# Does Momentum Pay in Currency Pairs Trading?

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## Abstract

**Purpose :** This study used pairs trading as a statistical arbitrage approach to experimentally examine possible arbitrage opportunities in the Indian currency market. Finding the best currency combinations and evaluating the selected pairs in terms of risk and return were the main goals.

**Methodology :** We focused on the Indian currency pairs EURINR, GBPINR, JPYINR, and USDINR because only these pairs were available for trading in India. Data reflecting the daily settlement price series from January 1, 2018 to December 31, 2022, was retrieved for the chosen currency pairs from Investing.com. In order to examine the dynamic pairs trading technique, we first used the distance approach to choose pairings according to how close they were. Next, we used the correlation and cointegration method to confirm the couples we had chosen.

**Findings :** The EURINR_GBPINR pair outperformed the other six currency pairings in our testing of the suggested pairs trading system. A robust return and a 10% significance level were found for the same pairs EURINR_GBPINR.

**Practical Implications :** The findings of this research are highly consequential for both investors and market players. Market players look for strategies to spread out their risks and maximize the likelihood of making a profit. This arbitrage strategy leads to more reliable hedging strategies for trading purposes. These findings may also interest investors and regulators, who must determine the suitability of their pairs for the Indian currency market.

**Originality :** We are aware of no previous research that looked at the pairs trading strategy's predictive ability in the other market categories but not in the Indian forex market. It is an intriguing potential to investigate the statistical mispricing between the values of currency pairings in this market, as the currency futures market is one of the biggest in the world and the Indian currency has seen substantial changes in recent times.

***Keywords* :** arbitrage opportunities, currency pair, cointegration, pairs trading, hedging funds

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A popular statistical arbitrage method that seeks to minimize exposure to overall market swings while capitalizing on relative price movements is pairs trading. It became more well-known after 1978, as Gatev indicated. Both corporate entities and individual investors use this method to hedge their funds. Gloukhov et al. (2014) and Miao (2014) have explained that in pairs trading, two highly correlated assets are chosen depending on market movement. It is a type of market-neutral technique that is necessary to evaluate past prices independent of the market's general trend in order to identify the market's typical pattern. The cointegration test and correlation coefficient are common statistical methods used by traders to evaluate the stability and strength of their assets. These tests essentially look for a long-term equilibrium relationship between the two variables, predicated on the assets' essential similarities. In order to attain a reasonably strong correlation that

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moves together and tends to return to its mean over time, couples are typically chosen from within the same industry or sector.

After determining a good pair, the trader takes a long position in the instrument that is predicted to perform well and a short position in the instrument that is likely to perform poorly. When buying and selling two connected assets at the same time, it's important to keep an eye on how the pair are performing in order to spot any changes in their anticipated relationship. This tactic is useful for producing the trade entry signal. If the spread, or the difference in value between the two assets, increases more than expected, selling the performing instrument and purchasing the underperforming one might result in profits. Conversely, if the spread contracts or reverses, holdings could be closed to reduce any losses.

To reduce possible trading losses, pairs trading demands meticulous risk management. When traders employ a range of risk-reduction techniques, like as stop-loss orders, to lessen losses in the event that a trade goes against them. In addition, measures for capital allocation and position sizing are employed to guarantee that capital is distributed appropriately throughout positions. The first scholarly work on pairs trading was published by Gatev et al. (1998, 2006), and since then, the trading strategy utilized in financial markets has been regularly modified and changed. This strategy has been altered multiple times to accommodate the demands of the modern financial industry, which mostly relies on technology. Krauss (2017) categorized pairs trading into a number of areas, including time series, distance, cointegration, stochastic control, and other methods that demonstrate flexibility and adaptability.

In the realm of pairs trading forward, several notable contributions have made important advances. Many scholars have made significant contributions to this field of inquiry, including Avellaneda and Lee (2010), Do and Faff (2010, 2012), Elliott et al. (2005), Gatev et al. (1998, 2006), Pizzutilo (2013), and Vidyamurthy (2004). It is important to note that these contributions predominantly focus on the utilization of daily data for implementing pairs trading strategies.

There has been a great deal of research done on pairs trading in the commodity and equity markets, but not as much on the currency market. No research has examined pairs trading in emerging markets for currencies, despite the fact that numerous articles concentrate on different facets of the currency market. The purpose of this study is to close that gap by investigating the potential for currency market arbitrage, with a particular emphasis on the Indian market. Trading currency pairs using the Indian Rupee (INR) dominates the Indian foreign exchange market. We choose these allowed currency pairs to trade on India's National Stock Exchange (NSE), including EURINR, GBPINR, JPYINR, and USDINR. I chose India as an emerging market due to the potential for currency trading to generate revenue within the country's economy and offer a more extensive selection of currency pairs for trading. As Miao (2014) noted, selecting possible couples is an essential first step in putting the market-neutral statistical arbitrage technique into practice. However, the ongoing pursuit of risk management, increased profitability, and flexibility in response to shifting market conditions is what propels pairs trading's significance in the developing market, particularly in Indian currency. The integration of macroeconomic information, central bank policies, and geopolitical events into pairs trading models can aid investors in comprehending trade patterns and the dynamics of the currency market.

## Literature Review/Theoretical Background

Hedge funds frequently use pairs trading as a market-neutral statistical arbitrage tactic. In order to profit from anomalous deviations, it seeks to find two asset classes that move in tandem and open long and short positions at the same time. The initial empirical work on pairs trading was conducted by Gatev et al. (1998) to analyze the performance of the arbitrage rule based on relative value. This study was later updated in 2006 with more recent data and framework. Additional studies by Elliott et al. (2005) and Gatev et al. (2006) used historical standard deviation of the spread to analyze pairs trading performance inside the US equities market. These studies proposed a mean-reverting Gaussian Markov chain model to generate wealth from financial markets. Similar empirical tests have been carried out by (Andrade et al., 2005; Bolgün et al., 2009; Broussard & Vaihekoski, 2012; Perlin, 2009) and others in a variety of markets, including Brazil, Turkey, Finland, and Taiwan. Mori and Ziobrowski (2011) investigated the same strategy in the US real estate market. Pairs trading has also been modeled as a mean-reverting process, and trading strategies have been proposed based on these models, as demonstrated by Do et al. (2006) and Elliott et al. (2005). Furthermore, co-integration, which refers to the tendency of pairs to exhibit an imperfect substitute relationship, has been closely associated with pairs trading. Cointegrated asset portfolio decision problems were studied by (Chiu & Wong, 2011; Liu & Timmermann, 2013; Tourin & Yan, 2013).

Kim (2011) conducted the initial study on pairs trading using high-frequency data. The many methods of pairs trading in the Asian stock market utilizing the Kalman filter are presented in this analysis. The research found that the technique can outperform even during down markets and that the time of market entry and exit has a significant impact on daily trading hours. Miao (2014) replicated these results on a broader sample of 177 American oil and gas firms, reporting high annual returns of up to 56.85% with the S&P 500 as a benchmark. Huck and Afawubo (2015) analyzed various pair trading methods to determine the optimal selection approach. In their empirical application of the pairs trading technique, they compared approaches like distance, cointegration, and stationary methods using the S&P 500 index. The findings demonstrated that the distance and cointegration approaches yielded reliable and consistent results; however, the stationary test performed poorly in the finance sector. Clegg and Krauss (2018) focused on an S&P 500 dataset and employed a cointegration approach to identify potential pairs.

Tokat and Hayrullahoğlu (2022) suggested a pairs trading framework for different asset categories using cointegration. Their structure performed effectively, with an average yearly return of 15%, even in challenging market conditions. Meanwhile, Ramos-Requena et al. (2020) identified several models for constructing pairs in pairs trading and observed that their new technique is more efficient than the prior equal-weighted strategy. Bhattacharjee and Swaminathan (2016) conducted a comparative analysis of India's stock market integration with global markets. Aggarwal and Khurana (2018) investigated the volatility of the stock market. In the foreign currency market, pairs trading using the cointegration-based technique was examined by Akhtar et al. (2021). They discovered that a large number of new pairings form and break at various times. The trading method to determine the price behavior of the Indian spot and futures markets for commodities was examined by Kumar and Shollapur (2015).

In conclusion, the research based on current studies indicates that pairs trading may prove to be a successful tactic if it is adopted and advances across many technologies. However, elements, including asset selection, trading restrictions, and market volatility, affect the strategy's performance. To optimize possible profits and reduce the danger of losses, traders must, like with any trading strategy, perform analysis and study prior to putting a pair's trading strategy into practice. Constant improvement is necessary to counteract the volatility of the market and avoid sudden mispricing corrections.

## Objective of the Study

This study aims to evaluate the risk-return analysis of the chosen currency and determine the optimal pairings for trading in the Indian currency market.

## Research Methodology

### *Dataset and Time Frame*

The present study is empirical and based on the Indian currency market. We selected the four currency pairs, EURINR, GBPINR, JPYINR, and USDINR, which are the only pairs available to trade in India. These two criteria determine the sampling period. In order to comprehend the long-term link between the price series, and must first meet the requirements of the model. The data for all the currency pairs are taken from investing.com and represent the daily closing prices of the series. A sample time range of five years, or 1308 daily observations, is obtained from January 1, 2018, to December 31, 2022. Our choice for processing and analyzing all the data is Microsoft Excel and EViews.

### *Construction of Methodology*

Three steps make up the current analysis of pairs trading on the forex market. We select the Indian currency pairs in order to screen the graph and determine the simultaneous and co-movement of the two currencies in order to select the best contender. To determine which final pair of currencies is suitable, we must measure the distance between the two series and use the cointegration test to validate the observed pairs. Once the ideal combination has been identified, we examine the risk-return analysis of the other pairs.

### *Distance Approach*

Currency pairs can be identified using the sum of square discrepancies between the normalized prices of the two-price series. A normalized series can be created using the following formula:

$$\text{norm}\, P_{it} = \frac{P_{it} - \overline{Xp}}{Sd_p} \qquad \text{……..} (1)$$

where norm $P_{it}$ denotes the normalized currencies, $P_{it}$ stands for the currency prices, $X_p$ represents the mean value of the currency series, and $Sd_p$ corresponds to the standard deviation of the currency prices.

The results are ranked in ascending order after calculating the sum of square differences for all price series. According to Gatev et al. (2006), the series that is most suited for pair trading is the one with the lowest sum of square differences.

### *Correlation*

Correlation is a statistical measure that describes the degree of association or relationship between the two pairs. It measures the strength and direction of the linear relationship between the two variables. This idea is essential to pairs trading since it serves as the basis for determining asset pairs that could be appropriate for a strategy based on pairs trading. It is commonly represented by a correlation coefficient, which has a range of –1 to +1.

### *Unit Root Test*

According to Brooks (2008), a time series is deemed strictly stationary if all higher-order moments remain constant and its probability distribution is invariant throughout time. Still, it is rare to find time series with strict stationarity. Thus, weakly stationary processes are appropriate to be viewed as stationary. The mean, variance, and autocovariance of a weak time series are all constant (Enders, 2010). Using the Augmented Dickey-Fuller (ADF) test with both constant and trend components, the degree of integration of the series was evaluated to match the Engle-Granger test's assumption:

$$\Delta y_t = \mu + \beta_t + a y_{t-1} + \sum\nolimits_{i=1}^{n} ci\, \Delta_{t-1} + \varepsilon_t \qquad \text{…….} (2)$$

where $y$ = the time series being tested, $T$ = a time trend term, $t$ = the first difference operator, $k$ = the optimal lag $t$ length, and $\varepsilon_t$ = a white noise disturbance term.

### *Cointegration Test*

The term cointegration refers to the relationship between two variables once the order of integration has been determined for each variable. If a stationary linear combination exists between two or more non-stationary series with the same order of integration, typically denoted as $I(0)$, then these series are considered cointegrated. This implies that a long-run equilibrium relationship exists between them. The concept of cointegration was introduced by Engle and Granger in 1987 and has since become an essential tool for analyzing the long-term dynamics and interdependencies among non-stationary time series.

$$y_t = \mu + \beta\chi_t + \varepsilon_t \qquad \text{..... (3)}$$

Here, we considered $x_t$ and $y_t$ are the currencies of the pairs and ε as the residual of the OLS equation.

### *Error Correction Model (ECM)*

Error correction models (ECMs) are regression models that incorporate both the current values of dependent variables and lagged values of the error correction term. The difference between the actual and anticipated values of the dependent variables is represented by the error correction term, which shows the tendency of the series to revert to the long-term equilibrium relationship. ECMs are theoretically based and offer insights into the dynamics of system changes made in the direction of equilibrium.

The basic form of an error correction model can be expressed as:

$$\Delta y_t = \alpha + \beta\Delta\chi_t + \gamma ECT_{t-1} + \varepsilon_t \qquad \text{...... (4)}$$

where $\Delta y_t$ and $\Delta\chi_t$ represent the first differences of the cointegrated time series $y$ and $x$, respectively, $ECT_{t-1}$ represents the lagged error correction term, α, β, and $y$ are the coefficient of the regression equation, and *et* is the white noise error term.

$ECT_{t-1}$ captures the deviation of the actual values of $y$ from the long-term equilibrium relationship between $y$ and $x$. The sign and magnitude of the *ECT* reflect the speed and direction of adjustment of $y$ back to its equilibrium relationship with $x$. An approach that is used to estimate the rate of speed of adjustment of a dependent variable's return to equilibrium about to change in other variables.

## Performance Evaluation

### *Sharpe Ratio*

Sharpe ratios are frequently employed in finance to evaluate the risk-adjusted performance of investments. It measures the excess return attained for each unit of risk assumed. The following formula can be used to get the Sharpe ratio:

$$\text{Sharpe Ratio} = (Rp - Rf) / \sigma p$$

where,

- $Rp$ stands for the expected return on investment.

- $Rf$ denotes the risk-free rate of return, typically derived from the yield of a risk-free asset like a government bond.
- $\sigma p$ signifies the standard deviation of the investment or portfolio's returns, which quantifies the volatility or risk.

### *Alpha Ratio*

The alpha ratio is a metric used to evaluate the risk-adjusted performance of an investment or portfolio by comparing its actual returns to the expected returns based on a benchmark. It makes it possible to determine whether an investment, taking into account the amount of risk taken, has fared better or worse than the benchmark. The alpha ratio can be calculated using the following formula:

$$\text{Alpha Ratio} = (Rp - (Rf + \beta p * (Rb - Rf))) / \sigma p$$

where,

- $Rp$ represents the actual return on the investment or portfolio.
- $Rf$ denotes the risk-free rate of return, typically derived from the yield of a risk-free asset like a government bond.
- $\beta p$ refers to the beta of the investment or portfolio, which measures its sensitivity to market movements.
- $Rb$ signifies the return of the benchmark index.
- $\sigma p$ represents the standard deviation of the investment or portfolio's excess returns.

### *Risk–Return Ratio*

The risk–reward ratio is a metric used to evaluate an investment or trade's possible benefit in relation to its possible loss. It aids investors in assessing the proportionality of the risk assumed and the possible return. This formula is used to compute the risk–reward ratio:

Risk–Reward Ratio = Potential Reward/Potential Risk

where,

- The potential reward is the expected profit or return from the investment or trade if it is successful.
- Potential risk is the potential loss or downside risk associated with the investment or trade if it is unsuccessful.

## Empirical Analysis and Results

The following outcomes are obtained from pairs trading simulations following an examination of several methodologies. The sample size of the data's descriptive statistics is shown in Table 1. It includes the number of observations in the sample size, the average, median, maximum, minimum, standard deviation, kurtosis, skewness, and Jarque–Bera probability. The fact that only one of the four currency pairs—JPYINR—is negatively skewed suggests that most of the data is concentrated on the negative side of the distribution. With the exception of the USDINR, which suggests that the series is not normally distributed, the likelihood of the Jarque–Bera test is almost nil. The requirement to use the pairs trading and cointegration models is satisfied when the observation of all currency pairs equals 1,308.

Table 1. ***Descriptive Statistics of the Sample***

| | Mean | Median | Max | Min | *SD* | Skew. | Kurt. | Jarque–Bera | Obs. |
|---|---|---|---|---|---|---|---|---|---|
| EURINR | 82.80 | 82.21 | 90.76 | 75.95 | 3.76 | 0.25 | 1.79 | 0* | 1308 |
| GBPINR | 94.93 | 94.42 | 105.05 | 83.64 | 4.93 | 0.09 | 1.96 | 0* | 1308 |
| JPYINR | 0.65 | 0.65 | 0.71 | 0.5512 | 0.04 | –0.57 | 2.71 | 0* | 1308 |
| USDINR | 73.04 | 73.33 | 83.01 | 63.34 | 4.08 | 0.05 | 3.21 | 0.19 | 1308 |

***Note.*** * Marks indicate a significant *p*-value at a 5% level of significance.

Pairs trading starts with graph screening, which involves analyzing a graph visually to determine how two currencies are moving simultaneously and co-moving. Chart patterns for the data are displayed in Figures 1 (a) – (d), and the combined chart pattern of EURINR and GBPINR is displayed in Figure 1(e).

**Figure 1.** ***Graphs of the Currencies (January 1, 2018 – December 31, 2022)***

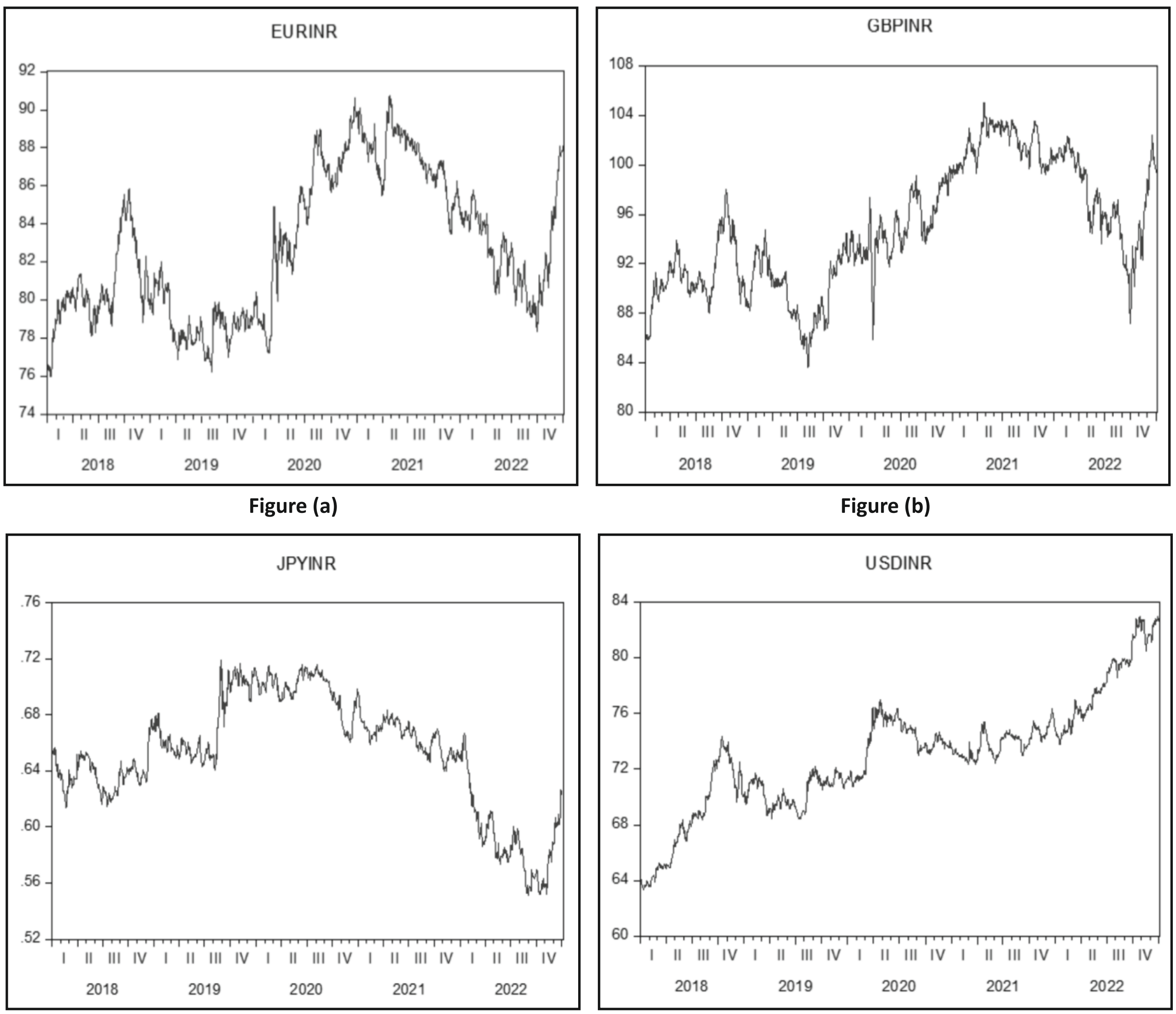


Figure (a) Figure (b)

Figure (c) Figure (d)

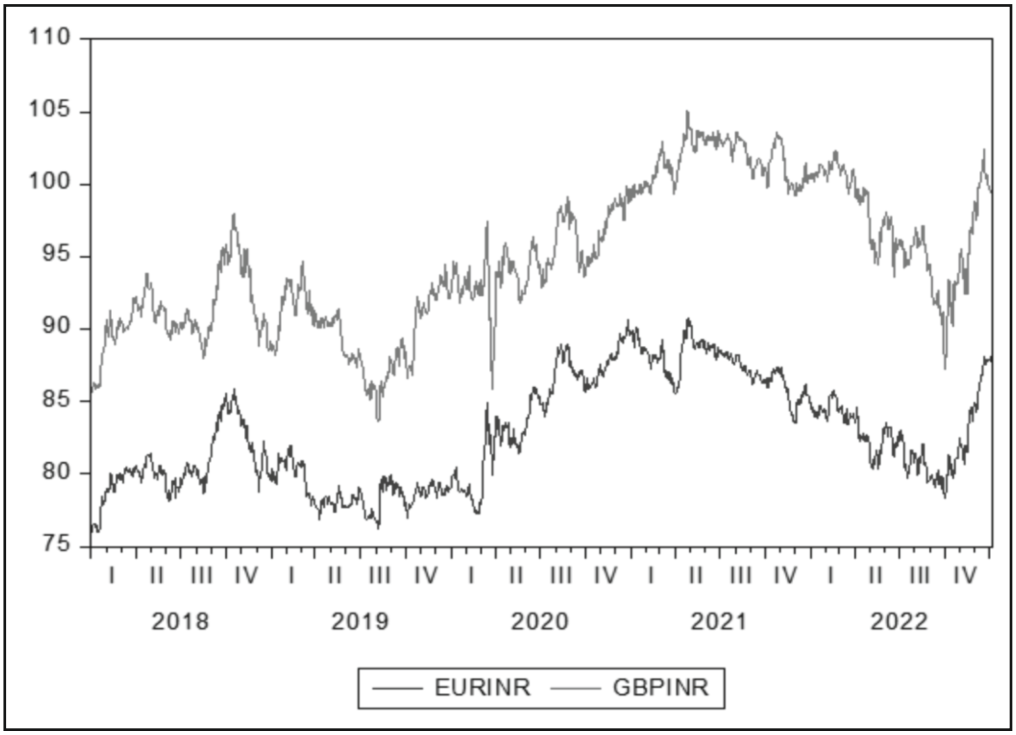


**Figure (e)**

**Table 2.** ***Correlation Between the Currency Pairs***

| Currency Pairs | Correlation | Percentage |
|---|---|---|
| EURINR & GBPINR | 0.870318 | 87% |
| EURINR & JPYINR | 0.16409 | 16% |
| EURINR & USDINR | 0.429621 | 43% |
| GBPINR & JPYINR | –0.02104 | –2% |
| GBPINR & USDINR | 0.501771 | 50% |
| JPYINR & USDINR | –0.35398 | –35% |

Table 2 illustrates the correlation among different currency pairs, and we utilized a correlation-based approach to select potential currency pairs for pairs trading. The initial step in the pair's trading strategy was to identify pairs with high correlation coefficients from the same sector, as described in Equation (1). A positive correlation between the price series of four pairs of currencies was found through analysis, suggesting that these pairings move in the same direction. However, the two pairs showed a strong tendency to move against each other and had extremely negative correlations. Among these pairs, EURINR_GBPINR exhibited the highest correlation coefficient of 87%, indicating a positive linear relationship between the price series of these currencies. Fortunately, this pair also satisfies the requirements of the pair's trading strategy.

Table 3 displays the outcomes of the ADF test, which was conducted to test for the presence of a unit root in both level data and first difference data. We were unable to reject the null hypothesis of the ADF test for level data for three pairings (EURINR, GBPINR, and JPYINR) because the $p$-value was higher than the 5% significance level. Nevertheless, the $p$-value was less than the 5% significance level when the first difference data was examined, suggesting that all of the series are integrated of order $I(1)$. On the other hand, USDINR was found to be integrated of order $I(0)$ since the null hypothesis was rejected for level data, suggesting that it is stationary at the level.

**Table 3.** ***ADF Test for Unit Root Test***

| | At Level | | 1st Difference | |
|---|---|---|---|---|
| | *t* - statistics | Pro* | *t* - statistics | Pro* |
| EURINR | –0.916076 | 0.3195 | –37.28507 | 0.000 |
| GBPINR | –0.779983 | 0.3783 | –35.77247 | 0.000 |
| JPYINR | 0.139347 | 0.7263 | –38.42244 | 0.000 |
| USDINR | –2.053560 | 0.0384* | –36.78161 | 0.000 |

***Note.*** * Marks indicate the significance *p*-value at a 5% level of significance.

**Table 4.** ***Ranks of Pairs by Distance Approach***

| Distance Approach | | |
|---|---|---|
| Pairs | Sum of Square | Rank |
| EURINR & GBPINR | 339.2468921 | 1 |
| EURINR & JPYINR | 1303.368244 | 2 |
| EURINR & USDINR | 1492.11124 | 3 |
| GBPINR & JPYINR | 2186.740024 | 4 |
| GBPINR & USDINR | 2671.04152 | 5 |
| JPYINR & USDINR | 3542.018159 | 6 |

**Table 5.** ***ADF Test on Residuals (Level)***

| Pairs | OLS Equation | *t*-value |
|---|---|---|
| EURINR & GBPINR | 19.809 + 0.663 × GBPINR | –3.18441* |
| EURINR & JPYINR | 72.879 + 15.200 × JPYINR | –1.67134 |
| EURINR & USDINR | – | – |
| GBPINR & JPYINR | 96.601 + –2.556 × JPYINR | –1.60891 |
| GBPINR & USDINR | – | – |
| JPYINR & USDINR | – | – |

***Note.*** *marks indicate the significant *t*-value at 10%, critical values for the Engle-Granger test at 10% levels are 3.04.

Table 4 shows the ranks of selected currency pairs that were obtained using the distance approach. There are a maximum of six conceivable combinations of two pairs because there are four currencies. The rankings are shown in ascending order and are based on the lowest sum of squared. All six pairs were selected for validity testing. The outcomes of the distance approach indicate that the currency pair EURINR_GBPINR performed the best among all six pairs. Consequently, we conducted a cointegration model to validate this pair.

Table 5 represents the result of Engle-Granger's two-step tests of cointegration. The third column shows the estimated parameters for Equation (2) for the respective pairs, while the fourth column displays the computed *t*-values of the ADF test applied to the residuals obtained from the respective regression equations. The Engle-Granger test of cointegration relies on these *t*-values to determine whether to accept or reject the null hypothesis. One currency pair equation, EURINR_GBPINR, is integrated of order $I(0)$ at the 10% level of significance despite the fact that the table displays an empirical test of all six currency pairs. This implies that the cointegration exists only between EURINR_GBPINR in all currency pairs. We fail to reject the null hypothesis for the remaining two pairs because the computed value is less than the critical value of the Engle-Granger test. Only three pairs out of six pairs satisfy the assumption that the series must be integrated of order $I(1)$ for the Engle-

Table 6. ***Results of ECM***

| Pairs | Coefficient of ECT | *t*-value | Prob. |
|---|---|---|---|
| EURINR & GBPINR | –0.01567 | –3.52988 | 0.0004* |

***Note.*** *marks indicate the significant *p*-value at the 5% level.

**Table 7. *Risk–Return Analysis Result of Hedging Between EURINR and GBPINR***

***(Sample Period January 1, 2018 to December 31, 2022)***

| Performance of Trading Result | 2018 | 2019 | 2020 | 2021 | 2022 | The Sum of 5 Years |
|---|---|---|---|---|---|---|
| Profit (%) | 80% | 163% | 200% | 116% | 179% | 738% |
| Absolute Profit | 30,093 | 35,153 | 79,801 | 29,680 | 47,347 | 222,074 |
| Average Profit | 5,015.58 | 3,905.89 | 8,866.78 | 3,590.63 | 5,344.72 | 5,345 |
| Average Profit (%) | 13.34% | 18.12% | 22.32% | 14.35% | 17.04% | 17% |
| No. of Portfolio | 6 | 9 | 9 | 9 | 8 | 41 |
| No. of Win | 83% | 78% | 100% | 89% | 100% | 90% |
| No. of Loss | 17% | 22% | 0 | 11% | 0% | 10% |
| Average Capital | 56,094.66 | 55,025.32 | 44,045.36 | 47,560.10 | 50,681.36 | 50,681.36 |
| Buy & Hold Return | 7% | 7% | 17% | –4% | 4% | 32% |
| Alpha Ratio | 73% | 156% | 183% | 120% | 175% | 706% |
| Sharpe Ratio | 80% | 72% | 273% | 86% | 74% | 74% |
| Risk–Reward Ratio | –0.05 | 0.01 | 0.06 | 0.16 | 0.04 | 0.04 |

Granger test; that is, the reason the remaining three cells are blank in the table because we cannot apply the test on these pairs.

Table 6 presents the results of the ECM. In column 2, the cointegrated currency pairs are mentioned for respective periods, and column 3 contains the coefficient of error correction term (ECT). Finally, only one pair is available to apply the ECM. In the empirical analysis, the coefficient of ECT is interpreted as the speed of adjustment, which is 1.5% per day between the exchange rates EURINR_GBPINR, and the coefficient of ECT is found negative and significant.

Table 7 presents the condensed outcome of the proposed market-neutral statistical arbitrage strategy. The statistically significant pair EURINR_GBPINR was used to derive the year-wise result from all sample testing periods from January 2018 to December 2022. The standard deviation is used to determine when to enter and quit a trade when building the portfolio. Based on the entry total of 41 trade portfolios are made, including 37 winning and 4 loss trades. The percentages of the winning and loss trade were 90% and 10%, respectively. In 2020, maximum opportunities were created with 200% profit due to volatility. The average capital used in these periods is 50,681.36. the absolute profit is 222,074 with transaction cost.

## Conclusion

The market-neutral statistical arbitrage approach forms the basis of Gatev's pair trading strategy. In order to examine every potential pairing of currency pairs, we employ the distance approach, correlation analysis, and the well-known mean-reversion cointegration approach in this work. More precisely, we determined six possible combinations among the four Indian foreign exchange currencies that we chose: EURINR, GBPINR, JPYINR, and USDINR. The currency data included in our simulation was obtained from investing.com, wherein volume and daily OHLC (open, high, low, close) values were obtained for every currency pair. The simulation lasted for five years, starting on January 1, 2018, and ending on December 31, 2022.

Our findings have important implications for both theoreticians and practitioners. Through the pre-selection process utilizing the distance approach, we identify the closest pair with the smallest distance number, which we deemed most suitable for pair trading. We use the Engle and Granger residual-based cointegration approach to validate these six currency pairs after ranking all other currency pairs based on the sum of square differences. Only the EURINR_GBPINR pair demonstrated statistical significance at a 10% level, according to our empirical findings.

To implement our trading strategy, we construct a portfolio specifically for the EURINR_GBPINR pair. We relied on upper and lower bands, determined by adding 1.5 times the standard deviation to the mean and subtracting 1.5 times the standard deviation from the mean, respectively, to identify entry and exit points for trades. Throughout our study, we created a total of 41 trade portfolios, consisting of 37 winning trades and 4 losing trades. The winning trades accounted for 90% of the total, while the losing trades constituted only 10% of the portfolio.

In the year 2020, we observed maximum opportunities due to volatility, resulting in a 200% profit. The average capital utilized during this period was 50,681.36, and the absolute profit generated, including transaction costs, amounted to 222,074. Our returns exhibited limited risk. To summarize, our research provides evidence of the effectiveness of pairs trading strategies with positive performance in recent times. Moving forward, both researchers and practitioners must adapt their trading strategies according to the prevailing market conditions. Future studies should consider exploring hybrid approaches that combine pair selection methods and trading thresholds, taking into consideration the dynamic nature of the market at any given time. This will enable a more comprehensive understanding and implementation of pairs trading strategies.

## Managerial and Theoretical Implications

The currency market contributes to the major economies of the world. It allows investors to hedge against the adverse movement of individual currencies. The current analysis of pairs trading offers opportunities for financial gain by taking advantage of the brief divergence in the relative prices of the currency pairs. It also adds to portfolio diversification by exposing investors to several currencies at once. The existence of arbitrage opportunities provides insight into the dynamics of the market microstructure. It will be necessary to do additional studies to fully investigate this implication, which will lead to an increasing need for investors to select currency combinations that will yield reliable outcomes.

## Limitations of the Study and Scope for Further Research

The cointegration model, for example, has certain assumptions that the series must be integrated with order $I(1)$, but these requirements are not always met because the study focuses on the ramifications of pairs trading in the currency market. In order to look at the long-term relationship between the price series, many econometrics models can be used. In order to find more couples, we might also employ other time frames with less observation. More research can be done on the several facets of pair trading, such as behavioral elements and market effects, such as transaction costs. Pairs trading's ultimate goal is to identify further market opportunities and risks that could prevent the strategy from being implemented successfully.

## Authors' Contribution

N. S. Malik proposed the idea of examining the foreign exchange market through a variety of pairs trading techniques. By employing keywords to find pertinent previously published work on this topic, Farhat Akhtar created the concepts. She also employed the appropriate statistical tools to fulfill the aims and reported the findings. N. S. Malik verified the conceptual and analytical approaches. Farhat Akhtar wrote the manuscript.

## Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or material discussed in this manuscript.


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