Applied Journal of Economics, Law and Governance https://doi.org/10.57017/ajelg.v1.i2(2).01

Structural Breaks and Market Anomalies in Indian Stock Markets during Catastrophic Periods

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Abstract

This study analyses the existence of structural breaks and market anomalies in the Indian stock market during catastrophic periods from 1990 to 2023. We employ OLS dummy variable techniques to identify seasonal anomalies and the Chow breakpoint test to detect structural breaks in the BSE and NSE indices. Our findings reveal a significant December effect in the NSE, while the BSE shows no such significant monthly anomalies. The Chow test results indicate that major crises, including the 1992 security scam, the 2008 global meltdown, the 2009 political regime change, and the 2020-21 pandemic, were significant catalysts for a continuing swing in the level of Indian stock indices.

This research contributes to the literature by demonstrating that while market anomalies can exist, structural breaks during catastrophic events are a more significant factor influencing the Indian stock market. Our findings have important practical implications for investors, policymakers, and regulators, highlighting the need to account for both seasonal effects and the impact of systemic crises when analysing market behaviour.

Keywords: structural breaks; India; stock market; crises.

JEL Classification: G01, G11, G12, G14, G15.

Introduction

Stock markets are vastly unpredictable and often broaden the risks caused by systemic, periodic occurrences, for instance, asset bubbles, comprehensive imbalances, negative externalities, correlated exposures, informational disturbance and contaminations, etc., to the existing economic and financial markets by means of diverse channels. Consequential to the happenings of a number of economic disasters like global financial crises, an enormous securities scam floated up linking a distraction of funds from the banking system in 1992, Asian financial crisis in1997 and more recently the COVID-19 pandemic, which emerged in early 2020, researchers started probing the likelihood of the existence of a structural break in Indian capital markets.

Systemic events root the basis for extensive fiscal unsteadiness that interrupts the implementation and execution of the financial system, which sequentially makes shocks in the bona fide economy (Duca & Peltonen, 2013; Thanh et al., 2020). A complete shock or transmittable idiosyncratic shocks direct to systemic crises, consequently, relentlessly weakening the financial system and knocking off the balance of the economy (De Bandt & Hartmann, 2000).

Structural break occurs while a time series unexpectedly alters at a particular point of time. This change could associate a transformation in mean or a transformation in the other parameters of the process which make the series. Structural breaks in stock exchanges refer to noteworthy shifts or discontinuities in the fundamental dynamics of market performance, frequently associated with economic, regulatory, or hi-tech changes. There is a thread of literature that indicates that structural break can happen owing to the diffusion of external shocks, important information or decisions of policymakers as well (Lamoureux & Lastrapes, 1990; Malik & Hassan, 2004).

The existence of structural breaks tends to generate incorrect or counterfeit statistical relationships among variables. The structural breaks might have mutually short-term and long-term effects on trading volume in stock exchanges. It repeatedly guides to changes in market unpredictability patterns which can drastically persuade investors' behaviour and market participation. Huang (2012) detects that momentous information shocks in a market can instigate structural change in the variance of other markets if they are integrated. Copious experiential studies have established that the persistence of volatility is considerably reduced due to the transmission of major external shocks (Ewing & Malik, 2005; Malik & Hassan, 2004; Miralles Marcelo, et al., 2008). Structural breaks might modify risk perceptions and risk eagerness among market participants. On the whole, investors in the stock market are considered to be poor Bayesian decision-makers and substantiation shows that they react excessively to new information. Investor buoyancy leads to a diminution in earnings volatility, whereas investor cynicism causes a boost in earnings volatility. As a result, stock prices diverge from their underlying fundamental value (De Bondt & Thaler, 1987; Lee et al., 2002).

This study investigates potential structural break in Indian capital markets following several crises along with analysis of monthly stock market anomalies.

For analysis of structural break, the entire study period is divided into five sub-sample periods, 1992 security scam period, 2008 as subprime lending crisis period,2009 as political regime change period, 2020 as outbreak of pandemic and 2021 as existence and recover of pandemic period. As the study is being conducted in an event study environment, therefore, a reasonable sample period has been taken before and after the event has been selected.

Table 1: Major catastrophic events

Year	Major Events	Prima facie Effect on the Stock Market
1992	In 1992, a massive securities scam surfaced involving a distraction of funds from the banking system, in particular the inter-bank market in government securities, to brokers for financing their operations in the stock market.	The immediate impact was a drastic fall in share prices and market index, causing a breakdown of the securities control system operation with the commercial banks and the RBI. Around Rs 35 billion from the Rs 2,500 billion market was inhibited, resulting the share market subside.
2008	The U.S subprime crisis broke out in October 2007, with the nation's top investment banks expecting to take USD 100 billion or more in write-downs because of subprime losses with the bursting of the	The Sensex, which had closed December 2007 above the 20,000-mark continued to move lower since then. SENSEX fell by 5.4% on September 15, 2008. After reaching its crisis induced ebb in February 2009, the Sensex

Year	Major Events	Prima facie Effect on the Stock Market
	housing bubble; this affected financial markets worldwide. The fall down of Lehman Brothers in September, 2008 instigated the largest bankruptcy proceedings in the US history and triggered massive financial and economic turmoil across the globe, the effect of which still hasn't dissipated.	recovered quite rapidly from an average closing value of below 9,000 to above 17,000 by September 2009 and above 20,000 in another year's time.
2009	In the May 2009 victory of Congress-Led Government Led by Dr. Manmohan Singh was perceived as a public endorsement for the continuation of economic reforms and liberalization policies that had been ushered in by Manmohan Singh in 1991.	The SENSEX surged 14.70% on the results day. The Sensex remained range bound within 18,000 and 22,000 in the next few years.
2020 & 2021	On 24 March 2020, a nationwide lockdown was announced in India to reduce the adverse consequences. Such social distancing measures and restrictions on transportation negatively impacted firms' productivity via increasing operation costs, decreasing revenue, and cash flow challenges. The usual consumption pattern was affected due to the growing panic among consumers. All these led to market abnormality.	After the outbreak of the COVID-19 in 2020, the stock market came under fear as BSE Sensex and NSE Nifty fell by 38%. It leads to a 27.31% loss of the total stock market from the beginning of this year. A total of 10 million new demit accounts were opened in 2020 owing to the low cost of trades and an industry-wide shift to online trading. Reports show that the MSCI World Index, which includes stocks from 23 developed countries and 24 emerging markets, lost 10.7% of its value between 23 January and 6 March 2020.

1. Literature Review

The literature thrives with lot of stock market seasonality. Month-of-the-year, week-of-the-month, day-of-the-week, and hour-of-the-day impacts are examples of documented seasonality. Numerous researches on security price anomalies have been developed since the ground-breaking exertion of Fama (1965). While the chronological substantiation of seasonality in stock market returns had been found by Fields (1931) & Wachtel (1942), scientific examination of anomalies in stock market started with Cross (1973) which was followed by French (1980). Although the past is full of studies which addressed various kinds of stock market anomalies, but unfortunately, the results are indecisive and contradictory. As the purpose in the current study is to empirically test the month-of-the-year effect, we found that majority of the research studies had recognized the January effect (Aggarwal & Rivoli, 1989; Agrawal & Tandon, 1994; Beyer et al., 2013; Georgantopoulos et al., 2011; Wilson & Jones, 1993).

In one of the earlier studies that compared the data for the period, 1904-1974 on the US stock market, Rozeff et al. (1976) proved that the January returns were statistically higher in comparison with the remaining eleven months. Gultekin & Gultekin (1983) found that the January effect was present in thirteen countries out of seventeen countries.

Brown et al. (1983) described 'January effect' as the tax-loss selling hypothesis under which investors are led to sell out stocks at the end of year in order to obtain tax related advantages. Thus, the prices become lowered and afterward bounce back during January. The following research studies also substantiated the tax-loss selling January effect hypothesis (Chen & Singal, 2003; Keim, 1983; Raj & Thurston, 1994; Choudhary, 2001; Pandey, 2002; Elango & Pandey, 2008).

Nevertheless, some authors maintain that the tax-loss selling hypothesis was correct before the Federal income taxes, and the January effect was of no consequence. There has been a superfluity of researches on the month-year-of-the-year influencing both Indian markets. There is a broad variety of research findings, but unfortunately, there is no agreement in finding the month-of-the-year effect. In France, Norway, US, Denmark, Spain, Germany, Sin/Mal, Malaysia and Switzerland also, January effect was found by different scholars across the world (Keim, 1983; Wong et al., 2007). In case of Chinese market, while Gao & Kling (2005) documented March and April effects data, whereas Luo et al. (2009) did not detect any effects of a month-of-the-year. The January effect did not occur in the New Zealand stock market (Li & Liu, 2010); Silva's (2010) study found no 'January effect' in the Portuguese stock market. July effect had been observed in Ghana's stock market (Albert et al., 2013), the Indonesian stock market's best month was December (Rahario et al., 2013).

In relation to literature review for the Indian stock market, March to May effect was discovered by Patel (2008), April, November, and December effects were discovered by Ramasamy & Pandey (2008), Diwali effect was discovered in Harshita et al. (2018). Raj& Thurston (1994) examined the January and April effects in case of the NZ stock market but unfortunately observed no important effect. Also, Ramachanran (1997) found no seasonal effect for the stock market of Jamaica. Following similar lines, Maghyereh (2003) found no evidence of either the January impact or monthly seasonality in the Amman Stock Exchange (ASE), returns using different techniques of GARCH family. In another study, Floros (2008) explored the Greek stock market and found no significant January effect, with daily returns between January and other months being statistically indistinguishable. Coutts & Sheikh (2002) examined the All-Gold Index and found no evidence of weekend, January, or pre-holiday effects, further supporting the notion that these anomalies may not be universal across all markets. Marquering et al. (2006) investigated anomalies before and after they were widely documented, revealing that once such anomalies become common knowledge, they tend to disappear.

However, Fama's Efficient Market Hypothesis (EMH), which asserts that stock prices always replicate all available information and consequently cannot be consistently predicted or exploited for extraordinary profits, has been a foundational theory in financial economics (Fama, 1983). According to EMH, stocks are always traded at their fair value, leaving little room for investors to outperform the market unless they take on additional risk. However, the prevalence of seasonal anomalies, such as the 'January effect', 'holiday effect', 'calendar effect' etc seems to challenge this idea, as these patterns suggest that certain periods yield higher or lower returns that would be expected in an efficient market.

While considering structural breaks in stock market movements, Pettenuzzo & Timmermann (2011) opined that structural breaks can cause unsteadiness in an economic mode, which will result in faulty prediction. Several academicians believe that excessive volatility spillover, consequent upon financial crises, may have consequence in structural breaks of volatilities of the markets (Arago & Fernandez-Izquierdo, 2007; Hammoudeh & Li, 2008; Miralles Marcelo, 2008; Mcmillan & Wohar, 2011).

Aggarwal et al. (1999) observed that markets of developing economies have witnessed copious volatility structural breaks in recent past. Some of these breaks were due to economic crises like periods of hyperinflation in Latin America, Mexican peso crisis, stock market scandal in India, and the October 1987 crash that affected various stock markets across the world. Correspondingly, Miralles Marcelo (2008) evidenced intra-market structural breaks in volatility while analysing the spill over effect between large and small-cap portfolios in the Spanish stock market. Their results show structural changes in volatilities due to shock transmission among these portfolios. Hammoudeh & Li (2008) have found that the transmission of external shock results in a significant decline volatility persistence of the market. Similarly, occurrences of volatility breaks have been found in Japanese and Korean stock markets consequent to the spill-over of external shocks (Kang et al., 2009). Sasidharan (2009) observed structural breaks in the index using Bai-Perron's method for endogenous multiple structural changes. Using non-parametric methods, the efficiency of the market across the periods corresponding to the structural breaks are tested.

Though the null hypothesis of random walk for the entire return series for the period 1991 to 2008 is rejected, it has been observed that the markets have become weak-form efficient since the second half of 2003, corresponding to the period of the third structural break identified. Hiremath & Kamaiah (2010) noticed noteworthy structural breaks in returns series for all chosen indices. They endow with adequate proof in favour of mean-reverting tendency in the Indian stock returns refuting market efficiency. Mishra et al. (2014) find that unit root tests allow for two structural breaks. Ewing & Malik (2005), Maderitsch & Jung (2014) confirmed unexpected well-built breaks in volatilities of markets owing to shock spillover. Saeed et al. (2013) have explored the diffusion of six financial crises shocks from developed economies to South Asian economies.

Results recommend that South Asian economies are getting more integrated with the world markets which results in greater volatility spillover from developed markets during financial crises. Abbas et al. (2013) have recognized the subsistence of volatility spill-over among China, Pakistan, India, Sri Lanka, USA, UK, and Singapore. They have also established the existence of spillover between hostile countries of the region provided there are trade relations between them. Jebran & Iqbal (2016) showed substantiation of noteworthy bidirectional and occasionally unidirectional spill-over of return and volatility between China, India, Pakistan, and Japan. Jebran et al. (2017) also investigated the volatility spillover among emerging stock markets from normal and turbulent time periods.

Huo & Ahmed (2017) investigated the spill-over effects generated due to recently introduced Shanghai-Hong Kong Stock Connect. They argue that after the introduction of new connects system, a weak and unstable co-integration relationship is found along with the increased level of conditional variances of both stock markets Habiba et al. (2019) also investigated the dynamics of volatility spill-over among various Asian economies by employing an extended version of EGARCH.

The analytical study on stock price behaviour in India initiated with early work of Rao & Mukherjee (1971) which endow with proof on market efficiency based on a single stock price. Empirical studies relating to judging market efficiency in the context of Indian stock market, at the same time as endogenously assessing the structural break dates, are quite small in number; these consists of studies by Sasidharan (2009),

Hiremath & Kamaiah (2010) and Mishra et al. (2014). Successive studies using a variety of methods, indices and sets of stock prices, over diverse time horizons, have once more produced rather contradictory results. Early studies have engendered noteworthy confirmation in favour of weak form efficiency of the Indian stock markets.

On the contrary, differing results on testing the weak form efficiency were attained by Ahmad et al. (2006), Gupta & Basu (2007), and Mishra (2012), among others, who established stock prices to be predictable. A pre-determined division of the sample period into sub-periods has often produced mixed evidence on market efficiency in different sub-periods according to a few studies like Gupta & Yang (2011). This indicates the need for testing the EMH with the presence of structural breaks in the series under consideration; exploration of Indian market data in this vein is limited. However, few studies do confirm the existence of structural breaks and find evidence of divergent results when structural breaks are endogenously determined.

Gil-Alana & Claudio-Quiroga (2020) investigated the impact of Covid19 pandemic on the stock markets of Asia for the period from July, 2006 to September,2020 by evaluating the proper tiers of these markets namely, the Korean SE Kospi index, the Japanese Nikkei 225, and the Chinese Shanghai Shenzhen CSI 300 Index. Using fractional integration methods, the results obtained on the basis of daily data suggests that mean reversion and consequently, transitory effects of shocks arise in the Nikkei 225 index. Conversely, for the Kospi and Shanghai Shenzhen indices, this hypothesis is rejected, entailing that shocks are enduring.

Mazur et al. (2021) investigate the US stock market performance during the collapse of March 2020 activated by COVID-19. The result suggests that natural gas, food, healthcare, and software stocks make elevated affirmative returns, while equity values in petroleum, real estate, entertainment, and hospitality sectors fall considerably. Furthermore, loser stocks display severe asymmetric volatility that correlates unenthusiastically with stock returns. Firms respond in a multiplicity of diverse ways to the COVID-19 revenue shock. The investigation of the 8K and DEF14A filings of poorest performers divulges departures of senior executives, remuneration cuts, and (most surprisingly) newly approved cash bonuses and salary increase.

Rai et al. (2022) conducted numerical investigation of stock market crash ,1987, financial crisis, 2008 and COVID-19 pandemic considering the definite crash times of the main shock and aftershocks. The results demonstrate that the main shock and aftershock in the stock market go after the Gutenberg–Richter (GR) power law. Additionally, the result showed higher β value for the COVID-19 crash as compared to the financial-crisis-2008 from the GR law. This entails that the recovery of stock price during COVID-19 may be quicker than the financial-crisis-2008. The result is unswerving with the present recovery of the market from the COVID-19 pandemic. The analysis illustrates that the high-magnitude aftershocks are unusual, and low-magnitude aftershocks are common during the recovery phase.

Souza et al. (2023) used a collective STR-Smooth Transition Regression model (EGARCH, STRIGARCH, and STR-FIEGARCH) to examine the contamination effects of the 2008 financial crisis. The projected device aimed to assist the study of infectivity and the impact of changes in long-term interest rates on the returns of international stock indices and forecasting, with particular importance on the effects caused by structural breaks, persistence, and conditioned heteroscedasticity. The results show that the developed blended models obtained superior performance in predicting the effect or impact of changes in interest rates on stock market indices when influenced by structural breaks. STR and the ARCH family are constructive instruments that create the decision-making process clearer and more objective when choosing instruments that evaluate the spill-over effect of long-term interest rates on the profitability of international financial indices.

Ndako et al. (2025) examines the impact of the COVID-19 pandemic and other global events on the global stock market, focusing on 16 countries of the world using quarterly data ranging from 1919-Q1 to 2020-Q2. The result suggests that while selected sample countries in Europe have at least ten break dates under the period of investigation, the US, Canada and Australia, have only twelve break dates. Asia and the other bloc of countries report ten and twelve break dates respectively. Remarkably, one most prominent reason of structural changes in stock markets (with the omission of Germany) emerges to be from the Global Financial Crisis (GFC), which had contrary effects on most important market around the world. The most outstanding source of structural breaks in the Asian markets appears to be from the 2008-2009 GFC. In addition, the results show the substantiation of structural breaks in a number of stock markets in the world, resulting from the 2009-2010 Global Pandemic.

Indian economy was also to a great extent affected by Global Financial Crises. This designates the call for testing the EMH with the existence of structural breaks in the series under consideration; examination of Indian market data in this stratum is inadequate. conversely, few studies do substantiate the existence of structural breaks and find proof of conflicting results when structural breaks are endogenously determined. The main contribution of the article in Indian context has been to focus on identifying the month-of-the-year effects along with a structural break analysis during specific, pre-defined crises periods. This seems to be the unique contribution of this research endeavour.

In pursuance of insight obtained after a thorough analysis of existing literature, the rationale behind the present analysis is to explore the existence of seasonal anomalies in terms of ‘month of the year effect’ in stock returns in Bombay Stock Exchange (BSE) SENSEX and NIFTY 50 and to explain whether there exist any structural breaks in stock returns during several crises period arising out in our study period.

2. Research Methodology

Data database

Monthly values of BSE SENSEX during the period January, 1990 to December, 2023 and NSE monthly data from Jan, 1996 to Dec, 2023 from NSE and BSE site has been considered. Many seasonality studies followed in emerging and developing economies took on the methodology similar to that of the research of the developed stock markets (Keim, 1983; Kato & Schallheim, 1985; Jaffe & Westerfield, 1989). We also list some external shocks to the stock market encompassing domestic and international events like political instability, political regime changes, stock market scams, global market meltdowns and financial crises and more recently pandemic effect on stock markets.

2.1. Modelling the Day-of-the-Week Effect

OLS Dummy Variable Regression Equation Model

In this study, OLS with dummy variables are used to model the volatility of two Indian stock markets-namely BSE and NSE. Most studies investigating month-of-the-year effect in returns employed the standard Ordinary Least Square (OLS) methods by regressing returns on 11 dummy variables. In this study, a dynamic OLS model on return series is used under the following assumptions:

Thus, the coefficient of each dummy variable measures the incremental effect of that month relative to the benchmark month of January. The existence of seasonal effect will be confirmed when the coefficient of at least one dummy variable is statistically significant (Pandey, 2002). Thus, similar to earlier studies, our initial model to test the monthly seasonality is as follows:

$$y_t = \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varepsilon_t \quad (1)$$

In order to avoid the dummy variable trap, dummy variable representing the month of January has not been included. So, the intercept term α_1 indicates mean return for the month of January and coefficients $\alpha_2 \ldots \alpha_{12}$ represent the average differences in return between January and each other month which commences from February trading month to December trading month, except for January. Hence, the coefficient of each variable computes the additional outcome of the respective month compared to the base month i.e., January. If the value of the coefficients of α_2 to α_{12} is zero, then the return for each month of the year is identical and no evidence of month-of-the-year effect exists, and r_{ep} resents the white noise error term. This approach, however, may be flawed because the residuals may have serial correlation.

Chow Breakpoint Test

Chow breakpoint test, created by Gregory Chow, is used to monitor if the coefficients in two linear regressions on different datasets are equal and it also used to detect structural breaks(a shift in the relation between the independent and dependent variables at a specific point in time) in panel or time series data can be explained by a log-likelihood ratio test, which relies on the difference in the data's likelihood under the null hypothesis (no break) to the alternative hypothesis probability (break) and uses the chi-square distribution to determine how significant the difference is.

Chows break test identifies structural breaks, in the time series, by identifying the difference between the coefficient of dummies, in the equation as follows:

$$y_t = \alpha + \beta y_{t-1} + \sum_{i==1}^{n_d} \gamma D_i + \mu \quad (2)$$

where: y_i is price series; y_{t-1} is lagged price series; n_d is the number of structural breaks expected.

Chows test has a null hypothesis that $\sum \gamma_i$ =0 which tells that null hypothesis, is that no structural breaks are present. This statistic compares the sum of squared residuals (SSR) from the pooled regression with the sum of SSRs from the two unrestricted regressions.

Chow test statistic: $[(S_T - (S_1+S_2))/k]/[(S_1+S_2)/(N_1+N_2-2k)]$. This test statistic follows the F-distribution with k and N_1+N_2-2k degrees of freedom.

where: S_T = the sum of squared residuals from the total data; S_1, S_2 = the sum of squared residuals from each group; N_1, N_2 = the number of observations in each group; K = the number of parameters.

If the p-value associated with this test statistic is less than a certain significance level, we can reject the null hypothesis and conclude that there is a structural break point in the data.

2.2. Hypothesis

For testing the month-of-the-year effect, the hypothesis is framed as follows:

H_0: All the coefficients of the variables are equal to zero.

i.e., H_0: $\alpha_0 = \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10} = \alpha_{11}$

H_1: At least one coefficient is different from 0.

If the dummy variable for any particular day/month is significant, we know that particular day/month to have a significant return effect. If no seasonal pattern exists, the hypothesis that the coefficients are all zero should not be rejected.

A lagged dependent variable is added as an independent variable in a regression model to capture the dynamic effects of a variable over time, essentially acknowledging that the current value of a dependent variable is influenced by its past values, helping to account for autocorrelation and provide a more accurate representation of the relationship between variables in time series data. When there is autocorrelation in the error term of a regression model (meaning the residuals are correlated with each other across time), including a lagged dependent variable can help to "clean up" the data and produce more reliable coefficient estimates.

In many situations, the impact of an independent variable on a dependent variable may not be immediate but occur over time, and including a lagged dependent variable allows the model to capture these lagged effects.

3. Analysis of Results

Table 2 indicates the descriptive characteristic of the return series of BSE and NSE for post liberalization period. During this period BSE and NSE showed the positive return however NSE depicted Negative skewness of return series. A left tail event is highly undesirable as it highlights the black swan event i.e., a negative event the occurrence of which is highly unpredictable. A negative skweness is highly undesirable from investors point of view as it indicates frequent small gain but few large losses. A fat-tailed or thick-tailed distribution has a value for kurtosis that exceeds 3. That is, excess kurtosis is positive. This is called lap to kurtosis.

The distribution is also leptokurtic in the nature i.e., the return series for both the indices display the thicker tail than normal distribution indicating many prices fluctuation positive or negative away from average return. In Indian Context, these movements were typically product of “euphoria to despondency cycles”. In other words, stock returns irrespective of the regime when standardized by their scale exhibit more probability mass in the tails than distributions like the standard normal distribution. This means that extremely high and low realizations occur more frequently than under the hypothesis of normality. Jarque-Bera test suggests significant departure of return distribution from standard normality conditions.

Table 2: Basic descriptive statistics

Descriptive statistics	BSE SENSEX		NSE NIFTY	
	Price	Return	Price	Return
Mean	15687.06	1.112638	5577.482	0.937327
Median	9788.060	1.115695	4902.175	1.356523
Maximum	63099.65	35.06322	18758.35	24.73758
Minimum	676.2300	-27.29919	817.7500	-30.66649
Std. Dev.	15188.22	7.716402	4580.376	6.730840
Skewness	1.197747	0.045601	0.969752	-0.612501
Kurtosis	3.690240	5.156539	3.187007	5.177182
Jarque-Bera	102.2855	76.67901	51.25475	83.99014
Probability	0.000000	0.000000	0.000000	0.000000
Observations	395	395	324	324

Source: Authors’ own estimate

Table 3 shows mean and standard deviation of returns for BSE Sensex and NSE, revealing some interesting features, BSE depicts negative returns in March and October due to tax-loss and Diwali effects with volatility patterns varying across months, with increased volatility in the beginning and decreasing from July.

Table 3: Mean and standard deviation of BSE and NSE returns based on months of a year

Month of the Year Effect	Mean Return		Standard Deviation	
	BSE	NSE	BSE	NSE
January	0.192131	-0.381137	8.015097	6.877145
February	2.347492	0.937327	7.868821	6.730840
March	-0.256430	-0.200241	11.18582	8.570380
April	1.150779	1.719050	6.733353	6.393365
May	0.173189	0.430091	9.295371	8.676088
June	1.361710	1.068575	6.265761	6.554274
July	2.842703	1.549484	8.000789	5.509808
August	2.196479	0.652087	6.188875	5.643058
September	1.237576	0.730878	7.049251	6.792821
October	-1.009041	-0.282526	7.981352	8.740575
November	0.803336	1.746289	7.437697	6.057401
December	2.349208	3.279630	4.963873	4.356517

While NSE shows negative January effects (year-end effect), negative March effects (Tax loss effect), and negative October Diwali effects, with volatility fluctuating throughout the year, with October being most volatile and December least volatile.

Figure 1 and Figure 2 below illustrates graphically the results of the test of clustering volatility of the residuals or error term. The Figure shows that big and small errors arise in clusters, which imply that big returns are succeeded by more big returns and small returns are followed by small returns. In summary, the Figure implies that intervals of high stock returns are generally more than the periods of high stock returns, whereas low stock return is going to be followed by much low stock return. This volatility clustering supports that error or residual term is conditionally heteroscedastic.

Figure 1: Graphical presentation of return in BSE SENSEX

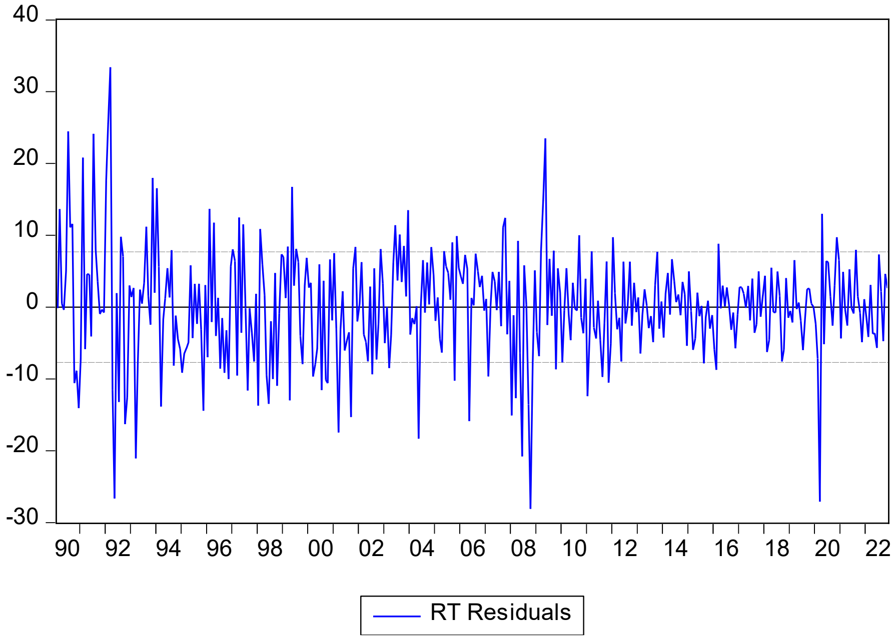
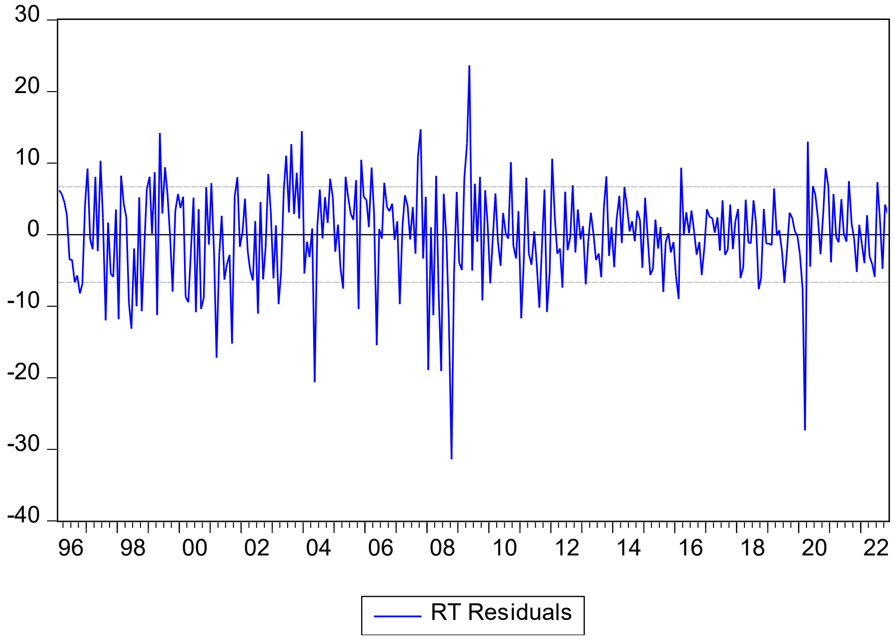


Figure 2: Graphical presentation of return in NSE



Empirical studies would typically make use of conservative unit root tests to look at the issue of market efficiency or the random walk hypothesis. The existence of a unit root suggests that shocks to the price series are enduring causing an irretrievable departure from the equilibrium price path, implying that future price movements cannot be predicted based on information about past changes. The Dickey & Fuller (1979) methodology has traditionally been used to test for the presence of a unit root. A common issue with the time series data is the existence of unit root, which leads to spurious results of the estimation. The stationarity of the data set has been checked using the Augmented Dickey-Fuller (ADF) Test and Philips-Perron (PP) tests. To determine the stationary property of data series, ADF and PP test has been conducted at their levels as well as their first difference. The total data set has been found stationary at first difference. The results of ADF and PP tests are as follows:

Table 4: ADF and PP test

Return	ADF - 1st diff	PP - 1st diff
BSE	-7.897406 (3.421788) # (0.0000) *	-163.8550 (-3.421299) # (0.0001) *
NSE	-10.37679 (-3.424247) # 0.0000*	-154.3829 (-3.423886) # (0.0001) *

Note: H_o: series has unit root; H_1: series is trend stationary; #MacKinnon critical values for rejection of hypothesis of a unit root; * indicates p value; AIC stands for Akaike info criterion; SBC stands for Schwarz Bayesian criterion; # indicates critical value at 5% level; * indicates Probability value

Source: Authors' own estimate

Table 4 indicates that for ADF and PP value, absolute value is greater than the critical t-value at 5% level of significance for both BSE and NSE at 1st difference thereby indicating the rejection of H_0, meaning the series are stationary at their 1stdifference. At the level (original form), none of the indices (in both ADF and PP tests) are stationary, as indicated by high p-values (greater than 0.05). This recommends the existence of a unit root, entailing non-stationarity at their levels. On the other hand, when difference has been taken just the once, all variables turn out to be stationary, substantiated by decidedly significant p-values (0.000) in both ADF and PP tests, which means that they reject the null hypothesis of a unit root at the first difference.

OLS specification for both NSE and BSE is presented in Table 5 to make a comparative efficacy of the techniques, with parameter estimates and Z-statistic values for the entire period. December effects, similar to the findings of Choithala & Ajmal (2016), are present in NSE.

Table 5: Month of the year effect on NSE and BSE

Variables	OLS with dummy variables [NSE]				OLS with dummy variables [BSE]			
	Coeff	Std. Error	z-Statistic	Prob.	Coeff	Std. Error	z-Statistic	Prob.
C	-0.000209	0.000598	-0.34871	0.7273	0.010264	0.094199	0.10895	0.9132
DFEB	0.000548	0.000861	0.63682	0.5243	0.135637	0.134861	1.00575	0.3146
DMAR	0.000126	0.000852	0.14799	0.8824	-0.025667	0.133847	-0.19176	0.8479
DAP	0.001118	0.000868	1.28714	0.1981	0.070210	0.136817	0.51316	0.6078

Variables	OLS with dummy variables [NSE]				OLS with dummy variables [BSE]			
	Coeff	Std. Error	z-Statistic	Prob.	Coeff	Std. Error	z-Statistic	Prob.
DMAY	0.000435	0.000845	0.51443	0.6070	0.006439	0.133028	0.04840	0.9614
DJUNE	0.000727	0.000844	0.86120	0.3892	0.074141	0.132609	0.55909	0.5761
DJULY	0.000899	0.000839	1.07182	0.2838	0.156020	0.131933	1.18257	0.2370
DAUG	0.000483	0.000847	0.57008	0.5686	0.123239	0.133655	0.92207	0.3565
DSEPT	0.000567	0.000853	0.66555	0.5057	0.068925	0.133652	0.51570	0.6061
DOCT	3.24E-05	0.000856	0.03785	0.9698	-0.079565	0.134911	-0.58976	0.5554
DNOV	0.000839	0.000849	0.98878	0.3228	0.046903	0.134703	0.34819	0.7277
DDEC	0.001729	0.000840	2.05710	0.0397	0.143473	0.134301	1.06829	0.2854
R_{t-1}	0.047597	0.011946	3.98428	0.0001	-0.281691	0.010595	-26.5865	0.0000
Durbin-Watson stat	1.90521				2.563			

Note: *Sig at 10% level; ** indicates sig at 5% level; *** indicates sig at 1%.
Source: Authors' own estimate

The "December effect" in the Indian stock market, where December tends to be a strong month for returns, is driven by a combination of factors, including portfolio rebalancing, increased festive season spending, and positive Foreign Institutional Investor (FII) activity. Institutional investors often rebalance their portfolios in December to align with their annual performance goals. This rebalancing frequently involves increasing their equity exposure, leading to higher demand for stocks and driving prices upward.

The festive season in India, which peaks in December, leads to increased consumer spending, boosting demand for certain sectors and potentially impacting stock prices by translating to better-than-expected corporate performance projections, boosting market sentiment and driving stock prices higher. It consistently contributes to positive returns during December, driven by seasonal demand and global contract renewals. Retail and Consumer goods, IT, and financial services companies often see a surge in sales during the festive periods like Diwali and Christmas and also see a surge in December due to global contract renewals and budget finalizations by international clients. This increased business activity enhances their earnings outlook and drives stock prices upward. Foreign Institutional Investors (FIIs) tend to be more active in the Indian stock market during December, which can lead to increased buying and positive market sentiment. Therefore, FIIs have been net buyers in the Indian stock market in December. Their increased buying activity contributes to the upward price movement during this month. In some years, the Indian economy may show signs of recovery, which can boost investor confidence and lead to positive market returns in December. Investors become optimistic and tend to be bullish about the next year's returns in December, further driving market activity. In total, the result asserts that there is a statistically significant December effect in the Indian stock market with heightened volatility and returns with regard to other months.

In case of NSE, historical trend shows that since 2000 onwards, the NIFTY Index has closed higher in December 17 out of 24 times expecting 71% of pretty impressive chances getting positive returns. Moreover, gains of 16.4 % in 2003,7.8% in 2020 and 7.9% in 2023 are not a coincidence because they are usually tied with favourable economic conditions, strong corporate earnings and an overall optimistic market sentiment. Moreover, in case of NSE, maximum average returns (or mean return) occurred in December (3.279630) and standard deviation for the month of December is also moderately high. This signifies that volatility in stock returns was maximum in December.

But December Effect could not be consistently found in the Indian stock market, especially in BSE as happened in our study. This may either be due varying study periods and indices and methodologies used in different research studies. Different research studies focus on diverse timeframes and use various BSE indices (SENSEX, BSE-100, BSE-200, BSE-500), leading to dissimilar findings. Some studies find noteworthy seasonality in broader indices, while others do not unearth it in the SENSEX over the analysed periods. This may so happen due to demonstration of seasonality in larger indices like the BSE-200 and BSE-500, indicating that while the SENSEX may appear less seasonal, other parts of the market might still demonstrate calendar effects.

On the other hand, a combination of factors might be responsible for having no December effect in BSE where it is very much present in NSE returns. This can be attributed to a combination of factors including the well-organized inclusion of information, the influence of festivals and tax-related behaviours like the March ended financial year. Differing fiscal and holiday years might be another rationale behind not finding December effect in BSE

Unlike many economies based on religious faith ‘Christianity’, where the year ends on December 31st, India's financial year and holiday structures may not arrange in a line with the traditional drivers of the December Effect. But OLS technique fails to provide any statistically significant anomaly in BSE stock market. Therefore, following same patter like NSE, OLS technique fails to provide any statistically significant anomaly in BSE stock market.

Table 6(a): Chow Break Point Test on BSE SENSEX. Break points: 1992, 2008, 2009, 2020 and 2021

Parameters	1992	2008	2009	2020	2021
F-statistic	1.471	0.557	0.607	0.188	0.0523
Log likelihood ratio	17.682	6.704	7.303	2.265	0.6305
Wald Statistic	17.649	6.687	7.285	2.258	0.6286
Prob. F (12,8190)	0.1270	0.8775	0.8381	0.9989	1.0000
Prob. Chi-Square (12)	0.1257	0.8765	0.8370	0.9989	1.0000
Prob. Chi-Square (12)	0.1268	0.8776	0.8382	0.9989	1.0000

Note: H_0: No Breaks at specified breakpoints; H_1: There is Breaks at specified breakpoints
Source: Authors’ own estimate

In case of BSE Sensex, since the p-value corresponding to F-statistic (0.1270 in 1992; 0.8775 in 2008; 0.8381 in 2009, 0.9989 in 2020; and 1.0000 in 2021) is not less than the significance level (e.g., 0.05), therefore, we failed to reject the null hypothesis and conclude that there is no indication of a structural break in 1992, 2008, 2009, 2020 and 2021 respectively.

Table 6(b): Chow Break Point of NSE Nifty. Breakpoint :1996, 2008, 2009, 2020 and 2021

Parameters	1992	2008	2009	2020	2021
F-statistic	1.579	1.518	1.529	1.528	1.527
Log likelihood ratio	18.99	18.26	18.39	18.38	18.36
Wald Statistic	18.96	18.22	18.36	18.34	18.32
Prob. F (12,8190)	0.0899	0.1095	0.1055	0.1061	0.1065
Prob. Chi-Square (12)	0.0886	0.1081	0.1041	0.1047	0.1051
Prob. Chi-Square (12)	0.0896	0.1092	0.1052	0.1058	0.1062

Note: H_0: No Breaks at specified breakpoints; H_1: There is Breaks at specified breakpoints.
Source: Authors' own estimate

Also, in case of NSE, since the p-value corresponding to F-statistic (0.0899 in 1996; 0.1095 in 2008; 0.1055 in 2009, 0.1061 in 2020; and 0.1061 in 2021) is not less than the significance level (e.g., 0.05), therefore, we failed to reject the null hypothesis and conclude that there is no evidence of a structural break in 1996, 2008, 2009, 2020 and 2021 respectively.

Therefore, apparently from Chow Breakpoint test, for both BSE and NSE, the tests did not detect any statistically significant structural breaks at the specified years (1992, 1996, 2008, 2009, 2020, and 2021). The results imply that the market structure remained relatively stable during these periods, despite potential events like the global financial crisis (2008) and the COVID-19 pandemic (2020).

Structural breaks are points in time at which the statistical patterns of a time series change (Andrews, 1993; Bai & Perron, 2003). Without recognition of such break points, the similar dynamic rule would be useful to the whole period of observation, which results in biases in the assessment of the system dynamics. On the contrary, fake recognition of structural breaks may divide the time period into unreasonably small subintervals, which affects statistical significance, initiates redundant parameters, and may lead to over fitting.

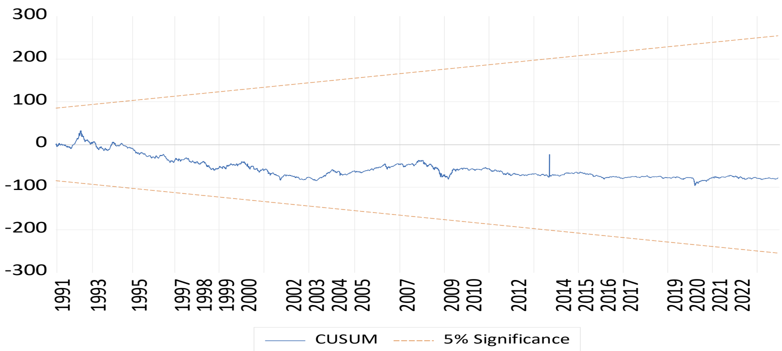
A seasonal irregularity is fundamentally a momentary, unanticipated divergence from a time series' normal seasonal pattern and normally a single, isolated event, while a structural break is a more enduring alteration in the fundamental patterns, such as a change in the average seasonal element itself or the timing of seasonal peaks which represents a continued variation of the seasonal behaviour over time. Seasonal anomalies sometimes may unveil structural break if prototype of anomalies is relentless in a specific season signalling a larger fundamental structural change in the seasonal pattern. Sometimes, on the contrary, structural break initiated by economic catastrophes, natural calamities like outbreak of recent pandemic, 2019 might be a reason of anomalies leading to divergence in expected time series pattern.

But, in our study, except 'December effect' in NSE, no other anomalies in both BSE and NSE are noticeably found. On the other hand, break points periods chosen in 1992, 2008, 2009, 2020 and 2021 taking into account several economic, financial and natural catastrophes have failed to identify statistically significant and noticeable break. Consequently, it has been quite visible from result that no noticeable change is found in seasonal effects(anomalies) during the assumed breakpoint periods (as no breaks exist) which could be influenced by structural breaks.

Cumulative sum (CUSUM) of recursive residuals and the CUSUM of square (CUSUMSQ) tests generally has been used to gauge the parameter stability (Pesaran & Pesaran, 1997). The CUSUM test makes out orderly changes in the regression coefficients and looks for continuing changes, whereas the CUSUMSQ test identifies abrupt changes from the steadiness of the regression coefficients as the CUSUMSQ test is more responsive to abrupt jumps or deviations.

The CUSUM test plot for BSE (Figure 3) shows the cumulative sum of residuals over time. If the CUSUM line stays within the critical boundaries (typically a 5% significance level), it indicates that the model's coefficients are stable and there are no significant structural breaks in the market over the period studied. If the CUSUM line crosses the boundary at any point, it suggests instability and the presence of a structural break in the mean level of the time series. Based on the results provided, in case of BSE, the CUSUM line appears to stay within the critical bounds, suggesting that the BSE did not experience any structural breaks or major shifts in the underlying model during the period under study. The parameters of the regression model remained stable.

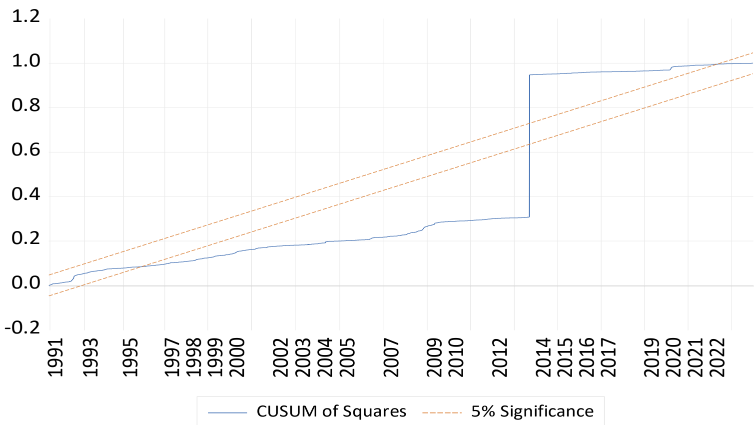
Figure 3: The Plot of the cumulative sum of recursive residuals (CUSUM)-BSE



Source: Authors' estimate from tabulated data

The CUSUMSQ test plots the cumulative sum of squared residuals, used to detect gradual or sudden changes in variance. If the CUSUMSQ line stays within the bounds, it means there were no significant changes in the variance of the residuals, indicating stability in volatility over time (see Figure 4). If the line crosses the critical bounds, it indicates a potential structural change in the variance or volatility. The CUSUM test is more powerful for detecting changes in the intercept (mean level), while the CUSUM of squares test is more powerful for detecting changes in the slope (variance/volatility).

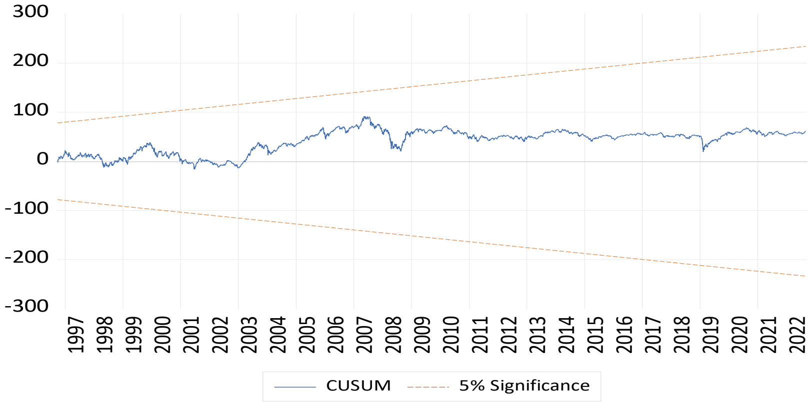
Figure 4: The Plot of the cumulative sum of squares of recursive residuals [CUSUMSQ]-BSE



Source: Authors' estimate from tabulated data

For BSE, the CUSUMSQ line excepting 1991 to 1996 and 2022 onwards, also remains outside the critical bounds, suggesting that there was significant change in market volatility over time excepting a few intermediate years. The variance of the residuals did not stay relatively constant, meaning that the market conditions were volatile.

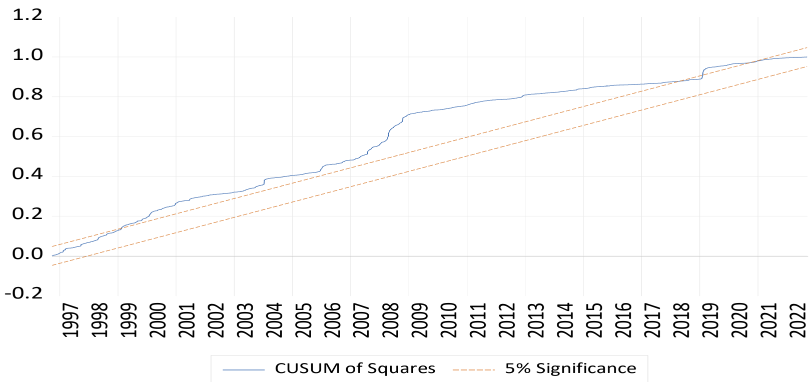
Figure 5: The plot of the cumulative sum of recursive residuals [CUSUM]-NSE



Source: Authors' estimate from tabulated data

Similarly, for NSE, the CUSUM line remains within the critical bounds, indicating that the NSE also experienced no significant structural breaks during the time period analysed. The coefficients remained stable over time, just like in the BSE case.

Figure 6: The plot of the cumulative sum of squares of recursive residuals [CUSUMSQ]-NSE



Source: Authors' estimate from tabulated data

Likewise, the CUSUMSQ line, for NSE, excepting 1996 to 1999 and 2021 onwards, stays also outside the bounds, showing that there was significant change in volatility over time excepting a few intermediate years. This suggests that the variance in market returns experienced sudden shifts or gradual changes in terms of volatility. So, it can be inferred that the CUSUM tests for BSE and NSE indicate stability in the regression models used. The fact that the lines remain within the critical bounds suggests that there are no structural breaks in either market. It indicates that the regression model's parameters (like the relationship between stock prices and other factors) have remained relatively consistent over the period analysed.

The CUSUMSQ test often indicates volatility, as it's designed to detect sudden changes in regression coefficients, which can reflect market instability. The CUSUMSQ test fails to accept the null hypothesis of no sudden shift in the regime for both markets. This implies that there is strong evidence that parameters are not stable for the Indian stock market's stock return volatility. So, CUSUMSQ test suggests instable volatility across the period analysed excepting a few years indicating that there have been significant shifts or deviations in the regression model's parameters, which can be a sign of market instability or volatility. This supports the conclusion that, for both BSE and NSE, the models used were stable over time in terms of mean, and there were major shifts in market behaviour or volatility during the major part of the period excepting a few years under investigation. This difference in sensitivity explains why the CUSUM test might suggest stability while the CUSUMSQ test indicates volatility, as the latter is more prone to flag instability caused by sudden events.

The above result of Chow breakpoint test indicates that the return of stock has not been affected by the occurrence of certain events. In 1991, the Indian stock market was booming, with prices soaring to unrealistic levels due to a bubble created by exploiting banking loopholes to channel money into the market. However, when the Harshad Mehta scam was exposed, the market lost almost 40% of its value as both domestic and foreign investors quickly pulled out their money. This caused a significant loss of confidence in stock market and financial system.

The crash led to increased market volatility and a sharp drop-in trading activity which was reflected in CUSUMSQ test (Figure 4). Foreign investors, who had started entering India after economic liberalization, began withdrawing their investments due to concerns about instability. While liberalization brought foreign investment, it was relatively small compared to the flows into China and other Asian economies. After another major market drop in late 1996, foreign portfolio investment (FPI) into India plummeted in 1997-98. Foreign direct investment (FDI) from Southeast Asia also fell but accounted for only 6.5% of total FDI into India, so the overall impact was limited.

Portfolio investment was a key source of external financing for India, but stock market volatility remained a serious issue. Between December 1997 and June 1998, India's stock market performed worse than several other emerging markets. The country was stuck in a challenging cycle, FPIs wouldn't return unless the stock market recovered, but the market recovery itself depended on FPI inflows. In 1996, the Indian government introduced reforms to encourage foreign investments through takeovers, but many felt these efforts weren't bold enough to create the market-driven mergers and acquisitions that foreign investor desired.

Also, in the year 2008-2009 the subprime crises impact was so strong on the Indian Market that it lost 50% of its value from highs leading to volatility surge in the period. Even though the main hub of the crises was in the West, both developed and developing nations have been impacted, and India is no different. The crises reached India primarily through financial and trade channels. With India being more connected to global financial markets, especially international capital markets, the effects were quickly felt. This led to heightened market volatility, reduced trading activity, and a decline in investor confidence, reflected in CUSUMSQ-BSE & NSE, Figure 4 and Figure 6. As a result, India's capital market took a hit, with domestic and foreign investors pulling out in large numbers.

The COVID crisis in 2020-2021 led to a 6.64% rise in India's market volatility index. During this time, there was a noticeable shift, with the skewness of index returns turning negative or becoming more negative for certain indices. The period also saw fluctuations in kurtosis, both increasing and decreasing for different indices. Negative skewness and higher kurtosis suggest a higher risk in the future. Interestingly, the Indian stock market had a similar standard deviation to developed economies like the US, Japan, and the UK, but it showed greater negative skewness and higher positive kurtosis, making it appear more volatile. So, market remains volatile up to 2020-21 and 2022 onwards, it became more or less stable.

Conclusion

The essay tries to examine the stock market anomalies and return volatility of two Indian stock markets, i.e., BSE Sensex from January, 1990 to December, 2023 and monthly observations of NSE during January, 1996 to December, 2023 based on dummy variable regression technique. No significant effect is found in case of BSE while using dummy variable regression analysis but December effect is present in case of NSE using same econometric technique. The Chow break point test along with CUSUM test result suggests that both BSE and NSE did not experience any structural breaks or major shifts in the underlying model in terms of mean equation during the period under study. But, CUSUMSQ line excepting a few years within study period remains outside the critical bounds, suggesting that there was significant change in market volatility over time covering our chosen catastrophe periods excepting a few intermediate years. Thus, the several crises period taken into study governs to be most significant grounds for a continuing swing in the level of stock indices in India, whether it may be security scam in 1992, global meltdown in 2008, political regime change in 2009 and not the least the pandemic outbreak in 2020-21.

Despite quite a lot of studies conducted about the calendar anomalies specifying 'month-of-the-year effect' by various researchers, the present study was conducted to analyse the stock market anomalies on two Indian stock markets, namely BSE and NSE for the period January, 1990 to December, 2023 keeping eyes on several political regime changes(UPA-1 & II; from UPA-II to NDA-I; NDA-I, II and III), several stock market catastrophes (initiating changes in macroeconomic yardsticks) like Harshad Mehta scam in 1992, Asian Financial Crisis in 1997, Global Meltdown in 2008 and more recent Covid 19 induced Pandemic catastrophes which had shaken the investors 'confidence profoundly influencing the Indian stock markets. Whereas we had not tried to comprehend the effect of such political transformation, but we wanted to see whether there is any break point or abnormality in returns or having any month-of-year effect during this critical period.

Structural breaks endow with insights into swings in market dynamics, assisting researchers and market participants comprehend changes in associations among variables over time. By evaluating these breaks, the researchers and interested people can learn more about the elementary foundations of stock market behaviour and identify the main forces that move the market. We have observed several limitations of the study which lies in the recognition and improvement of optimal methods for distinguishing break points in stock prices precisely. While there are several ways, including the Bayesian analysis, and change-point detection algorithms, test to detect break points in stock market anomalies, supplementary study can deliberate on improving existing strategies to boost their accuracy and efficacy.

The prospective researchers might also broaden their further analysis on structural break during catastrophic time in the context of Indian economy and related other economies by employing country specific data and also by extending their data base till 2024-25 which is noticeably deficient in this analysis.

Credit Authorship Contribution Statement

Both authors contributed significantly to the research, reviewed the final manuscript, and approved it for submission. The corresponding author affirms that the contribution descriptions are accurate and agreed upon by both authors. Firdous, A: data collection; econometric and statistical computation; visualization. Firdous, A. was responsible for statistical data collection, computation, and preparation of graphs and visual representations. Ray, S.: writing, original draft; writing, review & editing;

literature review. Ray, S. was responsible for conducting the review of literature and preparing the main written content of the manuscript and completion of final revisions as per hon'ble referees' recommendation and formal communication to the journal's editor.

Acknowledgments

The authors are thankful to anonymous referees for valuable comments and helpful suggestions in the earlier draft of the article. After careful revisions, if any error is found in the article, the responsibility solely lies on authors themselves.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

Data available on request: The data presented in this study are available on request from the corresponding author.

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How to cite this article:

Firdous, A., & Sarbapriya, R. (2025). Structural Breaks and Market Anomalies in Indian Stock Markets during Catastrophic Periods. *Applied Journal of Economics, Law and Governance*, Volume I, Issue 2(2), 115-138. https://doi.org/10.57017/ajelg.v1.i2(2).01

Article's history:

Received 27th of August, 2025; Revised 24th of September, 2025;
Accepted for publication 30th of September, 2025; Available online: 7th of October, 2025
Published as article in Volume I, Issue 2(2), 2025