Article

Interaction Between Spot and Future Currency Market of India: Empirical Evidence

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Abstract

The study empirically analyses the interdependence and price discovery mechanism between the spot and futures (S&F) prices of the Indian Foreign Exchange Market. Daily closing prices of S&F currency pairs were collected from February 2010 to March 2021. Before investigating causality, the descriptive statistical test and unit root test (augmented Dickey–Fuller) are used to test the stationarity of data. An error correction model examines the long- and short-run relationship between S&F market currency pairs. The currency returned series stationarity at I(1) identified the presence of heteroscedasticity and found the absence of the Autoregressive Conditional Heteroskedasticity effect. To avoid the possible ignorance of the long-run relationship between S&F and to confirm the trustworthiness of regression at levels, the cointegration technique was employed under Johansen's technique. The existence of cointegration at levels provides power to use Vector Error Correction Models, considering the level and difference in the estimation process. There is a long-run equilibrium relationship between spot rates and future rates, with a bidirectional causal association among currency S&F prices of all the currency pairs. Additionally, the futures market tends to regulate any new data quicker than the spot market. It suggests that spot price is led by future price, thus contributing substantially to the price-discovery process. The Generalized Autoregressive Conditional Heteroskedasticity models establish persistence in volatility, and the bad news gives rise to more volatility as compared to good news.

Keywords

Foreign exchange market, spot and futures prices, Vector Error Correction Models (VECM)

Introduction

The forex market in India has come a long way in terms of the number of participants, overall market turnover and variety of instruments. Today, the Indian forex market is an attractive destination for investors and has seen an increase in turnover for foreign currencies (Kharbanda & Singh, 2017).

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The gradual integration of the Indian economy with the global economy and the increased interest of foreign investors in Indian markets have led to growing volumes in Rupee trades in the offshore markets (RBI, 2019). Over the years, an increase in the number of participants and the profitable derivative products for trading and hedging risk have added to the depth and complexity of the market. The currency futures market ensures greater price transparency for traders by introducing exchange-traded currency futures.

The price discovery mechanism is essential to understanding the movement of prices between spot and futures (S&F) markets. It helps to detect how futures markets possess and share information (Kumar, 2018; Li et al., 2020). Hasbrouck (1995) defined price discovery as incorporating new information into the price of a security. Suppose one market assimilates new information faster than another market. In that case, it indicates a lead–lag relationship between the spot and the futures market (Kumar, 2018). An efficient market is one in which these forces do not pull and push, and information is freely available to all market participants. Suppose prices in both markets quickly adjust to new information. In that case, arbitrage opportunities for traders are eliminated, and the market becomes fully efficient (Kharbanda & Singh, 2017).

The market with the most prominent information shares leads the other markets by reacting to new information first. If the innovations in a market drive the reaction of the other markets, then this market is informationally dominant (Cabrera et al., 2008). The price discovery in the S&F market has varied results in different periods. The price discovery technique spells out short- and long-run association in prices in the S&F markets (Hasbrouck, 1995; Kawaller et al., 1987; Srivastava & Singh, 2015; Sakthivel et al., 2017). Some studies have documented that future markets assimilate the latest information at the earliest and then transfer happens at the spot market (Brooks et al., 1999; Kawaller et al., 1987; Chen & Gau, 2010; Boyrie et al., 2012; Sehgal et al., 2015; Sehgal & Dutt, 2018; Kharbanda & Singh, 2017). So, the future price ushers in to make necessary changes in spot prices. In some situations, the spot market leads the futures market (Cabrera et al., 2008; Rosenberg & Traub, 2009; Sakthivel et al., 2017; Kumar, 2018). In addition, there is a situation where these two markets do not lead to each other, in which price discovery occurs equally in both markets (Finnerty & Park, 1987).

Low-cost transactions and high liquidity are the main characteristics of the foreign exchange market, providing numerous sets of potential volatility patterns. The arrival of new information induces volatility (Harvey & Huang, 1991). The information flow among markets leads to high volatility transmission from one market to another (Sahoo et al., 2017). While many studies have analysed the volatility in the developed and emerging market, the primary focus has been on equity and commodity markets (Finnerty & Park, 1987; Stoll & Whaley, 1990; Harvey & Huang, 1991; Chan, 1992; Tse, 1999; Elyasiani & Kocagil, 2001; Xu & Fung, 2005; Barreto & Ramesh, 2018). Therefore, it is necessary to conduct an empirical analysis to confirm whether the futures market leads to the spot market or vice versa in a timely manner. The reason could be that the formal Indian currency market was introduced in 2008 and passed a journey of almost 14 years.

In this paper, we contribute to the literature in the following ways. First, we investigate the lead–lag relation between S&F in the Indian currency futures market—U.S. Dollar (USD), Euro (EUR), British Pound (GBP) and Japanese Yen (JPY) against the Indian rupee (INR). Second, we attempt to identify the association between short and long runs using S&F market prices. To identify which market leads, Johansen cointegration and error correction models were used. Thirdly, we analyse the causal association between S&F prices using the Granger causality test. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1), E-GARCH and GJR-GARCH were used to examine the volatility in currency futures markets. GJR GARCH was used to analyse the skewed character of volatility.

Therefore, this paper aims to study the currency market in India with a focus on price discovery and volatility. The paper is structured as follows: the second section provides a factual analysis of the literature. The third section explains the objectives. The fourth section deals with research methodology, and section five presents the empirical results. The sixth section concludes the findings and policy implications of the study.

Literature Assessment

Empirical evidence of price discovery

The literature shows some innovative observations on price discovery and volatility between S&F prices in the Indian context. Currency futures offer various advantages, including immense accessibility, clarity in pricing, default risk and control of counterparty. An important advantage offered by futures is better price discovery. The popular approach to understanding the price discovery function is to examine the lead–lag relationship between the market variables (Kharbanda & Singh, 2017). The researcher found that many studies reported the same result for the lead–lag relationship. It reveals that the futures market has the dominant information share.

The researcher presented a few of the studies done in the context of the Indian currency futures market and evaluated the notable findings of the studies. Raghavendra and Velmurugan (2013) examined the short-term causal association between the S&F return of GBP~INR to determine a one-way causal association between S&F returns. The Granger causality test shows that future return causes the spot to return. Srivastava and Singh (2015) attempted to study the pricing of USD~INR. The researcher has tested the cost of the carry model and convergence through Vector Error Correction Models (VECM). The study on market efficiency in India has a long-run stable relationship between the foreign currency S&F market. The inception of currency futures trading in NSE and BSE provided greater price transparency for traders. Kharbanda and Singh (2017) investigated the relationship between the USD~INR S&F market and lead–lag association in the currency futures market. VECM was used to determine which market is efficient or has a leading role. The result is that the Indian Forex market lacks informational efficiency because the future market is effectual in price discovery and leads the spot to attain long-run stability from 2010 to 2016. During the same period, Sakthivel et al. (2017) scrutinized price discovery and volatility transmission between S&F prices of USD~INR, JPY~INR, GBP~INR and EUR~INR. The outcome was a continuing association between currency S&F prices. There is unidirectional volatility transmission from currency spot to futures prices of JPY~INR, GBP~INR and EUR~INR, and bidirectional spillover between currency S&F prices of USD~INR. Raju and Manohar (2018) investigated the interdependence and mechanism of price discovery between the S&F prices of Indian foreign exchange. The result shows a cointegrating association between S&F currency pairs of USD~INR, EURO/INR and YEN/INR. The S&F return of USD~INR and GBP~INR showed a bidirectional or two-way causality relationship. GBP~INR and USD~INR take a very dominant role in the price discovery function.

Empirical affirmation of volatility transmission

Several studies reported that in developed countries, currency futures markets contributed to a reduction in volatility. The volatility in one market affects another market. Studies in the Indian context indicate that the hedging effectiveness of forward contracts is significantly higher than exchange-traded futures because of the lower popularity of the futures market in India (Kumar et al., 2017). The information flows from one market to another, driving an asset's volatility process (Andersen, 1996).

As of now, numerous studies have researched the volatility of different underlying assets using several models (Harvey & Huang, 1991; Bessembinder & Seguin, 1993; Crain & Lee, 1995; Cheung & Fung, 1997; Chatrath & Song, 1998; Sequeira et al., 2004; Antonakakis, 2012; Taskin & Kapucugil-Ikiz, 2013; Christou, 2017). Comparatively, lesser studies have scrutinized the emerging currency futures market like India.

However, the forex market's increasing significance, especially in emerging countries, increased the importance of research. Some of the notable studies done in the Indian currency futures market area are as follows: Sharma (2011) studied the connection between trading activity and exchange rate volatility using the GARCH model. He considered only USD~INR currency futures. The outcome reveals a mutual causality between the volatility in the spot exchange rate affecting the trading activity in this market. Pavaskar and Kala (2013) studied the connection between volatility and trade magnitude variables: intra-day price and trading volume of INR/USD. The result reveals that the regression coefficient is positive and statistically significant. It can be *prima facie* inferred that exchange rate volatility leads to higher intra-day trades to the benefit of currency hedgers.

Sushini and Chandrasekar (2013) measured the time-varying volatility of currency futures concerning USD~INR using the GARCH model. In the Indian market, shocks and volatility generated from its prices or market and the time-varying volatility affect the futures. The volatility is characterized by clustering manifestation, high endurance and predictability of currency futures. Mittal and Kumar (2016) examined the relationship between volatility in the exchange rate in the spot market and trading activity in the currency futures market by applying the GARCH model. Significant variation was observed in the volatility for pre and post-futures periods. With the advent of currency, futures volatility has substantially increased. Past volumes provide information on current returns, and current volume information is present past returns. Gupta (2017) studied the impact of EUR~INR futures on the exchange rate volatility using GARCH. Once the currency futures market was introduced in India, the volatility in the spot market for EUR~INR was destabilized.

Nath and Pacheco (2017) analysed the effectiveness of the currency futures prices in predicting the expected spot rate and the impact of the USD~INR currency futures trading on the underlying spot rate volatility. GARCH estimation results stipulated the existence of volatility clustering in the pre and post-futures phase. The constant conditional correlation–GARCH (CCC-GARCH) model indicated the presence of volatility clustering. Sehgal and Dutt (2018) examined price discovery and volatility linkages between USD~INR S&F contracts in India and between USD~INR futures contracts on the National Stock Exchange of India Limited (NSE), in addition to the following international exchanges: Singapore Exchange (SGX), Dubai Gold and Commodity Exchange (DGCX) and Chicago Mercantile Exchange (CME). At the national level, findings show that futures dominate the spot in the Indian currency market. At the international level, NSE is dominated by CME and DGCX in price discovery and short-term volatility spillovers.

In contrast, NSE dominates both exchanges in long-term volatility spillovers. The dominance of CME and DGCX over NSE may be because of their several advantages, such as longer trading hours, operations being open even after NSE has shut the business, much lower trading costs and lower regulatory restrictions. Biswal and Jain (2019) also analysed the Indian market to review the effective linkages of volatility and volume covering currency S&F. Due to the unavailability of volume data for the spot market, the researcher used tick data available in both S&F markets as a proxy for volume. The increase/

decrease in volumes causes a corresponding increase or decrease in volatility in both markets. Specifically, futures volume causes co-movement in spot market volatility.

Most of the research on Indian currency markets is based on USD or, otherwise, some selected single currencies. It does not disclose the complete market information. It necessitates scrutiny of price discovery and volatility transmission across the following currency futures (USD, EUR, GBP and JPY against INR) traded in India.

Objectives

- To empirically examine the price discovery and causal relationship between the S&F market of currency pairs.
- To verify whether the future or spot market of currency pair responds faster to the deviation from the equilibrium price.
- To analyse the volatility transmission between S&F currency market prices.

Methodology

Data

To analyse the dynamics of currency futures in India, the study preferred data set from NSE and RBI. The selection of stock exchange is based on the trading volume exhibited by the exchanges in terms of the number of futures contracts and volume traded for the respective currency futures. The currency futures started trading on NSE in August 2008. Initially, futures were traded only in USD. Later, in 2010, three other currencies (GBP, EUR and JPY) were permitted for trade. The sample data of the daily futures prices of four currencies, namely USD~INR, EUR~INR, GBP~INR and JPY~INR, are retrieved from NSE. The spot data are available on the RBI website. The present study collected data for all these four currencies from February 2010 to March 2021. The study considers only near-month futures prices to ensure liquidity in the futures contract.

Methodology

To analyse the price discovery process and volatility transmission across currency futures and spot prices of USD~INR, JPY~INR, GBP~INR and EUR~INR, the researcher used Johansen cointegration, ECM, Granger causality and variants of the GARCH model (GARCH (1, 1), E-GARCH, GJR-GARCH).

The study used augmented Dickey-Fuller (ADF and Phillips–Perron (PP) to test stationarity. Cointegration analysis was performed to investigate the existence of a long-term relationship between S&F prices of currency pairs. Because the S&F prices are cointegrated, this will simultaneously allow modelling of the long-run and short-run dynamics. Johansen and Juselius cointegration test (1991) was widely used among the available cointegration measures. Johansen procedure was used determine the actuality of cointegration among a set of nonstationary I (1) variables. The number of cointegration vectors is finalized by using trace and maximum eigenvalue tests. The null hypothesis of the maximum eigenvalue is 'k' cointegrating relation. The alternative hypothesis is cointegration relation of k+1 for $k = 0, 1, 2, \ldots, n-1$. The computational model of the test statistics is

$$R_{\max}\left(\frac{k}{n+1}\right) = -S * \log\left(1-\hat{\lambda}\right)$$

where S is the sample size and λ is the maximum eigenvalue.

The null hypothesis of the trace test is the same as the maximum eigenvalue test, i.e., k cointegration relations. While the alternative hypothesis considers n cointegration relations only, where $n = 0, 1, 2, \ldots,$ $n-1$, the computational form of it is given as follows:

$$R_{\text{tr}}\left(\frac{k}{n}\right) = -S * \sum_{i=k+1}^{n} \log\left(1-\hat{\lambda}\right).$$

The present study used the Johansen procedure to test the long-run association of two variables. Once cointegration was positively determined, VECM will employ to understand short-run characteristics of the series. Short-term fluctuation of the independent and dependent variables will stabilise in the long run, which is given by a negative ECM. The VECM regression equation is as follows:

$$\Delta S_t = \delta_1 + \rho_1 e_1 + \sum_{i=0}^{n} \alpha_i \Delta S_{t-i} + \sum_{i=0}^{n} \beta_i \Delta F_{t-i} + \sum_{i=0}^{n} \gamma_i \Delta u_{t-i}$$

$$\Delta F_t = \delta_2 + \rho_2 e_{i-1} + \sum_{i=0}^{n} \alpha_i \Delta S_{t-i} + \sum_{i=0}^{n} \beta_i \Delta F_{t-i} + \sum_{i=0}^{n} \gamma_i \Delta u_{t-i}.$$

Granger causality was applied to examine the impact of past values of the dependent variable on the current values of the independent variable, which in turn helps to measure the forecasting ability of the dependent variable. The following model specifies the causality in bivariate conditions:

$$S_t = \beta_0 + \beta_1 S_{t-1} + \cdots + \beta_i S_{t-i} + \gamma_1 F_{t-1} + \cdots + \gamma_i F_{t-i} + \mu$$

$$F_t = \beta_0 + \beta_1 F_{t-1} + \cdots + \beta_i F_{t-i} + \gamma_1 S_{t-1} + \cdots + \gamma_i S_{t-i} + \mu.$$

The absence of the cointegration relationship directly led to testing the Granger causality of the series. However, the inability of cointegration to specify the direction of the relationship, Granger causality will help.

Volatility Models

This section explains the justification for the use of GARCH models. The pictorial presentation of price returns exhibits evidence to doubt the absence of homoscedasticity for error variance. So, the GARCH model allows the conditional variance to be an autoregressive moving average process and ensures positive estimates of coefficients. The GARCH specification is

$$\boldsymbol{u_t = v_t \sqrt{h_t}}$$

where σ_{v^2} =1, and

$$h_t = \kappa + \sum_{i=1}^{q} \alpha_i u_{t-i^2} + \sum_{i=1}^{p} \beta_i + h_{t-i}$$

where $\alpha_1, \ldots\ldots \alpha_q$ and $\beta_1, \ldots\ldots\ldots \beta_p, k$ are constant parameters

Exponential GARCH

EGARCH is one of the popular asymmetric GARCH models that has a conditional variance equation, i.e.,

$$\ln(h_t) = k + \beta \cdot \ln(h_{t-1}) + \delta . \frac{u_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right]$$

where k, β, δ, and α are constant parameters. Other things remain the same; it is identified that positive return shocks create less volatility than negative shocks due to the negative coefficient of δ.

GJR-GARCH

The GJR_GARCH is also one of the asymmetric GARCH-type models, which allows the inclusion of volatility in the model. The model with volatility compensation term is given as

$$h_t = k + \beta h_{t-1} + \delta u^2{}_{t-1} + \gamma s^-{}_{t-1} u^2{}_{t-1}$$

where $s^-{}_t = 1$ if $u_t < 0, s^-{}_t = 0$, otherwise, γ is the asymmetric parameter.

Empirical Results

Descriptive Statistics

The future series shows lower returns and lower volatility juxtaposed to spots in the currency futures market. The descriptive statistics (Table 1) account for the characteristics of currency S&F returns of USD~INR, EUR~INR, GBP~INR and JPY~INR. It is seen from the table that an average return on future price is higher than the spot. USD~INR futures have the highest mean, and GBP~INR spot reported the lowest mean. JPY~INR spot return shows the highest standard deviation (SD), and USD~INR future has the lowest SD. INR witnesses the highest variation in its price against USD and

Table 1. Descriptive Statistics.

Variables	Mean	SD	Skewness	Kurtosis	Jarque–Bera
USD/INR (S)	0.000237	0.004954	0.072044	9.508265	3838.765
USD/INR (F)	0.000238	0.004716	0.365403	8.087457	2392.876
EUR/INR (S)	0.000145	0.006406	0.121736	7.144894	1561.605
EUR/INR (F)	0.000147	0.006096	0.213271	7.051671	1503.500
GBP/INR (S)	0.000136	0.006533	−0.523939	10.29101	4914.766
GBP/INR (F)	0.000137	0.006305	−0.514172	12.65522	8540.265
JPY/INR (S)	0.000173	0.008106	0.012216	6.445930	1075.680
JPY/INR (F)	0.000174	0.007953	0.293197	7.436195	1813.812

Source: Authors' calculation.

the lowest variation against JPY. The futures and spot price returns of GBP~INR are negatively skewed, and all other currencies are positively skewed. Kurtosis values show that all the currencies, futures returns and spot returns have excess kurtosis values, which means all these series are leptokurtic. The series' observed skewness and kurtosis values show that future and spot return prices have skewness and excess kurtosis values far from zero. It indicates that these series may not follow a normal distribution pattern. The Jarque–Bera (J–B) test of normality also confirms this observation. The test value of J–B and the associated probabilities for both series indicate that the series do not follow a normal distribution.

Stationarity in S&F Market

The study first performed a unit root test on the S&F markets price series of the following currency futures (USD, EUR, GBP and JPY) to investigate the stationarity. The S&F price series are tested for stationarity using ADF and PP. The ADF and PP unit root tests in Table 2 show that the series of currency S&F pairs are non-stationary at levels but become stationary at first difference. Thus, both series are integrated of the first order, that is, I (1).

Cointegration Between S&F Market Returns

The VAR lag order selection procedure was employed to determine the lag length. Among the various criteria listed by the VAR procedure, Akaike information criterion (AIC) value exhibited in Table 3 was adopted**.**

Table 4 represents the Johansen cointegration results for the currency pairs of S&F markets. Johansen cointegration test is employed to check the long-run relationship between the S&F Price series. The maximum eigenvalue and trace test values are utilized to clarify if the null hypothesis of no cointegration vector ($r = 0$) is not accepted against the alternate hypothesis at a 5% level, i.e., $r = 1$ (existence of one cointegrating vector). The empirical result shows that the null hypothesis of no cointegration is not accepted for all currencies at the 5% level, substantiating the long-run association among the S&F prices.

Table 2. Results of Unit Root Tests.

Variables	ADF in level	ADF in First Difference	PP in level	PP in First Difference
USD~INR(S)	−2.102190	−54.44809***	−2.452770	−54.15963***
	(0.5438)	(0.0000)	(0.3520)	(0.0000)
USD~INR (F)	2.148488	−52.33403***	−2.374720	−52.22887***
	(0.5177)	(0.0000)	(0.3928)	(0.0000)
EUR~INR(S)	−2.317418	−49.76573***	−2.329901	−49.76566***
	(0.4237)	(0.0000)	(0.4169)	(0.0000)
EUR~INR (F)	−2.215483	−48.55546***	−2.314449	−48.57706***
	(0.4801)	(0.0000)	(0.4253)	(0.0000)
GBP~INR(S)	−1.883172	−49.52434***	−1.902438	−49.52434***
	(0.6629)	(0.0000)	(0.6529)	(0.0000)
GBP~INR (F)	−1.840947	−48.30778***	−1.935573	−48.37417***
	(0.6845)	(0.0000)	(0.6353)	(0.0000)
JPY~INR(S)	−2.359888	−52.54539***	−2.400365	−52.54678***
	(0.4007)	(0.0000)	(0.3792)	(0.0000)
JPY~INR (F)	−2.349288	−52.44436***	−2.391133	−52.41683***
	(0.4064)	(0.0000)	(0.3841)	(0.0000)

Source: Authors' computation.
Note: *, ** and *** are statistically significant at the 10%, 5% and 1% significant levels (figures in brackets are *p*-values).

Table 3. Lag Selection Criteria: AIC Value.

Lags	USD	EUR	GBP	JPY
1	−16.97132	−16.10588	−15.83384	−15.22788
2	−17.00553	−16.12657	−15.84331	−15.23988
3	−17.01383	−16.13444	−15.84819	*−15.24217**
4	−17.01622	−16.13258	−15.84722	−15.23981
5	*−17.02121**	*−16.13550**	−15.85245	−15.23842
6	−17.02011	−16.13293	−15.85214	−15.23557
7	−17.01986	−16.13401	*−15.85455**	−15.23404
8	−17.01846	−16.13247	−15.85417	15.23213

Notes: The lowest AIC values are shown in italics for each currency and correspond to the number of lags taken. The number of lags chosen for USD and EURO is 5, GBP is 7 and JPY is 3.

Table 4. Johansen's Cointegration Result.

Currencies	Vector	Eigenvalue	Trace Test Statistics (λ_{trace})	Maximal Eigenvalue (λ_{max})
USD	0	0.142768	372.3601** (0.0001)	370.7904**(0.0001)
	1	0.000652	1.569630 (0.2103)	1.569630 (0.2103)
EUR	0	0.151062	396.3849** (0.0001)	394.1936** (0.0001)
	1	0.000910	2.191315 (0.1388)	2.191315 (0.1388)
GBP	0	0.122002	315.8153** (0.0001)	312.9179** (0.0001)
	1	0.001204	2.897380 (0.0887)	2.897380 (0.0887)
JPY	0	0.185303	499.6487** (0.0001)	493.6991** (0.0001)
	1	0.002467	5.949596 (0.4667)	5.949596 (0.4667)

Source: Authors' computation.
Note: *, ** and *** are statistically significant at the 10%, 5% and 1% significant level (figures in brackets are *p*-values).

Vector Error Correction Model

The unit root at levels and cointegration relation under Granger causality suggested the error correction model. The long-run association amongst S&F prices of individual currency has been proved with Johansen's cointegration test. The presence of cointegration validates the use of VECM for estimating the long-run dynamics.

VECM estimates for the selected currencies are shown in Tables 5–8.

Table 5. VECM Result for USD.

	USD	
Currency variables	ΔS_t	ΔF_t
Cons	0.000158** [1.88498]	0.000170** [1.74355]
ECT	−0.669858 [−10.4978]	0.138745 [1.87519]
S_{t-1}	−0.303216 [−5.13493]	−0.299070 [−4.36782]
S_{t-2}	−0.054724 [−0.99847]	−0.146904 [−2.31156]
S_{t-3}	0.136129 [2.74569]	0.057112 [0.99344]
S_{t-4}	0.122030 [2.86045]	0.046315 [0.93627]
S_{t-5}	0.012226 [0.41751]	0.027815 [0.81915]
F_{t-1}	0.294591 [4.87517]	0.211986 [3.02543]
F_{t-2}	0.129654 [2.32239]	0.203005 [3.13592]
F_{t-3}	−0.053648 [−1.05244]	0.019558 [0.33089]
F_{t-4}	−0.116115 [−2.55781]	−0.028243 [−0.53653]
F_{t-5}	−0.024658 [−0.70082]	−0.009731 [−0.23852]

Source: Authors' computations.
Note: *Figures in parentheses are t-values. The symbol ** indicates that the parameter is significant at the 5% level.*

Table 6. VECM Result for EUR.

	EUR	
Currency variables	ΔS_t	ΔF_t
Cons	0.000103** [0.92114]	0.000115** [0.92560]
ECT	−0.793051 [−10.8478]	0.04440 [0.54876]
S_{t-1}	−0.133141 [−1.98931]	−0.183997 [−2.48351]
S_{t-2}	0.069672 [1.14306]	−0.019408 [−0.28765]
S_{t-3}	0.142346 [2.60489]	0.063661 [1.05240]
S_{t-4}	0.141986 [3.04062]	0.079809 [1.54395]
S_{t-5}	0.039543 [1.18380]	0.028217 [0.76310]
F_{t-1}	0.199748 [2.90529]	0.181302 [2.38217]
F_{t-2}	0.031786 [0.50820]	0.107613 [1.55425]
F_{t-3}	−0.121303 [−2.14928]	−0.042213 [−0.67566]
F_{t-4}	−0.133075 [−2.67850]	−0.079489 [−1.44533]
F_{t-5}	−0.049154 [−1.25741]	−0.039878 [−0.92156]

Source: Authors' computations.
Note: Figures in parentheses are *t*-values. The symbol ** indicates that the parameter is significant at the 5% level.

Table 7. VECM Result for GBP.

Currency variables	GBP	
	ΔS_t	ΔF_t
Cons	0.000116** [0.99475]	0.000135** [1.02713]
ECT	−0.947846 [−11.0882]	−0.084920 [−0.87811]
S_{t-1}	0.056700 [0.71220]	0.075952 [0.84329]
S_{t-2}	0.193536 [2.63117]	0.151187 [1.81682]
S_{t-3}	0.249442 [3.71399]	0.218289 [2.87286]
S_{t-4}	0.271650 [4.42922]	0.221743 [3.19579]
S_{t-5}	0.227183 [4.17314]	0.256705 [4.16804]
S_{t-6}	0.155486 [3.40366]	0.163899 [3.17135]
S_{t-7}	0.041150 [1.30339]	0.036396 [1.01897]
F_{t-1}	0.199748 [2.90529]	0.181302 [2.38217]
F_{t-2}	0.031786 [0.50820]	0.107613 [1.55425]
F_{t-3}	−0.200350 [−2.91788]	−0.164959 [−2.12355]
F_{t-4}	−0.245673 [−3.90963]	−0.200283 [−2.81729]
F_{t-5}	−0.234332 [−4.15835]	−0.276863 [−4.34275]
F_{t-6}	−0.172283 [−3.54390]	−0.203738 [−3.70443]
F_{t-7}	−0.068463 [−1.85330]	−0.086928 [−2.08000]

Source: Authors' computations.
Note: Figures in parentheses are *t*-values. The symbol ** indicates that the parameter is significant at the 5% level.

Table 8. VECM Result for JPY.

Currency variables	JPY	
	ΔS_t	ΔF_t
Cons	0.000109** [0.73411]	0.000116** [0.70835]
ECT	−0.710837 [−9.53176]	0.173091 [2.10849]
S_{t-1}	−0.229796 [−3.48028]	−0.195411 [−2.68853]
S_{t-2}	−0.021859 [−0.39717]	0.015399 [−0.25416]
S_{t-3}	0.050650 [1.34033]	0.053979 [1.29763]
F_{t-1}	0.215444 [3.19841]	0.132512 [1.78709]
F_{t-2}	0.085558 [1.49211]	0.066111 [1.04739]
F_{t-3}	−0.042796 [−1.01173]	−0.049896 [−1.07156]

Source: Authors' computations.
Note: Figures in parentheses are *t*-values. The symbol ** indicates that the parameter is 5% level.

Table 9. Adjustment Coefficient.

Dependent variable	Coefficient	LR statistics
USD Spot	−0.669858	107.8502 (0.000000)**
USD Future	0.138745	3.517506 (0.060724)
EUR Spot	−0.793051	114.8459 (0.000000)**
EUR Future	0.044409	0.301075 (0.583209)
GBP Spot	−0.947846	119.6194 (0.000000)**
GBP Future	−0.084920	0.769374 (0.380411)
JPY Spot	−0.710837	88.63475 (0.000000)**
JPY Future	0.173091	0.815288 (0.335618)

Note: The symbol ** indicates the parameter is significant at 5% level.

The VECM identifies the estimation of the speed of adjustment coefficients between S&Fs (Table 9). The coefficients are greater and statistically significant in the currency futures of USD/INR, EUR/INR, GBP/INR and JPY/INR (USD Future = 0.138745, EUR Future = 0.044409, GBP Future = −0.084920 and JPY Future = 0.173091). It shows that the spot price corrects a greater imbalance between futures and spot prices. The result shows that the futures market adjusts to new information faster than the spot market. It signifies that the future price outperforms the spot price and plays a significant role in price discovery.

Ganger causality test

The casual relations between the variables are checked using Granger causality, which also provides evidence to identify the usefulness of one series to forecast the other. The Granger causality between foreign currency S&F return of currency pairs revealed a bidirectional causal relationship between currency spot to futures prices of JPY/INR, GBP/INR and EUR/INR. Likewise, currency spot prices Granger causes futures prices of USD/INR, JPY/INR, GBP/INR and EUR/INR. Thus, the existence of the bidirectional relationship between the variables is identified (Table 10)

Modelling of volatility in currency S&F market

Tables 11–14 depict the empirical outcome of GARCH analysis of currency S&F markets. GARCH (1,1), E-GARCH and GJR-GARCH have been applied to examine volatility in currency futures markets. A simple GARCH model provides the resultant interpretation; the vital hindrance of this model is the lack of divulging the asymmetric pattern of volatility in the time series. Hence, the researcher applied the extended GARCH model GJR GARCH to analyse the asymmetric nature of volatility. The significant GJR GARCH results reveal that Indian currency futures and the spot market are highly volatile toward market news. For spot returns, α of all the selected currencies is high per GJR-GARCH outcome. The persistent volatility in spot returns measured by the β value in the E-GARCH model indicates that volatility in GBP~INR and JPY~INR takes a long time to adjust. In currency futures, the persistent volatility is more in USD~INR and EUR~INR as per E-GARCH results. The long-term volatility of the currency spot, as per GARCH (1,1), is higher than the currency futures market. In the currency spot, USD~INR exhibited elevated long-term volatility.

Table 10. Granger Causality Test.

Hypothesis	*F*-statistic	*P*-value
SP does not cause FP of USD~INR	70.41323	0.0000
USD~INR FP does not cause SP	47.54715	0.0000
SP does not cause FP of EUR~INR	47.07384	0.0000
EUR~INR FR does not cause SP	25.28760	0.0001
SP does not cause FP of GBP~INR	38.78749	0.0000
GBP~INR FP does not cause SP	26.78333	0.0004
SP does not cause FP JYP~INR	20.40044	0.0001
JPY~INR FP does not cause SP	19.57136	0.0002

Source: Authors' computations.
Note: Lag length is chosen based on the Akaike information criterion (AIC)
(SP = spot price; FP = future price).

Table 11. Volatility Test for USD~INR Returns.

	USD SPOT			USD FUTURES		
	GARCH(1,1)	EGARCH	GJR	GARCH(1,1)	EGARCH	GJR
Ω	6.59E–07 **	−0.616933**	6.25E–07**	4.52E–07**	−0.106323**	4.14E–07**
Α	0.111753**		0.134222**	0.054787**		0.059964**
Β	0.861471**	0.958889**	0.873148**	0.924630**	0.992955**	0.930468**
Λ			−0.069153**			−0.020965**
γ		0.227149**			0.039991**	
θ		0.039797**			0.044391**	

Source: Author's computation.
Note: ** indicates importance at 5%.

Table 12. Volatility Test for EUR~INR Returns.

	EUR SPOT			EUR FUTURES		
	GARCH(1,1)	EGARCH	GJR	GARCH(1,1)	EGARCH	GJR
Ω	2.29E–06**	−0.995222**	2.46E–06**	1.88E–06**	−0.650255**	2.08E–06**
Α	0.073291**		0.082863**	0.057859**		0.066482**
Β	0.870476**	0.917265**	0.866034**	0.891009**	0.947014**	0.884115**
Λ			−0.019540**			−0.015071**
γ		0.202856**			0.146432**	
Θ		0.016213**			0.011243**	

Source: Author's computation.
Note: ** indicates importance at 5%.

Table 13. Volatility Test for GBP~INR Returns.

	GBP SPOT			GBP FUTURES		
	GARCH(1,1)	EGARCH	GJR	GARCH(1,1)	EGARCH	GJR
ω	2.90E–05**	−1.302442**	5.32E–06**	6.31E–06**	−1.666804**	6.59E–06**
α	0.1500**		0.120036**	0.098924**		0.115141**
β	0.6000**	0.886742**	0.787159**	0.746161**	0.852009**	0.738820**
λ			−0.056732**			−0.032313**
γ		0.215627**			0.221613**	
θ		0.031988**			0.015843**	

Source: Author's computation.
Note: ** indicates importance at 5%.

The likelihood of a high log value was the primary factor in model selection. Parameters γ and λ are used to measure the leverage effect in E-GARCH and GJR models, respectively. Based on the leverage effect, it is observed that the volatility increases on bad news more than the good news. A leverage effect is noticed in the E-GARCH instance. If futures volatility surges due to negative shocks, sign γ is anticipated as positive. In T-GARCH, when the shock is positive, the effect on volatility is α. However, when news is negative, the effect on volatility is $\alpha + \lambda$, that is, the leverage effect. If λ is significant and positive, adverse shocks have a larger effect on $\boldsymbol{\sigma}^2$ than positive shocks.

Table 14. Volatility Test for JPY~INR Returns.

	JPY SPOT			JPY FUTURES		
	GARCH(1,1)	EGARCH	GJR	GARCH(1,1)	EGARCH	GJR
ω	1.70E–06**	−0.505729**	1.76E–06**	2.26E–06**	−0.548001**	2.32E–06**
α	0.092739**		0.136860**	0.091802**		0.120908**
β	0.886418**	0.963711**	0.882650**	0.878421**	0.958358**	0.876386**
λ			−0.082668**			−0.058441**
γ		0.205518**			0.197513**	
θ		0.061839**			0.054190**	

Source: Author's computation.
Note: ** indicates importance at 5%.

GJR model outcome for the currency S&F return series indicates that values of coefficients for the asymmetric response are statistically significant. It indicates volatility in the S&F return series is asymmetric (GARCH coefficient values are higher than the ARCH values, which means the volatility is highly persistent and clustering), and volatility's response is not uniform to good and bad news. Based on this study's results, we deduce that bad news brings about increased volatility compared to good news for all the currencies included.

Conclusion

This research paper presents evidence for price discovery and volatility transmission between currency S&F prices of USD, EUR, GBP and JPY (against INR). The study concluded that both S&F series have unit roots at level but stationary at order one. Johansen cointegration test reveals there is a long-run association between currency S&F prices. When assessing price discovery, ECM is favourable because it considers the lag factors in the technical equation, which encourages short-run adjustments to be made in the long run. Any system with error-correcting dynamics ensures price discovery, allowing the market to converge towards equilibrium. The outcome of the Granger causality test indicates the existence of a bidirectional causal association between currency futures and spot prices. Hence, the futures market adjusts to new knowledge faster than the spot market. It suggests that currency future price leads to the spot price and promotes largely price discovery. This study concludes that the model confirms skewed volatility in the exchange rate return along with bad news causes increased volatility than good news for all the selected currencies.

Implications

The study has practical implications for market players who can take their position cues from the futures market. There is an urgent need for policymakers to impart attention to support this sector by encouraging financial instrument innovation and widening the participation of traders. The Indian government can look at currency distortions by considering inflation control policy by connection, focusing more on supply than demand. It should remove production blockage and increase domestic demand and export. It is helpful for policymakers to intervene and protect the exchange rate from extreme fluctuations in the worldwide market. RBI can empower the corporate by providing derivative tools for hedging and modifying and simplifying the guidelines for hedging the currency risk. Currency futures prices include beneficial information about cash flows embedded in the current cash price and can be used as price discovery vehicles, leading to a better assessment of risk management and portfolio management.

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