International Journal of Economics and Business Administration
Volume XIV, Issue 1, 2026

pp. 210-232

Analysis of Month of the Year Effect: Evidence from GARCH Model in Indian Stock Market

Submitted 20/11/25, 1st revision 01/12/25, 2nd revision 16/02/26, accepted 15/03/26

Arshi Firdous[1], Sarbapriya Ray[2]

Abstract:

Purpose: *The article investigates the stock market anomalies and volatility of returns for Indian stock market, namely, NSE comprising monthly data from January 1996 to December 2023.*
Design/Methodology/Approach: *Simultaneously, GARCH (1,1) and EGARCH (1,1) along with OLS dummy variable technique are applied to assess the volatility of the National Stock Exchange (NSE) of India. Test for presence of ARCH effects is done before the application of GARCH models. Augmented Dickey Fuller test as well as Phillips-Perron test is conducted to judge stationary. The presence of ARCH effect is judged first and then time varying volatility clustering is ascertained by ARCH heteroskedasticity test.*
Findings: *The result suggests that, for NSE, there exists July, November, December effect in returns while using GARCH (1,1); December effect for NSE while using EGARCH and dummy variable regression analysis. There exists asymmetric effect in NSE market, but the impact of unfavourable news (bad news) is weaker than favourable news (good news) and volatility take a very short time to die out. Evidently, 'July effect' is prominent in NSE suggesting novel findings as no 'July effect' is found in Indian stock market by any previous research studies and also November effect in case of NSE corroborates the findings of other researchers.*
Practical implication: *This result might be valuable for potential investors in protecting their equity portfolios from unanticipated shocks and making superior investment decisions to evade big, unforeseen losses. This study also underlines crucial periods which policymakers and potential investors ought to scrutinize intensively to be aware of the economic buoyancy in Indian financial market well.*
Originality /Value: *One very motivating result from the study is the 'July effect', which is in a prickly contract to several former studies conducted during their respective selected study period. This 'July effect' significantly appeared in NSE suggests novel findings as no 'July effect' is found in Indian stock market by any previous research studies. The implication of this research endeavour lies in its contribution to the greater perception of how prospective investors in India can resolve their investment decision with volatile stock market conditions.*

Keywords: *GARCH, EGARCH, NSE, stock returns, volatility, India.*

[1]*Research Scholar, Dept. of Commerce, University of Calcutta, India,*
ORCID: 0009-0004-6334-2224, e-mail: firdousarshi09@gmail.com;
[2]*Corresponding author, Dr., Associate Professor, Dept. of Commerce, Vivekananda College, under University of Calcutta, India, ORCID: 0000-0002-5848-4824,*
e-mail: sarbapriyaray@gmail.com;

JEL classification: *G11, G12, G14, G15.*

Paper type: *Research article.*

1. Introduction

Studying stock market's behaviour is one of complex topics in finance because different people interpret the market in different ways and accordingly take steps for stock market operation. Financial analysts and researchers approached this topic from various angles for having better insight on how the market behaves. Two key elements of stock market behaviour are returns and volatility, which are closely related.

The Efficient Market Hypothesis (EMH) is a fundamental assertion in portfolio management, proposing that in a fully informed market, asset prices should reflect their true values based on all available information (Fama, 1965; Fama *et al.,* 1969). It suggests that returns from stock are unpredictable and track no consistent pattern.

However, numerous market anomalies have been identified that challenge the EMH, such as 'day of the week effect', 'holiday effect', ' month of the year effect', ' turn-of-the-month effect', 'small-firm effect', and 'announcement effects'.This calendar anomalies are related to the major disparities in mean of returns for diverse months of particular year, which indicates that a specific month generates a considerably diverse (lower or higher) return in comparison to further remaining months of the year.

Since Fama (1965) and Cross (1973) began studying these anomalies, many other researchers, including Thaler (1987a, 1987b), have explored and documented these patterns in markets worldwide. Mills and Coutts (1995) observed that one of the most common anomalies is the January effect, where stock returns are typically superior in January than in other months. These anomalies are often linked to behavioural factors (Schwert, 2003) and have been found similarly in developed as well as emerging markets.

Some of these patterns had been present for over last 50 years, prompting a great deal of economic analysts to enquire into the validity of market efficiency and the Capital Asset Pricing Model (CAPM). The presence of such anomalies may indicate the yearn for alternative or substitute models of asset pricing. While certain anomalies, such as the 'day of the week' effect, may not directly contradict the CAPM, they are notable for their consistency.

Bowers and Dimson (1988) distinguish between anomalies that arise from trading inefficiencies (like 'half of the month' or the 'day of the week' effects) and those with broader economic significance (like the 'small firm' effects).

Researchers like Lakonishok and Smidt (1988) have cautioned against fully accepting these anomalies until they have been confirmed through various studies across different time periods and data sets.

In this light, our research focuses on assessing stock market anomalies through 'month of the year' effect based on a new data set, specifically the NIFTY 50 indices, from January 1996 to December 2022. Although research on anomalies in growing markets such as India is limited, our study seeks to highlight the subsistence of these effects, predominantly the most notable one 'month of the year effect'.

Our paper is arranged in the following manner: first, we re-evaluate existing narratives present in the domain on capital market anomalies, then we outline the objectives and hypotheses of our study. Next, we discuss the methodology and present statistical evidence on the anomalies, offering interpretations of the findings. Lastly, we examine the implications of our research and provide conclusions.

2. Review of Existing Literature

The literature thrives with lot of stock market seasonality. Month-of-the-year, week-of-the-month, day-of-the-week, and hour-of-the-day impacts are examples of documented seasonality. Numerous research on security price anomalies has been developed since the groundbreaking exertion of Fama (1965). While the chronological substantiation of seasonality in stock market returns had been found by Fields (1931) and Wachtel (1942), scientific examination of anomalies in stock market started with Cross (1973) which was followed by French (1980).

Although the past is full of studies which addressed various kinds of stock market anomalies, unfortunately, the results are indecisive and contradictory. As the purpose in the current study is to empirically test the month-of-the-year effect, we found that majority of the research studies had recognized the January effect (Aggarwal and Rivoli, 1989; Agrawal and Tandon, 1994; Asteriou and Kavetsos, 2006; Beyer *et al.,* 2013; Floros, 2011; Pettengill, 1986; Wilson and Jones, 1993).

Gultekin and Gultekini (1983) found that the January effect was prevalent in thirteen countries out of seventeen countries. Brown *et al.* (1983) illustrated 'January effect' as the tax-loss selling hypothesis under which investors are led to sell out stocks at the end of year in order to obtain tax-related advantages.

Thus, the prices become lowered and afterward bounce back during January. The following research studies also substantiated the tax-loss selling January effect hypothesis (Chen and Singal, 2003; Keim, 1983; Reinganum, 1983; Raj and

Thurston, 1994; Choudhary, 2001; Pandey, 2002; Elango and Pandey, 2008; Boudreaux, 1995; Rossi, 2015).

There is a wide range of research findings, but unfortunately, there is no agreement in finding the month-of-the-year effect. In France, Norway, US, Denmark, Spain, Germany, Sin/Mal, Malaysia and Switzerland also, January effect was found by different scholars across the world (Keim, 1983; Boudreaux,1995; Wong *et al.,* 2007). In case of China market, Gao and Kling (2005) documented 'March and April' effects, but Luo *et al.* (2009) had not detected any effects of a month-of-the-year.

The January effect did not occur in the stock market of New Zealand (Li and Liu, 2010). Silva's (2010) study found no 'January effect' in the stock market of Portugal. July effect had been observed in Ghana's stock market (Albert *et al.,* 2013), the Indonesian stock market's best month was December (Rahario, Siregar, and Anwar, 2013).

In relation to literature review for the Indian stock market, March to May effect was discovered by Patel (2008), April, November, and December effects were discovered by Rengasamy and Pandey (2008), Diwali effect was discovered in Harshita *et al.* (2018). Doran *et al.* (2008) found that Chinese stock markets, especially the more volatile stocks, tend to perform better around the Chinese New Year, but not in January.

Similarly, Brown and Luo (2004) discovered a new January effect in their study of the NYSE equal-weighted stock index from 1941 to 2002. They found that January's stock returns are better predictors of the following 12 months' returns compared to returns from any other month. Öztürk *et al.* (2018) conducted a study on the Turkish market using the BIST100 and KAT30 indices, concluding that anomalies such as Ramadan effect, day-of-the-week effect and January effect do not significantly affect stock returns and volatility.

This finding aligns with the EMH, suggesting that the stock market of Turkey is efficient and not prone to seasonal or timing-based strategies. Arendas and Kotlebova (2019) explored the Turn of the Month effect in eleven Central and Eastern European stock markets. Over a 20-year period (1999–2018), they observed this upshot in 7 of the 11 countries studied, though it influenced stock returns rather than price volatility.

Similarly, Bajaj *et al.* (2019) identified a 'September effect' in the stock market of India. Bhatia (2020) found no evidence of significant seasonal irregularities in the stock market of India, aside from minor volatility around the financial year-end. This further indicates a trend toward market efficiency, with little opportunity for investors to profit from timing strategies. Jumintang and Utami (2022) investigated the IHSG index and detected a month-of-the-year effect in April.

Global indices like the DJIA, SSEC, and N225 showed similar effects in October, September, and July, respectively, indicating that such anomalies continue to impact stock returns and may lead to market inefficiencies. Elangovan *et al.* (2022) studied 'month-of-the-year' effects in the stock markets of India applying BSE Ltd and NSE broad market cap indices. Their findings revealed a "March effect". Acharya *et al.* (2024) found evidence of a "September effect" in the returns of both Sensex and Nifty using GARCH models with help of time series data on daily basis of Sensex and Nifty from 1996 to 2021.

These studies highlighted that investor awareness, once heightened, reduces the profitability of such patterns, leading markets to revert to efficiency. However, some anomalies, such as the small firm effect, continue to persist despite increased awareness, suggesting that certain market inefficiencies may still linger in specific contexts.

Overall, these studies suggest that while seasonal anomalies have been observed in various markets, many of them appear to fade as markets become more efficient and investors become more informed. This evidence aligns with Fama's EMH, suggesting that over time, markets move toward efficiency, leaving less chances for investors to exploit predictable patterns for abnormal returns.

In pursuance of insight obtained after a thorough analysis of existing literature, the rationale behind the present analysis is to explore the existence of seasonal anomalies in terms of 'month of the year effect' in stock returns in NIFTY 50. We make use of daily closing share price data of the NIFTY 50 for the period, January 1996 - December 2023 which covers a number of notable macroeconomic, political and stock market reforms that happened in India.

2.1 Aim of the Research Study

The prime objective of the study is to explore the subsistence of 'month-of-the-year effect' in NSE Market of India. The overall goal is divided into the following sub-goals:

1) To empirically test month-of-the-year effect for the period 1st Jan 1996 to 31st Dec 2023 in National Stock Exchange of India.
2) To provide an explanation for the reasons of month-of-the-year effect in the Indian stock market context.

2.2. Hypothesis

The following hypothesis is formulated for assessing month of the year effect:

H_0 (Null Hypothesis): There is no month-of-the-year effect in National Stock Exchange of India.

H_1 (Alternate hypothesis): There is month-of-the-year effect in National Stock Exchange of India.

3. Research Methodology

3.1 Data Database

Monthly stock prices of NSE Nifty50 from 1st Jan 1996 to 31st Dec 2023 from NSE site have been considered. Many seasonality studies followed in emerging and developing economies took on the methodology like that of the research of the developed stock markets (Keim, 1983; Kato and Schallheim, 1985; Jaffe and Westerfield, 1989).

The techniques of voluminous studies have been disparaged as they failed to manage the issues of autocorrelation, normality, heteroskedasticity etc. In this research study, we employ a stronger methodology as discussed below. The seasonal impact is essentially verifiable on the market indices or massive portfolios of shares rather than separate shares (Boudreaux, 1995). This examination provides monthly returns of NSE Nifty50 Index during the period 1996-2023. We measure the stock return as the continuously compounded monthly change in terms of percentage in share price index as indicated above:

$$r_t = (\ln P_t - \ln P_{t-1}) \times 100 \quad (1)$$

where r_t is the return in the period t, Pt is the monthly average share price of the Sensex for the period t and ln natural logarithm.

3.2 Modelling the Day-of-the-Week Effect

OLS Dummy Variable Regression Equation Model:
Most studies investigating month-of-the-year effect in returns employed the standard Ordinary Least Square (OLS) methods by regressing returns on 11 dummy variables. In this study, a dynamic OLS model on return series is used in the following manner.

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

$$y_t = \alpha_1 + \alpha_2 D_{Feb} + \alpha_3 D_{Mar} + \alpha_4 D_{Apr} + \alpha_5 D_{May} + \alpha_6 D_{Jun} + \alpha_7 D_{Jul} + \alpha_8 D_{Aug} + \alpha_9 D_{Sep} + \alpha_{10} D_{Oct} + \alpha_{11} D_{Nov} + \alpha_{12} D_{Dec} + \varepsilon_t \quad (2)$$

In order to evade dummy variable trap, dummy variable representing the month of January has not been included. So, the intercept term α_1 indicates mean return for the month of January and coefficients $\alpha_2 \ldots \alpha_{12}$ represent the average differences in return between January and each other month which commences from February trading month to December trading month, except for January. Hence, the coefficient of each variable computes the additional outcome of the respective month compared to the base month i.e., January.

If the magnitude of the coefficients from $\alpha_2$to $\alpha_{12}$is reached zero, then the return for each month of the year is the same and no substantiation of month-of-the-year effect subsists. and ε_t indicates white noise error term. This approach, however, may be flawed because the residuals may have serial correlation.

A dummy variable for month of-the-year has been utilized for testing monthly seasonality. The approach quantifies qualitative variables, such as months, as independent variables of the regression equation. A dummy variable (also known as categorical, indicator or binary variable) is a variable which must have simply two values of 1 or 0. 1 represents the occurrence of an attribute, and 0refers to the lack of the attribute. In real life, for categorical variables with q categories, (q-1) dummies must be built, one category excluded.

Therefore, the dummy variable will have the value of unity for a specific month and zero value for all months. We have an intercept term and dummy variables for all but one of the months. The model also does not include the month of January which enables the month to serve as a base month in comparison to the rest of the months.

Therefore, the missing month, i.e., January, is our reference month. The omission of January was justified on the grounds that January- has no accurate monthly anomaly itself based on the review of the research. Several empirical research has found the 'year-end' effect and the 'January effect' in stock returns wide spread with the hypothesis of 'tax-loss selling' in industrialized countries (Wachtel, 1942), Rozeff and Kinney (1976), Keim (1983), Gultekin and Gultekin (1983), (Lewis, 1989) in UK, (Officer, 1975; Brown, Keim, Kleidon and Marsh, 1983) in Australia, (Berges, McConnell, and Schlarbaum, 1984; Tinic, Barone-Adesi and West, 1990) in Canada, (Aggarwal, Rao and Hiraki, 1990) in Japan, Boudreaux (1995) in Denmark, Germany and Norway, Raj and Thurston (1994) in NZ, Brown and Luo (2004) in USA.

Moreover, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Test were used to test stationary features. Autocorrelation and Heteroskedasticity test have been conducted prior to testing month of the year effect.

GARCH (1,1) Framework:

Using the GARCH framework, we examine the ‘month of the year’ effect for returns and volatility. As explanatory variables, we incorporate appropriate lagged values of returns. This will make certain that no specification inadequacies exist either in the conditional mean or in the conditional variance of return.

The GARCH model had been initiated by Bollerslev (1986), which was a generalized version of a seminal paper originated by Engle (1982), who pioneered the ARCH model. The GARCH model has been assumed as a unique model that could effectively include the original volatility of financial variables (Bera and Higgins, 1995).

We could have made use of the standard OLS technique, which was executed in the existing literature, for estimating the return along with volatility of stock market. But this model has two drawbacks. First, errors in the model may be auto correlated, and the second drawback is that the variance of the error terms may not be constant over time. Especially to solve the second drawback, the variance of the error terms is allowed to be time-dependent to include conditional heteroskedasticity. So, error terms have a zero mean and a variance that is changing with time.

There are different types of conditional heteroskedasticity models suggested in the literature. The main two are the ARCH and GARCH models. The ARCH model developed by Engle (1982) permits the variances of the forecasted return terms to change with the squared lag values of the previous error terms.

Therefore, he suggests a model that allows the forecast variance of the return equation to vary symmetrically over time. Here, the assumption is that conditional variance depends upon the past squared residual from the return equation, which is known as the Autoregressive Conditional Heteroskedasticity Model (ARCH):

$$h_t = V_c + \sum_{j=1}^{q} V_j \varepsilon_{t-j}^2 \tag{3}$$

Conditional variance may affect stock market return. The above-mentioned equation assumes the existence of constant variance. It may cause ineffective estimates if there is a time-varying variance. As a result, we incorporate the varying variance into our estimation. Here, we presuppose that error term of the return equation has a normal distribution with a zero mean and a time-varying conditional variance.

$$\varepsilon_t \left| \psi_{t-1} \sim N(0, h_t) \right. \tag{4}$$

ψ_{t-1} is the set of information at time t-1. ε_t is response to the error which is conditional to previous information ψ_{t-1} .The generalized version of the ARCH model seen above is developed by Bollerslev (1986) adding also the h_t terms.

$$h_t = V_c + \sum_{j=1}^{q} V_{Aj} \varepsilon_{t-j}^2 + \sum_{j=1}^{p} V_{Bj} h_{t-j} \qquad (5)$$

h_t s are conditional variances specified as GARCH(p,q). This model is known as GARCH (p,q). Here, this specification requires that $\sum_{j=1}^{q} V_{Aj} + \sum_{j=1}^{p} V_{Bj} < 1$ in order to satisfy the non-explosiveness of the conditional variance and each of $V_A > 0$; $V_B > 0$; $V_C > 0$. These must be positive to satisfy the non-negativity of the conditional variance. Furthermore, it is likely to include exogenous variables in the GARCH model, and its specifications are usually used in the literature.

EGARCH Framework:

The leverage effect is the correlation between past returns and future volatility. There is negative correlation between volatility and stock returns. With the decline in stock prices, volatility increases. With rising volatility, expected returns are anticipated to rise which leads to decline in stock prices. Also, when stock prices fall, financial leverage increases, leading to an increase in stock return volatility (Aydemir *et al.* (2007), Harvey (2013). Leverage effects enable the conditional variance of random variable, σ^2_t to respond asymmetrically to positive and negative values of r_t. Unfortunately, GARCH models enforce a symmetric response of volatility to positive and negative shocks.

Consequently, to capture leverage effect, on a logarithmic expression, Nelson (1991) proposed an Exponential GARCH (EGARCH) model; it is an improvement over the GARCH model, and it is useful in detecting the existence or nonexistence of the leverage (asymmetry) impact.

The traditional GARCH model assumes both positive and negative error terms will have a symmetric influence on the volatility i.e., good and bad news have an equal effect on the volatility; this assumption is mostly violated in economics and finance research.

That the magnitude of delayed innovations irrespective of their sign condition influences conditional variance is identified to be one of the disadvantages of GARCH model which can be solved by EGARCH model (Nelson 1991). Nelson (1991) introduced a measure of the sign of innovations.

GARCH model assumes that error terms, whether it is positive or negative, are having symmetric effect on volatility which ,in fact, is not proved true from several empirical studies, rather effect is asymmetric in time series owing to market imperfections (Aliyev *et al.* 2020) accompanied by diverse reactions of investors with respect to good or adverse information or news.

The literature on volatility clustering has documented asymmetric behaviours of volatility to shocks (Engle and Ng, 1993; Pagan and Schwert, 1990). Several asymmetric non-linear GARCH models have been proposed to model both volatility clustering and asymmetric effects of past shocks on volatility.

These models include the EGARCH model (Nelson, 1991) and the TGARCH model (Zakoian, 1994). The benefit of the EGARCH model over the TGARCH model is that EGRACH captures not only the asymmetry of stock returns but also overcomes the limitation of non-negativity constraints of the α_0, α_1, andβ_1.

The linear GARCH model, which states that equal positive and negative shocks produce the same fluctuations in equity prices, is insufficient for explaining the asymmetry effect in financial markets. Nelson introduced the exponential GARCH model, also known as the EGARCH model, which uses the same governing equation but with varying degrees of volatility. The conditional mean equation is given by:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \varepsilon_t \tag{6}$$

Indeed, the application of EGARCH suggests that the assumption of normal distribution has been relaxed in modelling the effect of volatility (Ali (2013). The EGARCH model is specified as follows (Nelson, 1991; Brooks, 2008) where the conditional variance equation is given by:

$$\ln \sigma_t^2 = \omega + \lambda \ln \sigma_{t-1}^2 + \theta \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \gamma \left[\frac{|\mu_{t-1}|}{\sigma_{t-1}^2} - \sqrt{\frac{2}{\pi}} \right] \tag{7}$$

where σ_t^2 is the conditional variance since it is a one period ahead estimate for the variance calculate on any past information thought relevant. ω, λ,θ and γ are parameters to be estimated. No restrictions on parameters ω,θ and γ.ω represents constant of volatility; However, to maintain stationarity, λ must be positive and less than 1. EGARCH takes into consideration log of the variance guarantying parameters to be positive which is diverse from GARCH model.

γ indicates, the “GARCH” effect; λ assures the persistence in conditional volatility. This entails that when λ is comparatively outsized, then volatility takes a long time to disappear after a catastrophe in the stock market (Alexander, 2009; Su, 2010). The leverage effect is assessed by the magnitude of θ. For having leverage effect, θ must have to be negative and significant.

If θ = 0, in that case, the model is assumed to be symmetric. When θ <0, then positive shocks (good news) generate less volatility than negative shocks (bad news). When θ >0, it would suggest that positive innovations are more destabilizing than negative innovations (Su, 2010).

In realty, both bad / adverse news and good / favourable news have a propensity to enhance the volatility in the stock market. Truly speaking, bigger changes follow the bigger changes, and lesser changes follow the little changes. Nevertheless, negative shocks have a much larger effect than positive shocks of the equivalent magnitude (Brooks, 2008; Ali, 2013).

Hypothesis:
For testing the stock return anomalies, the hypothesis is framed as follows:

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

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

H_1: At least one coefficient is different from 0.

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

A lagged dependent variable is added as an independent variable in a regression model to capture the dynamic effects of a variable over time, essentially acknowledging that the present value of a dependent variable is influenced by its past values, helping to account for autocorrelation and provide a more accurate representation of the association between variables in time series data.

When there is autocorrelation in the error term of a regression model (meaning, the residuals are correlated with each other across time), including a lagged dependent variable can help to "clean up" the data and produce more reliable coefficient estimates.

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

4. Analysis of Results

In this study, both GARCH (1,1) and EGARCH (1,1) along with OLS are applied to assess the volatility of the National Stock Exchange (NSE) of India. Test for presence of ARCH effects is done before the application of GARCH models. the presence of ARCH effect is judged first and then time varying volatility clustering is ascertained by ARCH heteroskedasticity test (Gujarati and Porter, 2009; Brooks, 2008).

Table 1 indicates the descriptive characteristic of the return series of NSE for post liberalization period. During this period, NSE showed positive returns, however

NSE depicted negative skews of return series. A left tail event is highly undesirable as it highlights the black swan event, i.e., a negative event the occurrence of which is highly unpredictable. A negative skew is highly undesirable from investors' point of view as it indicates frequent small gain but few large losses. A fat-tailed distribution is having a magnitude for kurtosis exceeding 3 which indicates leptokurtosis. The above distribution is also leptokurtic in the nature i.e. the return series for BSE indices display the thicker tail than normal distribution indicating many prices fluctuation positive or negative away from average return.

Table 1. *Basic Descriptive statistics*

Descriptive statistics	NSE NIFTY	
	Price	Return
Mean	5577.482	0.937327
Median	4902.175	1.356523
Maximum	18758.35	24.73758
Minimum	817.7500	-30.66649
Std. Dev.	4580.376	6.730840
Skewness	0.969752	-0.612501
Kurtosis	3.187007	5.177182
Jarque-Bera	51.25475	83.99014
Probability	0.000000	0.000000
Observations	324	324

Source: *Own estimates.*

In Indian Context, these movements were typically product of "euphoria to despondency cycles" (Gupta, 1997). Jarque-Bera test suggests significant departure of return distribution from standard normality conditions.

Table 2. *Mean and Standard Deviation of NSE Returns Based on Months of a Year*

Month of the Year Effect	Mean Return	Standard Deviation
January	-0.381137	6.877145
February	0.937327	6.730840
March	-0.200241	8.570380
April	1.719050	6.393365
May	0.430091	8.676088
June	1.068575	6.554274
July	1.549484	5.509808
August	0.652087	5.643058
September	0.730878	6.792821
October	-0.282526	8.740575
November	1.746289	6.057401
December	3.279630	4.356517

Source: *Own estimates.*

Table 2 shows mean and standard deviation of returns for NSE, revealing some interesting features, While NSE shows negative January effects (year-end effect), negative March effects (Tax loss effect), and negative October Diwali effects, with volatility fluctuating throughout the year, with October being most volatile and December least volatile.

To determine the stationary property of data series, ADF and PP tests have been conducted at their levels as well as their first difference.

Table 3 indicates that for ADF value, absolute value is greater than the critical t-value at 5% level of significance for NSE at level as well as 1st difference level thereby indicating the rejection of H_0, meaning the series are stationary at their levels as well as their 1st Difference.

Table 3. *ADF and PP Test*

Return	ADF		PP	
	Level	1st diff	Level	1st diff
NSE	-17.86915 (-3.423842)# (0.0000)*	-10.37679 (-3.424247)# (0.0000)*	-17.86946 (-3.423842)# (0.0000)*	-154.3829 (-3.423886)# (0.0001)*

H_o: series has unit root; H_1: series is trend stationary; #MacKinnon critical values for rejection of hypothesis of a unit root; value in parenthesis indicates p value;
**indicates critical value at 5% level;*
Source: *Own estimate*

In Table 4, Q(k) represents the Ljung Box statistics with k number of lags after adjusting the number of parameters. In each case 35 lags have been considered and just the Q- stats(k) values with 7, 10, 15,20,25,30 and 35 have been shown.

From Table 4, it is evident that no significant auto correlation has been observed for standardized residuals after applying GARCH (1,1).

Table 4. *Autocorrelation Test for NSE*

	NSE			
Lag	OLS		GARCH (1,1)	
	Q-Stat(k)	Prob*	Q-Stat(k)	Prob*
7	87.705	0.000	2.8211	0.728
10	90.574	0.000	5.5175	0.701
15	94.406	0.000	7.8674	0.852
20	95.046	0.000	9.2477	0.954
25	97.442	0.000	16.502	0.833
30	102.84	0.000	21.640	0.798
35	105.33	0.000	22.722	0.910

H_o: There is no autocorrelation; H_1: There is autocorrelation.
Source: *Own estimate*

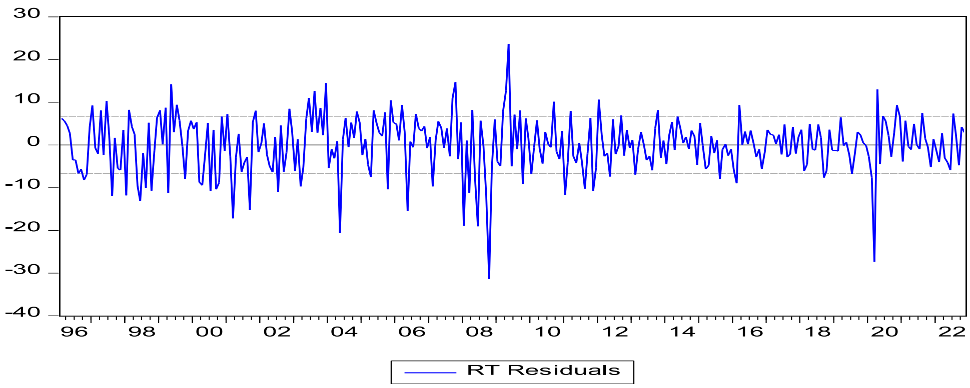
However, after applying OLS technique if we apply Q statistics it shows the presence of Auto Correlation. This indicates the OLS is not a suitable measure to judge stability of the 'month of year effect'.

Before evaluating the ARCH and GARCH models, the research effort tries to study the series of stock returns for identifying its statistical features and to observe whether it meets the pre-requisites for the ARCH and GARCH models, i.e., clustering volatility and ARCH effect in the residuals. Volatility clustering depicts the propensity of large changes in asset prices with either sign (positive/negative) to go after large changes and small changes of either sign to track minor changes (Brooks (2008).

Figure 1 illustrates graphically the 3 results of the test of clustering volatility of the residuals or error term. The Figure shows that big and small errors arise in clusters, which imply that big returns are succeeded by more big returns and small returns are followed by small returns.

In summary, the Figure implies that intervals of high stock returns are generally then more periods of high stock returns, whereas low stock return is going to be followed by much low stock return. This volatility clustering supports that error, or residual term is conditionally heteroscedastic, and it can be estimated using ARCH and GARCH models.

Figure 1. *Graphical Presentation of returns in NSE*



Source: *Authors' estimates from tabulated data.*

Table 5. *ARCH -LM TEST (Heteroskedasticity Test: ARCH)*

F-statistic	1.315708	Prob. F (1,392)	0.0000
Obs*R-squared	1.318510	Prob. Chi-Square (1)	0.0000

Source: *Own estimates.*

H_0: There is no heteroscedasticity i.e., variance for the errors is equal. In math terms, that's: $H_0 = \sigma^2{}_1 = \sigma^2$

H_1: There is heteroscedasticity i.e. variance for the errors is not equal. In math terms, that's: $H_1 = \sigma^2{}_1 \neq \sigma^2$

The statistic "Obs*R-squared" is the LM test statistic itself, which is calculated by multiplying the number of observations (Obs) by the R-squared value obtained from a regression of the residuals on their lagged values to detect serial correlation in the residuals of a regression model.

Table 5 shows the ARCH-LM test statistic where the value T^*R^2 (Obs*Rsquared) static is 1.318 with probability of 0.000 in case of NSE (p-value<0.05)suggesting rejection of null hypothesis of homoskedasticity.Since the lagged squared error term is statistically significant, it suggests that the error variances are correlated, implying that there is an ARCH effect indicating that the residuals are heteroskedastic, so there exist volatility clustering.

The study examines 'month of year effect' on the NSE over the study period, considering macroeconomic and environmental changes, market microstructure, and efficiency. The GARCH (1, 1), EGARCH (1,1) as well as OLS specification for NSE as shown in table 6 to make a comparative efficacy of the techniques, with parameter estimates and Z-statistic values for the entire period.

We witness from Table-6 that in case of NSE, the coefficients of the dummy variables for the months of July, November and December are positive and statistically significant while adopting GARCH (1, 1) technique. So, obviously, July effect is prominent in NSE suggesting novel findings as no 'July effect' is found in the context of stock market of India by any previous research studies and also November effect (corroborating the findings of Harshita *et al.,* 2018), and December effects (similar to the findings of Choithala and Ajmal, 2016) are present in NSE.

Table 6. *Month of the year effect on NSE*

	GARCH (1,1)				EGARCH (1,1)				OLS			
Variables	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000262	0.0003	0.68868	0.4910	-0.00021	0.0006	-0.354	0.723	-0.00020	0.00059	-0.34871	0.7273
DFEB	4.73E-05	0.0005	0.08189	0.9347	0.000582	0.0008	0.6681	0.504	0.000548	0.00086	0.63682	0.5243
DMAR	0.000795	0.0005	1.36223	0.1731	0.000127	0.0008	0.1537	0.877	0.000126	0.00085	0.14799	0.8824
DAP	0.000681	0.0005	1.14900	0.2506	0.001154	0.0008	1.3403	0.180	0.001118	0.00086	1.28714	0.1981
DMAY	0.000636	0.0005	1.13283	0.2573	0.000453	0.0008	0.5342	0.593	0.000435	0.00084	0.51443	0.6070
DJUNE	0.000594	0.0005	1.05441	0.2917	0.000755	0.0008	0.8728	0.382	0.000727	0.00084	0.86120	0.3892
DJULY	0.000943*	0.000	1.75773	0.0788	0.000943	0.0008	1.0683	0.285	0.000899	0.00083	1.07182	0.2838
DAUG	0.000397	0.0005	0.74255	0.4578	0.000506	0.0009	0.5589	0.576	0.000483	0.00084	0.57008	0.5686
DSEPT	0.000612	0.0005	1.11124	0.2665	0.000592	0.0008	0.6665	0.505	0.000567	0.00085	0.66555	0.5057
DOCT	0.000426	0.0005	0.74518	0.4562	2.96E-05	0.0008	0.0346	0.972	3.24E-05	0.00085	0.03785	0.9698
DNOV	0.00114**	0.0005	2.0462	0.0407	0.000877	0.0008	0.9799	0.327	0.000839	0.00084	0.98878	0.3228
DDEC	0.00110**	0.0005	2.0159	0.0438	0.0018**	0.0009	1.999	0.045	0.001729	0.00084	2.05710	0.0397
R_{t-1}									0.047597	0.01194	3.98428	0.0001
Variance Equation												
C	2.13E-06***	3.94E-07	5.40073	0.00	[ω] -8.456	6.813	-1.24	0.2145	Durbin-Watson stat	1.90521		

RESID(-1)^2	0.096226***	0.00758	12.6806	0.00	$[\lambda]$	0.0100	0.010	0.944	0.3451				
GARCH(-1)	0.8963***	0.00744	120.441	0.00	$[\theta]$	0.0100	0.007	1.370	0.1707				
T-DIST. DOF	6.854882	0.47816	14.3356	0.00	$[\gamma]$	0.0100	0.798	0.012	0.9900				
					T-DIST. DOF	20.000	1.068	18.71	0.0000				

Note: **Sig at 10% level; ** indicates sig at 5% level; *** indicates sig at 1%.*
Source: *Own estimates.*

Positive ‘July effect’ in NSE market could result from several environmental and economic factors, quantifying type of macroeconomic news like agricultural cultivators’ expectation for good *monsoon* during July and afterwards expecting higher crop yield leading to country’s GDP growth etc which might affect the stock market activities.

Therefore, Monsoon season, which remains at peak during July, is having a significant effect on the agriculture sector and the broader economy because a normal or above-normal monsoon is crucial to control food inflation and boost rural consumption. So, agricultural stocks might perform better during the monsoon season due to increased farming activities, highlighting another category of seasonal stocks in India. Moreover, July is a period when many companies (Tier-1 IT companies like TCS, Infosys, Wipro, and HCL Tech announcing their Q1 results in July) announce their quarterly earnings, which can impact stock prices. June quarter earnings will give further direction to the markets and expected to get reflected in July Stock price movements.

The observed patterns in the Indian stock market returns from, to some extent, low performance in October to strongly positive and some of the highest across the calendar months in November and December can be attributed to several economic and societal events that occur in the Indian context.

The month of October marks the beginning of the festive season with Onam, Navratri and other festivals. As we move into November, the festive season picks up with Diwali. All of this is culturally significant but also has an important impact on Indian stock markets. This is because the festive period is expected to potentially drive market momentum on the back of increased consumption spending. From purchasing items for the household to usher in the new year to receiving bonuses, all of this could contribute to increased liquidity and investment in Indian stock markets.

The "December effect" in the Indian stock market, where December tends to be a strong month for returns, is driven by a combination of factors, including portfolio rebalancing, increased festive season spending, and positive Foreign Institutional

Investor (FII) activity. Institutional investors often rebalance their portfolios in December to align with their annual performance goals. This rebalancing frequently involves increasing their equity exposure, leading to higher demand for stocks and driving prices upward.

The festive season in India, which peaks in December, leads to increased consumer spending, boosting demand for certain sectors and potentially impacting stock prices by translating to better-than-expected corporate performance projections, boosting market sentiment and driving stock prices higher. It consistently contributes to positive returns during December, driven by seasonal demand and global contract renewals.

Retail and Consumer goods, IT, and financial services companies often see a surge in sales during the festive periods like Diwali and Christmas and see a surge in December due to global contract renewals and budget finalizations by international clients. This increased business activity enhances their earnings outlook and drives stock prices upward. Foreign Institutional Investors (FIIs) tend to be more active in the Indian stock market during December, which can lead to increased buying and positive market sentiment.

Therefore, FIIs have been net buyers in the Indian stock market in December. Their increased buying activity contributes to the upward price movement during this month. In some years, the Indian economy may show signs of recovery, which can boost investor confidence and lead to positive market returns in December. Investors become optimistic and tend to be bullish about the next year's returns in December, further driving market activity.

In total, the result asserts that there is a statistically significant December effect in the Indian stock market with heightened volatility and returns regarding other months. The coefficient of the dummy variable for the month of December is positive and significant in EGARCH (1,1) signifying December effect in stock return series. The coefficients on dummy variables for the months November and December are not statistically significant in that there is no year-end effect in NSE return series.

In NSE, in the variance equation, all the parameters estimated are not statistically significant at1, 5, 10 percent level of significance. For the measure of asymmetric volatility, estimates suggest that the coefficient of the asymmetric volatility, θ, is positive [$\theta > 0$], which indicates positive innovations to be more disruptive compared to negative innovations. It demonstrates that indeed asymmetric effect does occur, but bad news (negative news) effect is weaker than good news. (good news). Here, λ (measuring the persistence in conditional volatility is 0.010 which is very small which indicates that volatility occurs in a very short duration to disappear following a catastrophe in the market.

While using OLS technique, it shows December effect in NSE stock market. The coefficient for the benchmark month of January indicated by constants is insignificantly positive in case of GARCH (1,1) and negative in both EGARCH (1,1) and OLS techniques.

Within the case of asymmetric volatility indicator, calculated values reveal that the coefficient for the asymmetric volatility, θ, to be negative, i.e., positive shocks demand a smaller next period conditional variance than negative shocks of the same sign. Explicitly, it suggests that positive shocks (positive news) create less volatility than negative news).

Therefore, if $\theta < 0$ is true, then asymmetry is true, and the impact of negative news available on the market is greater than the effect of good news; λ is the measure of persistence in conditional volatility. Now λ=0.2016 which is quite large meaning that volatility takes an elongated time to disappear following a catastrophe in the market.

In GARCH (1,1), the January (benchmark month) coefficient of NSE and BSE is0.000262 and 0.02879 respectively, that are not statistically significant and indicate there is no significant monthly return anomalies in both market as expected and thought while building econometric model.

The coefficients of intercept terms i.e., for the month of January not statistically significant maybe interpreted to accept the notion that there is no 'calendar year start effect' in Indian stock markets. The coefficients of ARCH and GARCH combined are in all cases, to some extent, less than 1 (<1) showing the variance is gradually and consistently decreasing overtime and the variance is mean reverting.

Conversely, the model would be unhealthy if the variance grew over time if ARCH + GARCH > 1. Although this can be a prerequisite, this concluding inference is precious for the overall model's point of view. All ARCH and GARCH parameters are significant at the 1% level showing that the model does very well in predicting the variance and error terms.

5. Conclusions

The essay tries to examine the stock market abnormalities and return volatility of Indian stock markets taking monthly observations of NSE during January 1996 to December 2023 based on dummy variable regression technique, GARCH (1,1) and specifically EGARCH model concurrently to assess the asymmetry of volatility clustering and the leverage effect in stock return.

The study found that the sum of the coefficients of the GARCH (1, 1) equation with constant term for NSE is less than one, indicating that volatility is persistent and decaying. The coefficient of ARCH (VA) is positive and significant in NSE market, indicating the existence of the ARCH effect.

The result also suggests that for NSE, there exists July, November, December effect in returns while using GARCH (1,1); December effect for NSE while using EGARCH and dummy variable, and December analysis.

Asymmetric effect is present in NSE market, but the effect of bad news is less than good news and volatility takes a very short time to die out.Evidently, 'July effect' is prominent in NSE suggesting novel findings as no 'July effect' is found in the context of Indian stock market by any previous research studies and also November effect in case of NSE corroborates the findings of Harshita *et al.* (2018), and 'December effects' in Indian stock market, NSE is similar to the findings of Choithala and Ajmal, (2016).

Despite fairly a lot of studies carried out about the calendar anomalies specifying 'month-of-the-year effect' by various researchers, the current study was accomplished to evaluate the stock market irregularities on one Indian stock markets, namely -NSE for the period January,1, 1990 to December,31, 2023 keeping eyes on several political regime changes (UPA-1&II; from UPA-II to NDA-I; NDA-I,II and III), several stock market catastrophes (initiating changes in macroeconomic yardsticks) like Harshad Mehta scam in 1992, Asian Financial Crisis in 1997, Global Meltdown in 2008 and more recent Covid 19 induced Pandemic catastrophes which had shaken the investors 'confidence profoundly influencing the Indian stock markets.

Whereas we had not tried to comprehend the effect of such political transformation, but we were desirous to identify whether there is any abnormality in returns or having any month-of-year effect during this critical period. This study could be an erudition in recognizing the trend of monthly mean stock return and its volatility in particular Indian stock market. This research endeavour might be accommodating for retail investors and portfolio managers in perceiving the portfolio allocation process in case of diverse month -of-the-week effect returns and volatility arising out of prevalent upheaval caused by the COVID-19 explosion.

References:

Acharya, P.N., Srinivasan, K., Mahapatra, R.P. 2024. Capturing the month of the year effect in the Indian stock market using GARCH models. Vilakshan - XIMB Journal of Management, 21(1), 2-14. Emerald Publishing Limited.

Aggarwal, R., Rivoli, P. 1989. Seasonal and day-of-the-week effects in four emerging stock markets. Financial Review, 24(4), 541-550.

Aggarwal, R., Rao, R.P., Hiraki, T. 1990. Price variations in the Tokyo Stock Exchange: International Evidence. Journal of Finance, 45(4), 1597-1606.

Agrawal, A., Tandon, K. 1994. Anomalies or illusions? Evidence from stock markets in eighteen countries. Journal of International Money and Finance, 13(1), 83-106.

Albert, L., Ida, L.A., Nasiru, S. 2013. Calendar anomalies in treasury bills rate in Ghana. International Journal of Finance and Accounting, 2(8), 417-421.

Alexander, C. 2009. Market Risk Analysis, Value at Risk Models. vol. 4, John Wiley and Sons, Hoboken.

Ali, G. 2013. E-GARCH, GJR-GARCH, T-GARCH, AV-GARCH, N-GARCH, I-GARCH and AP-ARCH Models for Pathogens at Marine Recreational Sites. Journal of Statistical and Econometric Methods, 2, 57-73.

Aliyev, F., Ajayi, R., Gasim, N. 2020. Modelling asymmetric market volatility with univariate GARCH models: evidence from Nas-daq-100. Journal of Economic Asymmetries, 22, e00167.

Arendas, P., Kotlebova, J. 2019. The impact of macroeconomic factors on stock market volatility. Ekonomický časopis, 67(4), 383-400.

Asteriou, D., Kavetsos, G. 2006. Testing for the existence of the ‘January effect’ in transition economies. Applied Financial Economics Letters, 2(6), 375-381.

Aydemir, A.C., Gallmeyer, M., Hollifield, B. 2007. Financial Leverage and the Leverage Effect: A Market and Firm Analysis. Paper 142, Tepper School of Business, Pittsburgh. http://repository.cmu.edu/tepper/142.

Bajaj, V., Nagpal, D., Thakur, A. 2019. Month-of-the-year effect: Evidence from Indian stock market. International Journal of Recent Technology and Engineering, 8(1), 443-446.

Barberis. N, Shleifer. A, Vishny, R. 1998. A model of investor sentiment. Journal of Finance and Economics, 49(3), 307-343.

Bentes, S.R. 2018. Is stock market volatility asymmetric? A multi-period analysis for five countries. Physica, A 499, 258-265.

Bera, A.K., Higgins, M.L. 1995. ARCH models: Properties, estimation and testing. Journal of Economic Surveys. 9(4), 305-366.

Berges, A., McConnell, J.J., Schlarbaum, G.G. 1984. An examination of seasonality in Canadian stock returns. Canadian Journal of Administrative Sciences, 1(1), 6-14.

Beyer, S., Beckmann, M., Menkhoff, L. 2013. The January effect revisited: Evidence against market microstructure explanations. Journal of Banking & Finance, 37(10), 4163-4174.

Bhatia, P. 2020. Spillover effects in the financial year cycle for Indian markets. Asian Journal of Accounting Research 6(1), 38-54.

Bowers, J., Dimson, E. 1988. Introduction in stock market anomalies (Ed.), Dimson E., Cambridge University Press, Cambridge, 3-15.

Bollerslev, T. 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

Boudreaux, D.O. 1995. The impact of political instability on stock market performance: Evidence from developing countries. Journal of Emerging Markets, 1(1), 20-37.

Boudreaux, D.O. 1995. The month of the year effect in international stock markets: Evidence and implications. Journal of Financial and Strategic Decisions, 8(1), 15-20.

Brooks, C. 2008. Introductory Econometrics for Finance, 2nd Edition. Cambridge University Press, New York.

Brown, P., Luo, Y. 2004. The January effect in Australia: A re-examination. Pacific-Basin Finance Journal, 12(1), 1-21.

Brown, P., Keim, D.B., Kleidon, A.W., Marsh, T.A. 1983. Stock return seasonality and the tax-loss selling hypothesis: Analysis of the arguments and Australian evidence. Journal of Financial Economics, 12(1), 105-127.

Chen, H., Singal, V. 2003. Role of speculative short sales in price formation: The Case of the Weekend Effect. Journal of Finance, 58(2), 685-705.

Choithala, F., Ajmal, T.K. 2016. December Volatility of Indian Stock Market with the special reference of Bombay Stock Exchange. International Journal of Business Quantitative Economics and Applied Management Research, 3(7), 19-24.
Choudhary, T. 2001. Month of the Year Effect and January Effect in pre-WWI Stock Returns: Evidence from a Non-linear GARCH. International Journal of Finance & Economics, 6, 1-11.
Cross, F. 1973. The Behavior of Stock Prices on Fridays and Mondays. Financial Analysts Journal, 29(6), 67-69.
Dickey, D.A., Fuller, W.A. 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427-431.
Doran, J.S., Jiang, D., Peterson, D.R. 2008. Gambling in the new year? The January effect in equity option volume. Journal of Banking and Finance, 32(11), 2103-2117.
Elango, S., Pandey, I.M. 2008. Anomalies in the Indian stock market: Day-of-the-week and other seasonal effects. International Journal of Emerging Markets, 3(3), 235-246.
Elangovan, R., Francis Gnanasekar Irudayasamy, F.R., Parayitam, S. 2022. Month of the Year effect: Evidence from Indian stock market. Asia Pacific Financial Market, 29, 449-476.
Engle, R.F. 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987-1007.
Engle, R.F., Ng, V.K. 1993. Measuring and testing the impact of news on volatility. The Journal of Finance, 48(5), 1749-1778.
Fama, E.F. 1965. The behavior of stock market prices. Journal of Business. 38(1), 34-105.
Fama, E.F., Fisher, L., Jensen, M.C., Roll, R. 1969. The Adjustment of Stock Prices to New Information. International Economic Review, 10(1), 1-21.
Fields, M.J. 1931. Stock prices: A problem in verification. Journal of Business, 4(4), 415-418.
Floros, C. 2011. Seasonality and calendar anomalies in emerging Balkan equity markets. International Journal of Emerging Markets, 6(3), 316-335.
French, K.R. 1980. Stock returns and the weekend effect. Journal of Financial Economics. 8(1), 55-69.
Gao, L., Kling, G. 2005. Calendar effects in Chinese stock market. Annals of Economics and Finance, 6(1), 75-88.
Gujarati, N.D., Porter, D.C. 2009. Basic Econometrics. International Edition McGraw-Hill/Irwin, A Business Unit of The McGraw-Hill Companies, Inc., New York.
Gultekin, M.N., Gultekin, N.B. 1983. Stock market seasonality: International evidence. Journal of Financial Economics, 12(4), 469-481.
Gupta, R. 1997. Forecasting stock market volatility. Journal of Financial Management and Analysis, 10(1), 12-20.
Harshita, H., Singh, S., Yadav, S.S. 2018. Calendar anomaly: Unique Evidence from the Indian Stock Market. Journal of Advances in Management Research, 15(1), 87-108.
Harvey, A.C. 2013. Dynamic Models for Volatility and Heavy Tails: With Applications to Financial and Economic Time Series. Econometric Society Monograph. Cambridge University Press, Cambridge.
Jaffe, J., Westerfield, R. 1989. Is there a monthly effect in stock market returns? Evidence from foreign countries. Journal of Banking & Finance, 13(2), 237-244.
Jumintang, F., Utami, K. 2022. Analysis of efficient market anomaly on stock returns on Indonesia's composite stock price index and global stock price index. International Journal of Business Ecosystem and Strategy, 4(1), 57-67.

Kato, K., Schallheim, J.S. 1985. Seasonal and size anomalies in the Japanese stock market. Journal of Financial and Quantitative Analysis, 20(2), 243-260.

Keim, D.B. 1983. Size-related anomalies and stock return seasonality: Further empirical evidence. Journal of Financial Economics, 12(1), 13-32.

Lakonishok, J., Smidt, S. 1988. Are seasonal anomalies real? A 90-year perspective. Review of Financial studies, 1, 403-425.

Lewis, M. 1989. Stock market anomalies: A re-assessment based on UK evidence. Journal of Banking & Finance, 13(2), 361-373.

Li, B., Liu, B. 2010. The January effect in the New Zealand stock market. International Journal of Business and Management, 5(1), 114-122.

Luo, Y., Li, J., Huang, Y. 2009. Political hazards and firm performance: Evidence from China. Strategic Management Journal, 30(12), 1231-1242.

Mills, T.C., Coutts, J.A. 1995. Calendar effects in the London Stock Exchange FT-SE Indices. The European Journal of Finance, 1, 79-93.

Nelson, D.B. 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347-370.

Officer, R.R. 1975. Seasonality in Australian capital markets: Market efficiency and empirical issues. Journal of Financial Economics, 2(1), 29-51.

Öztürk, M.B., Uysal, M., Arslan, H., Kayhan, T. 2018. The impact of calendar anomalies on stock return and volatility: evidence from Turkish stock market. Ömer Halisdemir Üniversitesiİktisadi Ve İdari Bilimler Fakültesi Dergisi, 11(1), 221-238.

Pagan, A.R., Schwert, G.W 1990. Alternative models for conditional stock volatility. Journal of Econometrics, 45(1-2), 267-290.

Pandey, I.M. 2002. Is There Seasonality in the Sensex Monthly Returns. IIMA Working Paper. IIM Ahmedabad.

Patel, J.B. 2008. Calendar Effects in the Indian Stock Market. International Business and Economic Research Journal, 7(3), 61-69.

Pettengill, G.N. 1986. An examination of the January effect in the stock returns of firms that issue securities. Journal of Financial Research, 9(2), 141-151.

Rahario, R., Siregar, H., Anwar, C. 2013. Stock price volatility and macroeconomic variables in Indonesia. International Journal of Business and Social Science, 4(11), 55-65.

Raj, M., Thurston, D. 1994. January or April? Tests of the turn-of-the-year effect in the New Zealand stock market. Applied Economics Letters, 1(4), 81-83.

Reinganum, M.R. 1983.The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects. Journal of Financial Economics, 12(1), 89-104.

Rengasamy, R., Pandey, R. 2008. Indian stock market volatility: Leverage or feedback effect? Vikalpa: The Journal for Decision Makers, 33(4), 23-34.

Rozeff, M.S., Kinney, W.R. 1976. Capital market seasonality: The case of stock returns. Journal of Financial Economics, 3(4), 379-402.

Rossi. 2015. The efficient market hypothesis and calendar anomalies: a literature reviews. International Journal of Managerial and Financial Accountin, 7(3/4), 285-296.

Schwert, G.W. 2003. Anomalies and market efficiency. in handbooks of the Economics of finance (Eds)., G. Konstantinides, M. Harris, R. Stulz. North-Holland, Amsterdam. 937-972.

Silva, P.M. 2010. Calendar "anomalies" in the Portuguese stock market. Investment Analysts Journal, 39(71), 37-50.

Su, C. 2010. Application of E-GARCH Model to Estimate Financial Volatility of Daily Returns: The Empirical Case of China. Master's degree Project No. 2010: 142. University of Gothenburg, Gothenburg.

Thaler, R.H. 1987a. Anomalies: The January effect. Journal of Economic Perspectives, 1, 197-201.

Thaler, R.H. 1987b. Anomalies: seasonal movements in security prices II: Weekend, holiday, turn of the month and intra-day effects. Journal of Economic Perspectives, 1, 167-77.

Timmermann, A., Granger, C.W.J. 2004. Efficient market hypothesis and forecasting. International Journal of Forecasting, 20(1), 15-27.

Tinic, S.M., Barone-Adesi, G., West, R.R. 1990. Seasonality in Canadian stock prices: A test of the "tax-loss-selling" hypothesis. Journal of Financial and Quantitative Analysis. 25(1), 109-123.

Wachtel, S.B. 1942. Certain observations on seasonal movements in stock prices. The Journal of Business of the University of Chicago, 15(2), 184-193.

Wilson, J.W., Jones, C.P. 1993. Comparison of Seasonal Anomalies across Major Equity Markets: A note. Quarterly Review of Economics and Finance, 33(1), 119-126.

Wong, K.A., Hui, Y.V., Chan, K.C. 2007. Day-of-the-week effects: Evidence from developing stock markets. Applied Economics Letters, 14(2), 1101-1104.

Zakoian, J.M. 1994. Threshold heteroskedastic models. Journal of Economic Dynamics and Control, 18(5), 931-955.