International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 07, July 2026)

Identifying Stock Pricing Anomalies in Indian FinTech Stocks: A Critical Evaluation for Retail Investor

Anil Yogappa Hanji[1], Dr. Sumera Aluru[2]
[1]*Student, RV Institute of Management, Bangalore, India*
[2]*Associate Professor, RV Institute of Management, Bangalore, India*

***Abstract*—This study examines stock pricing anomalies in ten listed Indian FinTech companies using daily closing price data spanning diverse listing periods up to early 2026, covering a total of 7,216 firm-trading-day observations. Three categories of anomaly are investigated: (i) stationarity and unit root properties of log prices and log returns using Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests; (ii) explosive price behaviour and bubble episodes using the Right-Tailed ADF and Supremum Augmented Dickey-Fuller (SADF) procedure of Phillips, Wu, and Yu (2011); and (iii) calendar effects in daily returns, specifically the day-of-week and month-of-year patterns, estimated via OLS regression with HAC standard errors and validated using Kruskal-Wallis non-parametric tests. Results indicate that while log prices are predominantly integrated of order one — confirming non-stationarity at levels — log returns are universally stationary across all ten firms, consistent with weak-form efficiency in the return space. No company exhibited statistically significant explosive pricing behaviour (all SADF values fall below the 10% critical value), suggesting the Indian FinTech sector has largely been free of speculative bubble formation during the sample period. Calendar effect tests reveal that neither day-of-week nor month-of-year patterns are statistically significant for the majority of firms, with the notable exception of One Mobikwik showing a significant day-of-week effect ($F = 3.78$, $p = 0.005$) and Suvidha Infoserve exhibiting a statistically significant month-of-year pattern. ARCH effects are pervasive across the sample, indicating pronounced volatility clustering — a finding with direct implications for risk management and derivative pricing. The results partially challenge simple efficiency narratives while offering nuanced guidance for retail investors in navigating FinTech equity markets.**

***Keywords*—Stock Pricing Anomalies, Indian FinTech, Unit Root Tests, Bubble Detection, SADF Test, Calendar Effects, Day-of-Week Effect, Month-of-Year Effect, Market Efficiency**

I. INTRODUCTION

The financial technology sector in India has grown rapidly over the past decade, expanding financial access through digital payments, algorithmic lending, and mobile trading platforms. By the early 2020s, India became one of the world's largest FinTech ecosystems, attracting many first-time retail investors due to low brokerage costs and easy account access.

However, FinTech stocks are highly volatile due to factors such as rapid information flow, regulatory sensitivity, and speculative sentiment. Their price movements often display irregular patterns — such as asymmetric volatility and sudden shifts — that traditional asset pricing models struggle to explain. These patterns, known as market anomalies, may offer opportunities for abnormal returns.

The benchmark for evaluating such anomalies is the Efficient Market Hypothesis (EMH), which argues that prices reflect available information. While EMH has support in developed markets, emerging markets like India show persistent anomalies, including calendar effects, momentum, and volatility clustering.

Although Indian markets have been widely studied, the FinTech sector remains under-researched. Most studies focus on aggregated markets or established firms, overlooking newly listed FinTech companies (2021–2025), which require deeper empirical analysis due to their unique behavioural characteristics.

This paper addresses that gap directly. Using daily stock price data for ten listed Indian FinTech firms, we deploy a battery of econometric tests spanning stationarity analysis, explosive-root detection, and calendar-effect identification. Our central aim is to determine whether Indian FinTech stocks display anomalous price behavior across three well-defined dimensions — and if so, to characterize those anomalies in terms meaningful to both academic theory and investment practice. The findings contribute to the literature on emerging market efficiency, sectoral anomalies, and the growing intersection between technological disruption and capital market behavior.

II. LITERATURE REVIEW

The theoretical base of this study is the Efficient Market Hypothesis (EMH), developed by Eugene Fama, which states that stock prices reflect all available information, making abnormal returns difficult to achieve. While EMH holds in developed markets, evidence from emerging economies like India remains mixed. Recent studies highlight unique dynamics in FinTech stocks.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 07, July 2026)

Karimi et al. (2025) found asymmetric volatility spillovers between FinTech and traditional markets, indicating non-linear price behavior. Truong et al. (2025) used machine learning to detect structural breaks and anomalies missed by traditional models. In India, Meher et al. (2023) demonstrated short-term predictability in FinTech stock returns, questioning weak-form efficiency.

Behavioral factors also play a role. Chaudhari and Jain (2025) showed that biases like overconfidence and herding influence Indian retail investors, contributing to mispricing. Event-based studies (Dranev et al., 2019) further confirm abnormal returns during FinTech-related announcements.

For bubble detection, this study adopts the SADF test by Phillips et al. (2011), which identifies explosive price behavior. While widely applied in other markets, its use in Indian FinTech remains limited. Calendar anomalies such as day-of-week and turn-of-month effects are well documented globally and in India. However, their persistence has declined over time. This study examines whether newly listed FinTech firms — characterized by high retail participation and information asymmetry — exhibit renewed anomaly patterns.

A. Research Gap

A careful review of the extant literature reveals five notable gaps that this study specifically addresses. First, while anomaly studies in Indian equity markets exist, none focuses comprehensively on the FinTech sub-sector using the complete set of listed companies available post-2021. Second, the application of right-tailed unit root tests and SADF-based bubble detection to Indian FinTech stocks has not been previously documented. Third, existing calendar-effect studies in India either predate the FinTech listing wave or use index-level data rather than firm-specific daily returns. Fourth, the combination of stationarity, bubble detection, and calendar-effect analysis within a single unified study — enabling cross-validation of efficiency claims — has been largely absent. Finally, the implications of these empirical findings for the growing population of retail investors trading through FinTech platforms have not been systematically articulated.

III. Objectives And Hypotheses

A. Objectives

The specific objectives of this study are:

1) To determine the existence of stock pricing anomalies in selected listed FinTech companies in India.
2) To examine the stationarity of FinTech stock prices using Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests.
3) To detect bubble behaviour in FinTech stock prices using right-tailed and supremum Dickey-Fuller tests.
4) To analyse calendar effects, such as day-of-the-week and month-of-the-year patterns, in FinTech stock returns.
5) To evaluate the implications of stock pricing anomalies for retail investors.

B. Research Hypotheses

Based on the theoretical framework and objectives, the following null hypotheses are tested:

H01: Stock pricing anomalies exist in Indian FinTech companies

H02: Stock prices are non-stationary in nature

H03: Bubble behaviour exists in FinTech stock prices

H04: Day-of-the-week effect exists in FinTech stock returns

H05: Month-of-the-year effect exists in FinTech stock returns

IV. Research Methodology

A. Research Design

The study adopts a quantitative, positivist research design grounded in the classical hypothesis-testing paradigm of empirical finance. The dependent variable throughout is the daily log return, computed as the natural logarithm of the ratio of consecutive closing prices:

$$r_t = \ln (P_t / P_{t-1})$$

Log returns are preferred over simple arithmetic returns because they are additive over time, approximately normally distributed, and exhibit more stable variance properties — features essential for the validity of the regression-based calendar effect models.

B. Sample and Data

The sample comprises ten listed Indian FinTech companies selected on the basis of continuous trading data availability and sector relevance. The companies span a range of sub-sectors — digital payments, insurance aggregation, utility connectivity, buy-now-pay-later, and online securities trading — providing sectoral diversity within the FinTech universe.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 07, July 2026)

Table I summarizes the sample firms, their listing boards, observation counts, and the time span of available data.

TABLE I
SAMPLE COMPANIES AND DATA SUMMARY

Company	Sub-sector	Exchange	Obs.	Study Period
MOS Utility	Digital Services	NSE/BSE	705	Apr 2023–Feb 2026
Pine Labs	POS Payments	NSE	68	Oct 2025–Feb 2026
One Mobikwik	Digital Payments	NSE/BSE	292	Dec 2024–Feb 2026
Seshaasai Tech.	FinTech Services	NSE/BSE	98	Sep 2025–Feb 2026
Suvidha Infoserve	Digital Finance	NSE/BSE	1,214	Apr 2021–Feb 2026
Billionbrains Garage	FinTech Platform	NSE	70	Oct 2025–Feb 2026
RNFI Services	Rural FinTech	NSE/BSE	384	Aug 2024–Feb 2026
AvenuesAI	Payment Gateway	BSE	2,450	Apr 2016–Feb 2026
Paytm (One 97)	Digital Payments	NSE/BSE	1,057	Nov 2021–Feb 2026
Policy Bazaar	InsurTech	NSE/BSE	1,060	Nov 2021–Feb 2026

Daily closing price data were sourced from the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) through their official historical data repositories and supplementary financial databases. Data quality checks were performed to identify and address missing trading days attributable to public holidays, trading halts, or corporate actions. Log prices (ln P_t) and log returns were calculated for all ten series, and the resulting time series were employed as inputs to all subsequent econometric procedures.

C. Econometric Methods

1) Unit Root and Stationarity Tests: The stationarity properties of log prices and log returns are assessed using two standard left-tailed tests. The Dickey-Fuller (DF) test, without augmentation, examines the null hypothesis of a unit root under the assumption that the residuals are serially uncorrelated. The Augmented Dickey-Fuller (ADF) test extends the DF procedure by including lagged differences of the dependent variable to control for autocorrelation in the residuals, with the lag order selected by minimizing the Akaike Information Criterion (AIC). Both tests are applied with a constant term but without a deterministic time trend, in accordance with standard practice for financial price series.

2) Explosive Behaviour and Bubble Detection: Bubble detection follows the SADF framework of Phillips, Wu, and Yu (2011). This approach tests the null hypothesis of a random walk (unit root) against the alternative of a locally explosive process, by recursively estimating right-tailed ADF statistics across forward-expanding sub-samples of the data. The supremum of these recursive statistics — the SADF statistic — is then compared against bootstrapped critical values appropriate to the sample size. A SADF value exceeding the 10% critical value is interpreted as evidence of at least one explosive sub-period within the sample, potentially corresponding to a speculative price bubble. The 10% significance level is chosen following standard practice in the bubble-detection literature (Phillips and Yu, 2011), which prioritizes detection power over Type I error control given the policy relevance of not missing genuine bubble episodes.

3) Calendar Effect Analysis: Calendar effects are estimated via OLS regression of daily log returns on a set of day-of-week (or month-of-year) dummy variables. For the day-of-week model, Monday is the omitted reference category; for the month-of-year model, January serves as the base. The regression equation takes the standard form:

$$r_t = \alpha + \Sigma\, \beta_i\, D_{it} + \varepsilon_t$$

where r_t is the daily log return, D_{it} represents dummy variables for each day (or month) relative to the reference category, and ε_t is an error term. Standard errors are corrected using the Newey-West HAC estimator to account for heteroskedasticity and serial correlation in the residuals. The Kruskal-Wallis non-parametric test provides a distribution-free cross-check on the parametric F-test from the OLS model.

V. DATA ANALYSIS AND INTERPRETATION

A. Stationarity Analysis

Table II presents the DF and ADF test results for log prices and log returns across all ten sample companies. The pattern that emerges is both consistent and theoretically meaningful. For log prices, six out of ten companies — MOS Utility, Pine Labs, One Mobikwik, Seshaasai Technologies, RNFI Services, and AvenuesAI — fail to reject the null hypothesis of a unit root at the 10% significance level, confirming non-stationarity. These series are integrated of order one (I(1)), meaning that price changes rather than price levels are stationary.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 07, July 2026)

TABLE II
UNIT ROOT TEST RESULTS FOR LOG PRICES AND LOG RETURNS

Company	DF (Price)	ADF (Price)	Result (Price)	DF (Return)	ADF (Return)	Result (Return)
MOS Utility	Non-Stat.	Non-Stat.	I (1)	Stat.***	Stat.***	I (0)
Pine Labs	Non-Stat.	Non-Stat.	I (1)	Stat.***	Stat.***	I (0)
One Mobikwik	Non-Stat.	Non-Stat.	I (1)	Stat.***	Stat.***	I (0)
Seshaasai Tech.	Non-Stat.	Non-Stat.	I (1)	Stat.***	Stat.***	I (0)
Suvidha Infoserve	Stat.**	Stat.**	I (0)	Stat.***	Stat.***	I (0)
Billionbrains	Stat.**	Stat.**	I (0)	Stat.***	Stat.***	I (0)
RNFI Services	Non-Stat.	Non-Stat.	I (1)	Stat.***	Stat.***	I (0)
AvenuesAI	Non-Stat.	Non-Stat.	I (1)	Stat.***	Stat.***	I (0)
Paytm	Non-Stat.	Non-Stat.	I (1)	Stat.***	Stat.***	I (0)
Policy Bazaar	Stat.**	Stat.**	Stat.	Stat.***	Stat.***	I (0)

*Note: *** denotes significance at 1%, ** at 5%, * at 10%. Non-Stat. = unit root not rejected; Stat. = unit root rejected.*

Three companies — Suvidha Infoserve, Billionbrains Garage, and Policy Bazaar — present stationary log prices in levels. This is a more unusual finding for stock price series and may reflect the particular trajectory of these firms during their respective data windows, including potential mean-reverting dynamics stemming from regulatory corrections, supply-demand equilibration at IPO valuations, or thin-trading effects associated with lower market capitalization.

In sharp contrast to the mixed picture for log prices, all ten companies exhibit strongly stationary log returns. DF and ADF statistics for returns are uniformly significant at the 1% level, with test statistics ranging from approximately -18 to -32 for companies with longer data histories. This universal stationarity of returns is consistent with the weak-form efficiency prediction that past returns carry no predictive information for future returns — though it is a necessary rather than sufficient condition for efficiency.

B. Bubble Detection Results

Table III summarizes the SADF bubble detection results for all ten sample firms. The critical value at the 10% significance level is determined by the Phillips, Wu, and Yu (2011) bootstrapped distribution and varies slightly across companies depending on sample size, ranging from approximately 1.10 to 1.22.

TABLE III
SADF BUBBLE DETECTION RESULTS

Company	Obs.	RT-ADF Stat.	SADF Stat.	CV 10%	Explosive?	Bubble Periods
MOS Utility	705	-1.5607	0.4621	1.1852	No	None
Pine Labs	68	-0.7371	0.1513	1.1008	No	None
One Mobikwik	292	-2.4001	0.2955	1.1592	No	None
Seshaasai Tech.	98	-1.4697	0.3604	1.1188	No	None
Suvidha Infoserve	1,214	-5.0650	-3.0356	1.1952	No	None
Billionbrains	70	-3.7254	-3.0056	1.1020	No	None
RNFI Services	384	-1.2689	0.7208	1.1684	No	None
AvenuesAI	2,450	-2.6631	-0.9832	1.2100	No	None
Paytm	1,057	-2.4014	-1.1213	1.1932	No	None
Policy Bazaar	1,060	-0.8490	0.0163	1.1932	No	None

The results clearly show no evidence of speculative bubble behaviour across the sample, as none of the firms record SADF statistics exceeding their 10% critical values. Additionally, BSADF tests across rolling sub-samples do not identify any periods of explosive price dynamics. This indicates that stock prices in the selected Indian FinTech companies follow stable and orderly patterns rather than speculative bubbles.

However, some variation is observed across firms. RNFI Services records the highest SADF value, followed by MOS Utility, though both remain below critical thresholds. While not indicative of bubble formation, these relatively higher values suggest the need for continued monitoring as more data becomes available. In contrast, firms like Billionbrains Garage show strongly negative values, highlighting heterogeneity in price behaviour across companies. Compared to other FinTech-related asset classes such as cryptocurrencies, where bubble episodes are common, the Indian FinTech equity market appears more stable. This stability may be attributed to regulatory oversight, disclosure requirements, and a balanced mix of institutional and retail participation.

C. Day-of-Week Effect

Table IV presents the regression coefficients, HAC-corrected standard errors, and significance levels for the day-of-week OLS models across all companies. Monday serves as the reference day. The F-statistics and Kruskal-Wallis H-statistics, along with their p-values, provide joint tests for the significance of any day-of-week pattern.

TABLE IV
DAY-OF-WEEK EFFECT — OLS REGRESSION RESULTS (SELECTED STATISTICS)

Company	F-Stat.	F p-val	KW H-Stat.	KW p-val	Sig. Days	DOW Effect?
MOS Utility	0.7506	0.5578	1.7185	0.7874	None	No
Pine Labs	2.5198	0.0502	5.0065	0.2866	Mon, Wed, Fri	Weak/Partial
One MobiKwik	3.7849	0.0051	8.8191	0.0658	Friday	Strong
Seshaasai Tech.	0.5373	0.7087	1.2930	0.8626	Monday (Base)	No
Suvidha Infoserve	0.5995	0.6631	4.9673	0.2907	Monday (Base)	No
Billionbrains	1.0590	0.3843	3.0909	0.5427	None	No
RNFI Services	1.6373	0.1642	5.4138	0.2474	None	No
AvenuesAI	1.4685	0.2091	9.2423	0.0553	Tue, Wed	Weak/Partial
Paytm	1.8078	0.1250	3.2938	0.5099	Thursday	No
Policy Bazaar	0.9452	0.4370	2.0320	0.7299	None	No

The analysis of ten Indian FinTech companies shows that the Day-of-the-Week (DOW) effect is largely absent across the sector. For most firms, both F-test and Kruskal-Wallis p-values exceed the 10% significance level, indicating no statistically significant variation in returns across trading days. This suggests that stock price movements are generally random with respect to weekdays, supporting weak-form efficiency.

However, One MobiKwik emerges as a clear exception, exhibiting a strong and consistent DOW effect where both statistical tests are significant. In this case, returns vary meaningfully across days, with Friday identified as a significant trading day. Pine Labs and AvenuesAI show only weak or partial evidence, as significance appears in only one test or for specific days, making the results inconclusive. The remaining firms — MOS Utility, Seshaasai Tech., Suvidha Infoserve, Billionbrains, RNFI Services, Paytm, and Policy Bazaar — do not exhibit any significant DOW effect, as both tests fail to reject the null hypothesis. Overall, the findings indicate that weekday-based anomalies are minimal and largely firm-specific, reinforcing the Efficient Market Hypothesis in the Indian FinTech sector.

D. Month-of-Year Effect

The month-of-year OLS results, summarized in Table V, reveal a more differentiated picture. January serves as the reference month throughout.

TABLE V
MONTH-OF-YEAR EFFECT — OLS SUMMARY RESULTS

Company	F-Stat.	F p-val	KW H-Stat.	KW p-val	Sig. Months	MOY Effect?
MOS Utility	1.5376	0.1133	8.9003	0.6311	June	No
Pine Labs	1.5919	0.2002	1.1944	0.7544	None	No
One MobiKwik	1.0846	0.3735	8.3753	0.6793	Jan, May, Dec	No
Seshaasai Tech.	1.3194	0.2686	2.7222	0.6053	None	No
Suvidha Infoserve	1.9991	0.0254	36.4100	0.0001	Jan, Jun, Jul, Dec	Strong
Billionbrains Garage	1.0831	0.3625	3.1111	0.3748	None	No
RNFI Services	0.5304	0.8826	4.0828	0.9674	March	No
AvenuesAI	0.7774	0.6631	13.1693	0.2824	March	No
Paytm	1.3869	0.1731	10.2328	0.5096	Apr, May, Jun, Jul, Aug, Oct	No
Policy Bazaar	0.7128	0.7271	5.8995	0.8800	None	No

The analysis of the Month-of-the-Year (MOY) effect across selected Indian FinTech companies reveals that monthly seasonality is largely absent in stock returns. For the majority of firms, both F-test and Kruskal-Wallis p-values exceed the 10% significance level, indicating no statistically significant differences in returns across months. This suggests that stock price movements do not follow predictable monthly patterns and are largely random, supporting weak-form efficiency.

However, Suvidha Infoserve emerges as a clear exception, showing a strong and consistent MOY effect. Both statistical tests indicate significance, and specific months such as January, June, July, and December exhibit notable return variations. This points to a firm-specific seasonal pattern that may offer limited predictability and a deviation from weak-form efficiency. In contrast, other firms such as MOS Utility, Pine Labs, One MobiKwik, and Paytm do not show consistent evidence across both tests. Although some individual months appear significant, the lack of overall model support suggests these are random fluctuations rather than true anomalies. Overall, MOY effects in the Indian FinTech sector are limited and firm-specific, reinforcing the Efficient Market Hypothesis.

VI. DISCUSSION AND KEY FINDINGS

This study examines DOW and MOY anomalies in Indian FinTech stocks and largely supports the Efficient Market Hypothesis (weak form).

Prices are non-stationary while returns are stationary, consistent with the random walk theory of Paul Samuelson and Eugene Fama.

No evidence of speculative bubbles is found, contrasting with studies like Bouri et al. (2019), indicating relatively stable price behaviour. DOW and MOY effects are largely insignificant across firms, aligning with Singh and Kaur (2015), who observed declining anomalies in Indian markets.

However, firm-specific exceptions exist. One MobiKwik shows a significant DOW effect, consistent with Gibbons and Hess (1981), while Suvidha Infoserve exhibits a MOY effect, aligning with traditional seasonal anomalies (Roll, 1983; Ariel, 1987).

Overall, calendar anomalies are limited and not widespread, suggesting that Indian FinTech stocks largely follow weak-form efficiency, with only minor, firm-level deviations possibly driven by behavioural factors.

VII. Implications

The findings extend the debate on market efficiency in emerging economies by supporting a nuanced, adaptive view of the Efficient Market Hypothesis. The absence of speculative bubbles across newly listed Indian FinTech firms challenges the perception of uniformly speculative post-IPO behaviour, suggesting that price corrections largely reflect adjustments to fundamentals rather than irrational exuberance. At the same time, the presence of limited, firm-specific calendar anomalies indicates that markets are broadly efficient but not perfectly so. This aligns with the Adaptive Market Hypothesis, where efficiency evolves over time and varies across firms depending on factors such as information asymmetry, investor behaviour, and operational seasonality.

From a managerial and investor perspective, the results imply that historical price patterns offer limited predictive power, reducing the effectiveness of purely technical trading strategies in FinTech stocks. The lack of bubble dynamics suggests relatively stable price formation, though caution remains necessary given market uncertainties. While isolated anomalies (e.g., in One MobiKwik) may exist, transaction costs and practical constraints limit their exploitability. Consequently, investors and portfolio managers should prioritize fundamental analysis, diversification, and risk management over time-based trading strategies when dealing with FinTech equities.

A. Conclusion, Limitations, and Future Research Directions

This study provides a comprehensive empirical assessment of stock pricing anomalies in ten listed Indian FinTech firms using unit root analysis, bubble detection techniques, and calendar effect models. The findings indicate a largely efficient market structure consistent with the Efficient Market Hypothesis, as stock returns are stationary and no evidence of speculative bubble behaviour is observed. This suggests that price movements are broadly aligned with underlying fundamentals rather than driven by speculative excess. While isolated anomalies are identified — such as a Day-of-the-Week effect in One MobiKwik and a Month-of-the-Year effect in Suvidha Infoserve — these are limited and firm-specific, reflecting heterogeneity in investor behaviour and company characteristics rather than widespread inefficiencies. Overall, the Indian FinTech sector demonstrates weak-form efficiency, with return patterns largely unpredictable and not systematically exploitable.

However, the study is subject to certain limitations. The relatively small sample size and shorter listing histories of some firms may affect result robustness. The use of linear calendar effect models may overlook more complex, time-varying dynamics, and while SADF/BSADF tests effectively detect bubbles, they may miss short-lived or multiple speculative episodes. Future research can address these gaps by applying panel data methods, incorporating market microstructure variables such as liquidity and trading volume, and extending the analysis over longer time horizons as more data becomes available. Such approaches would provide deeper insights into evolving market efficiency, particularly in line with the Adaptive Market Hypothesis.

REFERENCES

[1] Ariel, R. A. (1987). A monthly effect in stock returns. Journal of Financial Economics, 18(1), 161–174.

[2] Bodla, B. S., & Kiran, R. (2006). The day-of-the-week effect in Bombay Stock Exchange. The ICFAI Journal of Applied Finance, 12(6), 5–22.

[3] Bouri, E., Kristoufek, L., & Shahzad, S. J. H. (2019). Speculation and price crashes in the Bitcoin market. Journal of Futures Markets, 40(7), 1092–1110.

[4] Chaudhari, P., & Jain, A. (2025). Cognitive biases and retail investor decisions in Indian equity markets. Journal of Behavioural Finance, 26(2), 115–134.

[5] Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427–431.

[6] Dranev, Y., Frolova, K., & Ochirova, E. (2019). The impact of fintech M&A on acquirer returns. Research in International Business and Finance, 48, 353–364.

[7] Engsted, T., Hviid, S. J., & Pedersen, T. Q. (2016). Explosive bubbles in house prices? Evidence from the OECD countries. Journal of International Financial Markets, Institutions and Money, 40, 14–25.

[8] Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25(2), 383–417.

[9] Fama, E. F. (1991). Efficient capital markets: II. Journal of Finance, 46(5), 1575–1617.

[10] Gibbons, M. R., & Hess, P. (1981). Day of the week effects and asset returns. Journal of Business, 54(4), 579–596.

[11] Karimi, A., Esqueda, O. A., & Weerasinghe, D. (2025). Dynamic linkages between FinTech stocks and financial markets. International Review of Financial Analysis, 91, 103012.

[12] Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. Journal of Portfolio Management, 30(5), 15–29.

[13] MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics, 11(6), 601–618.

[14] Meher, B. K., Singh, M. K., Birau, R., & Anand, A. (2023). Forecasting stock prices of Indian FinTech using random forest and high-frequency trading data. Annals of Financial Economics, 18(2), 2350008.

[15] Phillips, P. C. B., & Yu, J. (2011). Dating the timeline of financial bubbles during the subprime crisis. Quantitative Economics, 2(3), 455–491.

[16] Phillips, P. C. B., Wu, Y., & Yu, J. (2011). Explosive behavior in the 1990s Nasdaq: When did exuberance escalate asset values? International Economic Review, 52(1), 201–226.

[17] Roll, R. (1983). On computing mean returns and the small firm premium. Journal of Financial Economics, 12(3), 371–386.

[18] Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. Industrial Management Review, 6(2), 41–49.

[19] Shi, S., & Arora, V. (2012). An application of models of speculative behaviour to oil prices. Economics Letters, 115(3), 469–472.

[20] Singh, S. P., & Kaur, M. (2015). Calendar anomalies in Indian stock market. Journal of Finance and Accounting, 3(3), 57–64.

[21] Truong, Q., Huynh, T., Nguyen, T., & Pham, T. (2025). Anomaly detection in FinTech using graph neural networks and feature selection. Expert Systems with Applications, 239, 122315.

[22] Mittal, M., & Jain, S. (2009). Stock market behaviour: Evidences from Indian market. Vision: The Journal of Business Perspective, 13(3), 19–29.

[23] Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

Corresponding Author: Anil Yogappa Hanji, E-mail: rvim24mba154.rvim@rvei.edu.in, Mobile/WhatsApp: +91 8660323831.

Co-authors: sumeraa.rvim@rvei.edu.in