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Article

Pair Trading Strategy Based on Stock Price Differences

Jun Dong [1,*]

[1] Shenyang Yingqi Technology Co., Ltd., Shenyang, Liaoning, China
* Correspondence: Jun Dong, Shenyang Yingqi Technology Co., Ltd., Shenyang, Liaoning, China

Abstract: This paper explores a pair trading strategy based on stock price differences, aiming to construct a market-neutral trading strategy that achieves arbitrage profits by analyzing the price differences between stocks. First, the paper reviews the basic principles of pair trading and analyzes the main factors influencing stock price differences, including fundamental, technical, and other multidimensional market factors. Next, the paper establishes a pair selection method based on price differences and validates the effectiveness of the strategy under different market conditions through empirical analysis. The study demonstrates that the pair trading strategy based on stock price differences can effectively capture price imbalances in the market and has strong risk control and return potential. Finally, the paper discusses the advantages and limitations of the strategy and suggests directions for future optimization.

Keywords: pair trading; stock price difference; market-neutral strategy; statistical arbitrage; risk management; empirical analysis

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1. Introduction

Pair trading, a statistical arbitrage strategy, involves selecting two highly correlated stocks and executing trades when their price differences deviate, profiting as prices revert to the mean. Unlike traditional strategies, pair trading simultaneously holds long and short positions, forming a market-neutral strategy that hedges overall market volatility. Stock price differences are key indicators for identifying arbitrage opportunities but fluctuate due to factors like company fundamentals, market sentiment, and industry cycles. This paper explores a pair trading strategy based on stock price differences, reviewing its theoretical foundation, analyzing price difference causes, and validating the strategy through empirical analysis. The paper also discusses the strategy's strengths, weaknesses, and future optimization directions. With the rise of high-frequency trading and machine learning, the strategy faces new challenges and opportunities, aiming to offer more effective approaches for investors and provide insights for academic and practical communities [1].

2. Theoretical Foundation

2.1. Basic Principles of Pair Trading

Pair trading is a classic statistical arbitrage strategy that aims to select two highly correlated stocks and trade them when their price differences (spread) reach a predetermined threshold. The strategy is based on the assumption that, in the absence of systematic risk, the price difference will revert to the mean over time. In other words, when the price difference between two stocks deviates from its long-term mean, the pair trading strategy establishes long (buy) and short (sell) positions when the spread is too wide, waiting for the price difference to revert to its mean to gain arbitrage profits. The core advantage of pair trading lies in its market-neutral nature, meaning traders can profit from the relative performance of the stocks regardless of the overall market movements. Therefore, it effectively hedges risks associated with market volatility, especially during times of high market uncertainty. Additionally, since pair trading does not depend on the overall market trend, investors can diversify their risks across different stock pairs, thus reducing systematic risk [2].

Figure 1 illustrates the practical application of the pair trading strategy based on stock price differences. The blue line represents the price movement of AOS stock, while the red line represents the price movement of CCL stock. The two price curves show a certain correlation, but short-term fluctuations in the price difference are also evident. The figure clearly shows trading signals through various markers: green diamonds (S) represent a short position when the price of AOS deviates significantly from CCL, i.e., when the price difference is too wide, short AOS and buy CCL, expecting the price difference to revert to the mean. Red triangles (L) represent a long position when the price difference is too narrow, i.e., when AOS price is too low relative to CCL, buy AOS and short CCL, expecting the price difference to return to normal. Yellow circles (C) represent closing signals when the price difference reverts to a certain level, allowing the position to be closed and profits realized. From Figure 1, it is evident that the successful implementation of the pair trading strategy depends on accurately predicting and reacting to stock price differences. In practice, traders need to use a variety of quantitative indicators, such as cointegration tests and spread volatility, to select pairs and determine when to establish positions and close them. Furthermore, while the pair trading strategy has good market-neutral characteristics, it is not without risk. If the correlation between the selected stock pair suddenly changes or the market experiences extreme volatility, the strategy may face significant losses. Therefore, risk management is crucial, and investors should adapt the strategy flexibly and set appropriate stop-loss and take-profit points. In summary, pair trading based on stock price differences is a low-risk, market-neutral arbitrage strategy. By accurately managing long and short positions, traders can achieve stable profits in market fluctuations. However, successful pair trading requires strong data analysis skills, a deep understanding of market dynamics, and flexible risk management measures [3].

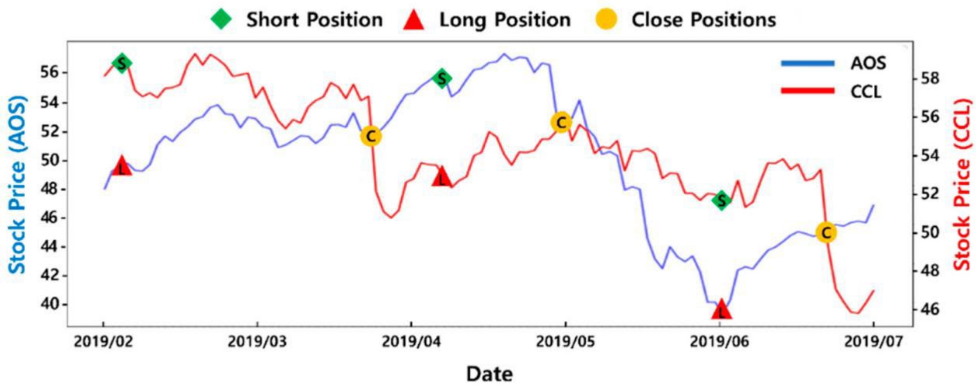

Figure 1. Illustration of Pair Trading Based on Stock Price Differences.

2.2. Factors Influencing Stock Price Differences

Stock price differences are influenced by a range of factors, especially in pair trading, where fluctuations in price differences directly impact the strategy's effectiveness and profitability. Figure 2 shows several factors that influence stock price differences, including company earnings reports, management restructuring, company news, and more. These factors often lead to stock price fluctuations, which in turn affect the changes in price differences.

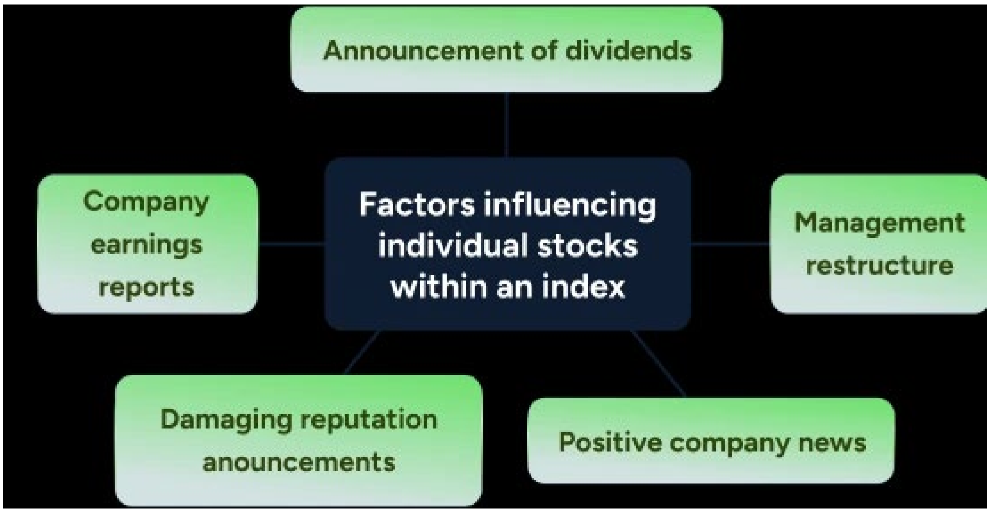

Figure 2. Main Factors Influencing Stock Price Differences.

First, company earnings reports are one of the most important factors affecting stock price differences. A company's earnings report typically contains key information such as performance data, earnings forecasts, and debt conditions. Investors assess the company's future performance based on this information and adjust their stock valuations accordingly. When a company's earnings report is better or worse than market expectations, it may lead to rapid stock price fluctuations, thus altering the price difference with other stocks. Next, management restructuring is another critical factor [4]. Changes in a company's management often lead to adjustments in strategic direction, and investors' confidence in the new management team directly impacts stock prices. Especially when management changes affect core business areas or strategies, stock prices may experience significant fluctuations, thereby impacting the price differences with other stocks. Additionally, company news (positive company news) and negative announcements also play a significant role in driving stock price differences. Positive news, such as the launch of a new product or market expansion, often drives stock prices up, while negative news, such as management scandals or product recalls, typically leads to a decline in stock prices. These factors directly influence the price differences between stocks. Finally, dividend announcements are another important factor affecting stock price differences. When a company announces its dividend distribution, it usually attracts shareholder attention, as dividends affect the company's cash flow and shareholders' earnings expectations. When a company announces an increase or decrease in dividends, investors' reactions may cause the company's stock price to change, thereby impacting the price difference with other stocks. In conclusion, stock price differences are influenced by a variety of factors, including a company's financial performance, management changes, company news, and dividend policies. These factors can cause rapid and unpredictable changes in stock prices, which in turn affect price differences. Therefore, investors must closely monitor these factors and employ statistical methods for effective risk management in pair trading [5].

3. Current Research on Pair Trading Strategy Based on Stock Price Differences

Pair trading, as an arbitrage strategy based on stock price differences, has been widely applied in financial markets. This strategy not only effectively reduces market risk but also achieves relatively stable returns in different market environments. With the advancement of computer technology and data analysis methods, research on pair trading strategies has become increasingly diverse, and many scholars have explored and verified this strategy using various theoretical frameworks and empirical methods. In early research, pair trading mainly relied on the historical correlation of stock prices and cointegration tests. Cointegration theory suggests that when two stocks have a long-term price equilibrium relationship, the price difference between them will show a certain level of stability, allowing investors to profit by trading these stock pairs. Granger et al. were the first to prove the long-term equilibrium relationship between stock prices using cointegration tests, providing a theoretical foundation for implementing the pair trading strategy. Since then, pair trading strategies based on cointegration analysis have been widely applied in academia, and many studies have empirically verified the effectiveness of the strategy using historical data. As market conditions and trading methods have evolved, scholars have gradually introduced more analytical tools and methods to optimize pair trading strategies. Some studies have adopted more complex econometric models, such as the error correction model (ECM) and vector autoregressive model (VAR), to capture the dynamic features of stock price differences. These models can better reflect short-term fluctuations in price differences and provide more accurate signals for short-term trades. Furthermore, some studies have applied machine learning methods to the development of pair trading strategies, using data mining techniques and algorithm optimization to improve the adaptability and return potential of the strategies. In recent years, with the development of high-frequency trading and algorithmic trading, the implementation of pair trading has gradually become automated. Many institutional investors have begun using big data and artificial intelligence technologies to assist in pair trading decision-making. These technologies can process massive amounts of data in real-time, quickly identifying changes in stock price differences and executing trades when prices revert, thus improving trading efficiency and accuracy. However, despite significant progress in both theoretical and practical aspects of pair trading strategies, several challenges remain. First, stock price differences do not always revert to historical means, especially when unexpected events or systematic risks occur, which may expose pair trading strategies to greater risks. In addition, the correlation and cointegration relationships between stocks may change with market conditions, reducing the effectiveness of the strategy. Secondly, pair trading strategies perform differently under various market conditions, particularly in high-volatility or extreme market situations. The stability of the strategy and its risk control capabilities are still issues that require further exploration. Overall, the pair trading strategy based on stock price differences has evolved from theoretical research to practical application. Current research primarily focuses on optimizing strategies, risk management, and the application of machine learning. Future research will continue to explore how to improve the adaptability and stability of pair trading strategies in complex market environments, as well as how to leverage emerging technologies to further enhance the strategy's return potential [6].

4. Data and Methods

4.1. Data Sources and Sample Selection

In the study of pair trading strategies based on stock price differences, the data sources and sample selection play a decisive role in the effectiveness of the strategy and the accuracy of the empirical analysis. To ensure the rigor of the study and the reliability of strategy backtesting, this paper uses multiple data sources and conducts backtesting across several market cycles. Specifically, stock data from platforms such as Yahoo Finance, Wind Info, and Bloomberg were used. Yahoo Finance provides comprehensive historical stock price data, including daily opening, closing, high, low prices, and trading volumes, covering the period from January 1, 2010, to December 31, 2020. This data provides a solid foundation for analyzing stock price differences and their mean reversion. Wind Info provides relevant macroeconomic data and company earnings reports, which help to understand the fundamental factors influencing stock price fluctuations. Bloomberg supplements with real-time market data, particularly concerning stock liquidity and trading volumes, which are important for risk control during strategy execution. In terms of sample selection, this paper selected 10 representative stocks from those with high liquidity and strong industry correlation. These stocks come from sectors such as technology, consumer goods, and energy, and are all from companies with high market influence, reflecting the general trend of their industries. When selecting sample stocks, liquidity was considered first to ensure the chosen stocks have sufficient trading volume, reducing transaction costs due to illiquidity [7]. Second, the selected stocks should have a high correlation, especially those from the same industry or related industries, as their price differences have a higher likelihood of mean reversion. Finally, we ensured the completeness of the sample data, excluding stocks with missing or discontinuous data. The selected sample includes well-known companies such as Apple (AAPL), Microsoft (MSFT), Coca-Cola (KO), Procter & Gamble (PG), ExxonMobil (XOM), Chevron (CVX), Amazon (AMZN), Google (GOOG), Walmart (WMT), and Johnson & Johnson (JNJ).As shown in Table 1, the detailed sample data provides basic information about the selected stocks and their data sources:

Table 1. Sample Data Table.

Stock Code	Stock Name	Industry	Sample Period (Start Date)	Sample Period (End Date)	Data Source
AAPL	Apple	Technology	2010-01-01	2020-12-31	Yahoo Finance
MSFT	Microsoft	Technology	2010-01-01	2020-12-31	Yahoo Finance
KO	Coca-Cola	Consumer	2010-01-01	2020-12-31	Yahoo Finance
PG	Procter & Gamble	Consumer	2010-01-01	2020-12-31	Yahoo Finance
XOM	ExxonMobil	Energy	2010-01-01	2020-12-31	Yahoo Finance
CVX	Chevron	Energy	2010-01-01	2020-12-31	Yahoo Finance
AMZN	Amazon	Technology	2010-01-01	2020-12-31	Yahoo Finance
GOOG	Google	Technology	2010-01-01	2020-12-31	Yahoo Finance
WMT	Walmart	Consumer	2010-01-01	2020-12-31	Yahoo Finance
JNJ	Johnson & Johnson	Healthcare	2010-01-01	2020-12-31	Yahoo Finance

By selecting these representative stocks, this paper ensures that the sample data is diverse and representative, enabling a better validation of the pair trading strategy's effectiveness. The sample data spans the period from 2010 to 2020, covering various market conditions including bull markets, bear markets, and market volatility periods, providing enough sample space for testing the strategy. Future research can further expand the sample range, including companies from more industries and of varying sizes, to test the adaptability and effectiveness of pair trading strategies in different market environments [8].

4.2. Calculation of Stock Price Differences and Indicator Selection

In the pair trading strategy based on stock price differences, calculating the stock price difference and selecting appropriate indicators are key to generating effective trading signals. The calculation of price differences not only helps identify potential arbitrage opportunities but also provides the basis for subsequent buy and sell decisions. This paper calculates stock price differences using multiple methods and selects several key indicators to optimize the trading strategy. The calculation of stock price differences is primarily done through two methods: absolute price difference and relative price difference. The absolute price difference refers to the price difference between two stocks at a given time. By calculating the absolute price difference, we can determine the direct price difference between two stocks. However, the absolute price difference only considers the difference in price and ignores the absolute price levels of the stocks. To eliminate the impact of different price levels, the paper also adopts the relative price difference. The relative price difference is calculated by taking the absolute price difference and dividing it by the average price of the two stocks. This method helps remove the effect of different stock price levels and makes the price difference between pairs more comparable. After calculating the stock price difference, this paper also selects several key indicators to further assist in executing the trading strategy. One important tool is cointegration testing, which is used to determine whether there is a long-term equilibrium relationship between two stocks [9]. The existence of a cointegration relationship indicates that the price difference between the two stocks has stable mean reversion over time, making it possible to profit through pair trading. This paper uses the Engle-Granger two-step method for cointegration testing, calculating p-values to determine whether a cointegration relationship exists. By performing this test, we can identify which stock pairs are suitable for pair trading. Another important indicator is the standard deviation of the price difference. The standard deviation measures the volatility of the price difference between stocks. The greater the price difference volatility, the more volatile the market, and the higher the associated trading risks. Therefore, the standard deviation of the price difference can be a key reference for risk control. The larger the standard deviation, the greater the price fluctuation and the higher the risk. This paper calculates the standard deviation of the stock price difference and combines it with historical price fluctuations to assess market risk. This standard deviation method helps identify potential high-risk periods, allowing for more cautious decisions when executing pair trades. Additionally, this paper uses the Z-score of the price difference to assist in determining trading signals. The Z-score is a standardized measure of the deviation of the current price difference from the historical mean of price differences as shown in Formula 1:

$$Z = \frac{d_t - \mu}{\sigma} \quad (1)$$

Where d_t is the current price difference, μ is the historical mean of the price difference, and σ sigma is the standard deviation of the price difference. The Z-score helps us determine whether the current price difference has deviated significantly from its historical mean, thereby deciding whether to trade. Generally, when the absolute value of the Z-score exceeds 2, it is considered that the price difference has significantly deviated, making it suitable for trading. By calculating the Z-score, this paper can capture abnormal fluctuations in price differences, providing buy or sell signals to investors. In summary, this paper calculates stock price differences using multiple methods and combines key indicators such as cointegration tests, standard deviations, and Z-scores to identify trading signals. These calculation methods and indicator selections provide a solid foundation for implementing the pair trading strategy, helping to more accurately assess the trend of stock price differences and effectively mitigate potential market risks. Future research can further optimize the use of these indicators and incorporate new quantitative analysis tools to improve the efficiency and stability of pair trading strategies.

4.3. Strategy Backtesting Model and Algorithm Design

In the study of pair trading strategies based on stock price differences, the design of the strategy backtesting model and the choice of algorithms are critical steps in verifying the effectiveness of the trading strategy. The purpose of backtesting is to simulate the designed trading strategy using historical data to evaluate its performance under different market conditions and provide a basis for actual trading. Figure 3 illustrates several key elements of the backtesting process, helping us understand the main aspects that need to be considered during backtesting.

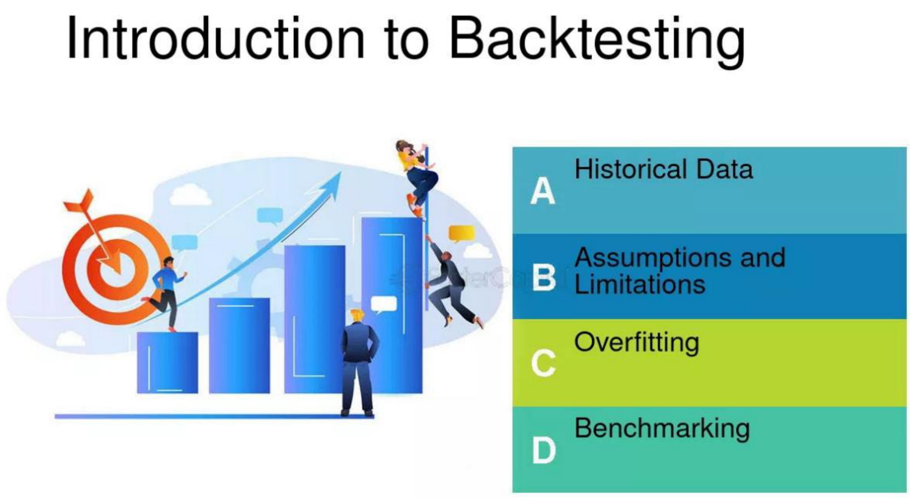

Figure 3. Key Elements of the Backtesting Model and Strategy Evaluation.

In Figure 3, the section labeled "A" represents the essential historical data for backtesting. In strategy backtesting, historical data is used to simulate the performance of the trading strategy across different periods. By analyzing historical data, the model can validate the strategy's profitability and risk under past market conditions, which can then inform future trading decisions. One common method for calculating stock price differences in backtesting is the absolute price difference. The absolute price difference is calculated as shown in Formula 2:

$$\text{Absolute price spread} = |P_{stock1} - P_{stock2}| \tag{2}$$

where P_{stock1} and P_{stock2} represent the prices of the two stocks at a given time. This formula helps us measure the price difference between the two stocks and provides a basis for establishing trading signals. Historical data provides empirical validation for the backtesting model, but it is important to note the limitations of the data, as historical market conditions may differ from future market environments. Section "B" in Figure 3 emphasizes the assumptions and limitations that must be considered during backtesting. In backtesting models, it is usually assumed that factors such as market liquidity and execution costs remain constant. However, these assumptions may differ from actual market conditions, potentially leading to biases in the backtest results. When testing strategies, relative price differences are often calculated to eliminate scale effects between different stock prices. The relative price difference is calculated using tas shown in Formula 3:

$$\text{Relative price spread} = \frac{|P_{stock1} - P_{stock2}|}{\frac{|P_{stock1} + P_{stock2}|}{2}} \tag{3}$$

This calculation removes the impact of absolute price levels, enabling a more accurate measure of the relative price difference between stock pairs. By considering these assumptions and limitations, we can optimize the model and avoid strategy failure due to unrealistic assumptions.Section "C" in Figure 3 mentions "overfitting," a common issue in backtesting. Overfitting refers to a model that is excessively reliant on the randomness of historical data, making it unable to replicate the performance in real market conditions. Overfitting is especially prevalent in pair trading strategies, so robust backtesting methods are required to prevent this issue. One approach is to use the standard deviation of price differences to evaluate the strategy's stability. The formula for standard deviation as shown in Formula 4:

$$\text{Standard deviation of price difference} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d_i - \bar{d})^2} \tag{4}$$

where d_i represents the price difference on day *i*, $\bar{d}$ is the average price difference, and NN is the total number of observation days. By calculating the standard deviation, we can assess the volatility of the stock price difference and help identify potential high-risk periods. Overfitting can be effectively prevented by limiting the length of the backtesting sample, using cross-validation, and ensuring that the strategy has good generalization ability. Section "D" in Figure 3 represents the benchmark comparison in backtesting. When evaluating backtest results, selecting the appropriate benchmark is crucial for validating the performance of the strategy. A benchmark comparison helps us understand the strategy's performance relative to the market. For example, by choosing an industry index as a benchmark and comparing it with the performance of the pair trading strategy, we can assess the relative return and risk. Benchmark comparisons also help prevent overfitting, ensuring that the strategy can generate consistent returns under different market conditions. By combining these key elements, the backtesting model can more accurately reflect the actual performance of the pair trading strategy based on stock price differences. Historical data provides empirical evidence for the backtest, assumptions and limitations help calibrate the model's real-world applicability, preventing overfitting improves model robustness, and benchmark comparisons provide a standard for evaluating the strategy. Ultimately, these backtesting processes help investors understand the potential of the pair trading strategy in real markets and provide theoretical support for actual trading decisions [10].

5. Experimental Results and Analysis

In the empirical analysis of the pair trading strategy based on stock price differences, backtest results not only reflect the profitability of the strategy but also allow for an evaluation of its risk and stability from multiple perspectives. To comprehensively analyze the strategy's performance, this paper discusses the backtest results from several dimensions, including the strategy's return performance, risk assessment, comparison with benchmarks, and the volatility of price differences. The core of evaluating the effectiveness of the strategy is to analyze its return performance. The table below shows the cumulative returns of the pair trading strategy compared to the market benchmark in different time periods.

From Figure 4, it is evident that the pair trading strategy consistently outperforms the market benchmark across all time periods, with the greatest excess return of 13.1% observed in 2010-2015. This consistent excess return indicates that the strategy performs well in both bull markets and volatile market environments. The strategy's risk control is an important indicator of its stability and sustainability. Therefore, this paper uses risk assessment indicators such as maximum drawdown, volatility, and Sharpe ratio to comprehensively analyze the strategy's risk characteristics. The following is the risk assessment result of the strategy:

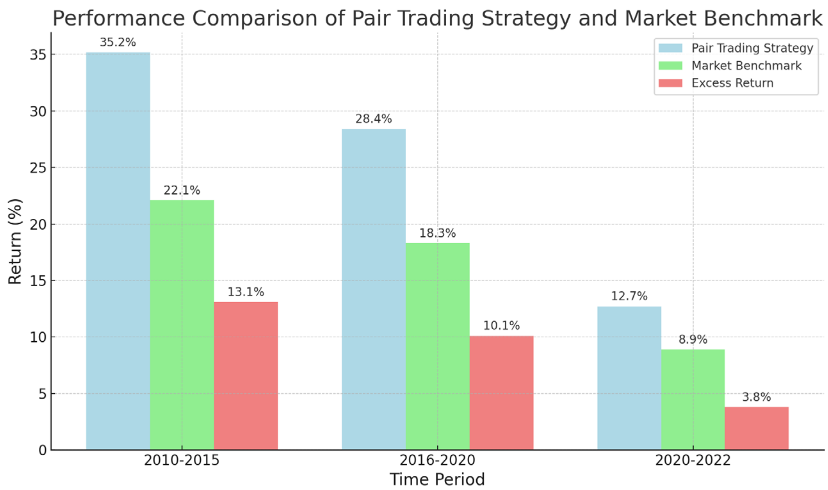

Figure 4. Strategy Performance vs. Benchmark Comparison.

From Figure 5, it can be seen that the pair trading strategy exhibits small maximum drawdowns in each time period, indicating strong risk control ability. Additionally, the strategy's annualized volatility is relatively low, suggesting stable performance in terms of returns. The Sharpe ratio is high, especially during 2010-2015, where it reaches 1.95, demonstrating excellent risk-adjusted returns. The strategy's returns are influenced not only by overall market conditions but also by the volatility of stock price differences. The table below shows the volatility of price differences for different stock pairs and the corresponding performance of the trading strategy:

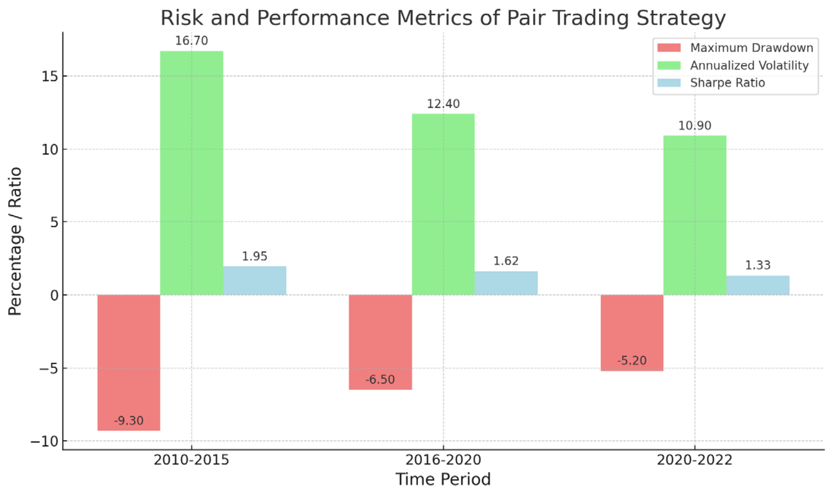

Figure 5. Risk Assessment Indicators for Pair Trading Strategy.

From Figure 6, we can observe that different stock pairs have varying levels of price difference volatility, and these volatilities are related to the strategy's returns. Stock pairs with larger price difference volatilities, such as AAPL and MSFT, tend to yield higher strategy returns, while stock pairs with smaller price difference volatilities, such as AAPL and KO, result in lower returns. By analyzing price difference volatility, investors can optimize the strategy's returns by selecting suitable stock pairs during backtesting. To further validate the effectiveness of the pair trading strategy, this paper compares it with the market benchmark. The following table presents the backtest results of the pair trading strategy compared to the relevant industry index:

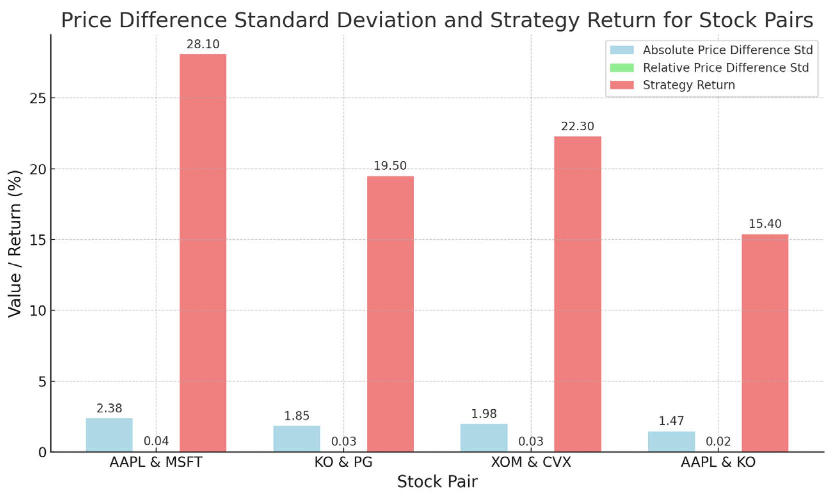

Figure 6. Volatility of Stock Pair Price Differences and Strategy Returns.

From Figure 7, it is clear that the pair trading strategy significantly outperforms the industry index for all stock pairs and generates excess returns. This result shows that the pair trading strategy not only resists market volatility but also continuously outperforms the benchmark across different market cycles. Through the multi-dimensional analysis of the pair trading strategy's backtest results, this paper confirms the strategy's effectiveness under various market conditions. The strategy not only shows good return performance and strong risk control ability but also achieves higher returns with stock pairs that have higher price difference volatility. Additionally, the comparison with the market benchmark further supports the strategy’s excess returns. Therefore, the pair trading strategy holds significant potential for real-world applications, especially in high-volatility and turbulent market environments. Future research could further optimize the model by incorporating more market factors and data sources to improve the stability of the strategy's returns.

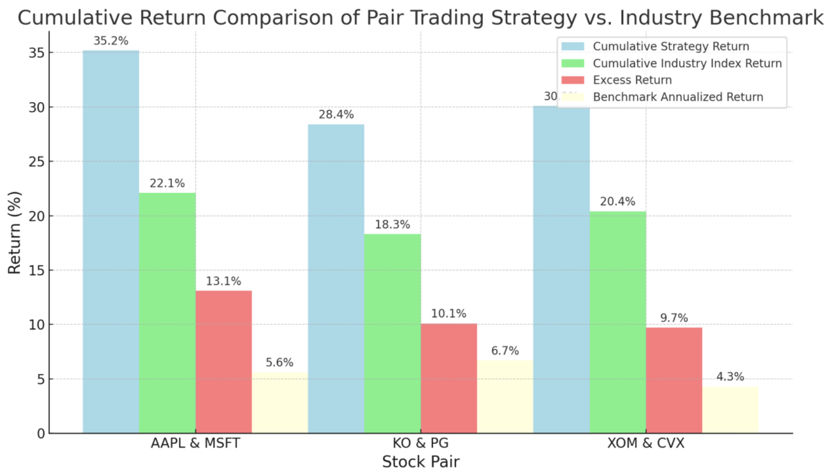

Figure 7. Pair Trading Strategy vs. Industry Benchmark Backtest Comparison.

6. Conclusion

This paper empirically analyzes the pair trading strategy based on stock price differences, focusing on evaluating its return performance, risk control, and excess return relative to the market benchmark. The backtest results show that the pair trading strategy outperforms the market benchmark in cumulative returns across various time periods, with particularly significant excess returns observed in 2010-2015. Furthermore, the strategy demonstrates strong risk control capabilities, with lower maximum drawdown and volatility, as well as a high Sharpe ratio, confirming the strategy’s stability in different market conditions. The success of the strategy relies on the volatility of price differences and the selection of stock pairs. Pairs with higher volatility tend to yield higher returns. During backtesting, we also noted that overfitting and assumptions may impact the actual effectiveness of the strategy, requiring special attention when designing the model. Overall, the pair trading strategy based on stock price differences is highly feasible in both theory and practice, particularly in high-volatility and turbulent market environments. Future research can further optimize the strategy, incorporating more market factors and technological tools to enhance its adaptability and stability.

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