iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 **Issue:** VI **Month of publication:** June 2023

DOI: https://doi.org/10.22214/ijraset.2023.53957

Analysing Volatility Dynamics of India and US Stock Market

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Abstract: Analysing the risk-return trade-off of financial assets, volatility is a key factor. Volatility promotes market liquidity and demonstrates the effectiveness of the financial system. To have an insights of India And US Market Volatility behaviour, this paper examines the volatility dynamics of India And US Stock market by taking Sensex And S & P 500 daily closing prices for the 2nd January 2003 to 31st December 2019. The authors have two questions to examine about volatility whether India and US stock market volatility shows volatility clustering and volatility persistence or not. ARCH LM test and Ljung Box Q^2 statistics were used to check for volatility clustering. And for volatility persistence GARCH (1,1) model is used. The results of the study confirm the presence of volatility clustering in in both India And US stock market. Additionally, Indian stock return volatility shows lower volatility persistence than US. The results of the study are quite useful for the academicians, policy makers and investor community in general.

Keywords: Volatility clustering, Volatility persistence, Indian stock market, US.

I. INTRODUCTION

Anything that is mutable or variable can be generically characterized as volatile. Volatility may be characterized as the variable's ability to change; the more the variable changes over time, the more volatile the variable is considered to be. Volatility is linked to irrationality, danger, and unpredictability. Since the word is viewed as being synonymous with risk by the general public, excessive volatility is seen as a sign of market disruption, in which securities are not being priced appropriately and the capital market is not operating as it should. Everyone active in the financial markets, where volatility is more commonly thought of as unpredictability, places a great deal of significance on it (Daly, 2008). The financial system's ability to operate smoothly can be harmed by excessive volatility, which can occasionally plunge an economy into disaster. In academia, there has been ongoing discussion on whether volatility changes through time or remains constant. Numerous studies have established the time-varying nature of volatility as well as some stylized facts, such as volatility clustering, leptokurtic distribution of returns, and leverage effect. These studies include (Babikir et al., 2012; Bhar & Nikolova, 2009; Mukherjee & Mishra, 2010). The variance or standard deviation is a typical way to quantify risk. To test for the stylized facts of the volatility ARCH model was developed by Engle which describe conditional volatility on its lagged squared error terms. However, determination of adequate lags for the model is cumbersome. To generalize this GARCH model was developed that becomes highly usable for estimating volatility. Studies modelling the volatility are scanty for Indian stock market. Therefore, to fulfill this gap, this paper examines the volatility dynamics of Indian stock market with GARCH (1,1) model. The results of study confirms the presence of stylized facts of volatility in Indian and US market. The rest of the paper is organized as follows : section 2 reviews the existing literature followed by section 3 puts the research question for the study. The next section 4 describes the research design. Thereafter, section 5 discusses empirical results of the study. And last section concludes the paper.

II. LITERATURE REVIEW

An increase in volatility is harmful to risk-averse investors and business houses (SCHWERT, 1989). Investors should learn how to ride the stock market's roller coaster as volatility is one of its intrinsic characteristics (Natarajan et al., 2014). Several studies have been conducted to analyze the various stylized facts of volatility, such as volatility clustering, persistence, asymmetric volatility, and risk-return trade off, in light of the relative importance of volatility and in order to provide adequate knowledge of the volatility behavior of stock markets. Various studies have been conducted to study the volatility dynamics of various stock markets. By using daily stock prices for the years 2001 to 2016, Islam and Hussain (2018) seek to characterize several features of volatility, such as volatility clustering, persistence, and leverage effects in the Indian and Chinese markets. Both the GARCH (1,1) and TGARCH (1,1) models have been used to analyze the impacts of leverage. The findings showed that both markets exhibit volatility clustering and the leverage effect, which suggests that the market's investors are risk averse.

Horpestad et al. (2018)used daily data from the period of January 3, 2000 to June 22, 2018, to observe the stylized fact of the asymmetric volatility effect, which states that the volatility is high when the prices started declining, in 19 equity indices from North America, Europe, Asia, and Australia. E-GARCH (1,1), GJRGARCH (1,1), GARCH (1,1), and LOG-GARCH are examples of GARCH class models (1,1). The findings suggest that asymmetric volatility was present in all of the examined markets, although it is more pronounced in the US and some European nations.

For the years 2009 to 2018, Waqar et al. (2019) examined the volatility clustering and asymmetry behaviour of volatility series in eight Asian developing markets: China, Hong Kong, India, Malaysia, Pakistan, Singapore, South Korea, and Taiwan. For this, symmetric GARCH, asymmetric EGARCH, and GJR- GARCH have all been employed. The findings support the notion that all Asian markets exhibit clustering of volatility and asymmetric behaviour. Using GARCH (1,1) and GJR-GARCH (1,1) models, Herbert et al. (2019) investigated the phenomena of volatility clustering and leverage impact in the stock returns of the Nigerian Stock Market over the time period spanning from January 2010 to August 2016. The results confirmed the existence of volatility clustering and its persistence in the returns on Nigerian stocks. Additionally, the findings reveal that asymmetric volatility is present in Nigerian stock return volatility.

On the basis of related reviewed literature, it can be said that volatility and its various aspects such as Volatility clustering, persistence, asymmetric volatility and risk return trade off etc., have always been the centre of attention among researchers, academicians, investors, stock traders and market regulators. Various studies have been conducted so far to understand the volatility behaviour of developed and developing nations (Horpestad et al., 2018; Mallikarjuna & Rao, 2019). However, studies in context of Indian along with US stock market volatility are scanty. Indian market has shown dramatic growth in recent years. It has become attraction of international investors, traders and fund managers so it become imperative to understand the nature of Indian stock market so they can get a glimpse of Indian and US market volatility.

III. RESEARCH QUESTION

Q.1 Does India and US Stock Market Shows volatility clustering?

Q.2 Does Innovations in India and US Stock Market Volatility persist over time?

IV. RESEARCH DESIGN

A. Data

The data for the study comprises 4434 daily closing prices of S&P BSE SENSEX and S&P 500 representing stock market activities for India and US respectively from 2_{nd} January 2003 to 31_{th} December 2019. The dates on which the stock market remained closed the closing price from previous day is taken. The Data has been taken from investing.com website.

B. Research Methodology

Daily log returns have been calculated by taking the log differences of the daily closing prices as follows:

$$r = log\ (Pt/Pt{-}t1)$$

We have examined the returns of the SENSEX via descriptive statistics, such as mean, standard deviation, skewness, kurtosis, and normalcy. These will offer information on the qualities of the examples and suggestions for using proper models for volatility. The Augmented Dickey Fuller (ADF) tests, as well as Phillips-Perron (PP) tests, have been used to examine the return series' stationarity. According to these two tests, the data is not steady.

Modelling volatility via GARCH model depends on the presence of ARCH effect and autocorrelation in the residuals of returns. For this purpose, first of all ARCH LM test at 1s and 5^{th} lag has been performed. After that lung box Q^2 statistics is also checked to know the autocorrelation in the squared residuals.

The conditional volatility for returns on Indian market has been modelled using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model proposed by Bollerslev in 1986. The conditional volatility can be a function of the squared forecast error from the previous period and its own lag when using the GARCH (1, 1) model. The mean equation and the variance equation, which make up the model's two components, may be written as follows:

Mean equation: $r_t = \mu + r_{t-1} + e_t$

Variance Equation : $h_t = \ \omega + \alpha\varepsilon_t{}^2{}_{-1} + \beta h_t{}^2{}_{-1}$; $\varepsilon_t = Z_t\sqrt{h_t}\ \ wh_{ereZ_t} \approx N(0, \sigma_t{}^2)$ Here, r_t is the return of stock index at time t, μ is the average return, r_{t-1} is previous lag return, ε_t is the error term, h_t is the conditional variance at time t, and h_{t-1} is the lagged volatility. Also, ω > 0, α ≥ 0 and β ≥, since volatility cannot be negative.

The GARCH (1, 1) model contains two terms. The ARCH (α) term represents the impact of previous period shock on error variance while as the GARCH (β) term represents the effect of yesterday's volatility viz-a-viz past shocks on today's volatility (Brooks, 2008). The (α+β) parameter shows the persistence of volatility that is the rate at which volatility decays over time. For the GARCH model to be meaningful, the (α+β) should be ≤ 1. If α+β = 1, it is said to be an explosive process which means the impact of shock will never die down and thus volatility is highly persistent. The value of (α+β) > 1 is meaningless in practice as it implies that the impact of news will never decay rather will amplify with time.

The presence of ARCH effects has been examined in the residuals of the volatility models for the Indian market. For residual diagnostics, the Ljung-Box Q2 (12 lags) and ARCH-LM tests (1 and 5 lags) have been employed.

V. RESULTS

A. *Descriptive Statistics*

Table 1 summarises the descriptive data of daily returns on the SENSEX and SSE Index for the sample period. Indian markets have shown comparatively positive and high average returns than US, it means India offers better average returns to their investors. This also suggests that stock index prices have increased over the study period. The negative skewness emphasises the likelihood of obtaining returns that are higher than average. Leptokurtic returns are those where the value of kurtosis is larger than 3.

The return series are not routinely disseminated, as seen by this. The Jarque-Bera statistics at the 1% level of significance have further disproved the premise of normality.

Table 1: Descriptive Statistics of Daily Returns from January 2003 to December 2019

Statistic	Sensex Returns	S& P 500 Returns
Mean	0.000564	0.000286
Median	0.000237	0.000397
Maximum	0.159900	0.109572
Minimum	-0.118092	-0.094695
Std. Dev.	0.013427	0.011123
Skewness	-0.079919	-0.366294
Kurtosis	13.84275	15.17359
Jarque-Bera	21724.88*	27472.21
Probability	0.000000	0.000000
Observations	4434	4433
Lung box Q^2 stat (12 lags)	1332.2*	
ARCH LM(1)	181.4946*	178.4734*
ARCH LM (5)	397.4398*	1099.658*

Source: Authors' own calculation using Eviews 9 software.

Note: * denotes significance at 5% level

B. *Volatility Clustering*

The daily returns of the S&P BSE SENSEX and S & P 500 Index from January 2 are depicted in Figures 1 and 2. from 2001 until December 30, 2019. It is obvious to observe that that there are times of extreme (very low) volatility periods of high (low) volatility, which is a sign of the volatility clustering phenomena. The Volatility Clustering has been quantitatively evaluated using data from Ljung-Box Q^2, which displays the first order squared return autocorrelation Table 1 displays the. Ljung-Box statistical findings. It can be observed that the squared returns are found significantly autocorrelated at a 12-lag interval. Additionally, this attests to the existence of volatility clustering. Finally, we used the ARCH-LM test at 1 and 5 lags to determine if the ARCH effect was present in the return series residuals. The test's outcomes are displayed in Table 1 of the report. At a 5% level of significance, the null hypothesis "no ARCH impact" may be ruled out in both scenarios. This leads us to the conclusion that volatility clustering, a need for modelling conditional volatility, is present in the returns of the SENSEX and US indexes and is heteroscedastic.

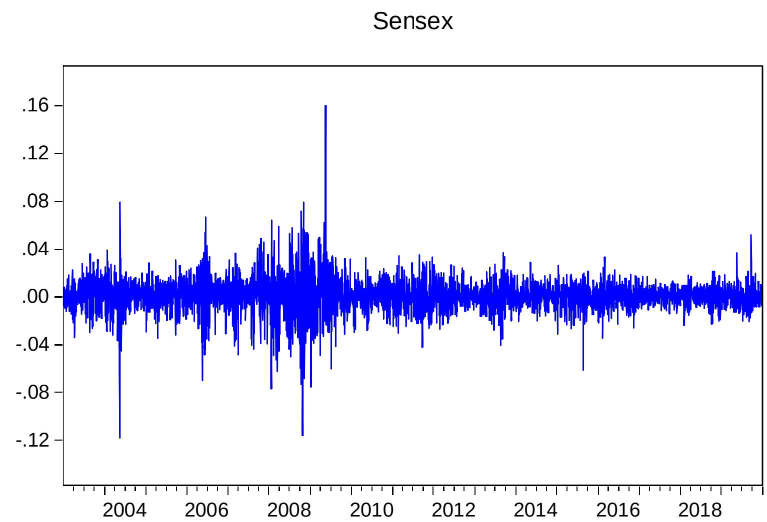

Fig. 1: Volatility Clustering of Daily Returns of SENSEX

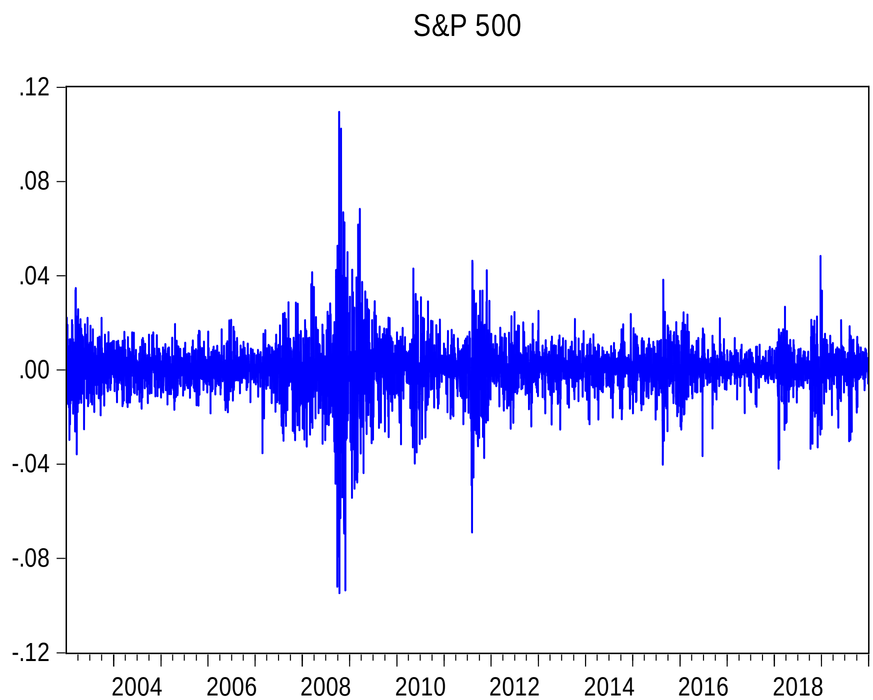

Fig. 2: Volatility Clustering of Daily Returns of S & P 500

Table 2 displays the outcomes of the GARCH (1,1) model for the SENSEX and S & P 500. According to the mean model's results, the average returns of both indices are positive and statistically significant at the 5% level of significance. Also, significant AR (1) term shows that today returns can be predicted to some extent with previous data prices, however, US past returns negatively affect today’s price. Additionally, all of the coefficients in the variance equation are positive, satisfying the simple GARCH model's nonnegativity criterion. It has been determined that the ARCH coefficient (α) is determined to be higher for both SENSEX and S & P 500. This indicates that the volatility of both markets is more susceptible to fresh shocks. The GARCH term (β) is considerable and larger than the ARCH (α) term, indicating that volatility is more sensitive to its one-period lag than any fresh market surprise. The sum of ($\alpha+\beta$) parameter is (0.990539) for India and 0.996679 for US approaches to 1 which is quite high. The results reveal that volatility shows persistence but degree varies for both markets. US showed higher volatility persistence than India. It means once a shock hit the market, it affects the volatility for a longer time period.

Table 2: Estimated Result for GARCH (1,1) Model

Coefficients	Sensex	S & P 500
Mean Equation		
Constant(c)	0.000880* (0.000145)	0.000753 (9.54E-05)
AR(1)	0.059140* (0.015698)	0.060851*(0.015905)
Variance Equation		
C	1.81E-06 (4.12E-07)	1.21E-06* (2.73E-07)
α	0.084492* (0.008916)	0.111952* (0.011729)
β	0.906047* (0.009077)	0.884727* (0.010670)
$\alpha+\beta$	0.990539	0.996679
Diagnostics Statistics		
Q2	16.299	14.6630.359678
ARCH LM test (1 lag)	0.354780	0.359678
ARCH LM test (5 lag)	3.751879	3.453644

Source : Eviews output estimation

Note: * significant at 5 % level of significance.

The Ljung-Box and ARCH-LM tests were used to perform diagnostic analysis on the residuals of the GARCH (1, 1) model. The findings indicate that there was no ARCH impact in the residuals and that the squared returns were not autocorrelated at 12 lags. This suggests that both markets' variance equations are well-defined.

VI. CONCLUSION

When analysing the risk-return trade-off of financial assets, volatility is a key factor. Volatility promotes market liquidity and demonstrates the effectiveness of the financial system. To have an insights of India and US Market Volatility behaviour, this paper analysis the volatility dynamics of both countries by taking Sensex and S & P 500 daily closing prices for the 2nd January 2003 to 31st December 2019. The authors have two questions to examine about volatility whether Indian And US stock market volatility shows volatility clustering and volatility persistence or not. The results of the study confirm the presence of volatility clustering in Indian as well as US stock market. Additionally, Indian stock return volatility shows lower volatility persistence than US. The results of the study are quite useful for the academicians, policy makers and investor community in general.

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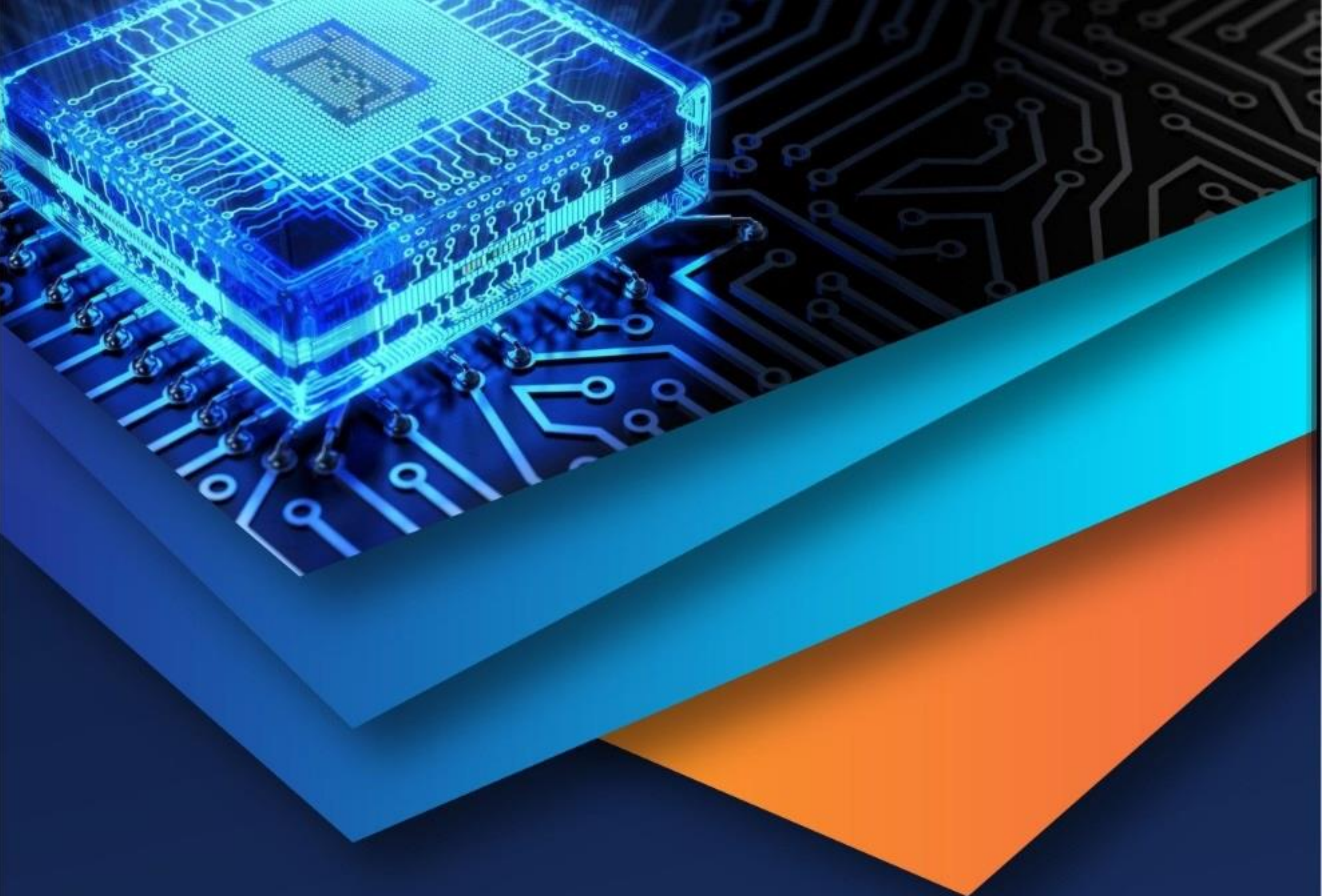

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