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Article

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Does index options trading destabilize Indian stock market volatility: an application of ARCH and GARCH models

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ABSTRACT

Many investors and financial managers are interested in derivatives, which are financial instruments that derive their value from an underlying asset. These instruments have become popular due to their low initial requirements for futures trading and the need to pay premiums for options. The aim of this research, then, was to examine how the inclusion of Nifty index options impacts underlying market volatility using ARCH and GARCH models. The data set used in this study consists of 5996 time-series observations of NSE Nifty index closing prices. Here, the observations span from November 7, 1994, to December 31, 2018. Of these, 1622 observations are from the period before the introduction of options trading, while the remaining 4374 observations are from the period after the introduction of options trading. To determine the robustness of the study, the ARCH family has been chosen in order to capture the volatility behaviour and accommodate for heteroscedasticity in the returns. The coefficient's negative sign suggests that the introduction of index options has a stabilised effect on underlying market volatility, even when taking into account structural breaks.

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1. Introduction

The Indian stock market has experienced significant shifts and structural changes due to various initiatives undertaken by the Indian government since 1991, the consequences of policies of 'liberalisation', 'privatisation', and 'globalisation', and consequential reforms in the financial sector (Jacob, 2017). The impact of options trading on stock market volatility has changed significantly since its inception in the 1970s.

Many studies demonstrate that futures trading reduces spot market volatility by adding more information to the price formation process, improving the efficiency of price discovery, eliminating information asymmetry, integrating sophisticated risk management systems, and boosting profits by minimising risk (Wu et al., 2022). Such a phenomenon is most prevalent at times of high market volatility, such as the global financial crisis during 2007–2009 and the U.S. stock market crash in 1987. Moreover, derivatives' introduction into the Indian stock market results in volatility behaviour, as derivatives open prominent avenues for speculation and hedging, which give rise to price instability and exaggerate the underlying market volatility (Nair, 2008). On the other hand, an immense number of investors and financial managers observe derivatives as highly captive by virtue of negligible initial requirements with the clearing house for futures, payment of premiums in the case of options, and shallow transaction costs when contrasted with cash market assets (Sahu, 2012).

Over the past few decades, academics and industry professionals have had immense interest in the economic effect of the Nefty index derivatives on volatility in the stock market because there is no convincing empirical evidence that indicates the index option causes volatility to fluctuate (Debasish & Das,

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2009). This raises important questions among financial managers, researchers, academics, and investors about the impact of index derivatives on the volatility of the underlying market (Ausloos et al., 2020). In fact, most earlier studies have shown that volatility might decrease or have a stabilised impact after the introduction of index futures (Antoniou et al., 2005; Chau, 2007).

A lengthy discussion has surrounded the establishment of an option market, in particular how options affect the volatility of the stock market. The impact of options trading on the volatility of the underlying stock market remains inconclusive. This unresolved question necessitates a precise evaluation to determine the impact of options trading on stock market volatility. The aim of this study was to assess the impact of option introductions on stock market volatility during the pre- and post-introduction phases. We also assessed the impact of options trading with structural breaks on stock market volatility. The reason is that ignorance of structural breaks would lead to overstated or spurred results (Arouri et al., 2012). Additionally, Singh and Kansal (2010) and Gakhar (2015) provide examples of previous research that examined how future trading affects the underlying spot market. As Sinha (2015) and Joshi (2018) highlight, there aren't many studies looking into how options trading affects spot market volatility. Therefore, as 'GARCH models link information (news) to volatility' (Satchell, 2016), a detailed exploration of the relationship between volatility and information (news) is necessary.

2. Literature review

Over the last few decades, the financial literature has devoted a great deal of study and documentation to the effects of derivatives trading on the underlying stock markets. The effect of options trading on the return volatility of the underlying stocks has been the subject of numerous studies.

2.1. Empirical research conducted in the global market

Pericli and Koutmos (1997) identified a decline in the long-term volatility of the 'S&P 500 index' following futures and option trading. Chatrath et al. (1995) conducted an analysis on the impact of option trading on 'OEX' by employing a VAR model and found a decreasing trend in the cash market's volatility. Pilar and Rafael (2002) discovered a conditional decrease in the volatility of the underlying index after the derivatives market commenced; however, the volume and liquidity of Ibex-35 increased significantly, probably enhancing their efficiency. Fong and Han (2015) investigated the impact of the 'Hang Seng Index (HSI)' and options on the stock market's fluctuation and indicated that the inception of the futures market diminishes the underlying market fluctuation, and this decrease persists as the market matures. Jongadsayakul (2023) on the SET50 index in Thailand also found that the introduction of derivative products can decrease stock market fluctuation.

By contrast, the results for options markets suggest the opposite. Siopis and Lyrouti (2007) and Sariannidis and Drimbetas (2008) studied how 'FTSE/ASE 20 index' futures and options affect the volatility of the Greek market for multiple stocks. The analysis indicated that the underlying market volatility of the 'FTSE/ASE-20 Index' diminished because the dummy variable's coefficient was negative. Becchetti and Caggese (2000) explored the influence of index options on six European countries (Austrian, French, Swiss, UK, Germany, and Dutch) using nine distinctive models. According to the empirical findings, the options market increased the volatility of the German market, but a decreasing trend was found in the Dutch market; however, it did not affect the other four markets.

2.2. Empirical research conducted in the Indian market

Regarding the Indian context, several researchers, including Gupta (2002), Thenmozhi (2002), Nath (2003), Bandivadekar and Ghosh (2003), and Sah and Omkarnath (2006), employed ARCH and GARCH models to analyse the impact of futures trading on market volatility. They find a strong association between derivative introductions and conditional volatility. This indicates that the latter news has a high impact, but the former news has a low impact (Tripathy et al., 2009; Bandivadekar & Saurabh, 2003).

Shenbagaraman (2003), Sah and Omkarnath (2006), and Mallikarjunappa and Afsal (2007) examined the underlying market volatility by implementing GARCH and indicated that the magnitude of the

futures and options coefficient is very small and depicts a negligible influence of futures and options derivatives on volatility. Vipul (2006) analysed the effect of derivative contracts over six equity shares and indices. According to empirical findings, derivatives trading has little impact on the cash market. Sakthivel (2007), Nair (2008), Singh and Kansal (2011), and Gakhar (2015) demonstrated an increase in market efficiency as underlying market volatility decreased following initial futures trading. Debasish and Das (2009), Rao and Tripathy (2008), and Gahlot et al. (2010) examined the effect of futures trading beginning in the Indian capital market by adopting symmetric GARCH methods from April 1997 to April 2007. The results are consistent with those of most previous studies and reveal no perceptible change in volatility. Patra and Mohapatra (2010), Ray and Panda (2011), Sakthivel and Kamaiah (2011), and Srinivasan (2011) applied ARCH/GARCH models to examine the impact of future contracts on the Indian cash market and found that the commencement of futures trading altered the volatility behaviour of index and individual stock volatility. Sinha (2015) analysed derivatives' impact on the underlying market for a period starting from January 1991 through December 2011 and employed GARCH to test the conditional volatility of the S&P CNX Nifty index and found an increase in S&P CNX Nifty index conditional volatility. Joshi (2018) stated that the effect of option listing on small, mid, and large caps is not uniform, and the volatility of optioned equities rises dramatically for large cap companies.

Based on the arguments mentioned above, we developed the following research hypotheses:

H1: There is a significant impact of NIFTY-50 index option trading on the volatility of the underlying stock market.

H2: NIFTY Index option trading has a stabilised impact on the volatility of the underlying stock market.

3. Data description and methodology

3.1. Research design

The present study is based on a longitudinal research design to examine the impact of NIFTY 50 Index option trading on the underlying stock market over a period of time, emphasising alterations that transpire gradually.

3.2. Data used in the study

This study is based on the NSE NIFTY 50 Index, which represents the 50 largest and most liquid Indian stocks listed on the National Stock Exchange (NSE). Investors frequently use it as a benchmark for the Indian stock market, reflecting its performance and tracking the health of India's economy. The study includes the daily closing prices of the Nifty 50 index, retrieved from the NSE website. It consists of 5996 observations of NSE Nifty index closing prices spanning from November 7, 1994, to December 31, 2018. Of these, 1622 observations concern the time before options trading was introduced on June 4, 2001, while the remaining 4374 observations concern the time after it was introduced. Here, near-month NIFTY 50 option data has been collected because they are frequently traded contracts. However, daily returns are calculated as the first difference of the log of the index daily closing prices, that is, $rt = \ln(p(t)) - \ln(p(t-1)) * 100$.

To achieve this objective, it is also important to look at volatility before and after the introduction of options trading as a whole and in the presence of post-introduction structural breaks, as structural breaks affect the results (Glynn et al., 2007). The main reasons for these structural changes could derive from variations in currency exchange system frameworks, worldwide financial market turbulence, or stock market development. The impacts resulting from major economic and political events can lead to deviations in the behaviour of financial time series from its calm state (Wang & Moore, 2009; Andreou & Ghysels, 2002). Using daily data from the Nifty index, we have considered recent significant changes in the structure, notably on May 18, 2009, and witnessed another decrease (Sensex Creates History: Two Upper Circuits in One Day, 2009). On August 24, 2015, the Sensex declined by 5.94%, resulting in a loss of around INR 7 lakh crore from the Indian market.

3.3. Data analysis

We used the ARCH family to test the study's robustness since it captures volatility and return heteroscedasticity. We used the GARCH model to investigate the conditional volatility of daily returns for the Nifty 50 option index to see if index options changed it. ARCH model mean equation regressed on historical values. We also regressed the conditional variance on the mean equation squared error terms at constant and lag values.

We used the GARCH (1, 1) model to assess the impact of index options on market volatility. The Conditional mean equation is as follows:

$$R_t = \mu_t + \beta_i R_{t-i} + \varepsilon_t \quad (1)$$

$$i = 1, 2, 3 \dots$$

$R_{(t-i)}$ represents the lagged day return, whereas R_t represents the daily return. Here,

$$\varepsilon_t = z_t \sigma_t \quad (2)$$

$$z_t \sim N(0, 1)$$

Therefore, z_t is normally distributed with a variance equal to σ_t^2 and a mean equal to zero.

$$\varepsilon_t \sim N(0, \sigma_t^2)$$

An ARCH (p) is specifies as:

$$\sigma_t^2 = \omega_t + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 \quad (3)$$

Here, σ_t^2 = conditional variance, ω_t = constant term, α_i = weight, ε_{t-i}^2 = lagged squared error term, and the parameters must satisfy $\omega_t > 0$ and $\alpha_i \geq 0$, and for all $t=1 \dots p$, to ensure a positive value of conditional variance. Bollerslev (1986) and Bollerslev (1988) proposed GARCH as the most accepted econometric model to interpret time-series data with time-varying conditional variance. In this model, the conditional variance does not rely only on the mean-squared residuals condition, in addition to its own previous values. The GARCH (p, q) model contains a feature to better execute volatility clustering and incorporate heteroscedasticity from the estimated procedure to capture return volatility (Tsay, 2005).

The conditional variance equation:

$$\sigma_t^2 = \omega_t + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (4)$$

Here, p stands for the ARCH degree, q for the GARCH degree, and ε_t for the error term that resembles white noise. The ARCH term, which is expressed by $\sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2$, the GARCH component expressed by $\sum_{j=1}^q \beta_j \sigma_{t-j}^2$ and conditional variance, is represented by the constant term ω_t .

In Eq. (4), the ARCH parameter α_i represents the short-term impact of 'recent news', the GARCH parameter β_j represents the long-term impact of 'former news', and the persistence effect of information is represented by the summation of both parameters $\alpha_i + \beta_j$ (Antoniou & Holmes, 1995). It also allows us to discover the impact of Nifty Index options on underlying spot market volatility and its magnitude. It is also notable that an increase in α_i proposes that recent news is possessed by faster information transmission into prices, and a decrease in β_j proposes that old news has a less persistent effect, whereas an increase in $\alpha_i + \beta_j$ signifies higher persistence throughout the post-option period (Butterworth, 2000).

The variance equation is as follows:

Where $\varepsilon_t / \varepsilon_{t-1} \sim N(0, 1)$

$$\sigma_t^2 = \omega_t + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \gamma D_o \quad (5)$$

$R_{(t-i)}$ represents the lagged day return, whereas R_t represents the daily return.

3.3.1. Structural breaks tests: identification of major events and application of Chow test to check structural breaks

This study employed the Chow test to identify structural changes (Ozdemir & Akif, 2019). We identified these using the unit root breakeven point test and return series analysis (Crosier, 1988). Examination of structural breaks in the financial time series data is crucial; otherwise, it may lead to spurious results that lead to imperfect forecasts (Arouri et al., 2012).

The Chow test equation

$$r_t = \beta_0 + \gamma_0 r_{t-1} + \dots + \varepsilon \quad (6)$$

$$F Stats = \frac{[SSR_t - (SSR_1 + SSR_2) / k]}{(SSR_1 + SSR_2) / [n - 2(k + 1)]} \quad (7)$$

In the above equation, β_0 represents the intercept and γ_0 represents coefficient of the lag returns. Here SSR_t represents the Sum of Squares regression while $n - 2(k + 1)$ represents the degree of freedom (Özdemir & Akif, 2019). The alternate hypothesis is represented as;

H_{a1} : There are significant structural breaks present at specified breakpoints.

4. Empirical findings of the research

The empirical results are presented in four parts. The first part represents the results of the structural breaks in return series which is further confirmed by application of Chow statistics. The second part shows the preliminary outcomes required to estimate the stock return's behavior from the premise of GARCH. These results include descriptive statistics, volatility clustering, and stationarity or unit root testing for Nifty index prices and returns. The third part presents the ARCH effect and presence of autocorrelation for the Nifty index return series, followed by the empirical results of the GARCH (1, 1) model and a diagnostic test for the adequacy of the model. Finally, the unconditional variance is estimated.

4.1 Structural breaks: Chow test

We carried out a Chow breakpoint test, which is a more powerful tool when structural breaks are known (Muthuramu & Maheswari, 2019). In this paper, two structural break dates, 'May 18, 2009, and August 24, 2015', are identified through the unit root breakeven point test and return series analysis.

Figure 1 illustrates a significant decrease in market prices in January 2008, which occurred at the same time as the beginning of the global crisis. Nevertheless, in the present investigation, we have considered recent significant changes in the structure, notably on May 18, 2009, and witnessed another decrease (Sensex Creates History: Two Upper Circuits in One Day, 2009). On August 24, 2015, the Sensex declined by 5.94%, resulting in a loss of around INR 7 lakh crore from the Indian market.

Table 1 confirms the presence of structural breaks on the above-detected dates. The F-statistics, log likelihood, and Wald test in the Nifty 50 Index are greater than the critical value and significant at the 1% level. Therefore, we rejected the null hypothesis that there was no structural break at the specified breakpoints.

4.2. Preliminary tests

This section discusses the statistical and econometric methods applied to investigate the eligibility for fitting the GARCH model, such as a summary of descriptive statistics, stationarity, unit root testing for

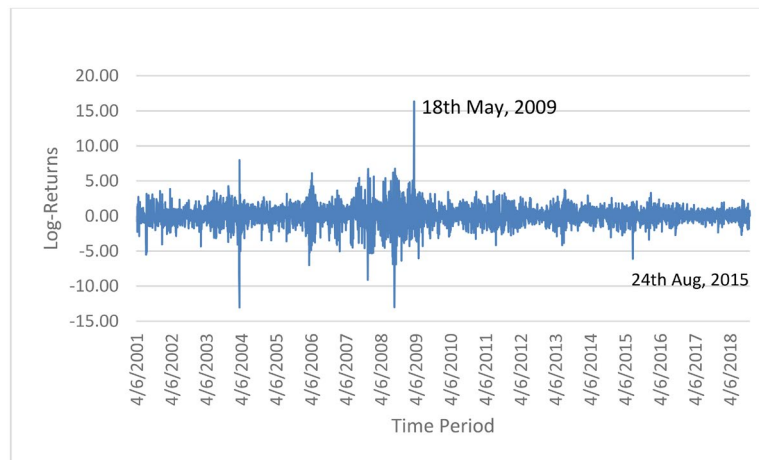


Figure 1. Nifty Index Daily Return in the Post-Introduction Period (4th June 2001 to 31st December 2018).

Table 1. The Chow test.

F-statistic	112.0781	Prob. F(2,4371)	0.0000
Log Likelihood Ratio	218.7478	Prob. Chi-Square(2)	0.0000
Wald Statistic	224.1562	Prob. Chi-Square(2)	0.0000

Table 2. Descriptive statistics for the Nifty index return series.

Particulars	Pre-Introduction November 7, 1994	Post-Introduction June 4, 2001	Post-Introduction 18 May, 2009	Post-Introduction August 24, 2015	Overall Period November 7, 1994
Start Date					
End Date	June 3, 2001	May 15, 2009	August 22, 2015	December 31, 2018	December 31, 2018
Mean	-0.0061	0.0596	0.0522	0.0325	0.0358
Median	0.0024	0.1439	0.0576	0.0543	0.0680
Maximum	9.9339	7.9691	16.3343	3.3115	16.3343
Minimum	-8.8405	-13.0539	-6.0216	-6.0973	-13.0539
Std. Dev.	1.7205	1.7084	1.1941	0.8341	1.4946
Skewness	0.0450	-0.7323	1.4901	-0.6474	-0.165380
Kurtosis	5.9175	8.7553	25.5404	7.1869	10.53861
Jarque-Bera	575.7928	2914.1230	33645.0300	662.6374	14225.5000
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1622	1984	1562	828	5996

Nifty index prices and returns, and testing of the ARCH effect (Heteroscedasticity) and presence of Autocorrelation for the Nifty index return series.

4.2.1. Descriptive statistics of daily return

A summary of the descriptive statistics for the Nifty index is provided in Table 1. The descriptive statistics of Nifty 50 Index are estimated for both the 'pre- and post-periods' including structural breaks for the sample period.

Table 2 represents the descriptive statistics and stated that Nifty Index series of returns does not follow normality, as shown by the skewness and kurtosis values. Here the Nifty index return series for the overall sample has 5996 values, with a mean return of 0.0358% per day and a standard deviation of 1.4946%. The Nifty average daily return is negative at -0.0061% before and positive at 0.0596%, 0.0522%, and 0.0325% after the options introduction. The volatility of the Nifty index, as measured by standard deviation, decreases from 1.7205% in the pre-introduction period to 1.7084%, 1.1194%, and 0.8341% and 1.4946% in the post-introduction period. The skewness statistics indicate that the nifty return distribution is not symmetric, as it is different from zero. The nifty return series is leptokurtic and highly peaks around the mean, as opposed to a normal distribution, as shown by the high positive kurtosis value. Jarque-Bera statistics were also calculated to test the normality assumption. The p-value (0.0000) indicates that daily index return series are leptokurtic and negatively skewed and not

normally distributed. Hence, these three statistics suggest that the ARCH/GARCH model is appropriate. Moreover, the leverage effect in symmetric models suggested an equal impact of good and bad news, while asymmetric models proposed that bad news has a stronger persistence effect than good news (Nelson, 1991; Ali et al., 2022).

4.3. Test for stationarity and volatility clustering

To analyse a time series, the data must be non-stationary and have a time-varying mean and variance (Gujarati, 2014). If a series is found to be non-stationary, it can be made stationary by taking the first difference. The data in the present study are time series and must be tested for stationarity with the help of graphs and unit root tests.

4.3.1. Graphical presentation

The Nifty index daily closing prices and return series are presented in Figures 2(a) to 2(e) and 3(a) to 3(e).

Figure 2 (a–e) of the Nifty index daily prices for different time periods shows non-stationarity, which means that the Nifty index level series is non-stationary. The closing price of the Nifty index is transformed into a daily lognormal return series to keep the series stationary.

Figure 3 (a–e) shows that the return series are stationary and confirm the presence of volatility clustering, i.e. 'low volatility' is succeeded by periods of 'low volatility' and 'high volatility' is succeeded by periods of 'high volatility', for a long time. This shows that, while the variance varies with time, the series of returns oscillates around a constant mean.

4.3.2. Unit root test with structural breaks

To test the stationarity of Nifty index time series data, we used the unit root test with structural breaks.

With regard to the ADF and PP tests, Table 3 shows that the null hypothesis is not rejected, indicating the presence of a unit root at the levels with constant, constant, and trend, but they are not statistically significant at the 1% level. However, the result of the KPSS test indicates that the null hypothesis is rejected at a significant level of 1%. This suggests that the time series is not stationary at the 1% level with a constant, constant, and trend.

4.4. Identification of ARCH effect and autocorrelation

According to Mandelbrot (1963), Fama (1965), and Amanulla and Kamaiah (1997), there is an elevated probability that the series will exhibit heteroskedasticity because the underlying asset under analysis is a stock or index. Therefore, this study starts by looking at whether the Nifty Index return series exhibits heteroskedasticity. To assess the presence of heteroscedasticity, (ARCH) and after that (GARCH) models is developed to analyze the time series data (Merton, 1980; Ahmed & Suliman, 2011). Hence, to test whether the ARCH effect is present first, the series of Nifty index returns are regressed on constant using the least squares method, and then in the residual diagnostics test, the ARCH or heteroscedasticity test is applied. The null hypothesis or ARCH effect is being tested at 1% significance level. To test the first-order serial correlation Durbin-Watson statistic is used, which has a range from 0 to 4 and more precisely captures the autocorrelation between neighbouring residuals from a regression model. No autocorrelation is represented by two number of 2, whereas positive autocorrelation is shown by values ranging from 2 to 0, and negative autocorrelation is represented by values ranging from 2 to 4. The results are as follows:

Table 4 shows that LM statistics (Obs*R-Squared) for all the sample periods are significant, as the p-value is less than 0.0001, for the return series and rejected the null hypothesis, which means no heteroscedasticity. However, the Durbin-Watson statistic, which is in the range of two, shows that there is no autocorrelation between the values of the series. Finally the outcomes showed that heteroskedasticity was present. As a result, a GARCH process is thought to be followed by the asset returns series.

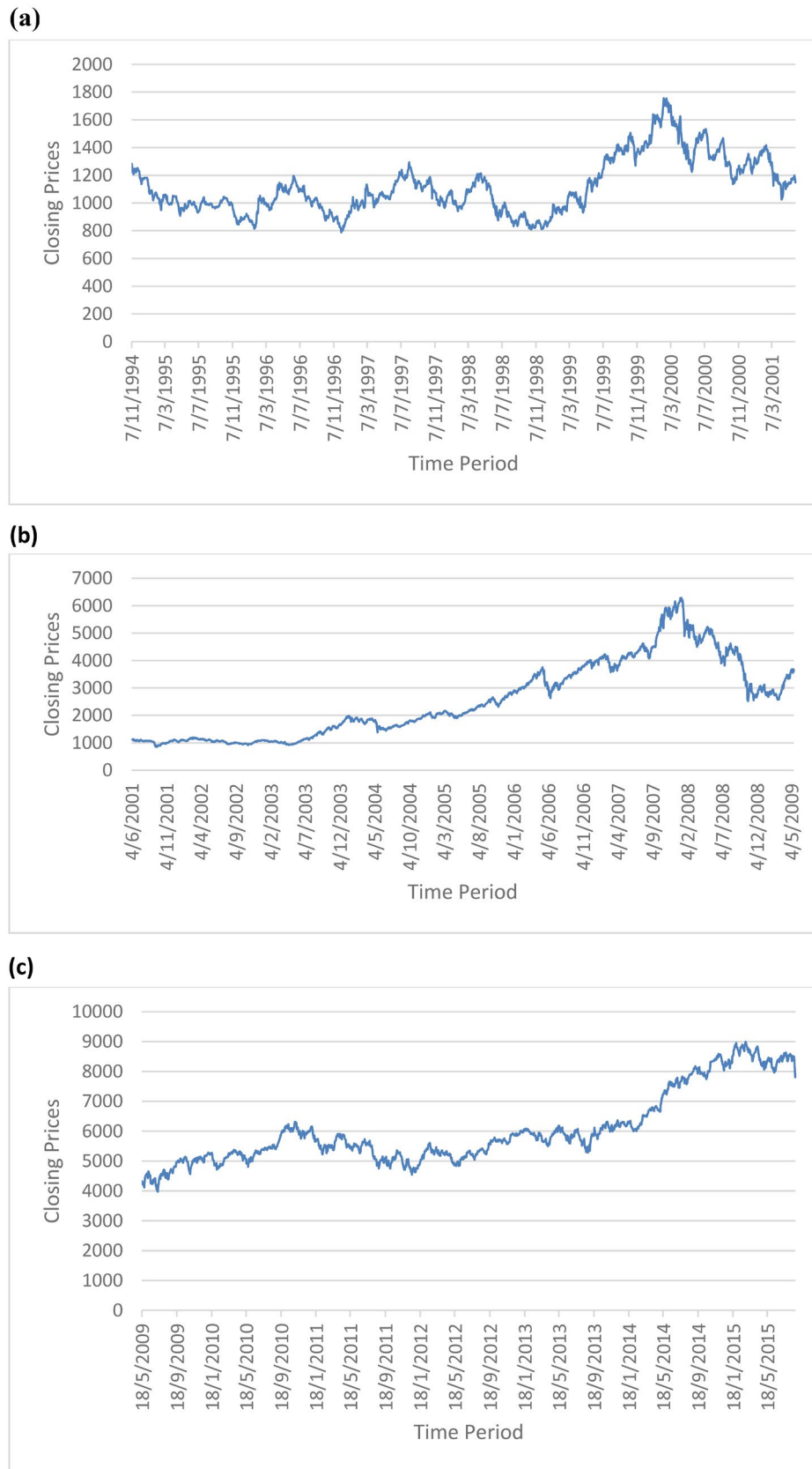
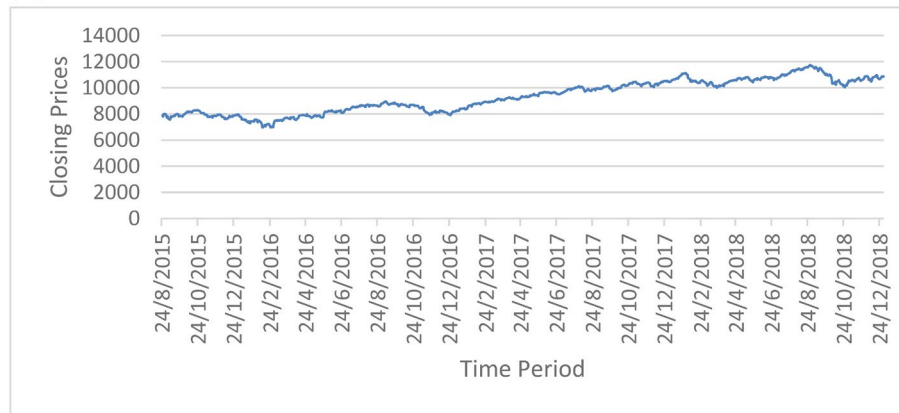


Figure 2. (a): Nifty Index Daily Closing Prices in the Pre-Introduction Period (7 November 1994 to 3 June 2001). (b): Nifty Index Daily Closing Prices in the Post Introduction Period (4 June 2001 to 15 May 2009). (c): Nifty Index Daily Closing Prices in the Post-Introduction Period (18 May 2009 to 22 August 2015). (d): Nifty Index Daily Closing Prices in the Post-Introduction Period (24 August 2015 to 31 December 2018). (e): Nifty Index Daily Closing Prices for the Whole Period (7 November 1994 to 31 December 2018).

(d)



(e)

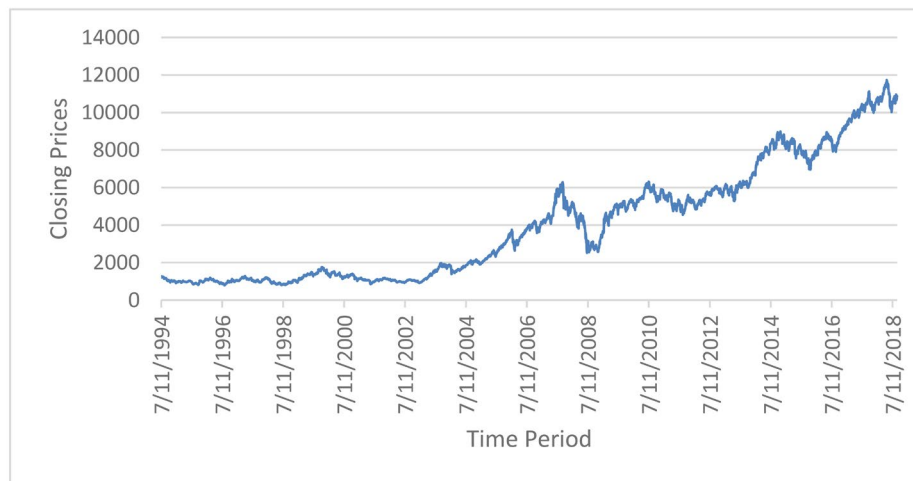


Figure 2. Continued.

4.5. Empirical results of GARCH (1,1) model

GARCH captures the impact of 'old news', which represents conditional variance. The clustering of volatility is indicated by the existence of high-value GARCH terms close to one. The sum of the ARCH and GARCH terms identifies the persistence of volatility. To test this empirically, the GARCH (1,1) model Eq. (5) is used for the given time series, and the results are discussed below after considering different structural breaks.

Table 5 represents volatility's characteristics for the options before and after periods, including structural breaks. The coefficient of conditional variance terms are positive and highly significant, suggesting that recent and old news can explain the current return volatility. The coefficient of ARCH has changed from 0.0952 in the pre-introduction period to 0.1045 in the post-introduction period, including 0.1319, 0.1063, and 0.1050 in post-introduction structural breaks and significant at 1% level, which indicates that past volatility of stock market returns is significantly influencing current volatility. However, the GARCH term remained positive and significant at the 1% level for all periods, and the GARCH coefficient shifted from 0.8464 in the pre-introduction period to 0.8795 in the post-introduction period. This shift included 0.8326, 0.8721, and 0.8786 in the post-introduction structural breaks, indicating a more effective response to old news following the introduction of options. Moreover, the pre-introduction phase found the summation of the ARCH and GARCH ($\alpha_i + \beta_j$) terms to be 0.9416, and 0.9840 in the post-introduction period and 0.9645, 0.9784, and 0.9836 in the post-introduction structural breaks, which are close to unity and show the persistence of long-lasting

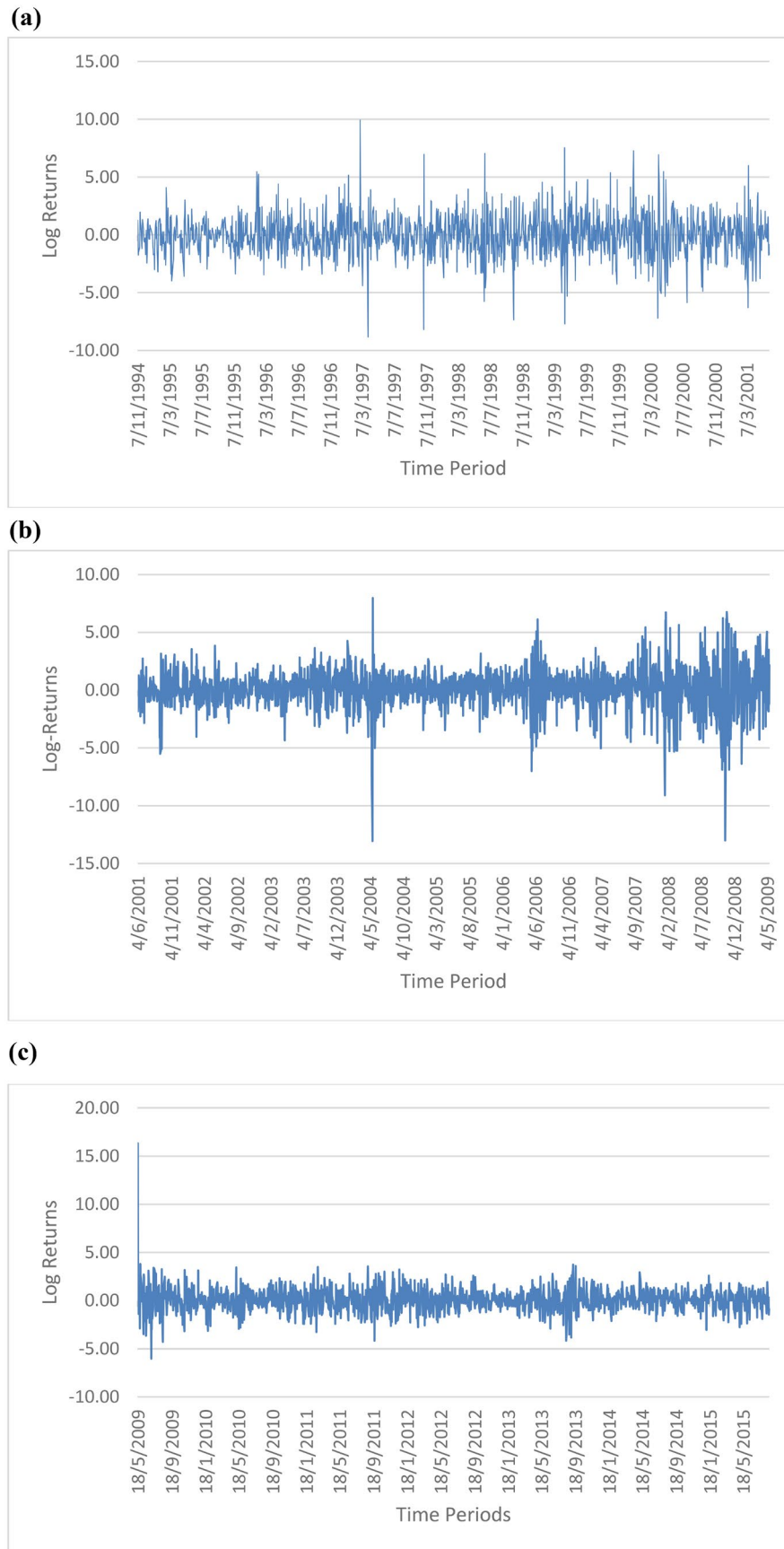


Figure 3. (a): Volatility Clustering of Nifty Index Daily Return in the Pre-Introduction Period (7 November 1994 to 3 June 2001). (b): Volatility Clustering of Nifty Index Daily Return in the Post-Introduction Period (4 June 2001 to 15 May 2009). (c): Volatility Clustering of Nifty Index Daily Return in the Post-Introduction Period (18 May 2009 to 22 August 2015). (d): Volatility Clustering of Nifty Index Daily Return in the Post-Introduction Period (24 August 2015 to 31 December 2018). (e): Volatility Clustering of Nifty Index Daily Returns for the Whole periods (7 November 1994 to 31 December 2018).

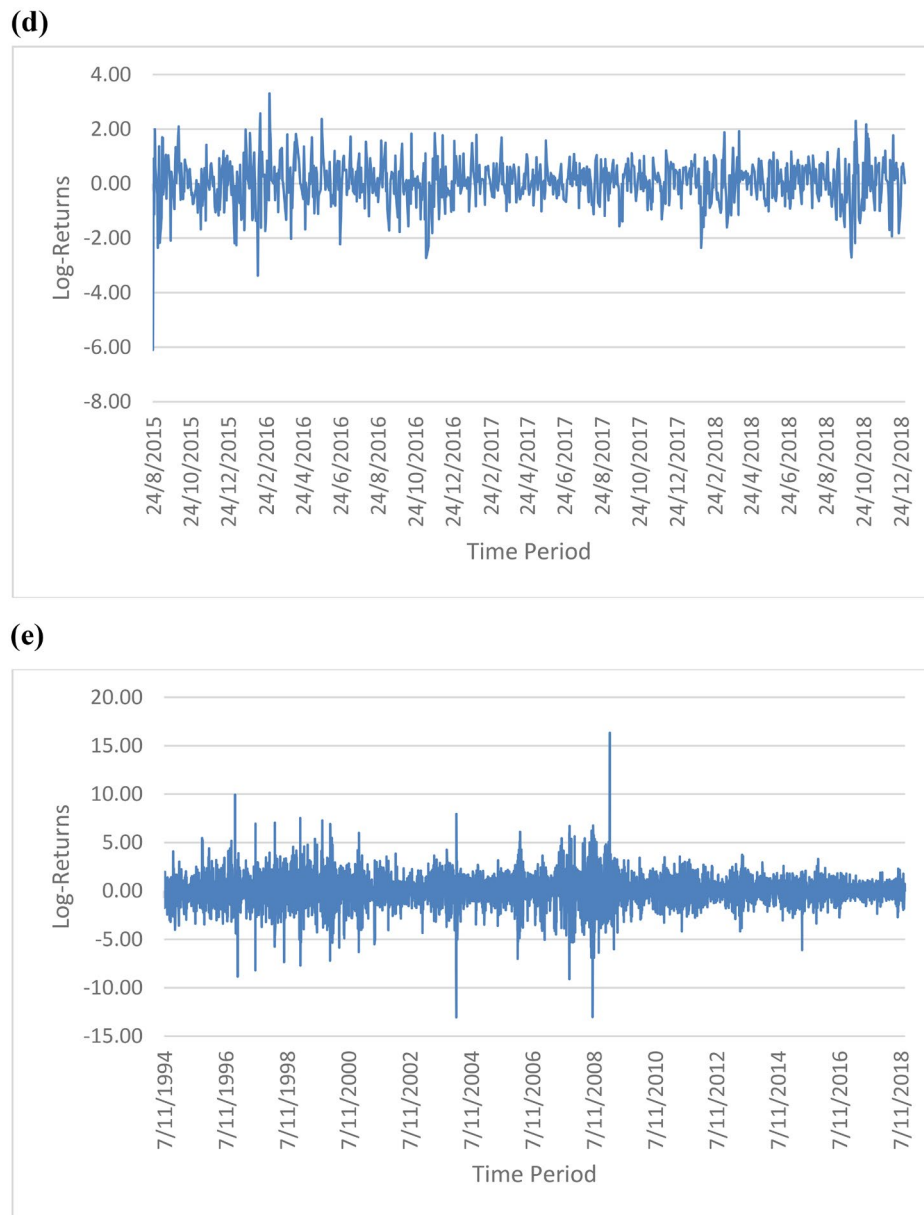


Figure 3. Continued.

volatility; today's volatility has an impact on both tomorrow's volatility and volatility in succeeding periods, which takes a lot of time to die out the effect of positive and negative news. Moreover, it is also stated that there is a marked increase in the recent news coefficient (α_i) from 0.0952 to 0.1045 in the post-introduction period and also marked an increase in the old news coefficient (β_j) from 0.8464 to 0.8795 after the introduction of options. However, coefficient (β_j) which is represent by GARCH is more as compare to coefficient (ai) ARCH term which states that old news has more impact than recent news and the existence of the options market has increased the rate at which information is incorporated into underlying spot prices as well as the persistence of information. Additionally, a larger value of ($\alpha_i + \beta_j$) suggested a volatility persistence hence shocks of conditional variance takes long time to die out. (Cheteni, 2016).

Finally, the implications of the inclusion of options on conditional volatility are examined, and the findings are shown in Exhibit 4. A significant positive (negative) coefficient indicates that the commencement of derivatives has a destabilized (stabilized) impact on the underlying market's volatility. For the Nifty index, the co-efficient of the dummy variable is -0.0647, -0.0352, and -0.0316 for the break 1, 2, 3, and -0.0540 for the overall post-introduction period, respectively. All results are significant at 1%, suggesting that the initiation of the index option has a stabilised impact on underlying market volatility, as

Table 3. Results of ADF, PP and KPSS Test Applied on the Closing Prices and Log Returns Series of Nifty 50 Index.

For Pre- Introduction Period from 7 November, 1994 to 3 June, 2001							
		ADF		PP		KPSS	
		Constant	Constant + Trend	Constant	Constant + Trend	Constant	Constant + Trend
Test/Series							
Levels	t-statistics	−2.0882	−2.8236	−2.1553	−2.9289	2.1585	0.3583
	p-value	0.2496	0.1888	0.2232	0.1535	0.0000***	0.0000***
First Difference	t-statistics	−11.9235	−11.9250	−37.3619	−37.3540	0.0827	0.0639
	p-value	0.0000***	0.0000***	0.0000***	0.0000***	0.8867	0.9936
For Post- Introduction Period from 4 June, 2001 to 15 May, 2009							
		ADF		PP		KPSS	
		Constant	Constant + Trend	Constant	Constant + Trend	Constant	Constant + Trend
Test/Series							
Levels	t-statistics	−1.1285	−1.9917	−1.0112	−1.7209	4.8231	0.3853
	p-value	0.7065	0.6049	0.7513	0.7419	0.0000***	0.0000***
First Difference	t-statistics	−9.1099	−9.1092	−41.4106	−41.4003	0.1128	0.1103
	p-value	0.0000***	0.0000***	0.0000***	0.0000***	0.3100	0.8415
For Post- Introduction Period from 18 May, 2009 to 22 August, 2015							
		ADF		PP		KPSS	
		Constant	Constant + Trend	Constant	Constant + Trend	Constant	Constant + Trend
Test/Series							
Levels	t-statistics	−1.1535	−2.1242	−1.0824	−2.0520	3.6015	0.8870
	p-value	0.6963	0.5313	0.7247	0.5716	0.0000***	0.0000***
First Difference	t-statistics	−35.6202	−35.6072	−35.4869	−35.4733	0.0605	0.0583
	p-value	0.0000***	0.0000***	0.0000***	0.0000***	0.1780	0.9608
For Post- Introduction Period from 24 August, 2015 to 31 December, 2018							
		ADF		PP		KPSS	
		Constant	Constant + Trend	Constant	Constant + Trend	Constant	Constant + Trend
Test/Series							
Levels	t-statistics	−0.8847	−2.8228	−0.8032	−2.8673	3.3459	0.1891
	p-value	0.7932	0.1894	0.8172	0.1739	0.0000***	0.0000***
First Difference	t-statistics	−13.3803	−13.3722	−27.3958	−27.3781	0.0582	0.0582
	p-value	0.0000***	0.0000***	0.0000***	0.0000***	0.1667	0.9734
For Whole Period from 7 November, 1994 to 31 December, 2018							
		ADF		PP		KPSS	
		Constant	Constant + Trend	Constant	Constant + Trend	Constant	Constant + Trend
Test/Series							
Levels	t-statistics	0.6528	−2.3240	0.7219	−2.2522	9.3008	1.5949
	p-value	0.9911	0.4202	0.9926	0.4598	0.0000***	0.0000***
First Difference	t-statistics	−17.4835	−17.4960	−71.9173	−71.9176	1.8563	0.7710
	p-value	0.0000***	0.0000***	0.0000***	0.0000***	0.0634	0.4407

Note: ***indicates significant at 1% level.

Table 4. ARCH-LM test and Durbin-Watson statistic.

Period	F- statistic	Prob F	Obs*R squared	Prob.Chi square (2)	Durbin-Watson statistic
7 November 1994 to 3 June 2001	44.5335	0.0000	43.3949	0.0000	2.0205
4 June, 2001 to 15 May, 2009	253.0083	0.0000	224.5808	0.0000	2.1128
18 May, 2009 to 22 August, 2015	5.2161	0.0055	10.3828	0.0056	2.0186
24 August, 2015 to 31 December, 2018	11.9991	0.0000	23.4032	0.0000	2.0359
7 November, 1994 to 31 December, 2018	289.2973	0.0000	276.0674	0.0000	2.0525

the coefficient's negative sign suggests a decrease in underlying market volatility. The results of this study are consistent with past findings for other emerging markets (Thenmozhi, 2002; Shenbagaraman, 2003; Gupta, 2002; Raju & Karande, 2003).

4.6. Diagnostic testing: ARCH effects using the ARCH Lagrange multiplier

Here, the appropriateness of the GARCH (1, 1) model is confirmed by employing ARCH-LM test. If F statistic and Obs *R-squared statistic is significant at the 1% level, the null hypothesis will be rejected the

Table 5. GARCH (1, 1) before and after introduction of Options including Structural Breaks.

Coefficients	GARCH (1,1) Model				
	Pre-Introduction	Post-Introduction (Break 1)	Post-Introduction (Break 2)	Post-Introduction (Break 3)	Post-Introduction (Overall Period)
	7 November 1994 to 3 June 2001	4 June, 2001 to 15 May, 2009	18 May, 2009 to 22 August, 2015	24 August, 2015 to 31 December, 2018	4 June, 2001 to 31 December, 2018
MEAN EQUATION					
μ	0.0249	0.0971	0.0787	0.0760	0.0758
p Value	0.5516	0.0000	0.0000	0.0000	0.0000
VARIANCE EQUATION					
μ (Constant Term)	0.1827	0.1517	0.0713	0.0478	0.0842
p Value	0.0000	0.0000	0.0000	0.0000	0.0000
α_i (ARCH Parameter)	0.0952	0.1319	0.1063	0.1050	0.1045
p Value	0.0000	0.0000	0.0000	0.0000	0.0000
β_j (GARCH Parameter)	0.8464	0.8326	0.8721	0.8786	0.8795
p Value	0.0000	0.0000	0.0000	0.0000	0.0000
$\alpha_i + \beta_j$	0.9416	0.9645	0.9784	0.9836	0.9840
Dummy	–	–0.0647	–0.0352	–0.0316	–0.0540
p Value	–	0.0000	0.0000	0.0000	0.0000
Log likelihood	–3121.4230	–6655.1850	–9018.5730	–10004.5700	–9987.2090
AIC	3.8538	3.6939	3.4921	3.3387	3.3336
SIC	3.8671	3.7025	3.4984	3.3443	3.3414
HQC	3.8587	3.6970	3.4943	3.3407	3.3363

Table 6. ARCH-LM test statistic.

Periods	F- statistic	Prob F	Obs*R squared	Prob.Chi square(2)
7 November 1994 to 3 June 2001	0.5268	0.4680	0.5273	0.4677
4 June, 2001 to 15 May, 2009	1.2300	0.2675	1.2303	0.2673
18 May, 2009 to 22 August, 2015	0.7002	0.4027	0.7004	0.4026
24 August, 2015 to 31 December, 2018	1.0126	0.3143	1.0127	0.3142
7 November, 1994 to 31 December, 2018	0.8102	0.3681	0.8103	0.3680

presence of ARCH effect in the standardized residuals. Below Table 6 represents the results of ARCH LM test statistics:

Table 6 shows that F statistic and Obs *R-squared statistic are insignificant at 1% level and accept the null hypothesis that is, no heteroscedasticity in the residuals for all the sample periods. Thus, it can be concluded that the GARCH (1, 1) model is appropriate for the present study.

4.7. Unconditional variance

Unconditional volatility represents the absolute volatility of a random variable, in the absence of additional information. However ARCH and GARCH parameters are non-negative in GARCH (1,1) model and its sum is less than one, which means the it has finite unconditional variances (Bologna & Cavallo, 2002). The unconditional variance can be calculated as follows:

$$\sigma^2 = \frac{\omega}{1 - (\alpha_1 + \beta_1)}$$

After making comparisons between pre- and post-onset of the Nifty Index option in the underlying stock market, it was found that the unconditional variances changed from 3.1200 in the pre-introduction period to 3.1000, 1.1010, and 0.5900 in the post introduction period. Hence, it is stated that the unconditional variance in the post-introduction period is lower than the pre-introduction period. In other words, the introduction of index options has stabilized the underlying stock market.

5. Conclusions

This study was done under the assumption that any observable changes over time after the introduction were solely attributable to options trading. The ARCH and GARCH models were used to assess the impact of the inclusion of the Nifty Index options on underlying market volatility. It was also important to take into account structural breaks, as failing to do so could result in overstated findings (Arouri et al., 2012). We used the NIFTY 50 index daily closing price data from November 7, 1994, to December 31, 2018. The sample period was divided for the pre- and post-introduction periods using the cut-off dates from November 7, 1994, to June 3, 2001, for the pre-introduction period, and from June 4, 2001, to December 31, 2018 for the post-introduction period. Then, the post-introduction period is further divided on the basis of the two breakeven points, i.e. May 18, 2009, and August 24, 2015. The coefficient of ARCH has changed from 0.0952 in the pre-introduction period to 0.1319, 0.1063, and 0.1050 for structural breaks and 0.1045 for the whole post-introduction period, and the GARCH coefficient has changed from 0.8464 in the pre-introduction period to 0.8326, 0.8721, and 0.8786 for structural breaks and 0.8795 in the post-introduction period. Moreover, a large β_j GARCH coefficient demonstrates that prices react to old news more effectively following the introduction of options.

Moreover, the sum of the ARCH and GARCH ($\alpha_i + \beta_j$) terms was found to be 0.9416 in the pre-introduction period and 0.9645, 0.9784, and 0.9836 for structural breaks, and 0.9840 in the post-introduction period, which are close to unity and indicate long-lasting volatility persistence. Over time, certain information entered into today's market has an impact on tomorrow's volatility as well as volatility in succeeding periods, and it takes a lot of time to die out the effect of negative and positive news. It is also stated that there is a marked increase in the news coefficient (α_i) from 0.0952 to 0.1045 in the post-introduction period and a marked increase in the persistence parameter (β_j) from 0.8464 to 0.8795 after the introduction of options. These results suggest that the existence of the options market has increased the rate at which information is incorporated into underlying spot prices, even with structural breaks.

6. Limitations and future research directions

This study primarily focuses on analyzing the impact of the Nifty Index option on stock market volatility in India. The study can be extended by investigate the volatility spillover among different countries. Furthermore, the effect of equity options trading with high-frequency data can also be used for further study.

Authors' contributions

Komal Bhardwaj played a main role in conceptualizing, designing, and conducting the data analysis. **Garima** also made contributions to the literature review section. **Habtamu Regassa Lemma** made a significant contribution in writing, reviewing, and editing the article. Lastly, **Matewos Kebede Refera** contributed by reviewing, editing, and preparing the article for publication.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available from Matewos Kebede Refera upon reasonable request.

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