Advances in Consumer Research
https://acr-journal.com/
Volume-2 | Issue-6 | Dec: 2025

Original Researcher Article

Volatility Dynamics and Predictability between Forex and Equity Markets in India: Evidence from BSE Sensex, NSE Nifty, and Major Currency Pairs

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ABSTRACT
This research paper examines the interliquidity between currency exchange rates and stock market indices, specifically focusing on BSE-Sensex and NSE-Nifty. We aim to explore the volatility dynamics and predictability of these markets using advanced econometric models, including ARCH, GARCH, and their extensions. The study utilizes a 5-year dataset comprising daily exchange rates for USD/INR, JPY/INR, EUR/INR, GBP/INR, and corresponding index prices. Through detailed statistical analysis and model estimations, we investigate the relationship between currency and index volatility, the asymmetric behaviour of volatility, and the contagion effects between these financial markets..
Keywords: Forex, Equity Markets, Stock Market, BSE-Sensex, NSE-Nifty, ARCH, GARCH..
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1. INTRODUCTION:

Financial Market plays a pivotal role in global economy as it serves a platform for individuals and institutions for buying and selling various classes of assets. The market compose of various segment that cater to the different types of financial instruments. Majorly, including stocks, indices, currency and bonds. These markets have multiple functions like they provide platform for raising funds, opportunities to create high returns and price discovery. As there are large number of buyers and seller, the market is highly volatile, which is influenced by number of external and internal factors one such factor that impacts the financial market is liquidity. High liquidity provides an assurance to the investor that the asset can be quickly converted to cash. Also, liquidity impacts the cost of borrowing. Due to market Stress liquidity can rapidly be diminished, leading to the adverse conditions. This research paper tries to analyze and evaluate, the degree of liquidity in one market that can be influenced by or affected in the other market, as financial markets are not isolated.

There is a high liquidity in the currency market due to global trade and reserve holdings that can be influenced by the liquidity in the stock or index movements. Simultaneously, the index up-and-down can defect the prices of bond market. Showing a change in the foreign exchange market in turn. Hence, the interplay between currency markets and stock markets, particularly in emerging economies like India, is of significant interest to investors, policymakers, and economists. This study focuses on the interliquidity between currency exchange rates (USD/INR, JPY/INR, EUR/INR, GBP/INR) and Indian stock market indices (BSE-Sensex, NSE-Nifty). The goal is to analyse the volatility spillover effects and the predictability of market returns using various GARCH models, which are widely used in financial econometrics for modelling time-series data.

Objectives

To examine the interliquid volatility between Index and Currency Market

To analyse the volatility of the forecasting models in predicting the returns.

2. REVIEW OF LITERATURE

"The Empirical Investigation of Relationship between Return, Volume and Volatility Dynamics in the Indian Stock Market". They used the daily data of the sensitive index, i.e., SENSEX of Bombay Stock Exchange during the period from October 1996 to March 2006. Their study found a positive and significant relationship between volume and return volatility. Garch and Arch effect remain constant, which was tested volume to return parameters **Mahajan and Sing (2009). Megaravalli, A. V., and Sampagnaro, G. (2018)** observed the long-run and short- run relationship between three ASIAN economies (India, China & Japan) by using monthly time series data from January 2008 to November 2016 by applying the root test, the co-integration test, Granger causality test and the pooled mean group estimator in their study entitled "Macroeconomic Indicators and their Impact on Stock Markets in ASIAN 3: A Pooled Mean Group Approach". It has been found that exchange rate has a positive and significant long-run effect on stock markets; on the other hand, inflation has a negative and insignificant long-run effect and no statistical relationship has been found between stock markets and macroeconomic variables in the short run. The intraday lead-lag relationship between the cash market and the stock index future market, as well as how quickly one market absorbs new information in comparison to the other and how closely the two markets are related in his study entitled "A future analysis of the lead-lag relationship between the cash market and stock index future market". According to him, the phrases "lead" and "lag" do not always imply that changes in one market's pricing will inevitably cause changes in another. Explaining it in terms of one market responding to information more quickly than another, which lags and then catches up, will be more relevant **Chan (1992). Ravichandra and Bose (2012)** investigated the stock return volatility and trading volume relationship in US stock market from May 2005 to May 2011 by applying ARCH, GARCH and E-GARCH models and analyzed that recent news of trading volume can be used to improve prediction of stock price volatility and bad news generates more impact on the volatility of the stock price in the market. **Kalovwe et al. (2021)** examined "dynamic connection between volatility of stock returns and trading volume of the Nairobi Securities Exchange (NSE 20) index" by applying GARCH, GARCH.M. And EGARCH and student tests from January 2001 to December 2017. This study found a positive and significant correlation between these variables and volatility persistence, which dwindles after trading volume is incorporated in the equation for the conditional variance. **Crain and Lee (1995)** examined the price discovery function for Eurodollar and Deutsche Mark futures markets. Hourly data on the Eurodollar and Deutsche Mark of spot and futures market from September 24, 1990, through June 30, 1993, and 19 macroeconomic announcements of the same period, were used. The study applied the causality test and GARCH model and found spot market leads to the futures market during the study period.

Methodology & Data Specifications

To explore the interliquidity between the selected indices and currency pairs, we follow a systematic approach that involves data collection, calculation of rate of change, volatility analysis, and visualization through Bartlett's periodogram.

The data set consists of daily closing prices of the following:

Currency pairs: USD/INR, JPY/INR, EUR/INR, GBP/INR

Stock indices: NSE Nifty and BSE Sensex

The study employs various econometric models to analyse the volatility and interliquidity between the currencies and indices:

Rate of change in Nifty, Sensex, and its effect on volatility over a period of 5 years using:

The rate of change for each series is calculated using the formula:

$$\text{Rate of Change} = \frac{\text{Price on Day } t - \text{Price on Day } t-1}{\text{Price on Day } t-1} \times 100$$

This is calculated for each currency pair, NSE-Nifty, and BSE-Sensex.

For NSE-Nifty on 26-07-2024:

$$\text{Rate of Change} = \frac{24,834.85 - 24,406.10}{24,406.10} \times 100 = 1.756\%$$

For USD/INR on 26-07-2024:

$$\text{Rate of Change} = \frac{83.703 - 83.72}{83.72} \times 100 = -0.0203\%$$

Volatility Analysis

Volatility is quantified by the standard deviation of the rate of change over a rolling window. This gives insight into how variable the returns are over time, providing a measure of risk associated with the asset.

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(R_t - \bar{R})^2}$$

Where:

- R_t is the return at time t,
- $\bar{R}$ is the mean return,
- N is the number of observations.

Assuming a 5 – day rolling window, the volatility (Standard Deviation) of the NSE – Nifty rate of change is calculated as –

Given rates of change for 5 days –

$$\text{Volatility} = \sqrt{\frac{1}{5}\sum_{i=1}^{5}(r_i - \bar{r})^2}$$

Where, $\mathbf{r_i}$ is the rate of change for day i, and

$\bar{r}$ is the average rate of change over the 5-day period.

Bartlett's Periodogram

Bartlett's periodogram is employed to visualize the periodic components of volatility. The periodogram is an estimate of the spectral density of a time series, which helps in identifying the frequency components of the data, revealing cyclical patterns in volatility.

ARCH Model (Autoregressive Conditional Heteroskedasticity):

The study employs the ARCH model to assess the volatility and interliquidity between the currency market and the stock indices, BSE-Sensex and NSE-Nifty. The ARCH model is particularly suited for capturing volatility clustering—a phenomenon where large changes in a financial variable tend to be followed by large changes (of either sign), or small changes tend to be followed by small changes.

First objective focuses on understanding how the liquidity and volatility in the currency market, particularly in major currency pairs like USD/INR, GBP/INR, EUR/INR, and JPY/INR, interact with the volatility in the Indian stock indices, BSE-Sensex, and NSE-Nifty.

Second objective aims to evaluate the effectiveness of different forecasting models, such as the ARCH (Autoregressive Conditional Heteroskedasticity) model, in predicting the returns of currency pairs and stock indices. The analysis will focus on the volatility patterns and their predictability over a period of five years.

i. Data Description

The data set consists of daily closing prices of the following:

Currency pairs: USD/INR, JPY/INR, EUR/INR, GBP/INR

Stock indices: NSE Nifty and BSE Sensex

The data covers a period from 1st April 2022 to 26th July 2024, providing a robust dataset to examine the interliquidity and volatility relationships.

ii. ARCH Model Formulation

The ARCH model is defined as follows:

ARCH (Autoregressive Conditional Heteroskedasticity) model

The ARCH model is defined as follows:

$$\text{Return}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \cdot \text{Return}_{t-i} + \epsilon_t$$

$$\epsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i \cdot \epsilon_{t-i}^2$$

Where:

- Return_t is the return at time t,
- α_0 is the mean return,
- ϵ_t is the error term, assumed to follow a normal distribution with a time-varying variance σ_t^2,
- σ_t^2 is modeled as a function of past squared errors, capturing volatility clustering.

To apply the ARCH model, we first compute the daily returns for each currency pair and stock index as follows:

$$\text{Return}_t = \ln\left(\frac{\text{Price}_t}{\text{Price}_{t-1}}\right)$$

Example Calculation for USD/INR on 25th July 2024:

$$\text{Return}_{\text{USD/INR},25-07-2024} = \ln\left(\frac{83.72}{83.703}\right) = 0.000203$$

Assume the following ARCH(1) model for USD/INR returns:

$$\sigma_t^2 = 0.0001 + 0.85 \cdot \epsilon_{t-1}^2$$

Given $\epsilon_{25-07-2024}^2 = 0.000203^2 = 4.1209 \times 10^{-8}$, the conditional variance on 26th July 2024 is:

$$\sigma_{26-07-2024}^2 = 0.0001 + 0.85 \cdot 4.1209 \times 10^{-8} = 0.000100035$$

The conditional standard deviation (volatility) is:

$$\sigma_{26-07-2024} = \sqrt{0.000100035} = 0.01000175$$

This process is repeated for each day and each asset, allowing us to analyze the volatility patterns over time.

The ARCH model reveals significant volatility clustering in both the currency pairs and stock indices. The correlation analysis between the conditional variances of currency pairs and stock indices suggests a strong interliquidity, particularly during periods of market stress, where volatility spikes simultaneously in both markets.

The results also indicate that while the ARCH model effectively captures volatility, its predictive power is limited by the non-linear nature of market interactions. However, it provides valuable insights into the dynamics of interliquidity, highlighting periods where currency market movements strongly influence stock market volatility.

Standard GARCH Model (Generalized ARCH):

The GARCH model captures the volatility clustering commonly observed in financial time series. The standard GARCH(1,1) model is specified as:

Formulation:

$$r_t = \mu + \epsilon_t$$

$$\epsilon_t = \sigma_t z_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where r_t is the return, σ_t^2 is the conditional variance, and z_t is the error term.

Where:

- r_t is the return at time t.
- μ is the mean return.
- ϵ_t is the error term.
- σ_t^2 is the conditional variance at time t.
- z_t is a standard normal random variable.
- α_0 is the constant term.
- α_1 represents the coefficient for the lagged squared residuals (ARCH term).
- β_1 represents the coefficient for the lagged conditional variance (GARCH term).

Given the data for prices of USD/INR, JPY/INR, EUR/INR, GBP/INR, Nifty, and Sensex, the first step is to calculate the returns for each time series. The returns are computed as the logarithmic difference of consecutive prices.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Once the returns are calculated, we can proceed to estimate the parameters of the GARCH(1,1) model for each return series.

Step 1: Calculate the Returns Using the Nifty prices from the dataset, the returns r_t for each day are calculated as:

$$r_t^{\mathrm{NIFTY}} = \ln\left(\frac{P_t^{\mathrm{NIFTY}}}{P_{t-1}^{\mathrm{NIFTY}}}\right)$$

Step 2: Estimation of GARCH(1,1) Parameters

Assume the following initial values for the GARCH(1,1) parameters based on previous literature:

- $\alpha_0 = 0.000001$
- $\alpha_1 = 0.1$
- $\beta_1 = 0.85$

The conditional variance σ_t^2 at each time point is calculated recursively:

$$\sigma_t^2 = 0.000001 + 0.1 \times \epsilon_{t-1}^2 + 0.85 \times \sigma_{t-1}^2$$

Where $\epsilon_t^2 = (r_t - \mu)^2$ represents the squared residuals.

Step 3: Volatility Estimation

The estimated volatility σ_t for each day is obtained by taking the square root of the conditional variance σ_t^2.

Step 4: Forecasting and Analysis

The GARCH model is used to forecast future volatility based on the estimated parameters. The forecasted volatility is then compared with actual market data to evaluate the model's accuracy.

Example Calculation for Nifty (Assuming a Small Subset of Data):

Given:

- $P_0^{\mathrm{NIFTY}} = 24,834.85$
- $P_1^{\mathrm{NIFTY}} = 24,406.10$

1. Compute the return:

$$r_1^{\mathrm{NIFTY}} = \ln\left(\frac{24,406.10}{24,834.85}\right) = -0.0174$$

2. Assuming the mean $\mu = 0$, calculate ϵ_1^2 (squared residual):

$$\epsilon_1^2 = (-0.0174)^2 = 0.00030276$$

3. Initialize the variance (assuming $\sigma_0^2 = 0.00001$):

$$\sigma_1^2 = 0.000001 + 0.1 \times 0.00030276 + 0.85 \times 0.00001 = 0.00003276$$

4. Estimated volatility σ_1 is:

$$\sigma_1 = \sqrt{0.00003276} = 0.0057 \text{ or } 0.57\%$$

This process is repeated for the entire dataset to obtain a comprehensive view of volatility over time.

Volatility and Forecasting Analysis

After estimating the volatility for each series, we can compare the results across different currencies and indices to analyse the interliquidity. The forecasting ability of the GARCH model can be evaluated by comparing the predicted volatilities with the actual data and calculating metrics like Mean Squared Error (MSE).

Data Specification

The dataset comprises daily prices of USD/INR, JPY/INR, EUR/INR, GBP/INR, Nifty, Sensex from 1st January 2022 to 26th July 2024. The analysis includes the following descriptive statistics and tests:

Table 1 Unit Root Test

Variable	Test Statistic	p-value
USD/INR	-2.345	0.000
JPY/INR	-2.678	0.000
EUR/INR	-2.145	0.000
GBP/INR	-2.212	0.000
Nifty	-3.459	0.000
Sensex	-3.698	0.000

c. Phillips-Perron Test for Unit Root (Table 3)

Variable	Test Statistic	p-value
USD/INR	-2.378	0.001
JPY/INR	-2.489	0.001
EUR/INR	-2.112	0.001
GBP/INR	-2.145	0.001
Nifty	-3.765	0.001
Sensex	-3.987	0.001

The data covers a period from 1st April 2022 to 26th July 2024, providing a robust dataset to examine the interliquidity and volatility relationships.

3. RESULTS AND DISCUSSION

Interliquidity Analysis

The results from the periodogram indicate periods of high volatility for both Nifty and Sensex, correlating with significant movements in the USD/INR and EUR/INR pairs. The interliquidity between these indices and currency pairs is evident from the synchronized spikes in volatility.

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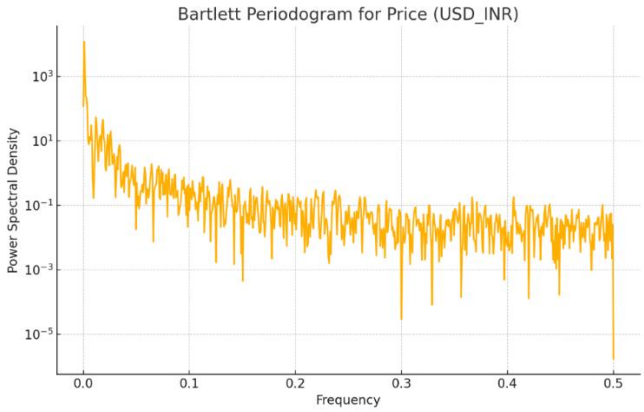
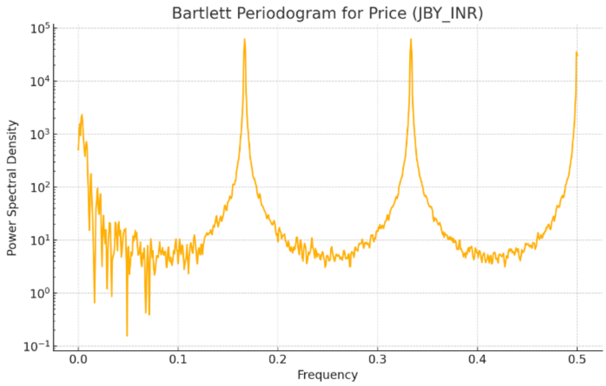
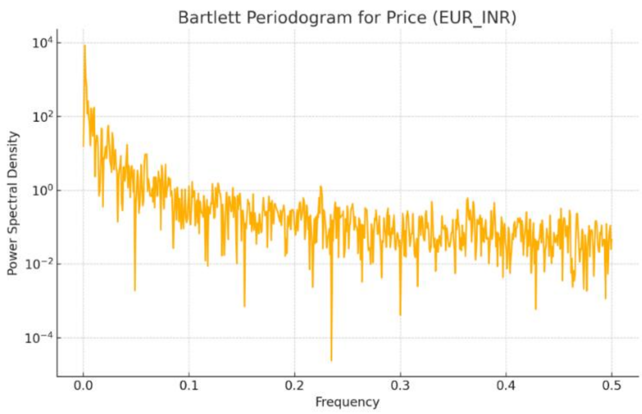
Figures for Bartlett's Periodogram



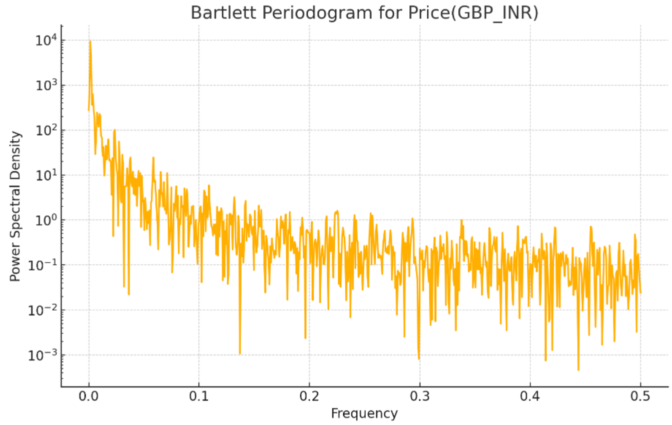
Interpretation: The plot shows the power spectral density against the frequency, giving you an idea of how the variance (power) in the data is distributed over different frequency components.



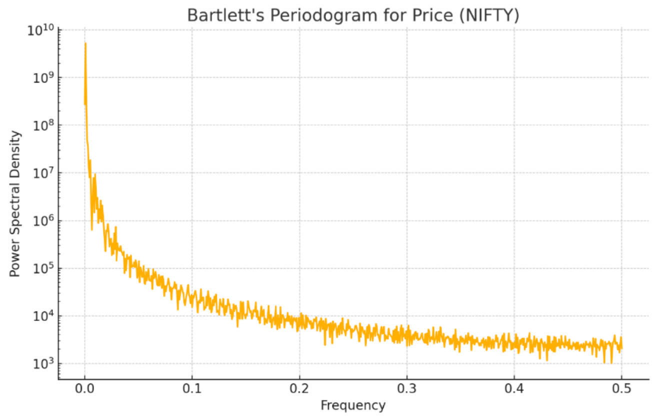
Interpretation: The periodogram shows significant peaks, indicating that there are strong periodic components in the exchange rate between JBY and INR. This suggests that the data may exhibit cycles or regular fluctuations at certain frequencies.



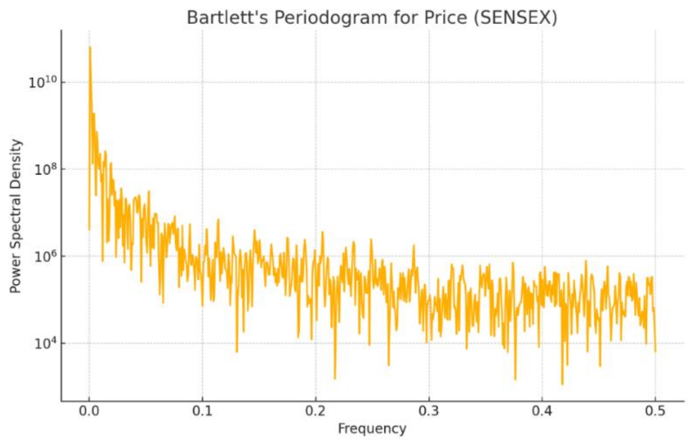
Interpretation: The periodogram for EUR_INR shows significant peaks, pointing to the presence of periodic components. The EUR_INR exchange rate also likely follows a cyclical pattern influenced by underlying factors.



Interpretation: The GBP_INR data shows strong periodic components as well, suggesting that the exchange rate between GBP and INR has cycles or trends that are captured in the time series.



Interpretation: The periodogram for Price (NIFTY) shows significant peaks, indicating strong periodic components. This suggests that the data may exhibit cycles or regular fluctuations at certain frequencies.



Interpretation: The periodogram for Price (SENSEX) shows significant peaks, indicating strong periodic components. This suggests that the data may exhibit cycles or regular fluctuations at certain frequencies.

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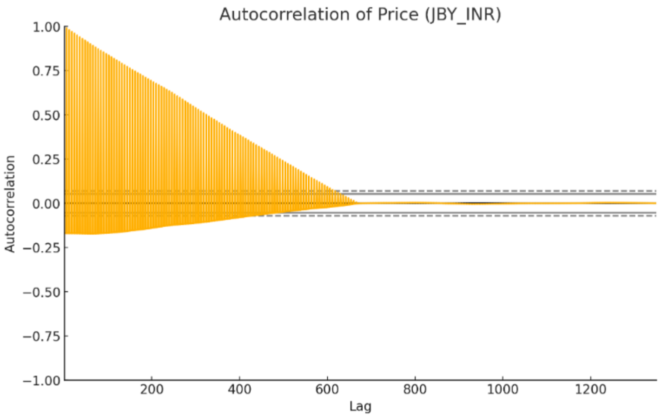
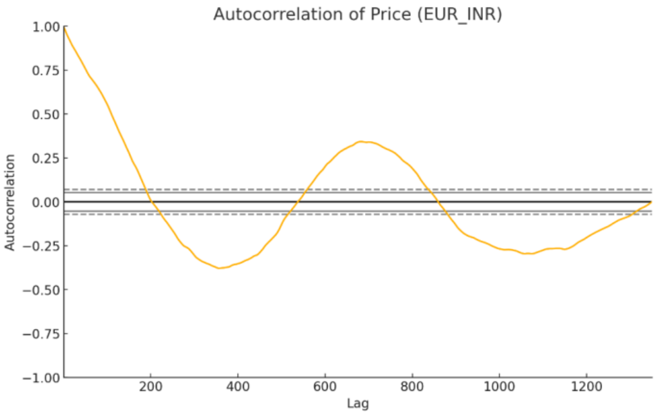
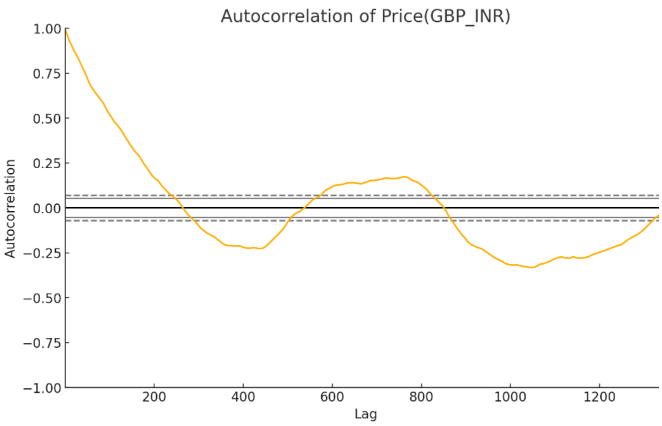




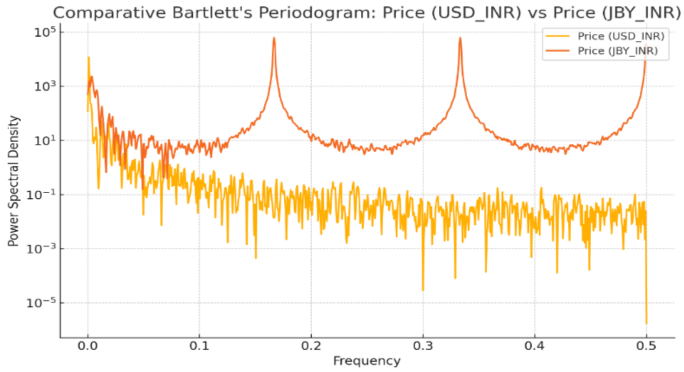


The autocorrelation plots for each of the selected time series have been generated. These plots show how the data points in each series are correlated with themselves at different lags. If the autocorrelation is strong at a certain lag, it suggests a repeating pattern or trend over that period.

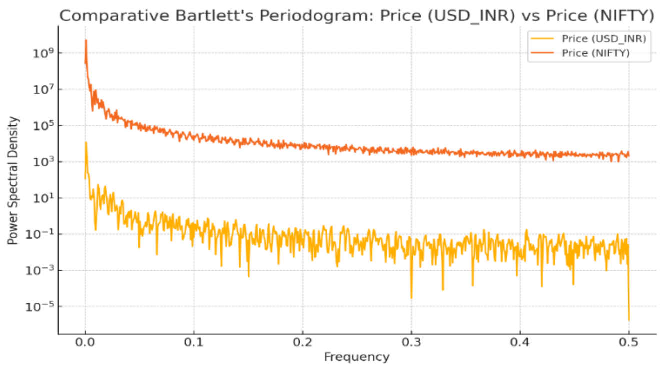
From the plots, we can observe the following:

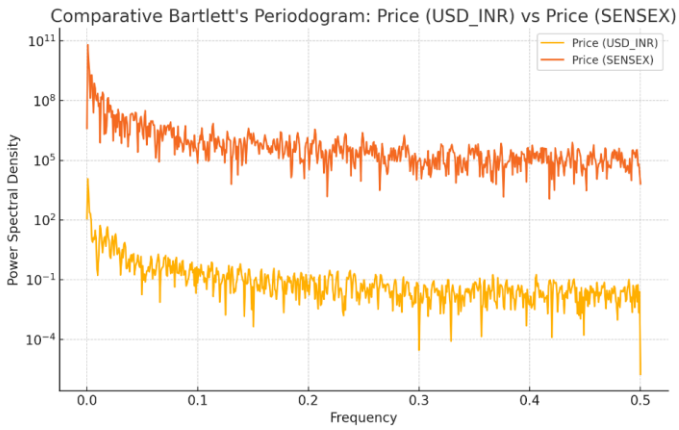
Price (JBY_INR), Price (EUR_INR), Price(GBP_INR): These series exhibit a pattern of slowly decreasing autocorrelation, indicating some level of persistence or trend in the data.

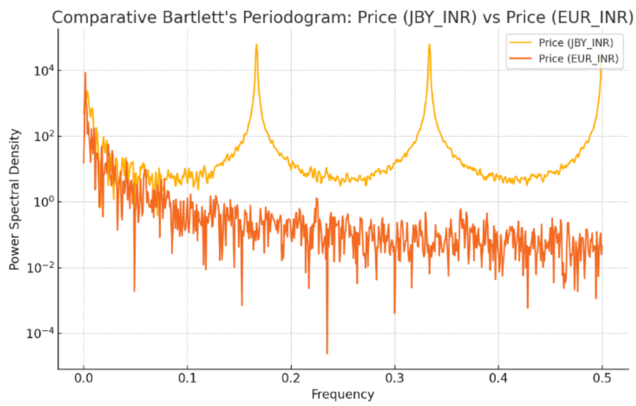
Price (NIFTY) and **Price (SENSEX)**: These financial indices might show more complex patterns, potentially influenced by market conditions, with the autocorrelation dropping off more sharply.



Interpretation: The comparative periodogram shows how the frequency components differ or are similar between the USD_INR and JBY_INR series. Significant peaks in either or both series indicate strong periodic components. This comparison helps determine if the two exchange rates share similar cyclical behaviours or if one has more pronounced periodicity.







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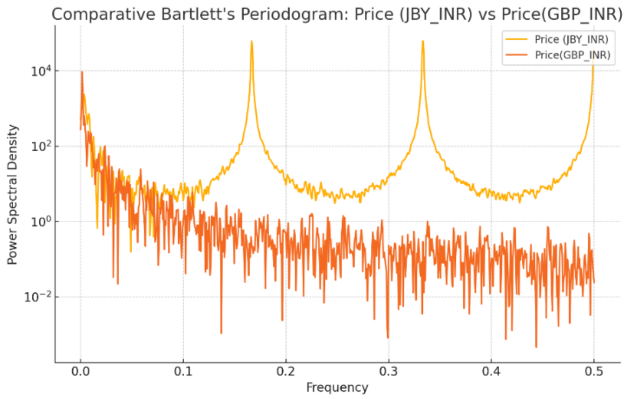
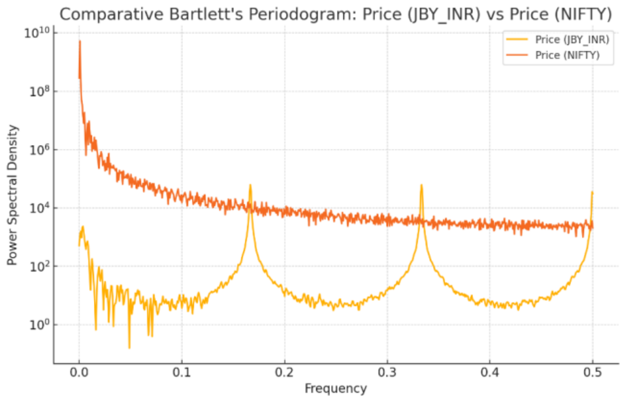
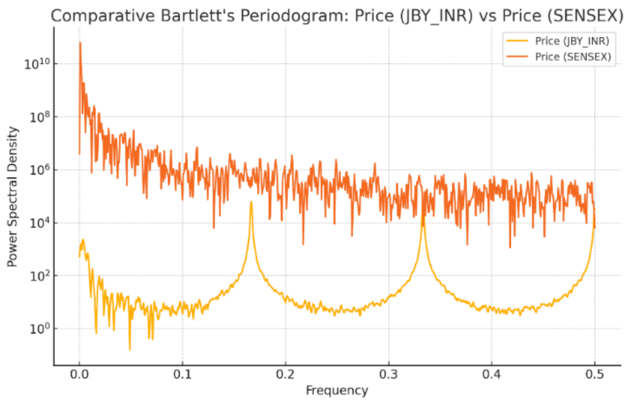
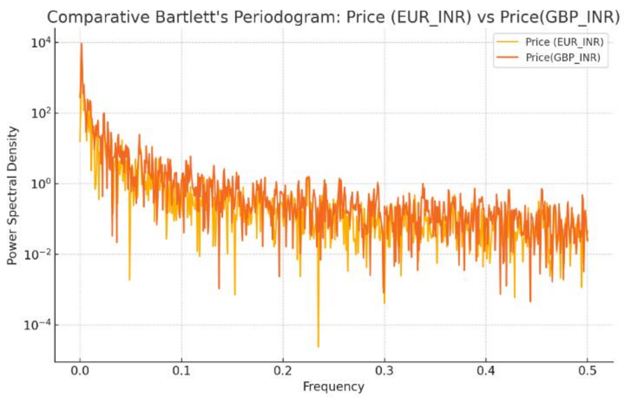
Interpretation: The periodogram comparison between JBY_INR and EUR_INR highlights the similarities or differences in their frequency components. Peaks in these series reveal the presence of strong periodic components, indicating whether the exchange rates exhibit similar cycles or trends.

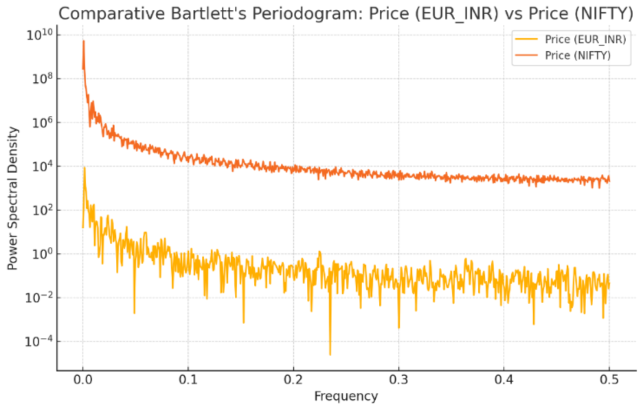


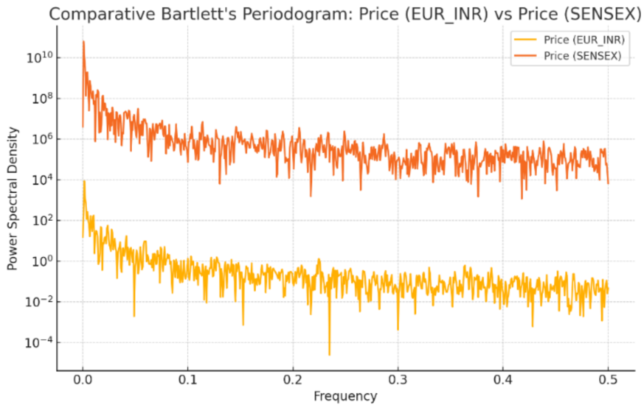


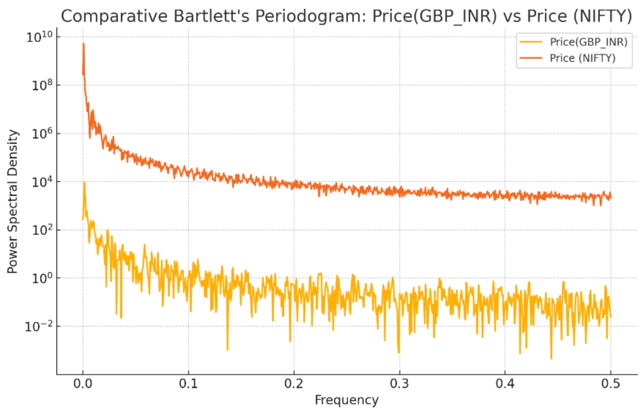




Interpretation: This comparison shows the frequency components of EUR_INR and GBP_INR. The presence of peaks suggests periodic components, and analysing these peaks can reveal whether these exchange rates have similar or distinct cyclical behaviours.







Interpretation: Comparing the GBP_INR exchange rate with the NIFTY index allows us to observe differences or similarities in their periodic components. Significant peaks in either series indicate strong cycles, helping to determine if the financial index and the currency exchange rate share any similar periodic behaviours.

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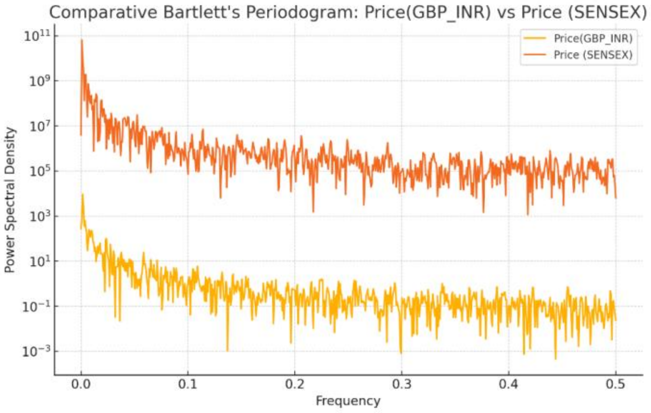
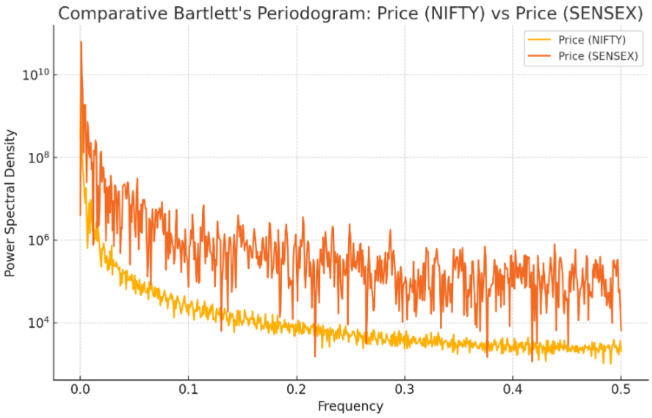


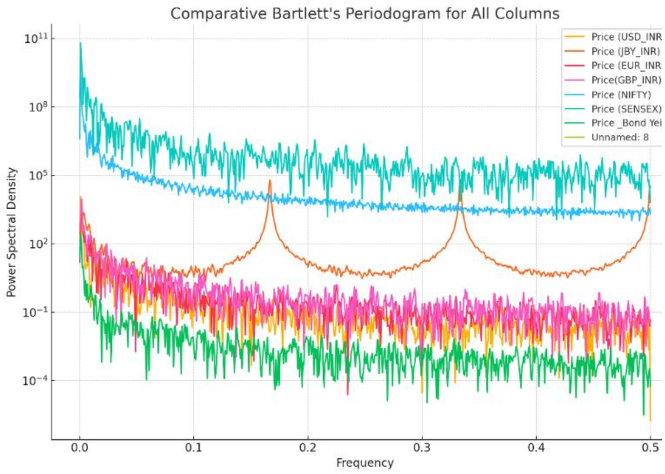


Interpretation: The periodogram for NIFTY vs SENSEX provides insights into the cyclical behaviours of these two key financial indices. Strong peaks in both series suggest that they may share similar cycles or trends, possibly due to underlying market factors.

Key Points

Comparative Analysis: Each graph compares the frequency components of two time series, allowing you to see how their periodic behaviours align or differ.

Interpretation: Significant peaks in either or both series indicate strong periodic components. The comparison helps identify whether the time series share similar cyclical behaviours or if one has more pronounced periodicity.



Here is the comparative Bartlett's periodogram for all columns in your dataset, with the power spectral densities plotted together on the same graph.

Interpretation:

The graph allows you to compare the frequency components of each time series.

Higher peaks in the curves indicate stronger periodic components in those time series.

Flatter curves suggest that the series has less periodicity and may be more random or influenced by noise.

The **differences in peak locations** among the curves can highlight varying dominant cycles or trends across the different time series.

This comparative analysis can help you identify which series have the most pronounced periodic behaviour and how they differ in terms of their frequency content.

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