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Research paper

Day-of-The-Week Effects and Volatility Clustering in Banking Stocks: GARCH-Based Evidence from India's Emerging Market

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Abstract

Understanding anomalies in stock markets, including day-of-the-week effects, is crucial for developing a comprehensive view of market behaviour and efficiency. It highlights the complex interplay between rational economic principles and behavioural factors in shaping financial markets. In this context, the present study evaluates how weekday patterns affect the daily market dynamics of BSE Bankex (from June 23, 2003, to July 31, 2024) and Nifty Bank (from June 9, 2005, to July 31, 2024), employing Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Fractionally Integrated GARCH (FIGARCH), Threshold GARCH (TGARCH), and Exponential GARCH (EGARCH) models. While overall returns do not exhibit significant weekday effects, the findings show a positive return on the baseline day (Monday), reduced volatility on Tuesdays, and elevated volatility levels on Fridays. The analysis also confirms robust volatility clustering driven by both past shocks and past volatility, along with leverage and long memory effects. The study concludes that Indian banking stock volatility shows strong day-of-the-week effects, most notably a "calm Tuesday and volatile Friday" pattern, alongside robust volatility clustering, persistence, leverage asymmetry, and long memory. Collectively, these results point towards the presence of persistent market reactions and potential inefficiencies in banking stock pricing, providing insights for investors seeking to capitalize on such inefficiencies and evidence for policymakers aiming to enhance financial market stability.

Keywords: *BSE Bankex; Nifty Bank; Day-of-the-Week; Generalized Autoregressive Conditional Heteroskedasticity.*

1. Introduction

The presence of market anomalies poses a fundamental challenge to the Efficient Market Hypothesis (EMH), underscoring the limitations of traditional financial theories and highlighting the need to incorporate behavioural and institutional factors in understanding market dynamics (Gilbert, 2010). One prominent anomaly is the day-of-the-week (DOW) effect, a well-documented phenomenon in which stock returns and volatility exhibit systematic variations across trading days. Empirical evidence shows that returns tend to be lower on Mondays and Tuesdays, with a noticeable pickup from mid-week through Friday (Grebe & Schiereck, 2024; Rystrom & Benson, 1989). In addition to return patterns, the DOW effect extends to volatility, with certain weekdays consistently displaying higher or lower levels of market turbulence (Berument & Kiymaz, 2001; Kiymaz & Berument, 2003; Farooq et al., 2013). This effect is particularly salient in emerging markets such as India, where evolving investor behaviour, structural reforms, and market development create dynamic conditions that may amplify or reshape calendar anomalies. Examining weekday-specific return and volatility patterns, therefore, offers valuable insights into market inefficiencies and the behavioural underpinnings of asset pricing in developing financial systems.

Against this backdrop, scholars have developed a range of theoretical explanations to account for the DOW effect anomaly. From a behavioural finance perspective, investors are more risk-averse and pessimistic at the beginning of the week, leading to Monday declines, while optimism builds toward Friday, boosting returns (Hirshleifer & Shumway, 2003; Bakar et al., 2014; Pettengill, 1993), though the validity of this mood-based account remains debated (Solnik & Laurence, 1990). The information hypothesis argues that firms release bad news after markets close on Fridays, leading to Monday price drops (French, 1980; Agrawal & Tandon, 1994), but this fails to account for Friday gains and is less applicable in markets with different weekend structures (Al-Khazali et al., 2010; Hasan et al., 2021). Institutional and settlement-based theories link the anomaly to delayed settlement cycles, which create opportunity costs and depress Monday returns (Gibbons & Hess, 1981; Dubois & Louvet, 1996), while short-seller activity adds to the pattern, with positions closed before weekends and reopened on Mondays (Chen & Singal, 2003). Similarly, institutional trading practices, such as rebalancing or window-dressing, can inflate Friday prices (Lakonishok & Smidt, 1988). Market microstructure explanations point to lower liquidity and higher volatility on Mondays (Keim & Stambaugh, 1986; Kamara, 1997), while the bid–ask bounce suggests that spreads distort measured returns (Harris, 1986). Risk-based views attribute Monday effects to time-varying premia and volatility clustering (Rogalski, 1984; Balaban, 1995), and recent multifractal analyses show Monday returns to be more complex and less efficient (Stosic et al., 2022). Cross-country studies highlight cultural and institutional factors, such as weekend structures in Islamic markets or time-zone differences in Japan and Australia (Jaffe & Westerfield, 1985; Balaban, 1995). Finally, the evolutionary view suggests the effect has weakened in developed markets due to arbitrage and efficiency gains, though it persists in emerging markets and small-cap stocks (Lakonishok & Smidt, 1988; Brooks & Persand, 2001; Kamara, 1997). Despite these diverse perspectives, no single theory explains the anomaly universally, and mixed findings reflect a replication crisis shaped by differences in time, region, and study design (Jensen et al., 2023; Conrad et al., 1997; Hou et al., 2020).

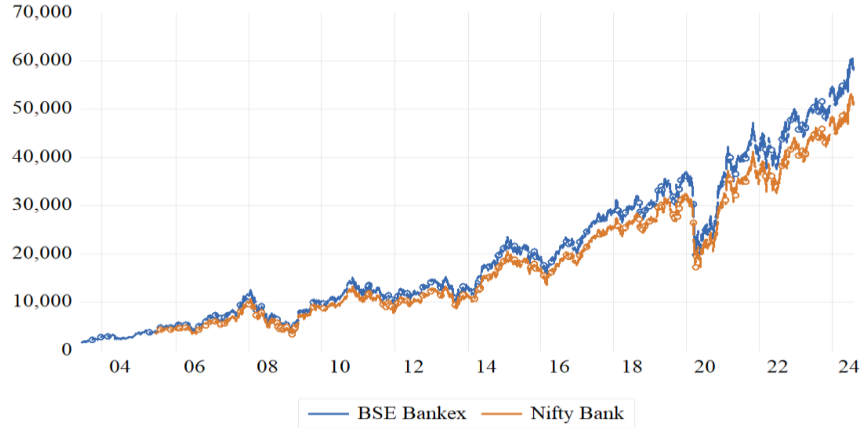

Fig. 1: Daily Closing Price of BSE Bankex and Nifty Bank.

Source: Author’s visualization.

While these explanations remain debated globally, recent Indian evidence highlights that volatility dynamics in bank stocks reflect both clustering and asymmetry. Das and Rout (2024) find that Indian bank stock price volatility exhibits distinct temporal patterns, characterized by volatility clustering wherein high-volatility and low-volatility regimes tend to aggregate, and volatility persistence, wherein these regimes exhibit temporal dependence. Furthermore, their findings reveal asymmetric effects in volatility responses to positive and negative price movements. However, the magnitude and nature of these volatility dynamics vary across individual banks. Building on these insights, the present study examines volatility clustering in the context of the DOW effect anomaly. The two banking indices considered for this purpose are the BSE Bankex, launched on June 23, 2003, and the Nifty Bank, introduced on September 15, 2003. These indices serve as key benchmarks for the Indian banking sector, representing the performance of major publicly listed banks. Their significance has grown in tandem with the rapid expansion and transformation of India’s banking industry over recent decades. The upward trajectory of these indices, as shown in Figure 1, reflects increased market sensitivity to economic shifts and investor sentiment, underscoring the importance of analysing volatility to gain insights into financial stability. Examining the volatility of both indices may therefore provide a deeper understanding of the stability dimensions of the industry.

Considering these volatility patterns within a broader institutional context, India’s banking sector has undergone a profound transformation since the liberalization reforms of the 1990s, which enhanced productivity, stock performance, and competitiveness (Kumar et al., 2010; Sharma & Sharma, 2015). These gains are attributed to technological advancements, regulatory reforms, and diversification into retail and investment banking, which attract investment and mitigate risks (Birt et al., 2017; Zhao et al., 2010; Nataraj & Ashwani, 2018). Additionally, mergers in public sector banks create notable stock price movements and volatility due to investor speculation, reflecting the sector’s dynamic environment and appeal (Srividya et al., 2021; Kumar & Suhas, 2010). The success of these mergers also influences long-term stock stability and valuations (Wang et al., 2014).

India’s financial market structure presents a relevant context for examining calendar anomalies and volatility dynamics, given structural and behavioural characteristics that distinguish it from mature markets. First, the rapid rise in retail participation, which is reflected in over 110 million unique investors registered with the NSE by February 2025, and the widespread use of digital payment platforms, with UPI recording 20 billion monthly transactions in August 2025, have broadened the diversity of investor behaviour and trading horizons (NSE, 2025a; NPCI, 2025). Second, uneven levels of financial literacy contribute to non-rational trading patterns and delayed information incorporation into prices (Jangili et al., 2023). Third, households’ continued preference for physical assets such as gold and real estate over financial instruments influences portfolio choices and reinforces behavioural biases, including herding (RBI Household Finance Committee, 2017). These factors are particularly evident in the banking and financial services sector, where herding behaviour is observed, especially during periods of market stress (Mishra & Mishra, 2021).

The period under study coincides with key market reforms since 2021. India has implemented structural upgrades such as the transition to T+1 settlement (completed in January 2023) and strengthened surveillance mechanisms, including the expansion of the Additional Surveillance Measure (ASM), aimed at improving market efficiency and curbing speculation. Evidence suggests these changes have led to narrower bid-ask spreads and improved liquidity, particularly for less-traded stocks (SEBI, 2021, 2022; Bhanu et al., 2024; NSE, 2024). Nevertheless, calendar-related patterns such as the DOW effect may persist due to their dependence on institutional routines, cultural trading habits, and investor psychology (Grebe & Schiereck, 2024).

The focus on banking indices under the study is justified by the sector’s central role in India’s financial system, accounting for approximately 60% of total financial assets (IMF, 2025), and its critical function in credit intermediation and monetary transmission. Empirical studies on Indian and BRICS markets indicate that high volatility persistence and asymmetric responses to negative shocks in equity returns, with banking stocks particularly responsive to macroeconomic announcements and regulatory communications (Tripathy, 2022; Gupta et al., 2024; Nikhil et al., 2022). This sensitivity aligns with Gupta et al. (2024), who show that both policy rate changes (“target” surprises) and forward guidance (“path” surprises) affect market volatility, reinforcing the need to examine bank-sector volatility dynamics within a robust econometric framework.

This study extends the prior research by providing a comprehensive analysis of intraday volatility dynamics in India’s banking sector indices, BSE Bankex and Nifty Bank, within a robust GARCH modelling framework. By integrating symmetric (GARCH), asymmetric (EGARCH, TGARCH), and long-memory (FIGARCH) specifications, the research uncovers strong evidence of DOW effects in conditional volatility, with significantly lower volatility on Tuesdays and a noticeable rise toward the week’s end, particularly on Fridays, while return patterns remain relatively less sensitive to weekday variation. The findings highlight the dominance of volatility clustering, the asymmetric impact of market shocks, and the presence of long memory, which indicate that volatility in these indices persists over extended periods and reacts disproportionately to negative news. These insights enhance the understanding of market microstructure and investor behaviour in an emerging economy marked by a growing retail participation and evolving information efficiency, and offer valuable implications for risk forecasting, trading strategies, and regulatory oversight in Indian financial markets.

2. Literature Review, Research Gap, and Hypotheses

Over the years, empirical research has substantiated the prevalence of the DOW effect in financial markets across cross-border economies. However, the intensity and direction of this phenomenon vary depending on geographical and time-related factors.

2.1. Global empirical evidence on weekday anomalies

While Öncü et al. (2017) found no significant anomalies in the BIST-100 index, Alagidede (2008) noted that calendar anomalies in African markets were context-specific. In Eastern Europe, Dimitar and Tae-Hwan (2004) observed a January effect in the Czech Republic, with weak DOW effect evidence in Slovenia. Berument and Kiymaz (2001) reported volatility peaking on Fridays in US markets. Miss et al. (2020) found no persistent Monday effect in DAX returns. Basher and Sadorsky (2006) identified the DOW effect in developing countries like the Philippines, Pakistan, and Taiwan, while Brooks and Persand (2001) provided mixed evidence from Southeast Asia. Dubois and Louvet (1996) found negative Monday returns across nine international markets, counterbalanced by positive returns on Wednesdays. In China, Cai et al. (2006) identified negative returns on Mondays and Tuesdays during specific weeks, persisting despite autocorrelation adjustments.

Chaouachi and Douagi (2014) highlighted a significant calendar anomaly in Tunisia, while Ahmed and Eskandar (2009) found the DOW effect prevalent in Arab markets. According to Farooq et al. (2013), the Saudi Stock Exchange experiences its lowest volatility on Saturdays and Sundays, attributed to the closure of international markets. Conversely, the highest volatility is recorded on Wednesdays. Karanovic and Karanovic (2018) identified the DOW effect only in Croatia among Balkan markets, attributing inconsistencies to market conditions. Solnik and Bousquet (1990) documented negative Tuesday returns in the Paris Bourse, while French (1980) proposed models explaining consistently negative Monday returns in the US. Gharaibeh and Al Azmi (2015) observed contrasting trends in Kuwait's stock exchange, and Cinko and Avci (2009) found strong positive Thursday and Friday returns in the ISE-100 index.

Alexakis and Xanthakis (1995) noted changing patterns in the Athens Stock Exchange, with earlier positive Monday returns turning negative. Al-Khazali (2008) rejected the DOW effect in UAE markets after adjusting for thin trading conditions. Similarly, Al-Jafari (2012) found no DOW effect in Muscat, indicating market efficiency. Richard et al. (2004) highlighted negative Monday returns in Estonia and Lithuania but no consistent patterns across other Eastern European markets. Khan et al. (2021) also found no DOW effect in India and Malaysia; however, they observed this effect in China, Pakistan, and South Korea. However, Choudhry (2000) reported end-of-week optimism in India and Malaysia. Sy and Derbali (2015) observed the DOW effect in Moroccan markets. Kiymaz and Berument (2003) found that Germany and Japan experienced the highest volatility on Mondays, while North America saw peaks on Fridays.

2.2. Evidence from India

Concerning the Indian stock market, Singh and Das (2020) reported no significant Monday or Thursday effect on both returns and volatility, suggesting limited evidence of weekday anomalies in BSE Bankex. This aligns with Aziz and Ansari (2015), who observed that the Monday anomaly common in developed markets does not exist in India, though the Friday effect was noted between 1990 and 2000. Arora (2018) found significant Monday and Friday returns in Nifty 50 before the introduction of the pre-opening session, with Thursday showing the highest volatility across trading days. Similarly, Bhattacharya et al. (2003) noted positive Friday and negative Monday returns, with elevated Monday and Thursday volatility. On the contrary, Patel and Mallikarjun (2014) found significantly lower volatility on Thursday. Other studies, such as Srinivasan and Kalaivani (2014), also identified positive Monday and Wednesday effects in both Nifty and Sensex, while Raj and Kumari (2006) attributed the positive Monday effect to India's settlement cycle. Kaur (2004) observed higher Wednesday returns and minimal volatility on Tuesdays. Additionally, Paital and Panda (2018) discovered that Nifty indices exhibited higher positive returns over weekends while showing negative performance on Tuesdays, with both the return rates and market volatility on Tuesdays falling below Monday's levels. Munusamy (2018) noted a significant Ramadan effect on returns and volatility, while Aggarwal and Jha (2023) observed positive returns across all days and a significant negative Tuesday effect on volatility in Nifty.

2.3. Research gap

Despite the extensive research on the DOW effect anomalies, a notable gap exists in the Indian literature on banking stocks. As evident from Table 1, prior studies have primarily focused on broader indices. However, no studies have specifically addressed the DOW effect within the context of Indian banking stocks using the FIGARCH model, which is essential for capturing both long memory and volatility clustering. This study aims to bridge this unexplored area by estimating the DOW effect on both returns and volatility dynamics of the BSE Bankex and Nifty Bank. By exploring this unexplored area, the study will contribute to the understanding of market behaviour and inefficiencies within the Indian banking sector, potentially revealing opportunities for abnormal profits and enhancing the existing body of literature.

Table 1: Research Gaps in DOW-Effect Studies Focusing on Indian Stock Market Volatility

Sl No.	Author (s) (Year)	Sample	Methodology	Research Gap
1	Bhattacharya et al. (2003)	BSE 100 (January 1991 – September 2000)	OLS and GARCH	No use of asymmetric or long-memory GARCH models; no sectoral analysis
2	Kaur (2004)	Sensex, Nifty, S&P 500, Nasdaq (January 1993 – March 2003)	GARCH, TGARCH, and EGARCH	No focus on banking indices
3	Raj and Kumari (2006)	Sensex (weekly/daily: 1979–1998); Nifty (daily/weekly: 1990–1998)	OLS	Did not employ GARCH family models; lacked analysis of sectoral indices

4	Patel and Mallikarjun (2014)	Sensex, Nifty (January 1999 – January 2013)	GARCH	No use of advanced GARCH variants; no sectoral analysis
5	Srinivasan and Kalaivani (2014)	NSE 50, Sensex (July 1997 – June 2012)	GARCH, EGARCH, and TGARCH	No inclusion of bank indices; did not apply the long-memory effect model
6	Aziz and Ansari (2015)	Sensex (April 1990 – February 2013); Nifty (November 1995 – February 2013)	GARCH	Lacks asymmetric and long-memory volatility models; excludes bank indices
7	Arora (2018)	Nifty 50 (January 2010 – March 2011)	GARCH	No sectoral index analysis; limited to the basic GARCH model
8	Paital and Panda (2018)	Nifty 50, Midcap 50, Smallcap 50 (April 2005 – June 2018)	GARCH	No use of long-memory or asymmetric GARCH models; excluded bank indices
9	Munusamy (2018)	Nifty Shariah, Nifty 50, Shariah 500, Sensex, MSCI (January 2010 – March 2016)	GARCH, TGARCH	No application of the FIGARCH model; no focus on banks
10	Singh and Das (2020)	BSE Bankex, BSE IT (2010–2019)	GARCH, EGARCH, and TGARCH	Did not analyse the Nifty Bank index; no use of long-memory models
11	Aggarwal and Jha (2023)	NSE Nifty (July 1990 – March 2022)	GARCH, EGARCH, and TGARCH	No consideration of bank indices; did not apply long-memory volatility models

Note: OLS- Ordinary Least Squares Method; GARCH- Generalized Autoregressive Conditional Heteroskedasticity; TGARCH- Threshold GARCH; EGARCH- Exponential GARCH; FIGARCH- Fractionally Integrated GARCH.

Source: Author's compilation.

2.4. Hypotheses

Drawing upon prior research examining stock market anomalies, the study proposes that the weekday effect exerts a significant influence on both the returns and volatility of banking stocks within the Indian market. Previous studies suggest that stock markets exhibit distinct patterns tied to trading days, often reflecting market inefficiencies and investor behaviour (Cross, 1973; Solnik & Bousquet, 1990; Chang et al.,1993; Alexakis & Xanthakis, 1995; French, 1980; Ahmed & Eskandar, 2009; Alagidede, 2008; Al-Jafari, 2012; Al-Khazali, 2008; Arora, 2018; Aziz & Ansari, 2015; Basher & Sadorsky, 2006; Berument & Kiymaz, 2001; Brooks & Persand, 2001; Cai et al., 2006; Chaouachi & Douagi, 2014; Kiymaz & Berument, 2003; Lo, 2004; Raj & Kumari, 2006; Srinivasan & Kalaivani, 2014; Aggarwal & Jha, 2023). Against this backdrop, the study anticipates that daily returns and volatility follow specific patterns across the week, influenced by factors such as market adjustments and liquidity changes.

Moreover, the well-documented autocorrelation in stock returns (Lo & MacKinlay, 1988; Lien & Yang, 2004; Chordia & Swaminathan, 2000; Chowdhury et al., 2015; Jain & Xue, 2017), along with the effect of past events and past volatility on present volatility, indicating the presence of ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH effects (Engle, 1982; Bollerslev, 1986; Baillie et al., 1996; Ding et al.,1993; Nelson, 1991; Patton & Sheppard, 2015), supports the inclusion of these effects in the model. The study also proposes that asymmetric reactions to positive and negative news (leverage effect) may be present, along with long memory effects in volatility, both of which have been observed in various stock markets and are also anticipated in the banking industry in India. Accordingly, the present study attempts to analyse weekday anomalies in daily returns and volatility patterns of the BSE Bankex and Nifty Bank using various GARCH family models, through testing the following hypotheses:

H_1: Daily returns exhibit a significant DOW effect anomaly.
H_2: Daily volatility exhibits a significant DOW effect anomaly.
H_3: ARCH effect (i.e., past shocks) significantly affects current volatility.
H_4: GARCH effect (i.e., past volatility) significantly affects current volatility
H_5: Daily volatility exhibits a significant leverage effect.
H_6: Daily volatility exhibits significant long memory.

3. Methodology

3.1. Data

The DOW effects on daily returns and volatility are estimated for the BSE Bankex from June 23, 2003, to July 31, 2024, and for the Nifty Bank from June 9, 2005, to July 31, 2024. The historical price data of the index was obtained from the official websites of BSE and NSE. The daily closing prices are considered to calculate the logarithmic return, which measures the compounded return over a designated period. It is calculated as $r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$, where, p represents the current day(t) price and p_{t-1} Denotes the previous day (t-1) price.

3.2. Estimation models

The analysis begins by testing the stationarity of the BSE Bankex and Nifty Bank daily returns, confirming that both series are stationary. The initial estimation employs OLS to confirm the appropriateness of using GARCH models, incorporating a constant term, an AR (1) process (autoregressive term of order 1), and DOW effect dummies. The mean equation is specified as follows:

$$r_t = \mu_0 + \mu_1 r_{t-1} + \sum_{j=2}^{5} \delta_j D_{t,j} + \epsilon_t \quad (1)$$

Where, μ_0, μ_1 Indicate intercept and autoregressive terms; δ_j measures the average return difference on the day relative to the base day (i.e., Monday); $D_{t,j}$ represents day dummy variables, where $j \in \{2,3,4,5\}$, corresponding to Tuesday, Wednesday, Thursday, and Friday, respectively; and ϵ_t Is the error term. The OLS estimation reveals significant ARCH effects and a strong AR(1) influence, i.e. significant coefficient value of μ_1. Additionally, the ARCH-LM test applied to the residuals reveals significant ARCH effects, thereby supporting the use of a GARCH model, initially introduced by Bollerslev (1986), which in this study incorporates both an AR(1) and DOW effect dummy variables.

The selection of the p and q orders in the GARCH (p, q) model depends on the model's ability to effectively capture volatility dynamics, which is assessed using residual diagnostic tests such as the Ljung-Box Q test and the ARCH-LM test. This approach is applied to other models as well.
The standard GARCH (1,1) model is presented as follows:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{j=2}^{5}\psi_j D_{t,j} \tag{2}$$

Where, ω, α and β Indicate coefficients of the intercept term, ARCH, and GARCH effects; $\epsilon_{t-1}^2$is the lagged squared error term (previous shock); σ_{t-1}^2 means lagged conditional variance (past volatility); and ψ_j measures the day-specific volatility adjustment for the day j Relative to Monday. Moreover, to investigate long-memory effects in volatility clustering, the study estimates Baillie et al.'s (1996) FIGARCH. Model. The FIGARCH (1,d,1) model is expressed as below:

$$\sigma_t^2 = \omega + \alpha(L)\epsilon_t^2 + \beta(L)\sigma_t^2 + \sum_{j=2}^{5}\psi_j D_{t,j} \tag{3.1}$$

By integrating the fractional difference operator $(1 - L)^d$, Eq.3.1 can be rewritten as:

$$[1 - \beta(L)]\sigma_t^2 = \omega + [1 - \beta(L) - \phi(L)(1 - L)^d]\epsilon_t^2 + \sum_{j=2}^{5}\psi_j D_{t,j} \tag{3.2}$$

Where, $\alpha(L)$ and $\beta(L)$ Are the polynomials in the lag operator? L; $\phi(L) = [1 - \alpha(L) - \beta(L)](1 - L)^{-1}$ Is the lag polynomial that adjusts the standard GARCH structure to incorporate fractional differencing, thereby generating long-memory behaviour in volatility, and the fractional parameter. $d \in (0,1)$ Indicates the degree of long-term persistence in volatility.
Recognizing that both GARCH and FIGARCH models account only for symmetric volatility clustering, the study further explores TGARCH and EGARCH models to capture asymmetry and leverage effects, originally designed by Glosten et al. (1993) and Nelson (1991). The TGARCH (1,1) model is as under:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma\epsilon_{t-1}^2\bar{I}_{t-1} + \beta\sigma_{t-1}^2 + \sum_{j=2}^{5}\psi_j D_{t,j} \tag{4}$$

Where, $\bar{I}_{t-1} = 1$ if $\varepsilon_t < 0$ and 0 otherwise, indicating that good news $(\varepsilon_{t-i} > 0)$ and negative news $(\varepsilon_{t-i} < 0)$ have differential effects. Thus, positive γ Suggest that +
Negative news tends to result in greater volatility than positive news. Moreover, the EGARCH(1,1) model can be provided as below:

$$log(\sigma_t^2) = \omega + \alpha\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right) + \beta log(\sigma_{t-1}^2) + \sum_{j=2}^{5}\psi_j D_{t,j} \tag{5}$$

Where, $\gamma \neq 0$ indicates the presence of asymmetric effects of news, and if $\gamma < 0$ Signifies a leverage effect, meaning negative news increases volatility.

3.3. Summary statistics and normality test

Summary statistics are essential for understanding the basic features of financial return series before conducting formal econometric analysis. The mean represents the average return over the sample period and provides insight into the central tendency of the data (Reilly & Brown, 2012). The maximum and minimum values indicate the range of observed returns, highlighting extreme gains or losses, which is particularly important in risk assessment. The standard deviation (Std. Dev) measures the dispersion or volatility of returns around the mean and serves as a key indicator of risk in financial markets (Sharpe, 1970). A higher standard deviation implies greater variability and thus higher investment risk.
To assess the shape of the return distribution, skewness and kurtosis are used. Skewness measures the asymmetry of the distribution; a negative skewness indicates a longer left tail (more frequent large negative returns), while positive skewness suggests a longer right tail. Kurtosis measures the tailedness or peakedness of the distribution. A kurtosis value greater than 3, which exceeds that of a normal distribution, indicates leptokurtic behaviour, characterized by fatter tails and a sharper peak. This suggests a higher probability of extreme outcomes or outliers compared to a normal distribution (Cont, 2001).
The Jarque-Bera (JB) test is used to evaluate whether the data follow a normal distribution by combining information from both skewness and kurtosis. Under the null hypothesis, the data are normally distributed. The test statistic is defined as:

$$JB = \frac{T}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{6}$$

Where, T Is the sample size, S Is skewness, and K It is excess kurtosis. A significant Jarque-Bera statistic (i.e., rejection of the null) indicates non-normality, which is commonly observed in financial return series due to volatility clustering and extreme events (Jarque & Bera, 1987).

3.4. Diagnostics and specification tests

To ensure the validity of the estimation process, several diagnostic tests are employed to assess stationarity, serial correlation, volatility clustering, and asymmetric effects in financial return series.

3.4.1. Augmented Dickey-Fuller (ADF) test

The ADF test is employed to determine whether a time series is stationary by testing for the presence of a unit root. The null hypothesis is that the series contains a unit root (i.e., it is non-stationary) (Dickey & Fuller, 1979). To account for higher-order serial correlation, the ADF test extends the standard Dickey-Fuller regression by including lagged differences of the return series. The model is specified as:

$$\Delta r_t = \alpha + \beta t + \gamma r_{t-1} + \sum_{i=1}^{p} \phi_i \Delta r_{t-1} + \epsilon_t \quad (7)$$

Where, $\Delta r_t = r_t - r_{t-1}$, α It is a constant (drift), βt is a time trend (if included), γ Is the coefficient on the lagged level of the series, p Is the number of lagged differences included to eliminate serial correlation in the residuals? The test statistic is based on the t-ratio of $\hat{\gamma}$, and if it is negative, the null hypothesis of a unit root is rejected (Said & Dickey, 1984).

3.4.2. Ljung-Box Q test

This test is used to detect autocorrelation in a time series up to a specified lag. m. It tests whether the first. m Autocorrelations of the return (or squared returns) are jointly zero. The null hypothesis is

$$H_0: \rho_1 = \rho_2 = \cdots = \rho_m = 0 \ (no\ autocorrelation)$$

The test statistic is given by:

$$Q(m) = T(T+2)\sum_{k=1}^{m} \frac{\hat{\rho}_k{}^2}{T-k} \quad (8)$$

Where, $\hat{\rho}_k$ Is the sample autocorrelation at lag k, and m Is the number of lags tested? Under the null $Q(m)$ follows a $\chi^2(m)$ Distribution asymptotically (Ljung & Box, 1978). When applied to squared returns, a significant $Q(m)$ Statistic indicates the presence of volatility clustering, which justifies the use of GARCH models.

3.4.3. ARCH-Lagrange multiplier (ARCH-LM) test

The ARCH-LM Test proposed by Engle (1982) formally tests for the presence of ARCH effects in the residuals of a model. It is particularly useful after estimating a mean equation to check whether volatility modelling is necessary.
The test involves regressing the squared residuals. $\hat{\epsilon}_t{}^2$ on a constant and q Lags of their own values:

$$\hat{\epsilon}_t{}^2 = \alpha_0 + \alpha_1 \hat{\epsilon}_{t-1}^2 + \alpha_2 \hat{\epsilon}_{t-2}^2 + \cdots + \alpha_q \hat{\epsilon}_{t-q}^2 + u_t \quad (9)$$

Where, u_t Is the error term and q Denotes the chosen lag order.
The test statistic is given by

$$TR^2 \sim \chi^2 q$$

Where, R^2 Is the coefficient of determination from the auxiliary regression?
The null hypothesis is

$$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_q = 0 \text{ (no ARCH effects)}$$

A significant TR^2 Statistic leads to rejection of the null, indicating the necessity of GARCH specification for accurate volatility modelling (Engle, 1982).

3.4.3. Engle-Ng sign bias test

This test, also known as the News Impact Test, is used to detect whether the sign of past shocks has a differential impact on current volatility (Engle & Ng, 1993). Specifically, it tests whether negative shocks increase volatility more than positive shocks of equal size.
The test involves estimating the following regression:

$$\hat{\epsilon}_t^2 = \alpha_0 + \alpha_1 S_{t-1} |\hat{\epsilon}_{t-1}| + \eta_t \quad (10)$$

Where, $S_{t-1} = 1$ if $\hat{\epsilon}_{t-1} < 0$ (i.e., negative shock), $S_{t-1} = 0$ Otherwise. The coefficient α_1Captures the sign bias. If $\alpha_1 > 0$ And statistically significant, it indicates that negative shocks lead to higher volatility than positive ones of the same magnitude.
This test can also be extended to include negative size bias, positive sign bias, and joint bias.
This negative size bias test examines whether larger negative shocks produce disproportionate increases in volatility. The regression is:

$$\hat{\epsilon}_t^2 = \beta_0 + \beta_1 S_{t-1} \hat{\epsilon}_{t-1} + \nu_t \quad (11)$$

Where, $S_{t-1}\hat{\epsilon}_{t-1}$ Interacts with the size and sign of the lagged shock. A significant β_1 Suggests that the effect of volatility depends not only on the size but also on the magnitude of negative shocks.
The positive size bias test captures the effect of large positive shocks. The regression is:

$$\hat{\epsilon}_t^2 = \gamma_0 + \gamma_1 (1 - S_{t-1}) \hat{\epsilon}_{t-1} + \xi_t \quad (12)$$

Where, $(1 - S_{t-1})\hat{\epsilon}_{t-1}$ Captures the interaction for positive shocks. A significant γ_1Indicates that large positive shocks have a distinct impact on volatility.
To jointly test for sign bias, negative size bias, and positive size bias, the following regression is estimated:

$$\hat{\epsilon}_t^2 = \delta_0 + \delta_1 S_{t-1} + \delta_2 S_{t-1} \hat{\epsilon}_{t-1} + \delta_3 (1 - S_{t-1}) \hat{\epsilon}_{t-1} + u_t \quad (13)$$

A joint Wald test on the coefficients ($\delta_1 \delta_2, \delta_3$) determines whether any combination of sign or size biases significantly affects volatility.

Where, if only δ_1 It is significant; it means sign bias exists, if only. δ_2 It is significant, it indicates that negative size bias dominates; if only. δ_3 It is significant; it implies positive size bias dominates; if multiple coefficients are significant, it provides evidence of joint asymmetries in volatility response.

3.5. Model selection criteria and distributional assumptions

The final model selection is guided by a combination of residual diagnostic tests and information criteria, prioritizing models that achieve the best balance between goodness-of-fit and parsimony. Specifically, the preferred model is selected based on the lowest values of the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HQC), as well as the highest log-likelihood (LL) value.
AIC is defined as:

$$AIC = -2\frac{LL}{T} + 2\frac{k}{T} \quad (14)$$

Where, LL is the maximised log-likelihood, k Is the number of estimated parameters. AIC tends to favour models with better fit but applies a relatively mild penalty for additional parameters (Akaike, 1974).
SIC is expressed as:

$$SIC = -2\frac{LL}{T} + \frac{k\,ln(T)}{T} \quad (15)$$

SIC imposes a stronger penalty for model complexity, especially as the sample size T Increases, and thus tends to select simpler, more parsimonious models (Schwartz, 1978).
HQC lies between AIC and SIC in terms of penalty strength, and it is given by:

$$HQC = -2\frac{LL}{T} + 2\frac{k\,ln(ln(T))}{T} \quad (16)$$

It is consistent under more general conditions and is commonly used in time series analysis (Hannan & Quinn, 1979).
In addition to information criteria, the LL Value itself is often examined directly, with a higher LL indicating a better fit to the observed data, assuming the same distributional form.
Furthermore, to ensure robustness, as suggested by Baker et al. (2008), the study considers three residual distributions: the Normal Distribution (ND), Student's t-distribution (TD), and Generalized Error Distribution (GED). This approach helps mitigate the risk of distributional misspecification, which is common in financial time series analysis. ND assumes symmetric and thin-tailed errors (Gujarati & Porter, 2009). However, it often fails to capture the excess kurtosis and fat tails empirically prevalent in financial returns, leading to potential underestimation of extreme events. TD allows for fatter tails through its degrees of freedom parameter, making it more robust to outliers and better suited for modelling financial data with extreme values (Bollerslev, 1987). A lower degree of freedom implies heavier tails, providing greater flexibility in capturing leptokurtic behaviour. GED is a flexible distribution that can model both fat-tailed and thin-tailed behaviour depending on its shape parameter. It generalizes the normal distribution and is widely used in volatility modelling to account for non-normal innovations (Nelson, 1991). When the shape parameter equals 2, the GED reduces to the normal distribution; values less than 2 indicate fatter tails, while values greater than 2 imply thinner tails.

4. Results and Discussion

4.1. Unit root test

The ADF test results, shown in Table 2, indicate that both the BSE Bankex and Nifty Bank time series are stationary. The significant negative test statistics across all specifications provide evidence against the unit root null hypothesis, confirming that the indices are suitable for financial modelling.

Table 2: Augmented Dickey-Fuller (ADF) Test

	Intercept	Intercept and Trend	None
BSE Bankex	-65.53557***	-65.54154***	-65.45664***
Nifty Bank	-62.59243***	-62.58690***	-62.54251***

Note: *** indicates significance at the 1% level.
Source: Author's estimations.

4.2. Summary statistics

Table 3: Summary Statistics of the Daily Return of BSE and NSE Bank Indices

	BSE Bankex	Nifty Bank
Mean	0.000684	0.000559
Max	0.175483	0.172394
Min	-0.184006	-0.183130
Std. Dev	0.018080	0.017852
Skewness	-0.287878	-0.218670
Kurtosis	11.60382	11.03602
Jarque-Bera Test	16250.14***	12805.34***
Observations	5245	4745

Note: *** indicates significance at the 1% level.
Source: Author's estimations.

Table 3 depicts summary statistics analysing the daily returns of BSE Bankex and Nifty Bank, based on 5,245 and 4,745 observations, respectively. The BSE Bankex has a mean return of 0.000684, slightly above the Nifty Bank's 0.000559. Both indices exhibit significant variability, with maximum daily returns of 0.175483 for the BSE Bankex and 0.172394 for the Nifty Bank, and minimum returns of -0.184006 and -0.183130, respectively. The Std. Dev. is 0.018080 for the BSE Bankex and 0.017852 for the Nifty Bank. Negative skewness values of -0.287878 for the BSE Bankex and -0.218670 for the Nifty Bank indicate a tendency towards larger negative returns. High kurtosis values (11.60382 for the BSE Bankex and 11.03602 for the Nifty Bank) indicate the presence of fat tails, which signifies a greater likelihood of extreme returns compared to what would be expected in a normal distribution. The non-normality of the return series data for both indices is confirmed by the Jarque-Bera test result, with test statistics of 16250.14 and 12805.34, both significant at $p < 0.01$.

4.3. Estimation result

4.3.1. GARCH model

Estimation results from the GARCH(2,1) model, reported in Table 4, reveal a consistent pattern of mild return seasonality and pronounced volatility clustering in the BSE Bankex and Nifty Bank indices. In the conditional mean equation, the intercept (μ_0) It is positive and statistically significant at the 1% level for both indices (BSE Bankex: 0.001431; Nifty Bank: 0.001298), indicating a small but persistent positive average return on Mondays. The autoregressive coefficient (μ_1) Is also highly significant (BSE Bankex: 0.089039; Nifty Bank: 0.086819, both $p < 0.01$), confirming moderate yet statistically robust return persistence. The DOW dummy coefficients are uniformly negative across Tuesday to Friday for both indices, suggesting a post-Monday decline in mean returns. While most of these effects lack statistical significance, Wednesday (δ_3) Exhibits a negative and marginally significant effect at the 10% level (BSE Bankex: -0.000939; Nifty Bank: -0.000905), implying systematically lower returns midweek relative to Monday, i.e., a tentative "Wednesday anomaly" observed in both indices.

In the conditional variance equation, the first ARCH term (α_1) is positive and highly significant for both indices (BSE Bankex: 0.112349, $p < 0.01$; Nifty Bank: 0.091101, $p < 0.01$). The second ARCH term (α_2), which measures the contribution of the squared shock from two days prior, is negative for both indices (BSE Bankex: -0.022585; Nifty Bank: -0.006054), though statistically insignificant. This suggests that while large shocks from two days ago may exert a slight dampening effect on current volatility, this effect lacks robust statistical support. The GARCH term (β), capturing persistence from lagged conditional variance, is positive and highly significant (BSE Bankex: 0.901028; Nifty Bank: 0.911183; both $p < 0.01$). The sum of $\alpha + \beta$ Equals 0.9908 for BSE Bankex and 0.9962 for Nifty Bank. Both are close to unity, indicating strong volatility persistence and near-unit-root behaviour in conditional variance.

The DOW dummies in the variance equation reveal a distinct intraweek volatility cycle. Tuesday exhibits significantly lower volatility than Monday at the 5% level (ψ_2 = -3.48e-05 for BSE Bankex; -2.71e-05 for Nifty Bank), confirming a robust "calm Tuesday" effect. In contrast, Friday displays a marginally significant volatility premium at the 10% level (ψ_5 = 2.18e-05 for BSE Bankex; 2.42e-05 for Nifty Bank), suggesting elevated volatility heading into the weekend — a "Friday effect." Thursday also shows a positive coefficient, reaching marginal significance for Nifty Bank (ψ_4 = 1.44e-05, $p < 0.10$), while Wednesday's effect remains statistically indistinguishable from zero (ψ_3 = 1.23e-05 for both indices).

4.3.2. FIGARCH model

The FIGARCH(1,d1) for BSE Bankex and FIGARCH(2,d1) for Nifty Bank yields results that reinforce persistent volatility clustering while revealing subtle but consistent DOW effects. In the conditional mean equation, the Monday intercept (μ_0) It is positive and statistically significant at the 1% level for both indices (BSE Bankex: 0.001306; Nifty Bank: 0.001269), indicating a significantly positive average return on the baseline day. The autoregressive coefficient (μ_1) It is also highly significant (BSE Bankex: 0.086707; Nifty Bank: 0.085741; both. $p < 0.01$), confirming strong persistence in daily returns. The DOW dummy coefficients are uniformly negative across Tuesday to Friday for both indices, implying that mean returns tend to be lower on these days relative to Monday; however, none attain conventional levels of statistical significance, suggesting that while a mild Monday return premium may exist, it is not robustly supported across the week.

In the conditional variance equation, the fractional integration parameter d is significantly greater than zero and less than one for both indices (BSE Bankex: 0.526059; Nifty Bank: 0.593066; both $p < 0.01$, confirming the presence of long memory in volatility. For BSE Bankex, estimated under FIGARCH(1,d1), the ARCH coefficient (α_1 = 0.257883, $p < 0.01$) captures the immediate impact of shocks on volatility, while the GARCH term (β = 0.670787, $p < 0.01$) reflects volatility persistence from lagged conditional variance. For Nifty Bank, estimated under FIGARCH(2,d1) The model includes an additional lag in the ARCH structure: α_1(0.252723, p< 0.01) remains highly significant, while α_2 (0.032268), Though statistically insignificant, it carries a positive sign; this suggests a potential extended volatility transmission mechanism in Nifty Bank, possibly reflecting its higher liquidity and institutional participation, which may prolong the impact of past shocks. The GARCH parameter for Nifty Bank (β = 0.752437, $p < 0.01$) It is higher than for BSE Bankex, indicating stronger persistence in the autoregressive volatility component.

Turning to intraweek effects, the DOW dummies in the variance equation reveal a statistically coherent weekly rhythm. Tuesday (ψ_2) Exhibits significantly lower volatility than Monday at the 1% level for both indices (BSE Bankex: -3.67e-05; Nifty Bank: -3.76e-05), confirming a robust "calm Tuesday" effect. In contrast, coefficients for Wednesday (ψ_3: BSE Bankex 9.67e-06; Nifty Bank 1.29e-05) and Thursday (ψ_4: BSE Bankex 9.36e-06; Nifty Bank 1.43e-05) are positive but statistically insignificant, offering no evidence of systematic midweek volatility shifts. Friday's coefficient is positive and marginally significant at the 10% level for both indices (BSE Bankex:2.55e-05; Nifty Bank: 2.42e-05), pointing to a modest but detectable increase in volatility heading into the weekend, i.e., a potential "Friday effect."

Regarding long memory dynamics, the FIGARCH differencing parameter is notably large for both indices (BSE Bankex: d = 0.526059, $p < 0.01$; Nifty Bank: d = 0.593066, $p < 0.01$), indicating statistically significant long memory in conditional volatility. Volatility shocks decay hyperbolically rather than exponentially, so their influence persists over long horizons. The larger d For Nifty Bank implies stronger persistence than for BSE Bankex. In both cases, volatility is slowly mean-reverting in the short run, and large swings tend to be followed by prolonged periods of elevated volatility. Hence, historical volatility remains highly relevant for forecasting, and models that ignore this persistence will underestimate future risk.

4.3.3. TGARCH model

The TGARCH (3,1) for BSE Bankex and TGARCH (2,1) for Nifty Bank reveal both leverage effects and statistically stronger DOW patterns in volatility. In the mean equation, results mirror prior specifications: Monday returns are significantly positive (μ_0: 0.001199 for BSE Bankex; 0.001191 for Nifty Bank; both $p < 0.01$), and return autocorrelation remains strong (μ_1: 0.090917 and 0.086327, respectively; both $p < 0.01$). The DOW dummies are again negative across weekdays, with only Wednesday in the Nifty Bank index attaining marginal significance (δ_3 = -0.000977 , $p < 0.10$), hinting at index-specific midweek return weakness.

In the variance equation, the leverage parameter (γ) is found significantly positive (BSE Bankex: 0.084717, $p < 0.05$; Nifty Bank: 0.081374, $p < 0.01$), confirming that negative shocks generate greater volatility than positive ones. The symmetric ARCH terms, which capture the contribution of past squared shocks irrespective of sign, reveal nuanced dynamics: for BSE Bankex, α_1 (0.072670, $p < 0.01$) is strongly positive, while α_2 (-0.051785, $p < 0.05$) is negative and significant, suggesting that large shocks two days prior are associated with reduced volatility today, possibly reflecting short-term mean reversion or institutional stabilization; α_3(0.027252) is insignificant. For Nifty Bank, α_1 (0.059448, $p < 0.01$) dominates, while α_2 (-0.023282, $p < 0.10$) is negative and marginally significant, indicating a similar but weaker dampening effect. The high persistence parameter (β> 0.89 for both indices; $p < 0.01$) reinforces strong volatility clustering. DOW effects in volatility are more pronounced: Tuesday (ψ_2) again exhibits significantly lower volatility (BSE Bankex: -2.85-05; Nifty Bank: -2.50e-05; both $p < 0.05$), while Friday (ψ_5) shows a positive and significant effect (BSE Bankex: 2.25e-05, $p < 0.10$; Nifty Bank: 2.45e-05, $p < 0.05$). Notably, Thursday's effect is significant for Nifty Bank (ψ_4 = 2.26e-05, $p < 0.05$ But not for BSE Bankex, suggesting index-specific mid-to-late week volatility buildup.

4.3.4. EGARCH model

The EGARCH (2,1) model for both indices yields robust evidence of leverage effects and pronounced DOW seasonality in log-volatility. In the conditional mean equation, the Monday intercept (μ_0) is positive and statistically significant at the 5% level for BSE Bankex (0.000837, $p < 0.05$), while it remains positive but insignificant for Nifty Bank (0.000661), suggesting that the "Monday return premium" is more reliably detected in the former index. The autoregressive coefficient (μ_1) is highly significant at the 1% for both indices (BSE Bankex: 0.090379; Nifty Bank: 0.085356), indicating strong persistence in daily returns. The DOW dummy coefficients are uniformly negative across Tuesday to Friday for both indices, consistent with a mild post-Monday return decline; however, none attain statistical significance, implying that mean return seasonality lacks robust empirical support.

In the conditional variance equation, the model reveals a statistically significant leverage effect, as captured by the negative and highly significant coefficient on the first lag of the standardized shock (γ): BSE Bankex (-0.054947, $p < 0.01$); Nifty Bank (-0.056866, $p < 0.01$). This confirms that negative return shocks (bad news) induce greater volatility than positive shocks of equal magnitude. The magnitude effect from the first lag (α_1) is positive and highly significant (BSE Bankex: 0.288340, $p < 0.01$; Nifty Bank: 0.244339, $p < 0.01$), indicating that large shocks (in absolute value) yesterday are associated with higher volatility today. However, the coefficient on the second lag (α_2) is negative and significant (BSE Bankex: -0.120380, $p < 0.01$; Nifty Bank: -0.09008, $p < 0.01$), suggesting that large-magnitude shocks from two days prior are associated with lower conditional volatility today.

Volatility persistence (β) is exceptionally high and significant (BSE Bankex: 0.983633; Nifty Bank: 0.987239; both $p < 0.01$), confirming strong clustering and near-unit root behaviour in the log-volatility process. Turning to intraweek effects, the DOW dummies in the variance equation reveal pronounced seasonality. Tuesday (ψ_2)exhibits a large, negative, and highly significant coefficient for both indices (BSE Bankex: -0.261626, $p < 0.01$; Nifty Bank: -0.295345, $p < 0.01$), implying a substantial and robust reduction in conditional volatility relative to Monday. In contrast, Wednesday (ψ_3) and Thursday (ψ_4) exhibit small positive coefficients that are statistically insignificant, offering no evidence of midweek volatility shifts. The Friday dummy (ψ_5) is positive for both indices and marginally significant at the 10% level for Nifty Bank (0.086341), while remaining insignificant for BSE Bankex (0.060903), suggesting a tentative but emerging "Friday volatility uptick," particularly in the broader and more liquid Nifty Bank index. The intercept term (ω) is negative and significant (BSE Bankex: -0.232060, $p < 0.05$; Nifty Bank: -0.185978, $p < 0.01$), which reflects the baseline level of log-volatility in the absence of shocks or seasonal effects.

Table 4: GARCH Family Models Estimation Result

	BSE Bankex				Nifty Bank			
	$GARCH(2,1)_{GED}$	$FIGARCH(1,d,1)_{TD}$	$TGARCH(3,1)_{GED}$	$EGARCH(2,1)_{ND}$	$GARCH(2,1)_{TD}$	$FIGARCH(2,d,1)_{TD}$	$TGARCH(2,1)_{GED}$	$EGARCH(2,1)_{ND}$
μ_0	0.001431***	0.001306***	0.001199***	0.000837**	0.001298***	0.001269***	0.001191***	0.000661
μ_1	0.089039***	0.086707***	0.090917***	0.090379***	0.086819***	0.085741***	0.086327***	0.085356***
δ_2	-0.000583	-0.000487	-0.000549	-0.000245	-0.000606	-0.000626	-0.000702	-0.000106
δ_3	-0.000939*	-0.000775	-0.000846	-0.000327	-0.000905*	-0.000887	-0.000977*	-0.000111
δ_4	-0.000673	-0.000477	-0.000617	-0.000412	-0.000454	-0.000428	-0.000581	-0.000513
δ_5	-0.000259	-0.000157	-0.000327	-0.000339	-0.000212	-0.000173	-0.000368	-0.000103
ω	1.40e-07	2.87e-06	-6.78e-08	-0.232060**	-4.09e-06	9.76e-07	-4.40e-06	-0.185978***
α_1	0.112349***	0.257883***	0.072670***	0.288340***	0.091101***	0.252723***	0.059448***	0.244339***
α_2	-0.022585	-	-0.051785**	-0.120380***	-0.006054	0.032268	-0.023282*	-0.09008***
α_3	-	-	0.027252	-	-	-	-	-
γ	-	-	0.084717**	-0.054947***	-	-	0.081374***	-0.056866***
β	0.901028***	0.670787***	0.898412***	0.983633***	0.911183***	0.752437***	0.915414***	0.987239***
ψ_2	-3.48e-05**	-3.67e-05***	-2.85e-05**	-0.261626***	-2.71e-05**	-3.76e-05***	-2.50e-05**	-0.295345***
ψ_3	1.23e-05	9.67e-06	1.12e-05	0.035346	1.23e-05	1.29e-05	1.36e-05	0.027335
ψ_4	1.44e-05	9.36e-06	1.51e-05	0.006022	2.28e-05*	1.43e-05	2.26e-05**	0.007218
ψ_5	2.18e-05*	2.55e-05*	2.25e-05*	0.060903	2.42e-05*	2.42e-05*	2.45e-05**	0.086341*
d	-	0.526059***	-	-		0.593066***	-	-

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.
Source: Author's estimations.

4.4. Robustness check result

The robustness of the estimation outcomes is evident, as the models selected for inference were grounded in thorough statistical evaluations. Various tests were employed to confirm model appropriateness, including the Ljung-Box Q test, which assesses autocorrelation in standardized and squared residuals up to 36 lags, and the ARCH LM test, which identifies ARCH effects in the residuals. The Engle-Ng sign test assessed asymmetric volatility reactions to both bullish and bearish market trends, while information criteria such as AIC, SIC, HQC, and LL were also used. These tests were conducted under three residual distribution assumptions: ND, TD, and GED.

For the BSE Bankex, selected models comprised GARCH(2,1)$_{GED}$, FIGARCH$(1,d,1)_{TD}$, TGARCH(3,1)$_{GED}$, and EGARCH(2,1)$_{ND}$, among others. In the case of the Nifty Bank, the models included GARCH(2,1)$_{TD}$, FIGARCH$(2,d,1)_{TD}$, TGARCH(2,1)$_{GED}$, and EGARCH(2,1)$_{ND}$. The Ljung-Box Q test (Table 5) indicates the absence of autocorrelation in the selected models since $p > 0.10$, reinforcing their reliability. The ARCH-LM test (Table 6) confirmed no significant ARCH effects, with $p > 0.10$, indicating the adequacy of models incorporating ARCH effects. Additionally, the Engle-Ng sign test (Table 7) revealed that the TGARCH and EGARCH models effectively captured return dynamics with $p > 0.10$. Lastly, the information criteria result (Table 8) further supported the selection procedure of the respective models. It is to be noted here that although EGARCH(2,1)$_{TD}$ attains the lowest AIC/SIC/HQC and highest LL for both indices, the residual diagnostic favours the ND. For BSE Bankex, TD leaves significant dependence in the squared residuals (Q^2_{36} = 48.034, $p < 0.10$) and exhibits residual ARCH (18.47667, $p < 0.05$), whereas ND passes both checks (Q^2_{36} =36.872; ARCH-LM= 5.818466). For Nifty Bank, ND again yields an insignificant diagnostic test result (Q^2_{36} = 37.673; ARCH-LM=2.941508, while GED shows residual ARCH (8.131385, $p < 0.05$) and TD reports a larger LM statistic (13.18184). Although TD provides a better in-sample fit due to its heavier tails, it does not eliminate residual heteroskedasticity as effectively as ND. Consequently, the EGARCH (2,1) model estimated under the ND specification is preferred in this study, as it offers more reliable residual diagnostics and, therefore, a more robust basis for drawing inferences on weekday-volatility effects.

Table 5: Ljung-Box Q Test

BSE Bankex	GARCH (2,1)			FIGARCH (1, d,1)			TGARCH (3,1)			EGARCH (2,1)		
	ND	TD	GED	ND	TD	GED	ND	TD	GED	ND	TD	GED
Q_{36}	27.485	28.926	28.437	28.922	29.794	29.678	36.999	28.403	28.347	29.748	30.150	30.071
Q^2_{36}	35.155	35.881	36.626	37.500	39.022	38.186	63.396***	38.884	35.183	36.872	48.034*	42.049
Nifty Bank	**GARCH (2, 1)**			**FIGARCH (2, d, 1)**			**TGARCH (2,1)**			**EGARCH (2, 1)**		
	ND	TD	GED	ND	TD	GED	ND	TD	GED	ND	TD	GED
Q_{36}	86.550***	27.231	86.601***	28.025	27.885	28.215	26.772	85.993***	27.352	27.035	26.982	27.264
Q^2_{36}	1503.2***	39.966	1503.2	40.558	41.393	40.610	36.017	1417.7***	37.105	37.673	44.436	40.570

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.
Source: Author's estimations.

Table 6: ARCH-LM Test

BSE Bankex	GARCH (2, 1)			FIGARCH (1, d, 1)			TGARCH (3, 1)			EGARCH (2, 1)		
	ND	TD	GED	ND	TD	GED	ND	TD	GED	ND	TD	GED
	4.552491	0.004482	5.849588	4.680937	7.072148	5.885822	10.76957**	1.145178	3.533973	5.818466	18.47677**	11.69475**
Nifty Bank	**GARCH (2,1)**			**FIGARCH (2, d, 1)**			**TGARCH (2, 1)**			**EGARCH (2, 1)**		
	ND	TD	GED	ND	TD	GED	ND	TD	GED	ND	TD	GED
	54.77019***	2.867819	54.77019***	0.494955	2.764679	1.603300	0.924304	45.67165***	3.455949	2.941508	13.18184	8.131385**

Note: *** and ** indicate significance at the 1% and 5% levels, respectively.
Source: Author's estimations.

Table 7: Engle-Ng Sign Test

Models	Sign -Bias	Negative-Bias	Positive-Bias	Joint-Bias
BSE Bankex				
TGARCH(3,1)$_{ND}$	0.310798	2.404802**	-1.113896	7.176493
TGARCH(3,1)$_{TD}$	0.146223	1.833230*	-0.394189	4.048600
TGARCH(3,1)$_{GED}$	0.264057	0.432635	0.093877	0.196254
EGARCH(2,1)$_{ND}$	-0.271528	0.319540	-0.459886	0.386394
EGARCH(2,1)$_{TD}$	-0.267601	-0.117019	0.291940	0.338185
EGARCH(2,1)$_{GED}$	-0.136979	0.135524	0.012596	0.099783
Nifty Bank				
TGARCH(2,1)$_{ND}$	1.106787	1.450479	-0.113649	2.517391
TGARCH(2,1)$_{TD}$	-0.073642	-5.187755***	5.587421***	58.29505***
TGARCH(2,1)$_{GED}$	1.112571	1.323019	0.327209	2.045722
EGARCH(2,1)$_{ND}$	0.835353	1.465243	0.115126	3.170450
EGARCH(2,1)$_{TD}$	1.135488	1.262001	1.023602	2.642281
EGARCH(2,1)$_{GED}$	0.885161	1.268270	0.580972	1.946124

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.
Source: Author's estimations.

Table 8: AIC, SIC, HQC, and LL

BSE Bankex	GARCH (2,1)			FIGARCH (1, d, 1)			TGARCH (3, 1)			EGARCH (2, 1)		
	ND	TD	GED	ND	TD	GED	ND	TD	GED	ND	TD	GED
AIC	-5.549452	-5.575473	-5.594261	-5.554477	-5.602626	-5.598105	-5.524222	-5.582048	-5.601605	-5.560362	-5.610342	-5.603922
SIC	-5.531929	-5.556698	-5.575486	-5.536754	-5.583850	-5.579330	-5.504195	-5.560769	-5.580327	-5.541587	-5.590315	-5.583895
HQC	-5.543325	-5.568908	-5.575486	-5.548150	-5.596061	-5.591540	-5.517220	-5.574608	-5.594165	-5.553798	-5.603340	-5.596920
LL	14567.44	14636.68	14685.95	14580.09	14707.89	14696.03	14503.27	14655.92	14707.21	14597.05	14720.12	14712.29
Nifty Bank	**GARCH(2,1)**			**FIGARCH(2,d,1)**			**TGARCH(2,1)**			**EGARCH(2,1)**		
	ND	TD	GED	ND	TD	GED	ND	TD	GED	ND	TD	GED
AIC	-4.951016	-5.640429	-4.950594	-5.592087	-5.644486	-5.639344	-5.597185	-4.990659	-5.644225	-5.601418	-5.654991	-5.647371
SIC	-4.931938	-5.619988	-4.930154	-5.571647	-5.622683	-5.617540	-5.576745	-4.968856	-5.622421	-5.580977	-5.633188	-5.625568
HQC	-4.944312	-5.633246	-4.943411	-5.584904	-5.636824	-5.631682	-5.590002	-4.982997	-5.636563	-5.594235	-5.647329	-5.639709
LL	11757.81	13394.10	11757.81	13279.43	13404.72	13392.52	13291.52	11853.84	13404.10	13301.56	13429.64	13411.56

Source: Author's estimations.

4.5. Discussions

4.5.1 DOW effect on daily return

H1 —that daily returns exhibit a significant DOW effect anomaly — is partially supported by the empirical findings. Since Monday is treated as the baseline category, the positive and statistically significant intercept indicates that Monday returns are, on average, higher than the returns of the other weekdays, after controlling for conditional volatility. This suggests the presence of a mild Monday return premium, although the anomaly is not uniformly strong across all weekday coefficients. This finding is broadly consistent with recent Indian evidence at sector and bank level indices (Verma et al., 2023; Swetha & Jegadeeswari, 2023). A plausible behavioural and institutional explanation is offered by the accumulated demand hypothesis (Lakonishok & Levi, 1982), which argues that investors who are unable to trade during the weekend execute pent-up orders on Monday, generating upward price pressure. This effect tends to be more visible in the banking sector, where strategic reassessment often occurs at the beginning of the week. Concurrently, favourable macroeconomic or regulatory announcements released over the weekend, such as interest rate decisions or earnings reports, may be rapidly priced in, consistent with the semi-strong form of the EMH (Fama, 1970). The persistence of this effect in Indian banking indices, despite its attenuation in global markets, is also compatible with meta-analytic and adaptive-market evidence showing that DOW patterns are context-sensitive and moderated by study design, outliers, culture, and evolving regimes; in India, recent microstructure shifts (e.g., standardizing index-derivatives expiries to Tuesday in 2025) provide a concrete structural channel through which Monday-tilted seasonality can persist or be reshaped (Grebe & Schiereck, 2024; Bassiouny et al., 2023; NSE, 2025b).
However, the lack of statistically significant return deviations on Tuesday, Thursday, and Friday, despite uniformly negative point estimates, under the study, indicates that a strong, pervasive DOW effect in mean returns is not empirically substantiated. Only Wednesday exhibits a marginally significant negative deviation from Monday (at the 10% level in GARCH and TGARCH models), suggesting a tentative "Wednesday return dip." This midweek anomaly may reflect institutional portfolio rebalancing, as large investors reassess exposures after early-week market movements (Chang et al., 1993; Kambal et al., 2018). Given the banking sector's sensitivity to monetary policy and macroeconomic signals (Lucca & Moench, 2015; Banegas et al., 2016; Kroencke et al., 2021; Guo et al., 2023), institutions may adjust positions midweek in response to emerging data or regulatory cues. Another plausible explanation is anticipatory selling pressure, where investors hedge against uncertainties expected later in the week, such as economic data releases or geopolitical events (Barberis & Thaler, 2003; Ariel, 1987). Psychological biases may further exacerbate this effect, as investors react to perceived market instability. These midweek adjustments suggest a transition from early-week optimism to cautious repositioning, reinforcing the dynamic nature of investor sentiment.
Notably, findings of other days, such as Tuesday, Thursday, and Friday, exhibit relative stability, with no significant return anomalies. This stability may indicate a lack of systematic behavioural biases or suggest that market participants rely more on fundamental analysis during these periods. The absence of anomalies on these days provides the supporting evidence of the adaptive market hypothesis (Lo, 2004), which posits that market behaviours develop as investors react to fluctuating circumstances and that short-term inefficiencies are arbitraged away over time. Recent cross-market tests of AMH using calendar anomalies corroborate this adaptive, time-varying behaviour (Bassiouny et al., 2023).

4.5.2. DOW effect on conditional volatility

H2 — that daily volatility exhibits a significant DOW effect anomaly — is strongly supported. The volatility estimation results in this study exhibit a statistically coherent and economically meaningful weekly rhythm relative to Monday. The study finds significantly lower conditional volatility on Tuesdays than on Monday across all four models and both indices, i.e., a robust "calm Tuesday" effect. This pattern may be attributed to post-Monday market stabilization (French, 1980; Cross, 1973; Tu, 2003; Marrett & Worthington, 2009), and is consistent with recent India-focused evidence documenting weekday asymmetries in volatility using GARCH-family models (Aggarwal & Jha, 2023) and with meta-analytic findings that day-dependent patterns persist but vary with design and regime (Grebe & Schiereck, 2024). After the aggressive buying pressure on Monday, investors may adopt a more calculated approach, allowing for price normalization and lower volatility.
In contrast, the study finds that volatility increases from Wednesday to Friday, with Friday showing a positive and marginally-to-fully significant volatility premium relative to Monday—particularly in the Nifty Bank index (significant at 5% in TGARCH and EGARCH). Thursday also registers a significant uptick in volatility for Nifty Bank under TGARCH, suggesting index-specific mid-to-late-week risk buildup. A plausible mechanism is derivatives-market microstructure and expiry dynamics, for which Indian evidence documents expiration-day effects on activity and (intra)day volatility (Vipul, 2005; Agarwalla & Pandey, 2013), while cross-market research often finds elevated end-week volatility (Kiymaz & Berument, 2003). This pre-weekend volatility surge is likely driven by position squaring and weekend risk hedging (Flannery & Protopapadakis, 2002). Additionally, concerns about holding positions over the weekend can increase Friday's volatility, as traders react to the risk of adverse news emerging during non-trading hours (French, 1980; Cross, 1973). As the market nears the weekend, speculative activity may rise due to uncertainty regarding potential global events, policy decisions, or market movements that could impact Monday's opening prices. Investor psychology also plays a role, as risk-averse behaviour leads to more pronounced market movements before the weekend (Barberis & Thaler, 2003). In the banking sector, where leverage and liquidity are critical, end-of-week adjustments have a significant impact. Investors may engage in profit-taking, risk management, or last-minute speculative trades, amplifying volatility levels. These findings confirm a clear intra-week cycle in Indian bank stocks: volatility declines after Monday, stabilizes midweek, and rises toward Friday. This outcome is aligned with adaptive, regime-sensitive calendar effects (Bassiouny et al., 2023; Grebe & Schiereck, 2024).

4.5.3. ARCH, GARCH, leverage, and long memory effects on conditional volatility

H3 — that ARCH effect (i.e., past shocks) significantly affects current volatility —is fully supported. The first-order ARCH coefficient (α_1) is positive and highly significant in all models, confirming volatility clustering (Engle, 1982; Bollerslev, 1986). Stated differently, if returns were volatile in the recent past, they are more likely to remain volatile in the current period. Recent empirical work using EGARCH/FIGARCH on sectoral indices likewise found evidence of strong ARCH responses and clustering (Fakhfekh et al., 2023; Tripathy, 2022).
H4 — that GARCH effect (i.e., past volatility) significantly affects current volatility — is fully supported. The GARCH persistence parameter (β) is high (≈0.67–0.99) and significant across specifications, indicating that volatility shocks decay slowly, most evident in EGARCH and GARCH models. Consistent with this, Ding et al. (1993) argue that very high β Values reflect the inherent "stickiness" of

volatility, especially in sectors like banking that are influenced by macroeconomic and regulatory factors. As previously noted, high-frequency trading can generate short-term autocorrelation, which in turn sustains volatility persistence in algorithmically driven markets. Likewise, global interconnectedness amplifies persistence, particularly in banking, which is sensitive to international conditions (Patton & Sheppard, 2015). Recent studies confirm high persistence across emerging markets and show asymmetric GARCH models often perform best when persistence is strong (Tripathy, 2022; Caiado & Lúcio, 2023).

H5 —that daily volatility exhibits a significant leverage effect — is strongly supported. While symmetric ARCH effects capture general shock persistence, the TGARCH and EGARCH estimates reveal a statistically significant leverage effect: negative return shocks generate higher subsequent volatility than positive shocks of equal magnitude. This aligns with financial theory and evidence that downside shocks dominate volatility formation (Mandimika & Chinzara, 2012) and with the EGARCH mechanism that formalizes asymmetry (Nelson, 1991). In the banking sector, this asymmetry is intuitive: adverse events, such as regulatory surprises, interest-rate hikes, or credit-quality deterioration, heighten perceived risk and amplify volatility. Bank-focused and India-focused evidence using EGARCH/TGARCH also finds pronounced asymmetry/persistence in recent samples (Nikhil et al., 2023; Tripathy, 2022; Fakhfekh et al., 2023). Notably, the discovery of negative and significant second-lag ARCH effects in TGARCH and EGARCH indicates that shocks from two days prior dampen current volatility and therefore suggest a short-horizon mean-reverting adjustment after the initial overreaction. Prior research further shows that macro-policy uncertainty and broad market instability can amplify both volatility and risk in banking (Acharya et al., 2017; Syed, 2023; Singh, 2017; Pástor & Veronesi, 2013).

H6 — that daily volatility exhibits significant long memory — is fully supported. The FIGARCH fractional integration parameter d Lies significantly between 0.5 and 1, confirming true long memory in volatility. Shocks therefore decay very slowly, i.e., a property highly relevant for banking stocks exposed to persistent macroeconomic and regulatory cycles. This accords with Baillie et al. (1996), who show that long memory in financial volatility is common (including in developing markets), and with sectoral evidence that banking volatility exhibits stronger persistence given its sensitivity to macro shocks and regulatory changes (Lin & Huang, 2012; Huang et al., 2014; Tennant & Tracey, 2014). Post-COVID studies further exhibit elevated persistence/long-memory parameters (Vera-Valdés, 2022; de Oliveira et al., 2024).

5. Conclusion and Implications

This study empirically investigates DOW effects in returns and volatility, alongside volatility clustering, asymmetry, and long memory, in India's two major banking indices — BSE Bankex and Nifty Bank — using four GARCH-class models: GARCH(2,1), FIGARCH(1,d,1)/(2,d,1), TGARCH(3,1)/(2,1), and EGARCH(2,1), with Monday as the baseline. The findings reveal a statistically significant positive intercept, indicating that Monday returns are modestly higher relative to the other weekdays. However, no robust return anomalies are observed for the remaining days, except for a marginally lower return on Wednesday. In contrast, volatility exhibits model-consistent weekly results: Tuesday displays significantly lower conditional volatility than Monday across all specifications ("calm Tuesday" effect), while Friday shows elevated volatility ("volatile weekend" effect). The study also confirms strong return autocorrelation, significant ARCH/GARCH effects (volatility clustering and persistence), a robust leverage effect, and long memory in volatility. Notably, the discovery of a negative and significant second-lag ARCH effect suggests that shocks from two days prior dampen current volatility, suggesting a volatility-correction mechanism whereby markets absorb or reverse earlier disturbances. This pattern may reflect liquidity restoration, delayed institutional adjustment, or correction of prior overreaction. Based on these findings, the study concludes that the volatility dynamics of Indian banking stocks are inherently complex and exhibit statistically robust temporal patterns.

The findings carry significant theoretical and practical implications as follows:

- Theoretically, the study contributes to behavioural finance and market microstructure literature by documenting in a unified framework the coexistence of intraweek seasonality, leverage asymmetry, long memory, and counterintuitive multi-lag volatility dynamics in an emerging market banking context.
- Practically, the robust "calm Tuesday–volatile Friday" cycle offers actionable guidance for portfolio managers and algorithmic traders: tactical entry on Tuesdays and hedging or profit-taking by Friday may enhance risk-adjusted returns, while incorporating DOW dummies can improve volatility forecasts for options pricing, VaR, and dynamic hedging.
- As confirmed in this study, the leverage effect underscores the need for robust downside protection during market stress, while long memory in volatility calls for institutional investors to integrate persistent risk into long-horizon asset allocation.
- For policymakers, the persistence of return autocorrelation and volatility clustering, alongside asymmetric responses, suggests residual inefficiencies in India's banking markets, highlighting the value of enhancing transparency, curbing herding, and improving real-time information dissemination to enhance more efficient price discovery and systemic stability.

While this study offers robust insights into DOW effects and volatility dynamics in India's banking sector, it is limited to index-level data from a single emerging economy. Future research could extend the framework in two directions: first, by examining firm-level heterogeneity, such as differences between public and private banks or large-cap versus mid-cap institutions, to assess whether intraweek patterns vary across bank types; and second, by incorporating macroeconomic and policy variables (e.g., monetary policy, inflation, global risk indicators) to disentangle domestic behavioural seasonality from international spillovers. Most importantly, this study lays a foundation for a broader, comparative analysis of DOW effects across emerging-market banking sectors. As India's financial system deepens and converges with peer economies—via cross-border banking linkages, regional fintech integration (e.g., UPI's diffusion in ASEAN and MENA), and the evolving BRICS financial architecture—it becomes imperative to examine whether the volatility patterns documented under the study (the robust 'calm Tuesday' effect, the Friday volatility uptick, leverage asymmetry, and the negative second-lag ARCH effect) are unique to India or reflect systemic features of emerging-market banking.

Conflict of Interest

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication.

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