Original Research Article

Calendar Anomalies and Volatility in the Indian Equity Market: Insight from 2008 Financial Crisis and COVID-19 Pandemic".

Abstract

This study explores the presence of calendar anomalies in the Indian equity market during two economic shocks: the 2008 Global Financial Crisis and the COVID-19 pandemic. This study employed Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Threshold GARCH models to analyze the impact of economic downturns on volatility in a sample of Indian Stock Indices. This research identifies notable patterns, including the Wednesday effect during the financial crisis and the Monday and Tuesday effects during the global pandemic. By addressing a crucial gap in the literature, this study offers a comparative analysis of these crises and elucidates market volatility and investor behaviour in emerging markets. This study illuminates the critical role of investor confidence in mitigating financial instability and emphasizes the necessity for efficacious policy interventions to address economic disruptions, enhance financial resilience, and avert future crises, particularly during endogenous economic downturns such as financial recessions. This study elucidates the multifaceted effects of crises on financial markets and the broader economy, revealing intricate mechanisms that influence market dynamics during periods of economic turbulence.

Keywords: Calendar Anomaly; Financial Crisis; COVID-19 Pandemic; EGARCH Model; BSE Sensex.

1. Introduction

Over the last 20 years, the global stock market has experienced two significant disturbances: the global crisis of 2008, which was triggered by subprime mortgage loans, and the COVID-19 pandemic in 2020. Both crises were characterized by significant declines in stock markets, resulting in severe losses. Research findings indicate that during times of crisis, there is a significant decline in stock market returns, characterized by severe downturns (Lien et al., 2018; Pesaran, 2015). The increasing interconnectedness of global financial markets has become crucial for investors and policymakers, as the evolving relationships between markets influence portfolio management decisions and the potential for financial contagion. Consequently, researchers have extensively examined the dynamics of these cross-market connections. Financial crises, such as the 2008 global financial crisis (GFC), the European sovereign debt crisis, and the recent COVID-19 pandemic, have underscored the significance of economic and financial linkages. Notably, various studies indicate that these crises intensify interdependence among financial markets, further emphasizing the importance of comprehending these relationships.(Choi, 2021; Contessi & De Pace, 2021; Kinateder et al., 2021; Mazur et al., 2021).

The Efficient Markets Hypothesis (EMH) has been fundamental in empirical finance since the 1960s (Fama, 1970; Miller & Modigliani, 1961). In a perfect capital market, no single entity can influence prices due to its size, and efficient arbitrage corrects price deviations from the fundamental values caused by noise trading. (Keim et al., 1989) found that standardizing payments at the start of each month significantly increased U.S. stock returns from 1969 to 1986. (Balaban, 1995; Keim et al., 1989) observed a day-of-the-week effect in the U.S. and emerging Asian markets, while (Aggarwal & Schatzberg, 1997) found negative returns on Mondays in nine countries and positive returns on Fridays in 17 countries. (economics & 1983, 1983; Jaffe & Westerfield, 1989) documented seasonal effects in several countries, raising questions regarding market efficiency in both developed and emerging markets. Despite attempts to explain these anomalies through the modified Capital-Asset-Pricing Models (CAPM), inconsistencies persist, highlighting the need to determine the economic and statistical reasons behind these excess returns. In India, EMH research (Fama, 1970) has focused on specific aspects such as hypothesis testing and data frequency, but not comprehensively, necessitating a large dataset analysis to evaluate the efficiency of Indian Stock Markets. However, this remains a critical area for further research.

Calendar anomalies in stock market returns are also called cyclical anomalies, as the cycle is based on the calendar. The most popular calendar anomalies observed (Keim, 1983; Schwert & William, 2003) are the day-of-the-week and turn-of-the-year effects. Some of the wide test anomalies include the day of the week effect (Adaramola & Adekanmbi, 2020; Aggarwal & Jha, 2023; Jaisinghani, 2016). The turn of the month effect (Sharma & Narayan, 2014; Vasileiou, 2018) , the January effect (Acharya et al., 2022; Elangovan et al., 2022; Harshita et al., 2019) , and the holiday effect (Njoroge & Matanda, 2023; Tadepalli et al., 2021; Tendulkar et al., 2023) .The presence of such market anomalies in any capital market is contrary to the efficient market hypothesis, as these market anomalies may allow participants to make abnormal profits by early prediction of patterns of market anomalies. Specifically, these studies have focused on the Global Financial Crisis (GFC) and the ongoing COVID-19 pandemic (Choi, 2021; Paramati et al., 2016) The objective of this study is to analyze the effects of financial crisis events, specifically the 2008 US financial crisis and the COVID-19 pandemic, on the level of stock market volatility observed in the Indian stock market index. This study insists on this by employing GARCH family models. Limited information specifically addresses calendar anomalies in the Indian equity market during the 2008 financial crisis and the COVID-19 pandemic. However, insights can be drawn about market behaviour during these crises: The Indian stock market experienced significant volatility and negative returns during the COVID-19 pandemic (Harjoto & Rossi, 2023), with major indices falling by approximately 40% (Thomson et al., 2022; Varma et al., 2021). An event study methodology revealed heterogeneous impacts across sectors; the financial sector was severely affected, while the pharma, consumer goods, and IT sectors saw positive or limited.(Bahrini & Filfilan, 2020; Gunay, 2021; Hassan et al., 2022) . (Setiawan et al., 2021) compared the COVID-19 pandemic to the 2008 global financial crisis, finding a more significant negative impact on stock market returns and higher volatility during the pandemic (Chakrabarti et al., 2021; Shaikh, 2021) . This increased volatility was due to lockdowns and restricted economic activities affecting supply and demand (Lu et al., 2023) . Although calendar anomalies are not specifically addressed, the severe impact of the COVID-19 pandemic on the Indian equity market, with sector-specific variations, suggests that traditional calendar anomalies may have been overshadowed by the unprecedented nature of the health crisis and its economic consequences. The primary aim of this study is to analyze the impact of financial crisis events on the level of stock market volatility in the Indian stock market, with an emphasis on the BSE Sensex Index. This study examines the impact of two crises, the COVID-19 pandemic and the financial crisis, on the BSE Sensex Indices.

The research paper is presented as: Section 2 briefing on Literature review; Section 3 presents sample data and methodology applied; Section 4 discuss empirical results from the methodology usage. Section 5 presents discussion and findings. Section 6 presents practical implications and finally conclusion is presented in Section 7.

2. Literature review

Global financial crisis and stock market returns

The global financial crisis of 2008 (GFC), which originated in the US subprime sector, is another significant global economic downturn with widespread implications. Numerous scholarly investigations have focused on the repercussions of the Global Financial Crisis (GFC) on the stock market, given its start in the financial industry. In light of the significant economic repercussions of the recent COVID-19 pandemic, numerous scholars have undertaken comparative analyses to examine the effects of other financial crises on the financial market.
Additionally ,(Aloui et al., 2011) reveals the extent of the global crisis by examining the profound financial interdependence between the United States and certain emerging markets (BRIC). This study examines the presence of a high amount of interdependence between the paired markets under consideration during both upward and downward market movements.(Bekiros, 2014) Through use of the multivariate GARCH model indicates that BRIC countries have established global interconnections subsequent to the financial crisis in the United States, and the presence of nonlinear causation can be established by observing the impact of volatility effects. (Zhang et al., 2013) highlight that the financial crisis resulted in an increased conditional correlation series between the stock markets of BRICS countries and developed economies. Therefore, this study presents compelling evidence that the financial crisis has diminished the benefits of diversification in the long term. (Burdekin & Siklos, 2012) attest to the impact of crises on the persistence of equity returns in the Asia-Pacific region and provide empirical evidence of the occurrence of contagion effects. Moreover, this study examines the long-term relationship between the US market and alleged markets.

COVID-19 Pandemic and stock market return

The confirmed global incidence of COVID-19 has increased substantially during the epidemic, resulting in temporary economic shutdowns in certain nations and a prolonged market decline. Research indicates that financial crises, such as the 2008 global financial crisis, the European sovereign debt crisis, and the recent COVID-19 pandemic, enhance financial market interconnectedness (Chang et al., 2021; Salisu & Akanni, 2020). The Global Fear Index (GFI) serves as a reliable predictor for forecasting stock returns during the epidemic, and incorporating the "asymmetry" effect and macroeconomic factors enhances the accuracy of the GFI-based model. (Topcu & Gulal, 2020) demonstrate that the pandemic has a severe impact on emerging markets, particularly in Asia, with state-level stimulus packages effectively mitigating these effects. (Akhtaruzzaman et al., 2021) explores financial contagion between China and G7 countries during the COVID-19 pandemic, noting significant increases in conditional correlations among stock returns, especially in the financial sector. (Ashraf, 2021) finds that a 1% rise in confirmed COVID-19 cases consistently decreases stock market returns across 43 countries, particularly in economies with high uncertainty aversion. (Liu et al., 2020) investigates the global impact of COVID-19 on financial markets from multiple perspectives.).The economic instability experienced during the early stages of the COVID-19 pandemic was not as intense as the disruption observed during the Global Financial Crisis.(Gunay, 2021). (Guru & Das, 2021) report a 69% rise in overall volatility spillovers during the pandemic, with the energy sector, especially oil and gas, being significant in transmitting volatility. (Sahoo, 2021) examines the day-of-the-week effect on Nifty indexes, noting a positive trend in Monday returns before COVID-19 and a negative trend afterward. Extensive research addresses the global financial crisis's effects on stock markets, while other studies focus on COVID-19's impact, considering case and death counts, industry classification, stimulus packages, and government restrictions.

The Interconnection and Crisis

Numerous scholars have examined the interconnected nature of financial markets during economic crises, categorized by the specific crisis studied. The first category examines the 1997 Asian currency crisis, focusing on interrelationships among international FX markets (Akhtaruzzaman et al., 2021; Bouri et al., 2020; Meng & Huang, 2019) and between FX and stock markets (Fang & Miller, 2002) .The second category addresses the Global Financial

Crisis (GFC), analyzing dynamic relationships across nations and various financial asset markets. Studies primarily focus on inter-country stock market dynamics (Chang et al., 2021; Hiang Liow, 2014; Lien et al., 2018; Mensi et al., 2016) and relationships between different financial assets, such as stocks, bonds, oil, and gold (Maghyereh et al., 2016; Roy & Roy, 2017; Trabelsi, 2019) . These studies reveal that relationships between countries and financial assets evolve, with increased interconnectedness observed during the GFC. This study investigates the impact of financial events, specifically the global Financial Crisis and the Covid-19 pandemic, on stock returns in India. The analysis is predicated on extant research in the global literature, as well as from the Indian perspective. Furthermore, this research contributes significantly to the existing body of knowledge by examining the effects of two financial shocks on stock returns within the Indian context.

3. Data and methodology

This study employs time-series data of the BSE Sensex index value from the Bombay Stock Exchange, specifically focusing on two distinct financial events: The Global Financial Crisis and the Global Pandemic. The analysis was divided into two parts based on the subject matter content. The first part relates to the financial crisis and stock market volatility in the BSE Sensex. By contrast, the second part is related to COVID-19 and stock market volatility in the six BSE Sensex indices. This study examines the daily Sensex values between August 10, 2007, and December 31, 2009, encompassing 587 observations to investigate the Global Financial Crisis. Additionally, the analysis includes the period from January 1, 2020, to June 30, 2021, with 373 closing values to explore the impact of the Global Pandemic. All the data were collected from the capital database.

Methodology

To investigate the impact of the day of the week on stock market returns in India, we derive the return series by employing closing prices as indicated in the equation, as follows:

$$R_t = log\left(\frac{P_t}{P_{t-1}}\right) \times 100 \quad (1)$$

The stock return at time t is R_t, the natural logarithm is log, and the stock closing prices at time t and t-1 are Pt and Pt-1, respectively. In order to test seasonality in stock pattern, it's very imperative to examine the stationary properties in the return series (*Brooks, C. (2014)* .

Initially, the stock price series are checked for stationary. Here the return series is said to be stationary, if they exhibit the properties of constant mean, also variance and covariance are both constant. The order of difference from the original series can be used to convert a non-stationary return series into a stationary return series (Engle, 1982b). Consequently, only a stationary return series is being used for estimation.

Several approaches and estimation methods have been employed in the scholarly literature to investigate the day of the week's impact. The traditional approach employed in early studies involved using the ordinary least squares (OLS) regression model, incorporating proper dummy variables for each day of the week.(Aggarwal & Jha, 2023; Raj & Kumari, 2006).

Day of the week effect Model

To measure the effects of the day of week, we employed the method applied by (Kunkel et al., 2003), whereas Y_t is the underlying seasonality in the return series we employed five dummies starting from day 1 Monday to day 5 as Friday, The Dummy variable will be taken the value of 1 for Monday trading days and value of 0 for all other days except Monday for study of Monday effect and $\mathcal{E}_t$ is consider as error term. The regression analysis is performed without an intercept term to avoid the dummy variable trap. The regression equation is as given below:

$$Y_t = \beta_1 \text{ Monday} + \beta_2 \text{ Tuesday} + \beta_3 \text{ Wednesday} + \beta_4 \text{Thursday} + \beta_5 \text{ Friday} + \mathcal{E}_t \qquad [1]$$

Model framework;

This study employed the ordinary least squares method to examine the day-of-the-week effect in a regression model. Owing to the time-varying nature of stock returns, ARCH, GARCH, and EGARCH models address this issue. Market returns are calculated from relevant indices, and volatility is measured using the GARCH model. This study evaluates conditional volatility considering the day-of-the-week effect by employing models such as GARCH, EGARCH, TGARCH, and PGARCH. The equations incorporate first-order autoregressive conditional heteroscedasticity (ARCH) and GARCH terms. The GARCH (1,1) model, a key framework developed by (Bollerslev, 1986) as an extension of (Engle, 1982a) ARCH model, serves as a pivotal tool for analyzing conditional variance over time, positing that past variances influence the current variance. GARCH models capture volatility clustering in financial time series;(Karmakar & Chakraborty, 2003). However, they possess the limitation of inherent symmetry, disregarding the sign of the error term by squaring it. To address both the positive and negative shocks in financial markets, (Ding et al., 1993; Glosten et al., 1993; Nelson, 1991) proposed modifications including TGARCH, EGARCH, and PGARCH. We present the mean and variance equations of the GARCH model.

In ARCH model, where as $\sigma_t^2$the conditional variance for the error value u_{t-1}^2, equation is as follows below:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \quad [2]$$

The Generalized ARCH (Generalized autoregressive conditional) model is more parsimonious and addresses the ARCH model's constraints. For the GARCH model, the conditional variance equation is mentioned below:

GARCH model

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \ + \beta h_{t-1}^2 \quad [3]$$

Equation (2) represents the variance, α represents ARCH coefficient and β denotes the GARCH coefficient.

EGARCH model

$$h_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{j=1}^{q} \gamma_j \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \beta_i \log(h_{t-i}) \quad [4]$$

By logarithmically representing the conditional variance of the return, the leverage effect is achieved in an exponential form compared to the quadratic method. Therefore, the conditional variance is greater than zero. The leverage parameter, denoted γ_j is equal to zero if $\gamma_1 = \gamma_2 = \gamma_3 = 0$. Thus, the model is asymmetric. When γ_j is less than zero, it can be stated that positive news causes less volatility than negative news.

T GARCH model

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \gamma_i u_{t-1}^2 d_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j} \quad [5]$$

Equation showing TGARCH employs a dummy variable "dt" that is assigned the value 1 if u_t is less than 0 , and 0 otherwise. Therefore, the $\gamma_j$coefficient in the TGARCH model represents the effect of positive news, whereas the effect of negative news can be determined by combining the coefficients of the residual term and the coefficient of the multiplicative dummy variable. A value greater than zero for coefficient γ_j signifies that negative news is the primary factor contributing to the rise in volatility.

PGARCH model

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \alpha_{i-1} \left(|u_{i-1}| - \gamma_i u_{t-j} \right) + \sum_{j=1}^{p} \beta_j \, {\sigma^{\delta}}_{t-j} \qquad [6]$$

where $\delta > 0, |\gamma| \leq 1$ for $i = 1,2,3, \ldots\ldots r$, $j = 0$ for all $i > r$ and $r \leq p$. Each value of i is set as 0 within this symmetric model, the PGARCH model is equivalent to a standard GARCH specification, if $\delta = 2$ and $i = 0$ .As the value of $\gamma_j < 1$, the asymmetric effect became apparent. δ is held constant at one in the present study. To calculate the standard deviation or volatility,

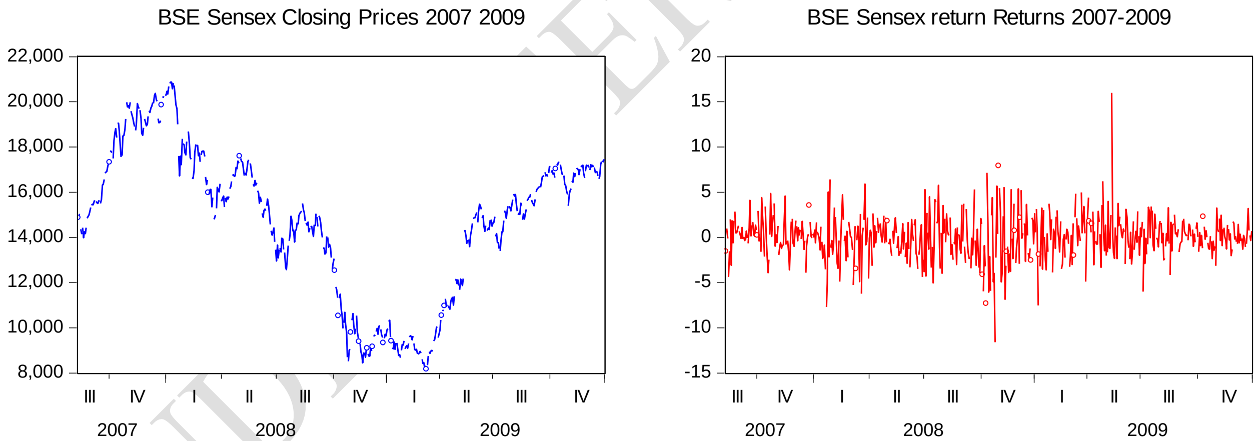

Figure 1 : BSE Sensex closing price and returns series for Financial Crisis 2008 period 2007-2009

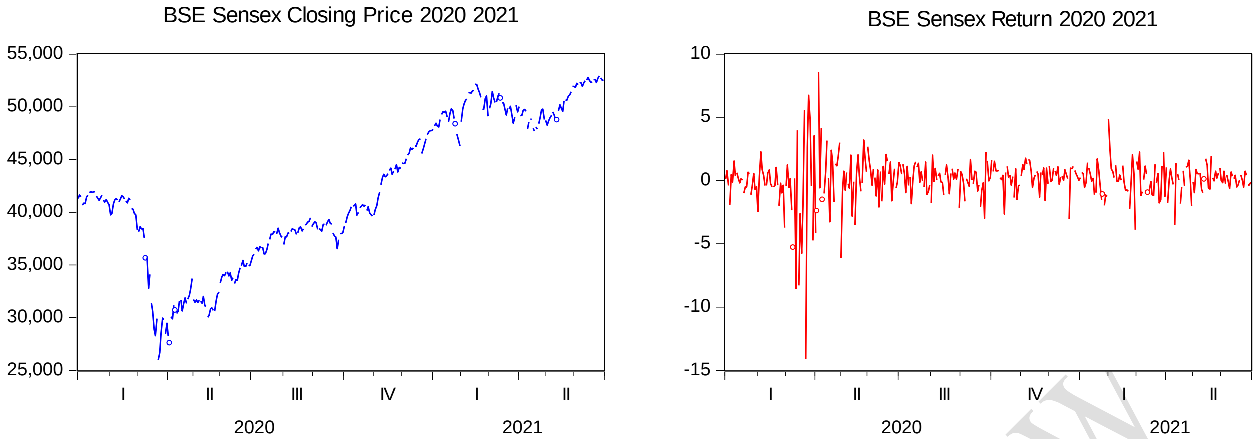

Figure 2 BSE Sensex closing price and returns series for COVID-19 Global Pandemic period 2020-2021

Figure 1and Figure 2 indicates the graphical illustration of the daily closing prices and return series over time, the graph demonstrates the daily closing price series are not stationary, while the return series indicated by the presence of volatility clustering. This indicates that, closing prices series are integrated at order 1 where the returns series is of order 0 integrated. In furthermore, the test study is conducted out on the return series.

Table 1 showing the unit root test and stationary test

	Financial Crisis 2008		COVID-19 Global Pandemic		
Test	Statistical value	P value	Statistical value	P value	remark
For Closing prices					
KPSS test	2.437	0.463	1.790	0.463	H_o rejected
PP test	0.565	0.988	-0.339	0.916	H_o not rejected
ADF test	0.549	0.988	-0.226	0.932	H_o not rejected
For Returns series					
KPSS test	0.2430	0.463	0.219	0.463	Ho not rejected
PP test	-22.152	0.000	-21.262	0.000	H_o rejected
ADF test	-22.232	0.000	-6.023	0.000	H_o rejected
Notes: KPSS Test H_0: the series is stationary in nature, ADF Test results H_o: the series has a unit root value; PP test value H_o: the series has a unit root;					

Table 2 shows the descriptive statistics

	Financial Crisis 2008	COVID-19 Global Pandemic

	BSE Sensex	Mon	Tues	Wed	Thu	Fri	BSE Sensex	Mon	Tues	Wed	Thu	Fri
Mean	0.028	0.014	-0.006	0.142	-0.235	0.136	0.064	-0.568	0.594	0.177	0.048	0.103
SD	2.447	3.087	2.148	2.314	1.948	2.667	1.806	2.562	1.470	1.572	1.688	1.436
Skew	0.232	1.024	0.028	-0.170	0.157	-0.685	-1.648	-2.587	1.971	0.093	-1.453	0.477
Kurt	7.005	8.354	4.010	3.848	3.525	6.005	17.148	13.354	14.142	8.691	11.669	6.286
J-B	397.04	156.05	4.865	3.969	1.778	51.82	3262.77	401.92	419.06	97.25	250.77	35.13
Prob	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	585	114	114	114	114	114	371	72	72	72	72	72

***Note**: The* Table 2 *shows the descriptive statistics of daily returns for all week days.SD denoted the standard deviation. Skew indicates skewness and Kurt indicate Kurtosis. J-B is the Jarque -Bera test statistics for normality and N denotes total number of observations*

Table 3 Showing Day of the week effect (GARCH) and (EGARCH) model analysis

	Financial Crisis 2008				COVID-19 Global Pandemic			
	GARCH (1,1)		EGARCH (1,1)		GARCH (1,1)		EGARCH (1,1)	
Particulars	Co-efficient	Prob.	Co-efficient	Prob.	Co-efficient	Prob.	Co-efficient	Prob.
Mean eqn.								
Mon	0.0198	0.8977	-0.0330	0.8315	-0.1681	0.1124	-0.3263	0.0009
Tue	0.0390	0.8468	0.0172	0.9327	0.4772	0.0046	0.4117	0.0073
Wed	0.4266	0.0187	0.3555	0.0348	0.0306	0.8367	0.0045	0.9756
Thur	-0.1300	0.5504	-0.1388	0.5172	0.1278	0.3300	0.1368	0.2804
Fri	0.2200	0.2415	0.2153	0.2876	0.1139	0.3840	0.0216	0.8762
Variance equation								
C	0.1457	0.0227	-0.1131	0.0004	0.0804	0.0146	-0.0967	0.0377
ARCH	0.1314	0.0000	0.2299	0.0000	0.1698	0.0000	0.1453	0.0109
GARCH	0.8529	0.0000	-0.0918	0.0003	0.8010	0.0000	-0.1657	0.0000
EGARCH			0.9592	0.0000	-624.10		0.9708	0.0000
Log lik.	-1302.31		-1292.8	4.4506	2.1914		-611.575	3.3454
D-W stat.	1.8188	0.5599	1.8195	4.5179	1.5497	0.2140	2.1949	3.4404
ARCH LM test	0.3402		0.7144	0.3983	3.4920		1.6910	0.1943
AIC	4.4797		4.4506		3.4411		3.3454	
SC	4.5395		4.5179				3.4404	

Source: Compiled from EViews 10

Table 4 Showing Day of the week effect (TGARCH) and (PGARCH) model analysis

	Financial Crisis 2008				COVID-19 Global Pandemic			
	TGARCH (1,1)		*PGARCH (1,1)*		*TGARCH (1,1)*		*PGARCH (1,1)*	
Particulars	Co-efficient	Prob.	Co-efficient	Prob.	Co-efficient	Prob.	Co-efficient	Prob.
Mean eqn.								
Mon	-0.0435	0.7822	-0.0622	0.6949	-0.2806	0.0049	-0.2758	0.0065
Tue	0.0136	0.9478	0.0518	0.7690	0.4144	0.0067	0.4206	0.0049
Wed	0.3661	0.0431	0.3707	0.0217	0.0714	0.6196	-0.0191	0.8945
Thur	-0.1593	0.4686	-0.1595	0.4264	0.0630	0.6504	0.0930	0.4605
Fri	0.206	0.3042	0.2078	0.2718	0.0580	0.6651	0.0305	0.8258
Variance equation								
C	0.1480	0.0263	0.0702	0.0043	0.0659	0.000	0.0474	0.0000
ARCH	0.0681	0.0024	0.1261	0.0000	-0.0325	0.120	0.0948	0.0087
GARCH	0.1094	0.0029	0.4859	0.0021	0.2282	0.000	0.9987	0.0084
EGARCH	0.8595	0.0000	0.8632	0.0000	0.8759	0.000	0.8952	0.0000
			0.6438	0.0074			0.9697	0.0001
Log likelihood	-1298.9		-1290.4		-612.29		-610.18	
D-W stat.	1.8196		1.8186		2.1927		2.1942	
ARCH LM test	0.5189	0.4716	1.0249	0.3118	1.4057	0.2365	1.9457	0.1639
AIC	4.4716		4.4460		3.3493		3.3433	
SC	4.5389		4.5208		3.4443		3.4488	
Source: Compiled from EViews 10								

4. Empirical results

The results of the study revealed that the day of the week impacts the return series of the BSE Sensex. Table 2, presented in this study, provides an overview of the descriptive statistics for the Sensex. The statistical measures included in the analysis include the mean, median, standard deviation, skewness, kurtosis, and Jarque-Bera test statistics, along with their respective probability values. The results demonstrate that both events yielded positive mean returns, with the Global Pandemic event exhibiting a more significant mean return and lower standard deviation. The presence of kurtosis indicates that the index data exhibits leptokurtic characteristics. Jarque-Bera statistics indicate that the assumption of normality for the index data series is rejected. Following the Global Financial crisis, Tuesday and Thursday exhibited negative mean returns of -0.006 and -0.235, respectively.

Conversely, Wednesdays demonstrate substantial positive mean returns. Mondays exhibited a higher standard deviation of 3.087. During the Global Pandemic, negative mean returns were observed only on Mondays (-0.568), whereas Tuesdays displayed more significant positive mean returns (0.594). Moreover, Monday exhibited a higher standard deviation (2.562) than other days. The financial crisis period demonstrates the highest positive mean returns on Wednesdays. The presence of kurtosis indicates that the dataset exhibited leptokurtic characteristics. Jarque-Bera statistics suggest that the assumption of normality for the index data series is rejected.

Table 1 presents the results of the unit root tests on the return series. The three widely applied tests, ADF, PP, and KPSS are consider for the results. For generating the stationary series, the closing prices series are converted into first difference by taking into the log price difference. The null hypothesis that the series has a unit root test, i.e., the series is non-stationary, is rejected by the ADF test (p value=0.000) and the PP test results (p value=0.000). Because the returns series are stationary, the KPSS test statistics value (P value 0.463) could not be rejected as the null hypothesis. Indicating that, return series are stationary in nature. It's confirmed from the tests that a unit root is absent.

The calculated mean and variance equations for the GARCH and EGARCH models are presented in Table 3. The occurrence of asymmetries in stock markets is apparent when the day-of-the-week effect is considered. Notably, the Wednesday impact has been observed during financial crises and in the context of global pandemics, with Monday and Tuesday exhibiting a notable level of significance. Observation of conditional volatility is also important.

Nevertheless, the significance of the GARCH coefficient indicates market volatility clustering. The estimated outcomes of the TGARCH and PGARCH models are shown in Table 4. Both analyses yielded statistically significant results at the 5% level, indicating an asymmetric evidence. There is a notable disparity in Wednesday returns during periods of economic contraction, while the return series for Monday and Tuesday exhibit substantial divergence during the Global Pandemic.

The PGARCH analysis demonstrated the existence of asymmetries, as the findings indicated comparable outcomes across occurrences. An examination of the variance equation reveals a leverage effect in both the return series. The coefficients of ARCH and GARCH, as well as the asymmetry coefficients, are statistically significant. Furthermore, the Durbin-Watson (DW) test, which approximates two in all cases, indicates no significant evidence of autocorrelation in estimating the day-of-the-week effect. Consistent with other estimations, the diagnostic tests revealed the absence of autocorrelation and the ARCH effect in the residuals. In both instances, the leverage parameter exhibits a statistically significant negative relationship. The presence of the negative leverage term suggests that the impact of negative news on volatility is more pronounced than that of positive news of a similar magnitude, while accounting for the influence of the day of the year. The results of the diagnostic tests indicate that the application of the autoregressive conditional heteroscedasticity (ARCH) LM test reveals the absence of the ARCH effect. This implies that the conditional variance equation of GARCH-type models is appropriately specified.

5. Discussion and the findings

This study investigates the influence of two significant events, the financial crisis of 2008 and the COVID-19 pandemic, on the returns of the BSE Sensex Index. It is noteworthy that reactions to the two events in Indian stock markets exhibit diverse patterns. This period encompasses the financial crisis of 2009 in 2007. This study reveals that the financial crisis had a discernible effect on the return series, particularly on Wednesdays. During the COVID-19 crisis, the Monday effect had a statistically significant negative impact, whereas the Tuesday effect demonstrated a statistically significant positive impact across all the GARCH models. The current investigation suggests that the ongoing pandemic has had a substantial influence on the selected stock markets. When examining the influence of the respective crises on individual stock markets, it is notable that each market responds differently.

6. Conclusion and policy suggestions

The primary objective of this study is to examine the presence of calendar anomalies, specifically focusing on the extensively researched day-of-the-week effect in Indian stock markets on two distinct occasions, as previous studies have yielded diverse findings. The observation of the Monday and Friday impacts in the extant literature warrants further investigation. The research conducted in this study determined that the returns of BSE Sensex indeed exhibit a day-of-the-week effect, particularly in the form of the Wednesday effect during the global financial crisis. Furthermore, during the Global Pandemic, the study identified Monday and Tuesday effects. This study employs an extended version of the

GARCH model to investigate the presence of asymmetry. The findings reveal a discernible disparity in the reactions observed in Indian stock markets towards two distinct events.

7 Practical Implications

This study provides valuable insights into investors' thinking abilities in relation to their risk perception. During the financial crisis, investors experienced fear due to market uncertainty, resulting in their inability to invest their capital. Conversely, in the context of the COVID-19 pandemic, investors exhibited an improved view of risk compared with the financial crisis. Conversely, during the pandemic period, the stock market presented more favorable investment opportunities for investors, particularly while investment prospects diminished in other nations. Moreover, the study suggests that it would be beneficial to conduct a similar investigation on emerging stock market indices and sectoral indices in many nations. This would enhance our comprehension of the effects of these two crises, which have unique characteristics. Therefore, the results indicate the presence of asymmetric information through the utilization of an expanded GARCH model, which can also be applied to investigate other economies. The discovery of a similar impact of the financial crisis prompted an investigation into the level of stock market integration across the economies of the G20 countries.

Data availability:

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Ethical approval:

This article does not contain any studies with human participants or animals performed by any of the authors.

Disclaimer (Artificial intelligence)

During the preparation of this work the authors declare No generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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