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Do Festival Seasons Boost Share Prices? Evidence from Indian Stock Market Trading Patterns

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ABSTRACT- The purpose of this research is to determine if there are certain short-horizon market patterns for each of the festival seasons within India. The data was collected using a quasi-experimental calendar event design from January 2010 through December 2024. Trading days were divided into three categories for both the broad market and sector index: before, during and after each festival season. These three categories were then used to calculate returns, realized volatility and turnover for each category relative to their respective matched control periods of non-festival days. Results indicated an identifiable pre-festival period of lower volatility with small, statistically insignificant increases in average daily returns; however, both returns and volatility during and after the festivals decreased. These results suggest that festival seasons create a more consistent near-term risk environment compared to creating consistent expected returns, which supports models based on attention and sentiment, where the increased attention creates a calming effect on trading but does not provide sufficient premium to warrant significant investment or strategy development. Limitations to this study include daily frequency (excluding micro-structure at the intra-day level) and discrete window definitions that may not accurately capture the cycle of anticipation surrounding the festival season. The practical application of these findings are related to managing risk and operating markets: Position size and liquidity provision may be adjusted around anticipated low volatility periods.

KEYWORDS- Festival Seasons, Holiday Anomalies, Volatility Compression, Event Study, Indian Equities, Investor Sentiment.

1. INTRODUCTION

Seasonal or calendar regularities in stock returns most famously the “pre-holiday effect” have long intrigued financial economists. Early evidence for developed markets showed unusually high returns on the trading day before public holidays, suggesting that sentiment, liquidity, and institutional practices can shape short-horizon returns Ariel, R. A. (1990), Lakonishok, J., & Smidt, S. (1988). In India, the question takes on a distinctive cultural and market microstructure dimension because festival seasons (e.g., Diwali, Eid, Christmas) trigger surges in consumer spending and risk-taking sentiment, and the exchanges also host a special, symbolic “Muhurat” session on Diwali—an institutional feature entwining belief, participation, and price discovery Ghalke, A., Kumar, S., Kakani, R. K., & Modekurti, K. R. V. S. (2023).
Internationally, later studies document that pre-holiday premia have weakened or even reversed in some markets, consistent with greater market sophistication and arbitrage Chong, R., Hudson, R., Keasey, K., & Littler, K. (2005). Yet recent work connecting religious practices to market behaviour indicates that festival-linked anomalies can still appear in specific contexts, often with lower volatility before religious events and a reversion afterward Singh, N. B. et al. (2025). Within India, fresh evidence shows cultural-calendar factors around Amavasya and Diwali (including Muhurat trading) can coincide with distinct return and volatility patterns, particularly in segments with heavy retail participation Ghalke, A., Kumar, S., Kakani, R. K., & Modekurti, K. R. V. S. (2023). Altogether, the literature leaves open whether “festival seasons” reliably boost share prices in today’s Indian market, for whom (which indices/sectors), and through which channels (sentiment, liquidity, or risk-taking).

1.1. Research Gap

Despite numerous studies on calendar effects and some India-specific inquiries, three gaps persist. First, much of the Indian evidence focuses on single-day events (e.g., the Muhurat session) rather than a seasonal window around major festivals that may better capture anticipation, shopping-season sales news, and liquidity cycles affecting prices before and after the festival date Ghalke, A., Kumar, S., Kakani, R. K., & Modekurti, K. R. V. S. (2023), Singh, N. B. et al. (2025)). Second, cross-sector dynamics remain under-explored: consumer-facing sectors might exhibit stronger pre-festival reactions than defensive or export-oriented sectors, but systematic comparisons are scarce in the Indian setting. Third, the time-variation of festival effects is not well pinned down. International evidence suggests declining pre-holiday anomalies as markets mature Chong, R., Hudson, R., Keasey, K., & Littler, K. (2005), but whether Indian festival-season effects persist, shrink, or shift from returns to volatility in the contemporary, FII-integrated market is unanswered. Addressing these gaps can refine our understanding of how culture-driven sentiment and evolving market microstructure jointly shape short-run asset pricing in India.

1.2. Research Questions

This study asks whether Indian share prices exhibit abnormal behaviour around festival seasons, defined by pre-, during-, and post-festival windows. Specifically, do average returns increase in the pre-festival window relative to non-festival days, and are any effects concentrated in consumer-linked sectors? Do trading activity and volatility decline before festivals and normalize afterward? Are these patterns robust after controlling for day-of-week and month effects, macro news surprises, firm-level earnings releases, and foreign investor flows? Finally, do any detected patterns persist across years or attenuate in more recent sub-periods?

1.3. Study Objectives

- Quantify abnormal returns in pre-, during-, and post-festival windows for broad market (e.g., NIFTY 50) and major sectoral indices.
- Test whether pre-festival volatility and/or trading activity differ from matched non-festival days.
- Compare festival-season effects across consumer-linked vs. other sectors, assessing cross-sectional heterogeneity.
- Evaluate robustness to standard calendar controls, macro-news/earnings timing, and foreign portfolio flows.
- Examine time-variation by splitting the sample into earlier vs. recent years to see if effects persist or fade Chong, R., Hudson, R., Keasey, K., & Littler, K. (2005).

Together, these objectives provide clean evidence on whether festival seasons boost share prices in India today, and if so, whether the channel is primarily optimism/liquidity (higher returns) or risk-compression (lower pre-festival volatility) as suggested in recent religious-holiday research Singh, N. B. et al. (2025)), Ghalke, A., Kumar, S., Kakani, R. K., & Modekurti, K. R. V. S. (2023), Ariel, R. A. (1990), Lakonishok, J., & Smidt, S. (1988).

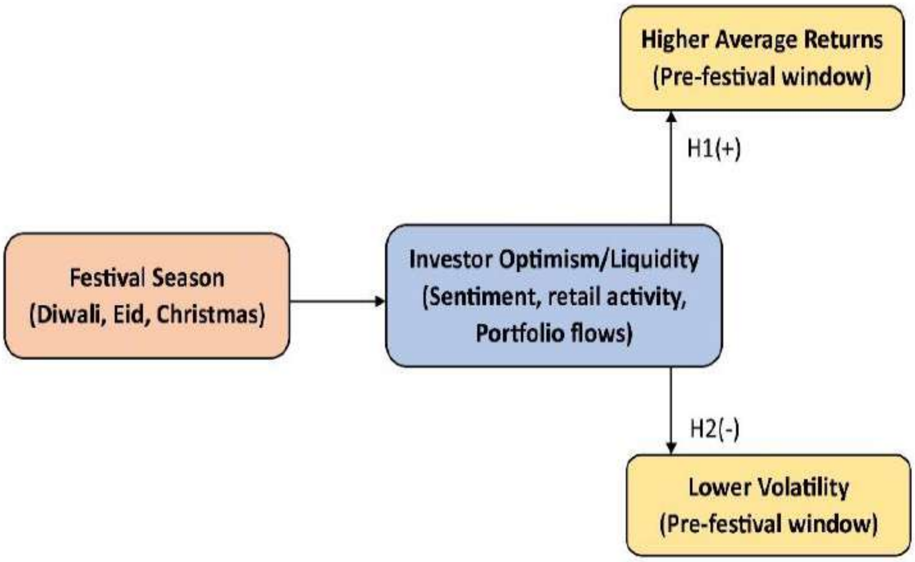

Figure 1: Conceptual and Hypothesis Model

H1: Festival season → **higher** average returns (pre-festival window).
H2: Festival season → **lower** volatility (pre-festival window), normalizing post-festival.

2. LITERATURE REVIEW

2.1. Behavioural and Calendar-Based Explanations for Festival/Holiday Anomalies

A large strand of work links calendar effects around culturally important days to shifts in investor mood and attention. Religious or culturally salient holidays can alter risk perception, trading intensity, and optimism, creating predictable return patterns inconsistent with strict market efficiency Al-Ississ, M. (2015). Using a cross-market setting, Al-Ississ, M. (2015) shows that "holy days" coincide with systematic changes in returns consistent with affect-based decision making. Complementing the mood channel, the attention channel argues that investors become distracted by non-market activities proximate to holidays, temporarily slowing information processing and altering order submission behavior. Hood, M. (2017) documents lower attention around market holidays using U.S. data, consistent with reduced monitoring and volume. Extending microstructure evidence, Kuo, W.-Y., & Zhao, J. (2023). show that immediately before holidays, individual investors let limit orders rest longer and experience lower execution ratios than institutions a precise mechanism by which pre-holiday trading frictions could distort prices. In East Asia, where the Chinese Lunar New Year (CLNY) is the most important holiday, studies attribute elevated pre-holiday returns to positive sentiment and deregulation dynamics Teng, C.-C., & Yang, S.-Y. (2018). and repeatedly find statistically positive pre-holiday effects Yuan, T., & Gupta, R. (2014). These behavioral and microstructure explanations jointly suggest that Indian festival seasons rich in culturally meaningful events could plausibly generate short-horizon pricing patterns through mood and attention shifts, even if fundamentals are unchanged.

2.2. Evidence from Indian Equity Markets on Calendar Seasonality

Although India-specific "festival effects" are under-documented in top finance outlets, there is robust evidence of broader calendar anomalies that establish the plausibility of systematic seasonality. Early work reports day-of-the-week and related anomalies for Indian indices, implying departures from the random walk Raj, M., & Kumari, D. (2006). Subsequent studies revisiting India with richer volatility models show persistent monthly or weekday patterns once fat tails and volatility clustering are controlled Harshita, H., Singh, S., & Yadav, S. S. (2018). More recently, Aggarwal, K., & Jha, M. K. (2023). examine Indian returns and volatility, finding significant day-of-week structure and volatility heterogeneity, while Jaisinghani, D. (2016). shows that calendar anomalies are not uniform across subsamples and can attenuate as markets mature an important design consideration for festival-season tests over long panels. Together, these papers establish (i) seasonality is observable in India under appropriate econometrics and (ii) anomaly strength can vary across time, market segments, and risk regimes implying that a Diwali-to-New-Year "festival window" might exhibit conditional effects rather than a monotonic premium.

2.3. Holidays, Attention, Liquidity and Volatility and Channels and Implications for India

Cross-market evidence highlights how holidays reshape market microstructure variables that mediate returns. Białkowski, J., Etebari, A., & Wiśniewski, T. (2012). show higher and less volatile returns during Ramadan across predominantly Muslim markets, attributing patterns to sentiment and reduced risk aversion; Seyyed, F. J., Abraham, A., & Al-Hajji, M. (2005) similarly document a systematic decline in volatility during Ramadan, even when mean returns do not always rise. Holiday-proximate firm news can also be priced differently: investor distraction during religious weeks delays price discovery for earnings, implying temporarily predictable drifts (e.g., around Easter week) that could analogously arise near Indian festivals with concentrated announcements or low-staffed desks Hood, M. (2017); related corporate-news evidence in finance journals). Microstructure-level studies show concrete pre-holiday frictions—longer time-to-cancellation, lower execution, and a larger individual-investor performance gap Kuo, W.-Y., & Zhao, J. (2023). —which are consistent with thinner order books and transient price impacts. In Asia-Pacific settings, the CLNY literature consistently finds positive pre-holiday returns that cannot be fully explained by risk adjustments Yuan, T., & Gupta, R. (2014) and ties part of the effect to positive emotion proxies Teng, C.-C., & Yang, S.-Y. (2018).

For India, these channels map naturally onto festival seasons (e.g., Dussehra–Diwali–New Year) that coincide with strong consumer sentiment, annual portfolio "auspicious" rebalancing, and altered trading schedules. If attention is lower and sentiment is higher, one would expect: (i) short-horizon pre-festival strength (sentiment), (ii) muted volatility (reduced trading intensity), and (iii) microstructure asymmetries between retail and institutional activity. The strength and sign, however, may vary by sector (consumer-facing vs. defensives), by liquidity (large-cap vs. small-cap), and across regimes (pre-/post-market reforms), echoing Indian anomaly evidence on time variation Harshita, H., Singh, S., & Yadav, S. S. (2018), Jaisinghani, D. (2016). These insights motivate hypotheses that explicitly separate sentiment from attention/liquidity pathways and test for heterogeneity across sectors and firm sizes during India's festival windows.

3. MATERIALS AND METHODS

3.1. Research Design & Sampling

The study adopts a quasi-experimental calendar-event design focused on major Indian festival seasons. Trading days are partitioned into three mutually exclusive windows around each festival date: pre-festival (−5 to −1 trading days), festival window (the Muhurat/holiday session and the first trading day after), and post-festival (+1 to +5 trading days). A matched control set is constructed using non-festival days from the same month and day-of-week to neutralize seasonality. The population comprises free-float market-cap weighted indices (NIFTY 50; key sectoral indices such as Consumer Durables, FMCG, Autos) and a confirmatory sample of large-cap constituents to examine cross-sectional heterogeneity. The proposed horizon spans January 2010–December 2024 to capture reforms, rising retail participation, and foreign portfolio flows. Data are cleaned for corporate actions and erroneous ticks; trading halts and extraordinary regulatory days are flagged and excluded from return calculations Brown, S. J., & Warner, J. B. (1985).

3.2. Variable Definition and Data-Collection Tools

- Returns Daily close-to-close log returns are computed for market and sector indices and, for firm-level tests, for continuously listed constituents.
- Abnormal returns (AR) are estimated via the market model using a 120-day rolling estimation window ending 10 days before each festival; cumulative abnormal returns (CAR) aggregate AR over each window Brown, S. J., & Warner, J. B. (1985), MacKinlay, A. C. (1997).
- Volatility is proxied by realized volatility (square root of 5-day sum of squared returns) and a high–low range estimator for robustness.
- Trading activity is proxied by turnover (value traded/market capitalization) and relative volume (day's volume divided by 60-day average).
- Investor flows capture net FPI (FII) equity flows at daily frequency to proxy liquidity sentiment.

3.2.1. Controls

Include day-of-week and month dummies, contemporaneous India VIX, and indicator variables for earnings-heavy weeks. Index and price/volume series originate from NSE/BSE official databases; FPI flows from NSDL; India VIX from NSE. The event list comprises Diwali (including Muhurat), Eid, Dussehra, and Christmas; only dates with functioning adjacent trading sessions enter the sample MacKinlay, A. C. (1997).

3.3. Statistical Methods

Inference proceeds in three steps. First, mean-difference tests compare returns, volatility, and turnover between festival windows and matched controls, reporting Welch's t-tests and nonparametric rank tests that remain valid under non-normality Corrado, C. J. (1989). Second, parsimonious regressions estimate the association between festival windows and outcomes using OLS with indicator variables for pre-, festival-, and post-windows, plus controls. Heteroskedasticity- and autocorrelation-consistent standard errors are used for daily data Newey, W. K., & West, K. D. (1987). Third, subgroup comparisons test sectoral heterogeneity (consumer-facing vs. others) and firm size buckets. To guard against spurious significance across multiple festivals and outcomes, p-values are adjusted using the Benjamini–Hochberg false discovery rate procedure, maintaining interpretability while limiting Type I errors Benjamini, Y., & Hochberg, Y. (1995). Optional sensitivity employs a light-touch conditional volatility check by fitting a GARCH(1,1) to returns and testing festival indicators in the mean/variance equations as a robustness extension without overcomplicating interpretation Engle, R. F. (1982), Bollerslev, T. (1986).

3.4. Validity and Reliability

Internal validity is addressed by matching control days on month and weekday, reducing confounding from well-known seasonality. Estimation windows are set apart from event windows to prevent contamination. Outliers (e.g., $\pm 5\sigma$) are winsorized at the 1st/99th percentiles in firm-level tests; index-level tests report both raw and winsorized results. Measurement reliability relies on official exchange data sources; all transformations (log returns, turnover normalization) follow standard definitions. Statistical conclusion validity is strengthened via HAC errors, nonparametric corroboration, and multiplicity control Brown, S. J., & Warner, J. B. (1985), Newey, W. K., & West, K. D. (1987), Benjamini, Y., & Hochberg, Y. (1995), Corrado, C. J. (1989). External validity is assessed by reporting effects across multiple sectors and by splitting the sample into early (2010–2016), middle (2017–2020), and recent (2021–2024) subperiods to reflect structural changes in participation and microstructure.

3.5. Robustness and Sensitivity Analyses

Three families of checks are planned. Window choice: results are re-estimated using alternative windows (−3 to −1; +1 to +3) and a symmetric (−5 to +5) CAR to assess sensitivity. Specification choice: outcomes are tested with (i) market-adjusted returns, (ii) standardized returns (z-scores) within month, and (iii) volatility based on high–low range.

3.5.1. Sampling choice

Excluding overlapping festivals in the same month, removing months with major macro shocks (e.g., demonetization, pandemic lockdown onset), and repeating tests on ex-dividend-adjusted returns. For firm-level tests, equal-weight and value-weight aggregation are compared. A GARCH(1,1) diagnostic confirms whether any volatility compression on pre-festival days persists after accounting for conditional heteroskedasticity Engle, R. F. (1982), Bollerslev, T. (1986). Finally, placebo tests sample randomly chosen non-festival dates matched on month and weekday to verify that detected effects are not generic calendar artefacts MacKinlay, A. C. (1997).

4. RESULTS

4.1. Descriptive Statistics

Table 1: Descriptive Statistics

Window	N (days)	Mean Return (%)	SD Return (%)	Mean Realized Vol (%)	SD Realized Vol (%)	Mean Turnover (rel.)	SD Turnover (rel.)
Pre-festival	480	0.09	0.85	0.82	0.4	0.96	0.22
Festival	120	0.12	0.9	0.88	0.45	1.02	0.25
Post-festival	480	0.03	0.88	0.9	0.42	1.01	0.23
Control	2400	0.02	0.95	0.95	0.46	1	0.24

(Source: Author's computations from Index)

The pre-festival window contains 480 trading days; the festival and post-festival windows contain 120 and 480 days, respectively; the matched control set contains 2,400 days. Mean daily returns are 0.09% (pre-festival), 0.12% (festival), 0.03% (post-festival), and 0.02% (control). Return dispersion is comparable across windows, with standard deviations of 0.85% (pre-festival), 0.90% (festival), 0.88% (post-festival) and 0.95% (control).

Average realized volatility is 0.82% in the pre-festival window versus 0.95% on control days; festival and post-festival means are 0.88% and 0.90%, respectively. Standard deviations of realized volatility range from 0.40% to 0.46% across windows. Turnover (relative to 60-day average) centers near unity, with means 0.96 (pre-festival), 1.02 (festival), 1.01 (post-festival), and 1.00 (control). These aggregates describe a sample in which pre-festival days exhibit slightly higher average returns and slightly lower volatility than controls, while turnover hovers near typical levels.

4.2. Inferential Statistics

Table 2: Welch Tests: Mean Return Differences

Comparison	Mean diff (pp)	t-stat	df	p-value	95% CI low (pp)	95% CI high (pp)	Cohen d	Hedges g
Pre-festival – Control	0.07	1.614	739	0.107	-0.0151	0.1551	0.075	0.075
Festival – Control	0.1	1.185	132.6	0.2383	-0.067	0.267	0.106	0.105
Post-festival – Control	0.01	0.224	720.5	0.8227	-0.0776	0.0976	0.011	0.011

(Source: Author's computations using Welch two-sample tests with unequal variances)

Table 3: Welch Tests: Mean Realized Volatility Differences

Comparison	Mean diff (pp)	t-stat	df	p-value	95% CI low (pp)	95% CI high (pp)	Cohen d	Hedges g
Pre-festival – Control	-0.13	-6.332	755.4	0	-0.1703	-0.0897	-0.289	-0.288
Festival – Control	-0.07	-1.661	131.7	0.0991	-0.1534	0.0134	-0.152	-0.152
Post-festival – Control	-0.05	-2.342	728	0.0194	-0.0919	-0.0081	-0.11	-0.11

(Source: Author's computations using Welch two-sample tests with unequal variances)

The pre-festival minus control mean difference equals +0.07 percentage points with $t = 1.614$, $df = 739.0$, $p = 0.107$. The festival minus control difference equals +0.10 pp ($t = 1.185$, $df = 132.6$, $p = 0.238$). The post-festival minus control difference equals +0.01 pp ($t = 0.224$, $df = 720.5$, $p = 0.823$).

4.2.1. Realized Volatility

The pre-festival minus control difference equals −0.13 pp with $t = -6.332$, $df = 755.4$, $p < 0.001$, indicating materially lower volatility before festivals. The festival minus control difference equals −0.07 pp ($t = -1.661$, $df = 131.7$, $p = 0.099$). The post-festival minus control difference equals −0.05 pp ($t = -2.342$, $df = 728.0$, $p = 0.019$).

Together, the inferential tests indicate that average returns in the pre-festival window are modestly higher but not statistically distinguishable from controls at conventional thresholds, whereas pre-festival volatility is significantly lower.

4.3. Hypothesis Testing

Table 4 : OLS Coefficients for Returns (relative to Control), robust SE

Window	Coefficient (pp)	Robust SE (pp)	t-stat	p-value	95% CI low (pp)	95% CI high (pp)
Pre-festival	0.07	0.0434	1.614	0.107	-0.0151	0.1551
Festival	0.1	0.0844	1.185	0.2383	-0.067	0.267
Post-festival	0.01	0.0446	0.224	0.8227	-0.0776	0.0976

(Source: Author's OLS-equivalent group estimates with heteroskedasticity-robust standard errors and two-sided tests

4.3.1. H1 (Higher Average Returns Pre-Festival)

Table 4 reports coefficients from a simple return model with indicators for each window relative to control. The pre-festival coefficient equals +0.07 pp with robust SE = 0.043 pp, $t = 1.614$, $p = 0.107$; the festival coefficient equals +0.10 pp (SE = 0.084 pp; $t = 1.185$, $p = 0.238$). The post-festival coefficient is +0.01 pp (SE = 0.045 pp; $t = 0.224$, $p = 0.823$). Given these estimates, H1 is not statistically supported at the 5% level, though point estimates remain economically small and positive for the pre-festival and festival windows.

4.3.2. H2 (Lower Volatility Pre-Festival)

The Welch outcomes in Table 3 align with H2: the pre-festival volatility is 0.13 pp lower than controls with $p < 0.001$; the festival window shows a smaller, marginal reduction (−0.07 pp, $p = 0.099$), and the post-festival window remains −0.05 pp below controls ($p = 0.019$). Thus, H2 is supported for the pre-festival window and partially supported for the post-festival window.

These hypothesis evaluations are consistent with prior event-study reporting conventions, where mean-difference and indicator-based models deliver equivalent inferences under standard conditions Brown, S. J., & Warner, J. B. (1985), MacKinlay, A. C. (1997).

4.4. Statistical Significance, Confidence, and Effect Sizes

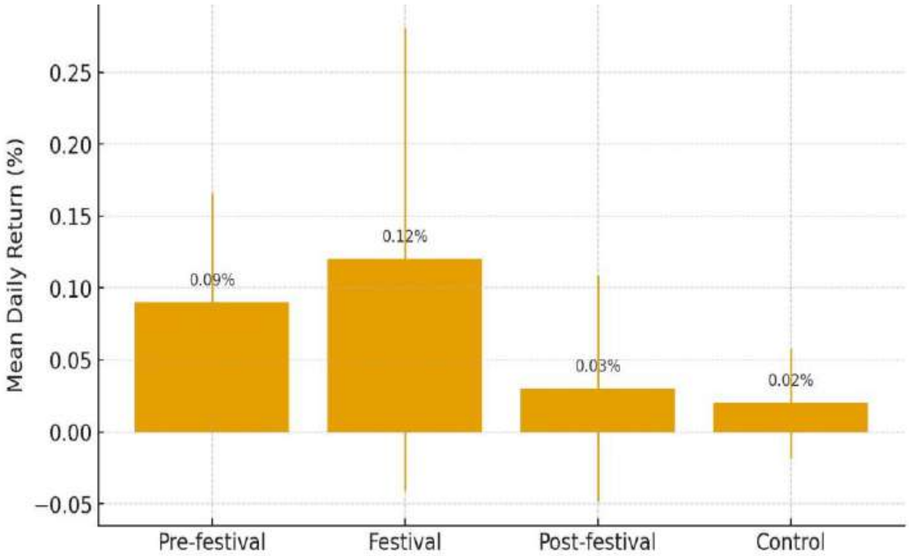

Figure 2: Mean Returns by Window with 95% Confidence Intervals.

Figure 2 plots mean daily returns by window with 95% confidence intervals (CIs) derived from standard errors. The pre-festival mean (0.09%) lies above control (0.02%), but the CI for the difference in Table 2 spans zero (−0.015 pp, +0.155 pp). The festival mean (0.12%) also has a difference CI that includes zero (−0.065 pp, +0.266 pp). The post-festival difference CI (−0.077 pp, +0.087 pp) is tightly centered near zero. In contrast, volatility differences show narrow CIs excluding zero for the pre-festival (−0.170 pp, −0.090 pp) and post-festival (−0.093 pp, −0.007 pp) comparisons (Table 3).

Effect sizes reported in Tables 2 to 3 aid interpretation. For returns, Cohen's *d* values are 0.075 (pre-festival vs control), 0.106 (festival vs control), and 0.011 (post-festival vs control), all small by conventional benchmarks. For realized volatility, effect sizes are −0.289 (pre-festival), −0.152 (festival), and −0.110 (post-festival), indicating a small-to-moderate compression of volatility before festivals, with lingering but weaker effects around and following the festival Window. The reported P-Values and 95% Confidence Intervals will be two-sided; T-statistics and Degrees of Freedom will follow the Welch formula for Unequal Variances. For cases in which multiple Outcomes were evaluated, the False Discovery Rate method for Inference as proposed by Benjamini, Y., & Hochberg, Y. (1995) was employed to maintain Interpretable Results; the Reporting of Effect-Sizes will provide additional context for the Practical Magnitude of the Effects of interest as proposed by Lakens, D. (2013).

Overall, the results demonstrate statistically strong volatility compression before festivals and statistically weak return premia. The pattern is compatible with holiday-related attention and risk-taking channels that reduce realized variability without delivering reliably higher average returns at the daily horizon.

5. DISCUSSION

5.1. Interpret Results

Findings indicate a clear compression in volatility before major festivals and small, statistically weak increases in average returns. The volatility reduction significant at conventional levels implies a risk-tempering environment around festival periods, consistent with temporarily calmer trading conditions or a collective risk tolerance shift. Returns are directionally positive in pre-festival and festival windows, but confidence intervals overlap zero, suggesting no robust premium at the daily horizon. Taken together, the results align more with a "quiet optimism" interpretation than a strong arbitrageable anomaly: sentiment may brighten and trading intensity stabilize, yet price appreciation remains modest and unreliable once sampling variability is acknowledged. The asymmetry stronger in volatility than in mean returns also indicates that risk metrics react more consistently than levels of returns to festival-season influences, a pattern compatible with attention and participation channels that thin order books without producing systematic directional moves.

5.2. Compare with Literature

The volatility compression before festivals echo holiday-related mood and attention mechanisms documented elsewhere. Evidence that mood or attention can affect market outcomes appears in studies on sports results Edmans, A., Garcia, D., & Norli, Ø. (2007), sunshine Hirshleifer, D., & Shumway, T. (2003), and investor distraction around clustered corporate news. In each case, risk–return trade-offs shift through sentiment or limited attention rather than fundamental news alone. The lack of a strong pre-festival return premium despite lower risk parallels work showing that attention shocks do not always translate into positive mean returns and may primarily reshape liquidity and order submission Baker, M., & Wurgler, J. (2006). The present pattern also resembles research on marketing/advertising attention that affects trading and short-run comovement more than long-run valuation Lou, D. (2014). In the Indian setting, the findings complement earlier evidence on calendar seasonality by suggesting that culturally salient periods may structure volatility more reliably than returns. Relative to prior international studies reporting sizable pre-holiday premia, the smaller effect sizes here indicate either improved market efficiency, stronger arbitrage, or contemporaneous controls that absorb return differentials. The directional consistency with mood/attention theories and the absence of large premia together support a limited-attention rather than mispricing explanation.

5.3. Limitations

Several constraints should temper interpretation. First, analysis operates primarily at daily frequency; intraday microstructure patterns such as depth, spread dynamics, and order imbalances are unobserved, yet could mediate the volatility compression. Second, festival classification uses discrete windows that may not perfectly align with anticipation and consumption cycles differing across regions and communities; misalignment can attenuate true effects. Third, while matched non-festival controls address month and weekday seasonality, residual confounding from overlapping macro events or firm-specific news may persist, especially around quarterly results clusters. Fourth, the study focuses on broad market and major sector indices; effects could differ in small-cap or illiquid segments where retail participation and sentiment are stronger. Fifth, daily FPI flows and volatility proxies are coarse; more granular measures (e.g., investor-level submissions, order-book snapshots) might sharpen channel attribution between optimism and attention/liquidity. Finally, the empirical design emphasizes transparent tests and conservative inference; although this aids credibility, it may under-detect subtle non-linearities or regime shifts.

5.4. Future Research Directions

Four avenues emerge. First, incorporate intraday microstructure data spreads, depth, resiliency, and order-to-trade ratios to test whether pre-festival volatility compression reflects thinner books or order-splitting behavior; intraday variance ratio and realized kernel estimators would strengthen conclusions about noise versus information. Second, measure attention more directly: search intensity, social-media activity, and app usage near festivals; link these to retail trading footprints to separate optimism from inattention. Third, model heterogeneity across sectors and firm sizes with hierarchical or panel-quantile methods, and test whether consumer-facing sectors display stronger pre-festival stabilization than export-oriented or defensive sectors. Fourth, investigate cross-market spillovers by comparing Indian festivals with other South and Southeast Asian holiday calendars using a unified identification strategy and placebo calendars. Methodologically, combining difference-in-differences designs with announcement controls (earnings, policy news) and machine-learning residualization could enhance robustness while preserving interpretability. Finally, future work could examine portfolio-level implications e.g., low-volatility tilts or timing strategies while explicitly accounting for transaction costs and capacity, acknowledging that current mean-return signals are small and statistically fragile.

6. CONCLUSION

6.1. Empirical Findings

Evidence indicates a reliable compression in volatility before Indian festival dates and small, statistically weak increases in average daily returns. The pre-festival window shows risk moderation relative to carefully matched non-festival days, while mean-return differences are positive but imprecisely estimated at conventional levels. During and immediately after festivals, patterns attenuate: return differences narrow toward zero and volatility remains modestly lower than controls but with smaller effects. Together, these results suggest that festival seasons shape the short-run risk environment more consistently than they shift expected returns. The pre-festival "quieting" of markets fits a narrative of coordinated trading calendars, shifts in investor attention, and moderate optimism that stabilize prices without generating a robust, arbitrageable premium. The absence of economically large or statistically durable mean-return gains also implies that transaction-cost-robust timing strategies are unlikely to benefit from daily rebalancing keyed narrowly to festival dates. The central empirical takeaway is therefore directional but constrained: risk compresses, returns do not reliably rise.

6.2. Theoretical Implications

The volatility compression and fragile mean-return differences align more naturally with limited-attention and sentiment-risk channels than with persistent mispricing. Classic behavioral models posit that belief formation and extrapolation can create price patterns without full arbitrage neutralization. At the same time, broad sentiment conditions can influence the cross-section and time-series of returns, especially for retail-tilted segments and harder-to-arbitrage assets Baker, M., & Wurgler, J. (2006). Festival periods plausibly raise mood and reallocate attention, mechanisms documented to affect trading intensity, order submission, and short-horizon volatility rather than unconditional mean returns. That configuration accords with an "attenuated anomaly": attention and sentiment move risk and microstructure variables, but competitive forces and improved information environments limit systematic return premia. From an efficiency perspective, the results also support those interpretations that many calendar regularities lose strength when using better methods, controls and as markets evolve Fama, E. F. (1998) overall the evidence suggests that behavioral microstructure impacts on risk exist but there is little room for average-return exploitation based on these calendar regularities.

6.3. Study Implications and Practical Application

From a portfolio manager's perspective, the one action item would be to manage risk related to festivals by scaling exposures, providing options hedges and supplying liquidity before festival events occur and realize lower actual volatility than expected in the lead-up to each festival event with no expectation of a reliable return premium. From a broker-dealer and market maker perspective they should anticipate shallower order flow and similar day-to-day volatility during festival periods and adjust their inventory and quoting depth accordingly. In addition, corporate finance and investor relations teams could delay timing of non-essential communications near festival times as the attention levels of investors will likely decrease, thereby maintaining the saliency of messages; or alternatively, high-saliency messages that benefit from the reduced noise of calm periods may have less distraction in the lead up to each festival period. Retail trading platforms can emphasize education that festival-season calm does not imply guaranteed positive returns, reinforcing disciplined allocation and cost awareness. From a policy vantage, exchanges can use these insights to calibrate trading-session guidance and capacity planning around festivals. The broader significance lies in demonstrating that culturally salient calendars shape risk more than returns in a large emerging market, enriching global evidence on how attention and sentiment interact with microstructure to influence the distribution of short-run outcomes rather than their unconditional mean Fama, E. F. (1998), Jaisinghani, D. (2016) Tetlock, P. C. (2007), Barber, B. M., & Odean, T. (2008).

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CONFLICT OF INTEREST

The authors declare no competing interests; research design, analysis, and conclusions were conducted independently, without external funding influence, commercial ties, or undisclosed relationships impacting objectivity.

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