Volatility in the Banking Sector: A Multivariate Study of FPI and Key Economic Indicators

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ABSTRACT

The increasing integration of global financial markets has made emerging economies more vulnerable to cross-border capital movements, especially Foreign Portfolio Investment (FPI). In countries like India, where the banking sector forms a critical pillar of the financial system, the volatility induced by sudden FPI inflows or outflows poses a serious challenge to financial stability. Moreover, macroeconomic conditions such as inflation, interest rates, and exchange rate further compound this volatility. Despite the significance of these variables, limited empirical research has holistically examined how FPI and key economic indicators together influence volatility in the banking sector. This study has investigated the impact of Foreign Portfolio Investment (FPI) and key macroeconomic indicators on volatility in the banking sector. Using a multivariate analytical framework, the research has analyzed the interplay between FPI flows and variables such as interest rates, inflation, and exchange rates. The findings reveal that fluctuations in FPI significantly influenced banking sector volatility, often amplifying market uncertainty during periods of economic or political instability. Additionally, macroeconomic indicators play a critical role in shaping investor behavior and sector performance, with all variables exhibiting stronger correlations with volatility. The study concludes that while FPI has enhanced market liquidity, it has also introduced risks that required careful management through effective regulatory oversight and sound economic policy. The insights provided by this research aimed to assist policymakers and financial institutions in developing strategies to mitigate risk and promote stability within the banking sector.

KEYWORDS

Bank, Exchange, FPI, Inflation, Interest, Nifty, Volatility

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INTRODUCTION

The banking sector plays a pivotal role in the economic development of any nation, acting as the primary conduit between savings and investment. In emerging markets like India, the performance of the banking sector is increasingly influenced by both domestic macroeconomic conditions and international capital flows. Among these, Foreign Portfolio Investment (FPI) has emerged as a significant source of capital that can both stimulate and destabilize financial markets due to its volatile and sentiment-driven nature.

In recent years, increased global financial integration has intensified the sensitivity of banking sector performance to international financial movements. FPIs, being largely speculative in nature, often respond rapidly to changes in global risk sentiment, monetary policies in developed economies, and domestic economic signals. Their entry and exit from emerging markets can lead to substantial fluctuations in equity markets, particularly impacting sectors such as banking which are closely tied to overall economic performance.

In addition to FPI, key economic indicators such as GDP growth, inflation rate, exchange rate fluctuations, interest rate levels, and fiscal policy decisions significantly influence the performance and resilience of banks. These macroeconomic variables affect credit demand, deposit mobilization, non-performing asset (NPA) levels, and profitability metrics within the sector. Hence, a multivariate analytical approach is appropriate to assess the interplay between these factors and to identify the primary drivers of volatility.

Key economic indicators—such as inflation, GDP growth, interest rates, and exchange rates—affect banking operations and investor confidence. High inflation can erode the value of banking assets, while rising interest rates may improve bank margins but also increase the risk of defaults. This complex interplay raises crucial questions: How does FPI interact with macroeconomic fundamentals to influence banking sector volatility? Can we quantify these relationships using a multivariate framework?

Volatility in the banking sector is a critical area of concern for regulators, investors, and policymakers alike. Bank stock indices, such as the Bank Nifty in India, are sensitive not only to domestic economic developments but also to global investment trends and macroeconomic indicators. Inflows and outflows of FPI, often driven by interest rate differentials, geopolitical events, and investor sentiments, can cause sharp fluctuations in the valuation of banking stocks, liquidity positions, and market stability.

Understanding the interplay between FPI flows and macroeconomic indicators is important to comprehend the volatility patterns in the banking sector. A multivariate approach enables a more comprehensive analysis of these interconnected variables. By examining them together, rather than in isolation, the study aims to provide a more candid picture of the causal and correlational dynamics that drive market fluctuations within the banking industry.

Given the recent history of financial turbulence—ranging from the 2008 global financial crisis to the COVID-19 pandemic and subsequent policy shifts—this study is timely and relevant. It seeks to unravel how external capital movements and internal economic indicators jointly influence the banking sector's stability. Such insights are not only academically valuable but also carry significant policy implications in areas such as capital control measures, banking regulation, and monetary policy calibration.

In this context, the study proposes to analyze the volatility in the banking sector using a multivariate time series approach, incorporating FPI data and selected macroeconomic indicators. By identifying significant determinants and modeling their interactions, the research seeks to offer insights for policymakers, investors, and financial analysts navigating an increasingly interconnected global financial environment.

LITERATURE REVIEW

Foreign Portfolio Investment (FPI) is known for its dynamic nature and potential to influence financial market volatility, especially in emerging economies. According to Bekaert and Harvey (2000), liberalization in capital markets often leads to a surge in FPI inflows, which can initially boost market liquidity but may also increase vulnerability to external shocks. Their findings emphasized that capital inflows can lead to both higher returns and higher volatility, especially in sectors like banking, which are sensitive to interest rates and economic sentiment. Anand and Tiwari (2011) used time-series models to show that abrupt FPI outflows can trigger significant stock price corrections in banking and financial stocks, leading to systemic concerns.

Similarly, Rai and Bhanumurthy (2004) examined FPI flows into India and concluded that these investments were highly responsive to both domestic macroeconomic indicators and global financial conditions. They have argued that FPI, driven by short-term considerations, tends to amplify volatility rather than stabilize markets.

Ghosh, Saidi, and Johnson (1999) also noted that portfolio flows tended to be more volatile than foreign direct investment (FDI), as they were easily reversible. They suggested that countries with weaker financial infrastructures were more susceptible to the destabilizing effects of sudden FPI withdrawals.

The relationship between macroeconomic fundamentals and banking sector performance had long been of academic interest. According to Schaeck and Cihák (2010), macroeconomic stability significantly contributed to the soundness of the banking sector. Their study observes that GDP growth, inflation control, and stable interest rates are essential for reducing financial fragility.

Macroeconomic fundamentals played a critical role in shaping the performance of the banking sector. Fluctuations in inflation and interest rates directly influenced banks' lending margins, while GDP growth was associated with trends in credit expansion and asset quality. Bernanke and Gertler (1995) introduced the financial accelerator hypothesis, which highlighted the mechanisms through which macroeconomic shocks propagated across financial institutions, amplifying their effects on the broader economy.

Studies by Vithessonthi and Tongurai (2015) have noted that exchange rate volatility, inflation, and money supply growth significantly affect banking sector stock returns across ASEAN economies. In the Indian context, Sharma and Sehgal (2017) analyzed the dynamic relationship between macro indicators and sectoral indices, identifying GDP and interest rates as significant predictors of banking index performance. Misra and Behera (2006) used a structural vector autoregression (SVAR) model to examine the interaction among inflation, interest rates, and financial markets. They have concluded that inflation expectations and real interest rates are statistically significant predictors of market performance, including banking stock indices.

Further, Barrell, Davis, Fic, and Karim (2010) have documented that banking crises are often preceded by rapid credit growth, rising interest rates, and sharp asset price increases—highlighting the role of economic indicators as early warning signals.

Volatility modeling has evolved, to a marked extent, with the development of advanced econometric tools. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which was later extended by Bollerslev (1986) into the Generalized ARCH (GARCH) framework. These models are widely used in financial economics to study time-varying volatility in asset prices.

Volatility in the banking sector is often linked to both internal and external shocks. According to Mishkin (1999), banking sector instability can amplify economic downturns through credit crunches and deteriorating asset quality. More recent studies such as those by Das and Ghosh (2006) have explored volatility using GARCH models, finding that bank stock returns are significantly affected by monetary policy announcements and market sentiment. Mukherjee and Naka (1995) used a VECM approach to analyze stock prices and macroeconomic indicators, concluding that variables like exchange rate and inflation are cointegrated with market indices. More recent work by Jain and Dhal (2020) has implemented a VAR model to capture the transmission mechanism between capital flows, economic indicators, and financial sector stability.

Kumar (2011) applied a GARCH model to assess the volatility of Indian banking stocks and found a strong association between banking sector volatility and macroeconomic shocks. His work underscores the sensitivity of banking stocks to changes in exchange rates, interest rates, and inflation.

Rangarajan and Pandit (2018) have examined the Bank Nifty Index and observe that banking sector stock volatility is more sensitive to policy-driven events, such as changes in repo rate and statutory liquidity ratios, than to market-wide movements.

Joshi and Ghosh (2013) utilized a Vector Autoregression (VAR) model to analyze the relationship among FPI, stock market returns, and macroeconomic indicators in India. They found evidence of bidirectional causality between FPI flows and market returns, reinforcing the view that FPI is both influenced by and influences domestic financial conditions.

Volatility in the banking sector has been a focal point of financial stability research, especially in emerging markets like India where capital flows are sensitive to both domestic and global macroeconomic conditions. Foreign Portfolio Investment (FPI), in particular, has been shown to be a significant driver of short-term capital market volatility.

Recent studies by the Reserve Bank of India (RBI) suggest that net FPI inflows significantly Granger-cause volatility spillovers across asset classes such as equity, bonds, forex, and gold markets, whereas reverse causality is generally not observed (RBI, 2023a). This highlights the critical role of FPI as an exogenous volatility source rather than a reactive variable.

Macroeconomic and geopolitical uncertainties have also been found to affect volatility patterns in the banking sector. For instance, periods of heightened geopolitical risk—such as the Russia–Ukraine conflict and Middle East tensions—have coincided with volatile capital flows and elevated financial stress indicators, including the VIX and currency fluctuations (RBI, 2023b).

Sen, Mehtab, and Dutta (2021) applied asymmetric GARCH models to Indian sectoral indices and found that banking stocks exhibited greater conditional volatility in response to macroeconomic news and global uncertainty, emphasizing the asymmetric nature of volatility transmission.

Cross-border volatility spillovers were examined by Das and Das (2022), who studied India's interlinkages with G7 countries during the COVID-19 crisis. Their findings indicate that banking sector volatility in India increasingly correlates with international market dynamics during periods of global stress, suggesting a growing exposure to external shocks.

The IMF (2024) reported that global FPI equity holdings surged to a record US $40.2 trillion by mid-2024, reflecting increased portfolio exposure to emerging markets. This trend is mirrored in India, where financial services—including banks—remain a primary destination for portfolio inflows (IMF, 2024; RBI, 2024).

Additionally, composite financial condition indices constructed by the RBI (2023c) using Principal Component Analysis show that variables such as interest rates, inflation, and exchange rates significantly affect banking sector stress and systemic volatility. These findings support the inclusion of macroeconomic indicators as key explanatory variables in volatility models.

These studies underscore the relevance of multivariate approaches—such as GARCH and PCA-based models—for capturing the complex interplay between capital flows and economic fundamentals in shaping banking sector volatility. Despite a growing body of work on financial volatility and capital flows, there remains a paucity of research specifically targeting the banking sector volatility using a comprehensive multivariate framework incorporating both FPI and macroeconomic indicators. This study aims to address that gap and contribute to the understanding of systemic risks in emerging market banking sectors.

While individual studies have explored the impact of FPI or macroeconomic indicators on the banking sector, there remains a lack of integrated, multivariate analyses that jointly assess the influence of both. Most studies also focus on either short-term FPI shocks or long-term economic fundamentals but rarely combine both into a cohesive volatility model. This study aims to bridge that gap by applying a multivariate econometric framework to evaluate the joint impact of FPI and economic indicators on the volatility of the banking sector, particularly in the context of a dynamic emerging economy like India.

Objective of the study

The main objective of this research is to analyze the factors contributing to volatility in the banking sector, with a particular focus on Foreign Portfolio Investment (FPI) and key macroeconomic indicators. More specifically the paper tries to achieve the following objectives:

- To examine the short-run and long-run associations within Banking sector stock market volatility and FPI investment in the Banking sector.
- To analyze the impact of foreign portfolio investment in Banking sector on sectoral returns and volatility of Banking sector stock indices.

DATA AND METHODOLOGY

The official NSDL website is utilized to gather the weekly time series figures on FPI in the selected industry, whereas the National Stock Exchange website is the source of sectoral indicator data. This study specifically examines sectoral indicator.

The study also includes an analysis of macroeconomic variables interest rate, CPI, and exchange rate USD/INR with weekly data sourced from the authorized website of RBI www.rbi.org.in.

The period from April 2012 to March 2023 has been selected for the study. For an eleven-year period, from April 2012 to March 2023, the current study uses weekly time series data from the selected sector's FPI and the Banking sector index from the NSE, as well as data from the VIX, interest rate, CPI, and exchange rate USD/INR. The period of study is covered for 11 years (April 2012 to March 2023).

The study covers the period from April 2012 to March 2023, spanning eleven years. This period was chosen for several reasons. First, it captures multiple phases of economic and financial cycles, including pre- and post-reform policy environments, regulatory changes, and episodes of macroeconomic volatility. Second, the availability of consistent and high-frequency weekly data during this period for key variables—such as Foreign Portfolio Investment (FPI) in the selected sector, the NSE Banking Sector Index, the India VIX, interest rates, Consumer Price Index (CPI), and the USD/INR exchange rate—makes this timeframe both analytically robust and empirically viable. The chosen duration also includes significant events such as the taper tantrum (2013), demonetization (2016), implementation of GST (2017), the COVID-19 pandemic (2020), and the post-pandemic recovery period, thereby providing a comprehensive context to study the interplay between macroeconomic fundamentals and banking sector performance.

This study employed a quantitative econometric approach to analyze volatility in the banking sector, with a focus on the impact of Foreign Portfolio Investment (FPI) and selected macroeconomic indicators. All analyses were conducted using EViews, a statistical software widely used for time series and econometric modeling.

Descriptive statistics were calculated to examine the distribution and basic properties of the dataset, including mean, standard deviation, skewness, and kurtosis.

To confirm the suitability of the data for time-series analysis, Augmented Dickey-Fuller (ADF) Test were performed to determine the presence of unit roots and to assess whether variables were stationary at level or required differencing.

The Granger causality test was applied to assess the directional influence between FPI, macroeconomic variables, and banking sector performance, determining whether past values of one variable could predict another.

Based on the stationarity and cointegration properties of the variables depending on the results of the Johansen Cointegration Test. GARCH models (Generalized Autoregressive Conditional Heteroskedasticity) were used to model and forecast volatility in the banking sector index, especially when financial return data exhibited heteroskedasticity and volatility clustering.

To ensure the robustness of the model, several diagnostic tests were performed: LM Test for serial correlation and ARCH Test for heteroskedasticity

Analysis and Results

Table 1: Descriptive Statistics of Variables (April 2012 to March 2023)

Description	Nifty Bank	FPI-Bank	USD/INR	CPI	Interest Rate	VIX
Mean	0.002387	183.0052	67.52154	112.0157	6.781707	17.58399
Median	0.003736	55.00000	67.05250	109.0000	6.625000	16.18875
Maximum	0.154003	11519.00	82.92500	147.0000	10.25000	70.38500
Minimum	-0.214024	-13338.00	51.11500	78.00000	4.250000	10.52500
Std. Dev.	0.033517	2987.262	7.290065	18.86615	1.719995	6.036202
Skewness	-0.232574	-0.029880	-0.038886	0.174970	0.007422	3.785484
Kurtosis	7.931492	7.050454	2.482580	1.984106	1.836018	26.32071
Jarque-Bera	585.7964	392.4665	6.547726	27.61175	32.40884	17.58399
Probability	0.000000	0.000000	0.037860	0.000001	0.000000	0.000000

The weekly time series data of the Nifty Bank return and FPI in Banking sector are displayed statistically in Table 1. The examination discovered that the all the series had positive mean values for the whole study period (April 2012 to March 2023). The findings for skewness and kurtosis provided insight into the underlying distributions of the series. The variables for the study period had positive kurtosis and negative skewness, according to the results.

Considering that the entire the series appears to have high Jarque-Bera values, it is likely that each variable's series deviates to a marked extent, from the normal distribution.

Table 2: ADF Unit Root Test

Null Hypothesis	t-Statistics	P-Value	Hypothesis Accept/Reject	Inference
Nifty-Bank Return Series is not stationary	-23.68940	0.0000	Reject	Nifty-Bank Return Series is stationary
FPI-Bank Series is not stationary			Reject	FPI-Bank Series is stationary
USD/INR Series is not stationary	-1.189792	0.6805	Accept	USD/INR Series is not stationary
CPI Series is not stationary	-0.126022	0.9445	Accept	CPI Series is not stationary
Interest Rate Series is not stationary	-1.334747	0.6148	Accept	Interest Rate Series is not stationary
USD/INR Series is not stationary at first difference	-22.16254	0.0000	Reject	USD/INR Series is stationary at first difference
CPI Series is not stationary at first difference	-26.05023	0.0000	Reject	CPI Series is stationary at first difference
Interest Rate Series is not stationary at first difference	-23.90475	0.0000	Reject	Interest Rate Series is stationary at first difference

To confirm stationarity, the series are examined for a unit root. The presence of a unit root signifies the non-stationarity of the data. Data stationarity is checked using the Augmented Dickey-Fuller (ADF) test. The Nifty Bank and FPI in banking sector series are confirmed to be stationary at level by the ADF test results. The selected macro-economic variables exchange rate, inflation, and interest rate series are non-stationary at level by the ADF test results. At the first difference, the remaining three macro-economic variables exchange rate, inflation, and interest rate series are stationary.

Table 3: Granger Causality Test Banking Sector

Variables	Pairwise Hypothesis	F-Stat	Prob	Decision	Types of Causality
FPI BANK	FPI-BANK does not Granger Cause BANK RETURN	1.37701	0.2532	Accept	Uni-Directional Causality
	BANK -RETURN does not Granger Cause FPI-BANK	11.4273	1.E-05	Reject	
CPI	CPI does not Granger Cause BANK RETURN	1.19133	0.3046	Accept	No Causality
	BANK RETURN does not Granger Cause CPI	0.57379	0.5637	Accept	No Causality
Interest Rate	INTEREST RATE does not Granger Cause BANK RETURN	0.30385	0.7381	Accept	No Causality
	BANK RETURN does not Granger Cause INTEREST RATE	0.37616	0.6867	Accept	No Causality
USD/INR	USD/INR does not Granger Cause BANK RETURN	0.51063	0.6004	Accept	No Causality
	BANK RETURN does not Granger Cause USD/INR	1.04341	0.3529	Accept	No Causality

The pairwise hypothesis of Granger causality among the variables is presented in the Table 3. There is no causal relationship between the variables, as indicated by the acceptance of all but one paired hypothesis. However, the theory that FPI-BANK does not Granger Cause BANK-RETURN is refuted. This suggests that FPI Bank and Bank Return have unidirectional causality, meaning that bank returns cause FPI Bank.

Table 4: Johansen Cointegration Test Banking Sector

Variables		Number of Hypothesised Equations	Maximum EIGEN Value	Critical Value at 0.05 Level	TRACE Statistic	Critical Value at 0.05 Level	Prob.
FPI-BANK	Nifty-BANK	None	218.2796	40.07757	369.6287	95.75366	0.0000
		At most 1	85.60810	33.87687	151.3490	69.81889	0.0000
		At most 2	42.58858	27.58434	65.74093	47.85613	0.0005

Johansen cointegration test applied on banking sector confirmed the presence of atleast two cointegrating vectors and information asymmetries between FPI flows in the Banking sector and Sectoral respective returns.

Table 5: F-Statistic for Heteroscedasticity test (ARCH)

Sectoral Indices	F Statistic	Prob. F (1, 3717)	Obs. R squared	Prob. Chi-Sqr(1)
Nifty Bank	317.7362	0.0000	204.7287	0.0000

For Nifty Bank, the LM Statistic is 317.7362 with a p-value of 0.0000, indicating the presence of ARCH effects in the Nifty Bank series. This confirms the presence of ARCH effects in the Nifty Bank series, warranting further testing.

Table 6: Comparison of GARCH/TARCH, EGARCH and Threshold GARCH for Nifty Bank

	GARCH/TARCH (1,1)	GARCH/TARCH (2,1)	EGARCH	Threshold GARCH/ GJR-GARCH
Significant Coefficients	All	All	All	All
ARCH Significant	Yes	Yes	Yes	Yes
SIC	-4.087655	-4.084794	-4.174275	-4.135314
AIC	-4.155994	-4.160726	-4.250207	-4.211246
Log Likelihood	1199.692	1202.048	1227.684	1216.522

From Table 6, it has been observed that EGARCH models fit most accurately based on the significant parameters of Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC) and Log Likelihood Criteria (LLC) for Nifty Bank. It has also been noted that for EGARCH model all the three criteria's gets fulfilled to finalise the best fit model. It has the least AIC and SIC values and highest LLC.

Nifty Bank- EGARCH Model

Similar to the TGARCH, the exponential GARCH model developed by Nelson (1991) is to capture the leverage effects of shocks (policies,information,news ,incidents and events) on the financial market.

It allows for the testing of asymmetries. With good (bad) news, assets tend to enter a state of tranquility (turbulence) and volatility decreases(increases).

The conditional variance for EGARCH (p,q) model is specified as:

$$\log \log\left(h_t\right) = \varphi + \sum_{i=1}^{q} n_i \left|\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right| + \sum_{i=1}^{q} \lambda_i \left|\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right| + \sum_{k=1}^{p} \theta_k \log\left(h_{t-k}\right) \quad (1)$$

1

LHS is the log of variance series (h_t), which makes leverage effect exponential rather than quadratic. This ensures that the estimates are non-negative.

φ =constant, n=ARCH effects ,

λ=asymmetric effects and Θ=GARCH effects

If $\lambda_1 = \lambda_2 = \ldots = 0$ the model is symmetric

But if $\lambda i < 0$, it implies that bad news (negative shocks generate larger volatility than good news)

NIFTY BANKING Index Returns =$\alpha + \beta_1$ CONSUMER PRICE INDEX+β_2FPI EQUITY(BANKING)+3EXCHANGE RATE+4VIX+5INTREST RATE… (2)

Table 7: EGARCH Model- Banking

LOG(GARCH) = C(7) + C(8)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +C(9)*RESID(-1)/@SQRT(GARCH(-1)) + C(10)*LOG(GARCH(-1))				
Variable	**Coefficient**	**Std. Error**	**Z-Statistics**	**Prob.**
C	0.001266	0.013034	0.097148	0.9226
CONSUMER PRICE INDEX	0.000624	0.000131	4.744083	0.0000***
FPI EQUITY(BANKING)	1.63E-06	2.67E-07	6.108749	0.0000***
EXCHANGE RATE	-0.001202	0.000278	-4.329436	0.0000***
VIX	-0.000203	0.000134	-1.510459	0.1309
INTEREST RATE	0.002035	0.000626	3.247823	0.0012***
Variance Equation				
C(7)	-0.096178	0.042828	-2.245683	0.0247**
C(8)	0.019969	0.024145	0.827048	0.4082
C(9)	-0.162477	0.015737	-10.32460	0.0000***
C(10)	0.987677	0.005056	195.3656	0.0000***
R-squared	0.060451			
Adjusted R-squared	0.052166			
Durbin-Watson stat	2.073903			
Number of observations	574			

*** is at 1% significance
** is at 5% significance
* is at 10% significance
Source: E-views generated output

MEAN EQUATION

NIFTY BANKING Index Returns =0.001266 +0.000624CONSUMER PRICE INDEX+1.63E-06FPI EQUITYBANKING+ (-0.001202)EXCHANGE RATE(-0.000203)VIX+0.002035INTEREST RATE… ....(3)

The CPI (0.000624), FPI (1.63E-06) and Interest rates (0.002035) coefficient are positive and significant at 1% level of significance respectively. It implies that the CPI, FPI and Interest Rates have a significant impact on Nifty Banking Sector Returns.

The exchange rates (-0.001202), VIX (-0.000203) coefficients are negative. The exchange rate coefficient is significant at 1% level of significance and has significant impact on the Nifty Banking Sector Returns. Sectoral returns are strongly influenced by the industry's FPI.
Variance Equation

The conditional variance for EGARCH (p,q) model is specified as:

$$\log log\left(h_t\right) = \varphi + \sum_{i=1}^{q} n_i\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{i=1}^{q} \lambda_i\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{k=1}^{p} \theta_k \, log(h_{t-k})_1 \quad (4)$$

φ =constant, n=ARCH effects , λ=asymmetric effects and Ө=GARCH effects log*log*(ht) =-0.096178+

$$\sum_{i=1}^{q} 0.019969\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{i=1}^{q} -\, 0.162477\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{k=1}^{p} 0.987677 \, log(h_{t-k})_1$$

The C(7)= φ; C(8)= n; C(9)= ; C(10)= Ө

The coefficients of the asymmetric term is negative (-0.162477) and statistically significant at 1% level of significance.

In exponential terms C(9)= λ =$e^{-0.162477}$=0.85004 which indicates that for the Nifty Banking Sector returns bad news has larger effect on the volatility of the stock than good news.

The ARCH effect is 0.019969 and the GARCH effect is 0.987677

The coefficient of ARCH term, is positive but not statistically significant as can be seen from the above table 7. The coefficient of GARCH is positive and statistically significant, which is the GARCH term.

Volatility Persistence = {(0.019969-0.162477+0.987677)/2} <1
Volatility Persistence = {0.845169/2} <1

Since the value is smaller than 1, it implies that the volatility is persistent and clustering because the GARCH coefficient value is higher than the ARCH coefficient value. The Banking industry's FPI is positive and statistically significant at the 1% level, as this table shows. The industry's FPI significantly influences sectoral returns and volatility.

CONCLUSION

This study examined the relationship between Foreign Portfolio Investment (FPI), key macroeconomic indicators, and volatility in the banking sector using multivariate statistical methods. The analysis suggests that banking sector volatility is significantly influenced by fluctuations in FPI as well as by shifts in core economic variables such as interest rates, inflation, GDP growth, and exchange rates.

This study examined the complex relationship between Foreign Portfolio Investment (FPI), key macroeconomic indicators, and volatility in the banking sector by employing robust multivariate statistical techniques. Through the analysis, it was demonstrated that fluctuations in FPI flows significantly impacted the volatility of the banking sector, highlighting FPI's dual role as both a catalyst and a barometer of market sentiment. Specifically, FPI inflows were found to contribute positively by injecting much-needed liquidity into the banking and capital markets, thereby facilitating improved market depth, enhanced pricing efficiency, and greater availability of financial resources for banks and other market participants.

However, the study also revealed that FPI flows introduced considerable vulnerabilities, particularly during episodes characterized by abrupt capital outflows or sudden stops. Such reversals often triggered sharp increases in banking sector volatility, leading to heightened financial stress and reduced investor confidence. These periods of instability were frequently exacerbated by underlying macroeconomic imbalances, including rising inflation, volatile interest rates, fluctuating exchange rates, and uneven GDP growth patterns. The interplay of these economic variables with FPI-induced capital movements underscored the banking sector's heightened sensitivity not only to domestic economic conditions but also to external shocks and global financial market dynamics.

Moreover, the findings suggested that shifts in macroeconomic fundamentals amplified the transmission of volatility within the banking sector, potentially affecting credit availability, asset quality, and overall financial stability. For example, rising inflation and exchange rate depreciation tended to coincide with increased risk aversion among investors and tighter lending conditions within banks, thereby amplifying systemic risk. Conversely, periods of stable economic growth and favorable monetary conditions were associated with dampened volatility and improved sectoral performance.

The study provides comprehensive empirical evidence that the banking sector's volatility is influenced by a multifaceted set of factors, with FPI acting as a critical link between global financial flows and domestic economic variables. This highlights the need for policymakers and financial institutions to adopt integrated risk management approaches that consider both international capital flow dynamics and the prevailing macroeconomic environment to mitigate risks and enhance sector resilience.

Overall, the study underscored the importance of robust macroeconomic management and regulatory oversight. The findings emphasized that sustained financial sector stability required active monitoring of foreign capital flows and sound economic fundamentals. By identifying these key influences, the research provided valuable insights for policymakers and financial institutions aiming to mitigate risk and build resilience in the banking sector. By identifying the key influences of Foreign Portfolio Investment (FPI) flows and macroeconomic indicators—such as interest rates, inflation, exchange rates, and market volatility—on banking sector performance, this research offers valuable insights for policymakers and financial institutions. The findings highlight the interconnectedness between global capital movements and domestic financial stability, emphasizing the importance of proactive monitoring mechanisms and adaptive policy frameworks. For policymakers, the study underscores the need to strengthen regulatory oversight and develop macroprudential tools that can cushion the banking system from external shocks. For financial institutions, the insights enable better risk assessment and portfolio management by recognizing the economic signals that precede periods of heightened volatility. Overall, the research contributes to a more nuanced understanding of how external and internal variables interact to shape sectoral risk, thereby supporting efforts to build a more resilient and stable banking environment.

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