Identifying Financial Bubbles in Selected Indian Sectors: An Empirical Study Using NIFTY Indices

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Abstract

This study investigates the presence of financial bubbles within the Indian equity market, focusing on the NIFTY 50 and five major sectoral indices—NIFTY Auto, NIFTY Bank, NIFTY Financial Services, NIFTY Energy, and NIFTY Pharma—over the period from August 2011 to March 2025. Employing advanced right-tailed econometric techniques such as the Right-Tailed Augmented Dickey-Fuller (RtADF), Rolling ADF (RADF), and Supremum ADF (SADF) tests, the research explores speculative dynamics across key sectors of the Indian stock market.

Analysis of 164 monthly return observations revealed that NIFTY Financial Services and NIFTY Auto yielded the highest average annual returns, while NIFTY Bank exhibited the highest volatility. All econometric tests consistently produced p-values of 1.000, indicating the absence of explosive price movements and suggesting that sectoral indices have remained stable over the study period. Regression analysis confirmed a significant positive influence of sectoral indices on overall market performance, led by Financial Services, while causality tests showed no bidirectional predictability among sectors.

Keywords: Financial Bubbles, NIFTY Indices, Econometric Analysis, Indian Stock Market

1. INTRODUCTION

Financial bubbles—defined as significant and sustained deviations of asset prices from intrinsic value driven by speculative fervour, liquidity surges, and behavioural biases—have long commanded academic and policy attention. Their emergence and collapse can induce severe macroeconomic dislocations, from liquidity crunches to prolonged recessions. The Harshad Mehta securities scam of 1992, the dot-com bubble of the early 2000s, and the global financial crisis of 2008 exemplify the disruptive potential of speculative excesses in both developed and emerging markets.

In the Indian context, understanding sector-specific bubble dynamics is crucial for pre-empting systemic vulnerabilities. Several studies have explored asset price anomalies in India using econometric diagnostics. Gangadharan and Suresh (2019) identified bubble episodes in NIFTY indices during the dot-com period via the Generalized Supremum Augmented Dickey-Fuller (GSADF) framework. Banerjee and Kayal (2021) analyzed sectoral run-ups and deflationary phases, demonstrating that inflationary periods often outperform the aggregate market. Jain (2016) reported evidence of asset price bubbles in the banking sector using recursive ADF procedures, while Manian and Kayal (2024) integrated machine learning with traditional econometrics to forecast speculative behaviour in the NIFTY 500. Other works, including

Suresh et al. (2022) and Dileep et al. (2023), confirmed the presence of sector-specific and index-wide bubbles, underscoring the heterogeneity of bubble formation across industries.

Despite this growing body of research, notable gaps persist. Prior studies have often excluded macroeconomic determinants—such as interest rate cycles, monetary policy shocks, and GDP fluctuations—that shape speculative intensity. Moreover, most have relied on annual or low-frequency data, limiting the temporal sensitivity of bubble detection. A further challenge lies in distinguishing fundamental valuation shifts from transient exuberance, an issue repeatedly highlighted in the econometric literature (Gürkaynak 2005; Zhao 2022).

Against this backdrop, the present study applies advanced right-tailed unit root tests (RtADF, RADF, and SADF) to detect speculative episodes in the NIFTY 50 and five principal sectoral indices—Auto, Bank, Financial Services, Energy, and Pharma—using monthly return data from January 2010 to March 2025. Complementary regression and Granger causality analyses evaluate inter-sectoral dependencies, aiming to elucidate whether market movements are fundamentally driven or exhibit signs of speculative contagion. By situating these findings within India's evolving financial landscape, the study contributes empirical evidence on market stability and offers insights relevant to investors, regulators, and policymakers seeking to pre-empt asset price distortions.

2. RESEARCH METHODOLOGY

This research investigates financial bubbles in the Indian stock market, focusing on the NIFTY 50 and five major sectoral indices—NIFTY Auto, NIFTY Bank, NIFTY Financial Services, NIFTY Energy, and NIFTY Pharma. The study adopts a quantitative and empirical approach using time-series econometric techniques to detect speculative patterns and assess the interrelationship between sectoral and aggregate market performance.

Study Design and Scope

The analysis encompasses a fourteen-year period, from August 1, 2011, to March 1, 2025, incorporating major economic milestones such as the post–global financial crisis recovery, demonetization (2016), Goods and Services Tax (GST) implementation (2017), the IL&FS liquidity crisis (2018), and the COVID-19 pandemic (2020–2021). This period provides a robust framework for examining potential bubble episodes within India's evolving financial ecosystem.

Data Collection

Data were sourced from the official website of the National Stock Exchange of India (www.nseindia.com). The dataset comprises daily and monthly closing prices of the NIFTY 50 and the five selected sectoral indices. Monthly returns were calculated for each index, yielding 164 observations per series across the fourteen-year window.

Although daily data; approximately 3,500 observations; would capture higher-frequency price movements, monthly returns were used due to data processing constraints, ensuring analytical consistency and interpretability.

Monthly returns were computed using the logarithmic difference of consecutive closing prices, expressed as:

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

where R_t denotes the monthly return, and P_t and P_{t-1} represent the closing prices at time t and t–1, respectively.

Variables

Dependent Variable: Monthly returns of NIFTY 50 (R_NIFTY50), representing overall market performance.

Independent Variables: Monthly returns of the sectoral indices; Auto (R_AUTO), Bank (R_BANK), Financial Services (R_FINSERV), Energy (R_ENERGY), and Pharma (R_PHARMA).

Analytical Framework

A series of econometric and statistical analyses were conducted using EViews for model estimation and Microsoft Excel for data cleaning, return computation, and preliminary statistical evaluation.

Descriptive Statistics

Descriptive metrics—mean return, standard deviation (risk), and coefficient of variation (CV)—were calculated to evaluate each index's risk-adjusted performance. The Jarque–Bera test was employed to assess the normality of return distributions, determining the suitability of subsequent parametric tests.

Multiple Regression Analysis

To examine the influence of sectoral indices on overall market performance, a multiple linear regression model was estimated as follows:

R_NIFTY50=β0 + β1*R_AUTO+β2*R_BANK+β3*R_FINSERV+β4*R_ENERGY+β5*R_PHARMA +ϵ

where \ β0 is the intercept, \ β1...\β5 represent the coefficients of the explanatory variables, and \ ϵ the stochastic error term.

The null hypothesis (H0) states that the sectoral indices do not significantly affect NIFTY 50 returns (βi= 0), while the alternative hypothesis (H1) posits that the relationship is statistically significant (\βi\neq 0). Model evaluation was conducted at a 95% confidence level (\alpha = 0.05) using R-squared, adjusted R-squared, t-statistics, and p-values.

Granger Causality Analysis

Granger causality tests were applied to identify predictive linkages between sectoral indices and the NIFTY 50. A lag length of two was chosen based on the Akaike Information Criterion (AIC) to ensure model efficiency.

The hypotheses are defined as:

H_0: Does not Granger-cause

H_1: Granger-causes

Causality is inferred when the p-value is less than 0.05, indicating that past values of one variable enhance the predictive accuracy of another. This procedure was applied pairwise across all indices to evaluate directional dependencies.

Bubble Detection Procedures

To detect speculative price behaviour, three complementary econometric tests were employed:

Right-Tailed Augmented Dickey-Fuller (RtADF) Test – Detects explosive dynamics in a fixed sample period.

Rolling ADF (RADF) Test – Identifies localized episodes of rapid price acceleration through moving windows.

Supremum ADF (SADF) Test – Recursively expands sample windows to capture multiple or overlapping bubbles across time.

Each test was conducted using a fixed lag of zero and a window size of 25, referencing Monte Carlo–simulated critical values to ensure robustness. The null hypothesis assumes a unit root (no bubble), while the alternative hypothesis indicates explosive behaviour.

Although the Generalized Supremum ADF (GSADF) test offers superior detection capability for multiple bubble episodes, its implementation was limited by the availability of daily price data. Future analyses incorporating GSADF on high-frequency data are therefore recommended.

The hypotheses are defined as:

H_1: NIFTY 50 returns are significantly influenced by sectoral returns.

H_2: Selected Indian sectoral indices exhibit speculative bubble characteristics.

H_3: The intensity and occurrence of bubbles vary across sectors due to structural and cyclical differences.

Software and Tools

All econometric analyses—including regression estimation, causality testing, and bubble detection—were performed using EViews, while Microsoft Excel facilitated data processing, visualization, and computation of returns.

3. DATA ANALYSIS AND INTERPRETATION

3.1 Average Returns and Risk of selected indices

Nifty Financial services and Nifty auto provided the highest average returns over the period of 14 years while Nifty 50 had the lowest average returns.

Nifty Bank exhibited the highest volatility, which indicates that there were greater fluctuations in the returns while Nifty 50 had the lowest risk, making it a relatively stable index.

3.2 Performance of selected indices

The coefficient of variation (CV) is a measure of risk- adjusted return and is calculated as the ratio of risk (standard deviation) to return. A lower CV indicates that the index provides higher returns relative to its risk. Nifty 50 is the most efficient index in terms of risk- adjusted performance. Nifty Financial Services and Auto offer good returns with moderate risk while Nifty Bank and Energy have higher volatility relative to their returns.

3.3 Normality Test

The Jarque- Bera statistic measures whether the data follows a normal distribution.

H_0: The selected data is normally distributed.

H_1: The selected data is not normally distributed.

The normality test results suggest that NIFTY 50 and the selected 5 indices over the period of 14 years do not follow a normal distribution. This deviation is evident from the p- values (<0.05) and high Jarque-Bera values. Therefore, the selected data is not normally distributed. Since the financial data is not normally distributed, we can conduct further tests to better understand the distribution characteristics.

3.4 Stationarity Test (By using ADF Test)

One of the Important assumption while performing empirical methods on historical financial data is that the sample data needs to be a stationary data so that its statistical properties such as mean, variance and covariance remains constant over the time period. Stationarity tests help detect these shifts, allowing researchers to differentiate between normal market cycles and bubble phases.

Hypothesis:

H_0: Data is non stationary (the data has a unit root problem)

H_1: Data is Stationary (the data does not have a unit root problem)
We run Augmented Dickey-Fuller test statistic on each of the selected index individually At Level. The resultant p value of each of the Index is >0.05 through which we interpret the data as Non-stationary hence we accept null hypothesis. ADF test At Level proved a unit root problem in the data, so we further apply ADF test at 1st Difference to get a stationary data. The resultant p value for each selected index is <0.01 so, we reject null hypothesis, hence the data is now stationary.

3.5 Correlation

R_NIFTY_FINANCIALSERVICE has the highest correlation with R_NIFTY_BANK and then with R_NIFTY50. Nifty_Financial service is also the most growing index in the selected time frame compared to other selected indices. This also shows that the growth of Indian market and Indian banking sector has been getting largely dependent on the financial services sector.

3.6 Multiple Regression Analysis

H_0: There is no significant impact from independent variables to nifty 50
H_1: There is a significant impact from independent variables to nifty 50
For all the independent variables the probability value is less than .05 when compared by alpha at 95% confidence interval, hence we reject Ho and can see that all the independent variables have a significant impact on the dependent variable that is NIFTY 50. We can see that financial services has the strongest positive impact on NIFTY 50 returns, suggesting that the financial sector plays a major role in market movement. The model has a very high explanatory power which means sectoral returns explain most of the variation in NIFTY 50 returns.

3.7 Pairwise Granger Causality Test

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
R_NIFTY_AUTO does not Granger Cause R_NIFTY50	162	0.89749	0.21
R_NIFTY50 does not Granger Cause R_NIFTY_AUTO		0.71893	0.4889
R_NIFTY_BANK does not Granger Cause R_NIFTY50	162	0.14982	0.861
R_NIFTY50 does not Granger Cause R_NIFTY_BANK		0.18122	0.8344
R_NIFTY_ENERGY does not Granger Cause R_NIFTY50	162	0.15172	0.8594
R_NIFTY50 does not Granger Cause R_NIFTY_ENERGY		1.99129	0.14
R_NIFTY_FINANCIALSERVICE does not Granger Cause R_NIFTY50	162	0.54427	0.5814
R_NIFTY50 does not Granger Cause R_NIFTY_FINANCIALSERVICE		0.95759	0.386
R_NIFTY_PHARMA does not Granger Cause R_NIFTY50	162	0.69574	0.5002
R_NIFTY50 does not Granger Cause R_NIFTY_PHARMA		0.63745	0.53
R_NIFTY_BANK does not Granger Cause R_NIFTY_AUTO	162	1.0668	0.3466
R_NIFTY_AUTO does not Granger Cause R_NIFTY_BANK		0.87101	0.4205
R_NIFTY_ENERGY does not Granger Cause R_NIFTY_AUTO	162	0.08617	0.9175
R_NIFTY_AUTO does not Granger Cause R_NIFTY_ENERGY		0.86426	0.4234

R_NIFTY_FINANCIALSERVICE does not Granger Cause R_NIFTY_AUTO	162	1.0802	0.342
R_NIFTY_AUTO does not Granger Cause R_NIFTY_FINANCIALSERVICE		0.21797	0.8044
R_NIFTY_PHARMA does not Granger Cause R_NIFTY_AUTO	162	1.08661	0.3399
R_NIFTY_AUTO does not Granger Cause R_NIFTY_PHARMA		0.36846	0.6924
R_NIFTY_ENERGY does not Granger Cause R_NIFTY_BANK	162	1.45751	0.2359
R_NIFTY_BANK does not Granger Cause R_NIFTY_ENERGY		2.06931	0.1297
R_NIFTY_FINANCIALSERVICE does not Granger Cause R_NIFTY_BANK	162	0.46479	0.6291
R_NIFTY_BANK does not Granger Cause R_NIFTY_FINANCIALSERVICE		0.61114	0.544
R_NIFTY_PHARMA does not Granger Cause R_NIFTY_BANK	162	0.46172	0.6311
R_NIFTY_BANK does not Granger Cause R_NIFTY_PHARMA		0.54888	0.5787
R_NIFTY_FINANCIALSERVICE does not Granger Cause R_NIFTY_ENERGY	162	2.3397	0.0997
R_NIFTY_ENERGY does not Granger Cause R_NIFTY_FINANCIALSERVICE		2.07583	0.1289
R_NIFTY_PHARMA does not Granger Cause R_NIFTY_ENERGY	162	2.33385	0.1003
R_NIFTY_ENERGY does not Granger Cause R_NIFTY_PHARMA		0.10767	0.898
R_NIFTY_PHARMA does not Granger Cause R_NIFTY_FINANCIALSERVICE	162	0.23578	0.7902
R_NIFTY_FINANCIALSERVICE does not Granger Cause R_NIFTY_PHARMA		0.7529	0.4727

Table. Pairwise Granger Causality Test results

All p-values >0.05 which shows that past returns of these sectors do not significantly impact each other and there is no unilateral and bilateral impact between the selected indexes. Hence no significant Granger causality relationships found between sectoral indices.

3.8 Analysing the presence of financial bubbles in the selected sectors

3.8.1 Right-Tailed ADF Test Analysis for Bubble Detection

The RtADF test is used to detect speculative bubbles in asset prices. Unlike the standard ADF test, which checks for stationarity, the RtADF test examines explosive behaviour which is a key characteristic of financial bubble.

The ADF test for all the 6 indices, p value is 1, hence we fail to reject the null hypothesis. Which implies that returns of NIFTY 50 follows a unit root process without explosive growth, further confirming the absence of a bubble.

All the indices indicate a stable market behaviour rather than unstainable price growth. If a bubble was present the t-stats value would be closer to or exceed the critical values, and the p-value would be much lower.

3.8.2 Rolling ADF test

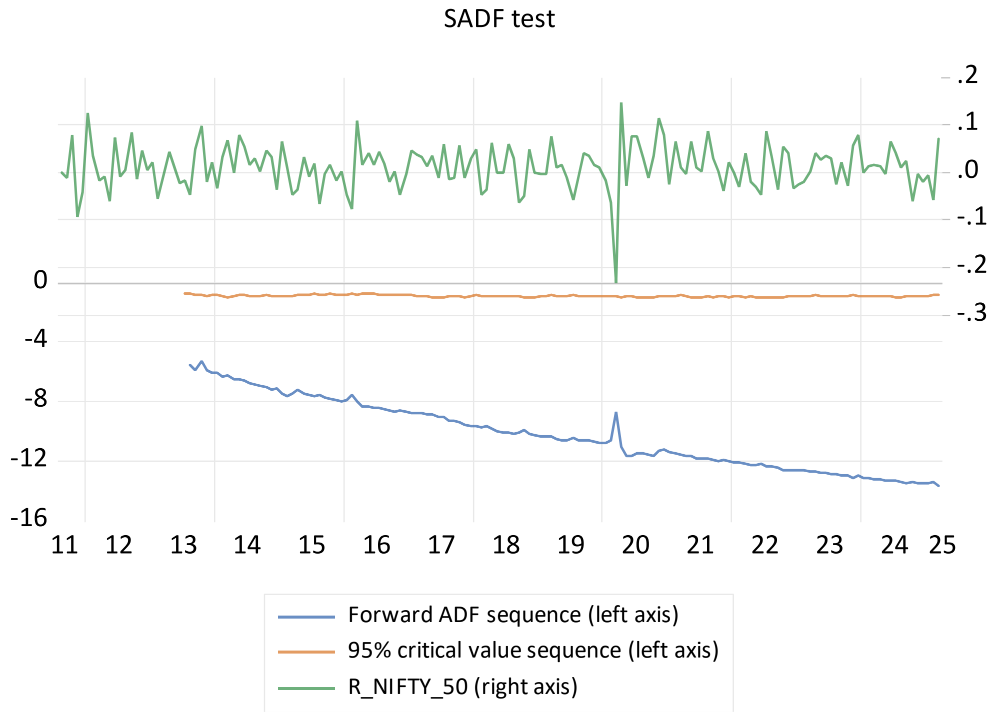
The rolling ADF test detects the most extreme explosive behaviour across a rolling window. It identifies the most extreme bubble periods in financial time series. It is a better test than ADF test for bubble detection.

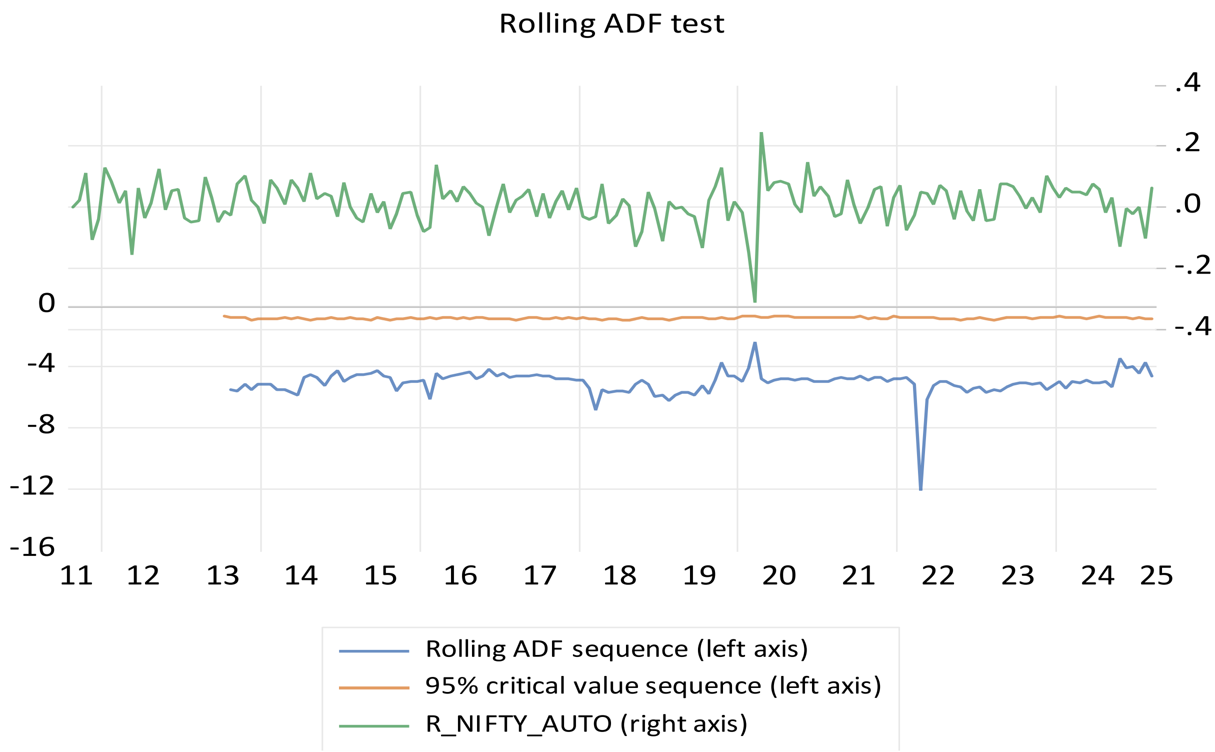
In our data RADF does not indicate the presence of bubble in any of the indices as the probability value is 1 in all case which is higher than 0.05 indicating no extreme explosive bubbles.

3.8.3 SADF test

The SADF test is an extension of RTADF test that detects explosive behaviour in a rolling manner rather than over a fixed sample. It works by applying the ADF test recursively on expanding windows, starting from a small sample and increasing step-by-step, to detect multiple instances of explosive behaviour in a time series. SADF is more flexible than RTADF since it helps detect bubbles at different points in time rather than just a single instance.

From the above inferences all are p-values are 1 indicating no explosive behaviour and the indices are free from any bubble. Hence, we can say all the sectors analysed during the time frame suggest an absence of speculative bubbles.

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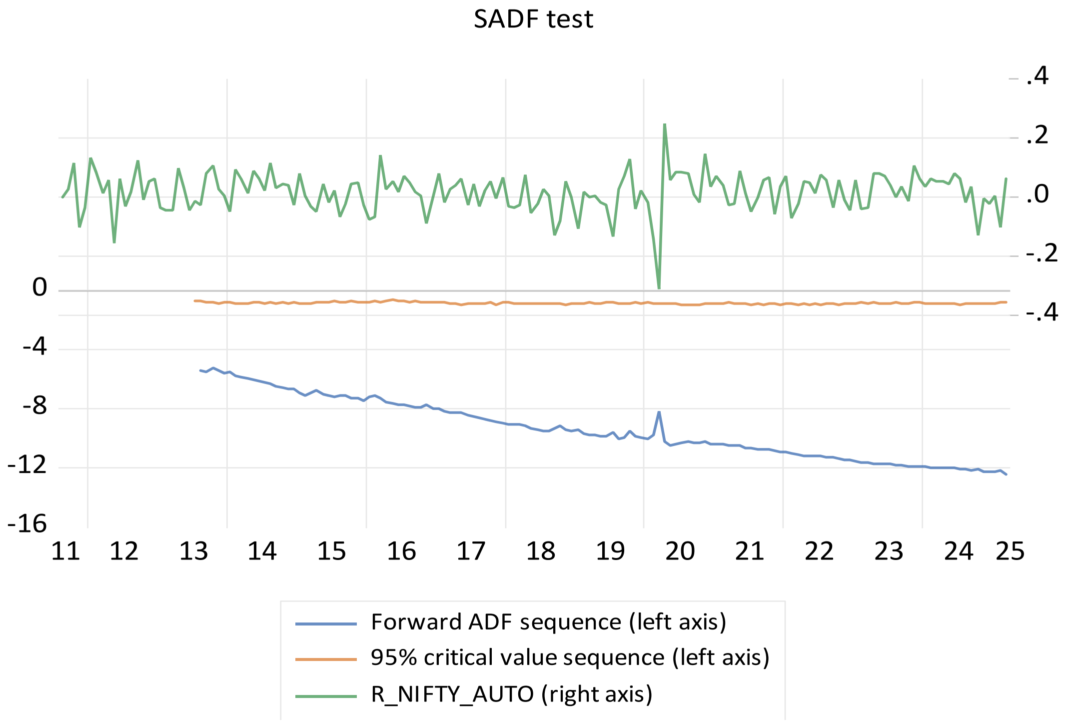
95% critical value sequence (left axis)
R_NIFTY_AUTO (right axis)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Forward ADF sequence (left axis)
95% critical value sequence (left axis)
R_NIFTY_AUTO (right axis)

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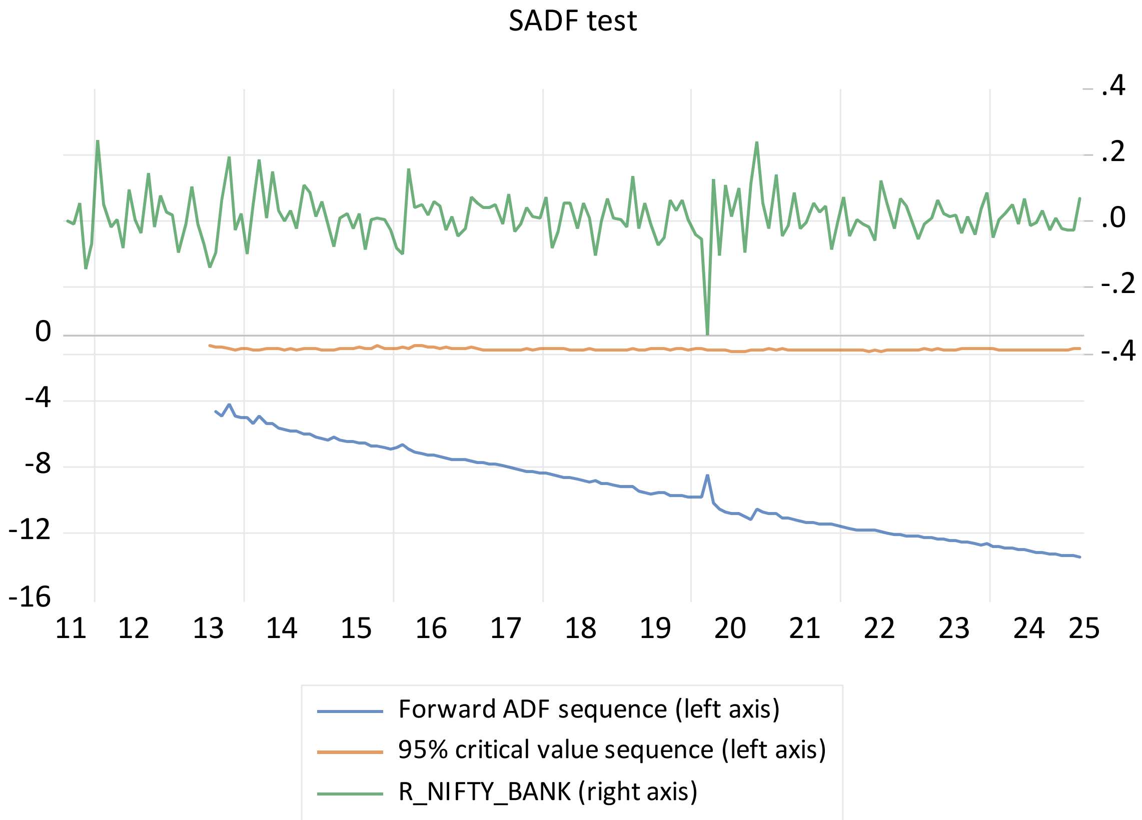

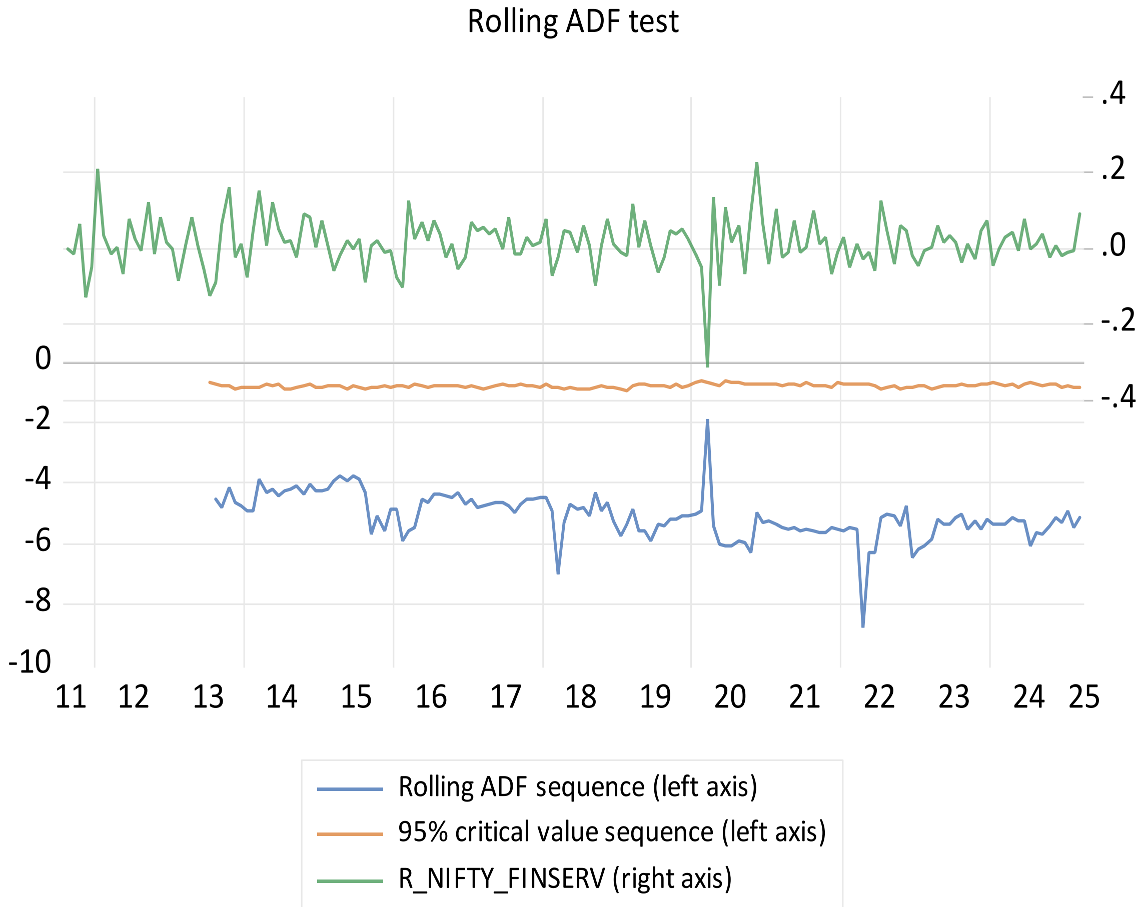

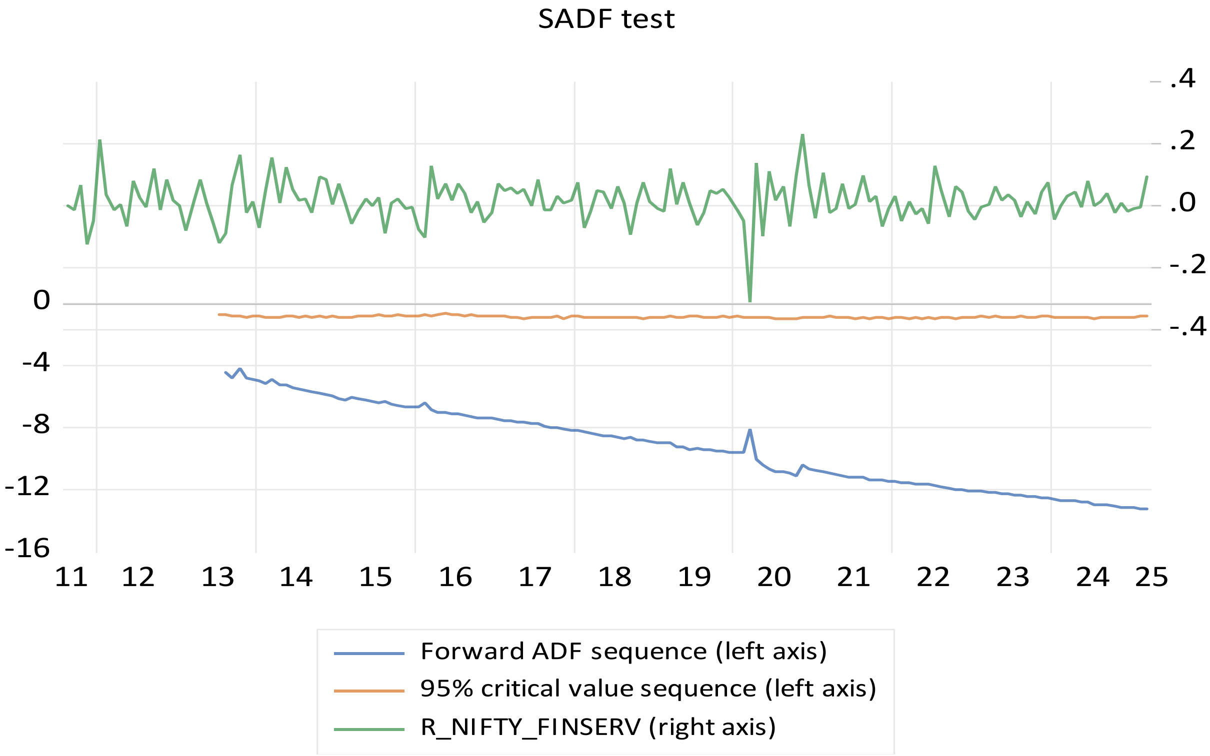
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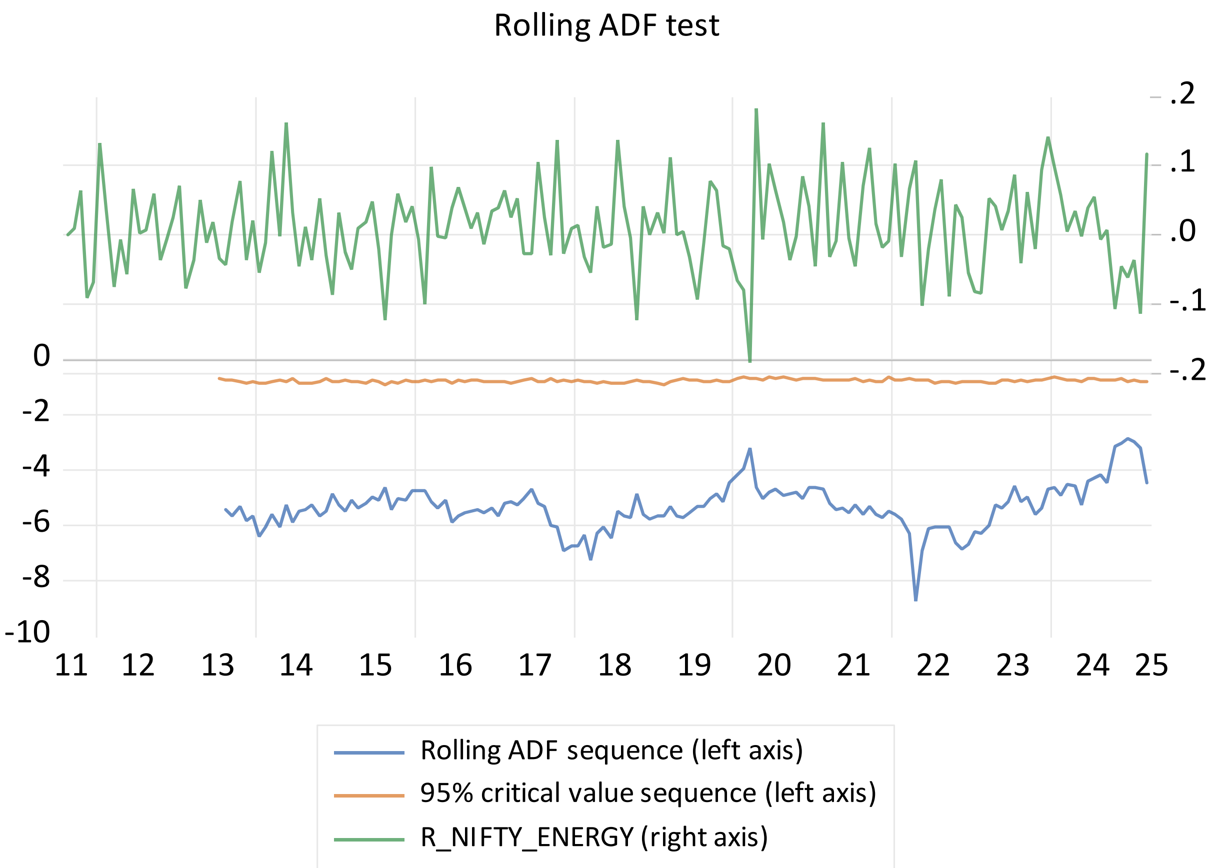
R_NIFTY_FINSERV (right axis)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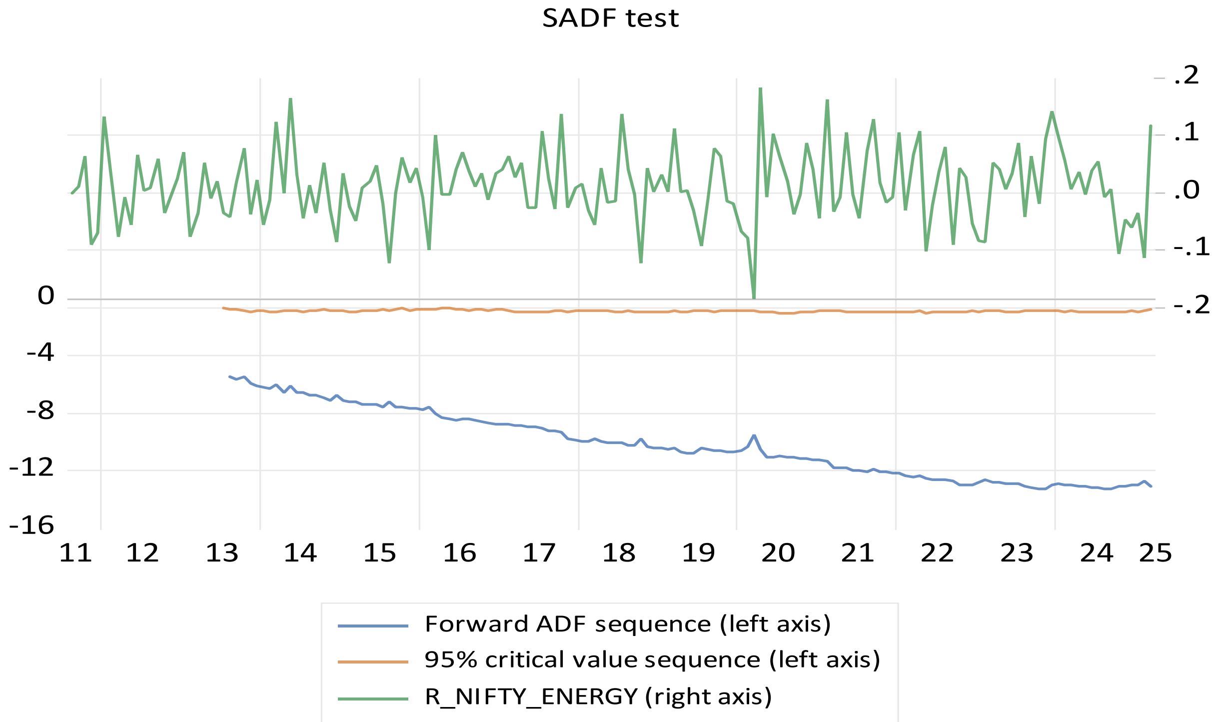
R_NIFTY_ENERGY (right axis)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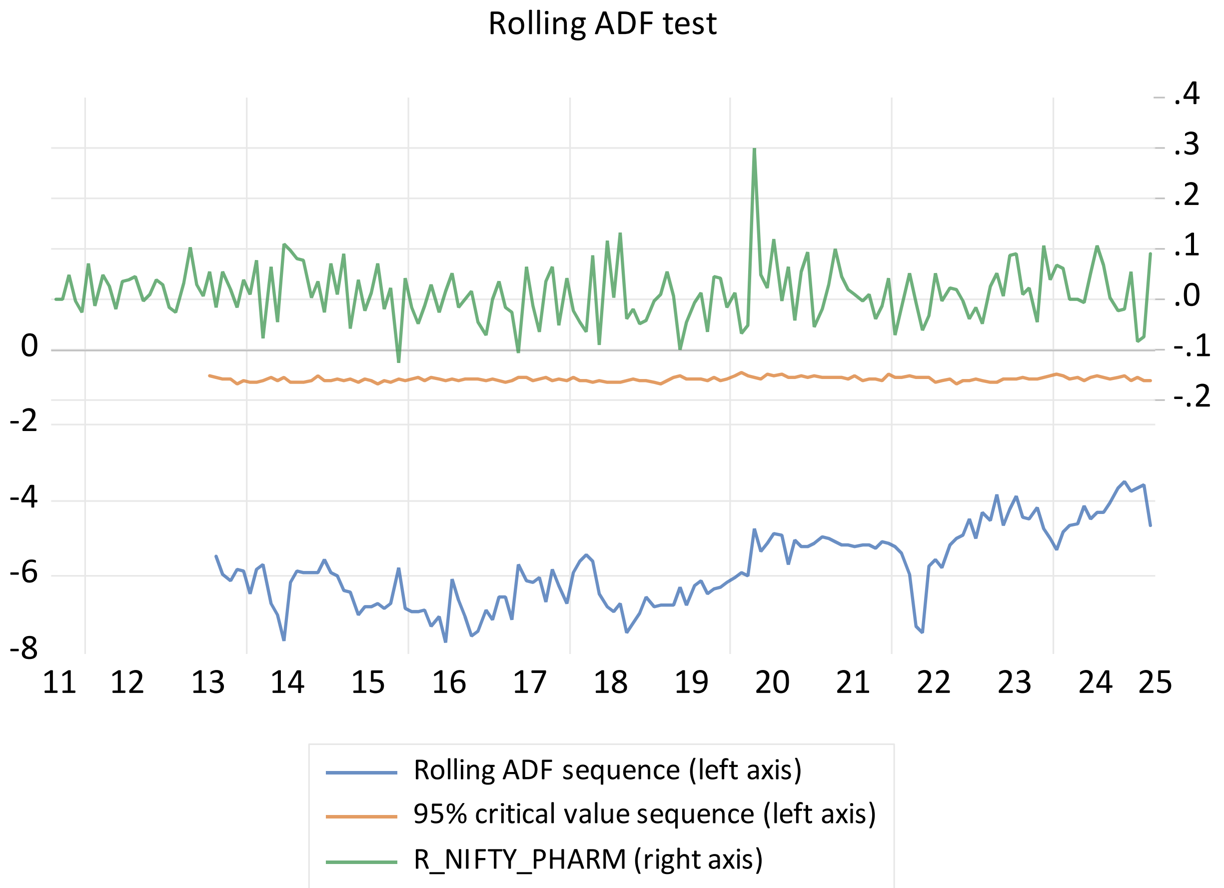
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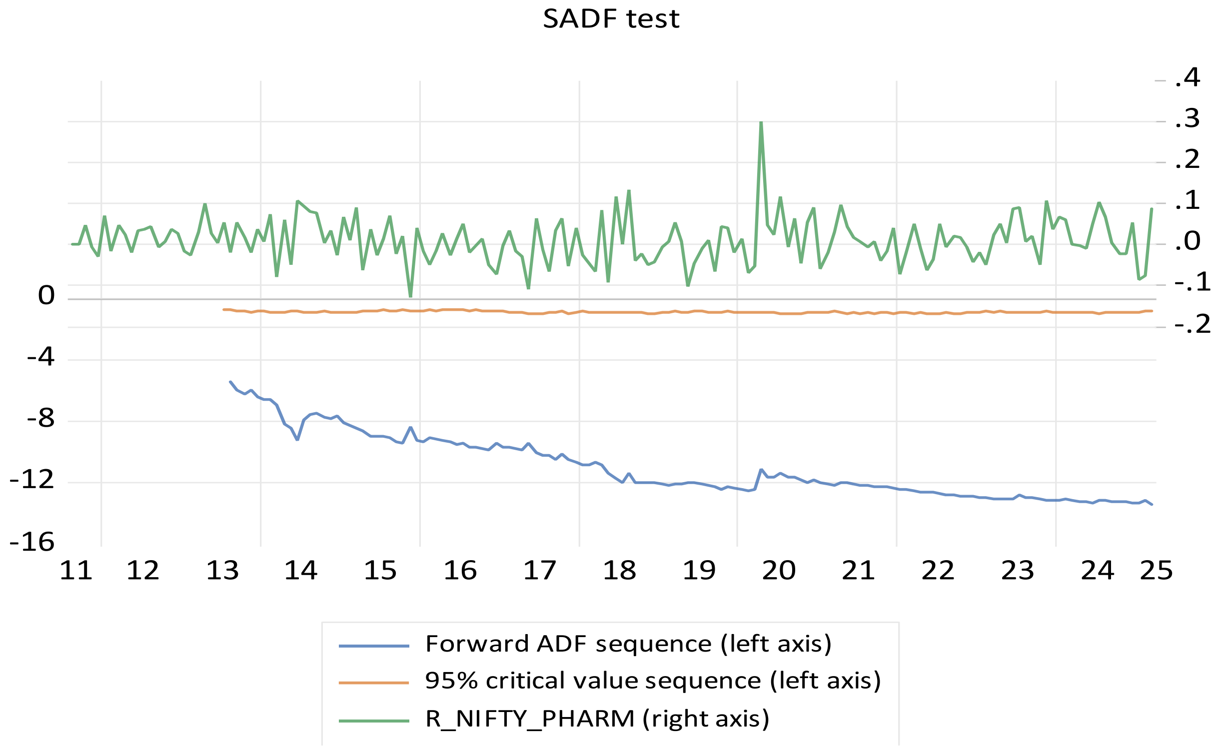
95% critical value sequence (left axis)
R_NIFTY_PHARM (right axis)



4. CONCLUSION

This study set out to identify the presence of speculative bubbles across key sectors of the Indian equity market using advanced econometric testing methods. By analyzing the NIFTY 50 and five sectoral indices—NIFTY Auto, NIFTY Bank, NIFTY Financial Services, NIFTY Energy, and NIFTY Pharma—over a fourteen-year period (August 2011 to March 2025), the research sought to evaluate whether market movements were driven by fundamental valuation or speculative exuberance.

The empirical results consistently indicated no statistical evidence of financial bubbles during the study period. Across all tests—the Right-Tailed Augmented Dickey-Fuller (RtADF), Rolling ADF (RADF), and Supremum ADF (SADF)—p-values of 1.000 were obtained for every index, signifying the absence of explosive price behaviour. This finding suggests that asset prices in the selected indices evolved primarily in alignment with intrinsic values rather than speculative distortions.

The multiple regression model further demonstrated that sectoral returns significantly influence the NIFTY 50, with Financial Services emerging as the strongest determinant of market performance. However, the Granger causality analysis revealed no predictive linkages among sectors, implying that the Indian equity market exhibits characteristics of weak-form efficiency, wherein historical price movements fail to forecast future trends.

Overall, the study concludes that the Indian market maintained a stable and fundamentally driven structure throughout the observed period. The absence of speculative bubbles serves as a positive signal for policymakers, regulators, and investors, reflecting resilience, rational valuation, and sustained confidence within India's financial ecosystem.

5. RECOMMENDATIONS FOR FUTURE RESEARCH AND IMPROVEMENTS

While the study is commendable for its scope, several methodological and analytical limitations could be addressed to enhance robustness and accuracy:

1. Data Frequency and Granularity: The use of monthly returns (164 observations) instead of daily closing prices (~3,500 observations) reduces sensitivity to short-term explosive behavior. This is a critical issue, as bubble detection literature (e.g., Phillips et al., 2015) emphasizes testing log prices rather than returns, since returns are often stationary and may mask bubbles.

- Improvement: Re-run the analysis using daily log prices. This would allow for more precise detection of multiple bubble episodes and better alignment with standard practices. Additionally, extend the window size beyond 25 (used here) to variable or optimized sizes based on data length, and incorporate lag selection via information criteria (e.g., AIC) rather than fixing at 0.

2. Incomplete Implementation of Advanced Tests: The paper mentions the Generalized Supremum ADF (GSADF) as a recommended extension but does not apply it, sticking to RtADF, RADF, and SADF on returns. GSADF is superior for detecting multiple bubbles in volatile series.

- Improvement: Implement GSADF on daily data to improve power against periodically collapsing bubbles. Validate results with bootstrap methods for critical values to account for small-sample bias.

3. Exclusion of Macroeconomic and Microeconomic Factors: The analysis ignores key bubble drivers like interest rates, GDP growth, inflation, monetary policy, or sector-specific events (e.g., auto industry regulations). It also overlooks individual stock constituents within indices, potentially missing micro-level bubbles.

- Improvement: Integrate macroeconomic variables into a vector autoregression (VAR) or panel data model to test for exogenous influences. Analyze index constituents individually or use factor models (e.g., Fama-French) to capture firm-level dynamics.

4. Multicollinearity and Model Assumptions: High correlation between NIFTY Bank and Financial Services (0.98) leads to potential multicollinearity, evidenced by the negative coefficient for Bank (-0.26) in regression, which undermines interpretability.

- Improvement: Apply variance inflation factor (VIF) tests to diagnose multicollinearity and use ridge regression or principal component analysis if needed. Test for heteroskedasticity and autocorrelation (e.g., via Breusch-Pagan and Durbin-Watson tests) to ensure model validity.

5. Sectoral Scope and Sample Period: Only five sectors are covered, excluding high-growth areas like IT or FMCG. The period (2010-2025) misses earlier bubbles (e.g., 2008 crisis).

- Improvement: Expand to all NIFTY sectoral indices and extend the timeline back to 2000 for historical comparison. Segment the analysis into sub-periods (e.g., pre- vs. post-COVID) to isolate event-driven effects.

6. Normality and Stationarity Handling: While Jarque-Bera confirms non-normality and ADF ensures stationarity at first difference, the paper proceeds with parametric tests without adjustments.

- Improvement: Use non-parametric alternatives (e.g., Wilcoxon tests) or robust standard errors for regression to handle non-normality.

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