Original Research Article

Calendar anomaly in Indian equity market: a comparative analysis of financial crisis (2008) and COVID-19 pandemic

Abstract

The primary purpose of this study is to examine the existence of the calendar anomaly during two major financial distress events, namely US Mortgage and credit crisis (Global Financial Crisis of 2008) and the COVID-19 pandemic. We consider BSE Sensex Indices to empirically examine the widely tested day of the week effect in the Indian equity market using daily stock closing prices. This study utilized an extended version of the GARCH model to investigate the presence of asymmetry. This study reveals the Wednesday effect of the global financial crisis. Additionally, during the Global Pandemic, the study identified Monday and Tuesday effects. This study aims to address the existing research gap pertaining to the chosen topic, as it is apparent from the literature that no prior inquiry has been conducted to assess and compare the effects of the Global Financial Crisis (GFC) and the COVID-19 pandemic in the Indian context.

Keywords: calendar anomaly, financial crisis, COVID-19 pandemic, EGARCH model, 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 Global Financial Crisis (GFC), which began with the bankruptcy of Lehman Brothers in the United States in 2008, rapidly evolved into a global financial meltdown. The crisis was distinguished by a pronounced credit crunch, failure of financial institutions, and significant contraction in worldwide economic activity. Even emerging economies, such as India, which possess reasonably stable economic fundamentals, are vulnerable to foreign shocks. Moreover, it can be observed that the stock markets experience a negative impact during the initial phase of a pandemic. However, they subsequently exhibited a positive response as a result of the easing of lockdown measures and the implementation of government stimulus initiatives (Sharma & Narayan, 2011).

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 (Dubois et al.,1996), the weekend effect (Lakonishok & Levi, 1982), the turn of the month effect (Compton et al., 2006), the January effect (Kim et al., 1994) , and the holiday effect (Ariel, 1990) .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. 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 (Bala & Takimoto, 2017; Chang et al., 2021). 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 global incidence of confirmed COVID-19 has experienced a significant increase in light of the epidemic. During this period, the economic systems of certain nations experienced temporary shutdown. The market was previously characterized by a sustained period of downward movement. Numerous studies have indicated that financial crises, such as the global financial crisis of 2008, the European sovereign debt crisis, and the recent COVID-19 pandemic, exacerbate the interconnectedness of financial markets(Chang et al., 2021). (Salisu

& Akanni, 2020) The Global Fear Index (GFI) shows the substantial value of the index as a reliable indicator for forecasting stock returns during the epidemic. Furthermore, it has been observed that incorporating the "asymmetry" impact and macroeconomic factors enhances the prediction accuracy of the GFI-based model in forecasting stock returns. (Topcu & Gulal, 2020)reveals the current pandemic's influence on emerging markets within the region. This study confirms that the impact of the episode has had a severe effect on the rising economies in Asia, whereas these markets experienced the most significant reduction. Moreover, state-level stimulus packages have effectively mitigated the adverse effects of pandemics. (Akhtaruzzaman et al., 2021)examines the occurrence of financial contagion between China and G7 countries in the context of the COVID-19 pandemic. The research findings indicate a significant increase in the conditional correlations among alleged stock returns, particularly within companies operating in the financial sector. This study examines the interplay between the States' financial crisis and the COVID-19 pandemic. (Ashraf, 2021)through the analysis of daily data on confirmed COVID-19 cases and stock market returns across 43 countries revealed a consistent pattern of decreased stock market returns in response to a 1% increase in the escalation of confirmed cases. This trend is particularly evident in economies characterized by higher levels of country-level uncertainty aversion. (Liu et al., 2020) Considering global COVID-19 pandemic, researchers have undertaken comprehensive inquiries into the effects of COVID-19 on financial markets, exploring this issue from several viewpoints. (Yalcin et al., 2012) examines the increased volatility observed in the United States stock market over the period spanning from January 2020 to April 2020, attributing it to the heightened levels of fear induced by news outlets in relation to the Covid-19 pandemic. (Guru & Das, 2021)indicate that there was a significant increase in overall volatility spillovers, reaching 69% during the COVID-19 pandemic. The energy sector, particularly the oil and gas industry, plays a significant role in transmitting the net volatility. (Sahoo, 2021) examines the day-of-the-week effect on specific Nifty indexes, both prior to and during the onset of the Covid-19 pandemic. The findings reveal that the return on Mondays displays a positive trend before the Covid-19 period, but exhibits a negative trend after the Covid-19 period. A significant amount of existing research examines the global financial crisis and its effects on stock market performance. Another segment of the research exclusively investigates the influence of Covid-19 on stock returns, considering factors such as reported cases and deaths related to Covid-19, industry categorization, stimulus packages, and government-imposed restrictions. This study examines the influence of financial events, specifically the global Financial Crisis and the Covid-19 pandemic, on stock returns in India. This analysis is based on existing research in the worldwide literature, as well as from the Indian perspective. Moreover, our research makes a valuable contribution to the extant literature by examining the effects of two financial shocks on stock returns in the Indian context.

3. Data and methodology

This research employed 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 content of the subject matter. The first part is related to the financial crisis and stock market volatility in the BSE Sensex. In 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 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:

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

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. 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 uses the ordinary least square approach to investigate the seasonal market anomaly, namely the day-of-the-week effect, in a regression model. Because stock returns have nonsystematic qualities due to time varying variation in the return series, ARCH, GARCH, and EGARCH models are used to address this problem.

The market return has been calculated from the concern indices and volatility is measured from the return series with the help of the GARCH Model. The primary objective of this study was to evaluate conditional volatility by incorporating the influence of the day of the week effect. Many models have been employed to study this objective, including GARCH (generalized autoregressive conditional heteroskedasticity, EGARCH (exponential generalized autoregressive conditional heteroskedasticity, threshold generalized autoregressive conditional heteroskedasticity (TGARCH), and PGARCH (power generalized autoregressive conditional heteroskedasticity. The equations employ autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) terms at a first-order level. The GARCH (1,1) model is a fundamental framework for exploring conditional variance within a given time series. The approach developed by Bollerslev (1986) extends the ARCH model of Engel. The underlying assumption of this model is that the current level of conditional variance is affected by previous levels of conditional variance. GARCH models effectively incorporate volatility clustering in time-series data on various financial instruments. However, a significant drawback of the fundamental GARCH model is its inherent symmetry. This implies that the sign of the error term is disregarded as it is squared in the equation for variance.

Nevertheless, the financial market experiences both positive and negative shocks. To incorporate these unexpected events into the time-series data, Ding et al. (1993), Glosten et al. (1993), and Nelson (1991) propose several modifications to the fundamental model. The models under consideration included TGARCH, EGARCH, and PGARCH. The mean and variance equations of the GARCH models are presented.

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 γ_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

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

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,

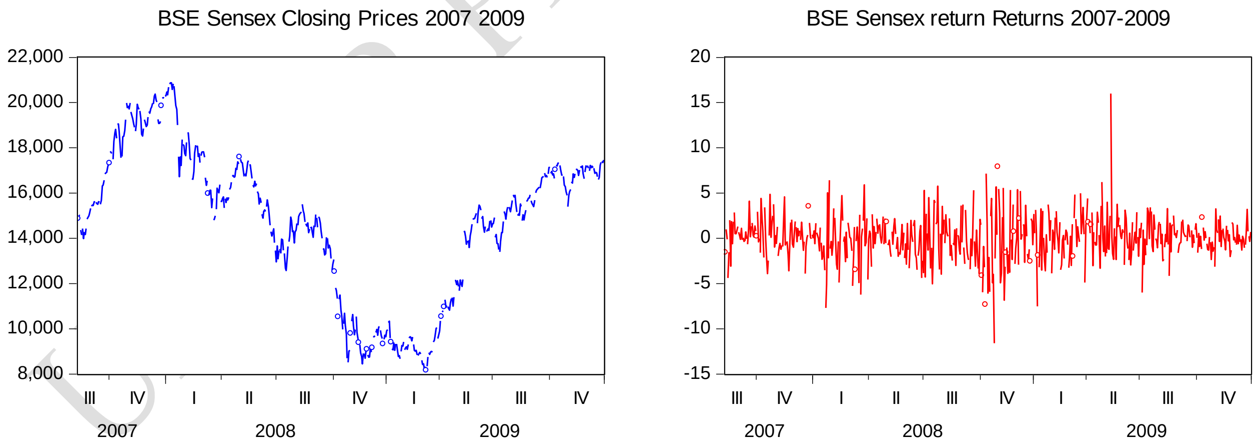

Figure 1 : BSE Sensex closing price and returns series for Financial Crisis 2008 period 2007-2009

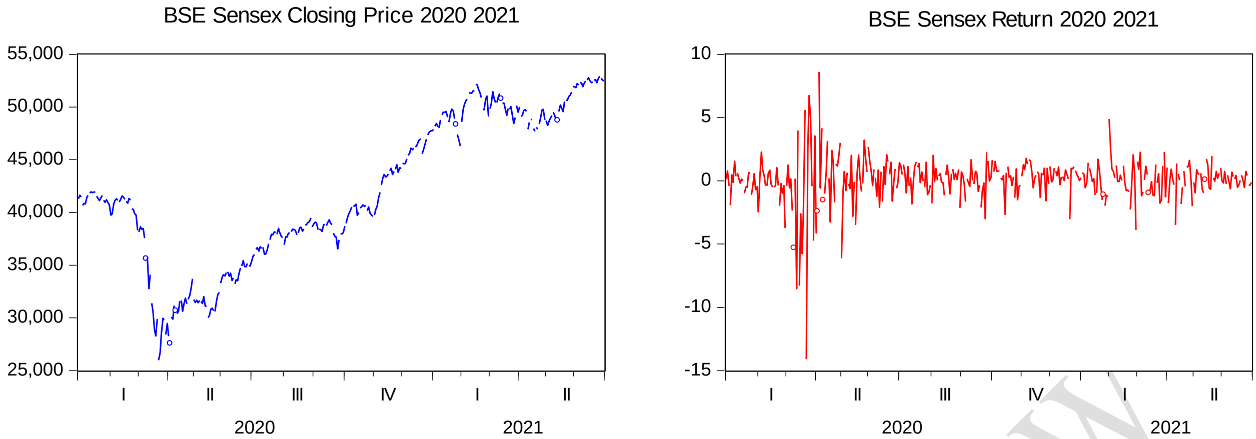

Figure 2 BSE Sensex closing price and returns series for COVID-19 Global Pandemic period 2020-2021

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 show more significant positive mean returns. In addition, Monday had a higher standard deviation of 3.087. During the Global Pandemic, negative mean returns were present only on Monday (-0.568), whereas Tuesday exhibited more significant positive mean returns (0.594). Additionally, Monday displayed a higher standard deviation (2.562) than other days. The financial crisis period exhibited the highest positive mean returns on Wednesdays. The presence of kurtosis indicates that the dataset exhibited leptokurtic characteristics. The Jarque-Bera statistics indicate 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 model 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, where Monday and Tuesday exhibit a notable level of significance. Observation of conditional volatility is also important.

Nevertheless, the significance of the GARCH coefficient suggests volatility clustering in the market. Similarly, the estimated outcomes of the TGARCH and PGARCH models are presented in Table 4, respectively. Both analyses yielded statistically significant results at the 5% level, suggesting 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 demonstrates the existence of asymmetries, according to the findings presents occurrences exhibited comparable outcomes. Upon examining the variance equation, it is evident that a leverage effect exists in both the return series. The coefficients of ARCH and GARCH are statistically significant, as are the asymmetry coefficients. Moreover, as shown by the Durbin-Watson (DW) test, which is approximately equal to two in all the cases, there is no significant evidence of autocorrelation while estimating day of the week effect. Similar to other estimations, the diagnostic tests indicated the absence of autocorrelation and ARCH effect in the residuals. In both instances, the leverage parameter exhibits a statistically significant negative relationship. The presence of the negative leverage term indicates 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 heteroskedasticity (ARCH) LM test reveals a lack of ARCH effect. This implies that the conditional variance equation of the GARCH-type models is well stated.

5. Discussion and the findings

This study investigates the influence of two significant events, the financial crisis of 2008 and the COVID-19 epidemic, 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 from 2007 to 2009. The study reveals that the financial crisis had an evident 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 GARCH models. The current investigation suggests that the ongoing epidemic has had a substantial influence on selected stock markets. When examining the influence of the respective crises on individual stock markets, it is intriguing to observe that each market responds differently to each crisis.

6. 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.

7. Conclusion and policy suggestions

The main purpose of this study is to investigate the presence of the calendar anomaly, specifically focusing on the well-researched day of the week effect in Indian stock markets on two distinct occasions, as previous studies have shown diverse findings. The observation of the Monday and Friday impact in the existing body of literature deserves attention. The research conducted in this study has determined that the returns of BSE Sensex indeed display a day-of-the-week effect, specifically in the form of the Wednesday effect during the global financial crisis. Additionally, during the Global Pandemic, the study identified Monday and Tuesday effects. This study utilized an extended version of the GARCH model to investigate the presence of asymmetry. The study reveals a discernible disparity in the reactions observed in the Indian stock markets towards two distinct events.

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.

Reference:

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