Nat. Volatiles & Essent. Oils, 2021; 8(4): 10683-10692

NVEO
Natural Volatiles & Essential Oils

Effect of Structural Breaks on Volatility Regime: Lessons from Leading European and Indian Indices

[1]Ajay Kumar Yadav, [2]Mohammad Irfan, [3]Rohit Singh, [4]Zakir Hossen Shaikh

[1]Pro-Vice Chancellor, IES University, Bhopal, Madhya Pradesh, India
[2]Associate Professor, CMR Institute of Technology, Bangalore, India
[3]Professor, School of Business, Auro University Surat, Gujrat, India
[4]Faculty, Commercial Studies Division, Bahrain Training Institute, Ministry of Education, Kingdom of Bahrain

Abstract

Stock market volatility has become a very prominent area of research during the last few decades several authors have come out with path breaking studies in this area which has helped both the academicians as well as practitioners in the market. But just studying the long term volatility does not serve the purpose as the environment in the market is so dynamic with shocks appearing at regular intervals. This paper is an attempt to understand the effect of structural breaks on the volatility persistence in the stock markets over the period of time. The study has been conducted on the top 3 European indices, CAC 40, FTSE and DAX and the Indian market ie., Nifty 50 of NSE. For the purpose of this study the time period for which the data has been collected is from April, 2000 to March, 2020. The study concludes that although there is volatility persistence even with structural breaks but it diminishes to an extent due to it.

Key Words: Stock markets. Volatility, Structural breaks, Regime switch and GARCH Models,

JEL Classification: C12, C13, G2, G12, Q1

Introduction

Volatility is one of the best indicators of market risk. It refers to the price fluctuation over a given period of time. This concept was first discussed by (Bachelier, 2000) in his study in 1999, related to the study for modelling stock prices. Bachelier described it as “the coefficient of instability” or “nervousness”. Since then, the study in volatility has come a long way and today it is one of the most important areas of study in finance. In finance, volatility quantifies the risk associated to a certain financial instrument. An important aspect in the study of financial market volatility is the identification of structural breaks in the financial time series. Researchers have concluded that the parameters of a typical time series do not remain constant over a period of time. It makes paradigm shifts at regular intervals. The time of this shift is called the structural break. There have been several studies aimed at measuring the breakpoints and in fact researches have shown that if structural breaks are present in the series, then ignoring it would cause unreliable results and thus the volatility measurement results may be spurious. There have been several studies which have been conducted to detect shifts in unconditional variance that is the volatility. This test is used extensively in financial time series to identify breaks in volatility (Wilson, Agarwal and Inclan, 1996; Aggarwal, Inclan and Leal, 1999, Huang and Yang, 2001). This test was later modified by Sanso, Arago and Carrion (2004) to account for conditional variance as well (Chitrakalpa Sen, 2012). Structural breaks are one of the most common properties of a financial time series. Structural breaks or structural changes refer to persistent and pronounced shifts in the data generating process. Longer the period under consideration, higher is the probability of observing structural breaks (Chitrakalpa Sen, 2012). Let us consider a simple AR(1) process.

$$y_t = \alpha + py_{t-1} + \varepsilon_t \tag{1.1}$$

$$E\varepsilon_t^2 = \alpha^2 \tag{1.2}$$

Where $\varepsilon_t$is a time series of serially uncorrelated shocks? If the series is stationary, the parametersα, p and $\alpha^2$are considered as constant over time. A structural break is said to be occurred if at least one of the parameters changes permanently at some point (Hansen, 2001). It is the date when one of the parameters changes permanently it is call the break date. According to (Brook, 2003), “structural breaks are irreversible in nature‟. There are several reasons behind a structural break Usually, such changes in the properties of a series are attributed to large-scale events, such as wars, financial panics, significant changes in government policy, such as the introduction of an inflation target, or the removal of exchange controls, or changes in market microstructure. However, it is also true that structural breaks can occur on a regular basis and at much higher frequency. Such changes may occur as a result of more subtle factors, but they still lead to a statistically important change in behaviour of the market / series. The best example of this is the intraday market volume which is higher at the beginning of the day, tapers down during the middle part of the trading session then widens again towards the end. There may also be some unidentifiable reasons that cause breaks in return or volatility (Marianna Valentinyi-Endrész, 2004). The studies on structural break began with the work of Gregory Chow in 1960. Since 1960, the initiation of a fundamental break mechanism started. For the first time, a known structural break has done predicted by Gregory Chow (1960). It is a test of equality in the coefficients of the parameters of regression, and there is a breakpoint mechanism. Simultaneously, an analysis of unknown structural change has carried by Quandt (1960). He discussed the constant-coefficient against alternative with changes in the error variance. However, during the second half of the 1970s – Brown, Durbin and Evans proposed the techniques to analyze recursive residuals using CUSUM test (Chitrakalpa Sen, 2012).

Importance of Structural Break Modelling

Studying structural breaks in the financial time series assumes importance because of the following reasons; Not incorporating structural breaks when it is actually present in a time series can lead to grossly imperfect conclusions. So it is imperative to check for structural breaks and if found to be present, model the data with the breaks accounted for. Some of the erroneous conclusions that arise from not taking breaks into account. It is further proved through researches that the presence of structural breaks, if not considered may lead to spurious results thus leading to imperfect forecasts. It is also mentioned in some of the important studies that structural breaks, if unspecified in the model, often results in spurious non- rejection of the unit root (Perron,1989; Reichlin, 1989). The fragility of unit root in presence of structural breaks are also supported by Nelson and Plosser (1982), Zivot and Andrews (1992). Persistence of conditional volatility in ARCH and GARCH models are affected by presence of structural breaks. If not taken into consideration, structural breaks may exaggerate the persistence of volatility in ARCH and GARCH parameters. In fact, in a dataset containing mostly stationary data, a single short subperiod of non-stationarity can make the overall volatility process persistent (Diebold, 1986; Lamoureux and Lastrapes, 1990; Pesaran and Timmerman 1999; Hwang et al. 2006). According to Hwang and Chu (2004), the persistence level of the entire time series tends towards the largest sub-AR parameter (Chitrakalpa Sen, 2012). If overlooked in a model, structural breaks can create long term persistence. If present in a financial time series, structural break can showcase long memory while there is actually none. The process will have some properties similar to a long memory process (Granger and Hyung, 2000 and Diebold and Inoue, 2001). Incorporating structural breaks in a model can change the random walk nature of the underlying series. (Kausik Chaudhuri, 2003) showed that when structural breaks are considered, in most of the cases the null hypothesis that the series are characterized by random walk is rejected. This is to say, if inherent breaks are ignored, the underlying characteristics of the time series can be completely misleading and wrong. If structural breaks are present and unaccounted for, standard cointegration tests lose power and it leads to spurious acceptance of the null hypotheses that cointegration doesn't exist. Where, if structural breaks are included, cointegration is indeed present (Campos, Ericsson and Hendry, 1996 and Gregory and Hansen, 1996). The present study is an attempt to identify the presence of multiple break points in the time series data of leading European and India indices from the period of 1st April, 2000 to 31st March, 2020.

Literature Review

Structural break(s) is/are sudden policy change(s) in government or serious international disaster (civil war). This sudden change can occur in time series data or cross sectional data, when there is a sudden change in the relationship being examined. A data can be found to be non-stationary if it has a unit root, or if it includes a structural break, before and after which data shows different patterns. As it is sometimes called in literature, this is part of the intricate play between unit roots and structural breaks (Perron 1989, 2005). Jushan Bai and Pierre Perron in their seminal research, 'Estimating and Testing Linear Models with Multiple

Structural Changes' (Perron J. B., 1998) considered the issues related to multiple structural changes, occurring at unknown dates, in the linear regression model estimated by least squares. The researchers proposed a procedure that allows one to test the null hypothesis of, say, l changes, versus the alternative hypothesis of l + 1 change. This is particularly useful in that it allows a specific to general modelling strategy to consistently determine the appropriate number of changes present. An estimation strategy for which the location of the breaks need not be simultaneously determined is discussed. Instead, our method successively estimates each break point. Jushan Bai and Pierre Perron, in their further research 'Computation and analysis of multiple structural change models' (Perron J. B., 2003) worked on the practical issues for the empirical applications of the procedures The research first addressed the problem of estimation of the break dates and present an efficient algorithm to obtain global minimizers of the sum of squared residuals. This algorithm is based on the principle of dynamic programming and requires at most least-squares operations of order O (T 2) for any number of breaks. The authors suggested that the method can be applied to both pure and partial structural change models. Secondly, they consider the problem of forming confidence intervals for the break dates under various hypotheses about the structure of the data and the errors across segments. Third, their research addressed the issue of testing for structural changes under very general conditions on the data and the errors. Fourth, they addressed the issue of estimating the number of breaks. Finally, a few empirical applications were presented to illustrate the usefulness of the procedures. Bialkowski, 2004, in his study investigated the time series behaviour of stock market returns of three CEEC countries viz., Hungary, Czech Republic, and Poland along with France, Germany and UK. The study used the monthly data for the period of 1995–2002. The study further compared the results of three Central Eastern European Countries (CEEC) markets with other three markets. The study applied extended MRS model with mixture of normal distributions. The study found that there is an existence of two or three volatility states. The results of model comparison indicated that the Markov switching mixture of normal distributions has given more robust results than the single normal distribution. The study concluded in favour of applying MRS model with different specifications compared to conventional volatility models. From policy perspective, the study concluded that the change from the normal to the crisis regime leads to the significant increase in volatility on the emerging markets. By comparing the volatilities of both CEEC and Western Europe, the study found that the markets of later is more stable than former (Bialkowski, 2004). Ismail Tahir Mohammed., 2008, in their study examined the appropriateness of non-linear models in identifying the implicit jumps and breaks in financial time-series data. The study analysed how the occurrence of regime shift can benefit the investor in minimisation of their risk level. The study also compared the regime shifts in mean and variance and tried to discern the different volatility patterns. . The findings of this study imply that the regime shifts in different indices may be used to characterize the level of volatility and timing of investment. Statistically, the model reported very interesting results in terms of nonlinearity in examined indices (Ismail Tahir Mohammed., 2008). Danialson, 2011, this research explains that the changes in the risk regimes could describe the formation of asset price cycles. It concluded that the current practice in risk models of using a rolling window estimate or GARCH model, might lead to an asset price bubble in stable periods, since underestimation of risk leads to an overvaluation of financial assets (Danialson, 2011). Claudio Morana, 2002, in the study reported the appropriateness of regime switching model to analyse and describe the regime switching behaviour of examined stock market return. The study went on to examine the in-and-out sample properties of MRS model. The study concluded that a poor performance of forecasted results. The findings of this study imply that the MRS model can be used to account for dynamic and nonlinear changes in the stock market return distribution (Claudio Morana, 2002).

Research Methodology

The study uses, the adjusted closing daily data for the purpose of analysis. It is because taking weekly or monthly data would smooth out the series too much and thus finding the structural breaks in the time series would be difficult. As this study concerns with volatility and the structural breaks, taking daily data would be much more beneficial as data with longer intervals would dampen the volatility impact on the series. As the study focuses on the understanding the presence of structural breaks and the impact of these breaks on the volatility of the selected European Markets namely FTSE, CAC40, DAX and Indian markets namely Nifty50 of National Stock Exchange of India. The time period selected for the purpose of the study is the period between 1stApril, 2000 to 31st March, 2020. There was a total of 5030 observation for each of the selected stock markets. Further for the purpose of this study the daily return series have been generated using the E-Views version 9. Mathematically the daily returns are determined using the following formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1.3}$$

Where

$R_t = Daily\ Return$

$P_t = Current\ Days\ Adjusted\ Closing\ Price$

$P_{t-1} = Previous\ Days\ Adjusted\ Closing\ Price$

This paper considers breaks in volatility and not the breaks in mean as several studies have focused on that.

$$\sigma_t^{\delta} = \alpha_0 + \sum_{i=1}^{n} \alpha_1 \varepsilon_{t-1}^{\delta} + \sum_{i=1}^{n} \alpha_2\, \sigma_{t-1}^{\delta} + \sum_{k=1}^{n} \gamma_k\, \varepsilon_{t-1}^{\delta}\, I_{t-k} \qquad \ldots\ldots(2)$$

Where It =1 if εt < 0 and 0 otherwise

If , εt-1 < 0 is not the sign of good result, and εt-1 > 0 is good sign to conditional variance.γ_k >0 it shows the volatility. It can be a leverage effect for order. If γ_k not equal to 0 the news impact is asymmetric.

The present study uses the Bai-Perron (1998) multiple break point test for identifying the number of structural breaks present in the time series data for all the selected markets. The multiple breakpoint tests that we consider for the purpose of this study is broadly be divided into three categories: tests employing global maximisers for the breakpoints, test that employ sequentially determined breakpoints, and the hybrid tests, which combine the two approaches For this study we use the global maximisers criteria. The present study uses the Bai and Perron (1998) tests of 'breaks versus none test' for determining the number of breaks.

Test of Normality: The Jarque-Bera test of all the stock market series rejects the normality of returns for all four indices as the p-value rejecting the null hypothesis that returns are normally distributed.

Test of Stationarity: Since the study proposes to apply the conditional volatility models on the time series data hence the first condition of this process is to see that the time series data set must be stationary i.e., the series should not have a unit root. During the analysis the results of the Augmented Dickey-Fuller Test and Phillip-Peron Test rejected the null hypothesis i.e. $H_0 = series\ has\ Unit\ root$ and alternate hypothesis was accepted. It is found that the time series data of all the 4 indices do not have unit root i.e., the data series are stationary and hence the conditional volatility models may be applied and structural breaks can be identified.

Bai – Perron Multiple Break point Test

Multiple Break Point Test: Tests for parameter instability and structural breaks in regression models have been important tool for researchers in applied econometrics and it goes back to 1960 when Chow first used the break point test with known dates using F statistic. Since then lots of modifications have been done to study the switching behavior from Quandt (1960), Andrews (1993), Andrews and Ploberger (1994) and more recently Bai and Phillip Perron (1998, 2003) provided a theoretical and computational results that further extend the results of Quadant by allowing for multiple break points (Chitrakalpa Sen, 2012).

The multiple breakpoint tests that we consider for the purpose of this study is broadly be divided into three categories: tests employing global maximisers for the breakpoints, test that employ sequentially determined breakpoints, and the hybrid tests, which combine the two approaches. For the purpose of this study we use the global maximisers criteria. These global breakpoint estimates are then used as the basis for several breakpoint tests. The present study uses the Bai and Perron (1998) tests of 'breaks versus none test' for determining the number of breaks.

Global L Breaks Vs. None (Bai – Perron, 2003a): Global Maximizer Tests, Bai and Perron (1998) explained simply the Quandt and Andrews (1993) test where test of equality of δ_j across multiple regimes. For testing a null hypothesis of no breaks f-statistic is used to show that $\delta_0 = \delta_1 = \ldots = \delta_{i+1}$. The statistics is (Bai – Perron, 2003a):

$$F(\hat{\delta}) = \frac{1}{T}\left(\frac{T-(l+1)q-p}{kq}\right)(R\hat{\delta})'(R\hat{V}(\hat{\delta})R')^{-1}R\hat{\delta} \tag{1.5}$$

Where $\hat{\delta}$ is the optimal break estimate of $\ell - break$ estimate of δ, $(R\delta)' = (\delta_0' - \delta_1', \ldots, \delta_l' - \delta_{l+1}')$, and V($\delta$) is an estimate of variance and covariance matrix of $\hat{\delta}$ which may be robust to serial correlation and heteroskedasticity, whose form depends on assumptions about the distribution of the data and the errors across segments.

Double Maximum Testing: According to Logan Kelly & David Sienko (Sienko, 2018) If the number of breaks is unknown, then Bai and Perron (1998) show it is possible to test the null of no structural break versus an unknown number of breakpoints up to some upper bound by extending the Global maximizer procedure to include various values of m . In other words, the global maximize F-statistic is calculated for l m =1, K breaks. Then these test statistics are aggregated either by selecting the maximum value, i.e. UDMax test statistic (Andrews, Lee, and Ploberger 1996), or by using a weighting scheme, i.e. WDMax test statistic (Perron J. B., 1998). This type of testing, referred to as double maximum testing, results in a test statistic with a non-standard distribution for which (Perron J. B., 2003) provide critical values. For the purpose of determining the breaks this study will use UDMax Test statistics.

Data Analysis and Interpretation
Break Dates

Table: 1.1 – Break Dates

Index	Break Date 1	Break Date 2
Nifty	17/05/04	NA
CAC	14/09/04	24/03/10
DAX	28/04/03	NA
FTSE	21/09/07	24/12/13

Sources: Author estimated

For the purpose of identification of break dates the Bai-Perron (1998) Multiple Break Point Test was used and tests of 'Global breaks versus none test' for determining the number of breaks was applied using EViews 9. The results of the test show that most of the Asian markets did not have any structural breaks with exception of India. Rest all the markets have witnessed 1 breaks each. FTSE and CAC 40 had 2 structural breaks each whereas the Indian market and the German market during the same period just has one break dates each.

Regime Switch

Once the break dates are identified using the Bai -Perron model then the regimes are identified. Structural breaks and regime are two different concept but have little difference. In fact in practice there is primarily no difference between the two although there may be theoretical difference between the two. (Perron J. B., 2003) state that the period between two break dates is identified as a regime. Structural breaks can efficiently capture regime switches (Altissimo and Corradi, 1999; Gonzalo and Pitarakis, 2002; Timmerman, 2001; Valentinyi-Endrész, 2004) The Bai-Perron Test is used to identify breaks in conditional volatility, i.e. the point where the conditional volatility jumps from one stationary level to another one. This is the same premise as presented by Markov regime switching models, where the system moves from a high (low) volatility regime to a low (high) volatility regime. In the current study, we define a regime as 'the sub period between two true breakpoints'. Once the breakpoints are identified, detailed analysis is carried out in each of the sub periods or "regimes" individually. But before that, the regimes are checked for the presence of unit root (Chitrakalpa Sen, 2012).

First using the multiple breakpoint test of (Perron J. B., 2003) we identify the break dates after which the regimes are identified. The findings of the multiple break point model of Bai-perron suggest that there are 10 regimes in the selected indices for the period of this study. Once the break dates are identified then preliminary analysis of data for each regime is analysed using the descriptive statistics in which we look for the values of skewness, kurtosis and Jarque-bera statistics for normality, followed by the Unit root test to see if the data is stationary or not. Once the data is fund stationary then we can apply the conditional volatility models. By looking at the descriptive statistics of each individual series we find that 5 out of 10 series have positive skewness and all the regimes have kurtosis higher than 3 which means all the series have leptokurtic distribution. The results of the Jargue-bera test suggests that all the series have non-normal distribution which means it is suitable for applying the conditional volatility models. Before moving on to the conditional volatility models it is necessary to check the individual series for stationarity. Each of individual regimes was checked for stationarity by running the individual series through the Augmented Dickey Fuller Test (ADF) and Philip Perron Test. The results show that all the 10 series are stationary. Once then preliminary conditions are fulfilled then we move on to the application of conditional volatility models.

Table: 1.2 Regime Analysis – CAC 40

CAC 40			
Regime 1			
GARCH			
	RESID(-1)^2	0.086069	0
	GARCH(-1)	0.891943	0
TGARCH			
	RESID(-1)^2*(RESID	0.12029	0
	SIC	3.806349	
EGARCH			
	C5	-0.095917	0
	C6	0.986133	0
	SIC	3.80115	
Regime 2			
GARCH			
	RESID(-1)^2	0.095835	0
	GARCH(-1)	0.889812	0
TGARCH			
	RESID(-1)^2*(RESID	0.172738	0
	SIC	2.870123	
EGARCH			
	C5	-0.130531	0
	C6	0.974264	0
	SIC	2.868773	
Regime 3			
GARCH			
	RESID(-1)^2	0.118140	0
	GARCH(-1)	0.871138	0
TGARCH			
	RESID(-1)^2*(RESID	0.225763	0

	SIC	3.174606	
EGARCH			
	C5	-0.176238	0
	C6	0.972368	0
	SIC	3.177707	

Sources: Author estimated

There is presence of volatility as there is presence of ARCH effect. The past volatility does affect the present volatility in all the three regimes as the past value is statistically significant. Thus, the past value can significantly predict the current value of CAC 40 returns in all the regimes. The coefficient of the variance equation i.e. the ARCH and the GARCH terms is positive and statistically significant in all the regimes. The sum of lagged value of conditional variance of squared error is <1 this satisfies the stability condition. We can say that the persistence of volatility shocks is large in all the regimes but much higher in regime 3 in comparison to regime 1 and 2. This shows that the effect of today's volatility will remain in the forecast of variance for many periods in future in all the three regimes.C (5) is asymmetric coefficient and C (6) is the GARCH coefficient. The asymmetric coefficient here is negative and statistically significant in the regime 1, 2 & 3. This indicates presence of asymmetry. This indicates that in case of CAC 40 bad news has a larger effect on the volatility of the index then the good news during all the regimes. In case of regime 3 TGARCH is the best fit model and in case of regime 1 and 2 EGARCH is the best fit. Thus we can say that long term volatility persistence is more prominent in regime 3 then in 1 and 2.

Table: 1.3 Regime Analyses – DAX

DAX			
Regime 1			
GARCH			
	RESID(-1)^2	0.092374	0
	GARCH(-1)	0.897334	0
TGARCH			
	RESID(-1)^2*(RESID	0.159017	0
	SIC	3.313551	
EGARCH			
	C5	-0.118828	0
	C6	0.979371	0
	SIC	3.309886	
Regime 2			
GARCH			
	RESID(-1)^2	0.144306	0
	GARCH(-1)	0.809062	0
TGARCH			
	RESID(-1)^2*(RESID	0.359823	0
	SIC	2.617848	
EGARCH			
	C5	-0.240881	0
	C6	0.917802	0
	SIC	2.621843	

Sources: Author estimated

There is presence of volatility as there is presence of ARCH effect. The past volatility does affect the present volatility in both the regimes as the past value is statistically significant. Thus the past value can significantly predict the current value of DAX returns in both the regimes. The coefficient of the variance equation i.e. the ARCH and the GARCH terms is positive and statistically significant in both the regimes. The sum of lagged value of conditional variance of squared error is <1 this satisfies the stability condition. We can say that the persistence of volatility shocks is large in both the regimes but much higher in regime 1 in comparison to regime 2. This shows that the effect of today's volatility will remain in the forecast of variance for many periods in future in both the regimes. C (5) is asymmetric coefficient and C (6) is the GARCH coefficient. The asymmetric coefficient here is negative and statistically significant in both the regime 1 & 2. This indicates presence of asymmetry. This indicates that in case of DAX bad news has a larger effect on the volatility of the index then the good news during both the regimes. In case of regime 1 EGARCH is the best fit model and I case of regime 2 TGARCH is the best fit. Thus we can say that long term volatility persistence is more prominent in regime 1 then in 2.

Table: 1.4 Regime Analysis – FTSE: England

FTSE			
Regime 1			
GARCH			
	RESID(-1)^2	0.084182	0
	GARCH(-1)	0.910962	0
TGARCH			
	RESID(-1)^2*(RESID	0.096999	0
	SIC	2.798589	
EGARCH			
	C5	-0.084679	0
	C6	0.986218	0
	SIC	2.793973	
Regime 2			
GARCH			
	RESID(-1)^2	0.100042	0
	GARCH(-1)	0.895447	0
TGARCH			
	RESID(-1)^2*(RESID	0.151457	0
	SIC	2.629056	
EGARCH			
	C5	-0.122222	0
	C6	0.987367	0
	SIC	2.645241	
Regime 3			
GARCH			
	RESID(-1)^2	0.081398	0
	GARCH(-1)	0.903572	0
TGARCH			
	RESID(-1)^2*(RESID	0.156867	0
	SIC	2.837983	
EGARCH			
	C5	-0.108059	0
	C6	0.982239	0
	SIC	2.839913	

Sources: Author estimated

There is presence of volatility as there is presence of ARCH effect. The past volatility does affect the present volatility in all the three regimes as the past value is statistically significant. Thus the past value can significantly predict the current value of FTSE returns in all the regimes. The coefficient of the variance equation i.e. the ARCH and the GARCH terms is positive and statistically significant in all the regimes. The sum of lagged value of conditional variance of squared error is <1 this satisfies the stability condition. We can say that the persistence of volatility shocks is large in all the regimes but much higher in regime 2 in comparison to regime 1 and 3. This shows that the effect of today's volatility will remain in the forecast of variance for many periods in future in all the three regimes. C (5) is asymmetric coefficient and C (6) is the GARCH coefficient. The asymmetric coefficient here is negative and statistically significant in the regime 1, 2 & 3. This indicates presence of asymmetry. This indicates that in case of FTSE bad news has a larger effect on the volatility of the index then the good news during all the regimes. In case of regime 2 and 3 TGARCH is the best fit model and in case of regime 1 EGARCH is the best fit. Thus we can say that long term volatility persistence is more prominent in regime 2 then in 1 and 3.

Table1.5: Regime Analysis – Nifty 50

NSE			
Regime 1			
GARCH			
	RESID(-1)^2	0.123433	0
	GARCH(-1)	0.711828	0
TGARCH			
	RESID(-1)^2*(RESID	0.052073	0
	SIC	3.268383	
EGARCH			
	C5	-0.015466	0
	C6	0.854114	0
	SIC	3.267674	
Regime 2			
GARCH			
	RESID(-1)^2	0.108386	0
	GARCH(-1)	0.887207	0
TGARCH			
	RESID(-1)^2*(RESID	0.140343	0
	SIC	3.065434	
EGARCH			
	C5	-0.101969	0
	C6	0.979359	0
	SIC	3.064288	

Sources: Author estimated

There is presence of volatility as there is presence of ARCH effect. The past volatility does affect the present volatility in both the regimes as the past value is statistically significant. Thus the past value can significantly predict the current value of Nifty returns in both the regimes. The coefficient of the variance equation i.e. the ARCH and the GARCH terms is positive and statistically significant in both the regimes. The sum of lagged value of conditional variance of squared error is <1 this satisfies the stability condition. We can say that the persistence of volatility shocks is very high in regime 2 but it seems to decay during regime 1. However it still shows that the effect of today's volatility will remain in the forecast of variance for many periods in future in both the regimes. C (5) is asymmetric coefficient and C (6) is the GARCH coefficient. The asymmetric coefficient here is negative and statistically significant in both the regime 1 & 2. This indicates presence of asymmetry. This indicates that in case of Nifty bad news has a larger effect on the volatility of the index then the good news during both the regimes. In case of both regimes 1 and 2 EGARCH is the best fit model as far as Nifty series is considered. We can say that long term volatility persistence is more prominent in regime 1 then in 2.

Conclusion

From the above study we can easily understand that the existence of structural breaks does affect the volatility levels in the markets and it also suggests that though stock markets are highly interconnected but at the same time they are not guided by each other at all given point of time rather there are certain independent factors which do affect them. If we compare the output of the analysis between the Indian and the European Markets, we find lots of similarity in output; there is presence of asymmetry in all the markets thus suggesting like the other markets in the Indian markets also the bad news has a larger impact on the volatility of the index then the good news; the volatility persistence tend to decay with the break in the series.

References

1. Bachelier, L. (2000). Introduction: Bachelier's Thesis from 1900. In S. A. Bernard, *LLectures on Probability Theory and Statistics* (pp. 111-126). Springer.
2. Bialkowski, J. (2004). Modelling returns on stock indices for western and central european stock exchanges-a Markov switching approach. *www.researchgate.com*.
3. Brooks, C. (2014). *Introductory Econometrics for Finance .* New York: Cambridge University Press.
4. Brook, C. a. (2003). Information Criteria for GARCH Model Selection: An Application to High Frequency Data'. *European Journal of Finance,, 9*(2), 557-580.
5. Cesario Mateus, R. C. (2014). Intraday Industry-Specific Spillover Effect in European Equity Markets. *https://papers.ssrn.com/*, 36.
6. Chitrakalpa Sen, G. C. (2012). *Anatomy of Global Stock Market Crashes.* Kolkate: Springer.
7. Claudio Morana, A. B. (2002). The Effects of the Introduction of the Euro on the Volatility of European Stock Markets. *Journal of Banking & Finance*, 2047-2064.
8. Danialson, J. (2011). *Financial Risk Forecasting: The Theory and Practice of Forecasting Market .* The John Wiley ^ Sons.
9. Ismail Tahir Mohammed., &. I. (2008). Identifying regime shifts in Malaysian stock market returns. *International Research Journal of Finance and Economics,*.
10. Marianna Valentinyi-Endrész. (2004). Structural breaks and financial risk management. *MNB Working Papers, Magyar Nemzeti Bank (Central Bank of Hungary).*
11. Oxford, d. (2020, 12 07). *Oxford Dictionary*. Retrieved from www.dictionary.oxford.org: https://dictionary.cambridge.org/dictionary/english/volatility
12. Perron, J. B. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica* , 47-78.
13. Perron, J. B. (2003). Critical values for multiple structural change tests. *The Econometrics Journal*.
14. Sienko, L. K. (2018). Before-and-after analysis: An application of structural break testing to the determination of economic damages. *ASSA Annual Meeting.* River Falls.
15. Buche, Anish. "Factors Affecting Volatility in Indian Stock Markets." *International Journal of Financial Management (IJFM)* 5.3 (2016): 1-8.
16. Elsegai, Heba. "Collective Behaviour Detection of Stock Markets: Evidence From 2007-2008 CRISIS." International Journal of Applied Mathematics & Statistical Sciences (IJAMSS) 6.5 (2017) 69-80
17. Kottiyattil, Aparna Vijayaraghavan. "A Study on Impact of COVID-19 on Stock Market Indices." *International Journal of Financial Management (IJFM)* 10.1 (2021) 1-14
18. Ramzi, Siagh Ahmed, and Hachemane Mouloud. "Predict Crude Oil Prices in the International Market an Alternative Forecasting Technique." *International Journal of Financial Management (IJFM)* 5.4 (2016): 23-36.
19. Al-Edari, Adnan Dawood M., Adel Salam K. Al-Hashimi, and Hayder Jawad K. Murshedi. "Use the Reduce form Equation to Estimate the Impact of Rice Prices on Indian Markefor Period 1990-2015 (An Econometrics Study)." International Journal of Applied Mathematics & Statistical Sciences (IJAMSS) 5.6 (2016) 91-100
20. Ramdasani, Hitesh N., and B. B. Rayate. "Marketing Through Mobile Phone: The Next Big Thing in India." *International Journal of Sales & Marketing Management (IJSMM)* 6.1 (2017): 1-4.