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CALENDAR ANOMALIES IN THE BANKING AND IT INDEX: THE INDIAN EXPERIENCE

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ABSTRACT

The present study seeks to inspect the calendar effects in major service sector indices in the Indian securities market. The Banking sector and Information technology sector are identified as the prominent service sectors in the Indian economy. BSE Information Technology Index and BSE Bankex are considered as a proxy for the Information Technology and Banking sector. Period of study is chosen from the year 2010 to 2019 to examine the impact of calendar anomalies post-recession. Daily index returns are considered during the period of study .GARCH family models and OLS regression techniques were utilized for the study. Empirical findings indicate the presence of the January effect and turn of the month effect on the index returns and volatility. The study also suggests the possibility of a weak form of efficiency for the IT sector. Significant volatility persistence is observed in both the indices. The study has benefits for regulators to understand the price movements of the service sector after the global recession and frame their policies accordingly. Investors will benefit from this study for effective portfolio management.

Contribution/ Originality: This study is one of very few studies which have investigated the calendar anomalies in the Banking sector and Information technology sector indices for the Indian securities market. The paper's primary contribution is finding the presence of calendar anomalies in index returns and volatility.

1. INTRODUCTION

The validity of fundamental and technical analysis to forecast the price of securities has been questioned in many studies (Malkiel, 2003; Roberts, 1959). These authors argue about prices reflecting all the available information. However, Fama (1991) explained that it is not possible to measure the efficiency of markets but mentioned certain aspects that can be captured and studied. Calendar anomaly is one such aspect that has a growing body of literature for understanding the price response of securities.

Several studies have discussed the incidence of calendar anomalies in the Indian market (Jaisinghani, 2016; Kumar, 2016; Raj & Kumari, 2006). Indian market is developing compared to other emerging markets and has been the focus of global investors. Knowledge of different calendar anomalies may help investors to reap gains by timing their investments. However, there have been not many studies to test the calendar anomalies in the Banking Sector and the Information Technology sector post-recession. The global recession has created a lot of turbulence in the Indian equity markets. The service sector has also been affected. Banking and Information Technology are the main

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facets of service marketing in India. Therefore the importance lies in understanding the anomalies effect on the pricing pattern of these two sectors after the recession period from 2008 to 2009.

The present study attempts to bridge this gap by examining the calendar anomalies in BSE-BANKEX and BSE-IT indices. The Bombay stock exchange(BSE) is the oldest and is the major stock exchange in India. BSE-BANKEX index comprises of select stocks of listed banks from the banking sector. Similarly, the BSE-IT index comprises of select stocks of listed Information Technology companies from the Information Technology sector. Hence these two indices can be considered as a suitable representation for the Banking and Information Technology industry. The next portions of the paper are segregated as follows. Section 2 deals with extant literature, section 3 is about the sample and research equation, section 4 discuss findings, section 5 provides the conclusion and section 6 is about the future scope of the study.

2. REVIEW OF LITERATURE

Several studies have discussed calendar effects in stock markets. The popular calendar effects discussed in various papers are Day of the Week (DOW) effect (Narayan, Mishra, & Narayan, 2014; Solnik & Bousquet, 1990) and month of the year effect (Roll, 1983; Rozeff & Kinney, 1976).

2.1. Day of the Week Effect (DOW)

Gibbons and Hess (1981) suggest that returns are always lower on Mondays. Keim and Stambaugh (1984) find that for various indices, the returns are negative on Mondays and positive on Fridays. A strand of literature explains the absence of Institutional trading behind the Monday effect (Lakonishok & Maberly, 1990; Ritter, 1988). Some other studies argue about the scarcity of analyst reports as a possible reason for the negative returns on Mondays (Dubois & Louvet, 1996; Solnik & Bousquet, 1990). However, Jaffe and Westerfield (1985) observe that Tuesdays have the highest negative returns compared to Mondays. In a striking difference, recent work by Abdalla (2012) finds the absence of the day of the week effect in the Sudanese stock market.

Similar studies have been done on the Weekend effect (Abraham & Ikenberry, 1994; Boudreaux, Rao, & Fuller, 2010; Poshakwale, 1996). Jaffe and Westerfield (1985) also find the presence of weekend effects in Australia, Canada, Japan, and the UK. However, Demirer and Karan (2002) find no evidence of the weekend effect in Australia, Canada, Japan, and the UK. Lauterbach and Ungar (1992) also explain weak evidence of the weekend effect in the Israeli stock market.

2.2. Month of the Year Effect

Many researchers suggest that due to differences in returns in different months, an investor can find opportunities for abnormal gains (Floros & Salvador, 2014; Haug & Hirschey, 2006; Rozeff & Kinney, 1976). There have been studies that discuss the January effect (Chatterjee & Maniam, 1997; Keim, 1983). Ligon (1997) explains about higher turn over having significance with the January effect. Bensman (1997) describes the January effect as an outcome of the irrational exuberance of investors. In contrast to these studies, Raj and Thurston (1994) argue that there is an absence of the month of the year effect in New Zealand.

2.3. Volatility Clustering

Volatility has been assumed as a proxy for risk. The risk lies in a change of asset value. Highly volatile stocks are expected to have a wider change in value, while for less volatile stocks the change may be marginal. Volatility modeling is important for portfolio management and the pricing of securities (Engle & Ng, 1993). Most authors have applied GARCH family models to examine the volatility patterns (Corrado & Miller, 2005; Guidi, Gupta, & Maheshwari, 2011; Pagan & Schwert, 1990).

There have been studies to look into calendar effects on stock return volatility. Tsoukalas (2000) applied the autoregressive conditional heteroscedasticity (ARCH) model and discovered the presence of volatility clustering in Japan, the USA, and the UK. In a similar study in India, Karmakar (2007) deploys various GARCH-based models and provides evidence of volatility clustering.

Based on these studies, the research tries to investigate whether Monday has the day of the week effect(DOW) and January has the month of the year effect in Banking and IT indices. Further, the research seeks to examine the presence of two other calendar anomalies in these indices. Thursday in the Indian stock market has its importance due to the settlement of delivery contracts. Most of the derivative contracts expire on Thursdays. The study seeks to examine whether its impact on the volatility and returns of these two indices. The second anomaly the research tries to examine is the turn of the month effect. For this purpose, the study period is the final trading day of the previous month and the next three consecutive trading days of the current month to detect turn of the month (TOM) effect.

3. DATA AND METHODOLOGY

3.1. Dataset and Variable Representation

The data for indices are downloaded from the BSE website, maintained by the Bombay stock exchange platform of India. Daily closing prices of BSE-BANKEX and BSE-IT are selected for the study. The reason behind choosing daily data is that daily observations exhibit more volatility than weekly and monthly data (Jebran, 2018). Both the indices are a good representative of Banking and Information Technology securities of the Indian capital market. The current study examines the various calendar anomalies and volatility clustering for the financial year 2010-2019. The study period is chosen to examine the effect of anomalies post-recession. Data is available for both the indices during the period of study.

Consistent with prior studies the different calendar anomalies to be applied in this paper have been proxied by dummy variables. The different dummy variables mentioned are as follows:

D1 - Detect the calendar anomaly by considering Monday as day of the week (DOW) effect.

D2 - Investigate the calendar impact by considering Thursday, when most of the derivative settlement contract has expired.

D3 - Look at the calendar effect by considering the final trading day of the previous month and the next three consecutive days of the current month as turn of the month (TOM) effect.

D4 - Find the presence of calendar effect by taking the month of January as the January effect.

Table 1 provides a brief description of the different types of anomalies mentioned in this paper. The research has considered four different anomalies to study its effect on Banking and Information and Technology industry.

Table-1. Description of different anomalies.

Variable	Day	Purpose of Anomalies
D1	Monday	Monday effect according to prior studies
D2	Thursday	Expiry of derivative contracts
D3	Last trading day of previous month and first three consecutive days of current month	Turn of the month effect
D4	All days in January	January effect according to prior studies

3.2. Methodology

The daily returns of an Index are estimated as logarithmic differences between current day and previous day closing prices. Therefore Index return at a particular day(t) denoted as R_t is estimated as follows :

$$R_t = Ln(I_t/I_{t-1}) = Ln(I_t) - Ln(I_{t-1}) \tag{1}$$

I_t and I_{t-1} refers to the daily closing prices of a particular index on day (t) and day(t-1).Here t indicates time period as daily observation.

3.2.1. OLS Regression for Calendar Anomalies

The various dummy regressors as a proxy for various calendar anomalies are embedded into the multiple regression model to find their association with returns of indices. The equation similar to that applied by Guidi et al. (2011) as a standard methodology for seasonality test is written as follows :

$$R_t = \beta 1 D1 + \beta 2 D2 + \beta 3 D3 + \beta 4 D4 + e_t \tag{2}$$

R_t is the daily index return estimated as mentioned in Equation 1.

while D1, D2, D3, and D4 are the dummy predictors which represent the various calendar anomalies.

Here,

D1 = 1 when t = Monday, else 0.

D2 = 1 when t = Thursday, else 0.

D3 = 1 when t= last trading day of the previous month and three consecutive trading days during the start of the current month, else 0.

D4=1 when t= trading day is in January, else 0.

$\beta 1, \beta 2, \beta 3, \beta 4$ coefficients represent the average daily returns for various anomalies. The coefficients of dummy regressors indicate the difference in mean returns from the mean returns observed on a normal trading day. For illustration, the coefficient of D1 explains the difference between the mean return on other trading days and the mean return on Monday. If the coefficient of a dummy predictor is significant, it means that the mean return due to that particular calendar anomaly is different from mean returns on other trading days.

e_t is the error term.

The econometric technique to model volatility clustering employs general autoregressive conditional heteroscedastic (GARCH) family equations suggested by Derbali and Hallara (2016) in the Tunisian stock market.

3.2.2. Volatility Clustering

GARCH(1,1) model (Bollerslev, 1986) suggested the generalized ARCH model(GARCH) for modeling the volatility process of an asset return. The GARCH (1,1) model incorporating the calendar anomalies in the form of the equation is as follows :

$$R_t = a_t R_{t-1} + \beta 1 D1 + \beta 2 D2 + \beta 3 D3 + \beta 4 D4 + e_t \tag{3}$$

$$\sigma^2_t = \omega_1 + \alpha_1 a^2_{t-1} + \S_1 \sigma^2_{t-1} + \beta 1 D1 + \beta 2 D2 + \beta 3 D3 + \beta 4 D4 \tag{4}$$

Equations 3 and 4 depict the mean and variance equation. R_{t-1} represents the historical information of the mean of R_t at time t-1. The four calendar anomalies used in the study are represented by D1, D2, D3, and D4. The β parameters capture the mentioned anomalies. Here a_t is the innovation captured during time t.

σ_t is a symbol for the conditional variance for the period t. ω_1 is the notation for constant. α_1 and $\S_1$ are referred to as the ARCH and GARCH parameters in the model.

EGARCH(1,1) model

The conventional GARCH(1,1) does not capture the asymmetries which are also known as leverage effects in financial time series analysis. Nelson (1991) introduced the exponential GARCH(EGARCH) model to include the asymmetric effects inherent in asset returns.

The EGARCH(1,1) model incorporating the calendar anomalies can be written as :

$$R_t = a_t R_{t-1} + \beta 1 D1 + \beta 2 D2 + \beta 3 D3 + \beta 4 D4 + e_t \tag{5}$$

$$\ln(\sigma^2_t) = \omega_1 + \S_1 \ln(\sigma^2_{t-1}) + \alpha_1 |\epsilon_{t-1}/\sigma_{t-1}| + \gamma_1(\epsilon_{t-1}/\sigma_{t-1}) + \beta 1 D1 + \beta 2 D2 + \beta 3 D3 + \beta 4 D4 \tag{6}$$

Equations 5 and 6 are the mean and variance equation. σ^2_t explains the connection between current and previous volatility. $|\epsilon_{t-1}/\sigma_{t-1}|$ is a proxy for size effect happening from unexpected disturbances. $\epsilon_{t-1}/\sigma_{t-1}$ represents leverage effect ($\gamma_1 > 0$) and the assymetry effects($\gamma_1 = 0$). ϵ_t is the error distribution as zero mean iid sequences. $\omega_1, \alpha_1, \S_1$ and γ_1 represent the parameters similar to GARCH(1,1) equation to be estimated from the model. $\beta 1, \beta 2, \beta 3, \beta 4$ capture the mentioned anomalies.

TGARCH(1,1) model

The Threshold GARCH model (TGARCH) suggested by Glosten, Jagannathan, and Runkle (1993) takes zero as its threshold to segregate the impact of past shocks. The model deals with leverage effects by capturing the asymmetries in terms of positive disturbances and negative disturbances.

The TGARCH(1,1) model incorporating the calendar anomalies can be written as :

$$R_t = a_t R_{t-1} + \beta 1 D 1 + \beta 2 D 2 + \beta 3 D 3 + \beta 4 D 4 + e_t \tag{7}$$

$$\sigma^2_t = \omega_1 + \S_1 \sigma^2_{t-1} + \alpha_1 \mu^2_{t-1} + \gamma_1 \mu^2_{t-1} N_{t-1} + \beta 1 D 1 + \beta 2 D 2 + \beta 3 D 3 + \beta 4 D 4 \tag{8}$$

Equations 7 and 8 describe the mean and variance equation.

Equation 7 is the conditional mean equation where current index return is a function of past index return(R_{t-1}) and calendar anomalies represented by D1,D2,D3,and D4. The coefficients $\beta 1, \beta 2, \beta 3$,and $\beta 4$ are the coefficients for these anomalies whereas a_t is the shock of index return at time t.

Equation 8 is the conditional variance equation where σ^2_t captures the positive and negative shocks by N_{t-1}. N_{t-1} separates the positive and negative events where 1 is a proxy for negative shock and 0 for the positive shock. Here N_{t-1} represents an indicator for negative and positive μ_t. It can be written as :

$$N_{t-1} = \begin{cases} 1 \text{ if } \mu_{t-1} < 0 \\ 0 \text{ if } \mu_{t-1} \geq 0 \end{cases}$$

From the model, it is evident that for good news(positive shock), $\alpha_1 \mu^2_{t-1}$ impact is visible for σ^2_t. Similarly, for bad news(negative shock), the larger consequence of $\gamma_1 \mu^2_{t-1} N_{t-1}$ is a contribution to σ^2_t for $\gamma_1 > 0$. The intensity of shocks in this model is tested by using zero as the reference point. $\beta 1, \beta 2, \beta 3$,and $\beta 4$ imply the effect of calendar anomaly constructed by dummy regressors D1,D2,D3,and D4 in the conditional variance equation. $\omega_1, \S_1, \alpha_1$ and γ_1 are the non-negative constants equivalent to the above-mentioned GARCH models.

4. RESULTS AND ANALYSIS

Figure 1 exhibits the distribution of BSE-BANKEX returns. It is observed that returns are volatile with the existence of volatility clusters.
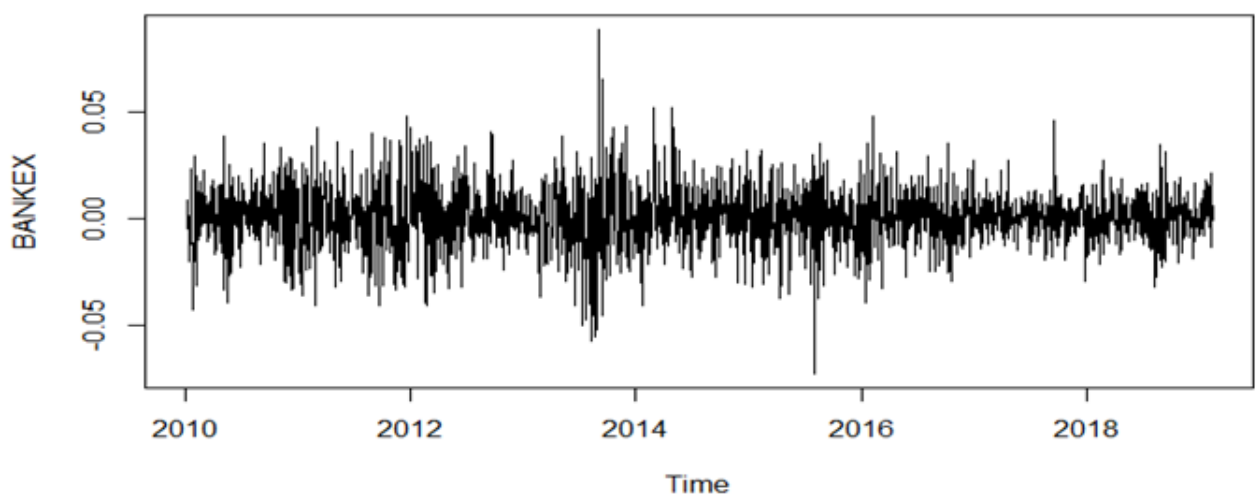

Figure-1. BANKEX returns over the period from 2010 to 2019.

Source: The graph is plotted in R package by using daily index returns of BSE BANKEX. The returns are estimated with daily closing prices of BSE BANKEX retrieved from the website of Bombay Stock Exchange, one of the popular stock exchange in India.

Figure 2 reports the distribution of BSE-IT returns. Here also there is a marked presence of volatility clusters.
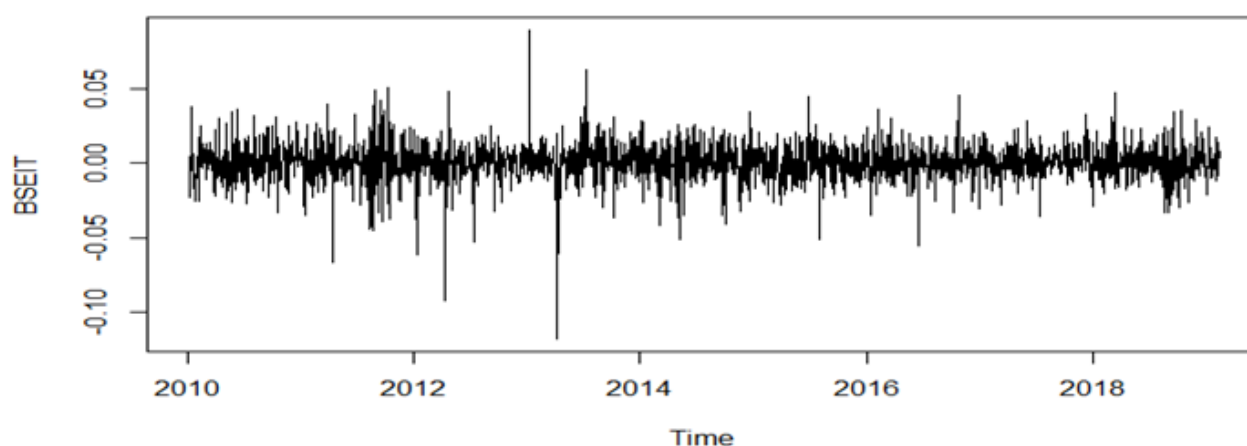

Figure-2. BSE-IT returns over the period from 2010 to 2019.
Source: The graph is plotted in R package by using daily index returns of BSE-Information Technology. The returns are estimated with daily closing prices of BSE-Information Technology retrieved from the website of Bombay Stock Exchange, one of the popular stock exchange in India.

Table 2 reports the various statistical parameters of BSE- BANKEX index returns considered for the study. The returns are highest on Mondays (0.0009192) compared to other anomalies. The Lowest return is observed for the January effect(0.0001504). Variance is marginally higher for the January effect(0.0002134) compared to other anomalies. The kurtosis coefficients point out fat-tailed distribution in their volatilities.

Table-2. Descriptive statistics – BANKEX

Summary statistic	D1 Monday effect	D2 Thursday effect	D3 Weekend effect	D4 January effect
Mean	0.0009192	0.0006713	0.0016955	0.0001504
Median	0.0001896	0.0001974	0.0001990	0.0002134
Std.Deviation	0.0137712	0.0140496	0.0141082	0.0146074
Skewness	–0.4198759	0.5676533	0.5825522	–0.1293436
Kurtosis	5.085313	7.256527	6.6312000	3.625663

Note: The dataset consists of daily index returns estimated with daily closing prices of BSE BANKEX retrieved from the website of Bombay Stock Exchange, one of the popular stock exchange in India. The duration is from April 1st, 2010 to March 31st, 2019.

Table 3 reports the various statistical parameters of BSE- IT index returns considered for the study. It is observed that the returns are highest on Mondays (0.0008256) compared to other anomalies. Negative return is observed for the Thursday effect(-0.0002441). Variance is marginally higher for the January effect(0.0002090) compared to other anomalies. The kurtosis coefficients point out fat-tailed distribution in their volatilities.

Table-3. Descriptive statistics - BSE-IT.

Summary statistic	D1 Monday effect	D2 Thursday effect	D3 Weekend effect	D4 January effect
Mean	0.0008256	–0.0002441	0.0010533	0.0006928
Median	0.0001470	0.0001488	0.0001094	0.0002090
Std.Deviation	0.0137712	0.0140496	0.0141082	0.0146074
Skewness	–0.2706330	–0.6590055	0.1530208	0.8943419
Kurtosis	4.864066	5.525175	3.762374	11.300480

Note: The dataset consists of daily index returns estimated with daily closing prices of BSE-Information Technology retrieved from the website of Bombay Stock Exchange, one of the popular stock exchange in India. The duration is from April 1st, 2010 to March 31st, 2019.

Table 4 presents the OLS regression estimates of various anomaly effects on returns of both the indices. Turn of the month effect has a positive statistical significance with Bank index returns. Further, findings confirm that there is no effect of the calendar anomalies understudy on the Information Technology index. The results support

the findings of Raj and Kumari (2006) where the authors discuss the absence of the Monday effect and January effect in India. Overall findings indicate the turn of the month as a seasonality pattern in BSE-BANKEX.

Table-4. Results of estimated OLS models.

Variable	BANKEX		BSE-IT	
	Coefficient	p-value	Coefficient	p-value
D1 Monday effect	0.0004876	0.497	0.0004487	0.491
D2 Thursday effect	0.0001748	0.811	– 0.000884	0.181
D3 Weekend effect	0.0014399**	0.050	0.0007234	0.278
D4 January effect	– 0.0004147	0.691	0.0002452	0.796

Notes: *significance at 10% level; **significance at 5% level; ***significance at 1% level.

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Table 5 reports the empirical findings of the GARCH family models applied to BSE-BANKEX. From the mean equation is observed that one lagged return (t-1) has a positive effect on volatility at a significance of 1% and is consistent across al GARCH models. This possibly suggests that the index exhibits weak form inefficiency. There is an absence of statistical significance for the mentioned anomalies with stock returns. The variance equation depicts significant evidence of volatility clustering and leverage effects. There is a significant positive turn of month effect for the EGARCH(1,1) model. However, the results are not in conformity with the other two GARCH statements.

Table-5. Results of estimated GARCH models for BANKEX.

Mean equation	GARCH(1,1)		EGARCH(1,1)		TGARCH(1,1)	
Variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
R_{t-1}	0.078641***	0.000	0.080943***	0.000	0.081169***	0.000
D1 Monday effect	0.000620	0.321	0.000570	0.220	0.000605	0.279
D2 Thursday effect	0.000268	0.672	0.000222	0.788	0.000205	0.703
D3 Turn of month	0.000626	0.356	0.000553	0.321	– 0.000581	0.305
D4 January effect	0.000767	0.440	– 0.000237	0.810	– 0.000063	0.944
Variance equation						
ω_1	0.000002	0.934	–0.123212***	0.000	0.000195***	0.000
α_1	0.057057	0.780	– 0.048122**	0.000	0.046446***	0.000
$\S_1$	0.931121***	0.001	0.985383**	0.000	0.950174***	0.000
γ_1			0.090593***	0.000	0.558503***	0.000
D1 Monday effect	0.000590	0.351	0.000813	0.15	0.000822	0.137
D2 Thursday effect	0.000322	0.724	0.000581	0.305	0.000559	0.497
D3 Turn of month	0.000637	0.371	0.000817***	0.008	0.000824	0.270
D4 January effect	– 0.000781	0.613	– 0.000179	0.835	0.000057	0.981

Notes:*significance at 10% level; **significance at 5% level; ***significance at 1% level   .

Table 6 reports the empirical findings of the GARCH family models applied to BSE-IT. From the mean equation is seen that there is no statistical significance of one lagged return(t-1) on volatility. This provides a possible explanation of the weak form of market efficiency. There is also no evidence about the statistical significance of the mentioned anomalies with stock returns except the January effect. Findings provide evidence of seasonality pattern for January. The variance equation provides evidence of significant positive turn of the month effect and January effect. EGARCH (1,1) and TGARCH(1,1) analysis confirm the turn of month effect and January effect. The GARCH (1,1) model also depicts a positive term for the turn of the month effect and January effect, though not significant. The variance equation of all models, it is observed that all the volatility parameters are highly significant at a 1% level. Overall findings suggest that the BSE-IT index has a favorable reaction to turn of the month and January effect.

Table-6. Results of estimated GARCH models for BSEIT.

Mean equation	GARCH(1,1)		EGARCH(1,1)		TGARCH(1,1)	
Variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
R_{t-1}	0.042248**	0.000	0.080943***	0.000	0.081169***	0.000
D1 Monday effect	0.000471	0.321	0.000570	0.220	0.000605	0.279
D2 Thursday effect	- 0.000541	0.672	0.000222	0.788	0.000205	0.703
D3 Turn of month	0.000391	0.356	0.000553	0.321	- 0.000581	0.305
D4 January effect	0.000281	0.440	- 0.000237	0.810	- 0.000063	0.944
Variance equation						
ω_1	0.000001	0.974	-1.067432**	0.000	0.001658***	0.000
α_1	0.004284***	0.000	- 0.067650***	0.000	0.105191***	0.000
$\S_1$	0.994489***	0.000	0.877182***	0.000	0.790829***	0.000
γ_1			0.175117***	0.000	0.405254***	0.002
D1 Monday effect	0.000760	0.193	0.000777	0.169	0.000747	0.183
D2 Thursday effect	- 0.000229	0.697	0.000581	0.551	- 0.000359	0.500
D3 Turn of month	0.000622	0.371	0.000817***	0.057	0.001065*	0.058
D4 January effect	0.000492	0.593	- 0.000179	0.010	0.002084***	0.008

Notes:*significance at 10% level; **significance at 5% level; ***significance at 1% level.

5. CONCLUSION AND IMPLICATIONS

5.1. Conclusion

The findings suggest that Day of the week effect is not observed in the Banking and Information Technology sector. However, the Thursday effect has a negative relationship with volatility, although not significant. This implies that the derivative settlement possibly reduces the index volatility. The January effect and turn of the month effect are observed in the Information Technology sector. Turn of the month affects index returns in the Banking sector. This study is quite different from extant literature in detecting the presence of different anomalies in the service industry.

5.2. Implications

This study has several implications. Findings from this study will benefit the investors in understanding the pricing pattern of these sectors. Regulators and analysts may seek to identify the causes behind the month effect in these indices. Finally, the study is a valuable contribution to the current studies on calendar effects in the Indian securities market.

6. FUTURE SCOPE OF STUDY

The scope of the work was limited to the Indian securities market. The study can be extended in a cross country approach for understanding the volatility patterns and the nexus with different anomalies. Further, a firm-specific study on different anomalies in Banking and Information Technology sector can be carried out relying on the findings from this study.

REFERENCES

Abdalla, S. (2012). Day-of-the-week effect on returns and conditional volatility: Empirical evidence from Sudanese stock market. *Middle Eastern Finance and Economics, 16*(1), 167-180.

Abraham, A., & Ikenberry, D. L. (1994). The individual investor and the weekend effect. *Journal of Financial and Quantitative Analysis, 29*(2), 263-277. Available at: https://doi.org/10.2307/2331225.

Bensman, M. (1997). Putting the market on the couch. *Institutional Investor, 31*(1), 133-135.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. Available at: https://doi.org/10.1016/0304-4076(86)90063-1.

Boudreaux, D., Rao, S., & Fuller, P. (2010). An investigation of the weekend effect during different market orientations. *Journal of Economics and Finance, 34*(3), 257-268. Available at: https://doi.org/10.1007/s12197-008-9050-6.

Chatterjee, A., & Maniam, B. (1997). Market anomalies revisited. *Journal of Applied Business Research, 13*(4), 47-56.

Corrado, C. J., & Miller, J. T. W. (2005). The forecast quality of CBOE implied volatility indexes. *Journal of Futures Markets: Futures, Options, and Other Derivative Products, 25*(4), 339-373. Available at: https://doi.org/10.1002/fut.20148.

Demirer, R., & Karan, M. B. (2002). An investigation of the day-of-the-week effect on stock returns in Turkey. *Emerging Markets Finance & Trade, 38*(6), 47-77.

Derbali, A., & Hallara, S. (2016). Day-of-the-week effect on the Tunisian stock market return and volatility. *Cogent Business & Management, 3*(1), 1147111. Available at: https://doi.org/10.1080/23311975.2016.1147111.

Dubois, M., & Louvet, P. (1996). The day-of-the-week effect: The international evidence. *Journal of Banking & Finance, 20*(9), 1463-1484. Available at: https://doi.org/10.1016/0378-4266(95)00054-2.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance, 48*(5), 1749-1778. Available at: https://doi.org/10.1111/j.1540-6261.1993.tb05127.x.

Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance, 46*(5), 1575-1617. Available at: https://doi.org/10.1111/j.1540-6261.1991.tb04636.x.

Floros, C., & Salvador, E. (2014). Calendar anomalies in cash and stock index futures: International evidence. *Economic Modelling, 37*, 216-223. Available at: https://doi.org/10.1016/j.econmod.2013.10.036.

Gibbons, M. R., & Hess, P. (1981). Day of the week effects and asset returns. *Journal of Business, 54*(4), 579-596. Available at: https://doi.org/10.1086/296147.

Glosten, L. R., Jagannathan, R., & Runkle, D. (1993). On the relationship between GARCH and symmetric stable process: Finding the source of fat tails in data. *Journal of Finance, 48*(5), 1779-1802.

Guidi, F., Gupta, R., & Maheshwari, S. (2011). Weak-form market efficiency and calendar anomalies for Eastern Europe equity markets. *Journal of Emerging Market Finance, 10*(3), 337-389. Available at: https://doi.org/10.1177/097265271101000304.

Haug, M., & Hirschey, M. (2006). The January effect. *Financial Analysts Journal, 62*(5), 78-88.

Jaffe, J., & Westerfield, R. (1985). Patterns in Japanese common stock returns: Day of the week and turn of the year effects. *Journal of Financial and Quantitative Analysis, 20*(2), 261-272. Available at: https://doi.org/10.2307/2330959.

Jaisinghani, D. (2016). An empirical test of calendar anomalies for the Indian securities markets. *South Asian Journal of Global Business Research, 5*(1), 53-84. Available at: https://doi.org/10.1108/SAJGBR-07-2014-0050.

Jebran, K. (2018). Volatility spillover between stock and foreign exchange market of China: Evidence from subprime Asian financial crisis. *Journal of Asia Business Studies, 12*(2), 220-232. Available at: https://doi.org/10.1108/JABS-01-2016-0003.

Karmakar, M. (2007). Asymmetric volatility and risk-return relationship in the Indian stock market. *South Asia Economic Journal, 8*(1), 99-116. Available at: https://doi.org/10.1177/139156140600800106.

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics, 12*(1), 13-32. Available at: https://doi.org/10.1016/0304-405x(83)90025-9.

Keim, D. B., & Stambaugh, R. F. (1984). A further investigation of the weekend effect in stock returns. *The Journal of Finance, 39*(3), 819-835. Available at: https://doi.org/10.1111/j.1540-6261.1984.tb03675.x.

Kumar, S. (2016). Revisiting calendar anomalies: Three decades of multicurrency evidence. *Journal of Economics and Business, 86*, 16-32. Available at: https://doi.org/10.1016/j.jeconbus.2016.04.001.

Lakonishok, J., & Maberly, E. (1990). The weekend effect: Trading patterns of individual and institutional investors. *The Journal of Finance, 45*(1), 231-243. Available at: https://doi.org/10.1111/j.1540-6261.1990.tb05089.x.

Lauterbach, B., & Ungar, M. (1992). Calendar anomalies: Some perspectives from the behaviour of the Israeli stock market. *Applied Financial Economics, 2*(1), 57-60. Available at: https://doi.org/10.1080/758527547.

Ligon, J. A. (1997). A simultaneous test of competing theories regarding the January effect. *Journal of Financial Research, 20*(1), 13-32. Available at: https://doi.org/10.1111/j.1475-6803.1997.tb00234.x.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives, 17*(1), 59-82. Available at: https://doi.org/10.1257/089533003321164958.

Narayan, P. K., Mishra, S., & Narayan, S. (2014). Spread determinants and the day-of-the-week effect. *The Quarterly Review of Economics and Finance, 54*(1), 51-60. Available at: https://doi.org/10.1016/j.qref.2013.07.008.

Nelson, D. B. (1991). Conditional Heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347-370. Available at: https://doi.org/10.2307/2938260.

Pagan, A. R., & Schwert, G. W. (1990). Alternative models for conditional stock volatility. *Journal of Econometrics, 45*(1-2), 267-290. Available at: https://doi.org/10.1016/0304-4076(90)90101-x.

Poshakwale, S. (1996). Evidence on weak form efficiency and day of the week effect in the Indian stock market. *Finance India, 10*(3), 605-616.

Raj, M., & Kumari, D. (2006). Day-of-the-week and other market anomalies in the Indian stock market. *International Journal of Emerging Markets, 1*(3), 235-246. Available at: https://doi.org/10.1108/17468800610674462.

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*(5), 81-83. Available at: https://doi.org/10.1108/17468800610674462.

Ritter, J. R. (1988). The buying and selling behavior of individual investors at the turn of the year. *The Journal of Finance, 43*(3), 701-717. Available at: https://doi.org/10.1080/135048594358195.

Roberts, H. V. (1959). Stock-market" patterns" and financial analysis: Methodological suggestions. *The Journal of Finance, 14*(1), 1-10. Available at: https://doi.org/10.2307/2976094.

Roll, R. (1983). Vas ist das? *The Journal of Portfolio Management, 9*(2), 18-28. Available at: https://doi.org/10.3905/jpm.1983.18.

Rozeff, M. S., & Kinney, J. W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics, 3*(4), 379-402. Available at: https://doi.org/10.1016/0304-405X(76)90028-3.

Solnik, B., & Bousquet, L. (1990). Day-of-the-week effect on the Paris Bourse. *Journal of Banking & Finance, 14*(2-3), 461-468. Available at: https://doi.org/10.1016/0378-4266(90)90059-b.

Tsoukalas, D. (2000). An autoregressive heteroskedastic in the mean (ARCH-M) analysis of international stock market indexes. *Managerial Finance, 26*(12), 46-56. Available at: https://doi.org/10.1108/03074350010767043.