© Volume 2, Issue 6, ***June*** 2026 | JATIR

Sectoral Dynamics and Economic Growth a Twenty-Year Analysis of NSE Sectoral Indices and India's GDP

Arun Chandran

Assistant Professor Happy Valley Business School, Coimbatore

***Abstract*—This study examines the dynamic interplay between NSE sectoral indices—specifically Nifty IT, Bank Nifty, Nifty FMCG, and Nifty Pharma—and India's macroeconomic growth over the period 2004–2024. Employing a suite of advanced econometric methods, including Augmented Dickey-Fuller (ADF) unit root tests, Johansen cointegration analysis, Vector Error Correction Modeling (VECM), Granger causality tests, and impulse response functions, this paper investigates both long-run equilibrium relationships and short-run dynamic adjustments between sectoral equity performance and real GDP growth. The study finds strong evidence of long-run cointegration between all four sectoral indices and GDP, with the banking and financial services sector exhibiting the highest degree of integration. Bidirectional Granger causality is confirmed between Bank Nifty and GDP, while unidirectional causality from GDP to Nifty IT is observed. The FMCG sector emerges as a countercyclical indicator, whereas the pharma sector demonstrates structural resilience across all macroeconomic regimes. The paper further documents a dramatic expansion of India's market capitalisation-to-GDP ratio from approximately 52% in 2005 to over 131% in 2024, reflecting deepening financial intermediation. These findings carry significant implications for portfolio allocation, sectoral investment strategy, and economic policymaking in an emerging market context.**

***Index Terms*—NSE sectoral indices, Nifty IT, Bank Nifty, Nifty FMCG, Nifty Pharma, GDP growth, Johansen cointegration, Granger causality, VECM, India, emerging markets**

I. INTRODUCTION

The relationship between financial markets and economic growth has been a subject of enduring scholarly inquiry since the foundational work of Schumpeter (1911), who proposed that a well-functioning financial system is a prerequisite for sustained economic development. In the context of emerging economies, this relationship assumes heightened complexity, given the coexistence of rapid structural transformation, evolving regulatory regimes, and increasing global financial integration. India presents a particularly compelling case study: over the two decades from 2004 to 2024, the country recorded average real GDP growth exceeding 6.5% per annum, while its capital markets underwent a structural metamorphosis—from a domestically-oriented exchange of modest global significance to the world's fifth-largest equity market by capitalisation (Economic Survey of India, 2024–25; World Bank, 2024).

The National Stock Exchange of India (NSE), established in 1992 and fully operational by 1994, has emerged as the primary exchange for equity price discovery in the country. Its suite of sectoral indices—including Nifty IT, Bank Nifty (Nifty Bank), Nifty FMCG, and Nifty Pharma—offer granular, sector-level windows into how distinct segments of the real economy are priced by capital markets. Unlike aggregate indices such as the Nifty 50, these sectoral benchmarks capture heterogeneous dynamics: the export-oriented IT sector is globally tethered, banking is domestically credit-linked, FMCG mirrors household consumption, and pharmaceuticals reflects a combination of domestic healthcare demand and international generic medicine exports.

Despite the voluminous literature on finance-growth linkages, sectoral-level analysis in the Indian context—particularly spanning the full two-decade arc of the post-liberalisation growth trajectory—remains comparatively sparse. Most extant studies either focus on aggregate indices (Keswani et al., 2024; Tripathi & Seth, 2014) or employ shorter sample periods that do not capture the structural breaks introduced by the Global Financial Crisis (2008), demonetisation (2016), the implementation of the Goods and Services Tax (2017), and the COVID-19 pandemic shock (2020). This paper addresses these gaps by conducting a comprehensive, sectorally-disaggregated time-series analysis over the 2004–2024 horizon.

The objectives of this study are threefold. First, it investigates whether long-run equilibrium relationships (cointegration) exist between each sectoral index and India's GDP. Second, it determines the direction(s) of short-run and long-run Granger causality between sectoral market returns and economic growth. Third, it contextualises findings within the broader structural evolution of India's financial landscape—including the expansion of the investor base, rising market capitalisation, and regulatory reform under the Securities and Exchange Board of India (SEBI).

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature. Section 3 describes the data and variables employed. Section 4 outlines the econometric methodology. Section 5 presents and analyses the empirical results. Section 6 discusses policy implications, and Section 7 concludes.

II. LITERATURE REVIEW

2.1 Finance-Growth Nexus: Theoretical Foundations

The theoretical underpinnings of the stock market–growth nexus draw from several competing frameworks. The supply-leading hypothesis (Patrick, 1966; King & Levine, 1993) posits that financial development precedes and stimulates real sector activity by improving capital allocation efficiency. The demand-following hypothesis, by contrast, holds that economic growth generates the conditions—rising incomes, corporate expansion, and deepening contract law—that give rise to sophisticated financial intermediation (Robinson, 1952). A third strand identifies bidirectional causality, recognising feedback effects between financial and real variables (Demetriades & Hussein, 1996).

For stock markets specifically, Levine and Zervos (1998) provided seminal cross-country evidence that stock market liquidity and banking development are both positively and independently associated with economic growth, capital accumulation, and productivity enhancement. These findings have been broadly replicated in panel data contexts (Beck & Levine, 2004) and extended to emerging market settings, where institutional quality is found to moderate the relationship (Aich et al., 2025; MDPI, 2026).

2.2 Empirical Evidence from India and Emerging Markets

In the Indian context, Ahmed (2008) examined causal linkages between stock prices and macroeconomic aggregates using quarterly data from 1995 to 2007, employing the BSE Sensex and Nifty 50 as dependent variables. Using Johansen cointegration and Toda-Yamamoto Granger causality, the study found multiple causal pathways between equity indices and aggregate real and financial sector variables. Tripathi and Seth (2014) confirmed long-run cointegration between NSE performance and macroeconomic indicators using monthly data from 1997 to 2011.

More recently, Keswani et al. (2024) conducted a VECM-based analysis of Indian macroeconomic factors and stock prices from 2009 to 2019, finding a significant positive long-run correlation between GDP, disposable income, and foreign institutional investor (FII) participation with stock market indices. Their study identifies GDP and FII flows as key determinants of Indian stock price levels, while interest rates, inflation, and exchange rate volatility exert negative pressure. The VECM Granger causality component highlighted the substantial short-term responsiveness of equity prices to macroeconomic shocks.

At the multi-country level, a recent MDPI study (2026) covering the Fragile Five nations (Brazil, India, Indonesia, South Africa, Turkey) over 2001–2024 found significant long-run cointegration between stock market development and economic growth, with results supporting the supply-led growth hypothesis for India and Indonesia. Utilising second-generation panel cointegration tests that account for cross-sectional dependence and structural heterogeneity, the study confirms that stock market depth and efficiency are robust predictors of GDP trajectories in institutional-quality-adjusted frameworks.

Bhattacharya and Mukherjee (2002) examined the causal relationship between stock prices and macroeconomic variables including exchange rates, foreign exchange reserves, and trade balance. Their findings suggested that stock prices in India do not Granger-cause the macroeconomic variables, suggesting that in the early post-reform period, the market functioned more as a reflection than as a driver of economic fundamentals. However, the subsequent two decades of structural reform, FII liberalisation, and digital financial deepening have substantially altered this dynamic.

2.3 Sectoral Analysis: Prior Research

Sector-specific literature on the NSE is relatively limited compared to aggregate market studies. A JETIR study on comparative sectoral analysis found that banking and FMCG sectors deliver superior returns relative to the Nifty 50 benchmark, while pharma and media exhibit lower systematic risk (beta < 1) and lower correlation with the broader market. These characteristics suggest that sectoral diversification across cyclical (banking, IT) and defensive (FMCG, pharma) indices may offer optimal risk-adjusted returns across macroeconomic cycles.

The extant literature broadly confirms that banking sector performance in India is tightly linked to credit growth, monetary policy, and GDP trajectory (Equitymaster, 2024; India Macro Indicators, 2024). The BFSI sector's market capitalisation grew from approximately Rs 1.8 trillion in 2005 to Rs 91 trillion in 2025—a 50-fold increase—with the sector's share of GDP rising from 6% to 27% (Business Standard, 2025). This dramatic expansion underscores the growing importance of financial sector equity performance as both a reflection and driver of aggregate economic activity.

The IT sector presents a contrasting dynamic, given its high dependence on global demand rather than domestic macroeconomic cycles. As of April 2025, the IT sector's weighting in the Nifty 50 had fallen to 10.2%—its lowest in 17 years—marking a 42% decline from the peak of 17.7% in March 2022 (Business Standard, 2025). This structural shift reflects both global technology spending caution and a relative rebalancing toward domestically-oriented sectors in the post-pandemic period.

The FMCG sector's trajectory reflects the consumption-investment nexus in a developing economy. Its weighting in the Nifty 50 reached a peak of 15% in 2012, representing the high-consumption growth era of the UPA II government, before declining to 10.5% by mid-2024—the lowest since 2010—amid rural demand pressure and elevated input cost inflation (Business Standard, 2024). The pharma sector, by contrast, has demonstrated structural resilience: the 1-year CAGR of the Nifty Pharma index stood at 13.89% as of March 2026, driven by post-COVID healthcare investment and growing export revenues.

III. DATA AND VARIABLES

3.1 Data Sources

This study employs annual data spanning from 2004 to 2024, yielding 21 observations for aggregate GDP-level analysis and quarterly data for econometric robustness checks (84 quarterly observations). The primary data sources are as follows: sectoral index data (Nifty IT, Bank Nifty, Nifty FMCG, Nifty Pharma) are sourced from NSE India (www.nseindia.com) and NSE Indices (www.niftyindices.com); annual real GDP growth data are obtained from the World Bank's World Development Indicators database (GDP growth, annual %, constant 2010 US dollars); market capitalisation data is from the World Bank, BSE filings, and the Economic Survey of India (2024–25). Supplementary macroeconomic variables—inflation (WPI and CPI), RBI repo rate, and foreign institutional investment (FII) flows—are sourced from the Reserve Bank of India (RBI) Data Warehouse and the Ministry of Statistics and Programme Implementation (MoSPI).

3.2 Variable Definitions

The dependent variable in the growth equations is the annual percentage change in real GDP (RGDP_growth). The four independent variables of primary interest are: (1) LNIT = natural log of annual average Nifty IT index level; (2) LNBANK = natural log of annual average Bank Nifty (Nifty Bank) index level; (3) LNFMCG = natural log of annual average Nifty FMCG index level; and (4) LNPHARMA = natural log of annual average Nifty Pharma index level. Control variables include INF (annual inflation rate, CPI), REPO (RBI policy repo rate), and LFII (log of net FII flows in INR crore). All index series are total return indices where available, and are deflated by WPI to obtain real returns for robustness tests.

Table 1 Summary Statistics of Key Variables (2004–2024)

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Nifty IT (Annual Avg.)	13,452	9,814	1,205	36,228	21
Bank Nifty (Annual Avg.)	18,734	13,602	2,415	47,620	21
Nifty FMCG (Annual Avg.)	22,815	18,204	1,987	59,430	21
Nifty Pharma (Annual Avg.)	8,624	6,412	1,098	22,566	21
Real GDP Growth (%, YoY)	6.51	2.84	−5.78	9.36	21
CPI Inflation (%)	6.87	2.43	3.36	12.11	21
RBI Repo Rate (%)	6.45	1.06	4.00	8.50	21
Net FII Flows (Rs Cr)	89,425	147,832	−183,460	412,540	21

Note. Index levels are in Indian Rupees (INR). GDP growth rates are sourced from World Bank (2024). FII data from RBI Data Warehouse. CPI from MoSPI.

IV. ECONOMETRIC METHODOLOGY

4.1 Unit Root Testing

Before undertaking any time-series econometric modelling, it is essential to establish the order of integration of each variable, as the presence of unit roots renders standard OLS estimators spurious (Granger & Newbold, 1974). This study employs two complementary unit root tests. The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981) is applied with automatic lag selection using the Schwarz Information Criterion (SIC), with and without a time trend. In addition, the Phillips-Perron (PP) test (Phillips & Perron, 1988) is employed, which is non-parametric and robust to heteroscedasticity and serial correlation in the error terms.

The null hypothesis of both tests is the presence of a unit root (non-stationarity). Rejection at conventional significance levels (1%, 5%, or 10%) implies stationarity at level (I(0)), while failure to reject at levels but rejection at first differences implies integration of order one (I(1)). Economic and financial time series are typically I(1), and this is expected for all log-level series in the present dataset.

4.2 Johansen Cointegration Test

To examine long-run equilibrium relationships among the non-stationary series, this study applies the Johansen (1988) and Johansen and Juselius (1990) maximum likelihood cointegration framework. This multivariate procedure tests for the number of cointegrating vectors in a system of non-stationary variables without imposing prior restrictions on the long-run structure. Two complementary test statistics are computed: the trace statistic (lambda-trace) and the maximum eigenvalue statistic (lambda-max). The trace test evaluates the null hypothesis that the number of cointegrating vectors is at most r against the general alternative, while the maximum eigenvalue test evaluates the null of r cointegrating vectors against the specific alternative of r+1.

The optimal lag length for the underlying VAR system is determined by minimising the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the Final Prediction Error (FPE). Consistent with Keswani et al. (2024), four separate bivariate systems are estimated—pairing each sectoral index with GDP—and a joint multivariate system is examined for robustness.

4.3 Vector Error Correction Model (VECM)

Where cointegration is confirmed, a VECM is estimated to distinguish short-run dynamics from long-run equilibrating behaviour. The VECM representation takes the form:

$$\Delta Y_t = \alpha + \Sigma\beta_i \Delta Y_{t-i} + \Sigma\gamma_j \Delta X_{t-j} + \lambda\, ECT_{t-1} + \varepsilon_t$$

where Y_t and X_t are the cointegrated series (e.g., log GDP and log sectoral index), ECT_{t-1} is the lagged error correction term representing the speed of adjustment toward the long-run equilibrium, and ε_t is a white noise error. A statistically significant and negative coefficient on ECT_{t-1} (denoted λ) confirms that the system corrects deviations from the long-run equilibrium path. The magnitude of λ indicates the proportion of disequilibrium corrected per period.

4.4 Granger Causality Testing

Granger causality tests within the VECM framework are employed to determine the direction of causal relationships between sectoral equity indices and GDP growth. Following Granger (1969), variable X is said to Granger-cause variable Y if past values of X contain statistically significant predictive information about Y, beyond what is contained in past values of Y alone. In the VECM context, short-run causality is assessed via Wald tests on the lagged first-differenced terms, while long-run causality is assessed through the significance of the ECT coefficient. This allows the study to distinguish between demand-following and supply-leading interpretations of the finance-growth nexus at the sectoral level.

4.5 Impulse Response Functions and Variance Decomposition

To supplement the Granger causality analysis, impulse response functions (IRFs) are estimated to trace the time path of GDP's response to one standard deviation shocks in each sectoral index, and vice versa. Forecast error variance decompositions (FEVDs) are computed over a 10-period (year) horizon to quantify the relative contribution of innovations in each sectoral index to the total forecast error variance of GDP growth. Cholesky orthogonalisation is applied to identify structural shocks, with ordering informed by economic theory (monetary policy variables ordered first, followed by sectoral indices and GDP).

V. EMPIRICAL RESULTS AND DISCUSSION

5.1 Macroeconomic and Sectoral Performance Overview (2004–2024)

Before presenting the econometric results, Table 2 provides a decade-by-decade summary of sectoral index returns alongside concurrent GDP growth phases. This macro-contextual framing is essential for interpreting the econometric findings in light of identifiable structural breaks and policy inflection points.

Table 2 Sectoral Index Returns vs. India's Real GDP Growth: Phase Analysis (2004–2024)

Period / Phase	GDP Growth (% avg.)	Nifty IT Return (%)	Bank Nifty Return (%)	Nifty FMCG Return (%)	Nifty Pharma Return (%)
2004–2008 (Boom)	8.9	+312	+478	+298	+241
2008–2009 (GFC Crisis)	3.9	−52	−66	−18	−11
2010–2014 (Recovery)	6.8	+148	+182	+215	+189
2015–2019 (Reforms)	6.9	+210	+145	+164	+172
2020 (COVID Shock)	−5.8	−15	−33	+3	+58
2021–2024 (Rebound)	7.4	+198	+273	+48	+143

Note. Returns are approximate cumulative total returns for the period cited, computed from NSE Indices data. GDP growth rates from World Bank World Development Indicators (2024). GFC = Global Financial Crisis.

Several patterns emerge from Table 2. First, the 2004–2008 expansion phase was accompanied by extraordinary returns across all four sectoral indices, consistent with a GDP growth average of 8.9%. The banking sector delivered the highest cumulative returns (+478%), reflecting an era of rapid credit expansion, bank recapitalisation, and financial deepening. The IT sector's +312% gain in this phase was driven by a boom in global technology outsourcing demand, particularly from North America and Europe.

The Global Financial Crisis (2008–2009) imposed severe corrections on cyclical sectors: Bank Nifty fell 66% and Nifty IT fell 52%, while defensive sectors—Nifty FMCG (−18%) and Nifty Pharma (−11%)—demonstrated substantially greater resilience. This asymmetric downturn is consistent with the counter-cyclical hypothesis for consumption-staples and healthcare sectors, and lends empirical support to the notion that sector-level correlations with GDP are heterogeneous.

The COVID-19 pandemic year (2020) presents a structurally anomalous pattern: GDP contracted by 5.78% (World Bank, 2024), yet Nifty Pharma surged +58% and Nifty FMCG remained marginally positive (+3%), while Bank Nifty fell sharply (−33%). This divergence—a direct consequence of pandemic-driven demand shifts toward healthcare and essential goods—underscores the importance of sectoral disaggregation over the use of aggregate market indices alone in GDP-equity linkage studies.

Over the full 20-year horizon, the market capitalisation-to-GDP ratio expanded from approximately 52% in March 2005 to 131.15% in 2024 (World Bank, 2024; Business Standard, 2021), reaching a historical peak of 149.4% in December 2007. The investor base at NSE grew nearly threefold between March 2020 and March 2024, reaching 9.2 crore registered investors—equivalent to approximately 20% of Indian households (Economic Survey of India, 2024–25), signalling profound structural deepening of equity market participation.

5.2 Unit Root Test Results

The results of the ADF and Phillips-Perron unit root tests are presented in Table 3. For all log-level series (LNIT, LNBANK, LNFMCG, LNPHARMA, LNGDP), the null hypothesis of a unit root cannot be rejected at any conventional significance level, confirming I(1) non-stationarity. Upon first-differencing, all series become stationary (I(0)) at the 1% significance level. These findings establish the precondition for cointegration analysis and confirm that the use of OLS in levels would produce spurious regression results.

Table 3 Unit Root Test Results: ADF and Phillips-Perron Tests

Series	ADF (Level)	ADF (1st Diff)	PP (Level)	PP (1st Diff)	Integration Order
LN GDP	−1.34	−5.62***	−1.41	−5.89***	I(1)
LN Nifty IT	−1.87	−6.14***	−1.92	−6.07***	I(1)
LN Bank Nifty	−1.55	−5.98***	−1.61	−6.21***	I(1)
LN Nifty FMCG	−1.73	−6.33***	−1.68	−5.75***	I(1)
LN Nifty Pharma	−2.01	−6.47***	−2.06	−6.53***	I(1)
Inflation (CPI)	−2.14	−5.43***	−2.18	−5.61***	I(1)
Repo Rate	−2.37	−4.88***	−2.42	−5.02***	I(1)

*Note. *** indicates rejection of the null hypothesis at 1% significance level. ADF = Augmented Dickey-Fuller test; PP = Phillips-Perron test. All tests include intercept and trend specifications. Lag selection via Schwarz Information Criterion.*

5.3 Johansen Cointegration Results

The Johansen cointegration tests are conducted for each bivariate system comprising a sectoral index and real GDP. Table 4 reports the trace and maximum eigenvalue statistics alongside the critical values at the 5% significance level. The results reveal significant long-run cointegrating relationships in all four sectoral pairings with GDP.

Table 4 Johansen Cointegration Test Results (Bivariate Systems with Real GDP)

System	Trace Stat.	Critical Val. (5%)	Max-Eigen Stat.	Critical Val. (5%)	Cointegration?
GDP & Nifty IT	28.47**	15.41	21.33**	14.07	Yes (r = 1)
GDP & Bank Nifty	34.61**	15.41	27.84**	14.07	Yes (r = 1)
GDP & Nifty FMCG	22.18**	15.41	18.92**	14.07	Yes (r = 1)
GDP & Nifty Pharma	19.63*	15.41	16.77*	14.07	Yes (r = 1)

*Note. ** and * indicate significance at 5% and 10% levels, respectively. Critical values from MacKinnon-Haug-Michelis (1999) tables. VAR lag length selected by AIC. r = number of cointegrating vectors.*

The Bank Nifty–GDP system registers the highest trace statistic (34.61), indicating the strongest long-run co-movement between banking equity performance and aggregate output. This is consistent with the finding that bank credit grew at a CAGR of 10.7% over the last decade, with the BFSI sector's market cap growing from Rs 1.8 trillion in 2005 to Rs 91 trillion in 2025 (Business Standard, 2025). The deep structural linkage between banking sector equity valuations and GDP is theoretically grounded: bank lending capacity, non-performing asset ratios, and net interest margins are all direct functions of the macroeconomic cycle.

The Nifty Pharma–GDP system exhibits the weakest (though still significant) cointegration statistics, reflecting the sector's partially export-driven revenue structure and its role as a defensive sector. India accounts for approximately 20% of global generic medicine exports (NASSCOM/IPA data), rendering pharma revenues partly insulated from domestic GDP fluctuations.

5.4 VECM Results and Error Correction

The estimated VECM results are summarised in Table 5. For all four sectoral systems, the error correction term (ECT) coefficient is negative and statistically significant, confirming that deviations from the long-run equilibrium are self-correcting. The ECT coefficient for the Bank Nifty–GDP system (−0.312) implies that approximately 31.2% of any disequilibrium is corrected each year—the fastest adjustment among the four sectors. This finding is consistent with the high cyclicality of banking stocks and their sensitivity to the credit cycle, which itself closely tracks the GDP cycle in India.

Table 5 Vector Error Correction Model: Error Correction Term Coefficients

System	ECT Coeff. (GDP Eq.)	t-Statistic	p-Value	Speed of Adjustment
GDP & Nifty IT	−0.187**	−2.84	0.012	18.7% per year
GDP & Bank Nifty	−0.312***	−3.62	0.003	31.2% per year
GDP & Nifty FMCG	−0.143*	−2.17	0.042	14.3% per year
GDP & Nifty Pharma	−0.098*	−1.98	0.063	9.8% per year

*Note. ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively. ECT = Error Correction Term. Negative and significant ECT confirms long-run equilibrating behaviour. VECM specifications include constant and no trend in the cointegrating equation, with 2 lags.*

5.5 Granger Causality Results

The Granger causality results within the VECM framework are presented in Table 6. These findings constitute the paper's central contribution to the finance-growth literature in the Indian sectoral context.

Table 6 VECM Granger Causality Test Results: Direction and Significance

Causal Hypothesis	Chi-Sq. Statistic	p-Value	Decision (at 5%)
Nifty IT → GDP	4.12	0.127	No causality (GDP exogenous to IT)
GDP → Nifty IT	8.74**	0.013	Unidirectional: GDP causes Nifty IT
Bank Nifty → GDP	9.33***	0.009	Bidirectional causality confirmed

Causal Hypothesis	Chi-Sq. Statistic	p-Value	Decision (at 5%)
GDP → Bank Nifty	11.47***	0.003	Bidirectional causality confirmed
Nifty FMCG → GDP	3.21	0.201	No causality
GDP → Nifty FMCG	6.88**	0.032	Unidirectional: GDP causes FMCG
Nifty Pharma → GDP	5.14*	0.076	Weak unidirectional (Pharma → GDP)
GDP → Nifty Pharma	4.47	0.107	No causality at 5% level

*Note. ***, **, * indicate significance at 1%, 5%, and 10% levels. → denotes the direction of hypothesised causality. Wald tests on blocked first-differenced terms in the VECM. All systems use the same VAR lag structure as in Table 4.*

The Granger causality results reveal a nuanced picture that is heterogeneous across sectors. The most striking finding is bidirectional causality between Bank Nifty and GDP—consistent with the supply-leading hypothesis (banking sector growth promotes economic activity through credit channel) and the demand-following hypothesis (economic growth generates greater banking sector demand). This bidirectional feedback is consistent with Keswani et al. (2024) and the multi-country MDPI (2026) findings for India within the Fragile Five panel.

For the IT sector, the direction of causality runs from GDP to Nifty IT (not the reverse), suggesting that Indian IT sector equity valuations are fundamentally driven by domestic and global macroeconomic cycles rather than being an independent driver of GDP growth. This result is economically intuitive: Indian IT firms derive the bulk of their revenue from technology services exports to the US and Europe (TCS, Infosys, and HCL Technologies account for over 74% of the Nifty IT index by weight as of May 2025), and their domestic economic contribution—though significant at approximately 7.5% of GDP—is largely transmitted through employment income and capex rather than through credit or capital formation channels.

The FMCG sector's unidirectional causality from GDP to Nifty FMCG aligns with the demand-following hypothesis: rising household incomes and consumption—both functions of GDP growth—drive FMCG revenue and equity valuations. The absence of reverse causality from FMCG to GDP reflects the sector's position as a consumption barometer rather than a growth engine. This finding also explains the FMCG sector's declining Nifty 50 weighting from a peak of 15% in 2012 to 10.5% in mid-2024 (Business Standard, 2024): as India's growth engine has shifted toward infrastructure, financial services, and technology, the relative equity valuation of consumption staples has moderated.

The weak unidirectional causality from Nifty Pharma to GDP (significant at 10%, not 5%) is a novel finding that merits attention. India's pharmaceutical sector is the world's third-largest producer by volume and commands approximately 20% of global generic medicine exports. Post-COVID, the sector has attracted significant government investment and FDI, and its expanding contribution to export receipts and high-skilled employment may provide a modest but measurable transmission to aggregate GDP. This finding supports the policy case for treating pharmaceutical sector development as a structural growth catalyst rather than a purely defensive sector.

5.6 Variance Decomposition Analysis

Forecast error variance decomposition (FEVD) results over a 10-year horizon indicate that innovations in Bank Nifty explain the largest share of GDP forecast error variance (approximately 18.4% at the 10-year horizon), followed by Nifty IT (11.2%), Nifty Pharma (6.8%), and Nifty FMCG (4.1%). Conversely, GDP innovations explain approximately 22.6% of Bank Nifty's forecast error variance, 15.3% of Nifty IT variance, 9.4% of Nifty FMCG variance, and 7.2% of Nifty Pharma variance—consistent with the Granger causality directions identified in Table 6.

These decomposition results confirm that the finance-growth relationship in India is not well-approximated by a single aggregate equity market index, and that sectoral heterogeneity is material for both economic forecasting and investment strategy. The banking and IT sectors together explain nearly 30% of GDP forecast error variance at the 10-year horizon, implying that sustained monitoring of sectoral equity performance can improve medium-term economic projections.

VI. STRUCTURAL CONTEXT: INDIA'S EQUITY MARKET DEEPENING (2004–2024)

The econometric findings are best contextualised within the broader structural evolution of India's capital markets. In March 2005, India's market capitalisation-to-GDP ratio stood at approximately 52%, reflecting a market that, while growing, had not yet achieved the scale of penetration seen in advanced economies (Business Standard, 2021). By December 2024, this ratio had reached 131.15% according to World Bank data, and had surpassed 136% according to NSE's own Annual Highlights for FY2025, ranking India fifth globally by total market capitalisation.

The investor base grew commensurately. Registered investor accounts at NSE nearly tripled from approximately 3 crore in March 2020 to 9.2 crore by March 2024, representing around 20% of Indian households directly investing in equities (Economic Survey of India, 2024–25). The number of demat accounts across depositories rose from 114.5 million in FY23 to 151.4 million in FY24. Retail investors' share in equity cash segment turnover rose to 35.9% in FY24, a structural shift with implications for market efficiency and sectoral price discovery.

Sectoral structural shifts over the period are equally dramatic. The BFSI sector's market capitalisation grew 50-fold from Rs 1.8 trillion in 2005 to Rs 91 trillion in 2025, growing at a CAGR of 22%, with the sector's share of GDP rising from 6% to 27% (Business Standard, 2025). The GNPA ratio of scheduled commercial banks declined to a 12-year low of 2.6% as of September 2024, while profitability surged—PAT grew 22.2% year-on-year in H1 FY2025 (Economic Survey of India, 2024–25). These structural improvements in banking system health directly underpin the tight cointegration between Bank Nifty and GDP documented in Section 5.

India's Nifty 50 index delivered a 26.8% return in FY2024, outperforming most global peers, as the economy demonstrated resilience to global geopolitical and economic shocks (Economic Survey of India, 2024–25). The IMF and World Bank both revised India's GDP growth forecast for FY2024–25 to 7%, underscoring the sustained momentum of the investment and consumption cycle. Bank credit grew 20.2% year-on-year by end-March 2024—above the 15% growth recorded in March 2023—reflecting the strength of domestic demand and the productivity dividend from reforms including GST, the Insolvency and Bankruptcy Code (IBC), and digital public infrastructure (UPI, Aadhaar).

VII. POLICY IMPLICATIONS

The findings of this study generate several concrete implications for policymakers, institutional investors, and regulators.

First, the bidirectional Granger causality between Bank Nifty and GDP implies that sustained banking sector stability and profitability is a prerequisite for—not merely a consequence of—economic growth. Policies that maintain low GNPA ratios, adequate capitalisation, and competitive lending rates therefore have a dual function: improving financial intermediation efficiency and supporting the real economy's growth trajectory. The RBI's proactive supervision and the government's bank recapitalisation programmes post-2016 are thus not merely financial sector interventions but are macroeconomic stabilisers.

Second, the finding that GDP Granger-causes Nifty IT (but not vice versa) implies that IT sector valuations are macroeconomically endogenous—exposed to global demand cycles and domestic growth trends—rather than being an autonomous growth engine. Portfolio construction strategies that treat IT as a counter-cyclical diversifier may therefore be misconceived; conversely, sectors like pharma, with weak causality running to GDP, may provide more genuine defensive diversification.

Third, the FMCG sector's role as a demand-following sector has direct implications for consumption-oriented fiscal policy. Policies that support rural income, reduce indirect taxes on mass-market goods, and improve distribution infrastructure have first-order effects on FMCG revenue and equity performance, and can be monitored in real-time through Nifty FMCG movements as a leading indicator of household consumption trends.

Fourth, for SEBI and capital market regulators, the tripling of the investor base since 2020 introduces both opportunities and systemic risks. The increased participation of retail investors—particularly through derivatives markets, where India now ranks among the world's largest in terms of contract volumes—requires robust investor protection frameworks, margin requirements, and financial literacy infrastructure to prevent destabilising pro-cyclical behaviour.

VIII. CONCLUSION

This study has conducted a comprehensive econometric analysis of the dynamic relationship between NSE sectoral indices—Nifty IT, Bank Nifty, Nifty FMCG, and Nifty Pharma—and India's real GDP growth over the period 2004 to 2024. Employing Johansen cointegration, VECM, Granger causality, and variance decomposition techniques, the study generates robust evidence of long-run equilibrium relationships between all four sectoral indices and GDP, with significant heterogeneity in the nature and direction of causal relationships.

The central empirical finding is that banking sector equity performance exhibits the strongest integration with GDP growth, with bidirectional causality and the fastest error correction speed (31.2% per annum). The IT sector is GDP-driven, the FMCG sector follows domestic consumption trends, and the pharma sector provides a weak but statistically discernible impulse to GDP through its export and employment channels. These heterogeneous results underscore the importance of sector-level disaggregation in empirical finance-growth analyses and caution against over-reliance on aggregate indices as proxies for financial development.

The study is subject to several limitations. The use of annual data limits the number of observations and may obscure intra-year dynamics better captured in quarterly or monthly series. Future research could incorporate structural break tests (Zivot-Andrews, Clemente-Montanes-Reyes) to formally model the 2008, 2016, and 2020 shocks, and could extend the analysis to include mid-cap and small-cap sectoral variants to assess whether the finance-growth nexus is concentrated in large-cap equities.

In sum, this paper contributes to the emerging literature on sectoral finance-growth linkages in India, affirms the deepening integration between NSE equity markets and macroeconomic performance over two decades of structural transformation, and provides an empirically grounded platform for sectoral investment strategy and economic policy design in one of the world's most dynamic emerging market economies.

REFERENCES

[1] Aich, B. R., Tareque, M., Ahmed, T. T., & Rahman, M. M. (2025). Unveiling the nexus of financial inclusion and political stability for capital market participation in South Asian regions. Borsa Istanbul Review, 25(6), 1101–1115. https://doi.org/10.1016/j.bir.2025.03.001

[2] Ahmed, S. (2008). Aggregate economic variables and stock markets in India. International Research Journal of Finance and Economics, 14(1), 141–164.

[3] Beck, T., & Levine, R. (2004). Stock markets, banks, and growth: Panel evidence. Journal of Banking & Finance, 28(3), 423–442. https://doi.org/10.1016/S0378-4266(02)00408-9

[4] Bhattacharya, B., & Mukherjee, J. (2002). Causal relationship between stock market and exchange rate, foreign exchange reserves, and value of trade balance: A case study for India. Calcutta Statistical Association Bulletin, 53(1), 52–71.

[5] Business Standard. (2021, January 18). India's m-cap to GDP ratio crosses 100% for first time in over a decade. https://www.business-standard.com
[6] Business Standard. (2024, July 3). FMCG sector weightage in Nifty 50 falls to lowest level since 2010. https://www.business-standard.com
[7] Business Standard. (2025, April 17). IT companies' slice of Nifty 50 pie shrinks sharply to 17-year low. https://www.business-standard.com
[8] Business Standard. (2025, November 3). India's BFSI sector grows 50-fold in 20 years, market cap hits Rs 91 trillion. https://www.business-standard.com
[9] Demetriades, P. O., & Hussein, K. A. (1996). Does financial development cause economic growth? Time-series evidence from 16 countries. Journal of Development Economics, 51(2), 387–411. https://doi.org/10.1016/S0304-3878(96)00421-X
[10] Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49(4), 1057–1072. https://doi.org/10.2307/1912517
[11] Economic Survey of India. (2024–25). Ministry of Finance, Government of India. https://www.indiabudget.gov.in
[12] Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica, 37(3), 424–438. https://doi.org/10.2307/1912791
[13] Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. Journal of Econometrics, 2(2), 111–120. https://doi.org/10.1016/0304-4076(74)90034-7
[14] International Monetary Fund. (2024). World Economic Outlook database. https://www.imf.org/en/Publications/WEO
[15] Johansen, S. (1988). Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12(2–3), 231–254. https://doi.org/10.1016/0165-1889(88)90041-3
[16] Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. Oxford Bulletin of Economics and Statistics, 52(2), 169–210. https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x
[17] Keswani, S., Puri, V., & Jha, R. (2024). Relationship among macroeconomic factors and stock prices: Cointegration approach from the Indian stock market. Cogent Economics & Finance, 12(1), Article 2355017. https://doi.org/10.1080/23322039.2024.2355017
[18] King, R. G., & Levine, R. (1993). Finance, entrepreneurship, and growth. Journal of Monetary Economics, 32(3), 513–542. https://doi.org/10.1016/0304-3932(93)90028-E
[19] Levine, R., & Zervos, S. (1998). Stock markets, banks, and economic growth. American Economic Review, 88(3), 537–558.
[20] MacKinnon, J. G., Haug, A. A., & Michelis, L. (1999). Numerical distribution functions of likelihood ratio tests for cointegration. Journal of Applied Econometrics, 14(5), 563–577.
[21] MDPI Economies. (2026). Stock market development and economic growth nexus: Evidence from the Fragile Five countries. Economies, 14(2), Article 52. https://doi.org/10.3390/economies14020052
[22] Ministry of Statistics and Programme Implementation (MoSPI). (2024). National accounts statistics. Government of India. https://www.mospi.gov.in

[23] NSE India. (2024). NSE annual report and factsheets. National Stock Exchange of India. https://www.nseindia.com
[24] NSE Indices. (2024). Nifty sectoral index factsheets. https://www.niftyindices.com
[25] Patrick, H. T. (1966). Financial development and economic growth in underdeveloped countries. Economic Development and Cultural Change, 14(2), 174–189. https://doi.org/10.1086/450153
[26] Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335–346. https://doi.org/10.1093/biomet/75.2.335
[27] Reserve Bank of India. (2024). RBI annual report 2023–24 and data warehouse. https://www.rbi.org.in
[28] Robinson, J. (1952). The generalisation of the general theory. In The rate of interest and other essays (pp. 67–142). Macmillan.
[29] Schumpeter, J. A. (1911). The theory of economic development. Harvard University Press.
[30] Tripathi, V., & Seth, R. (2014). Stock market performance and macroeconomic factors: The study of Indian equity market. Global Business Review, 15(2), 291–316. https://doi.org/10.1177/0972150914523599
[31] World Bank. (2024). World development indicators: India GDP growth (annual %). https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=IN