Month-of-the-Year Effect: Empirical Evidence from Indian Stock Market

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Abstract

The present study aims to examine the existence of month-of-the-year effects in the Indian stock market. For analysis, we selected the BSE Ltd and NSE broad market cap indices, namely S&P BSE 500 and NIFTY 500, which are a comprehensive representation of the Indian stock market. The time selected for this study is from April 1, 2011, to March 31, 2021 (i.e., ten years). The study used secondary data collected from the 'monthly open, high, low and closing prices of broad market indices of the Indian stock market through the official websites (www.bseindia.com; and www.nseindia.com). The study's findings indicate that the ADF and PP test confirms the presence of unit root of the return series of S&P BSE 500 and NIFTY 500 Indices. The results from the KPSS test confirm the stationarity of the return series of both Indices. The regression coefficients for March were negative and significant for both indices. These results suggest that the month-the-of-the-year effect is the 'March effect.'

Keywords Calendar anomalies · Month-of-the-year effect · KPSS test · ARIMA and GARCH

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1 Introduction

The humorous comment by Mark Twain implies that speculation has no place in stock markets, and there is no good time to speculate. One of the heavily debated topics in finance and economics is the efficient market hypothesis (EMH) which states that stock prices reflect all the available information (Fama, 1970). Therefore, investors can't enjoy abnormal returns than the market rate of return. If stock markets are efficient, the market capitalization represents the firm's fair value, i.e., future cash flows discounted by the cost of capital. The EMH is built on two assumptions: (i) all available information is fully incorporated into the stock prices, and (ii) investors would not be in a position to earn a risk-weighted excess return than the market return. In the weak form, market efficiency does not yield any excess return. In semi-strongly efficient markets, the current stock prices reflect historical information. Still, they include the information which is currently available (for example, announcements of mergers, dividend pay-outs, changes in the top management team members, etc.). In the strong form of efficient markets, current stock prices reflect all available, including insider information, in addition to the publicly available information. Therefore, in a strong form of market efficiency, researchers contend that it is impossible to earn excess profits relying on insider information (Malkiel, 2003).

Fluctuations in stock prices challenge EMH due to calendar anomalies, and researchers in finance and economics documented the effect of these anomalies. Changes in calendar effects have been on the research agenda for the last four decades. Researchers identified three types of anomalies seasonal, technical, and fundamental anomalies that significantly affect stock returns (Srinivasan & Kalai-vani, 2013). A plethora of research is available on the day-of-the-week effect, weekly effect, weekend effect, month-of-the year effect, semi-month effect, turn-of-the-month effect, holiday effect, Ramadan effect, Diwali effect, Independence Day effect (July 4th in the USA), Halloween effect, etc., (Agrawal & Tandon, 1994; Barone, 1990; Compton et al., 2013; Haroon & Shah, 2013; Harshita et al., 2018; Patel & Sewell, 2015). Digging up literature, one can find that some studies provided strong support for the seasonal fluctuations (e.g., Easterday et al., 2009). On the other hand, some did not support evidence for seasonality in stock prices (Cheung & Coutts, 1999; Zinbarg & Harrington, 1964). Some critics argue that the data might have been tortured until it confessed (Merton, 1987).

The objective of the present study is to test the presence or absence of the month-of-the-year effect in the Indian stock market. Several studies in the past have documented that returns on financial assets exhibited systematic patterns at certain calendar months so that investors can benefit from these seasonal variations (Brooks, 2019; Jacobs & Levy, 1988). The financial year in India runs from April to March, and extant research supported effects in January and November (see Table 1 for pieces of evidence from previous studies conducted in India). The study period covered transition of political power in India in 2014, thus necessitates study of stock market anomalies. We organize the paper as follows. First, we present the literature review in Sect. 2, followed by data and methodology in

Table 1 A summary of the month-of-the-year effect in the Indian context

References	Sample	Result
Patel (2008)	Bombay Stock Exchange (BSE) 500 index for the period July 1997 to June 2007	Identified March to May effect
Rengasamy & Pandey (2008)	Important indices of the National Stock Exchange of India (NSE) for the period from 1999 to 2007	Significant differences in the month of April, November and December when compared to January returns
Chandra(2009)	Bombay Stock Exchange (BSE) SENSEX index for the period April 1998 to March 2008	Turn of the Month effect as well as the Time of the Month effect was significant
Verma and Kumar (2012)	Bombay Stock Exchange (BSE) SENSEX index; January 1991 to December 2010	There is no month of the year effect in the Bombay stock market
Debasish (2012)	Selected leading companies Gas, Oil and Refineries sectors in the Indian economy; 1st January 2006 to 31st December 2010	Evidenced month of the year effect and mostly either on September, August or February
Deepak and Viswanath (2012)	The data consists of monthly prices for NSE NIFTY Index; from 1990 to 2011	The patterns are month effect-March and May (1991–2001) and October (2002–2011)
Pathak (2013)	Indian stock market for the S&P CNX NIFTY (NSE); 1st April 2007 to 31st March 2012	Non-existence of the month of year effect means the seasonality is not present in Indian stock Market
Sriram and Devi (2013)	Bombay Stock Exchange (BSE) Sensex for the period April 2004 to March 2012	The results do not confirm the existence of seasonality in stock returns and the January effect
Yadav (2013)	National Stock Exchange's index during the period of January 1996 to 31st March 2013	Month of the year effect, is present in both market volatility and market returns
Nageswari et al. (2013)	National Stock Exchange's indices of S&P CNX NIFTY and S&P CNX 500; 1st April 2002 to 31st March 2011	Absence of January Anomaly during the study period
Neeraja and Srikanth (2014)	BSEIT Index as a proxy of Indian Information Technology sector stocks and BSE Sensex is surrogated for Indian stock market; 1999 to 2013	Indian IT Sector was experiencing seasonality effect
Patel (2014)	National Stock Exchange (NSE) CNX 500 Index; June 1999 to June 2012	Indian stock market does not possess a monthly barometer
Lodha and Soral (2015)	Major indices of Bombay Stock Exchange;	September and December were providing significant returns
Sudarvel and Velmurugan (2015)	Bombay Stock Exchange's Bank Index for the period from January 2002 to June 2015	Confirm the existence of January effect

Table 1 (continued)

References	Sample	Result
Choithala and Ajmal (2016)	Bombay Stock Exchange (BSE) SENSEX Index; June 1999 to June 2012	Significant December effect of volatility in Indian stock return
Kumar and Dawar (2017)	Major indices of Bombay Stock Exchange; from January 1999 to December 2015	SENSEX index does not show any significant calendar effect
Kushwah and Munshi (2018)	National Stock Exchange NIFTY 50; from 2007 to 2017	Do not support the existence of seasonality in the Indian stock market
Kumari and Uthra (2018)	Bombay Stock Exchange (BSE) Healthcare Index; 01st April 2012 to 31st March 2016	Turn-of-the-month effect still exists, but its occurrence has moved to earlier dates

Sect. 3. We offer the analysis and findings in Sect. 4 and discussion and managerial implications in the final section.

2 Literature Review

While the historical evidence on the seasonality of stock market returns provided by Fields (1931) and Wachtel (1942), systematic analysis of stock market anomalies started with Cross (1973), followed by French (1980). History is replete with studies that focused on day-of-the-week effect, weekly effect, weekend effect, month-of-the-year effect, semi-month effect, turn-of-the-month effect, and holiday effect. Unfortunately, the results are inconclusive and inconsistent. Since our objective in the present research is to examine the month-of-the-year impact empirically, we found that most of the studies documented the January effect (Aggarwal & Rivoli, 1989; Agrawal & Tandon, 1994; Asteriou & Kavetsos, 2006; Beyer et al., 2013; Floros, 2011; Pettengill, 1986; Wilson & Jones, 1993).

One of the classic studies that analyzed data from 1904 to 1974 in the US stock market, Rozeff and Kinney (1976), showed that the returns in January were significantly higher than in the other eleven months. High returns in January were labelled as 'month-of-the-year effect,' and subsequent research conducted on seventeen countries, the January effect was significant in thirteen countries (Gultekin & Gultekin, 1983). The January effect was explained by Brown et al. (1983) as the tax-loss selling hypothesis according to which investors are motivated to sell stock at the end of the year to get tax benefits. Therefore the prices get depressed and then bounce back in January. This was supported because, in 1917, there was no January effect. After all, there was no tax incentive (Schultz, 1985), which made the January hypothesis strong. The subsequent researchers also supported the tax-loss selling hypothesis for the January effect (Chen & Singal, 2003). However, some researchers argue that the tax-loss selling hypothesis was true before the Federal income taxes (Berges et al., 1984; Jones et al., 1991), and the January effect was insignificant.

A plethora of researches has been done concerning the month-year-of-the-year effect in both international markets and the Indian stock market. There is a diversity of results, and there is no unanimity in finding out the month-of-the-year effect. In the US, Denmark, France, Germany, Norway, Sin/Mal, Spain, Switzerland, and Malaysia, the January effect found support from several researchers (Boudreaux, 1995; Keim, 1983; Wong et al., 2007). The January effect was not found in the New Zealand stock market (Li & Liu, 2010), In the Chinese market, while Gao and Kling (2005) found support for March and April effects, whereas Luo et al. (2009) did not find any month-of-the-year effects. In a study by Silva (2010), the January effect was not found in the Portuguese stock market. The July effect was found in Ghana (Albert et al., 2013), December was the best month in the Indonesian stock market (Rahario et al., 2013).

Regarding literature review concerning the stock market in India, March to May effect was found by Patel (2008), April, November, and December effects were found by Rengasamy & Pandey (2008), Diwali effect was found in Harshita et al. (2018). Moreover, some researchers found significant results during September and

December (Lodha, 2015). On the contrary, some studies did not find any month-of-the-year effect (Verma & Kumar, 2012; Sairam & Devi, 2013; Patel, 2014). The summary of previous studies conducted in the Indian and international stock markets is presented in Tables 1 and 2.

2.1 Rationale for the Present Study

After going over the literature review, one may question why another study? The rationale for the present study stems from three reasons: First, the literature review reveals that different scholars have focused on different years to study the month-of-the-year effect. For example, Patel (2008) studied the Bombay Stock Exchange (BSE) 500 index during 1997–2007; Verma and Kumar (2012) studied BSE SENSEX during 1998–2008, and Kushwah and Munshi (2018) have studied National Stock Exchange (NSE) NIFTY 500 from 2007–2017. Likewise, several researchers in the past studied BSE, NSE during different periods. The present study explores BSE 500 and NIFTY 500 indices during the last decade (2011–2021). Our study extends growing literature on stock market returns concerning the month-of-the-year effect. The other studies conducted in the Indian context were presented in Table 1, and the reflections in the non-Indian context are shown in Table 2.

Second, the rationale for the present study is because of the diversity of results from previous studies, as documented in Tables 1 and 2. For example, while some studies found the March to May effect, others found the September and December effects. Now, during this current period, we wanted to explore what was regarded as the month-of-the-year effect.

Third, researchers have been trying to find if there is any possibility for the investors to secure an above-average rate of returns (example, January effect, April effect, November effect, etc.). In simple words, the month-of-the-year effect refers to the identification of month (or months) in a calendar year that gives statistically significant abnormal returns. The term month of the year effect implies that among the month of the year, i.e., (January to December), any one of the months gives statistically significant abnormal returns. Therefore, to earn an abnormal return, the investors have to frame the trading strategies called seasonal anomalies viz., day of the week effect, the month of the year effect, monthly effect, holiday effect, and quarter of the year effect. The present study focuses on identifying the month-of-the-year effect in the Indian stock market.

2.2 Objectives of the Study

The study's primary objective is to examine the existence of the month-of-the-year effect in Indian Stock Markets. The primary objective is split into the following sub-objectives:

- (1) To empirically examine the month-of-the-year effect from 1st April 2011 to 31st March 2021 in India.

Table 2 Summary of the month-of-the-year effect in the non-Indian context

Study	Sample	Result
Keim (1983)	Firms which were listed on the NYSE or AMEX	Fifty per cent of the January premium is attributable to large abnormal returns during the first week of trading in the year
Boudreaux (1995)	Major indices of the countries Denmark, France, Germany, Norway, Sin/Mal, Spain and Switzerland	January effect and a monthly effect in U.S. stocks
Gao and Kling (2005)	Market index of the Shanghai and Shenzhen stock exchanges,	As the Chinese year-end is in February, the highest returns can be achieved in March and April
Wong et al. (2007)	Malaysian Stock Market KLCI index from January 1994 to December 2006	Found evidence of the January effect in the post-crisis period
Ciccone & Etebari (2008)	CRSP monthly index returns including distributions from January 1926 through December 2006	Two powerful monthly anomalies occurring in January and September
Luo et al. (2009)	Chinese stock markets consist of the daily prices of Shanghai and Shenzhen A-shares Closing Index and Shanghai and Shenzhen B-shares Closing Value-Weighted Index	There is no significant monthly effect in the Shanghai A-shares market in all testing periods
Rompotis (2009)	Greek equity mutual funds during the period 2002–2005	Well-known January effect does not apply to Greek equity funds
Silva (2010)	Portuguese stock market, PSI-Geral is a capitalization-weighted index	Did not find the January “anomalies”
Li and Liu (2010)	4 stock market indices and 16 industry indices in the New Zealand stock market	Do not find any January effect in all 4 market indices
Deepak and Viswanath (2012)	The data consists of monthly prices for NSE NIFTY Index; from 1990 to 2011	The patterns are month effect-March and May (1991–2001) and October (2002–2011)
Raharjo et al. (2013)	Indonesia Stock Exchange (IDX) from January 1998 through to December 2012	Finding that December is the best month for an investor to buy stock in Indonesia Stock Exchange
Albert et al. (2013)	Ghanaian Treasury bill rate; considering the 91-day and 182-day bills rate	Exists pronounced month-of-the-year effects; the month of July averagely had the highest rate
Alagidede (2013)	NSE All-Share Index for Nigeria, NSE20 index for Kenya, Tunindex for Tunisia, MASI index for Morocco and FTSE/JSE All Share index, CASE30 Share Index and ZSE Industrial index for South Africa, Egypt and Zimbabwe	The month of the year effect is prevalent in African stock returns

Table 2 (continued)

Study	Sample	Result
Darrat et al. (2013)	Johannesburg daily stock returns from January 1973 to September 2012	No compelling evidence for either a January or December effect in the South African market
Kuria and Riro (2013)	Major indices of the National Stock Exchange	Presence of December effect in NSE monthly returns
Hafeez et al. (2014)	January effect has been employed for KSE 100, KSE 30 and BR 30 indices i.e. from March 2007 to February 2013	There exist January, March and April anomalies for the three sample
Angelovska (2014)	Major Macedonian Stock Exchange index, the MB110 Index, January 4, 2005 to December 31, 2009	There is evidence of month of the year effect; negative November effect
Khan and Khan (2014)	Karachi Stock Exchange (KSE) KSE 100 Index; 2002–2004	Slight evidence witnessed regarding the time of the month effect
Abedin et al. (2015)	Dhaka Stock Exchange (DSE), Bangladesh; from 2000 to 2012	The significant month of the year effect presents in DSE
Simbolon (2015)	12 firms listed on the Indonesian Stock Exchange; from January 2006 to December 2013	The results did not support the January effect by using the unconditional method and the conditional method
Adinya et al. (2019)	Nigerian Stock Exchange (NSE) for the period spanning January 1985 to December 2015	March and April have the highest mean returns and there is significant evidence of the month of the year effect
Arendas and Kotlebova (2019)	11 Central and Eastern European (CEE) region stock markets; (1999–2018)	Significant Turn of the month effect was present in the stock markets

- (2) To explain the reasons for the month-of-the-year effect and suggest to investors the consequences of the month-of-the-year impact in India.
- (3) To provide directions for future research concerning the month-of-the-year effect in the Indian context.

To study the month-of-the-year effect, we need to examine whether monthly return series of the indices are stationary or not. We also need to examine the descriptive statistics for S&P BSE 500 and NIFTY 500 indices for the month of the year. Thirdly, it is essential to examine whether the stock market indices follow a normal distribution. To achieve these, the following hypotheses are formulated.

3 Hypothesis

Since the objective of the present study is to empirically examine the month-of-the-year effect in the Indian stock market, the following hypothesis is formulated:

H₀ (Null Hypothesis): In Indian stock market, there is no month-of-the-year effect.

H₁ (Alternate hypothesis): In Indian stock market, there is month-of-the-year effect.

The sub-hypotheses to test the above main hypothesis are:

H₀₁: The series has a unit root

H₀₂: The series is stationary

H₀₃: The monthly mean returns are statistically equal across the trading month of the year

4 Methodology

In this research, we started with the identification of the problem, outlined the study's objectives and hypotheses, selected the sample and collected the data, selected the right econometric tools to analyze the data, and presented the results. The methodology is mentioned in the flowchart (Fig. 1).

4.1 Sample

In India, the two leading recognized stock exchanges, viz., the BSE Ltd and NSE, play a vital role in the growth of the Indian economy. Hence, most researchers consider these two-stock exchange's market cap indices, namely S&P BSE 500 and NIFTY 500. The sample included for the study is from 1st April 2011 to 31st March 2021, which consists of 10 years.

Fig. 1 Methodology

4.2 Data Collection

The present empirical study was mainly based on the secondary data collected from the official websites of the Bombay Stock Exchange (i.e., www.bseindia.com) and the National Stock Exchange (i.e., www.nseindia.com). The data collected for this study included: 'monthly open,' 'high,' 'low,' and 'closing prices' of market cap indices of the Indian Stock Market. It should be noted that NSE does not provide monthly open, high, low, and closing prices. Instead, NSE provides daily open, high, low, and closing prices, and hence we took the prices on the first day of every month. The monthly returns are calculated on the basis of average price. While prior researchers have used only closing prices as if the trading is done at the closing price, Lodha and Soral (2015) recommended using the simple arithmetic mean of the four prices. The underlying logic is that by considering the average price the volatility of prices can be controlled to some extent. We used the following formulae for the returns:

$$r_t = \ln (p_t/p_{t-1}) * 100$$

where r_t is the return at the time t , $\ln$ represents natural log, p_t and p_{t-1} are closing prices at time t and $t-1$ respectively. If the returns series is detected to be stationary, the analysis is supposed to be performed on the stationary series. As we recall the fundamentals, a series is said to be stationary only if has (a) a constant mean (μ), (ii) a constant variance (σ^2), and (iii) a constant covariance structure (γ_s). Though there are two types of stationarity (viz., deterministic, stochastic). When the series has a linear trend making it non-stationary, it is called a deterministic non-stationarity series. It should, however, be noted that if the series is stationary around that trend, it is called trend-stationary series (Brooks, 2019). In financial economics, time series in general exhibit stochastic non-stationarity, if not stationarity.

4.3 Econometric Tools used in the Study

For analysing the data, we used Eviews-7. The econometric tools used in this study are:

- (i) Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) tests to detect the unit root of the monthly return series; PP test is used to adjust possible autocorrelation in the residuals
- (ii) Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and correlogram to verify the stationarity of monthly return series; KPSS test serves as a confirmatory data analysis. One should note that while ADF and PP tests have null hypotheses that unit root is present in the series, the null hypothesis in KPSS is that the series is stationary
- (iii) Regression for examining the month of the year effect by considering all twelve months in a year. The following regression equation used to find the month of the year effect

$$Y_t = \alpha_1 + \alpha_{2D}Feb + \alpha_{3D}Mar + \alpha_{4D}Apr + \alpha_{5D}May + \alpha_{6D}Jun + \alpha_{7D}Jul \\ + \alpha_{8D}Aug + \alpha_{9D}Sep + \alpha_{10D}Oct + \alpha_{11D}Nov + \alpha_{12D}Dec + \varepsilon_t$$

where, the constant term (α_1) is the average mean return for the January trading month, and coefficients α_2 to α_{12} denotes the average differences between the return from February trading month to December trading month, except for 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 ε_t represents the white noise error term.

- (iv) ARIMA model to remove the persistence of serial correlation
- (v) GARCH model to remove the heteroskedasticity effect.

5 Results

The Unit root test and stationarity test results for monthly closing prices and monthly returns of S&P BSE 500 and NIFTY 500 Indices return series were presented in Table 3.

As can be seen in the Intercept of ADF test statistics of the closing price of S&P BSE 500 (0.380) and NIFTY 500 (0.357) is greater than their critical values of 1 percent, 5 percent, and 10 percent levels of insignificant respectively (the values were given in parenthesis). Hence, H_0 (the series has a unit root) is not rejected (following the ADF test). Likewise, the Intercept of PP test statistics of the closing price of S&P BSE 500 (0.498) and NIFTY 500 (0.457) is greater than their critical values of 1 percent, 5 percent, and 10 percent levels of insignificant respectively (the values were given in open parenthesis). Hence, H_0 (the series has a unit root) is not rejected (following the PP test). Finally, the KPSS test statistic (1.261) of the closing price of S&P BSE 500 and NIFTY 500 is greater than the critical value at a 1% significance level (0.739), rejects the null hypothesis of a stationary series. Hence, H_0 (the series is stationary) is rejected (following the KPSS test).

The Intercept of ADF test statistics of return series of S&P BSE 500 (−7.588) and NIFTY 500 (−7.641) is less than their critical values of 1 percent, 5 percent and 10 percent levels of significance respectively (the values were given in parenthesis). Hence, H_0 (the series has a unit root) is rejected (following the ADF test). The Intercept of PP test statistics of return series of S&P BSE 500 (−6.484) and NIFTY 500 (−6.454) is less than their critical values of 1 percent, 5 percent and 10 percent levels of significance respectively (the values were given in parenthesis). Hence, H_0

Table 3 Unit root test and stationarity test for monthly closing prices and monthly returns. Source: Compiled from Eviews7

Index	Test	Test statistic	<i>p</i> value	Comment
<i>Closing prices</i>				
S&P BSE 500	ADF Test	0.380 (-3.487) (-2.886) (-2.580)	0.981	Ho: not rejected
	PP test	0.498 (-3.486) (-2.886) (-2.580)	0.986	Ho: not rejected
	KPSS Test	1.262 (0.739) (0.463) (0.347)	0.000	Ho: rejected
NIFTY 500	ADF Test	0.357 (-3.487) (-2.886) (-2.580)	0.980	Ho: not rejected
	PP test	0.457 (-3.486) (-2.886) (-2.580)	0.985	Ho: not rejected
	KPSS Test	1.261 (0.739) (0.463) (0.347)	0.000	Ho: rejected
<i>Returns</i>				
S&P BSE 500	ADF Test	-7.588 (-3.487) (-2.886) (-2.580)	0.000	Ho: rejected
	PP test	-6.484 (-3.487) (-2.886) (-2.580)	0.000	Ho: rejected
	KPSS Test	0.070 (0.216) (0.146) (0.119)	0.808	Ho: not rejected
NIFTY 500	ADF Test	-7.641 (-3.487) (-2.886) (-2.580)	0.000	Ho: rejected
	PP test	-6.454 (-3.487) (-2.886) (-2.580)	0.000	Ho: rejected
	KPSS Test	0.070 (0.216) (0.146) (0.119)	0.758	Ho: not rejected

ADF Test H_0 : the series has a unit root; PP Test: H_0 : the series has a unit root; KPSS Test: H_0 : the series is stationary

(the series has a unit root) is rejected (following the PP test). Therefore, it could be interpreted that the ADF and PP test confirms the unit root of the return series of S&P BSE 500 and NSE NIFTY 500 Indices. The p-value of the KPSS test of return series of S&P BSE 500 (0.808) and NIFTY 500 (0.758) is greater than the significance level of (0.05). Hence, H_0 (the series is stationary) is not rejected. KPSS test confirms the stationarity of the return series of both Indices.

The confirmatory data analysis revealed that (i) the monthly closing prices series is not stationary, and (ii) the returns series exhibit stationarity. These findings are consistent with the results from the previous studies in the literature on finance, adding to the growing body of literature. The graphical representation of these two series over time are presented in Figs. 2 and 3.

As can be seen in the Figs. 2 and 3, the closing share price is non-stationarity because it is continuously changing in the line graph.

The graphs of the return series of S&P BSE 500 and NIFTY 500 indices were presented in Figs. 4 and 5.

The figures indicate that indices are fluctuating between high and low, and the proportions of deviation are different at different time periods of the study, but they return to their respective means. It is not surprising to find that during the year 2020, both indices of the graph line showed high volatility because of the impact of Covid-19 global pandemic. It is understood that both indices have constant mean returns over the period and the mean values lie on 0. It can be interpreted that both indices are stationarity in nature.

The descriptive statistics of monthly returns of S&P BSE 500 and NIFTY 500 indices were shown in Figs. 6 and 7.

As can be seen in Fig. 6, descriptive statistics of monthly returns of S&P BSE 500 report a kurtosis of 7.142. Since the value is greater than 3, the returns series

Fig. 2 Monthly closing price of S&P BSE 500. Source: Compiled from Eviews7

Monthly closing price of NIFTY 500

Fig. 3 Monthly closing price of NIFTY 500. Source: Compiled from Eviews7

Monthly return series of S&P BSE 500

Fig. 4 Monthly return series of S&P BSE 500. Source: Compiled from Eviews7

is leptokurtic (Brooks, 2019). The descriptive statistics presented in Fig. 7 for the monthly returns of NIFTY 500 show the kurtosis of 6.3707 reveal that the returns series is leptokurtic as the value is greater than 3 (Brooks, 2019).

Kurtosis represents the possibility of the stock prices to fluctuate significantly and hence is very important from investors' point of view. The shape of distribution

Fig. 5 Monthly return series of NIFTY 500. Source: Compiled from Eviews7

Fig. 6 Histogram and descriptive statistics of monthly returns of S&P BSE 500. Source: Compiled from Eviews7

explains whether the stocks are pricing risky assets by looking at the distribution and volatility of the prices (Ivanovski et al., 2015). The results indicate that significant variations in daily prices are noticeable than those estimated by normal distribution. The leptokurtic distribution, representing the excessive positive kurtosis, suggests that risk-seeking investors experience fluctuations resulting in substantially high or low returns. Sometimes, the investors make maximum profits when returns are very high and sometimes they also suffer losses when the returns are low.

Histogram and descriptive statistics of monthly returns of NIFTY 500

Fig. 7 Histogram and descriptive statistics of monthly returns of NIFTY 500. Source: Compiled from Eviews7

The Correlogram analysis was done and the results were shown in Tables 4 and 5.

The autocorrelation function did not show large spikes at lag 1 and autocorrelation hurriedly fall from 0.420 to -0.046 for S&P BSE 500 and 0.422 to -0.050 for NIFTY 500, when the lag length increased. The ACF after the lag 1 to lag 16 coefficients values of both indices are nearly zero. Moreover, the PACF after the lag 1 to

Table 4 The results of Autocorrelation test for return series of S&P BSE 500. Source: Compiled from Eviews7

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. ***	. ***	1	0.420	0.420	21.491	0.000
. .	** .	2	-0.046	-0.270	21.753	0.000
. .	. *	3	-0.057	0.105	22.162	0.000
* .	* .	4	-0.077	-0.138	22.911	0.000
. .	. .	5	-0.051	0.052	23.241	0.000
. .	. .	6	0.038	0.028	23.427	0.001
. *	. *	7	0.103	0.078	24.789	0.001
. .	. .	8	0.038	-0.054	24.977	0.002
. .	. .	9	-0.047	-0.023	25.272	0.003
. .	. .	10	-0.017	0.034	25.308	0.005
* .	** .	11	-0.149	-0.221	28.273	0.003
** .	* .	12	-0.242	-0.077	36.123	0.000
* .	. .	13	-0.128	-0.043	38.365	0.000
. .	. .	14	-0.004	0.016	38.367	0.000
. .	. .	15	0.013	-0.039	38.390	0.001
. .	* .	16	-0.049	-0.076	38.723	0.001

Table 5 The results of Autocorrelation test for return series of NIFTY 500. Source: Compiled from Eviews7

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. ***	. ***	1	0.422	0.422	21.733	0.000
. .	** .	2	−0.050	−0.278	22.041	0.000
. .	. *	3	−0.060	0.111	22.483	0.000
* .	* .	4	−0.076	−0.141	23.206	0.000
. .	. .	5	−0.049	0.057	23.505	0.000
. .	. .	6	0.042	0.029	23.735	0.001
. *	. *	7	0.104	0.077	25.131	0.001
. .	. .	8	0.036	−0.056	25.300	0.001
. .	. .	9	−0.049	−0.021	25.613	0.002
. .	. .	10	−0.026	0.022	25.702	0.004
* .	** .	11	−0.149	−0.209	28.649	0.003
** .	* .	12	−0.238	−0.084	36.295	0.000
* .	. .	13	−0.128	−0.040	38.530	0.000
. .	. .	14	−0.002	0.014	38.531	0.000
. .	. .	15	0.016	−0.034	38.567	0.001
. .	* .	16	−0.048	−0.078	38.886	0.001

lag 16 coefficients values of both indices are adjacent zero. Hence, the Correlogram clearly corroborate the stationarity in the series.

Month-wise descriptive statistics of S&P BSE 500 and NIFTY 500 indices return series were presented in Table 6

As can be observed in Table 6, the maximum average (or mean return) occurred in July, and the lowest returns occurred in March for both indices. These results suggest that among the trading month of the year, mean returns for all the months were having different returns distributions. Therefore, H_{02} (the monthly mean returns are statistically equal across the trading month of the year) is rejected. The standard deviation of returns series was greater in March when compared to other months for both the indices. These results indicate that volatility in stock was maximum in March. From intraday trader standpoint, these results suggest that March is an appropriate month. The value of Skewness returns distribution is found to be negative for all the months of the year except February, June and December. The monthly trading returns are asymmetrical distributions. The values of Kurtosis are less than three for all the months of the year except March, October and December for both the indices. It represents that return distribution for the months of the year shows platykurtic curve. The coefficient value of the Jarque–Bera test statistic is insignificant for all the month of the year except March and October. It evident that the month-wise average returns distribution follows the normal distribution.

Table 6 Month wise descriptive statistics of S&P BSE 500 and NIFTY 500 indices. Source: Compiled from Eviews7

Index	D. Statics	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
S&P BSE 500	Mean	1.474	0.226	-0.742	0.988	0.994	1.250	1.931	-0.369	0.195	1.544	1.545	0.729
	Median	1.964	-1.177	0.808	1.826	1.690	0.598	2.527	0.811	0.811	2.442	1.963	0.962
	Maximum	3.848	9.468	5.589	5.668	5.788	7.394	6.495	5.365	3.787	5.858	6.053	9.219
	Minimum	-2.623	-6.437	-18.380	-7.249	-4.007	-3.324	-3.731	-6.906	-4.289	-7.645	-3.519	-5.732
	Std. Dev	2.064	4.663	6.954	4.084	3.159	3.564	2.895	4.242	2.918	3.620	3.015	3.998
	Skewness	-0.710	0.590	-1.740	-0.825	-0.169	0.732	-0.550	-0.201	-0.528	-1.666	-0.256	0.522
	Kurtosis	2.495	2.634	5.270	2.786	1.891	2.392	2.943	1.701	1.840	5.412	2.053	3.531
	Jarque-Bera	0.946	0.636	7.192	1.038	0.560	1.048	0.505	0.770	1.026	7.051	0.483	0.572
	Probability	0.623	0.727	0.027**	0.595	0.756	0.592	0.777	0.681	0.599	0.029**	0.785	0.751
	Observations	10	10	10	9	10	10	10	10	10	10	10	10
NIFTY 500	Mean	1.494	0.142	-0.608	1.012	0.926	1.304	1.950	-0.444	0.176	1.595	1.565	0.767
	Median	1.966	-1.132	0.913	1.846	1.645	0.607	2.592	0.792	0.807	2.486	1.972	0.959
	Maximum	3.937	9.528	5.747	5.824	5.785	7.438	6.542	5.252	3.888	6.099	6.103	9.234
	Minimum	-2.570	-6.331	-17.557	-7.455	-4.190	-3.340	-3.740	-6.965	-4.536	-7.715	-3.467	-5.722
	Std. Dev	2.065	4.706	6.747	4.180	3.194	3.592	2.934	4.281	2.965	3.672	3.023	4.011
	Skewness	-0.678	0.624	-1.681	-0.844	-0.152	0.732	-0.567	-0.211	-0.524	-1.647	-0.235	0.499
	Kurtosis	2.449	2.640	5.094	2.830	1.947	2.402	2.909	1.681	1.893	5.413	2.041	3.484
	Jarque-Bera	0.893	0.703	6.535	1.078	0.500	1.043	0.539	0.798	0.968	6.949	0.476	0.512
	Probability	0.640	0.704	0.038**	0.583	0.779	0.594	0.764	0.671	0.616	0.031**	0.788	0.774
	Observations	10	10	10	9	10	10	10	10	10	10	10	10

** $p < .05$

5.1 OLS Dummy Variable Regression Equation Model

The descriptive statistics from the study reveal that there is no strong evidence of the month-of-the-year effect of both indices. Therefore, we wanted to identify the month-of-the-year effect by using the Ordinary Least Square (OLS). The regression equation used to find the month of the year effect is as follows:

$$Y_t = \alpha_1 + \alpha_{2D}Feb + \alpha_{3D}Mar + \alpha_{4D}Apr + \alpha_{5D}May + \alpha_{6D}Jun + \alpha_{7D}Jul + \alpha_{8D}Aug + \alpha_{9D}Sep + \alpha_{10D}Oct + \alpha_{11D}Nov + \alpha_{12D}Dec + \varepsilon_1$$

The dummy variables for February, March, April, May, June, July, August, September, October, November and December were included in the regression equation. For each dummy variable, the value '1' represents the corresponding month and 0 represents the rest of the months. Since majority of previous studies reported January effect in the stock market, the monthly average mean returns of January taken as 'Yardstick month' for comparing returns of other trading months for both indices.

The results of the OLS dummy variable regression model of the month-of-the-year effect for S&P BSE 500 and NIFTY 500 indices were presented in Table 7.

As can be seen in Table 7, the regression coefficients of February, March, April, May, June, August, September and December are negative but insignificant for both indices. The regression coefficient for January, July, October and November are positive but not significant for both indices. The Adjusted R-square is negative for both indices. Moreover, the F-statistic was very low with the p-value. These results indicate that the OLS dummy variable regression model spurious. i.e., the OLS dummy variable regression model does not indicate the month-of-the-year effect. Besides,

Table 7 The results of the OLS dummy variable regression model of the month-of-the year effect for S&P BSE 500 and NIFTY 500 indices. Source: Compiled from EViews7

Variables	S&P BSE 500	NIFTY 500
January (C)	1.474 (1.182)	1.494 (1.197)
February	-1.248 (-0.708)	-1.352 (-0.766)
March	-2.216 (-1.257)	-2.101 (-1.191)
April	-0.486 (-0.268)	-0.481 (-0.266)
May	-0.480 (-0.272)	-0.568 (-0.322)
June	-0.225 (-0.127)	-0.190 (-0.107)
July	0.456 (0.259)	0.456 (0.259)
August	-1.843 (-1.045)	-1.938 (-1.099)
September	-1.279 (-0.725)	-1.318 (-0.747)
October	0.070 (0.040)	0.101 (0.057)
November	0.071 (0.040)	0.071 (0.040)
December	-0.745 (-0.422)	-0.727 (-0.412)
Adj.R ²	-0.055	-0.054
F-Stat	0.442	0.449
D-W Stat	1.104	1.101
AIC	5.678	5.678
SBC	5.958	5.958

the Durbin-Watson statistics values for both indices are less than the acceptable value of two, indicating the existence of serial correlation in this model. To confirm the serial correlation, we applied the Breusch-Godfrey LM test to the OLS dummy variable regression results.

It should be noted that when serial correlation is present, it is necessary to test it further by conducting the Breusch-Godfrey Lagrange-Multiplier (LM). In general, the LM-test is conducted before and after ARIMA, which is consistent with the procedures by the previous researchers. The results of LM-test statistics before and after ARIMA modelling of the month-of-the-year effect in S&P BSE 500 and NIFTY 500 indices were presented in Table 8.

As can be seen in Table 8, the LM test value before ARIMA for both indices had a very high value ($p < 0.000$), indicating strong evidence for the existence of serial correlation. Since serial correlation in the time series data was confirmed, removing the serial correlation by employing appropriate ARIMA is essential.

Following the Box-Jenkins methodology, we added the appropriate ARIMA terms to the equation for both indices to remove the persistence of serial correlation. After the inclusion of ARIMA terms in the OLS dummy variable regression equation, the Breusch-Godfrey LM test value for S&P BSE 500 decreased from 30.035 ($p < 0.000$) to 0.643 ($p = 0.725$); and Breusch-Godfrey LM test value for NIFTY 500 decreased from 30.688 ($p < 0.000$) to 0.602 ($p = 0.740$). That means after inclusion, the appropriate AR and MA terms in the equation serial correlation have been removed.

Following the previous researchers, we used GARCH model in this study. The Auto Regressive Conditionally Heteroskedastic (ARCH) is the most frequently used volatility models by the researchers in the field of finance. The basic model consists of equations about (i) conditional mean, and (ii) conditional variance of the error term (of conditional mean).

The conditional variance equation is:

$$\sigma_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2$$

where σ_t^2 = conditional variance of the error term.

μ_{t-1}^2 = lagged error square term.

The Generalized Auto Regressive Conditionally Heteroskedastic (GARCH) is used (called GARCH (1,1)) is employed where the conditional variance is expressed in the following equation:

Table 8 The results of LM-test statistics before and after Arima modelling of the month-of-the-year effect in S&P BSE 500 and NIFTY 500 indices. Source: Compiled from EViews7

Indices	Before ARIMA		After ARIMA			
	LM-TEST	P-Value	AR Terms	MA Terms	LM-TEST	P-Value
S&P BSE 500	30.035	0.000	1	1	0.643	0.725
NIFTY 500	30.688	0.000	1	1	0.602	0.740

$$\sigma_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 + \gamma \sigma_{t-1}^2$$

It can be observed that the lagged value of the error term and its own lagged value determines the conditional variance of the error term. A higher order GARCH (p,q) which includes 'p' terms of squared own lags, and 'q' terms of squared error terms, is rarely used in the finance literature (Brooks, 2019).

The results of GARCH Model in S&P BSE 500 and NSE NIFTY 500 indices for month-of-the-year effect were presented in Table 9.

As can be seen in Table 9, the summarized estimates viz., the coefficients of the different trading months of the year, z-Statistic (shown in parentheses), adjusted R-square, Akaike Info Criterion (AIC), and Schwarz Criterion (SBC). The regression coefficients for February, March, April, August, September, October, December were negative but insignificant for both indices. The regression coefficients of November were negative and insignificant for the NIFTY 500 Index alone. However, the regression coefficients for March are negative and significant for both indices. On the other hand, the regression coefficients for January, May, June, July and (November only for S&P BSE 500) are positive but not significant for the index. It is exciting to note that the month-of-the-year effect was negative and significant only for March for both indices. Therefore, the results document that the month-of-the-year effect is the 'March effect.'

Table 9 The Results of GARCH Model in S&P BSE 500 and NIFTY 500 indices for month-of-the-year effect. Source: Compiled from EViews7

Variables	S&P BSE 500	NIFTY 500
January (C)	1.653 (1.133)	1.466 (1.025)
February	-1.563 (-1.259)	-1.374 (-1.107)
March	-3.042 (-1.837)**	-3.001 (-1.817)**
April	-0.407 (-0.159)	-0.163 (-0.067)
May	0.033 (0.015)	0.368 (0.166)
June	0.105 (0.055)	0.325 (0.169)
July	0.527 (0.242)	0.482 (0.218)
August	-1.857 (-0.958)	-2.139 (-1.074)
September	-1.507 (-0.788)	-1.347 (-0.708)
October	-0.076 (-0.037)	-0.117 (-0.056)
November	0.011 (0.005)	-0.123 (-0.061)
December	-0.780 (-0.512)	-0.694 (-0.479)
Adj.R ²	0.207	0.212
AIC	5.407	5.373
SBC	5.806	5.772

** $p < .01$

6 Discussion

Consistent with the previous researchers, the findings of the study reveal that the ADF and PP test confirms the unit root of the return series of S&P BSE 500 and NIFTY 500 Indices. Likewise, the KPSS test confirms the stationarity of the return series of both indices. Moreover, the graphical analysis and correlogram of the study also demonstrate the stationarity of the return series of both Indices.

The maximum average or mean return occurred in July for both indices. The lowest returns occurred in March for both indices. These results indicate that among the trading months of the year, mean returns for all the months were different returns distributions. The standard deviation of the returns series occurred maximum in March for both indices. The series found that utmost volatility occurred during March. It is suggested that for intraday traders, March month is an appropriate month. The coefficient value of the Jarque–Bera test statistic is insignificant for all the months of the year except March and October. It is evident that the month-wise average returns distribution follows the normal distribution. The regression coefficients for March were negatively significant for both indices. It is exciting to note that the month-of-the-year effect was negatively significant only during March for both indices. Therefore, the results document that the month-of-the-year effect is the 'March effect.'

6.1 Explanation to the March Effect

The objective of the present study is to empirically examine the evidence of monthly seasonality in the Indian stock market during 2011 and 2021. We tested the seasonality using standard methods—testing the stationarity, kurtosis, and volatility clustering— and found that the returns showed high volatility during March. In one of the recent studies conducted in India, Harshita et al. (2018) reported significant volatility in November because of the Diwali effect. Surprisingly, we did not find the November (Diwali effect) effect in our study.

In India, the Union Finance Minister announces the budget every year at the end of February. The budget effect can be found in the prices of goods and services, and the stock market is not an exception. Now, the fundamental question remains whether the presence of the March effect signifies market inefficiency. As Brooks (2019) contends, if investment brokers cannot employ seasonality in their investment strategy, it would not be considered market inefficiency. However, some scholars argue that intelligent investors can still profit from the seasonal fluctuations (Beyer et al., 2013; Chen & Singhal, 2003; Jaisinghani, 2016). As the results indicated that significant volatility occurred in March from 2011 to 2021, it is necessary to identify the reasons or causes for the March effect. Digging up literature, various reasons were identified for results in other months. These are tax-loss selling hypothesis (Johnston & Cox, 1996; Ligon, 1997; Sias & Starks, 1997), tax-gain selling hypothesis for December month (Chen & Singal, 2003), information hypothesis (Gultekin & Gultekin, 1983), portfolio rebalancing hypothesis (Beyer et al., 2013),

liquidity hypothesis (Sharma & Narayan, 2014), optimistic expectations hypothesis (Barone, 1990).

Our results indicate the budget effect (March effect). The budget presented by Union Finance Minister plays a critical role in influencing the cost-of-living index, consumer price index, and prices in stock markets. The annual budget announced by Union Finance Minister gives information about the proposed government spending and income and sectoral allocation of funds in the coming year. The budget announcement about annual financial of estimated revenues and expenditures of the government for a fiscal year (which runs from 1st April to 31st March) provides not only the 'quantity (in terms of money to be spent and taxes on various commodities) but 'quality (which is reflected in terms of macroeconomic impact on the country) of information that is received and digested by population significantly impact the consumer behavior and investor behavior. To minimize risk and maximize returns, investors pay close attention to the budget announcements. Several studies were conducted to see the reaction of policy announcements such as budget, natural disasters such as floods, elections, and change of leadership at the Parliament on stock prices (Kaur, 2004). Some studies predominantly focused on the impact of union budget on stock prices and found that budget announcements resulted in volatility in stock prices (Gupta & Kundu, 2006; Singhvi, 2014). For example, in one study conducted by Varadharajan and Vikkraman (2011), the findings indicated that volatility in the stock market was higher in the post-budget month when compared to the pre-budget month. Other studies by Kutchu (2012) and Babu and Venkateswarlu (2013) also supported the findings of earlier researchers about the effect of the budget on the stock market. The results from our study corroborate the earlier findings of the budget effect on the stock market. Though we did not study specifically the effect of the budget on stock prices, the plausible explanation for the March effect could be linked to the Union budget announcement.

One very interesting finding from our study is the March effect, which is in a sharp contrast to some of the earlier studies conducted during June 1999- September 2015, that found November effect (Harshita et al., 2018). We were also surprised to see that there was no Diwali effect in our study period (2011 to 2021), though the Diwali effect which comes normally in the month of November. The logical explanation for the lack of Diwali effect (during November) is that the investors expect the stock prices to deviate from the ordinary course. As such, the information gets factored into the current prices. Therefore, it is not abnormal not to have a Diwali effect.

One plausible explanation for the negative deviation in March effect, which comes immediately after the budget announcement, could be in terms of pessimistic behavior of investors. Second, India being one of the largest democratic countries, the sentiments of the investors reflect the conditions in the stock market, and political factors could be factored into the equation. Though it is very difficult to explain how and why political influences would hold, investors expect growth in the economy and when they see that the growth is less than expected, the sentiments get reflected in the stock market. It is also equally possible to have positive deviation in the March effect, provided the investors are optimistic about the rate of growth in

the economy. Thus, the macroeconomic factors combined with the political influences affect the stock market anomalies, especially in Indian context.

We need to explain that when the budget is declared on 1st February every year, why could we not find the February effect? Up to 2016, the finance minister presented the budget on the last working day of February. Since 2016, the budget was presented on the 1st February in the parliament around 11 am, and there is hardly any time for the investors to assimilate information, interpret and react (businessinsider.in, 2021). Therefore, from 2011 to 2016, the budget effect was reflected in March every year. However, from 2016 to 2021, though the budget was presented on 1st February, the influence was felt only in March. It would be logical to assume that it takes at least some days to gather complete information and infer the effects of the budget on the economy. This information may be reflected in March (when we see the month-of-the-year effect). Our results support this assumption that investors take time to evaluate the budget and react to it, and hence the results are not contrary to the expectation.

6.2 Contributions of the Present Study

Despite several studies conducted about the calendar anomalies (month-of-the-year effect) by various scholars, the present study was conducted to analyze the stock market anomalies during the decade 2011–2021. The results from the study have several contributions to both the literature on finance and practicing managers. First, the study highlights the importance of studying the month-of-the-year effect during the fascinating period that has changed political power (shifting of power from the Congress to Bharatiya Janata Party in 2014), which may profoundly influence the stock market. Though we did not study the effect of change in political power, we wanted to see whether there is any month-of-the-year effect during this crucial period. One significant contribution of the results from the study is that throughout the ten years, the ‘March effect’ was pronounced, implying that change in political power did not have any impact on the month-of-the-year effect.

Second, the results show that contrary to the previous studies that documented the November effect (Harshita et al., 2018), December effect (Choithala & Ajmal, 2016), January effect (Sudarvel & Velmurugan, 2015), and February, August, and September (Debasish, 2012), our results showed March effect during the present decade (2011–2021). The study periods were, however, different from the previous studies.

Third, our results provide statistical evidence for the abnormal returns during March of every year during the study period. The results also suggest the investors be mindful of the March effect in subsequent years (2021 onwards). It is also astonishing to notice that the March effect was also pronounced even during the global pandemic COVID-19. Though the world economy was hard-hit by the pandemic, the Indian economy is not an exception, as stock prices have become highly volatile and showed a somewhat downward return trend. Finally, as the countries are coming back to normal, the stock market is expected to return to normal in the years to come.

6.3 Suggestions for Future Research

The present study provides several avenues for future research. First, future researchers may study the pre-budget and post-budget effects on the stock market over the last ten years (from 2011–2021) and see whether the effect is significant one week or two weeks before implementing the budget (during April). However, insider information about budget announcements may also have some impact on stock prices. In a democratic country, it is not impossible to get inside information before the announcement of the budget by the Union Minister. Second, future researchers can make international comparisons (by comparing the stock markets in developing countries such as Pakistan and Bangladesh) to see whether the March effect is present in those comparable countries. Third, future research can focus on the differences in stock market volatility due to global disturbances (for example, COVID global pandemic) at the international level. In the present study, the last year (the year 2020) fell under the worldwide pandemic's grip and showed some deep dip; future researchers can see how the drop was for different countries. However, international comparisons were outside the scope of the present research.

6.4 Conclusion

The findings of the study disclose the regression coefficients for March are negatively significant for both indices. It is fascinating to note that the month-of-the-year effect was negatively significant only during March for both indices. Therefore, the results document that the month-of-the-year effect is the 'March effect.' The results suggest that investment brokers and organizations take into account the March effect while making strategic financial and investment decisions. Since the investment climate has undergone paradigmatic change during the COVID global pandemic, it would be interesting to examine the post-pandemic effect on the stock market. It also would be interesting to see whether the history gets repeated after the pandemic about a century ago in the world, where most of the countries had suffered. However, the stock market was not that robust. With the increase in technology and resilience strategies of global companies to turn around and bounce back, it would be interesting to see how investors react during the post-pandemic era. Despite the setbacks, we hope the stock market bounces back and assumes normality. The interest in studying stock market anomalies continues to remain on the agenda of research in the field of finance and economics.

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