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DYNAMICS OF CURRENCY EXCHANGE RATES CO-MOVEMENTS AND VOLATILITY: INDIAN RUPEE AGAINST MAJOR TRADING CURRENCIES

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Abstract

Foreign exchange markets have intrigued not only corporations engaged in export and import, but also individuals and other entities seeking to achieve decent risk-adjusted returns and protect themselves from future currency exchange rate exposure. Hence, researchers are drawn to examine the volatility of returns and identify diversification and hedging opportunities to mitigate country and financial risks of the five largest trading currencies with respect to the Indian currency, the rupee. The study used historical daily exchange rate data for the Indian currency with respect to American dollar, euro, British pound, Japanese yen, and Australian dollar, spanning from January 1, 2008 to December 31, 2025.

American dollar has the highest average daily return among the five currencies, followed closely by euro and pound. Pound exhibits the highest standard deviation, and its volatility suggests greater uncertainty for investors dealing in these transactions. High correlations between dollar-euro and euro-pound indicate that they are influenced by similar economic factors or market sentiments. Frequent structural breaks highlight the possibility for currency exchange rates to shift dramatically due to unforeseen events. This is a crucial insight for risk management, as it signals the need for dynamic hedging strategies that can adapt to sudden changes in market conditions. Investors and policymakers can leverage these findings to optimize currency portfolios and reduce financial risk, especially when seeking diversification benefits and long-term stability amidst global market shifts.

Keywords volatility, structural break, ARCH, GARCH, currencies, time series, exchange rate

JEL Classification F31, G15, C58

INTRODUCTION

Exchange rate markets, where exchange rates are quoted, make it easier to convert currencies. As a result, cross-border trade of goods and services is possible. Exchange rate markets are utilized by exporters and importers for trade settlement and hedging. Further, individuals use these markets to trade and protect themselves from possible currency exposure. From the perspective of governments in open economies, exchange rates affect a country's economic growth, imported inflation, and foreign exchange reserves. Especially for emerging countries like India, behavior of Indian Rupee (INR) against major trading currencies has far-reaching implications encompassing cost of imported goods, export competitiveness and debt-servicing burden of external loans. Consequently, corporations, scientists, and politicians alike are interested in understanding the causes of exchange rate fluctuations and the movements of a curren-

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cy with major world currencies and its principal trading partners. Exchange rates between currencies are indeed influenced by macroeconomic factors such as economic growth, inflation, interest rate and balance of payments and many more. Further, movement of a nation's currency can influence these very macroeconomic factors.

From the perspective of country's economic strength and external trade, a likewise stable currency is considered good. But, there are times when exchange rates move way too fast, as compared to the speed of adjustment of exporters and importers. Volatility in exchange rates can result in jeopardizing external trade of a nation. Different researchers have identified currencies to exhibit similar movements or patterns, referred to as co-movement (Karatas & Unal, 2021; He et al., 2025). In other words, the phenomenon of co-movement implies interdependency of a currency with other currencies through volatility spill-over and contagion. Such dependency can also be influenced by macroeconomic factors such as economic growth and exchange rates (Djemo & Eita, 2024). Co-movement of currencies has profound implications for economic policies, trade diversification, and trading. The very fact that exchange rate of a country s influenced by the exchange rate of another country indicates that negative shocks affecting one nation can be transmitted immediately to another nation via contagious effects (Carsamer, 2016). Different statistical techniques, such as Correlation analysis, Co-Integration Analysis, Principal Component Analysis, GARCH, and ARIMA, can reveal this co-movement of currencies.

INR is most exposed to the American dollar, euro, British pound, Japanese yen, and Australian dollar. These currencies vary in terms of monetary regimes, liquidity features and vulnerability to global risk sentiment. The present study seeks to untangle the co-movement of the Indian currency, INR, with respect to these five major traded currencies.

1. LITERATURE REVIEW

Currency exchange rates markets are seen as an avenue for the exchange of currencies so that trade of goods and services across borders is possible. Further, exchange rates between currencies are seen to influence economic dimensions such as economic growth and a country's exports (Awadzie et al., 2024; Ahmed et al., 2024). Apart from corporates engaged in export and import, individuals and other entities are attracted to this market to earn decent risk-adjusted returns and to protect themselves from future currency exchange rates exposure. Hence, practitioners and academicians are interested in studying factors affecting the movement of currencies exchange rates in terms of direction and volatility, and also in analyzing the relationships between different world currencies. Some studies have pointed to macroeconomic factors or fundamentals such as balance of payment position, inflation, and interest rate differentials as determinants of exchange rates (Kumar et al., 2025; H. Vo & D. Vo, 2023). However, these factors are valid over the long-term and not much over the short-term. In the short to medium run, market microstructures dominate currency returns and volatility (Fang et al., 2024; Lee et al., 2024). Exchange rates and the implied volatility are influenced by the currency futures market volumes (Chuang et al., 2012; Kumar, 2019). This price-volume relationship has been examined in a number of other studies, albeit with mixed results (Abdullahi et al., 2014; Kumar, 2017). Mougoué and Aggarwal (2011) found substantial negative concurrent correlation between daily trading volumes and return volatility for currency futures of British pound, Canadian dollar, and Japanese yen vis-à-vis the US dollar. Kumar (2017) demonstrated the influence of trading volumes on currency futures in the case of India, especially for the USD/INR pair. Herding has also been recognized as a significant phenomenon affecting returns and volatility in currency markets (Park, 2011). Further, positive investor sentiments can lead to anti-herding behavior in currency markets (Sibande et al., 2021).

Exchange rate movements in one currency can impact the corresponding movement in other currencies, and understanding these co-movements is essential for risk mitigation and diversification in currency markets (Djemo & Eita, 2024). Currency co-movements are a major area of research in international finance, as they have important implications for risk management through diversification strategies and in the context of policymaking. Accordingly, co-movements in currencies have been observed in several research works. These co-movements are attributed to a number of factors, such as trade channel (Carsamer, 2016) and financial channel, including stock markets (Kumar, 2013). Trade policy uncertainty leads to asymmetric spillovers and connectedness amongst major global currencies (Huynh et al., 2023). Inagaki (2007) demonstrated volatility spillovers from Euro to pound. Wen and Wang (2020) found USD and Euro to be substantial net-transmitters of volatility. Fasanya et al. (2021) found significant volatility and return spillovers in the case of major currency pairs comprising EUR/USD, USD/JPY, USD/CHF, GBP/USD, USD/CAD, and AUD/USD during the initial period of the coronavirus pandemic. There is a strong correlation among the US dollar, Euro, and Japanese Yen (Sadhwani, 2020). Karatas and Unal (2021) revealed the correlation between GBP, EUR, CHF, and CAD with the USD. Talking about G10 currencies, the USD and the Norwegian krone influence other currencies (Bettendorf & Heinlein, 2023). Whereas, Mo et al. (2023) found the Euro and the Australian dollar to be profound transmitters of currency exchange rates risks. Volatility spillovers in currency markets were found to be high, especially in times of financial crisis (Kočenda & Moravcová, 2019). The volatility spillover during the coronavirus pandemic was roughly 8 times more than the 2008 global financial crisis (Gunay, 2021). Chu (2020) finds evidence of financial contagion between the Euro and the Yen and between the Euro and the Pound in foreign exchange markets during the global financial crisis and the European debt crisis. Bhatia and Tuteja (2024) demonstrated the existence of a contagion effect amongst currencies of developed nations during the crisis periods between 2005 and 2022.

Evidence of volatility spillover from the currencies of developed nations to the currencies of emerging BRICS nations has been perceived (Das & Roy, 2023). Interconnections between emerging currencies were seen from 2011 to 2021, with South Africa, Poland, and Mexico being the key transmitters (Naeem et al., 2023). South African ZAR is a key transmitter to other BRICS currencies as well (He et al., 2024). Mittal et al. (2019) found the Brazilian real to be a significant transmitter to emerging currencies. Co-movements have been seen on a larger scale amongst BRICS currencies after 2008, especially amplified during pre-crisis and post-crisis periods (Qureshi et al., 2023). Further, BRICS currencies are highly dependent on USD and EUR (Z. Zhang & T. Zhang, 2022). African currencies exhibit little systemwide spillover connectedness, thereby providing appropriate diversification opportunities in times of crisis (Boakye et al., 2023). A strong USD leads to an increased dependence within the Regional Comprehensive Economic Partnership (RCEP) and the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP) nations (Wang et al., 2024). High return spillovers were seen in the currencies of the Asia Pacific Economic Cooperation (APEC) bloc during the COVID-19 pandemic and the Russo-Ukrainian armed conflict in 2022 (Kakran et al., 2025). Won, baht, and Australian dollar were seen as consistent transmitters of currency shocks during these periods. Likewise, Anwer et al. (2022) found currencies in the Asia-Pacific region to develop contagions during times of crisis. Increased connectedness between Asian-Pacific currencies has been observed after the 2008 crisis (Boonman & Fittje, 2024). Asia-Pacific currencies reveal a high level of connectedness during extreme optimistic and adverse events (Bouri et al., 2020). Further, these currencies are also seen to be associated with the Chinese Renminbi after China's exchange rate liberalization in 2015 (Chow, 2020; Dai et al., 2024). Chinese Yuan has been a receiver for volatility spillovers from ASEAN currencies, particularly the Singapore dollar, since this reform (Liu et al., 2024). USD/INR exhibits a positive correlation with USD/EUR and USD/JPY currency pairs (Marisetty, 2024). Safe-haven currencies like Japanese Yen and Swiss Franc tend to shield themselves from shocks of other currencies during times of financial turbulence (Kim & Lee, 2023). Spatial effects, especially the geographical ones, tend to influence currency co-movements (Djemo & Eita, 2024). The extant literature thus reveals the differing presence of co-movements of currencies between nations, as well as different trading blocs or groupings during different economic conditions. Along with economic conditions, researchers have also explored the factors influencing the co-movements of currencies

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This study aims to unravel the co-movement of the Indian currency, INR, with respect to the five major traded currencies. Accordingly, the currency pairs – USD/INR, EUR/INR, GBP/INR, JPY/INR, and AUD/INR – were studied spanning from January 1, 2008 to December 31, 2025, using ARIMA and GARCH.

2. METHODS

The study used historical daily exchange rate data from reliable financial databases, such as Bloomberg, Thomson Reuters, and the Reserve Bank of India. Data have been collected for the USD/INR, EUR/INR, GBP/INR, JPY/INR, and AUD/INR exchange rates spanning from January 1, 2008 to December 31, 2025. Daily returns for each currency were calculated as the difference between consecutive daily closing prices to capture the relative price changes accurately. For each currency, the primary variable of interest is the daily return, which captures daily percentage changes in the exchange rate value. Other variables calculated include skewness, kurtosis, and standard deviation of returns to understand the characteristics of each currency's distribution. Correlations among currency returns have also been included to assess co-movement and diversification potential. To understand the distributional characteristics of each currency's daily returns, descriptive statistics have been computed. The Jarque-Bera test was applied to determine the normality of each currency's return distribution.

2.1. ARCH (Autoregressive Conditional Heteroskedasticity)

The initial analysis highlighted each currency's level of volatility and potential risks involved in holding these assets. Currencies with high skewness or kurtosis might indicate significant risk or potential for larger price swings. The Dickey-Fuller test was conducted to confirm whether each currency's return series is stationary. A non-stationary series would be transformed by differencing to achieve stationarity, which is crucial for reliable time-series modeling. To detect conditional heteroskedasticity, or ARCH effects, in each return series, the ARCH (Autoregressive Conditional Heteroskedasticity) test is applied. A significant ARCH effect indicates time-varying volatility, which is a key assumption for employing GARCH models. If returns exhibit ARCH effects, the shocks to currency prices are persistent, justifying the use of volatility models to capture risk and predict future volatility.

2.2. GARCH(1, 1)

A GARCH(1,1) model has been employed for each currency's return series to model conditional volatility. The standard GARCH(1,1) model assumes that current volatility depends on past shocks (ARCH effect) and past volatility (GARCH effect), capturing volatility clustering common in financial data.

The GARCH(1, 1) model is specified as

$$\sigma_t^{\ 2} = \alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^{\ 2} + \beta_1 \sigma_{t-1}^{\ 2}, \tag{1}$$

where α_0 (constant term) reflects the long-term average variance. α_1 (ARCH parameter) represents the effect of shocks or unexpected changes from the prior period on current volatility. β_1 (GARCH parameter) captures the influence of past volatility on current volatility. The sum of α_1 and β_1 close to 1 indicates high volatility persistence, meaning volatility is likely to remain elevated after a shock. This persistence is crucial for estimating the long-term risk associated with each currency. The GARCH parameters have been compared across the five currencies to identify those with high persistence in volatility, indicating potentially greater financial risk. This insight can guide hedging strategies where higher volatility currencies may require more robust risk management.

2.3. Correlation matrix

A correlation matrix has computed for the return series of all five currencies to identify the degree of co-movement. Higher positive correlations (close to +1) indicate that the currency pairs tend to move together, while lower or negative correlations suggest more independent movements. Correlations have been used to assess diversification opportunities. For instance, a currency with a lower correlation with other currencies may serve as a valuable diversifier, reducing the portfolio's overall risk by balancing gains and losses across assets.

2.4. Structural break tests

Structural break analysis was conducted using breakpoint detection methods to identify significant shifts in currency return behaviors over time. These breaks might correspond to macroeconomic events, policy changes, or financial crises that could affect exchange rate dynamics. Understanding structural breaks helped identify periods of regime shifts, when currency relationships may have altered, thus affecting long-term volatility and risk predictions. The identification of structural breaks helps to refine hedging and diversification strategies by adjusting risk assessments.

2.5. ARIMA (Auto-Regressive Integrated Moving Average)

The ARIMA model is used to analyze the exchange rate returns of each currency, which involves selecting optimal AR and MA terms based on historical data. GARCH Extension, i.e., an ARIMA-GARCH approach, combines return with volatility modeling, capturing both predictable return components and conditional volatility. The parameters (mean return, autoregressive, and moving average terms) for each currency would be interpreted in the context of their significance in explaining past returns and volatility patterns. By comparing the ARIMA-GARCH results for each currency, we can assess the predictability of returns and volatility. High values for the GARCH parameters (α_1 and β_1) across currencies indicate a persistent risk profile, which may be relevant for devising tailored hedging strategies.

3. RESULTS

3.1. Descriptive analysis

Table 1 encapsulates the descriptive statistics of daily returns of five major trading currencies (GBP, USD, AUD, EUR, JPY) with respect to INR. The period of study ranges from January 1, 2008 to December 31, 2025, thereby including 4,698 days. The results reveal that the average highest return is generated by USD/INR, viz., 0.010742. It is then followed by EUR/INR with 0.010225, GBP/INR with 0.009113, AUD/INR with 0.005415, and JPY/INR with 0.004693. However, the highest return daily generated has been by GBP/INR, viz., 3.748. It is then followed by JPY/INR with 3.07, EUR/INR with 2.97, USD/INR with 2.49, and AUD/INR with 2.45. Positive skewness means the distribution has a longer or fatter right tail (more values on the higher end). Negative skewness means the distribution has a longer or fatter left tail (more values on the lower end). USD/INR has positive skewness, indicating the distribution has a slight right tail. This means there are a few instances where exchange rate returns were higher than expected, but the skewness is relatively small, suggesting near symmetry.

REUR/INR has very slight positive skewness; this distribution is close to symmetric. There is a min-

Table 1. Descriptive analysis of five major traded currencies with respect to the Indian rupee

Return of exchange rate	RUSD/INR	REUR/INR	RGBP/INR	RJPY/INR	RAUD/INR
Number of observations	4,697	4,697	4,697	4,697	4,697
Minimum	–2.250000	–3.657000	–7.238000	–3.370000	–2.443000
Maximum	2.495000	2.973500	3.748000	3.070000	2.453000
Mean	0.010742	0.010225	0.009113	0.004693	0.005415
Median	0.000000	0.009500	0.009000	–0.010000	0.012000
SE Mean	0.003793	0.006721	0.008360	0.006529	0.005198
Variance	0.067586	0.212193	0.328289	0.200245	0.129128
Standard Deviation	0.259972	0.460644	0.572965	0.447487	0.356266
Skewness	0.230037	0.068787	–0.525982	0.101142	–0.148733
Kurtosis	7.553068	3.135138	8.102816	5.211036	4.022676
Jarque-Bera test	11220	1930.5	13081	5329.6	3189
Significance	< 2.2e–16**	< 2.2e–16**	< 2.2e–16**	< 2.2e–16**	< 2.2e–16**

Note: RUSD/INR, REUR/INR, RGBP/INR, RJPY/INR, and RAUD/INRUS are the return series of US dollar, Euro, Great British Pound, Japanese Yen, and Austrian Dollar with respect to INR, respectively. ** significant at 1 percent.

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imal right tail, implying that exchange rate fluctuations are nearly balanced on both sides of the mean. RGBP/INR negative skewness suggests the distribution has a moderate left tail. This indicates that there are more instances of lower-than-expected exchange rate returns. The skewness is not extreme, but the distribution leans towards lower values. RJPY/INR has slight positive skewness, indicating that this distribution has a small right tail. It shows a mild tendency toward higher exchange rate values, but the skewness is minimal, implying near symmetry. RAUD/INR's slight negative skewness suggests the distribution has a slight left tail. This indicates a few instances of lower-than-average returns, but the distribution is not heavily skewed.

Positive skewness (RUSD/INR, REUR/INR, RJPY/INR) indicates that these distributions have slight tendencies for higher extreme values, though REUR/INR and RJPY/INR are almost symmetric. Negative skewness (RGBP/INR, RAUD/INR) means that these distributions lean more towards lower extreme values, with RGBP/INR being moderately skewed compared to RAUD/INR. Overall, the skewness values indicate mostly symmetric distributions, with RGBP/INR showing the most asymmetry towards lower values.

Standard deviation quantifies the amount of variability or volatility in a data set. A higher standard deviation means the data points are more spread out from the mean, indicating more volatility or risk. A lower standard deviation indicates that the data points are closer to the mean, showing more stability and less volatility. RUSD/INR, a standard deviation of 0.259972, suggests that the U.S. Dollar (USD) index has relatively low volatility compared to the other currencies. The exchange rate fluctuations are moderate, and the values don't deviate significantly from the mean. REUR/INR, a standard deviation of 0.460644 for the Euro (EUR) index, indicates more volatility than the USD index. The fluctuations in the exchange rate are more spread out, implying a higher level of risk or variability in Euro exchange rates. RGBP/INR (0.572965) has the highest standard deviation among the indices, indicating that the British Pound (GBP) is the most volatile index. The exchange rate for GBP shows significant fluctuations, meaning data points are widely dispersed from the mean, suggesting greater uncertainty or risk in GBP exchange rates. RJPY/INR, a standard deviation of 0.447487 for the Japanese Yen (JPY) index implies a moderate to high level of volatility, similar to the Euro. The JPY exchange rate has notable fluctuations, with data points spread relatively far from the mean, indicating some level of risk. RAUD/INR, a standard deviation of 0.356266 for the Australian Dollar (AUD) index, reflects moderate volatility, higher than USD but lower than EUR, GBP, and JPY. This suggests that the AUD exchange rate fluctuates, but not as extensively as GBP or JPY. RUSD/INR has a low volatility, suggesting stability in USD exchange rates. REUR/INR and RJPY/INR moderate volatility, indicating more fluctuations in EUR and JPY rates. RGBP/INR has the highest volatility, showing significant fluctuations in GBP rates, which implies the highest risk. RAUD/INR has moderate volatility, indicating a more stable exchange rate than EUR, GBP, and JPY, but is more volatile than USD. Overall, GBP is the most volatile currency in this dataset, while USD exhibits the most stable change rate with India.

All five indices show significant deviation from a normal distribution, as indicated by their extremely small p-values (< 2.2e-16) and large Jarque-Bera test statistics. RGBP/INR has the largest Jarque-Bera statistic, indicating the greatest deviation from normality. This is consistent with its higher skewness and kurtosis values. RUSD/INR and RJPY/INR also show substantial deviations from normality. REUR/INR and RAUD/INR have lower Jarque-Bera statistics but still significantly deviate from normality. The high Jarque-Bera test values across all indices indicate that these exchange rate distributions are non-normal, with substantial skewness and kurtosis affecting data shape. This can imply the presence of outliers or frequent extreme movements in exchange rates, which is important for risk management and modeling.

3.2. Correlation matrix

This correlation in Table 2 presents the relationships between various currency indices (USD, EUR, GBP, JPY, AUD). Strongest Correlations: USD and EUR (0.90) indicate a very strong positive correlation; when one increases, the other tends to increase as well. EUR and GBP (0.88)

Table 2. Correlation matrix

Exchange rate	USD/INR	EUR/INR	GBP/INR	JPY/INR	AUD/INR
USD/INR	1.00 \(NA)	0.90 \(0)	0.82 \(0)	0.52 \(0)	0.63 \(0)
EUR/INR	0.90 \(0)	1.00 \(NA)	0.88 \(0)	0.54 \(0)	0.72 \(0)
GBP/INR	0.82 \(0)	0.88 \(0)	1.00 \(NA)	0.39 \(0)	0.70 \(0)
JPY/INR	0.52\(0)	0.54 \(0)	0.39 \(0)	1.00 \(NA)	0.66 \(0)
AUD/INR	0.63 \(0)	0.72 \(0)	0.70 \(0)	0.66 \(0)	1.00 \(NA)

Note: US dollar (USD/INR), Euro (EUR/INR), Great British Pound (GBP/INR), Japanese Yen (JPY/INR), and Austrian Dollar (AUD/INR) with respect to INR, respectively.

show another strong positive correlation, suggesting that movements in the Euro are closely mirrored by the British Pound. Moderate to Strong Correlations: USD and GBP (0.82) have a strong positive correlation. AUD and EUR (0.72) have a moderate to strong correlation, indicating that these currencies often move together. AUD and GBP (0.70) are similar to the previous correlation. Weaker Correlations: USD and JPY (0.52) have a moderate positive correlation but are weaker compared to the others. GBP and JPY (0.39) show a weak positive correlation, suggesting that these currencies do not move together as closely. JPY's Independence: The JPY shows the weakest correlations with other currencies, particularly with GBP and EUR, indicating it may behave differently in the market compared to the others. Table 2 indicates strong correlations among the USD, EUR, and GBP, while JPY stands out with weaker correlations. Traders and analysts can use these correlations to understand potential movements in currency pairs and to inform their trading strategies.

3.3. Structure break analysis

All p-values in Table 3 are less than 0.05, indicating extremely strong evidence against the null hypothesis of no structural breaks. This suggests significant shifts in exchange rates over time.

In the USD/INR events analysis, on the 23rd of April, 2012, the INR faced sharp depreciation against the USD, because of weak global sentiment from the Eurozone crisis and India's growing fiscal deficit. Concerns about inflation and a widening trade deficit further pressured the INR. On the 10th of December, 2014, falling crude oil prices supported the INR, while the USD strengthened due to the tightening monetary policy by the U.S. Federal Reserve. On the 26th of March, 2018, rising crude oil prices, U.S. protectionist policies, and speculation about Federal Reserve rate hikes caused the INR to depreciate. On the 13th of August, 2018, the INR hit record lows as Turkey's financial crisis sparked emerging market pressures, alongside a strong USD and rising crude oil prices.

In the EUR/INR events analysis, on the 22nd of August, 2012, the Eurozone's debt crisis and India's fiscal challenges influenced the EUR/INR exchange rate. ECB's bond-buying programs aimed at stabilizing the euro. On the 13th of February, 2015, the ECB's quantitative easing program weakened the euro, while declining crude oil prices provided mixed effects for the INR. On the 25th of August, 2017, European growth recov-

Table 3. Structure break analysis of the five exchange rates

Exchange rate	P-values	Breakpoints at observation numbers
USD/INR	< 2.2e-16	647, 1547, 2505, 3192, corresponding dates (23-04-2012, 10-12-2014, 13-08-2018, 26-03-2018)
EUR/INR	< 2.2e-16	1080, 1798, 2458, 3105, corresponding dates (22-08-2012, 13-02-2015, 25-08-2017, 27-05-2020)
GBP/INR	< 2.2e-16	1041, 2103, 2861, 3508, corresponding dates (04-02-2011, 30-07-2013, 24-06-2016, 21-07-2020)
JYP/INR	< 2.2e-16	647, 1294, 2120, 2767, 3414, corresponding dates (16-06-2011, 09-12-2013, 01-06-2016, 01-08-2019, 24-01-2022)
AUD/INR	< 2.2e-16	1074, 2509, 3455, corresponding dates (20-04-2011,04-12-2014, 04-06-2020)

Note: US dollar (USD/INR), Euro (EUR/INR), Great British Pound (GBP/INR), Japanese Yen (JPY/INR), and Austrian Dollar (AUD/INR) with respect to INR, respectively.

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ery and India's post-demonetization recovery impacted the EUR/INR rate amidst uncertainties around GST implementation. On the 27th of May, 2020, COVID-19 fiscal measures in the Eurozone supported the euro, while India's pandemic-related economic challenges pressured the INR.

In the GBP/INR events analysis, on the 4th of February, 2011, the GBP faced pressure due to UK austerity measures, while the INR benefited from India's economic growth. On the 30th of July, 2013, the INR depreciated sharply due to the "taper tantrum," while the GBP experienced mixed performance amid global uncertainty. On the 24th of June, 2016, the Brexit referendum caused significant volatility, weakening the GBP, with the INR reacting modestly to global risk aversion. On the 21st of July, 2020, Optimism over a post-Brexit trade deal strengthened the GBP, while the INR faced pandemic-driven depreciation.

In the JPY/INR events analysis, on the 16th of June, 2011, the Yen appreciated as a safe-haven asset amid the European debt crisis, while the INR weakened due to inflation and trade deficits. On the 9th of December, 2013, the INR stabilized following earlier depreciation, supported by RBI interventions, while the Yen remained strong amid global uncertainties. On the 1st of June, 2016, the Yen's strength under Japan's negative interest rate policy contrasted with India's inflation concerns, impacting the JPY/INR exchange rate. On the 1st August, 2019, Global trade tensions and economic slowdown fears strengthened the Yen as a safe-haven currency, while the INR weakened due to reduced foreign investment inflows. On the 24th of January, 2022, pandemic impacts on global economies influenced both currencies, with Japan's stimulus measures contrasting India's inflation-driven pressures.

In the AUD/INR events analysis, on the 20th of April, 2011, high global commodity prices strengthened the AUD, while rising oil import costs pressured the INR during the Arab Spring. On the 4th December, 2014, falling commodity prices, especially iron ore, weakened the AUD, while lower oil prices supported the INR. On the 4th June, 2020, the AUD recovered due to rebounding commodity prices and China's economic recovery, while the INR faced pandemic-related depreciation pressures.

3.4. Unit root test and ARCH effect

Table 4. Unit root test and ARCH effect

Stationarity (Initial series)	Dickey-Fuller test	Lag Order	P-value
USD/INR	–3.3987	16	0.0536
EUR/INR	–3.4557	16	0.04652
GBP/INR	–2.7998	16	0.2396
JPY/INR	–1.5403	16	0.773
AUD/INR	–1.8171	16	0.6558
Stationarity (Return series)	**Dickey-Fuller test**	**Lag Order**	**P-value**
RUSD/INR	–16	16	0.01
REUR/INR	–17	16	0.01
RGBP/INR	–17	16	0.01
RJPY/INR	–16	16	0.01
RAUD/INR	–17	16	0.01
ARCH_Effect (Return series)	**Chi-squared**	**DF**	**P-value**
RUSD/INR	901.52	12	< 2.2e–16
REUR/INR	693.8	12	< 2.2e–16
RGBP/INR	358.53	12	< 2.2e–16
RJPY/INR	421.56	12	< 2.2e–16
RAUD/INR	917.9	12	< 2.2e–16

Note: RUSD/INR, REUR/INR, RGBP/INR, RJPY/INR, RAUD/INRUS are the return series of US dollar, Euro, Great British Pound, Japanese Yen, and Austrian Dollar with respect to INR, respectively.

This study aims to capture the behavior of returns from FOREX markets of the five largest trading currencies with respect to INR from January 1, 2008 to December 31, 2025. Before diving into the analysis, certain assumptions must be established: the stationarity of the time series, the presence of an ARCH effect, and volatility clustering (Mandelbrot, 1963). Table 4 summarizes the results of the Dickey-Fuller test, which assesses both stationarity and the ARCH effect to determine the relationship between current and lagged returns.

The Dickey-Fuller test indicates that all return series in the periods are stationary or integrated at level I(0). The ARCH test confirms the presence of an ARCH effect in all return series, which is crucial for further volatility analysis. The p-values for the coefficients of ARCH (ε^2_{t-1}) are below the 0.05 significance threshold, leading to the rejection of the null hypothesis that there is no ARCH effect. This finding indicates that all series exhibit an ARCH effect.

Volatility clustering is depicted through the time-varying return plots for the five largest trading

Table 5. ARIMA(1,1) & GARCH(1,1) model for top five trading currencies with respect to INR

Variables	Model	mu	ar1	ma1	omega	alpha1	beta1
RUSD/INR	coef.	0.00503	0.37851	–0.4175	0.00097	0.09103	0.89845
	p_value	0.08736	0.04727	0.02537	0.00007	0.00000	0.00000
REUR/INR	coef.	0.002165	0.267618	–0.316875	0.004134	0.067991	0.912608
	p_value	0.702591	0.273763	0.187750	0.000136	0.000000	0.000000
RGBP/INR	coef.	0.006155	0.975933	–0.981828	0.013713	0.096559	0.860710
	p_value	0.041608	0.000000	0.000000	0.000000	0.000000	0.000000
RJPY/INR	coef.	-0.004642	0.629463	–0.653449	0.004946	0.089723	0.887354
	p_value	0.379288	0.035578	0.024920	0.000001	0.000000	0.000000
RAUD/INR	coef.	0.002946	0.107331	–0.178823	0.002746	0.065953	0.911312
	p_value	0.495175	0.603735	0.381696	0.000053	0.000000	0.000000

Note: RUSD/INR, REUR/INR, RGBP/INR, RJPY/INR, RAUD/INRUS are the return series of US dollar, Euro, Great British Pound, Japanese Yen, and Austrian Dollar with respect to INR, respectively.

currencies with respect to INR, with significant evidence shown in Figures A1 and A2 (Appendix A). Large price movements tend to be followed by similarly large movements, whether positive or negative, while small movements tend to follow small movements (Mandelbrot, 1963).

3.5. ARIMA(1,1) & GARCH(1,1)

Table 5 presents a comparative analysis of the return time-series model results for five currency indices: USD, EUR, GBP, JPY, and AUD w.r.t INR. Each index is examined in terms of its mean trend (mu), the effects of past values (ar1), past shocks (ma1), and three key volatility parameters (omega, alpha1, and beta1). By comparing these factors across currencies, we can identify similarities and differences in how past returns and volatility influence each currency index.

3.6. Comparative analysis by parameter

Mean (mu): The mean (mu) is only statistically significant for GBP ($p = 0.0416$), with a positive coefficient (0.0062), suggesting a slight upward trend in the GBP index. In contrast, the mean values for USD, EUR, JPY, and AUD are not statistically significant, indicating that these indices lack a strong average trend over time. GBP may exhibit a slight upward drift, while the other indices show no strong underlying trend.

Autoregressive Term (ar1): The autoregressive term (ar1), which indicates how much past values influence the current index, is highly significant for GBP (0.976, $p < 0.001$) and moderately significant for USD (0.379, $p = 0.0473$) and JPY (0.629, $p = 0.0356$). EUR and AUD show no significant ar1 effect, indicating that past returns do not impact these indices strongly. GBP has a particularly strong dependence on its past values, suggesting high persistence in returns, while EUR and AUD exhibit little to no autoregressive influence from past returns.

Moving Average Term (ma1): The moving average term (ma1), representing the impact of past shocks, is significantly negative for GBP (–0.982), JPY (–0.653), and USD (–0.418), suggesting that previous shocks have a notable dampening effect on current values for these indices. In contrast, EUR and AUD do not show significant ma1 values, indicating that past shocks do not substantially impact these indices. The USD, GBP, and JPY indices respond more strongly to past shocks compared to the EUR and AUD, implying that fluctuations in these three indices may be more reactive to sudden changes or corrections.

Baseline Variance (omega): All indices have a significant baseline variance (omega), indicating an inherent level of volatility. GBP shows the highest baseline variance (0.0137), suggesting it has relatively higher inherent volatility than other currencies, with USD and EUR having smaller values (0.00097 and 0.00413, respectively). While all indices have a statistically significant baseline level of volatility, GBP exhibits the highest inherent volatility, whereas USD and EUR show relatively lower baseline volatility.

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ARCH Term (alpha1): The ARCH term (alpha1), which captures the immediate impact of past shocks on current volatility, is significant across all indices. This suggests that volatility clustering, where high volatility is followed by high volatility, is a common feature for each currency. GBP and USD exhibit slightly higher alpha1 values (0.0966 and 0.0910, respectively) compared to EUR (0.0680) and AUD (0.0660). This indicates that GBP and USD may experience more immediate reactions to recent shocks, leading to higher short-term volatility. Although all indices show significant short-term volatility clustering, GBP and USD may react more acutely to recent market shocks compared to EUR and AUD.

GARCH Term(beta1): which indicates the persistence of volatility over time, is highly significant and large across all indices, ranging from 0.861 in GBP to 0.912 in EUR and AUD. This means that once volatility is high, it tends to remain high for an extended period across all currency indices. EUR and AUD show the highest beta1 values (0.913 and 0.911, respectively), suggesting they have the most persistent volatility. GBP has the lowest, though still high, beta1 (0.861), indicating that while it is persistent, GBP volatility may decay slightly faster than other currencies. Volatility persistence is a common feature across all currencies, but EUR and AUD might maintain periods of volatility for slightly longer durations compared to GBP.

4. DISCUSSION

Based on the analysis of the five major trading currencies with respect to the Indian Rupee (INR) from January 1, 2008 to December 31, 2025, this study discusses currency returns, volatility patterns, comovements, and potential hedging opportunities.

The U.S. Dollar (USD) has the highest average daily return among the five currencies, followed closely by the Euro (EUR) and the British Pound (GBP). This suggests a relatively consistent appreciation of USD against INR over the analyzed period, which is significant for international trade and financial planning. Skewness values show a trend where USD, EUR, and JPY have slight positive skewness, indicating tendencies toward higher-than-average values, while GBP and AUD show negative skewness, reflecting more instances of returns below average. This skewness informs risk profiles, where a negative skew suggests a heavier chance of downside movements (Jiang et al., 2019). The findings contradict Yeboah et al. (2025), who report that major currencies move closely over the long run.

GBP exhibits the highest standard deviation among the currencies, denoting the highest volatility and suggesting a greater degree of uncertainty and risk for investors dealing in GBP/INR transactions. The Euro and Japanese Yen also show moderate volatility, while USD is relatively more stable, which aligns with its status as a global reserve currency and its use as a common trade currency. The Jarque-Bera test results show that none of the currency return distributions follow a normal distribution. This is further supported by significant kurtosis values, which indicate the presence of extreme returns or "fat tails" in the distribution, which is critical for understanding potential shocks or unusual fluctuations in returns.

High correlations between USD/EUR and EUR/GBP suggest that movements in these currencies are often in tandem (Singh et al.,2024), indicating that they are influenced by similar economic factors or market sentiment. This finding is significant for those seeking to diversify, as holding both EUR and USD or EUR and GBP may not significantly reduce risk. The weaker correlations between JPY and the other currencies reflect that it operates relatively independently of the USD and Euro, possibly due to Japan's unique economic policies and external economic factors. The correlations indicate that while USD, EUR, and GBP have similar trends and may not provide substantial diversification benefits relative to each other, JPY and AUD might serve as better diversifiers.

Structural breakpoints identified in all five currency returns, especially during global financial crises and significant policy changes, underscore that exchange rate movements are not uniformly stable over time (Asteriou et al., 2025). Frequent structural breaks highlight the potential for currency rates to shift dramatically due to unforeseen events. This is a crucial insight for risk management, as it signals the need for dynamic hedging strategies that can adapt to sudden changes in market conditions.

For USD and JPY, the persistence of volatility over time (high beta coefficients) indicates a slow decay of volatility shocks, which can be critical for longer-term investors aiming to mitigate exposure to periods of high market fluctuation. The diversification and hedging opportunities in this analysis suggest that although USD, EUR, and GBP exhibit high correlation, currencies such as JPY and AUD, due to their unique economic factors and lower correlations, offer viable hedging options for portfolios exposed to INR. Investors and policymakers can leverage these findings to optimize currency portfolios and reduce financial risk, especially when seeking diversification benefits and long-term stability amidst global market shifts. Additionally, high correlations among USD, EUR, and GBP indicate limited diversification when investing within this subset, highlighting JPY and AUD as effective hedging tools in a diversified currency strategy. Overall, this analysis serves as a valuable framework for assessing currency volatility, co-movement patterns, and risk management in INR-based currency trading.

CONCLUSION

This study aims to unravel the co-movement of the Indian currency, INR, with respect to the five major traded currencies. The study relies solely on historical data from January 1, 2008 to December 31, 2025, meaning that it assumes past patterns will help predict future behavior. This backward-looking perspective does not account for potential shifts in currency exchange rate dynamics due to evolving economic, geopolitical, and policy factors. Consequently, future currency behavior may diverge from historical patterns, limiting the study's applicability in the long term. The analysis primarily focuses on currency returns, volatility, correlation, and structural breaks without including key macroeconomic factors such as interest rates, inflation rates, trade balances, or GDP growth. These variables have significant impacts on currency values, and their exclusion may limit the robustness of the findings. The addition of such factors in a multivariate model could provide a more comprehensive analysis of exchange rate determinants. Central bank policies, including currency interventions and interest rate adjustments, are not directly considered. Since central banks can have a substantial influence on currency values, especially during periods of economic stress, their exclusion may overlook significant factors affecting currency returns and volatility. The study focuses on only five major currencies (USD, EUR, GBP, JPY, and AUD) in relation to the Indian Rupee. Although these are highly traded currencies, this limited scope may not reflect the full range of INR-related currency dynamics, particularly with respect to emerging market currencies or key trade partners that are also significant for India's economy.

Real-world trading involves transaction costs, market liquidity constraints, and bid-ask spreads, which affect actual returns. By focusing on daily closing prices without accounting for these practical aspects, the study may overstate the potential profitability of trading strategies or hedging opportunities. Structural breaks were identified in this study, but the methods used assume abrupt changes rather than gradual shifts in currency trends, which may not fully capture the complex nature of currency market shifts.

AUTHOR CONTRIBUTIONS

Conceptualization: Mahesh Kumar.
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Formal analysis: Mahesh Kumar, Ankita Bhatt.
Investigation: Ameya Anil Patil, Kunal Gaurav.
Methodology: Mahesh Kumar, Kunal Gaurav.
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Software: Ameya Anil Patil, Diksha Dubey Jaroliya, Ankita Bhatt.

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Writing – original draft: Mahesh Kumar.
Writing – reviewing & editing: Mahesh Kumar, Ameya Anil Patil, Diksha Dubey Jaroliya, Ankita Bhatt, Kunal Gaurav.

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APPENDIX A

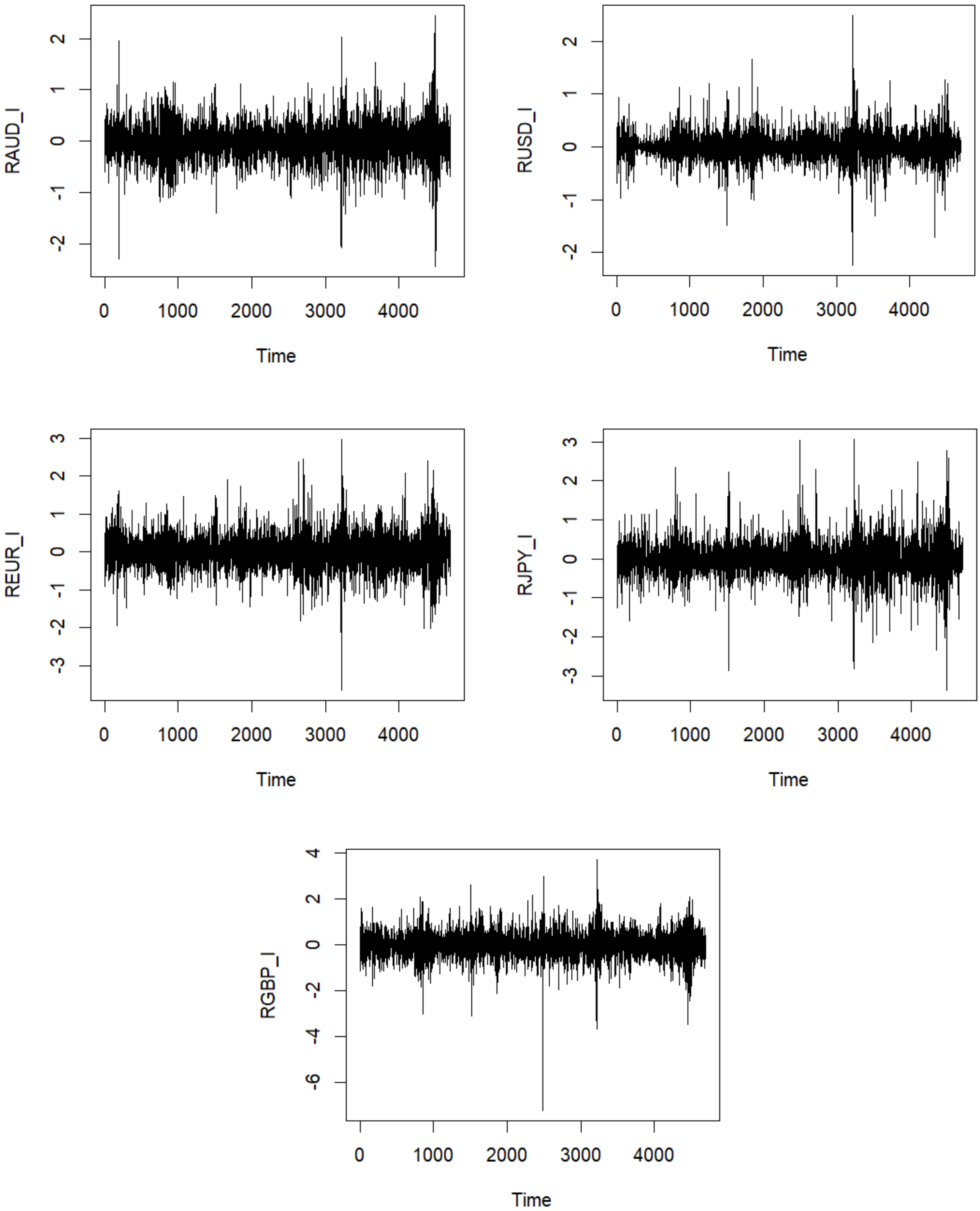

Figure A1. Volatility clustering on return data

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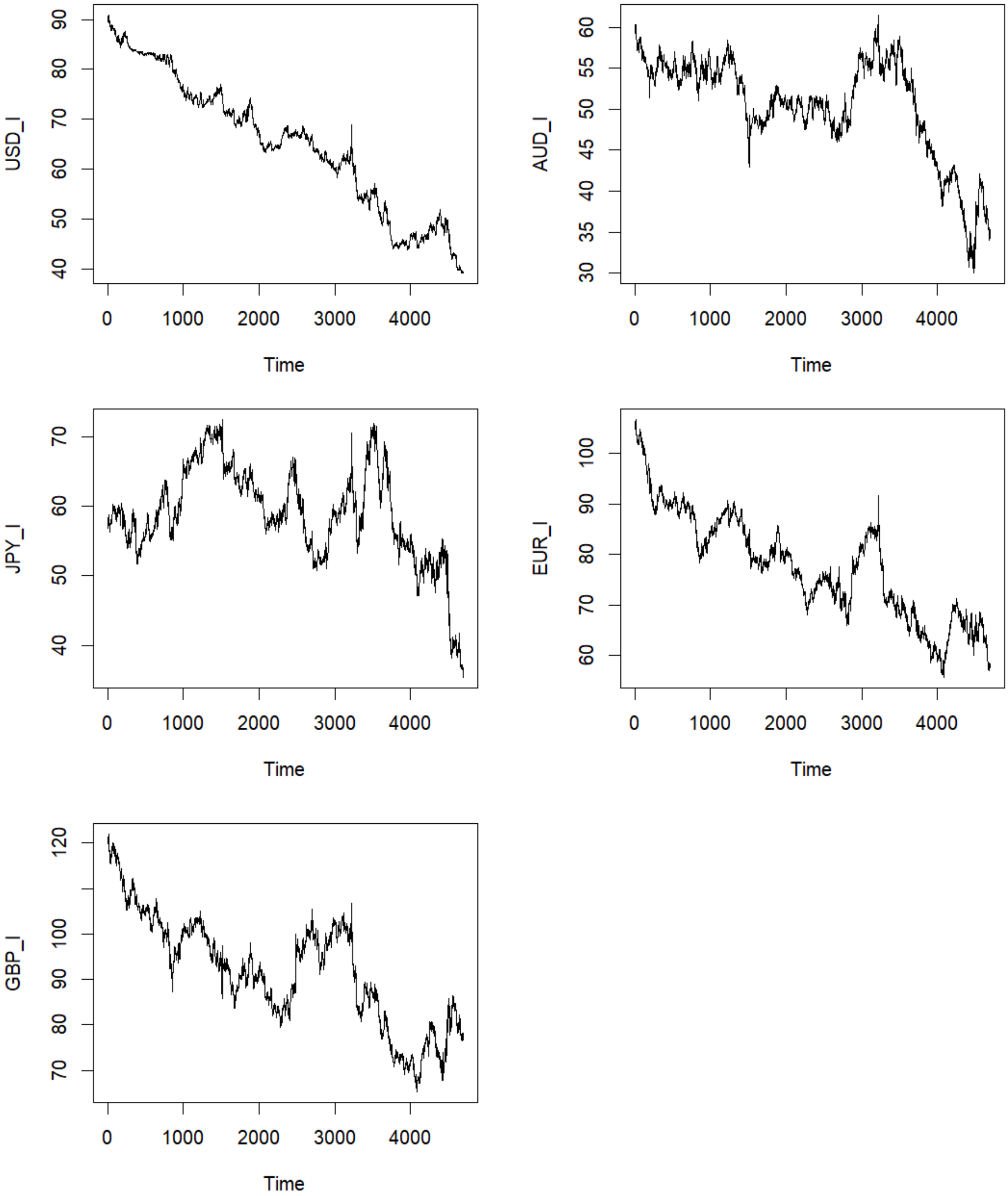

Figure A2. Graphical representation of all five countries' exchange rates with respect to India