Theoretical and Applied Economics
Volume XXXIII (2026), No. 1(646), Spring, pp. 115-130

Information transmission in the foreign exchange market: evidence from India

Karthika P DEVAN
Vishwakarma University, India
karthika.devan@vupune.ac.in
Pallavi INGALE
Vishwakarma University, India
Pallavi.ingale@vupune.ac.in
Johney JOHNSON
Mahatma Gandhi University, India
j.johney@gmail.com

Abstract. *The present study sets out to examine the volatility and the resulting spillovers in the spot and futures prices of four different currency pairs (USD/INR, EUR/INR, GBP/INR, and JPY/INR) traded on the National Stock Exchange (NSE). The study employs the GARCH model to analyse volatility in the Indian currency futures market. The Reserve Bank of India (RBI) website provides spot prices, while the NSE provided daily futures prices for the specified currency pairings from 2010 to 2023 comprise the sample data. The GARCH-BEKK model investigates the transfer of volatility between spot and futures prices. The results highlight the importance of the GARCH model, demonstrating that the conditional variance exhibits slow mean-reverting behaviour and takes a considerable amount of time to subside. The study also shows that past and future innovations, as well as cross-volatility effects, significantly impact spot market volatility, suggesting the cross-market volatility transmission from the future prices to spot prices are greater than the cross-market volatility transmission within the spot series.*

Keywords: Currency futures, Volatility spillover, GARCH-BEKK, Futures price, Spot price.

JEL Classification: G13, G14, G15.

1. Introduction

Over the years, the global financial system has undergone substantial changes driven by financial innovation and increased competitive pressures. These changes have significantly altered the institutions and structure of the foreign exchange market (Sequeira et al., 2004). Every new technological layer has tightened spreads, sped up reaction times, and, ironically, increased the very turbulence that participants were trying to control (BIS, 2024). Consequently, there is an increasing demand for a wider array of hedging mechanisms to assist market participants in alleviating the risks linked to currency rate volatility. Consequently, financial products such as commodity, currency, and equity derivatives have been developed to effectively manage and control these risks (Nath & Pacheco, 2017; Patel & Rao, 2025).

India, in particular, has seen a rise in cross-border flows, both in capital and current accounts, due to globalization and more relaxed regulations on external transactions (Nath & Pacheco, 2017). These developments, along with shifting dynamics in capital flows and global imbalances, have contributed to increased exchange rate volatility. As a result, the currency futures market has become increasingly important for managing exchange rate risk and volatility (Malliaris& Ziemba, 2016).

India, in particular, has seen cross-border flows swell in both capital and current accounts as globalisation met relaxed external-sector regulations (RBI, 2024). Every fresh tide of portfolio money or export receipt lifted or lowered the rupee with growing force, making the currency-futures segment the busiest emergency room for volatility surgery (Ha et al., 2025).

Futures contracts are significantly influenced by volatility, which has implications for both speculators and hedgers. Hedgers are exposed to the risk of paying higher prices when prices fluctuate, while sellers may receive lower prices. To manage these risks, hedgers can take offsetting positions in futures contracts. Conversely, speculators perceive changing prices as opportunities for potential profits. Buyers aim to liquidate their positions at higher prices, whereas sellers seek to do so at lower prices. Motivated by the potential for profit, speculators take positions in futures contracts to capitalize on expected price changes (Malliaris& Ziemba, 2016).

Exchange rate volatility has diverse economic effects and serves as a critical factor for decision-makers. It introduces uncertainty to the return rates of unhedged foreign investments when expressed in the home currency (Eun& Resnick, 1994). Several factors contribute to increased volatility in exchange rates, including deviations from underlying economic fundamentals, excessive speculative activity, macroeconomic shocks, and other forms of news (Andersen et al., 2003). It is essential to remember that extreme fluctuations and volatility in exchange rates can potentially distort monetary policy signals, cause issues in other areas of the financial market, and even threaten financial stability.

2. Review of literature

The focus has shifted significantly in recent seasons to price discovery and the movement of volatility as futures contracts are introduced. The majority of the attention has been focused on the equity and commodity arenas (Harvey & Huang, 1991; Tse, 1999; Fung & Patterson, 1999; Ferris et al., 2002; Dennis et al., 2006; Antonakakis, 2012; Fang et al., 2017; Cho et al., 2019); however, the foreign-exchange side of the futures industry has received little attention.

This disparity is significant because, in cases where the underlying currency is a national currency, the rate at which news is incorporated into quotes determines how well central banks, exporters, and treasurers can prepare for unexpected fluctuations. The time-zone pulse was first mapped by Harvey & Huang (1991). This shows that macro announcements have a timestamp because USD-EUR and USD-JPY futures flare at their peak during North American hours, whereas EUR-cross contracts reach their volatility crest once London and Frankfurt awaken.

Asymmetry Wang & Yang (2009) later rediscover across AUD, GBP, and JPY, and Emter, McQuade, and Schuler (2025) now quantify at high frequency: negative global headlines travel about 40% faster than positive ones, tilting the volatility distribution toward the downside. Bessembinder & Seguin (1993) added the depth dimension—an order book already thinned by earlier trades amplifies the same shock, and positive volume surprises bite deeper than negative ones.

While the spot market sustains the tension for a longer period of time—an early indication that cash prices process news more slowly—EUR and DEM futures nearly always end the session more volatile than on non-announcement days, according to Crain & Lee (1995), who kept an eye on announcement days. The two-way street between Eurodollar spot and futures was identified by Cheung & Fung (1997), who demonstrated that information does not respect the theoretical boundary and bounces back and forth within minutes. By focusing just on planned U.S. macro releases, Chatrath & Song (1998) showed how yen futures consistently feed volatility back into the underlying spot quote, with the spot serving as the receiver and the futures as the transmitter.

Ha et al., (2025) recently elevated this relationship to global-financial-cycle status, arguing that currency futures are the primary channel through which the global liquidity pulse leaks into local spot rates. Sequeira et al., (2004) expanded the aperture once more, revealing that both domestic and foreign risk-free rates leave distinct fingerprints on the conditional variance of futures and spot returns.

While Antonakakis (2012) demonstrated how the introduction of the euro rewired the global board, making the single currency the dominant transmitter, sterling the largest net recipient, and European trading sessions the most powerful source of cross-market shocks, Sharma (2011) brought the microscope to India and discovered the same two-way street between USD/INR futures turnover and spot volatility. Higher intraday volatility attracts

more trading volume, which is good news for hedgers who require counterparties, according to Pavaskar & Kala (2013), who focused on the INR/USD tick.

While Babu & Reddy (2024) use millisecond NSE data to demonstrate that the futures-to-spot information lag has now shrunk to less than three seconds, the volatility half-life of the shock persists for hours, highlighting why the current study is still important. Suhashini & Chandrasekar (2013) fitted a GARCH lens to USD/INR futures and reported the well-known trio—clustering, persistence, predictability. Although Sehgal et al., 2015) compared four trading venues and concluded that futures prices consistently take the lead, Patel & Rao (2025) support this conclusion with data from 2022–2023, showing that the cross-correlation between futures returns and next-period spot volatility reaches 0.42, twice the reverse coefficient. Sriram & Senthil (2013) detect a long-run gravitational pull from spot to futures, especially when the dollar itself jerks.

Gupta (2017) demonstrated that the derivative can either calm or agitate the underlying market, contrary to Singh & Tripathi's (2014) claim that the introduction of currency futures in India reduced the daily volatility of GBP/INR. The news-flow twist was provided by Kumar (2015), who confirmed an asymmetric reaction that Enter et al., (2025) now confirm globally: positive headlines amplify spot volatility more than negative ones. When comparing four trading platforms, Sehgal et al., (2015) discovered that futures prices continuously outperform spot prices over time; Babu & Reddy (2024) even trace this leadership down to the microsecond.

While Gupta (2017) found that the introduction of EUR/INR futures increased spot volatility, Kumar et al., (2017) found that negative forex headlines actually decreased volatility—more proof that the derivative's overall impact varies depending on the context. While Sehgal & Dutt (2018) found that Indian futures dominate domestic price discovery, global platforms like CME and DGCX win the sprint over shorter horizons, Nath & Pacheco (2017) documented stubborn volatility clustering in both pre- and post-futures eras, with a stronger bite following rupee depreciation.

The final brushstroke of the pre-2022 canvas was added by Devan & Johnson (2021), open interest pulls futures volatility down, but speculative volume pushes it up, suggesting that who holds the contract is more important than the number of contracts held. Devan et al., (2022) support our conclusion that volatility primarily spills from futures to spot pricing by showing that the Indian currency-futures market responds to new information more quickly than the spot segment using daily INR data from February 2010 to March 2021. Our BEKK model uses the greater cross-volatility coefficient from futures to spot to capture this speed advantage.

All of the evidence points to currency futures as the market's early warning system since they detect, magnify, and then export volatility to the spot market. The few studies that make the opposite claim are accurate; they only depict distinct parts of the same neural system. The present paper keeps the electrodes on the Indian rupee and asks whether, in

2023-24, the warning signal still travels from futures to spot faster and louder than any other channel—an answer that updates the narrative and clarifies where risk managers should now place their sensors.

3. Data

This study focusses on the Indian currency futures market and employs quantitative secondary data available in the public domain, including data from the NSE (National Stock Exchange) for future prices and RBI (Reserve Bank of India) databases for spot prices. The dataset included daily closing prices for spot and futures contracts transacted in the Indian forex market. Near-month futures contracts were used to generate the futures price series because they had considerable liquidity and trading activity. This approach avoids using observations close to contract maturity dates, which might reflect a weakening and volatile market interest.

August 2008 saw the NSE launch currency futures trading, which was initially restricted to USD exclusively. Subsequently, in 2010, trading was extended to include three other currencies. The sample data included daily futures prices in four currencies: Yen, U.S. Dollar, GBP and Euro. The data sets were collected from the NSE. The corresponding spot prices were taken from the RBI website. The data was obtained from the NSE and is based on the trading volume of the exchanges in relation to the quantity of futures contracts and volume traded for the respective currency futures. The spot and futures prices have been converted into a natural logarithm for estimation purposes.

4. Research Methodology

The time series of currency prices are noteworthy at first differences but not at level, according to stationarity tests done on futures and spot prices. However, the stationary series may also exhibit volatility clustering if the residual variances are autocorrelated. It was found that the returns series of both future price and spot price of currency futures were stationary, and this is necessary as the models developed for ARCH assume stationarity. Generalized ARCH, or GARCH for short, is one variation of ARCH model. Following represents the GARCH model at lag 1:

$$\sigma^2_t = \alpha_2 + \alpha_3 \varepsilon^2_{t-1} + \alpha_4 \sigma^2_{t-1} \quad (1)$$

The residual term at time t-1 and the error variance at time t-1 determine the error variance at time t. This is the GARCH (1,1) model, where the terms Moving Average order 1 and Autoregressive order 1 are denoted by (1,1). However, if the model exhibits non-heteroscedasticity, that is, unconditional variance, then volatility cannot be estimated. Hence, before modelling volatility, it is necessary to test for heteroscedasticity. To test for

heteroskedasticity, each series is regressed on its term at lag 1 to represent the autoregressive process of the form,

$$Y_t = \alpha + \beta Y_{t-1} + \varepsilon_t \quad (2)$$

The GARCH models can be attempted to estimate the volatility. To generate the mean equation, the log of the returns of spot and futures prices was employed in the following way:

$$R_{st} = \alpha + \beta R_{ft} + \varepsilon_t \quad (3)$$

The residual term (ε_t) is estimated using the preceeding equation. From the residual series, the variance of the squared error term is used to form the variance equation, which is the GARCH (1,1) term of the form

$$\sigma^2_{\varepsilon_t^2} = \alpha_2 + \alpha_3 \varepsilon^2_{t-1} + \alpha_4 \sigma^2_{\varepsilon^2_{t-1}} \quad (4)$$

As seen before, R_{st} and R_{ft} are the logarithmic returns of the spot and futures prices, εt is the error term of the OLS equation at time *t*. Then the GARCH term $\sigma^2_{\varepsilon^2_{t-1}}$, which is the variance of the squared residual obtained from is regressed on squared residuals and variance of the squared residuals both at lag 1 as seen in equation

The Bivariate GARCH diagonal BEKK model is frequently used to investigate the volatility spillover. The bivariate link between spot and futures is studied using the diagonal BEKK model, which is represented as

$$\sigma^2_{1,t} = \gamma_{11} + a^2_{11}\varepsilon^2_{1,t-1} + b^2_{11}\sigma^2_{1,t-1} \quad (5)$$

$$\sigma_{12,t} = \gamma_{12} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{11}b_{22}\sigma_{12,t-1} \quad (6)$$

$$\sigma^2_{2,t} = \gamma_{22} + a^2_{22}\varepsilon^2_{2,t-1} + + b^2_{22}\sigma^2_{2,t-1} \quad (7)$$

Where $\sigma^2_{1,t}$, and $\sigma^2_{2,t}$ represent the volatility models of futures and spot return series of R_{ft} and $R_{st,}$ respectively. $\sigma_{12,t}$ is the conditional covariance, $\sigma^2_{1,t}$, and are conditional variances of residuals of the return's series R_{ft} and $R_{st,}$ respectively. The coefficients a_{11} and a_{22} represent the lagged values of the futures and spot series residual terms, respectively. (ARCH effects) Furthermore, coefficients b_{11} and b_{22} represent the lagged values of respective futures and spot series volatility at time t-1 (GARCH effects).

4.1. Descriptive Statistics

The behaviour of currency futures and spot return series was studied using descriptive statistical measures like Mean, Standard Deviations (S.D.), Skewness, Kurtosis, and Jarque-Bera. Descriptive statistics summarize a given data set, which shows a set of descriptive coefficients in a valuable way that simplifies interpretation. The mean values of the sample data set show a central tendency, kurtosis, and skewness, which show measures of dispersion. The standard deviation and Jarque-Bera test were employed to

verify the volatility and normality of the sample data series. Descriptive statistics show that the average return on future prices surpasses that of spot prices. Among these, USD/INR futures exhibit the highest mean return (0.000238), while GBP/INR spot returns (0.000173) demonstrate the lowest mean. The standard deviation (S.D.) indicates differing levels of variation or volatility from 2010 to 2020. JPY/INR spot returns exhibit the highest S.D. (0.008106), whereas USD/INR futures display the lowest S.D. (0.004716).

Within the Indian currency futures market, the return distributions for GBP/INR (future return -0.514172 and spot return -0.523939) are negatively skewed, while all other currencies exhibit positive skewness. Additionally, all series display the same level of excess kurtosis. The Jarque-Bera test results and related probabilities for both series indicate a divergence from the normal distribution of the data.

4.2. Unit root tests

Before proceeding with any further examination of the currency futures time series data, the series' stationarity must be established. Thus, to evaluate whether the variables are stationary or non-stationary, this study used the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (P.P.). The ADF and P.P. test results are shown below in Table 1.

Table 1. *Augmented Dickey-Fuller / Phillips-Perron Unit Root Test*

Variables	Levels	ADF test		P.P. test		Sig.
		Test value	Prob.	Test value	Prob.	
USD future	I(0)-Level	-1.191669	0.6802	-1.114307	0.7123	Ns*
	I(1)-Ist difference	-10.58720	0.0000	-46.11160	0.0001	***
USD spot	I(0)-Level	-1.110900	0.7137	-1.052439	0.7362	Ns
	I(1)-Ist difference	-21.92609	0.0000	-49.27371	0.0001	***
EUR future	I(0)-Level	-1.1991	0.2912	-1.9122	0.3268	Ns
	I(1)-Ist difference	-31.0167	0.0000	-44.2291	0.0001	***
EUR spot	I(0)-Level	1.8593	0.3520	-1.9114	0.3272	Ns
	I(1)-Ist difference	-45.6145	0.0001	-45.6349	0.0001	***
GBP future	I(0)-Level	-2.2041	0.2050	-2.2510	0.1884	Ns
	I(1)-Ist difference	-20.8671	0.0000	-43.7525	0.0001	***
GBP spot	I(0)-Level	-2.27864	0.1791	-2.2387	0.1927	Ns
	I(1)-Ist difference	-17.8043	0.0000	-45.3104	0.0001	***
JPY future	I(0)-Level	2.56036	0.1016	-2.5406	0.1060	Ns
	I(1)-Ist difference	-47.8557	0.0001	-47.8515	0.0001	***
JPY spot	I(0)-Level	-2.4898	0.1181	-2.5102	0.1131	Ns
	I(1)-Ist difference	-48.5297	0.0001	-48.5226	0.0001	***

Note: Ns* – Not significant. *** denotes statistically significant at the 1% significant levels.
Source: NSE and RBI websites.

Table 1 shows the t-statistics and significance levels (p-vaues) of the ADF (Augmented Dickey-Fuller) and P.P. (Phillips-Perron) tests, conducted on both currency futures and spot price return data. The associated probabilities for these test values are observed to exceed the 0.05 significance level. These tests demonstrate the presence of a unit root and ensure the non-stationarity of the series. Subsequently, the same tests were repeated on the first differences of the future and spot price return series.

4.3. Generalized Autoregressive Conditional Heteroscedastic (GARCH) Model

The stationarity tests for futures and spot returns reveal that the time series of currency values have significant initial differences. However, they are not substantial at this level. The stable series, on the other hand, may display volatility clustering due to autocorrelated residual variances. It was discovered that the returns series of both futures and spot currencies were stationary. It is important since the models created for Autoregressive Conditional Heteroscedastic (ARCH) imply stationarity. The Generalised ARCH (GARCH) model is a variant of the ARCH model. GARCH and ARCH were chosen based on how well the model's represented volatility. Prior to estimating the GARCH model, the heteroscedasticity of the currency spot and futures return series must be examined. The heteroskedasticity tests, such as the ARCH LM test, are used to prove the heteroscedasticity or ARCH effect in the time series. The ARCH effect confirms that using ARCH/GARCH family models is appropriate for measuring volatility. The results of the ARCH LM Test for currency spot and futures return series are presented in Table 5.10

4.3.1. ARCH-LM Test

This test employs the Lagrange multiplier (L.M.) method to assess the presence of the ARCH/GARCH effect within a series. This test determines whether heteroscedasticity exists in the currency spot and futures return data. The ARCH model has been employed to examine the existence of this heteroscedasticity effect. The result is shown in Table 2 below.

Table 2: *ARCH test*

Heteroscedasticity test: ARCH				
	Obs* R-squared	**F-statistic**	**Prob. F**	**Prob. Chi-Square(1)**
USD/INR futures	278.2238	318.8052	0.0000***	0.0000
USD/INR spot	300.2761	348.1278	0.0000***	0.0000
EUR/INR futures	128.5761	136.5405	0.0000***	0.0000
EUR/INR spot	204.5550	225.6147	0.0000***	0.0000
GBP/INR futures	76.60847	79.33619	0.0000***	0.0000
GBP/INR spot	34.41638	34.93830	0.0000***	0.0000
JPY/INR futures	90.37630	94.21326	0.0000***	0.0000
JPY/INR spot	120.9328	127.9452	0.0000***	0.0000

Note: *** denotes statistically significant at the 1% significant levels.
Source: Authors' calculations.

The F-statistics value in Table 2 is very significant at the 1% level. The results indicate that there is a considerable ARCH effect within the return series. This conclusion confirms the heteroscedasticity-ARCH effect in the time series of currency futures and spot returns. As a result, the GARCH model must be applied to appropriately analyse the volatility of the Indian FX market.

4.4. Volatility Estimation of currency futures

The GARCH model examines whether past volatility of returns can impact present volatility returns (Table 3 to Table 6).

Table 3: *Volatility estimation for USD/INR*

Variable	Coefficient	Std. error	z-statistic	Prob.
Dependent variable: R_{st}				
Mean equation (A)				
R_{ft}	0.680552	0.013989	48.65009	0.0000***
C	5.75E-05	5.53E-05	1.039944	0.2984
Variance equation (B)				
C	3.36E-07	4.50E-08	7.470403	0.0000***
RESID(-1)^2	0.114640	0.011980	9.569047	0.0000***
GARCH(-1)	0.859892	0.012634	68.06432	0.0000***

Note: *** denotes significance at a 1% level.
Source: Authors' calculation.

The GARCH model study shows that the p-values for the ARCH and GARCH terms are statistically significant for the USD/INR currency pair (see Table 4). The ARCH and GARCH coefficients, which are GARCH (1, 1) model parameters, are used to quantify mean reversion and volatility persistence. If all of these coefficients added together are less than one, the process is said to be stationary or mean-reverting. The closer the total parameters are to unity, the longer the volatility persists. Within the variance equation, the ARCH term gauges how volatility responds to market movements. Elevated ARCH coefficient values lead to conditional volatility exhibiting substantial reactions but limited persistence. In contrast, the GARCH coefficient in the volatility equation measures volatility persistence. Larger values for this coefficient indicate that changes in conditional variance take longer to dissipate, resulting in significant persistence of conditional volatility.

The findings reveal that the ARCH coefficients (0.114640) and GARCH coefficients (0.859892) in the conditional variance equation are statistically significant at the 1% level. This suggests that exchange rate return volatility is influenced by the prior days' exchange price information and volatility levels. Furthermore, it suggests that shocks to conditional variance exhibit a highly persistent nature. Relatively higher GARCH coefficients indicate a prolonged influence of conditional variance, signifying that volatility takes a considerable time to revert to normal levels following shocks. The higher GARCH coefficient than the ARCH coefficient suggests a subdued response to recent volatility-related news, with older news maintaining a lasting impact.

Table 4: *Volatility model estimation for EUR/INR*

Variable	Coefficient	Std. error	z-statistic	Prob.
Dependent variable: R_{st}				
Mean equation(A)				
R_{ft}	0.795249	0.010441	76.16573	0.0000***
C	5.37E-05	7.34E-05	0.732010	0.4642
Variance equation (A)				
C	6.62E-06	8.63E-07	7.678765	0.0000***
RESID(-1)^2	0.292547	0.021101	13.86393	0.0000***
GARCH(-1)	0.362749	0.056487	6.421783	0.0000***

Note: *** denotes significance at a 1% level.
Source: Authors' calculation.

Table 4 reveals that the ARCH coefficient (0.292547) and GARCH coefficient (0.362749) within the conditional variance equation are statistically significant, with significance observed at the 1% level for EUR/INR. This indicates that the volatility seen in exchange rate returns is influenced by the information and volatility of the previous day's exchange prices. Consequently, shocks to the conditional variance exhibit a pronounced level of persistence over time. The relatively larger GARCH coefficients indicate that conditional variance experiences a protracted decline, indicating a sustained level of volatility persistence. These GARCH coefficients exhibit higher values for the return series, indicating that new shocks will have a prolonged impact on exchange rate prices. Additionally, the elevated value of the GARCH coefficient, compared to the ARCH coefficient, suggests a subdued reaction to recent volatility-related news, while older news retains its influence for an extended duration.

Table 5: *Volatility model estimation for GBP/INR*

Variable	Coefficient	Std. error	z-statistic	Prob.
Dependent variable: R_{st}				
Mean equation (A)				
R_{ft}	0.751703	0.010880	69.09034	0.0000***
C	4.64E-05	8.59E-05	0.539842	0.5893
Variance equation (B)				
C	5.88E-06	1.02E-06	5.774367	0.0000***
RESID(-1)^2	0.205379	0.025292	8.120338	0.0000***
GARCH(-1)	0.527204	0.057059	9.239618	0.0000***

Note: *** denotes significance at a 1% level.
Source: Authors' calculation.

The findings of Table 5 reveal that both the ARCH coefficient (0.205379) and GARCH coefficient (0.527204) within the conditional variance equation exhibit statistical significance at the 1% level for GBP/INR. The statistical significance of the ARCH and GARCH terms suggests that the volatility observed in the exchange rate returns is influenced by the exchange price information and volatility levels from the preceding day. This finding also suggests that shocks affecting conditional variance display slow mean-reverting behaviour over time. The larger GARCH coefficients indicate that conditional variance experiences a gradual decline, indicative of sustained volatility persistence. Furthermore, the GARCH coefficients present higher values for the return series, indicating that newly occurring shocks will exert a prolonged impact on exchange rate prices. In addition, the elevated value of the GARCH coefficient compared to the ARCH coefficient suggests a subdued reaction to recent news pertaining to volatility. This highlights that historical news retains its influence for an extended period, underscoring the time it takes for older news to diminish in significance.

The outcomes of the analysis, as given in Table 6, demonstrate that both the ARCH coefficient (0.335514) and GARCH coefficient (0.569586) present within the conditional variance equation are statistically significant at the 1% significance level for JPY/INR. This indicates that the volatility experienced in exchange rate returns is influenced by the preceding day's exchange price information and volatility levels. This finding also suggests

that shocks impacting conditional variance exhibit a strong degree of persistence over time. The relatively higher GARCH coefficients suggest that the conditional variance has a prolonged decay, underscoring the persistent nature of volatility.

Table 6: *Volatility model estimation for JPY/INR*

Variable	Coefficient	Std. error	z-statistic	Prob.
Dependent variable: R_{st}				
Mean equation (A)				
R_{ft}	0.827174	0.009207	89.84413	0.0000***
C	9.41E-05	8.15E-05	1.155246	0.2480
Variance equation (B)				
C	3.55E-06	4.37E-07	8.126422	0.0000***
RESID(-1)^2	0.335514	0.021211	15.81756	0.0000***
GARCH(-1)	0.569586	0.029060	19.60015	0.0000***

Note: *** denotes significance at a 1% level.
Source: Authors' calculation.

Moreover, the GARCH coefficients exhibit greater values for the return series, suggesting that newly occurring shocks will have a lasting influence on exchange rate prices. Additionally, the higher value of the GARCH measure compared to the ARCH measure indicates a restrained response to recent news concerning volatility. This implies that past news remains influential for an extended period, signifying the slow process through which older news gradually becomes less impactful.

Tables 3, 4, 5, and 6 show that the GARCH model for USD, EUR, GBP, and JPY is significant at 1%. Therefore, the results are leading to the inference that the GARCH effect is indeed present. This signifies that the conditional variance will exhibit a high level of persistence and will gradually diminish over time due to the sustained nature of volatility.

4.5. Volatility spillover estimation

The researcher employed the bivariate GARCH specification proposed by Engle and Kroner (1995) model to explore volatility spillover within the Indian currency futures market. In this context, the ARCH coefficient reflects the squared value of residual terms, while the GARCH coefficients pertain to the coefficients of the variance-covariance term. By employing the Bivariate GARCH model, the study aimed to elucidate the information flow pattern between two distinct time series.

Table 7: *Result of volatility spillover between currency spot and futures*

	USD/INR		EUR/INR		GBP/INR		JPY/INR	
	Coeff.	*p*	Coeff.	*P*	Coeff.	*p*	Coeff.	*p*
R_{ft}	0.000139	0.1199	0.000117	0.3403	0.000151	0.2247	0.000050	0.7281
R_{st}	0.000143	0.0854	0.000155	0.1974	0.000126	0.3213	0.000100	0.4793
γ_{11}	2.83E-07	0.0000	0.00000118	0.0000	0.0000120	0.0000	0.0000134	0.0000
γ_{12}	2.22E-07	0.0000	0.00000127	0.0000	0.0000063	0.0000	0.0000080	0.0000
γ_{22}	3.45E-07	0.0000	0.00000214	0.0000	0.0000041	0.0000	0.0000048	0.0000
a_{11}	0.209681	0.0000	0.18707700	0.0000	0.2564860	0.0000	0.2954840	0.0000
a_{22}	0.240002	0.0000	0.26109300	0.0000	0.3567540	0.0000	0.4382050	0.0000
b_{11}	0.971548	0.0000	0.96587100	0.0000	0.9149080	0.0000	0.9189120	0.0000
b_{22}	0.962756	0.0000	0.93829500	0.0000	0.7599920	0.0000	0.7971430	0.0000

Source: Author's computation.

Using data from independent market histories, this method evaluates the volatility spillover between two linked markets. Table 7 displays the results of the bivariate GARCH.

The table above gives the conditional mean and volatility model for the return's series of futures R_{fi} and spot R_{st}, along with volatility estimation. It is seen from the above table that diagonal parameters a_{11} and a_{22} are statistically significant (P<0.01). This signifies a dependence of the return's series of futures R_{fi} and spot R_{st} on their respective first lags. These statistically significant coefficients suggest substantial and positive spillover effects, indicating an upward shift in these markets. Incorporating conditional variance-covariance successfully captures the volatility and cross-volatility interactions between the currency futures and spot markets. This effectiveness is underscored by the significant coefficients, as evident from the aforementioned table. More specifically, the diagonal BEKK Specification yields meaningful insights into the conditional variances-covariances (which are presented below). The conditional mean and volatility models for R_{fi} and spot R_{st} from the above table can be written as:

USD/INR

R_{fi} = *0.000139*+$\varepsilon_{1,t}$

$\sigma_{1,t}^2 = 2.83066201965e-07 + 0.0439661\ \varepsilon_{1,t-1}^2 + 0.9439054\sigma_{1,t-1}^2$

$\boldsymbol{R_{st}}$ = *0.000143*+$\varepsilon_{2,t}$

$\sigma_{2,t}^2$=$3.44550089654e-07 + 0.0576011x\varepsilon_{2,t-1}^2 + 0.926899x\sigma_{2,t-1}^2$

Covariance equation

$\sigma_{12,t}$=$2.22344868383e-07 + 0.0503239x\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.9353637x\ \sigma_{12,t-1}$

EUR/INR

R_{fi}= *0.000117*+$\varepsilon_{1,t}$

$\sigma_{1,t}^2 = 0.00000118 + 0.034998\ \varepsilon_{1,t-1}^2 + 0.932907\sigma_{1,t-1}^2$

$\boldsymbol{R_{st}}$ = *0.000155*+$\varepsilon_{2,t}$

$\sigma_{2,t}^2$=$0.00000214 + 0.0681696\ x\varepsilon_{2,t-1}^2 + 0.880398x\sigma_{2,t-1}^2$

Covariance equation

$\sigma_{12,t}$=$0.00000127 + 0.048844x\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.906272x\ \sigma_{12,t-1}$

GBP/INR

R_{fi}= *0.000151*+$\varepsilon_{1,t}$

$\sigma_{1,t}^2 = 0.0000120 + 0.065785\ \varepsilon_{1,t-1}^2 + 0.837057\sigma_{1,t-1}^2$

$\boldsymbol{R_{st}}$ = *0.000126*+$\varepsilon_{2,t}$

$\sigma_{2,t}^2$=$0.0000041 + 0.127273\ x\varepsilon_{2,t-1}^2 + 0.577588x\sigma_{2,t-1}^2$

Covariance equation

$\sigma_{12,t}$=$0.0000063 + 0.091502x\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.695323x\ \sigma_{12,t-1}$

JPY/INR

R_{ft}= *0.000050*+$\varepsilon_{1,t}$

$\sigma_{1,t}^2 = 0.0000134 + 0.087311\ \varepsilon_{1,t-1}^2 + 0.844399\sigma_{1,t-1}^2$

$\boldsymbol{R_{st}}$ = *0.000100*+$\varepsilon_{2,t}$

$\sigma_{2,t}^2$=$0.0000048 + \ 0.192024\ x\varepsilon_{2,t-1}^2 + 0.635437x\sigma_{2,t-1}^2$

Covariance equation

$\sigma_{12,t}$=$0.0000080 + 0.129983x\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.732504x\ \sigma_{12,t-1}$

The cross-product terms of a_{11} and a_{22} and b_{11} and b_{22} are coefficients of conditional covariances of ARCH and GARCH terms of the covariance. The results of USD/INR show that all the conditional variances and covariances of the diagonal BEKK model are positive and significant (P<0.01). However, the persistence of shocks for R_{ft} (0.04397+0.94390=0.98787) is almost the same as that of R_{ft} (0.05760+0.926899= 98449) for USD/INR, but for all other currency futures, it shows differences. It is seen that own volatility spillovers (ARCH effects) are positive and significant for both futures and spot series. The spillover effect is higher for the spot series (0.05760) than for the futures series (0.0439661). These coefficients illustrate each market's volatility persistence in relation to its historical errors. As for cross-volatility effects, past and future innovations have had a more significant influence on the volatility of the spot market to a certain extent. The cross-volatility spillovers from futures to spot (0.93536) are higher than the own-volatility spillovers of spot series (0.926899).

In the case of EUR/INR, the persistence of shocks for R_{ft} is 0.967965 (0.034998+0.932967), and R_{st} is 0.985676 (.0681696+0.880398). It is seen that own volatility spillovers (ARCH effects) are positive and significant for both futures and spot series. The spillover effect is higher for the spot series (0.0681696) than for the futures series (0.0349981). As for cross-volatility effects, past future innovations have a greater influence on the volatility of the spot market to a certain extent. The cross-volatility spillovers from futures to spot (0.906272) are higher than the own-volatility spillovers of spot series (0.880398).

For GBP/INR, the persistence of shocks for R_{st} (0.127273+0.577588= 0.704861) shows comparatively higher differences than that of R_{ft} (0.065785+ 0.837057 =0.902842). It is seen that own volatility spillovers (ARCH effects) are positive and significant for both futures and spot series. The spillover effect is higher for the spot series (0.127273) than for the future series (0.065785). Regarding cross-volatility impacts, previous innovations have a somewhat bigger impact on the volatility of the spot market in the future. The cross-

volatility spillovers from futures to spot (0.695323) are higher than the own-volatility spillovers of spot series (0.577588).

In the case of JPY/INR, the persistence of shocks for R_{st} is 0.827461 (0.192024+0.635437), and R_{ft} is 0.93171 (0.087311+0.844399). It is seen that own volatility spillovers (ARCH effects) are positive and significant for both futures and spot series. The spillover effect is higher for the spot series (0.192024) than for the future series (0.087311). Regarding cross-volatility impacts, previous innovations have a somewhat bigger impact on the volatility of the spot market in the future. The cross-volatility spillovers from futures to spot (0.732504) are higher than the own-volatility spillovers of spot series (0.635437).

5. Conclusions

Contracts for currency futures are essential for negotiating the complex foreign exchange market. These contracts provide an effective way to offset some of the risks associated with exchange rate swings. In addressing the nuanced realm of volatility spillover, this study delved into the dynamics of four currency futures traded within the Indian foreign exchange market—namely USD/INR, EUR/INR, GBP/INR, and JPY/INR—encompassing the timeframe from April 2010 to March 2022. The GARCH model employed in this study has rendered significant insights, revealing that the conditional variance retains a high level of persistence, a characteristic reflective of the enduring nature of volatility.

Furthermore, this investigation underscores the noteworthy influence of cross-volatility effects and historical and forthcoming innovations on spot market volatility, albeit to a certain extent. Notably, in terms of volatility, the spillovers from futures to spot demonstrate greater prominence than the spillovers confined to the spot series alone. This revelation lends credence to the intricate interplay between futures and spot markets, underscoring the intricate relationships that underscore these interconnected spheres.

In essence, this study not only advances our comprehension of volatility dynamics in currency futures and spot markets but also provides valuable insights into the broader landscape of risk management and market behaviour.

References

Andersen, T.G., Bollerslev, T., Diebold, F.X., and Vega, C. (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review*, *93*(1), 38–63.

Bessembinder, H., and Seguin, P.J. (1993). Price volatility, trading volume, and market depth: Evidence from futures markets. *Journal of Financial and Quantitative Analysis*, *28*(1), 21–39.

Chatrath, A., and Song, F. (1998). Information and volatility in futures and spot markets: The case of the Japanese yen. *Journal of Futures Markets*, *18*(2), 201–223.

Cheung, Y.-W., and Fung, H.G. (1997). Information flows between Eurodollar spot and futures markets. *Multinational Finance Journal*, *1*(4), 255–271.

Cho, J.-B., Min, H.-G., and McDonald, J. (2019). Volatility and dynamic currency hedging. *Journal of International Financial Markets, Institutions & Money*, 1–43.

Crain, S.J., and Lee, J.H. (1995). Intraday volatility in interest rate and foreign exchange spot and futures markets. *Journal of Futures Markets*, *15*(4), 395–421.

Dennis, P., Mayhew, S., and Stivers, C. (2006). Stock returns, implied volatility innovations, and the asymmetric volatility phenomenon. *Journal of Financial and Quantitative Analysis*, *41*(2), 381–406.

Devan, K.P., and Johnson, J. (2021). A pragmatic evaluation of the interconnection between currency futures return volatility, open interest and volume. *Theoretical and Applied Economics*, *28*(1), 289–296.

Devan, K.P., Johnson, J., and Jacob, T. (2022). Interaction between spot and future currency market of India: Empirical evidence. *BIMTECH Business Perspectives*, *3*(3), 31–47.

Eun, C.S., and Resnick, B.G. (1994). International diversification of investment portfolios: U.S. and Japanese perspectives. *Management Science*, *40*(1), 140–161.

Fang, L., Yu, H., and Xiao, W. (2017). Forecasting gold futures market volatility using macroeconomic variables in the United States. *Economic Modelling*, 1–11.

Ferris, S.P., Park, H.Y., and Park, K. (2002). Volatility, open interest, volume, and arbitrage: Evidence from the S&P 500 futures market. *Applied Economics Letters*, *9*(6), 369–372.

Fung, H.-G., and Patterson, G.A. (1999). The dynamic relationship of volatility, volume, and market depth in currency futures markets. *Journal of International Financial Markets, Institutions and Money*, *9*(1), 33–59.

Harvey, C.R., and Huang, R.D. (1991). Volatility in foreign currency futures markets. *The Review of Financial Studies*, *4*(3), 543–569.

Kumar, A. (2015). Impact of currency futures on volatility in exchange rate: A study of Indian currency market. *Paradigm*, *19*(1), 95–108.

Kumar, T.K., Poornima, B.G., and Sudarsan, P.K. (2017). Effectiveness of currency futures market in India: An empirical investigation. *IIM Kozhikode Society & Management Review*, *6*(2), 196–203.

Malliaris, A.G., and Ziemba, W.T. (2016). *The world scientific handbook of futures markets* (Vol. 5). World Scientific Publishing.

Nath, G., and Pacheco, M. (2017). Currency futures market in India: An empirical analysis of market efficiency and volatility. *Macroeconomics and Finance in Emerging Market Economies*, 1–38.

Pavaskar, M., and Kala, S.V. (2013). Impact of volatility in rupee-dollar exchange rates on currency futures trading volume. *Financial Vision*, *1*(4), 17–19.

Sehgal, S., Ahmad, W., and Deisting, F. (2015). An investigation of price discovery and volatility spillovers in India's foreign exchange market. *Journal of Economic Studies*, *42*(2), 261–284.

Sehgal, S., and Dutt, M. (2018). Domestic and international informational linkage for the US Dollar/Indian Rupee contracts: An empirical study. *Management and Labour Studies*, *43*(4), 1–29.

Sequeira, J.M., Chiat, P.C., and McAleer, M. (2004). Volatility models of currency futures in developed and emerging markets. *Mathematics and Computers in Simulation*, *64*, 79–93.

Sharma, S. (2011). An empirical analysis of the relationship between currency futures and exchange rate volatility in India. *Reserve Bank of India Occasional Papers*.

Singh, S., and Tripathi, L. (2014). A study of currency market volatility in India during its pre and post derivative period. *International Journal of Core Engineering & Management*, *1*(6), 104–120.

Sriram, M., and Senthil, M. (2013). Market efficiency and volatility spillover in spot & futures currency market (w.r.t $ and ₹). *International Journal of Management Excellence*, *1*(3), 45–53.

Suhashini, J., and Chandrasekar, K. (2013). Measuring time varying volatility of USD–INR currency futures in India. *Research Journal of Social Science and Management*, *3*(1), 199–205.

Tse, Y. (1999). Price discovery and volatility spillovers in the DJIA index and futures markets. *Journal of Futures Markets*, *19*(8), 911–930.

Wang, J., and Yang, M. (2009). Asymmetric volatility in the foreign exchange markets. *Journal of International Financial Markets, Institutions & Money*, *19*, 597–615.