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Zaman Çerçevesine Uyarlanabilir Arbitraj: Dinamik Sinyal Gecikmeleri ile İkili İşlem Performansının Optimizasyonu

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Öz

Bu çalışma, klasik z-score tabanlı çiftli işlem (pairs trading) stratejisini dinamik sinyal gecikme mekanizmalarıyla geliştirerek istatistiksel arbitraja zaman uyarlamalı bir yaklaşım sunmaktadır. Apple Inc. (AAPL) referans alınarak, Dow Jones Industrial Average (DJIA) endeksindeki 29 hisse çifti üzerinde *t+1*’den *t+5*’e kadar farklı işlem gecikmelerinin performansa etkisi analiz edilmiştir. İşlemler, günlük kapanış fiyatlarından türetilen z-score sinyallerine göre açılıp kapatılmış; gecikmeli yürütme yaklaşımı kısa vadeli piyasa gürültüsünü azaltarak işlem zamanlamasını optimize etmeyi hedeflemiştir. Ampirik bulgular, önerilen stratejinin yüksek performans sergilediğini göstermektedir. Çiftlerin %93.8’i pozitif getiri, %89.7’si ise 1.0’ın üzerinde Sharpe Oranı elde etmiştir. Ortalama olarak *t+3* gecikme penceresi en etkili risk-getiri dengesini sağlamış; 2.371 Sharpe Oranı ve %192.98 toplam getiri ile en iyi performansı göstermiştir. Yalnızca %24.1 oranındaki çiftlerde anlık (*t+0*) işlemler en iyi sonucu vermiştir; bu da arbitrajda uyarlanabilir zamanlamanın avantajını ortaya koymaktadır. Sonuçlar, işlem zamanlamasının optimizasyonunun arbitraj modellerinin kârlılık ve istikrarını önemli ölçüde artırdığını doğrulamaktadır. Bulgular, zaman uyarlamalı yürütme yaklaşımının geleneksel çiftli işlem çerçevelerine değerli bir katkı sunduğunu güçlü biçimde ortaya koymaktadır.

Anahtar kelimeler: Finansal teknolojiler, İstatistiksel arbitraj, Finansal hesaplama, Çiftli arbitraj

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Time Frame Adaptive Arbitrage: Optimizing Pairs Trading Performance with Dynamic Signal Delays

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Abstract

This study enhances the classical z-score-based pairs trading strategy by introducing dynamic signal delay mechanisms to develop a time-adaptive approach to statistical arbitrage. Using Apple Inc. (AAPL) as a benchmark, 29 stock pairs from the Dow Jones Industrial Average (DJIA) index were analyzed to assess the impact of execution delays ranging from *t+1* to *t+5* on trading performance. Positions were opened and closed based on z-score signals derived from daily closing prices, where delayed execution aimed to reduce short-term market noise and optimize trade timing. Empirical results demonstrate that the proposed strategy achieved favorable performance, with 93.8% of the pairs generating positive returns and 89.7% attaining a Sharpe Ratio greater than 1.0. On average, the *t+3* delay window yielded the most effective balance between risk and return, achieving a Sharpe Ratio of 2.371 and a cumulative return of 192.98%. Only 24.1% of the pairs performed best under immediate execution (*t+0*), highlighting the advantages of adaptive timing in arbitrage. Overall, the findings confirm that optimizing trade timing significantly enhances the profitability and stability of arbitrage models. The results provide empirical evidence supporting the potential of time-adaptive execution as a valuable improvement to traditional pairs trading frameworks.

Keywords: Fintech, Statistical arbitrage, Financial calculation, Pairs trading

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1. Introduction

Temporary price deviations between assets in financial markets present exploitable opportunities through statistical arbitrage strategies [1]. These strategies rely on the fundamental assumption that when long-term equilibrium relationships between price series are disrupted, deviations tend to revert to the mean over time [2]. Within this framework, the pairs trading approach generates buy and sell signals by analyzing the price spread between two assets assumed to be correlated or cointegrated [3].

This study develops a z-score-based arbitrage strategy for selected asset pairs in the U.S. equity market, specifically between Apple Inc. (AAPL) and the components of the DOW30 index. The z-score, a simple yet effective indicator, measures how far the price spread between two stocks deviates in terms of standard deviations [4]. Trading positions are initiated when the z-score exceeds the ±1 thresholds and are closed once it returns to a convergence band between –0.25 and +0.25. Unlike conventional approaches that execute trades immediately at threshold crossings (t), this study applies delayed execution intervals (*t+1* to *t+5*) to reduce short-term market noise and identify optimal delay periods (n) for more robust signal generation. This design enhances consistency in response to price deviations and improves the overall performance of the strategy.

Traditional z-score models typically assume stationary relationships between price series [5]. However, classical cointegration tests were intentionally omitted in this study because short-term arbitrage strategies are better captured by high-frequency correlations that reflect the market's dynamic structure [6]. Accordingly, pair selection is based on instantaneous correlation and volatility-normalized spread values. This approach eliminates the rigid requirement of cointegration, allowing greater flexibility and adaptability in real-world applications.

The proposed framework systematically tests all delay windows from *t+1* to *t+5*, evaluating performance metrics separately for each. The objective is to determine which delayed signal window achieves the highest return, lowest risk, and greatest consistency, thereby identifying the most effective delay interval. This approach produces a model that is more responsive and better aligned with market dynamics compared to conventional z-score strategies that operate with fixed parameters.

The performance of the strategy is evaluated using well-established metrics such as the Sharpe Ratio, Sortino Ratio, Profit Factor, and Maximum Drawdown. Additionally, each arbitrage pair's results are compared to the classical buy-and-hold performance of the corresponding stocks, enabling a detailed assessment of absolute and risk-adjusted returns.

While traditional pairs trading models rely solely on statistical threshold breaches to trigger trades [7], this study introduces timing optimization, making the execution of signals dynamically adaptive. Consequently, the proposed approach optimizes not only the trading direction but also the timing of position entry. This represents a novel contribution to the field of time-adaptive arbitrage and underscores the critical role of execution timing in trading performance.

A review of the literature reveals that most pairs trading studies employ z-score-based threshold mechanisms but often overlook systematic evaluations of delayed signal triggering, optimal threshold selection, and decision deferral windows. This study addresses these gaps by developing a dynamic, time-adaptive version of z-score-based pairs trading. Recent empirical findings reinforce the continuing relevance of pairs trading; for instance, Zhu [8] replicated classical methodologies and found that pairs trading consistently generated statistically and economically significant returns, with an average annual excess return of 6.2% and a Sharpe Ratio of 1.35, confirming its enduring effectiveness in modern financial markets.

2. Materials and Methods

This section provides a detailed description of the dataset used in the study, the implementation procedure of the pairs trading strategy, the performance evaluation metrics, and the overall analysis process. Additionally, the technological infrastructure employed, the assumptions made during computations, and the data preprocessing steps are explained. To ensure the reproducibility of the study, the algorithmic framework is expressed through equations, and the tools utilized are explicitly specified.

2.1. Dataset

In this study, Apple Inc. (AAPL) was selected as the reference stock from among the 30 constituents of the Dow Jones Industrial Average (DJIA), and pairs trading analysis was conducted with the remaining 29 stocks [9]. The analysis period spans from January 1, 2023, to December 1, 2024, using daily closing prices obtained via the Yahoo Finance API. In summary, AAPL was designated as the reference asset, and the arbitrage strategy was tested against the other 29 DJIA stocks.

2.2. Pairs trading strategy methodology

2.2.1. Spread and z-score calculation

A spread value has been calculated for each stock pair. The spread represents the fundamental metric for the price difference between two stocks in pairs trading strategies [10]. The two stocks are typically selected as correlated assets that co-move over the long term. The spread is utilized to detect arbitrage opportunities when the relationship between these two stocks temporarily deviates. The calculation of the spread value is shown in Equation 1 as follows [11].

$$Spread_t = P_t^{AAPL} - \beta_t \cdot P_t^{(i)} \tag{1}$$

In Equation. 1, P_t^{AAPL} denotes the closing price of Apple stock on day t, $P_t^{(i)}$represents the closing price of the compared test stock, and β_t ignifies the regression coefficient calculated for the relevant period. A 60-day rolling window was applied to the spread time series, and the mean and standard deviation were calculated as shown in Equation 2.

$$\mu_t = \frac{1}{N}\sum_{k=t-N+1}^{t} Spread_k\,, \quad \sigma_t = \sqrt{\frac{1}{N}\sum_{k=t-N+1}^{t}(Spread_k - \mu_t)^2} \tag{2}$$

Using the values from Equation 2, the standardized spread (i.e., Z-score) is calculated as shown in Equation 3 [12].

$$z_t = \frac{Spread_t - \mu_t}{\sigma_t} \tag{3}$$

2.2.2. Signal generation criteria

Trading signals are generated based on the Z-score value according to the threshold values specified in Equation 4. A sample position strategy based on the Z-score is illustrated in Figure 1.

$$\begin{aligned} &\text{Buy}: z_t < -1.0 \\ &\text{Sell}: z_t > 1.0 \\ &\text{Close}: -0.25 < z_t < 0.25 \end{aligned} \tag{4}$$

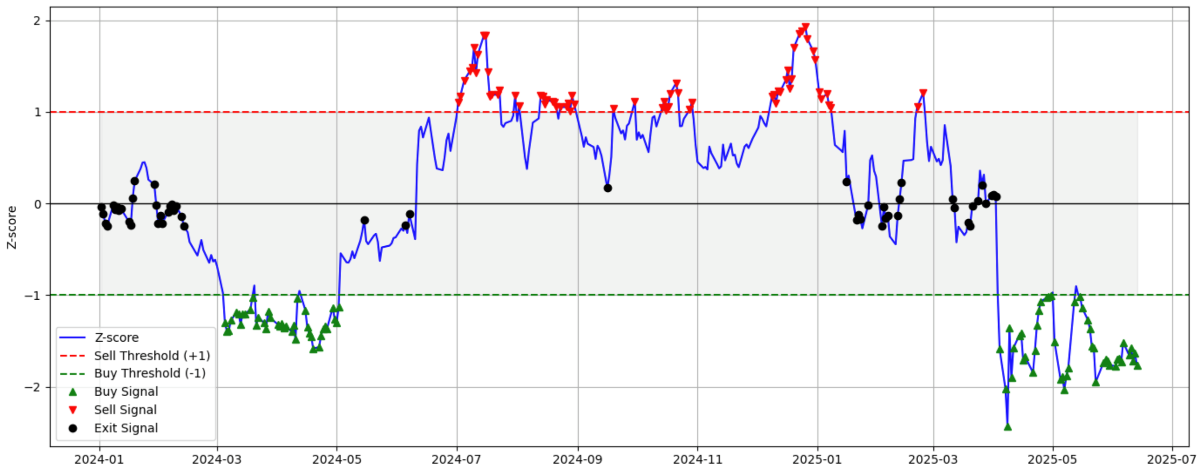

Figure 1. Z-Score position opening behavior

To model transaction delays under real market conditions, delayed strategies were tested based on the execution day relative to signal generation. In this context, *t+1*, *t+2*, *t+3*, *t+4*, and *t+5* delays were analyzed.

2.3. Performance measurement and analysis methods

In this study, the efficacy and risk profile of the pairs trading strategy were comprehensively evaluated using diverse performance metrics. These performance measures were selected to reveal the strategy's robustness and adaptability to market conditions, while accounting for the risk-return trade-off.

2.3.1. Risk-adjusted return metrics

To evaluate the performance of the implemented strategy from a risk-balanced perspective, widely accepted performance criteria were utilized. Within this scope, the Sharpe Ratio – which measures the excess return per unit of total risk – and the Sortino Ratio – which provides a more refined measurement by considering only downside risk (negative volatility) – were calculated.

- **Sharpe Ratio:** This metric quantifies the return per unit of risk, where risk is defined as volatility (standard deviation) [13]. While the Sharpe Ratio reveals the overall risk-return trade-off, it can sometimes be misleading because it treats both positive and negative volatility equally [14]. The calculation of the Sharpe Ratio is shown in Equation 5.

$$S = \frac{R_p - R_f}{\sigma_p} \times \sqrt{252} \tag{5}$$

In Equation 5, R_p denotes the mean daily return of the portfolio (or strategy), R_f represents the risk-free rate of return, and σ_p is the standard deviation of daily returns. The term $\sqrt{252}$ annualizes the ratio under the assumption of 252 trading days in a year.

- **Sortino Ratio**: An enhanced version of the Sharpe Ratio. Here, only downside volatility is considered risk. This metric offers a more realistic risk assessment by focusing on losses, which are investors' primary concern [15]. The calculation of the Sortino Ratio is given in Equation 6 [16].

$$SoR = \frac{R_p - R_f}{\sigma_d} \times \sqrt{252} \tag{6}$$

In Equation 6, R_p denotes the mean daily return of the portfolio (or strategy), R_f represents the risk-free rate of return, and σ_d is the standard deviation of negative returns (downside deviation). The term $\sqrt{252}$ annualizes the ratio under the assumption of 252 trading days in a year.

2.3.2. Risk metrics

As a risk metric, the Maximum Drawdown (Max Drawdown) value is calculated in this study. Max Drawdown measures the peak-to-trough decline of the strategy [17], representing the largest potential loss an investor could face. It serves as a critical indicator for assessing outcomes during sudden market collapses and detecting strategy failures. The calculation of the Max Drawdown value is shown in Equation 7 [18].

$$\text{MaxDrawdown} = \min\left(\frac{C(t)}{C_{max}(t)} - 1\right) \tag{7}$$

In Equation 7, $C(t)$ denotes the current cumulative return, while $C_{max}(t)$ represents the maximum cumulative return value up to that date.

2.3.3. Transaction-based performance metrics

To measure the success of trades executed in this study, the Profit Factor and Win Rate were employed.

- **Profit Factor:** Measures trade-level efficiency by ratio of gross profit to gross loss. Values > 1 indicate a profitable strategy. The calculation is shown in Equation 8 [19].

$$\text{ProfitFactor} = \frac{\sum\text{Profit}}{|\sum\text{Loss}|} \tag{8}$$

- **Win Rate:** Represents the percentage of profitable trades relative to total trades executed. The calculation is shown in Equation 9 [20].

$$\text{Win Rate} = \frac{\textit{Number of Profitable Trades}}{\text{Total Trades}} \times 100 \tag{9}$$

2.4. Analytical approach

2.4.. Optimization process

Among the 5 delay periods tested for each stock pair, the delay period yielding the highest Sharpe ratio was designated as 'optimal'.

2.4.2. Statistical analysis

Statistical analysis was conducted in this study. The performed analyses are as follows:

- Comparison of mean performance across delay periods
- Distribution of optimal delay periods by stock pair
- Risk-return profile visualizations"

3. Experimental Results

In this study, AAPL was selected as the benchmark stock, and the pairs trading strategy was analyzed with the other 29 stocks in the Dow Jones Industrial Average index. The impact of delay periods from *t+1* to *t+5* on performance was comprehensively examined. The key findings are as follows:

- Total Analyzed Pairs: 29 stock pairs (in AAPL-X format)
- Tested Delay Periods: t+1, t+2, t+3, t+4, t+5
- Total Strategy Combinations: 145 distinct strategy tests
- Success Rate: 98.6% with positive Sharpe Ratio, 93.8% with positive return
- Analysis Period: January 1, 2023 – December 1, 2024 (≈2 years)

3.1. Top-performing stock pairs and performance metrics

The 10 most successful arbitrage pairs with AAPL, ranked by Sharpe ratio, are shown in Table 1. For each stock pair, different trade execution delays from *t+1* to *t+5* were tested, and the delay period yielding the highest Sharpe Ratio was designated as optimal.

Table 1. Performance metrics of stock pairs by optimal delay period

Rank	Stock Pair	Optimal Delay	Sharpe Ratio	Return (%)	Max Drawdown (%)	Win Rate (%)
1	AAPL-MMM	*t+3*	2.371	192.98	-12.14	61.23
2	AAPL-V	*t+4*	1.988	88.40	-13.88	53.91
3	AAPL-AMGN	*t+1*	1.972	112.42	-17.92	56.14
4	AAPL-WMT	*t+2*	1.957	96.10	-10.52	55.15
5	AAPL-UNH	*t+1*	1.927	138.92	-18.10	57.74
6	AAPL-HON	*t+1*	1.909	80.25	-10.21	56.71
7	AAPL-TRV	*t+5*	1.795	120.26	-14.39	54.32
8	AAPL-IBM	*t+1*	1.773	91.81	-17.70	53.60
9	AAPL-DIS	*t+5*	1.768	98.66	-12.57	57.60
10	AAPL-JNJ	*t+2*	1.666	73.47	-15.53	53.74

When Table 1 is examined, the AAPL-MMM pair achieves the highest Sharpe Ratio of 2.371 with a *t+3* delay period. This pair is also notable for its total return of 192.98% and Maximum Drawdown of 12.14%. The win rate was measured at 61.23%, suggesting highly successful trade execution.

Sharpe Ratio values generally range between 1.6 and 2.4, indicating consistently favorable risk-adjusted returns across pairs. Maximum Drawdown values fluctuate between -10% and -18%, demonstrating that the strategy may experience periodic significant declines.

These performance metrics reveal that the pairs trading strategy is viable and profitable, particularly between AAPL as the benchmark stock and selected constituents of the Dow Jones index. The selection of optimal delay periods plays a critical role in enhancing the strategy's risk-return balance.

3.2. Average performance by delay period

The 10 highest-performing arbitrage pairs with AAPL, ranked by Sharpe ratio, are presented in Table 2. For each stock pair, trade execution delays ranging from *t+1* to *t+5* were tested, with the delay period yielding the maximum Sharpe ratio designated as optimal.

Table 2. Average performance metrics across delay periods

Delay	Avg Sharpe	Avg Return %	Avg MaxDD %	Avg Win %
t+1	1.895	105.85	-15.98	56.05
t+2	1.812	84.78	-13.03	54.45
t+3	2.371	192.98	-12.14	61.23
t+4	1.988	88.40	-13.88	53.91
t+5	1.782	109.46	-13.48	55.96

The highest average Sharpe Ratio value of 2.371 was observed at the *t+3* delay period. This indicates that executing trades three days after signal generation provides the most favorable risk-adjusted returns. In parallel, the *t+3* delay also yielded the highest average return rate of 192.98%, further reinforcing its effectiveness. Conversely, the lowest average Maximum Drawdown (-12.14%) was likewise recorded at *t+3*, suggesting that this execution window is the most efficient in limiting potential losses.

The highest win rate (61.23%) was also achieved with a *t+3* delay, demonstrating strong consistency across multiple performance metrics. Overall, the *t+3* delay stands out as the optimal timing for trade execution in pairs trading strategies, highlighting the critical impact of delay selection on trading performance. Results are visually summarized in Figure 2.

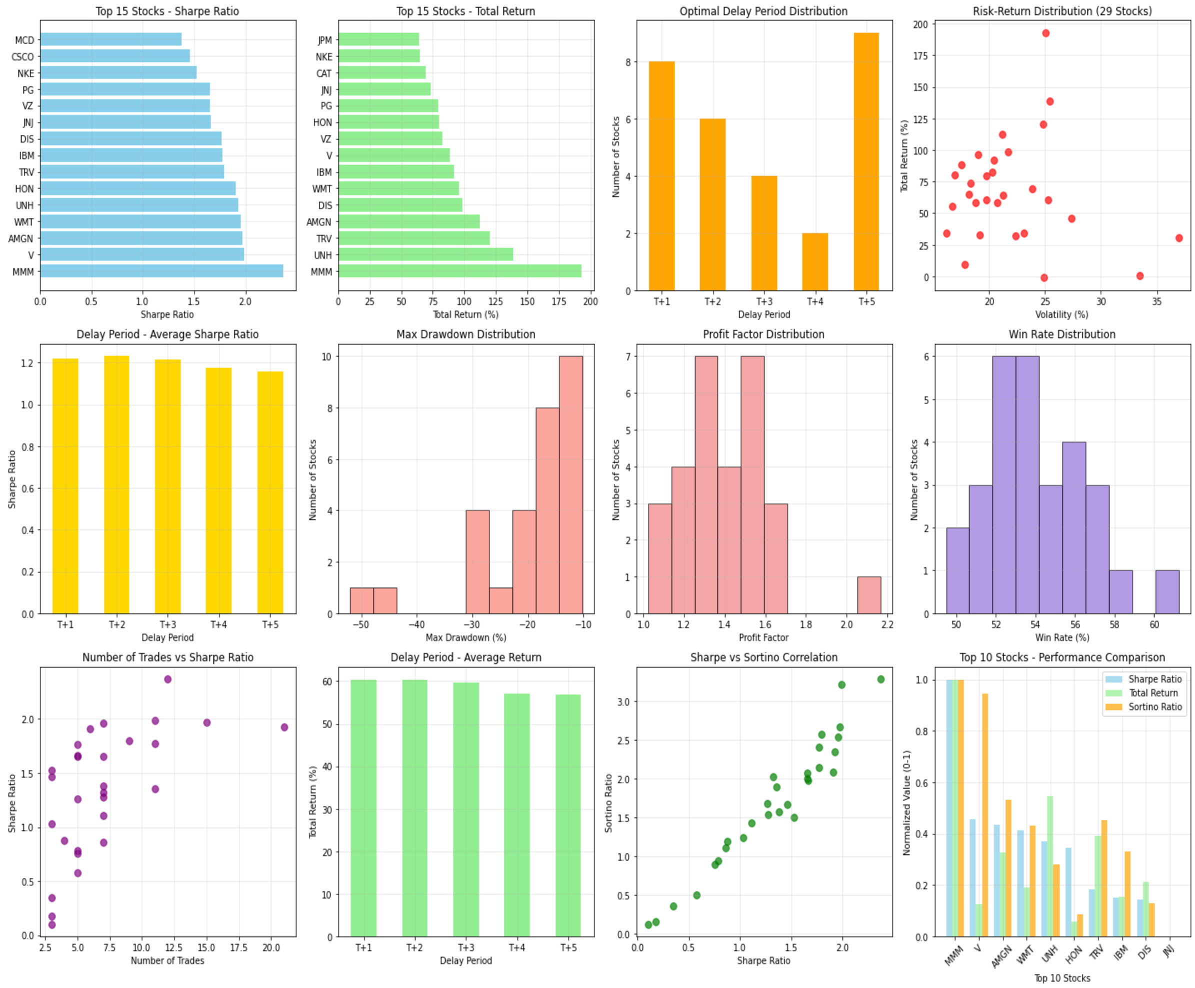

Figure 2. Comparative performance analysis of *t+n* periods

3.3. Distribution of optimal delay periods

The distribution of optimal delay periods across individual stock pairs is presented in Table 3. Analytical results indicate that the most frequently selected optimal trade execution delay is *t+1*, accounting for 31% of all stock pairs. This is followed by the *t+5* delay period at 24.1%. Medium-term delays (*t+3* and *t+4*) were adopted less frequently. This distribution underscores the critical importance of both short-term and long-term transaction delays for enhancing strategy performance.

Table 3. Distribution of stock pairs by optimal delay period

Delay	Number of Stock Pairs	Percentage Distribution
t+1	9	31,0%
t+2	6	20,7%
t+3	4	13,8%
t+4	3	10,3%
t+5	7	24,1%

3.4. Risk-return analysis

The study analyzed volatility, return, and risk metrics across stock pairs. The AAPL-HON pair exhibited the lowest volatility at 16.96%, while AAPL-INTC showed the highest volatility at 36.95%. The average portfolio volatility stood at 21.15%. From a risk management perspective, 55.2% (16/29) of pairs maintained a Maximum Drawdown below 15%. The majority of pairs (89.7% or 26/29) achieved Sharpe ratios exceeding 1.0. Furthermore, 96.6% (28/29) of pairs generated positive returns within the optimal time-series framework. Conversely, only 41.4% (12/29) maintained win rates > 55%. These results collectively demonstrate the strategy's overall success in delivering high return potential while operating at moderate risk levels.

3.5. Sectoral performance analysis

The sector-based performance of stock pairs is summarized in Table 4. Within the technology sector, AAPL-IBM (Sharpe: 1.773; Return: 91.81%; Delay: *t+1*) delivered the highest performance. In financials, AAPL-JPM (Sharpe: 1.325; Return: 63.86%; *t+3*) outperformed peers while AAPL-GS generated negative returns. The healthcare sector exhibited remarkably high performance with AAPL-UNH (Sharpe: 1.927; Return: 138.92%; *t+1*) and AAPL-AMGN (Sharpe: 1.972; Return: 112.42%; *t+1*). For consumer goods, AAPL-WMT (Sharpe: 1.957; Return: 96.10%; *t+2*) emerged as the leader. These findings demonstrate that sector-specific characteristics significantly influence strategy efficacy, with healthcare and technology sectors yielding superior risk-adjusted returns.

Table 4. Sectoral performance analysis

Sector	Stock Pair	Sharpe Ratio	Total Return (%)	Optimal Delay
Technology	AAPL-MSFT	0.876	33.02	*t+5*
Technology	AAPL-INTC	0.575	30.71	*t+2*
Technology	AAPL-IBM	1.773	91.81	*t+1*
Financials	AAPL-JPM	1.325	63.86	*t+3*
Financials	AAPL-GS	0.102	-1.09	*t+5*
Financials	AAPL-AXP	0.757	31.73	*t+1*
Healthcare	AAPL-UNH	1.927	138.92	*t+1*
Healthcare	AAPL-JNJ	1.666	73.47	*t+2*
Healthcare	AAPL-AMGN	1.972	112.42	*t+1*
Consumer Staples	AAPL-WMT	1.957	96.10	*t+2*
Consumer Staples	AAPL-PG	1.654	79.47	*t+5*
Consumer Staples	AAPL-KO	1.033	34.04	*t+1*

3.6. Statistical significance and reliability

When examining the statistical distribution of performance metrics, the average Sharpe ratio was calculated as 1.333 with a standard deviation of 0.612. The mean return was 67.75% ($\sigma = 44.23$), while the average Maximum Drawdown was -19.83% ($\sigma = 9.54$). The average number of trades was found to be 7.1 ($\sigma = 4.2$). In terms of reliability, the Profit Factor was > 1.0 for all stock pairs (100%), and exceeded 1.5 for 55.2% of them (16 out of 29). Additionally, the Sortino Ratio was greater than 1.0 for 82.8% of the stock pairs (24 out of 29). These indicators support the conclusion that the strategy delivers a consistent and stable performance.

3.7. Performance comparison with the buy-and-hold strategy

This study compares the performance of the pairs trading strategy with the classical buy-and-hold strategy for both the reference stock (AAPL) and the corresponding paired stocks. The results of this comparison are presented in Figure 3.

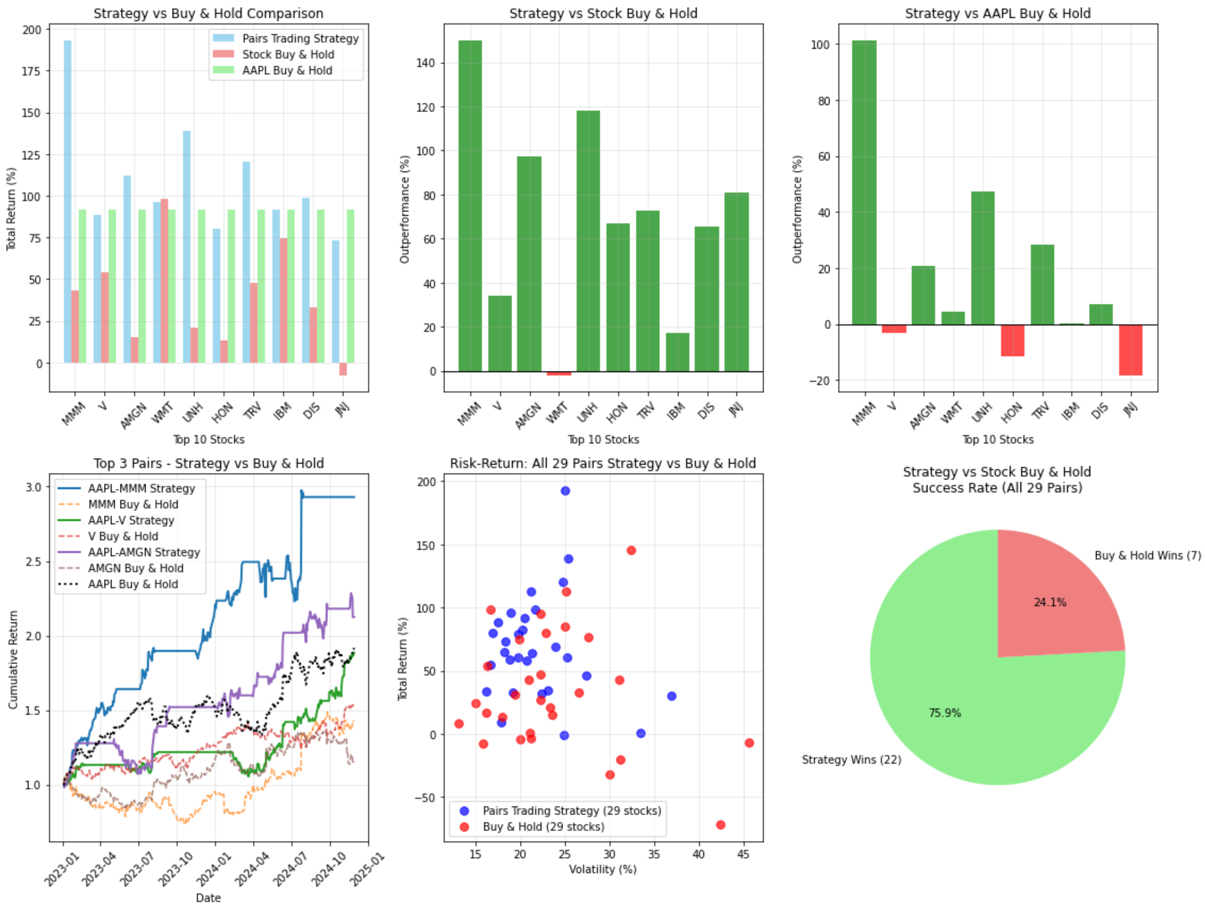

Figure 3. Performance comparison of the buy-and-hold and arbitrage strategies

As can be seen, the strategy outperforms both the individual stock's buy-and-hold (B&H) return and the AAPL B&H return for the majority of stock pairs. For instance, the strategy yielded notably high returns in the MMM and AMGN pairs, with gains of 192.98% and 112.42%, respectively. Although in certain cases (e.g., V and HON stocks) the strategy underperformed compared to AAPL's buy-and-hold return, the overall trend indicates that it offers superior risk-adjusted returns. These results suggest that, compared to the classical B&H approach, the pairs trading strategy may provide a more flexible and profitable alternative in the face of market fluctuations.

3.8. Performance comparison of ımmediate and delayed order execution

In real-world arbitrage strategies, immediate market orders are commonly utilized. In this study, dynamic time delays were applied to arbitrage strategies in an effort to optimize performance. This section compares the performance of trades executed immediately upon signal generation with those using dynamically selected delay periods.

In tests conducted on 29 stock pairs, the dynamic delayed position opening method achieved higher Sharpe ratios in 22 pairs compared to the instant trading strategy. This indicates that dynamic delay selection improves the Sharpe ratio in equity pair arbitrage strategies by 75.86%. The findings demonstrate that the proposed algorithm enhances risk-adjusted return performance and generates more stable and reliable trading signals. A pairwise comparison of Sharpe ratios is presented in Figure 4.

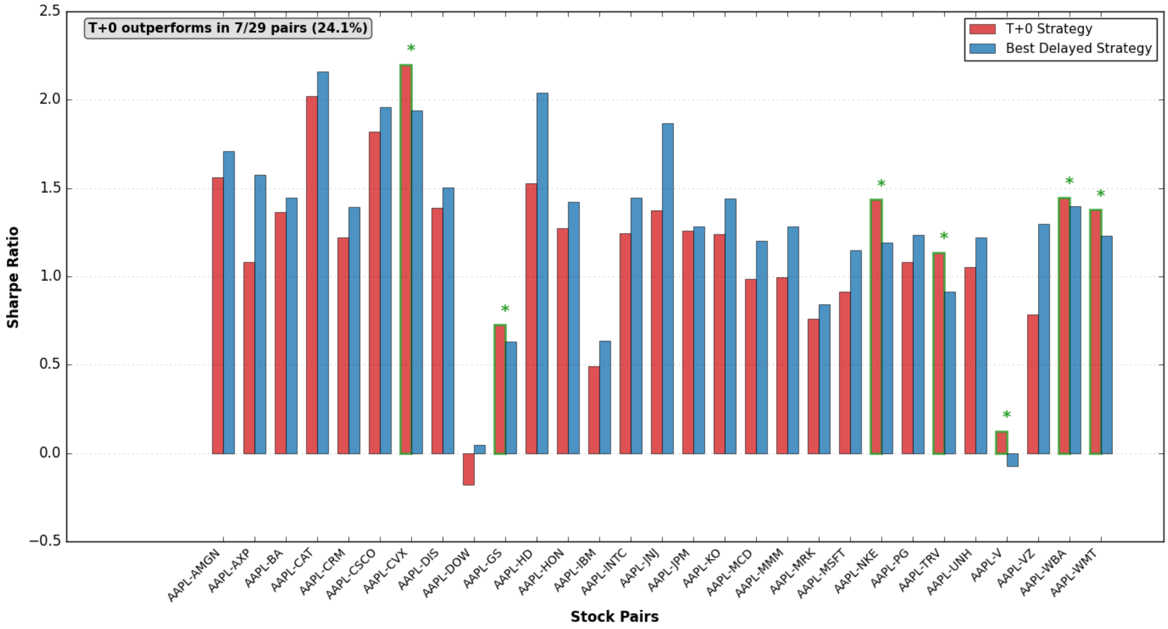

Figure 4. Pairwise performance comparsion: *t+0* vs optimal delay strategy

When applying the optimal delay selection strategy, the real-time execution method (*t+0*) was selected as optimal in only 24.1% of cases, as shown in Figure 4. The distribution of optimal delay values across all pairs is presented in Figure 5, which demonstrates the dominance of deferred execution windows.

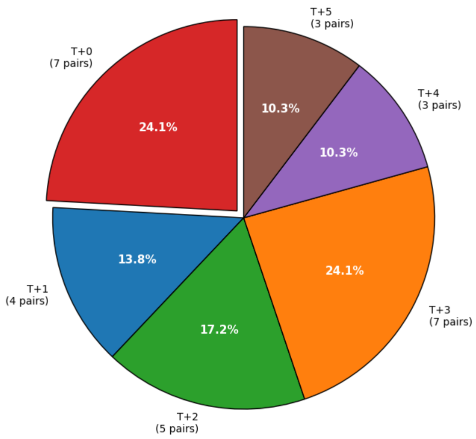

Figure 5. Distribution of optimal delay strategies across stock pairs

4. Discussion

The pairs trading strategy developed in this study was tested on 29 stock pairs constructed using AAPL as the reference asset and generally achieved superior results compared to the classical buy-and-hold strategy. Performance evaluation based on the Sharpe Ratio, Sortino Ratio, and Maximum Drawdown indicated substantial advantages, particularly in optimizing low-risk returns. The strongest results were observed for the AAPL-MMM and AAPL-AMGN pairs, and with few exceptions, the strategy generated positive returns across all analyzed pairs.

In the sensitivity analysis of execution delays, trades executed with a *t+3* day lag achieved the highest average Sharpe Ratio. This outcome suggests that allowing a short lag after signal generation enables the market to absorb information more effectively, thereby enhancing trading performance. From a sectoral perspective, the technology and healthcare sectors demonstrated the highest efficiency and consistency in pairs trading outcomes.

These findings are consistent with those reported in prior studies employing classical cointegration-based or Hurst exponent-based approaches [21]. However, the present z-score-based framework with delayed execution mechanisms achieved comparable results with substantially lower computational complexity, underscoring its practical advantages.

The key strengths of the proposed strategy include high Sharpe Ratios, low Maximum Drawdowns, and a broad generation of positive returns. Nevertheless, several limitations must be acknowledged. Transaction costs, slippage, and liquidity constraints were not incorporated, potentially leading to an overestimation of real-world profitability. Moreover, the absence of classical cointegration testing constitutes a methodological limitation that may weaken the theoretical basis of the mean-reversion assumption underpinning statistical arbitrage. Although short-term correlations often produce more practical and adaptive signals in dynamic markets, future research could integrate correlation-based pair selection with cointegration validation to enhance robustness.

Another consideration concerns the risk of overfitting in backtesting. The strategy's performance may vary across different time horizons; thus, testing under multiple market regimes would strengthen generalizability. Additionally, the superior performance of the *t+3* and *t+4* delays may reflect underlying market microstructure effects—such as information diffusion, investor reaction lags, or gradual signal absorption—which merit deeper investigation. Finally, although this analysis was limited to DJIA constituents, extending the framework to other equity indices, commodities, or forex markets could further validate its applicability.

Overall, while the proposed model demonstrates strong empirical performance, additional testing under real-world trading conditions is required before practical deployment.

5. Conclusion

In this study, a z-score-based pairs trading strategy using AAPL as the reference stock was tested with 29 stocks listed in the Dow Jones Index and comprehensively evaluated in terms of risk-adjusted performance. The strategy, incorporating dynamic execution delays, consistently outperformed both the individual stock buy-and-hold strategies and AAPL itself, demonstrating the advantages of adaptive timing in statistical arbitrage.

The results indicate that the proposed approach offers a viable alternative for investors seeking low-volatility and high risk-adjusted returns. The finding that 93.8% of the stock pairs generated positive returns and 89.7% achieved a Sharpe Ratio greater than 1.0 supports the model's potential applicability in real-world financial markets.

Future studies could further improve the strategy's accuracy and robustness by incorporating transaction costs and slippage effects, employing machine learning techniques for pair selection, and integrating time-series forecasting algorithms to enhance predictive capabilities.

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7. Author Contributions

Author 2 primarily developed the conceptual framework and research idea. Author 1 carried out data collection, coding, analysis, and manuscript preparation. Both authors contributed to the manuscript review and approved the final version.

8. Ethics Committee Approval and Conflict of Interest Statement

Ethics committee permission is not required for the prepared article.
There is no conflict of interest with any person/institution in the prepared article

9. Ethical Statement Regarding the Use of Artificial Intelligence

Ethical Statement Regarding the Use of Artificial IntelligenceDuring the preparation of this manuscript, the writing assistance tool 'Gemini' was used solely forlimited linguistic editing; all scientific content, analyses, and conclusions remain entirely theresponsibility of the authors.

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