

**EXAMINING LEAD-LAG DYNAMICS IN THE INDIAN STOCK MARKET:
EVIDENCE FROM SEPTEMBER 2026**

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ABSTRACT

This study investigates the presence of lead-lag relationships in selected securities in the Indian stock market by examining whether the direction of price movement on one trading day is systematically followed by a similar movement on the subsequent trading day. The analysis covers eleven securities representing major banking, information technology, energy, consumer goods, and gold-related segments: HDFC Bank, Axis Bank, State Bank of India (SBI), Tata Consultancy Services (TCS), Infosys, ONGC, Nippon India ETF Gold BeES, Hindustan Unilever (HUL), Wipro, Nestle India, and UCO Bank. Daily closing prices were observed from 31 August to 30 September 2026, with 31 August serving as the reference date for calculating subsequent daily returns. The dataset comprises 231 security-day observations and 220 usable consecutive-day return pairs. Of the 231 daily observations, 87 recorded positive returns, 142 recorded negative returns, and 2 remained unchanged. The direction of returns persisted from one trading day to the next in 97 out of 220 pairs, representing approximately 44.1% of the observations. Furthermore, the pooled correlation between the previous day's return and the subsequent day's return was approximately -0.23 , indicating a modest inverse relationship rather than evidence of consistent directional continuation. At the security level, all eleven securities closed below their respective 31 August levels by the end of the observation period, although the magnitude of decline varied considerably. HDFC Bank registered the smallest change (-0.04%), whereas TCS (-14.53%), Wipro (-14.09%), Nestle India (-12.46%), and Infosys (-12.32%) experienced the largest declines. At the aggregate level, the simple average movement of the eleven securities continued in the same direction on only 8 of the 20 day-to-day comparisons. Overall, the findings provide limited evidence of a dependable next-day directional continuation effect and suggest that the previous trading day's movement alone is insufficient to predict the direction of the following session. The contemporaneous market environment—including elevated crude oil prices, global interest-rate concerns, and sector-specific pressures—provides

important contextual factors for interpreting the observed market movements and highlights the role of broader information in shaping short-term price dynamics.

KEYWORDS: - Indian stock market; daily returns; previous-day effect; banking; information technology; crude oil; Gold ETF; investor sentiment.

1.0 INTRODUCTION

The Indian stock market responds continuously to a complex combination of domestic and international information. Changes in crude oil prices, interest-rate expectations, foreign portfolio investment, corporate announcements, exchange-rate movements, geopolitical developments, and sector-specific regulatory measures can influence investor sentiment and contribute to substantial short-term fluctuations in security prices. In such an information-sensitive environment, an important question in financial market research is whether the price movement observed on one trading day provides any indication of the direction of movement on the subsequent trading day. In other words, does a negative or positive market condition tend to persist, or are daily price movements more likely to be followed by reversals?

The question is particularly relevant from the perspective of short-term market dynamics and the predictability of security returns. For instance, when a market decline is associated with a sharp increase in crude oil prices or heightened geopolitical uncertainty, it is pertinent to examine whether the downward pressure persists into the following trading session. Conversely, following a substantial decline, the emergence of bargain buying or an improvement in investor sentiment may result in a short-term rebound. Such continuation and reversal patterns are closely related to the broader discussion of lead-lag relationships return predictability, and market efficiency. Examining these relationships over a short and clearly defined period can therefore provide useful insights into the extent to which information and market sentiment carry over from one trading session to the next.

September 2026 provides an interesting period for examining this issue in the Indian securities market. The month witnessed a combination of repeated negative trading sessions and intermittent short-lived recoveries. Market sentiment during this period was influenced by factors including elevated crude oil prices, geopolitical tensions in the Middle East, changing expectations regarding global interest rates, movements in the Indian rupee, foreign fund outflows, and sector-specific regulatory developments. However, the market response was not uniformly persistent. Several instances of sharp reversals were observed, with a negative trading session sometimes being followed by a recovery and, conversely, positive sessions occasionally being followed by renewed declines. This combination of continuation and reversal provides a

useful setting for investigating whether the direction of one trading day's movement is systematically associated with the direction of the following session.

Against this background, the present study examines the lead-lag relationship between consecutive trading-day movements in a selected group of eleven securities during September 2026. The securities considered in the analysis are HDFC Bank, Axis Bank, State Bank of India (SBI), Tata Consultancy Services (TCS), Infosys, ONGC, Nippon India ETF Gold BeES (Gold BeES), Hindustan Unilever (HUL), Wipro, Nestle India, and UCO Bank. These securities represent a diverse range of sectors and market segments, thereby allowing the study to examine whether the observed pattern is confined to a particular type of security or appears across different segments of the market. The Nifty 50 is considered primarily as a benchmark for understanding the broader market environment rather than as one of the securities forming the principal sample.

The primary objective of the study is to determine whether the direction of a security's return on one trading day is followed by a similar direction on the next trading day. The analysis therefore focuses on consecutive daily returns and examines the extent to which positive movements are followed by positive movements and negative movements by negative movements. A secondary objective is to place these observed return patterns in the context of important market and economic news reported during the preceding trading session. This provides an opportunity to examine whether major information developments offer a useful contextual explanation for subsequent market movements.

The study does not attempt to establish a direct causal relationship between individual news events and changes in security prices. Rather, news is considered as part of the information environment within which investors make decisions. The central purpose is to determine whether the previous trading day's price direction, considered alongside the prevailing news environment, provides any consistent indication of the direction of the subsequent trading session. By combining a simple analysis of consecutive daily returns with an examination of the broader market context, the study seeks to contribute to a clearer understanding of short-term lead-lag dynamics in selected Indian securities during September 2026.

2.0 LITERATURE REVIEW

The question of whether information contained in past prices can be used to anticipate future price movements has been central to financial economics for several decades. The issue is closely associated with the Efficient Market Hypothesis (EMH), according to which security prices rapidly incorporate available information. Fama (1970) provided one of the most influential formulations of the efficient-market framework and distinguished among weak, semi-

strong, and strong forms of market efficiency. Under the weak form of efficiency, historical price and return information should already be reflected in current prices. Consequently, systematic prediction of future returns based solely on previous price movements should be difficult. This proposition provides an important theoretical benchmark for examining whether the direction of one trading day is systematically followed by a similar direction on the next trading day.

2.1 Market Efficiency, Random Walk and Return Predictability

The question of whether historical market information can be used to anticipate future price movements is fundamentally connected with the Efficient Market Hypothesis (EMH). Fama (1970) argued that security prices incorporate available information rapidly, implying that historical price information should not provide a systematic basis for predicting abnormal future returns under weak-form efficiency. From this perspective, if markets are weak-form efficient, the direction of a previous trading day's return should provide little dependable information about the direction of the following day's return.

However, subsequent empirical research has shown that financial markets do not always behave as perfectly independent random walks. Lo and MacKinlay (1988) provided evidence against a strict random-walk description of stock prices, encouraging researchers to investigate serial dependence and other forms of return predictability. More recent research has continued to question whether market efficiency should be regarded as a constant condition rather than a time-varying phenomenon.

Sing and Singh (2024), in their examination of the Indian equity market, reported significant periods of both efficiency and inefficiency, supporting the Adaptive Market Hypothesis and suggesting that market efficiency can vary with changing market conditions. Similarly, Kundu and Banerjee (2024), using data for 611 Indian firms across 11 industries, found that the assimilation of disclosed financial information into stock prices was inefficient for a significant number of stocks and that efficiency displayed mean-reverting characteristics. These findings are particularly relevant to the present study because they suggest that information may not always be incorporated into prices at exactly the same speed.

A further challenge to a simple efficient-market interpretation is provided by Murray, Xia, and Xiao (2024). Their machine-learning analysis found that historical price information contained nonlinear predictive patterns for the cross-section of future stock returns, with predictive power remaining significant across different periods and among large-cap stocks. The findings do not imply that simple next-day prediction is necessarily possible, but they demonstrate that historical market information can contain patterns that are not fully captured by conventional linear models.

Thus, recent evidence suggests that market efficiency may be better understood as a dynamic condition influenced by market structure, investor behaviour, liquidity and information processing rather than as an absolute state.

2.2 Lead–Lag Effects and Information Transmission

The concept of a lead–lag relationship is directly relevant to the present research because it concerns the possibility that information reflected in one price movement may subsequently appear in another price movement. Although lead–lag relationships have been examined extensively in financial economics, recent research has expanded the analysis by considering information networks, market structure and the speed of information diffusion.

Li et al. (2022) systematically examined lead–lag effects in stock markets and emphasized that securities can exhibit systematic delayed responses to the price movements of other securities. Their study demonstrated that lead–lag relationships can contain information relevant to investment strategies, although the existence and stability of such relationships depend on market characteristics.

Lee, Huang, Song, and Xiang (2022) provided further evidence by examining the relationship between information arrival and lead–lag returns among economically connected firms. Their results showed that investors can under react to information arriving gradually, while information arriving in more discrete forms may be incorporated more quickly. This finding suggests that the speed of information assimilation can influence the strength of lead–lag relationships.

More recently, Lee, Shi, Sun, and Zhang (2024) examined production-complementarity networks and found significant lead–lag effects among firms connected through their production relationships. Their evidence indicates that information can travel through economic networks and that stock prices do not necessarily adjust instantaneously to information originating from economically connected firms.

Cartea, Cucuringu, and Jin (2023/2026) developed a directional approach for identifying lead–lag relationships in daily US equity returns and investigated the economic value of using lagged returns from inferred leading securities. Their work illustrates the increasing sophistication of recent research in identifying directional information transmission rather than simply measuring contemporaneous correlations.

These studies strengthen the theoretical relevance of examining whether a previous trading day's return is associated with the subsequent day's return. However, most recent lead–lag studies

examine relationships across securities, industries or economically connected firms. The present study takes a simpler but complementary approach by investigating **consecutive-day directional persistence within a selected group of Indian securities**.

2.3 Momentum, Reversal and Short-Term Return Behaviour

The literature on momentum and reversal provides another important theoretical foundation for the present study. Momentum implies that securities experiencing positive returns tend to continue performing positively, whereas reversal implies that previous positive returns are followed by negative returns, or previous negative returns by positive returns. The distinction is particularly important when examining the relationship between one trading day and the next.

The classical momentum literature began with Jegadeesh and Titman (1993), who documented continuation in stock returns over intermediate horizons. Conversely, De Bondt and Thaler (1985) provided evidence of longer-term reversal, suggesting that securities with extreme past performance can subsequently move in the opposite direction.

Recent Indian evidence provides particularly strong support for the coexistence of momentum and reversal effects. Chui, Ranganathan, Rohit, and Veeraraghavan (2023) examined 3,956 stocks listed on the Bombay Stock Exchange over 2000–2021 and found significant momentum effects as well as short- and intermediate-term reversals, particularly among less liquid stocks. Their results demonstrate that liquidity plays an important role in determining whether continuation or reversal is observed.

A 2024 study by researchers examining Indian equities further investigated relative, absolute and combined momentum strategies. The study found that enhanced momentum strategies could provide additional information beyond conventional price momentum and examined their robustness under adverse market conditions and the role of investor attention.

At the international level, Lee et al. (2022) showed that information arriving gradually can generate persistent lead-lag momentum effects, suggesting that momentum may partly arise from delayed investor response to information rather than purely from mechanical price continuation.

Similarly, recent machine-learning evidence from Murray, Xia, and Xiao (2024) indicates that historical price information contains nonlinear predictive structures that are distinct from conventional momentum and reversal signals.

These studies suggest that continuation and reversal should not be treated as mutually exclusive characteristics of a market. Their relative importance can vary according to investment horizon, liquidity, investor attention and the information environment. This provides a strong justification for directly examining consecutive-day movements in the present study.

2.4 Investor Sentiment and Stock Returns

Investor sentiment represents another important explanation for short-term deviations from purely information-efficient price behaviour. Traditional financial theory assumes that investors process information rationally, whereas behavioural-finance research recognizes that optimism, pessimism, attention and expectations can influence trading decisions and asset prices.

Baker and Wurgler (2006, 2007) established an important foundation for the sentiment literature by demonstrating that investor sentiment can influence stock returns and that the effects can differ across securities. More recent research has extended this literature to emerging markets and, particularly, India.

Yadav and Naik (2024) examined irrational investor sentiment and Indian stock-market excess returns using a quantile-regression framework. Their results indicated that the relationship between sentiment and excess returns is not uniform across different return quantiles. This suggests that sentiment may have different effects during different market conditions rather than exerting a constant influence on returns.

Kamath et al. (2024) examined the relationship between investor sentiment and the Nifty 500 as well as selected Indian sectoral indices. Their results indicated a significant positive relationship between investor sentiment and returns, including for information technology, FMCG and other sectoral indices.

Ahn and Hambusch (2024), using international market evidence, found that optimistic and pessimistic sentiment can produce predictable variations in asset prices, with pessimistic sentiment associated with greater return volatility and correlation. Their evidence also supports the possibility of reversal effects arising from sentiment-driven mispricing.

More recent Indian evidence by Sardar and Khan (2024) found that an investor-sentiment index Granger-caused Nifty 50 returns, while the effect of stock returns on sentiment was comparatively limited and temporary. In addition, research by Banerjee and Kundu (2024) using millions of tweets associated with major Indian firms found that public sentiment affected stock-price movements, with the effect being particularly pronounced during trading hours.

These findings are relevant to the present research because a previous day's market direction may reflect not only fundamental information but also investor sentiment. Consequently, a subsequent reversal or continuation may partly reflect changes in collective investor expectations.

2.5 News, Information Arrival and Market Reaction

Financial markets continuously process new information. News concerning monetary policy, inflation, crude oil prices, exchange rates, geopolitical developments and corporate events can alter expectations about future cash flows and risk. Therefore, understanding short-term market movements requires consideration of both historical returns and the information environment.

Tetlock (2007) established an important connection between financial-media sentiment and market movements by showing that pessimistic media content was associated with downward pressure on prices and changes in trading activity. Tetlock, Saar-Tsechansky, and Macskassy (2008) subsequently demonstrated that information contained in firm-specific news could provide useful information concerning corporate fundamentals and stock-price movements.

Recent literature has extended this perspective by emphasizing the speed and manner in which information is incorporated into prices. Lee et al. (2022) showed that the form in which information arrives affects the strength of subsequent lead-lag effects. Information arriving continuously can generate investor underreaction, whereas discrete information may receive more immediate attention.

Kundu and Banerjee (2024) found that the efficiency with which disclosed financial information is incorporated into Indian stock prices differs across firms and is influenced by investors' reference points and price anchors.

Yang and Yin (2024) provided further evidence concerning delayed information incorporation by distinguishing between daytime and overnight information. Their findings suggest that asynchronous information absorption and stock-price delay can have implications for subsequent returns.

Banerjee and Kundu (2024) also demonstrated, using approximately 5.4 million tweets relating to 437 large Indian firms, that public sentiment can affect stock-price movements and that the effect is stronger during trading hours.

The literature therefore supports the use of news as contextual information in the present study. However, the purpose of the news analysis should remain interpretative rather than causal

because the short observation period and descriptive research design do not permit rigorous identification of the causal effect of individual news events.

2.6 Liquidity, Market Microstructure and Delayed Price Adjustment

Market liquidity is an important consideration when interpreting short-term relationships between successive returns. Securities with high liquidity generally incorporate information more rapidly, whereas illiquid securities may exhibit delayed adjustment, wider bid–ask spreads and stronger short-term price reversals.

Chui et al. (2023) provide particularly relevant evidence from India. Their large-sample analysis found that liquidity strengthened momentum among highly liquid stocks, while short- and intermediate-term reversals were more pronounced among illiquid stocks.

Yang and Yin (2024) similarly demonstrated that the timing of information arrival—during the trading day versus overnight—can influence price adjustment and future returns. Their findings provide evidence of information delay and asynchronous adjustment that may contribute to apparent predictability.

Poutré, Dionne, and Yergeau (2024) examined the profitability of lead–lag arbitrage using high-frequency limit-order-book information and showed that lead–lag effects can potentially generate predictive signals, while emphasizing the importance of market microstructure in identifying and exploiting such relationships.

Li et al. (2022) likewise demonstrated that lead–lag effects can exhibit stable patterns that may contain information relevant to investment strategies.

These studies imply that an observed relationship between yesterday's and today's returns may partly reflect differences in liquidity, information arrival and trading mechanisms rather than genuine forecasting ability. Although the present study does not explicitly model liquidity or bid–ask spreads, these factors should be recognized when interpreting the empirical findings.

2.7 Indian Stock Market, Global Factors and Time-Varying Behaviour

The Indian stock market is increasingly integrated with global financial markets. International interest rates, crude oil prices, exchange-rate movements, foreign portfolio flows and geopolitical developments can influence domestic investor sentiment and asset prices. Consequently, the relationship between successive Indian market returns may vary according to the broader global environment.

Recent Indian research supports the proposition that market behaviour is time-varying. Sing and Singh (2024) found evidence of alternating periods of efficiency and inefficiency in the Indian equity market, consistent with the Adaptive Market Hypothesis. Kundu and Banerjee (2024) similarly reported that financial information is not assimilated with identical efficiency across Indian firms.

Chui et al. (2023) demonstrated that momentum and reversal effects in India vary with liquidity and remain relevant even after controlling for several macroeconomic and risk factors.

Yadav and Naik (2024) further showed that the influence of investor sentiment on Indian excess returns differs across market-return quantiles, indicating that market conditions matter when interpreting the relationship between sentiment and returns.

Recent evidence therefore suggests that Indian market behaviour should not be interpreted through a single, permanently applicable model. Rather, return predictability, sentiment effects, liquidity effects and information absorption may change according to prevailing market conditions.

This perspective is particularly relevant for September 2026, when the market experienced a combination of commodity-price pressures, global monetary-policy concerns, geopolitical uncertainty, foreign-investor activity and sector-specific developments. The present study therefore treats the observed lead–lag relationship as **conditional on the market environment of the study period**, rather than assuming that the relationship necessarily persists across all periods.

2.8 Research Gap

The literature reviewed above establishes that the relationship between past and future returns is more complex than a simple random-walk assumption might suggest. Recent research has documented lead–lag effects, momentum, reversal, information delays, investor sentiment effects and time-varying market efficiency. Importantly, evidence from India also indicates that momentum and reversal can coexist and that their strength may depend on liquidity, investor sentiment and prevailing market conditions.

Nevertheless, an identifiable gap remains. A substantial part of the recent literature uses large datasets covering many years and employs sophisticated econometric, portfolio-based or machine-learning techniques. Such approaches are valuable for establishing generalizable patterns, but they can sometimes obscure the simple question of whether **the direction observed**

on one trading day was actually followed by the same direction on the immediately subsequent trading day during a particular market episode.

The present study addresses this narrower question by examining eleven selected Indian securities during September 2026. Rather than attempting to construct a profitable trading strategy or make a definitive claim regarding market efficiency, the study provides exploratory evidence on next-day directional continuation and reversal. It also complements the return analysis with a review of the prevailing news environment, allowing the observed patterns to be interpreted in relation to crude oil prices, global interest-rate expectations, geopolitical developments, foreign investment flows, currency movements and sector-specific information.

The study consequently occupies a useful position between purely descriptive market commentary and large-scale predictive modelling. Its findings can provide preliminary evidence that may guide future research based on longer periods, larger samples, security-level liquidity measures, formal autocorrelation tests, Granger-causality analysis, event studies and multivariate forecasting models.

3.0 RESEARCH METHODOLOGY

3.1 Research Design and Approach

The present study adopts an **empirical, descriptive and exploratory research design** to examine the short-term lead-lag relationship among a selected group of securities traded in the Indian stock market during September 2026. The central purpose is to investigate whether the direction of a security's return on one trading day tends to be followed by a movement in the **same direction on the subsequent trading day**.

The study is deliberately designed as a short-horizon observational analysis rather than as a formal predictive or trading-strategy model. Accordingly, the analysis focuses on identifying patterns of **directional continuation, reversal and return association** between consecutive trading sessions. The approach is particularly appropriate for examining whether the market movements observed during a period characterized by considerable domestic and international uncertainty exhibit any consistent next-day pattern.

The sample consists of eleven securities representing several important segments of the Indian financial market: banking, information technology, oil and energy, consumer goods, and gold. The securities included are HDFC Bank, Axis Bank, State Bank of India (SBI), Tata Consultancy Services (TCS), Infosys, Wipro, ONGC, Hindustan Unilever (HUL), Nestle India, UCO Bank and Nippon India ETF Gold BeES (Gold BeES).

The selection is **observational and purposive rather than probability-based**. These securities were selected because they were regularly monitored during the study period and together provide exposure to different sectors and asset characteristics. Consequently, the findings should be interpreted as evidence relating to the selected securities during the specified period and should not be generalized automatically to the entire Indian stock market.

3.2 Study Period and Data Structure

The study covers the trading period from **31 August 2026 to 30 September 2026**. Daily closing prices were recorded for each of the eleven selected securities. The closing price on 31 August 2026 is included as the initial reference observation because it is required to calculate the return for the first trading session of September.

The market was closed on **14 September 2026** due to Ganesh Chaturthi. Therefore, no artificial observation or zero return is introduced for the non-trading day. The analysis follows the actual sequence of trading sessions, such that a return is calculated only when a preceding trading-day closing price is available.

The **Nifty 50** is considered only as a broad-market reference for contextual interpretation. It is not included as one of the eleven securities in the principal security-level statistical analysis. This distinction enables the study to examine individual-security behaviour while using the broader market index only to provide market-level background.

3.3 Sample Selection

The eleven securities were selected to provide representation across different sectors and asset types. The composition of the sample is presented in Table 1.

Table 1. Selected Securities Used for the Daily Observations

Security	Symbol	Category
HDFC Bank	HDFCBANK	Banking
Axis Bank	AXISBANK	Banking
State Bank of India	SBIN	Banking / PSU Bank
Tata Consultancy Services	TCS	Information Technology
Infosys	INFY	Information Technology
Wipro	WIPRO	Information Technology
ONGC	ONGC	Oil and Energy
Hindustan Unilever	HINDUNILVR	Consumer Goods / FMCG
Nestle India	NESTLEIND	Consumer Goods / FMCG
UCO Bank	UCOBANK	Banking / PSU Bank
Nippon India ETF Gold Bees	GOLDBEES	Gold ETF

The sample therefore contains **four banking securities, three information-technology securities, one oil and energy security, two consumer-goods securities, and one gold exchange-traded fund**. The inclusion of Gold Bees is intended to provide an asset with a different underlying price driver from the company-specific equities.

3.4 Data and Return Measurement

The primary variable used in the study is the **daily percentage return** of each selected security. The daily return is calculated as:

$$R_{i,t} = [P_{i,t} / P_{i,t-1} - 1] \times 100$$

Where:

- $R_{i,t}$ = daily percentage return of security i on trading day t ;
- $P_{i,t}$ = closing price of security i on day t ;
- $P_{i,t-1}$ = closing price of security i on the previous trading day.

Using 31 August 2026 as the base observation results in **21 daily September return observations for each of the eleven securities**, producing:

$$11 \times 21 = 231$$

Security-day return observations.

The analysis subsequently examines the relationship between a return on one trading day and the return of the **same security on the immediately following trading day**. Since the first September return does not have a preceding September return within the study period for the purpose of a previous-day/next-day comparison, the consecutive-return analysis produces **20 paired observations per security**, or:

$$11 \times 20 = 220$$

Previous-day/next-day return pairs.

3.5 Measurement of Directional Continuation

A principal objective of the study is to determine whether a positive or negative return tends to be followed by a return having the **same directional sign**.

For each consecutive pair:

- Positive return $\rightarrow$ Positive return = **same-direction continuation**

- Negative return → Negative return = **same-direction continuation**
- Positive return → Negative return = **directional reversal**
- Negative return → Positive return = **directional reversal**

Thus, the continuation rate for security i is calculated as:

$$CRI_i = \frac{\text{Number of same-direction consecutive pairs}}{\text{Total consecutive return pairs}} \times 100$$

Since each security contributes 20 consecutive return pairs:

$$CRI_i = \frac{\text{Same-direction pairs}}{20} \times 100$$

A continuation rate of 50% would indicate that same-direction and opposite-direction movements occurred equally often. A rate substantially above 50% would provide descriptive evidence of directional continuation, whereas a rate below 50% would indicate that **reversals occurred more frequently than continuations**.

The measure is used as a descriptive indicator and is not interpreted as evidence of a statistically exploitable trading strategy.

3.6 Lagged Return Correlation

To supplement the directional analysis, the study calculates the correlation between the return on the previous trading day and the return on the subsequent trading day for each security.

The lagged correlation can be represented as:

$$\rho_i = \text{Corr}(R_{i,t-1}, R_{i,t})$$

Where $R_{i,t-1}$ represents the previous trading day's return and $R_{i,t}$ represents the return on the subsequent trading day.

A **positive correlation** indicates that higher previous-day returns tend, descriptively, to be associated with higher next-day returns, whereas a **negative correlation** indicates an inverse association and is consistent with short-term reversal behaviour.

Importantly, the correlation coefficients are interpreted as measures of **association rather than causality**. Given the relatively small number of observations available for each security, the

coefficients are used primarily to identify the direction and relative strength of the observed relationship rather than to establish a definitive statistical law.

3.7 Group-Level Return Analysis

In addition to security-specific analysis, the study calculates the **simple cross-sectional average return** of the eleven securities for each trading session:

$$R_t = 1/11 \sum_{i=1}^{11} R_{i,t}$$

This measure provides a simple indication of the overall directional movement of the selected group on each trading day.

The average return is subsequently compared across consecutive trading sessions to determine whether the group, considered as a whole, tends to continue in the same direction or reverse direction on the following trading day. This procedure helps distinguish security-specific patterns from a broader movement shared across the sample.

The simple average is not intended to represent the return of an investable portfolio because the securities are not weighted according to market capitalization, liquidity, or any portfolio construction rule.

3.8 Descriptive Performance Measures

Several descriptive measures are employed to summarize the behaviour of the selected securities during September 2026. These include:

1. **Number of positive-return days;**
2. **Number of negative-return days;**
3. **Change in closing price between 31 August and 30 September 2026;**
4. **Number of same-direction consecutive return pairs;**
5. **Continuation rate;** and
6. **Lagged correlation between previous-day and next-day returns.**

The period change is calculated as:

$$\text{Period Change (\%)} = [P_{30\text{Sep}} - P_{31\text{Aug}} / P_{31\text{Aug}}] \times 100$$

These measures provide complementary information. While the period change captures the overall performance during the month, the positive/negative day counts describe the frequency of

daily movements and the continuation rate and lagged correlation focus specifically on the short-term lead-lag relationship.

Table 2. September 2026 Performance of the Eleven Observed Securities

Security	31 Aug. Close	30 Sep. Close	Period Change	Positive Days	Negative Days
HDFC Bank	709.00	708.70	-0.04%	11	10
Axis Bank	1,300.00	1,226.00	-5.69%	9	11
State Bank of India	1,060.00	959.50	-9.48%	8	13
Tata Consultancy Services	2,399.30	2,050.60	-14.53%	4	17
Infosys	1,133.80	994.10	-12.32%	6	15
Wipro	184.50	158.50	-14.09%	7	14
ONGC	231.80	225.80	-2.59%	11	9
Hindustan Unilever	1,967.40	1,879.10	-4.49%	9	12
Nestle India	1,496.50	1,310.00	-12.46%	6	15
UCO Bank	24.89	23.28	-6.47%	8	13
Nippon India ETF Gold BeES	127.32	121.59	-4.50%	8	13

3.9 News and Event-Based Contextual Analysis

The quantitative analysis is supplemented by a **qualitative review of relevant financial and economic news** reported during the study period. The purpose of this component is not to establish causal relationships but to provide contextual information that may assist in interpreting unusually strong or persistent price movements.

News items are broadly classified into the following categories:

- overall Indian market developments;
- banking and interest-rate developments;
- information-technology and global technology developments;
- crude oil and energy-related developments;
- consumer-sector developments;
- gold and precious-metals developments; and
- International and geopolitical developments.

The relevance of different news categories is considered in relation to the securities most directly exposed to them. For example, crude-oil developments are considered in interpreting ONGC and the broader market, while global technology developments are considered in relation to TCS, Infosys and Wipro. Banking-sector and interest-rate developments are considered in relation to HDFC Bank, Axis Bank, SBI and UCO Bank.

Gold Bees is treated separately because its price behaviour is primarily linked to movements in gold and related global market conditions rather than to the operating performance of an individual company.

The news analysis is therefore **contextual rather than causal**. The occurrence of a news event followed by a price movement is not, by itself, sufficient to establish that the news event caused that movement. This distinction is particularly important in a short-period observational study because several information events may occur simultaneously and market prices may respond to multiple factors.

3.10 Summary of Previous-Day/Next-Day Analysis

The principal security-level measures obtained from the consecutive-return analysis are presented in Table 3.

Table 3. Previous-Day and Next-Day Relationship for Each Security

Security	Same Direction (out of 20)	Continuation Rate	Lag Correlation
HDFC Bank	9	45%	-0.05
Axis Bank	6	30%	-0.39
State Bank of India	4	20%	-0.36
Tata Consultancy Services	13	65%	-0.50
Infosys	15	75%	-0.17
Wipro	9	45%	-0.13
ONGC	9	45%	-0.17
Hindustan Unilever	6	30%	-0.32
Nestle India	10	50%	-0.51
UCO Bank	9	45%	-0.18
Nippon India ETF Gold BeES	7	35%	-0.22

The table is used to compare the two complementary dimensions of the lead-lag relationship. The **continuation rate** captures the frequency with which consecutive returns have the same sign, whereas the **lag correlation** captures the linear association between the magnitude and direction of consecutive returns.

3.11 Scope and Methodological Limitations

Several limitations should be recognized when interpreting the findings.

First, the study covers only **one month of trading activity**, resulting in a relatively small number of observations. Consequently, the findings should be regarded as period-specific rather than as evidence of a persistent market phenomenon.

Second, the securities are selected through an **observational and purposive approach** rather than a statistically representative sampling procedure. The sample therefore cannot be considered representative of all securities listed on Indian stock exchanges.

Third, the analysis focuses exclusively on **daily closing prices**. Intraday price movements, opening-price effects, trading volume, order flow, volatility, bid–ask spreads and other market-microstructure variables are not incorporated.

Fourth, the study uses simple return correlations and directional comparisons rather than a formal econometric model incorporating control variables, structural breaks, volatility clustering or statistical significance testing. The reported relationships should therefore be interpreted as **descriptive evidence of short-term dependence**, not as proof of a causal lead–lag mechanism.

Finally, the news analysis provides contextual interpretation but does not employ a formal event-study methodology. Hence, the study does not attempt to estimate abnormal returns attributable to individual news events.

3.12 Methodological Framework

This framework is designed to answer the central research question of whether the direction of a selected security's return on one trading day is systematically reflected in its movement on the following trading day during September 2026. The approach deliberately prioritizes **transparency, direct measurement and descriptive interpretation** over complex predictive modelling, thereby making the observed continuation and reversal patterns readily interpretable within the context of the selected sample and study period.

4.0 EMPIRICAL ANALYSIS

4.1 Overall Performance of the Selected Securities

The empirical evidence indicates that **September 2026 was a predominantly weak month for the securities included in the study**, although the magnitude of the decline varied considerably across individual securities and sectors. All eleven securities recorded a lower closing price on 30 September 2026 than on 31 August 2026. This broad decline, however, was not uniform and therefore highlights the importance of examining security-level and sector-level behaviour rather than relying exclusively on aggregate market indicators.

HDFC Bank exhibited the greatest relative stability, declining by only **0.04%** over the study period. ONGC also experienced a comparatively moderate decline of **2.59%**. Hindustan Unilever and Nippon India ETF Gold BeES declined by approximately **4.49%** and **4.50%**, respectively. The banking securities displayed greater dispersion: Axis Bank declined by **5.69%**, UCO Bank by **6.47%**, and State Bank of India by **9.48%**.

The most pronounced deterioration was observed among the information-technology securities. TCS declined by **14.53%**, Wipro by **14.09%**, and Infosys by **12.32%**. Nestle India also recorded a substantial decline of **12.46%**. The difference between the relatively stable performance of HDFC Bank and the substantial decline in the IT securities demonstrates that the September market environment affected sectors and securities differently.

Thus, the first important empirical observation is that **aggregate market weakness coexisted with substantial cross-sectional heterogeneity**. A market-level index may indicate the direction of the overall market, but it does not necessarily capture the intensity or persistence of movements in individual securities.

4.2 Distribution of Daily Returns

The daily return observations provide further evidence of the predominantly negative market environment. Across the **231 security-day observations**, 87 observations were positive, 142 were negative, and 2 were unchanged. Consequently, approximately **61.5%** of the observations were negative, compared with approximately **37.7%** positive observations, with the remaining **0.9%** unchanged.

The frequency distribution therefore indicates a clear predominance of negative daily movements during the study period. However, the negative returns were not distributed evenly across trading sessions. Several sessions exhibited exceptionally broad-based weakness.

On **7 September**, all eleven securities declined, producing an average sample return of approximately **-1.25%**. The same broad-based pattern occurred on **9 September**, when all eleven securities again declined and the average return fell to approximately **-1.51%**. Further episodes of widespread weakness occurred on **24 September** and **28 September**, when ten of the eleven securities declined.

The market also experienced intermittent rebounds. On **25 September**, eight of the eleven securities recorded positive returns, resulting in an average sample return of approximately **+0.41%**. These alternating episodes of widespread declines and partial rebounds are important

for interpreting the lead-lag results because they suggest that the market was characterized by **short-lived directional episodes rather than a uniform, uninterrupted trend**.

4.3 Previous-Day and Next-Day Return Relationship

The central empirical objective of the study is to determine whether the direction of a security's return on one trading day is systematically followed by the same direction on the next trading day.

The analysis generates **220 previous-day/next-day return pairs** across the eleven securities. Of these, **97 pairs**, or approximately **44.1%**, exhibited movement in the same direction. Conversely, approximately **55.9%** of the pairs involved a reversal in direction.

The continuation rate below 50% is noteworthy. If daily movements had shown an approximately balanced continuation-reversal pattern, the continuation rate would be expected to be close to 50%. The observed rate of **44.1%** instead indicates that, within this sample and period, directional reversals occurred somewhat more frequently than directional continuations.

The pooled correlation between previous-day and next-day returns was approximately **-0.23**. The negative sign indicates an inverse association between consecutive daily returns at the aggregate level. In descriptive terms, relatively positive returns tended to be followed by relatively weaker returns, while relatively negative returns tended to be followed by relatively stronger returns. This pattern is more consistent with **short-term reversal behaviour** than with a systematic momentum or continuation effect.

Nevertheless, the magnitude of the correlation should not be interpreted as evidence of a stable predictive relationship. The study covers only one month and contains a limited number of observations. The negative association therefore provides evidence of a pattern within the sample rather than proof of a persistent market anomaly.

4.4 Group-Level Evidence

The same relationship becomes apparent when the eleven securities are considered collectively. The simple average return of the eleven securities continued in the same direction on only **8 of the 20 consecutive comparisons**, corresponding to a continuation rate of **40%**.

Thus, at the group level, the direction of the previous trading session was followed by the same direction in less than half of the subsequent sessions. The one-day lag correlation of the equally weighted average return was approximately **-0.31**, again indicating a negative short-term association.

Taken together, the security-level and group-level evidence points in the same general direction. The previous trading day's return did **not provide a reliable directional continuation signal** during September 2026. If anything, the negative correlations suggest a tendency toward short-term reversal within the observed sample.

It is important, however, to distinguish statistical association from economic predictability. A negative lag correlation does not imply that investors could necessarily construct a profitable trading strategy based solely on the previous day's return. Transaction costs, market liquidity, execution prices, risk, and the statistical stability of the relationship would all need to be considered before drawing such a conclusion.

4.5 Security-Level Heterogeneity in Lead-Lag Behaviour

Although the aggregate evidence suggests weak continuation, considerable variation exists across individual securities.

Infosys recorded the highest number of same-direction movements, with **15 out of 20 pairs**, corresponding to a continuation rate of **75%**. TCS followed with **13 out of 20 pairs**, or **65%**. Nestle India recorded 10 same-direction pairs, corresponding to **50%**.

At the other end of the distribution, SBI recorded only **4 same-direction pairs out of 20**, giving a continuation rate of **20%**. Axis Bank and Hindustan Unilever recorded 6 same-direction pairs each, corresponding to continuation rates of **30%**.

The differences are even more informative when continuation rates are considered alongside lagged correlations. For example, Infosys and TCS displayed relatively high same-direction frequencies, yet their lag correlations were **-0.17 and -0.50**, respectively. Similarly, Nestle India had a 50% continuation rate but a lag correlation of **-0.51**.

This apparent difference between **directional continuation frequency and return correlation** is important. A security can experience several consecutive movements in the same direction without the magnitude of today's return being positively related to tomorrow's return. Therefore, repeated negative observations during a weak market should not automatically be interpreted as evidence that the size or direction of the following day's return was predictable from the previous day's return.

4.6 Sectoral Comparison

The sectoral comparison provides further evidence that the September decline was not homogeneous across the market.

The three information-technology securities—TCS, Infosys and Wipro—recorded an average period decline of approximately **13.65%**, substantially greater than the average decline of approximately **5.42%** across the four banking securities. Within banking itself, however, considerable variation was evident. HDFC Bank declined by only **0.04%**, compared with a **9.48%** decline in SBI. This demonstrates that even securities belonging to the same sector did not respond identically to the prevailing market conditions.

The two consumer/FMCG securities, HUL and Nestle India, recorded an average decline of approximately **8.48%**. ONGC declined by approximately **2.59%**, while Gold BeES declined by approximately **4.50%**.

The sectoral comparison suggests that the effect of market-wide information cannot be considered independent of **sector-specific exposure and security-specific characteristics**. Global technology concerns, for example, may affect IT stocks differently from banks or consumer companies, while crude-oil developments may have a different relevance for energy-related securities.

4.7 Trading-Session Evidence and Market Reversals

A closer examination of individual trading sessions reinforces the absence of a mechanical continuation pattern.

The period beginning in early September provides an illustrative example. On **7 September**, all eleven securities declined, producing an average return of approximately -1.25% . However, the following session, 8 September, produced a considerably more mixed outcome, with five securities rising and six declining. On 9 September, all eleven securities again declined, followed by a mixed session on 10 September, when six securities gained and five declined.

A similar pattern appeared during the final week of the month. On **24 September**, ten securities declined and the average return was approximately -1.24% . The following session, **25 September**, saw eight securities rise and the average return turn positive to approximately $+0.41\%$. On **28 September**, ten securities again declined, with the average return falling to approximately -1.66% . On 29 September, however, the distribution became more mixed, with four securities rising, six declining and one remaining unchanged. On **30 September**, six securities gained and five declined, although the average return remained slightly negative at approximately -0.30% .

These episodes demonstrate that even when market-wide weakness was unusually broad, the direction of the following session could change substantially. Thus, the previous session appears

to have provided **information about the prevailing market environment**, but not a deterministic signal about the direction of each security on the next trading day.

4.8 News and Market Context

The quantitative results can be interpreted more effectively when considered alongside the broader information environment prevailing during September 2026. The period was characterized by concerns relating to crude-oil prices, international interest rates, geopolitical developments, currency movements and foreign investor activity. Such factors potentially affected different sectors through different transmission channels.

The early-September weakness coincided with concerns over higher crude prices, global interest-rate expectations and pressure on the rupee. During subsequent sessions, changes in crude prices, global yields and investor sentiment contributed to alternating periods of selling and recovery.

The **24 September** session provides a useful illustration. Ten of the eleven selected securities declined, while Axis Bank experienced a particularly sharp decline of approximately **4.56%**. ONGC was the only security in the sample to record a gain. On the following day, however, eight of the eleven securities advanced, producing an average return of approximately **+0.41%**. This sharp change in cross-sectional direction illustrates how a weak market session could be followed by a broad partial recovery.

The late-September sequence provides another example. On 28 September, ten securities declined amid continued concerns regarding crude oil and international developments. Weakness persisted on 29 September, when six securities declined and the average return was approximately -0.54% . By 30 September, however, six securities recorded positive returns, even though the equally weighted average remained slightly negative.

These observations suggest that **news persistence and price persistence were related but not identical phenomena**. A continuing macroeconomic concern could contribute to repeated market weakness, but the arrival of new information, changes in expectations, bargain buying, or security-specific factors could alter the direction of prices on the subsequent trading session.

Accordingly, news events are best interpreted as **contextual explanations rather than deterministic causes**. The empirical design does not permit individual news items to be isolated statistically and therefore does not establish that any particular event caused a specific security's return.

4.9 Summary of Previous-Session Conditions and Subsequent Market Response

Table 4 summarizes selected trading sessions to illustrate the relationship between the prevailing market/news environment and the subsequent movement of the eleven securities.

Table 4. Previous-Session Conditions and Next-Session Responses

Previous Session	Main Market/News Condition	Next Session Response
31 Aug	Global concerns, rising crude-oil prices and rate-related uncertainty; August FPI inflows remained relatively strong.	1 Sep: 4 up, 7 down; average -0.85%
1 Sep	Market remained subdued amid oil, inflation and global-rate concerns.	2 Sep: 1 up, 10 down; average -1.07%
2 Sep	Middle East tensions contributed to higher oil prices and broader market weakness.	3 Sep: 5 up, 6 down; average $+0.06\%$
3 Sep	Oil concerns continued to offset gains in banking securities.	4 Sep: 6 up, 5 down; average $+0.10\%$
4 Sep	Four-session losing sequence ended, although crude-oil and broader market concerns remained.	7 Sep: 0 up, 11 down; average -1.25%
7 Sep	IT selling, crude-oil concerns and expectations of higher US rates affected sentiment.	8 Sep: 5 up, 6 down; average -0.27%
8 Sep	Private banks and large-cap securities weakened as crude approached \$100.	9 Sep: 0 up, 11 down; average -1.51%
9 Sep	Brent crude moved above \$100 and the rupee weakened beyond ₹95 per US dollar.	10 Sep: 6 up, 5 down; average $+0.27\%$
10 Sep	Market recovered modestly, although crude remained elevated and rate uncertainty persisted.	11 Sep: 4 up, 6 down, 1 flat; average -0.16%
11 Sep	Oil and inflation concerns kept yields elevated and strengthened rate-hike expectations.	15 Sep: 6 up, 5 down; average $+0.17\%$
15 Sep	Nifty remained under pressure as crude approached \$108 and global yields increased.	16 Sep: 7 up, 4 down; average $+0.23\%$
16 Sep	Market rebounded despite continuing international risks.	17 Sep: 1 up, 10 down; average -0.59%
17 Sep	Following the Fed decision, crude eased somewhat and the rupee stabilized with RBI support.	18 Sep: 8 up, 3 down; average $+0.22\%$
18 Sep	Bargain buying and lower oil provided support despite a weak broader weekly trend.	21 Sep: 5 up, 6 down; average $+0.07\%$
21 Sep	Bargain buying continued while geopolitical concerns remained.	22 Sep: 3 up, 8 down; average -0.43%
22 Sep	IT-demand concerns exerted pressure despite some easing in oil prices.	23 Sep: 6 up, 5 down; average $+0.21\%$
23 Sep	Oil below \$100 improved market sentiment and supported financials.	24 Sep: 1 up, 10 down; average -1.24%

24 Sep	Oil moved above \$105 and financial-sector concerns intensified.	25 Sep: 8 up, 3 down; average +0.41%
25 Sep	A partial rebound occurred, although oil and yields remained elevated.	28 Sep: 1 up, 10 down; average -1.66%
28 Sep	US-Iran tensions and higher Brent prices contributed to broad market weakness.	29 Sep: 4 up, 6 down, 1 flat; average -0.54%
29 Sep	Crude, US yields and foreign selling remained important market pressures.	30 Sep: 6 up, 5 down; average -0.30%

The session-level evidence therefore complements the statistical findings. Periods of persistent market concern were sometimes associated with consecutive negative sessions, but they were also frequently interrupted by reversals or partial rebounds. The next trading session was consequently influenced by the evolving information environment rather than being mechanically determined by the previous day's direction.

4.10 Broad Market Comparison

The empirical findings are broadly consistent with the weak market environment observed during September 2026. The broader market recorded a substantial monthly decline, while the IT segment experienced particularly pronounced weakness. This provides an external context for the relatively large declines observed in TCS, Infosys and Wipro in the present sample.

However, the comparison should be interpreted cautiously. The eleven securities were selected through an observational approach and do not constitute a statistically representative sample of the Indian equity market. Consequently, similarities between the selected securities and the broader market should be regarded as **contextual consistency rather than evidence of market-wide statistical representativeness**.

4.11 Overall Interpretation of the Empirical Findings

The empirical analysis yields four principal findings.

First, **September 2026 was characterized by broad-based negative performance**, with every security in the selected sample ending the month below its 31 August closing level.

Second, the magnitude of the decline varied substantially across securities. IT stocks experienced the most pronounced deterioration, while HDFC Bank and ONGC were comparatively resilient. This confirms considerable **cross-sectional heterogeneity** within the sample.

Third, the previous-day/next-day analysis does not support a simple **directional continuation hypothesis**. Only 97 of 220 consecutive return pairs, or 44.1%, moved in the same direction. The

pooled lag correlation of approximately -0.23 and the group-level lag correlation of approximately -0.31 instead indicate a negative short-term association.

Fourth, the relationship was **security-specific and strongly dependent on the prevailing information environment**. Some securities, particularly Infosys and TCS, exhibited relatively high frequencies of same-direction movements, but their negative lag correlations demonstrate that directional persistence should not automatically be interpreted as predictable return magnitudes.

Overall, the evidence suggests that **previous-day performance alone was not a dependable indicator of next-day direction during September 2026**. Market-wide developments, sector-specific conditions and newly arriving information appear to have interacted with previous price movements, producing a combination of continuation and reversal rather than a stable one-day forecasting relationship. The findings therefore provide descriptive evidence against treating the previous trading day's return as a universal signal for predicting the next day's movement across the selected securities.

5.0 CONCLUSION

This study examined whether the return direction observed on one trading day was systematically followed by a similar movement on the subsequent trading day across eleven selected Indian securities during September 2026. The empirical evidence indicates that the month was characterized by generally weak performance, although substantial differences existed across individual securities and sectors. All eleven securities recorded lower closing prices at the end of September than on 31 August, with particularly pronounced declines in Tata Consultancy Services (TCS), Wipro, Infosys and Nestle India. In contrast, HDFC Bank remained broadly stable over the study period.

The principal finding concerns the short-term lead-lag relationship between consecutive daily returns. Of the 220 previous-day/next-day return pairs examined, only 97 pairs, representing approximately **44.1%**, moved in the same direction. The pooled correlation between previous-day and next-day returns was approximately -0.23 , indicating a negative rather than positive short-term association. At the aggregate sample level, the simple average return of the eleven securities continued in the same direction on only **8 of 20 consecutive trading-day comparisons**, equivalent to 40%. Taken together, these findings do not support the existence of a consistent one-day directional continuation pattern during the study period.

The evidence therefore suggests that the previous trading day's return may be more appropriately viewed as an indicator of the **prevailing market environment** than as a reliable standalone

signal for predicting the next day's movement. The alternating episodes of market-wide weakness and partial recovery further indicate that changing information, sector-specific conditions and security-level factors could alter the direction of prices from one session to the next. Importantly, the negative correlations observed in the sample should not be interpreted as evidence of a guaranteed reversal strategy or as proof of exploitable market inefficiency.

6.0 LIMITATIONS OF THE STUDY

The findings should be interpreted in light of several methodological limitations.

First, the study covers only **one month of trading activity** and examines eleven deliberately selected securities. The relatively small and non-random sample limits the external validity of the findings and prevents their direct generalisation to the broader Indian stock market.

Second, the news component of the analysis is primarily **qualitative and manually compiled**. Although relevant market and sectoral developments were considered, the review does not necessarily capture every information release during the study period, nor does it systematically account for the precise time at which individual announcements became publicly available.

Third, the empirical analysis is based on **daily closing prices and simple daily percentage returns**. It does not formally control for potentially important explanatory factors such as sector indices, exchange-rate movements, crude-oil prices, gold prices, and government bond yields, foreign portfolio flows, trading volume, market volatility or company-specific announcements.

Fourth, the study primarily employs descriptive measures, directional comparisons and correlation analysis. Consequently, the observed relationships should be interpreted as **associations rather than causal effects**. A negative lag correlation, for example, does not establish that a previous day's return or news event caused the subsequent movement.

Finally, the study does not incorporate transaction costs, liquidity constraints, bid–ask spreads or portfolio-level risk considerations. Therefore, the empirical evidence should not be interpreted as demonstrating the profitability of a trading strategy based on previous-day returns.

7.0 SCOPE FOR FUTURE RESEARCH

Future research can address these limitations by extending the observation period to **one or two years or longer**, thereby providing a substantially larger number of trading-day observations and allowing the stability of the observed relationships to be examined across different market conditions. The analysis can retain the present securities while expanding the sample to include a broader range of large-, mid- and small-cap stocks.

A more systematic **news-classification framework** could also be developed. News events could be categorized into major groups such as crude-oil movements, interest-rate decisions, geopolitical developments, currency movements, regulatory changes, foreign investment flows and company-specific announcements. Recording both the publication time and the subsequent trading response would permit a more precise examination of information transmission.

Future studies could additionally incorporate **sector indices and relevant macro-financial variables** to determine whether the lead–lag relationship differs across banking, information technology, energy, consumer goods and other sectors. Variables such as the Nifty 50, sector indices, the Indian rupee, crude oil, gold, bond yields and foreign portfolio investment flows could be incorporated into a multivariate framework.

With a larger dataset, the analysis could progress from descriptive observation to **formal statistical testing and predictive modelling**. Tests for autocorrelation, statistical significance, structural changes and asymmetric responses could be employed to determine whether the observed continuation or reversal patterns are statistically robust. Machine-learning or time-series forecasting techniques could also be explored, provided that appropriate training, validation and out-of-sample testing procedures are followed.

A particularly useful extension would be to divide the observations into **in-sample and out-of-sample periods**. Any pattern identified in the initial sample could then be tested against a separate period to determine whether it persists beyond the conditions under which it was originally observed. Such an approach would provide stronger evidence regarding whether short-term lead–lag relationships represent temporary market-specific patterns or more persistent features of the Indian stock market.

Overall, the present study provides an exploratory foundation for examining short-horizon return dependence in selected Indian securities. Its principal contribution lies not in establishing a universal forecasting rule, but in demonstrating that **previous-day market conditions, while informative as contextual indicators, do not necessarily translate into a consistent next-day directional movement across securities**.

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