The Ripple Effect : Influence of Exchange Rate Volatility on Indian Sectoral Indices

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Abstract

Purpose : The study aimed to analyze the spillover effect of foreign exchange rate volatility on the sectoral indices of India. The paper included five exchange rates (USD-INR, EURO-INR, GBP-INR, CNY-INR, and JPY-INR) and seven (automobile, banking, energy, FMCG, infrastructure, information & technology, and pharmaceutical) sectoral indices in this study.

Methodology : The study used the generalized autoregressive conditional heteroscedasticity (GARCH) (1,1) model for modeling volatility. T-GARCH model was used to estimate the leverage effect; and DCC-GARCH was used for analyzing the spillover effect of exchange rates on select sectoral indices.

Findings : The study found that leverage effect existed in all the series as the sum of α and λ of T-GARCH is less than 1, and the model was found acceptable. In the long-run, there was a spillover effect from all the exchange rates to all the sectoral indices. A short-run USD-INR spillover was observed on five sector indices, excluding banks and infrastructure. For every sectoral index, the DCC α of EURO-INR was determined to be negligible. Therefore, there was no transmission of short-term volatility from the EURO-INR to sectoral indices. Indexes of the FMCG, infrastructure, and IT sectors were not affected by the short-term volatility of the GBP-INR. DCC α and DCC β of CNY-INR were found to be significant for all the indices, which revealed transmission of information in the short-run as well as in the long-run. The three indices for which DCC α of JPY-INR was found insignificant are the bank, FMCG, and pharma sectors.

Implications : The results of this study shall aid policymakers and regulators in formulating investor-friendly rules and regulations to maintain a steady stock market. Prospective stakeholders shall also benefit from this research by using it to make reliable and well-informed investment decisions and portfolios. This study could be used as a reference document in other research and academic discussions as well.

Originality : Foreign exchange rates and sectoral indices, the focus of this study, have received relatively little attention in the literature despite the fact that research on stock markets has gained a lot of attention recently. This research will be a trailblazer in examining how fluctuations in foreign exchange rates impact India's sectoral indexes.

Keywords : foreign exchange rate, volatility, sectoral indices, GARCH, India

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Global financial interdependence is a prominent feature of the modern global economy, with several facets. Fintech, cross-border trade, foreign direct investments, capital flow through international capital markets, cross-border lending and borrowing, and technology improvements through digital finance expand the breadth and extent of globalization. Global interconnectedness and interdependence bring much-needed opportunities in fostering economic growth but pose a lot of challenges as well. Trade openness and ease of capital flows among the nations are key drivers of the global economy. Trade linkages play a vital role in financial integration, which is evident from empirical findings from the gravity model and trade network. Cross-border exchange of goods and services necessitates financial transactions and fosters interconnectedness in the currency markets and the capital markets. The global financial ecosystem is positioned around the international capital markets, which comprise foreign exchange markets, global stock exchanges, and bond markets. The vitals of cross-border financial integrations revolve around the foreign exchange market, as it determines exchange rates and trade competitiveness and the state of balance of payment as well (Singh et al., 2022).

An open economy will always have volatile exchange rates. According to Chauque and Rayappan (2018), exchange rate variations have a significant impact on a country's output, interest rate, inflation, and balance of payments from a macroeconomic standpoint. It impacts a nation's sector indices in addition to the stock market, but to varying degrees and in different proportions. It not only affects the stock market, but also affects the sectoral indices of a country with varied degree and magnitude. As a result, studies of the exchange rate and its ripple effects on the economy are essentially taken as the most prominent research agenda of free trade and globalization. Therefore, the study of exchange rate volatility and its effect on sectoral indices has been undertaken in this research endeavor, with special reference to India, to evaluate its country-specific and sector-specific impact and spillover.

Review of Literature and Background of the Study

The nexus between the exchange rate and stock market in general, and sectoral indices in particular, plays a decisive role in financial market dynamics (Aksöz Yilmaz & Güzel, 2021). The movement in foreign exchange rates is vital in determining the performance of various sectors by influencing profitability and competitiveness in different industries (Mohanty et al., 2023). A strong domestic currency exerts a positive impact on import-dependent sectors, while on the other hand, a weak domestic currency can benefit export-oriented industries with enhanced competitiveness. Trade is a key mechanism via which the exchange rate affects sectoral indexes. According to the literature now in publication, the effects frequently extend beyond the economic requirements brought on by monetary policy, fiscal policy, political unpredictability, and cross-border conflicts. Changes in the value of assets due to fluctuations in exchange rates impact the flow of capital between countries; these changes also have an impact on market sentiment, risk appetite, investment portfolios, and sectoral indexes. Changes in currency values affect market dynamics, including interest rates, inflation rates, and cost of production of export–import-dependent industries, and thereby affect the economy and also the sectoral indices.

Much research has been carried out in different economies to assess how changes in exchange rates affect the stock prices of different industries (He et al., 2020; Singhal et al., 2019). The studies have highlighted the presence of both negative as well as positive correlations between exchange rate volatility and stock prices (Rai & Garg, 2022; Yadav, 2016; Zheng et al., 2023). The negative relationship can be explained based on the premise that firms that are export-driven are forced toward uncertainty in terms of future revenue. This impacts their stock prices negatively. Similarly, firms that are manufacturing units and import a high degree of raw materials from foreign countries are severely affected due to exchange rate volatility (Pandey et al., 2021; Sugiharti et al., 2020).

On the other hand, other research has suggested that changes in exchange rates may be advantageous for businesses that have a strong system in place for hedging against a variety of exchange rate risks (Das &

Kumar, 2023). Firms have been found to use different kinds of operational and financial leverage strategies to reduce their market exposure and risks (Matta et al., 2022; Sikarwar & Gupta, 2019). Moreover, these would involve the utilization of elements such as contractual arrangements in the form of derivative instruments to reduce the degree of risks. Studies have also based their arguments on prominent models, such as the risk exposure model and asset pricing model, to highlight the causal connection between exchange rate movements and sectoral indices (Zarei et al., 2019). These theories highlighted that parameters such as cash movements, valuations, and degree of competitiveness vary across industries.

Since they are the representatives of numerous economic sectors, including banking, energy, infrastructure, information & technology, and pharmaceuticals, the sectoral indices of India effectively depict the country's whole financial landscape. These indices enable investors to make useful and informed decisions based on in-depth insights from the performance of these industries (Rezitis & Stavropoulos, 2011). As benchmarks for mutual funds and exchange-traded funds (ETFs), leading indices like the Nifty Bank, Nifty IT, Nifty Pharma, and Nifty Energy, among others, also help investors diversify their holdings and manage risk (Kapoor & Goel, 1990; Pandey & Mohapatra, 2017). These indices also show how different sectors' economies are doing generally. Thus, exchange rate swings play a crucial role in the complex dynamics of the stock market, forcing traders, investors, and companies to keep a careful eye on and negotiate the constantly fluctuating foreign exchange market currents (Reddy et al., 2019; Tang, 2015).

Financial econometrics has been studying stock market volatility modeling for a long time (Aggarwal & Khurana, 2018; Vikram et al., 2022). Two well-liked models for volatility analysis are the generalized autoregressive conditional heteroskedasticity (GARCH) and autoregressive conditional heteroskedasticity (ARCH) (Brooks & Rew, 2002; Khanna & Kumar, 2020). The knowledge of the dynamics of volatility in financial markets has greatly benefited from these models (Engle et al., 2008). The financial sector has found the ARCH and GARCH models to be beneficial in various areas, including risk management, option pricing, and portfolio optimization (Rastogi, 2014; Yadav et al., 2023). These models are particularly valuable for estimating conditional variances and forecasting volatility, which is essential for making informed investment decisions (Bollerslev, 1986).

Objectives of the Study

Foreign exchange rate plays a crucial role in international trade, due to its impact on import and export prices and competitiveness, and also affects the economy of a country. Scholarly interest has focused on the effects of exchange rate variations on the Indian stock market. The focus of this study is on the effects of foreign exchange rates on sectoral indices, which have received little attention in the literature, despite the fact that research on stock markets has been more and more prevalent in recent years. To analyze the nexus between foreign exchange rates and sectoral indices, five exchange rates (USD-INR, EURO-INR, GBP-INR, CNY-INR, and JPY-INR) and seven (automobile, banking, energy, FMCG, infrastructure, information & technology, and pharmaceutical) sectoral indices are taken in this study. The objectives of the study are:

- To model volatility of select Indian sectoral indices.
- To analyze the effect of foreign exchange rate volatility on select Indian sectoral indices.

Research Methodology

Sample

The variables selected in this study are five exchange rates and seven sectoral indices of India. The data of all the variables were collected from websites like investing.com, the National Stock Exchange (NSE) of India and the Bombay Stock Exchange (BSE) of India from November 2012 to November 2022. The select exchange rates are US Dollar-Indian Rupee (USD-INR), Euro-Indian Rupee (EURO-INR), Great Britain Pound-Indian Rupee (GBP-INR), Chinese Yuan-Indian Rupee (CNY-INR), and Japanese Yen-Indian Rupee (JPY-INR). The automobile, banking, energy, FMCG, infrastructure, IT, and pharmaceutical industries are among the sectors for which sectoral indices have been chosen based on capitalization (Table 1). At the time of data collection, the total number of observations for the variables varied between 2,470 and 2,490. However, after the sanitization of data, a total of 2,363 observations have been kept for further studies. A return series of 2,362 observations was created from the daily price series. The following formula has been used to transform each price series into a log return series:

$$Log\,return = \ln(P_t / P_{t-1}) \qquad \ldots\ldots (1)$$

where, P_t is today's price; P_{t-1} is the previous day's price.

Table 1. *Market Capitalization*

S. No.	Sector	Market-Cap in ₹ Crore (INR)	No. of Stocks
1	Nifty Auto	1,175,926.18	15
2	Nifty Banks	3,109,694.76	12
3	Nifty Energy	3,152,358.23	10
4	Nifty FMCG	1,923,080.99	15
5	Nifty Infra	4,789,867.74	30
6	Nifty IT	2,702,390.57	10
7	Nifty Pharma	922,687.12	20

Tools and Techniques

In line with the objectives of the study, different models of time series analysis are applied by using EViews & RStudio software. The augmented Dickey–Fuller (ADF) test is used to check the unit root of the series. In order to apply models of the GARCH family, a series must possess an ARCH effect. So ARCH effect is checked for all the series by using the ARCH L-M test. In order to model and check the volatility, the GARCH (1,1) model is applied. T-GARCH model is used to estimate the leverage effect; and DCC-GARCH is used for analyzing the spillover effect of exchange rates on select sectoral indices of India (Perumandla & Kurisetti, 2018).

Data Analysis and Results

Descriptive Statistics

Descriptive statistics of five different exchange rates are shown in Table 2. The CNY-INR has the second-highest mean return, while the USD-INR shows the highest among all. The kurtosis of USD-INR is the largest, while the

Table 2. *Descriptive Statistics of Exchange Rate Return*

Statistics	*LUSD*	*LEURO*	*LGBP*	*LCNY*	*LJPY*
Mean	0.000152	7.54E–05	4.79E–05	0.000127	–7.27E–05
Median	–2.53E–05	8.70E–05	–1.99E–05	–4.24E–06	–0.000297
Maximum	0.040920	0.035776	0.039375	0.037161	0.046549
Minimum	–0.036848	–0.040660	–0.075051	–0.033435	–0.042194
Std. Dev.	0.004363	0.006052	0.006505	0.004370	0.007292
Skewness	0.377087	0.184977	–0.560342	0.230672	0.105621
Kurtosis	14.37733	6.961905	13.49079	12.37339	8.395961
Jarque–Bera	12795.38	1558.286	10955.02	8667.887	2869.930
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.359447	0.178104	0.113150	0.300299	–0.171603
Sum Sq. Dev.	0.044951	0.086468	0.099898	0.045091	0.125536
Observations	2,362	2,362	2,362	2,362	2,362

Table 3. *Descriptive Statistics of Sectoral Indices*

Statistics	*LAUTO*	*LBANK*	*LENERGY*	*LFMCG*	*LINFRA*	*LIT*	*LPHARMA*
Mean	0.000503	0.000542	0.000523	0.000503	0.000308	0.000693	0.000359
Median	0.000956	0.000651	0.000734	0.000862	0.000818	0.000793	0.000467
Maximum	0.098997	0.136733	0.082818	0.079906	0.106207	0.089220	0.098650
Minimum	–0.149055	–0.183130	–0.102167	–0.111998	–0.128356	–0.126825	–0.093507
Std. Dev.	0.014518	0.016194	0.013790	0.011481	0.013715	0.013635	0.013052
Skewness	–0.413415	–0.563726	–0.423805	–0.461587	–0.177447	–0.688612	–0.136014
Kurtosis	12.43499	17.32991	9.114389	13.02114	11.93366	12.66710	7.809005
Jarque–Bera	8828.237	20334.60	3750.088	9967.197	7867.054	9383.988	2283.319
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.188012	1.280394	1.235172	1.188479	0.726590	1.637221	0.847154
Sum Sq. Dev.	0.497646	0.619158	0.448957	0.311199	0.444109	0.438927	0.402193
Observations	2,362	2,362	2,362	2,362	2,362	2,362	2,362

kurtosis of EURO-INR is the lowest. The kurtosis of all the series is more than 3, and it is observed that all the series are leptokurtic and are heavily-tailed. All other rates are right-skewed except for GBP-INR, which is left-skewed. The standard deviation of all the currency rates is largest for JPY-INR and lowest for USD-INR. It is observed that every exchange rate data set is volatile.

Table 3 gives the details of descriptive statistics of all the selected sectors. All the data have produced a positive mean, which indicates that over a while, all the selected series give positive returns. The return series of the information & technology sector's mean is found to be the highest. Among all the selected seven sectoral indices, infrastructure has the lowest mean. As per the standard deviation of the series, the banking sector is found to be the most volatile among all. The FMCG sector has the lowest standard deviation, which makes it the least volatile sector in the period of study. The skewness of the series is negative. So, all the series are left-skewed and heavily-tailed. For the select sectors, the returns' kurtosis is more than 3, which depicts that the series is leptokurtic.

Unit Root Test

The ADF test is utilized to assess the stationarity of the data. The prior literature has employed two optimal criteria, which are the Akaike Information Criterion (AIC) and the Schwarz Criterion (Dickey & Fuller, 1979). AIC has been selected for this investigation. The ADF test probabilities are presented in Tables 4 and 5. All the exchange rate return series are stationary at levels and are found to be suitable for applying the time series model. The stationarity of each of the chosen sectoral indices is shown in Table 5. At the 5% significance level, it is determined that each of the seven indices is stationary.

Heteroscedasticity Test of Sectoral Indices

The usual test to identify autoregressive conditional heteroscedasticity is the ARCH-LM test (Engle, 1982). The basic condition for applying any higher level of GARCH is that there should be an ARCH effect in the data, and the data should be mean reverting. On the other hand, volatility clustering is the main criterion for applying the ARCH model. However, for the ARCH-LM test, the basic process is to run an OLS and then check the ARCH effect.

Table 6 displays the ARCH test results. The F-statistics are described in the first row of the table, and the test probability is reported in the second row. The data have been examined using EViews with a maximum of 36 delays. There is an ARCH effect in all seven series, as shown by the probability of the F-statistics, and the chi-square for each series is significant at 5%.

Analysis of Indices' Volatility Through the GARCH Model

The GARCH model can be used to manage time series data that do not fit the basic assumptions of the classical linear regression model (CLRM). The conditional mean and variance of stock returns were initially thought to be influenced by past returns and volatility under the GARCH model, given the information available at a given time. The GARCH model offers a novel framework for investigating the connection between risk and return (Engle et al., 1987). In order to find the values of alpha (α) and beta (β), the GARCH (1,1) model has been used. A "shock" at the time *"t"* will last for a very long time if ($\alpha + \beta$) is close to unity. In other words, a high value for $\alpha + \beta$ denotes a "long memory," and any "shock" may cause a lasting shift in the values of *"t"* in the future, showing that

Table 4. ***Unit Root Test of Exchange Rates***

	LUSD	*LEURO*	*LGBP*	*LCNY*	*LJPY*
At Levels	0.0001	0.0000	0.0001	0.000	0.000

Table 5. ***Unit Root Test of Sectoral Indices***

	LAUTO	*LBANK*	*LENERGY*	*LFMCG*	*LINFRA*	*LIT*	*LPHARMA*
At Levels	0.0001	0.000	0.0001	0.0000	0.0001	0.0001	0.0000

Table 6. ***ARCH Test Results***

	LAUTO	*LBANK*	*LENERGY*	*LFMCG*	*LINFRA*	*LIT*	*LPHARMA*
F-Statistics	25.47084	20.05719	137.3134	110.3779	38.95335	99.59711	47.10622
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 7. ***GARCH Test***

	LAUTO	*LBANK*	*LENERGY*	*LFMCG*	*LINFRA*	*LIT*	*LPHARMA*
Constant	0.000000648	0.000000344	0.000000934	0.000000574	0.000000599	0.00000158	0.000000797
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
α	0.095673	0.086620	0.084092	0.075201	0.093623	0.111316	0.057727
β	0.873702	0.902314	0.863377	0.879261	0.874696	0.803056	0.894470
α*+ β*	0.969375	0.988934	0.947469	0.954462	0.968319	0.914372	0.952197

conditional variance is persistent. As the sum of the α and β (α + β) coefficients is less than 1, the results also demonstrate a mean-reverting process. Additionally, the speed of mean reversion is controlled by the absolute value of α + β (Chaudhary et al., 2020).

In the GARCH (1,1) model, the duration of a time series until a change dies out is calculated. Table 7 depicts the results of the GARCH analysis of all the sectoral indices. Constant, ARCH term, GARCH term, and probabilities of variance equation are presented in Table 7. The coefficients of mean equations are positive and are found to be statistically significant. The coefficients of variance equations are also positive. However, the coefficients are also statistically significant at a 5% level (0.0000). The observed GARCH values of automobile, banking, energy, FMCG, infrastructure, IT, and pharmaceutical sectors are 0.873702, 0.902314, 0.863377, 0.879261, 0.874696, 0.803056, and 0.894470, respectively. As the value of α is positive and significant in the case of all the indices, it can be concluded that all the indices show a degree of responsiveness to the news. However, it can be observed that the β value is significantly greater than the α value of the corresponding index, showing that the moving-average effect, which implies that the new market information, is primarily responsible for the volatility of the market return for all indices. It can also be observed that Bank Nifty has the highest β, which means it is the most volatile among all the selected indices. The fact that the total of α and β is less than 1 further suggests that volatility shocks are persistent. Some sectors' values for α + β are as follows: Automobile: 0.969375, Infrastructure: 0.968319, Information & Technology: 0.914372, FMCG: 0.954462, Banking: 0.988934, Energy: 0.947469, and Pharmaceutical: 0.952197.

Using the T-GARCH model, the asymmetry of stock market volatility is taken into account. The threshold GARCH model (T-GARCH) is an illustration of an asymmetric GARCH model (Oskooe, 2010). Black (1976) developed the predictable volatility model, which is used to assess the leverage impact of a series. The T-GARCH term in the EViews program is (RESID (–1) ⁴^2*(RESID(–1)<0).

In Table 8, "α" is the ARCH term, "β" is the GARCH term, and "λ" is the T-GARCH term. The values of these terms are listed in Table 8. The coefficient of variance equation of the automobile return series is 0.114036, and it is statistically significant (0.0000). The coefficient of an automobile is the highest among all the selected indices. The value of the bank return's T-GARCH term is positive (0.102945) and also statistically significant. The

Table 8. ***T-GARCH***

	LAUTO	*LBANK*	*LENERGY*	*LFMCG*	*LINFRA*	*LIT*	*LPHARMA*
α	0.027032	0.022691	0.037868	0.068582	0.043787	0.074022	0.031591
β	0.883179	0.914744	0.856594	0.879605	0.882152	0.820583	0.886777
λ	0.114036	0.102945	0.092903	0.010905	0.089177	0.050986	0.052505
(α + λ)	0.141068	0.125636	0.130771	0.079487	0.132964	0.125008	0.084096
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

coefficient of Nifty Energy series is also positive, which is 0.092903. The T-GARCH model applied to FMCG also shows a positive coefficient at a 5% level of significance (0.010905). Infrastructure has a moderate (0.089177) coefficient among all, and it is also found to be positive. The IT sector shows the lowest value of the coefficient; however, it is also significant and positive (0.050986). The pharma sector also has a positive coefficient (0.052505) and is found to be significant. So, it can be interpreted that there is an information asymmetry in all the variables. The modeling of information, news, or events is very significant in determining an asset's volatility. There exists a leverage effect in all the series. Furthermore, as the sum of α and λ is less than 1, the model is found acceptable.

Impact of Exchange Rate Volatility on Sectoral Indices

In the GARCH (1,1) model, exchange rates are taken as regressors individually, and the result of its coefficients and their probabilities are reported in Table 9. All the exchange rates are used as exogenous variables, and the autoregressive term (AR) is used in the OLS regression. The models are run to find if there is any impact of the selected exchange rates on the sectoral indices.

Impact of Exchange Rates on Automobile Index

Table 9 displays the correlation between the volatility of Nifty Auto and all exchange rates. All of the exchange rates have a probability of 0.0000, which means the coefficients are significant at the 5% level. The variance equation shows that the USD-INR has the largest coefficient, and the GBP-INR has the lowest. Here are the model's equations:

$$GARCH = 0.000000576 + 0.081507 * RESD(-1)\char`^2 + 0.888481 * G(-1) + 0.001860 * LUSD \quad \text{----}\ (2)$$

$$GARCH = 0.000000584 + 0.083186 * RESD(-1)\char`^2 + 0.887329 * G(-1) + 0.001242 * LEURO \quad \text{----}\ (3)$$

$$GARCH = 0.000000606 + 0.087424 * RESD(-1)\char`^2 + 0.882890 * G(-1) + 0.000894 * LGBP \quad \text{----}\ (4)$$

$$GARCH = 0.000000613 + 0.087397 * RESD(-1)\char`^2 + 0.881607 * G(-1) + 0.001775 * LCNY \quad \text{----}\ (5)$$

$$GARCH = 0.000000694 + 0.084495 * RESD(-1)\char`^2 + 0.880626 * G(-1) + 0.001544 * LJPY \quad \text{----}\ (6)$$

From the above equations, it can be observed that one unit change of the volatility of Nifty Auto is described by 0.001860 unit of return series of USD-INR. The constant in this model is 0.000000576, and the GARCH term is 0.888481. In Equation (3), the model of GARCH is run by using EURO-INR as a regressor. ARCH term in the model is 0.083186, and the beta in the model is 0.887329. The return series of EURO-INR with the unit of 0.001242 describes Nifty Auto. In the following model, which uses GBP-INR as a regressor, the ARCH and GARCH terms are, respectively, 0.087424 and 0.882890. The model's coefficient in GBP is 0.000894. CNY-INR has a coefficient of 0.001775. The following model's coefficient is 0.001544 (JPY-INR).

Table 9. ***GARCH Model of Auto Index and Exchange Rates as Regressor***

	USD-INR	EURO-INR	GBP-INR	CNY-INR	JPY-INR
Coefficient	0.001860	0.001242	0.000894	0.001775	0.001544
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Impact of Exchange Rates on Bank Index

Table 10 displays the volatility effect of exchange rates on Nifty Bank. All the exchange rates have a probability of less than 5%. In the variance equation, EURO-INR has the largest coefficient and CNY-INR the smallest. Here are the model's equations:

$$GARCH = 0.000000339 + 0.082845 * RESD(-1)^2 + 0.905280 * G(-1) + 0.000613 * LUSD \quad \text{----} \ (7)$$

$$GARCH = 0.000000317 + 0.079460 * RESD(-1)^2 + 0.909214 * G(-1) + 0.000991 * LEURO \quad \text{----} \ (8)$$

$$GARCH = 0.000000353 + 0.082654 * RESD(-1)^2 + 0.904982 * G(-1) + 0.000647 * LGBP \quad \text{----} \ (9)$$

$$GARCH = 0.000000336 + 0.084793 * RESD(-1)^2 + 0.904058 * G(-1) + 0.000424 * LCNY \quad \text{----} \ (10)$$

$$GARCH = 0.000000363 + 0.079654 * RESD(-1)^2 + 0.907191 * G(-1) + 0.000837 * LJPY \quad \text{----} \ (11)$$

For USD-INR, EURO-INR, GBP-INR, CNY-INR, and JPY-INR, the corresponding exchange rate coefficients are 0.000613, 0.000991, 0.000647, 0.000424, and 0.000837, respectively. The variables' ARCH and GARCH terms are presented in the equations. When it comes to ARCH terms, CNY-INR has the highest, whereas EURO-INR has the highest GARCH terms. While 0.904058 for CNY-INR is the lowest GARCH term, the lowest ARCH term is 0.079460 for EURO-INR. According to the findings, every factor is favorably influencing the volatility of the Bank Nifty.

Impact of Exchange Rates on Energy Index

The models have been created by taking exchange rates as variance regressors. Table 11 displays the results of the GARCH (1,1) model with regressors. Among all the regressors, USD-INR has the highest coefficient, which implies that it explains the volatility of the energy index better than any other variables. However, GBP-INR has the lowest contribution to it. The equation mentions both GARCH and ARCH terms. The highest GARCH term is found in USD-INR, while the highest ARCH term is found in CNY-INR.

$$GARCH = 0.000000708 + 0.064574 * RESD(-1)^2 + 0.892557 * G(-1) + 0.001904 * LUSD \quad \text{----} \ (12)$$

$$GARCH = 0.000000838 + 0.071245 * RESD(-1)^2 + 0.879553 * G(-1) + 0.001423 * LEURO \quad \text{----} \ (13)$$

$$GARCH = 0.000000857 + 0.077360 * RESD(-1)^2 + 0.873779 * G(-1) + 0.000616 * LGBP \quad \text{----} \ (14)$$

Table 10. ***GARCH Model of Bank Index and Exchange Rates as Regressor***

	USD-INR	EURO-INR	GBP-INR	CNY-INR	JPY-INR
Coefficient	0.000613	0.000991	0.000647	0.000424	0.000837
Probability	0.0004	0.0000	0.0004	0.0284	0.0000

Table 11. ***GARCH Model of Energy Index and Exchange Rates as Regressor***

	USD-INR	EURO-INR	GBP-INR	CNY-INR	JPY-INR
Coefficient	0.001904	0.001423	0.000616	0.001535	0.001400
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

$$GARCH = 0.000000851 + 0.077404 * RESD(-1)^2 + 0.872940 * G(-1) + 0.001535 * LCNY \quad ---- \ (15)$$

$$GARCH = 0.000000953 + 0.074142 * RESD(-1)^2 + 0.871051 * G(-1) + 0.001400 * LJPY \quad ---- \ (16)$$

Impact of Exchange Rates on the FMCG Index

All the variables are found to be significant at the 5% level in the variance equation (Table 12). USD-INR contributes the highest to the volatility of the FMCG index, whereas JPY-INR has the lowest impact in this case. The beta term is highest in GBP-INR and lowest in the case of JPY-INR. The FMCG index's GARCH model is represented by five distinct equations in equations (17) through (21). The currency rate has a considerable impact on the FMCG index despite its observed volatility.

$$GARCH = 0.000000560 + 0.068006 * RESD(-1)^2 + 00.885558 * G(-1) + 0.000735 * LUSD \quad --- (17)$$

$$GARCH = 0.000000574 + 0.071693 * RESD(-1)^2 + 0.881620 * G(-1) + 0.000692 * LEURO \quad --- (18)$$

$$GARCH = 0.000000529 + 0.071803 * RESD(-1)^2 + 0.886000 * G(-1) + 0.000482 * LGBP \quad --- (19)$$

$$GARCH = 0.000000573 + 0.072959 * RESD(-1)^2 + 0.880685 * G(-1) + 0.000474 * LCNY \quad --- (20)$$

$$GARCH = 0.000000606 + 0.072385 * RESD(-1)^2 + 0.878848 * G(-1) + 0.000340 * LJPY \quad --- (21)$$

Impact of Exchange Rates on Infrastructure Index

Infrastructure is also one of the leading sectors of the NSE (Table 13). The constant terms vary from 0.000000531 to 0.000000627. The variable with the highest ARCH term is CNY-INR (0.094403), and JPY-INR has the lowest ARCH. The GARCH term is highest in the case of EURO-INR and lowest in CNY-INR. The variables are significant at a 5% level, and EURO-INR contributes the highest to the volatility of the infrastructure index with a coefficient of 0.001102. CNY-INR makes the lowest contribution with a coefficient of 0.000572. All other variables are positively contributing to the volatility of Nifty Infrastructure.

$$GARCH = 0.000000595 + 0.089765 * RESD(-1)^2 + 0.877174 * G(-1) + 0.001023 * LUSD \quad ---- \ (22)$$

$$GARCH = 0.000000531 + 0.087948 * RESD(-1)^2 + 0.883168 * G(-1) + 0.001102 * LEURO \quad ---- \ (23)$$

$$GARCH = 0.000000569 + 0.091482 * RESD(-1)^2 + 0.878316 * G(-1) + 0.000600 * LGBP \quad ---- \ (24)$$

Table 12. ***GARCH Model of FMCG Index and Exchange Rates as Regressor***

	USD-INR	EURO-INR	GBP-INR	CNY-INR	JPY-INR
Coefficient	0.000735	0.000692	0.000482	0.000474	0.000340
Probability	0.0000	0.0000	0.0002	0.0018	0.0003

Table 13. ***GARCH Model of Infrastructure Index and Exchange Rates as Regressor***

	USD-INR	EURO-INR	GBP-INR	CNY-INR	JPY-INR
Coefficient	0.001023	0.001102	0.000600	0.000572	0.001022
Probability	0.0000	0.0000	0.0019	0.0096	0.0000

$$GARCH = 0.000000614 + 0.094403 * RESD(-1)^{\wedge}2 + 0.872592 * G(-1) + 0.000572 * LCNY \quad \text{----} \quad (25)$$

$$GARCH = 0.000000627 + 0.086751 * RESD(-1)^{\wedge}2 + 0.878879 * G(-1) + 0.001022 * LJPY \quad \text{----} \quad (26)$$

Impact of Exchange Rates on the Information & Technology (IT) Index

Table 14 shows the volatility effect of exchange rates on the IT sector. Unlike other indices, USD-INR contributes negatively to the volatility of the IT index. EURO-INR has the highest contribution to the volatility of the return series of the IT index. All the coefficients are statistically significant at a 5% level except JPY-INR, because of which it is excluded from the regression equation. In terms of ARCH, USD-INR is the highest, while in GARCH terms, EURO-INR is found to be the highest.

$$GARCH = 0.00000163 + 0.117079 * RESD(-1)^{\wedge}2 + 0.795757 * G(-1) + 0.000674 * LUSD \quad \text{------} \quad (27)$$

$$GARCH = 0.00000151 + 0.108932 * RESD(-1)^{\wedge}2 + 0.808765 * G(-1) + 0.001122 * LEURO \quad \text{----} \quad (28)$$

$$GARCH = 0.00000158 + 0.111198 * RESD(-1)^{\wedge}2 + 0.803243 * G(-1) + 0.00000245 * LGBP \quad \text{----} \quad (29)$$

$$GARCH = 0.00000156 + 0.109278 * RESD(-1)^{\wedge}2 + 0.805517 * G(-1) + 0.000728 * LCNY \quad \text{----} \quad (30)$$

Impact of Exchange Rates on Pharmaceutical Index

The data of the pharmaceutical return series (Table 15) are regressed one by one with exchange rates from USD-INR to JPY-INR. The probabilities observed for all the variables are 0.0000, which shows that the variables are significant at 5%. To the volatility of this index, JPY-INR contributes the most, whereas it is the lowest in the case of GBP-INR. The highest GARCH term is of JPY-INR, and the lowest is of EURO-INR.

$$GARCH = 0.0000000754 + 0.050102 * RESD(-1)^{\wedge}2 + 0.903092 * G(-1) + 0.001035 * LUSD \quad \text{----} \quad (31)$$

$$GARCH = 0.00000000902 + 0.055883 * RESD(-1)^{\wedge}2 + 0.888887 * G(-1) + 0.000802 * LEURO \quad \text{----} \quad (32)$$

$$GARCH = 0.0000000735 + 0.052751 * RESD(-1)^{\wedge}2 + 0.902789 * G(-1) + 0.000578 * LGBP \quad \text{----} \quad (33)$$

$$GARCH = 0.0000000811 + 0.052965 * RESD(-1)^{\wedge}2 + 0.897230 * G(-1) + 0.000804 * LCNY \quad \text{----} \quad (34)$$

$$GARCH = 0.0000000716 + 0.044563 * RESD(-1)^{\wedge}2 + 0.912411 * G(-1) + 0.001101 * LJPY \quad \text{----} \quad (35)$$

Table 14. ***GARCH Model of IT Index and Exchange Rates as Regressor***

	USD-INR	EURO-INR	GBP-INR	CNY-INR	JPY-INR
Coefficient	–0.000674	0.001122	2.45E–05	0.000728	0.000301
Probability	0.0326	0.0000	0.0075	0.0116	0.9210

Table 15. ***GARCH Model of Pharma Index and Exchange Rates as Regressor***

	USD-INR	EURO-INR	GBP-INR	CNY-INR	JPY-INR
Coefficient	0.001035	0.000802	0.000578	0.000804	0.001101
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Residual Diagnostics and Spillover Analysis

The Correlogram Q test, the Correlogram squared residuals, and the ARCH L-M test for the examination of heteroscedasticity of residuals are the recommended residual diagnostics for the GARCH models.

ARCH-LM Test & Correlogram Q and Squared Residual

Table 16 lists the probabilities of the *F*-statistics and chi-square for each of the seven sectors. For each variable, a single lag has been used for the heteroscedasticity test.

For all the sectors, the probabilities of *F*-statistics and chi-square are greater than 0.05, which indicates that there is no ARCH effect in the models. Hence, the models are found to be fit and free from heteroscedasticity. The autocorrelation function (ACF) and partial autocorrelation function (PACF) indicate the robustness of the model. The Correlogram Q and squared residuals are also performed by taking 36 lags. As ACF and PACF for all the sectors are within the boundaries, the models are found to be robust. It can also be concluded that the models are free from serial correlation.

Spillover Analysis

The DCC-GARCH method examines how one variable affects another. Table 17 displays DCC α and DCC β for

Table 16. ***Residual Diagnostics Test Using ARCH L-M Test***

	AUTO	BANK	ENERGY	FMCG	INFRA	IT	PHARMA
Prob. *F*	0.8044	0.2850	0.0612	0.5036	0.5931	0.5585	0.5935
Prob. Chi-Square	0.8043	0.2848	0.0611	0.5034	0.5929	0.5583	0.5933

Table 17. ***Dynamic Conditional Correlation Parameters***

	Variables	USD-INR		EURO-INR		GBP-INR		CNY-INR		JPY-INR	
	Coefficients	*t*-value	Sig. Value	*t*-value	Sig. Value	*t*-value	Sig. Value	*t*-value	Sig. Value	*t*-value	Sig. Value
LAUTO	DCC α	3.10682	0.00189	2.69608	0.07020	2.38883	0.01690	2.52861	0.01145	2.36120	0.01821
	DCC β	37.04794	0.00000	87.25846	0.00000	25.02539	0.00000	26.91589	0.00000	34.01200	0.00000
LBANK	DCC α	1.84973	0.06435	1.10177	0.27056	2.67230	0.00753	2.20057	0.02777	1.61880	0.10548
	DCC β	3.02064	0.00252	0.37114	0.00000	2.23942	0.02513	2.53058	0.01139	1.72550	0.08444
LENERGY	DCC α	16.26202	0.00000	10.33403	0.71053	223.12483	0.00000	366.96080	0.00000	21.96020	0.00000
	DCC β	9.05861	0.00000	19.62743	0.00000	190.99415	0.00000	11.90319	0.00000	26.15030	0.00000
LFMCG	DCC α	2.83482	0.00459	1.80523	0.07104	1.95489	0.05060	2.75493	0.00587	1.84690	0.06476
	DCC β	97.37823	0.00000	51.66657	0.00000	24.92308	0.00000	52.44867	0.00000	51.44220	0.00000
LINFRA	DCC α	1.58406	0.11318	0.64724	0.51748	1.31923	0.18709	2.08871	0.03673	2.51240	0.01199
	DCC β	9.23683	0.00000	13.39544	0.00000	108.07295	0.00000	14.50294	0.00000	32.62350	0.00000
LIT	DCC α	3.57170	0.00036	0.56600	0.57140	0.82959	0.40677	2.42058	0.01550	2.40360	0.01623
	DCC β	130.74430	0.00000	6.40412	0.00000	11.86805	0.00000	40.18474	0.00000	194.47600	0.00000
LPHARMA	DCC α	2.26647	0.02342	1.56945	0.11654	2.15264	0.03135	2.52279	0.01164	1.51690	0.12930
	DCC β	2.37074	0.01775	83.79702	0.00000	85.64418	0.00000	14.86541	0.00000	29.18860	0.00000

all the variables, and it also includes the estimates, standard error, *t*-value, and significance. DCC displays spillovers throughout the long and short-terms. It can be said that there is a volatility spillover if the *p*-value is less than 0.05.

Discussion and Conclusion

To assess and validate the nexus between foreign exchange rates and sectoral indices, five currencies and seven sectoral indices have been considered in the study. The tools used are ARCH, GARCH (1,1), T-GARCH, and DCC-GARCH. The results of GARCH (1,1) indicate that there is a persistence of volatility shocks as the sum of α and β is less than 1. The values of $\alpha + \beta$ for all the series are Automobile: 0.969375, Banking: 0.988934, Energy: 0.947469, FMCG: 0.954462, Infrastructure: 0.968319, IT: 0.914372, and Pharmaceutical: 0.952197. In addition, there exists a leverage effect in all the series as the sum of α and λ of T-GARCH is less than 1, and the model is found acceptable. The coefficient of an automobile is the highest among all the selected indices.

The purpose of this study is to investigate how Indian sectoral indexes are impacted by fluctuations in currency values. It is examined how all exchange rates affect each of the seven sectoral indices. A short-term USD-INR spillover has been observed on five sectoral indexes besides infrastructure and banks. We can conclude that volatility can be conveyed because there is a long-term spillover of USD-INR in all sectors. It is determined that the DCC α of EURO-INR for each sectoral index is negligible. Hence, there is no short-run volatility transmission from EURO-INR to sectoral indices, whereas the DCC β is found to be significant (0.0000). It indicates that in the long-run, there is a spillover effect of EURO-INR on all the sectoral indices. GBP-INR has no short-run volatility spillover on FMCG, infrastructure, and IT sector indices. Other than these indices, all the indices have a short-run spillover effect. However, the spillover effect of GBP-INR is found to be significant for all the indices at 5%. DCC α and DCC β are significant of CNY-INR for all the indices, which depicts the transmission of information in the short run as well as in the long-run. The three indices for which DCC α of JPY-INR is insignificant are bank, FMCG, and pharmaceutical. But in the long-run, all of them show a significant volatility transmission.

Implications

The findings of this study will help regulators and policymakers create rules and laws that will protect investors and keep the stock market stable. The study discovered a strong long-term relationship between indices and currency rates. Thus, long-term stock or index investors need to consider currency volatility. Long-term spillover will also make it more difficult for investors to use currency derivatives to reduce risk in their portfolios. Indexes, on the other hand, provide the inclusion of currencies without any short-term spillover. By applying this information to create trustworthy and knowledgeable investment decisions, potential stakeholders may also gain from it. Furthermore, local businesses that engage in international trade would have greater flexibility in selecting the ideal periods to import and export commodities. By utilizing the present variations, businesses can protect themselves against potential excessive volatility in currency rates. This study can be used as a reference document in other research and academic discussions as well.

Limitations of the Study and the Way Forward

One of the major limitations of this study is that it takes into account only five exchange rates and seven sectoral indices, and that too for 10 years. Exchange rates, indices, and time are only a few of the data points and databases that future scholars can expand. Moreover, the research did not separate the 10 years into periods prior to and during the COVID-19 epidemic. Improved understanding may result from such division and examination. The study utilizes DCC-GARCH as one of its econometric tools. Further research that may be predictive can use more sophisticated GARCH models.

Authors' Contribution

Dr. Amiya Kumar Mohapatra and Dr. Debasis Mohanty conceptualized the idea and translated the idea into a detailed research framework. In addition, Varda Sardana and Dr. Amit Shrivastava have identified the research gaps by a thorough study of the literature. Using the proper research methods and procedures, Dr. Debasis Mohanty and Dr. Amiya Kumar Mohapatra gathered and evaluated the data, and then presented the results along with the relevant interpretation. The comprehensive paper was prepared by Dr. Amiya Kumar Mohapatra, Dr. Debasis Mohanty and Varda Sardana. Finally, Dr. Amit Shrivastava, Varda Sardana, and Dr. Debasis Mohanty completed the research findings and made the necessary revisions, formatting, and copy-editing.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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