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Trading Volume, Subsequent Stock Returns and Calendar Effects: Evidence from NIFTY 50 Companies

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Abstract

Many investors believe that heavy trading signals the next price move and that some days or months are better for investing. This paper tests these ideas for large Indian companies. It asks two questions: whether the previous day's trading volume is related to the next day's return, and whether returns and trading volume follow day-of-week or month-of-year patterns. The sample covers ten NIFTY 50 companies selected from ten different sectors and the NIFTY 50 index, using 982 trading days from January 2022 to December 2025. Trading volume is measured as abnormal volume relative to the previous twenty trading days. The study uses regression with a lagged-return control, Welch's t-test, one-way ANOVA and the Kruskal–Wallis test, and checks the volume–return results in two sub-periods. Previous-day volume is significantly related to next-day returns for only two companies in the regression and three in the t-test, explains at most about 1.5 per cent of return variation, and the significant companies change between sub-periods. Returns show a day-of-week effect for only one series and a month-of-year effect for only one series, and the NIFTY 50 shows neither. In contrast, trading volume shows strong calendar patterns: it is usually lowest on Mondays and highest on Thursdays, and it differs significantly across months for all ten companies. The results suggest that calendar regularities in this market lie in trading activity rather than in prices. Investors should not rely on volume spikes or calendar rules to predict returns, but they can use volume patterns to plan the timing of large trades.

Keywords: *Trading Volume, Stock Returns, Calendar Effects, Day-of-the-Week Effect, Market Efficiency, NIFTY 50.*

Introduction

Trading volume is often treated as a signal. Market commentators say that a price rise on heavy volume is more trustworthy, and many investors look for unusual trading as a clue to the next move. Popular beliefs also suggest that returns are weaker on Mondays, stronger in certain months or affected by the timing of holidays and expiry days. If such beliefs were correct, investors could use them to improve returns. If they are not, acting on them would add cost and risk without benefit. This paper tests these beliefs for ten large Indian companies over 2022–2025. It examines two related questions. The first is whether the previous day's trading volume is related to the next day's return. The second is whether returns and trading volume follow regular weekly or monthly patterns. A key feature of the paper is that it applies the same calendar tests to both returns and volume. This makes it possible to see whether calendar patterns, where they exist, appear in prices, in trading activity or in both. The distinction matters because predictable trading activity does not contradict market efficiency, while predictable returns would.

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Literature Review

Research on the link between past volume and future returns offers three competing expectations. Campbell et al. (1993) found that price changes on high-volume days in the U.S. market tended to reverse, which is consistent with trading by investors who need cash rather than investors with information. Llorente et al. (2002) showed that high-volume returns tend to continue in companies with more informed trading and to reverse in companies where trading is mainly for hedging. Gervais et al. (2001) found a high-volume return premium, which they linked to the extra attention that unusual trading attracts, and Barber and Odean (2008) showed that individual investors buy attention-grabbing shares. In contrast, Lee and Rui (2002) found that volume did not Granger-cause returns in major markets. A meta-analysis of 44 studies by Bajzik (2021) showed that reported estimates vary widely with data and methods, and Yamani (2023) reached a similar view in a review of the return–volume literature. In India, Chaudhuri and Kayal (2022) found that search volume had little power to predict excess returns, and Joshi and Misra (2024) studied how returns affect trading volume.

Calendar effects in returns have a long history. French (1980) reported negative average returns over the weekend, and Rozeff and Kinney (1976) reported unusually high January returns. Later research showed that many such effects weakened over time or lost significance once the large number of tested rules was considered (Sullivan et al., 2001; Zakamulin, 2026). Indian evidence is mixed: studies of day-of-the-week effects (Aggarwal & Jha, 2023; Chawla, 2018), month-of-the-year effects (Elangovan et al., 2022) and weekend effects in banking shares (Mittal et al., 2025) report results that vary with the period and index. Calendar patterns in trading volume have received less attention. Lakonishok and Maberly (1990) found lower volume on Mondays in the United States, Kiymaz and Berument (2003) found day-of-the-week effects in volume and volatility in several markets, and Stoll and Whaley (1987) documented unusual activity around derivative expiry. Few Indian studies compare calendar patterns in volume with those in returns for individual companies.

Theoretical Foundation

The efficient market hypothesis (Fama, 1970) provides the main benchmark. In its weak form, it states that prices already reflect the information contained in past prices and trading data. If this holds, previous-day volume should not predict next-day returns by more than a very small amount, and returns should not follow reliable calendar patterns. The hypothesis does not, however, require volume to be random. Volume can follow regular patterns without creating any profit opportunity.

Two further ideas explain why volume might follow calendar patterns. Admati and Pfleiderer (1988) showed that traders who can choose when to trade prefer to trade when others are active, which makes trading cluster at certain times. Institutional schedules, such as derivative expiry days, fund inflows and results seasons, can reinforce this clustering (Stoll & Whaley, 1987). The attention and liquidity-trading ideas discussed above (Barber & Odean, 2008; Campbell et al., 1993) explain why small links between volume and next-day returns may exist for some companies, even in an efficient market.

Methodology

The sample consists of ten NIFTY 50 companies selected from ten different sectors (Reliance Industries, HDFC Bank, Tata Consultancy Services, Bharti Airtel, ITC, Mahindra & Mahindra, Larsen & Toubro, Sun Pharmaceutical, Tata Steel and NTPC) and the NIFTY 50 index. Daily data were obtained from Yahoo Finance for 1 January 2022 to 31 December 2025. After removing placeholder rows and special sessions, 982 common trading days remain, and every test uses the same estimation window of 956 observations. Returns are daily log returns from adjusted closing prices, $r = 100 \times \ln(P_t/P_{t-1})$. Trading volume is measured as abnormal volume, AV = ln(V) − average of ln(V) over the previous twenty trading days, which removes trends and makes companies comparable. Index volume is not used because the values supplied by the data source were unreliable.

The previous-day volume relationship is tested with the regression $r_t = a + c \cdot r_{t-1} + b \cdot AV_{t-1} + e_t$, in which yesterday's return is included so that b measures the information in yesterday's volume alone. As a second test, days are divided into two groups according to whether the previous day's abnormal volume was above or below its median, and the mean next-day returns are compared with Welch's (1947) t-test. Calendar effects are tested with one-way ANOVA across the five weekdays and the twelve months. Because returns and volume are not normally distributed, the Kruskal–Wallis (Kruskal & Wallis, 1952) rank test is reported as a check. The volume–return tests are repeated for 2022–23 and 2024–25 to check their stability. The significance level is 0.05.

Results

- **Previous-Day Volume and Next-Day Returns**

Table 1: Previous-Day Abnormal Volume and Next-Day Returns

Company	b (AV_{t-1})	p (b)	R^2	Return Difference, high − low (%)	p (Welch)
RELIANCE	0.084	.4400	0.0008	0.069	.4409
HDFCBANK	−0.136	.1600	0.0024	−0.061	.4662
TCS	0.136	.1710	0.0024	0.180	.0321
BHARTIARTL	0.040	.6376	0.0032	0.016	.8531
ITC	0.179	.0229	0.0080	0.170	.0208
M&M	0.256	.0566	0.0045	0.067	.5545
LT	0.067	.5602	0.0015	0.012	.8990
SUNPHARMA	0.000	.9985	0.0047	0.090	.2518
TATASTEEL	0.216	.1519	0.0022	0.252	.0406
NTPC	0.267	.0145	0.0147	0.053	.6120

Note. b is the coefficient on previous-day abnormal volume in $r_t = a + c \cdot r_{t-1} + b \cdot AV_{t-1} + e_t$. The return difference compares mean next-day returns after above-median and below-median volume days. n = 956 for each company.

Table 1 shows that previous-day volume is significantly related to next-day returns for only 2 companies in the regression test, ITC and NTPC, and for 3 companies in the t-test, Tata Consultancy Services, ITC and Tata Steel. Only ITC is significant in both. The coefficient is positive for 9 of the ten companies, but the explanatory power is very small: R^2 never exceeds 0.0147, or about 1.5 per cent. In the sub-period checks, the regression effect is significant for ITC and NTPC in 2022–23 and for Mahindra & Mahindra in 2024–25, so the significant companies change over time. The null hypothesis is therefore rejected for only a minority of companies, and the results do not show a general or stable relationship.

- **Calendar Effects in Returns and in Trading Volume**

Table 2: ANOVA p-Values for Day-of-Week and Month-of-Year Effects in Returns and Abnormal Volume

Series	Returns: Weekday	Returns: Month	Volume: Weekday	Volume: Month
RELIANCE	.5679	.6070	< .0001	.0060
HDFCBANK	.9316	.4723	< .0001	< .0001
TCS	.5351	.6602	< .0001	.0017
BHARTIARTL	.8479	.3353	< .0001	.0002
ITC	.0477	.1078	< .0001	.0001
M&M	.3722	.2034	.0001	< .0001
LT	.6844	.7216	< .0001	.0040
SUNPHARMA	.1335	.0229	< .0001	.0063
TATASTEEL	.9349	.8143	.0290	.0224
NTPC	.7927	.8428	.2069	.0487
NIFTY50	.9228	.6781	n/a	n/a
Significant (of tested)	1 of 11	1 of 11	9 of 10	10 of 10

Note. p-values from one-way ANOVA; values below .05 indicate a significant calendar effect. Kruskal–Wallis tests give the same conclusions except for NTPC (month effect in volume not significant) and Sun Pharmaceutical (weekday effect in returns close to significance). Index volume is not tested.

Table 2 shows a sharp contrast between returns and volume. In returns, a weekday effect is significant only for ITC and a month effect only for Sun Pharmaceutical. The NIFTY 50 shows neither (p = .9228 for weekdays and .6781 for months). Average NIFTY 50 returns on Mondays were positive, so there is no weekend effect, and January was one of the weaker months, so there is no January effect. With 22 return tests and about one significant result expected by chance, the evidence of return seasonality is very weak.

In trading volume, the weekday effect is significant for 9 of the ten companies, and the month effect for all ten in the ANOVA test (9 in the Kruskal–Wallis test). Averaged across companies, abnormal volume is −0.108 on Mondays and 0.086 on Thursdays, which means that Monday volume is about 10 per cent below normal and Thursday volume about 9 per cent above normal. Monday is the lowest-volume day for 9 companies and Thursday the highest for 8 (Figure 1). Across the year, volume is relatively high in January, March and September and low in October, December and August.



Figure 1: Mean Abnormal Volume by Weekday and Company

Note. Calculated from the thesis workbook (sheet Obj3_Seasonality). Negative values indicate below-normal volume.

A supplementary test also shows that, for 5 of the ten companies (ITC, Mahindra & Mahindra, Larsen & Toubro, Tata Steel and NTPC), abnormal volume is significantly higher on days when the price rises than on days when it falls. This asymmetry is consistent with Karpoff (1987) and is concentrated in the more volatile, cyclical companies.

Discussion

The weak link between previous-day volume and next-day returns is consistent with the weak form of the efficient market hypothesis (Fama, 1970) and with studies that find little predictive power of volume for returns in large markets (Lee & Rui, 2002). It also agrees with the cautious view of recent reviews (Bajzik, 2021; Yamani, 2023) and with Indian evidence that attention measures relate to trading volume more than to future returns (Chaudhuri & Kayal, 2022). The mostly positive coefficients are weakly in line with the attention-based high-volume return premium (Barber & Odean, 2008; Gervais et al., 2001), but the effects are too small and unstable to be useful on their own. For large, closely followed companies, unusual trading may add little new visibility.

The absence of return seasonality differs from early findings of weekend and January effects (French, 1980; Rozeff & Kinney, 1976) but matches later evidence that such effects weaken over time and are sensitive to data mining (Sullivan et al., 2001; Zakamulin, 2026), as well as the mixed Indian results (Aggarwal & Jha, 2023; Elangovan et al., 2022). The strong volume seasonality agrees with evidence of lower Monday volume (Kiymaz & Berument, 2003; Lakonishok & Maberly, 1990). The Thursday peak coincides with the weekly and monthly expiry of NIFTY 50 derivatives for most of the study period, which is consistent with expiry-related trading in the cash market (Stoll & Whaley, 1987), although the paper does not test this mechanism directly. These patterns fit the idea that trading clusters around institutional routines (Admati & Pfleiderer, 1988). Because the extra trading does not systematically favour buyers or sellers, predictable volume can coexist with unpredictable returns.

Conclusion

This paper found that the previous day's trading volume tells investors very little about the next day's return in large Indian companies. Significant effects appeared for only a few companies, were very small and changed between sub-periods. Returns showed no general weekday or monthly patterns, and the NIFTY 50 showed none. Trading volume, in contrast, followed clear calendar patterns, being lowest on Mondays and highest on Thursdays and varying across months. Calendar regularities in this market are therefore found in how much investors trade rather than in the returns they earn.

Practical Implications

Investors should not use previous-day volume as a standalone signal of the next day's price direction; it may at most be one supplementary indicator. Calendar-based return strategies, such as avoiding Mondays or favouring particular months, are not supported by the evidence for these companies. However, the regular volume patterns are useful in practice. Investors placing large orders

may find more liquidity later in the week, while remaining aware that heavier trading around expiry can bring larger price movements. Brokers and exchanges can use the weekly and monthly patterns to plan capacity, staffing and liquidity provision.

Limitations and Future Research

The study covers ten large companies over four years, so each month appears only four times, which limits the power of the month-of-year tests. The results may not apply to smaller companies, where information may spread more slowly. The paper does not test the expiry mechanism behind the Thursday volume peak. Future research could use longer samples, include mid-cap and small-cap companies, examine whether the 2025 changes to weekly expiry days altered the weekly volume pattern, and use event-study methods around expiry days and results announcements.

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