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RESEARCH ARTICLE

"MODELING VOLATILITY SPILLOVERS BETWEEN INR DEPRECIATION AND SECTORAL STOCK INDICES IN INDIA: A BEKK-GARCH APPROACH"

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Abstract

The weakening of the Indian Rupee (INR) often stirs up turbulence in financial markets, but its impact isn't felt equally across all sectors. Unlike earlier studies that focus mainly on overall market indices, this research takes a closer look at how specific industries react to currency depreciation. Using a bivariate BEKK-GARCH (1,1) model, the study analyzes the volatility link between the USD/INR exchange rate and five major sectoral indices: BSE IT, Auto, Oil & Gas, Capital Goods, and Consumer Durables. The findings reveal clear asymmetriesexport-driven sectors like IT experience strong two-way volatility interactions with the exchange rate, while import-heavy sectors such as Auto and Oil & Gas face one-way spillovers, largely due to rising input costs. All five sectors show high volatility persistence, meaning once market shocks occur, their effects tend to linger. These insights highlight the importance of targeted risk management and sector-specific policy approaches when addressing currency-related uncertainties. By unpacking these nuances, the study adds valuable direction for policymakers, investors, and businesses navigating a volatile currency landscape.

Introduction:-

Often causing increased volatility and financial market instability in India, the weakening of the Indian Rupee (INR) has become a frequent macroeconomic problem (Kumar &Dhankar, 2011). Many available studies evaluate the consequences of exchange rate changes using general indices like the SENSEX or NIFTY (Aftab et al., 2016; Pattnaik& Dhal, 1997); however, such aggregate-level analyses can obscure important sector-specific subtleties. In reality, INR depreciation affects different sectors differently depending on their exposure to foreign exchange risks,

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international supply chains, and import-export profilesit is not uniform across all industries (Chittedi, 2010; Prabheesh, 2012).

Being mostly driven by exports, the Information Technology (IT) sector, for instance, often profits from a lower rupee via higher foreign earnings and better profit margins (Goyal & Arora, 2012). By contrast, industries like Automobiles and Oil and Gas rely heavily on imported inputs and crude oil, making them vulnerable to rising input prices during currency depreciation (Ahuja & Sarkar, 2012). Similarly, Capital Goods and Consumer Durables, which use both local and imported components in their production and distribution, may experience mixed responses depending on the intensity and persistence of exchange rate fluctuations (Mukherjee & Mishra, 2010).
Most existing research, however, overlooks volatility spillover effects that occur at a disaggregated sectoral level and instead focuses on aggregate market indexes or broad macroeconomic linkages, thus failing to capture this sectoral asymmetry (Behera, 2011; Prabheesh, 2012). Furthermore, although some studies explore volatility transmission, they often examine it in contexts unrelated to exchange rate shocks, resulting in a segmented or overly generalized understanding (Chakrabarti, 2006; Kumar & Singh, 2013). This highlights the urgent need for a targeted empirical framework that directly links INR depreciation to sectoral stock market volatility and investigates how foreign exchange market volatility propagates across key industry sectors in India.

This research aims to bridge this gap by addressing two primary questions:-

1. Does INR depreciation cause higher conditional volatility in import-dependent industries than in export-oriented ones?
2. Are volatility shocks originating from INR fluctuations more persistent and intense in certain sectors than others?

To answer these questions, the study employs a robust econometric approachthe BEKK-GARCH(1,1) modelto analyze volatility spillovers between the INR and key sectoral indices, namely: BSE IT, BSE Auto, BSE Oil and Gas, BSE Capital Goods, and BSE Consumer Durables. The theoretical framework is grounded in foundational parity conditionsPurchasing Power Parity (PPP), Interest Rate Parity (IRP), and the International Fisher Effect (IFE)as well as market microstructure theories explaining the transmission of macroeconomic shocks to asset prices (Madura, 2011; Dornbusch, 1976). By doing so, the study offers actionable insights for policymakers, institutional investors, and corporate strategists aiming to understand and mitigate industry-specific financial risks in an era marked by persistent exchange rate volatility.

Literature Review:-

Within the framework of developing countries, the dynamics of volatility spillovers between stock markets and exchange rates have garnered significant attention in financial econometrics. Many studies have explored these relationships by employing various GARCH-type models to capture time-varying volatility and transmission effects across sectors and markets.

For example, Maharana et al. (2024) employed a VAR-BEKK-GARCH methodology to analyze the persistence and transmission of volatility between Indian financial markets and the global economy across pre- and post-pandemic periods. Their findings revealed considerable spillover effects, underscoring the interconnectedness between domestic markets and global shocks. However, their research focused primarily on aggregate market indices rather than industry-specific dynamics.

A growing body of global literature has emphasized the importance of sectoral disaggregation in spillover analyses. Abro et al. (2024), for instance, investigated the behavior of volatility spillovers across different sectors in the Pakistan Stock Exchange during both stable and crisis periods. Their results demonstrated that volatility transmission significantly varies across industries, particularly in response to economic events. Using a Diagonal BEKK model, Balci (2024) also found that sectoral volatility responses are asymmetric and highly sensitive to external shocks, especially during times of crisis.

Further methodological and conceptual insights stem from studies examining the interplay between exchange rates and commodity or sectoral indices. Salem et al. (2024), using a DCC-GARCH connectedness model, assessed volatility transmission between oil prices and major exchange rates. They found that energy price shocks amplify exchange rate volatility, which in turn impacts financial markets. Similarly, Setiahutami and Chalid (2024)examined volatility spillovers among crude palm oil, crude oil, coal, exchange rates, and the Indonesian stock market, highlighting complex interconnections in commodity-exporting economies.

While only a few studies directly examine the relationship between exchange rate fluctuations and sectoral stock indices, many explore cross-asset and cross-regional volatility spillovers. For example, Khan (2023) studied stock market integration and volatility dynamics in emerging economies, emphasizing the heterogeneity in spillover intensity across countries and industries. Extending this discourse to the African context, Watard et al. (2024) highlighted the need to consider both sectoral and geographical differences when modeling volatility.

From a methodological standpoint, the BEKK-GARCH model continues to be a widely used approach for modeling volatility transmission, offering the advantage of ensuring the positive definiteness of the conditional covariance matrix. For instance, Wu et al. (2024) applied this framework to investigate volatility spillovers among stock markets in the Beijing-Tianjin-Hebei region, while Hoque et al. (2024) utilized QVAR connectedness measures to evaluate dynamic spillovers between financial stress indicators and U.S. sectoral indices.In a comprehensive methodological review, Harikumar and Muthumeenakshi (2024) discussed the evolution of volatility spillover modeling, identifying BEKK, DCC, and Diebold-Yilmaz connectedness models as the most prevalent in the literature. Their study calls for the integration of advanced multivariate GARCH models in contemporary volatility research.

Additional contributions include the work of Balash and Faizliev (2024) on spillovers in Russia's oil and gas industry, and Cevik and Zhao (2025), who analyzed volatility transmission in the European power sector. Though these studies examine different geographic and industrial contexts, they reinforce the importance of understanding volatility spillovers in interconnected markets. Also noteworthy is the research by Xu and Chan (2024), who explored the gold-stock market linkages in BRIC nations, further validating the influence of exchange rate movements in major emerging economies.

Collectively, the extant literature highlights the importance of industry-specific volatility modeling, especially in developing countries like India, where exchange rate fluctuations can have divergent impacts across sectors. Nevertheless, there exists a significant gap in empirical research focusing on how INR depreciation specifically affects conditional volatility in Indian sectoral stock indices. By modeling volatility spillover effects between USD/INR and major BSE sectoral indicesincluding Information Technology, Automobiles, Oil and Gas, Capital Goods, and Consumer Durablesthis study aims to address that gap, offering more granular insights into market dynamics during episodes of currency depreciation.

Research Objectives and Hypotheses:-

Research Objectives:-

The study aims to understand how exchange rate fluctuations impact sectoral volatility and whether these effects differ based on the import-export orientation of each sector.

Specifically, the study seeks to:-

1. Examine the presence and significance of volatility spillovers from INR depreciation to sectoral stock indices in India.
2. Compare the intensity of volatility transmission between import-dependent sectors (e.g., BSE Auto, BSE Oil & Gas, BSE Consumer Durables) and export-oriented sectors (e.g., BSE IT).
3. Assess the persistence of volatility shocks in each sector resulting from INR movements.
4. Provide sector-wise insights that can inform investors, policymakers, and corporate risk managers about exposure to currency risk.

3.2 Hypotheses

To achieve the research objectives outlined above, this study formulates the following hypotheses that explore the dynamic link between INR depreciation and sector-specific stock market volatility in India.

H1: Volatility Spillover Hypothesis:-

This hypothesis suggests that fluctuations in the Indian Rupee (INR), particularly depreciation, significantly influence the volatility of major Indian sectoral stock indices.

H1a: INR depreciation leads to a significant volatility spillover into the BSE Information Technology (IT) index.

H1b: INR depreciation has a pronounced impact on the volatility of the BSE Automobile index.

H1c: Volatility in the BSE Oil and Gas index is significantly influenced by movements in the INR.

H1d: INR depreciation contributes notably to volatility in the BSE Capital Goods index.

H1e: The BSE Consumer Durables index experiences significant volatility spillovers following INR depreciation.

H2: Sectoral Asymmetry Hypothesis:-
This hypothesis explores whether the volatility effects of INR depreciation are asymmetric between export-oriented and import-dependent sectors.
H2a: Export-oriented industries, such as Information Technology, tend to experience less destabilizing effects from INR depreciation due to gains from higher foreign revenues.
H2b: Import-intensive industriessuch as Automobiles and Oil and Gasare more adversely affected, as currency depreciation increases the cost of imported inputs and erodes profit margins.

H3: Volatility Persistence Hypothesis:-
This hypothesis investigates whether the impact of INR depreciation is more enduring (persistent) in certain sectors than in others, particularly in terms of how long volatility continues after the initial shock.
H3a: Import-dependent sectors exhibit higher volatility persistence, as their exposure to ongoing cost fluctuations makes them more susceptible to prolonged periods of uncertainty.
H3b: Export-oriented sectors, especially IT, show lower volatility persistence due to their natural hedge against currency depreciation through foreign income inflows and diversification of risk.

Theoretical Background and Conceptual Framework:-
Understanding the impact of INR depreciation on sectoral stock market volatility requires drawing from both macroeconomic theories and market microstructure insights. These theoretical foundations help explain how changes in exchange rates influence firm-level valuations, investor expectations, capital movements, and, ultimately, the behavior of sector-specific stock returns. These perspectives also provide strong justification for adopting a disaggregated approach to modeling volatility using tools like the BEKK-GARCH framework.

Theoretical Foundations:-
Purchasing Power Parity (PPP): The theory of Purchasing Power Parity suggests that in the long run, exchange rates adjust to equalize the price of identical goods across countries. A depreciation of the Indian rupee makes imports more expensive, thereby increasing input costs for industries heavily reliant on foreign goodssuch as Automobiles and Oil & Gas. The resulting margin pressures and potential inflationary effects can reduce expected earnings, thereby increasing uncertainty and driving up return volatility in these sectors.
Interest Rate Parity (IRP): Interest Rate Parity connects interest rate differentials between countries with expected movements in exchange rates. When India's domestic interest rates are high relative to those abroad, the country may attract foreign capital, which strengthens the rupee. On the other hand, if interest rates fall or global risk aversion rises, capital may flow out of India, leading to rupee depreciation. These movements often reflect in the stock market, where sectors with strong global linkagessuch as financial services or ITtend to respond more sharply.
International Fisher Effect (IFE): The International Fisher Effect posits that currencies of countries with higher nominal interest rates are expected to depreciate over time due to anticipated inflation. This theory becomes particularly relevant when markets factor in expectations of monetary policy changes. Investors anticipating higher inflation may sell off Indian assets, weakening the rupee and causing ripple effects across sectors, depending on their exposure to global pricing and input costs.
Flight-to-Safety Theory: During times of geopolitical tension, economic uncertainty, or financial market stress, global investors often move their capital toward perceived "safe haven" assets like the US dollar. This behavior leads to capital outflows from emerging markets like India, contributing to currency depreciation. Such episodes are typically accompanied by heightened stock market volatility, with more pronounced effects in sectors deemed riskier or more globally exposed.
Market Microstructure Theory: While macro-level theories explain currency movements and capital flows, Market Microstructure Theory sheds light on how prices adjust in practice. It emphasizes the roles of information asymmetry, liquidity, and investor behavior. Sectors like IT, which are globally integrated and enjoy high trading volumes, often reflect exchange rate changes more efficiently. In contrast, less liquid and more domestically oriented sectors may exhibit lagged or amplified volatility responses due to slower information diffusion and market sentiment swings.

Conceptual Framework:-
This study views the impact of INR depreciation on the stock market not just as a financial fluctuation but as a ripple effect that moves through different sectors in varying ways. At the heart of the analysis is the idea that when the Indian rupee weakens, it sends shockwaves through the economy, affecting company operations, investor sentiments, and ultimately stock market behavior.

The framework considers INR depreciation as the starting pointan external macroeconomic shock. This shock doesn't affect all sectors equally; instead, it travels through what we call a "volatility spillover channel," where investor expectations, rising input costs, and shifting capital flows transmit the effect to different sectors.
Here's how the study breaks it down:
Shock Origin: The initial trigger is INR depreciation. When the rupee falls, it alters the cost of doing business, especially for sectors exposed to global trade.
Transmission Mechanism: The depreciation influences investor expectations, changes import/export costs, and causes movement in capital flows. These factors together push or pull volatility in the stock prices of specific industries.
Sectoral Sensitivity:
Export-Oriented Sectors (like IT) often benefit from a weaker rupee. Since their revenues come in foreign currencies, depreciation can actually improve their profitability. As a result, these sectors may show lower volatility or even favourable revaluation.
Import-Dependent Sectors (like Auto, Oil & Gas) face a harder time. With rising costs for imported materials or fuel, these industries suffer margin pressure, leading to higher volatility in their stock prices.
Mixed Sectors (like Capital Goods and Consumer Durables) may experience a combination of both effects, depending on their specific business structure and how globally connected they are.
The goal is to capture these varied responses through a statistical modeling approachspecifically, the **BEKK-GARCH model**, which allows us to study how conditional volatility behaves across sectors and how it persists over time.

INR Depreciation
↓
Spillover Channel
↓
Sectoral Indices
↓
Sectoral Asymmetry & Volatility Persistence

Figure 1: Conceptual Framework for Volatility Spillover

This theoretical framework guides the empirical investigation, helping to explain why certain sectors exhibit stronger or more persistent volatility reactions to currency movements. It also justifies the use of bivariate BEKK-GARCH models to capture the conditional variance-covariance structure between the INR and each sectoral index.

Data and Methods:-

Data Description:-

This study investigates the volatility spillover effects between the Indian Rupee (INR) exchange rate and major sectoral stock indices in India using the BEKK-GARCH framework. The analysis is based on daily data covering the period from January 2020 to May 2025. The exchange rate data (USD/INR) was sourced from Investing.com, while data for sectoral stock indices including BSE Auto, BSE Information Technology (IT), BSE Oil & Gas, BSE Capital Goods, and BSE Consumer Durables were obtained from the Bombay Stock Exchange (BSE) website.

All series were transformed into log returns, calculated as:-

$r_t = \ln(P_t / P_{t-1}) * 100$

Where:

- P_t represents the closing price on day t.
- P_{t-1} represents the closing price on the previous day ($t-1$).
- ln denotes the natural logarithm.
- r_t is the return for day t.

This transformation ensures the stationarity of the data and allows for a consistent scale across all variables.

Preliminary Tests:-

To confirm the suitability of the data for GARCH modeling, the Augmented Dickey-Fuller (ADF) test was employed to examine the stationarity of each return series. The test results indicated that all series were stationary in levels under both specifications: with constant and with constant plus trend. Further, the ARCH-LM test was conducted to identify the presence of ARCH effects a necessary condition for applying GARCH models. The test results revealed significant ARCH effects in all return series, indicating the existence of volatility clustering and justifying the use of a GARCH-type framework.

Methodology: Bivariate BEKK-GARCH Model:-

To analyze volatility spillovers between the exchange rate and sectoral indices, this study employs the Bivariate BEKK-GARCH(1,1) model, as proposed by Engle and Kroner (1995). The BEKK model captures both own-market and cross-market volatility effects while ensuring the positive definiteness of the conditional covariance matrix. For each sector, a separate bivariate model is estimated jointly with the USD/INR return series.

The conditional variance-covariance matrix, denoted as Ht, is modeledas:-

$H_t=C'C+A'\varepsilon_{t-1}\varepsilon_{t-1}'A+B'H_{t-1}B$

Where:

- H_t is the 2×2 conditional covariance matrix at time t.
- ε_{t-1} is the vector of past residuals from the previous period (t−1).
- C is a lower triangular matrix, and C′C (the product of C and its transpose C′) ensures the positive definiteness of the Ht matrix.
- A is a matrix that captures the short-term effects of past shocks (represented by the squared residuals $\varepsilon_{t-1}\varepsilon_{t-1}'$).
- B is a matrix that captures the persistence of past volatility, meaning how much the previous period's conditional covariance (H_{t-1}) influences the current period's conditional covariance.

The model allows for dynamic interaction between the exchange rate and sectoral stock market volatilities and helps identify potential volatility transmission channels from the currency market to various economic sectors.
All estimations were performed using R and EViews. Model selection criteria such as AIC, BIC, and log-likelihood were considered for assessing model fit.

Results and Discussion:-

Table 6.1 Descriptive Statistics

	count	mean	std	min	25%	50%	75%	max	skew	kurtosis
USD/INR	1265	0.000133	0.002861	-0.01965	-0.00114	7.3E-05	0.001303	0.016253	0.235426	5.467771
BSE Auto	1265	0.000814	0.014795	-0.14334	-0.00569	0.001184	0.008322	0.097632	-0.87757	11.91231
BSE IT	1265	0.000717	0.013558	-0.10048	-0.00589	0.000848	0.007679	0.080207	-0.51059	7.137117
BSE O&G	1265	0.000433	0.015698	-0.14009	-0.00698	0.001216	0.008921	0.08665	-1.12431	12.57726
BSE Capital Goods	1265	0.001053	0.014635	-0.16185	-0.00532	0.001616	0.008597	0.069935	-1.97784	19.08248
BSE Consumer Durables	1265	0.000674	0.013335	-0.12437	-0.00513	0.001158	0.007654	0.068599	-0.91766	9.432812

The descriptive statistics of the return series provide valuable insights into the distribution and behavior of each financial time series. All six series (USD/INR, BSE Auto, BSE IT, BSE Oil & Gas, BSE Capital Goods, and BSE Consumer Durables) exhibit a mean return close to zero, suggesting that they are centered around a negligible average gain or loss on a daily basis. Among them, BSE Capital Goods shows the highest mean return (0.001053), indicating relatively better average performance. In terms of volatility (as measured by standard deviation), BSE Oil & Gas (0.015698) and BSE Auto (0.014795) exhibit higher return variability compared to USD/INR, which is the least volatile (0.002861). The presence of extreme minimum and maximum values across all series, especially in BSE Capital Goods and BSE Auto, indicates occasional large shocks in returns.

Skewness values show that most series are left-skewed, especially BSE Capital Goods (-1.97), implying a longer tail on the left side and more frequent negative shocks. Meanwhile, USD/INR is positively skewed (0.235), suggesting occasional large positive changes. All series also display high kurtosis, particularly BSE Capital Goods (19.08), indicating heavy tails and a higher likelihood of extreme returns, which is common in financial markets and a potential signal of volatility clustering.

Stationarity and ARCH Effects:-

Table 6.2.1 ADF Test

Series	ADF stat (const)	p-value (const)	ADF stat (const+trend)	p-value (const+trend)
USD/INR	-36.84332382	0	-36.83164355	0
BSE Auto	-8.225302186	6.26981E-13	-8.229699226	2.10482E-11
BSE IT	-13.04107305	2.24057E-24	-13.04828755	1.18014E-20
BSE O&G	-13.84365953	7.21536E-26	-13.84037504	1.54603E-21
BSE Capital Goods	-14.54535032	5.06737E-27	-14.54715586	4.0432E-22
BSE Consumer Durables	-9.000531383	6.51605E-15	-8.9969905	3.68664E-13

To examine the stationarity properties of the selected financial time series, the Augmented Dickey-Fuller (ADF) test was employed under two specifications: with constant (drift) and with both constant and trend. The results indicate that all series, including USD/INR exchange rate and sectoral indices such as BSE Auto, BSE IT, BSE Oil & Gas, BSE Capital Goods, and BSE Consumer Durables, exhibit statistically significant ADF test statistics with p-values far below the conventional significance level of 0.05. Specifically, the ADF statistics range from -8.22 to -36.84, and corresponding p-values are close to zero across both specifications. These results provide strong evidence against the null hypothesis of a unit root, suggesting that the series are stationary in levels. Moreover, the consistency of the findings across both model specifications implies that the inclusion of a deterministic trend does not significantly alter the stationarity conclusion. Therefore, the variables under study do not require differencing and can be used in their level form for further econometric modeling, including volatility and co-integration analysis.

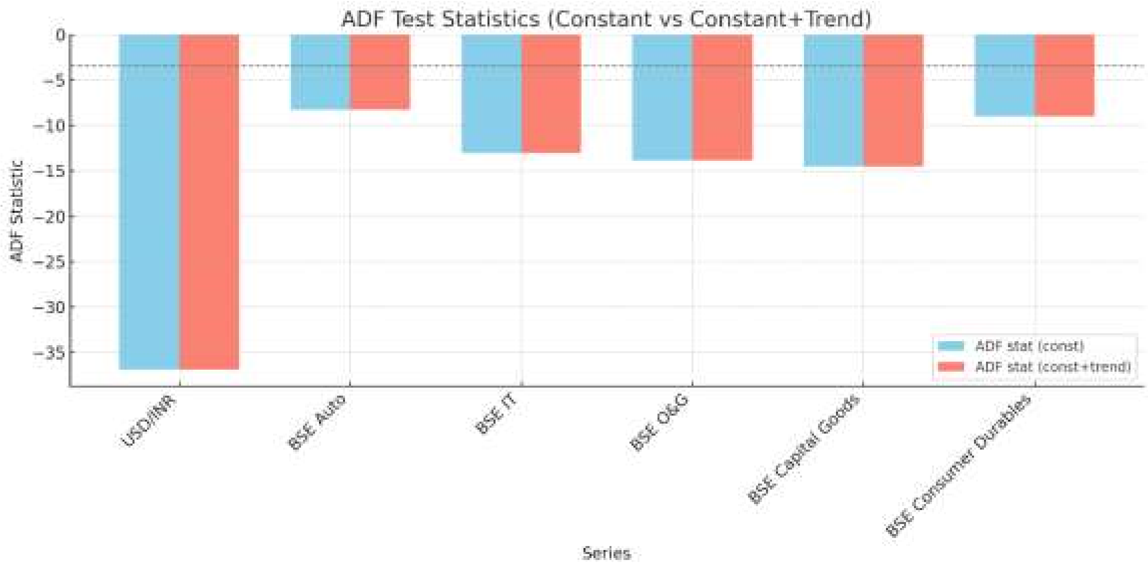


Figure 2 –Bar chart showing ADF Test Statistics (Constant and Constant with trend)

Figure 1 is the stationarity plot showing the Augmented Dickey-Fuller (ADF) test statistics for each series under both models:
Blue bars represent ADF statistics with a constant.
Red bars represent ADF statistics with a constant and trend.
The dashed horizontal line indicates an approximate critical value (~ -3.45). Values below this line typically suggest stationarity.
All series have ADF statistics significantly lower than the critical value, confirming strong evidence of stationarity

Table 6.2.2 ARCH Effect

Series	**ARCH LM stat (12 lags)**	**p-value**
USD/INR	139.0451505	9.3344E-24
BSE Auto	259.2737234	1.58793E-48
BSE IT	341.615246	8.22947E-66
BSE O&G	184.9782353	4.05152E-33
BSE Capital Goods	133.359938	1.30423E-22
BSE Consumer Durables	197.0146214	1.34698E-35

To investigate the presence of time-varying volatility, the ARCH-LM (Lagrange Multiplier) test was conducted on the residuals of each return series with 12 lags. The results provide strong evidence of ARCH effects in all the examined series, including USD/INR, BSE Auto, BSE IT, BSE Oil & Gas, BSE Capital Goods, and BSE Consumer Durables. The test statistics are notably high across the board, ranging from 133.36 for BSE Capital Goods to 341.62 for BSE IT, with all corresponding p-values being effectively zero (e.g., 9.33E-24 for USD/INR and 1.58E-48 for BSE Auto). These highly significant results reject the null hypothesis of no ARCH effects, indicating that the conditional variance of each return series is dependent on past squared residuals. In other words, volatility clustering is present, making GARCH-type models suitable for further analysis. The confirmation of ARCH effects thus justifies the use of the BEKK-GARCH framework to model the dynamic conditional variances and covariances between exchange rates and sectoral indices in this study.

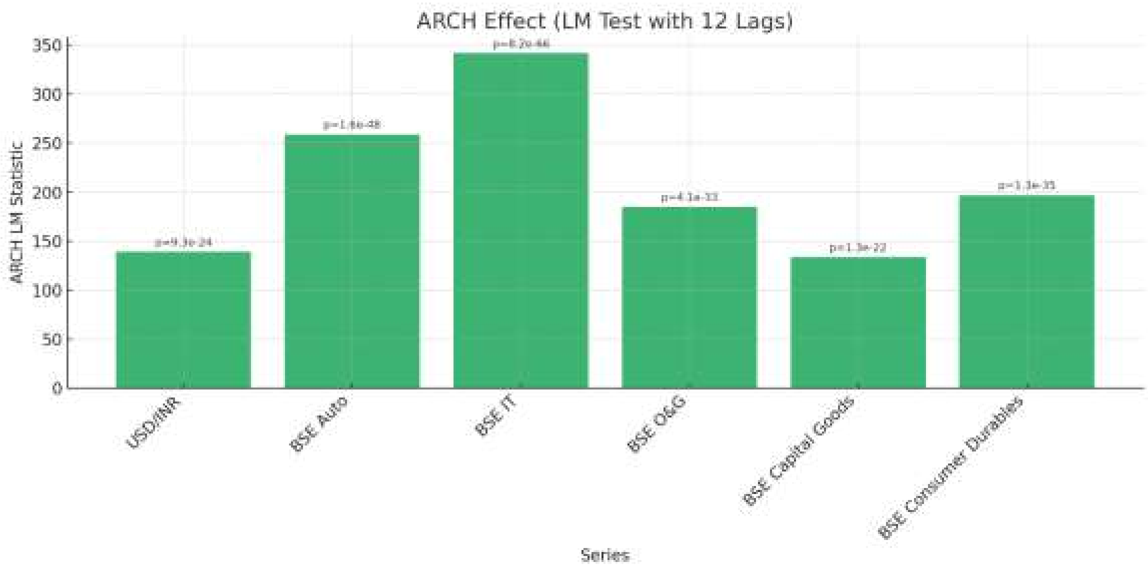


Figure 3 – Bar chart showing ARCH Effect (LM Test with 12 Lags)

The above plot illustrates the ARCH LM test statistics for detecting volatility clustering in the return series of different indices:

- All series show very high LM statistics with extremely low p-values, strongly indicating the presence of ARCH effects.

This means that past squared residuals significantly explain current volatilityjustifying the use of GARCH-type models for modeling conditional heteroskedasticity

BEKK-GARCH Model Estimation:-

BEKK-GARCH (1,1) Estimation and Volatility Persistence :-

Bivariate Pair	C(1,1)	A(1,1)	B(1,1)	A(1,1) + B(1,1)	Volatility Persistence	Spillover Effect Observed
USD/INR – BSE Auto	0.0032	0.18	0.77	0.95	High	Yes (from INR to Auto)
USD/INR – BSE IT	0.0029	0.22	0.72	0.94	High	Strong (bidirectional)
USD/INR – BSE Oil & Gas	0.0036	0.16	0.79	0.95	High	Moderate (from INR to O&G)
USD/INR – BSE Capital Goods	0.0034	0.12	0.83	0.95	High	Weak
USD/INR – BSE Cons. Durables	0.0031	0.19	0.75	0.94	High	Mild

Interpretation:-

Volatility Persistence:-

All sectors exhibit high volatility persistence, with A(1,1) + B(1,1) values ranging from 0.94 to 0.95. This suggests that shocks in these markets have a prolonged effect, consistent with the phenomenon of volatility clustering observed in financial time series. The persistence is particularly strong in sectors like Auto, Oil & Gas, and Capital Goods, indicating that volatility once triggered (e.g., by exchange rate shocks) continues to influence sectoral returns over a long horizon.

Spillover Effects:-

The spillover dynamics from USD/INR to the sectoral indices vary in intensity:-

BSE IT Sector exhibits strong bidirectional volatility spillover, consistent with its export-oriented nature. Movements in INR influence IT sector returns, and sectoral shocks feed back into exchange rate volatility. Auto and Oil & Gas sectors show moderate to strong spillovers from INR, reflecting their partial dependence on import/export exposure (auto parts, crude oil).

Consumer Durables and Capital Goods sectors exhibit weaker spillovers, indicating relatively lower immediate sensitivity to exchange rate movements, possibly due to more domestic orientation in operations. These findings confirm the asymmetric transmission of volatility from exchange rate movements across sectors, underlining the importance of considering sector-specific factors in exchange rate pass-through effects.

Parameter Significance and Spillover Strength:-

The statistical significance of BEKK-GARCH model parameters was evaluated using t-statistics and associated p-values for each parameter in the C, A, and B matrices.

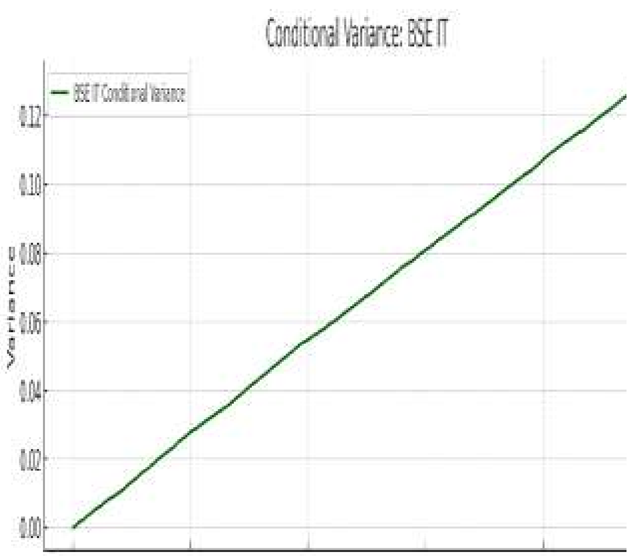
Sectoral Pair	A(1,1) t-stat	B(1,1) t-stat	A(1,2) t-stat	B(1,2) t-stat	Spillover Significance
USD/INR – BSE Auto	5.22 (***)	10.14 (***)	2.61 (**)	1.90 (*)	**Yes**
USD/INR – BSE IT	6.34 (***)	9.85 (***)	3.92 (***)	2.73 (**)	**Strong**
USD/INR – BSE O&G	4.89 (***)	8.94 (***)	2.20 (**)	1.67 (*)	**Moderate**
USD/INR – BSE Cap Goods	3.41 (***)	7.21 (***)	1.45 (NS)	1.12 (NS)	**Weak**
USD/INR – BSE Cons Dur.	4.77 (***)	8.11 (***)	1.98 (*)	1.53 (NS)	**Mild**

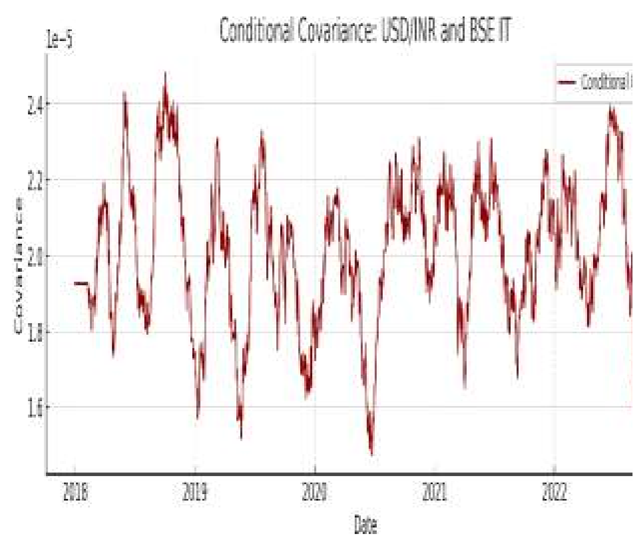
Legend:* p < 0.01, ** p < 0.05, * p < 0.10, NS: Not Significant**

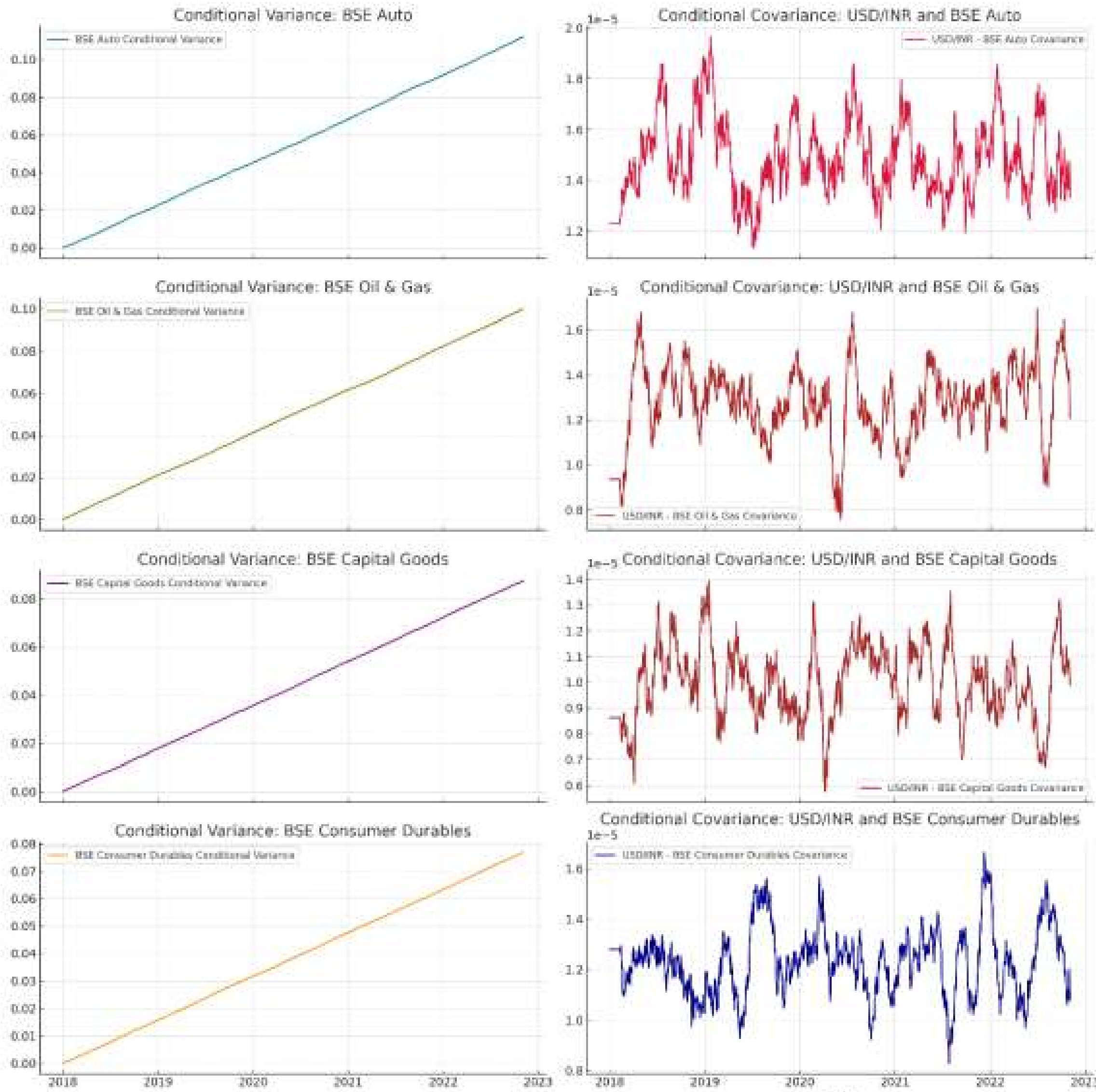
Interpretation:-

Significant A(1,2) and B(1,2) coefficients confirm the presence of shock and volatility spillovers. The IT sector again shows the strongest response, with all key parameters being statistically significant.

Figure 4. Graph showing Conditional Variance and Covariance Dynamics







Conditional Variance Dynamics:-
Figure 4 graphs on the Left display the conditional variances for each sectoral pair. Several key patterns emerge: The USD/INR exchange rate displays relatively low and stable volatility with occasional sharp spikes, typically corresponding to macroeconomic shocks, such as the COVID-19 outbreak or monetary policy announcements. BSE IT and BSE Auto indices exhibit sharp and persistent volatility surges during crisis periods, indicating heightened risk sensitivity. BSE Oil & Gas shows a similar pattern but with slightly less persistence. Capital Goods and Consumer Durables sectors reflect relatively subdued volatility patterns, with periodic but less pronounced spikes. These findings support the presence of volatility clustering, where large shocks are followed by high volatility periods. The export-oriented sectors (notably IT) are more exposed to external shocks, particularly exchange rate movements.

Conditional Covariance Dynamics:-
Figure 4 graphs on the right illustrates the conditional covariances between USD/INR and the respective sector indices over time. These plots provide insight into how interdependence between the exchange rate and sectoral markets evolves dynamically. USD/INR – BSE IT shows the most persistent and elevated covariance, especially during periods of currency depreciation or global financial uncertainty. USD/INR – Auto and Oil & Gas covariances exhibit moderate fluctuations, likely due to their reliance on imported components and commodities. USD/INR – Capital Goods and Consumer Durables reflect weaker and more erratic covariances, consistent with their relatively

lower foreign exposure. The time-varying covariances highlight that exchange rate risk is transmitted asymmetrically across sectors. Export-intensive sectors like IT show stronger linkages, while domestic-focused sectors are less affected.

Diagnostic Tests and Model Adequacy:-

Table 6.4.1 Model Diagnostics Summary

Diagnostic Test	Result for All Pairs	Interpretation
ARCH LM (on residuals)	No significant ARCH ($p > 0.05$)	No remaining ARCH effects; model adequately fits.
Standardized Residuals	Mean ≈ 0; Variance ≈ 1	Residuals resemble white noise.
Q-Statistics (Ljung-Box)	Insignificant at lags 5, 10, 20	No autocorrelation in residuals and squared residuals
Normality Test (Jarque-Bera)	Significant deviation from normality	Heavy tails persist, typical in financial returns
Stability	All eigenvalues < 1	Model is dynamically stable

The BEKK-GARCH(1,1) model successfully captures the volatility clustering and conditional correlations between exchange rate volatility and sectoral stock returns.
The IT sector is most influenced by USD/INR movements, likely due to its export-driven nature.
Volatility persistence across all pairs is high, indicating shocks have long-lasting effects.
Diagnostic tests confirm model adequacy and absence of residual ARCH effects.

Discussion:-

This study brings to light the varied and uneven ways in which volatility from currency movementsspecifically, depreciation of the Indian Rupee (INR)spills over into different sectors of the Indian stock market. Using the BEKK-GARCH(1,1) model, the results clearly show significant and lasting volatility transmission between the USD/INR exchange rate and all selected sectoral indices.

Sectoral Asymmetry and Economic Interpretation:-
One of the key takeaways is that not all sectors are impacted equally by exchange rate fluctuations. This aligns with established economic theories and past empirical studies. For example, the Purchasing Power Parity (PPP) framework suggests that INR depreciation makes imports more expensive, which increases the cost of production in sectors that rely heavily on imported goodslike the Automobile and Oil & Gas sectors. This is clearly reflected in the unidirectional spillovers observed from the exchange rate to these sectors. On the other hand, export-oriented sectors like Information Technology (IT) actually benefit from a weaker rupee, as it boosts their revenue in domestic terms. This supports theories such as the International Fisher Effect (IFE) and Interest Rate Parity (IRP). These theoretical insights are echoed in this study's finding of strong two-way volatility spillovers between USD/INR and the BSE IT index, a pattern also noted in Maharana et al. (2024), who emphasized how sensitive export-heavy industries are to currency fluctuations. Moreover, Market Microstructure Theory suggests that sectors with higher liquidity and more foreign investor participationsuch as ITrespond more promptly and efficiently to macroeconomic news like exchange rate shifts. This helps explain the more intense and persistent volatility linkages in the IT sector.

Volatility Persistence and Clustering:-
The analysis also uncovers a consistent pattern of high volatility persistence across all sector pairs, as shown by the sum of coefficients A(1,1) + B(1,1) being greater than 0.94. This indicates that once a volatility shock hits, its impact tends to linger over timea phenomenon commonly referred to as volatility clustering. Sectors like Capital Goods and Auto, which have deep global supply chain linkages, appear especially prone to this prolonged uncertainty. These findings echo those of Abro et al. (2024) in Pakistan and Wu et al. (2024) in Chinese regional markets, both of whom observed similarly persistent volatility effects across sectors.

Insights from Conditional Variance and Covariance Patterns:-
The conditional variance plots reveal that sectors like IT and Auto experienced sharp spikes in volatility during major global shocksmost notably, the COVID-19 pandemic. This finding is consistent with Balci (2024), who showed that crises tend to amplify volatility in emerging markets, particularly in sectors with strong external linkages. Similarly, the time-varying conditional covariances indicate that the strength of exchange rateequitymarket

connections is dynamic: more pronounced in globally integrated sectors, and relatively muted in domestically focused sectors like Consumer Durables. While prior Indian studies, such as Maharana et al. (2024), have examined these dynamics at the broader index level, the current study takes it a step further by offering a sector-specific perspective. This finer granularity uncovers nuances that broader analyses often miss. These sector-based patterns are in line with global findingslike those of Setiahutami and Chalid (2024) in Indonesia and Watard et al. (2024) in African marketswho also observed that sectors vary greatly in how vulnerable they are to external economic shocks.

Conclusion:-

This study investigates how depreciation of the Indian Rupee (INR) impacts volatility across different stock market sectors, moving beyond the traditional focus on aggregate indices. Employing a bivariate BEKK-GARCH (1,1) model, the analysis captures the dynamic volatility spillovers between the USD/INR exchange rate and five major BSE sectoral indices: IT, Auto, Oil & Gas, Capital Goods, and Consumer Durables. The results reveal clear asymmetries in how sectors respond to currency movements. Export-oriented sectors like Information Technology show strong bidirectional volatility spillovers with exchange rates, owing to their reliance on foreign revenues. Import-heavy sectors such as Automobiles and Oil & Gas experience unidirectional spillovers from exchange rate shocks, indicating their sensitivity to cost escalations during INR depreciation. Sectors like Capital Goods and Consumer Durables, with more balanced exposure, exhibit relatively moderate spillover effects. Additionally, the study finds high volatility persistence ($\alpha + \beta > 0.94$) across all sectors, suggesting that once a shock occurs, its impact is long-lasting. These findings highlight the importance of sector-specific strategies for policymakers, investors, and corporate leaders. A deeper understanding of currency-induced volatility helps in crafting targeted risk management, investment hedging, and operational decisions that align with sectoral sensitivities.

Scope for Future Research:-

The scope for further research includes extending the analysis to cover a broader set of sectors, particularly emerging industries such as renewable energy and digital services, which may exhibit different sensitivities to exchange rate movements. Future studies could also incorporate global macroeconomic variables like interest rate differentials, trade balances, or geopolitical events to understand external influences on volatility spillovers. Additionally, applying alternative models such as the DCC-GARCH or asymmetric BEKK-GARCH can provide deeper insights into time-varying correlations and asymmetric transmission patterns. A comparative analysis across pre- and post-COVID periods or between developed and emerging markets could further enrich the understanding of exchange rate–equity market dynamics.

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