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Foreign Portfolio Investment and Indian Sectoral Equity Returns: A Comparative Analysis of NIFTY BANK and NIFTY IT, 2012–2024

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Abstract

This paper examines the differential impact of net Foreign Portfolio Investment (FPI) equity flows on two major sectoral indices of the National Stock Exchange of India—NIFTY BANK and NIFTY IT—over April 2012 to March 2024 (N = 144 monthly observations). Using OLS regression with heteroscedasticity-corrected standard errors, Johansen co-integration, Granger causality, and Vector Error Correction Modelling (VECM), the study finds that FPI flows exert a statistically significant positive effect on both indices: NIFTY BANK ($\beta = 0.421$, $p < .001$) and NIFTY IT ($\beta = 0.387$, $p < .001$). A Chow structural difference test confirms that the two sector equations are significantly distinct ($F = 4.83$, $p < .001$): NIFTY BANK returns are sensitive to INR/USD exchange rate and domestic G-Sec yield changes, while NIFTY IT returns are driven by NASDAQ returns and the U.S. Federal Funds Rate. Johansen co-integration establishes a long-run equilibrium between FPI flows and each index. Granger causality results support bi-directional causality with the flow-to-return direction more robust. VECM adjustment speeds are approximately 21% (NIFTY BANK) and 19% (NIFTY IT) per month. These findings carry actionable implications for SEBI, the Reserve Bank of India, fund managers, and domestic institutional investors.

Keywords: Foreign Portfolio Investment · NIFTY BANK · NIFTY IT · Johansen Co-integration · Granger Causality · VECM · Indian Equity Markets · Capital Flows

INTRODUCTION

India's capital account liberalisation in 1992 allowed Foreign Portfolio Investors (FPIs) to invest in domestic equities, transforming the character of Indian financial markets. By the early 2020s, FPIs collectively held approximately 18–22% of the total market capitalisation of NSE-listed companies (Securities and Exchange Board of India [SEBI], 2023). In systemically important sectors such as private banking and information technology (IT) services, FPI ownership frequently exceeded 30–40% of free-float shares, making the question of how FPI flows affect domestic equity prices a genuine concern for regulators and investment practitioners alike.

A considerable body of empirical literature has examined FPI flows and Indian equity market performance, yet almost exclusively at the aggregate level using broad market indices such as the SENSEX or NIFTY 50 as the dependent variable. Such studies are helpful in establishing the approximate direction and magnitude of the FPI effect on broad market returns but are less helpful in answering whether this relationship is uniform across sectors with fundamentally different drivers. The present study addresses this gap by asking whether net FPI equity flows affect the banking and IT sectors equally, or whether the differential nature of the two sectors produces meaningfully different sensitivities.

The NIFTY BANK index tracks twelve of India's most liquid large-capitalisation banking and financial services stocks, accounting for approximately 26–28% of the NIFTY 50 weight (National Stock Exchange of India [NSE], 2024). The NIFTY IT index represents the top IT services companies by free-float market capitalisation, deriving the majority of constituent revenues from the United States and Europe. The contrast between a domestically oriented sector whose fortunes are bound to the Indian

monetary cycle and a globally oriented sector whose revenues arrive in foreign currency makes these two indices an ideal comparative pair for studying FPI influence.

This paper makes five contributions to the literature: (a) it provides the first formal sector-specific comparison of FPI sensitivity in India within a unified econometric framework; (b) it employs a sample spanning April 2012 to March 2024, the longest in the published Indian sectoral FPI literature; (c) it tests a lagged FPI specification that enables distinction between price-pressure and information-diffusion channels; (d) it applies a Chow structural difference test to confirm structural inequality between sector equations; and (e) it derives policy implications at the sector-specific level.

LITERATURE REVIEW

Theoretical Foundations

The intellectual foundation for cross-border equity flows and asset prices is the Portfolio Balance Theory, traceable to Tobin (1958) and formalised for open-economy settings by Frankel (1983). The central argument is that investors hold a basket of domestic and foreign assets and continuously rebalance in response to changes in expected risk-adjusted returns, thereby predicting a positive contemporaneous relationship between net FPI inflows and equity returns.

Three additional theoretical lenses are relevant. The Efficient Market Hypothesis in its semi-strong form (Fama, 1970) suggests that FPI trades may contain a private information component, implying that FPI activity should Granger-cause future returns beyond publicly available signals. The noise trader model of De Long et al. (1990) argues that FPIs may exhibit momentum-driven behaviour in markets where they have limited fundamental information relative to domestic participants, generating feedback loops between price increases and inflows. Finally, the push-pull factors framework (Calvo et al., 1993) distinguishes between conditions in advanced economies that drive capital outward—such as low U.S. interest rates—and domestic conditions that attract capital, such as strong GDP growth.

Empirical Evidence: India

Early aggregate-level studies established the positive FPI–equity return relationship in India. Babu and Prabheesh (2008) found a significant positive correlation ($r = 0.68$) between net FPI equity flows and the BSE SENSEX using monthly data from 1993 to 2003. Chakrabarti (2001) showed, using daily data, that price increases preceded FPI inflows during bull markets while FPI outflows appeared to lead price declines during bear markets. Mukherjee et al. (2002) found clear evidence of positive feedback trading—FPIs systematically buying after positive return performance and selling after negative returns. Sultana and Pardhasaradhi (2011) used a decade of monthly data to regress SENSEX returns on net FPI flows, exchange rate, and call money rate, achieving an R^2 of 0.432.

Sectoral evidence is sparse. Bose (2012) found that IT and banking sectors attracted roughly 45% of total FPI equity investments between 2001 and 2012, with IT returns correlated with NASDAQ performance and banking returns responsive to the repo rate and IIP growth. Kulkarni (2017) examined the FPI–NIFTY IT relationship over 2010–2016 using Johansen co-integration and VECM, estimating an adjustment speed of approximately 18% per month. Rao and Reddy (2019) identified the 2013 Taper Tantrum as a structural break in the NIFTY BANK–FPI relationship.

Exchange Rate and Global Push Factors

Phylaktis and Ravazzolo (2010) found that currency appreciation was robustly associated with FPI equity inflows across eight Asian emerging markets. Mishra et al. (2012) documented that INR depreciation was associated with FPI outflows, with the banking sector exhibiting greater sensitivity than other sectors. Poshakwale and Thapa (2012) showed that the flow-to-return Granger causality was stronger before the 2008 Global Financial Crisis, while the return-to-flow direction strengthened in the post-crisis period.

Four gaps remain that this study is designed to fill: (a) Indian studies almost exclusively use broad market indices; (b) most published studies end their sample before 2020, excluding the COVID-19 shock and the 2022–23 Federal Reserve tightening cycle; (c) the moderating roles of NASDAQ and the Federal Funds Rate for individual Indian sectors have not been systematically tested; and (d) formal structural difference testing applied simultaneously to NIFTY BANK and NIFTY IT is absent from the literature.

DATA AND METHODOLOGY

Data Sources and Sample

All data are secondary and span April 2012 to March 2024, yielding 144 monthly observations. Table 1 summarises the variables, sources, and measurement. Monthly log returns for each index are computed as R_t = ln(P_t / P_{t-1}) × 100, where P_t denotes the month-end closing value. The 10-year G-Sec yield series was sourced from the RBI's Month-End Yield of SGL Transactions dataset and supplemented by RBI DBIE Table F.4 for early years. All software used was IBM SPSS Statistics 26 (descriptive statistics, OLS, VIF) and EViews 12 (ADF, Johansen, Granger, VECM).

Regression Models

Two OLS models incorporating both contemporaneous and one-period lagged FPI equity flow are estimated. Model 1 for NIFTY BANK:

$$R\_BANK,t = \alpha_1 + \beta_1 FPIeq,t + \beta_2 FPIeq,t-1 + \beta_3 FPIdebt,t + \beta_4 \Delta EX\_t + \beta_5 \Delta GSEC\_t + \beta_6 \Delta FFR\_t + \beta_7 R\_NASDAQ,t + \varepsilon_1,t$$

Model 2 for NIFTY IT replaces the dependent variable and substitutes γ coefficients for β. A significant positive lagged coefficient would be consistent with a gradual information hypothesis; a significant contemporaneous coefficient alongside an insignificant lagged coefficient would instead support a pure price-pressure mechanism.

Time-Series Methods

Stationarity is assessed using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981) with lag length selected by AIC. When two series are both I(1), the Johansen (1988) maximum likelihood procedure tests for a co-integrating relationship using the trace and maximum eigenvalue statistics. The Granger (1969) causality test assesses whether lagged values of one variable help predict another beyond its own lags. Given co-integration, the Vector Error Correction Model (VECM) estimates short-run dynamics and the speed of adjustment ($\lambda_1 < 0$ indicates convergence to long-run equilibrium). A Chow structural difference test formally tests whether the two sector regression structures are statistically distinct.

RESULTS

FPI Flow Trends and Index Performance

Table 2 presents annual FPI flows over the study period. Total cumulative net FPI equity flows amounted to INR 7.16 lakh crore over twelve years, but with dramatic year-to-year variability. FY 2020–21

recorded the highest single-year equity inflow (INR 2,74,946 crore), reflecting the global liquidity surge following the Federal Reserve's near-zero rate policy. The following year produced the largest recorded reversal (−INR 1,40,009 crore) as the Fed signalled tapering—illustrating the push-factor dominance in Indian FPI dynamics theoretically predicted by Calvo et al. (1993).

The sectoral return divergence is equally instructive. In FY 2019–20, NIFTY BANK fell −27.4% while NIFTY IT declined only −4.8%, reflecting the banking sector's acute COVID-19 vulnerability relative to IT's recession-resilient revenue model. In FY 2022–23, the pattern reversed: NIFTY IT fell −24.7% as rising U.S. interest rates compressed growth stock valuations, while NIFTY BANK held at −5.1%. This asymmetric pattern provides intuitive support for sector-specific FPI sensitivity.

Descriptive Statistics

NIFTY IT produced a marginally higher mean monthly return (1.78%) than NIFTY BANK (1.42%), but NIFTY BANK exhibited higher volatility (SD = 6.84% vs. 6.23%). The NIFTY BANK return series shows pronounced negative skewness (−2.31) and extreme excess kurtosis (10.18), driven primarily by the March 2020 observation of −39.46%. The standard deviation of FPI equity flows (INR 21,347 crore) is more than four times the mean (INR 4,972 crore), indicating that foreign investors constitute a lumpy, episodic, and externally sensitive source of capital. The Jarque-Bera test rejects normality for both return series at the 1% level. The 10-year G-Sec yield averaged 7.37% over the study period, ranging from 5.69% (July 2020, RBI accommodative stance post-COVID) to 8.97% (November 2013, tightening during the Taper Tantrum).

Correlation Analysis

Pearson correlations reveal five pre-regression findings. First, FPIeq correlates more strongly with R_BANK (r = 0.487) than with R_IT (r = 0.412). Second, R_NASDAQ correlates more strongly with R_IT (r = 0.548) than with R_BANK (r = 0.324), consistent with NIFTY IT's global technology orientation. Third, ΔEX correlates negatively with R_BANK (r = −0.312) but positively though insignificantly with R_IT (r = +0.104), reflecting the sectors' different currency exposures. Fourth, ΔFFR is negatively correlated with FPIeq (r = −0.234), confirming that higher U.S. interest rates reduce emerging market capital inflows. Fifth, no predictor–predictor correlation exceeds 0.35, suggesting the absence of severe multicollinearity.

Unit Root Tests

ADF test results confirm that the return and FPI flow series are all stationary at levels [I(0)]. The G-Sec yield level and Federal Funds Rate are non-stationary at levels but become stationary when first-differenced [I(1)]; ΔGSEC and ΔFFR are therefore entered in the OLS models as first differences. The stationarity of the primary dependent and independent variables of interest enables direct OLS estimation without risk of spurious regression.

OLS Regression Results

Table 3 presents the extended OLS regression results for both indices side by side. All core predictors are statistically significant at least at the 5% level in their respective models.

The model explains approximately 41% of monthly variation in NIFTY BANK returns (adjusted $R^2 = 0.411$) and 46% for NIFTY IT (adjusted $R^2 = 0.459$). The lagged FPI coefficient (FPIeq,t−1) is not significant in either model (p = .330 for BANK; p = .189 for IT), suggesting the FPI effect operates

primarily through a contemporaneous price-pressure mechanism consistent with Warther (1995), rather than through a gradual information-diffusion process.

The exchange rate coefficient for NIFTY BANK (−0.848, p < .001) indicates that INR depreciation is harmful to banking returns through three channels: imported inflation and consequent RBI rate hikes, coincident FPI equity outflows, and credit risk deterioration in trade-related loan books. For NIFTY IT, the exchange rate coefficient is positive but statistically insignificant (0.163, p = .377), reflecting the sector's natural currency hedge: Indian IT companies invoice primarily in USD and employ primarily in INR, so a weaker rupee boosts INR-equivalent revenues without proportionate cost increases. Rising domestic G-Sec yields significantly reduce NIFTY BANK returns (−1.242, p = .003) through mark-to-market losses on SLR-mandated government security portfolios and NIM compression, but do not significantly affect NIFTY IT (−0.613, p = .120). The NASDAQ coefficient is more than twice as large for NIFTY IT (0.541) compared to NIFTY BANK (0.268), reflecting the direct revenue dependency of TCS, Infosys, HCL Technologies, and Wipro on North American client budgets.

Diagnostic Tests

Durbin-Watson statistics of 1.97 and 2.03 and Breusch-Godfrey p-values of 0.401 and 0.343 confirm the absence of autocorrelation in both models. The White test identifies mild heteroscedasticity in the NIFTY BANK model (p = .047), addressed through HC3 robust standard errors that preserve the validity of t-statistics. Maximum Variance Inflation Factor (VIF) values of 1.48 in both models are well below the problematic threshold of 10, confirming the absence of severe multicollinearity. Non-normal residuals (Jarque-Bera p < .01 for both) are expected given the fat-tailed return distributions and do not invalidate OLS inference given the HC3 correction and sample size of 143.

The Chow structural difference test produces F(7, 270) = 4.83, p < .001, confirming that the two sector regression equations are fundamentally distinct—not merely accidentally different in coefficient estimates. This rejects $H_{0,3}$ and validates the comparative analytical design of the study.

Co-integration and Granger Causality

Table 4 presents Johansen co-integration results. For both indices, the null of no co-integration (r = 0) is rejected at the 5% level by both Trace and Maximum Eigenvalue statistics. The null of at most one co-integrating vector (r ≤ 1) is not rejected, indicating exactly one stable long-run relationship between FPI flows and each sectoral index. The normalised co-integrating equations are: $R\_BANK,t = 1.824 + 0.0000312 \times FPIeq,t$ and $R\_IT,t = 2.143 + 0.0000247 \times FPIeq,t$.

Granger causality tests establish bi-directional causality in both sectors. For NIFTY BANK, the flow-to-return direction yields F(2, 138) = 5.42, p = .005, which is stronger than the return-to-flow direction (F = 3.18, p = .044). For NIFTY IT, the flow-to-return direction yields F = 4.83, p = .009, compared to the return-to-flow direction at F = 2.94, p = .056. The consistently stronger flow-to-return F-statistics indicate that FPI activity is more of a market driver than a market follower in the Indian sectoral context, lending support to the information hypothesis over the pure momentum hypothesis.

VECM Adjustment Speeds

The error correction term (ECT) in the ΔRBANK equation is −0.213 (p < .05), indicating that approximately 21% of any short-run deviation from the FPI-BANK long-run equilibrium is corrected within one

month. The corresponding figure for NIFTY IT is −0.186 ($p < .05$), implying approximately 19% correction per month—suggesting full adjustment occurs over four to five months. The positive and marginally significant ECT (0.118, $p < .10$) in the FPI equation for the BANK system confirms momentum-driven behaviour: when NIFTY BANK returns are above the FPI-implied equilibrium level, FPI inflows subsequently increase.

DISCUSSION

The FPI-Return Relationship

The positive and significant coefficient on contemporaneous FPIeq,t in both regression models is consistent with the Portfolio Balance Theory prediction and with the empirical results of Sultana and Pardhasaradhi (2011), Bose (2012), Kulkarni (2017), and Rao and Reddy (2019). A net inflow of INR 10,000 crore is associated with a return uplift of between 39 and 42 basis points in the same month. Given average monthly FPI equity inflows of approximately INR 4,972 crore, the average monthly FPI contribution to index returns is around 20 basis points, compounding to roughly 2.4 percentage points per annum. The insignificance of the lagged FPI coefficient in both models is an important finding: the FPI effect is concentrated within the same calendar month, consistent with a price-pressure mechanism (Warther, 1995) rather than gradual information diffusion.

The fact that direct FPI coefficients for the two sectors are not statistically different from each other ($F = 0.89$, $p = .35$) but the overall regression structures are significantly different ($F = 4.83$, $p < .001$) is a critical nuance. Identical FPI flow shocks can therefore produce quite different sectoral outcomes depending on the prevailing macroeconomic regime.

Differential Sector Sensitivity

The contrast between the significantly negative exchange rate coefficient for NIFTY BANK (−0.848, $p < .001$) and the insignificant positive coefficient for NIFTY IT (+0.163, $p = .377$) is arguably the single most practically important finding of this study. For the banking sector, INR depreciation operates through at least three adverse channels: imported inflation and associated RBI rate hike probability; coincident FPI equity outflows ($r = −0.247$ between ΔEX and FPIeq); and concerns about sovereign creditworthiness and trade-credit-related advances in loan books. For the IT sector, the picture is architecturally different—Indian IT companies invoice primarily in USD and employ primarily in INR, making them natural-hedge entities for which the positive earnings effect of depreciation approximately cancels the negative macroeconomic sentiment effect. This is consistent with Mishra et al. (2012).

NIFTY IT's NASDAQ coefficient (0.541) being more than twice the NIFTY BANK coefficient (0.268) reflects a direct earnings-level transmission channel for the IT sector: NASDAQ performance proxies North American client budget cycles that directly affect revenue guidance for TCS, Infosys, HCL Technologies, and Wipro. NIFTY BANK's significant negative response to ΔGSEC (−1.242, $p < .01$) reflects two banking-sector-specific mechanisms mark-to-market losses on SLR-mandated government securities portfolios, and NIM compression as deposit repricing lags the lending rate cycle in India by one to three quarters.

Long-Run Dynamics and Causality

The Johansen co-integration finding establishes that sustained shifts in FPI equity activity will, over time, be reflected in proportionate adjustments in sectoral equity valuations. The VECM

suggests that approximately 21% (NIFTY BANK) and 19% (NIFTY IT) of any deviation from long-run equilibrium is corrected per month, implying full adjustment over four to five months—a direct input for risk managers calibrating sector Value-at-Risk using mean-reversion assumptions.

The Granger causality results support both the information hypothesis (FPI flows Granger-cause returns) and the momentum hypothesis (returns Granger-cause flows). The stronger significance of the flow-to-return direction for both sectors—particularly for NIFTY BANK ($p = .005$ vs. $p = .044$)—suggests that the information effect modestly dominates the momentum effect during this period, consistent with Griffin et al. (2004) and Froot et al. (2001).

POLICY IMPLICATIONS

For SEBI, the evidence of bi-directional causality and long-run co-integration confirms that FPI activity is actively shaping sectoral market performance in both the short and long run. The high FPI ownership concentration in private sector banking raises systemic risk concerns: a sudden reversal would be felt most acutely in the sector whose stability is critical for credit intermediation. SEBI should consider whether sectoral FPI investment limits require more granular, sector-specific calibration rather than a blanket approach. A blanket inflow limit treating all sectors equally may inadvertently constrain the IT sector—which benefits most from global integration—while failing to adequately address systemic risk concentrated in banking.

For the Reserve Bank of India, NIFTY BANK's sensitivity to ΔGSEC implies that the RBI's forward guidance on monetary policy directly affects banking sector equity valuations through the bond yield channel. Clearer communication about the policy rate trajectory would reduce uncertainty premiums embedded in banking equity risk premiums. Episodes of sharp INR depreciation create a two-channel vulnerability for the banking system affecting both equity valuations and credit quality simultaneously.

For fund managers and portfolio strategists, the findings suggest specific tactical rotations: investors anticipating U.S. monetary tightening should reduce NIFTY IT exposure relative to NIFTY BANK, given IT's greater FFR and NASDAQ sensitivity; investors anticipating INR depreciation should reduce NIFTY BANK exposure relative to NIFTY IT. The VECM adjustment-speed finding also suggests that monitoring deviation from the FPI-BANK co-integrating relationship may offer tactical mean-reversion opportunities with a four-to-five-month horizon.

For domestic institutional investors, FY 2021–22 demonstrated that Domestic Institutional Investors (DIIs) can serve as an effective countervailing force against FPI outflows. Policy measures that deepen domestic institutional participation—through pension fund expansion, insurance sector reforms, and sustained retail mutual fund inflows—will make Indian equity markets structurally more resilient to FPI flow shocks.

CONCLUSION

This paper investigated how net FPI equity flows affect the monthly returns of NIFTY BANK and NIFTY IT over April 2012 to March 2024, using a comprehensive analytical framework encompassing OLS regression, Johansen co-integration, Granger causality, and VECM. All seven null hypotheses are rejected across multiple methodological approaches, lending convergent robustness to the main findings.

The central finding is that FPI flows exert a statistically significant positive effect on both sectors, but the macroeconomic transmission channels are fundamentally different. NIFTY BANK is sensitive to INR/USD exchange rate movements and domestic bond yield changes through the SLR mark-to-market and NIM channels; NIFTY IT is driven by NASDAQ returns and the Federal Funds Rate through direct earnings-level linkages. The Chow test confirms these structural differences are statistically significant ($F = 4.83$, $p < .001$). Co-integration establishes a long-run equilibrium with mean-reversion speeds of approximately 21% and 19% per month for NIFTY BANK and NIFTY IT, respectively. Granger causality results indicate that the flow-to-return direction is more robust than the reverse, supporting the information hypothesis over the pure momentum hypothesis.

These findings have direct implications for how policymakers, regulators, and practitioners should think about FPI risk. The vulnerability associated with FPI dependence is not evenly distributed across Indian equity market sectors. Policymakers and investors who treat NIFTY BANK and NIFTY IT as interchangeable in the context of capital flow risk are likely to be surprised during precisely the episodes sharp currency depreciation, aggressive Fed tightening, domestic credit events when the sectoral differences matter most.

Future research should examine: (a) daily data with a GARCH-DCC framework to estimate time-varying conditional correlations; (b) a Markov-Switching VAR to formally identify bull and bear market regimes; (c) extension to NIFTY PHARMA, NIFTY AUTO, and NIFTY FMCG for a cross-sectoral FPI sensitivity map; (d) analysis of the FPI debt flow channel as Indian bonds enter global bond indices; and (e) an instrumental variables approach using VIX and MSCI EM net flows as instruments for Indian FPI flows.

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Table 1

Data Sources and Variables

Variable	Source	Freq.	Period
NIFTY BANK / IT Returns	NSE India Official Website	Monthly	Apr 2012–Mar 2024
Net FPI Equity Flows	SEBI Monthly Bulletin	Monthly	Apr 2012–Mar 2024
Net FPI Debt Flows	SEBI Monthly Bulletin	Monthly	Apr 2012–Mar 2024
INR/USD Exchange Rate	RBI DBIE (Table F.1)	Monthly	Apr 2012–Mar 2024
India 10-yr G-Sec Yield	RBI SGL Month-End YTM Dataset	Monthly	Apr 2012–Mar 2024
US Federal Funds Rate	Federal Reserve / FRED	Monthly	Apr 2012–Mar 2024
NASDAQ Composite Return	Yahoo Finance / Bloomberg	Monthly	Apr 2012–Mar 2024

Note. SEBI = Securities and Exchange Board of India; RBI = Reserve Bank of India; DBIE = Database on Indian Economy; SGL = Subsidiary General Ledger; FRED = Federal Reserve Economic Data.

Table 2

Annual Net FPI Flows into India, 2012–2024

Financial Year	Net FPI Equity (INR Cr.)	Net FPI Debt (INR Cr.)	Total (INR Cr.)
2012–13	1,40,033	28,334	1,68,367
2013–14	79,709	−28,192	51,517
2014–15	1,11,333	1,66,127	2,77,460
2015–16	−14,172	−4,936	−19,108
2016–17	55,703	−1,17,173	−61,470
2017–18	25,425	−44,743	−19,318
2018–19	15,472	−56,375	−40,903
2019–20	−5,599	−13,028	−18,627
2020–21	2,74,946	14,325	2,89,271
2021–22	−1,40,009	−3,453	−1,43,462
2022–23	−37,631	4,929	−32,702
2023–24	2,10,745	1,22,650	3,33,395
Total	**7,15,955**	**68,465**	**7,84,420**

Note. Data sourced from SEBI Monthly Bulletins. Values in INR crore (1 crore = 10 million). Negative values indicate net outflows.

Table 3

OLS Regression Results: NIFTY BANK and NIFTY IT Monthly Returns (%)

Variable	NIFTY BANK β	p	NIFTY IT γ	p	Differ?
Constant	1.183	.002***	0.742	.041**	—
FPIeq,t (per INR 10,000 Cr.)	0.421	.000***	0.387	.000***	No
FPIeq,t−1 (lagged 1 month)	0.087	.330 n.s.	0.112	.189 n.s.	No
FPIdebt,t	0.143	.035**	0.048	.454 n.s.	Yes**
ΔEX (INR/USD % change)	−0.848	.000***	0.163	.377 n.s.	Yes***
ΔGSEC (G-Sec yield change)	−1.242	.003***	−0.613	.120 n.s.	Yes**
ΔFFR (Fed Funds Rate change)	−0.621	.030**	−0.794	.003***	No
R_NASDAQ	0.268	.000***	0.541	.000***	Yes***
Adjusted R^2	**0.411**		**0.459**		
F-Statistic	**16.21*** **		**18.67*** **		
Durbin-Watson	**1.97**		**2.03**		
N	**143**		**143**		

Note. HC3 robust standard errors applied. 'Differ?' reports individual coefficient F-test results across sector equations. Chow structural difference test: $F(7, 270) = 4.83$, $p < .001$. n.s. = not significant. ** $p < .05$. *** $p < .01$.

Table 4

Johansen Co-integration Test Results

System	Null Hypothesis	Trace Stat.	5% CV	Max-Eig. Stat.	5% CV
NIFTY BANK – FPIeq	r = 0	31.42**	25.87	27.84**	19.39
	r ≤ 1	3.58	12.52	3.58	12.52
NIFTY IT – FPIeq	r = 0	27.83**	25.87	24.31**	19.39
	r ≤ 1	3.52	12.52	3.52	12.52

Note. VAR lag order = 2 (AIC). Linear trend assumed. MacKinnon-Haug-Michelis p-values. ** $p < .05$.

Hypothesis Testing Summary

Table 5

Summary of Hypothesis Testing Results

H_0	Null Statement	Test	Result
$H_{0,1}$	FPI flows do not affect NIFTY BANK returns	OLS	Rejected***
$H_{0,2}$	FPI flows do not affect NIFTY IT returns	OLS	Rejected***
$H_{0,3}$	FPI impact not different across sectors	Chow Test	Rejected***
$H_{0,4}$	No co-integration between FPI and NIFTY BANK	Johansen	Rejected**
$H_{0,5}$	No co-integration between FPI and NIFTY IT	Johansen	Rejected**
$H_{0,6}$	FPI does not Granger-cause R_BANK	Granger	Rejected***
$H_{0,7}$	FPI does not Granger-cause R_IT	Granger	Rejected***

Note. ** $p < .05$. *** $p < .01$. Chow test: $F(7, 270) = 4.83$, $p < .001$.