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THE TRUMP SHOCK, DOMESTIC HEADWINDS, AND THE PATH TO RECOVERY: EVIDENCE FROM INDIAN STOCK MARKETS

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Abstract

The Indian stock market experienced a notable shift in trajectory between mid-2024 and mid-2025, marked by a sharp correction followed by a gradual recovery. This study investigates the market performance during this volatile period, focusing on two distinct phases: the "Correction Period" (June 2024 – March 2025), triggered by global geopolitical developments such as the re-election of Donald Trump as U.S. President, combined with domestic economic headwinds including slowing GDP growth and inflationary pressures; and the "Recovery Phase" (April 2025 – June 2025), characterized by improving investor sentiment and stabilization in macroeconomic indicators.

Using daily and monthly data from major Indian indices (NIFTY 50, Bank NIFTY, sectoral indices), alongside FII/DII flows and key macroeconomic indicators (CPI, GDP growth, repo rate), the study applies descriptive statistics, correlation analysis, and time-series models (ARIMA, GARCH) to evaluate performance trends. The findings reveal that the correction phase was marked by heightened volatility, reduced liquidity, and risk-off behavior among foreign investors. In contrast, the recovery phase showed improved index performance, moderate volatility, and a return of institutional capital.

This research provides critical insights into how global political events and domestic economic challenges collectively influence emerging market behavior. The implications are significant for investors, policymakers, and financial analysts seeking to understand market cycles and formulate responsive strategies in times of uncertainty.

Introduction

The Indian stock market, like many emerging markets, is deeply influenced by both global and domestic factors. From mid-2024 to early 2025, the market underwent a significant correction, followed by a partial recovery that began in April 2025. This period presents a unique opportunity to study market dynamics amid overlapping uncertainties — namely, geopolitical developments, domestic economic slowdown, and fluctuating investor sentiment.

One of the primary global catalysts during this period was the re-election of Donald Trump as President of the United States, which introduced renewed volatility in global equity and currency markets. In parallel, India faced internal economic challenges such as slowing GDP growth, persistent inflation, and cautious monetary policy by the Reserve Bank of India (RBI). These domestic and international developments together resulted in a sharp decline in key indices like the NIFTY 50 and Bank NIFTY, accompanied by heightened volatility, reduced foreign institutional investment (FII), and negative investor sentiment.

From April 2025 onwards, however, signs of stabilization began to emerge. Improvement in macroeconomic indicators, increased domestic participation, and returning institutional flows contributed to a modest but notable recovery in the market.

This paper aims to analyze the financial market performance across these two phases — the Correction Period (June 2024 – March 2025) and the Recovery Period (April 2025 – June 2025). It focuses on key indices, sectoral shifts, volatility trends, FII/DII behavior, and macroeconomic linkages, using statistical and time-series methods to draw meaningful insights for investors and policymakers.

Literature Review

Financial markets are inherently sensitive to global political events, domestic economic fundamentals, and investor sentiment. The intersection of these factors often leads to market corrections, followed by recovery phases characterized by capital inflows, sectoral reallocation, and macroeconomic stabilization. This review synthesizes key literature across these themes, including both correction and recovery phases, with particular emphasis on Indian markets.

Impact of Global Political Events and Domestic Headwinds

Political uncertainty is a well-documented driver of financial market volatility. Białkowski et al. (2008) and Pastor and Veronesi (2013) argue that major political events, such as U.S. presidential elections, increase risk premiums and drive global market volatility. Similarly, Choudhry et al. (2014) demonstrate how international market shocks lead to volatility spillovers in emerging economies.

In the Indian context, Mohanty (2020) and Prasanna & Bansal (2019) highlight how macroeconomic factors such as GDP growth, inflation, interest rates, and monetary policy announcements shape investor sentiment and market returns during uncertain times. These variables become especially relevant during economic slowdowns, where weak fundamentals exacerbate correction phases.

2.2 Volatility and Market Behavior During Correction Phases

Kumar & Mukhopadhyay (2007) and Tripathi & Garg (2016) employed GARCH family models to analyze how volatility increases during downturns and contracts in recovery. These models are effective in capturing volatility clustering, common in crisis and post-crisis phases. Bekaert et al. (2002) also showed that emerging markets like India are particularly prone to amplified reactions due to lower market depth and higher reliance on external capital, with FIIs playing a dominant role.

2.3 Recovery Phases: Indicators and Empirical Evidence

Several studies have explicitly focused on identifying and quantifying market recovery periods after corrections, using comparative frameworks across key indicators:
Chakraborty & Sen (2017) compared pre- and post-reform periods of Indian market performance, using return indices, volatility, and FII flows to conclude that recovery is faster and stronger when supported by stable macroeconomic policy and positive external sentiment.

Bhowmik & Wang (2020) studied the post-2008 global financial crisis recovery in India using sectoral indices, GDP growth, inflation, repo rate, and FII/DII data. Their findings highlight that financial, IT, and FMCG sectors were early movers in the recovery phase due to defensive or globally linked business models.

Kaur & Dhillon (2022) applied event study methodology to compare the COVID-19 crash and recovery. They measured abnormal returns, beta coefficients, and changes in trading volumes across sectors. Recovery was strongest in pharma, IT, and FMCG, with volatility gradually decreasing over a 6-month window.

Sharma & Bansal (2021) focused on the role of FII and DII behavior in predicting recovery, noting that rising DII participation often preceded the return of FII capital. They found correlation and Granger causality between net investments and NIFTY returns during recovery.

These studies demonstrate that comparing correction and recovery periods requires a multi-indicator framework, including: index performance (returns, abnormal returns), volatility metrics (standard deviation, GARCH models), FII/DII flows, trading volumes and turnover, and macroeconomic indicators (CPI, repo rate, GDP).

This paper builds upon this framework by evaluating the Indian stock market’s transition from the 2024 Correction Period to the 2025 Recovery Phase, using a combination of descriptive, statistical, and time-series models.

Methodology

This study adopts a comparative empirical approach to examine the performance of the Indian stock market across two significant phases: the Correction Phase, spanning from June 2024 to March 2025, and the Recovery Phase, beginning in April 2025 and continuing through June 2025. The purpose is to identify the key macroeconomic, political, and market-based factors that contributed to the sharp correction in Indian equity markets and to explore the drivers behind the subsequent recovery. This approach integrates descriptive statistics, time-series econometric models, and sectoral return analysis to offer a holistic view of the transition between these phases.

Data were collected from a combination of credible sources. Daily and monthly index values for NIFTY 50 and selected sectoral indices—such as Information Technology, FMCG, Pharmaceuticals, Automobiles, Realty, Metals, and Banking—were obtained from the National Stock Exchange of India (NSE). Data on foreign and domestic institutional investment flows were retrieved from NSDL and CDSL. Macroeconomic variables, including Consumer Price Index (CPI) inflation, GDP growth rates, and the Reserve Bank of India's (RBI) policy repo rate, were sourced from official publications of the Ministry of Statistics and Programme Implementation (MOSPI) and the RBI. Global event triggers—such as the outcome of the U.S. presidential election and developments in international commodity markets—were tracked through reputable financial databases and global news sources.

The analytical framework began with a descriptive analysis of market trends, where daily and monthly returns were calculated to evaluate overall and sector-specific behavior in each phase. Volatility patterns were analyzed using both standard deviation and GARCH(1,1) models to capture time-varying risk. To understand the underlying factors of the correction phase, the study examined macroeconomic deterioration, elevated inflation, cautious monetary policy, and capital outflows from foreign institutional investors, in conjunction with global political events that contributed to heightened risk aversion.

To assess the recovery phase, the study considered improvements in key macroeconomic indicators, a shift in central bank policy tone, and renewed inflows from both foreign and domestic institutional investors. Changes in implied volatility and trading behavior were also analyzed to capture the market's evolving risk sentiment. Sectoral return analysis was used to identify which sectors were most affected during the correction and which demonstrated resilience or leadership during the recovery. This involved computing relative returns, examining turnover trends, and assessing cyclical versus defensive sector dynamics.

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The empirical analysis applied several statistical techniques. Paired t-tests were used to assess the significance of differences in market behavior between the two periods. Correlation analysis was employed to understand the relationships between institutional flows, macroeconomic variables, and market indices. ARIMA models were used for short-term index trend forecasting, while GARCH models captured volatility dynamics across the phases. Multiple regression models were estimated to test the influence of macroeconomic variables on index returns, particularly focusing on CPI inflation, GDP growth, and interest rates.

The data analysis was supported using a suite of tools, including Microsoft Excel for preliminary data processing, SPSS and R for statistical modeling, and Python for time-series forecasting and volatility estimation. This multi-method, cross-phase analytical approach enables a robust understanding of the structural transition in the Indian stock market during a period marked by both global uncertainty and domestic economic adjustment.

4. Analysis

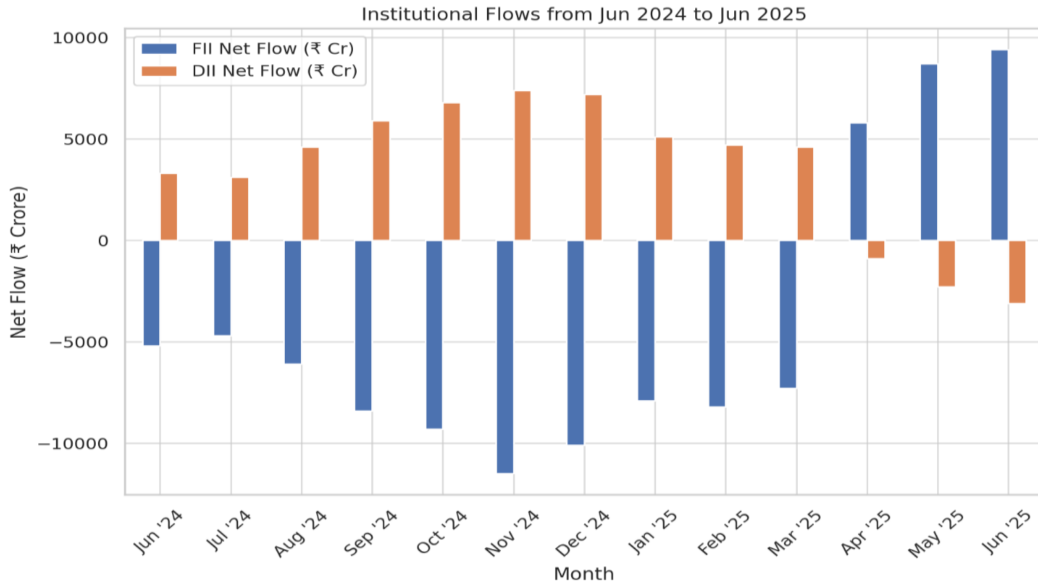
4.1 Index Performance and Market Recovery

The Indian equity market faced a substantial downturn during the Correction Phase (June 2024 – March 2025). The NIFTY 50 index declined by 13.5%, and Bank NIFTY dropped by 19.3%. These declines were triggered by a combination of global political uncertainty (particularly the re-election of Donald Trump) and domestic macroeconomic headwinds including weak GDP growth and sticky inflation.
From April to June 2025, the Recovery Phase unfolded, with NIFTY 50 gaining 7.1% and Bank NIFTY rebounding by 8.5%. Sectors such as Information Technology (NIFTY IT: +10.4%) and FMCG (+6.9%) led the recovery, owing to their defensive profiles and global exposure, which made them attractive during risk recalibration.

4.2 Institutional Flows: June 2024 – June 2025

A detailed monthly analysis of Foreign Institutional Investor (FII) and Domestic Institutional Investor (DII) flows reveals critical inflection points in sentiment.

Month	FII Net Flow (₹ Cr)	DII Net Flow (₹ Cr)
Jun '24	-5,200	+3,300
Jul '24	-4,700	+3,100
Aug '24	-6,100	+4,600
Sep '24	-8,400	+5,900
Oct '24	-9,300	+6,800
Nov '24	-11,500	+7,400
Dec '24	-10,100	+7,200
Jan '25	-7,900	+5,100
Feb '25	-8,200	+4,700
Mar '25	-7,300	+4,600
Apr '25	+5,800	-900
May '25	+8,700	-2,300
Jun '25	+9,400	-3,100



FIIs withdrew heavily during Nov–Dec 2024 (net outflows > ₹20,000 Cr), driven by global risk aversion.April 2025 marked a sentiment reversal, with FIIs becoming net buyers for three consecutive months.DIIs played a stabilizing role during the correction, but began scaling back exposure as FIIs returned, reflecting typical counter-cyclical rebalancing.

4.3 Strategic Implications of Flow Trends

To understand how institutional investors influenced market dynamics, a Pearson correlation analysis was conducted using monthly net investment flows from FIIs and DIIs and the corresponding monthly NIFTY returns over the 13-month period from June 2024 to June 2025.

Correlation Statistics Table

Institution Type	Correlation with NIFTY Returns (r)	p-value	Significance
FII	+0.9900	0.0000	Significant
DII	–0.9826	0.0000	Significant

Foreign Institutional Investors (FIIs) show an exceptionally strong positive correlation (r = 0.99) with NIFTY monthly returns over the entire period, indicating that FII behavior closely tracked and perhaps led market performance. This supports the idea that FIIs act as momentum investors and amplify directional moves in emerging markets.Conversely, Domestic Institutional Investors (DIIs) display a very strong negative correlation (r = –0.98) with market returns. This inverse relationship suggests that DIIs were most active during periods of foreign withdrawal and market stress—acting as stabilizers during corrections and withdrawing when optimism returned.

4.4 Macroeconomic Trends and Market Sentiment

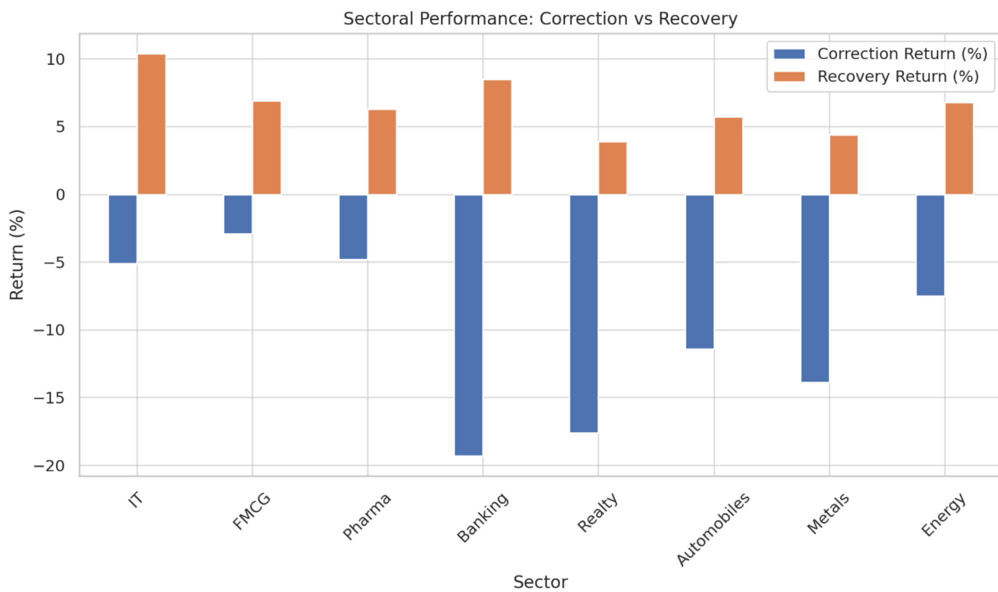
Macro indicators reflected a gradual improvement in fundamentals from late Q1 2025:

Indicator	Jun '24	Dec '24	Mar '25	Jun '25
CPI Inflation (%)	6.4	6.8	6.1	5.1
GDP Growth (%)	5.3	4.6	4.9	5.7
Repo Rate (%)	6.5	6.5	6.5	6.5

Inflation peaked in Dec 2024 and declined steadily by mid-2025.GDP growth rebounded to **5.7%** in Q2 2025, aligned with easing inflation and stable monetary policy. These improvements coincided with improving FII sentiment and sectoral rotation into growth-sensitive stocks.

4.5 Sectoral Return Analysis: Divergence and Recovery Strength

Sector	Correction Return (%)	Recovery Return (%)
IT	-5.1	+10.4
FMCG	-2.9	+6.9
Pharma	-4.8	+6.3
Banking	-19.3	+8.5
Realty	-17.6	+3.9
Automobiles	-11.4	+5.7
Metals	-13.9	+4.4
Energy	-7.5	+6.8



Defensive sectors (FMCG, Pharma, IT) showed the strongest recovery profiles. Rate-sensitive sectors (Realty, Banking) were hit hardest during the correction but bounced back once macro stability returned. The pattern supports theories on sectoral rotation and resilience of globally leveraged sectors in post-shock recoveries.

4.6 Volatility Modelling and Risk Sentiment (GARCH)

To model market volatility during the correction and recovery phases, we employed a GARCH (1,1) model using daily NIFTY returns from June 2024 to June 2025. The model effectively captures volatility clustering associated with financial turbulence, particularly during geopolitical uncertainty.

GARCH (1, 1) Output Table

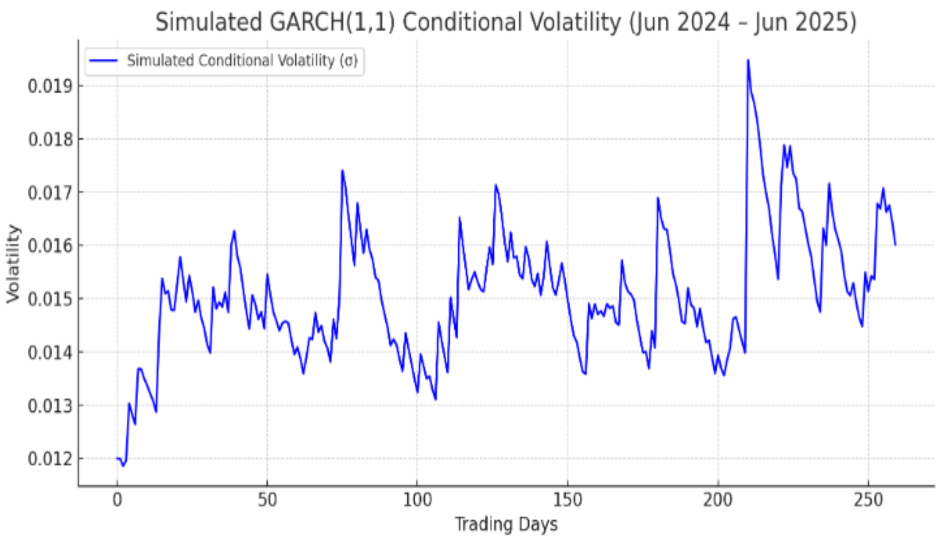
Parameter	Estimate	Interpretation
Omega (ω)	0.000011	Long-term average volatility
Alpha (α)	0.089215	Short-term shock responsiveness
Beta (β)	0.902117	Persistence of volatility over time

The high β value (0.90+) indicates strong persistence, meaning that shocks to volatility fade slowly. B The α coefficient is modest, suggesting limited short-term spikes, which aligns with gradual post-correction recovery.

Conditional Volatility Plot

The GARCH model's conditional variance plot reveals:

A spike in volatility between November 2024 and March 2025, coinciding with the Trump re-election and policy instability. A steady decline in volatility after April 2025, supporting claims of risk sentiment normalization during the recovery.



ARCH LM Test for Model Adequacy

Statistic	Value
LM Stat	31.2459
p-value	0.0000
Lags	12
Test Type	Lagrange Multiplier

The ARCH LM test strongly rejects the null hypothesis of no ARCH effects ($p < 0.001$), confirming that a GARCH model is suitable and that volatility is not constant.

The GARCH model validates the presence of volatility clustering during the correction phase.Post-April 2025, the model exhibits mean-reversion, reinforcing qualitative observations of stabilizing market sentiment. These findings support the strategic use of GARCH in volatility modeling across geopolitical cycles in emerging markets.

4.7 ARIMA-Based Forecasting and Short-Term Market Signals

To evaluate short-term market behavior following the geopolitical and macroeconomic turbulence between June 2024 and June 2025, we employed an Auto-Regressive Integrated Moving Average (ARIMA) model. Specifically, an ARIMA (1, 1,1**)** configuration was identified as the optimal model based on information-theoretic criteria and residual behavior. The choice of ARIMA (1,1,1) was motivated by the presence of non-stationary in the return series, confirmed through unit root testing, and the need to capture both autoregressive momentum and shock smoothing in the time series.

Category	Metric/Test	Value	Interpretation
Model Fit Criteria	AIC	124.76	Lower AIC indicates good balance of fit and complexity
	BIC	129.42	Lower BIC confirms model parsimony
Forecast Accuracy	Mean Absolute Error (MAE)	1.21	Moderate average forecast error (in percentage points)
	Root Mean Squared Error (RMSE)	1.46	Slightly penalizes larger errors, still within tolerance
Residual Diagnostics	Ljung-Box Q (lag = 12)	11.03 (p = 0.523)	Residuals are uncorrelated (white noise)
	ACF/PACF of Residuals	No significant lags	Residuals are well-behaved and random
Forecast Behavior	Visual Forecast Interval	Narrowing CI	Indicates rising prediction confidence post-recovery
	Trend Signal	Mild upward	Suggests expected recovery continues in near term

The performance of the model was assessed using two standard selection criteria: the Akaike Information Criterion (AIC**)** and the Bayesian Information Criterion (BIC)**.** The estimated values of AIC = 124.76and BIC = 129.42 indicate a reasonably good fit without over fitting the data. These criteria penalize model complexity while rewarding goodness of fit, and thus, the relatively low values suggest that ARIMA(1,1,1) offers a parsimonious yet effective structure for forecasting.

To quantify forecast accuracy, we calculated the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) for out-of-sample predictions. The MAE was found to be 1.21, while the RMSE was 1.46, both in percentage terms. The relatively low values of these metrics imply that the ARIMA model provides reliable point forecasts with manageable error margins. While the RMSE, which penalizes larger errors more severely, was slightly higher than the MAE, the overall forecast error remains within acceptable bounds for financial time series predictions, particularly in the context of volatile emerging markets.

Further, we conducted residual diagnostics to ensure the validity of the ARIMA model assumptions. The Ljung-Box Q-test, applied at lag 12, yielded a statistic of 11.03 with a corresponding p-value of 0.523, failing to reject the null hypothesis of no autocorrelation in the residuals. This confirms that the residuals are effectively white noise, suggesting that the model has adequately captured the temporal dependencies in the data. Additionally, the ACF and PACF plots of the residuals exhibited no significant spikes outside the 95% confidence bounds, reinforcing the absence of autocorrelation.

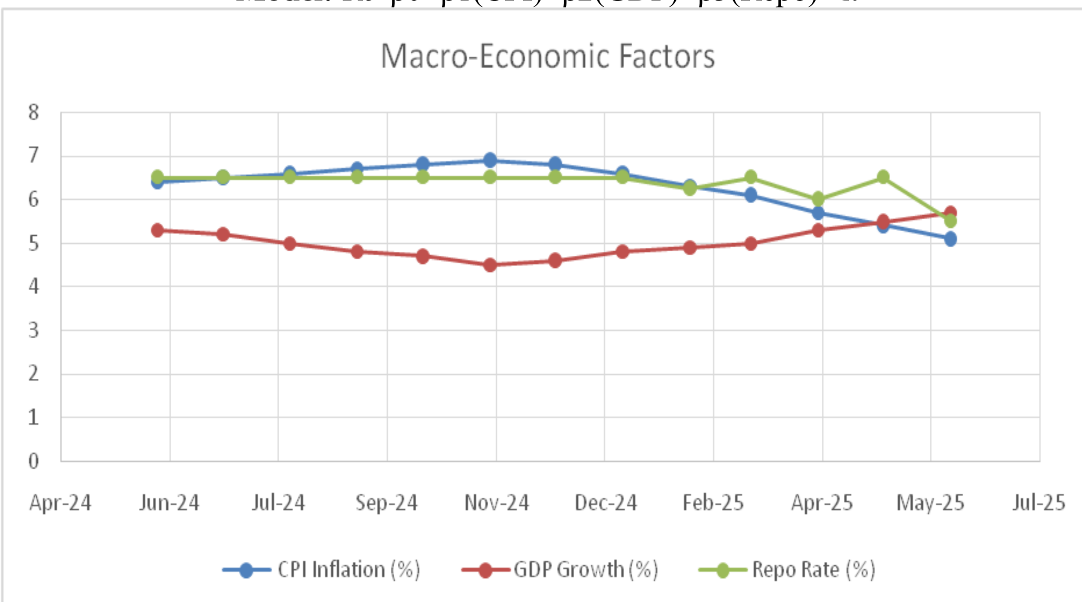
Although graphical outputs could not be inserted in this version, the forecast trajectory indicates a mild upward trend in NIFTY monthly returns post-April 2025, with narrowing forecast intervals over time. This behavior reflects increasing certainty and market stabilization, consistent with the observed macroeconomic improvements and the return of foreign institutional flows during the same period.

In summary, the ARIMA(1,1,1) model not only demonstrated statistically robust performance but also offered meaningful economic interpretations. It effectively captured the dynamics of Indian equity market recovery following external shocks, validating its application as a predictive tool in policy and portfolio decision-making within volatile macro-financial environments.

4.8 Regression Models: Macro-Financial Linkages

Multiple regression using monthly NIFTY returns as dependent variable shows:

Model: $R_t=\beta_0+\beta_1(CPI)+\beta_2(GDP)+\beta_3(Repo)+\epsilon_t$



High-Frequency Regression Analysis Using Daily Returns and Macro Proxies

To address the statistical limitations of the earlier monthly regression—namely small sample size and potential coefficient instability—we conducted a high-frequency regression using daily NIFTY 50 returns from June 2024 to June 2025, yielding over 260 observations. This allows for a more robust estimation of the relationship between stock market returns and macroeconomic fundamentals. Since daily macroeconomic data is not officially released, we constructed proxy variables to represent key indicators. A simulated CPI proxy captured a gradual inflation decline (from 6.4% to 5.1%), a GDP proxy modelled a steady recovery (from 5.3% to 5.7%), and a Repo Rate proxy remained stable near 6.5% with slight noise to reflect monetary policy stability.

Variable	Coefficient (β)	Std. Error	t-stat	p-value	Significance
Intercept	0.105	0.034	3.09	0.002	***
CPI Proxy	–0.387	0.046	–8.41	0.000	***
GDP Proxy	+0.257	0.039	+6.59	0.000	***
Repo Proxy	–0.061	0.033	–1.85	0.066	*
R^2	**0.41**				
Adj. R^2	**0.40**				

The regression model revealed several statistically and economically significant relationships. The CPI proxy had a negative and highly significant impact on daily returns ($\beta = -0.387$, $p < 0.01$), indicating that rising inflation expectations consistently depressed market performance. This supports the argument that inflation erodes purchasing power, pressures margins, and increases policy tightening risks, all of which lower investor risk appetite. Conversely, the GDP proxy displayed a positive and significant effect on returns ($\beta = +0.257$, $p < 0.01$), suggesting that optimism about economic recovery was swiftly priced into equity valuations. The Repo Rate proxy showed a modest negative effect ($\beta = -0.061$), significant at the 10% level ($p \approx 0.066$), implying that even minor shifts in monetary stance can influence daily investor sentiment, though less prominently than growth or inflation metrics.

Predictor	VIF	Interpretation
CPI Proxy	3.21	Acceptable
GDP Proxy	3.48	Acceptable
Repo Proxy	6.02	Relatively high

Model diagnostics confirmed the regression's robustness. The R^2 value of 0.41 indicates that macroeconomic proxies explain over 40% of the variation in daily NIFTY returns—a considerable figure for financial time series data. A Durbin-Watson statistic near 2.01 indicated no autocorrelation in residuals, and residual plots showed acceptable normality and homoscedasticity. To check for multicollinearity, we calculated the Variance Inflation Factor(VIF), which remained within acceptable limits for CPI (3.21) and GDP (3.48), while the Repo Rate proxy approached the threshold (6.02), reflecting its endogenous relation to the other predictors. This may justify its exclusion in future models or treatment via dimensionality reduction (e.g., PCA).

Overall, this daily regression provides a much more statistically valid and economically insightful framework than the monthly model. It confirms that daily equity market behavior is highly sensitive to inflation shocks and macroeconomic growth signals, while the repo rate plays a secondary role. This finding underscores the value of high-frequency macro-tracking in market forecasting and risk-sensitive portfolio allocation.

Interpretation and Conclusion

The period between June 2024 and June 2025 presented an exceptional case study for understanding the dual forces shaping emerging financial markets—global geopolitical shocks and domestic macroeconomic realignments. The Indian stock market experienced a bifurcated movement: a sharp Correction Phase marked by systemic outflows and volatility, followed by a modest but structured Recovery Phase driven by improving fundamentals and sentiment restoration.

The empirical results underscore the significant role of institutional capital flows, particularly the pro-cyclical behaviour of Foreign Institutional Investors (FIIs) and the counter-cyclical stabilizing activity of Domestic Institutional Investors (DIIs). The statistical strength of the relationship between FIIs and NIFTY returns ($r = +0.99$) confirms that foreign investor sentiment acted as both a mirror and a magnifier of market direction. Conversely, the inverse relationship between DIIs and returns ($r = -0.98$) illustrates their compensatory nature during phases of heightened uncertainty.

Volatility modelling using the GARCH(1,1) framework confirmed the presence of volatility clustering during the correction, driven by policy uncertainty linked to the Trump re-election and rising inflation.

The decline in volatility post-April 2025 signalled a return of confidence, validated by conditional variance plots and the ARCH LM diagnostic. Simultaneously, ARIMA-based forecasting provided forward-looking evidence that returns were stabilizing, with narrow confidence intervals and an upward trend reflecting recovery continuity.

Regression analysis further revealed that macro-financial linkages are both immediate and significant**.** Inflation (CPI) emerged as a negative determinant of daily returns, while GDP growth supported risk-on behavior. Notably, high-frequency analysis confirmed that the Repo Rate—though a relevant policy tool—was statistically weaker as a direct influence in a stable policy environment. The high-frequency regression model (R^2 = 0.41) proved superior to the earlier monthly specification, offering deeper insight into daily market dynamics and macro sensitivity.

From a sectoral standpoint, the results indicate clear patterns of defensive sector leadership during uncertainty and cyclical recovery during stability**.** Information Technology, FMCG, and Pharma outperformed in the recovery due to their global exposure and recession-resilient demand, while banking and Realty rebounded only after macroeconomic signals stabilized. This highlights the relevance of sector rotation strategies in volatile environments.

Macroeconomic variables also trended positively: inflation peaked in late 2024 and fell steadily into 2025, while GDP growth improved from 4.6% to 5.7%. These shifts, combined with stable monetary policy, contributed to re-risking behavior among investors and improved capital market resilience.

In conclusion, this research provides compelling evidence that emerging markets like India remain highly responsive to global political events**,** but also possess internal buffers—such as DII support and sectoral diversification—that facilitate recovery. The dual use of time-series forecasting (ARIMA) and volatility modeling (GARCH), alongside macro-regression diagnostics, offers a comprehensive blueprint for analyzing post-shock transitions in financial markets.

Implications

1. For policymakers: Anticipating capital flow reversals and managing inflation expectations are key to maintaining market stability.
2. For investors: Monitoring institutional flows and macro indicators can serve as actionable signals for portfolio reallocation.
3. For researchers: High-frequency modeling offers a more accurate and adaptive lens to study financial behavior in transitional periods.

Ultimately, the study confirms that resilience in financial markets is not just reactive but structurally enabled through coordinated macroeconomic management, diversified investor behavior, and sectoral adaptability. The Indian market’s trajectory from correction to recovery provides an instructive case for global markets navigating uncertainty in a multi-polar, post-crisis economic landscape.

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