Pairwise Trading: A Quantitative Approach to Exploiting Market Inefficiencies

A

report submitted in fulfillment of colloqium for the course IMMG-4993

By

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DECLARATION

I hereby certify that the work, which is being presented in the report, entitled ”Pair Trading: A Quantitative Approach to Exploiting Market Inefficiencies”, in fulfillment of the requirement for the course IMMG-4993(Colloqium) and submitted to the institution is an authentic record of our own work carried out during the period May-2024 to Aug-2024. I also cited the reference about the text(s)/figure(s)/table(s) from where they have been taken.

Dated: **Signature of the candidate**

Acknowledgements

I am highly indebted to the professors, for their esteemed mentorship, and for allowing me to freely explore and experiment with various ideas in the course of making this project a reality. The leeway I was given went a long way towards helping cultivate a genuine hunger for knowledge and keeping up the motivation to achieve the best possible outcome. I can genuinely say that this Bachelor's Thesis Project (BTP) made me explore many areas of machine learning that are new to me, and kindled an interest to further follow up on some of those areas. Moreover, the semi-successful completion of this project has brought with it great satisfaction and more importantly, confidence in my ability to produce more high-quality non-trivial artificial intelligence systems that can make a difference in the real-world. I would like to sincerely express my gratitude to this prestigious institution for providing me and my colleagues with the opportunity to pursue this BTP. It is an honor to be able to work on such an important academic project under the guidance and support I am provided with. I am grateful for the resources and facilities provided by this institution, which have been instrumental in enabling me to conduct my research and complete this project. Moreover, I deeply appreciate the efforts of my professors in mentoring and fairly evaluating our works.

Kodarapu Kaushik

Abstract

Pairwise trading is a vital strategy in the realm of algorithmic trading, offering a market-neutral approach that leverages the price relationship between two correlated assets to capitalize on market inefficiencies. By simultaneously taking opposing positions in these paired assets, traders can profit from the convergence of their prices, irrespective of broader market trends. This strategy is particularly important for reducing portfolio risk while maintaining the potential for profit, even in volatile or bear markets. In this study, we develop and implement a pairwise trading model, focusing on the critical aspects of pair selection, signal generation, and risk management. Through extensive backtesting, we demonstrate that pairwise trading can consistently generate risk-adjusted returns, highlighting its significance as a tool for managing risk and enhancing profitability in diverse market conditions.

Keywords: Pairwise Trading, Statistical Arbitrage, Cointegration strategy, Market-Neutral Strategy, Correlated Assets, Mean Reversion, Algorithmic Trading, Risk Management, Backtesting, Financial Markets, Quantitative Finance.

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List of Acronyms

ECM	Error Correction Model
ADF	Augmented Dickey-Fuller
OLS	Ordinary Least Squares
ECM	Error Correction Model
Z-Score	Standard Score
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
VAR	Vector Autoregression
RMSE	Root Mean Square Error
VaR	Value at Risk
SMA	Simple Moving Average
R^2	Coefficient of Determination (R-squared)
VIX	Volatility Index
ROI	Return on Investment
ETF	Exchange-Traded Fund
CAGR	Compound Annual Growth Rate

1

Introduction

In financial markets, prices of assets that are correlated often move in tandem. Pairwise trading seeks to exploit discrepancies in these movements by trading two such correlated assets. The strategy involves identifying pairs of financial instruments whose price movements are closely linked, and then taking long and short positions when the spread between their prices deviates from the expected norm. The premise is that the prices will revert to their historical relationship, allowing for profitable trades..

1.1 Background and Rationale

Pairwise trading, also known as Pairs trading, is a market-neutral strategy rooted in statistical arbitrage. It was first conceptualized by quantitative traders in the 1980s and has since become a fundamental strategy in algorithmic trading. The strategy involves identifying two historically correlated financial instruments and placing simultaneous long and short positions when the price spread between them diverges from its historical mean. The underlying assumption is that the prices of these correlated assets will eventually revert to their historical relationship, allowing the trader to profit from the convergence. This strategy is particularly appealing because it is market-neutral, meaning it is designed to profit regardless of overall market direction. This makes it an effective tool in various market conditions, including periods of high volatility or market downturns, where traditional long-only strategies may suffer.

The evolution of pairwise trading has been marked by significant advancements in statistical methods and computational power. With the advent of high-frequency trading and the availability of vast amounts of historical data, traders can now implement more sophisticated models to enhance the accuracy and profitability of pairwise trading strategies. Additionally, the integration of machine learning techniques has opened new avenues for improving pair selection, signal generation, and risk management.

Implementing a pairwise trading strategy stems from several key factors:

- Market Neutrality
- Risk Reduction
- Consistency of Returns
- Advancements in Technology
- Exploit Market Inefficiencies
- Scalability across Different Markets

1.2 Significance of Pairwise Trading in Financial Markets

1.2.1 Market Neutrality

Pairwise trading is inherently market-neutral, which means it is designed to profit regardless of the direction of the broader market. This characteristic is crucial during periods of market turbulence or when overall market movements are unpredictable. By focusing on the relative price movements of two correlated assets, pairwise trading reduces exposure to systemic risks and market-wide fluctuations. This neutrality allows traders to generate returns in both bullish and bearish market conditions, making it a valuable strategy for maintaining profitability in diverse market environments.

1.2.2 Risk Mitigation

One of the primary advantages of pairwise trading is its ability to mitigate risk. Traditional trading strategies often involve taking long positions in individual assets, which can expose traders to significant market risk and sector-specific volatility. In contrast, pairwise trading involves simultaneously taking long and short positions in correlated assets. This balanced approach helps offset potential losses from adverse price movements, reducing the overall risk in a portfolio. Effective risk management is essential for maintaining stable returns and protecting against significant drawdowns.

1.2.3 Consistent Returns

Pairwise trading strategies are designed to capitalize on the mean-reverting behavior of asset price spreads. By identifying pairs of assets with a historically stable price relationship, traders can exploit deviations from this norm to generate consistent returns. The ability to generate returns regardless of market direction, combined with a systematic approach to trading, contributes to the strategy's potential for stable and predictable performance. This consistency is particularly appealing to institutional investors and hedge funds seeking reliable sources of alpha.

1.2.4 Exploiting Market Inefficiencies

Financial markets are not perfectly efficient, and price discrepancies can arise due to various factors such as news, earnings reports, or market sentiment. Pairwise trading provides a systematic method for identifying and exploiting these inefficiencies. By focusing on the relative pricing between correlated assets, traders can take advantage of temporary mispricings and profit from the expected convergence of prices. This ability to exploit market inefficiencies contributes to the strategy's effectiveness and profitability.

1.2.5 Diversification

Pairwise trading allows for diversification across different asset classes and markets. By trading pairs of assets that are correlated but belong to different sectors or geographic regions, traders can achieve diversification while maintaining a focus on relative price movements. This diversification reduces the impact of sector-specific or regional risks on the overall portfolio, enhancing its stability and resilience.

1.2.6 Adaptability

The flexibility of pairwise trading makes it suitable for various market conditions and asset types. Traders can apply this strategy to equities, commodities, currencies, and other financial instruments. Additionally, advancements in data analytics and machine learning enable traders to refine their pair selection and trading models continuously. This adaptability ensures that pairwise trading remains relevant and effective in evolving market environments.

1.2.7 Regulatory Compliance

In regulated markets, pairwise trading can provide a method for achieving compliance with certain trading restrictions. By focusing on relative price movements and employing a market-neutral approach, traders can avoid positions that might trigger regulatory concerns related to market manipulation or excessive exposure. This characteristic makes pairwise trading a suitable strategy for institutional investors operating under stringent regulatory frameworks.

In summary, pairwise trading holds significant importance in financial markets due to its market-neutral nature, risk mitigation capabilities, potential for consistent returns, and ability to exploit market inefficiencies. Its adaptability and suitability for diversification further enhance its value as a trading strategy. As financial markets continue to evolve, pairwise trading remains a relevant and effective tool for achieving stable, risk-adjusted returns.

2

Related Work

This chapter reviews the existing literature and foundational studies related to pair trading strategies, including traditional methods and recent advancements. The sections below outline the evolution of pair trading systems, the statistical techniques employed, the role of machine learning in pair selection, and a comparative analysis of various trading techniques.

In [1], Kok and Timmer provide a comprehensive review of the evolution and foundational developments in pairwise trading systems. They summarize significant studies and seminal works that have shaped the concept of statistical arbitrage and pairwise trading. Their review highlights how early theoretical frameworks, such as cointegration, have contributed to the development of contemporary trading strategies. By examining the historical progression of these models, Kok and Timmer emphasize the crucial role that theoretical foundations play in understanding and improving statistical arbitrage practices. Their work sets the stage for understanding how historical developments have influenced modern trading strategies.

Engle and Granger [3] introduced the concept of cointegration, which is central to early statistical arbitrage models. Their seminal research demonstrated that even if individual time series are non-stationary, their linear combinations can be stationary. This groundbreaking insight allows for the generation of meaningful trading signals from otherwise non-stationary data. Their work laid the theoretical foundation for many subsequent studies in the field, and their approach has been fundamental in the development of cointegration-based trading strategies. The implications of their research continue to influence modern statistical arbitrage methods.

Fang and Yao [4] explore practical implementations of statistical arbitrage models, focusing on the advancements made possible by increased computational power and data accessibility. Initially, simpler tools like moving averages were employed, but Fang and Yao highlight how the incorporation of high-frequency data and sophisticated econometric models has significantly improved the accuracy of trading signals. Their research underscores the impact of modern technology on enhancing the precision and effectiveness of trading strategies, marking a shift from basic to more advanced analytical techniques.

Recent advancements in machine learning are explored in [16], where the authors discuss how machine learning algorithms have transformed pair selection in trading strategies. Machine learning techniques such as clustering, regression, and classification are now used to identify and forecast optimal asset pairs more effectively. This progress reflects a shift towards leveraging complex algorithms to analyze large datasets and uncover intricate relationships between assets, significantly enhancing the ability to develop predictive trading strategies.

Zhang and Wang [13] delve into how machine learning models can improve traditional pair trading strategies. They examine the integration of machine learning features to capture market dynamics better, enhancing the performance of trading strategies. Their work demonstrates how advanced models, including those using machine learning, can refine and elevate traditional statistical methods by incorporating more dynamic and responsive features. This research highlights the evolving nature of pair trading strategies and the growing role of technology in finance.

Despite technological advancements, traditional methods such as cointegration remain valuable, as discussed by He and Liu [12] and Zhao and Liu [18]. These researchers emphasize the ongoing relevance of cointegration-based methods due to their robustness and theoretical grounding. Their studies argue that while machine learning offers new capabilities, traditional methods continue to be crucial for reliable trading signal generation. This balance between traditional and modern approaches underscores the importance of maintaining a theoretical foundation while integrating new technologies.

Momentum trading and trend-following strategies are analyzed in [20], which provides a comparative perspective on various trading methods. Momentum trading, based on the persistence of asset price trends, and trend-following strategies, which capture sustained price movements, are examined alongside pairwise trading. This comparison reveals that pairwise trading can be particularly effective in stable or mean-reverting markets where asset performance is more predictable. The study highlights the strengths and weaknesses of different strategies and the conditions under which pairwise trading may excel.

The distance-based approach to pair trading is discussed by Tan and Chen [17] and Kim and Park [15]. They investigate how distance metrics can identify trading pairs with similar price trajectories. While distance-based methods offer simplicity and ease of implementation, the authors note that they may not fully capture market dynamics compared to more complex techniques like cointegration. This research provides insight into the practical advantages and limitations of distance-based methods, contributing to the broader understanding of pair trading strategies.

The choice of cointegration, distance, and statistical arbitrage strategies is supported by prior research, as highlighted in [4] and [25]. These methods offer unique advantages, including robust theoretical foundations and practical applications. Cointegration approaches are praised for their solid theoretical basis in modeling long-term asset price relationships, while statistical arbitrage strategies are effective in exploiting short-term price inefficiencies. The research underscores the value of these methods in various trading contexts and their continued relevance in financial analysis.

Finally, the assessment of potential advantages and limitations of different trading strategies is discussed in [6] and [27]. Cointegration-based methods, while robust, may require frequent adjustments to remain effective in changing market conditions. Distance-based approaches, although simpler to implement, may lack the theoretical depth of cointegration methods. The integration of these traditional methods with advanced machine learning techniques represents a promising direction for future research and application, offering a comprehensive view of pair trading methodologies and their evolving landscape.

3

Existing Methodologies

In this section, you will discuss the various methodologies that have been employed in the field of pair trading and financial market analysis. This includes both conventional approaches and modern techniques that incorporate machine learning and artificial intelligence..

3.1 Conventional Approaches

This section outlines traditional methodologies used in pairwise trading as discussed in [9]. It includes:

- **Distance Method:** This approach relies on the Euclidean distance between the price series of two assets. It assumes that if two stocks behave similarly (e.g. belong to the same industry), their price series should move closely together. When the distance between them widens, it creates a trading opportunity, with the expectation that they will eventually converge.

- **Statistical Arbitrage:** As described in [12], statistical arbitrage involves exploiting statistical mispricings in the market by identifying pairs of securities that historically move together. When the prices of these securities diverge beyond a certain threshold, the strategy involves taking a long position in the underperforming security and a short position in the outperforming one, with the expectation that they will converge.

- **Mean Reversion Models:** These models are based on the assumption that asset prices will revert to their historical mean over time. Techniques such as the Ornstein-Uhlenbeck process are used to model the price dynamics and generate trading signals based on deviations from the expected mean.

- **Cointegration Analysis:** Cointegration analysis is crucial in pair trading strategies as it identifies pairs of assets with prices that tend to move together over the long term. This section explores the principles of cointegration, its implementation in pair trading, and the successful outcomes observed in previous studies.

- **Copula-Based Strategy:** Copula functions are used to model and simulate the joint distribution of asset returns, allowing traders to capture the dependency structure between different assets more accurately. This approach is particularly useful for understanding tail dependencies, which are crucial in risk management, as it allows for modeling and analyzing the dependency structure between asset pairs beyond linear correlation.

3.2 Modern Approaches: Machine Learning and AI

This section covers contemporary methodologies incorporating machine learning and artificial intelligence in pairwise trading as discussed in [30]. It includes:

- **Machine Learning Models:** The use of algorithms like Support Vector Machines (SVM), Random Forests, and Neural Networks in refining pair selection and generating trading signals. Machine learning models excel in analyzing large datasets, uncovering intricate patterns, and identifying relationships that traditional methods might miss.

- **Deep Learning Techniques:** This section discusses the application of deep learning approaches, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to predict price movements and detect trading opportunities. These models can capture non-linear relationships and temporal dependencies in financial data.

- **Algorithmic Trading Systems:** Reviews the integration of machine learning models into algorithmic trading platforms for real-time decision-making and automated execution of trades. This includes the use of reinforcement learning to optimize trading strategies dynamically based on market conditions.

- **Enhanced Pair Selection:** Covers advancements in using machine learning for more accurate and dynamic pair selection. Techniques such as clustering algorithms and factor analysis are used to identify and maintain optimal asset pairs for trading.

- **Hybrid Approaches:** Hybrid approaches combine conventional statistical methods with modern ML and AI techniques to create more robust trading models. This section provides examples of how these hybrid models are constructed, their performance in empirical studies, and the benefits of integrating different methodologies.

Despite the advancements, modern approaches come with their own set of challenges. These include the limitations of ML and AI in pair trading, such as issues related to overfitting, data quality and computational complexity. Considerations for selecting the appropriate methodology based on market conditions and data availability are also addressed.

4

Proposed Methodology

This section will provide a high-level summary of the methodologies employed to evaluate and compare various pair trading strategies. The primary focus will be on the application of Cointegration combined with Statistical Arbitrage strategies and the Distance method. We will explore how these approaches are utilized to identify and capitalize on trading opportunities. Additionally, a comparative analysis will be conducted to assess the effectiveness and performance of these strategies in relation to other relevant methodologies. This will help in understanding their relative advantages and limitations within the context of pair trading..

4.1 Selection of Sectors and Asset Pairs

Sectors were selected based on key factors such as volatility and historical performance. The study focuses on five diverse sectors from the NSE: reality, banking, information technology (IT), pharma, and auto. For each sector, three asset pairs were chosen using correlation analysis and economic rationale to ensure relevance and potential for profitable trading. The proposed strategy involves the use of the cointegration and distance methods for pairs trading. These methods have been selected based on their proven effectiveness in different market conditions, as well as their strong theoretical foundations.

4.2 Data Collection and Preprocessing

- **Data Sources:** Historical price data were sourced from Yahoo Finance.
- **Data Preprocessing Steps:**
  - *Handling Missing Data:* Missing or incomplete data points can distort analysis results. We will address this by identifying any gaps in the data, which might involve missing trading days or incomplete price information. Common methods for handling missing data include interpolation (estimating missing values based on surrounding data points) or using forward-fill/backward-fill techniques to fill in missing values with the last known price.
  - *Normalizing Prices:* To facilitate meaningful comparisons and analysis, especially when dealing with stocks of different price levels, we will normalize the prices. Normalization may involve adjusting prices to a common scale or converting them to percentage changes, which allows for comparison across different stocks and time periods.
  - *Transforming Variables:* Depending on the analysis methods used, certain transformations might be necessary. This could include calculating logarithmic returns (which stabilize variance and make data more normally distributed) or

applying other mathematical transformations to better meet the assumptions of statistical models.

- *Data Integration and Alignment:* Ensuring that the data for all selected stocks is aligned in terms of time periods is crucial. We will synchronize the data to ensure that comparisons are made on equivalent dates, handling any discrepancies between trading calendars or non-trading days.

4.3 Implementation of Pair Trading Strategies

4.3.1 Cointegration Approach

This method involves identifying pairs of stocks whose price series are cointegrated, meaning they have a long-term equilibrium relationship and tend to move together. When these pairs diverge from this equilibrium, trades are initiated based on the expectation that the prices will revert to their mean.

4.3.2 Distance-Based Approach

The Distance Method involves selecting pairs of stocks that have historically exhibited similar price movements. This approach is based on identifying pairs that have a high historical correlation or have shown a tendency to converge after periods of divergence.
To implement this method:

Pair Selection: Begin by selecting stock pairs that have demonstrated a strong historical correlation. This can be assessed by examining the historical price data to identify pairs with a consistent tendency to move in tandem over time.

Threshold Adjustment: Set the distance threshold for identifying trading opportunities. This threshold is adjusted to 5% of the initially calculated distance between the price series of the selected stock pairs. This adjustment helps in defining the boundary for divergence and convergence.

Spread Calculation: For the selected pairs, compute the daily spread, which is the absolute difference between the prices of the two stocks. The spread at time t is defined as:

$$\text{spread}_t = |X_{2,t} - X_{1,t}| \tag{4.1}$$

This measure helps in quantifying the divergence between the stock prices and assessing potential trading signals based on their historical convergence patterns.
The threshold is calculated as:

$$\text{threshold} = |\text{mean\_spread} + k \times \text{standard\_deviation}| \tag{4.2}$$

where k is a constant that determines how many standard deviations away from the mean will trigger a trade.
By applying the Distance Method, we aim to identify stock pairs likely to revert to their historical price relationship. This helps to spot trading opportunities based on the convergence and divergence of their price spreads.

4.3.3 Statistical Arbitrage

This approach also involves cointegration but adds an extra layer by using Ordinary Least Squares (OLS) regression. It refines the identification of opportunities by analyzing the residuals (the differences between actual and predicted values) to make trading decisions. This method is more data-driven and quantitative, aiming for precision in predicting mean reversion. The Error Correction Model (ECM) is then applied to capture the mean-reverting behavior of the spread, which is used to execute trades.
The spread at time t is given by:

$$\text{spread}_t = |X_{2,t} - \beta X_{1,t}| \tag{4.3}$$

where $X_{1,t}$ and $X_{2,t}$ represent the price series of the two stocks at time t.
The Error Correction Model is represented as:

$$\Delta y_t = \alpha + \beta \Delta x_t + \gamma \text{ECM}_{t-1} + \epsilon_t \tag{4.4}$$

where ECM_{t-1} is the error correction term (deviation from the equilibrium).

4.3.4 Calculation of the Stock Returns Correlation Matrix

A correlation matrix is computed for each sector, visualized using a heatmap from the Seaborn library. This matrix displays Pearson's correlation coefficients among the 10 stocks within each sector, covering 45 unique pairs. The correlation coefficients are derived from the percentage change in the closing prices of the stocks.

4.3.5 Detection of Cointegrated Stock Pairs

Cointegrated stock pairs are identified using the `coint` function from the `statsmodels` library's `stattools` submodule. Pairs with p-values less than 0.05 are deemed cointegrated. Results are represented through heatmaps, which help in pinpointing suitable pairs for inclusion in a trading portfolio.

4.3.6 Development of OLS Regression Model for Pairs

For pairs that are found to be cointegrated, an Ordinary Least Squares (OLS) regression model is constructed. The stock with the higher average closing price serves as the predictor in this model. Key outputs from the OLS regression include the hedge ratio, p-values for t-statistics and F-statistics.

4.3.7 Stationarity Testing of OLS Model Residuals

The stationarity of the residuals from the OLS model is evaluated using the Augmented Dickey-Fuller (ADF) test, implemented through the `adfuller` function from `statsmodels`. Residuals are considered stationary if the ADF test statistic is significantly negative and below the critical values, or if it is positive and exceeds the critical values, confirming cointegration.

4.3.8 Trading Signal Generation for Pairs

Trading signals are generated based on the Z-scores of the price ratio between the predictor and target stocks. The ratio is standardized, and Z-scores are calculated and compared against predefined thresholds (± 1). A Z-score exceeding the upper limit triggers a short position on the predictor stock, while a Z-score falling below the lower limit prompts a long position. These signals are recorded in a dataframe that includes columns for date, asset1, asset2, Z-score, upper limit, lower limit, and trading signals.

4.3.9 Identifying Potential Investment Points

Investment opportunities are identified by analyzing changes in trading signals. Additional columns for `positions1` and `positions2` track changes in signals for asset1 and asset2, respectively. These changes help in identifying when to enter or exit positions. A graph is plotted to visualize these triggers over the test period.

4.3.10 Calculation of Pair Portfolio Returns

The portfolio starts with 100,000 rupees allocated to each asset on January 1, 2021, amounting to a total investment of 200,000 rupees. The daily values of the holdings and cash are calculated to monitor the portfolio's total value.

The annual returns and risk-adjusted performance of portfolios based on each trading strategy are compared. This involves analyzing how well each strategy performed across the five sectors: auto, banking, it , pharma, and realty sector. Key metrics include total return, accuracy and maximum drawdown.The strategies' reliability is tested through out-of-sample testing and sensitivity analysis. This checks how well the strategies perform on unseen data and their sensitivity to changes in key parameters. Practical challenges encountered during the implementation of these strategies includes data limitations, such as quality and availability, as well as computational complexity these factors impact the strategies' effectiveness.

5

Experiment and Results

This section offers an in-depth evaluation of the pair-trading portfolios' performance across different sectors. The analysis was conducted using Python 3.9.7, with essential libraries such as NumPy, pandas, Matplotlib, statsmodels, and seaborn for data processing, model development, and performance evaluation. The computational models were executed in a GPU-enabled environment on Google Colab to enhance processing efficiency and manage large datasets effectively.

5.1 It Sector

In the IT sector, we examined three pairs of stocks using both Cointegration and Statistical Arbitrage strategies. Out of ten pairs in this sector that showed significant cointegration results, the following three pairs were selected for detailed study:

- TCS (TC) and CoForge (CF)
- Infosys (IF) and HCL Technologies (HC)
- Tech Mahindra (TM) and L & T Tech Services (LS)

Each pair is assessed for cointegration, followed by the application of Statistical Arbitrage using OLS -regression.

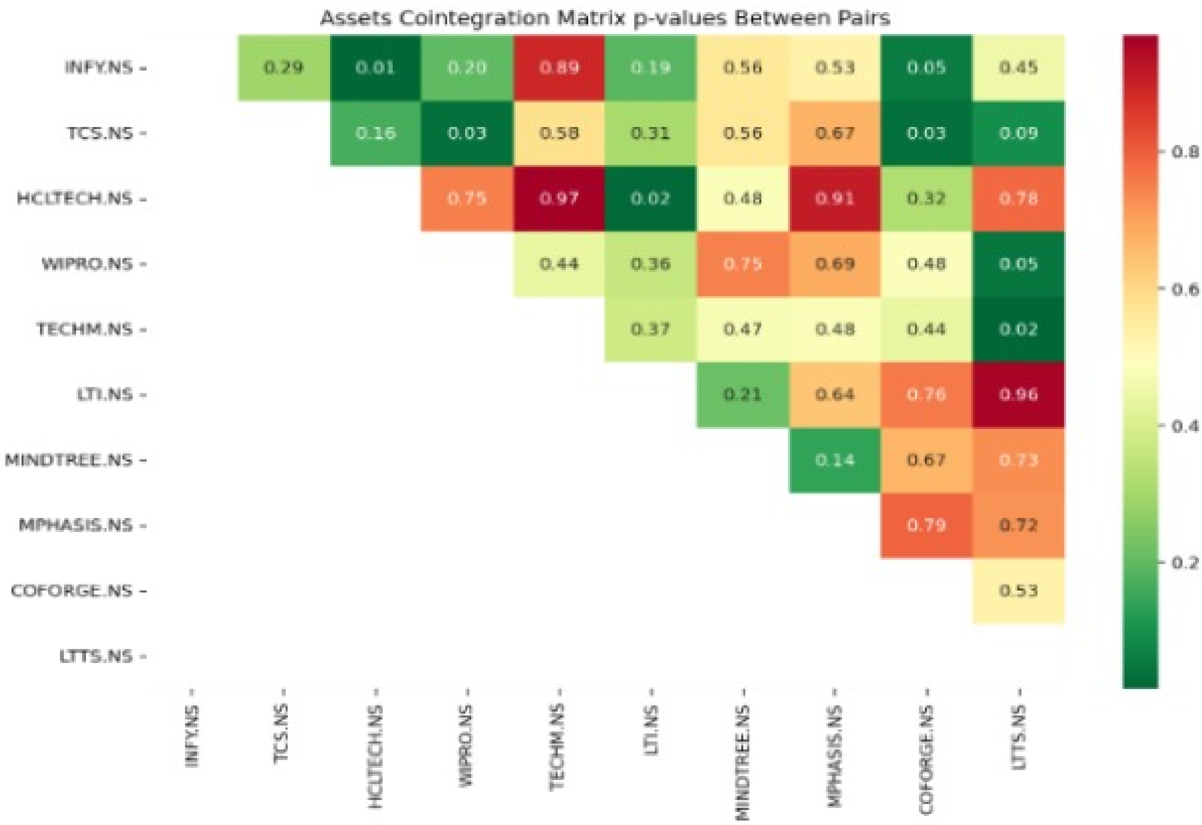

Figure 5.1: Asset Cointegration Matrix

The residual spread plot for the TC-CF OLS model

Figure 5.2: Pairs Spread

The residual z-value plot for the TC-CF OLS model

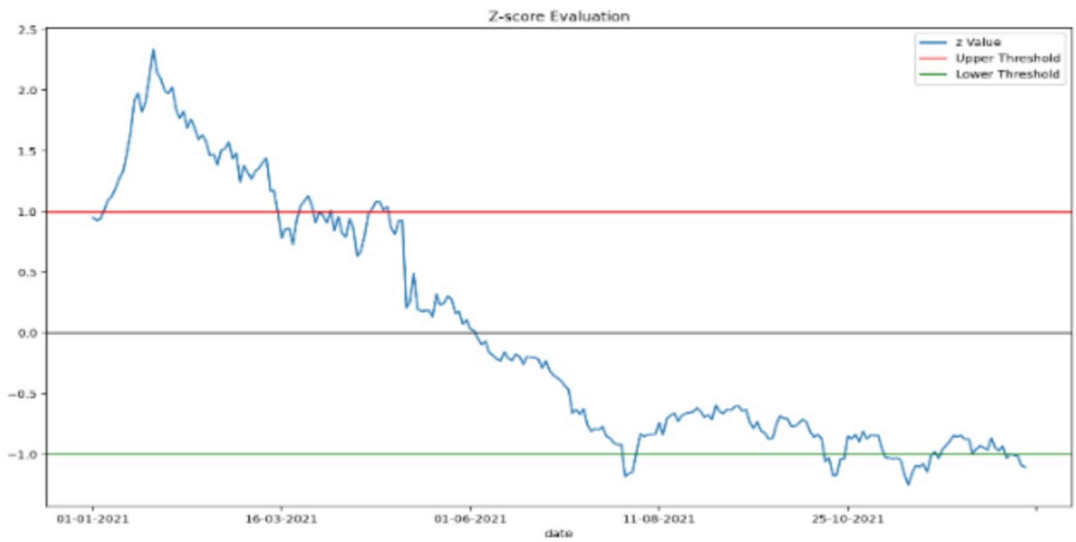

Figure 5.3: Z-values

The initial investment of 200,000 on January 1, 2021, the pair trading strategy yielded a return of 8.73%. The Augmented Dickey-Fuller (ADF) test conducted on the ratio series produced a test statistic of -1.2592. This value is higher than the critical value of -3.4392 at the 1% significance level, suggesting that the residuals are not stationary. Despite this, the pair trading strategy was implemented.

Figure 5.4: The pair trading scenario for the pair TC and CF, including the identification of trading signals and their respective positions.

```
Model Summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Close   R-squared:                       0.780
Model:                            OLS   Adj. R-squared:                  0.779
Method:                 Least Squares   F-statistic:                     1724.
Date:                Sun, 25 Aug 2024   Prob (F-statistic):          3.98e-162
Time:                        14:31:54   Log-Likelihood:                -3003.0
No. Observations:                 489   AIC:                             6010.
Df Residuals:                     487   BIC:                             6018.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        711.7564     30.069     23.670      0.000     652.674     770.838
Close          1.0180      0.025     41.526      0.000       0.970       1.066
==============================================================================
Omnibus:                       19.779   Durbin-Watson:                   0.099
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               21.474
Skew:                           0.513   Prob(JB):                     2.17e-05
Kurtosis:                       2.978   Cond. No.                     7.24e+03
==============================================================================
```

Figure 5.5: OLS Regression Results

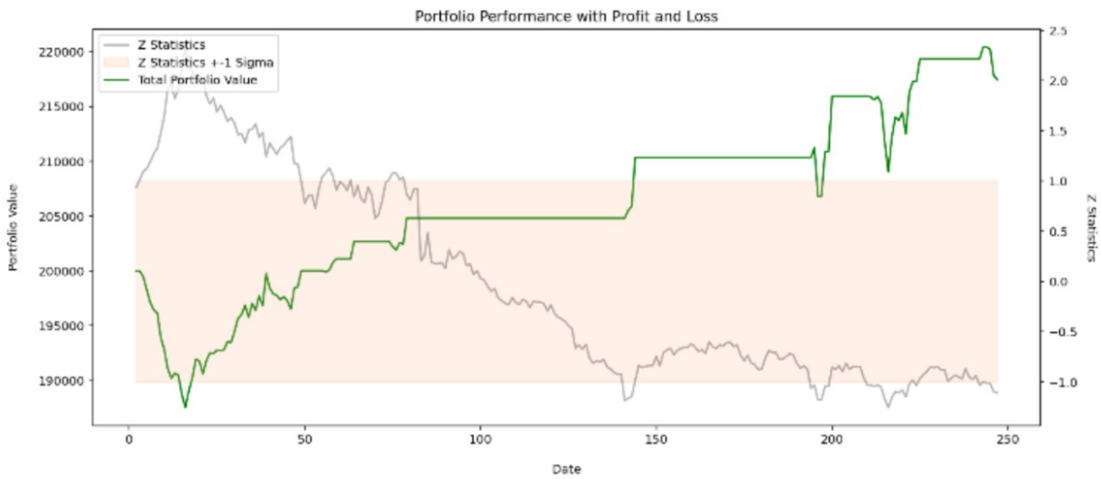

Figure 5.6: Portfolio Performance

Table 5.1: Financial Performance of Selected Stock Pairs Using cointegration

Stock Pair	Init Investment	Profit	Annual Return
IF - HC	200000	10940	5.47
TM - LS	200000	6720	3.36
TC - CF	200000	17460	8.73

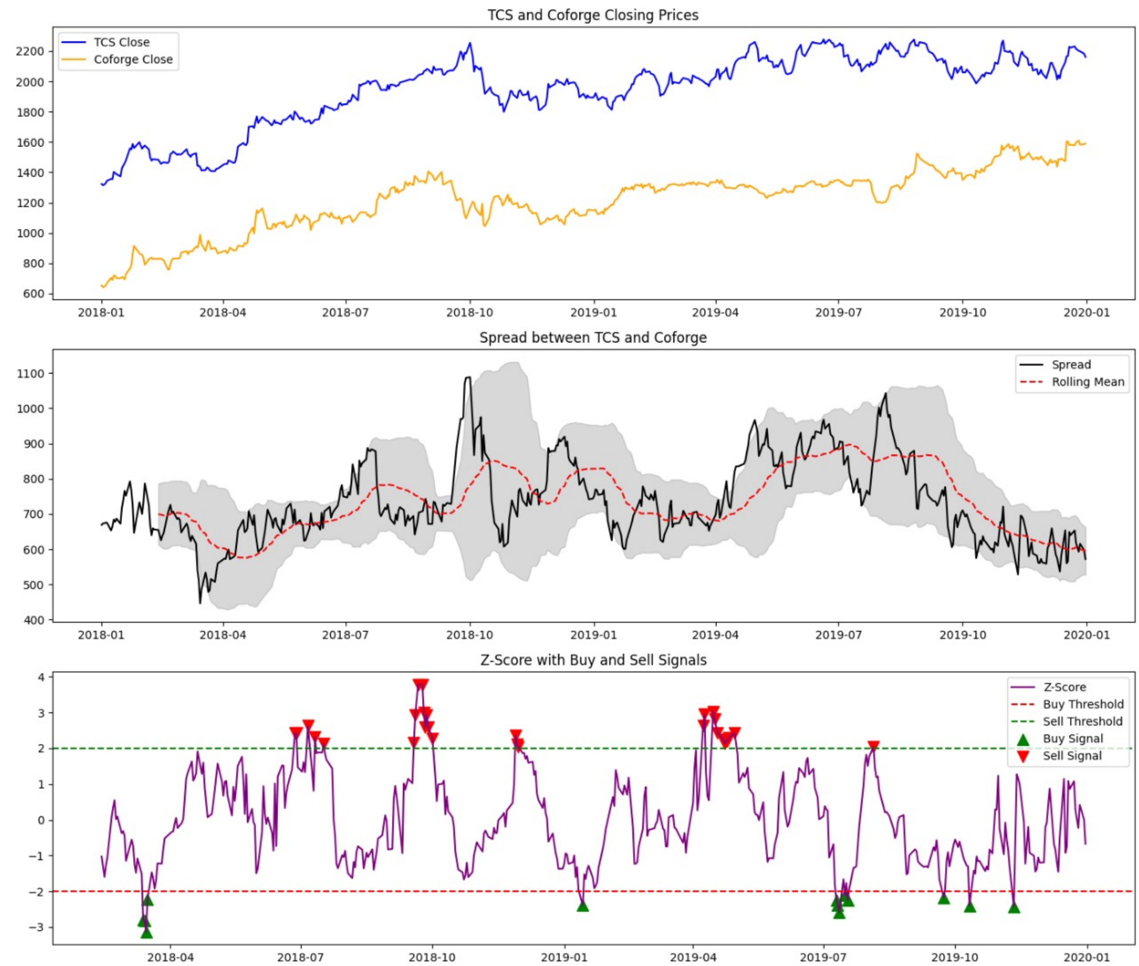

Figure 5.7: Distance Approach

Table 5.2: Financial Performance of Selected Stock Pairs Using distance

Stock Pair	Init Investment	Profit	Annual Return
IF - HC	200000	11320	5.66
TM - LS	200000	10320	5.16
TC - CF	200000	18400	9.2

5.2 Auto Sector

In the Auto sector, we examined three pairs of stocks using both Cointegration and Statistical Arbitrage strategies. Out of ten pairs in this sector that showed significant cointegration results, the following three pairs were selected for detailed study:

- Maruti Suzuki (MS) and Eicher Motors (EM)
- Ashok Leyland (AL) and Bharat Forge (BF)
- Ashok Leyland (AL) and Eicher Motors (EM)

Each pair is assessed for cointegration with Statistical Arbitrage using OLS regression, followed by the application of distance method.

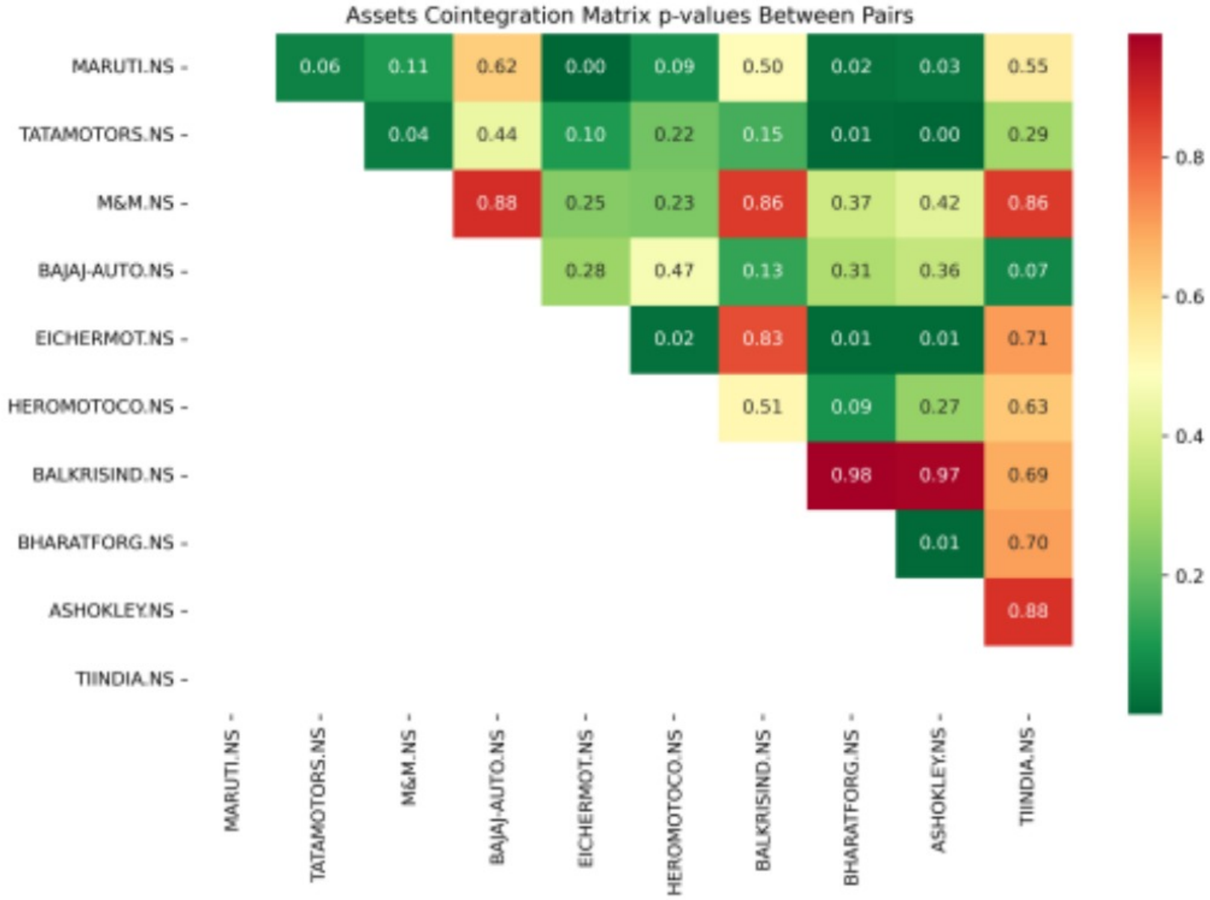

Figure 5.8: Asset Cointegration Matrix

The residual spread plot for the AL-BF OLS model

Figure 5.9: Pairs Spread

The residual z-score plot for the AL-BF OLS model

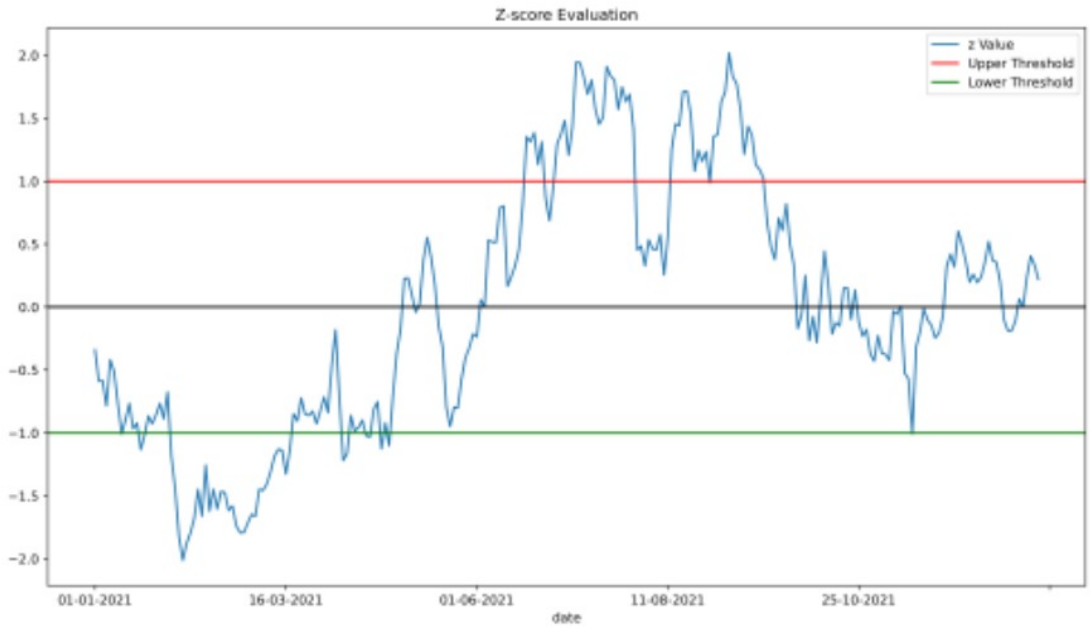

Figure 5.10: Z-values

The initial investment of 200,000 on January 1, 2021, the pair trading strategy yielded a return of 9.96%. The Augmented Dickey-Fuller (ADF) test conducted on the ratio series produced a test statistic of -2.5566. This value is higher than the critical value of -3.4392 at the 1% significance level, suggesting that the residuals are not stationary. Despite this, the pair trading strategy was implemented.

Figure 5.11: The pair trading scenario for the stocks BF and AL , including the identification of trading signals and their respective positions.

```
Model Summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Close   R-squared:                       0.905
Model:                            OLS   Adj. R-squared:                  0.905
Method:                 Least Squares   F-statistic:                     4640.
Date:                Sun, 25 Aug 2024   Prob (F-statistic):          4.29e-251
Time:                        14:11:53   Log-Likelihood:                -1742.2
No. Observations:                 489   AIC:                             3488.
Df Residuals:                     487   BIC:                             3497.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -28.4678      1.984    -14.348      0.000     -32.366     -24.569
Close          0.2405      0.004     68.121      0.000       0.234       0.247
==============================================================================
Omnibus:                        5.844   Durbin-Watson:                   0.108
Prob(Omnibus):                  0.054   Jarque-Bera (JB):                6.015
Skew:                          -0.196   Prob(JB):                       0.0494
Kurtosis:                       3.375   Cond. No.                     2.88e+03
==============================================================================
```

Figure 5.12: OLS Regression Results

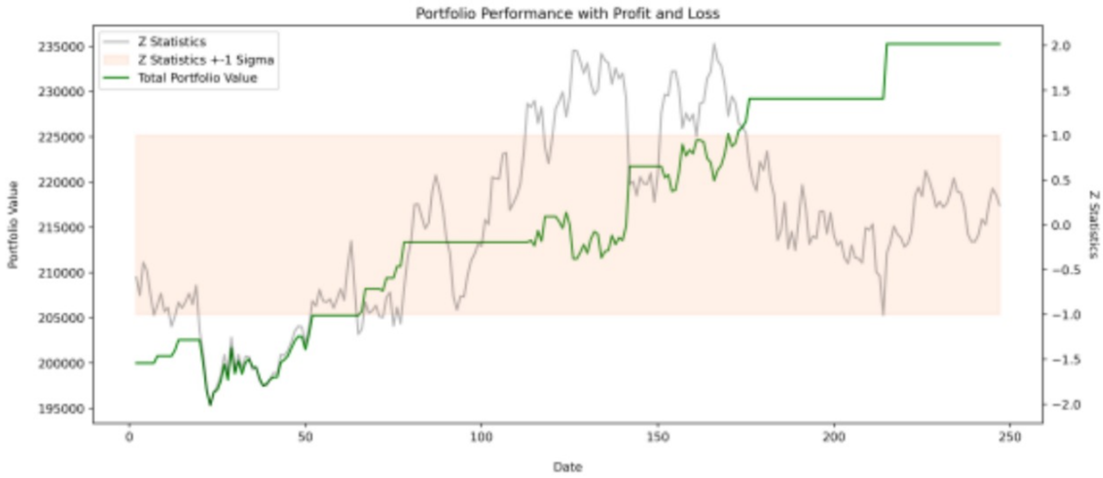

Figure 5.13: Portfolio Performance

Table 5.3: Financial Performance of Selected Stock Pairs Using cointegration

Stock Pair	Init Investment	Profit	Annual Return
EM - MS	200000	23968	11.98
AL - BF	200000	35270	17.63
EM - AL	200000	27773	13.89

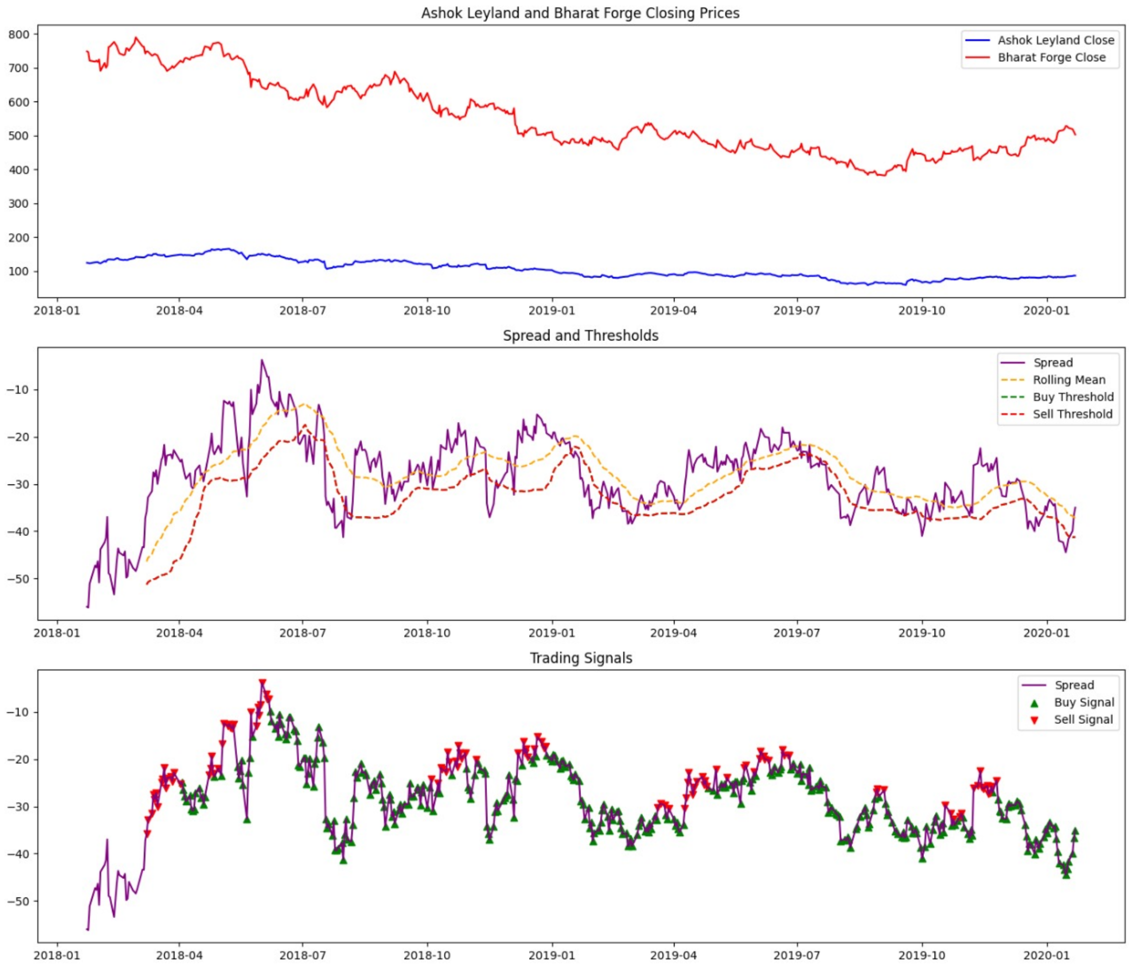

Figure 5.14: Distance Approach

Table 5.4: Financial Performance of Selected Stock Pairs Using distance

Stock Pair	Init Investment	Profit	Annual Return
EM - MS	200000	22160	11.08
AL - BF	200000	25260	12.63
EM - AL	200000	21780	10.89

5.3 Pharma Sector

In the Pharma sector, we examined three pairs of stocks using both Cointegration and Statistical Arbitrage strategies. Out of ten pairs in this sector that showed significant cointegration results, the following three pairs were selected for detailed study:

- Biocon (BI) and Lupin (LP)
- Lupin (LP) and Alkem Labs (AK)
- Divi's Labs (DV) and Dr. Reddy's Labs (DR)

Each pair is assessed for cointegration, followed by the application of Statistical Arbitrage using OLS regression.

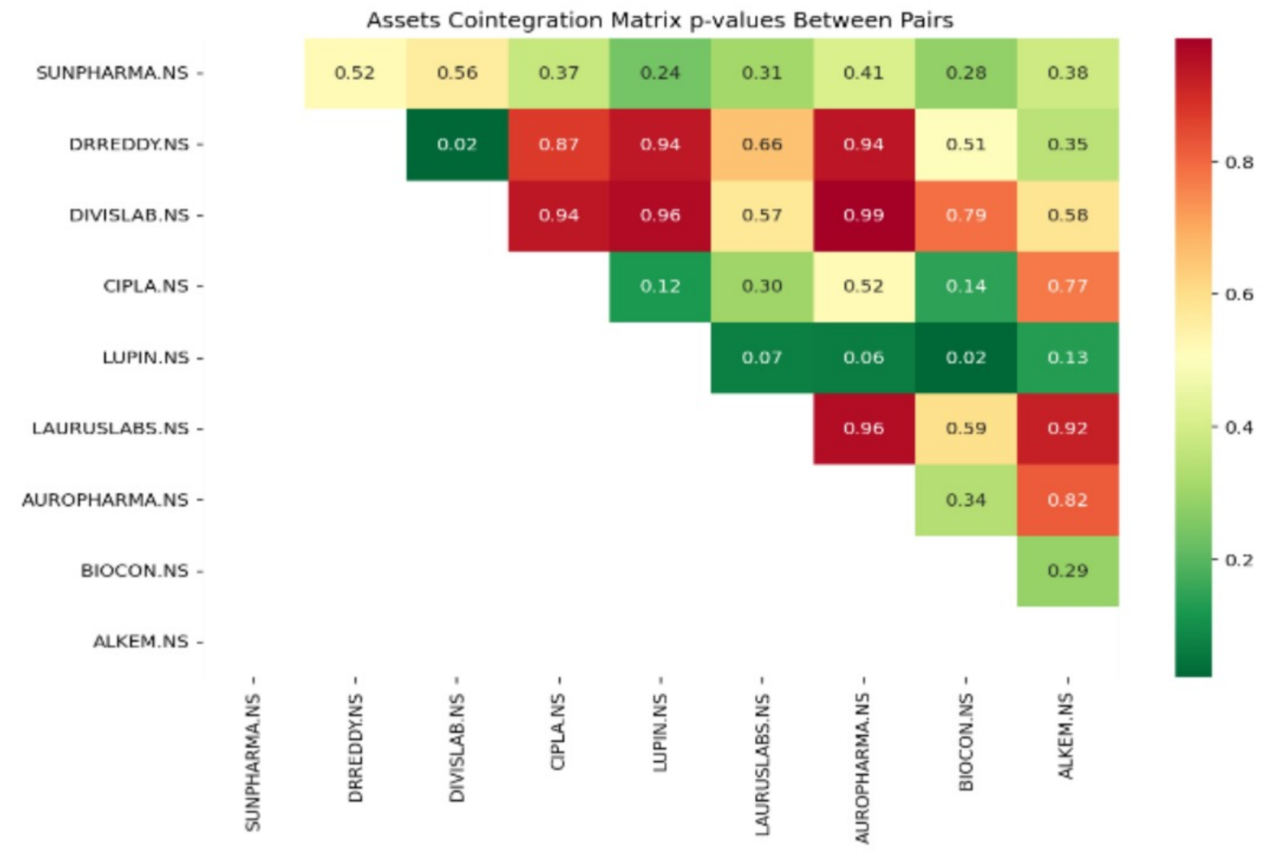

Figure 5.15: Asset Cointegration Matrix

The residual spread plot for the LP-AK OLS model

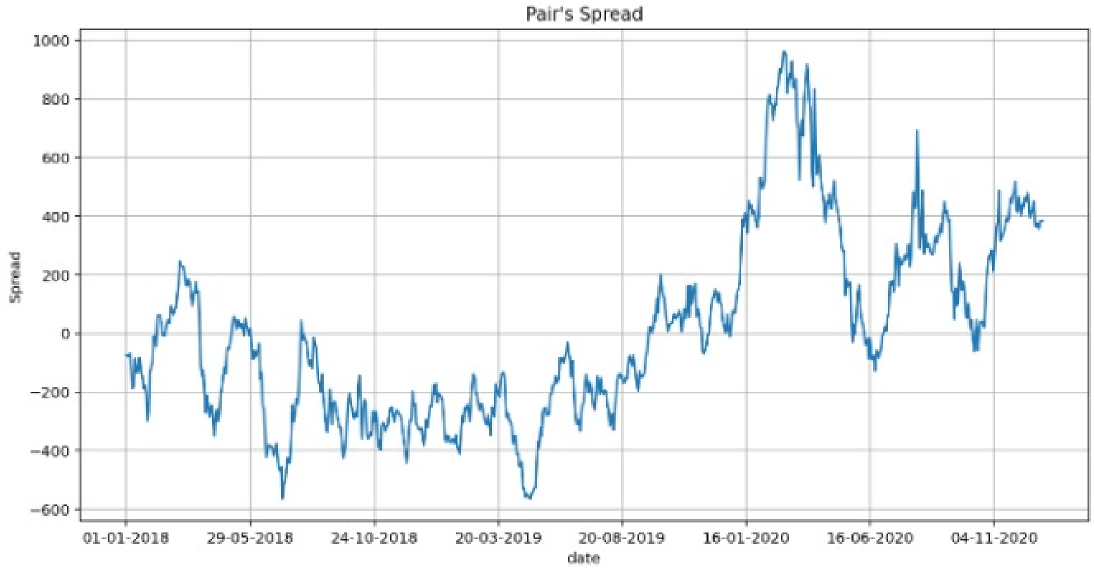

Figure 5.16: Pairs Spread

The residual z-value plot for the LP-AK OLS model

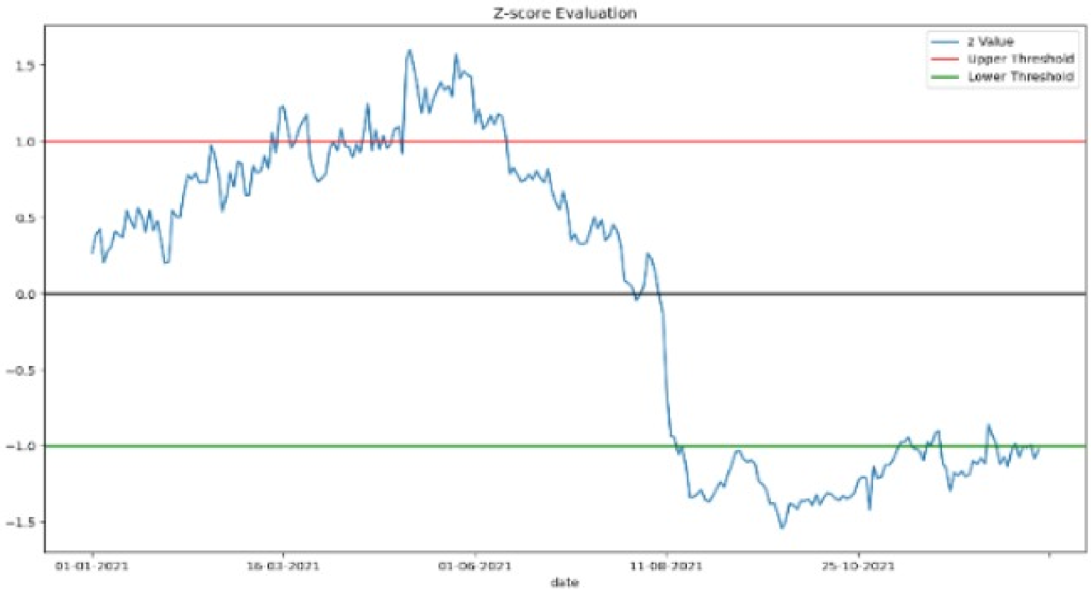

Figure 5.17: Z-values

The initial investment of 200,000 on January 1, 2021, the pair trading strategy yielded a return of 17.49%. The Augmented Dickey-Fuller (ADF) test conducted on the ratio series produced a test statistic of -2.0947. This value is higher than the critical value of -3.4392 at the 1% significance level, suggesting that the residuals are not stationary. Despite this, the pair trading strategy was implemented.

Figure 5.18: The pair trading scenario for the stocks AK and LP, including the identification of trading signals and their respective positions.

```
Model Summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Close   R-squared:                       0.146
Model:                            OLS   Adj. R-squared:                  0.145
Method:                 Least Squares   F-statistic:                     83.58
Date:                Sun, 25 Aug 2024   Prob (F-statistic):           1.66e-18
Time:                        14:39:35   Log-Likelihood:                -3118.2
No. Observations:                 489   AIC:                             6240.
Df Residuals:                     487   BIC:                             6249.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1171.7928     83.776     13.987      0.000    1007.186    1336.399
Close          0.9442      0.103      9.142      0.000       0.741       1.147
==============================================================================
Omnibus:                       47.365   Durbin-Watson:                   0.043
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               19.543
Skew:                           0.268   Prob(JB):                     5.70e-05
Kurtosis:                       2.180   Cond. No.                     1.05e+04
==============================================================================
```

Figure 5.19: OLS Regression Results

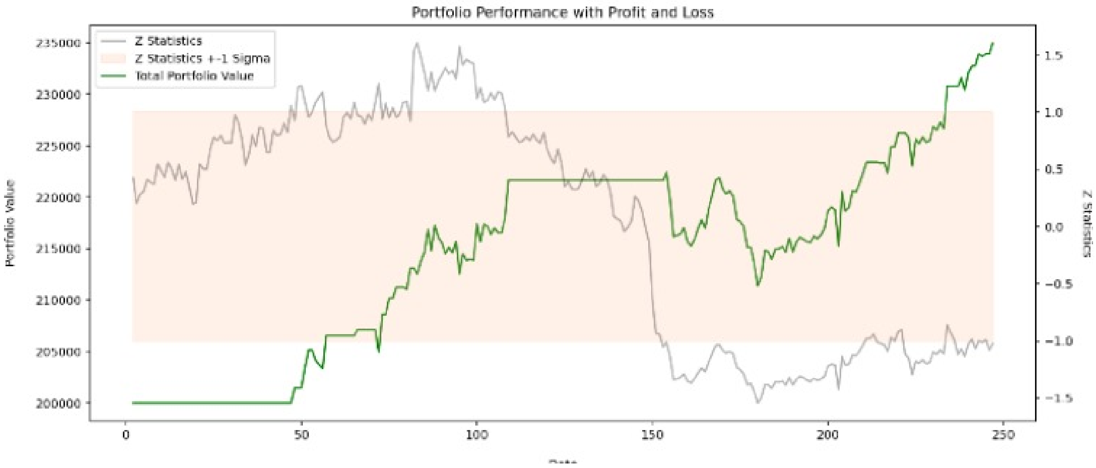

Figure 5.20: Portfolio Performance

Table 5.5: Financial Performance of Selected Stock Pairs Using cointegration

Stock Pair	Init Investment	Profit	Annual Return
DV - DR	200000	10942	5.47
LP - BI	200000	26993	13.50
AK - LP	200000	34986	17.49

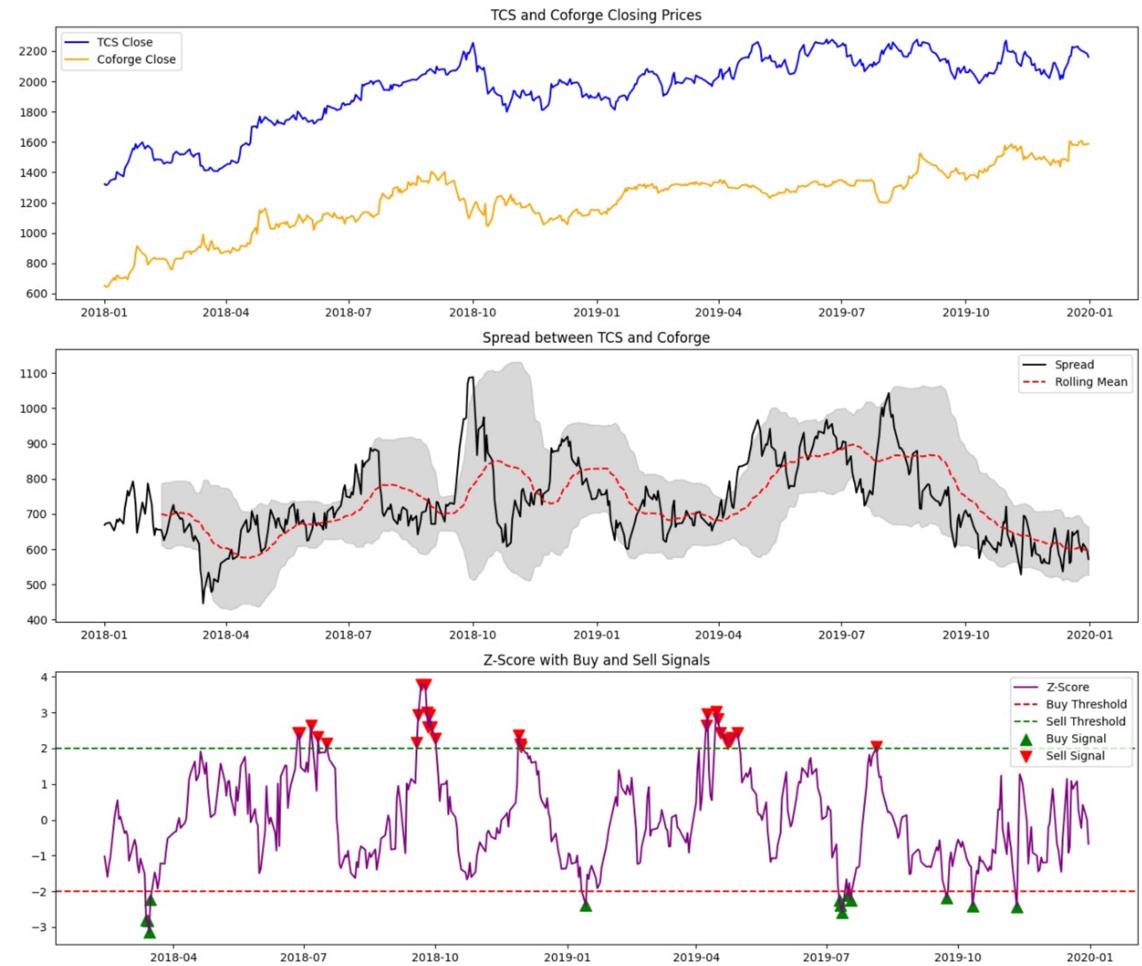

Figure 5.21: Distance Approach

Table 5.6: Financial Performance of Selected Stock Pairs Using distance

Stock Pair	Init Investment	Profit	Annual Return
DV - DR	200000	19460	9.73
LP - BI	200000	24960	12.48
AK - LP	200000	30060	15.03

5.4 Realty Sector

In the Realty sector, we examined three pairs of stocks using both Cointegration and Statistical Arbitrage strategies. Out of ten pairs in this sector that showed significant cointegration results, the following three pairs were selected for detailed study:

- Oberoi Realty (OR) and DLF (DL)
- Prestige Estate Projects (PE) and Oberoi Realty (OR)
- Prestige Estate Projects (PE) and Phoenix Mills (PM)

Each pair is assessed for cointegration, followed by the application of Statistical Arbitrage using OLS regression.

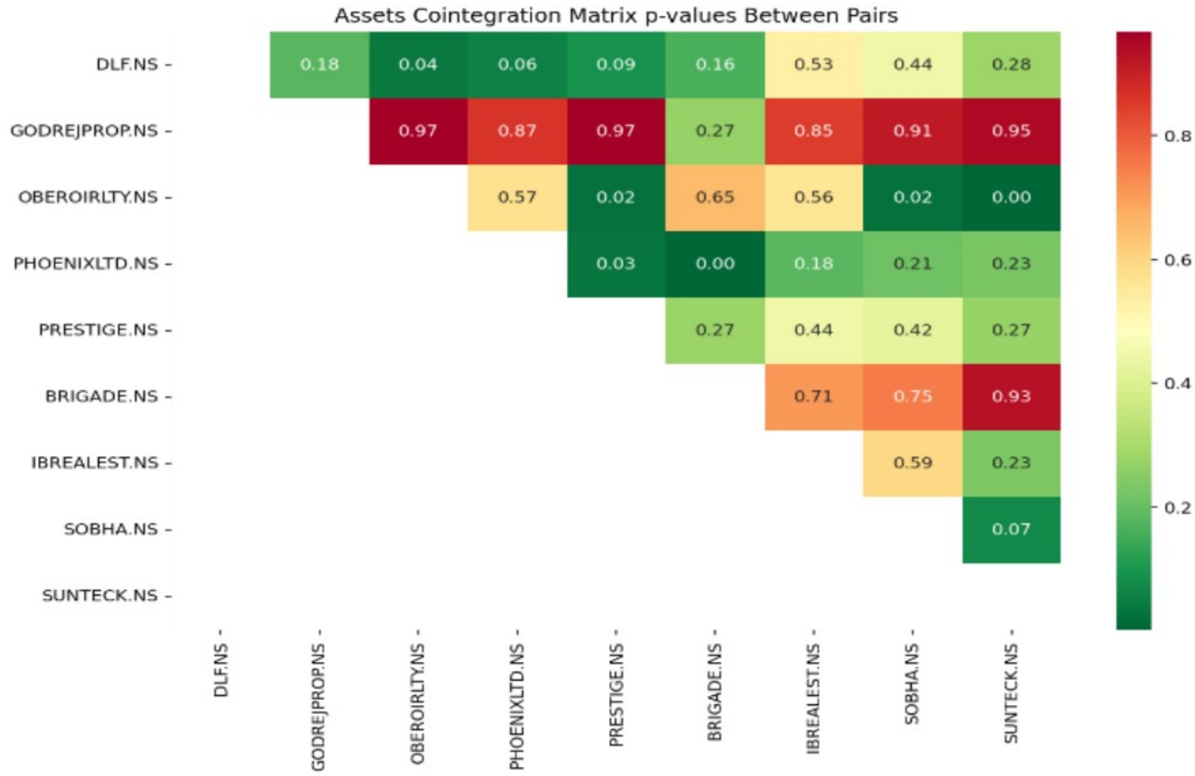

Figure 5.22: Asset Cointegration Matrix

The residual spread plot for the OR-PE OLS model

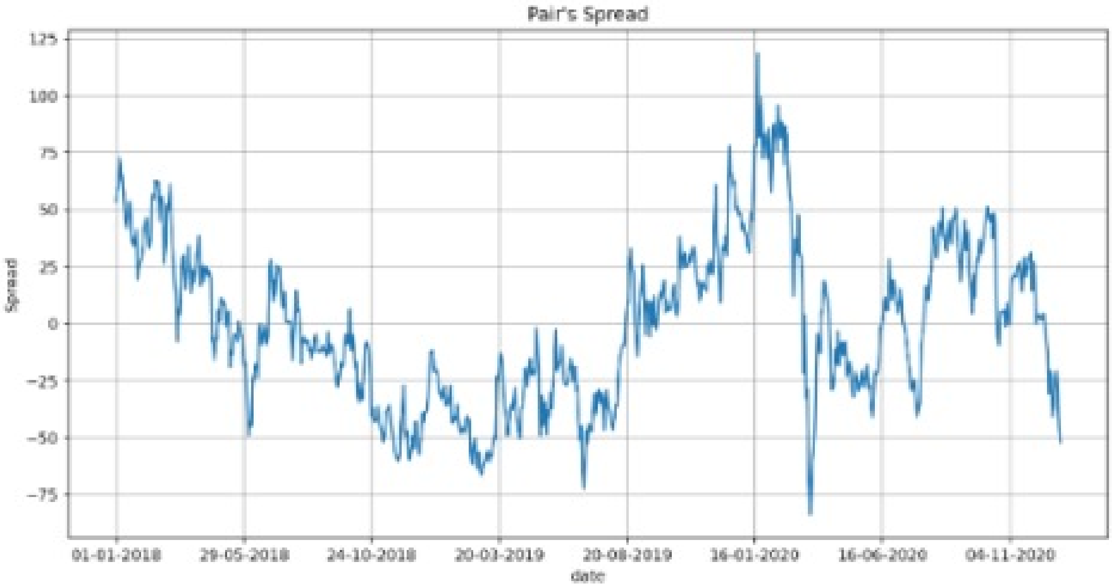

Figure 5.23: Pairs Spread

The initial investment of 200,000 on January 1, 2021, the pair trading strategy yielded a return of 16.24%. The Augmented Dickey-Fuller (ADF) test conducted on the ratio series produced a test statistic of -3.4499. This value is higher than the critical value of -3.4392 at the 1% significance level, suggesting that the residuals are stationary.The pair trading strategy is executed.

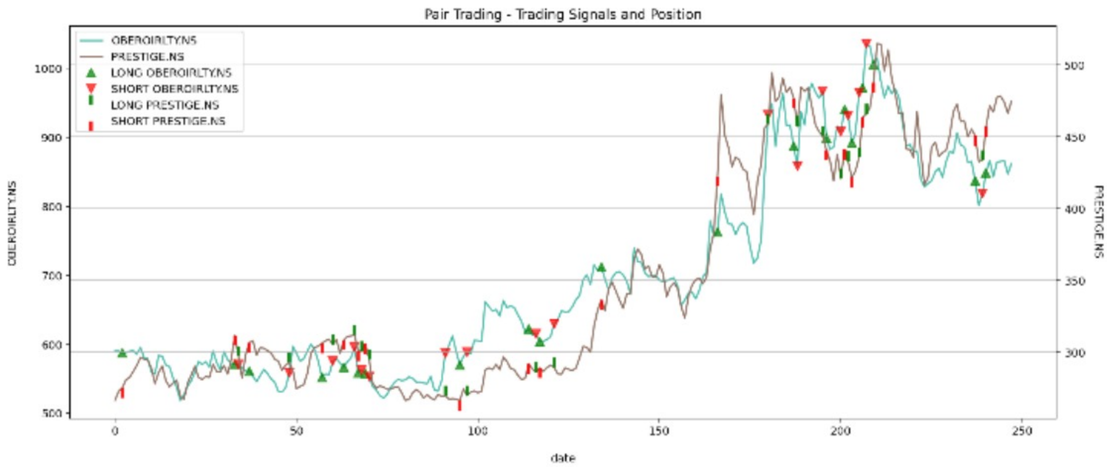

Figure 5.24: The pair trading scenario for the stocks PE and OR, including the identification of trading signals and their respective positions.

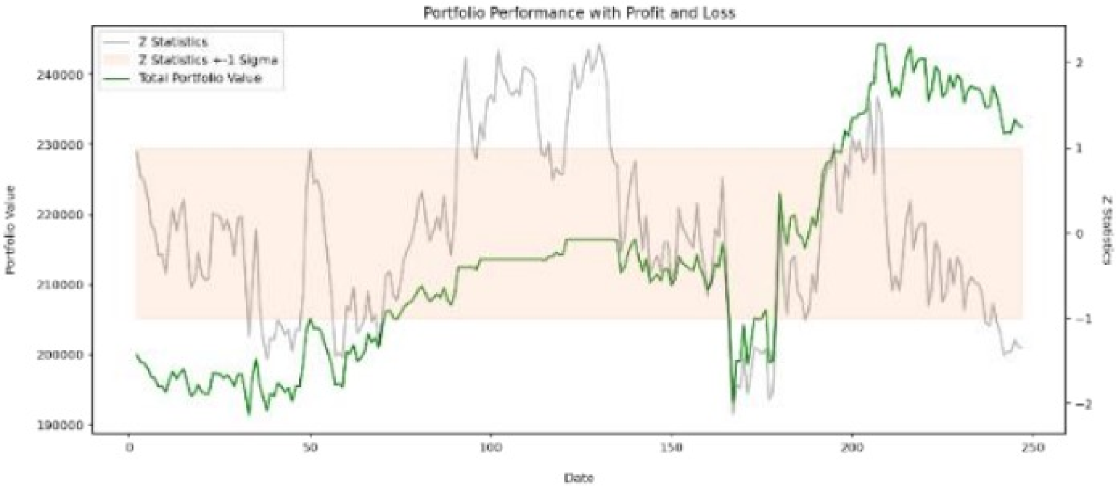

Figure 5.25: Portfolio Performance

Table 5.7: Financial Performance of Selected Stock Pairs Using cointegration

Stock Pair	Init Investment	Profit	Annual Return
PM - PE	200000	27184	13.59
OR - DL	200000	27337	13.67
PE - OR	200000	32488	16.24

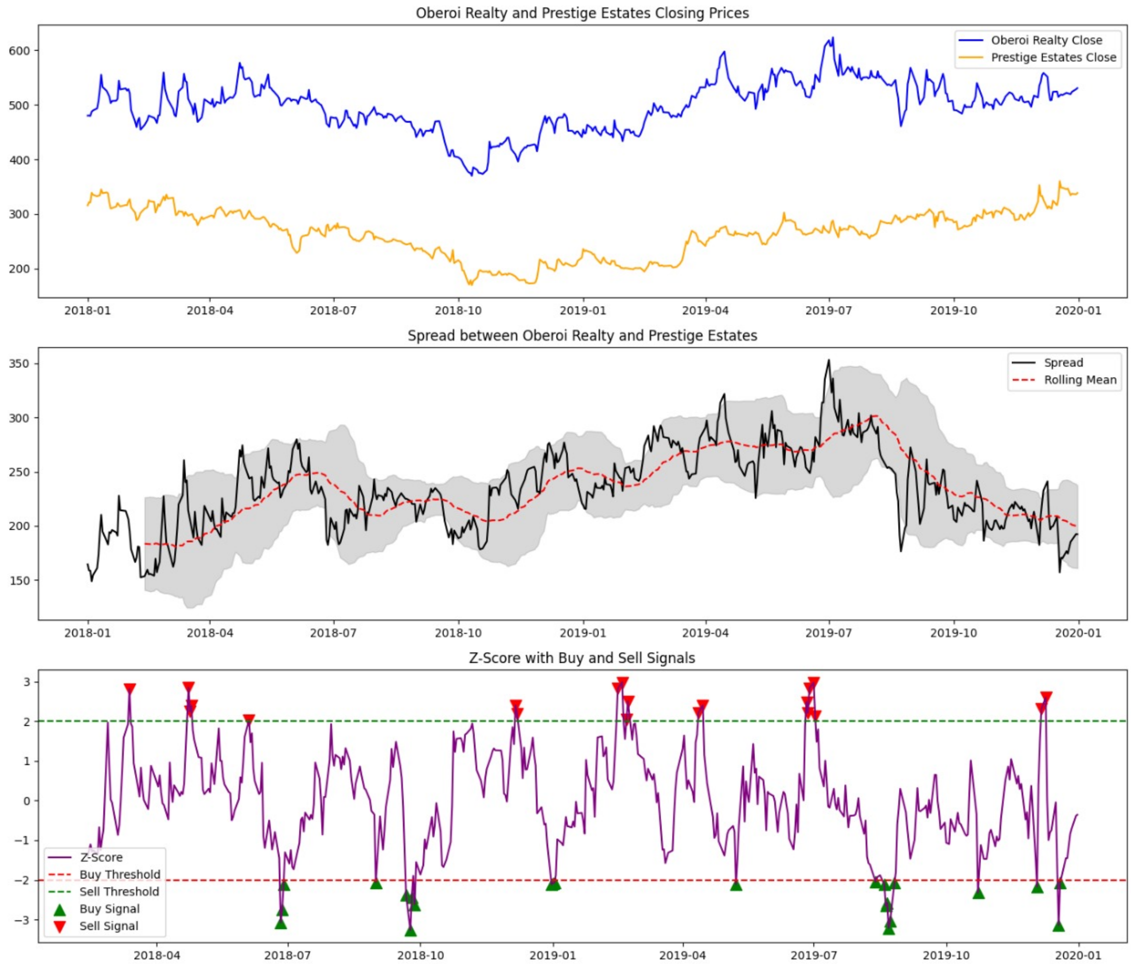

Figure 5.26: Distance Approach

Table 5.8: Financial Performance of Selected Stock Pairs Using distance

Stock Pair	Init Investment	Profit	Annual Return
PM - PE	200000	29900	14.95
OR - DL	200000	29520	14.76
PE - OR	200000	34080	17.04

5.5 Banking Sector

In the Banking sector, we examined three pairs of stocks using both Cointegration and Statistical Arbitrage strategies. Out of ten pairs in this sector that showed significant cointegration results, the following three pairs were selected for detailed study:

- Federal Bank (FB) and IDFC First Bank (IF)
- State Bank of India (SB) and IDFC First Bank (IF)
- HDFC Bank (HD) and Kotak Mahindra Bank (KM)

Each pair is assessed for cointegration, followed by the application of Statistical Arbitrage using OLS regression.

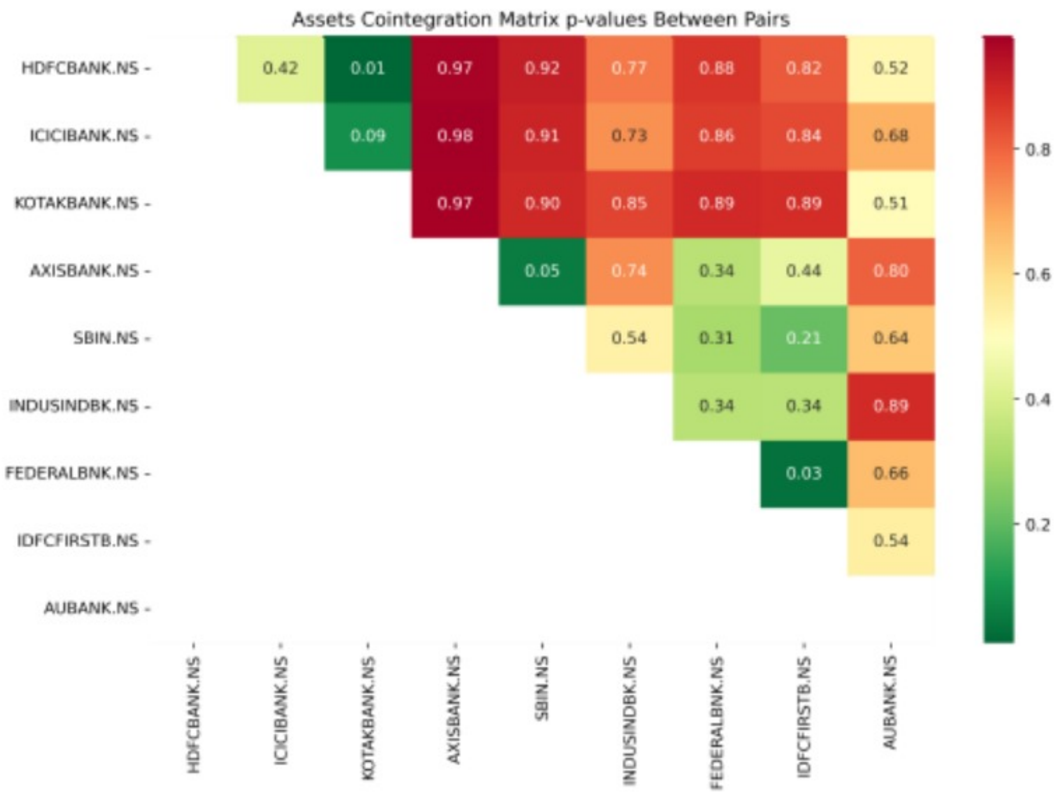

Figure 5.27: Asset Cointegration Matrix

The residual spread plot for the IF-SB OLS model

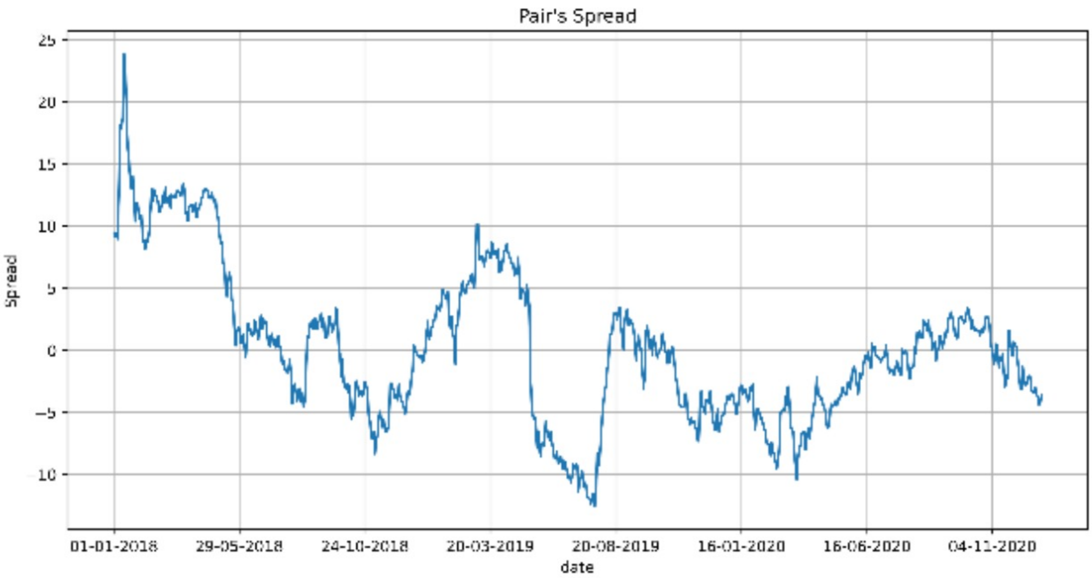

Figure 5.28: Pairs Spread

The residual z-value plot for the IF-SB OLS model

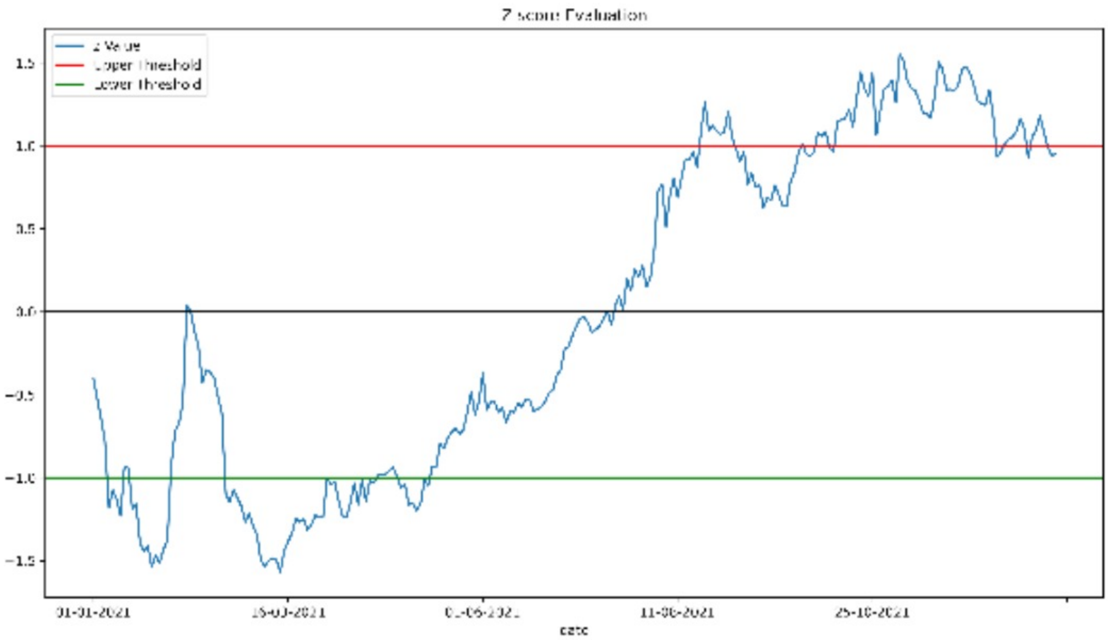

Figure 5.29: Z-values

The initial investment of 200,000 on January 1, 2021, the pair trading strategy yielded a return of 9.96%. The Augmented Dickey-Fuller (ADF) test conducted on the ratio series produced a test statistic of -2.5566. This value is higher than the critical value of -3.4392 at the 1% significance level, suggesting that the residuals are not stationary. Despite this, the pair trading strategy was implemented.

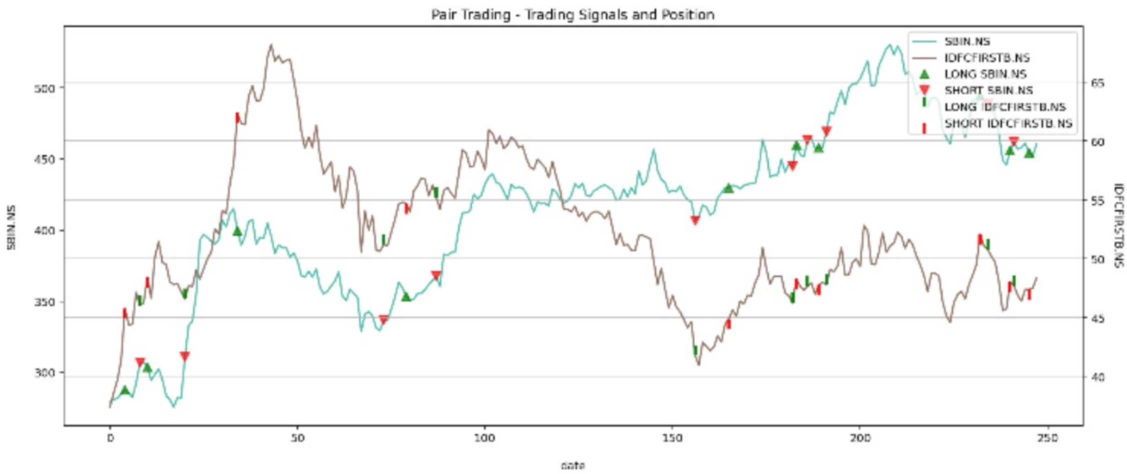

Figure 5.30: The pair trading scenario for the stocks IF and SB, including the identification of trading signals and their respective positions.

```
Model Summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Close   R-squared:                       0.021
Model:                            OLS   Adj. R-squared:                  0.019
Method:                 Least Squares   F-statistic:                     10.42
Date:                Sun, 25 Aug 2024   Prob (F-statistic):            0.00133
Time:                        14:41:13   Log-Likelihood:                -2369.9
No. Observations:                 489   AIC:                             4744.
Df Residuals:                     487   BIC:                             4752.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        257.9259     10.674     24.165      0.000     236.954     278.898
Close          0.7670      0.238      3.228      0.001       0.300       1.234
==============================================================================
Omnibus:                       23.416   Durbin-Watson:                   0.035
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               25.922
Skew:                           0.557   Prob(JB):                     2.35e-06
Kurtosis:                       2.828   Cond. No.                         344.
==============================================================================
```

Figure 5.31: OLS Regression Results

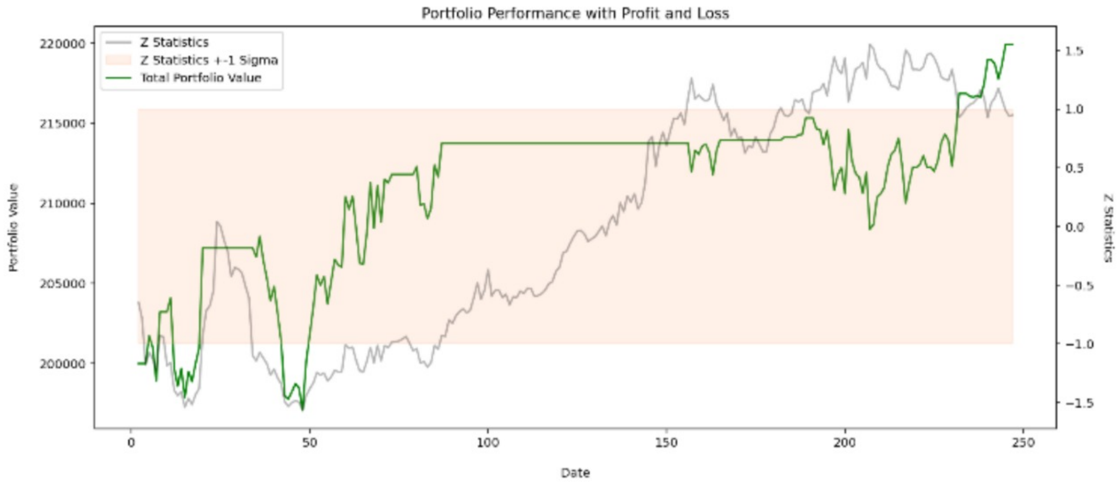

Figure 5.32: Portfolio Performance

Table 5.9: Financial Performance of Selected Stock Pairs Using cointegration

Stock Pair	Init Investment	Profit	Annual Return
KM - HD	200000	11056	5.53
IF - FB	200000	19300	9.65
IF - SB	200000	19926	9.96

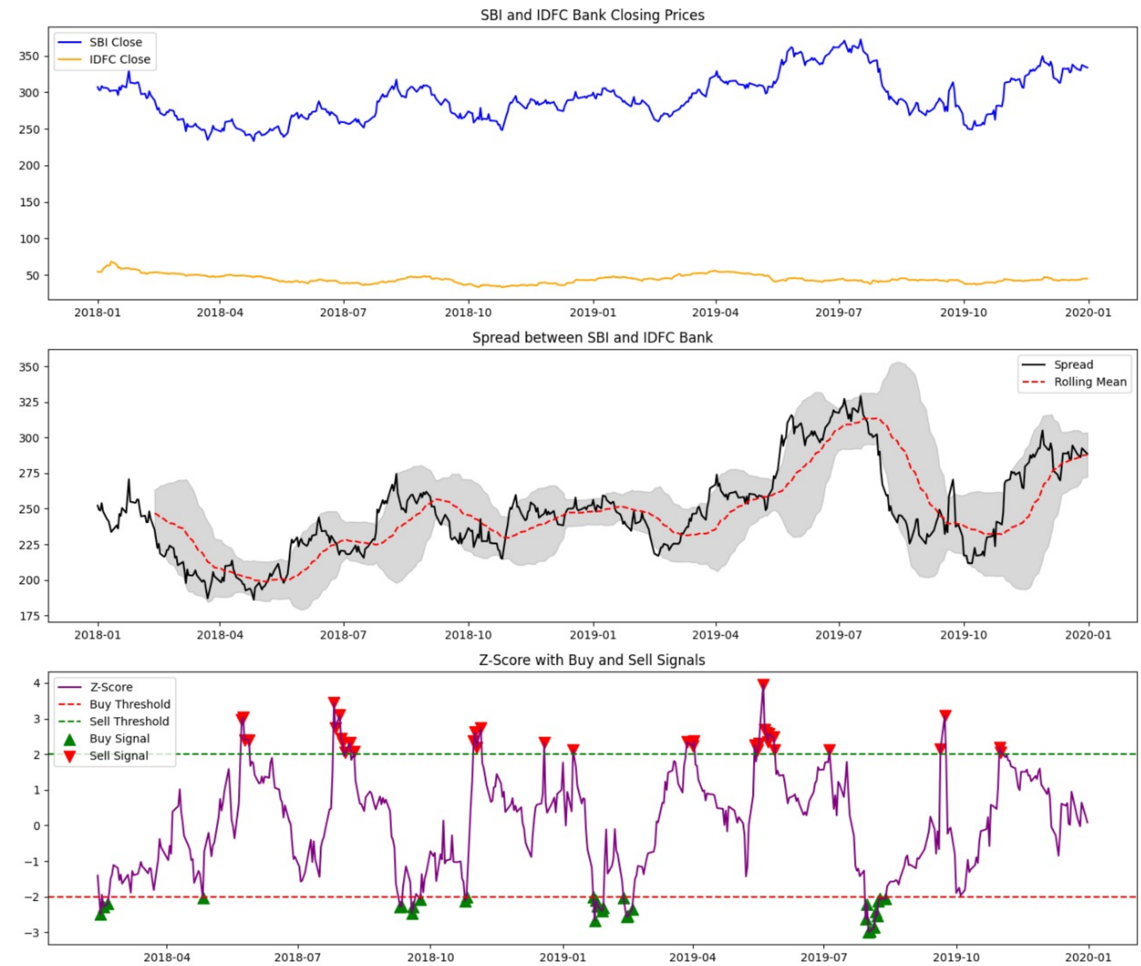

Figure 5.33: Distance Approach

Table 5.10: Financial Performance of Selected Stock Pairs Using distance

Stock Pair	Init Investment	Profit	Annual Return
KM - HD	200000	17060	8.53
IF - FB	200000	22160	11.08
IF - SB	200000	23980	11.99

Table 5.11: Comparative Results of Cointegration (Co) and Distance (Dis) Methods across Various Sectors

Sector	**Pair**	**Co Acc (%)**	**Dis Acc (%)**	**Co MDD (%)**	**Dis MDD (%)**
Auto	BF - AL	50.72	49.67	-2.6	-2.7
Pharma	LP - AK	45.81	49.08	-2.73	-3.14
Realty	OR - PE	51.06	53.92	-3.1	-2.42
Banking	SB - IF	48.47	50.40	-2.15	-2.94
It	TC - CF	49.06	52.72	-2.74	-2.49

6

Conclusions and Future Scope

This chapter of the report is dedicated to the conclusion and future scope. This section presents a thorough summary of the principal discoveries and understandings attained through the research conducted in the preceding sections.

6.1 Conclusion

the key insights derived from the research, focusing on the effectiveness of cointegration and statistical arbitrage strategies in pair trading. The analysis was conducted on a selection of sectors from the NSE of India, with portfolios designed based on cointegrated stock pairs. The evaluation covered stock price data from January 1, 2018, to December 31, 2020, and the portfolios were assessed during 2021.

Summary of Findings

- The IT sector showed moderate returns, reflecting the relatively stable and correlated nature of tech stocks. The Auto sector performed well, with the strategy capturing significant divergences due to market volatility, leading to higher returns. The Pharma sector exhibited strong results, likely due to the distinct behavior of pharmaceutical companies, where price movements are often driven by unique factors such as drug approvals. The Realty and Banking sectors also performed well, with noticeable differences in the performance of cointegration and distance methods.

- The study affirmed that cointegration is a reliable method for identifying stock pairs that exhibit long-term co-movement. The mean reversion strategy based on cointegration yielded consistent trading signals, demonstrating a strong potential for profitability.

- The distance method, which assesses the similarity of price movements between pairs, was effective in identifying trading opportunities based on short-term deviations. This method complemented the cointegration approach by offering additional trading signals.

- Compared to momentum and trend-following strategies, pair trading strategies using cointegration and distance methods showed higher stability and lower risk during volatile market conditions.

- One unexpected finding was the higher returns in the Pharma sector compared to IT, despite the general perception of IT as a more predictable and stable sector. This suggests that pair trading strategies may be more effective in sectors with higher volatility and higher risks, where deviations from equilibrium are more pronounced.

- Incorporating cointegration and distance methods into portfolio management strategies can enhance both performance and risk management. These methods offer a robust approach for constructing and managing trading portfolios.

- The methods demonstrated resilience across various market conditions, suggesting their suitability for diverse trading environments.

6.2 Prospects for Future Work

The methodology presented here lays the foundation for several exciting future directions and potential advancements in the field of trading strategies

The ares where the improvements and advancement can be done are

1. Expansion to Additional Sectors and Asset Classes: Extend the study to include additional sectors beyond those analyzed, such as energy, consumer goods, and utilities. Consider incorporating other asset classes, such as bonds, commodities, or exchange-traded funds (ETFs), to test the robustness of the strategies across diverse financial instruments.

2. Incorporation of Advanced Machine Learning Techniques: Integrating advanced machine learning algorithms, such as deep learning, reinforcement learning, and ensemble methods, may enhance predictive accuracy and trading signal generation. Utilizing natural language processing (NLP) to analyze sentiment from various sources, including news articles and social media, could also improve decision-making.

3. Enhancing Computational Efficiency: Investigate methods to optimize the computational efficiency of the algorithms, such as parallel processing or the use of more efficient programming languages and frameworks, to handle larger datasets and more complex

models. Consider the use of cloud computing or high-performance computing resources to scale the analysis for real-time and high-frequency trading applications.

4. Exploration of Alternative Cointegration and Arbitrage Models: Research and test alternative approaches to cointegration and statistical arbitrage, such as nonlinear models, fractional cointegration, or regime-switching models, to capture more complex relationships between asset prices. Experiment with different time horizons and rebalancing frequencies to determine the optimal conditions for the strategies' success.

5. Global Market Application: Apply the methodologies to global financial markets, including emerging markets, to assess the strategies' effectiveness across different economic environments and regulatory frameworks. Study the impact of global macroeconomic factors, such as interest rates, inflation, and geopolitical events, on the performance of the strategies.

6. Collaboration and Cross-Disciplinary Research:Encourage collaboration with experts in fields like economics, data science, and behavioral finance to further refine and innovate on the pair trading strategies. Explore the intersection of quantitative finance with areas such as behavioral finance and market microstructure to develop more comprehensive trading models.

7

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References of The Report are given in this section

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