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Assessing currency market equilibrium: Cointegration and correlation analysis of USD/INR and major global currencies

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Abstract
This article explores the equilibrium dynamics of the USD/INR and four other major currency pairs-USD/EUR, USD/GBP, USD/JPY, and USD/CHF-using daily exchange rate data from 2014 to 2023. The analysis applies Pearson's correlation, Unit root tests (ADF and KPSS), and cointegration methods, including the Johansen and Engle-Granger tests and Vector Error Correction Model, to assess both short-term and long-term relationships between these currencies. Descriptive statistics and visual analysis provide insights into the fluctuations and volatility patterns during this period, characterized by significant global economic events.
The results show limited evidence of cointegration among most currency pairs, with the exception of USD/CHF, which exhibits a strong long-term equilibrium relationship. The Vector Error Correction Model (VECM) highlights that while USD/CHF has a robust mechanism for correcting short-term deviations, other pairs like USD/INR and USD/GBP show weak or insignificant adjustment toward equilibrium. These findings suggest that factors such as interest rate changes, geopolitical shifts, and market risk perception play a more prominent role in influencing short-term fluctuations in the currency market, particularly for the USD/INR pair.

Keywords: Engle-Granger residual cointegration, global currencies, Johansen cointegration, USD/INR, and vector error correction model (VECM)

1. Introduction

Currency markets play a crucial role in the global economy, facilitating international trade, investment, and financial flows. As economies become more interconnected, exchange rates between currencies reflect a multitude of factors, ranging from interest rates, inflation, and trade balances to political stability and market sentiment. The USD/INR exchange rate, which tracks the value of the Indian Rupee against the U.S. Dollar, is of particular interest given India's rapidly growing economy and its increasing integration into the global financial system. Understanding the relationships between USD/INR and other major global currencies, such as USD/EUR, USD/GBP, USD/JPY, and USD/CHF, is essential for policymakers, investors, and economists as it can offer insights into potential risks, opportunities, and long-term trends in currency markets.

Exchange rate movements are influenced by a variety of global factors. Currencies do not move in isolation; rather, they are often linked by common economic forces. For instance, the strength of the U.S. Dollar, as the world's primary reserve currency, has a ripple effect across global currency markets. Countries with strong trade ties or financial relationships with the U.S. may experience similar exchange rate movements relative to the dollar. Conversely, currencies may also exhibit inverse relationships, reflecting divergent economic fundamentals or monetary policies. By examining both correlation and cointegration between currency pairs, we can assess the extent to which these currencies move together in the short term and whether they maintain a stable long-term relationship.

Correlation measures the degree to which two currencies move together over a specified period. A high positive correlation suggests that two currencies tend to rise or fall in tandem, while a negative correlation indicates that they move in opposite directions. Correlation, however, does not capture the long-term equilibrium between currencies. This is where cointegration comes into play.

Cointegration refers to a statistical relationship between non-stationary time series, suggesting that while two or more variables may wander in the short term, they share a long-term equilibrium path. For currency pairs, cointegration indicates that while exchange rates may fluctuate due to short-term factors, they are anchored by fundamental economic relationships in the long run.

The present study focuses on the USD/INR exchange rate and its relationships with four other major global currencies: the euro (USD/EUR), the British pound (USD/GBP), the Japanese yen (USD/JPY), and the Swiss franc (USD/CHF). Each of these currencies represents significant global economies with unique characteristics that influence their exchange rates. The euro is the currency of the Eurozone, a major trading partner for India and a key player in global financial markets. The British pound, despite the UK's relatively smaller economic size compared to the U.S. or Eurozone, remains influential due to London's status as a global financial hub. The Japanese yen is traditionally seen as a safe-haven currency, with its value driven by Japan's low-interest-rate environment and global market conditions. The Swiss franc, similarly, is viewed as a safe haven due to Switzerland's political and economic stability.

Understanding the correlation between these currencies and USD/INR can provide valuable insights for investors and policymakers alike. For example, a strong positive correlation between USD/INR and USD/EUR could suggest that movements in the euro, driven by factors such as Eurozone economic conditions or European Central Bank policy, have a significant impact on the Indian rupee's exchange rate against the dollar. On the other hand, a negative correlation with the British pound might indicate divergent economic conditions or market expectations between India and the UK.

Beyond correlation, this study delves into the concept of cointegration to assess whether these currency pairs share a long-term equilibrium relationship with USD/INR. If USD/INR is found to be cointegrated with USD/EUR or USD/JPY, for example, this would suggest that, despite short-term fluctuations, these exchange rates tend to move towards a long-term equilibrium driven by fundamental economic factors. In contrast, a lack of cointegration would indicate that these currencies do not share a long-term relationship, implying that their movements are driven by more transient, short-term factors.

This analysis is crucial for understanding the dynamics of the Indian rupee in a global context. For Indian policymakers, a clearer understanding of the factors driving USD/INR movements can aid in formulating more effective monetary and fiscal policies. For investors and currency traders, identifying cointegrated relationships between currencies can provide a basis for developing long-term investment strategies. Furthermore, the global nature of currency markets means that fluctuations in the exchange rates of major currencies like the euro, yen, or pound can have significant spillover effects on emerging market currencies like the Indian rupee.

The methodology of this study includes conducting both correlation and cointegration tests, using techniques such as the Johansen Cointegration Test and the Engle-Granger two-step method. These tests allow for a thorough examination of the relationships between USD/INR and other currencies, providing insights into both short-term correlations and long-term equilibrium dynamics. Additionally, unit root tests like the Augmented Dickey-Fuller (ADF) test are employed to assess the stationarity of the currency pairs, a necessary step before conducting cointegration tests.

In conclusion, this study aims to shed light on the complex relationships between USD/INR and major global currencies by examining both their correlation and cointegration. Through this analysis, we seek to provide a deeper understanding of how the Indian rupee interacts with global economic forces, offering valuable insights for policymakers, investors, and researchers interested in currency markets and global financial integration. The findings of this study will not only enhance our knowledge of currency market dynamics but also contribute to the broader literature on exchange rate determination and global financial interdependence.

2. Review of Literature

The literature on currency market equilibrium and cointegration has evolved less over the years. A number of studies have employed advanced econometric techniques, such as Johansen's cointegration test, Engle-Granger Residual cointegration test and Vector Error Correction Models (VECM), to explore the dynamics of currency markets and their interactions with global currencies, futures, and spot markets. This body of work highlights the varying degrees of efficiency, causality, and co-movement across different markets, including emerging economies.

Building on the exploration of cointegration in different financial markets, Baillie and Bollerslev (1994) [4] apply Johansen's multivariate tests to foreign exchange rates, finding mixed evidence of cointegration. Their research shows that deviations from long-term exchange rate relationships display long memory, suggesting that shocks to equilibrium exchange rates, like the USD/INR pair, can have persistent effects. This highlights the challenge in restoring currency market equilibrium once disrupted, as the effects may last for an extended period. Ozun and Erbaykal (2009) [25] similarly investigate Turkey's foreign-exchange markets, discovering a unidirectional causality from futures to spot markets, thus pointing to the informational efficiency of Turkish currency markets.

Related to cointegration of ASEAN national currencies, Thanakijsombat *et al.*, (2016) [32] Finds indicate that ASEAN is unprepared for OCA formation, with diminishing currency linkages and weak ties post-crisis, challenging previous literature that suggests crises enhance currency integration. The nature of the GFC significantly influenced the observed minimal relationships among ASEAN currencies, highlighting the importance of understanding asymmetric responses to external shocks. Yadav, Kumar, and Tyagi (2023) [34] findings reveal that Bitcoin, Ethereum, and Litecoin exhibit long-term efficiency and cointegration, though there is no short-run causality between them. However, Stellar and Dogecoin show short-run causality, indicating quicker responses to market changes.

Expanding the focus to policy-driven impacts, Lopez (2005) [20] examines how central bank interventions affect cointegration in foreign exchange markets. His research reveals that shifts in central bank policy, such as the Plaza Agreement of 1985, can significantly alter the number of cointegrating vectors, suggesting that central bank actions have lasting effects on exchange rates. In the Indian context, Kharbanda, and Singh (2017) [16] demonstrate that futures markets lead spot markets, offering a price discovery mechanism through a Vector Error Correction Model (VECM). Similarly, Diebold, Gardeazabal, and Yilmaz (1994) [5] challenge earlier assumptions about cointegration in exchange rates, noting that out-of-sample forecasting using the martingale model outperforms the error-correction model, underscoring the complexities of predicting exchange rate movements.

The integration of stock markets and currency rates is a central focus of many studies. Ferreira *et al*., (2019) [10] employ detrended cross-correlation methods to reveal significant long-range correlations between stock markets in major economies. In contrast, emerging markets such as India show a negative correlation with USD exchange rates. The study underscores how correlations vary between developed and emerging markets, particularly in the context of stock market integration. The relationship between stock indices and exchange rates has been examined from various perspectives. Oskooee and Saha (2015) [3] provide a comprehensive review, suggesting that while stock prices and exchange rates are often interlinked, the direction and strength of these relationships can differ. Long and Hien (2021) [19] add to this by showing the time-varying impact of inflation on gold prices and exchange rates in Vietnam. Solnik (1987) [30] explores the relationship between real exchange rates, economic activity, and monetary policy, using real stock returns as an indicator of expected economic changes.

In Middle Eastern economies, Parsva and Tang (2017) [26] find bi-directional causality between stock prices and exchange rates in Iran, Oman, and Saudi Arabia. Their study, which covers data from 2004 to 2011, highlights the stability of these relationships over time. In contrast, Aydemir and Demirhan (2009) [2] investigate Turkey and find a bidirectional causal relationship between exchange rates and stock prices, with negative causality from stock indices to exchange rates and vice versa. In India, Marisetty (2024) [22-23] highlights the moderate impact of currency fluctuations, particularly the USD/EUR exchange rate, on the NSE NIFTY, suggesting its influence on trade and capital flows. The analysis indicates that while currency movements play a role in short-term dynamics, they do not establish significant long-term equilibrium relationships with the Indian stock market. Hwang (2003) examines the relationship between stock prices and exchange rates in Korea, finding them to be cointegrated. The study indicates that domestic currency devaluation negatively affects stock prices in the short run. This suggests a one-way linkage from exchange rates to stock prices.

The relationship between stock indices and commodity prices, especially crude oil, currency rates and gold, has been extensively analysed. Dinçer, Yüksel, and Uluer (2021) [7] explore the impact of the U.S.-China trade war on global oil prices, suggesting a significant relationship between geopolitical tensions and crude oil prices. Their findings, based on cointegration and causality tests, indicate that while oil prices are influenced by the trade war, other factors also contribute to their volatility. Similarly, Manasseh *et al*. (2019) [21] study the interaction between stock prices and exchange rates, using VAR-GARCH models. Their analysis suggests a significant long-term relationship between stock prices and oil prices, while gold often serves as a hedge in times of economic uncertainty. These results are crucial for international portfolio managers aiming to diversify risk. Marisetty (2024) [22-23] employs advanced econometric techniques, including Johansen cointegration tests and the Vector Error Correction Model (VECM), to uncover both long-term equilibrium relationships and short-term dynamics among major global stock indices, emphasizing their interconnectedness in response to global macroeconomic factors.

Emerging markets are of particular interest in understanding the global stock market dynamics. Abdalla and Murinde (1997) [1] research found significant unidirectional causality from exchange rates to stock prices, indicating that currency fluctuations play a substantial role in influencing stock prices in smaller markets. Moving beyond emerging markets, some studies explore relationships in transitioning economies. For example, Michael (2018) [24] investigates the Egyptian stock market, emphasizing the role of foreign exchange market stabilization measures on stock prices. The findings highlight the critical role of currency management in influencing stock market performance in smaller, emerging economies. Long and Hien (2021) [19] findings align with other research showing the significance of inflation in financial markets, but their use of dynamic coefficients provides a more nuanced understanding of how inflation influences monetary policy, exchange rates, and gold prices over time.

The global financial crisis and COVID-19 pandemic have provided unique opportunities to study the resilience of stock markets and their relationships with other financial variables. Manasseh *et al*. (2019) [21] examine the volatility transmission effects between stock prices and exchange rates during crisis periods, revealing heightened volatility spillover effects. Many studies explore both long-term and short-term relationships between stock indices and other variables. Subayyal and Shah (2011) [31] examine the Karachi Stock Exchange (KSE) index and exchange rates, finding bidirectional causality in both the short and long run.

Raza and Aravanan (2014) [28] explored the long-term and short-term relationships between stock markets and exchange rates in India, using the BSE Sensex and Nifty indices. They found no long-term cointegration, but short-term dynamics, such as unidirectional causality between stock returns and exchange rates, were significant. While many studies find significant relationships, others show weak or no relationships. Namini (2017) [29] finds no significant relationship between stock prices and exchange rates in Iran from 1994 to 2010, indicating that financial markets may not always exhibit strong correlations. Kurihara (2006) [18] highlights that while interest rates did not significantly affect Japanese stock prices, both exchange rates and U.S. stock prices played crucial roles in influencing them.

The analysis of currency market dynamics and cointegration provides valuable insights into the long-term and short-term relationships among global currency pairs, such as USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF. The literature emphasizes the significance of these relationships for understanding market efficiency, forecasting accuracy, and the impact of external factors, such as central bank interventions and economic shocks. However, a major limitation of this study is the scarcity of sufficient literature that specifically focuses on cointegration between these particular currency pairs, especially in the context of emerging markets like India. While broader studies on cointegration in foreign exchange markets offer useful frameworks, further research tailored to the specific dynamics of these currency pairs is needed to enhance the understanding of their interactions in the global financial system.

Another important point highlighted in the reviewed literature is the significant focus on the relationship between stock indices and currency markets. Numerous studies explore how fluctuations in stock indices are interlinked with exchange rate movements, often revealing complex bi-directional or unidirectional causality between the two. These findings suggest that stock markets and currency markets are often deeply interconnected, with factors such as inflation, central bank policies, and geopolitical events influencing both asset classes. However, while many studies have explored this relationship, there remains a lack of research specifically targeting the cointegration of currency pairs alone, leaving a gap in the understanding of how these currencies interact independently of stock market dynamics. This further underscore the need for more targeted research on currency pair cointegration.

3. Research Methodology

The data used for this analysis focuses on daily exchange rates for the USD/INR and four other major global currency pairs: USD/EUR, USD/GBP, USD/JPY, and USD/CHF for the period of 2014-2023. A total of 2,608 daily exchange rate quotes were observed for this study, covering the period from 2014 to 2023. These exchange rates are sourced from reliable financial databases such as the Yahoo finance, and other leading financial data providers to ensure accuracy. The selection of daily quotes allows for a detailed examination of both short-term fluctuations and long-term trends, which are crucial for understanding currency market equilibrium and the dynamics between these major currency pairs.

3.1. 2014-2023 Period Selection

The period from 2014 to 2023 was chosen for this analysis due to the significant global economic and financial developments during this time. This decade captures key events such as the aftermath of the 2008 financial crisis, Brexit, the U.S. Federal Reserve’s interest rate changes, and the economic disruptions caused by the COVID-19 pandemic. These events have had profound impacts on currency markets, causing volatility and shifts in exchange rates, making this period ideal for analysing both long-term cointegration and short-term correlations among the selected currency pairs.

3.2. Currency Pair Selection

The USD/INR pair was selected due to the growing importance of India in the global economy and the increasing influence of the Indian rupee in international trade and investment flows. The USD/EUR, USD/GBP, USD/JPY, and USD/CHF pairs represent major global currencies from economically significant regions: the Eurozone, the United Kingdom, Japan, and Switzerland. These currencies are often used as safe havens or reserve currencies, and their interaction with the USD provides insights into global market trends, making them essential for assessing broader currency market equilibrium.

3.3. Descriptive Statistics

Descriptive statistics provide a summary of the data, including measures like mean, standard deviation, skewness, kurtosis, and IQ range, to capture the central tendency and variability of the selected currency pairs. These statistics help in understanding the overall distribution and behaviour of each USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF over the 2014-2023 period.

3.4. Visual Analysis

Visual analysis through charts such as line plots helps identify trends, patterns, and anomalies in the selected indices and currency pair over time. It provides a clear depiction of movements, volatility, and correlations between USD/INR and other major global currencies, such as USD/EUR, USD/GBP, USD/JPY, and USD/CHF during the 2014-2023 period.

3.5. Pearson’s Correlation

Pearson's correlation among the selected variables measures the strength and direction of linear relationships between USD/INR and other major global currencies, such as USD/EUR, USD/GBP, USD/JPY, and USD/CHF. This analysis reveals how closely these variables move together, highlighting potential interdependencies or inverse relationships.

3.6. Unit Root Test

The Augmented Dickey-Fuller (ADF) test (1979) [6] and the Kwiatkowski, Phillips, Schmidt, Shin (KPSS) test (1992) are commonly used for testing stationarity. The ADF test is often criticized because its inability to reject the null hypothesis of a unit root may result from low power against alternatives that are weakly stationary. In contrast, the KPSS test assumes stationarity as the null hypothesis and tests it against the alternative of a unit root. To conduct the ADF test, a regression model is estimated to check for the presence of a unit root.

Regression Model as follows

$$\Delta X_t = \alpha + \beta X_{t-1} + \sum_{j=1}^{k} \gamma_j \, \Delta X_{t-j} + \varepsilon_t \quad (1)$$

In this context, the difference operator is denoted as Δ, which represents the change in the series. Therefore, if X is the series being tested, then $\Delta X_t = X_t - X_{t-1}$ is the first difference of the series. The variable k refers to the number of lagged differences included in the regression model to account for potential autocorrelation in the error term.

KPSS Test statistics is

$$\eta_u = T^{-2}\,\eta_u = T^{-2} \sum \left(\frac{S_t^2}{S^2(L)}\right) \quad (2)$$

Where

$$S_t = \sum_{i=1}^{t} e_t,\ S^2 = T^{-1} \sum_{t=1}^{T} e_t^2 + 2T^{-1} \sum_{s=1}^{L} \left(1 - \frac{s}{L+1}\right) \sum_{t=s+1}^{T} e_t e_{t-s}$$

In this context, S_t represents the partial sum process of the residuals e, while T denotes the total number of observations in the dataset. Additionally, L indicates the lag length used in the analysis.

3.7. Cointegration Tests and Vector Error Correction Model (VECM)

Assess the existence of a long-run relationship between exchange rates and stock prices by employing a cointegration test. Cointegration indicates that a combination of the variables can be stationary, despite each individual variable being non-stationary. If cointegration is established among the variables, we can further explore the short-run dynamics between the series using a Vector Error Correction Model (VECM). The concept of cointegration was first introduced by Granger (1981) and further elaborated by researchers such as Engle and Granger (1987) [8], Engle and Yoo (1987, 1989) [9], Phillips and Ouliaris (1990) [27], Phillips (1991), and Johansen (1988) [13], Johansen (1991) [14], and Johansen (1995), among others. In this study, Johansen cointegration and Engle and Granger Residual techniques are employed to assess the number of cointegrated equations.

3.8. Johansen Cointegration Test

The Johansen cointegration method provides specific test statistics, outlined below:

$$\text{Trace} = -T\sum_{i=r+1}^{k} \ln(1 - \lambda_i) \tag{3}$$

$$\lambda_{max} = -T \ln(1 - \lambda_{r+1}) \tag{4}$$

3.9. Engle-Granger Cointegration Test

The Engle-Granger cointegration approach elucidates the long-run relationship between two variables. The first step in this analysis involves determining the order of integration for each series. Next, the cointegration equation is identified using the Ordinary Least Squares (OLS) method. In the final step, the residuals obtained from the OLS regression are tested for stationarity at levels.

Cointegration Regression Model as follows.

$$y_t = \beta_0 + \beta_1 x_t + e_t \tag{5}$$

In the next step, conduct the ADF test on the residuals (e_t) to determine whether they are stationary.

$$\Delta e_t = \beta\, e_{t-1} + v_t \tag{6}$$

3.10. Vector Error Correction Model

The Vector Error Correction Model (VECM) is a widely used method for examining both long-run and short-run relationships between variables, particularly when all variables are integrated of the same order. It describes how changes in the independent variables affect the dependent variable. The general form of the VECM is provided below.

$$\Delta y_{1,t} = \delta + \alpha\,(y_{2,t-1} - \mu - \beta\, y_{1,t-1}) + \varepsilon_{1,t} \tag{7}$$

$$\Delta y_{2,t} = \delta + \alpha\,(y_{2,t-1} - \mu - \beta\, y_{1,t-1}) + \varepsilon_{2,t} \tag{8}$$

In the above two equations, the cointegrating terms are represented by β, while the speed of adjustment is denoted by α.

4. Data Analysis

4.1. Descriptive Statistics

Table 1: Descriptive Statistics of USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF currency pair's daily prices for the period of 2014 to 2023

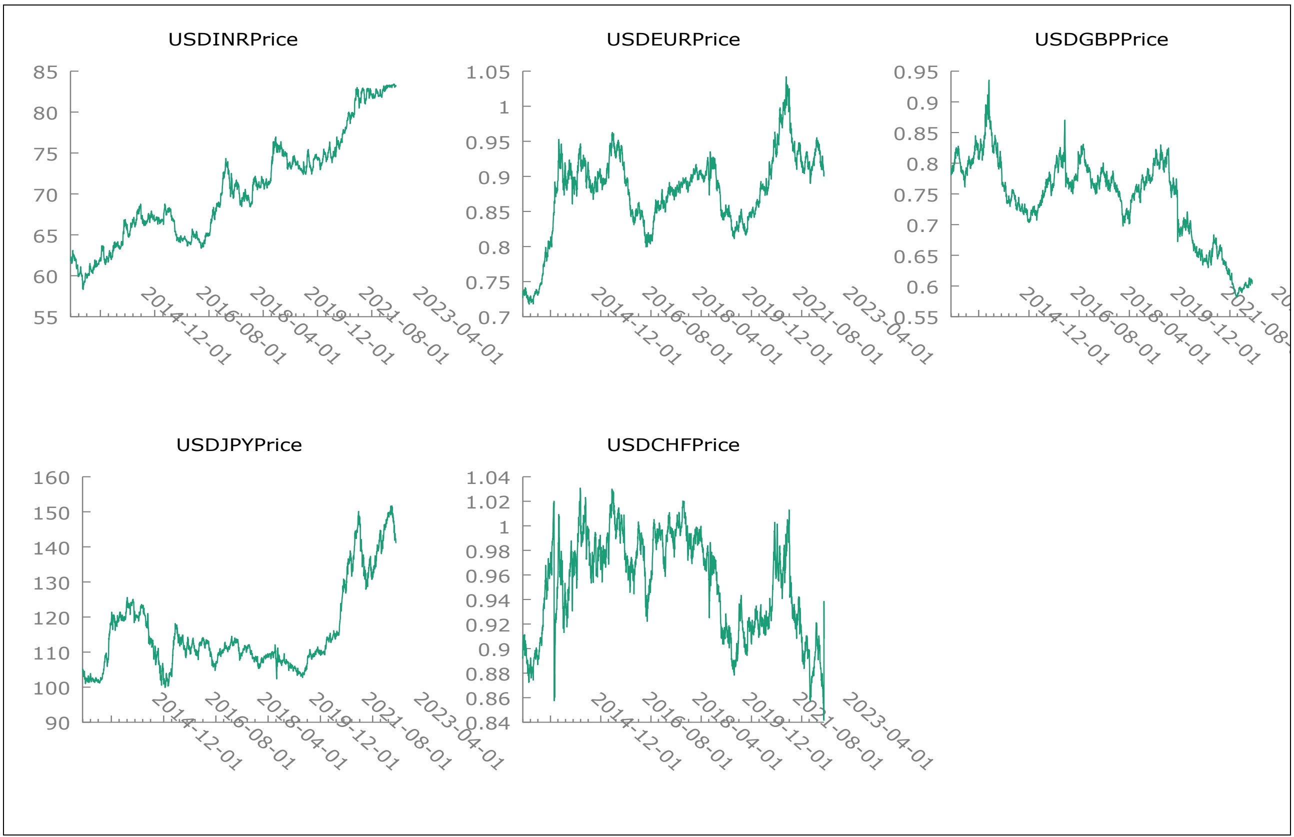
Stat	USDINR Price	USDEUR Price	USDGBP Price	USDJPY Price	USDCHF Price
N	2608	2608	2608	2608	2608
Mean	70.538	0.87844	0.74338	115.58	0.95258
Median	69.85	0.8876	0.7605	111.26	0.9619
Minimum	58.285	0.7177	0.5826	99.87	0.8415
Maximum	83.426	1.0421	0.9355	151.71	1.0308
Std. Dev.	6.621	0.058858	0.068545	12.206	0.04019
C.V.	0.09386	0.067003	0.092206	0.10561	0.042191
Skewness	0.36181	-0.66307	-0.598	1.3104	-0.32253
Ex. kurtosis	-0.8295	0.77056	-0.28073	0.82201	-1.0132
IQ range	9.772	0.0686	0.0867	12.085	0.0697

(***Source***: Author's Calculations)

The descriptive statistics (table 1) for the five international currency exchange rates reveal several important characteristics that highlight their behaviours over the observed period. The sample size (N) for all currencies is consistent at 2608 observations, providing a robust dataset for analysis. The mean values indicate that the average exchange rate for USDINR is significantly higher (70.538) compared to the other currencies, reflecting the Indian rupee's long-term depreciation against the U.S. dollar. The mean values for USDEUR (0.87844) and USDGBP (0.74338) suggest a generally weaker performance compared to the U.S. dollar but not as low as USDJPY (115.58) or USDCHF (0.95258), indicating varying levels of strength among these currencies. The standard deviation further emphasizes the volatility; USDJPY exhibits the highest standard deviation (12.206), signifying greater variability in exchange rates, while USDCHF has the lowest standard deviation (0.04019), indicating relative stability.

Skewness values indicate that the distributions of these exchange rates are not perfectly symmetrical. For instance, USDINR's positive skewness (0.36181) suggests a longer tail on the right side, meaning higher values are more frequent, whereas the negative skewness in USDEUR (-0.66307) and USDGBP (-0.598) implies a concentration of values toward the higher end. The excess kurtosis values further enhance this understanding; negative kurtosis in USDINR, USDEUR, and USDGBP suggests flatter distributions, while USDJPY and USDCHF have positive kurtosis, indicating sharper peaks in their distributions. The interquartile range (IQR) provides insight into the dispersion of the central 50% of the data, with USDJPY exhibiting the widest IQR (12.085), again signifying its volatility. Overall, these statistics illustrate the dynamic nature of currency exchange rates and the differing levels of volatility and stability among them, which can be crucial for financial analysis and decision-making.

4.2. Visual Analysis - Time Series Trend



(***Source***: Author's Calculations)

Chart 1: Time series trend of USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF Currency pairs daily prices for the period of 2014 to 2023

The provided charts 1 depict the historical trends of five different currency exchange rates over a period of several years. These charts likely represent the exchange rates of popular international currencies against the U.S. dollar. The first chart (top left) shows the steady upward trend of what appears to be USDINR (U.S. Dollar to Indian Rupee), with fluctuations but a clear long-term rise from around 60 in 2014 to over 80 in 2023. This suggests that the Indian rupee has depreciated significantly against the dollar over the years, reflecting a weakening rupee or strengthening U.S. dollar in the global market. In contrast, the second chart (top centre) displays more volatile movements, with the exchange rate fluctuating between 0.75 and 1.05 over the years, possibly representing USDEUR (U.S. Dollar to Euro). There is no clear long-term trend of appreciation or depreciation, but the volatility may indicate changing economic conditions in both the U.S. and Eurozone. The peaks and troughs show periods of euro strength and weakness, likely influenced by macroeconomic factors like monetary policy shifts or geopolitical events.

The third chart (top right) shows a downward trend, representing USDGBP (U.S. Dollar to British Pound), where the value declines from around 0.95 to below 0.65. This suggests that the pound has strengthened against the U.S. dollar over this period. The long-term downward movement could be attributed to various factors, such as Brexit, economic policy changes, and fluctuating market confidence in the British economy relative to the U.S. The fourth chart (bottom left), which shows an upward trajectory, likely represents USDJPY (U.S. Dollar to Japanese Yen). The value starts around 100 and climbs to above 140, indicating that the yen has depreciated substantially against the dollar over the last decade. This pattern suggests ongoing economic challenges in Japan, such as persistent deflation, low interest rates, and intervention by the Bank of Japan to weaken the yen in order to stimulate the economy and boost exports.

Lastly, the fifth chart (bottom centre) displays relatively stable movements, possibly showing USDCHF (U.S. Dollar to Swiss Franc). The exchange rate fluctuates between 0.84 and 1.04 over the years, without a clear long-term trend. This stability suggests that the Swiss franc has maintained its role as a safe-haven currency, with its value remaining fairly steady against the dollar despite global financial fluctuations. The occasional spikes in value might be tied to periods of financial uncertainty, when investors tend to flock to the franc for stability. Overall, these charts reflect various economic dynamics that influence exchange rate movements, including interest rate differentials, inflation, trade balances, and political events in the respective countries. The divergence in trends-depreciation for the yen and rupee, stability for the franc, and volatility for the euro and pound-highlights the different economic conditions and policies driving currency markets over the past decade.

4.3. Pearson's Correlation Test

Table 2: Correlation matrix of USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF Currency pairs

Currency pair	USDINR	USDEUR	USDGBP	USDJPY	USDCHF
USDINR	1	0.5804*	-0.798*	0.6552*	-0.271
USDEUR	0.5804*	1	-0.5429*	0.6384*	0.4113*
USDGBP	-0.798*	-0.5429*	1	-0.6841*	0.2242
USDJPY	0.6552*	0.6384*	-0.6841*	1	-0.1507
USDCHF	-0.271	0.4113*	0.2242	-0.1507	1

(***Source***: Author's Calculations) (* Significance @ 5% level)

The correlation table 2 between various currency pairs highlights significant relationships, with some strong positive and negative correlations. USDINR shows a positive correlation with USDEUR (0.5804) and USDJPY (0.6552), suggesting that as the euro and yen strengthen against the U.S. dollar, the Indian rupee tends to weaken in comparison to the dollar. These correlations are statistically significant, as indicated by the asterisks (*). On the other hand, USDINR has a strong negative correlation with USDGBP (-0.798), suggesting that as the British pound strengthens against the U.S. dollar, the Indian rupee tends to strengthen as well. This inverse relationship might point to divergent market forces affecting the pound and the rupee relative to the U.S. dollar. Interestingly, USDINR has a weaker, non-significant correlation with USDCHF (-0.271), suggesting that movements in the Swiss franc are less directly linked to changes in the Indian rupee.

The other currency pairs also exhibit noteworthy correlations. USDEUR is positively correlated with both USDJPY (0.6384) and USDCHF (0.4113), indicating that movements in the euro tend to coincide with those of the yen and the Swiss franc. However, USDEUR is negatively correlated with USDGBP (-0.5429), suggesting that the euro and the pound tend to move in opposite directions relative to the dollar. USDGBP, in turn, shows a strong negative correlation with USDJPY (-0.6841), further indicating contrasting movements between these two currencies. USDCHF stands out with generally weaker correlations compared to the others, particularly with USDJPY (-0.1507) and USDGBP (0.2242), implying that its behaviour relative to the dollar is less influenced by these currencies. Overall, the table reveals a complex web of relationships among major international currencies, with some pairs showing strong interdependence and others moving relatively independently.

4.4. Unit Root Test Constant with Trend

Table 3: Unit root test constant with trend for USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF Currency pairs

Currency Pair	At Level				At First difference			
	ADF	***p-value***	***KPSS***	***p-value***	***ADF***	***p-value***	***KPSS***	***p-value***
USDINR	-2.8191	0.1902	1.9100	<0.01	-25.548*	0.0000	0.0267	>0.10
USDEUR	-2.4316	0.3629	1.3558	<0.01	-20.957*	0.0000	0.0767	>0.10
USDGBP	-2.5553	0.3012	2.7110	<0.01	-21.218*	0.0000	0.0322	>0.10
USDJPY	-1.3588	0.8728	3.7713	<0.01	-50.999*	0.0000	0.0778	>0.10
USDCHF	-3.3352	0.0605	2.9252	<0.01	-18.842*	0.0000	0.0147	>0.10

(***Source***: Author's Calculations) (* Significance @ 5% level)

The unit root test constant with trend (table 3) results for various currency pairs provide insights into the stationarity of their price series. The Augmented Dickey-Fuller (ADF) test at levels indicates that none of the currency pairs (USDINR, USDEUR, USDGBP, USDJPY, and USDCHF) are stationary, as their p-values are all above the conventional significance level of 0.05. For instance, USDINR shows an ADF statistic of -2.8191 with a p-value of 0.1902, and USDCHF has an ADF statistic of -3.3352 with a p-value of 0.0605, suggesting that while USDCHF is close to being stationary, it does not reach significance. The KPSS test results further corroborate these findings, as they indicate the presence of a unit root at level for all pairs, given that the KPSS p-values are all less than 0.01. These results collectively suggest that the price series of these currency pairs follow a random walk, indicating non-stationarity at their levels.

Upon examining the first difference, the ADF test results show that all currency pairs exhibit strong evidence of stationarity, as indicated by their highly negative ADF statistics and p-values of 0.0000. For example, USDINR's first difference ADF statistic is -25.548, which strongly rejects the null hypothesis of a unit root, indicating that the first differences of the series are stationary. Similarly, USDCHF also demonstrates a significant level of stationarity with an ADF statistic of -18.842. The KPSS test results for the first difference further support the stationarity findings, with p-values exceeding 0.10 for all pairs. These outcomes confirm that while the level series of the currency pairs is non-stationary, their first differences are stationary, which is a typical characteristic observed in financial time series data, thereby indicating that these series can be differenced to achieve stationarity for further analysis.

4.4. VAR Lag Selection

Table 4: VAR Lag Selection of USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF Currency pairs.

lags	loglik	p(LR)	AIC	BIC	HQC
1	28276.6222	None	-21.8627	-21.7947*	-21.8381
2	28295.6793	0.0451	-21.8581	-21.7334	-21.8129
3	28389.0687	0.0000	-21.9110*	-21.7297	-21.8453*
4	28401.9697	0.4182	-21.9017	-21.6637	-21.8154
5	28412.5365	0.6851	-21.8905	-21.5958	-21.7837
6	28445.6281	0.0000	-21.8968	-21.5454	-21.7694
7	28466.2300	0.0219	-21.8934	-21.4854	-21.7455
8	28482.7522	0.1300	-21.8868	-21.4221	-21.7184
9	28491.2873	0.8792	-21.8741	-21.3527	-21.6851
10	28516.2470	0.0022	-21.8740	-21.2960	-21.6645

(***Source***: Author's Calculations) (* Significance @ 5% level)

The VAR lag selection results point to lag 3 as the optimal choice for the model based on a balance of multiple criteria. The Akaike Information Criterion (AIC) and Hannan-Quinn Criterion (HQC) both favour lag 3, with the lowest values of -21.9110 and -21.8453, respectively, indicating that this lag minimizes information loss and strikes a good balance between model complexity and fit. Additionally, the Likelihood Ratio (LR) test for lag 3 produces a highly significant p-value (0.0000), suggesting that adding this lag substantially improves the model compared to lag 2. Although the Bayesian Information Criterion (BIC) prefers lag 1 with a value of -21.7947 due to its stronger penalization for additional parameters, BIC tends to prioritize simplicity over model improvement. In contrast, both the AIC and HQC show that lag 3 provides a better trade-off by allowing for more explanatory power without excessive complexity. Therefore, considering the combination of significant improvement in the LR test and the alignment of AIC and HQC, lag 3 emerges as the most appropriate lag selection, offering an optimal balance between fit and parsimony.

4.5. Johansen Cointegration Test

Table 5: Johansen Cointegration Test (Lag order 3) for USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF Currency pairs.

Rank	Eigenvalue	Trace test	p-value	Lmax test	p-value
0	0.011084	55.437	[0.4035]	29.047	[0.1728]
1	0.005448	26.39	[0.8732]	14.235	[0.8023]
2	0.00307	12.155	[0.9227]	8.0125	[0.8948]
3	0.001459	4.1424	[0.8858]	3.8043	[0.8717]
4	0.00013	0.33817	[0.5609]	0.33817	[0.5609]

(***Source***: Author's Calculations) (* Significance @ 5% level)

The Johansen cointegration test (table 5) with lag order 3 provides insights into the number of potential cointegrating relationships among the analysed variables. The test results reveal that for rank 0 (the null hypothesis of no cointegration), the Trace test statistic is 55.437 with a p-value of 0.4035, and the Lmax (maximum eigenvalue) test statistic is 29.047 with a p-value of 0.1728. Since both p-values are above conventional significance level (0.05), the null hypothesis of no cointegration cannot be rejected at this rank. The same pattern is observed for rank 1, where the Trace test yields a statistic of 26.39 and a p-value of 0.8732, and the Lmax test shows 14.235 with a p-value of 0.8023, again indicating no significant evidence of cointegration.

As we move further down the ranks (2, 3, and 4), the test statistics and p-values continue to support the absence of cointegration. For rank 2, the Trace test has a value of 12.155 and a p-value of 0.9227, while the Lmax test shows 8.0125 with a p-value of 0.8948. Similarly, for rank 3, the Trace test statistic is 4.1424 with a p-value of 0.8858, and the Lmax test is 3.8043 with a p-value of 0.8717. Finally, for rank 4, the Trace and Lmax tests yield identical values of 0.33817, with p-values of 0.5609. These high p-values consistently suggest a lack of significant cointegrating vectors across all ranks, indicating that there is no long-term equilibrium relationship among the currencies being tested in this Johansen test.

4.6. Engle Granger Cointegration Test

Table 6: The Engle Granger Cointegration Regression of USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF Currency pairs. (USD/INR Dependent)

Variable	Coefficient	Std. Error	t-ratio	p-value	F Stat	R Square	Adj R Square
Constant	116.886*	2.2041	53.0300	0.0001	1893.96* (0.0000)	0.7442	0.7438
USDEUR	59.256*	2.1309	27.8100	0.0001			
USDGBP	−44.728*	1.4597	−30.64	0.0001			
USDJPY	−0.0309*	0.0090	−3.444	0.0006			
USDCHF	−64.642*	2.4204	−26.71	0.0001			

(***Source***: Author's Calculations) (* Significance @ 5% level)

The Engle-Granger cointegration regression table 6 provides an analysis where USDINR is the dependent variable, and the other currency prices (USDEUR, USDGBP, USDJPY, USDCHF) serve as independent variables. The constant term is significant, with a large coefficient of 116.886 and a p-value of 0.0001, suggesting a significant base level for the USDINR exchange rate when all other variables are held constant. Each of the independent variables has a highly significant impact on USDINR, as indicated by their p-values (all are 0.0001). The coefficient for USDEUR is positive (59.256), meaning that an increase in the USDEUR price is associated with an increase in USDINR. This suggests a positive relationship between these two exchange rates, likely indicating that when the euro strengthens against the dollar, the Indian rupee weakens against the dollar.

On the other hand, the coefficients for USDGBP (-44.728), USDJPY (-0.0309), and USDCHF (-64.642) are negative. This implies that increases in the prices of these currencies (relative to the dollar) are associated with a decrease in the USDINR exchange rate. Specifically, the strong negative coefficients for USDGBP and USDCHF suggest a particularly inverse relationship, meaning that as the British pound or Swiss franc appreciates, the Indian rupee tends to strengthen against the U.S. dollar. The overall model is statistically significant, as indicated by the high F-statistic (1893.96) and its corresponding p-value (0.0000). The R-squared value of 0.7442 indicates that approximately 74.42% of the variation in USDINR is explained by the independent variables in this model. The adjusted R-squared value of 0.7438, which accounts for the number of variables, is very close to the R-squared, suggesting a good fit of the model. In summary, this regression highlights strong and significant relationships between USDINR and the selected international currencies, with the USDEUR exchange rate having the most substantial positive influence, while the USDGBP and USDCHF exert strong negative influences.

Table 7: The Engle Granger Cointegration Unit root test with constat for USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF Currency pairs.

Currency pair	Estimated Value (a-1)	ADF Test Static	p Value
USDINR	-0.000195060	-0.2819	0.9252
USDEUR	-0.003982310	-2.6769	0.0780
USDGBP	-0.001396860	-1.0748	0.7280
USDJPY	-0.000742191	-0.6985	0.8454
USDCHF	-0.010681700	-3.6323*	0.0052
EG Cointegration Residuals	-0.009580210	-3.4364	0.3562

(***Source***: Author's Calculations) (* Significance @ 5% level)

The Engle-Granger cointegration test results (table 7), paired with the Augmented Dickey-Fuller (ADF) unit root tests for the five currency pairs (USDINR, USDEUR, USDGBP, USDJPY, and USDCHF), reveal varied levels of long-term equilibrium relationships. For most currency pairs, the test statistics and p-values indicate no significant cointegration. Specifically, the USDINR pair has a test statistic of -0.2819 and a p-value of 0.9252, indicating a strong failure to reject the null hypothesis of no cointegration. Similarly, the USDGBP and USDJPY pairs show test statistics of -1.0748 and -0.6985, and p-values of 0.7280 and 0.8454, respectively, both suggesting a lack of cointegration. Although the USDEUR pair has a test statistic of -2.6769 and a lower p-value of 0.0780, it still does not reach conventional significance thresholds (e.g., 5% level), but it is closer to showing some cointegration compared to the other pairs.

On the other hand, the USDCHF pair stands out with a test statistic of -3.6323 and a p-value of 0.0052, showing strong evidence of cointegration at the 1% significance level. This indicates that there is a long-term equilibrium relationship between USD and CHF. The combined cointegration regression result, with an estimated value of -0.009580210 and a test statistic of -3.4364, shows a non-significant p-value of 0.3562, suggesting that when all the currency pairs are considered together, there is no evidence of a shared long-term relationship. In summary, while most of the currency pairs do not exhibit significant cointegration, the USDCHF pair clearly stands out as having a stable long-term relationship.

4.7. Vector Error Correction Model

Table 8: Error Correction Terms (ECT) of USD/INR, USD/EUR, USD/GBP, USD/JPY, and USD/CHF Currency pairs.

Currency Pair	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*
USDINR	7.19E-05	0.0006508	0.1104	0.9121
USDEUR	−0.000271581	0.0009578	−0.2835	0.7768
USDGBP	−0.000899907	0.0011617	−0.7747	0.4386
USDJPY	−0.00203173	0.0010747	−1.891	0.0588
USDCHF	−0.00601772*	0.0012394	−4.855	0.0001

(***Source***: Author's Calculations) (* Significance @ 5% level)

The Vector Error Correction Model (VECM) for global currency pairs presents (table 8) insights into the long-term relationships and short-term dynamics between USD and other major currencies (INR, EUR, GBP, JPY, CHF). The error correction term (ECT) for USD/INR has a small positive coefficient (7.19E-05) and an insignificant p-value of 0.9121, indicating that USD/INR does not significantly adjust toward a long-term equilibrium following short-term deviations. This suggests that USD/INR movements are influenced by other factors, and short-term fluctuations may not lead to immediate corrections in response to misalignments with other currency pairs. Similarly, USD/EUR and USD/GBP also show insignificant ECTs, with p-values of 0.7768 and 0.4386, respectively. This suggests that these currency pairs do not exhibit strong short-term adjustments toward long-term equilibrium, possibly reflecting broader influences such as interest rate differentials, trade balances, or geopolitical factors that drive short-term market movements without immediate correction.

On the other hand, the USD/JPY and USD/CHF pairs demonstrate different behaviors. USD/JPY has a negative coefficient of -0.00203173 and a marginally significant p-value of 0.0588, indicating that the USD/JPY pair has some tendency to adjust toward long-term equilibrium, though not strongly enough to be considered statistically significant at conventional levels. This suggests that while there may be a correction mechanism in place for USD/JPY, it is relatively slow or weak. In contrast, USD/CHF shows a highly significant error correction term, with a negative coefficient of -0.00601772 and a p-value of 0.0001, indicating that this pair adjusts significantly toward long-term equilibrium after short-term deviations. This suggests that the USD/CHF pair has a stronger mechanism for correcting short-term misalignments, possibly due to the Swiss franc's traditional role as a safe-haven currency and its sensitivity to global economic shifts. The significant adjustment in USD/CHF could be reflective of more stable and predictable factors influencing this pair, such as monetary policies or risk-averse market behaviour.

5. Conclusion

The analysis of the correlations between various currency pairs reveals important interrelationships that offer insights into the global currency markets. Notably, USDINR displays a positive correlation with USDEUR and USDJPY, indicating that as the euro and yen strengthen against the U.S. dollar, the Indian rupee tends to weaken. In contrast, USDINR has a strong negative correlation with USDGBP, suggesting divergent market forces affecting the pound and the rupee relative to the dollar. These findings highlight the sensitivity of the Indian rupee to global currency movements, with the British pound's fluctuations having a particularly significant inverse relationship with the INR. Other pairs, such as USDCHF, show weaker correlations with USDINR, reflecting the lower direct linkage between the Swiss franc and the Indian rupee.

The Johansen cointegration test results further emphasize the absence of significant long-term cointegrating relationships among the currency pairs. Across all ranks, the test statistics and corresponding p-values fail to reject the null hypothesis of no cointegration, indicating that the currency pairs do not move together in a stable long-term equilibrium. This result suggests that while these currencies may experience short-term co-movements, their long-term trajectories are independent of one another. The lack of cointegration among most pairs indicates that market forces, geopolitical events, and individual macroeconomic factors exert distinct influences on each currency's value, preventing the formation of a shared equilibrium over time.

Despite the general absence of cointegration, the Engle-Granger test results for USDCHF provide a notable exception, revealing strong evidence of a long-term equilibrium relationship between the U.S. dollar and the Swiss franc. This finding suggests that USD and CHF tend to move in a stable relationship over time, possibly due to their roles as safe-haven currencies during periods of market uncertainty. While other currency pairs, including USDINR, exhibit no significant cointegration, the USDCHF result highlights the potential for specific currency pairs to maintain long-term relationships.

The Vector Error Correction Model (VECM) analysis sheds light on the short-term dynamics of these relationships, particularly highlighting the error correction terms (ECT). While USDINR, USDGBP, and USDEUR show weak tendencies toward long-term equilibrium correction, USDCHF displays a significant adjustment mechanism, suggesting that deviations from equilibrium are corrected promptly. This divergence underscores the different behaviours of currency pairs in response to short-term fluctuations. Overall, the combined insights from correlation analysis, Johansen cointegration tests, Engle-Granger cointegration, and VECM provide a comprehensive view of the intricate relationships among major global currencies, illustrating the complexities and dynamics that influence foreign exchange markets.

6. Scope for Further Research

This analysis of currency pair correlations and cointegration provides a foundational understanding of short- and long-term relationships among major global currencies. However, there remains significant scope for further research to deepen these insights. One area of interest could be expanding the study to include additional currencies, particularly those from emerging markets, to assess how global economic shifts and geopolitical events impact a broader range of currencies. Furthermore, future research could explore the influence of macroeconomic indicators, such as interest rates, inflation, and trade balances, on currency movements, which may provide more precise explanations for observed correlations and potential cointegrating relationships. Another valuable avenue for investigation would be to apply advanced econometric techniques, such as nonlinear cointegration or machine learning models, to capture more complex relationships that may not be revealed through linear analysis. Finally, the dynamic impact of events like financial crises, pandemics, or shifts in monetary policies could be studied to understand their long-term effects on currency markets, offering more real-time, adaptable models for investors and policymakers.

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