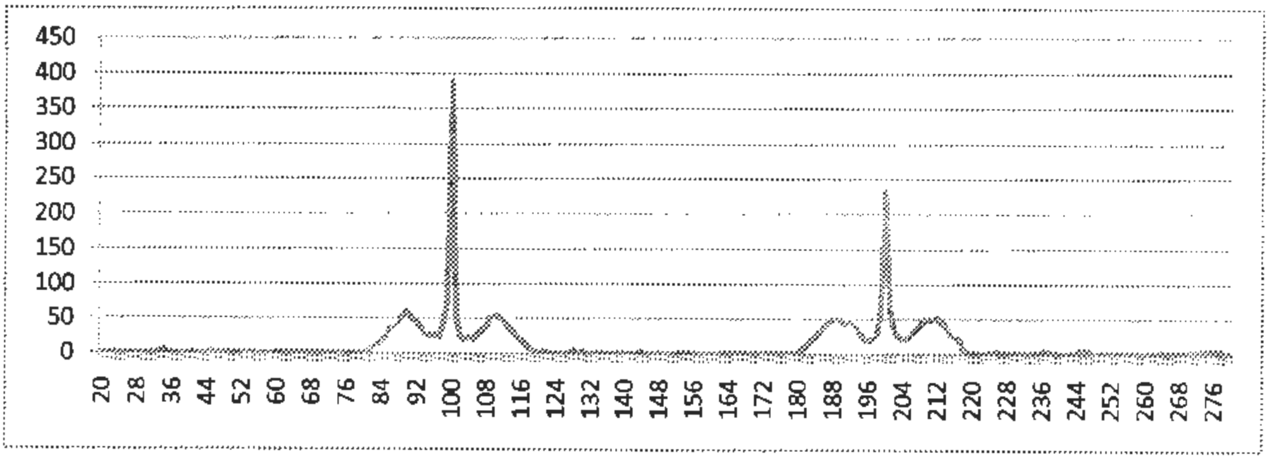
Change in RSS for sample size of 40:

Change in RSS in samples each consisting of 40 observations is shown below. Disturbance in data occurs after observation 100 and 200 indication possibility for structural beak. RSS is quite stable below 100 and after 240 and same for 140 to 200. Data assumes values with constant mean and SD in these intervals



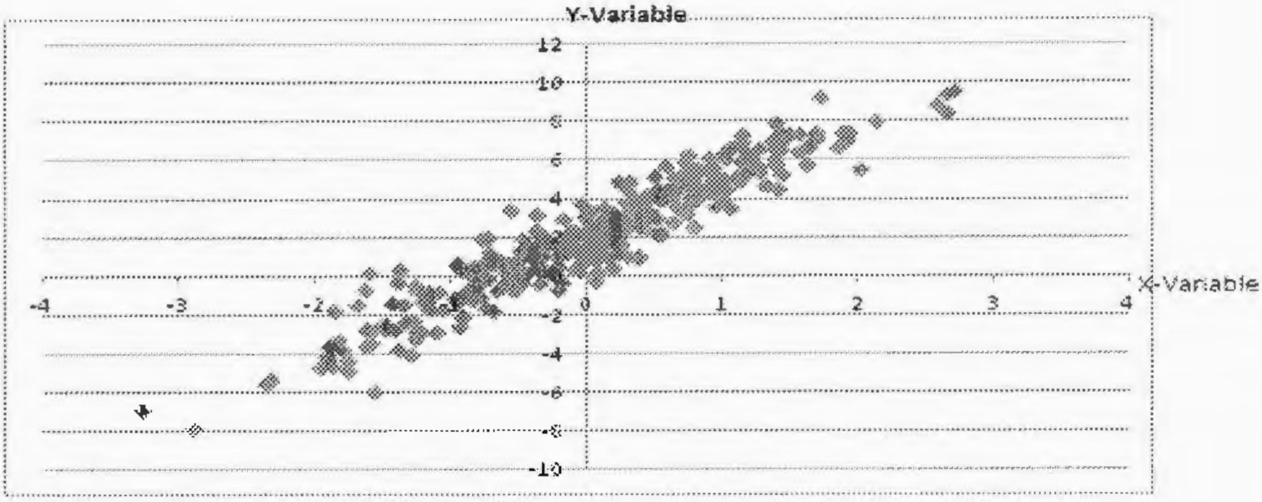
Change in F statistics:

Change in F statistics in chows test is shown below. F statistics has very sharp peaks at values exactly 100 and 200 indicating structural break at these points. Each peak of Chow F value has a local maximum at left and right side. The reason for these local maxima is the disturbance ctreate4d in the RSS of sub samples size 20 each. RSS of subsamples start to disturb after lower limit of 80 or in other words after upper limit of 100. Same logic applies to relative maxima around second F value peak at observation 200.

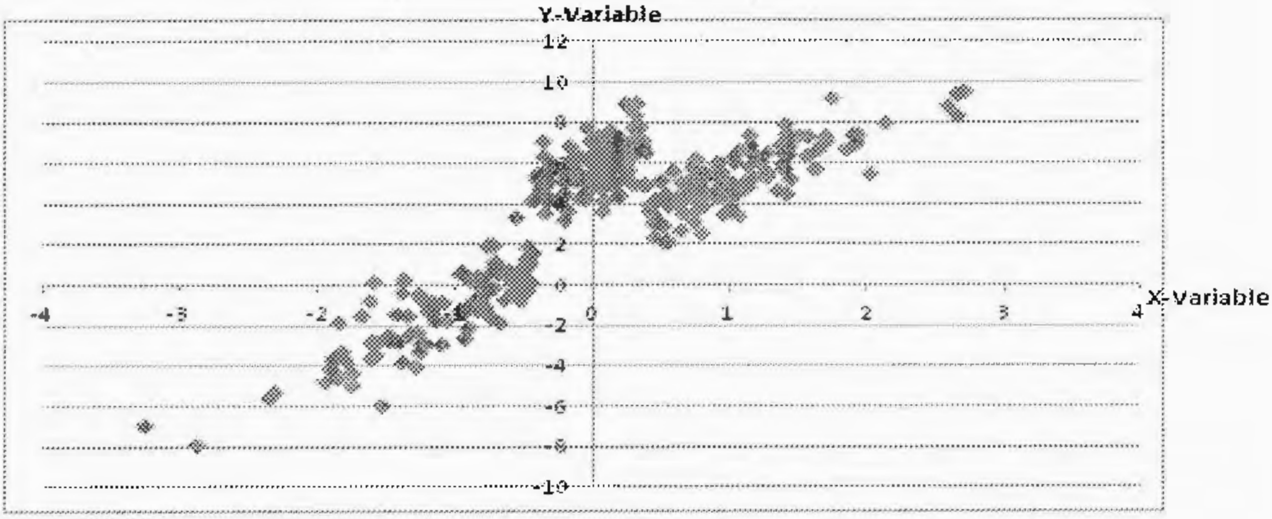


4.3 CASE 3: Structural breaks for bivariate time series data

Data before introducing break depicts following scatter diagram.



Data after introducing break, depicts following diagram,



We can see all the results in oxmatrix window. Here only results from observation number 180 to 120 are reported. The thing worth noticing is the sharp rise in F value as we move towards 100^{th} observation. .

Point	Intercept	Slope	RSS(40)	Fstatistics
80	2.5037	3.2472	49.469	0.70931
81	3.4485	4.6382	64.922	3.4748
82	4.1549	5.6295	78.303	8.5733
83	4.8112	6.6016	88.071	23.128
84	5.4868	7.7043	92.446	25.305
85	6.3505	9.0079	110.83	37.592
86	7.3646	10.835	108.60	50.390
87	8.0724	12.027	116.00	53.839
88	8.2086	12.190	117.20	62.635
89	8.6037	12.982	114.84	53.967
90	8.6618	13.152	114.39	43.079
91	9.3778	14.660	105.48	37.886
92	9.8228	15.675	99.365	29.939

93	10.424	17.003	92.892	24.656
94	11.119	18.544	86.105	20.145
95	11.153	18.604	86.147	23.259
96	11.277	19.118	82.978	13.871
97	11.783	20.401	76.395	15.876
98	11.289	19.478	82.612	36.971
99	11.120	19.299	83.244	62.540
100	10.303	17.566	95.115	50.202
101	9.8994	16.721	98.895	34.496
102	9.6971	16.320	100.16	27.172
103	9.4964	16.186	98.951	50.471
104	9.4096	15.899	98.219	40.912
105	9.0586	14.998	99.354	45.302
106	8.9255	14.670	99.777	57.633
107	8.5747	13.603	96.593	61.101
108	8.3119	12.793	95.101	58.252
109	7.9471	11.652	92.734	48.420
110	7.6722	10.786	91.992	38.056
111	7.5457	10.290	90.112	34.604
112	7.1877	9.1852	92.610	30.870
113	6.8960	8.1388	90.315	27.288
114	6.5917	7.1282	92.023	29.297
115	6.1384	5.3076	81.464	22.082
116	6.1970	5.1046	77.872	8.4935
117	6.0077	3.9590	63.420	5.7383
118	5.7363	2.4468	45.123	1.1708

Maximum F values from each segment of 20 F values are given as follow.

Observation	Max F
31	2.9978
51	4.6783
70	6.1304
88	62.635
107	61.101
135	8.7310
149	10.052
160	6.0545
188	39.445
208	75.220
230	3.4107
256	4.5799
263	3.0012

Structural break occurred at observation number 88, where F value at this point is 62.635

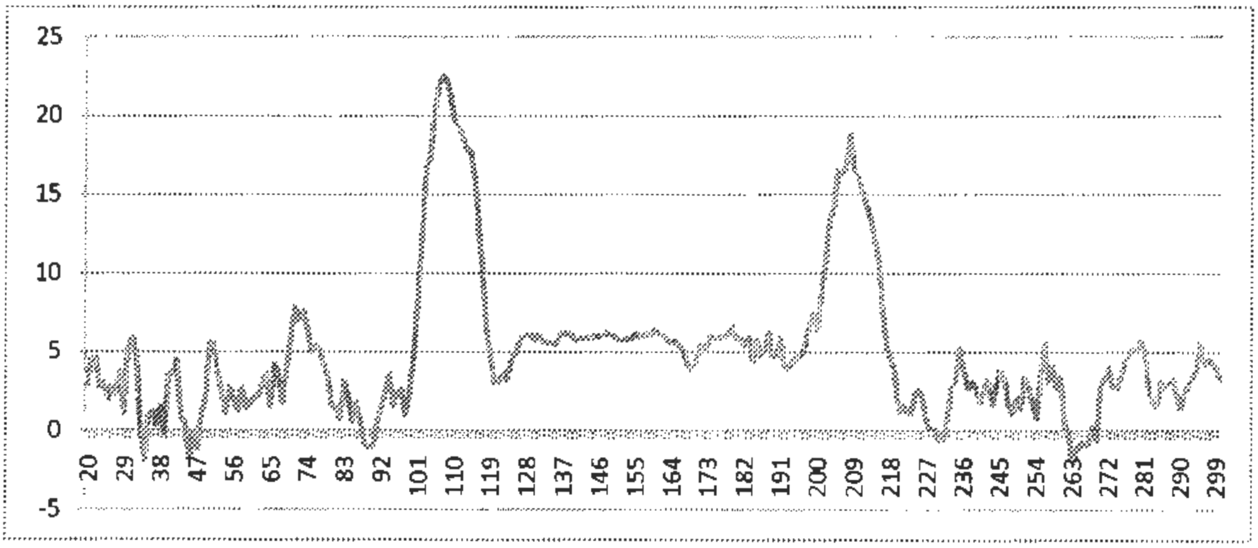
Structural break occurred at observation number 107, where F value at this point is 61.101

Structural break occurred at observation number 188, where F value at this point is 39.445

Structural break occurred at observation number 208, where F value at this point is 75.220

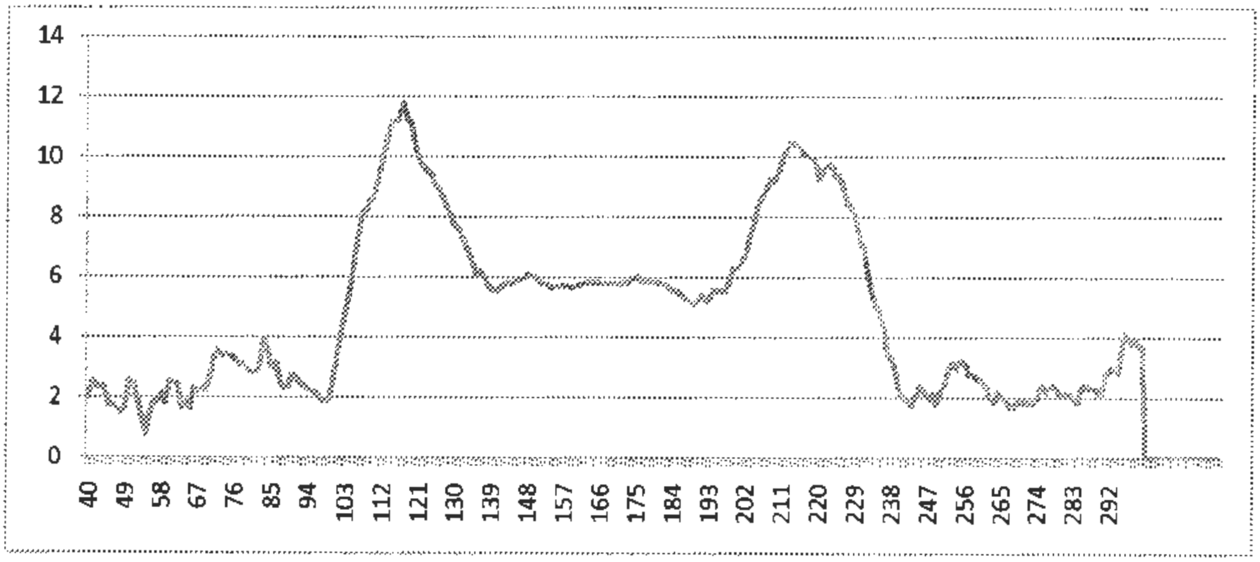
Change in intercept for sample size of 20:

Intercept is fluctuating around a mean value of 2 units up to observation 100. Then intercept starts rising sharply, reaches a maximum at around 110, start to decline then and assumes normal fluctuation after 120. Same pattern can be seen between observations 200 and 220. It indicates a structural break at observation 100 and 200.



Change in intercept for sample size of 40:

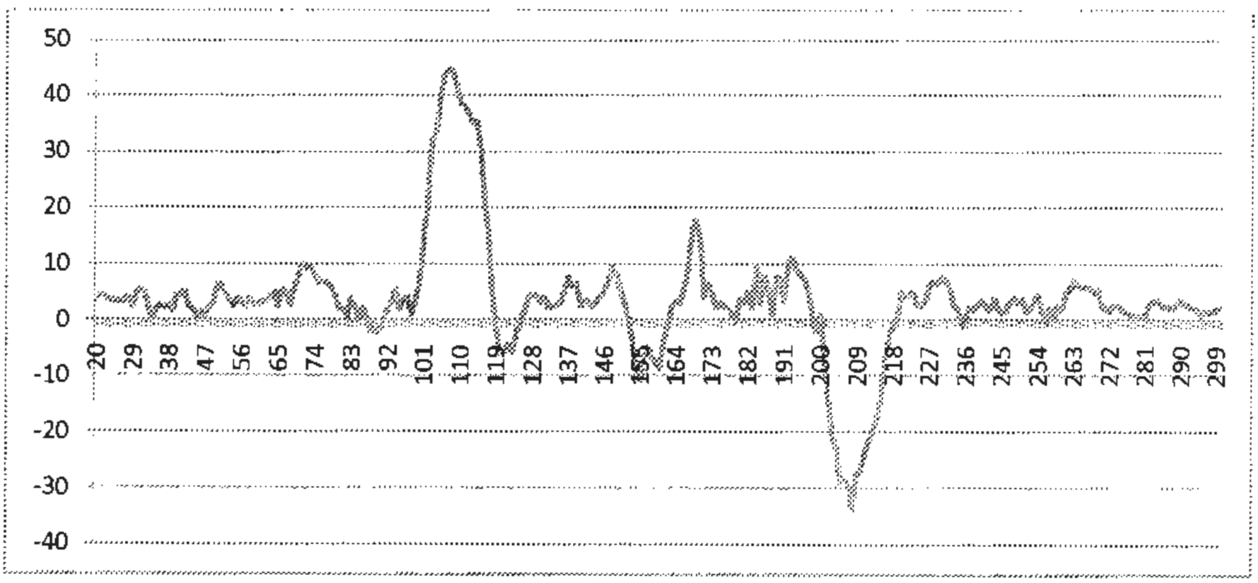
Values of intercept term for a window of size 40 swapping over the data set are given below.



In DGP, we assumed intercept to be 2. It can be seen that intercept remains almost stable around the value of 2 units up to sample with upper limit 100. Then disturbance starts due to structural break. After observation 140, intercept again takes a stable value around 6 units which is just in accordance with our DGP. Disturbance again starts after 200 and then intercept gains a stable value of 2 units after observation 240. We get two peak values at approximately 100 and 200 indicating the point of structural break in the data.

Change in slope for sample size of 20:

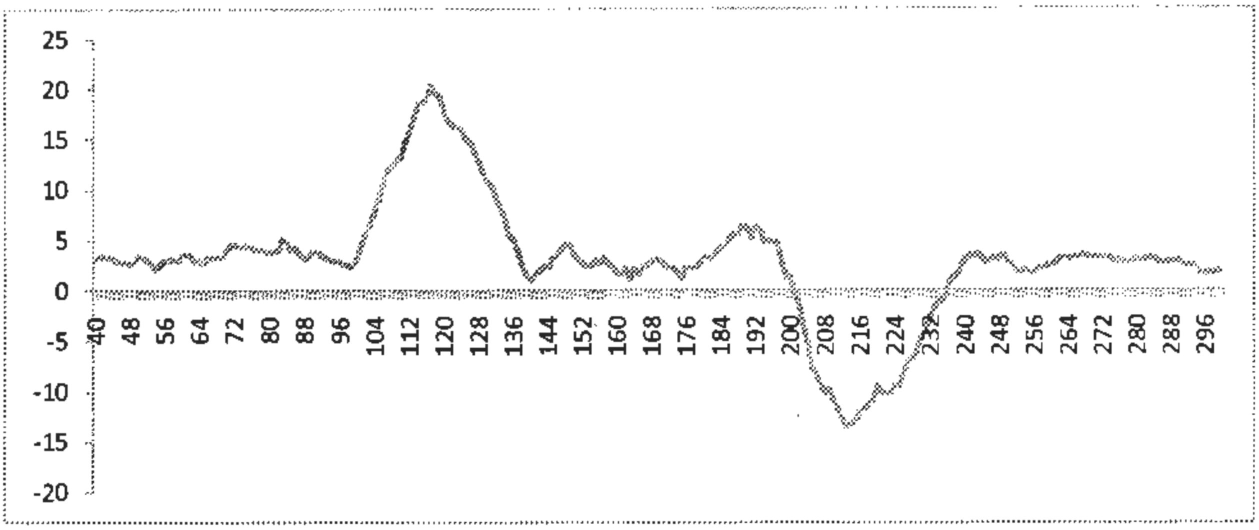
We can note a change in pattern of beta fluctuation as compared to previous cases. Here fluctuations are more violent. The reason may be that in previous cases only Y variable was random while X or T variable was not random. But in this case both Y and X variables are random.



Besides relatively high fluctuation, a sharp rise can be seen after observation number 100 which reaches to a maximum at around 110 and then starts declining. After 120 beta again starts fluctuating around a mean value of 3 units. After 200, beta starts to decline, reaches a minimum at 210 and starts to rise again and assumes normal fluctuation a after 120. It indicates that a structural break occurred around the points 100 and 200.

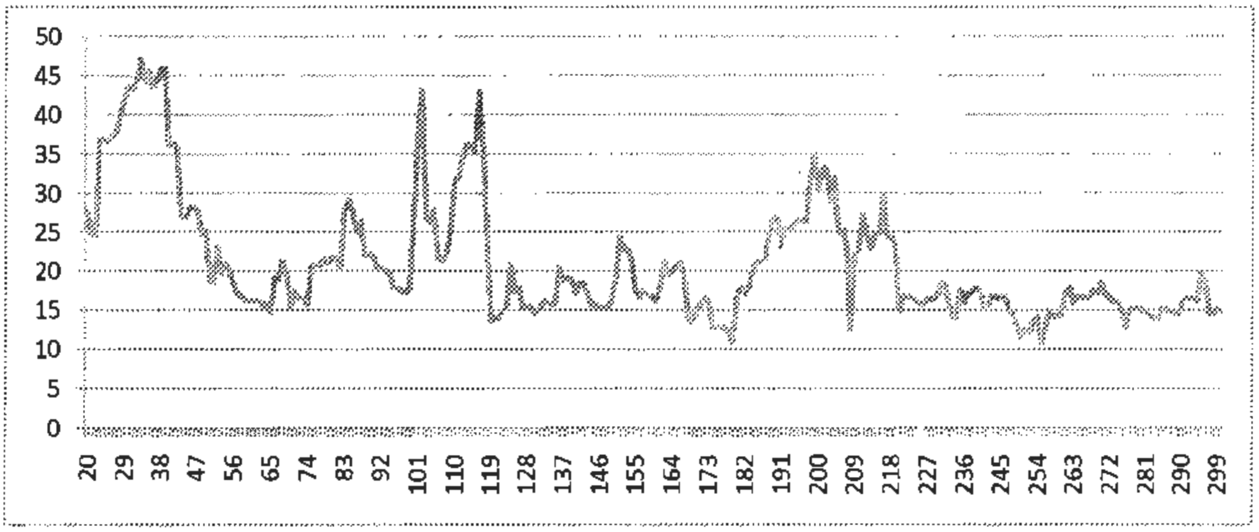
Change in slope for sample size of 40:

Change in lope of the regression line is depicted in the graph below. Slope assumes almost stable value of 3 units throughout the data except around the structural break at point 100 and 200. Explanation for a maximum peak at 100 and minimum trough at 200 is same as given in the case 2 (changes for trended data) of this study.



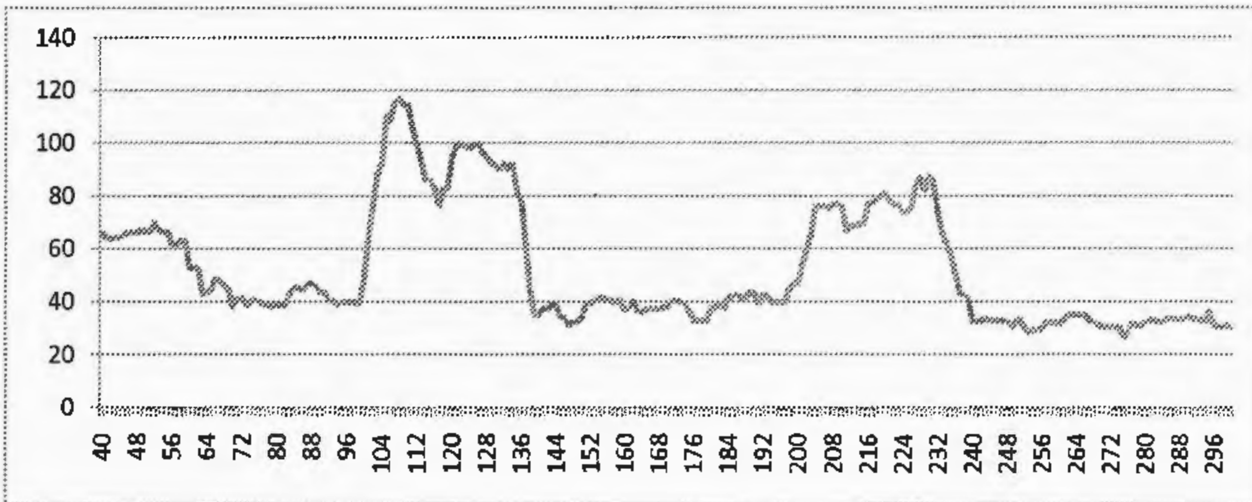
Change in RSS for sample size of 20:

RSS for the sample size of 20 are given below. In initially we have somewhat high values of RSS. This may be due to outliers in the data as it is understood that pseudo random numbers generated by the built-in algorithm of the computer are not purely random. We observe two peak values around observation 100 and 200 indicating presence of structural break.



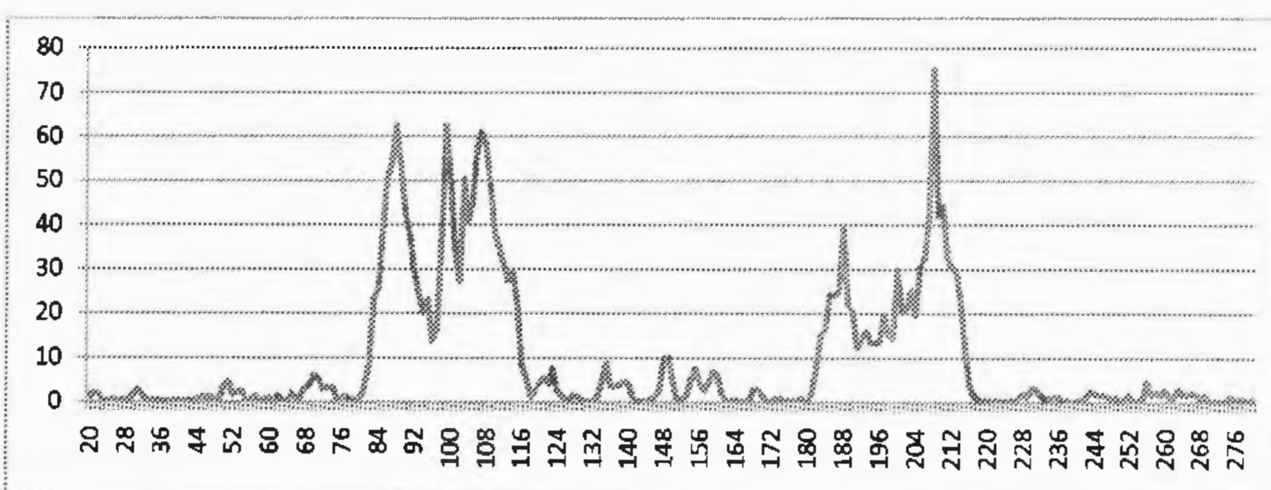
Change in RSS for sample size of 40:

Changes in RSS for sample size of 40 are given below. Here we can predict structural break at point 100 easily but it is not the case if we think of the peak value after point 200. It shows that bigger window size ids more helpful if we want to predict the structural break in data by observing RSS only. Anyhow in this case too disturbance starts after point 200. So if we take decision on the basis of the point from where disturbance starts then the second break is occurring at point 200.



Change in F statistics:

Changes with Chow f statistics are depicted in the graph below. F value remains below the critical level up to observation 90. Then it changes rapidly and moves to a very high peak at observation 100. Then it declines rapidly and again becomes below critical level after observation 105. Same type of changes can be observed around the second structural beak point 200.



5-Results for Econometrics Time Series

Three econometrics time series are selected. These are Karachi Stock Exchange (KSE) 100 Index, Gold (10 grams) price and Treasury Bill rate. Period covered is from January 2001 to October 2016. From T-Bill rate, we can derive data for T-Bill value. It means rise in value of a 100 rupees note with time. We assume that we invest Rs 100 on January 2001 and then we calculate its value as the rate on T-Bill changes over time. Data is analyzed with programs written according to algorithms explained in chapter three of this thesis. This analysis is given as follows.

5.1 Analysis of KSE Index

KSE hundred index was 1518 on first January 2001. It rose with fluctuations up to 17 April 2005 where it became 12274. After that KSE crashed and with several fluctuations KSE 100 index fell to 6971 on 11 August 2005. KSE index started to rise with fluctuations and reached to 12137 on 14^{th} April 2006. Then market declined and index was 9029 on 27 June 2006.

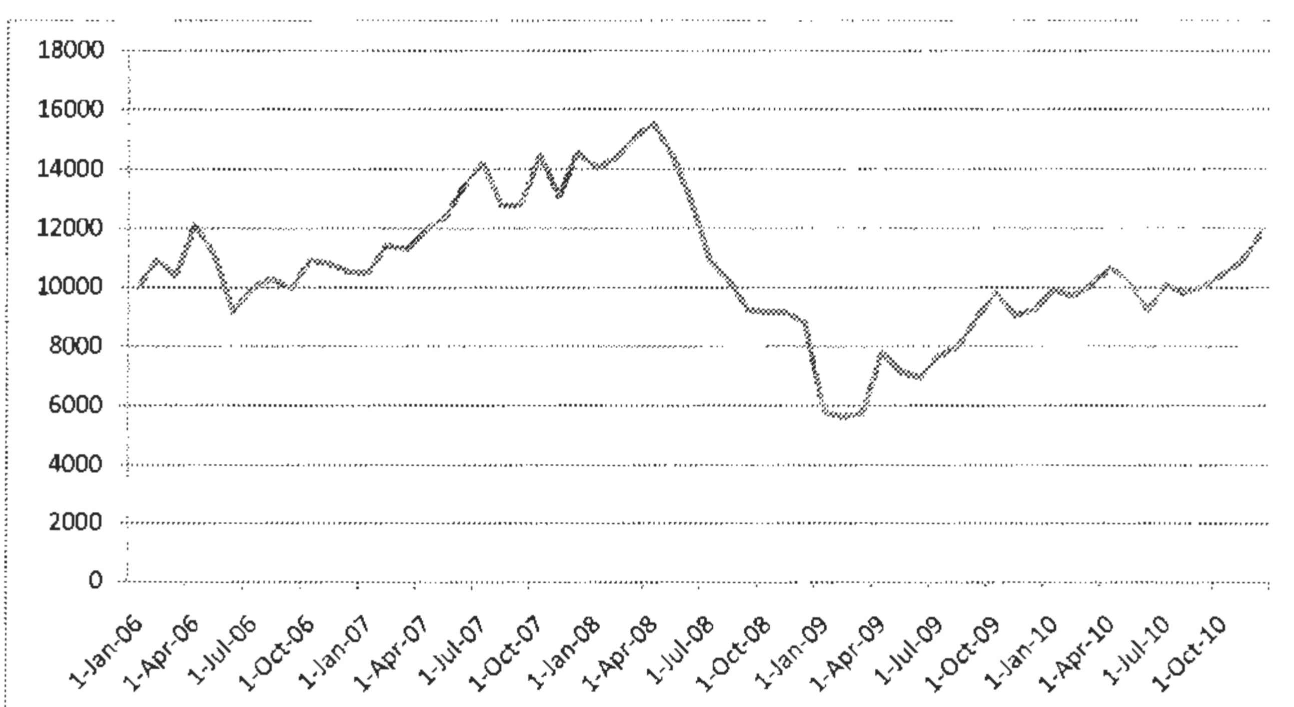
Index then started to rise and reached to peak value 15655 on 21 April 2008. The market crashed and index declined to 4815 on 26 January 2009. Market had several fluctuations up to 6 August 2015 where it reached to maximum 36229. After it market declined to 30564 on 23 February 2016. Then market started to rise and it is 41546 on 20 October 2016. In tabulated form, it is given as follows.

Day	Month	Year	Index
1	January	2001	1518
17	April	2005	12274
11	**August**	**2005**	**6971**
14	April	2006	12137
27	**June**	**2006**	**9029**
21	April	2008	15655
26	**January**	**2009**	**4815**
6	August	2015	36229
23	February	2016	30564
20	October	2016	41546

We observe that during past sixteen years, the first crash occurred in April 2005, when Index fell from 12274 to 6971 within four month. Second crash was relatively less sever but even then index fell in April 2006 from 12137 to 9029 within two and half months. Third crash actually shocked the market. KSE 100 index fell in April 2008 from 15655 to 4815 in January 2009.

We want to check if similar shocks (though less sever) occurred in other time series and if there is some lead and follow relationship among the shocks of different econometrics time series. Now we apply our algorithm to find out changes in different characteristics of data. We use window size of 19, 38 and 76. Window size must be divisible to our data size 380, so that we have integral number of windows as in order to run loop number of widows must be an integer. This analysis is given below.

A closer look at the 2008 shock is given as follows.

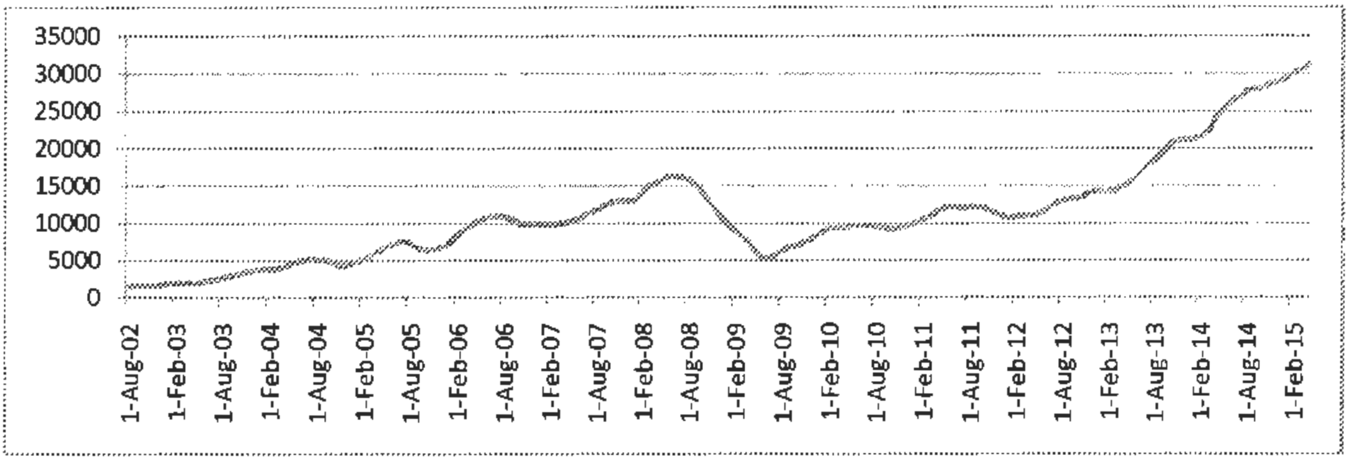


Now we will see how closely our algorithms can detect the structural breaks.

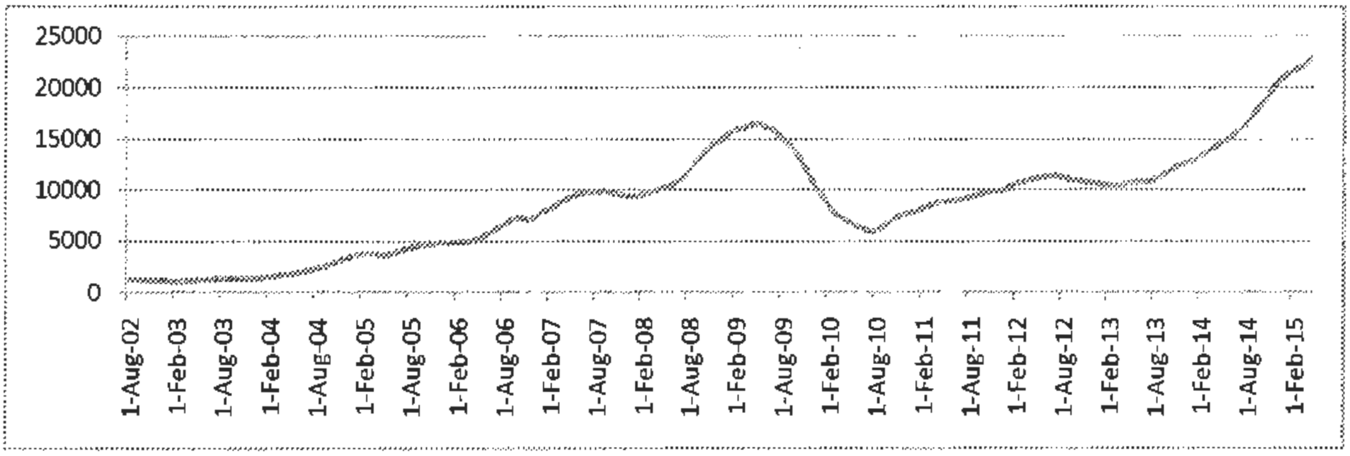
Change in Intercept (KSE 100 Index):

With the increase of window size, indications for structural break decreases. If we want to know about structural break in short time period, we may use small window size as large window size will skip many short period fluctuations. This is depicted as follow.

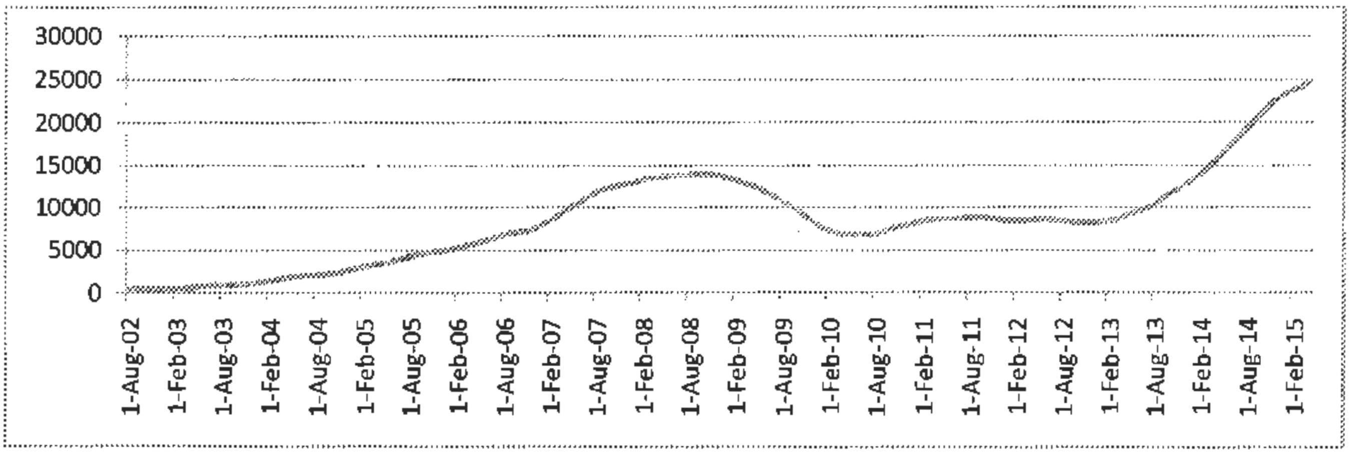
Window size 20



Window size 38



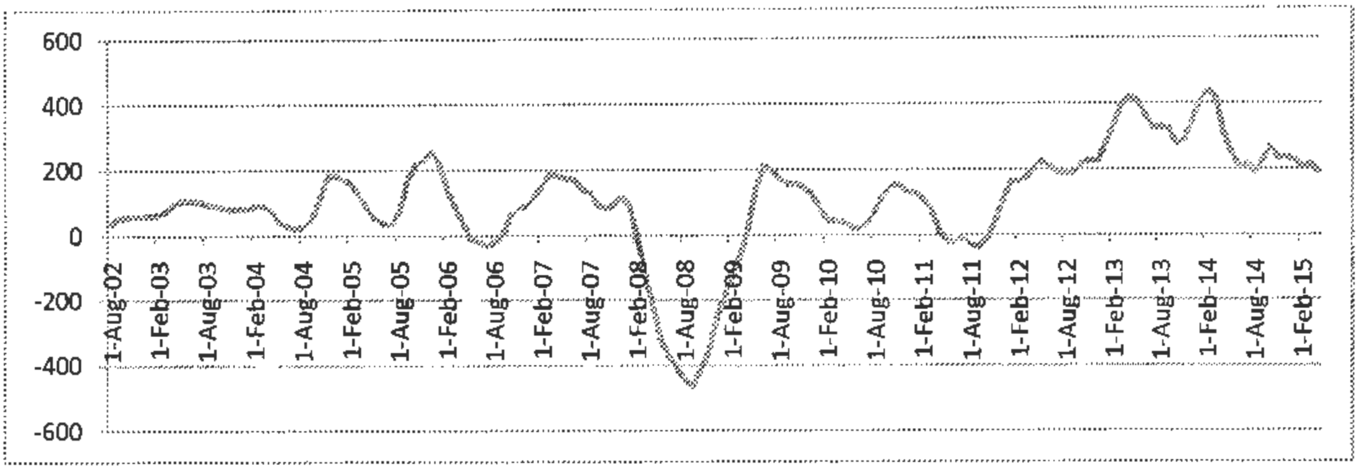
Window Size 76



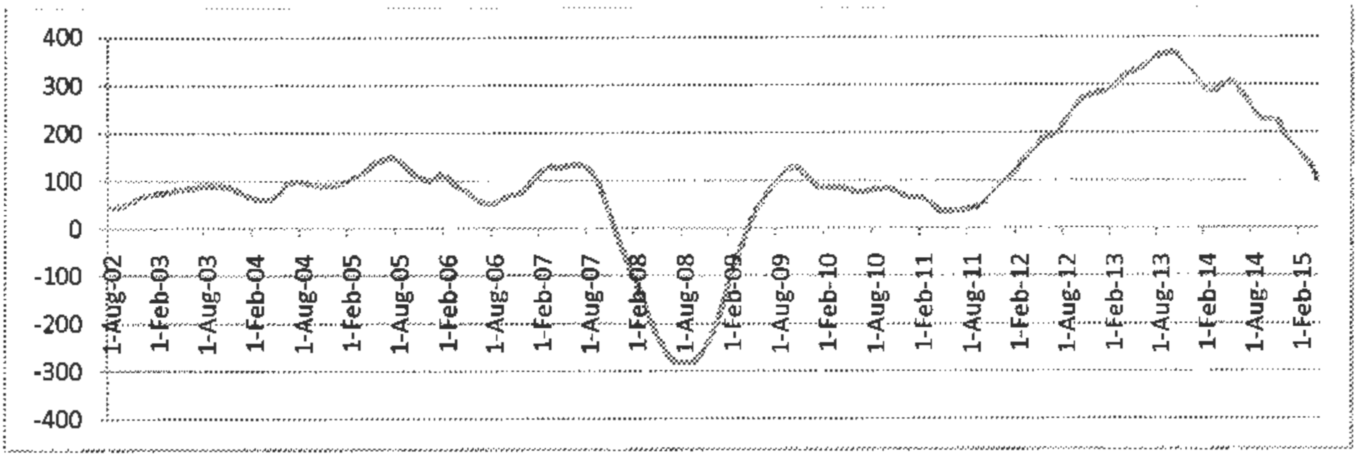
Change in Slope (KSE 100 Index):

Change of slope is more informative as compared to change in intercept. If slope is negative, it means that market is declining, otherwise it is rising. For short period structural breaks, small window size is appropriate.

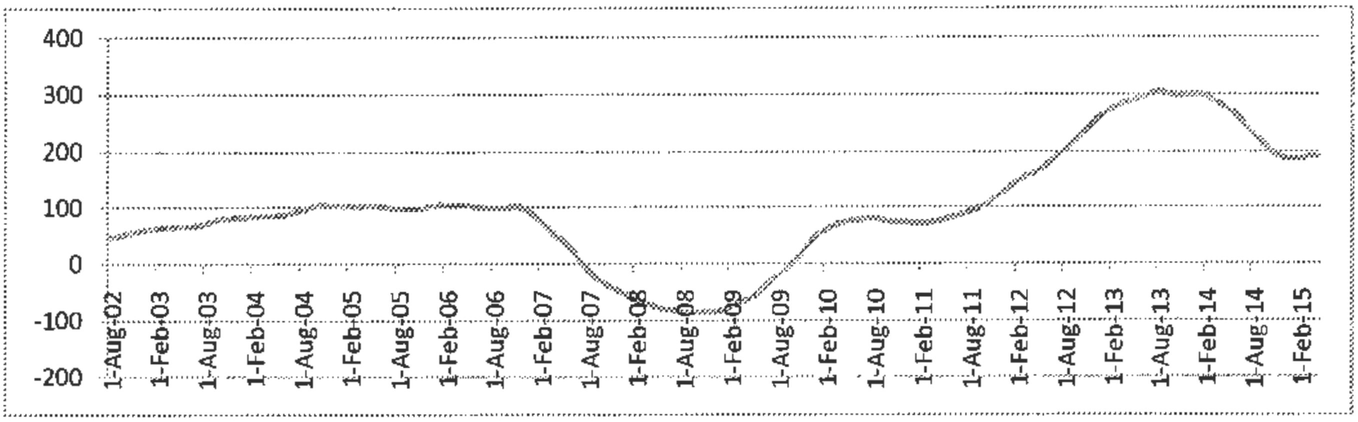
Window size 20



Window size 38



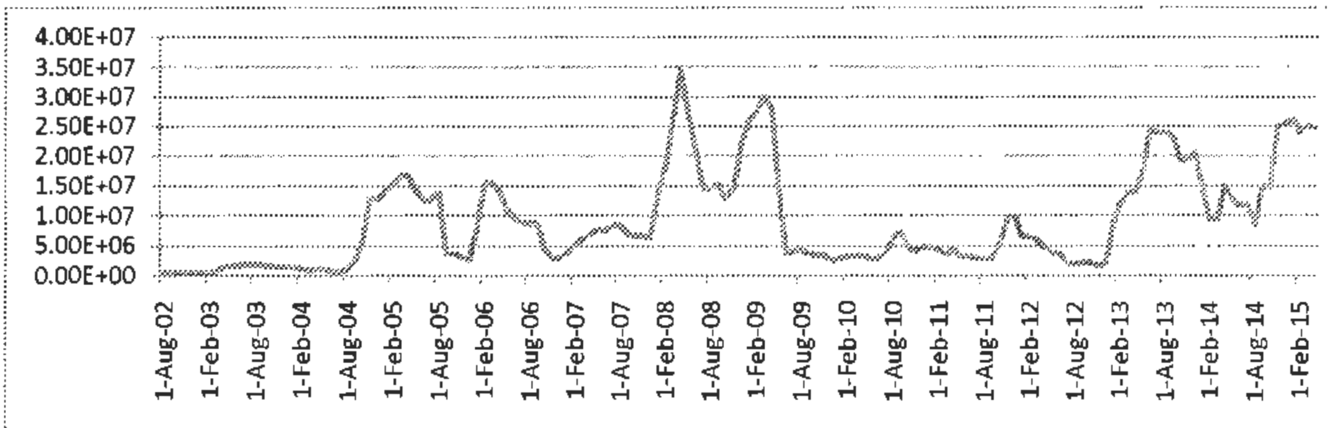
Window Size 76



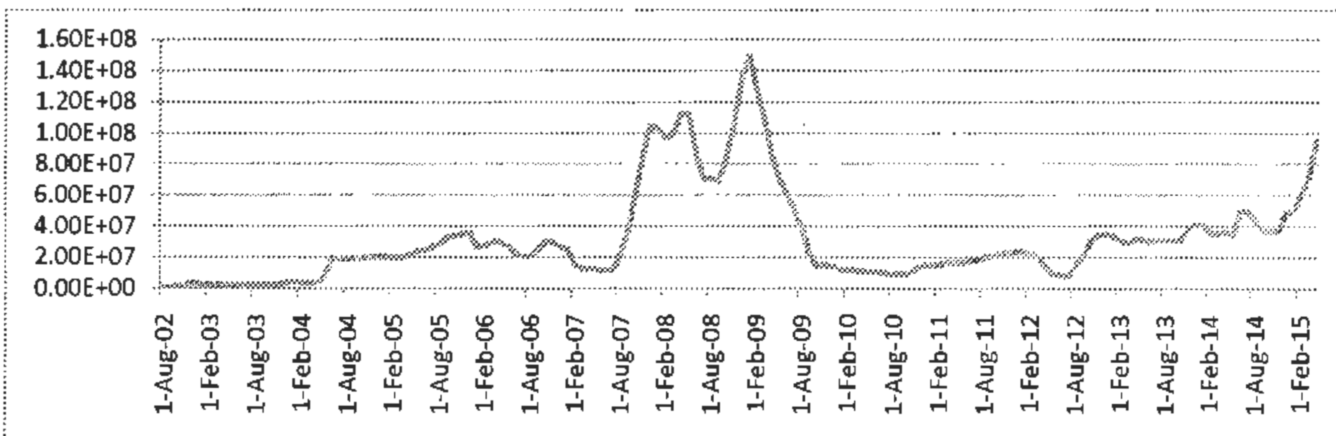
Change in RSS (KSE 100 Index):

Change in RSS is also a good indicator of structural changes. RSS cannot be negative so we cannot predict about change of slope of regression line from data of RSS. Still RSS indicates structural breaks more sharply as compared to data of slope of regression line.

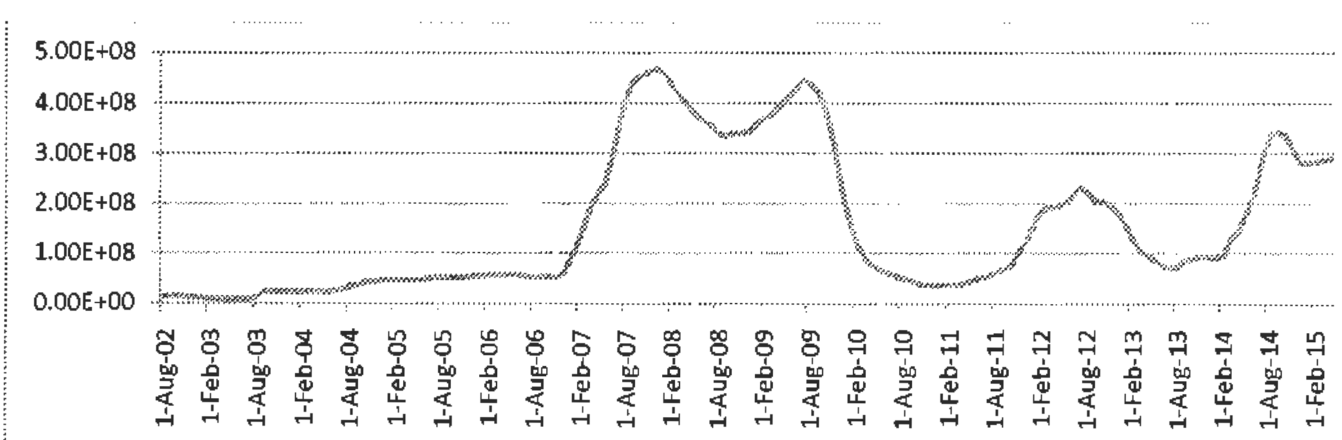
Window size 20



Window size 38



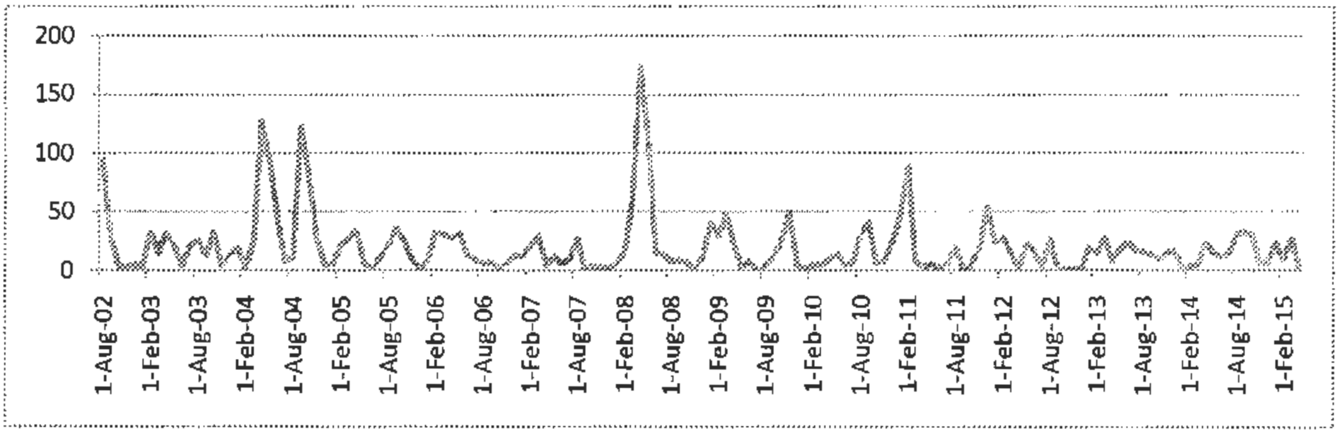
Window Size 76



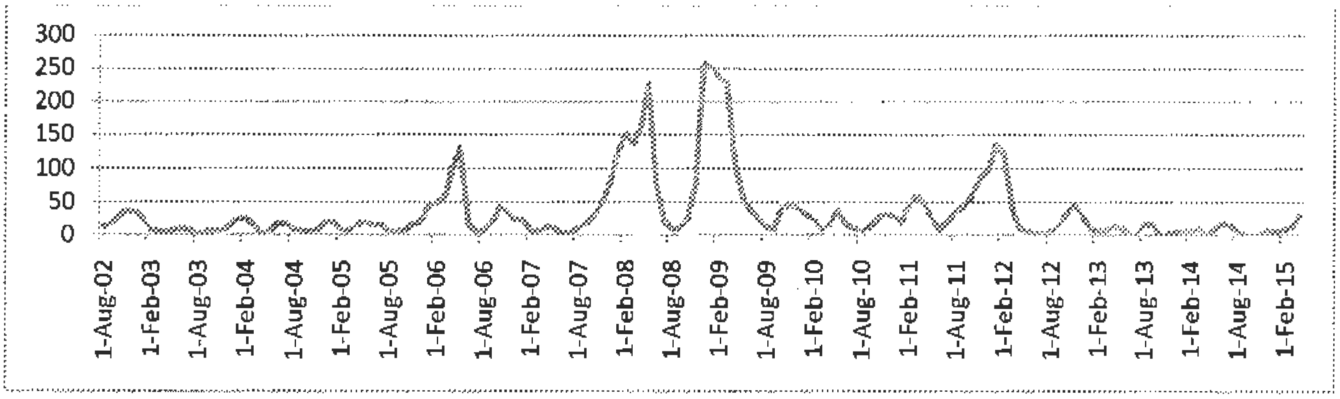
Change in Chow F Statistics (KSE 100 Index):

Chow F statistics is the ultimate source to measure change in characteristics of data set. A high value of F statistics indicate structural break. Like RSS and unlike Slope, Chow f statistics cannot tell about increasing or decreasing trend along with the time, but F statistics points to the structural break more sharply as compared to any other statistics. Here change in data of F statistics is depicted as we change window size from 19 to 38 and then to 76.

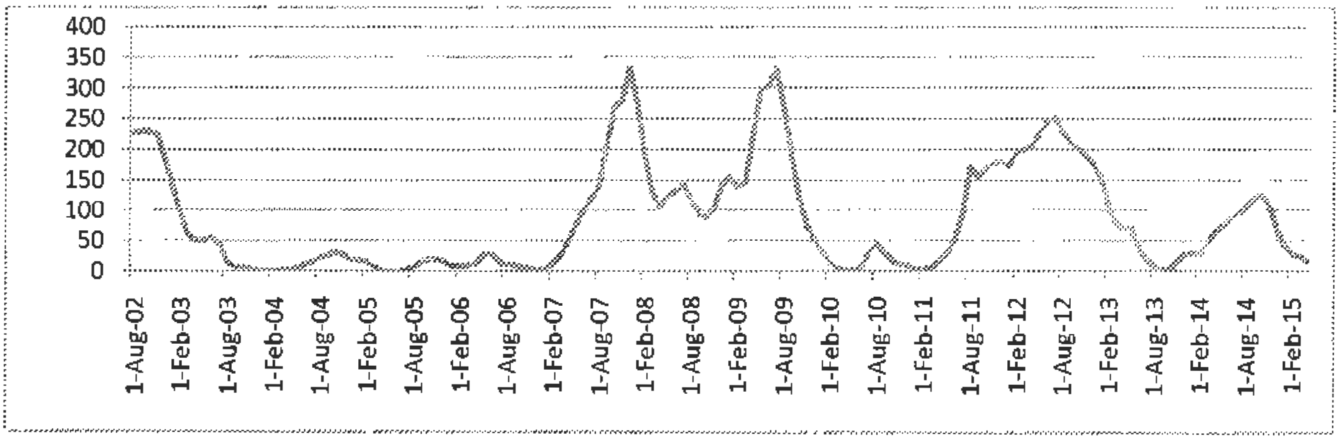
Window size 20



Window size 38



Window Size 76



5.2 Analysis of Gold Price

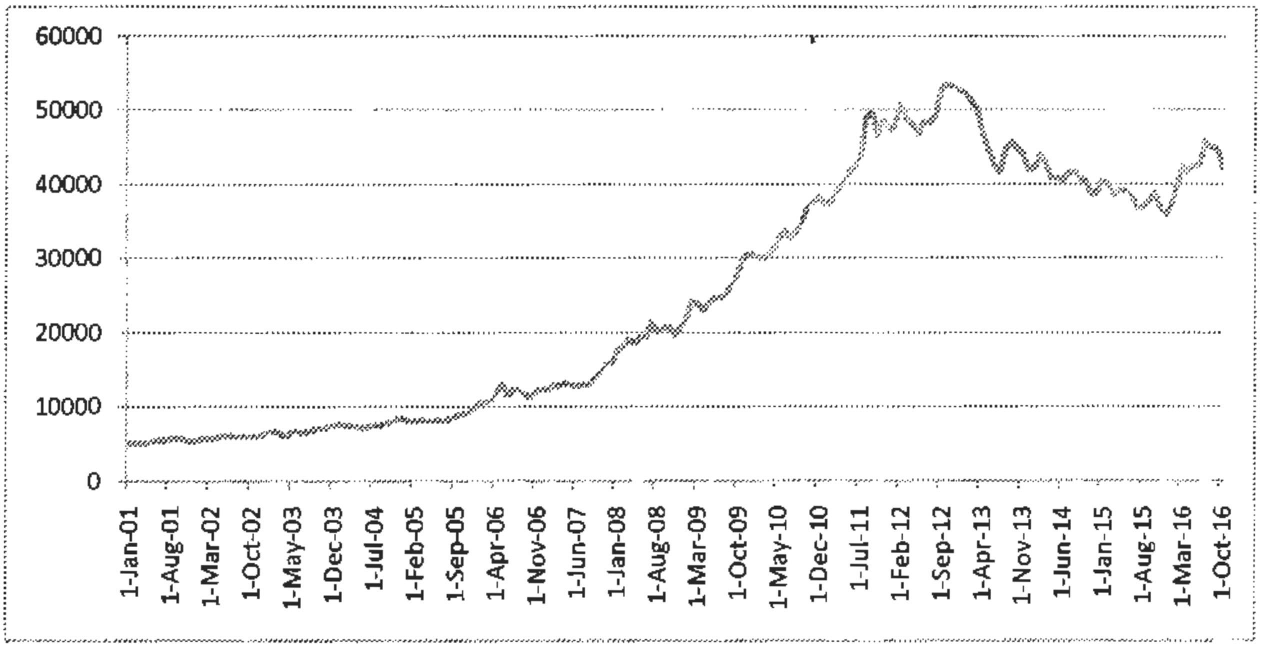
In January 1995, price for 10 grams of gold was Rs, 3760. In November 1996, it was Rs 4890. With fluctuations, it remained almost constant November 2000 when it was Rs 4850.

In January 2001 price was Rs 5049. Then it started to rise with fluctuation and reached to Rs 37400 in January 2011. Within an year it rose to Rs 50830 in February 2012. It gained its peak value Rs 53585 in October 2012.

Then price started to decline and got lowest value of Rs 35991 in December 2015. Then it started to rise and it was Rs 44040 on 30th September 2016. This information is given in tabulated form as follows.

Month	Year	Price
January	1995	3760
November	1996	4890
November	2000	4850
January	2001	5049
January	2011	37400
February	2012	50830
October	**2012**	**53585**
December	**2015**	**35991**
September	2016	44040

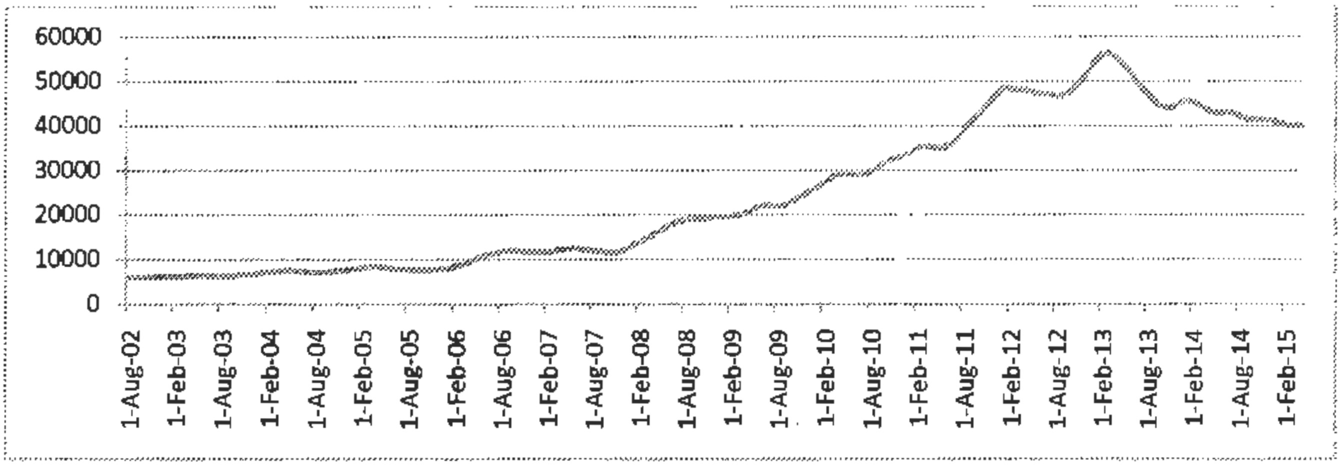
Graph of gold price in Pakistan is given below.



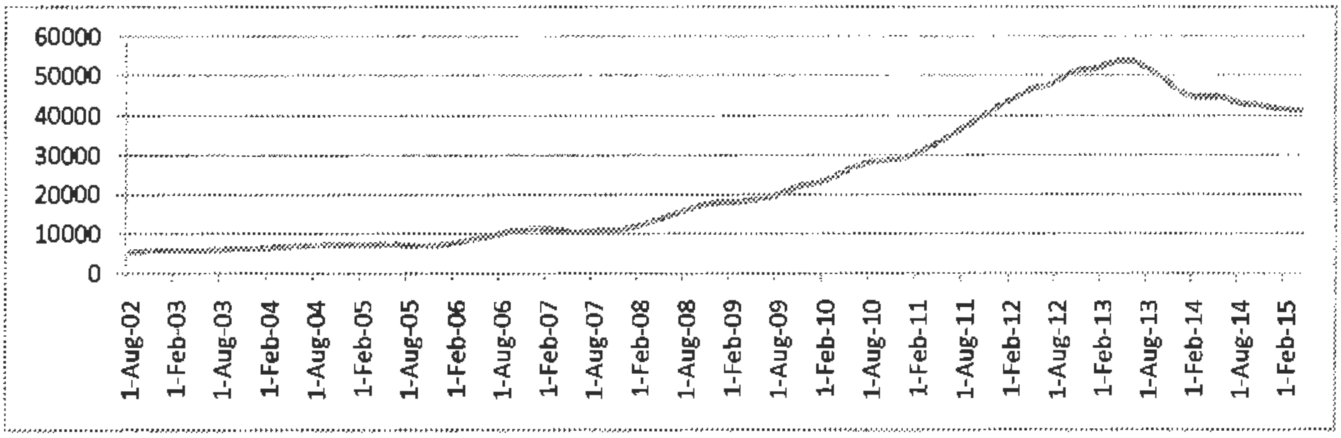
Change in Intercept (Gold Price – 10 grams):

Change in data for intercept for gold price covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 41.

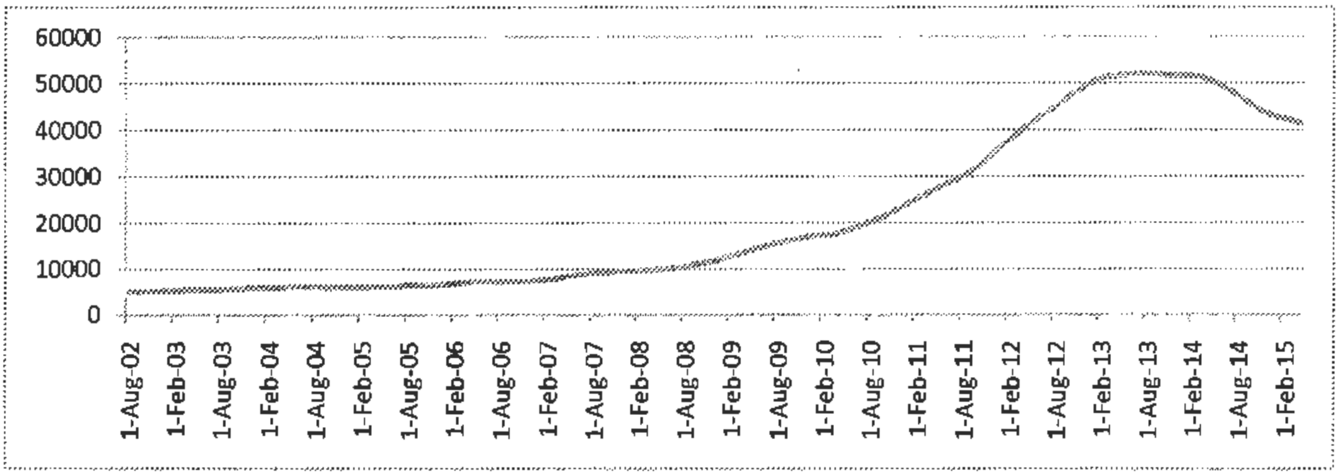
Window size 20



Window size 38



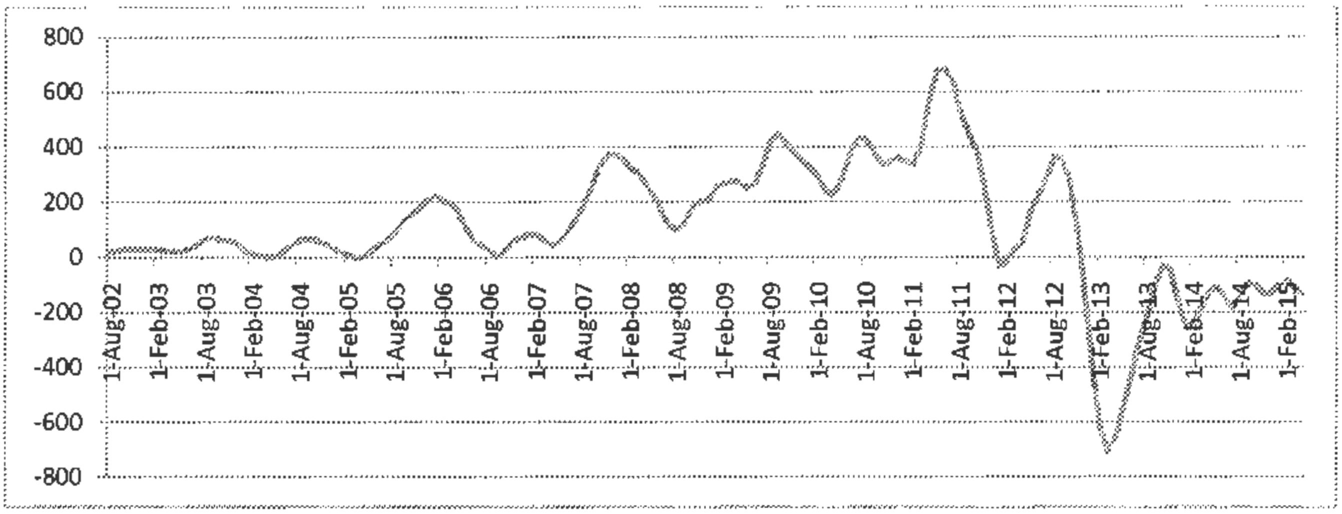
Window Size 76



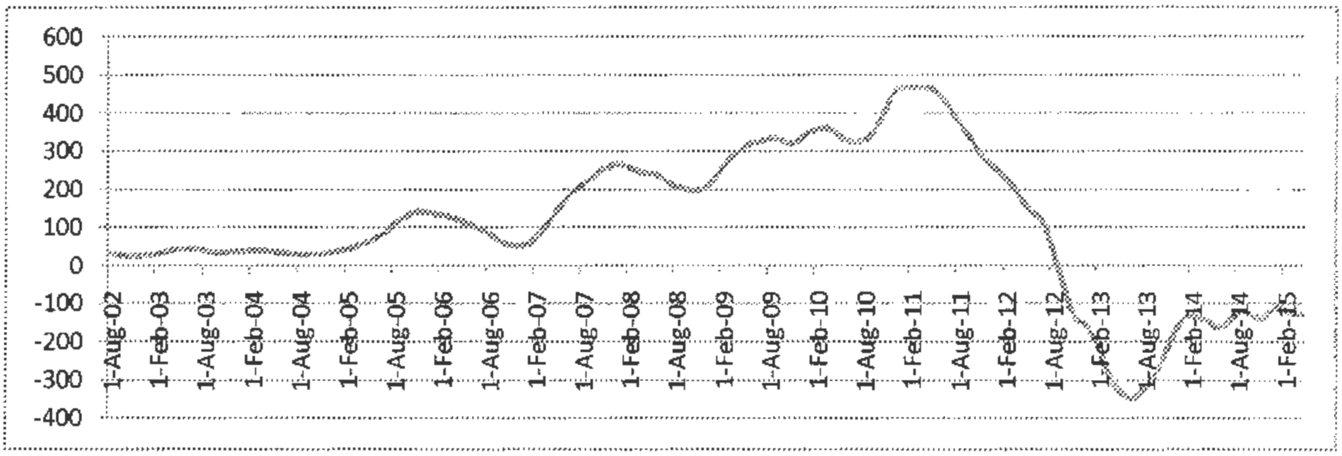
Change in Slope (Gold Price – 10 grams):

Change in data for slope for gold price covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 42.

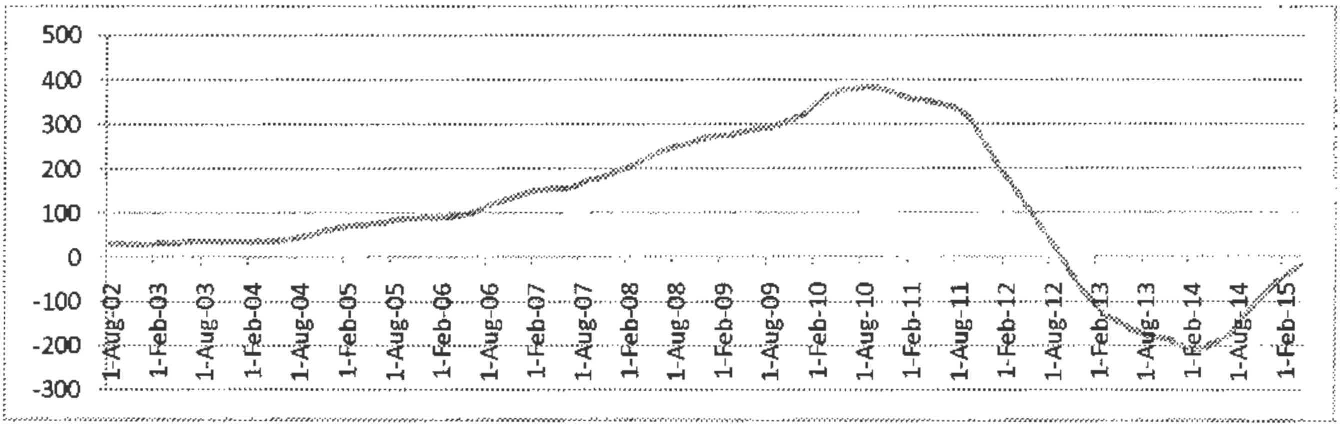
Window size 20



Window size 38



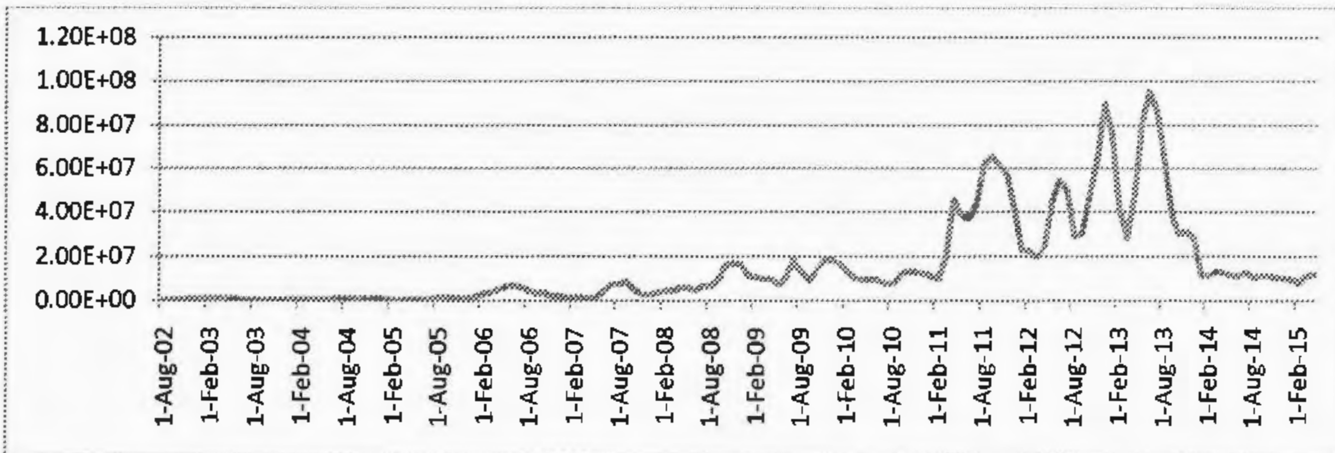
Window Size 76



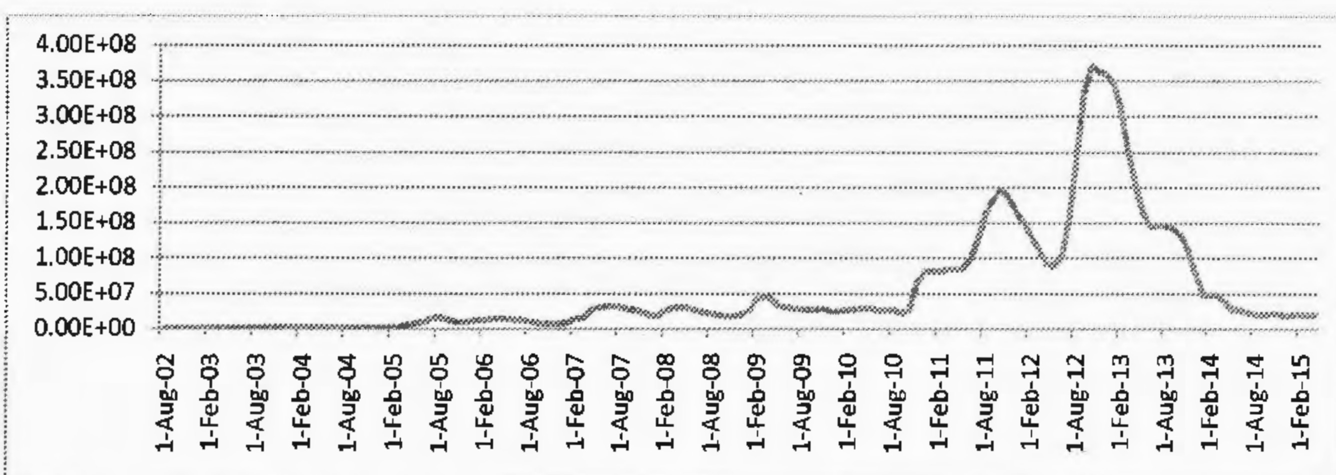
Change in RSS (Gold Price – 10 grams):

Change in data of RSS for gold price covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 43.

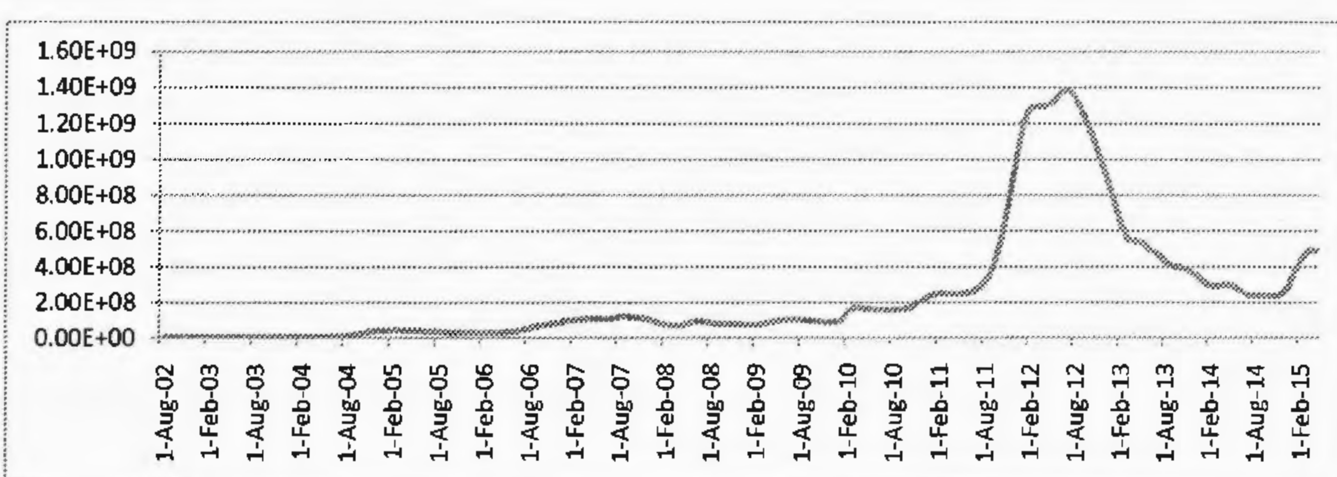
Window size 20



Window size 38



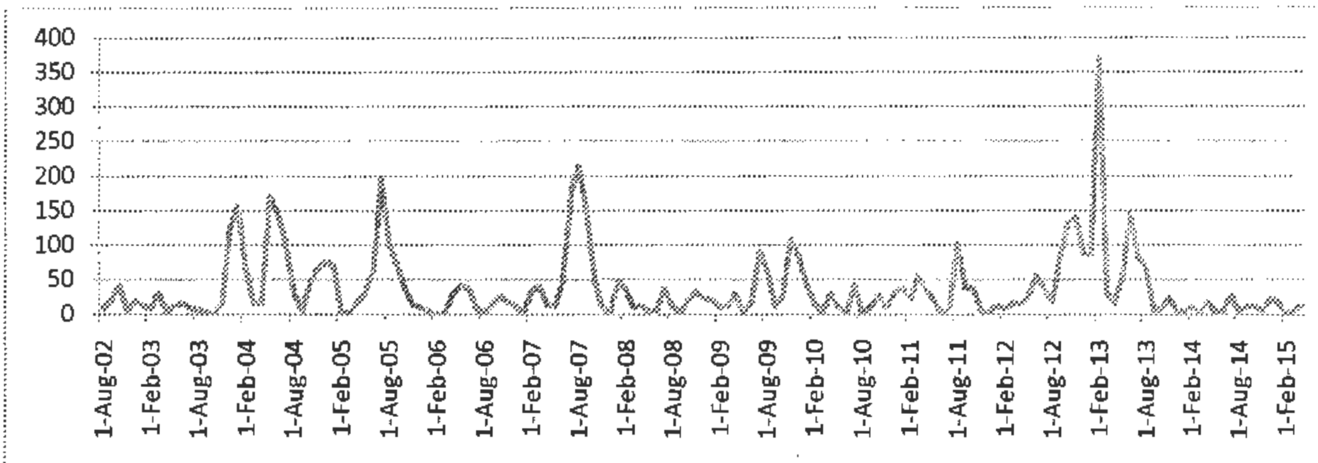
Window Size 76



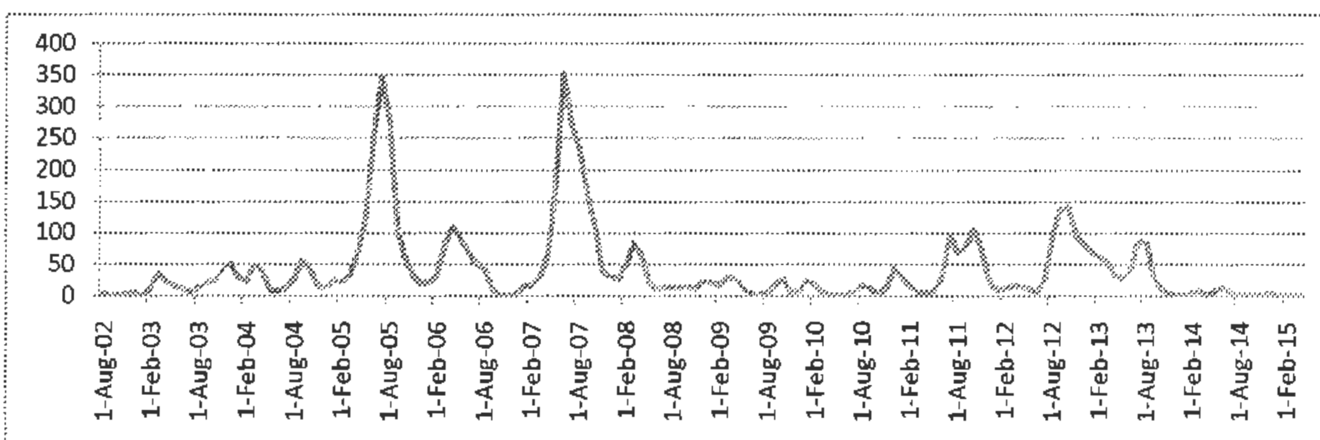
Change in Chow F Statistics (Gold Price – 10 grams):

Change in data of F values for gold price covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 44.

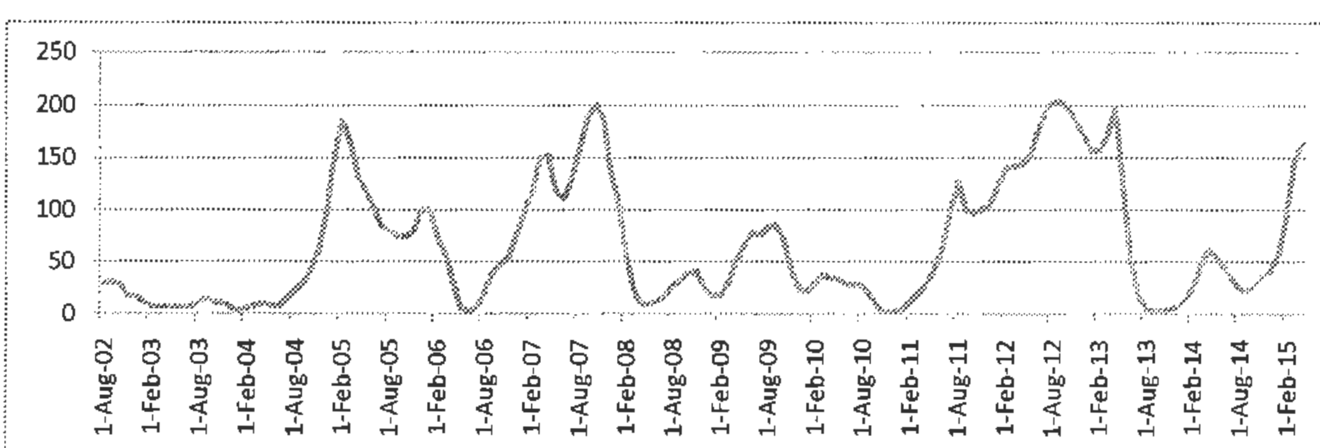
Window size 20



Window size 38



Window Size 76



5.3 Analysis of Treasury Bill rate and Value

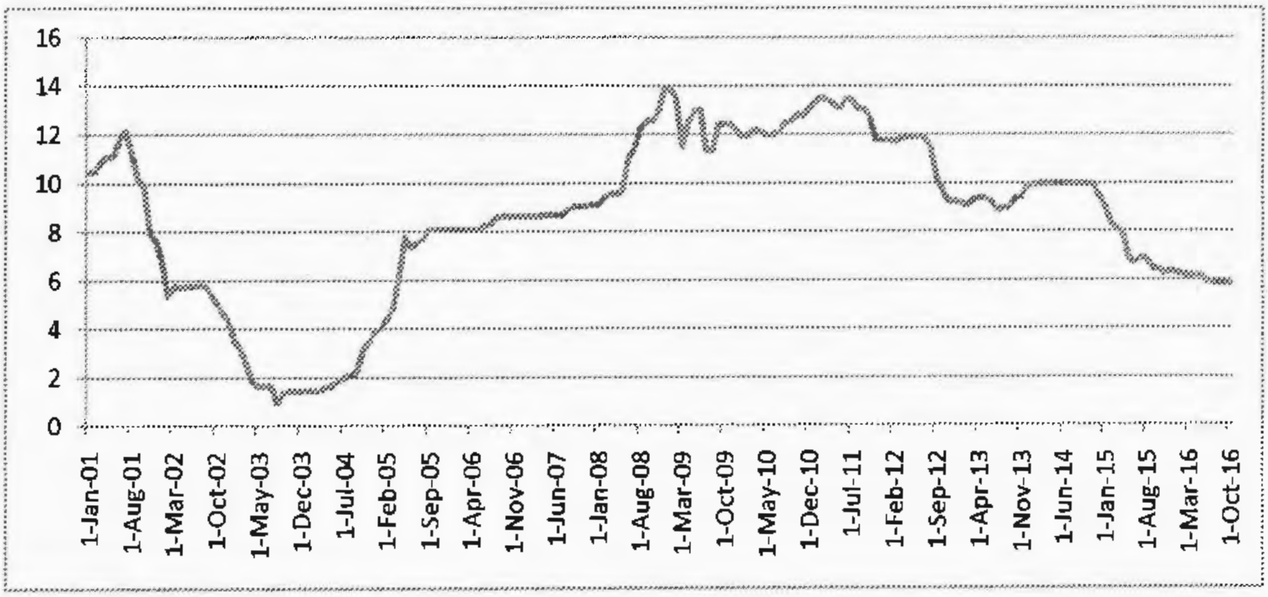
Treasury Bill rate was 15.7% in June 1998. With minor fluctuation it was reduced with time and became 10.5% in January 2001. It had fluctuations and then highest value 12.22% in June 2001. Then it almost continuously decreased. It reached to it minimum value of 0.99% in August 2003.

Treasury Bill rose almost steadily with minor fluctuations over the years and reached to maximum value of 13.85% in January 2009. For about two and half year it fluctuated between 11 and 13%. It was 13.52% in July 2011.

After July 2011, interest rate decline almost steadily and in October 2016, it was 5.9%. This information in tabulated form is given as follows.

Month	Year	Rate
June	1998	15.7%
January	**2001**	**10.5%**
June	2001	12.22%
August	**2003**	**0.99%**
January	**2009**	**13.85%**
July	2011	13.52
October	**2016**	**5.9%**

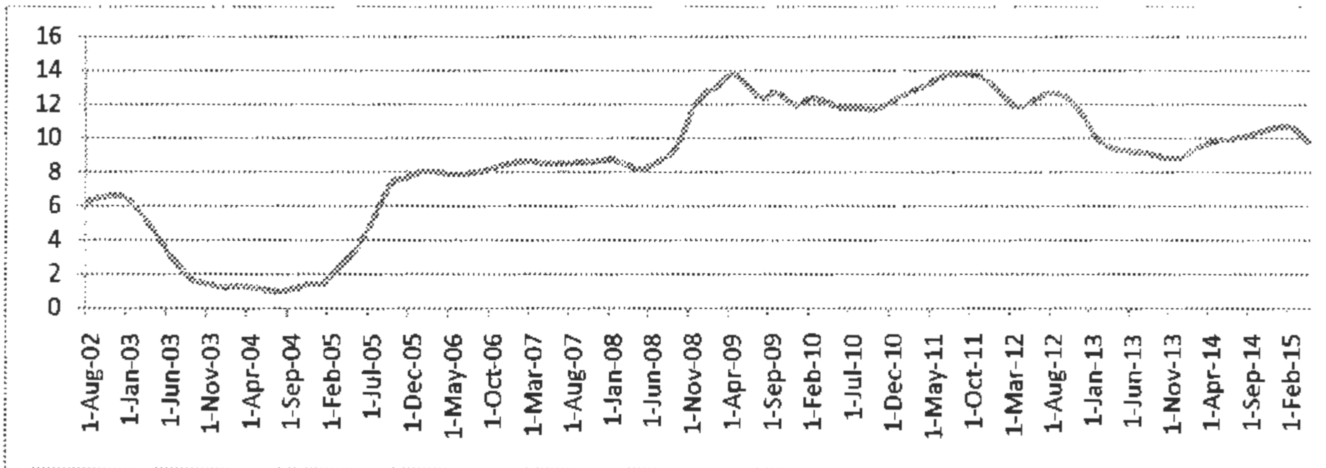
Change in Treasury Bill rate over time is depicted in the following graph.



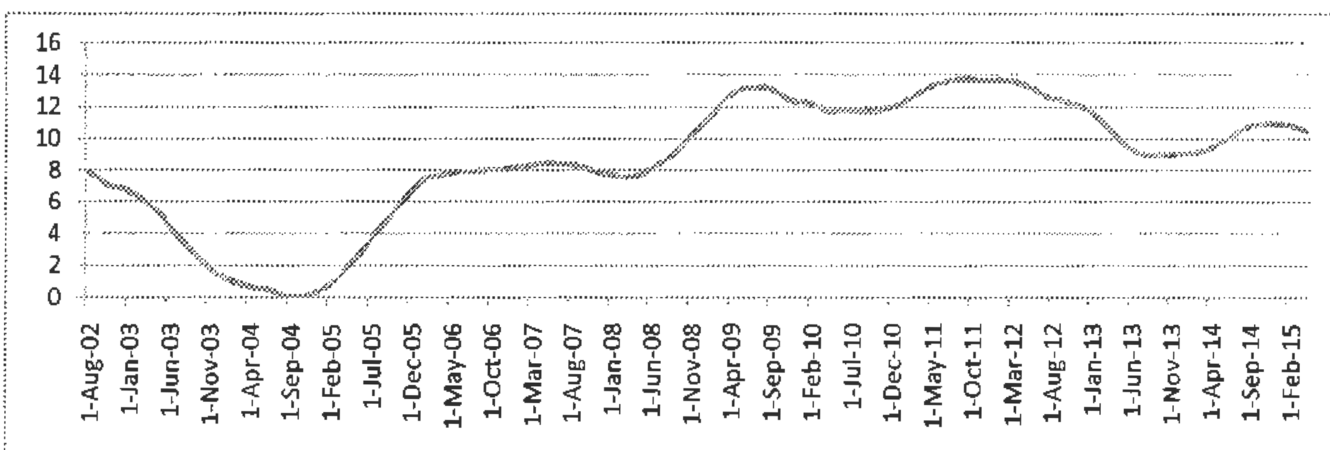
Change in Intercept (T-Bill Rate):

Change in data for intercept for T-Bill rates price covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 41.

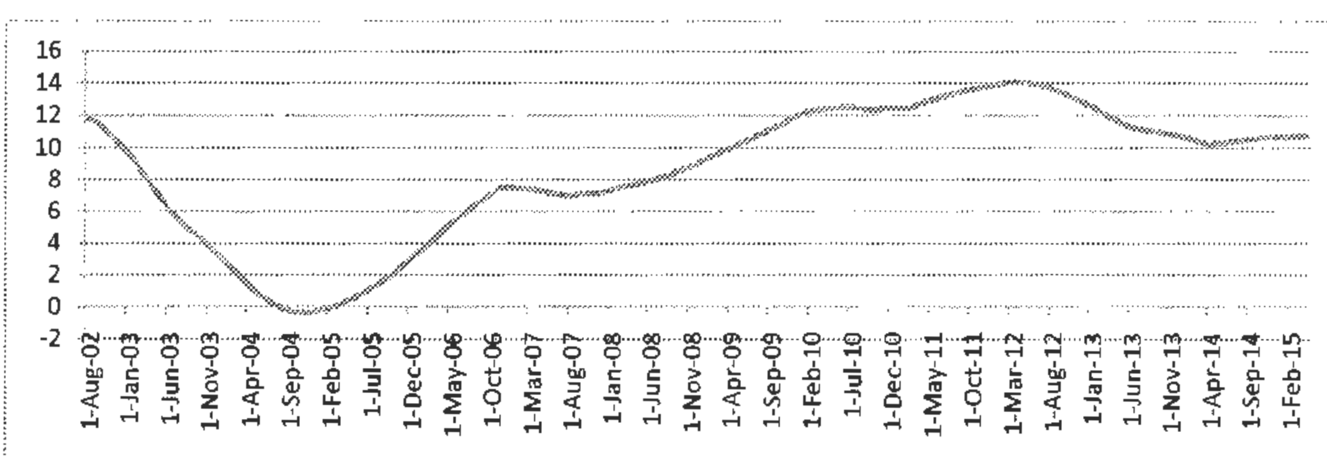
Window size 20



Window size 38



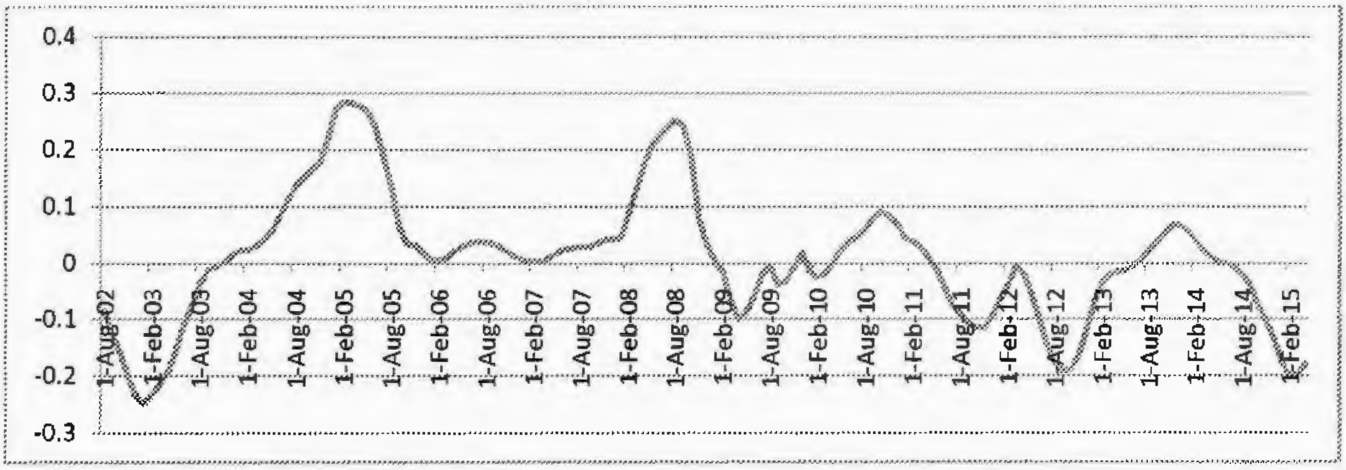
Window Size 76



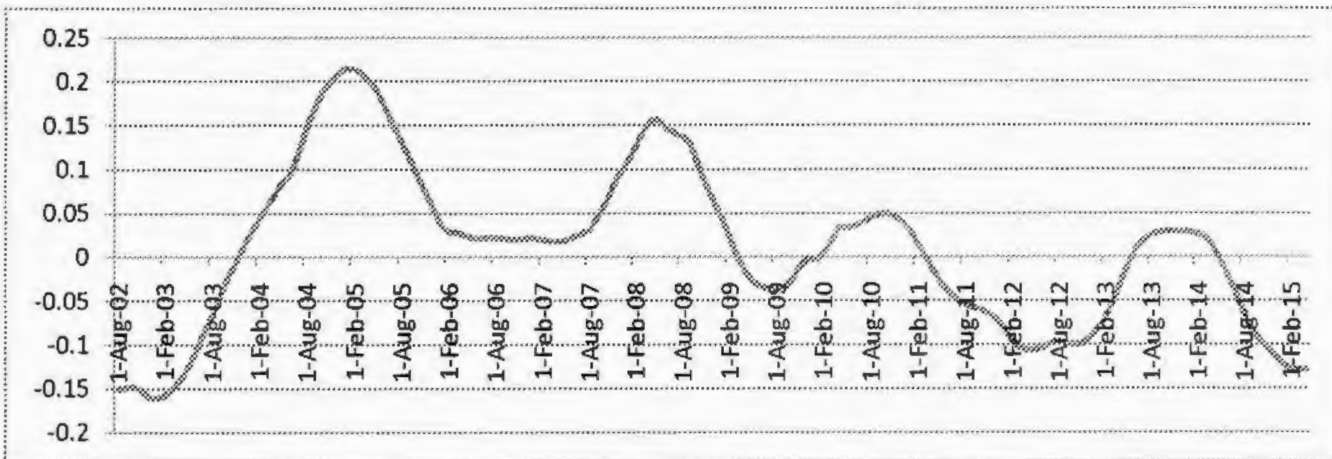
Change in Slope (T-Bill Rate):

Change in data of Slope for T-Bill rate covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 42.

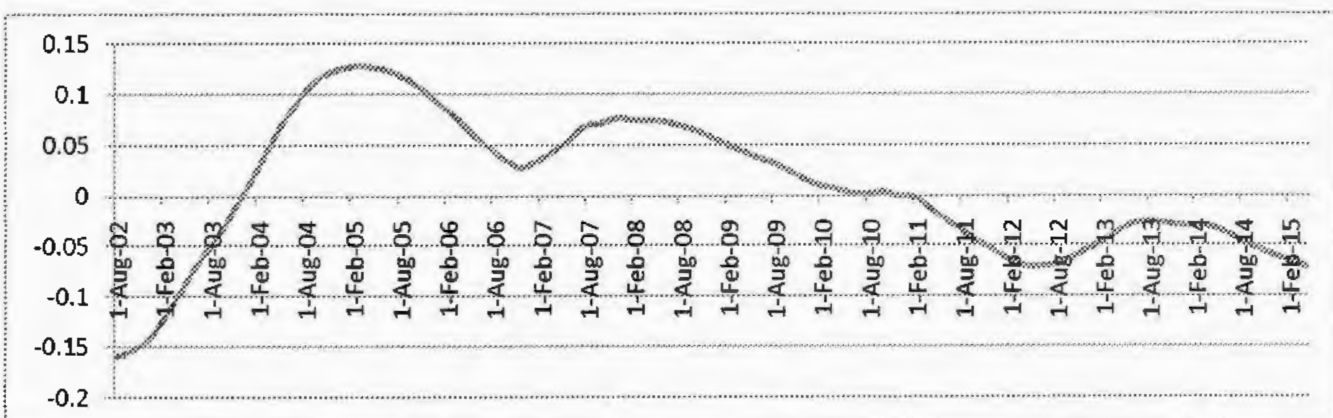
Window size 20



Window size 38



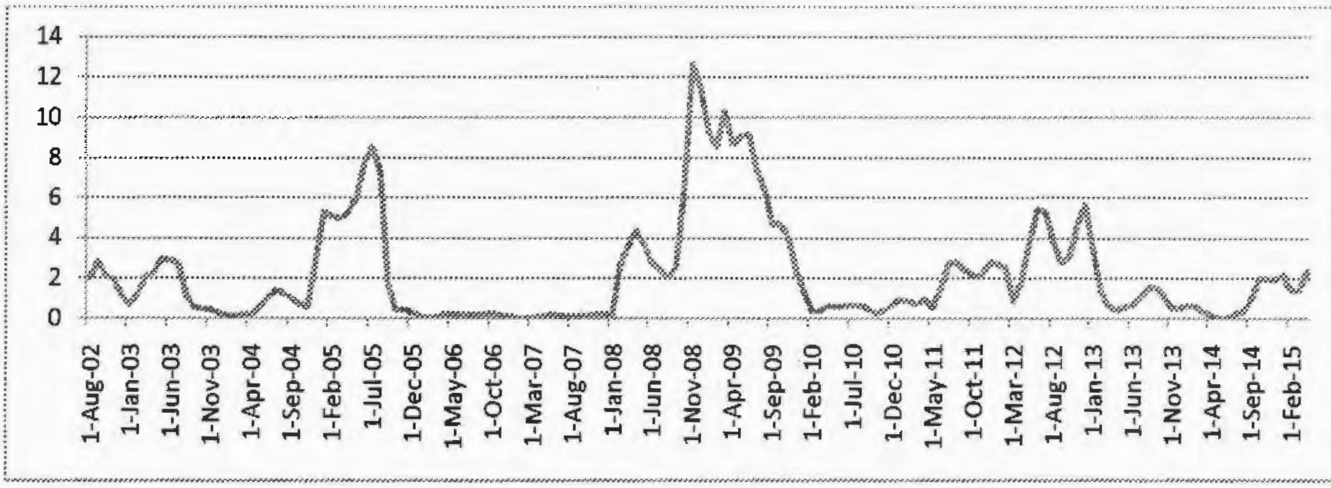
Window Size 76



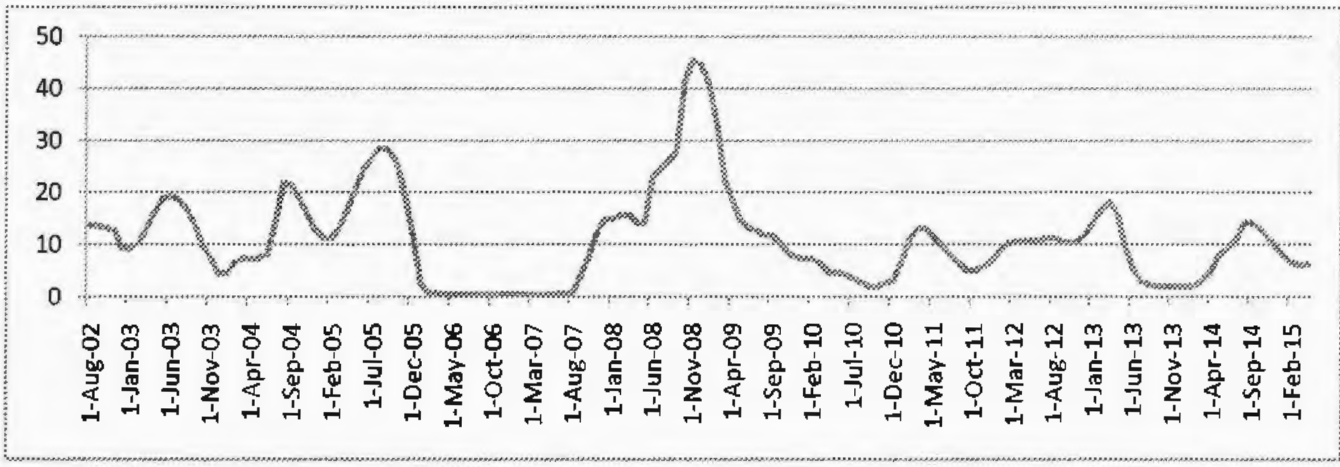
Change in RSS (T-Bill Rate):

Change in data of RSS for T-Bill rates covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 43.

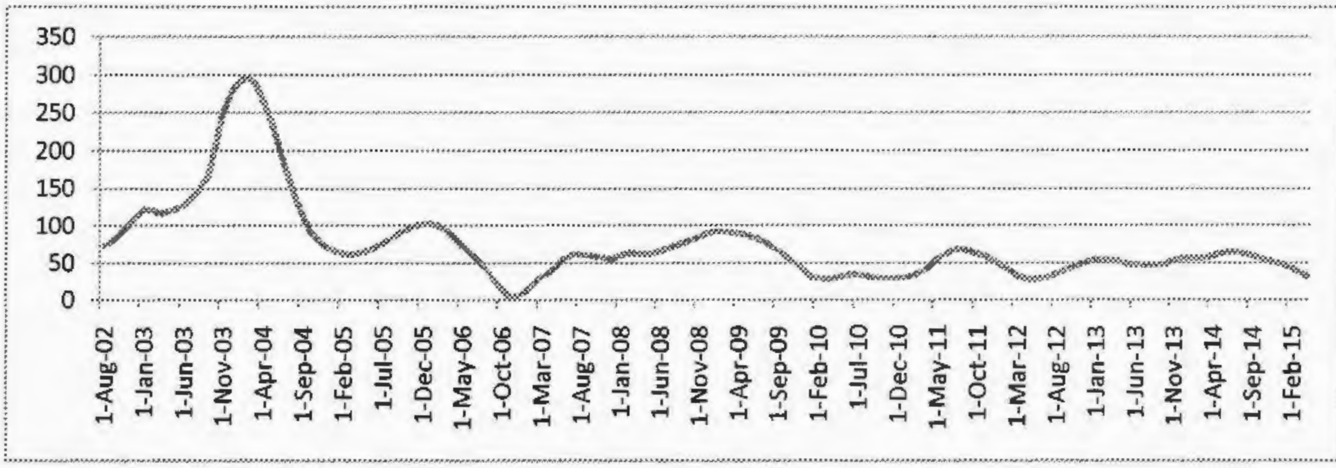
Window size 20



Window size 38



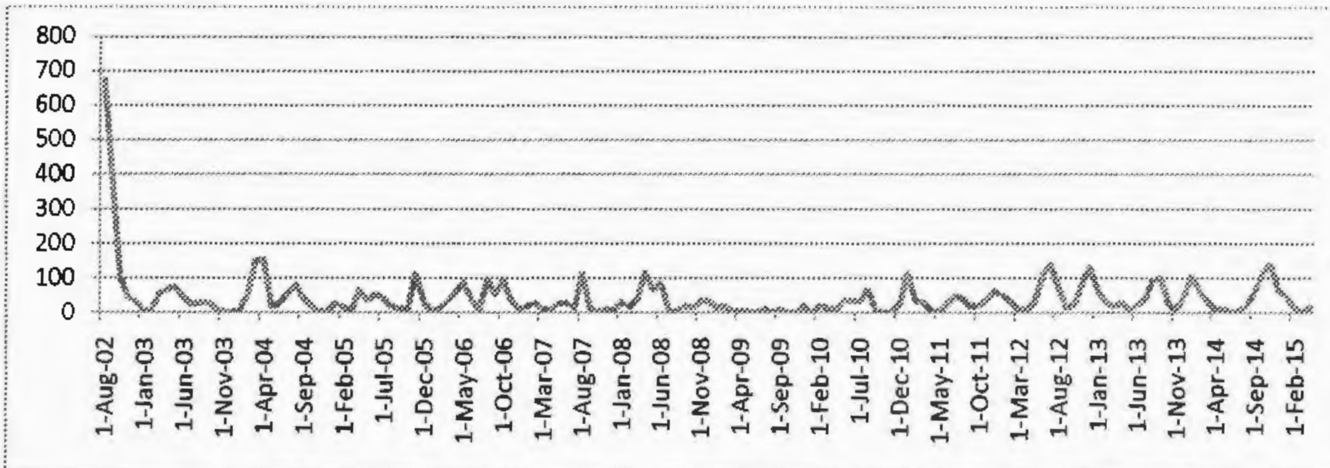
Window Size 76



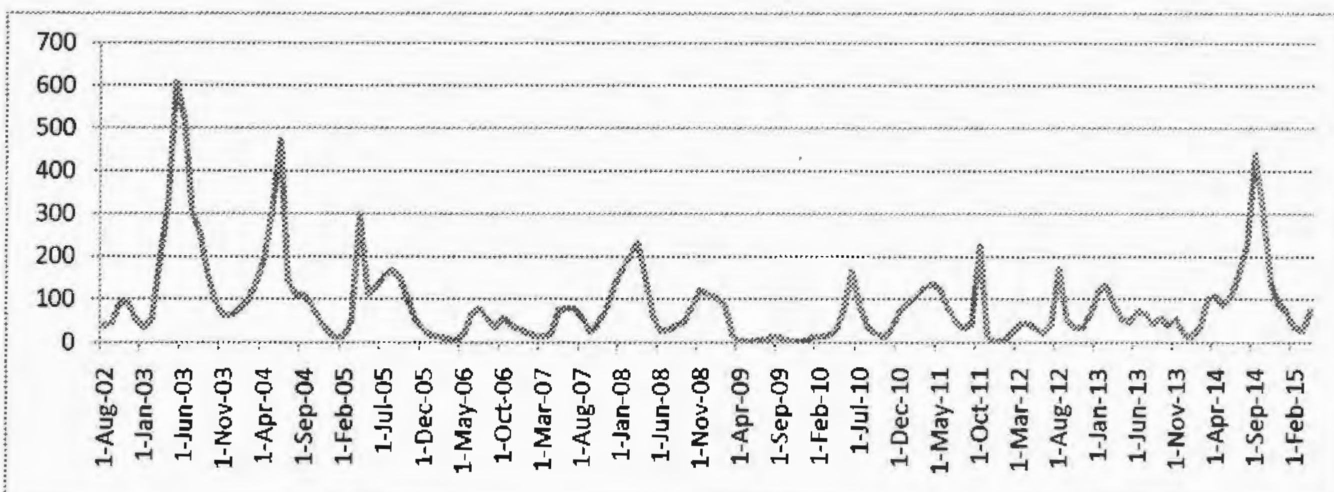
Change in Chow F Statistics (T-Bill Rate):

Change in data of F Values for T-Bill rates covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 44.

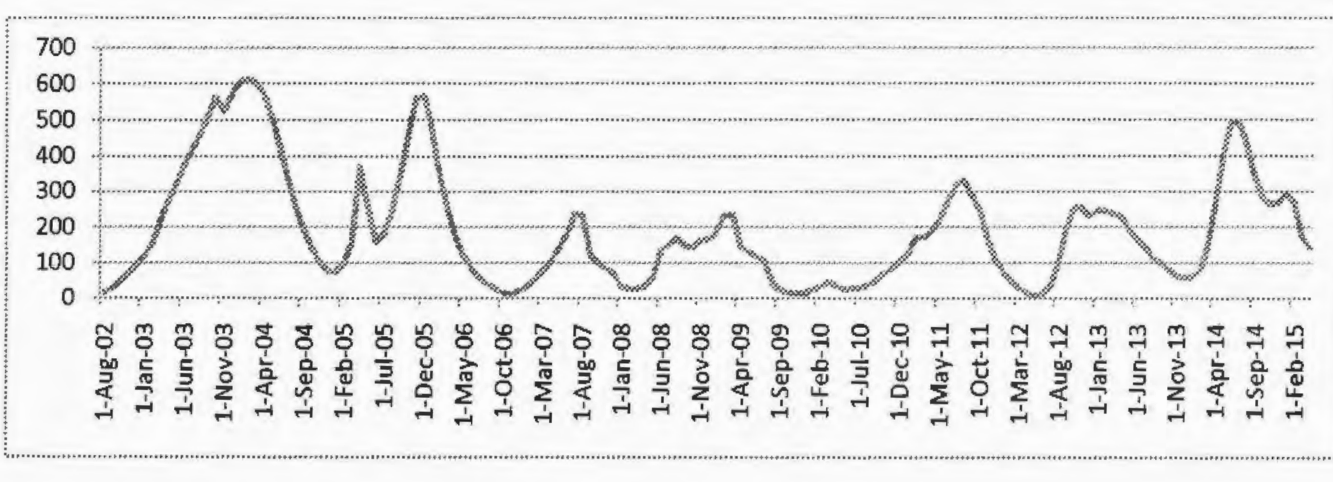
Window size 20



Window size 38

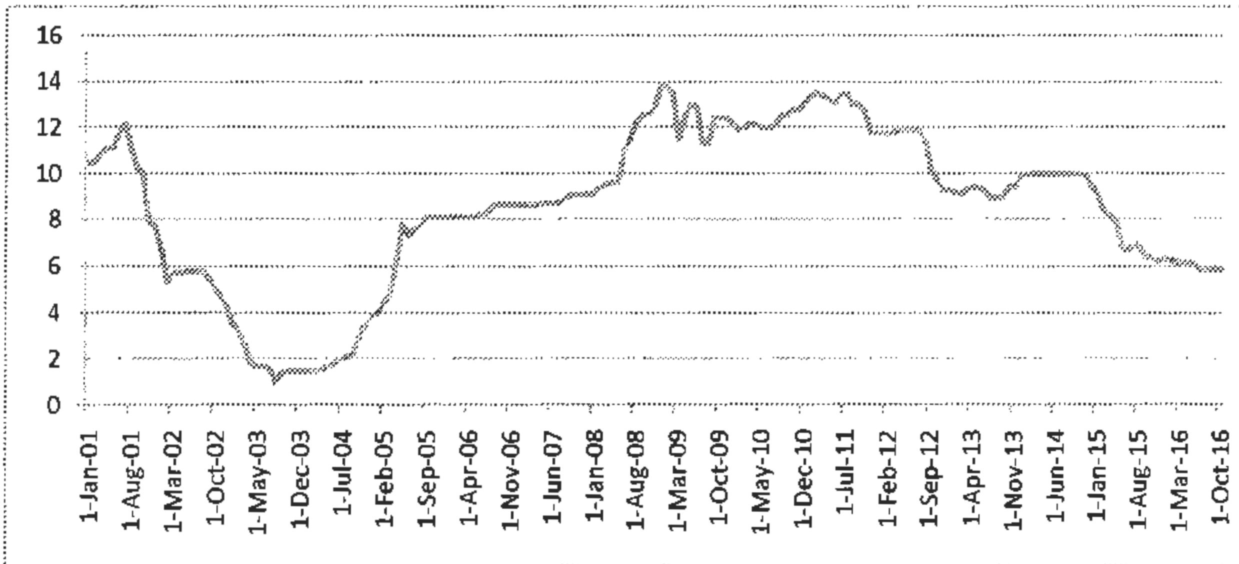


Window Size 76

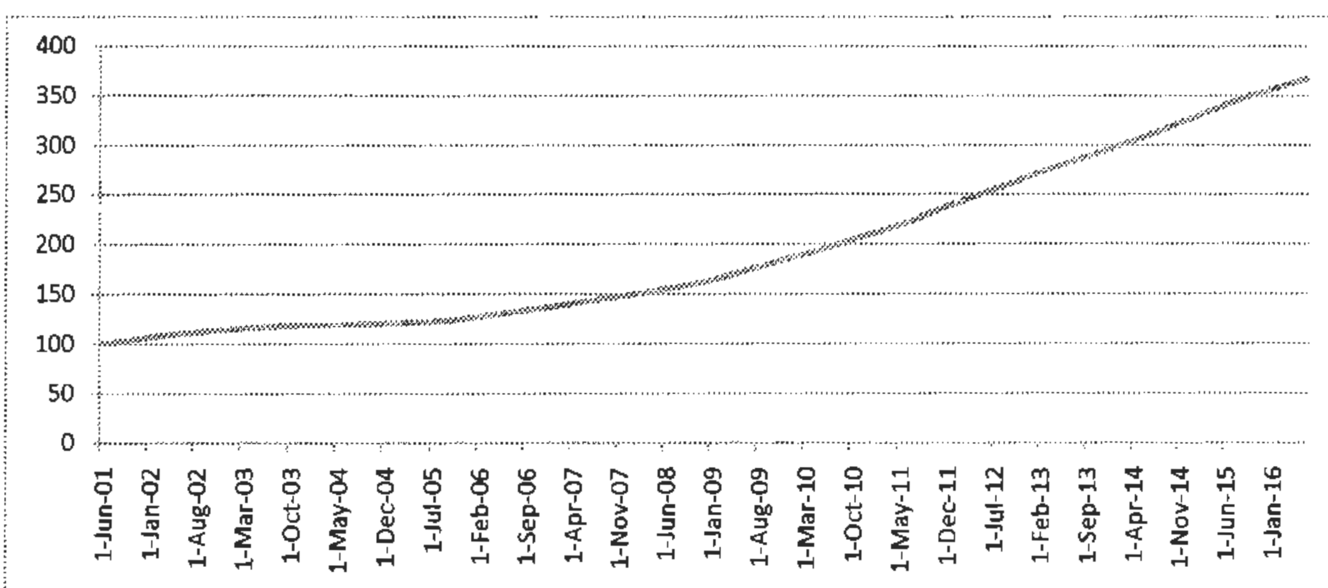


5.4 Analysis of T-Bill Value

Treasury Bill value is calculated according to rate of interest. It is assumed that we have Rs 100 in January 2001.Treasury Bill rate may increase or decrease but its value must always decrease. If rate becomes low then value increases at decreased rate and if rate in increasing over time then value increases at increasing rate. In the upper graph T-Bill rates and in the lower graph T-Bill value over time is depicted.



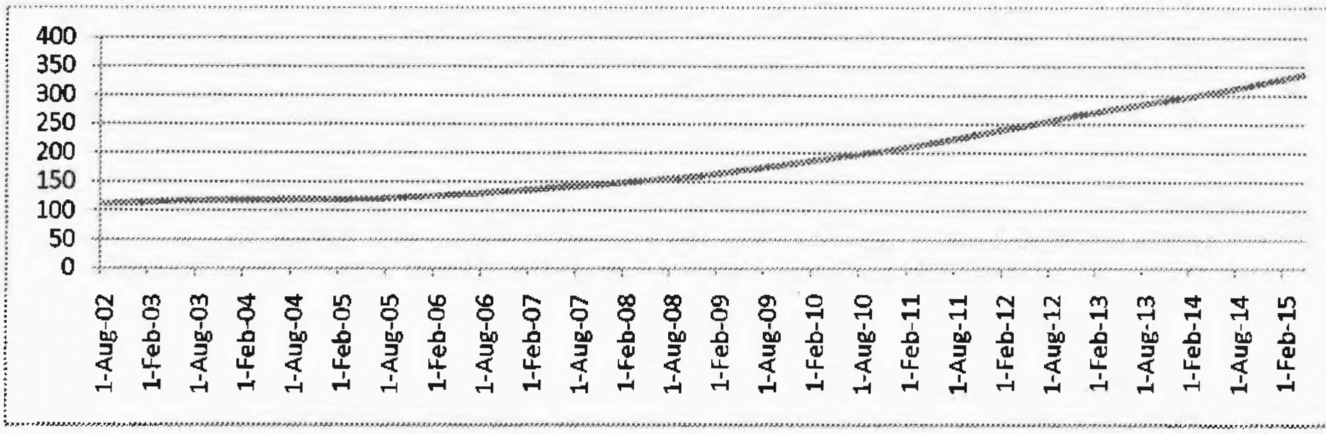
Now its value over the years is given as follows.



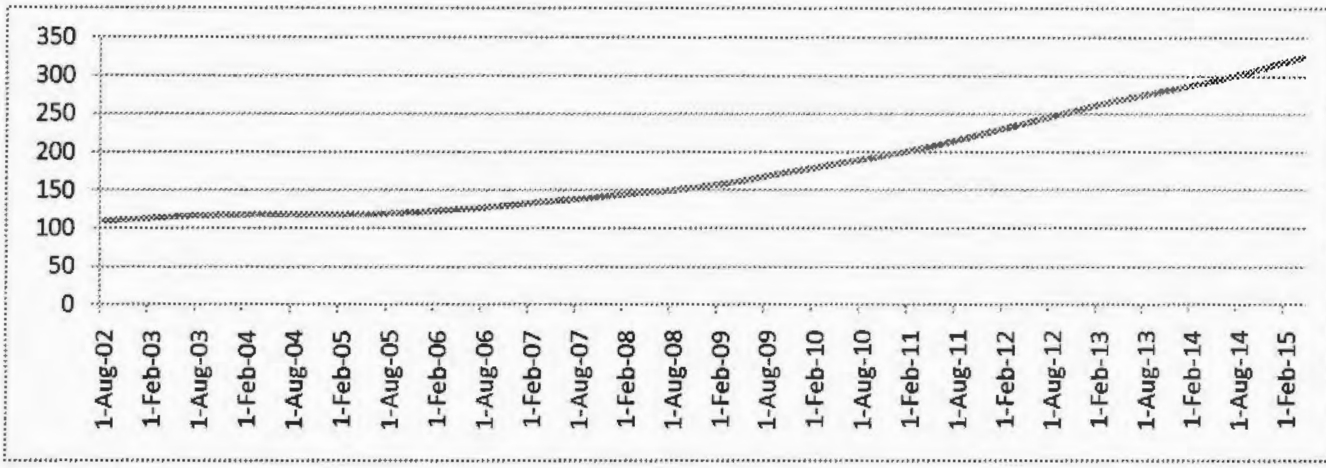
Change in Intercept (T-Bill Value):

Change in data for intercept for gold price covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 41.

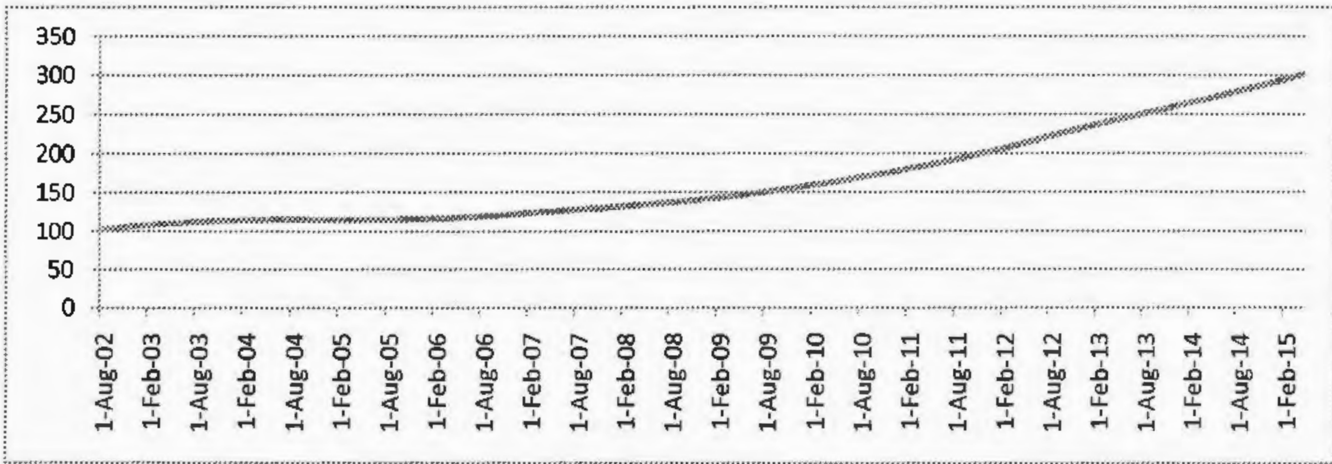
Window size 20



Window size 38



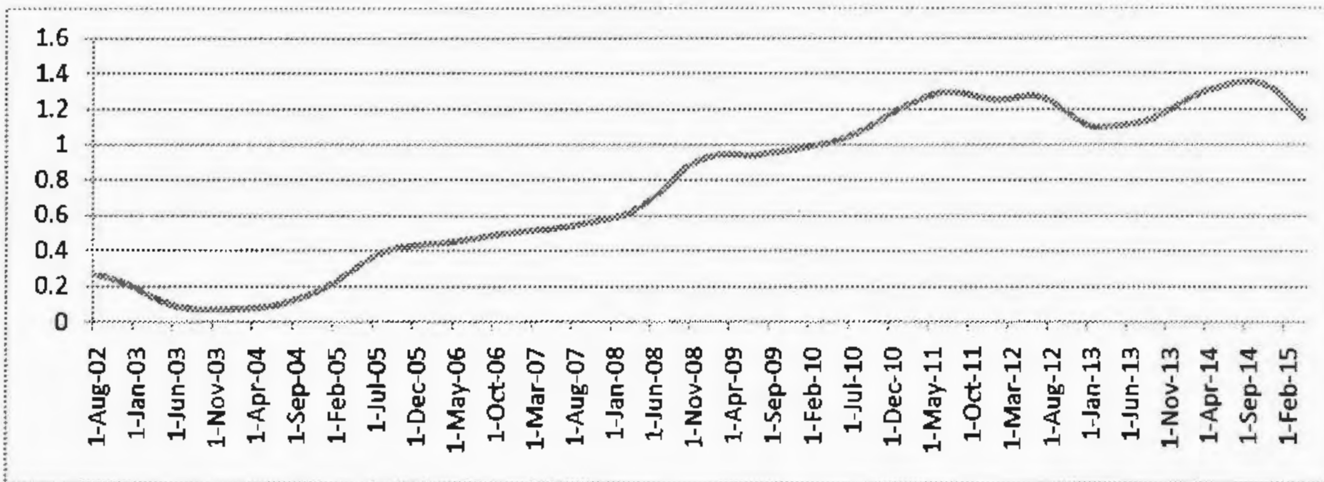
Window Size 76



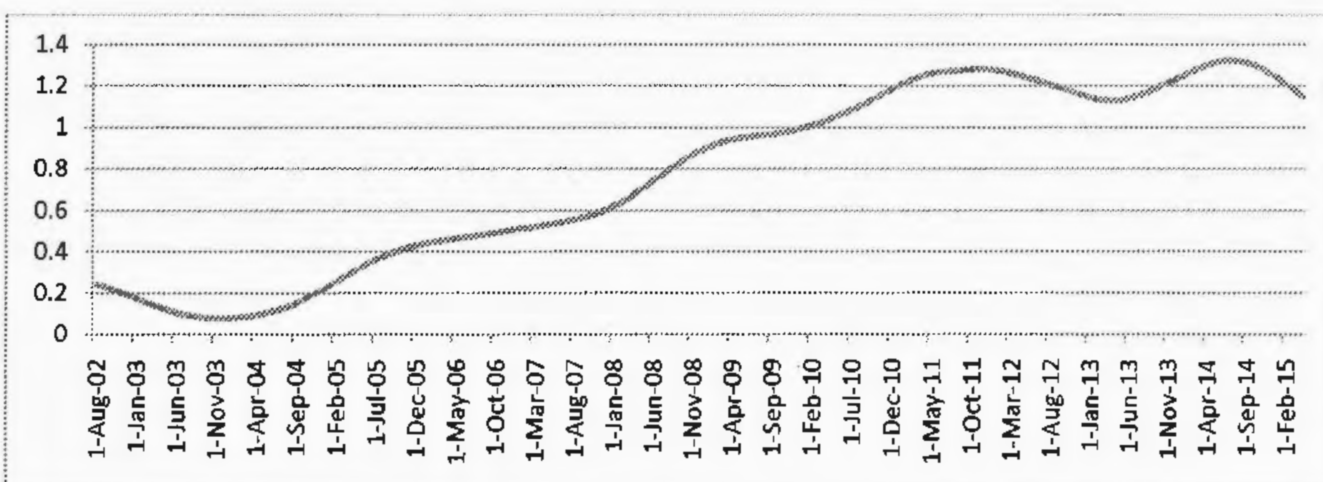
Change in Slope (T-Bill Value):

Change in data of Slope for T-Bill value covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 42

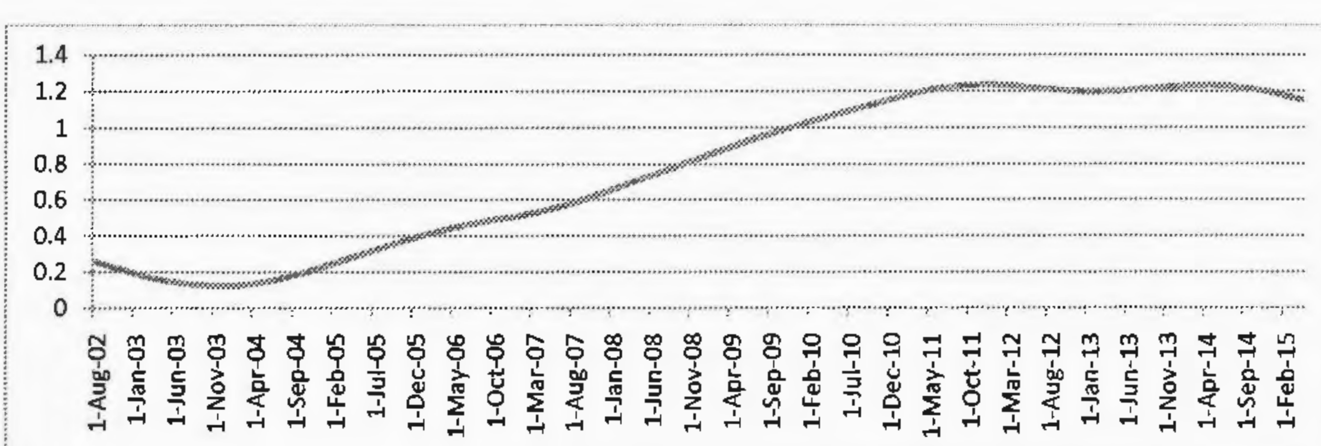
Window size 20



Window size 38



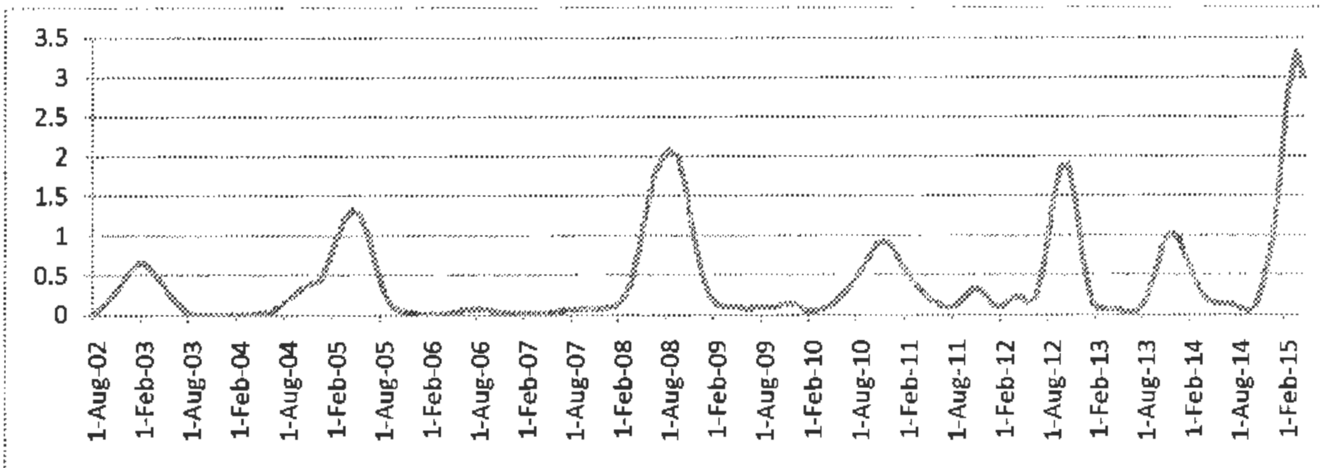
Window Size 76



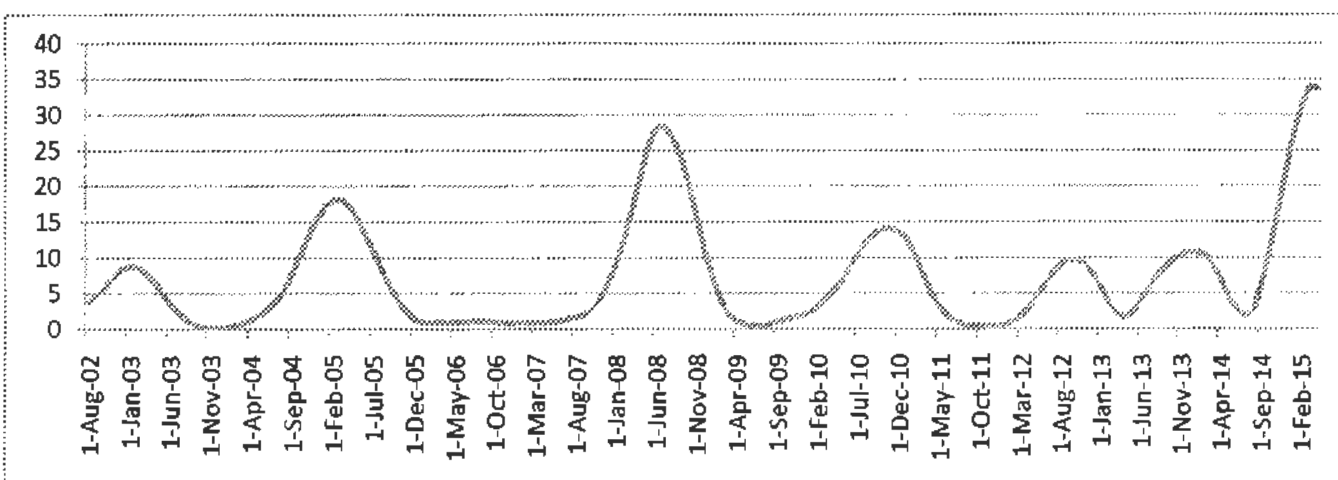
Change in RSS (T-Bill Value):

Change in data of RSS for T-Bill value covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 43.

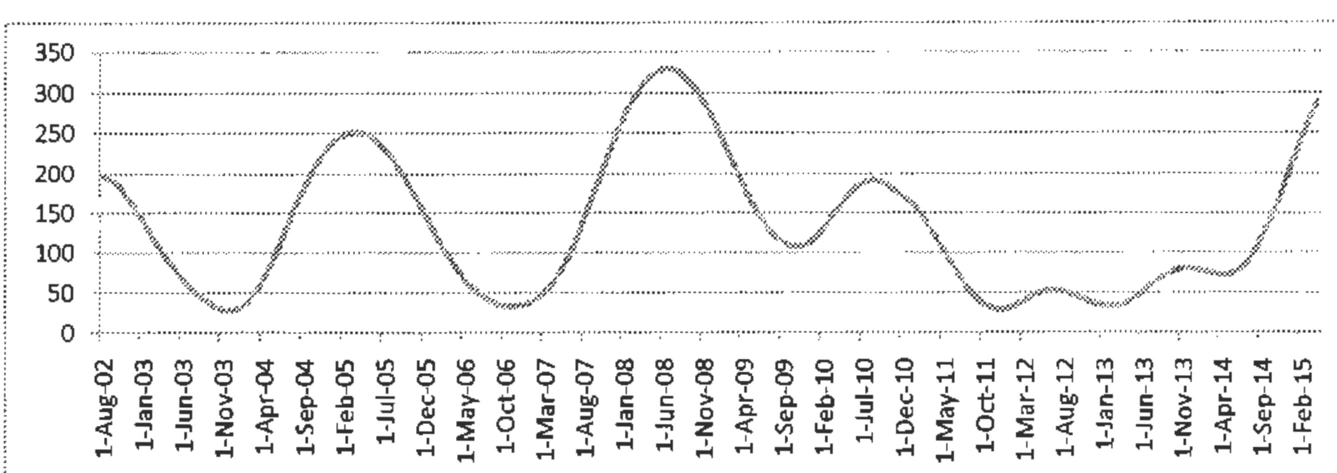
Window size 20



Window size 38



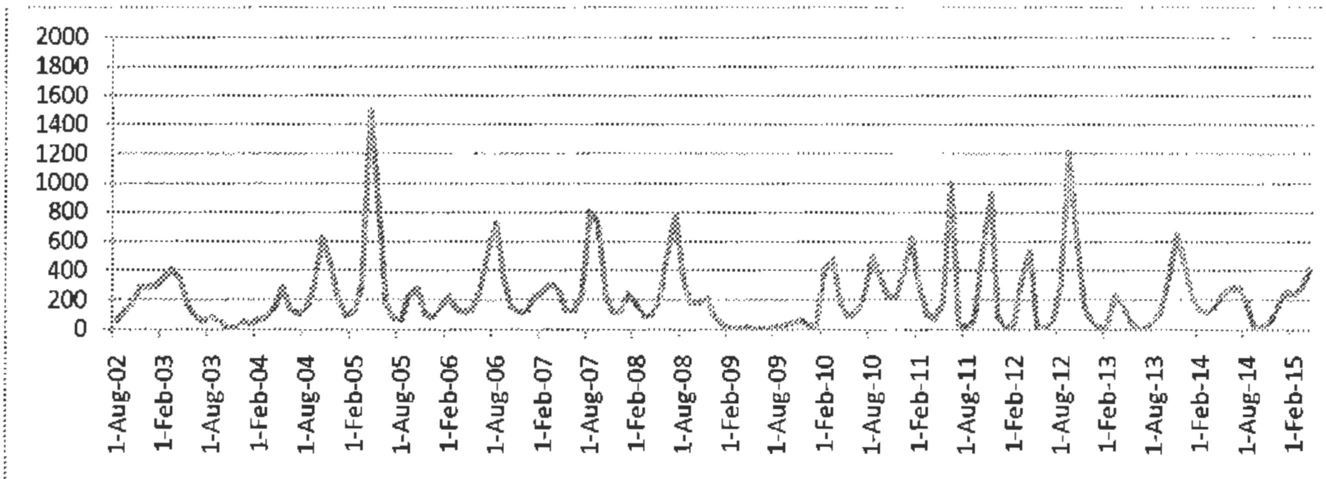
Window Size 76



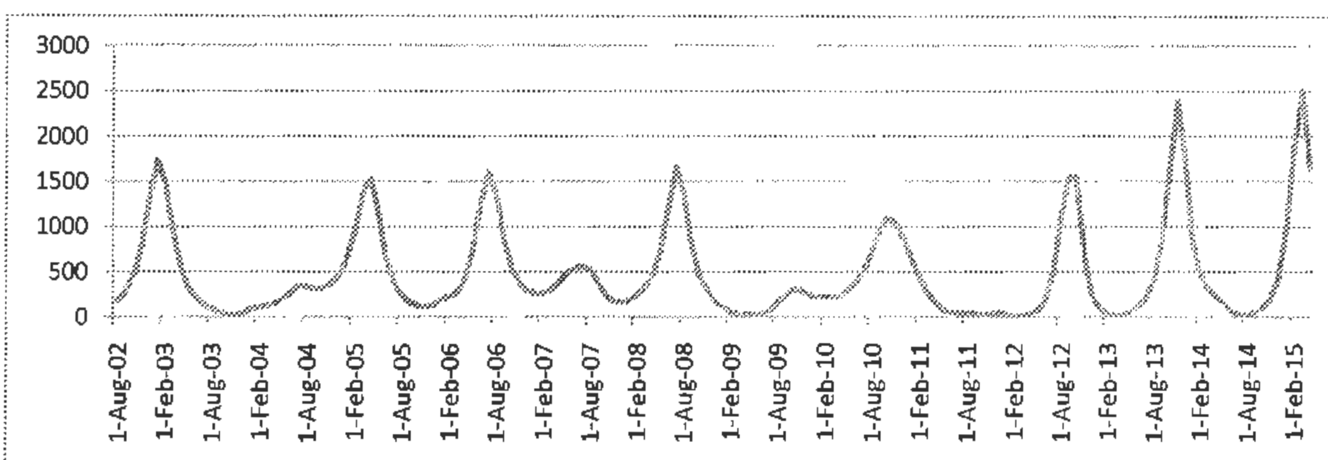
Change in Chow F Statistics (T-Bill Value):

Change in data of F Statistics for T-ill value covering 16 years period from 2001 to 2016 is depicted below. Explanation is same as is given on page 44.

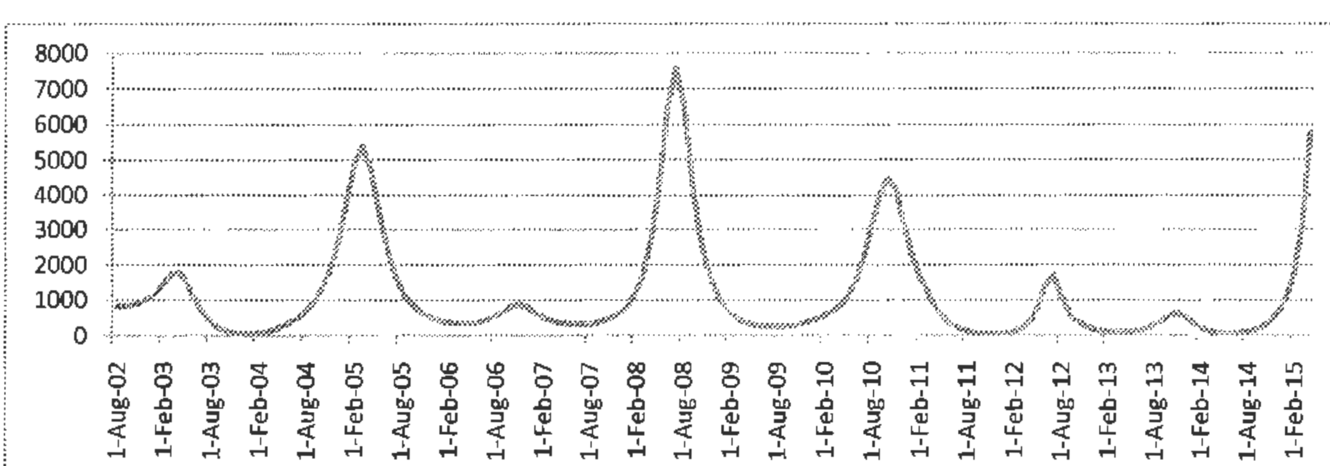
Window size 20



Window size 38



Window Size 76

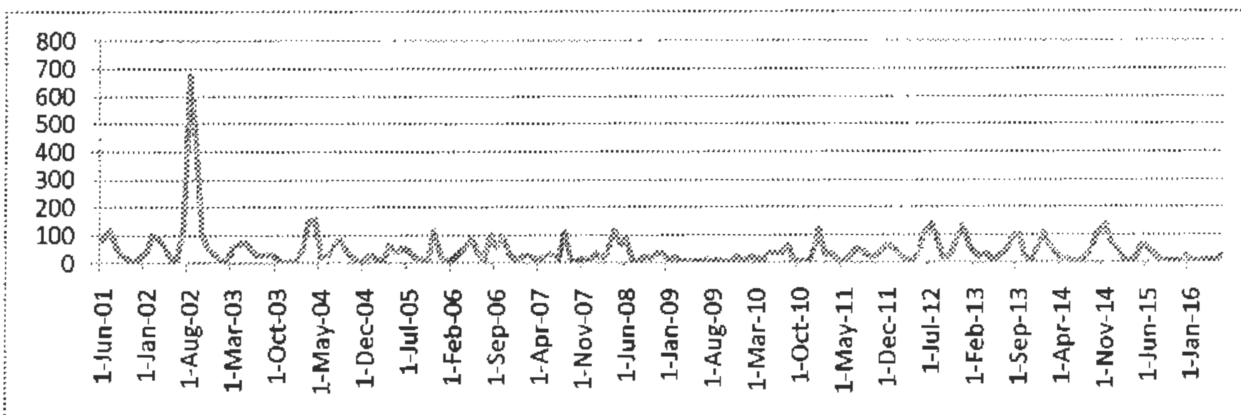


5.5 Comparison of Chow F Statistics for all Variables

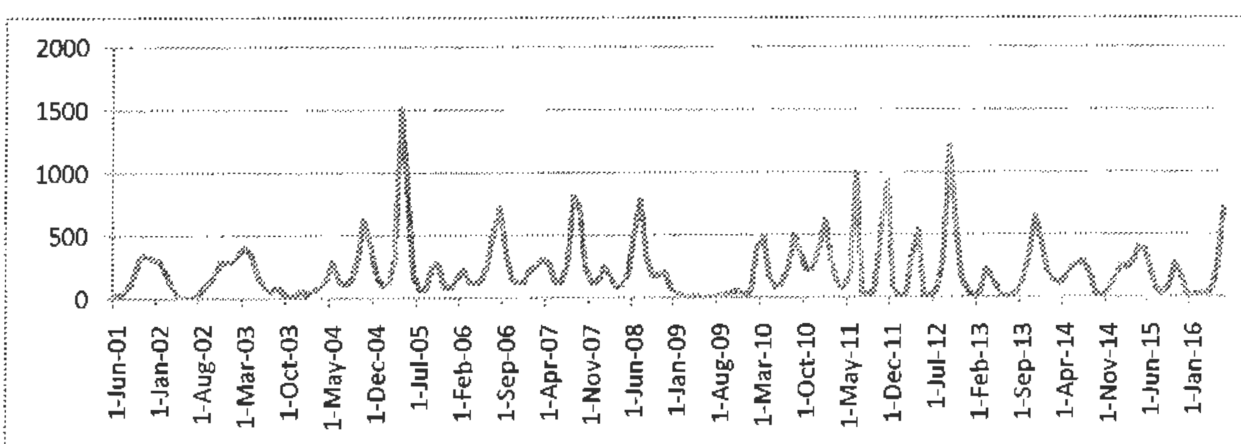
Window Size 20

For window size 20, we have lot of structural breaks. At small window size we have maximum of information about structural change but it becomes difficult to compare the structural breaks in one time series with other time series.

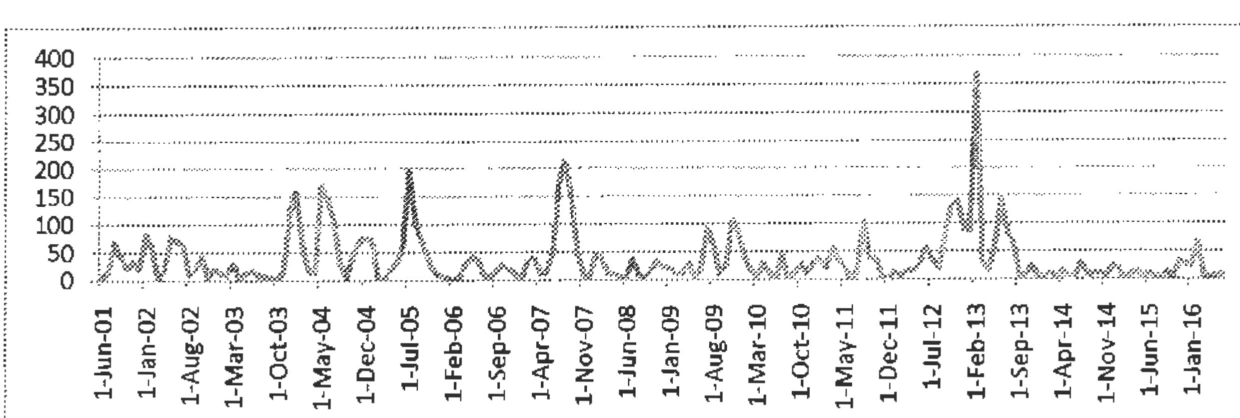
T-Bill Rates:



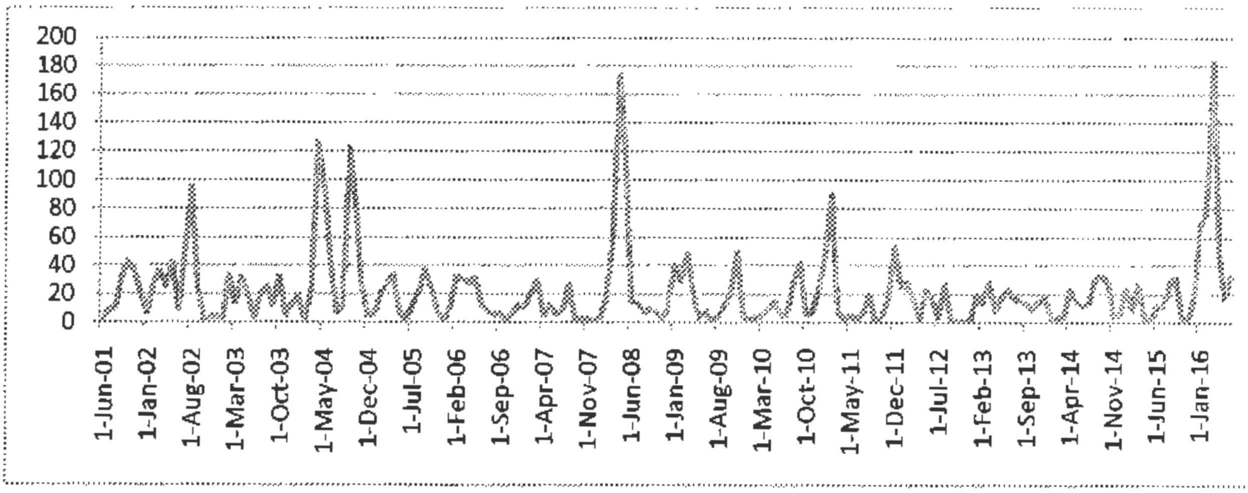
T-Bill Value



Gold



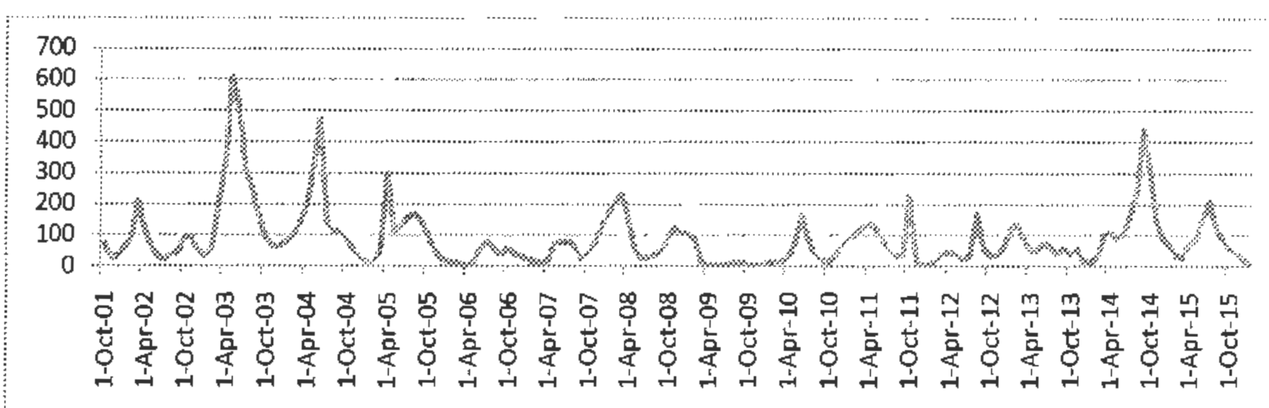
KSE



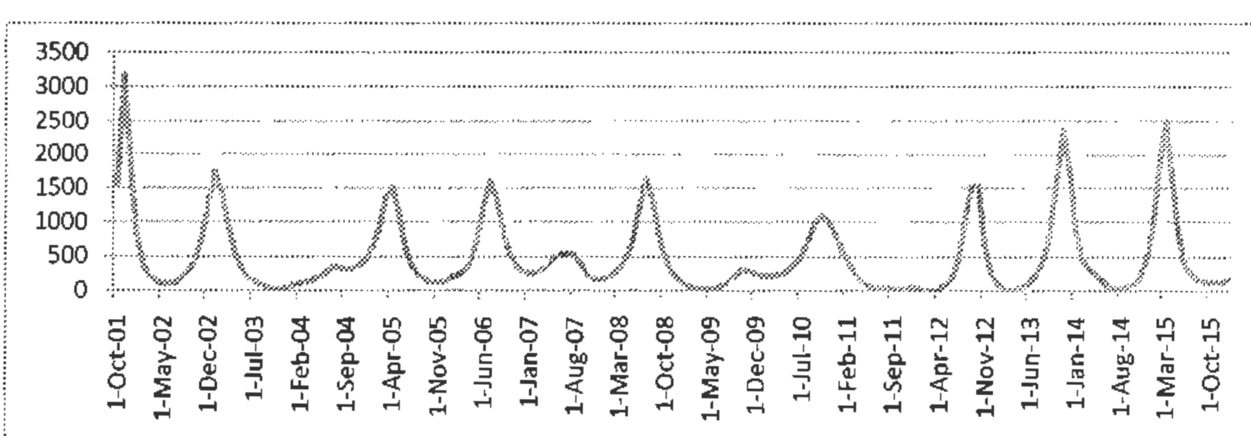
Window Size 38

As we increase window size from 19 to 38, we observe that data of F statistics has fewer peak values. It becomes somewhat easier to compare change in the F statistics of different time series but we lose information about the short run fluctuations.

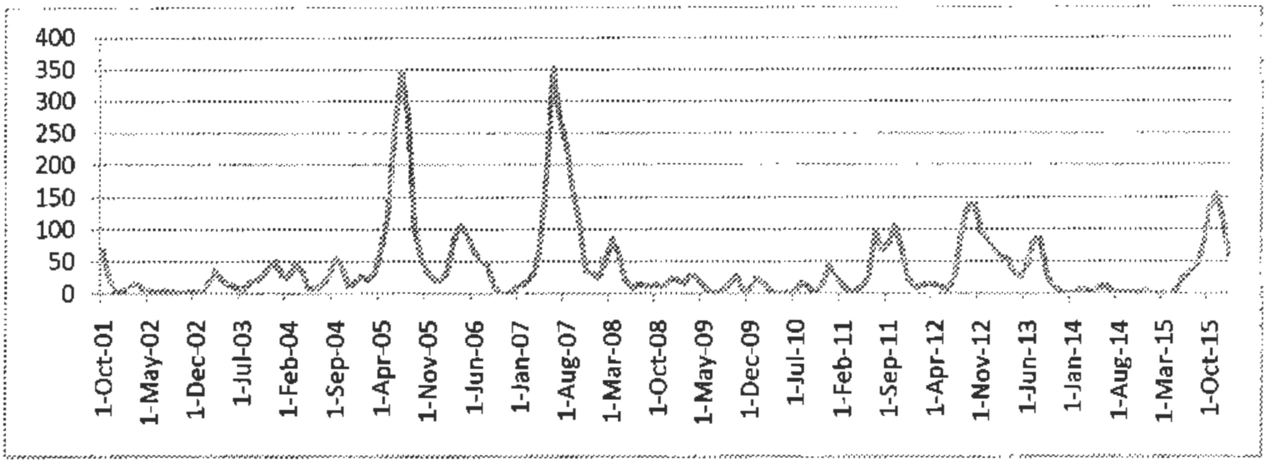
T-Bill Rate:



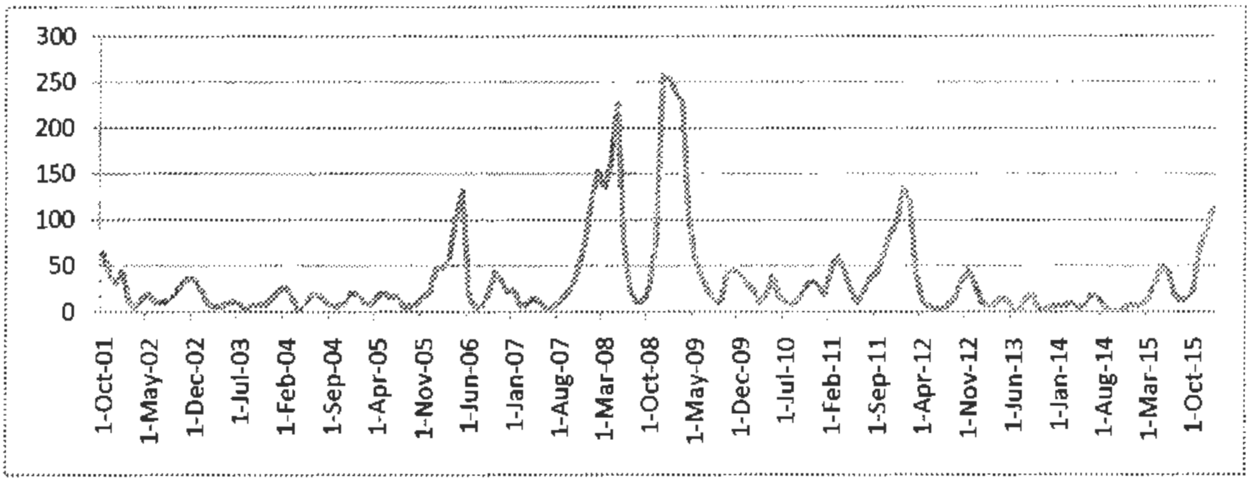
T-Bill Value



Gold



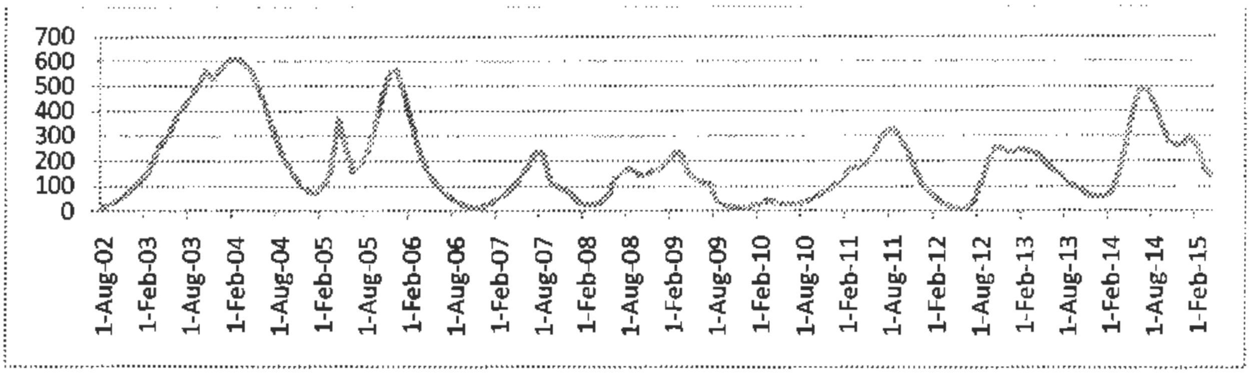
KSE



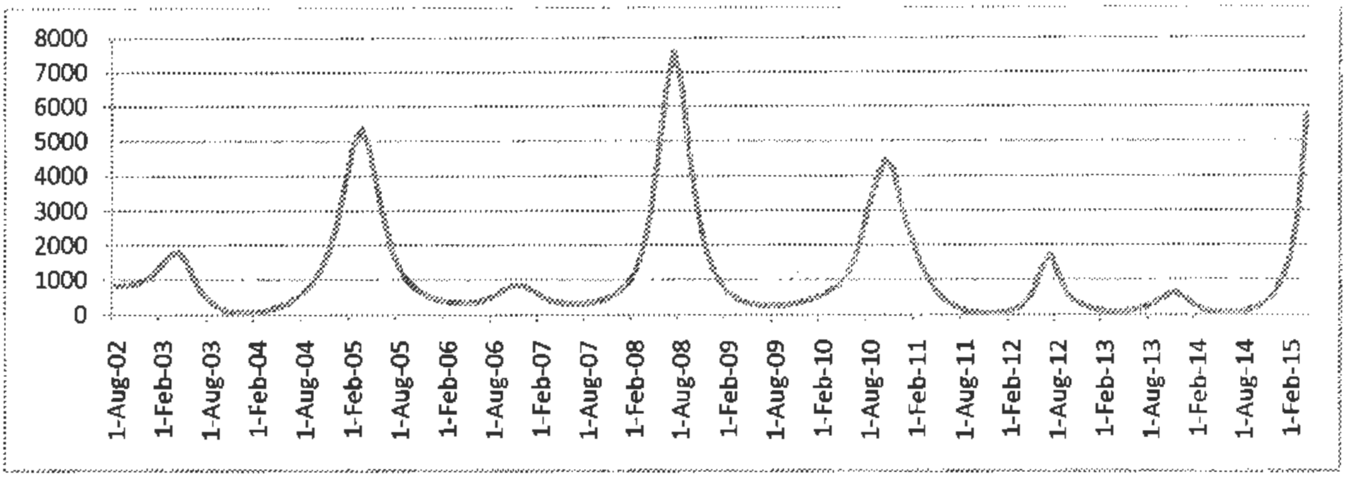
Window size 76:

With very large window size of 76, we can easily compare peaks and troughs in data of F statistics of different time series. The problem here is that f value does not immediately reaches to peak value after the structural change in actual time series as now window is covering a very wide time period and regression line is fitted on a large data set embedding the break point in it.

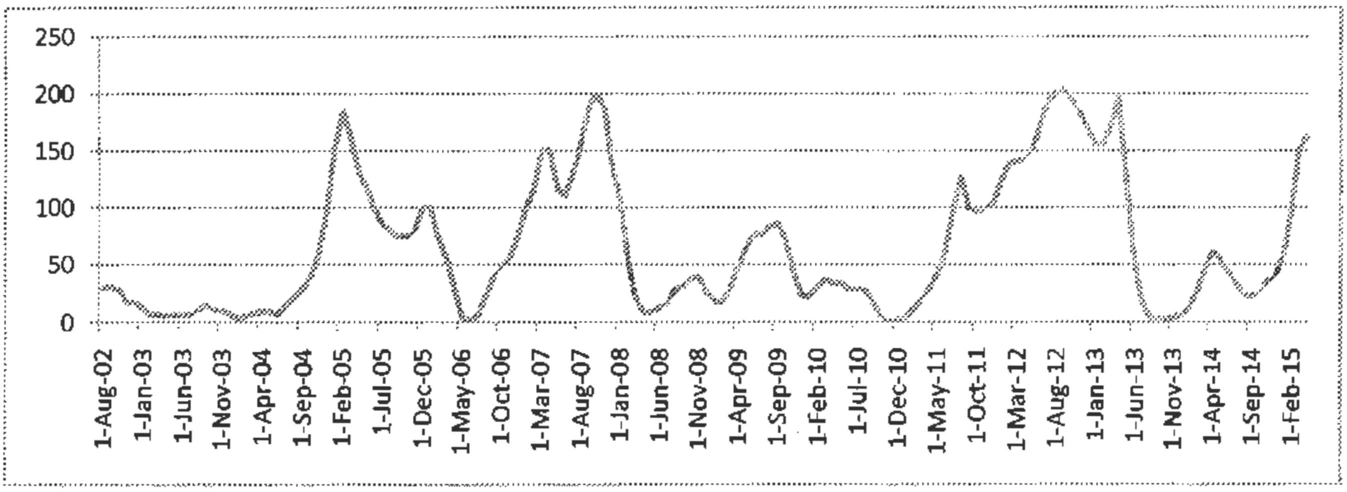
T-Bill Rate



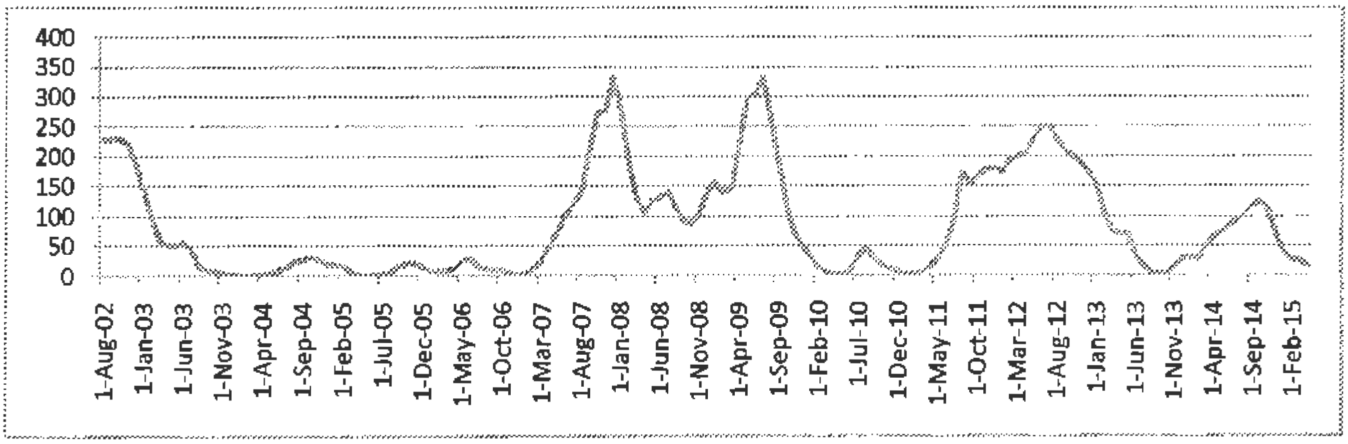
T-Bill Value



Gold



KSE



5.6 Granger Causality

From the graphs above we see that all time series have structural breaks. We want to know about lead and follow relationship among structural breaks. In other words we say that different time series may have cause and effect relationship. We use Granger Causality test to find out cause and effect relationship between different variable.. We use F test calculated according to the formula

$$F = \frac{(RSSR - RSSUR)/m}{RSSUR/(n-k)}$$

Theory of Granger causality has very briefly been explained in chapter3 Granger causality tests from two to six lags are performed as follows.

Granger Causality for two Lags:

This Granger Causality test for two lags is conducted in EVIEWS. Tabulated value at 5% prob (for given 4 df of numerator and 374 df of denominator) is 2.42.

Pairwise Granger Causality Tests

Observation: 378

Lags: 2

Critical F statistics: 2.42

Null Hypothesis	F-Statistics	prob	Decision
Gold does not Granger Cause TBill	1.37034	0.2553	Don't Reject
TBill does not Granger Cause Gold	4.21510	0.0155	Reject
KSE does not Granger Cause TBill	1.98760	0.1385	Don't Reject
TBill does not Granger Cause KSE	5.03576	0.0070	Reject
KSE does not Granger Cause Gold	0.81205	0.4447	Don't Reject
Gold does not Granger Cause KSE	2.79185	0.0626	Reject

Conclusion :

1- T-Bill is Granger cause for both KSE and Gold

2- Gold is Granger cause for KSE

Granger Causality for three Lags:

This Granger Causality test for three lags is conducted in EVIEWS. Tabulated value at 5% prob (for given 3 df of numerator and 371 df of denominator) is 2.65.

Pairwise Granger Causality Tests

Observation: 377

Lags: 3

Critical F statistics: 2.65

Null Hypothesis	F-Statistics	prob	Decision
Gold does not Granger Cause TBill	1.18727	0.3144	Don't Reject
TBill does not Granger Cause Gold	3.41512	0.0176	Reject
KSE does not Granger Cause TBill	2.07511	0.1031	Don't Reject
TBill does not Granger Cause KSE	3.56937	0.0143	Reject
KSE does not Granger Cause Gold	0.51294	0.6736	Don't Reject
Gold does not Granger Cause KSE	1.96539	0.1187	Don't Reject

Conclusion:

T-Bill is Granger cause for both KSE and Gold

Granger Causality for four Lags:

This Granger Causality test for four lags is conducted in EVIEWS. Tabulated value at 5% prob (for given 4 df of numerator and 368 df of denominator) is 2.41.

Pairwise Granger Causality Tests

Observation: 376

Lags: 4

Critical F statistics: 2.41

Null Hypothesis	F-Statistics	prob	Decision
Gold does not Granger Cause TBill	0.92081	0.4518	Don't Reject
TBill does not Granger Cause Gold	2.41878	0.0482	Reject
KSE does not Granger Cause TBill	1.51917	0.1959	Don't Reject
TBill does not Granger Cause KSE	2.65774	0.0327	Reject
KSE does not Granger Cause Gold	1.13000	0.3420	Don't Reject
Gold does not Granger Cause KSE	1.85139	0.1184	Don't Reject

Conclusion:

T-Bill is Granger cause for both KSE and Gold

Granger Causality for five Lags:

This Granger Causality test for five lags is conducted in EVIEWS. Tabulated value at 10% prob (for given 10 df of numerator and 365 df of denominator) is 1.88.

Observation: 375

Lags: 5

Critical F statistics: 1.88

Null Hypothesis	F-Statistics	prob	Decision
Gold does not Granger Cause TBill	0.66740	0.6484	Don't Reject
TBill does not Granger Cause Gold	2.21853	0.0519	Reject
KSE does not Granger Cause TBill	1.85289	0.1019	Don't Reject
TBill does not Granger Cause KSE	2.11228	0.0634	Reject
KSE does not Granger Cause Gold	1.11982	0.3493	Don't Reject
Gold does not Granger Cause KSE	1.70466	0.1327	Don't Reject

Conclusion:

T-Bill is Granger cause for both KSE and Gold

Granger Causality for six Lags:

This Granger Causality test for six lags is conducted in EVIEWS. Tabulated value 10% prob (for given 6 df of numerator and 362 df of denominator) is 1.80.

Observation: 374

Lags: 6

Critical F statistics: 1.80

Null Hypothesis	F-Statistics	prob	Decision
Gold does not Granger Cause TBill	0.83195	0.5458	Don't Reject
TBill does not Granger Cause Gold	1.92585	0.0758	Reject
KSE does not Granger Cause TBill	2.09084	0.0536	Reject
TBill does not Granger Cause KSE	1.70489	0.1179	Don't Reject
KSE does not Granger Cause Gold	1.31329	0.2502	Don't Reject
Gold does not Granger Cause KSE	1.24039	0.2848	Don't Reject

Conclusion:

T-Bill is Granger cause for Gold

KSE is Granger cause for T-Bill

We reject the null hypothesis that T-Bill is Granger cause for KSE index and Gold Price at 5% level for two, three and four lags. Although we cannot reject for five and six lags at 5% level but we can do so at 10% level. Ganger causality is very sensitive to number of lags. At six lags, KSE index is Granger cause for T-Bill value, although it is not so for lags two, three, four and five. Six lags mean three months and a period of three months is too long for the market where change can be realize fortnightly. So we conclude that T-Bill is the cause of both KSE index and Gold price. It means that movement in interest rate leads to movements in KSE index and Gold price.

5.7 Stationarity versus Structural Breaks:

Several studies including Perron (1989), Fernandez (1997), Lumsdaine and Papell (1997), Perron (1997) have shown that in case of structural breaks data may appear to be non stationary, though in actual it is stationary. It happens where a shock disturbs the trend and trend settles to a new level after the shock. These studies have been briefly discussed in Literature review.

Here in our case, we have checked for stationary for all the variables. KSE index, T-Bill rate and T-Bill value appeared to be non stationary for the level. But their first difference is stationary indicating that they all are integrated of order one. Gold prices showed a different behavior. It became stationary at the level. The result is astonishing. Let us look at the structural breaks in gold price

Month	Year	Price
November	2000	4850
January	2001	5049
January	**2011**	**37400**
February	2012	50830
October	**2012**	**53585**
December	**2015**	**35991**
September	2016	44040

We find three structural breaks. When we tested the data in between the structural breaks, we found that data is non stationary at level and stationary at first difference. So our discovery is that in presence of structural breaks data may appear stationary though in actual it is non stationary. Our finding is in contrary to most of the studies given in Literature Review where stationary data appeared to be non stationary. The reason for contradiction is that in those studies a shock caused the trend to adjust to the new level permanently but in our case trend returned to its original path after a second structural break.

6. CONCLUSION AND RECOMMENDATIONS

Structural change is pervasive in economic time series relationships, and it can be quite perilous to ignore. We have presented a new approach to the online monitoring of econometric time series which includes programming techniques on regression estimates. These techniques can be implemented without any knowledge of breaks to the underlying parameters. Online monitoring of structural breaks that are unknown but suspected to present is more natural and more revealing than the commonly employed retrospective techniques. We come to know about changes whenever an additional observation is included in the data set. We do not skip structural break at any point inside data set so it becomes easier to pinpoint the actual breakpoint. This approach can be extended to the tests other than the one we have used.

We developed algorithm in three stages. In first stage, we estimate regression coefficients, which lead to estimation of residual sum of squares (RSS). During first stage we get all the values of intercept and slope as the data window is swapped throughout the data set. In second stage, we compute our test statistics. In our case this is Chow F statistics. In third stage we analyze the results and sort out the break points.

By applying our programming techniques on simulated data, we get results. These results reveal many interested thing. Slope of the data window may appear negative if positively sloped data set settles after a structural break to a lower level of positively sloped data set. So although sub sample are both positively sloped but if regression is run on combined data without realizing possibility of break, slope appears to be negative (page 41 and page 42). This finding shows how much misleading the results may be in presence of structural breaks.

Inspection of RSS is a helping tool in detection of structural breaks at unknown locations. RSS starts to increase as soon as break point is included in the estimation window/sample. RSS reaches to maximum when break point is in the middle of the estimation window. RSS becomes normal as soon as break point is excluded from the estimation window. RSS does not pinpoint structural break as sharply as Chow F statistics can but it can indicate the lower and upper bound of the data set in which structural break is present.

Results of Chow F statistics show that local maximum is not a solution to the problem in case of single structural break. In case of single structural break, we have to search for global maximum. In case of multiple structural breaks, global maximum too is not a solution (page 43). We have to search the locations where F statistics is below the critical value. Then in between first and second stable values, we may find a global maximum, which is first break point. Then in between second and third stable F values, we find another global maximum which is second structural break and so on.

Our approach points out the structural breaks with very strong evidence. Power is calculated only if there is some insufficiency in evidence. Strong evidence of structural breaks makes us free to calculate the power of the test. Similarly, confidence set can be computed relatively easily by simply taking lower bound and upper bound. Lower bound is the date when our test statistics rises above critical value and upper bound is the date when our test statistics comes back to its normal value. By swapping the window, we can cover any magnitude of the break. The confidence sets so obtained hence control coverage for a small break too.

Our approach is useful to apply when there is false indication of non-stationarity of data. Our study has proved that detection of structural breaks is necessary prior to testing the data for stationarity. Gold price data appears to be stationary when fortnightly data of sixteen years is used. But if we use data between two structural breaks, it appears to be non stationary.

We have detected structural breaks and it appears that some lead and follow relationship may exist between structural breaks of different time series. Structural break in first time series is the cause of structural break in second time series and so on. To confirm our finding, we use Granger Causality test which is used for cause and effect relationships. The conclusion drawn is that

1. Changes in T-Bill rates Granger Cause the changes in KSE index.
2. Change in T-Bill Granger Cause the Gold prices in Pakistan and

We may present logic as if interest rate is high, then investors may prefer to give their funds on interest based securities (though not an Islamic decision). It will cause crowding out of the funds for gold market as well as for stock exchange market resulting in decline of stock exchange index.

RECOMMENDATIONS

Various tests are available for detection of structural breaks. We have used Chow F statistics in our algorithms and coding. In the fact any test can be used while swapping the window throughout the data set. Stage 1 will remain almost the same. Stage 2 of our algorithm will completely be written for another type of test with minor changes in stage 3.

Algorithms can be written which can compute power of the test as window is swapped. This is rather more complex task as compared to our work. No software in the market can do it. We will have to use many built-in functions from the library of the language. Coding may require object oriented programming in this case.

We may change data generating process in such a way that it accommodate for disturbances. For example data can be generated with changing variances. Then we can test the data by applying different type of tests such as Chow F, LR, Wald, MZ etc. We will have to write algorithms and coding separately for each type of test. This will perhaps result in a new software specific for detection of structural breaks at unknown location. This complex task is left for future research.

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8-APPENDIX

Complete Program with Comments

```
// Program begins from here !
//OX STANDARD LIBRARY HEADER FILE IS INCLUDED WHICH HAS VARIABLES
AND FUNCTIONS NECESSARY TO RUN THE PROGRAM
#include <oxstd.h>
// DATABASE CLASS IS IMPORTED
#import <database>
        //main function of our program starts from here
                main()
{
                //LOAD DATABASE FROM HARD DISK:
                 // database is declared,
                decl dbase;
                // database object is derived from Database class
                dbase = new Database();
                //file loaded from Hard Disk Drive D
                dbase.Load("D:/data2.in7");
                // data base information is displayed
                dbase.Info();
                // maY Matrix consisting of all data of Y is declared
                decl maY;
                // maY is assigned all the values of database
                maY = dbase->GetAll();
                // Data size N and Sample size n is declared
                decl n,N;
                // Data size is defined
                N=300;
                // Sample size is defined
                n=20;
                // three variables are declared to run the for loops
                decl i,j,h;
//***************************************************************************
// STAGE 1 : DECLARE WINDOWS AND RUN REGRESSIONS ON SAMPLES:
                // matrix X is declared
                decl    mX;
                 // Matrix X is defined and all entries initialized to ones.
                mX = ones(2*n,2) ;
                //Trend will be introduced in second column of matrix mX starting from 1.
                mX[0][1]=1;
// matrix X is defined as consisting of all ones in first column and trend in second column
```

```
            for(i=1 ; i<2*n; ++i)
            {
                    mX[i][1]=mX[i-1][1]+1;
            }
             print("\n X matrix for the samples is given as",mX);
//*************************************************************************
//matrix consisting of Y variable data for a specific window is declared
            decl mY;
            // matrix Y is defined and initialed to all zeros
            mY = zeros(2*n,1);
            // matrix to store estimated betas is declared
            decl b=zeros(2,1);
            //matrix mB is declared to store values of betas from combined window
            decl mB;
            // mB is initialized to all zeros and size of mB is defined
            mB =  zeros (N-n+1,2) ;
            //matrix mRSS is declared to store values of RSS from combined window
            decl mRSS;
            // mRSS is initialized to all zeros and size of mRSS is defined
            mRSS = zeros (N-n+1,1) ;
//*************************************************************************
//for loop is used to create N-2n windows and statistical analysis of each window
            for (i=0 ; i<=N-2*n; ++i)
        {
            // sample information is displayed as follows
print ("\n \n Sample No.(", i+1 , ") has Lower Limit = ", i+1, " and Upper Limit = ", i+2*n) ;

//*************************************************************************
//nested for loop is ued to populate each window
            for ( j=0 ;       j<2*n  ;  ++j)
            {       //combined window mY is populated with data
                    mY[j] = maY[j+i];
            }
            //OLS is run on each window
            olsc(mY, mX, &b);
            //mB matrix is populated with Beta of respective sample
            mB[i][0] = b[0];        //mB matrix is populated with Beta of respective sample
            mB[i][1] = b[1];
            print("\n  In Sample (",i+1, ") values of Betas are ", b[0], " and ", b[1]);
//*************************************************************************
//Computations for Residual Sum of Squares start from here
// matrix of Y Explained is declared
            decl mYE;
```

```
            // mYE is defined and initialized to all zeros
            mYE = zeros(2*n,1);
            // mYE is calculated
            mYE = mX*b ;
            // Matrix me of residual term is declared where, e = Y actual - Y explained
            decl me;
            // Size of matrix me is defined and matrix is initialized to all zeros.
            me = zeros(2*n,1);
            // Nested for loop is used to populate me
            for (h=0 ; h<2*n; ++h)
            {       // Matrix me is populated.
                    me[h] = mY[h] - mYE[h] ;
            }
//*************************************************************************
        //RSS is declared and initialized to a value of zero.
            decl RSS=0;
// for loop is used to get RSS for given sample and put the value in matrix of RSS at respective index
            for (h=0 ; h<2*n; ++h)
            {       // RSS is calculated.
                    RSS = RSS + (me[h])^2 ;
            }
            // Value of RSS is put at respective index in column matrix mRSS.
            mRSS[i] = RSS           ;
            print ("\n  In this sample value of RSS = "  , RSS ) ;
            //  RSS initialized to zero        before starting the next sample.
            RSS=0;
        }
//*************************************************************************
// DECLARE WINDOWS AND RUN REGRESSIONS ON SUB SAMPLES:
            // matrix X is declared
            decl    mXs;
            // Matrix X is defined and all entries initialized to ones.
            mXs = ones(n,2) ;
            //Trend will be introduced in second column of matrix mX starting from 1.
            mXs[0][1]=1;
// martix X is defined as consisting of all ones in first column and trend in second column
            for(i=1 ; i<n; ++i)
            {
                    mXs[i][1]=mXs[i-1][1]+1;
            }
            print("\n X matrix for the samples is given as",mXs);
//*************************************************************************
```

```
    // Matrix consisting of Y variable data for a specific window is declared.
            decl mYs;
            // Matrix Y for sub sample s is defined and initialed to all zeros.
            mYs = zeros(n,1);
            // Matrix mBs is declared to store values of betas from sub sample window.
            decl mBs;
            // mB is initialized to all zeros and size of mB is defined.
            mBs =  zeros (N-n+1,2) ;
            // Matrix mRSSs is declared to store values of RSS from sub sample window.
            decl mRSSs;
            // mRSSs is initialized to all zeros and size of mRSSs is defined.
            mRSSs = zeros (N-n+1,1) ;
//***************************************************************************
//for loop is used to create N-n windows and statistical analysis of each window
            for (i=0 ; i<=N-n; ++i)
    {
            // Sub sample ample information is displayed as follows
print ("\n \n Sub-Sample No.(", i+1 , ") has Lower Limit = ", i+1, " and Upper Limit = ", i+n)
;
//***************************************************************************
//nested for loop is ued to populate each window
            for ( j=0 ;      j<n  ; ++j)
            {       // Sub Sample window mYs is populated with data
                    mYs[j] = maY[j+i];
            }
            //OLS is run on each window
            olsc(mYs, mXs, &b);
            //mBs matrix is populated with Beta of respective sample
            mBs[i][0] = b[0];  //mB matrix is populated with Beta of respective sample
            mBs[i][1] = b[1];
            print("\n  In Sub Sample (",i+1, ") values of Betas are ", b[0], " and ", b[1]);
//***************************************************************************
//Computations for Residual Sum of Squares start from here
            // matrix of Ys Explained is declared
            decl mYsE;
            // mYsE is defined and initialized to all zeros
            mYsE = zeros(n,1);
            // mYsE is calculated
            mYsE = mXs*b ;
            // Matrix me of residual term is declared where, e = Y actual - Y explained
            decl me;
            // Size of matrix me is defined and matrix is initialized to all zeros.
            me = zeros(n,1);
```

```
            // Nested for loop is used to populate me
            for (h=0 ; h<n; ++h)
            {       // Matrix me is populated.
                    me[h] = mYs[h] - mYsE[h] ;
            }
//*****************************************************************************
//RSS for sub sample is declared and initialized to a value of zero.
            decl RSSs=0;
// for loop is used to get RSS for given sample and put the value in matrix od RSS at
respective index
            for (h=0 ; h<n; ++h)
            {       // RSS is calculated.
                    RSSs = RSSs + (me[h])^2 ;
            }
            // Value of RSS is put at respective index in column matrix mRSSs.
            mRSSs[i] = RSSs        ;
            print ("\n  In this sample value of RSS = "  , RSSs ) ;
            //  RSS initialized to zero         before starting the next sample.
            RSSs=0;
    }
//*****************************************************************************
//STAGE 2 : GET F STATITICS :
// Declare matrix mRSSss which holds sums of RSS values of two sub-samples
        decl mRSSss = zeros(N-2*n+1 , 1);
            // Declare matrix mRSSd        where mRSSd = mRSS - mRSSss
            decl mRSSd = zeros(N-2*n+1 , 1);
// Declare matrix mF which will hold values of all the Chow Tests on all windows
            decl mF;
            // mF is defined and initialized to all zeros.
            mF = zeros (N-n+1,1) ;
            // Matrix mF is populated using for loop.
            for(i=0 ; i<N-2*n+1 ;++i)
            {
                    mRSSss [i] =  mRSSs[i] + mRSSs[i+n];
                    mRSSd [i] = mRSS[i] - mRSSss[i]  ;
                    // F value is calculated and put in respective index in matrix F
                    mF[i] = mRSSd[i]/(mRSSss[i]/((2*n)-2));
            }
// An index is declared and defined to help in reading results stored in different matrices.
            decl Index;
            Index = <20:300>';
print(" \n \n Values of  , Beta, RSS,F statistics  out of all the samples are given below \n \n");
            print ("\t Point No.    mRSSs \t \t Beta1 \t \t Beta2 \t \t RSS \t \t F statistics" );
```

```
		print (Index~mRSSs~mB~mRSS~mF);
//**************************************************************************
//	STAGE 3: ANALYSE RESULTS:
		// Required variables are declared.
		decl w, mF1 ,mz, max;
		// Window equal to sample size is declared
		w=n;
// Matrix mZ is declared and initialized to hold 20 adjacent F values out of each Chow Test F statistics
		mz = zeros(w,2) ;
// Matrix mF is declared and initialized to hold maximum value out of each of adjacent 20 F Chow Test statistics.
		mF1 = zeros(13,2);
// Maximum F value out of chunks of consecutive n F values are extracted using outer for loop.
		for(i=0 ; i<13 ; ++i)
	{	// Nested for loop is used to populate window with F values.
		for(j=0; j<w	; ++j)
		{
// first column is filled with observation number from where a particular window for Chow Test starts.
		mz[j][0] = (i*w)+j+21 ;
		// Second column is filled with respective F statistics.
		mz[j][1] = mF[(i*w)+j];
		}
		// Maximum F value is extracted from the recently filled mZ matrix.
		max = maxc( mz[][1] ) ;
//Maximum F value extracted from mZ is put in mF1 along with the respective observation number
		for(j=0; j<w	; ++j)
		{
		if(max == mz[j][1])
			{
		mF1[i][0]= mz[j][0] ;
		mF1[i][1]=max		;
			}
		}
	}
print(" \n Given below are the maximum F values at respective observation \n for each segment of 20 regression lines");
		print ("\n \n \t observation \t Max F ");
		print(mF1);
```

// All maximum F values stored in mF1 are compared against critical F value in F Table and results are displayed on screen.

```
                decl crt,mmy ;
                crt=8.1 ;
                for( i=0 ; i<10; ++i)
                {
                  if(crt < mF1[i][1] )
                        {
print ( " \n Structural break occurred at observation number " , mF1[i][0]);
                        print("\n F value at this point is  " , mF1[i][1] , "\n");
                        }
                }
                print(" \n This Program to detect 'Structural Change of Unknown Time'" );
                print ("\n is written by 'Muhammad Naoman Khan'. ");
```

// Database object is deleted at the end of the program in order to free the memory space (RAM) of the computer.

```
                delete dbase;
}
```

// Program ends here!