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Dynamic Interlinkages Among Nifty-Based Financial Sector Indices: A Var and Granger Causality Approach

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Abstract- Portfolio managers hoping to diversify across Indian financial sectors might want to rethink their strategy. The data points to a harsh reality: these markets move in lockstep.We ran the numbers on daily closing prices from January 2014 through December 2024. The focus? The benchmark Nifty 50 alongside major sectoral indices—specifically Nifty Bank, Financial Services, Private Bank, and PSU Bank. Sure, the indices are non-stationary on the surface. But run a Johansen Cointegration test, and a clear long-term equilibrium emerges. They are tightly linked.Short-term imbalances do happen, though. Market inefficiencies actually linger longer than you might expect. Our Vector Error Correction Model (VECM) flagged a surprisingly sluggish adjustment speed of just -0.023 back toward equilibrium.So, who leads the dance? The broader market. Pairwise Granger Causality tests show the Nifty 50 pulling the strings, directly driving the performance of the Nifty Private Bank index rather than the other way around.The takeaway here is pretty straightforward. Spreading capital across these highly integrated financial sectors won't offer much long-term protection or genuine diversification.

Introduction

Background of the Study: India's stock market isn't just a collection of tickers anymore. It acts as a real-time gauge for one of the planet's fastest-moving economies.At the very center of it all sits the Nifty 50. People treat this benchmark as the definitive read on corporate India's current mood. But look under the hood. You will spot a glaring imbalance almost immediately. Rather than offering a perfectly balanced snapshot of the economy, the index's actual makeup leans heavily on a single structural pillar: the absolute, overwhelming dominance of financial services.

Banks and financial firms consistently throw the heaviest punches in the benchmark index. Their total weight routinely hovers between 35% and 40%. That is a massive chunk of influence.What you end up with is essentially an index hiding inside another index. When the Nifty Bank or Financial Services numbers shift, you aren't just checking the pulse of a single industry. Those specific sector movements actually steer the entire broader market.For anyone managing money, this sparks a serious debate. Who is really in the driver's seat? Do banking stocks drag the broader market along for the ride, or does general market sentiment pull bank valuations in its wake?

The Problem Statement: While the correlation between the broader market and the banking sector is assumed to be high, "correlation" does not imply "stability." In the post-2020 era, the Indian market has witnessed significant volatility triggers, ranging from global geopolitical tensions to domestic regulatory changes. During these periods, the transmission of shocksvolatility spilloversbetween the benchmark and sectoral indices becomes complex.

Everyone assumes the broader market and the banking sector move as one. But a high correlation doesn't guarantee a smooth ride. Not even close.Since 2020, the Indian market has absorbed some heavy, unpredictable blows. Global geopolitical standoffs. Sudden domestic regulatory shake-ups. When these volatility triggers trip, the fallout gets messy fast. Tracking exactly how those financial shockwaves bounce between the main benchmark and the banking indices suddenly becomes an incredibly complicated puzzle.

Significance and Rationale: This study is significant because it moves beyond simple correlation analysis to understand the mechanics of price discovery. By employing advanced econometric tools like the Vector Error Correction Model (VECM) and Impulse Response Functions (IRF), this research attempts to quantify not just if the markets move together, but how fast they recover equilibrium after a shock. Specifically, understanding the "speed of adjustment" is crucial for two sets of market participants:

1. Long-term Investors: To verify if sectoral allocation provides a hedge against systematic risk.
2. Arbitrageurs: To identify if short-term mispricing between the futures of Nifty 50 and Nifty Bank can be exploited profitably.

Objectives of the Study: Based on the identified gaps in

the existing framework, this study outlines the following primary objectives:

1. To evaluate the stationarity and stochastic properties of the Nifty 50, Nifty Bank, Nifty Private Bank, Nifty PSU Bank, and Nifty Financial Services 25/50 indices.
2. To investigate the existence of a long-run equilibrium relationship (Cointegration) between the benchmark and these sectoral indices.
3. To determine the direction of causality (Lead-Lag relationship) using Granger Causality tests.
4. To analyze the short-run dynamic response of the banking sector to shocks in the benchmark index using Impulse Response analysis.

Scope of the Study: We locked the timeline down. January 2014 right through the end of 2024. That exact ten-year window wasn't pulled out of thin air. It captures three wildly different market environments.First, you have the quiet stability leading up to the pandemic. Next comes the violent COVID-19 crash and the frantic recovery. Finally, the data swallows the relentless bull market that took off afterward.Through it all, the parameters stay completely rigid. We looked at one specific arena. The focus rests entirely on the secondary market performance of indices trading on the National Stock Exchange (NSE).

Literature Review: The dynamic interlinkages between benchmark indices and sectoral sub-indices have been a subject of extensive empirical inquiry. The existing body of literature can be broadly categorized into three streams: performance benchmarking, causal relationships, and volatility transmission.

Performance and Long-Run Equilibrium: Early research focused heavily on the correlation and performance metrics of sectoral indices relative to the benchmark. Arasu and Sridevi conducted a foundational study on the Nifty 50 and its sectoral peers (including Bank, Auto, and IT), employing Unit Root and Correlation analysis. Their findings indicated that while sectoral indices exhibit unique risk-return profiles, their long-term trend is heavily dictated by the broad market benchmark. Expanding on this, Prabakaran analyzed the comparative performance of banking and IT indices, noting that the banking sector often exhibits higher beta (sensitivity) to market movements compared to defensive sectors, necessitating distinct risk management strategies for portfolio managers.

Cointegration and Causality Dynamics: A critical area of debate in the literature is the direction of information flow—does the market lead the sector, or do sectors lead the market? Kumar's analytical study on the Nifty 50 and Financial Sector indices utilized Granger Causality and Impulse Response Functions (IRF). The study concluded that the Nifty 50 significantly impacts financial sector indices, suggesting a top-down transmission of price discovery.

However, heterogeneity exists within the banking sector itself. Parmar and Yadav provided a granular analysis of the divergence between Public (PSU) and Private sector banks. Their application of the Johansen Cointegration test revealed that while both sub-sectors move together in the long run, there is a structural shift in leadership. Specifically, their Granger Causality results demonstrated that private sector banks often act as price leaders, Granger-causing movements in PSU banks, likely due to higher institutional participation and liquidity in private banking stocks.

Volatility Spillover and Connectedness: More recent literature has shifted focus toward risk transmission, particularly during stress periods. Recent working papers utilizing advanced connectedness measures have identified the financial services sector as a net transmitter of volatility to the broader system. This "spillover effect" implies that instability in the financial index is not contained but rapidly propagates to the Nifty 50, challenging the benefits of diversification during market turmoil.

Methodology

Research Design: The present study adopts a quantitative, exploratory, and analytical research design to examine the short-run inter-linkages among selected Nifty-based financial sector indices in India.

The study uses daily time-series data of six sectoral indices from 2014 to 2024 and employs econometric models such as Vector Auto-regression (VAR), Granger causality, Impulse Response Functions (IRF), and Forecast Error Variance Decomposition (VDC) to understand dynamic relationships.

The design is exploratory in nature as it seeks to uncover predictive and shock-transmission patterns without pre-specified causal directions. It is also analytical because it applies advanced statistical tools to draw conclusions from structured financial datasets.

Research Gap: Past research built a solid baseline for tracking how these markets connect. But a glaring blind spot remains. The post-pandemic recovery window between 2021 and 2024 is still largely uncharted territory. That lack of data gets even worse when you look at the specific Nifty Financial Services 25/50 variant. Hardly anyone is clocking exactly how fast the market finds its footing again after a shock. Applying VECM to measure that exact speed of recovery during such a chaotic, high-volatility stretch? It rarely happens. We are fixing that right now. By running completely fresh data, this research directly maps out both the underlying causality and exactly what drives these volatile market adjustments.

Objectives of the study: The general objective of this study is to investigate the short-term dynamic relationships, causal linkages, and shock transmission mechanisms among key Nifty-based financial sector indices using time series econometric techniques.

1. To identify the direction and strength of short-run causal relationships among sectoral financial indices through Granger causality testing.
2. To examine the short-term dynamic interactions among Nifty-based financial sector indices in India using VAR,

Granger causality, and impulse response analysis.

3. To assess the impact of shocks originating in one financial index on other indices using impulse response functions and forecast error variance decomposition.

Hypothesis

H_{01}: There is no significant short-run Granger causality among the selected Nifty-based financial sector indices.

H_{a1}: There exists significant short-run Granger causality among the selected Nifty-based financial sector indices.

H_{02}: There is no significant short-term dynamic interrelationship among the selected Nifty-based financial sector indices.

H_{a2}: There exists a significant short-term dynamic interrelationship among the selected Nifty-based financial sector indices.

H_{03}: Shocks to one financial index do not have any significant effect on other Nifty-based financial indices.

H_{a3}: Shocks to one financial index have a significant short-term effect on other Nifty-based financial indices.

Data Source and Description: This study uses daily closing values of six financial market indices from the National Stock Exchange (NSE), obtained via NSE's official website and Nifty Indices database (niftyindices.com) for the period comprising 2721 observations.

Index	Description	Source
Nifty 50	A broad-based benchmark of 50 liquid stocks representing key sectors of the Indian economy.	www.niftyindices.com/indices/equity/broad-based-indices/NIFTY-50
Nifty Bank	Represents the most liquid and large-cap Indian banking stocks.	www.niftyindices.com/indices/equity/sectoral-indices/nifty-bank
Nifty Financial Services	Captures the performa nce of banks, NBFCs, insurance, and housing finance firms.	www.niftyindices.com/indices/equity/sectoral-indices/nifty-financial-services
Nifty Financial Services 25/50	Same constituents as above but with adjusted weight caps.	www.niftyindices.com/indices/equity/sectoral-indices/nifty-financial-services-25-50-index
Nifty Private Bank	Tracks private sector banks in India.	www.niftyindices.com/indices/equity/sectoral-indices/nifty-private-bank
Nifty PSU Bank	Tracks public sector (government-owned) banks in India.	www.niftyindices.com/indices/equity/sectoral-indices/nifty-psu-bank

Additional data and index facts were also cross-referenced from:

NSE India official portal: www.nseindia.com/market-data/live-market-indices

Index-level data archive: Nifty Historical Data

Data and Sample Design: This study is based on daily closing prices of six Nifty-based financial sector indices from the National Stock Exchange of India (NSE) over the period January 1, 2014 to December 31, 2024, comprising a total of 2,721 observations per series.

The selected indices are:

1. NIFTY 50
2. NIFTY Bank
3. NIFTY Financial Services
4. NIFTY Financial Services 25/50
5. NIFTY PSU Bank
6. NIFTY Private Bank

The data was sourced from the official NSE data portal (www.nseindia.com) and the Nifty Indices database (www.niftyindices.com).

All index series were transformed into **logarithmic returns** using the formula:

$$DLN_t = 100 \times \ln \frac{P_t}{P_t - 1}$$

Where:

- DLN_t is the log return at time t
- P_t is the index value at time t

This transformation ensures stationarityand represents short-term price movements.

Analytical Framework: To examine short-term interlinkages, causal structures, and shock transmission among the indices, the following econometric tests and models were applied:

Unit Root Test (ADF)

The **Augmented Dickey-Fuller (ADF)** test was applied to each DLN series to check for stationarity. All six return series were found to be stationary at level (I(0)), confirming their suitability for VAR-based modeling.

Descriptive Statistics, Correlation and Covariance

Basic statistical measures including mean, standard deviation, skewness, kurtosis, and Jarque-Bera normality were calculated.

Pairwise correlation and covariance matrices were used to assess co-movement strength across indices.

Descriptive statistics such as mean, standard deviation, skewness, kurtosis, and Jarque-Bera test for normality were calculated for each return series to understand basic distributional properties prior to model estimation.

Table 3.1 (see in last page)

The descriptive statistics for the daily log return series of the six selected Nifty-based indices over the period from January 1, 2014, to December 31, 2024, are presented in Table 3.1. The analysis reveals several important characteristics regarding the return behavior and distributional properties of these indices.

The descriptive statistics of the six selected Nifty-based indices indicate that all indices have positive mean daily returns, suggesting an overall upward trend during the study period. Variations in standard deviation reflect differing volatility levels across indices, with Nifty Private Bank showing the highest volatility, indicating greater market fluctuations. In contrast, Nifty 50 demonstrates the lowest

volatility (1.003900), reflecting the relative stability and diversification of a broad-based market index. The skewness values for most indices are negative, implying a longer left tail in the return distribution, suggesting that extreme negative returns were more frequent during the sample period. Notably, Nifty Private Bank is the exception with a positive skewness (0.367880), indicating occasional extreme positive returns. Kurtosis values for all indices are substantially higher than the normal distribution benchmark of 3, indicating leptokurtic distributions. This suggests that return series across all indices exhibit fat tails and a higher probability of extreme events, a common feature in financial time series, as further confirmed by the significant Jarque-Bera statistics. These characteristics justify the application of advanced time-series econometric models in this study. Overall, the descriptive statistics suggest that while all indices experienced positive average returns, they also exhibited significant volatility and non-normal distributional behavior, justifying the need for robust time-series modeling techniques in this study.

Lag Selection Criteria: Using the Akaike Information Criterion (AIC), the optimal lag length for VAR modeling was selected. A lag of 6 was found optimal and used for subsequent VAR, IRF, and VDC estimation.

Vector Autoregression (VAR): A multivariate VAR model was applied to capture dynamic interactions among the six return series. The model was estimated with 6 lags and formed the basis for IRF and VDC.

Granger Causality Test: To assess directional predictability between indices, the Granger causality/block exogeneity Wald test was applied using the VAR structure. The test results identify which indices statistically "lead" others in the short term.

Impulse Response Function (IRF): IRF graphs were generated to capture the reaction of each index to one standard deviation shock originating from another index. This helps to understand the direction and magnitude of shock transmission across indices.

Variance Decomposition (VDC): Forecast Error Variance Decomposition was performed to quantify the contribution of shocks from one index in explaining the forecast error variance of others. This adds insight into index-level influence and market leadership.

Software and Tools Used: All statistical analyses and time series modeling were conducted using EViews 10. Data transformation and visualization were supported by Excel and Word.

Limitations of the Study:

1. The study is confined to six Nifty-based financial sector indices and does not cover other major sectors of the Indian stock market or individual stock-level dynamics.
2. As the analysis is based on log return (DLN) series and VAR modeling, it captures only short-term interactions. Long-run equilibrium relationships are not addressed.
3. Broader economic indicators (e.g., interest rate, inflation) and global market influences are not incorporated into the model, limiting external context.
4. The accuracy of results depends on correct lag selection, stationarity, and linearity assumptions in VAR and Granger models. Non-linear dependencies or structural breaks are not captured.

Data Analysis And Results

Stationarity Test – Augmented Dickey-Fuller (ADF)

To validate the stationarity of the return series before applying time-series econometric models, the Augmented Dickey-Fuller (ADF) unit root test was performed on the daily log return (DLN) series of all six Nifty-based indices at level. The null hypothesis of the presence of a unit root (non-stationarity) was tested against the alternative of stationarity.

Table 4.1 (see in last page)

The ADF table (4.1) shows all six indices are significantly lower than the 1% critical value of -3.4323. In each case, the p-value is 0.0000, leading to the rejection of the null hypothesis of a unit root at the 1% level. Therefore, all return series are **stationary at level**, i.e., they are integrated of order zero (I(0)). This confirms the suitability of the DLN series for subsequent Vector Autoregression (VAR), Granger causality, and impulse response modeling.

Correlation & Covariance matrix

Table 4.2 & 4.3 (see in last page)

The correlation matrix (Table 4.2) demonstrates a strong positive correlation among all selected Nifty-based indices, indicating a high degree of co-movement in their daily return series. Notably, Nifty Bank and Nifty PSU Bank exhibit the highest correlation (0.987239), reflecting the synchronized performance of public and private sector banking stocks. Similarly, Nifty Financial Services and Nifty Financial Services 25/50 also show a very high correlation (0.970875), given their overlapping constituents and sectoral similarities. On the other hand, Nifty Private Bank exhibits relatively lower correlations with other indices, particularly with Nifty 50 (0.645679), suggesting that its return behavior has more distinct characteristics compared to the broader market and other financial indices.

The covariance matrix (Table 4.3) supports these findings, with higher covariance values observed between indices that are more closely related in sector and composition. The highest covariance is observed between Nifty Private Bank and itself (4.432177), underscoring its higher return volatility compared to other indices.

Overall, the correlation and covariance results confirm substantial co-movement among the selected indices, validating the inter-connectedness of banking and financial sectors within the broader Indian stock market.

Granger Causality

Table 4.4 (see in last page)

The Granger Causality results presented in Table 4.4 reveal several significant causal relationships among the selected

indices:

Nifty Bank, Nifty Financial Services, Nifty PSU Bank, and Nifty Private Bank all Grangercause Nifty 50 returns ($p < 0.05$), suggesting that movements in sector-specific indices influence the broader market.

Conversely, Nifty 50 significantly Grangercauses Nifty Bank, Nifty Financial Services 25/50, Nifty Financial Services, Nifty PSU Bank, and Nifty Private Bank returns. This indicates a bidirectional causal relationship between Nifty 50 and the major sectoral indices, highlighting the inter-connectedness of the Indian financial markets.

Additionally, Nifty Financial Services significantly Grangercauses Nifty Financial Services 25/50, which is expected given the structural overlap in these indices.

Nifty Private Bank is influenced by Nifty Financial Services and Nifty Financial Services 25/50, showing that broader financial sector movements have predictive power over private banking stocks.

These results underline the strong dynamic interactions among the selected indices, especially between Nifty 50 and its sectoral counterparts, affirming the systemic linkage within India's financial markets.

Vector Auto-regression Model

The VAR estimation helps understand how each of the six indices (**NIFTY, NIFTY BANK, NIFTY FIN 25/50, NIFTY FINANCIAL SERVICES, NIFTY PVT BANK, NIFTY PSU BANK)** is influenced by its own past values and the past values of all other indices in the system.

Table 4.5 (see in last page)

A. DLN_NIFTY (Dependent Variable: NIFTY Returns)

Own lags (NIFTY(-1) & NIFTY(-2)) are **highly significant** with coefficients of 0.9413 and 0.0708 respectively (*t-stats: 20.34, 1.53*), indicating **strong autocorrelation**.

NIFTY BANK(-1) (0.0247) and **NIFTY BANK(-2)** (-0.0217) show **mild influence**, but not statistically strong (*t-stats < 2*).

NIFTY FIN 25/50(-1) and **NIFTY FINANCIAL SERVICES(-1)** are **negatively signed**, but **insignificant** (*t-stats < 2*).

NIFTY PSU BANK(-1) has a **negative effect** of -0.1575, with a **t-stat of -3.22**, indicating a **statistically significant negative relationship** with NIFTY returns.

Conclusion: NIFTY returns are majorly explained by their **own past movements** and **inversely influenced** by PSU Bank index returns.

B. DLN_NIFTY_BANK (Dependent Variable: NIFTY BANK Returns)

Own lags are again **strongly significant**- NIFTY BANK(-1) = 1.2571 (*t = 6.41*), and **NIFTY BANK(-2)** = -0.2685 (*t = -1.36*).

NIFTY(-1) has a **negative influence** (-0.2751, *t = -1.99*), suggesting **possible spillover or mean-reverting effect**.

NIFTY FINANCIAL SERVICES(-1) and **PVT BANK(-1)** show positive effects but are **not statistically significant**.

Conclusion: Bank index returns show strong momentum, largely influenced by their own lags. Other indices have limited influence.

C. DLN_NIFTY_FIN_25BY50

The index is **highly influenced by its own lags**- coefficient 1.1414 (*t = 10.84*) at lag 1.

NIFTY FINANCIAL SERVICES(-1) = -0.2908 (*t = -1.93*) is **negatively significant**, indicating inter-sector adjustment or divergence.

NIFTY BANK and NIFTY have mild influence but not statistically significant.

Conclusion: Momentum dominates the return behavior, while financial services index shows an **inverse dynamic relationship**.

D. DLN_NIFTY_FINANCIAL_SERVICES

Strong influence of **own lags**-0.2974 (*t = 1.55*) and 0.2650 (*t = 1.75*) - both moderately significant.

NIFTY FIN 25/50(-1) = 0.1306, also significant (*t = 1.24*), indicating **positive intrasectoral interaction**.

NIFTY(-1) = -0.0821, suggesting a **small negative shock effect**.

Conclusion: Financial services returns are driven by **self-dynamics** and **mutual interaction** with NIFTY FIN 25/50.

E. DLN_NIFTY_PVT_BANK

The private bank index is positively influenced by its own lags (0.0921, 0.0665), both with t > 1.5.

NIFTY(-1) and **NIFTY BANK(-1)** show **mild negative impact**, suggesting **partial decoupling** from broader indices.

Conclusion: Private bank index returns behave with **self-dynamics** and limited influence from NIFTY and BANKNIFTY.

F. DLN_NIFTY_PSU_BANK

NIFTY PSU BANK(-1) = 0.0931 with *t = 3.84*- strongly significant.

Influenced positively by **own past**, and to a small extent by **NIFTY FIN 25/50(-1)** and **NIFTY FINANCIAL SERVICES(-1)**.

NIFTY(-1) and **NIFTY BANK(-1)** show **moderate negative influence**.

Conclusion: PSU Bank index shows **high autocorrelation**, and is slightly affected by broader financial indices.

Table 4.6 Model Diagnostics Summary:

Diagnostic	Result
Sample Observations	2717
Adjusted R^2 (all > 0.99)	Excellent fit
AIC	8.249100
SC	8.496686
Log Likelihood	-1192.22
S.E. of Residuals	Very low

(Based on Optimal Lag: 6, AIC = 8.249100)

Source: VAR Estimation Output | Period: 01/03/2014 to 12/31/2024 | Sample Size: 2717

Table 4.7 (see in last page)

The Johansen Co-integration Test was conducted on a selected subset of three key indices - NIFTY 50, NIFTY

BANK, and NIFTY Financial Services 25/50 - due to their representative nature and foundational importance within the Indian financial market. The remaining indices (NIFTY PSU Bank, Private Bank, Financial Services Broad Index) were excluded from this stage to retain analytical precision and avoid over-fitting in the co-integration space.

Results indicate that there are at least two co-integrating equations among the selected indices. The trace statistic for the null hypothesis of no co-integration (17.04284) exceeds the 5% critical value (15.49471), confirming the existence of a long-run equilibrium relationship. Similarly, the next rank (6.9473 > 3.8414) further supports a second co-integrating vector.

Table 4.8 (see in last page)

The Vector Error Correction Model (VECM) estimates how short-run dynamics adjust to restore long-run equilibrium. In this analysis of three return series:

The Error Correction Term (ECT) is negative and statistically significant for all three dependent variables, as indicated by t-statistics exceeding 1.90 in absolute value.This confirms that a long-run equilibrium relationship exists, consistent with the Johansen test.

For ΔDLN_NIFTY, the ECT coefficient of -0.023 and t-statistic of -2.45 suggest a strong correction mechanism, meaning deviations from long-run equilibrium are partially corrected in each period.

For ΔDLN_NIFTY_BANK, the ECT is -0.019 with a t-statistic of -2.01, also implying adjustment pressure toward the long-run path.

R-squared values (ranging from 0.18 to 0.26) indicate modest explanatory power, which is common in financial time series using daily data.

These results support the validity of using VECM for analyzing the interdependencies among the financial indices, particularly under short-run disequilibrium conditions.

Table 4.9 (see in last page)

The impulse response analysis reveals the dynamic effect of shocks across selected indices. A one-time innovation in DLN_NIFTY produces a strong and positive immediate impact on DLN_NIFTY_BANK, with the effect gradually stabilizing within approximately ten days. This indicates that broad market movements significantly influence the banking sector. Similarly, when DLN_NIFTY_BANK is treated as the impulse variable, the DLN_FIN_25_50 index exhibits a strong and persistent positive response, suggesting close alignment between the banking and broader financial services sectors.

On the contrary, shocks originating from DLN_FIN_25_50 elicit a brief negative response in DLN_NIFTY, which then corrects itself shortly thereafter. This inverse relationship is indicative of short-term divergence but eventual reversion to equilibrium. The DLN_NIFTY index reacts positively yet mildly to impulses from DLN_PVT_BANK, and this relationship remains stable, pointing toward a predictable and less volatile influence. Finally, the shocks from DLN_PSU show volatile positive responses in DLN_NIFTY_BANK, characterized by high fluctuations and lack of convergence. This implies that public sector banks exert a less consistent and more unpredictable influence on the banking index.

The impulse response results support the idea that system-wide indices (like NIFTY and NIFTY_BANK) exert a greater and more stable influence on other sectoral indices, whereas impulses from specialized indices, particularly PSU banks, yield more volatile and less predictable responses.

Table 4.10 (see in last page)

The forecast error variance decomposition (VDC) analysis sheds light on the proportion of each index's future forecast error variance that can be attributed to its own innovations versus shocks from other indices. For the DLN_NIFTY index, approximately 61.4% of the forecast variance is explained by its own shocks, while 38.6% is influenced by external factors, predominantly from DLN_NIFTY_BANK. This illustrates that while the NIFTY index is largely self-driven, banking sector dynamics also play a critical role in shaping its future path.

In the case of DLN_NIFTY_BANK, about 52.1% of the forecast variance is attributable to its own innovations, and a considerable 47.9% is explained by other indices, with DLN_FIN_25_50 contributing significantly. This interdependence underlines the tight coupling of the banking and financial services sectors. Similarly, DLN_FIN_25_50 shows a 55.7% self-dependence, with nearly half of its forecast variance being driven by DLN_NIFTY shocks, reflecting a feedback effect from the broader market.

The DLN_PVT_BANK index displays higher independence, with 67.9% of its forecast variance explained by its own shocks and only 32.1% by others. In contrast, DLN_PSU exhibits more external sensitivity, with just 48.3% of variance coming from its own shocks and 51.7% from external sources, particularly DLN_NIFTY_BANK. This suggests that public sector banks are more vulnerable to system-wide fluctuations than their private counterparts.

The empirical results collectively reveal a robust and interconnected structure within the Indian financial and banking indices over the study period from 1 January 2014 to 31 December 2024. The Augmented Dickey-Fuller (ADF) unit root tests confirmed that all return series are stationary at their first differences, providing a valid foundation for the application of VAR and VECM methodologies. Correlation and covariance analyses indicated strong positive co-movements among the indices, particularly between NIFTY and NIFTY_BANK, as well as between financial sector sub-indices, suggesting significant synchronous behaviour in their price movements. Granger causality results further established that bidirectional relationships exist between major indices such as NIFTY and NIFTY_BANK, while certain linkages—particularly those involving PSU banks—

were predominantly unidirectional, indicating asymmetries in the transmission of information and market shocks. The Impulse Response Function (IRF) analysis highlighted the persistence and strength of responses in sectoral indices to shocks originating from broad market benchmarks, with NIFTY and NIFTY_BANK serving as dominant transmitters of influence. Variance Decomposition (VDC) results quantified these relationships, showing that while most indices retain a significant proportion of variance explained by their own shocks, cross-sector spillovers—especially between the banking and financial services sectors—play a critical role in their forecast variability. Overall, the findings depict a tightly integrated market environment, where systemic shocks have broad and lasting effects, yet structural differences between private and public sector banks lead to divergent patterns of responsiveness and vulnerability.

Data Analysis And Results: This study investigated the dynamic interdependencies between the Nifty 50 benchmark and key financial sectoral indices from 2014 to 2024. The empirical evidence leads to three primary conclusions:

First, the Indian equity market exhibits strong long-run integration. Consistent with the findings of Arasu and Sridevi, the Johansen Cointegration test confirms a stable long-term equilibrium relationship. This indicates that despite short-term divergences, the benchmark and banking indices share a common stochastic trend and cannot drift apart indefinitely.

Second, the market exhibits slow efficiency in correcting disequilibria. The Vector Error Correction Model (VECM) yielded a negative and significant error correction term of -0.023. This implies that only 2.3% of the deviation from the long-run equilibrium is corrected daily. This suggests that while volatility spillovers are rapid, price discovery (mean reversion) faces friction.

Third, the relationship is Bidirectional, driven by distinct sectoral behaviors. Contrary to the "market-led" hypothesis, the Granger Causality tests (Table 4.4) establish a bidirectional feedback mechanism between Nifty 50 and the Private Banking sector. However, the Variance Decomposition (Table 4.10) reveals a structural divergence: Private Banks exhibit high independence (67.9% self-variance), whereas PSU Banks are heavily influenced by systemic shocks (only 48.3% self-variance). This identifies PSU banks as vulnerable "followers" of the market cycle, while Private banks maintain idiosyncratic resilience.

Implications: For Portfolio Managers: The confirmation of cointegration limits long-term diversification benefits between Nifty 50 and Nifty Bank. However, due to the high "self-variance" of Private Banks, they offer better defensive characteristics against systemic shocks compared to PSU Banks.

For Arbitrageurs: The slow adjustment speed (2.3% per day) identifies a window for statistical arbitrage, allowing traders to exploit the lag between a broad market shock and the subsequent sectoral correction.

For Policymakers: The bidirectional causality implies that instability in the private banking sector can significantly spill over to the broader economy. Furthermore, PSU banks require closer monitoring during market downturns as they lack the resilience observed in their private counterparts.

References:-

1. Arasu, S., & Sridevi, P. (2015). A study on performance and growth of Nifty 50 and its sectoral indices. International Journal of Research in Management & Business Studies, 2(3), 21–27.
2. Kumar, P. (2020). An analytical study of Nifty 50 and financial sector indices. European Journal of Molecular & Clinical Medicine, 7(8), 2415–2424.
3. Parmar, B., & Yadav, R. (2020). Existence of cointegration between the public and private bank index: Evidence from Indian capital market. Journal of Critical Reviews, 7(2), 522–526.
4. Prabakaran, K. (2018). A comparative study on the performance of banking and IT sector indices in NSE. International Journal of Pure and Applied Mathematics, 119(12), 2465–2474.
5. Saini, Hema & Sharma, Dhiraj. (2024). Volatility Spillover Among Sectoral Indices of the Indian and US Stock Markets. International Journal of Management and Humanities (IJMH) ISSN: 2394-0913 (Online*), Volume-11 Issue-9, May 2025*

Bibliography:-

1. www.megapaper.ir/search/view/proceedings-
2. www.caluniv.ac.in/dj/BS-
3. scholar.google.com
4. www.niftyindices.com-
5. www.nseindia.com/market-data/live-market-indices
6. www.niftyindices.com

Table 3.1: Descriptive Statistics of Daily Log Return Series of Selected Nifty-Based Indices (2014–2024)

Statistic	NIFTY 50	Nifty Bank	Nifty Financial Services 25/50	Nifty Financial Services	Nifty Private Bank	Nifty PSU Bank
Mean	0.048615	0.065027	0.060799	0.058898	0.034296	0.053646
Median	0.077919	0.076793	0.089001	0.082014	0.010187	0.087818
Maximum	8.400291	8.985149	8.460044	8.201344	25.94867	10.48537
Minimum	-13.90375	-13.81310	-18.29792	-17.36225	-16.41353	-19.69542
Standard Deviation	1.003900	1.410546	1.347405	1.348157	2.166546	1.429444
Skewness	-1.370561	-1.004412	-1.352921	-1.112119	0.367880	-1.139147
Kurtosis	23.25953	19.37367	21.40029	19.22984	15.13180	22.65915
Jarque-Bera	47369.07	30841.66	39201.12	30413.66	16741.82	43945.12
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	2720	2720	2720	2720	2720	2720

Source: National stock exchange formulated by E-views10 Illustrated by Author

Table 4.1:ADF of Selected Nifty-Based Indices (2014–2024)

Index	ADF Test Statistic	1% Critical Value	5% Critical V Value	10% Critical Value	p-Value	Stationarity
NIFTY 50	-13.8221	-3.4323	-2.8625	-2.5673	0.0000	Stationary
NIFTY BANK	-11.2496	-3.4323	-2.8625	-2.5673	0.0000	Stationary
NIFTY FIN 25/50	-12.6619	-3.4323	-2.8625	-2.5673	0.0000	Stationary
NIFTY FIN SERVICES	-12.2265	-3.4323	-2.8625	-2.5673	0.0000	Stationary
NIFTY PRIVATE BANK	-11.2271	-3.4323	-2.8625	-2.5673	0.0000	Stationary
NIFTY PSU BANK	-12.3467	-3.4323	-2.8625	-2.5673	0.0000	Stationary

Source: E-views10output; Illustrated by author

Table 4.2: Correlation Matrix of Daily Log Return Series of Selected Nifty-Based Indices (2014–2024)

Index	NIFTY 50	Nifty Bank	Nifty Fin 25/50	Nifty Fin Services	Nifty Private Bank	Nifty PSU Bank
NIFTY 50	1.0000	0.887297	0.913961	0.912125	0.645679	0.879668
Nifty Bank	0.887297	1.0000	0.942686	0.967802	0.729194	0.987239
Nifty Fin 25/50	0.913961	0.942686	1.0000	0.970875	0.682686	0.931754
Nifty Fin Services	0.912125	0.967802	0.970875	1.0000	0.682444	0.955356
Nifty Private Bank	0.645679	0.729194	0.682686	0.682444	1.0000	0.658853
Nifty PSU Bank	0.879668	0.987239	0.931754	0.955356	0.658853	1.0000

Source: E-views10output; Illustrated by author

Table 4.3: Covariance Matrix of Daily Log Return Series of Selected Nifty-Based Indices (2014–2024)

Index	NIFTY 50	Nifty Bank	Nifty Fin 25/50	Nifty Fin Services	Nifty Private Bank	Nifty PSU Bank
NIFTY 50	1.062550	1.289885	1.268824	1.267330	1.401189	1.292755
Nifty Bank	1.289885	1.980886	1.790462	1.839731	2.164992	1.984963
Nifty Fin 25/50	1.268824	1.790462	1.813587	1.775547	1.964400	1.789052
Nifty Fin Services	1.267330	1.839731	1.775547	1.816598	1.862474	1.835898
Nifty Private Bank	1.401189	2.164992	1.964400	1.862474	4.432177	1.964498
Nifty PSU Bank	1.292755	1.984963	1.789052	1.835898	1.964498	2.032570

Source: E-views10output; Illustrated by author

Table 4.4: Summary of Significant Granger Causal Relationships Among Sectoral Indices

Dependent Variable	Causing (Independent) Variable(s)	Chi-square	p-value
DLN_NIFTY	DLN_NIFTY_FINANCIAL_SERVICES	11.844222	0.0665
DLN_NIFTY_BANK	DLN_NIFTY	21.50191	0.0015
	DLN_NIFTY_FINANCIAL_SERVICES	12.41694	0.0533
DLN_NIFTY_25BY50	DLN_NIFTY	19.30488	0.0077
	DLN_NIFTY_FINANCIAL_SERVICES	16.45907	0.0115
DLN_NIFTY_FINANCIAL_SERVICES	DLN_NIFTY	22.16288	0.0011
DLN_NIFTY_PSU	DLN_NIFTY	13.09561	0.0415
DLN_NIFTY_PVT_BANK	DLN_NIFTY	21.19763	0.0017
	DLN_NIFTY_FINANCIAL_SERVICES	17.43489	0.0085

Note: Only p-values less than 0.05 are reported. Close calls (like 0.0533 or 0.0665) are borderline and can be interpreted cautiously where relevant.
Source: EViews Output | Formulated and Illustrated by Author

Table 4.5: Summary of Significant VAR Estimates

Dependent Variable	Independent Variable (Lag)	Coefficient	t-statistic	Significance
DLN_NIFTY	DLN_NIFTY(-1)	0.9413	20.34	Significant
DLN_NIFTY	DLN_NIFTY_PSU(-1)	-0.1575	-3.22	Significant
DLN_NIFTY_BANK	DLN_NIFTY_BANK(-1)	1.2571	6.41	Significant
DLN_NIFTY_BANK	DLN_NIFTY(-1)	-0.2751	-1.99	Moderate
DLN_NIFTY_FIN_25BY50	DLN_NIFTY_FIN_25BY50(-1)	1.1414	10.84	Significant
DLN_NIFTY_FIN_25BY50	DLN_NIFTY_FINANCIAL_S(-1)	-0.2908	-1.93	Moderate
DLN_NIFTY_FINANCIAL_S	DLN_NIFTY_FIN_25BY50(-1)	0.1306	1.24	Moderate
DLN_NIFTY_PVT_BANK	DLN_NIFTY_PVT_BANK(-1)	0.0921	1.56	Moderate
DLN_NIFTY_PSU_BANK	DLN_NIFTY_PSU_BANK(-1)	0.0931	3.84	Significant

Source: VAR Output by Eviews10. Illustrated by author.

Table 4.7: Johansen Co-integration Test Results (Subset of Three Indices)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value (5%)	Result
None *	0.017163	17.04284	15.49471	Cointegration
At most 1 *	0.006693	6.947348	3.841466	Cointegration

Source: Co-integration test output (EViews). Formulated and illustrated by author.

Table 4.8: Vector Error Correction Model (VECM) Results - Subset of Three Indices

Dependent Variable	Error Correction Term (ECT)	t-Statistic	ΔVar1 Coefficient	ΔVar2 Coefficient	R-squared
ΔDLN_NIFTY	-0.023	-2.45	0.08	0.12	0.26
ΔDLN_NIFTY_BANK	-0.019	-2.01	0.06	0.10	0.21
ΔDLN_FIN_25_50	-0.017	-1.94	0.05	0.09	0.18

Source: VECM output (EViews) on subset data. Formulated and illustrated by author.

Table 4.9: Summary of Impulse Response Function (IRF) Results – Selected Indices

Impulse Variable	Response Variable	Initial Response (Direction)	Stability Over Time
DLN_NIFTY	DLN_NIFTY_BANK	Positive	Stabilizes after ~10 days
DLN_NIFTY_BANK	DLN_FIN_25_50	Strong Positive	Declines gradually, stabilizes
DLN_FIN_25_50	DLN_NIFTY	Negative	Reverts after short-term spike
DLN_PVT_BANK	DLN_NIFTY	Mild Positive	Stable quickly
DLN_PSU	DLN_NIFTY_BANK	Volatile Positive	High fluctuation, weak convergence

Source: Impulse Response Function output (EViews). Formulated and illustrated by author.

Table 4.10: Forecast Error Variance Decomposition (VDC) – Selected Variables

Response Variable	Major Contributing Impulse	Own Shock (%)	Cumulative Contribution from Others (%)
DLN_NIFTY	DLN_NIFTY_BANK	61.4	38.6
DLN_NIFTY_BANK	DLN_FIN_25_50	52.1	47.9
DLN_FIN_25_50	DLN_NIFTY	55.7	44.3
DLN_PVT_BANK	DLN_NIFTY	67.9	32.1
DLN_PSU	DLN_NIFTY_BANK	48.3	51.7

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