Decision Making Advances

Journal homepage: www.dma-journal.org
ISSN: 2956-2384

News-Driven Volatility: A Deep Dive into Leading Nifty Healthcare Stocks

Sonal Mohapatra[1,*], Sayan Chakraborty [2]

[1] Department of Operations and IT, ICFAI Business School Hyderabad, Hyderabad, India

ARTICLE INFO

Article history:
Received 17 August 2024
Received in revised form 13 September 2024
Accepted 3 October 2024
Available online 8 October 2024

Keywords:
Healthcare stocks; News; Volatility; ANOVA.

ABSTRACT

This study conducts a comprehensive analysis of stock price volatility within the healthcare sector, concentrating on five prominent companies: Sun Pharma, Dr. Reddy, Cipla, Apollo Hospitals, and Divis Laboratories. Leveraging annual daily data from the Nifty Healthcare Index for 2023, the research delves into the intricate relationship between stock price fluctuations and market-sensitive news events. Employing a robust methodology that integrates slope calculations, ANOVA, Tukey's HSD tests, moving averages, and standard deviation metrics, the study evaluates the differential impact of these events on stock volatility. The findings reveal significant volatility, with Apollo Hospitals demonstrating the highest levels of price variability. The research highlights the profound influence of regulatory shifts, financial performance metrics, and macroeconomic conditions on stock behavior. These insights are pivotal for investors and financial analysts seeking to navigate the complex dynamics of the healthcare market. The application of moving averages further refines the analysis, offering a sophisticated lens through which to assess and interpret market trends, ultimately enhancing the strategic decision-making process within this critical sector.

1. Introduction

Media can be regarded as the fourth pillar of democracy [1]. News and media are essential in influencing public opinion and keeping society updated on current events. In our fast-paced world, a variety of platforms—such as traditional newspapers, television, digital outlets, and social media—offer immediate access to information. It aims to inform the public about important local, national, and international happenings. This shift has changed the way we consume news, encouraging global discussions and connecting different communities. However, the quick spread of information brings concerns about accuracy, bias, and misinformation [2]. It's vital for consumers to assess sources critically and interact with media responsibly, ensuring the public remains well-informed and capable of navigating the complexities of contemporary life [3].

* *Corresponding author.*
E-mail address: sonalmohapatra502@gmail.com

https://doi.org/10.31181/dma31202554

The Nifty Healthcare Index, on India's National Stock Exchange, highlights the healthcare sector, including pharmaceuticals, hospitals, diagnostics, and wellness services. It serves as a crucial benchmark for investors by reflecting market sentiment and economic factors in healthcare. Calculated using the free float market capitalization method, it adjusts for public trading shares, determining each company's market value. The index value aggregates these capitalizations, with regular rebalancing for stock splits, dividends, and company adjustments, ensuring accurate sector representation [4]. Stock weightage is based on free float market capitalization, favoring larger companies but capped to avoid over-concentration [5]. This diverse representation covers pharmaceuticals, hospitals, and diagnostics, providing a comprehensive sector overview. Regular evaluations ensure its continued relevance and precision. Investing in the Nifty Healthcare Index typically involves mutual funds or ETFs that track the index. These funds provide liquidity, flexibility, and diversification benefits, allowing easy access to the healthcare sector for retail investors. Managed mutual funds offer professional expertise in portfolio management and stock selection within the sector.

Healthcare stocks have gained prominence following the COVID-19 pandemic, emphasizing the critical role of healthcare infrastructure and innovation [6]. Increased investor interest in biotechnology, pharmaceuticals, medical equipment, and telemedicine reflects broader societal trends prioritizing health and well-being. Media coverage significantly influences investor sentiment, with positive news boosting stock prices and negative news causing declines. Post-COVID-19, there's a notable shift in personal health behaviors [7]. Individuals are prioritizing regular check-ups, preventive care, and boosting immunity through healthier diets and exercise. Mental health awareness has grown, with increased use of therapy and wellness resources. Telehealth services have surged, providing convenient access to healthcare. People are committing to fitness routines, nutritious home-cooked meals, and preventive measures like vaccinations. Overall, there's a greater focus on holistic well-being, reassessment of work-life balance, and stronger social connections to enhance quality of life.

The objective of our work is to analyze the volatility of selected stocks from the Nifty Healthcare Index in response to news events. By examining the fluctuations in stock prices relative to health-related news coverage, we aim to identify patterns and assess the impact of media on stock market performance within the healthcare sector. This analysis will provide insights into the sensitivity of healthcare stocks to news, offering valuable information for investors and policymakers. In the following sections, we discuss the relevant literature and the methodology of the study. Finally, we present the discussion of the study to draw conclusions.

2. Literature review

This literature review examines the complex interplay of investor sentiment, health sector stock volatility, and broader market dynamics, particularly in the context of crises. It explores how investor psychology, influenced by factors such as media coverage and public mood, impacts stock market fluctuations. The review analyzes research on the relationship between news and stock prices, with a specific focus on the healthcare sector. By understanding these interconnections, this study aims to provide insights into market behavior during times of crisis. The review is structured into two sections: the impact of investor psychology on stock market behavior during crises and the general relationship between news and stock market movements; and the specific influence of news on health sector stocks.

2.1 Health sector volatility and stock market psychology

Many researchers have attempted to understand the impact of investor psychology on stock market behavior during crises and the frame the relationship between news and stock market movements. To discuss a little, one can refer to the work of [8] where they examine how the outbreak of COVID-19 affected investor sentiment and stock market volatility across different regions. They also highlight the significant negative impact of the pandemic on investor psychology and stock market returns, demonstrating a strong correlation between health crises and market behavior. In addition, [9] explores investor psychology and stock market behavior during the initial phase of COVID-19. It analyzes how investors in China, Japan, and the United States reacted to the pandemic, highlighting differences and similarities across these markets. The research reveals that investor sentiment was significantly impacted by the pandemic, with increased market volatility and changes in investment strategies providing insights into how psychological factors influenced market behavior during the crisis and suggests that understanding these dynamics is crucial for managing future financial uncertainties. Similarly, [10] examines the psychological impact of the COVID-19 pandemic on financial markets in the US and Europe. It highlights how investor behavior, market sentiment, and stock market volatility were influenced by the pandemic. The research finds that negative news and uncertainty significantly affected market dynamics, causing sharp declines and increased volatility. The study underscores the importance of understanding psychological factors during crises to better manage financial markets and mitigate adverse effects on the economy. Additionally, [11] explores the relationship between COVID-19 fear and stock market volatility in ASEAN countries. Analyzing data from various ASEAN stock markets, the research finds that heightened fear of the pandemic significantly increased market volatility providing empirical evidence that investor sentiment driven by COVID-19 news and developments plays a crucial role in market fluctuations. These insights emphasize the need for policymakers and investors to consider psychological factors when assessing market stability during global health crises. Moreover, [12] investigates the impact of investor sentiments on stock markets during the COVID-19 pandemic. It examines how shifts in investor emotions, such as fear and optimism, affected market volatility and stock prices. The research highlights that negative investor sentiments led to increased market turbulence, while positive sentiments contributed to brief market recoveries. The study underscores the significant role of psychological factors in shaping market dynamics during the pandemic, offering insights into the interplay between investor behavior and stock market fluctuations. Further, [13] analyze the relationship between media-driven investor sentiment related to COVID-19 and stock market volatility. They discovered that COVID-19 news increases uncertainty and market volatility. Additionally, [14] state how behavioral finance factors, such as emotions and cognitive biases, influence the US stock market, particularly the S&P 500. It provides a comprehensive analysis of how psychological factors like loss aversion, overconfidence, and herding behavior contribute to market anomalies and volatility. Moreover, [15] explores the impact of investor sentiment on stock market volatility, using data from China's green stock markets. It shows how investor sentiments, particularly those driven by internet and trading activities, significantly affect stock price movements, especially during the COVID-19 pandemic.

2.2 Impact of news on stock market and healthcare sector

The influence of news on stock market dynamics is particularly profound in the healthcare sector, where information about health crises, regulatory changes, and technological advancements can trigger significant market reactions. Various studies have delved into this relationship to understand

how news can drive investor behavior and market outcomes. For instance, [16] analyze how different types of news events, including economic, political, and social news, influence the fluctuations in stock market prices. They employ statistical methods to examine the correlation between news and stock market movements, demonstrating that news plays a significant role in increasing or decreasing market volatility. The study provides insights into the behavioral aspects of investors and the importance of news in financial markets. Similarly, [17] examine the relationship between public news and stock market prices, focusing on the S&P 500 index. The study investigates how different types of news—both economic and non-economic—affect stock market volatility and returns. The authors utilize a variety of statistical methods to analyze the sentiment and impact of news articles on the stock market. They explore how positive and negative news sentiments correlate with market movements and measure the immediate and lagged effects of news releases on stock prices. The study also considers the role of trading volume and investor behavior in response to news. Furthermore, [18] investigates the predictive power of financial news on stock returns, with a particular focus on the distinction between Islamic and non-Islamic stocks. The study uses data from both types of stocks to analyze whether financial news can serve as a reliable predictor of stock returns. It explores how news sentiment and content impact market performance in different contexts, considering the specific investment criteria of Islamic stocks, which are governed by Sharia law. The findings suggest that financial news does have predictive value, but the strength and nature of this relationship may vary between Islamic and non-Islamic stocks due to their differing financial and ethical constraints. Moreover, [19] explore the effects of news on the stock prices of green firms operating in emerging markets. It examines how various types of news, including environmental and financial news, influence the market performance of companies that focus on sustainable and environmentally friendly practices. The study investigates whether positive or negative news impacts stock prices differently for green firms compared to their non-green counterparts. The results reveal that news about environmental issues can significantly affect the stock prices of green firms, highlighting the importance of media coverage and public perception in shaping market outcomes for companies committed to sustainability in emerging markets. In addition, [20] investigates how news affects stock price trends using a deep bidirectional Long Short-Term Memory (LSTM) model. The study aims to understand the relationship between news sentiment and stock price movements by leveraging advanced machine learning techniques. The bidirectional LSTM model is employed to capture and analyze the temporal dependencies and contextual information in news data, providing insights into how past and future news sentiments influence stock price trends. The findings demonstrate that the deep bidirectional LSTM model can effectively predict stock price changes by incorporating news information, offering a nuanced understanding of the impact of news on financial markets. In another study, [21] examines how positive news affects stock market volatility by analyzing various types of good news and their subsequent impact on market volatility, the research seeks to understand whether positive news leads to increased or decreased market uncertainty. The findings suggest that good news can have a significant impact on stock market volatility, potentially reducing it by stabilizing market expectations or, conversely, increasing it if the news leads to overreactions or speculative trading. It contributes to the broader understanding of how news sentiment influences market dynamics and investor behavior. Likewise, [22] investigates how both news and public sentiment influence stock price movements. The study explores the interplay between news events—such as economic reports and corporate announcements—and the overall mood of the public, which is often gauged through sentiment analysis of social media and news articles. By analyzing these factors, the paper aims to determine how news and collective public mood impact stock market fluctuations, investor behavior, and stock prices. The results reveal that both news content and public sentiment significantly affect stock movements, with public mood

playing a critical role in shaping market reactions and trends. Notably, [23] focuses on analyzing the immediate and delayed impacts of news on stock prices, using sophisticated techniques to quantify the effects of news sentiment and timing. By integrating various data sources and applying advanced analytical models, the research examines how news timing influences market reactions, investor behavior, and stock price volatility. The findings indicate that not only the content of the news but also its timing plays a crucial role in shaping stock market movements, highlighting the importance of news release schedules and investor responses in financial markets. Significantly, [24] analyze the impact of the U.S. Affordable Care Act on various sectors of the healthcare industry. Using an event study methodology, researchers examined stock price reactions of health insurance companies, hospitals, and drug manufacturers to the law's passage. The findings indicate positive effects for hospitals and brand-name drug makers, but negative impacts on health insurance companies and generic drug manufacturers. Furthermore, [25] explores the use of machine learning to predict healthcare sector stock prices. It investigates the impact of social media and financial news on stock market behavior and develops predictive models using techniques like SVM and reinforcement learning aiming to enhance the accuracy of stock price predictions by incorporating sentiment analysis. Similarly, [26] explores the use of machine learning techniques to analyze and predict stock prices in the healthcare sector. The research applies various machine learning models to historical stock price data to forecast future trends and provide insights into market behavior. The findings demonstrate that machine learning can effectively improve prediction accuracy for healthcare stocks, offering valuable tools for investors to make informed decisions in a sector influenced by complex factors such as policy changes and market dynamics. In addition, [27] examines the impact of universal health coverage (UHC) healthcare systems on stock returns during the COVID-19 pandemic. It analyzes global stock indices to determine whether countries with UHC experienced different stock market behaviors compared to those without. The research finds that UHC systems generally provided more stability and less market volatility during the pandemic, suggesting that comprehensive healthcare coverage might contribute to more stable stock returns by reducing investor uncertainty and enhancing market confidence in times of crisis. Lastly, [28] discusses implications for diversifying investors' portfolios during epidemics and pandemics as well as for companies in the health care industry This further consolidates the need to analyze the relationship between news events and healthcare stocks.

3. Methodology and approach

The study utilizes annual daily data from the Nifty Healthcare Index, sourced from The Economic Times, covering the period from January 2023 to December 2023. From the index, five stocks were selected based on their sectoral distribution: Sun Pharma (21.15%), Dr. Reddy (10.04%), Cipla (10.01%), Apollo Hospitals (8.02%), and Divis Laboratories (7.54%). The daily opening and closing prices of these stocks and the index were recorded for analysis. The data employed in this study is secondary in nature, obtained from The Economic Times. The daily closing prices of the Nifty Healthcare Index and the five selected stocks were recorded. In order to calculate the relative change in a particular stock price, we calculated the daily slope of the closing prices using the following formula:

$$M = (x_2 - x_1)/(\,(y_2 - y_1) \quad (1)$$

where:

M represents the slope of the daily closing price,
y_2 is the closing price of the stock on the current day,

y_1 is the closing price of the stock on the previous day,
x_2 is the closing price of the Nifty Healthcare Index on the current day,
x_1 is the closing price of the Nifty Healthcare Index on the previous day.

The slope values for each of the five stocks were organized into separate columns based on the dates of significant news events, labeled as A, B, C, D, and E. The mean of each table was then calculated. To assess the volatility of the stocks in response to news events, a single-factor ANOVA was conducted. The null hypothesis (H0) for the ANOVA test was that all group means are equal. Following the ANOVA, Tukey's HSD test was performed to determine which specific group means were significantly different from each other. This methodology ensures a thorough analysis of the volatility of the selected stocks in response to significant news events, providing insights into their behavior under varying market conditions.

4. Results and discussions

In order to compare variances across the means of individual stocks, we analyze the data using ANOVA. The findings from the ANOVA are depicted in Table 1.

Table 1
ANOVA Test Statistic

Source of Variation	Sum of Squares	df	Mean Square	F	P value	F critical
Between the groups	143014089381.91	4	35753522345.4775	88909.4332	0	2.3896
Within the groups	203077762.8672	505	402134.1839			
Total	143217167144.777	509				

It is observed that the ANOVA analysis has yielded a high F statistic, indicating substantial variability between the groups relative to the variability within the groups. The p-value was found to be 0, signifying that the results are statistically significant. The mean square (MS) for between-group variance was higher than that for within-group variance. Consequently, we reject the null hypothesis that all group means are equal. This suggests that at least one stock's behavior is significantly different from the others.

In order to further investigate and identify which specific stocks exhibit significant differences, Tukey's HSD Test has been performed through the following steps. To this purpose, we first established the pairs of groups for comparison. For each pair, we calculated the absolute values of the differences in their means. The Standard Error (SE) was determined from the ANOVA output using the Mean Square Error (MSE) and the sample size for each group, denoted as n_j. The equation for SE is given by:

$$SE_{Anova} = \sqrt{\frac{MS_E}{n_j}} \tag{2}$$

Subsequently, we computed Tukey's q scores for each pair of groups using the formula for q. The q score is given by the equation:

$$q_{tukey} = \frac{Absolute\ difference}{SE_{Anova}} \tag{3}$$

These q scores were then compared with the critical value from the q table for a significance level of 5%, given that there are five groups and a denominator degree of freedom of 505 as indicated in the ANOVA results. This comparison allowed us to assess whether the differences in means between the pairs were statistically significant, thus providing insight into the relationships among the group means.

Finally, compare the calculated q_{tukey} scores above with the q critical value for the given number of groups, degree of freedom, and significance level. Here, the number of groups is 5 and the degree of freedom of the denominator is 505 as can be seen under the df column in the Within Groups row of the ANOVA section of the ANOVA test result. An excerpt of the q table for 5% significance level is shown below.

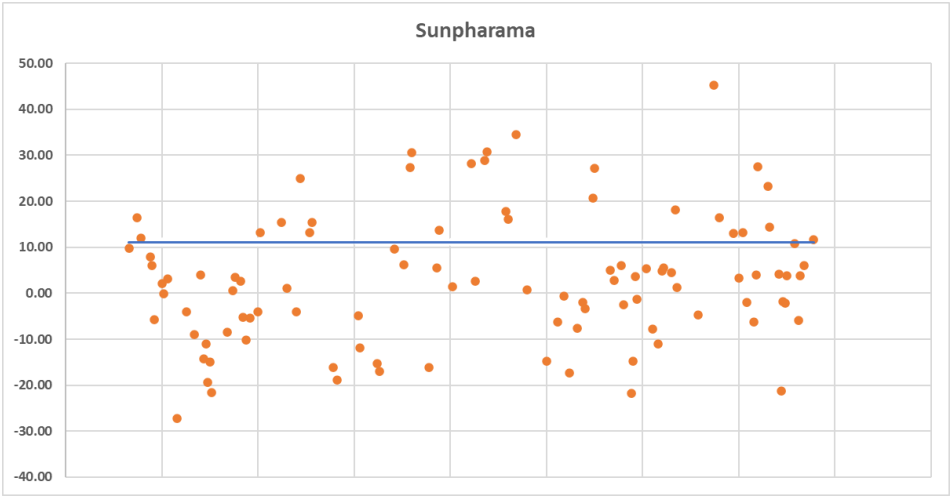
df	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
26	2.907	3.514	3.880	4.141	4.345	4.511	4.652	4.773	4.880	4.975	5.061	5.139	5.211	5.277	5.339	5.396	5.450	5.500	5.548
27	2.902	3.506	3.870	4.130	4.333	4.498	4.638	4.758	4.864	4.959	5.044	5.122	5.193	5.259	5.320	5.377	5.430	5.480	5.528
28	2.897	3.499	3.861	4.120	4.322	4.486	4.625	4.745	4.850	4.944	5.029	5.106	5.177	5.242	5.302	5.359	5.412	5.462	5.509
29	2.892	3.493	3.853	4.111	4.311	4.475	4.613	4.732	4.837	4.930	5.014	5.091	5.161	5.226	5.286	5.342	5.395	5.445	5.491
30	2.888	3.486	3.845	4.102	4.301	4.464	4.601	4.720	4.824	4.917	5.001	5.077	5.147	5.211	5.271	5.327	5.379	5.429	5.475
31	2.884	3.481	3.838	4.094	4.292	4.454	4.591	4.709	4.812	4.905	4.988	5.064	5.134	5.198	5.257	5.313	5.365	5.414	5.460
32	2.881	3.475	3.832	4.086	4.284	4.445	4.581	4.698	4.802	4.894	4.976	5.052	5.121	5.185	5.244	5.299	5.351	5.400	5.445
33	2.877	3.470	3.825	4.079	4.276	4.436	4.572	4.689	4.791	4.883	4.965	5.040	5.109	5.173	5.232	5.287	5.338	5.386	5.432
34	2.874	3.465	3.820	4.072	4.268	4.428	4.563	4.680	4.782	4.873	4.955	5.030	5.098	5.161	5.220	5.275	5.326	5.374	5.420
35	2.871	3.461	3.814	4.066	4.261	4.421	4.555	4.671	4.773	4.863	4.945	5.020	5.088	5.151	5.209	5.264	5.315	5.362	5.408
36	2.868	3.457	3.809	4.060	4.255	4.414	4.547	4.663	4.764	4.855	4.936	5.010	5.078	5.141	5.199	5.253	5.304	5.352	5.397
37	2.865	3.453	3.804	4.054	4.249	4.407	4.540	4.655	4.756	4.846	4.927	5.001	5.069	5.131	5.189	5.243	5.294	5.341	5.386
38	2.863	3.449	3.799	4.049	4.243	4.400	4.533	4.648	4.749	4.838	4.919	4.993	5.060	5.122	5.180	5.234	5.284	5.331	5.376
39	2.861	3.445	3.795	4.044	4.237	4.394	4.527	4.641	4.741	4.831	4.911	4.985	5.052	5.114	5.171	5.225	5.275	5.322	5.367
40	2.858	3.442	3.791	4.039	4.232	4.388	4.521	4.634	4.735	4.824	4.904	4.977	5.044	5.106	5.163	5.216	5.266	5.313	5.358
48	2.843	3.420	3.764	4.008	4.197	4.351	4.481	4.592	4.690	4.777	4.856	4.927	4.993	5.053	5.109	5.161	5.210	5.256	5.299
60	2.829	3.399	3.737	3.977	4.163	4.314	4.441	4.550	4.646	4.732	4.808	4.878	4.942	5.001	5.056	5.107	5.154	5.199	5.241
80	2.814	3.377	3.711	3.947	4.129	4.277	4.402	4.509	4.603	4.686	4.761	4.829	4.892	4.949	5.003	5.052	5.099	5.142	5.183
120	2.800	3.356	3.685	3.917	4.096	4.241	4.363	4.468	4.560	4.641	4.714	4.781	4.842	4.898	4.950	4.998	5.043	5.086	5.126
240	2.786	3.335	3.659	3.887	4.063	4.205	4.324	4.427	4.517	4.596	4.668	4.733	4.792	4.847	4.897	4.944	4.988	5.030	5.069
inf	2.772	3.314	3.633	3.858	4.030	4.170	4.286	4.387	4.474	4.552	4.622	4.685	4.743	4.796	4.845	4.891	4.934	4.974	5.012

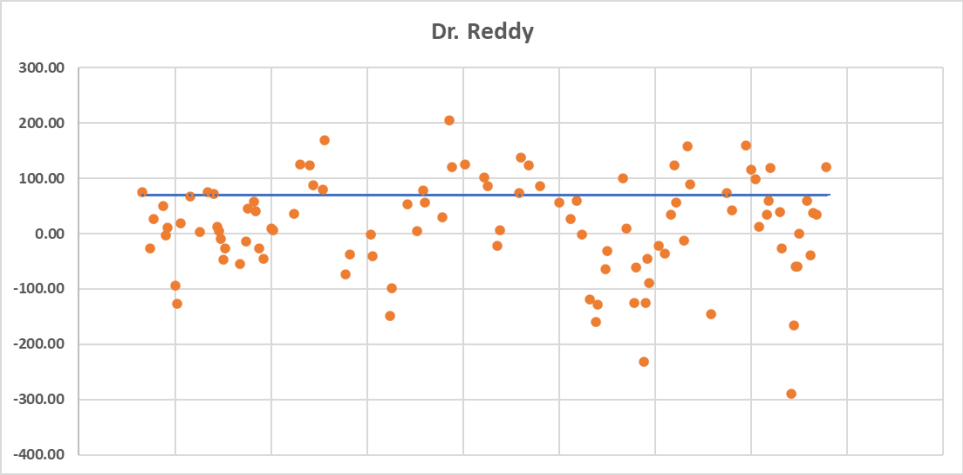
Fig. 1 Critical Values of Studentized Range Distribution (q) for Familywise (ALPHA=0.05)

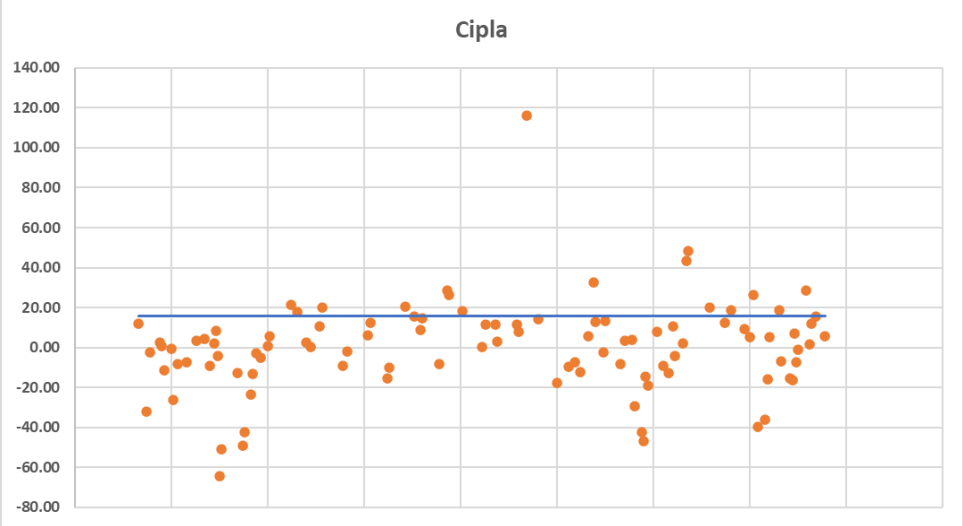
The critical value for Tukey's test at a 5% significance level was determined to be 3.858. Upon comparing the calculated q scores for the pairs (Sunpharma vs. Dr. Reddy) and (Cipla vs. Apollo Hospitals) against this critical value, it was found that both scores were less than 3.858. Consequently, these results indicate that there are no significant differences between the means of these pairs. This lack of statistical significance suggests that the groups compared do not exhibit meaningful variation in their means, contributing to the understanding of the relationships among the tested groups.

Unfortunately, the analysis from Tukey's test did not allow for a definitive assessment of stock volatility, as it was unable to determine whether the stock exhibited high or low volatility. To further investigate the relationship between stock volatility and news events, we propose adopting a moving average mechanism. This approach will facilitate a more comprehensive analysis of stock price fluctuations over time, enabling us to better understand how news impacts volatility. By utilizing moving averages, we aim to identify trends and patterns that may not be apparent through traditional methods, ultimately enhancing our analysis of stock behavior in response to various news stimuli.

In our study, we first collected the complete annual data for five major stocks. Focusing on specific news dates, we computed the closing prices of these stocks on those dates. Subsequently, for each news date, we calculated the moving average by taking the average of the closing prices from the preceding five days. This moving average served as our predicted stock price. We then determined the difference between the actual closing price on the news date and the predicted moving average. These differences were plotted on a scatter plot, with a trend line representing the average of these moving averages. This process was systematically repeated for each of the five stocks under consideration.


Sunpharama
50.00
40.00
30.00
20.00
10.00
0.00
-10.00
-20.00
-30.00
-40.00


Dr. Reddy
300.00
200.00
100.00
0.00
-100.00
-200.00
-300.00
-400.00


Cipla
140.00
120.00
100.00
80.00
60.00
40.00
20.00
0.00
-20.00
-40.00
-60.00
-80.00

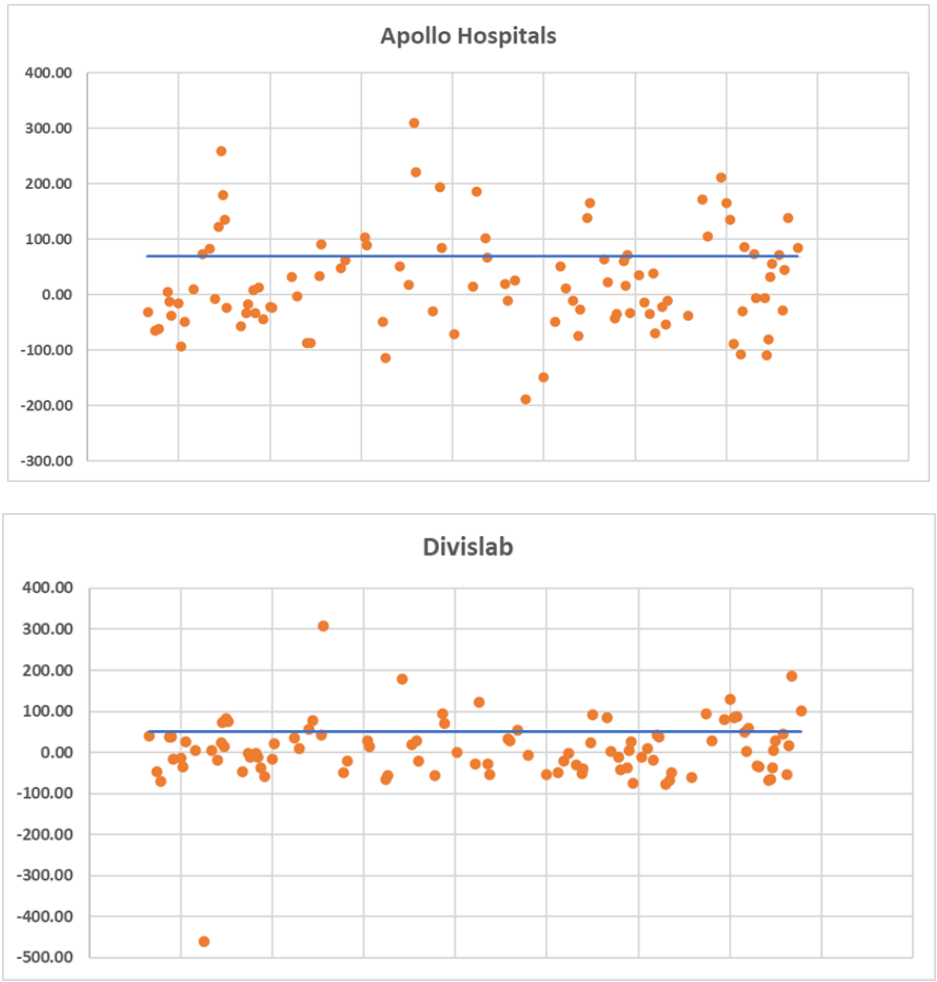


Fig. 2. Scatterplot of moving average analysis of the five stocks

The scatterplot shows the difference between the five-day moving average and closing price of the day on which the news breakout. Primarily, this captures the immediate shift of the stock price on the day of the release of the news. The blue line depicts the centerline for these deviations. The scatterplots effectively visualize the relationships between news events and stock performance and reveal patterns, including correlations between news events and stock price movements, as well as deviations from moving averages.

To assess the volatility of each stock, we calculated the standard deviation for the differences across all five stocks. This analysis provided insights into the price fluctuations in relation to the predicted moving averages and helped quantify the volatility associated with each stock.

$$Standard\ deviation = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{4}$$

$x_i = Each\ individual\ stock\ value$
$\mu = Average\ stock\ value$
$N = Number\ of\ days$

The study analyzed the volatility of stock prices for five major pharmaceutical companies: Sunpharma, Dr. Reddy, Cipla, Apollo, and Divislab. Utilizing the standard deviation of daily stock price changes as a measure of volatility, the analysis revealed that Apollo exhibited the highest level of

volatility (standard deviation 89.43), followed by Dr. Reddy (standard deviation 88.24). In contrast, Sunpharma showed the lowest volatility (standard deviation 14.08), with Cipla and Divislab displaying moderate volatility levels of 22.78 and 78.07, respectively.

The substantial volatility observed in Apollo's stock prices may be attributed to heightened sensitivity to market news, including regulatory developments, financial performance reports, and competitive pressures within the pharmaceutical industry. Furthermore, external factors such as investor sentiment, macroeconomic conditions, and geopolitical events could have exacerbated the fluctuations in Apollo's stock prices. The findings suggest that while Apollo presents significant investment opportunities due to its dynamic price movements, it also entails a higher risk profile compared to its peers in the sector.

The volatility of Apollo's stock can be attributed to several interrelated factors, each of which has a significant impact on investor behavior and market dynamics. Firstly, regulatory developments often play a crucial role in the pharmaceutical sector. For instance, any approvals or rejections by the Food and Drug Administration (FDA) or other regulatory bodies can lead to substantial stock price fluctuations. An example includes the approval of a new drug, which could drive a positive spike in stock prices due to anticipated revenue growth, whereas delays or rejections could result in sharp declines. Secondly**,** financial performance reports significantly influence investor sentiment. Quarterly earnings reports that exceed or fall short of market expectations can cause considerable volatility. For example, if Apollo reports earnings that surpass analyst forecasts, it may lead to a surge in stock prices due to increased investor confidence. Conversely, underperformance relative to expectations can trigger sell-offs, amplifying volatility. Moreover, competitive pressures within the industry can also lead to fluctuating stock prices. The introduction of generic versions of drugs or the emergence of new competitors with similar products can erode market share and profitability, leading to negative investor reactions. An instance of this could be a competitor launching a similar drug at a lower price, which might prompt a decline in Apollo's stock as investors anticipate reduced future earnings. Additionally, external economic factors such as changes in interest rates, inflation, and broader market trends can have a pronounced effect on Apollo's stock. For example, rising interest rates might lead to reduced consumer spending on healthcare products, thereby impacting the company's revenue and causing volatility in stock prices. Lastly, geopolitical events and macroeconomic conditions, such as trade policies or global health crises, can induce volatility. The COVID-19 pandemic serves as a prime example, where pharmaceutical stocks, including Apollo, experienced significant volatility due to uncertainties regarding drug development, supply chain disruptions, and fluctuating demand for healthcare services.

This research underscores the importance of understanding stock volatility in the context of market reactions to news and external influences. The results provide valuable insights for investors and financial analysts, highlighting the need for cautious investment strategies when dealing with highly volatile stocks such as Apollo. Future studies could delve deeper into specific events or periods that triggered significant volatility, offering a more granular understanding of the factors influencing stock price dynamics in the pharmaceutical industry.

5. Conclusions and Limitations

The results of the ANOVA, Tukey's HSD tests, Moving Average and Standard Deviation reveal significant insights into the volatility of selected stocks within the Nifty Healthcare Index in response to news events. The high F statistic and significant p-value from the ANOVA indicate substantial variability between the stock groups, leading to the rejection of the null hypothesis that all group means are equal. This suggests that certain stocks exhibit distinct behavior compared to others. The

Tukey's HSD test further elucidates these differences by identifying specific stocks that demonstrate significant volatility. The analysis conducted using Tukey's test was inconclusive in assessing stock volatility, as it failed to definitively classify the stock as having either high or low volatility. The moving average was used as the predicted stock price, and the differences between the actual closing prices on the news dates and the predicted values were plotted on a scatter plot. A trend line, representing the average of these differences, was included to further visualize stock volatility. The standard deviation was calculated to identify the stock with the highest volatility. Among the analyzed stocks, Apollo Hospitals exhibited the greatest level of volatility.

Apollo Hospitals showed significant responses to news events, as evidenced by standard deviation value. This indicates that this stock is more sensitive to market news, making it critical point of focus for investors and analysts.

Conversely, Sunpharma, Dr. Reddy, Cipla and Divis Laboratories did not exhibit significant differences, implying relative stability in their responses to news. This stability can be advantageous for risk-averse investors seeking less volatile options within the healthcare sector. These findings underscore the necessity of individualized analysis of stock behavior within an index, as aggregate index trends may mask the diverse responses of constituent stocks. Future research could expand on these results by exploring the underlying factors driving the differential sensitivity of these stocks, such as company-specific news, sectoral dynamics, or broader market conditions. Such analyses would provide deeper insights into strategic investment decision-making in the healthcare sector.

The study is limited by its reliance on secondary data from a single year, which may not capture longer-term trends and variability. Additionally, the analysis is constrained to five stocks, potentially limiting the generalizability of the findings to the entire Nifty Healthcare Index. Future research should consider a broader time frame and a more comprehensive set of stocks to validate and extend these findings, as well as explore underlying factors contributing to stock-specific responses.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Kumar, P., & Singh, K. (2019). Media, the Fourth Pillar of Democracy: A Critical Analysis. International Journal of Research and Analytical Reviews, 6(1), 370-378.

[2] Aïmeur, E., Amri, S., & Brassard, G. (2023). Fake news, disinformation and misinformation in social media: a review. Social Network Analysis and Mining, 13(1), 30. https://doi.org/10.1007/s13278-023-01028-5

[3] Middleton, M. (2009). Social responsibility in the media. Center for International Media Ethics CIME, Oxford University PCMLP, 2-3.

[4] Pettit, J. (2007). Strategic corporate finance.

[5] Ding, X. S., Ni, Y., & Zhong, L. (2016). Free float and market liquidity around the world. Journal of Empirical Finance, 38, 236-257. https://doi.org/10.1016/j.jempfin.2016.07.002

[6] Bag, S., Gupta, S., Choi, T. M., & Kumar, A. (2021). Roles of innovation leadership on using big data analytics to establish resilient healthcare supply chains to combat the COVID-19 pandemic: A multi methodological study. IEEE Transactions on Engineering Management, 71, 13213-13226. https://doi.org/10.1109/TEM.2021.3101590

[7] Teyhen, D. S., Robbins, D., & Ryan, B. A. (2018). Promoting and sustaining positive personal health behaviors–putting the person first. Military medicine, 183(3), 213-219. https://doi.org/10.1093/milmed/usy212

[8] Jiang, B., Zhu, H., Zhang, J., Yan, C., & Shen, R. (2021). Investor sentiment and stock returns during the COVID-19 pandemic. Frontiers in Psychology, 12, 708537. https://doi.org/10.3389/fpsyg.2021.708537

[9] Naseem, S., Mohsin, M., Hui, W., Liyan, G., & Penglai, K. (2021). The investor psychology and stock market behavior during the initial era of COVID-19: A study of China, Japan, and the United States. Frontiers in Psychology, 12, 626934. https://doi.org/10.3389/fpsyg.2021.626934

[10] Shehzad, K., Xiaoxing, L., Arif, M., Rehman, K. U., & Ilyas, M. (2020). Investigating the psychology of financial markets during covid-19 era: a case study of the us and european markets.Frontiers in Psychology, 11, 1924. https://doi.org/10.3389/fpsyg.2020.01924

[11] Sadiq, M., Hsu, C. C., Zhang, Y., & Chien, F. (2021). COVID-19 fear and volatility index movements: empirical insights from ASEAN stock markets. Environmental Science and Pollution Research, 28, 67167-67184. https://doi.org/10.1007/s11356-021-15064-1
[12] Cevik, E., Altinkeski, B. K., Cevik, E. I., & Dibooglu, S. (2022). Investor sentiments and stock markets during the COVID-19 pandemic. Financial Innovation, 8, 69. https://doi.org/10.1186/s40854-022-00375-0
[13] Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. Journal of behavioral and experimental finance, 27, 100343. https://doi.org/10.1016/j.jbef.2020.100343
[14] Akin, I., & Akin, M. (2024). Behavioral finance impacts on US stock market volatility: an analysis of market anomalies. Behavioural Public Policy, 1-25. https://doi.org/10.1017/bpp.2024.13
[15] Gao, Y., Zhao, C., Sun, B., & Zhao, W. (2022). Effects of investor sentiment on stock volatility: New evidence from multi-source data in China's green stock markets. Financial Innovation, 8, 77. https://doi.org/10.1186/s40854-022-00381-2
[16] Goonatilake, R., & Herath, S. (2007). The volatility of the stock market and news. International Research Journal of Finance and Economics, 3(11), 53-65.
[17] Ormos, M., & Vázsonyi, M. (2011). Impacts of public news on stock market prices: Evidence from S&P 500. International Journal of Economics and Finance, 1(2), 1-17.
[18] Narayan, P. K., & Bannigidadmath, D. (2021). Does financial news predict stock returns? New evidence from Islamic and non-Islamic stocks. Pacific-Basin Finance Journal, 42, 24-45. https://doi.org/10.1016/j.pacfin.2015.12.009
[19] Robinson, J., Glean, A., & Moore, W. (2021). How does news impact the stock prices of green firms in emerging markets? Research in International Business and Finance, 45, 446-453. https://doi.org/10.1016/j.ribaf.2017.07.176
[20] Ren, Y., Liao, F., & Gong, Y. (2020). Impact of news on the trend of stock price change: An analysis based on the deep bidirectiona LSTM model. Procedia Computer Science, 174, 128-140. https://doi.org/10.1016/j.procs.2020.06.068
[21] Malik, F. (2021). Estimating the impact of good news on stock market volatility. Applied Financial Economics, 21(8), 545-554. https://doi.org/10.1080/09603107.2010.534063
[22] Li, Q., Wang, T., Li, P., Liu, L., Gong, Q., & Chen, Y. (2014). The effect of news and public mood on stock movements. *Information Sciences*, *278*, 826-840. https://doi.org/10.1016/j.ins.2014.03.096
[23] Merello, S., Ratto, A. P., Ma, Y., Luca, O., & Cambria, E. (2018, November). Investigating timing and impact of news on the stock market. In 2018 IEEE International Conference on Data Mining Workshops (ICDMW) (pp. 1348-1354). https://doi.org/10.1109/ICDMW.2018.00191
[24] Ababneh, M., & Tang, A. (2013). Market reaction to health care law: An event study. International Journal of Accounting and Financial Reporting, 3(1), 108. https://doi.org/10.5296/ijafr.v3i1.3356
[25] Ahmed, D., Neema, R., Viswanadha, N., & Selvanambi, R. (2022). Analysis and Prediction of Healthcare Sector Stock Price Using Machine Learning Techniques: Healthcare Stock Analysis. International Journal of Information System Modeling and Design (IJISMD), 13(9), 1-15. https://doi.org/10.4018/IJISMD.303131
[26] Shaik, D. A., Neema, R., Viswanadha, S. N., & Selvanambi, R. (2023). Analysis and prediction of healthcare sector stock price using machine learning techniques: Healthcare stock analysis. International Journal of Information System Modeling and Design, 13(9), 1-15. https://doi.org/10.4018/IJISMD.303131
[27] Tang, C. H., Lee, Y. H., Liu, W., & Wei, L. (2022). Effect of the universal health coverage healthcare system on stock returns during COVID-19: Evidence from global stock indices. Frontiers in Public Health, 10, 919379. https://doi.org/10.3389/fpubh.2022.919379
[28] Alberti, E., Herberger, T. A., & Ender, M. (2023). Short-Term Stock Performance of Health Care Companies in Times of Viral Epidemics and Pandemics. Atlantic economic journal, 51(2), 131-148. https://doi.org/10.1007/s11293-023-09778-5