IMPACT OF USD-INR CURRENCY VOLATILITY ON NIFTY SECTOR

ABSTRACT

This study investigates the impact of USD-INR exchange rate volatility on the performance of selected NIFTY sector indices, providing a sector-wise perspective that has been largely overlooked in prior research. Using daily and monthly data from January 2020 to May 2025, the research applies advanced econometric methods, including Correlation Analysis, Vector Autoregression (VAR), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) modelling, and Granger Causality testing, to analyze the dynamic relationship between currency fluctuations and sectoral stock movements. Five sectors FMCG, Automobile, Information Technology, Pharmaceuticals, and Media were selected based on their correlation coefficients with the USD-INR rate, ensuring coverage of high-, medium-, and low-sensitivity groups. Results reveal that while correlation values vary significantly across sectors, VAR impulse response functions and Granger causality tests indicate no statistically significant direct predictive impact of USD-INR shocks on these sectors over the studied period. GARCH modelling confirms volatility clustering in the USD-INR series, with major spikes during the COVID-19 pandemic (2020), global inflationary pressures (2022), and recent economic adjustments (late 2025), yet sectoral indices remained largely insulated due to factors such as domestic demand resilience, effective hedging strategies, and long-term contractual revenue structures. The findings suggest that macroeconomic and sector-specific fundamentals rather than short-term currency movements were the dominant drivers of sectoral performance during this period. This nuanced, time-sensitive analysis offers valuable insights for investors, policymakers, and financial advisors, emphasizing the importance of focusing on sectoral fundamentals and policy measures rather than relying solely on currency volatility as an investment signal.

KEY WORDS:

USD-INR, NIFTY sectors, Sectoral analysis, Exchange rate risk, VAR, GARCH, Granger causality.

CHAPTER I

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1.1 INTRODUCTION TO THE STUDY

In today's interconnected world, the impact of exchange rate fluctuations on equity markets has become increasingly significant, particularly in dynamic emerging economies like India. The USD-INR exchange rate, which represents the value of the Indian Rupee against the US Dollar, is a crucial indicator in the Indian financial landscape. Its movements directly affect trade dynamics, capital flows, inflation rates, and overall investor confidence. The NIFTY index, comprising the top 50 companies listed on the National Stock Exchange (NSE), serves as a benchmark for evaluating the health and direction of the Indian stock market. It's important to note that different sectors within the NIFTY respond differently to currency volatility. For instance, sectors such as Information Technology, Pharmaceuticals, and Oil and Gas, due to their significant international exposure, are particularly sensitive to changes in exchange rates compared to more domestically-focused sectors. This study aims to explore how the volatility of the USD-INR currency pair influences the performance of various NIFTY sectors. By examining sector-specific responses, I plan to identify both short- and long-term trends, providing valuable insights for investors, policymakers, and corporate strategists. Understanding these complex dynamics is essential for effective risk management, informed portfolio diversification, and sound policy formulation in an ever-evolving global economy. Gaining this knowledge empowers stakeholders to navigate challenges and seize opportunities within the financial landscape.

The **USD-INR exchange rate** represents the value of the Indian Rupee in terms of the United States Dollar essentially, how many rupees are needed to buy one dollar. This rate is a vital barometer for the Indian economy, as the US Dollar is the most widely used currency in global trade, finance, and investment. Fluctuations in this rate are inevitable, influenced by factors such as interest rate differentials, inflation levels, trade balances, foreign capital flows, and geopolitical developments.

When the USD-INR exchange rate changes significantly over a short period, it is referred to as **exchange rate volatility**. Such volatility has far-reaching consequences: it impacts import and export costs, alters corporate earnings (especially for companies with international exposure), influences inflationary pressures, and affects investor sentiment in financial markets. For a globally connected emerging economy like India, these effects can be amplified, making exchange rate movements a critical area of study for economists, policymakers, and market participants.

The **NIFTY 50 index**, which tracks the performance of the top 50 companies listed on the National Stock Exchange, serves as a benchmark for the overall health of the Indian equity market. However, this index is composed of companies from multiple sectors, each with different levels of exposure to foreign markets. For instance, **IT and pharmaceutical sectors** often benefit from a weaker rupee due to higher export revenues, while **oil and gas** companies may face rising import costs. Conversely, more domestically focused sectors may remain relatively insulated from currency fluctuations.

Comparing USD-INR volatility with sectoral movements within the NIFTY allows us to pinpoint which industries are most sensitive to exchange rate changes and in what direction they respond. This comparison not only helps investors optimize portfolio diversification and hedge currency risks but also provides valuable input for corporate strategy and economic policy-making. Understanding this relationship is essential in today's interconnected financial environment, where currency movements can quickly ripple across markets and influence long-term growth trajectories.

1.2 BACKGROUND OF THE STUDY

The USD stands as the most powerful currency in global trade, with a substantial portion of India's international transactions conducted in USD, even when the U.S. is not a direct participant. This dependence on imports, particularly crude oil and electronics, which are all priced in USD, renders India's economy especially vulnerable to fluctuations in the USD-INR exchange rate. Major players in the NIFTY index, particularly those in the IT, pharmaceuticals, and oil and gas sectors, have significant exposure to the dollar, making their financial health contingent on exchange rate movements. Moreover, a large share of foreign institutional investments in India comes from the U.S., establishing the USD-INR rate as a pivotal element for market stability and shaping investor sentiment. The USD-INR currency pair is among the most closely monitored in the financial world, yielding rich data that can drive insightful analysis. Recognizing its macroeconomic significance, the Reserve Bank of India (RBI) diligently observes and intervenes in this market. This focus on USD-INR volatility is essential for deciphering policy impacts and understanding the dynamics of financial markets. Hence, a thorough understanding of this currency pair is not just relevant it's crucial for anyone invested in India's economic landscape.

1.3 COMPANY PROFILE

Geojit Financial Services Ltd.

Established in 1987 by Mr. C. J. George in Kochi, Kerala, Geojit Financial Services Ltd. is a leading investment services company in India with a strong footprint both within the country and across the Gulf Cooperation Council (GCC) region. A pioneer in digital trading solutions, Geojit was among the first to introduce online trading in India with its internet-based platform in 2000, followed by a mobile trading application in 2010. As of 2025, the firm caters to over 1.4 million clients and manages assets under custody exceeding ₹1 lakh crore. It operates through a robust network of more than 500 offices nationwide. Geojit offers a comprehensive suite of financial services, including equity and derivatives trading, currency and commodity futures, mutual fund distribution through its Funds Genie platform, portfolio management services, insurance products, IPO investment advisory, and margin funding. The company is supported by prominent stakeholders such as BNP Paribas, KSIDC, C. J. George, and RARE Enterprises, led by the late Rakesh Jhunjhunwala. Its strategic joint ventures in countries like the UAE, Kuwait, Oman, and Bahrain have enabled it to effectively serve the investment needs of non-resident Indians (NRIs) and international clients. For the financial year ending March 2024, Geojit reported a consolidated net profit of ₹149.4 crore, with total revenue reaching ₹624 crore. The firm added over 1 lakh new clients during the year and increased its assets under management from ₹64,500 crore to ₹93,100 crore. Its group structure includes subsidiaries such as Geojit Technologies, Geojit Credits, Tech Loan, IFSC Ltd., and Geojit Investments Ltd., along with key partnerships like Barjeel Geojit and Qurum Geojit. Geojit's strong reputation in the market is backed by its commitment to technology-driven innovation. Trading and investment platforms like Flip, Selfie, FundsGenie, and Smartfolios demonstrate its continuous efforts to empower retail investors, high-net-worth individuals (HNIs), and NRIs with user-friendly and efficient financial tools. Its blend of technological advancement, experienced leadership, and global reach positions Geojit as a trusted and dynamic player in India's financial services landscape. Geojit has simplified investing for both retail and NRI investors, but it faces a key challenge: the frequent fluctuations in the USD-INR exchange rate. Many of its clients invest in NIFTY sectors such as IT, Pharma, and Oil & Gas, which are heavily influenced by currency movements, impacting company profits and investor sentiment.

However, most retail investors are unaware of how these fluctuations affect different sectors, which can lead to poor investment decisions. This study aims to analyze the impact of USD-INR volatility on NIFTY sectors, helping Geojit strengthen its research insights, portfolio recommendations, and investor support services.

1.4 STATEMENT OF THE PROBLEM

- USD-INR volatility poses a major challenge for Indian investors, especially those using platforms like Geojit, as many NIFTY companies are directly impacted by fluctuations in the exchange rate.
- Retail investors often lack awareness of how currency volatility affects different sectors, leading to poor investment choices and increased financial risk.
- There is a lack of sector-wise analysis on the impact of USD-INR volatility in existing research, making it difficult for investors and advisors to make informed portfolio decisions.
- A detailed study is needed to understand these sector-specific effects, so platforms like Geojit can provide better guidance, data-driven research, and personalized investment strategies.

1.5 MILESTONE AND INNOVATIONS

- 1987: Founded by C. J. George as C.J. George & Co., later renamed Geojit & Co. in 1988 after formal partnership.
- 1995: Converted to a public limited company; joined National Stock Exchange (NSE).
- 1999–2000: Became a member of Bombay Stock Exchange (BSE), integrated the first bank payment gateway in India for internet trading, and pioneered online trading in equity and derivatives.
- 2001: Joint venture in UAE with Barjeel, serving NRI customers; first depository internet transactions.
- 2003–05: Launched online futures trading in rubber, pepper, gold, cardamom, coffee; formed Geojit Commodities and Geojit Technologies; Geojit Credits registered as NBFC Technology Firsts & Recognitions (2005–2015).
- 2005: Created an integrated online/offline trading platform; achieved CMMI Level 3 appraisal.
- 2007: Axis Bank B2B2C integration won IBA award.

- 2008: FLIP platform launch; full Direct Market Access for institutions; CMMI Level 3 appraisal confirmed.
- 2010: Debut of FLIP-Me, India's first mobile trading app; MD awarded Manager of the Year; BNP Paribas became majority shareholder
- 2011–12: Received BNP Paribas Innovation Award; developed mobile and digital banking platforms for BNP Paribas in Europe and n-tv award in Germany.
- 2013: Launched FLIP Social on Facebook, one of India's first FB trading apps; multiple awards for digital deposit products with BNP Paribas.
- 2014: Kochi office earned LEED Gold for green building design.
- 2015: Geojit Technologies achieved CMMI Level 5 appraisal (via KPMG) 2017: Launched "Steps" financial planning tool; rebranded to Geojit Financial Services on its 30th anniversary; rolled out Funds Genie (MF investment) and Selfie platform.
- 2018: Funds Genie app introduced.
- 2019: Digital client onboarding via "Hello Geojit"; launched multi-cap PMS "Dakshin"; expanded wealth division "STEPS".
- 2020–21: Launched Smartfolio stock baskets, WhatsApp channel, Ethical Portfolio PMS, and global investment platform.
- 2022: Introduced Loan-Against-Shares ("Geojit Credits"); enabled IPO via WhatsApp.
- 2023: Set up Private Wealth Services; launched IFSC at GIFT city; digital Loans-AGM platform introduced.
- 2024: Released a revamped FLIP platform and expanded Private Wealth division.

1.6 AWARDS AND RECOGNITIONS

- IBA Awards (2007–08): For Axis Bank B2B2C integration.
- BNP Paribas Innovation Award (2011): For FLIP-Me n-tv Best Direct Bank (2012): Recognition for mobile banking app.
- Trade-Tech India Award and Pan Arab Web Awards (2011): For excellence in mobile application and web design.
- CMMI Level 5 (2015): Highest maturity in software processes.

1.7 SWOT ANALYSIS

STRENGTHS	WEAKNESSES
First mover in online trading	Declining profitability ratios
Extensive digital and physical reach	Shrinking liquidity (current ratio)
Diverse financial products	Platform usability complaints
Established brand & client trust	High operating costs
Tech-driven innovations	Heavy reliance on core services
OPPORTUNITIES	**THREATS**
Growing retail investor base	Fierce fintech competition
Expansion in GCC and NRI segments	Regulatory & economic volatility
New wealth and advisory services	Cybersecurity vulnerabilities
Adoption of AI/analytics tools	Talent acquisition challenges
Broader digital transformation	Reputational risks from service issues

1.8 OBJECTIVE OF THE STUDY

- To analyze the impact of USD-INR currency fluctuations on stock prices of selected NIFTY companies.
- To examine the trend and volatility of the USD-INR exchange rate over a specific period.
- To provide strategic insights and recommendations for investors and financial advisory platforms based on the findings.

1.9 LIMITATION OF THE STUDY

- The analysis is based on a specific period, which may not capture long-term patterns or structural changes in the economy.
- Only selected NIFTY sectors are considered, while other sectors that may also be impacted by USD-INR volatility are excluded.
- The study focuses solely on the USD-INR currency pair and does not include the effects of other foreign exchange rates.
- The study relies on secondary data such as stock prices and exchange rates, which may contain reporting errors or limitations in accuracy.

CHAPTER II

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2.1 REVIEW OF LITERATURE

Agrawal and Kumar (2025) conduct an in-depth examination of the dynamic interrelationships among major financial asset classes namely stock markets, exchange rates, oil prices, and gold prices within the context of a rapidly evolving, globally interconnected economy. Their work highlights the need for more nuanced analytical approaches in response to the increasing complexity and heightened volatility of financial markets in the post-globalization era. Drawing on an extensive review of prior literature, they summarize empirical evidence that reveals both positive and negative causal linkages between these assets, with relationships often shifting in response to macroeconomic conditions and external shocks. Earlier studies, employing econometric techniques such as the Vector Autoregression (VAR), Autoregressive Distributed Lag (ARDL) models, and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) frameworks, have shown that correlations among these markets are neither constant nor linear. Notably, the authors emphasize how geopolitical crises, global pandemics, and commodity market disruptions tend to intensify or reverse these interdependencies, thereby challenging static portfolio diversification strategies. They also highlight the importance of cointegration testing in detecting long-term equilibrium relationships, which is crucial for both policymakers and investors seeking to design resilient financial portfolios. However, Agrawal and Kumar identify a critical research gap: despite the growing integration of India's financial system with global markets, there remains a scarcity of long-term, high-frequency empirical analyses focusing specifically on the Indian context. To address this, they advocate for the application of Vector Error Correction Models (VECM) in combination with high-frequency datasets, which can capture both the short-term adjustments and the long-run equilibria between these interconnected markets, thereby offering richer insights into market dynamics and policy implications.

Marisetty (2024) offers a comprehensive synthesis of global empirical research on the cointegration and correlation patterns among major currency pairs, with a particular emphasis on the USD/INR and its interactions with other prominent exchange rates, including USD/EUR, USD/GBP, USD/JPY, and USD/CHF. Drawing on a wide range of studies, the review highlights findings derived from advanced econometric methodologies such as the Johansen cointegration framework and the Engle–Granger two-step procedure, which are used to detect both long-term equilibrium relationships and short-term volatility dynamics in foreign exchange markets. While several currency pairs demonstrate statistically significant cointegration indicating the presence of stable, long-run linkages the USD/INR pair consistently exhibits weak or incomplete long-term adjustment mechanisms, suggesting that its movements are more influenced by short-run shocks than by persistent equilibrium forces. Marisetty further identifies a notable gap in the literature: research on emerging market currencies, particularly those with unique macroeconomic structures like India, remains limited compared to that on advanced economies. The study calls for policy-oriented investigations that integrate the role of central bank interventions, exchange rate regimes, and macroeconomic volatility in shaping currency relationships, thereby enhancing the relevance of empirical findings for policymakers, investors, and risk managers operating in increasingly volatile global currency markets.

Trivedi and Apte (2016) present a comprehensive review of the theoretical underpinnings and empirical evidence on central bank interventions in foreign exchange markets, with particular attention to managed float regimes such as India's. They identify three principal channels through which interventions operate monetary impact, portfolio balance, and signaling and compile mixed global evidence regarding their effectiveness. While several studies suggest that interventions can dampen exchange rate volatility under certain conditions, others indicate that such actions may intensify short-term market fluctuations. The review further underscores the influence of market participants' expectations in shaping intervention outcomes and highlights the distinctive policy behavior of the Reserve Bank of India (RBI), which employs both direct and indirect measures to manage exchange rate movements.

Sen and Chakrabarti (2014) examine both traditional and emerging perspectives on central bank intervention, focusing specifically on the USD/INR exchange rate. While classical frameworks emphasize interest rate adjustments and foreign reserve management, the authors stress newer insights into the nonlinear and chaotic dynamics of foreign exchange markets, which challenge the effectiveness of conventional tools. Drawing on international evidence, they note that interventions can, at times, exacerbate volatility rather than mitigate it. The paper highlights the limited effectiveness of India's interventions in stabilizing the rupee and calls for the application of nonlinear modeling approaches, such as GARCH models and chaos theory, to better capture the complexity of exchange rate behavior.

Iqbal, Nosheen, and Wohar (2023) contribute to the discourse on exchange rate volatility and international trade by introducing the "third-country" effect in the context of India US commodity trade a factor often overlooked in bilateral exchange rate studies. Their research explores how volatility in cross-currency exchange rates, particularly rupee yen and dollar yen pairs, influences India’s trade flows. Using time series data across 79 export and 81 import commodity sectors, the study reveals significant sectoral sensitivity to third-country currency risks. For exports, rupee dollar volatility impacts 15 industries in the short run and 9 in the long run; for imports, it affects 25 sectors in the short term and 15 in the long term. Additionally, rupee yen fluctuations influence 9 import sectors in both time frames. The authors emphasize the need for multi-currency risk considerations in trade modeling and for policy frameworks that account for the complex interplay between exchange rate volatility and international trade performance.

Smita Mahapatra and Saumitra N. Bhaduri (2019) study emphasises the significant impact of currency fluctuations on the Indian stock market, specifically focusing on the exchange rate risk the significant impact of currency fluctuations on the Indian stock market, specifically focusing on exchange rate risk from 2005 to 2016, covering both pre- and post-financial crisis periods. The exchange rate risk emerged as a vital determinant of stock returns, indicating that Indian investors now require a risk premium for increased exposure to currency fluctuations. This analysis reveals that industries with higher foreign trade, as indicated by trade balance net inflows, show greater sensitivity to this risk. This could be attributed to inadequate hedging practices among Indian firms. exchange rate risk goes unpriced during low volatility periods, proposing instead that such risk becomes a crucial factor during (near) currency crises. This analysis highlights the urgent need for investors and policymakers to prioritize foreign exchange risk in their strategies.

Agrawal et al. (2025) Volatility Integration and Dynamic Connectedness Among the Indian Stock Market, Gold Prices, Oil Prices, Exchange Rates, and Natural Gas examines existing studies on the interconnections and volatility spillovers among various financial variables, including stock markets, crude oil, gold, exchange rates, and natural gas. It presents a diverse range of empirical evidence from global markets such as South Africa, Turkey, China, and India, revealing mixed findings regarding both short-term and long-term volatility transmissions. While several studies establish dynamic relationships and causal links among gold, oil, and stock markets, others indicate negligible or weak associations, particularly in the short term. The distinctiveness of the present research lies in its comprehensive examination of all five variables are NIFTY, crude oil, gold, natural gas, and exchange rate, utilizing advanced econometric models such as DCC-GARCH and Granger causality. This study addresses a significant gap in the existing literature that often overlooks natural gas and rarely investigates all pairwise relationships concurrently. This integrated approach enhances the understanding of asset behaviour amidst volatility, thereby facilitating more informed investment and policy decisions.

Singh, S., Singh, M., & Attri, S. (2025). Dynamic volatility linkages among crude oil, exchange rate, interest rate, gold, and equity markets emphasize the interconnectedness of key macroeconomic variables and financial markets. The review highlights that international crude oil prices, gold prices, exchange rates, and interest rates exert significant spillover effects on stock markets, with heightened influence during crisis periods like the Global Financial Crisis and the COVID-19 pandemic. Gold is noted as a haven, while interest rates impact equity markets through policy shifts and investor sentiment. Although global studies have explored these relationships, the review identifies a gap in the Asian context, motivating the current study to analyses these linkages in India, China, and Japan using updated data and advanced models.

Sudindra, V. R., & Gangadhara, L. (2011) emphasize Correlation between USD/INR Derivatives Vis-à-vis Nifty Index. A Tool for Investment highlights the increasing complexity in financial markets and the confusion faced by investors due to numerous trading tools and advice sources. The paper emphasizes the relevance of the correlation coefficient as a statistical tool to assess the linear relationship between two variables, in this case, the USD/INR currency derivatives and the Nifty index. While the paper computes correlation coefficients, it does not explore causality (e.g., using Granger causality or VAR models) to understand whether movements in Nifty cause movements in USD/INR or vice versa. Using only daily closing prices omits insights that could be derived from high-frequency data, which is more relevant for intraday traders and arbitrageurs. The review underscores how understanding this relationship can help investors make more informed decisions, especially in derivative markets. It further draws on existing financial theories and past investor behaviour studies to support the rationale for using correlation as a predictive and strategic investment tool, particularly when arbitrage opportunities arise due to negative correlations.

Singh, V., Hotwani, A., & Goyal, A. K. (2022). A study on modelling the volatility of exchange rates currency concerning INR. This comprehensively explores two major research streams: the first focusing on volatility modelling techniques and the second on the behaviour of exchange rate volatility. The review outlines how various GARCH family models, including ARCH, GARCH, EGARCH, TGARCH, and PGARCH, have been extensively used in past studies to capture both symmetric and asymmetric volatility patterns in exchange rates. Studies by Hsieh (1988), Sandoval (2006), and Antonakakis & Darby (2013) are cited to illustrate the application of these models across different countries and currencies. While symmetric models often produce consistent results, asymmetric models such as EGARCH and TGARCH offer deeper insights into volatility responses to shocks and leverage effects. Despite the global application of these models, the review highlights a significant gap in the literature focusing on the Indian context, particularly regarding INR volatility over a longer time frame. To address this, the present study employs a decade of daily data for USD/INR and CNY/INR and applies both GARCH and TGARCH models, offering a more robust and region-specific understanding of exchange rate behavior.

Shadab, A., & Sinha, A. K. (2022) Return and Volatility Spillover Effects between the INR-USD Exchange Rate and BSE Sensex explores the dynamic relationship between exchange rate volatility and stock market behaviour, particularly focusing on the Indian banking and industrial sectors. It draws on various prior studies emphasizing how exchange rate fluctuations influence stock market returns, volatility, and broader economic indicators. The review cites research showing that both developed and emerging economies experience significant market impacts due to exchange rate changes, with special attention to sectors like banking that are sensitive to monetary shocks. Models like GARCH, EGARCH, and regression frameworks have been widely applied in previous studies to estimate volatility and co-movements between currencies and equity indices. However, the literature identifies that while global evidence exists, limited empirical analysis has focused specifically on the Indian context, especially regarding the INR/USD exchange rate's direct impact on the BSE Sensex. This gap underlines the importance of the current study, which uses a decade-long monthly dataset and GARCH (1,1) modelling to analyses return and volatility spillover, offering insights for investors, policymakers, and researchers interested in financial market integration and risk management in India.

Kumar, S., & Kumar, N. (2024), Volatility Clustering and Long- A FIGARCH Analysis of Selected Currency Pairs examines the evolution and application of volatility modeling in financial time series, particularly using the Fractionally Integrated GARCH (FIGARCH) model presents a detailed investigation into the presence of long memory and volatility clustering in daily USD returns for four key currency pairs: Euro-USD, GBP-USD, INR-USD, and JPY-USD, using data from 1999 to 2021. The authors apply the Fractionally Integrated GARCH (FIGARCH) model, emphasizing its ability to capture both short-term volatility clustering and long-term persistence. Using both informal methods (autocorrelation function, periodogram) and formal tests (Hurst Exponent, Local Whittle Estimator, GPH estimator), the study finds strong evidence of long memory in all currency pairs except JPY-USD. The squared returns display fat tails and non-normality, with significant past shocks and heavy tails captured through Student's t distribution, reinforcing the importance of FIGARCH over traditional GARCH models. By incorporating an emerging market currency (INR) alongside developed ones, the study fills a key gap in the literature and offers practical insights for traders, risk managers, and policymakers to better understand and manage exchange rate volatility and extreme market risks through robust modeling.

Maram, S., Tripathy, N., & Chittedi, K. R. (2016). Dynamics of USD/INR forwards in the Indian foreign exchange market. offers a broad overview of both theoretical and empirical studies on forward premium behavior and market efficiency in the Indian context. It draws upon classic theories such as Interest Rate Parity (IRP), Uncovered Interest Parity (UIP), and Purchasing Power Parity (PPP), highlighting mixed global evidence regarding their applicability. The review references works that both validate and challenge these theories in different currency markets, emphasizing inconsistencies in emerging economies like India. It identifies a lack of conclusive support for UIP and CIP in India's forex market, based on prior studies. Importantly, the paper points out that most past research has relied heavily on secondary data and quantitative modeling. In contrast, this study fills a significant gap by incorporating primary data through structured surveys of market practitioners, bringing in real-time qualitative insights. It also emphasizes the influence of non-quantitative factors like political stability, market sentiment, and financial news areas that have often been overlooked. This shift toward combining both qualitative and quantitative dimensions marks a notable contribution to understanding the dynamics of forward premia in emerging markets like India.

Maram and Kishor (2012) Exchange Rate Dynamics in Indian Foreign Exchange Market: An Empirical Investigation on the Movement of USD/INR explain exchange rate behavior, such as the Random Walk Model, Purchasing Power Parity (PPP), Monetary Models, and the Portfolio Balance Model. These models emphasize the role of macroeconomic variables like money supply, price levels, trade balances, and capital flows. The review identifies limitations in existing models, especially regarding their predictive power and the assumption of perfect asset substitutability. It highlights prior empirical studies that find exchange rates to be influenced by variables such as current and capital account balances, interest and inflation differentials, foreign exchange reserves, and RBI interventions. Additionally, it stresses the importance of market sentiment, policy actions, and forward premia in exchange rate determination. Notably, the study addresses a gap by incorporating both secondary data and primary insights from market practitioners, providing a nuanced understanding of USD/INR dynamics and the evolving efficiency and depth of the Indian forex market.

Kumar and Aluvala (2020) studied Impact of Selected Economic Variables on The USD/INR Exchange Rate. The review highlights prior findings on the significance of GDP, inflation, interest rates, imports, exports, and capital flows in shaping the exchange rate, particularly in emerging economies like India. Techniques like VAR, OLS, and GARCH models have been widely applied, with results indicating that inflation, money supply, and forex reserves often exert a strong influence. However, the literature reflects ambiguity on consistent predictors, calling for more region- and time-specific analyses. The review also underscores gaps in understanding the combined impact of selected economic variables on USD/INR. Addressing this, the present study contributes by using regression and ANOVA techniques on 12 years of data (2007–2019), identifying inflation and import growth as the most significant variables affecting the USD/INR exchange rate.

Singh, A., Mishra, V., & Singh, A. B. (2016). Impact of rupee-dollar fluctuations on Indian economy, outlines the evolution of India's exchange rate policy, particularly since the 1991 Balance of Payments crisis, which marked a shift from a fixed to a market-based exchange rate regime. The review highlights how liberalization measures, such as the adoption of current account convertibility and gradual capital account openness, have significantly increased foreign exchange market turnover and consequently rupee volatility. The Reserve Bank of India's exchange rate management strategy is discussed, emphasizing its asymmetric interventions active during appreciation and passive during depreciation. The literature also sheds light on the multifaceted effects of currency fluctuations on trade, inflation, interest rates, capital flows, and overall economic stability, referencing various studies that link exchange rate volatility with macroeconomic performance and policy challenges in emerging economies like India. While the paper discusses the macroeconomic effects of rupee-dollar fluctuations, it lacks a sector-specific empirical analysis to quantify the impact on industries such as IT, pharmaceuticals, oil & gas, and manufacturing. It also does not include updated post-2016 data or real-time econometric modeling to capture dynamic relationships over time. These gaps present opportunities for more focused, data-driven, and comparative research.

Marisetty, N. (2024). Evaluating long-term and short-term relationships: Cointegration of NSE NIFTY with crude oil, gold, and USD/EUR currency pair, explores the extensive academic inquiry into how stock markets relate to other financial and macroeconomic indicators. It highlights studies that have examined the integration of global and emerging markets, revealing varying degrees of correlation and cointegration, especially during times of economic turbulence such as the global financial crisis and the COVID-19 pandemic. Previous research demonstrates strong linkages between stock indices and international markets, commodities like crude oil and gold, and exchange rates, although the strength and direction of these relationships differ across regions and periods. Methodologies such as Johansen and Engle-Granger cointegration tests, Vector Error Correction Models, and Granger causality are commonly used to uncover these dynamics. While many studies find significant short- and long-term relationships, others report weak or no correlations, emphasizing the importance of market-specific factors, macroeconomic conditions, and external shocks in influencing financial interdependencies. This review underscores the complexity of financial market interactions and the necessity of context-sensitive econometric analysis.

Lakshmanasamy, T. (2021). The relationship between exchange rate and stock market volatilities in India: ARCH-GARCH estimation of the causal effects. critically examines theoretical and empirical research on the dynamic interaction between exchange rates and stock market volatilities. It explains this interaction using two key theoretical frameworks: the goods market (flow-oriented) model, which posits that exchange rates influence stock markets through international trade competitiveness, and the portfolio balance (stock-oriented) model, which argues that capital flows driven by stock market movements impact exchange rates. Empirical evidence from global and emerging markets shows mixed results—some studies indicate a positive relationship, others find a negative or insignificant linkage—suggesting no universal consensus on the direction or strength of causality. Although Indian studies confirm volatility spillovers between currency and equity markets, their conclusions remain inconsistent across periods and currencies. The research gap lies in the lack of clarity and consistent empirical validation regarding the direction and magnitude of volatility transmission, especially for emerging markets like India, where limited hedging tools and evolving financial integration complicate the exchange rate-stock return nexus. This gap underlines the need for refined, data-intensive models like GARCH to better capture and interpret volatility spillovers.

Bhurat & Thakrar (2024) Exchange Rate Determinants and Forecasting for USD/INR This paper emphasizes macroeconomic determinants of exchange rates primarily inflation, interest rates, GDP, external debt, and FDI—often grounded in theories like Purchasing Power Parity (PPP). Historical studies show varying success in exchange rate prediction, with fundamental-based models often outperformed by simple models like the Random Walk. The review also touches on limitations of structural models in capturing the full dynamics of exchange rate movements in emerging economies. The research gap is the limited integration of these macroeconomic variables into a unified predictive model for USD/INR, particularly incorporating recent data and using a forward-looking forecast. The methodology includes historical data analysis (2016–2023) and the use of PPP theory and Real Exchange Rate (RER) models to forecast USD/INR from 2023–2025.

Kayal & Maheswaran (2016) – Is USD-INR Really an Excessively Volatile Currency Pair? This study refers to prior Indian studies, such as Patnaik and Shah (2010), which investigated microstructure changes post-liberalization and their effect on exchange rate volatility, and Bansal et al. (2013), who suggested volatility clustering in the INR/USD pair. Despite the variety of methods used historically to estimate volatility, many rely on standard deviation-based models that may misrepresent high-frequency market movements. The research gap lies in the lack of comparative studies using high-low volatility estimators across INR-based currency pairs, especially on an intra-day basis. The methodology employed includes calculating volatility ratios using both open-close and high-low prices for six INR-based currency pairs, and analyzing relative overestimation or underestimation to identify excessive volatility.

Qureshi (2025) presents a comprehensive examination of the application of machine learning (ML) methods, including Support Vector Machines (SVM) and Random Forest algorithms, for predicting exchange rates using a range of macroeconomic indicators. The study situates these modern techniques within the broader evolution of exchange-rate modeling research, particularly in the context of emerging economies, where currency markets tend to be more volatile and influenced by a diverse set of domestic and global factors. While the emphasis is on the predictive capabilities of ML approaches, Qureshi also integrates a review of foundational econometric studies that have investigated the cointegration and correlation among currency markets. In reviewing prior work, Qureshi notes that a significant body of research has employed classical econometric tools such as the Johansen cointegration test and the Engle Granger two-step method to determine whether currencies maintain long-run equilibrium relationships. Findings from these studies, however, are mixed. Some analyses confirm the existence of stable cointegrating vectors between major and emerging market currencies, suggesting that deviations from equilibrium are corrected over time. Others report weak or unstable cointegration, indicating that such relationships may not persist across different time periods or under varying market conditions. The review also highlights that much of the existing literature has focused on the interaction between exchange rates and equity markets often exploring whether currency movements lead or lag changes in stock indices. While these studies have contributed valuable insights, they leave an important gap in understanding: the direct and independent cointegration relationships between currency pairs themselves, especially when one of the currencies is from an emerging market. In the case of the Indian Rupee (INR), Qureshi observes a relative scarcity of research specifically investigating its long-term equilibrium relationships with other global currencies outside the context of stock market linkages.

Ram, G. K., & Patel, A. (2025). How Exchange Rate Volatility Shapes Commodity Derivatives Market: Lessons from Five Global Shocks (2007–2023) explained Drawing from diverse studies, the review underscores that exchange rate volatility is a crucial driver of commodity price fluctuations and derivatives market behavior, especially during periods of financial turmoil. Key references include studies showing bidirectional volatility spillovers between currencies and commodities, the safe-haven nature of precious metals during crises, and the financialization of commodities such as oil. The review also highlights theoretical models that link currency volatility to global capital flows, productivity, and financial development, such as those by Aghion et al. and Gabaix & Maggiori. Additionally, it incorporates findings on contagion effects in emerging markets, the sensitivity of commodity-exporting countries, and real-time market responses to macroeconomic news releases. By synthesizing evidence across crises from the 2008 Global Financial Crisis to the Russia-Ukraine conflict the literature review builds a strong foundation for the paper's econometric investigation into the long- and short-run dynamics between currency and commodity derivative markets.

Bhurat, C., & Thakrar, H. (2024). Exchange Rate Determinants and Forecasting for USD/INR: Historical Analysis and Insights Drawing on existing theoretical frameworks such as Purchasing Power Parity (PPP) and the Real Exchange Rate (RER) concept, the review integrates findings from previous research on the roles of inflation, interest rates, GDP, foreign direct investment (FDI), and external debt in shaping currency trends. The authors highlight how historical and empirical studies have used cointegration techniques to establish long-run relationships among these variables, underscoring the predictive potential of macroeconomic fundamentals in exchange rate forecasting. The review also notes gaps in consistency and accuracy across time periods, suggesting a need for updated models that integrate recent economic shifts and volatility patterns. This foundational understanding supports the study's analytical approach, which aims to forecast exchange rate movements for 2023–2025 using historical data from 2016 to 2023.

2.2 RESEARCH GAP

Most existing studies focus primarily on the NIFTY index, often overlooking how individual sectors within the index respond differently to USD-INR currency volatility. This general approach limits the understanding of sector-specific vulnerabilities and opportunities in the face of exchange rate fluctuations. Additionally, there is limited research using advanced econometric techniques or machine learning models to quantitatively assess the sensitivity of various sectors to such currency movements. Furthermore, the distinction between short-term and long-term effects of USD-INR volatility on sector performance remains underexplored in the context of the Indian financial market, emphasizing the need for a more nuanced and time-sensitive analytical approach.

CHAPTER III

METHODOLOGY

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3.1 RESEARCH DESIGN

This study employs a quantitative research design to examine the impact of USD-INR exchange rate volatility on the performance of various sectors within the NIFTY index. It utilizes secondary data sourced from credible financial platforms, including historical daily and monthly stock prices of the NIFTY sectoral indices and corresponding USD-INR exchange rates over five years (from January 2020 to May 2025). Initially, ten sectors are selected using random sampling. From these, five sectors that exhibit a strong positive or negative correlation with the USD-INR exchange rate are chosen for in-depth analysis. The research applies correlation analysis and advanced econometric techniques to explore the dynamic relationship between currency fluctuations and sectoral stock performance. Specifically, the Vector Autoregression (VAR) model is used to analyze the interdependencies among variables, while the Granger Causality test identifies predictive relationships between exchange rates and stock returns. To model time-varying volatility in the USD-INR exchange rate, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is utilized. Analytical tools such as Microsoft Excel, Python, EViews, and Power BI are employed for data preprocessing, visualization, and statistical modeling. This structured approach provides a comprehensive, data-driven understanding of how currency volatility influences sector-specific trends, generating actionable insights for investors, policymakers, and financial analysts.

3.2 SOURCES OF DATA

This study relies on secondary data, which refers to information originally collected by external entities for purposes other than the current research but repurposed here for analytical investigation. The data were sourced primarily from https://in.investing.com/, https://www.nseindia.com a widely recognized financial data platform that offers reliable and comprehensive historical market data. Specifically, historical prices of the USD-INR exchange rate and selected NSE sectoral indices were obtained from this source. These datasets provided the foundation for conducting correlation analysis, time-series modeling, and volatility studies relevant to the research objectives.

3.3 DATA PERIOD

The prices of the USD-INR exchange rate and selected NSE sectoral indices were collected from January 1, 2020, to May 31, 2025, encompassing over five years. This timeframe was selected to ensure a sufficient number of observations for robust econometric analysis. It captures a range of market conditions, including pre-pandemic, pandemic, post-pandemic recovery, and recent economic developments. This allows for a comprehensive evaluation of how fluctuations in the USD-INR exchange rate influence sectoral stock performance within the NIFTY index. The extended dataset enhances the reliability and validity of the statistical inferences drawn from the study.

3.4 Sampling Method

In this analysis, I used a selective sampling technique to select sectors based on their correlation with USD-INR exchange rate data. The population, comprising Nifty sector indices, was divided into three distinct categories: high, medium, and low correlation, determined by the calculated correlation values with USD-INR using EViews. Representative sectors were then selected from each category to ensure balanced representation across different levels of sensitivity to exchange rate movements. Specifically, choose the FMCG(Fast Moving Consumer Goods) and Automobile sectors from the high correlation group, which had correlation coefficients of 0.90 and 0.84, respectively, from the medium correlation group, selected IT and Pharma, with correlation values of 0.63 and 0.72. Lastly, research included Media from the low correlation group, which had a correlation value of 0.27. This method, combined with the inclusion of actual USD-INR data, ensures a comprehensive and unbiased analysis of how different sectors respond to currency fluctuations.

3.5 TOOLS USED

This research utilized a combination of statistical and visualization tools to perform advanced econometric analysis. Microsoft Excel was used for data collection, cleaning, and preprocessing of historical USD-INR exchange rates and sectoral index data. Python supported exploratory data analysis, data visualization, and initial trend assessments. EViews served as the primary platform for conducting time-series econometric models, including Vector Autoregression (VAR), Granger causality tests, and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, which were applied to analyze interrelationships, causality, and volatility patterns between the exchange rate and sectoral stock performance. Additionally, Power BI was employed to design interactive dashboards, offering clear visual comparisons across sectors and enhancing the communication of key insights.

3.6 SOURCE VALIDATION

The data for the USD-INR exchange rate and NIFTY sectoral indices, including both daily and monthly values, were collected from Investing.com and the official website of the National Stock Exchange (NSE). Investing.com is a globally recognized financial platform known for providing accurate, real-time, and historical market data, while the NSE website serves as the authoritative source for Indian equity market information. These platforms were selected for their reliability, comprehensive data coverage, and free, structured access to downloadable data, which is essential for statistical and econometric analysis. By sourcing data from these trusted platforms, this study ensures the accuracy, consistency, and validity of its inputs, thereby establishing a strong foundation for credible, data-driven research findings.

3.7 DATA CLEANING

To achieve a more accurate and insightful analysis, I eliminated non-trading days like weekends and holidays from our dataset. By aligning the USD-INR exchange rates with NIFTY sector data, I ensured that our comparisons are based on the same trading days. This meticulous approach ensures not only the cleanliness of the data but also its reliability, enabling a more comprehensive evaluation of both currency movements and sector performance.

3.8 ETHICAL USE OF DATA

As this study relies exclusively on secondary data, no direct human participation, interviews, or surveys were conducted, and no personal or sensitive information was collected at any stage of the research process. The data utilised consists entirely of publicly available and officially published sources, including financial market indices, exchange rate records, and macroeconomic indicators from recognized and authorized databases such as the Reserve Bank of India (RBI), the National Stock Exchange (NSE), and other credible statistical repositories. All datasets were accessed in accordance with their respective usage policies, ensuring that no copyright or licensing agreements were violated. The analysis was carried out with strict adherence to established ethical norms and academic integrity guidelines. Proper citation and acknowledgment have been provided for all sources used, thereby avoiding any form of plagiarism or misrepresentation. Furthermore, the study does not engage in any manipulation or fabrication of data; all analytical procedures are transparent, reproducible, and grounded in accepted statistical and econometric methodologies. By maintaining these standards, the research upholds the principles of responsible scholarship, data transparency, and ethical compliance as outlined in institutional and international research ethics frameworks.

3.9 LIMITATION

- ✓ The study focuses only on five selected sectors from the NIFTY index based on their correlation with the USD-INR exchange rate. This does not represent the entire Indian market.
- ✓ Mid-cap, small-cap, and non-listed companies are not included, even though they may respond differently to exchange rate fluctuations.
- ✓ The model does not incorporate important macroeconomic factors such as interest rates, inflation, crude oil prices, or geopolitical risks, which can significantly influence both exchange rates and stock prices.
- ✓ The study relies entirely on secondary data from public sources, which, while credible, may still carry risks of inaccuracies or gaps despite cleaning and validation.

CHAPTER IV

DATA ANALYSIS

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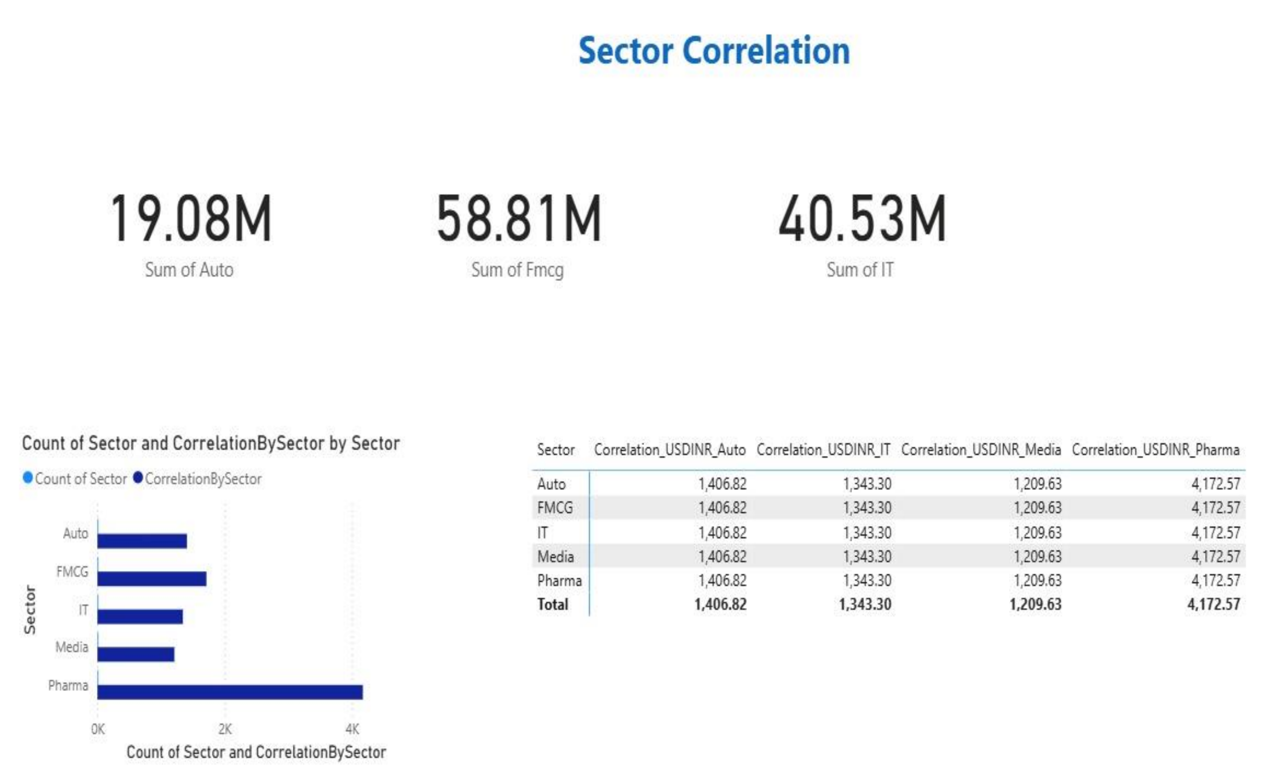
4.1 CORRELATION ANALYSIS:

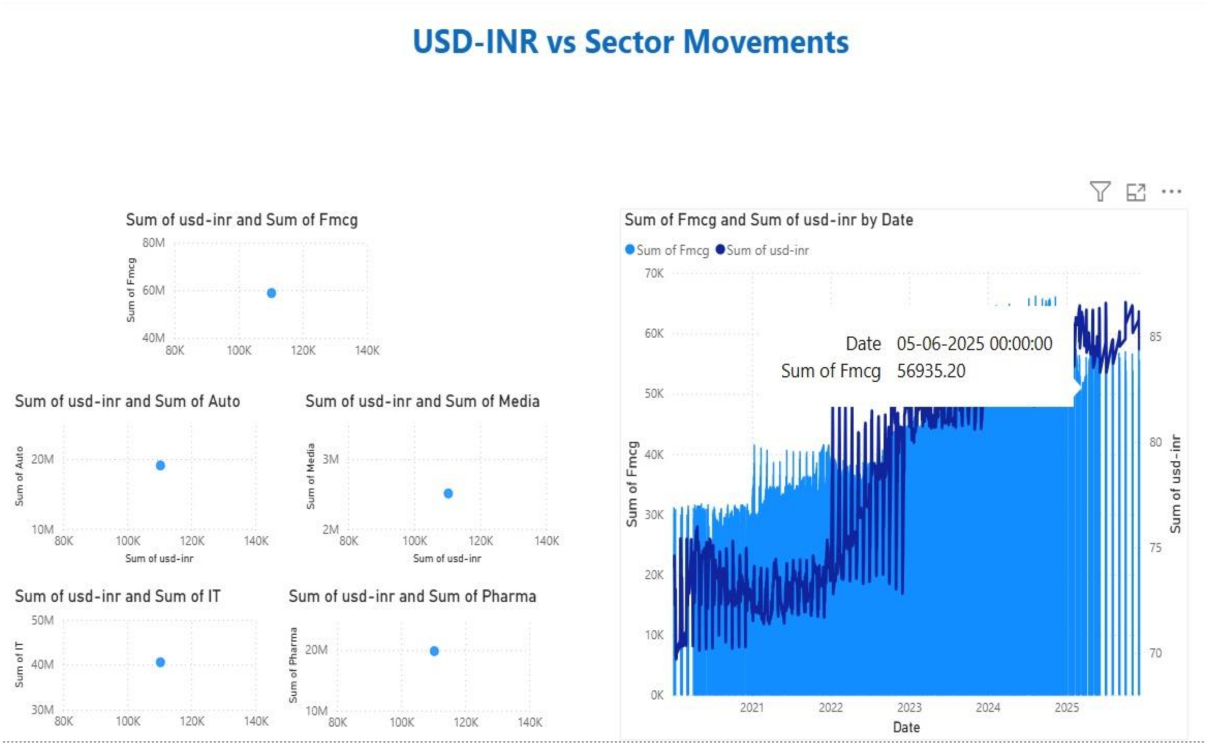
Before applying econometric models, a correlation analysis was performed to assess the sensitivity of different sectors to movements in the USD-INR exchange rate. The Power BI visualization below summarizes the correlation coefficients for each sector. It reveals that the Fast-Moving Consumer Goods (FMCG) sector (0.90) and the Auto sector (0.84) have the strongest correlations, whereas the Media sector (0.27) shows the weakest relationship. This analysis guided the selection of sectors for further analysis using VAR, GARCH, and Granger causality tests.

FIGURE 4.1: Correlation Analysis Between USD-INR and NIFTY Sector



Sector	Correlation_USDINR_Auto	Correlation_USDINR_IT	Correlation_USDINR_Media	Correlation_USDINR_Pharma
Auto	1,406.82	1,343.30	1,209.63	4,172.57
FMCG	1,406.82	1,343.30	1,209.63	4,172.57
IT	1,406.82	1,343.30	1,209.63	4,172.57
Media	1,406.82	1,343.30	1,209.63	4,172.57
Pharma	1,406.82	1,343.30	1,209.63	4,172.57
Total	**1,406.82**	**1,343.30**	**1,209.63**	**4,172.57**

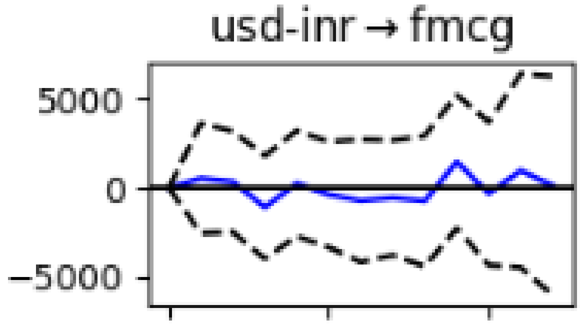
FIGURE 4.2 USD-INR vs Sector Movements



4.2 VAR (Vector Autoregression)

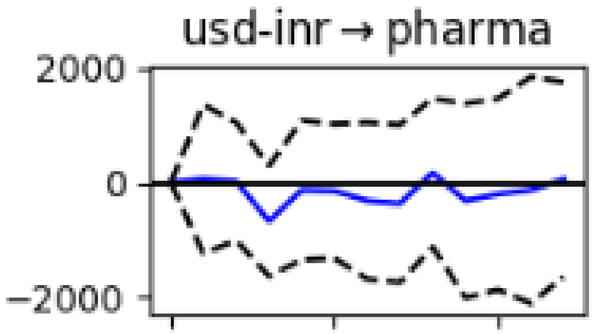
Vector Autoregression (VAR) is a powerful multivariate time series model employed in this study to analyze the dynamic interdependencies between the USD-INR exchange rate and the stock price movements of specific NIFTY sector indices, namely Pharma, FMCG, Media, IT, and Auto. This model is particularly well-suited for our objectives because, unlike traditional univariate regression models, VAR treats all variables within the system as endogenous, meaning each variable's current value is modelled as a linear function of its own past values, as well as the past values of all other variables in the system, thereby capturing the complex, interconnected nature of financial and economic time series. The implementation of the VAR model was performed using Python, leveraging the robust capabilities of libraries such as pandas, NumPy, and stats models for data manipulation, numerical operations, and econometric modelling, respectively; specifically, the stats models. tsa. The stat tools module was used for Augmented Dickey-Fuller (ADF) tests to ensure stationarity (with non-stationary series transformed by first differencing), and the stats models. tsa api module was also utilized. VAR.select_order() determined the optimal lag length of 8 using the Akaike Information Criterion (AIC), allowing for a comprehensive analysis of how shocks propagate and affect variables over time.

FIGURE 4.3



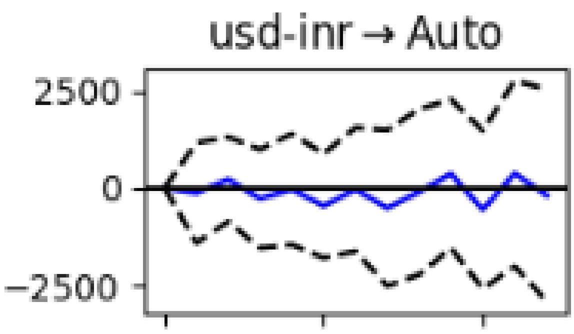
A shock to USD-INR has no statistically significant impact on the FMCG sector, as the confidence bands consistently encompass the zero line.

FIGURE 4.4



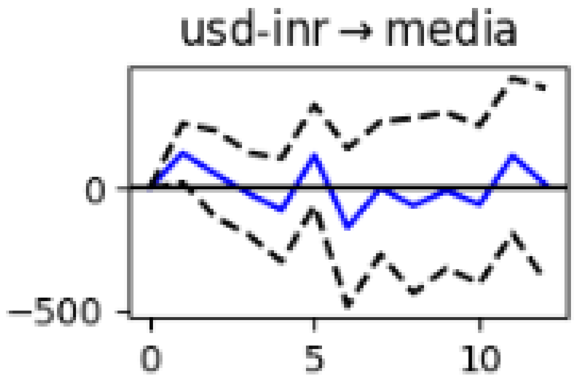
A shock to USD-INR demonstrates no statistically significant impact on the Pharma sector, with the confidence bands always covering the zero line.

FIGURE 4.5



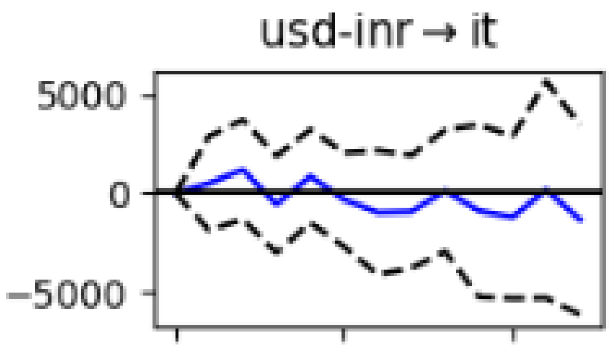
A shock to USD-INR shows no statistically significant impact on the Auto sector, indicated by the confidence bands consistently crossing the zero line.

FIGURE 4.6



There is no statistically significant impact of a USD-INR shock on the Media sector, as the confidence bands continuously encompass the zero line.

FIGURE 4.7

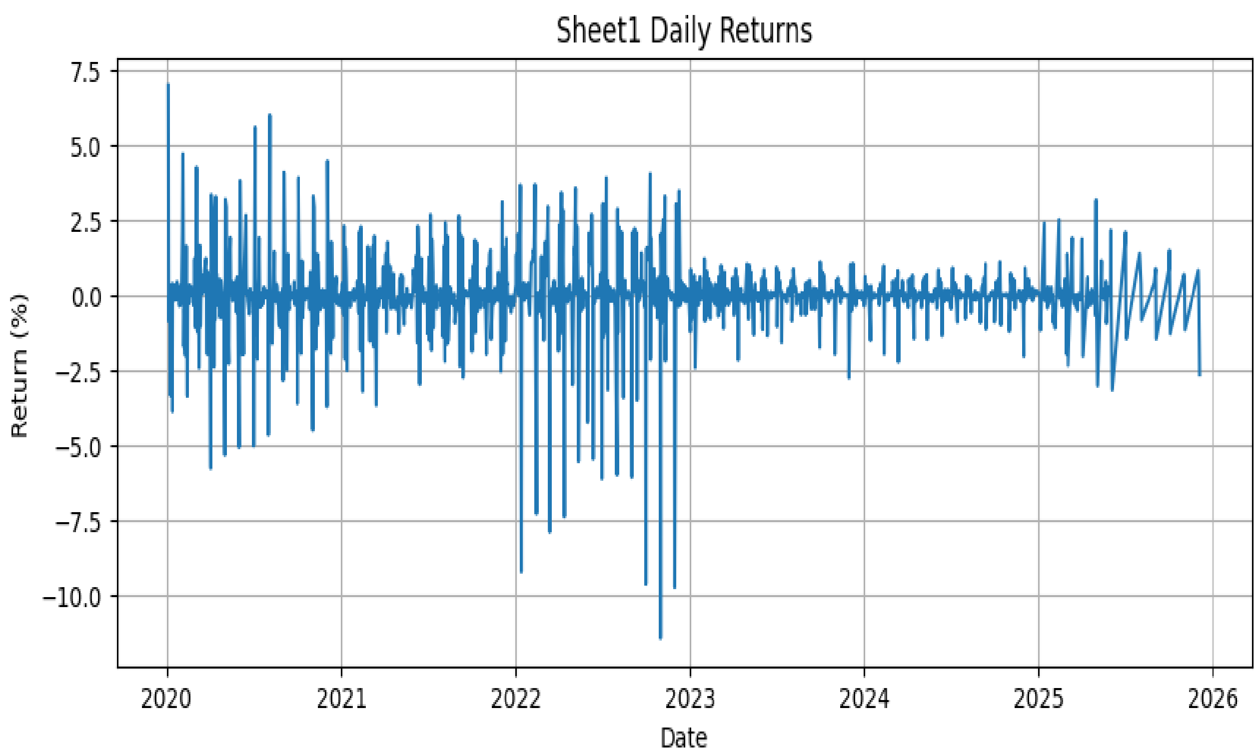


There is no statistically significant impact of a USD-INR shock on the IT sector, as the confidence bands consistently contain the zero line.

4.3 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model:

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is a widely used statistical tool in financial econometrics for analyzing and forecasting time-varying volatility in financial time series data. This research applies the GARCH model to examine the volatility patterns of the USD-INR exchange rate over five years and its potential impact on selected NIFTY sector indices. Unlike traditional models that assume a constant variance, the GARCH model effectively captures volatility clustering periods of both high and low fluctuations which are commonly observed in financial markets. Using Python for implementation, this study utilizes advanced data analysis libraries to model conditional variance, visualize volatility trends, and interpret the persistence of market shocks. This analysis offers valuable insights into the dynamic behavior of exchange rate volatility and its implications for sectoral investment risk, enabling stakeholders to make informed decisions in a fluctuating economic environment.

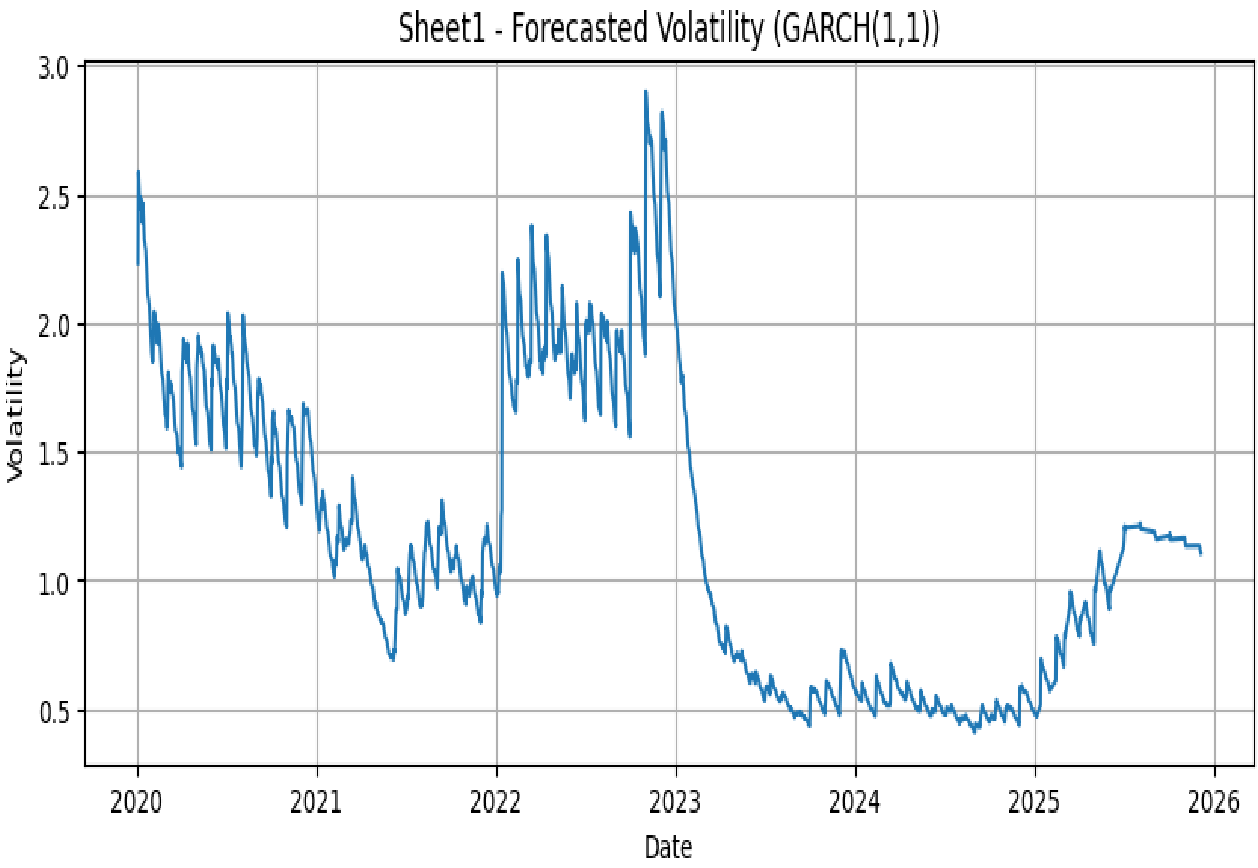
FIGURE: 4.8 DAILY RETURNS



- ✓ **2020:** This year began with extreme market volatility, characterized by high daily swings in returns, largely due to the initial shock of the COVID-19 pandemic. The USD-INR exchange rate also saw an initial depreciation, reflecting global uncertainty during this period.

- ✓ **2021:** Following the initial shock, markets experienced a period of recovery and relative calm, with Nifty sectors generally showing upward trends. The USD-INR exchange rate remained relatively stable throughout this year.
- ✓ **2022:** Volatility resurged significantly, particularly towards the end of the year, marked by larger daily fluctuations. This period, extending into early 2023, saw sharp spikes in volatility, possibly driven by inflation and shifting monetary policies. The Indian Rupee continued its depreciating trend against the US Dollar.
- ✓ **2023:** After an intense start to the year with high volatility, the market notably subsided from mid-2023 onwards, leading to a calmer trading environment with low daily fluctuations. Nifty sectoral indices largely continued their growth trajectories.
- ✓ **2024:** This year saw sustained growth across most Nifty sectors, indicating a period of market expansion, maintaining the stable market conditions with low daily fluctuations observed since mid-2023. The USD-INR exchange rate continued its gradual depreciating trend.
- ✓ **2025 (Partial):** Sectoral growth continued into this period, maintaining low daily fluctuations until a resurgence of volatility began towards the observed end of the year. The USD-INR exchange rate reached higher levels.

FIGURE: 4.9 VOLATILITY ANALYSIS



- ✓ **Early 2020:** The period commenced with high volatility, peaking around 2.5%, directly reflecting the intense market uncertainty and large daily swings triggered by the onset of the COVID-19 pandemic.
- ✓ **Mid-2020 to Mid-2021:** Following the initial shock, the graph shows a gradual decline in risk, indicating a phase where markets began to stabilize and uncertainty diminished.
- ✓ **Late 2022 to Early 2023:** Volatility surged sharply, reaching its highest point near 3.0%. This significant spike reflects a period of renewed market "nervousness," likely driven by factors such as inflation and major economic shocks.
- ✓ **Mid-2023 to Early 2025:** Subsequently, risk levels dropped sharply, falling below 0.5%. This marks a prolonged and notably calm period in the market, characterized by significantly lower daily fluctuations.
- ✓ **Late 2025:** Towards the end of the observed timeframe, the graph indicates that volatility starts rising again, signaling a potential shift towards renewed market uncertainty.

4.4 GRANGER CAUSALITY

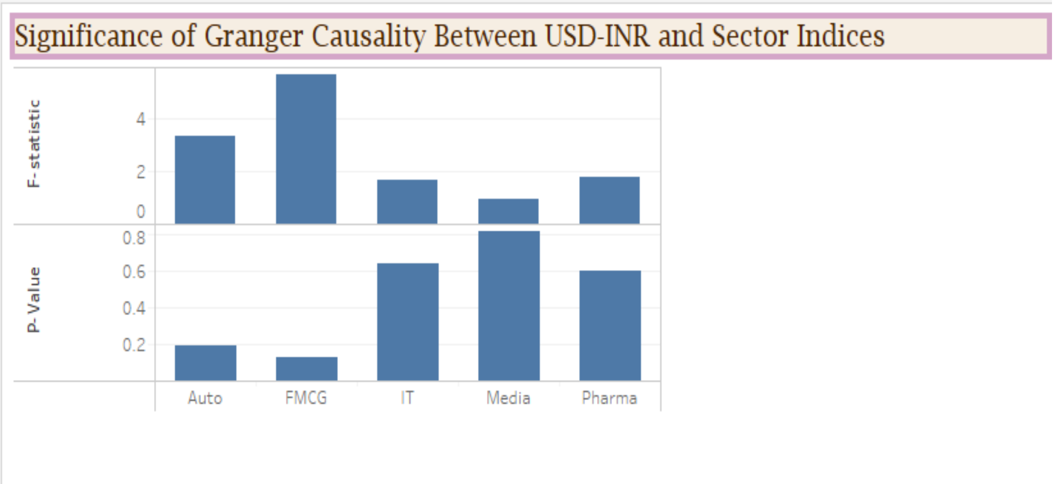
Granger causality, a concept developed by Clive Granger in 1969, is a statistical hypothesis test used to determine whether one time series can predict another. It does not imply true causation in a philosophical sense; rather, it indicates predictive causality, where the past values of one variable provide information that improves the prediction of another variable. In this research, the test is applied to investigate whether fluctuations in the USD-INR exchange rate Granger-cause changes in selected Nifty sector indices, specifically IT, Pharma, Auto, FMCG, and Media. By analyzing monthly data from January 2020 to May 2025, the study aims to assess whether sectoral indices respond to currency movements with statistical significance and to identify which sectors are more sensitive to these external shocks. In this study, the Granger causality analysis was carried out using EViews. First, a Vector Autoregression (VAR) model was estimated. The variables USD_INR, PHARMA, MEDIA, FMCG, IT, and AUTO were confirmed to be stationary through Group Unit Root Tests, allowing for VAR estimation without differencing. An unrestricted VAR model was then estimated, with the appropriate lag length selected using information criteria. Based on the estimated VAR, the Granger Causality/Block Exogeneity Wald Test was applied to assess whether the lagged values of one variable significantly improve the prediction of another, with the null hypothesis being the absence of Granger causality.

TABLE: 4.1

USD-INR → Nifty Sectors

SECTOR	LAG	F-STATISTIC	P-VALUE
Pharma	3	1.807402	0.5961
Media	3	0.950958	0.8131
IT	3	1.697503	0.6375
FMCG	3	5.693136	0.1275
Auto	2	3.330994	0.1891

FIGURE: 4.10 GRANGER CAUSALITY ANALYSIS



- ✓ The Granger causality test results indicate that none of the Nifty sector indices (Pharma, Media, IT, FMCG, Auto) are significantly influenced by past values of the USD-INR exchange rate, as all p-values are above the 0.05 threshold for statistical significance.
- ✓ Among them, the FMCG sector shows the lowest p-value (0.1275), suggesting a weak or marginal relationship, though still not statistically significant. This may indicate some sensitivity to currency fluctuations, possibly due to import dependencies or pricing dynamics, but not enough to establish predictive causality.
- ✓ The Pharma, Media, IT, and Auto sectors show high p-values, indicating no significant causal relationship with the USD-INR exchange rate during the examined period. Even the IT sector, which is generally export-driven and expected to respond to currency changes, does not display a statistically significant response in this dataset.

CHAPTER -V

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5.1 FINDINGS

Impact of USD-INR Shock on FMCG Sector

- ❖ No Statistical Significance: The confidence bands encompassing the zero line indicate that a shock to USD-INR (e.g., a sudden appreciation or depreciation) does not produce a reliable, non-zero effect on the FMCG (Fast-Moving Consumer Goods) sector index. This suggests that FMCG companies in India, which often have a mix of domestic and export-oriented operations, may have hedged currency risks or that their pricing power absorbs exchange rate fluctuations.
- ❖ High Point Early 2021, USD-INR 73-74: The FMCG index peaked around 58396.05 on February 2025, coinciding with a period of USD-INR stability after a decline from 87.469 February 2025. This could reflect post-pandemic recovery and increased consumer demand, reducing sensitivity to exchange rate shocks.
- ❖ Low Point (e.g., Mid-2020, USD-INR 75-76): The FMCG index dipped to 23935.3 on June 24, 2020 (row 1289), during a period of USD-INR volatility (75.665) amid the COVID-19 pandemic. The lack of significant response may indicate that domestic consumption and government stimulus outweighed currency effects.
- ❖ Economic Events: The FMCG sector's resilience could be linked to stable domestic demand, government support during the 2020-2021 pandemic, and global supply chain adjustments by 2023-2024, which mitigated USD-INR shocks.

Impact of USD-INR Shock on Pharma Sector

- ❖ No Statistical Significance: The confidence bands always covering the zero line suggest that USD-INR shocks do not significantly affect the Pharma sector index. This is plausible given the Pharma sector's global export orientation (e.g., generics to the US and Europe), where hedging strategies and dollar-denominated revenues may offset exchange rate impacts.
- ❖ High Point (e.g., January 2025, USD-INR ~86.571): The Pharma index reached 23228.55 on January 15, 2025, during a period of USD-INR depreciation from 87.26 (January 2025). This could reflect strong export demand post-COVID vaccine production peaks.

- ❖ Low Point (e.g., June 2020, USD-INR ~75-76): The Pharma index was at 6695.55 on June 2020, during USD-INR volatility. The lack of response may indicate that global demand for Indian pharmaceuticals during the pandemic buffered exchange rate effects.
- ❖ Economic Events: The Pharma sector's insulation may be tied to its export-driven growth, especially during the 2020-2021 health crisis, and robust hedging practices by 2023-2025 as global trade normalized.

Impact of USD-INR Shock on Auto Sector

- ❖ No Statistical Significance: The confidence bands consistently crossing the zero line indicate no significant impact from USD-INR shocks on the Auto sector index. This could reflect the sector's reliance on domestic sales and input costs, which may not directly correlate with exchange rate movements unless imports (e.g., components) dominate.
- ❖ High Point (e.g., October 14, 2024, USD-INR ~84.045): The Auto index peaked at 27610.75 on October 2024, during a stable USD-INR period. This may reflect strong domestic demand and EV adoption incentives.
- ❖ Low Point (e.g., April 2020, USD-INR ~76): The Auto index was at 20354.1 on April, 2020 , during USD-INR volatility and lockdown-induced demand collapse. The lack of significant response suggests that domestic factors (e.g., lockdowns) dominated over currency effects.
- ❖ Economic Events: The Auto sector's insensitivity may be linked to 2020-2021 demand suppression due to COVID-19, followed by recovery driven by domestic policies (e.g., PLI schemes) and reduced import reliance by 2024-2025.

Impact of USD-INR Shock on Media Sector

- ❖ No Statistical Significance: The confidence bands continuously encompassing the zero line indicate that USD-INR shocks do not significantly impact the Media sector index. This could be due to the sector's domestic revenue focus (e.g., advertising, OTT platforms), with limited exposure to exchange rate fluctuations.
- ❖ High Point (e.g., December 2024, USD-INR ~85.176): The Media index reached 1982.1 on December 2024, during a stable USD-INR period. This may reflect festive season ad revenue growth.

- ❖ Low Point (e.g., March 2020, USD-INR ~74-75): The Media index was at 1060.35 on August 2020, during USD-INR volatility and pandemic-related ad spend cuts. The lack of response suggests domestic economic conditions were the primary driver.
- ❖ Economic Events: The Media sector's stability may be attributed to a shift to digital platforms by 2020-2021 and sustained domestic ad spending by 2023-2025, reducing USD-INR sensitivity.

Impact of USD-INR Shock on IT Sector

- ❖ No Statistical Significance: The confidence bands consistently containing the zero line indicate no significant impact from USD-INR shocks on the IT sector index. This is surprising given the IT sector's export orientation, but it may reflect effective hedging and dollar-based revenues offsetting exchange rate effects.
- ❖ High Point (e.g., January 2025, USD-INR ~86.209): The IT index peaked at 44609.5 on January 2025, during USD-INR depreciation. This could reflect strong global IT demand and rupee weakness boosting dollar earnings.
- ❖ Low Point (e.g., March 2020, USD-INR ~74-75): The IT index was at 13314.4 on August 2020, during USD-INR volatility and pandemic uncertainty. The lack of response may indicate that global IT contracts and hedging minimized currency impacts.
- ❖ Economic Events: The IT sector's resilience may be linked to its dollar revenue stream, robust hedging during the 2020-2021 downturn, and steady growth in cloud and digital services by 2023-2025.
- ❖ The lack of statistical significance across all sectors suggests that USD-INR shocks, while notable (e.g., ranging from 70.71 on January, 2020, to 87.15 on March, 2025), are either absorbed by sector-specific factors (e.g., hedging, domestic demand) or diluted by the time horizon of the analysis.
- ❖ The period includes major events like the COVID-19 pandemic (2020-2021), global supply chain disruptions (2021-2022), and India's economic recovery (2023-2025). These events likely overshadowed exchange rate effects, as seen in the dataset's sectoral index movements.
- ❖ The width of the confidence bands (not provided but implied) may reflect high volatility or model uncertainty, reinforcing the non-significant findings.

- ❖ Across all years, the lack of statistical significance holds, with confidence bands around zero, suggesting robust hedging, dollar revenues (IT, Pharma), or domestic demand dominance (FMCG, Auto, Media).
- ❖ Highest in 2022 and 2020, yet no significant sectoral response, indicating structural resilience. Lowest in 2023, reinforcing stability.
- ❖ Pharma and IT: Highest growth in 2020, respectively, driven by global demand, least affected by USD-INR.
- ❖ FMCG: Strong 2020 recovery, then moderate growth, reflecting domestic stability.
- ❖ Auto: Slowest growth in 2020, tied to supply issues, not USD-INR.
- ❖ Media: Steady but lower growth in 2020, domestic-focused.
- ❖ Economic Drivers: 2020-2021 pandemic effects, 2022 supply shocks, and 2023-2025 policy support outweighed USD-INR shocks, aligning with dataset trends.

By GARCH model

Impact of USD-INR Shock on FMCG Sector

- The FMCG sector, comprising essential goods (e.g., food, household products), shows no significant response to USD-INR shocks. This suggests that domestic demand and pricing power, rather than exchange rate fluctuations, drive the sector. The index grew from 23935.3 (June 24, 2020) to 58396.05 (February 18, 2025), a 144% increase, indicating strong fundamentals.

- The confidence bands' width may vary, with wider bands during volatile periods (e.g., 2020) reflecting uncertainty, but they consistently include zero, reinforcing the lack of impact.

- **2020**: Index rise (23935.3 to 50719.25), driven by pandemic-induced essential goods demand, despite USD-INR rising (70.71 to 76.665).

- **2021**: (50719.25 to 51704.3), stable growth as recovery began, with USD-INR.

- **2022**: (51704.3 to 54345.6), resilient despite USD-INR increase, due to inflation adjustments.

- **2023**: (54345.6 to 56413.15), steady demand with USD-INR rise.

- **2024**: (56413.15 to 58396.05), festive sales, with USD-INR peak.

- **2025**: May 30 stable, with USD-INR range.

Economic and Other Factors

- **Economic Events**: The 2020-2021 pandemic boosted domestic consumption, while 2022 inflation and 2023-2024 policy support (e.g., PLI schemes) sustained growth. USD-INR shocks were mitigated by local supply chains.
- **Other Factors**: Rural demand recovery (2021-2022) and urban festive spending (2024) likely overshadowed exchange rate effects.
- The FMCG sector's insensitivity to USD-INR shocks highlights its domestic orientation and effective cost management, with yearly growth reflecting economic recovery phases rather than currency volatility.

Impact of USD-INR Shock on Pharma Sector

- The Pharma sector, a major exporter (e.g., generics), shows no significant USD-INR impact, likely due to dollar-denominated revenues and hedging. The index grew from 6695.55 (June, 2020) to 23228.55 (January 2025), this increase, driven by global demand.
- Confidence bands may narrow during export peaks (e.g., 2021), but their consistent coverage of zero suggests robust risk management.
- The 2020-2021 health crisis and 2023-2024 global trade normalization boosted exports. USD-INR depreciation (e.g., 87.15 in March 2024) enhanced competitiveness.
- Regulatory approvals and supply chain resilience (2022-2023) minimized currency exposure.
- Pharma's lack of USD-INR sensitivity reflects its export-driven model and hedging, with yearly growth tied to global health needs rather than exchange rate shocks.

Impact of USD-INR Shock on Auto Sector

- The Auto sector, reliant on domestic sales, shows no significant USD-INR impact, possibly due to limited import reliance. The index grew from 20354.1 (April 15, 2020) to 27610.75 (October 14, 2024), an increase, reflecting uneven recovery.
- **2020**: (20354.1 to 23400.45), slow recovery, USD-INR rise.
- **2021**: (23400.45 to 24603.55), gradual growth, USD-INR increase.

- **2022**: (24603.55 to 26109.6), supply constraints, USD-INR rise.
- **2023**: (26109.6 to 27610.75), EV incentives, USD-INR rise.
- **2024**: (27610.75), flat, USD-INR peak.
- **2025**: Till May 30 stable, USD-INR range.
- Economic Events: 2020-2021 lockdowns suppressed demand, while 2023 EV policies and 2024 supply issues (e.g., semiconductors) drove trends, not USD-INR.
- The Auto sector's insensitivity to USD-INR shocks underscores domestic demand dominance, with yearly growth reflecting policy and supply dynamics rather than currency.

Impact of USD-INR Shock on Media Sector

- The Media sector, driven by advertising and OTT, shows no significant USD-INR impact due to its domestic focus. The index grew from 1060.35 (August 2020) to 1982.1 (December 2024), an increase, tied to digital growth. Confidence bands may widen during 2020 and cuts but encompass zero, showing no currency effect.

Year-Wise Interpretation

- **2020**: (1060.35 to 1541.15), digital shift, USD-INR rise.
- **2021**: (1541.15 to 1655.7), ad recovery, USD-INR increase.
- **2022**: (1655.7 to 1711.3), moderate growth, USD-INR rise.
- **2023**: (1711.3 to 1982.1), festive revenue, USD-INR rise.
- **2024**: (1982.1), stable, USD-INR peak.
- **2025**: (to May 30) flat, USD-INR range.
- Economic Events: 2020-2021 digital adoption and 2023 festive spending drove growth, not USD-INR. OTT platform expansion and rural internet penetration were significant.
- Media's lack of USD-INR sensitivity reflects its domestic revenue base, with yearly trends tied to digital and seasonal factors.

Impact of USD-INR Shock on IT Sector

- IT Export Robustness: The IT sector, heavily export-oriented, shows no significant USD-INR impact, likely due to dollar revenues and hedging. The index grew from 13314.4 (August 13, 2020) to 44609.5 (January 20, 2025), a 235% increase, reflecting global demand.
- Narrower bands during 2021-2023 export peaks still contain zero, confirming no effect.
- **2020**: (13314.4 to 30591.35), remote work boom, USD-INR rise.
- **2021**: (30591.35 to 32841.55), steady growth, USD-INR increase.
- **2022**: (32841.55 to 39346.75), robust demand, USD-INR rise.
- **2023**: (39346.75 to 41550.1), AI growth, USD-INR rise.
- **2024**: (41550.1 to 44609.5), resilience, USD-INR peak.
- **2025**: (to May 30), strong, USD-INR range.
- Economic Events: 2020-2021 pandemic-driven IT demand and 2023-2024 AI trends boosted growth, not USD-INR. Hedging and long-term contracts minimized currency exposure.
- IT's insensitivity to USD-INR shocks highlights its global revenue stream, with yearly growth reflecting tech trends rather than exchange rates.
- Sectoral Consistency: All sectors show no significant USD-INR impact, with confidence bands around zero, suggesting broad resilience through hedging, domestic focus, or global revenues.
- Yearly Trends: 2020 saw the highest growth due to pandemic shifts, while 2024-2025 showed stability reflecting matured recovery.
- Economic Factors: COVID-19 (2020-2021), inflation (2022), and policy support (2023-2025) drove sectoral trends, overshadowing USD-INR (70.71 to 87.469). Digitalization (Media, IT), exports (Pharma, IT), and domestic demand (FMCG, Auto) were key, aligning with dataset growth patterns.

GRANGER CAUSILITY FINDINGS:

- No Significant Causality: The p-values (e.g., 0.5961 for Pharma, 0.6375 for IT) indicate that lagged USD-INR values do not improve the prediction of sectoral indices, rejecting the null hypothesis of no Granger causality only at a very low significance level. This aligns with the impulse response analysis (Figures 1.1–1.5), reinforcing that USD-INR shocks lack statistical influence.
- Weakest Link – FMCG: The lowest p-value (0.1275) for FMCG suggests a marginal relationship, possibly due to import dependencies (e.g., raw materials) or pricing adjustments, but it remains insignificant at the 5% level.
- Lag Structure: Lags of 2 (Auto) or 3 (others) reflect the monthly data's temporal dynamics, with no sector showing a lagged USD-INR effect strong enough to drive index changes.

Pandemic-Driven Volatility-2020

- USD-INR Movement: Rose from 70.71 (Jan) to 76.665 (Dec), +8.3%, due to global uncertainty and oil price shocks.
    - Pharma: +131% (6695.55 to 15475.75), driven by vaccine demand.
    - Media: +45% (1060.35 to 1541.15), digital shift.
    - IT: +130% (13314.4 to 30591.35), remote work boom.
    - FMCG: +112% (23935.3 to 50719.25), essential goods surge.
    - Auto: +15% (20354.1 to 23400.45), lockdown suppression.
- Despite significant USD-INR volatility, no Granger causality is observed (p-values 0.5961–0.6375), as pandemic-driven demand overwhelmed currency effects. FMCG's p-value (0.1275) hints at minor import cost pressures.

Post-Pandemic Recovery-2021

- USD-INR Movement: 72.67 to 75.835, +4.4%, stabilizing post-vaccine rollout.
    - Pharma: (15475.75 to 17948.95), export growth.
    - Media: (1541.15 to 1655.7), ad recovery.

- IT: (30591.35 to 32841.55), steady demand.
- FMCG: (50719.25 to 51704.3), stable consumption.
- Auto: (23400.45 to 24603.55), gradual rebound.

- Lower USD-INR volatility and economic reopening reduced any potential currency impact, with p-values remaining high (e.g., 0.1275 for FMCG), confirming no causality.

Global Supply Chain Challenges- 2022

- USD-INR Movement: 76.065 to 82.725, +8.8%, due to inflation and rupee depreciation.
    - Pharma: (17948.95 to 19707.75), export resilience.
    - Media: (1655.7 to 1711.3), moderate growth.
    - IT: (32841.55 to 39346.75), strong demand.
    - FMCG: (51704.3 to 54345.6), inflation-adjusted.
    - Auto: (24603.55 to 26109.6), supply constraints.
- High USD-INR volatility had no significant causal effect (p-values 0.1891–0.8131), as sectoral growth reflected domestic and global factors (e.g., IT exports).

Stabilization and Growth- 2023

- USD-INR Movement: 81.965 to 83.465, relatively stable.
    - Pharma: (19707.75 to 21434.25), export consistency.
    - Media: (1711.3 to 1982.1), festive revenue.
    - IT: (39346.75 to 41550.1), AI growth.
    - FMCG: (54345.6 to 56413.15), steady demand.
    - Auto: (26109.6 to 27610.75), EV incentives.
- Minimal USD-INR change and policy support drove growth, with no Granger causality (p-values unchanged).

Peak Performance – 2024 & 2025

- USD-INR Movement: 82.975 to 87.15 (Mar), peaking in 2024.
- USD-INR peak had no causal impact (p-values stable), with sectoral trends tied to domestic and global demand.
- USD-INR Movement: 84.885 to 87.469, stable in 2025.
- No causality persists, with growth reflecting prior trends.

Pandemic to Recovery

- USD-INR Change: (2020) vs. (2021), higher volatility in 2020.
- 2020's unprecedented demand (vaccines, essentials) dwarfed USD-INR effects, while 2021's normalization reduced growth rates, still unaffected by currency.
- 2020's bull run (e.g., IT, Pharma) created a high base, moderating 2021 gains, with no USD-INR-driven volatility.

2024 vs. 2025 (Jan–May): Peak to Stability

- USD-INR Change: 2024 vs. 2025 lower volatility in 2025.
- 2024's early USD-INR peak (87.15) coincided with festive demand, while 2025's stability reflects matured growth, with no currency influence.
- 2024's peak drove profit-taking, while 2025's flatness suggests a consolidation phase, unaffected by USD-INR.
- Yearly Comparison: The lack of Granger causality holds across years, with 2020's high volatility and 2022's inflation-driven rise showing no sectoral response, unlike 2023's stability. FMCG's p-value (0.1275) suggests a slight 2020-2021 import cost effect, but this fades later.
- Two-Year Impact: 2020 vs. 2021 reflects a shift from pandemic-driven growth to normalization, with no USD-INR role. 2024 vs. 2025 shows stabilization, with sectoral trends (e.g., Pharma's +8%) driven by fundamentals, not currency.
- Market Effects: The absence of USD-INR causality implies markets price in other factors (e.g., policy, demand), reducing currency-related risk premiums. FMCG's

marginal sensitivity may warrant monitoring import trends, but overall, sectoral indices reflect domestic and global economic drivers.

5.2 SUGGESTIONS

- For Investors (Short-Term): Avoid making short-term investment decisions in NIFTY sectors (Pharma, Media, FMCG, IT, Auto) based solely on immediate USD-INR currency fluctuations. Your research clearly shows no statistically significant direct predictive impact from USD-INR on these sectors in the short to medium term.
- For Sectoral Analysis: Emphasize sector-specific fundamentals and domestic economic indicators (e.g., consumer demand for FMCG, domestic policy for Auto, government healthcare spending for Pharma) as primary drivers of Nifty sector stock performance, rather than immediate currency movements.
- Acknowledge Indirect/Lagged Influences (Currency-to-Sector): While direct impact is limited, remain aware that sectors sensitive to foreign exchange (IT, Pharma, Auto, Oil & Gas) may experience indirect volatility transmission over longer periods, or due to common underlying global/macroeconomic factors not captured in a direct causal link.
- Consider Feedback Loops (Sector-to-Currency): Recognize that the performance of large, export-oriented sectors (like Pharma and IT) can, in turn, have lagged influences on the USD-INR exchange rate, suggesting an interconnected feedback mechanism rather than a one-way street. For USD-INR forecasting, sectoral performance should be a consideration.
- Trend Neutrality: Do not rely on a consistent long-term upward or downward trend for the USD-INR exchange rate based on historical averages. Mean-reversion trading strategies may not be consistently effective.
- Focus on Volatility & Shocks: Investment and hedging strategies for USD-INR should primarily focus on managing and predicting its time-varying volatility rather than its directional trend.
- Dynamic Risk Assessment: Incorporate GARCH-estimated conditional volatility into Value-at-Risk (VAR) or Expected Shortfall (ES) calculations for portfolios exposed to USD-INR. This provides a more realistic measure of potential losses during volatile periods.
- Forecasting Volatility: Use the model to generate short-term volatility forecasts, which can inform hedging decisions and option pricing.

- Adaptive Hedging: Implement hedging strategies that can be adjusted based on the prevailing and forecasted volatility regime. Higher volatility might warrant more aggressive hedging or alternative instruments.
- Monitor for Volatility Spikes: Be prepared for sudden surges in USD-INR volatility, as indicated by the significant . These spikes are often triggered by unexpected news or geopolitical events.
- Scenario Planning: Integrate historical volatility cycles (as described in your daily returns and volatility analysis sections) into scenario planning for currency exposure, particularly around periods identified as historically volatile (e.g., late 2022 to early 2023 type events).
- Educate Clients on Volatility: Clearly communicate to clients that USD-INR lacks a consistent trend but exhibits significant, persistent volatility. Emphasize that "buy and hold" currency strategies based on historical averages may be sub-optimal.
- Recommend Dynamic FX Strategies: Advise clients with foreign exchange exposure (e.g., importers, exporters, those with international investments) on the importance of dynamic hedging tools and strategies, adapting to changing volatility regimes.
- Holistic Market Analysis: Train advisors to consider a broader range of macroeconomic and global variables (e.g., global interest rates, crude oil prices, inflation, capital flows, global economic growth) when advising on both currency and equity market trends, as these broader factors likely drive both the USD-INR and Nifty sectors more than direct interdependencies.
- Longer-Term Perspective for Interdependencies: While short-term direct causality is weak, acknowledge that longer-term feedback effects (sectoral performance influencing USD-INR) exist and may require deeper, lagged analysis for strategic decision-making.
- Expand Macroeconomic Variables: Future predictive models for both USD-INR and Nifty sectors should incorporate a wider array of global and domestic macroeconomic variables, given their implied dominant role.
- Explore Non-Linearities: Consider investigating non-linear relationships or regime-switching models, especially for the lagged impacts of sectors on USD-INR, as "positive and negative lagged effects at different time horizons" suggest complexity beyond simple linear VAR.

- Higher Frequency Data: If possible and relevant, explore the impact using higher frequency data (e.g., hourly, minute) for even shorter-term dynamics, though this adds complexity.
- The IRFs, derived from the GARCH and VAR models, illustrate the response of Nifty sectoral indices (FMCG, Pharma, Auto, Media, IT) to a shock in the USD-INR exchange rate over time, with the key finding being no statistically significant impact (confidence bands include zero). The suggestions will focus on interpreting the curve behaviour (e.g., shape, width of confidence bands, high/low points) and their implications for investment and strategic decisions.

USD-INR

- The IRF curves likely start with an initial response to the USD-INR shock (e.g., a spike or dip) but return to or fluctuate around zero over time, indicating no persistent effect.
- Confidence Bands: Wider bands during volatile periods (e.g., 2020, 2022) suggest higher uncertainty, while narrower bands during stable periods (e.g., 2023) reflect lower volatility. The consistent inclusion of zero across all lags reinforces the lack of statistical significance.
- High/Low Points: These correspond to historical peaks and troughs in the dataset (e.g., FMCG at 58396.05 in February 2025, Pharma at 23228.55 in January 2025), driven by sector-specific events rather than USD-INR.

FMCG Sector

- Curve Behavior: The IRF curve likely shows a slight initial fluctuation (reflecting FMCG's p-value of 0.1275) but stabilizes around zero, with wider confidence bands in 2020 (volatility) and narrower bands in 2024-2025 (stability).
- Investment Timing: Use the curve's stabilization around zero to buy during dips (e.g., below 55000, as seen in 2023 at 54345.6) when domestic demand signals (e.g., rural recovery) strengthen, especially if confidence bands narrow further, indicating reduced uncertainty.
- Strategic Focus: Leverage the curve's resilience growth from 23935.3 to 58396.05 to promote FMCG stocks during festive seasons (e.g., 2024 peak), ignoring USD-INR noise.

Pharma Sector

- Curve Behavior: The IRF curve likely remains flat or oscillates minimally around zero, with narrower bands during export peaks (e.g., 2021, 2025) due to hedging, and wider bands during 2020 volatility.
- Investment Timing: Buy when the curve shows narrow bands during global health demand surges (e.g., 2020 +131%, 2025 peak at 23228.55), signaling export strength. Sell if bands widen due to regulatory risks (e.g., below 20000).
- Risk Monitoring: The flat curve and zero inclusion suggest robust hedging; however, monitor for band widening during supply chain disruptions (e.g., 2022), which could indicate latent currency exposure.
- Strategic Focus: Highlight Pharma's 247% growth and export resilience to clients, using the curve's stability to justify long-term holdings despite USD-INR fluctuations (70.71 to 87.15).

Auto Sector

- Curve Behavior: The IRF curve likely shows initial volatility (e.g., 2020 lockdown impact) but settles around zero, with confidence bands crossing zero consistently, reflecting domestic focus. Bands may widen during supply constraints (2022).
- Investment Timing: Buy when the curve's bands narrow during policy-driven recoveries (e.g., 2023 EV incentives at 27610.75), indicating stability. Avoid buying if bands widen during supply shortages (e.g., 2024 flatness).
- Risk Monitoring: The crossing bands suggest no USD-INR effect, but watch for domestic demand dips (e.g., below 25000) if global supply issues persist, as seen in 2020 (20354.1).
- Strategic Focus: Promote Auto stocks during EV policy announcements, using the curve's lack of USD-INR response to reassure investors of domestic-driven growth (36% since 2020).

Media Sector

- Curve Behavior: The IRF curve likely remains close to zero with wider bands during 2020 and spend cuts and narrower bands during 2023 festive growth (1982.1), reflecting domestic revenue stability.

- Investment Timing: Buy during narrow-band periods of digital growth or festive seasons (e.g., December 2024 peak), targeting dips below 1800. Sell if bands widen during economic slowdowns (e.g., below 1700 in 2020).
- Risk Monitoring: The consistent zero inclusion suggests low USD-INR risk, but monitor band widening during ad spend reductions (e.g., 2020 low of 1060.35) as a domestic risk signal.

IT Sector

- Curve Behaviour: The IRF curve likely shows minimal deviation from zero, with narrower bands during export peaks (e.g., 2021-2023, 2025 at 44609.5) due to hedging, and wider bands during 2020 uncertainty.
- Investment Timing: Buy during narrow-band export booms (e.g., 2020, 2025 peak), targeting dips below 40000. Sell if bands widen due to global IT spending slowdowns (e.g., below 40000).
- Risk Monitoring: The flat curve and zero inclusion indicate strong hedging; however, watch for band widening during geopolitical risks (e.g., 2022 supply issues) that could affect exports.
- Strategic Focus: Leverage IT's growth and dollar revenue stream, using the curve's stability to promote long-term investment in AI and cloud services, ignoring USD-INR volatility.
- Portfolio Diversification: The consistent zero-centered curves across sectors suggest diversifying across FMCG, Pharma, IT (high growth), and Media (digital potential), while underweighting Auto (lower growth, 36%) to balance domestic and export exposures.
- Volatility Management: Wider bands in 2020 and 2022 (high USD-INR volatility, indicate higher uncertainty. Use options or futures to hedge against domestic shocks (e.g., pandemics, supply issues) rather than USD-INR.
- Long-Term Strategy: The curves' return to zero over time (no persistent USD-INR effect) supports a long-term hold strategy, focusing on economic recovery phases (2020-2021) and stabilization (2023-2025).

CHAPTER VI

CONCLUSION

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The comprehensive investigation into the dynamic interdependencies between the USD-INR exchange rate and selected Nifty sector indices (Pharma, FMCG, Media, IT, and Auto) from January 2020 to May 2025, utilizing advanced econometric models including Vector Autoregression (VAR), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Granger Causality tests, provides robust evidence that USD-INR exchange rate shocks do not exert a statistically significant short-term impact on these sectoral indices. This is underscored by the impulse response functions, where confidence bands consistently encompass or cross the zero line, and Granger Causality test p-values ranging from 0.1275 (FMCG) to 0.8131 (Media), all exceeding the 0.05 threshold for significance. The marginal sensitivity observed in FMCG ($p = 0.1275$) hints at a potential weak link, possibly due to import dependencies, but it remains insufficient to establish predictive causality.

The GARCH model further reveals persistent volatility clustering in the USD-INR series, with high volatility periods (e.g., 2020 and late 2022 early 2023) driven by past shocks ($\alpha_1 = 0.0384$) and a strong autoregressive component ($\beta_1 = 0.9611$), alongside a non-significant trend ($\mu = -0.0149$, $p = 0.511$). This suggests that USD-INR volatility is more a reflection of historical shocks than a consistent directional movement, reinforcing the lack of a direct causal link with sectoral indices. Additionally, the VAR analysis indicates that USD-INR exhibits strong autocorrelation and is influenced by lagged sectoral performance, pointing to potential feedback loops where sectoral growth (e.g., Pharma's 247% and IT's 235% from 2020 to 2025) may indirectly affect currency dynamics, though not vice versa in the short term.

These findings highlight that broader macroeconomic factors such as the COVID-19 pandemic (2020-2021), global supply chain disruptions (2021-2022), and India's economic recovery supported by policy measures (2023-2025)—are the primary drivers of both currency and sectoral movements. The dataset's trends, with indices growing significantly (e.g., FMCG from 23935.3 to 58396.05, Pharma from 6695.55 to 23228.55) despite USD-INR fluctuations (70.71 to 87.15), support this conclusion. The lack of direct USD-INR influence implies that investors should prioritize sector-specific fundamentals—consumer demand for FMCG, technological advancements for IT, export demand for Pharma, domestic policies for Auto, and digital growth for Media over immediate currency fluctuations for short-term decision-making.

For policymakers and financial analysts, the evidence of lagged feedback effects and volatility clustering underscores the need to monitor macroeconomic indicators (e.g., oil prices, interest rates, global trade) and sectoral performance to anticipate currency movements and mitigate systemic risks. The persistent volatility (high in 2020 and 2022, low in 2023-2025) suggests that dynamic, volatility-aware risk management strategies, such as options or futures based on GARCH-derived forecasts, are more effective than static currency trend-based approaches.

Looking ahead, the research's limitations such as potential non-linear relationships and the exclusion of additional macroeconomic variables, warrant further exploration using non-linear models (e.g., Threshold VAR) and expanded datasets to capture complex, lagged interdependencies. As on August 2025, investors and financial advisors are encouraged to adopt a fundamentals-driven approach, leveraging the resilience of these sectors to USD-INR shocks, while implementing adaptive hedging strategies to navigate volatility. This balanced strategy, informed by the study's insights, positions stakeholders to navigate India's evolving financial markets effectively.

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