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Market Trend Analysis of Nifty 50 Stocks using Technical, Fundamental and Time Series Approaches

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ABSTRACT: This study conducts a structured market trend analysis of all 50 constituent stocks of the Nifty 50 index over January 2021 to December 2025, employing three complementary analytical frameworks: technical analysis (Moving Averages, RSI, MACD, Bollinger Bands), fundamental analysis (P/E, P/B, ROE, EPS growth), and time series modelling (ARIMA, GARCH). The integrated framework reveals that technical signals are most informative for short-term trend identification, fundamental indicators provide medium-to-long-term return context, and time series models offer structured forecasting with quantifiable uncertainty bounds. Sector-specific analysis demonstrates heterogeneous trend patterns across financial services, consumer durables, energy, FMCG, and pharmaceuticals. The combined multi-framework approach produces meaningfully superior risk-adjusted outcomes (Sharpe ratio 1.67) compared to any single method in isolation, offering practical guidance for investment strategy construction and risk management within Indian equity markets.

Keywords — Nifty 50, Market Trend Analysis, Technical Analysis, Fundamental Analysis, Time Series Modelling, ARIMA, GARCH, RSI, MACD, Moving Averages, Sectoral Trends, Indian Equity Market.

I. INTRODUCTION

The Nifty 50 index, India's premier large-cap equity benchmark, comprises 50 major companies listed on the National Stock Exchange (NSE) representing approximately 65% of NSE's total free-float market capitalisation across thirteen sectors. As a primary economic indicator for India and a major investment platform for domestic and foreign investors, understanding the Nifty 50's price behaviour is critical for investors, portfolio managers, and policymakers alike.

Navigating the Nifty 50's price dynamics remains a formidable challenge, as the index responds to a diverse and interacting set of influences: global commodity cycles, domestic monetary policy, corporate earnings trajectories, foreign capital flows, and investor sentiment. The study period from January 2021 to December 2025 encompasses four structurally distinct market phases: the post-COVID recovery rally of 2021; the inflationary shock and rate-tightening cycle of 2022; the gradual stabilisation of 2023–2024; and renewed market volatility in 2025.

The central motivation is that no single analytical framework adequately captures the full complexity of equity market trends. Technical analysis excels at identifying price momentum and pattern-based signals but ignores a company's underlying financial health. Fundamental analysis grounds investment decisions in earnings quality and valuation, yet lacks temporal precision for trend timing. Time series models bring statistical rigour to forecasting and volatility estimation but may oversimplify behavioural and sectoral nuances. By combining all three frameworks, this research provides a richer, more complete understanding of how market trends form, sustain, and reverse across the Nifty 50 universe.

II. REVIEW OF LITERATURE

The literature on stock market analysis spans three principal traditions. Technical analysis, grounded in Dow Theory and extended by Elliott Wave Theory, rests on the premise that prices discount all available information, move in identifiable trends, and that historical patterns recur due to consistent human behavioural responses. Murphy (1999) provides a comprehensive treatment of these tools. Roy and Kumar (2009) and Chande and Singh (2018) document the empirical performance of technical indicators specifically in Indian equity markets.

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Fundamental analysis, rooted in Graham and Dodd's (2008) security analysis tradition, examines valuation multiples, earnings quality, and business fundamentals. Gupta and Kumar (2022) demonstrate mean-reverting behaviour in Nifty 50 valuation multiples. Sehgal and Pandey (2018) analyse equity valuation using price multiples for Indian large-cap stocks, finding evidence of return predictability from fundamental screens. The behavioural finance dimension is addressed by Mittal and Jain (2009) and Chattopadhyay et al. (2017), who document anchoring bias, herding tendencies, and sentiment effects in the Indian market.

Time series analysis for Indian equities has been explored by Banerjee (2014) using ARIMA models, and by Karmakar (2017) using VAR-GARCH frameworks for volatility spillover analysis. The Efficient Market Hypothesis (Fama, 1970) provides the theoretical null hypothesis, while Lo's (2004) Adaptive Market Hypothesis offers a more nuanced framework accommodating time-varying market efficiency, which better characterises the 2021–2025 study period. A key identified gap in the literature is the absence of an integrated multi-framework approach applied simultaneously across all Nifty 50 constituents for the post-pandemic period.

III. RESEARCH METHODOLOGY

A. Scope and Data

This study covers all 50 constituent stocks of the Nifty 50 index from January 2021 through December 2025. Daily price and volume data were obtained from the NSE via MoneyControl and Yahoo Finance APIs using Python's yfinance library. Macroeconomic data, including inflation and interest rate data, were sourced from the Reserve Bank of India (RBI) and MOSPI. Fundamental data were collected quarterly from company filings and consensus analyst estimates.

B. Technical Analysis Framework

Four technical indicators were computed: (1) Simple Moving Averages (50-day and 200-day) for trend identification via golden cross and death cross signals; (2) Relative Strength Index (RSI) on a 14-period basis to identify overbought (>70) and oversold (<30) conditions; (3) Moving Average Convergence Divergence (MACD) using 12/26/9 parameters for momentum and trend-change signals; and (4) Bollinger Bands (20-day, $\pm 2\sigma$) to identify volatility compression and breakout signals. A composite multi-indicator strategy was constructed combining all four indicators.

C. Fundamental Analysis Framework

Fundamental screening employed five metrics: Price-to-Earnings (P/E) ratio, Price-to-Book (P/B) ratio, Return on Equity (ROE), Earnings Per Share (EPS) growth rate, and Debt-to-Equity ratio. Stocks were ranked into quartiles relative to sector medians. Twelve-month forward returns were regressed on composite fundamental scores to assess predictive content across sectors. Stable (FMCG, pharmaceuticals) and cyclical (financial services, technology) sector groups were compared.

D. Time Series Framework

ARIMA models were estimated using the Box-Jenkins methodology with order selection via AIC minimisation. GARCH(1,1) models were fitted to return residuals to capture volatility clustering and estimate conditional variance dynamics. Out-of-sample forecasting was evaluated using MAE and RMSE across high-volatility and low-volatility sub-periods. An integrated strategy combining signals from all three frameworks was constructed and evaluated on a risk-adjusted basis using Sharpe ratios with bootstrapped confidence intervals.

E. Research Hypotheses

H1a: Moving average crossover signals will generate statistically significant cumulative abnormal returns (CARs) across Nifty 50 stocks. H1b: RSI signals will exhibit stronger mean-reversion predictive content during range-bound phases than during trending phases. H1c: Multi-indicator composite strategies will outperform single-indicator approaches on a risk-adjusted basis. H2a: Stocks in the lowest P/E quartile will deliver significantly higher forward returns than highest P/E quartile stocks. H2b: Fundamental analysis will demonstrate higher predictive R^2 for stable sectors versus cyclical sectors. H3a: ARIMA forecasting accuracy will be significantly higher during low-volatility phases. H4: The integrated multi-framework approach will produce superior risk-adjusted returns compared to any single analytical framework.

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IV. DATA ANALYSIS AND FINDINGS

A. Preliminary Findings

Preliminary exploratory analysis reveals pronounced heterogeneity in risk-return characteristics across the Nifty 50 universe. Daily return distributions exhibit positive skewness and excess kurtosis, most pronounced during 2022. Annualised returns span a wide range, with the top performers (BEL: +980.6%, Coal India: +418.4%, NTPC: +308.5%) concentrated in financial services, consumer durables, and defence-linked industrials, while the weakest performers (IndusInd Bank: –17.8%, HDFC Life: –14.8%, TCS: –12.5%) reflect sector-specific headwinds. Cross-sectional correlation averaged 0.58–0.63 over the full period, rising above 0.75 during the 2022 inflation shock.

Table I: Nifty 50 Top Gainers and Losers (January 2021 – December 2025)

Stock	Sector	5-Year Return (%)
BEL (Bharat Electronics)	Defence/Industrials	+980.6
Coal India	Energy	+418.4
NTPC	Energy	+308.5
Mahindra & Mahindra	Consumer Durables	+296.4
ONGC	Energy	+277.6
IndusInd Bank	Financial Services	–17.8
HDFC Life	Insurance	–14.8
TCS	Information Technology	–12.5

B. Technical Analysis Findings

Moving average analysis confirms the utility of the 50-day and 200-day SMAs for major trend phase identification. Golden cross signals generated statistically significant positive CARs of approximately 4.2% over the subsequent 20 trading days on average (event study across all golden cross occurrences, 2021–2025), while death cross signals produced average CARs of approximately –3.7% over the same window, supporting H1a at the 5% significance level.

RSI analysis demonstrates significant mean-reversion properties during range-bound phases ($p = 0.003$, directional accuracy 68%) versus trending phases (52–57%), confirming H1b. Multi-indicator composite strategies combining MACD, RSI, and Bollinger Band signals generated average annualised Sharpe ratios of 1.42 versus 0.87–1.05 for individual indicators, supporting H1c.

Table II: RSI Signal Effectiveness by Market Phase

Market Phase	RSI Oversold Avg 5-day Return	Signal Accuracy (%)	p-value
2021 Bull Market (Trending)	+0.9%	52%	0.21
2022 Correction (Volatile)	+0.6%	49%	0.37
2022–23 Range-Bound	+1.8%	68%	0.003
2023–24 Recovery (Trending)	+1.1%	57%	0.09
2025 High Volatility	+0.7%	51%	0.28

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C. Fundamental Analysis Findings

Stocks in the lowest P/E quartile (relative to sector median) delivered average 12-month forward returns of 22.4% compared to 14.1% for the highest P/E quartile ($t = 2.83$, $p = 0.008$), supporting H2a and consistent with the value premium documented in broader equity literature. The value premium was most pronounced during the 2023–2024 recovery phase and weakest during the liquidity-driven 2021 bull market, where high-P/E growth stocks outperformed.
ROE analysis reveals a positive relationship between capital efficiency and risk-adjusted returns: highest ROE quartile stocks generated average Sharpe ratios of 1.38 versus 0.82 for the lowest quartile (ANOVA $F = 6.47$, $p = 0.001$). Cross-sectoral comparison supports H2b: fundamental score regressions yield R^2 of 0.31–0.38 for FMCG and pharmaceutical stocks versus 0.14–0.21 for financial services and technology stocks, reflecting the stronger earnings predictability of defensive sectors.

Table III: Fundamental Analysis Predictive Power by Sector

Sector	Type	R^2 (12M Fwd Returns)	Avg Sharpe (High ROE Q)
FMCG	Defensive	0.35	1.42
Pharmaceuticals	Defensive	0.33	1.38
Consumer Durables	Mixed	0.28	1.35
Financial Services	Cyclical	0.21	1.28
Information Technology	Cyclical/Global	0.14	1.05
Energy	Cyclical/Global	0.16	0.98

D. Time Series Findings

ARIMA models demonstrate significantly lower out-of-sample forecast errors during low-volatility phases (MAE 0.82%) versus high-volatility phases (MAE 2.31%), with a paired t-test confirming the difference at the 1% significance level ($t = 4.17$, $p < 0.001$), supporting H3a. ARIMA forecasting performance deteriorated most severely during the 2022 inflation shock and the 2025 high-volatility episodes, where non-linear regime shifts exceeded the model's linear assumptions.

GARCH(1,1) models reveal high volatility persistence (GARCH β coefficients averaging 0.87–0.92) across all Nifty 50 sectors, confirming strong volatility clustering. Defensive sectors (FMCG, pharmaceuticals) exhibit lower GARCH persistence and faster mean reversion in conditional volatility, while financial services and energy sectors display the highest persistence. GARCH-informed position sizing, scaling down exposure during high-persistence phases, reduces maximum drawdown by an average of 18% relative to static position sizing across the study period.

V. INTEGRATED FRAMEWORK RESULTS

The integrated multi-framework strategy, combining technical entry/exit signals, fundamental stock selection screens, and GARCH-informed position sizing, produces a risk-adjusted Sharpe ratio of 1.67 over the full 2021–2025 study period, significantly outperforming standalone technical (Sharpe 1.08), fundamental (Sharpe 0.94), and time series (Sharpe 0.79) approaches (bootstrapped 95% CI for integration premium: 0.41–0.87), confirming H4.
The integration advantage is most pronounced during market regime transitions — notably the 2022 correction onset and the 2023–2024 recovery — where no single analytical framework alone provided sufficient signal clarity. During stable trending phases, technical signals dominate the combined strategy's contribution; during volatility spikes, GARCH-based risk management contributes most; during recovery phases, fundamental value signals drive stock selection.

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Table IV: Framework Performance Comparison (2021–2025)

Framework	Annualised Return	Sharpe Ratio	Max Drawdown	Signal Accuracy
Technical Only	16.4%	1.08	–22.3%	54–68%
Fundamental Only	14.9%	0.94	–19.8%	N/A
Time Series Only	11.2%	0.79	–17.1%	58–62%
Integrated (All Three)	21.3%	1.67	–13.6%	71–78%
Nifty 50 Benchmark	13.8%	0.86	–24.1%	—

VI. SECTOR-LEVEL ANALYSIS

Sector-level disaggregation reveals substantial heterogeneity in analytical framework effectiveness across the Nifty 50's thirteen sectors. Financial services emerge as the most analytically tractable sector, exhibiting strong co-movement with the aggregate index and offering the most reliable cross-framework predictability, driven primarily by sensitivity to monetary policy and domestic credit conditions. Consumer durables demonstrate the second-strongest predictability, with technical momentum signals and fundamental screens both contributing meaningfully.

Information technology stocks are most strongly influenced by global factors — US bond yields, USD/INR exchange rate, and US technology sector performance — making domestic analytical frameworks less predictive in isolation; global context supplementation is required for this sector. Energy stocks show strong sensitivity to crude oil price fluctuations and geopolitical developments. Defensive sectors (FMCG and pharmaceuticals) exhibit comparatively stable trend behaviour and lower GARCH volatility persistence across market cycles, providing reliable portfolio stabilisation properties during stress periods, despite lower cross-framework return predictability.

VII. DISCUSSION AND IMPLICATIONS

A. Theoretical Implications

The findings challenge the strong form of the Efficient Market Hypothesis (Fama, 1970), as persistent predictability patterns were observed across time horizons and sectors. The evidence aligns more closely with Lo's (2004) Adaptive Market Hypothesis, reflecting time-varying efficiency and exploitable anomalies that emerge and dissipate as market participants adapt. The temporal dynamics of analytical framework contribution — technical tools dominating short horizons, fundamental screens governing medium-term signals — provides empirical support for the hypothesis that distinct market mechanisms operate across different investment horizons.

B. Practical Implications

For individual investors, the findings support a sequential multi-framework approach: initial stock shortlisting through fundamental screening (below-median P/E, above-median ROE, positive EPS growth), followed by technical confirmation of upward trend positioning before entry, and application of GARCH-informed volatility assessment to calibrate position sizing. For portfolio managers, sector rotation decisions should incorporate sector-level technical trend assessment alongside fundamental valuation comparisons, with active weights directed toward financial services and consumer durables during positive trend phases and toward defensive sectors during high-volatility regimes. For risk managers, the high GARCH persistence documented argues for sustained risk budget adjustments following market shock events rather than temporary responses.

VIII. Limitations and Future Research

The study is confined to Nifty 50 large-cap stocks characterised by high liquidity and extensive analyst coverage; the documented analytical relationships may not extend to mid-cap or small-cap Indian equities where market microstructure differs substantially. The specific 2021–2025 macroeconomic configuration — post-COVID stimulus, global inflation cycle, subsequent stabilisation — is unlikely to recur in identical form, and some period-specific return premia may not be fully robust structural relationships. Backtested strategy returns do not incorporate all

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implementation costs including brokerage commissions and market impact, implying real-world returns would be modestly lower. Future research should examine mid-cap and small-cap Indian equity segments, explore the incorporation of news sentiment and social media indicators as supplementary inputs, and investigate whether the integration benefit is stable or regime-concentrated across a longer historical window.

IX. CONCLUSION

This research has conducted a systematic multi-framework analysis of Nifty 50 market trends over January 2021 to December 2025. The evidence firmly establishes that each of the three analytical frameworks — technical, fundamental, and time series — carries genuine informational value for equity trend analysis within the Indian large-cap market. Technical moving average crossover systems and multi-indicator composite strategies deliver reliable directional signals during trending market phases. Fundamental screens based on P/E and ROE effectively discriminate medium-to-long-term return potential, with highest effectiveness during recovery and stabilisation phases. GARCH frameworks provide indispensable insights into dynamic volatility structure, enabling more sophisticated risk management and context-sensitive signal interpretation.

Crucially, the integration of all three frameworks produces a Sharpe ratio of 1.67, meaningfully superior to any individual approach used in isolation, confirming that technical, fundamental, and time series tools capture genuinely distinct and complementary dimensions of market trend behaviour. Sector-level disaggregation reveals that financial services and consumer durables offer the strongest cross-framework predictability, while defensive sectors provide reliable volatility stabilisation properties during stress periods. These findings offer a practical and theoretically grounded analytical foundation for Nifty 50 investment strategy construction and risk management in an era of increasing market complexity.

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