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SENSITIVITY ANALYSIS USING GARCH MODEL: EVIDENCE FROM INDIAN STOCK MARKET

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Abstract *The sensitivity of a financial market can be assessed by understanding the volatility in the stock returns. Volatility forecasting measures the riskiness of the investments. In a financial time series, there are periods where volatility is higher in comparison to other periods. Furthermore, the volatility in the stock movement tends to increase during economic disturbances such as recessions and financial crises due to compulsive selling and buying of stocks. The aim of the study is to conduct a sensitivity analysis of the Indian Stock Market across time and different frequencies. The S&P BSE 500 index has been selected to study the sensitivity of the Indian stock market as it represents 93% of market capitalisation of 20 major industries of the Indian economy. The daily returns, calculated using the closing value of the selected BSE index for a period of 19 years from 01-02-1999 to 31-08-2018, has been used as the variable for the study. The stationarity of time series data has been assessed using Augmented Dickey fuller test with breakpoints to identify the significant date in the time series. The Augmented Dickey Fuller test suggests that, at level difference, 18th May 2009 is a significant breakpoint date in the daily returns series, which coincides with the report on recession by National Bureau of Economic research. Hence, two time series, one before and one after 18th May 2009 were created. The normality of the two series has been tested using Jarque Bera Test, which suggests that the time series data are not normally distributed. The Autoregressive Conditional Heteroscedasticity (ARCH) model was applied to study the sensitivity of the Indian stock returns. The ARCH LM test highlights the significant existence of ARCH effect in the series before the breakpoint date, yet no ARCH effect was found in the series from 18-05-2009 to 31-8-2018. The results demonstrate that there is a significant decrease in the volatility in the daily returns after the recession period. The results of the study further suggest that volatility in daily returns existed before the period of recession, which was caused due to excessive leverage effect. However, the volatility in the daily returns has significantly reduced. This feature of the stock market movement can be attributed to increased financial literacy among investors and improved prudential norms of Securities Exchange Board of India. Hence, it can be concluded that minor fluctuation no longer cause panic amongst investor as they did before the 2009 market crash.*

Keywords: *GARCH, ARCH effect, S&P BSE 500 Index, Breakpoint Unit Root*

INTRODUCTION

In developing countries, especially India, the financial markets have been the backbone for the development and recapitalisation of resources. Over the past decade, the Indian stock market has seen tremendous increase in the companies listed for trading equity. The number of listed companies on NSE and BSE increased from 6,445 in FY10 to 7,501 in March 2018. The market capitalisation of all the companies listed on the BSE reached a record Rs.150 lakh crores (IBEF, 2018).

Moreover, the stock markets make a significant contribution to economic development as they channelize the capital inflows and foreign direct investments. Thus, the study of the movements of the stock prices across time horizon has become very crucial to understand the factors affecting the fluctuations. With the changing aspirations of the middle income group, there is a quiet revolution taking place in saving and investment pattern among Indian investors. The slow and steady flow of funds from traditional investment avenues such as fixed deposits, real estate, gold and precious metals to other class of assets such as mutual funds, stocks and bonds are becoming a reality. Dominant physical assets such as land and gold have seen a downtrend from 15.5 percent in 2011-2012 to 10.8 percent of savings in 2014-2015. The household savings as a ratio of GDP has fallen from 22 percent to 19 percent (Das and Rebello, 2017). This is evident from the stock market performance between October 2016 and January 2017 after foreign investors had withdrawn Rs. 39,979crores from the Indian equity market (Kapoor, 2017). A few years ago, such a significant withdrawal would have resulted in a market rout. However, the stock market barely saw a dip of one percent in the following four months. This is because as foreign portfolio investors exited Indian market, domestic institutions slipped in to compensate with a matching purchase of Rs. 39,823 crores (Kapoor, 2017). However, the financial crisis of 2007-2008 had a substantial impact on the psyche of investors. Many investors gripped by panic shifted away from risky assets toward safer and more liquid investments. Since, the young adults (Generation Y) have experienced a decade of

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flat and extremely volatile stock market returns followed by a financial crisis resulting in a dramatic drop in stock market value, the financial crisis may have a persistent impact on the risk tolerance and perceptions of this generation Y. Although the recovering economy and improved financial markets may trigger a return to pre-crisis risk appetite and investments, the current investor behaviour of this age group suggests otherwise (Zick et al., 2012).

As, the stock market investments have become more vibrant, so has the volatility associated with the movement of the daily returns. Thus, to gauge the riskiness of an investment, volatility forecasting is paramount. Furthermore, volatility is an important component of portfolio management. With the increasing stock trades, financial analysts have become more concerned with accurate forecasting of the stock prices, which can assist in higher earnings and reduced risk. According to Poon (2005), volatility is the spread of a likely outcome of uncertain variables. Usually, the financial series contains time period where there is higher volatility followed by less volatility, especially during turbulent economic phases such as the financial crisis, oil crisis and recessions. It implies that volatility is the degree of change in the stock prices due to certain events. Thus, the uncertain risk appetite of investors, ever-changing world dynamics and a more prudent involvement of the intermediaries and authorities, have immense impact on the pricing mechanism and movement of the daily stock returns. Although, volatility can be attributed to external and internal factors, yet the final impact can be observed in the erratic movement of the stock market. This study is an attempt to capture the impact of exogenous and endogenous variables on the returns generated through the stock market. It further studies how the impact of these variables has changed over the past 19 years. Thus, the objective of the study is to conduct a sensitivity analysis on the movement of the Indian stock market across time horizon and understand the changing sentiments of the market participants.

THEORETICAL BACKGROUND AND LITERATURE REVIEW

The study intends to understand the sensitivity of the Indian stock market. The theoretical concept of sensitivity can be understood in terms of the magnitude of change in the financial instrument's response due to an underlying factor. The sensitivity of an underlying asset can be a negative or a positive response because of factors, which affect the fluctuations of the stock market. Sensitivity can be judged on micro and macro level. For example, stocks and bonds are theoretically impacted by the interest rate, while at macro level, economic growth, inflation rate etc., can impact the sensitivity of the stock market movements. Furthermore, Sensitivity analysis has two approaches; namely local sensitivity and global sensitivity analysis. The local Sensitivity analysis is based on simple cost functions that depend on analysis of one parameter at a time. However, the global sensitivity analysis entails the use of Monte Carlo Simulation technique and relative sensitivity analysis such as correlation, regression and other econometric models. In other words, sensitivity is a reaction to firm, organisational, national or internationally volatile markets. Thus, volatility is the key to making portfolio or investment strategies as the fluctuations are rapid and significant.

The theoretical concept of volatility in stock returns dates back to Fisher Black's extended theory of 1976, which states that leverage effect has an impact on the volatility in the stock returns. The concept implies that the debt/equity ratio increase with the decrease in the firm's equity holding (other things remaining constant). This inherently increases the riskiness of an investment. The Black (1976) model of Option Price Formula was an extension to the Black Scholes model (1973) model, which was used to measure the volatility of the commodity futures only. The model catered for two adjustments on intercept terms and on the dependency in time of volatility. Although, the model was developed to price the derivatives, yet it provided the base for studying the volatility in the stock returns. Volatility, in itself, is an important forecasting element in the future financial market movement. Moreover, volatility is an indicator of an underlying economic problem. The primary example is the financial crisis of 2009, where the volatility in stock prices served as red flags for an underlying economic recession. It further indicated the slow industrial growth, decrease in the consumption level and declining GDP. Thus, volatility is considered a leading indicator by many policymakers. However, it can stimulate curiosity among researchers and policy maker, alike.

The sensitivity analysis has been undertaken in terms of firm performance, macroeconomic analysis, technical and fundamental analysis. Many researches have been directed towards forecasting the sensitivity of the movement of the stock market, interest rate and exchange rate. Bajaj (2014) conducted a sensitivity analysis to examine the dynamic relationship between stock return and trading volume in response to the changing flow of Foreign Institutional Investments in the Indian stock market. The daily data of S&P CNX Nifty was observed and the study utilised various econometric models such as Granger Causality, Variance Decomposition and Vector Autoregressive models to conclude that the amount of information contributed by stock return is very useful in predicting trade volume. The study further documented serial correlation between trading volume coefficients and its lagged values. Deepak (2015) conducted another sensitivity analysis of the Indian stock market. The researcher examined the anomalies in the Indian stock market to show a 360-degree causal relationship, interlinking one calendar anomaly with the other anomalies. While another researcher, Tessaromatis (2003) studied the sensitivity of stocks in response to the changing nominal and real interest rate. Furthermore, the author studied government regulation, cyclicality of future cash flows and growth versus value characteristics of stocks. As cited above, the sensitivity analysis of the stock market can be studied in numerous aspects. Yet, one such aspect is the study of conditional variance and leverage effect of the sensitive Indian stock market. For this, literature regarding the use of autoregressive conditional heteroscedasticity models to study the volatility has been cited.

The development of GARCH model is often attributed to the lack of conclusive results in movements of the stock market returns. Thus, to measure the leverage effects, various econometric models were proposed. One of the most important models was the Autoregressive Conditional Heteroscedasticity model (ARCH) by Engle (1982) and Generalized ARCH model later called GARCH by Bollerslev (1986). The ARCH/GARCH model is a more advanced technique than the traditional econometric models due to its assumption of conditional variance. The model accommodated the change over the time-period by measuring conditional variance and corrects the stock prices by adjusting the past errors in the form of constant unconditional variance. This model proved to very useful to capture the changing dynamics of business environment, such as the changing inflation rate as constructed by Engle. These models have become popular because these capture the volatility clustering of a financial time series. Franses and Van Dijk (1996) noted that GARCH models provide an appropriate estimate for the long-time varying volatility in the stock markets. Furthermore, a number of studies have attempted to test the Efficient Market Hypothesis using the GARCH models to explain the movements of the stock prices. These studies have repeated attempted to forecast the stock market fluctuations due to the changing factors, external and internal, which make it difficult to predict the stock returns of any financial market. There are several cited studies, which have used ARCH and GARCH models to measure the stock volatility using. Karmakar (2005) used ARCH-GARCH model to capture the volatility in the Indian stock market. The study investigated the leverage effect in the stock market to suggest that GARCH (1, 1) model can make a reasonably appropriate forecast. Furthermore, Karmakar (2007) conducted another study using E-GARCH as a statistical model. He concluded that the conditional variance during the period was asymmetric and established a positive relation between returns and risk.

Floros (2008) used different variants of the GARCH models such as E-GARCH, T-GARCH Component GARCH (C-GARCG) and Asymmetric Component (A-GARCH) to study volatility of daily return of two Middle East stock index; Egyptian CMA index and the Israeli tase-100 index. The study concluded the existence of the leverage effect in the E-GARCH model as the value of coefficients of the model were negative. While, the A-GARCH model established weak transitory leverage effect on the basis of the conditional variance, suggesting an increase in risk may not necessarily increase the returns. Hojatallah Goudarzi (2009) used ARCH model to study the asymmetry in the stock during 2008-2009 financial crisis because of good and bad news on volatility in the BSE 500 index using a data of 10 years. The results of E-GARCH and T-GARCH suggested the need for a well-regulated financial market to avoid volatility. Goudarzi and Ramanarayanan (2010) used various selection criterion such as Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) on BSE 500 index to examine the volalitility in the stock market for a data of 14 years. The researchers suggested GARCG (1, 1) was the most appropriate model for the Indian stock market, which could explain the clustering and mean reverting in the time-period. They further studied the volatility, Goudarzi and Ramanarayanan (2011), using asymmetric models (E-GARCH and T-GARCH) to suggest that E-GARCH (1, 1) and T-GARCH (1, 1) were the most suitable models based on selection criterion.

Mittal, Arora, and Goyal (2012) examined asymmetry in the volatility of the daily returns of the Indian stock market for a period of 10 years from 2000 to 2010. The study has concluded that GARCH and Power-GARCH were the best-fitted model to find the symmetry and asymmetry in the forecasted prices. Singh and Tripathi (2013) have examined the daily closing prices of Nifty index for 15 years from 1st March 2001 to April 2016, to capture the conditional variance and leverage effect. The symmetric and asymmetric GARCH models suggests the existence of relationship between positive and negative shocks. However, the asymmetric negative effect has been observed to be greater than the positive. Vijayalakshmi and Gaur (2013) attempted to forecast volatility in Indian and foreign stock markets, using BSE and NSE returns and exchange rate of Indian Rupee via foreign currency from 2000 to 2013. They utilised eight variants of GARCH models to find that TARCH AND PARCH are better at forecasting volatility. While for the foreign markets, ARMA (1, 1) and ARCH (5) made appropriate forecast.

Srikanth (2014) measured asymmetry in volatility using GJR-TGARCH and PGARCH models to suggest that shocks due to negative news has more effect on the conditional variance than the positive news (GJR-TGARCH). Sahu and Kumari (2018) estimated the volatility in twelve BSE indices. They studied the volatility clustering using variants of the ARCH models such as ARCH, GARCH, IGARCH, GARCH-M, EGARCH, TARCH, GJR TARCH, SAARCH, PARCH, NARCH, NARCHK, APARCH, and NPARCH. The results suggest the presence of an ARCH effect in BSE OIL, which in turn affected the other selected indices. The study further highlights that due to difference in the prices of real estate in different locations, the volatility clustering is present. The study also establishes the dominance of BSEBANK and SPBSEIT as important indicators of the BSE stock market. In most of the Indian research work the volatility has been modelled using GARCH models. It has further been suggested that GARCH (1, 1) is the most effective model to capture the symmetry in volatility and the leverage effect. While, some other variants of EGARCH and PGARCH have also been found effective to examine volatility.

However, these studies fail to incorporate the essence of structural breaks in the time series. A time series is a series of random values for a particular time-period, making it difficult to predict the future movement of any variable. This randomness of the times series results in significant changes in the structure of the series. These structural changes may alter the stationarity of the series. Thus, by incorporating non-stationary or unit root variables while estimating the regression equations using OLS method, the inferences could be misleading. Many methods have been proposed to study the structural breaks in the time series. Researchers have suggested the modelling the time series to having their own distribution at given intervals based on the likelihood function which could identify the change point (Ozaki and Tong, 1975). However, modern researchers, Starica and Granger (2005), proposed the use of goodness of fit to detect the structural break. Perron (1989) made an important contribution by demonstrating how the failure to accommodate an existing break could lead to a false rejection of the unit root hypothesis. Since the presence unit root was tested using Augmented Dickey-Fuller (1979) test, Perron proposed the addition of an exogenous structural break in the Augmented Dickey-Fuller test. This development further evolved, when Zivot and Andrews (1992) and Perron (1997) proposed the determining of the break point 'endogenously' in the time series. For a time series whose structure may change over time, it is important to fit the model to a non stationary series by breaking it into locally stationary series. Thus, the previous researches have not analysed the volatility using structural breaks. This study is an attempt to understand how conditional variance of the altered structure of the time series affects the sensitivity of the Indian Stock market.

RESEARCH METHODOLOGY

This study attempts to examine the stock movement of Indian stock market. The S&P BSE 500 index has been selected for sensitivity analysis of the Indian stock market. The S&P BSE 500 index has been designed to represent 93% of market capitalisation and it covers all major industries in the Indian Economy. Moreover, the calculation methodology of BSE Free- float, which adapts to the changing pattern of the economy. The variable used for the study are the daily returns calculated using the closing value of the selected BSE index for a period of 19 years from 01-02-1999 to 31-08-2018. The daily closing prices has been selected for the study as it sets the tone of the opening prices of the next trading day. Moreover, it causes panic selling and panic buying in the stock market, which has a direct impact on the volatility in the market.

The stationarity of time series data will be assessed using Augmented Dickey fuller test with breakpoints unit root test. Furthermore, the normality of the time series is required to be tested using Jarque Bera Test. The Autoregressive Conditional Heteroscedasticity (ARCH) model and General Autoregressive Conditional Heteroscedasticity (GARCH) tests have been used to measure and study the volatility dynamics in the financial literature. In GARCH models, the model calculates current conditional variance, which is dependent on lags of its previous variance. However, the models have limitations as they have a symmetric response to both positive and negative volatility shocks.

RESULTS AND ANALYSIS

Diagnostic Analysis

The study of the stock market begins with the critical analysis of the daily returns of closing value of S&P BSE 500. Figure 1 depicts how the movements of the daily returns from the selected index is both positive and negative.

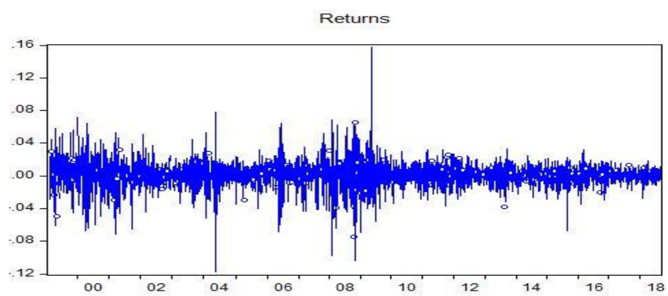

Fig. 1: Daily Returns from S&P BSE 500 Index

It can be observed that before the year 2009, the returns were more volatile. It can be further be noted that the larger fluctuations cluster together after a period of small fluctuations. Fama (1990) not exhibits by periods of calmness. This is the general norm with stock returns. Fama (1990) observed that volatility clustering exhibits fluctuations in the stock returns. Fig. 1 plots the daily stock returns of the S&P BSE 500 to suggest that volatility clustering was the highest till date during the recession period of 2008-2009 from 1999-2018.

Unit Root Test

The time series was subject to a stationarity test and Augmented Dickey Fuller (ADF) test was used to study the breakpoints in the time series. Table 1 depicts the results of the breakpoint point unit root test. The ADF test statistics rejects the null hypothesis that there exists of a unit root in the return data series. The ADF t-statistic is less than the critical values at all three significance levels of significance suggesting that the time series is stationary. Using the Schwarz information criteria and Dickey Fuller T-Statistics suggesting that 18th May, 2009 is a significant break date from 1999-2018.

Table 1: Results from Breakpoint Unit Root Analysis

Significant Date	**18/05/2009**	**Probability**
Augmented Dickey-Fuller t statistics	**-63.31847**	**<0.01**
1% Level	-4.949133	
5% Level	-4.443649	
10% Level	-4.193627	

Source: Author's Own Calculations

Fig. 2 depicts the results of the T-Statistics and Autoregressive coefficient of the daily returns, which represents the statistically significant breakpoint in the time series. Thus, the analysis of the movements of the daily stock returns time series has been divided into two time series; a) 1st February 1999- 18th May, 2009 b) 18th May, 2009 – 31st August, 2018.

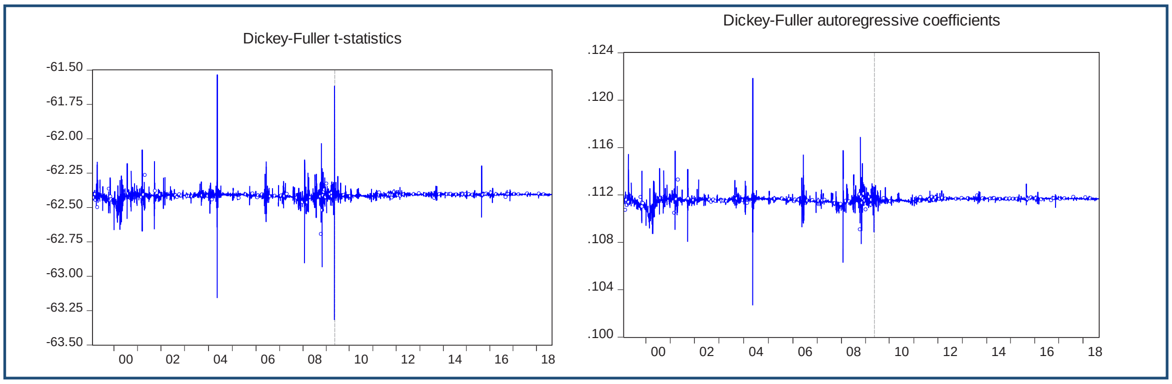

Fig. 2: Dickey- Fuller T-statistics and Autoregressive Coefficient Graphs

Normality Test

The times series created for the analysis were tested for normality using Jarque-Beratest. Fig. 3 and 4 depicts the results for the Normality Tests for the period preceding the break date. Furthermore, the figures show the descriptive statistics for the stock returns for the time period under study. It can be noted that both time series preceding and succeeding the breakpoint date of 18th May, 2009 exhibit negatively skewed statistics, indicating that the returns are not symmetric and the distribution is left tailed.

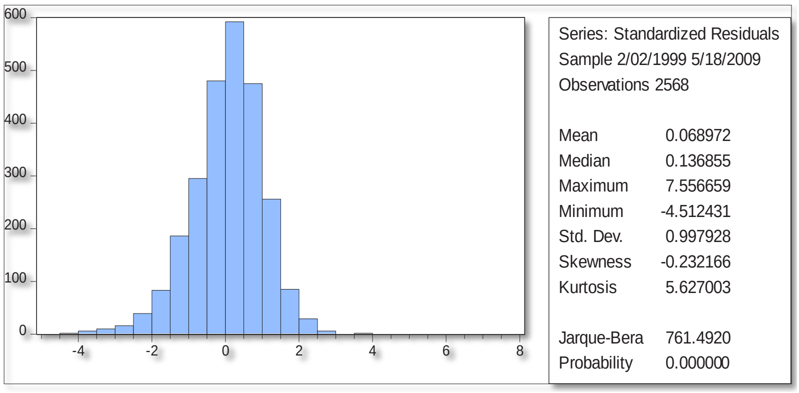

Fig. 3: Normality Test Results for the Time Series: 2nd February 1999- 18th May 2009

The kurtosis of the first and second sample period is 5.627 and 4.868, which is over 3, suggesting that the time series data is heavily tailed and peaked in comparison to a normal distribution. In Fig. 3, the descriptive statistics show that the sample from 2/2/1999-18/5/2009 has an average return of .068% while maximum returns were 7.55% on a particular day. In Fig. 4, the study period after 18th May, 2009 shows an average return of -.03% and maximum return of 4.24%. Thus, it can be concluded that despite an increase in the volume of trade, market players have become more prudent and cautious while investing and taking risk in the stock market.

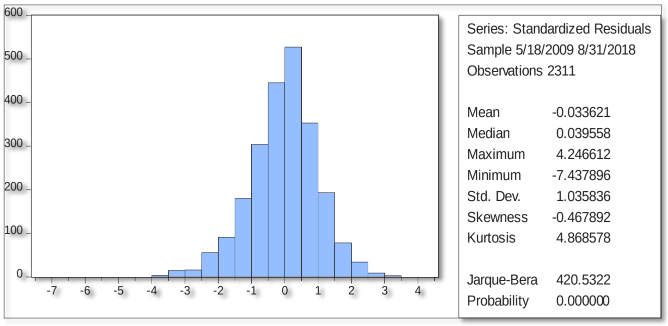

Fig. 4: Normality Test Results for the Time Series: 18th May, 2009-31st August, 2018

Standard deviation as a measure of volatility shows that there is negligible difference between both the sample I and sample II, .9979% and 1.0358% respectively. It can be inferred that time period, before and after 18th May, 2009, had similar volatility percentage. The Jarque-Bera statistics is way the observed value, thus, rejecting the assumption of normality. It further confirms that the stock returns do not follow above the normal distributed or skewed.

ARCH Test Results

The ARCH test has been applied to detect the presence of ARCH in the time series data. From table 2, it can be observed that before the breakpoint date of 18-05-2009, the F-Statistics and LM-Statistic are statistically significant, suggesting the presence of ARCH in sample I. Whereas in sample II, period after 18-05-2009, the ARCH effect is not present as the F-statistics and LM test are insignificant. Table 2 reflects the results of the LM ARCH test.

Table 2: Results of ARCH LM Test

	Sample I	Sample II
ARCH LM Test	10.98160	0.874056
Prob. Chi-square	0.0009	0.3499
F-Statistics	11.02019	0.874482
Prob. (F-Stat)	0.0009	0.3497

Source: Author's Own Calculations

GARCH Results

The volatility and the leverage effect of the time series data has been fitted in GARCH (1, 1) model. Since, the ARCH effect is present in one sample (sample I) and non-existent in the other (sample II). Thus, the Log (Variance) has been included in the mean equation. The Presample variance was backcasting with smoothing parameter $\lambda = 0.7$. Using the iterative algorithm for non-linear optimisation, Broyden–Fletcher-Goldfarb-Shanno (BFGS) method GARCH model was applied. Table 3 shows the results of the model for Sample I, which included 2568 observations, and Sample II, which included 2311 observations. The following is the GARCH Equation for the model:

GARCH Equation = C (2)*RESID(-1)^2 +(1-C(2))*GARCH(-1)

The coefficients on both the lagged squared residual and lagged conditional variance in the Variance Equation are highly statistically significant in both before and after time-period. It can be observed from Table 3 that the sum of the ARCH and GARCH ($\alpha+\beta$) coefficients of both the Sample I and Sample II are close to one, that is, 0.90999 and 0.99999 respectively. The results show that the volatility shocks are persistent despite the difference over the time horizon. This implies that larger positive and negative returns, larger is the variance in the long run. Therefore, the GARCH model implies that conditional volatility is consistent in both time-periods, which will take a longer duration to correct the course of the stock market movement.

Table 3: GARCH (1, 1) Results

Variable	Sample I			Sample II		
	Coefficient	Z-Stats	Prob.	Coefficient	Z-Stats	Prob.
Mean Equation						
LOG (GARCH)	-0.000146	-8.1248	0.000	-7.46	-4.88961	0.000
Variance Equation						
RESID (-1)^2 (α)	0.097721	24.5120	0.000	0.07474	13.4802	0.000

Variable	Sample I			Sample II		
	Coefficient	Z-Stats	Prob.	Coefficient	Z-Stats	Prob.
GARCH (-1)(β)	0.902279	226.323	0.000	0.92525	166.872	0.000
(α+ β)	0.90999			0.99999		
R-squared	-0.000129			-0.001020		
Adjusted R –squared	-0.000129			-0.001020		
Log Likelihood	7017.004			7477.451		
Durbin Watson	1.736437			1.736186		

As shown in table 3, β sample I and sample II are .902279 and 0.92525 respectively, which suggests that the time volatility after 18-05-2018 has increased slightly. This variable can be attributed to the increased volume of trade and increasing participation of the retail and foreign investors. Furthermore, it can interpreted that past news (β) has more influence on the current scenario as compared to before. Yet, a the value error coefficient (α) is lower in sample II, suggesting that after the recession, the Indian stock market sudden movements induce relatively lesser volatility. In other words, the ability to adapt to any sudden change has improved after recession.

Conditional Variance Analysis

Conditional Variance was the significant improvement in the conventional time series econometric models, which assumed constant variance. With the development of the ARCH GARCH models, the changing financial scenario could be captured. Conditional Variance is a variance in a probability distribution. In ARCH GARCH, the past errors are considered to be unconditional (constant) values.

Figures 4 (a) and 4 (b) depict the conditional variance of period before and after the breakpoint date of 18-05-2009. As shown in the graph, the conditional variance from 1999 to 2009, shows significant large variance as suggested by the ARCH LM test. The highest volatility clustering can be observed from 2006-2009. Thus, it was an underlying signal to an unprecedented economic problem of a financial recession. While after the recession, it can be observed that the volatility clustering almost negligible as depicted by the ARCH LM Test, yet some spike can be observed in 2013 and 2015. This can be attributed to correctional pricing of the Indian stock prices. Any change in the prices, which is more than 30-40%, is considered an economic crash, while minor changes in the prices are regarded as the correctional pricing.

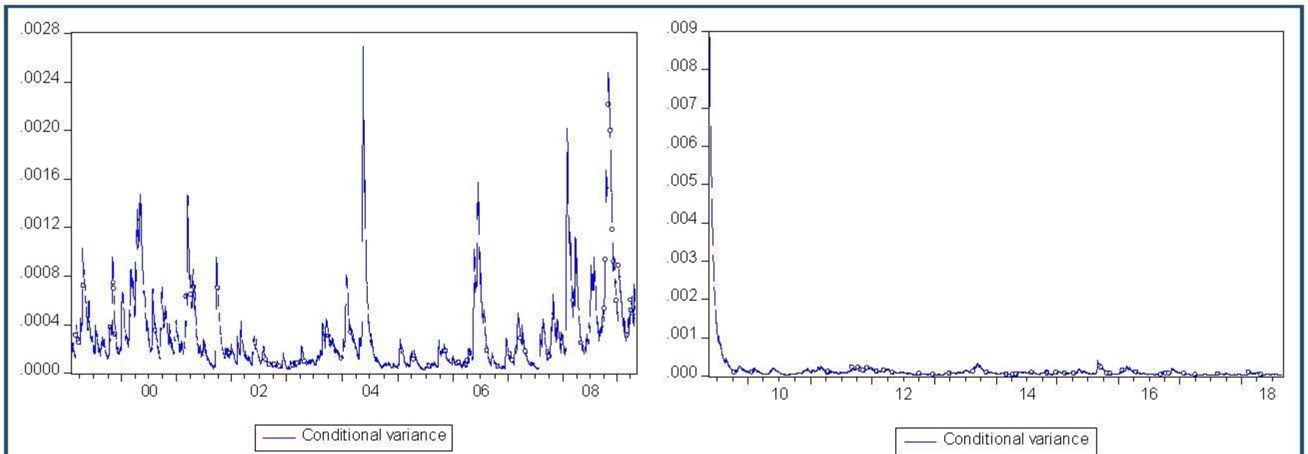

Figure 4 (a): Conditional Variance of Sample I

Figure 4 (b): Conditional Variance of Sample II

Residual Analysis

Figures 5 (a) and (b) are the graphical presentation of the coefficients of residuals (α), which is error correction value of the GARCH model. As the results of the GARCH (1, 1) model show that Sample I has a higher α (.0977) than sample II (.0747). The results suggest that before 2009, the ability to adapt to sudden financial shocks was less in comparison to the 2010-2018. Thus, the immediate correction of the prices has averted another financial crisis.

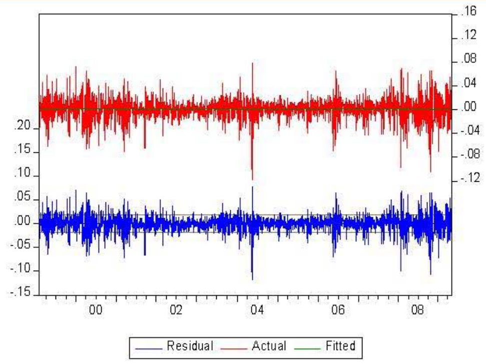

Figure 5 (a): Residuals of Sample I

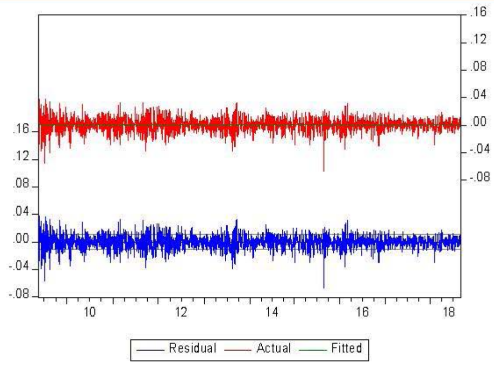

Figure 5 (b): Residuals of Sample II

This change in the reaction to the sudden changes in the stock movements can be assigned to two developments. Firstly, before 2009, there was high degree of information asymmetry, which has been reduced with active role of Security Exchange Board of India. The misinformation or rumours about the stock market movement created a mayhem among the investors. Secondly, the awareness of the retail investors, use of better technical econometric models and the experience of the financial intermediaries has improved the ability of the stock market to adapt to changes.

CONCLUSION

The Indian Stock market has played an important role in the development of the country's economy. Furthermore, the volume of trade of the stock market has been increasing. Thus, the stake to predict the volatility in the stock market are higher than ever. Although there are a number of factors, which affect the fluctuations, some important factors are economic condition, global markets, fluctuating oil prices, stages of business cycle volatility and operating leverage of firms. This objective of the study is to conduct a time and frequency analysis of the Indian Stock market to assess its sensitivity. For this purpose, returns from daily closing value of S&P BSE 500 index has been taken as a proxy to study the Indian Stock market as it includes major industries.

When a study is conducted for a long period of time, it is expected to have some breakpoints in the time series data. Thus, a breakpoint unit root test was conducted to suggest that 18-05-2009 is a significant breakpoint for the time-period ranging from 01-02-1999 to 31-08-2018. Thus, the data was used to develop two time series to analyse the before and after effect of volatility. The study provided some valuable empirical evidence of volatility clustering and leverage effect. The results of the GARCH (1, 1) model suggested that the volatility in the present market conditions is more than the year 2006-2009. Yet, the response to the sudden internal and external factors is much better than before, as suggested by the error correction value. Moreover, the conditional variance showed high volatility clustering from 2006-2009. The volatility clustering of such an extent should have been an indicator of an indefinite economic crisis. However, after 2009, results suggest the reduced ARCH effect due to correctional changes in the prices. This has averted the start of another financial crisis. The results also suggest that GARCH (1, 1) is an appropriate model for analysing the Indian stock market. The study has certain limitation as more variants of the GARCH model could be applied to improve the fitting of the model. The study concludes that despite the increase in the volatility in the present scenario, the active participation of SEBI, experienced financial intermediaries and more financially literate investor, the focus is more on the long- term investment strategies, which does not let an investor exit the market due to short-term fluctuations. Although there is requirement of more awareness among the investors, yet the faith of the investors in the financial market has significantly improved.

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