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IMPLEMENTING SIMPLIFIED SHORT-TERM PAIRS TRADING STRATEGY IN EQUITY MARKET: UNDERSTANDING THE RISKS OF RETAIL INVESTOR

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Abstract. This study examines the profitability of a simplified short-term pairs trading strategy for retail investors in real-time equity markets, comparing the performance of individual stock pairs versus clusters of stocks. The research employs a simplified strategy implemented using accessible tools like "eToro" for trading and "MS Excel" for calculations. Stock pairs were selected based on historical correlations. The strategy was tested over a six-week trading period, comparing the performance of individual pairs versus a cluster of pairs. Key risk factors such as market trends, divergence risk, idiosyncratic news, and transaction costs were analysed. The research revealed that while the strategy can mitigate large losses when well-diversified, profitability is limited in stable or rising markets, idiosyncratic events also significantly impacted profitability. Trading clusters of stocks offers greater stability but reduced profit potential, whereas individual pairs provide higher but riskier returns. This research provides practical insights for retail investors seeking the simplified methods for pairs trading. It emphasises the importance of effectively managing key risks, diversifying portfolios, and adjusting trading strategies to improve investment outcomes. By concentrating on real-time market dynamics and a simplified framework, this study distinguishes itself from prior studies by offering practical guidance for retail investors, emphasizing the accessibility and flexibility of its methodology, in contrast to the complex algorithmic methods discussed in other studies.

Keywords: pairs trading, retail investors, risk management, equity markets, short-term trading, portfolio diversification.

JEL Classification: G10, G11, G14, G15, G17.

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1. Introduction

The importance of risk management for retail investors in dynamic financial markets remains a consistent concern. Market-neutral strategies such as pairs trading provided opportunities for profit regardless of market direction (Brunetti & Luca, 2023), increasing complexity and technological evolution reduced their accessibility for individual traders (Lee et al., 2023; Wang et al., 2023). Since its introduction in the 1980s, pairs trading has been widely adopted by hedge funds and institutional investors, supported by advances in algorithmic trading and machine learning (He et al., 2023). Nevertheless, retail investors can still apply core principles to exploit market inefficiencies.

Previous studies (Balladares et al., 2021; Haddad & Talebi, 2023; Krauss, 2015) largely focus on improving profitability and risk management within algorithmic settings, while the short-term applicability of these strategies remains underexplored. A short-term trading horizon may benefit retail investors seeking rapid results, reinvestment opportunities, and improved long-term performance through repeated cycles of trades within a year. Furthermore, strategies that can be implemented using commonly available platforms remain underexplored. This study seeks to address this gap by testing a simplified short-term trading approach in real-time market conditions, with the aim of offering individual investors a practical method for identifying opportunities and managing risk.

Given these observations, this research investigates the implementation of a simplified short-term pairs trading strategy under real-time market conditions. Using accessible tools like "eToro" and "Microsoft Excel", this study aims to test a methodology that reduces complexity while maintaining effectiveness. Furthermore, the research explores whether using the simplified approach trading individual stock pairs or clusters yields higher profitability because recent research highlights the advantages of trading clusters of stock pairs over individual pairs, especially in algorithmic frameworks (Lee et al., 2023; Wang et al., 2023).

The research problem is to determine whether a simplified short-term pairs trading strategy is profitable for both individual stock pairs and stock clusters. The research question addressed is how this simplified strategy performs under the conditions faced by retail investors. The novelty lies in evaluating simplified methodology tested in real-time, rather than relying solely on historical data or large algorithmic portfolios, which are typically studied. By focusing on the practical application for retail investors, this study fills a gap in the existing literature, contributing practical insights for managing risk and optimizing returns in today's volatile markets.

The aim of this study is to test a simplified short-term pairs trading strategy comparing trading the individual stock pairs and a cluster of stock pairs. By addressing key risk factors such as market trends, divergence risk, risk of idiosyncratic news and transaction costs, the research offers a framework that helps retail investors better manage risks.

In summary, this research makes a unique contribution by testing pairs trading strategies under real-time market conditions, with implications for retail investors who seek a more accessible yet effective approach to market-neutral trading. It highlights the importance of real-time testing, broader portfolio diversification, and the potential to enhance profitability through simplification.

This paper is structured as follows: the theoretical part explores the concept, implementation methods, and risk factors of pairs trading; the methodology section outlines the simplified pairs trading approach, the research data, procedure and empirical results section outlines the data used and provides the results; the analysis of the results and discussion section analyses key findings and provides comparison to other researches; the conclusion summarises findings and provides practical implications; the limitations section discusses the study's constraints; the final section outlines future research directions. The paper concludes with a disclosure statement and references.

2. Theoretical aspects of the pairs trading strategy in equity market

2.1. The concept and the methods of the implementation of pairs trading strategy

Pairs trading is a market-neutral investment strategy aimed at generating stable profits while reducing market risk (Brunetti & Luca, 2023). A key element of the strategy is understanding divergence and convergence. Divergence occurs when the price ratio of two strongly correlated stocks deviates from its usual pattern, signalling an opportunity to buy the undervalued stock and sell the overvalued one, with the expectation that prices will revert to their historical mean. Selecting stocks from the same sector is common, as companies in similar industries often show stronger correlations and react similarly to market events (Gatev et al., 2006; Engelberg et al., 2008; Sahu et al., 2023). Divergence may be driven by company-specific events such as financial reports, management changes or legal issues (Engelberg et al., 2008; Papadakis & Wysocki, 2007), macroeconomic or political developments affecting sectors unevenly (Do & Faff, 2010; Schizas et al., 2011), sector-specific shocks (Broussard & Vaihekoski, 2012), market sentiment and behavioural biases (Kazemian et al., 2014; Jacobs & Weber, 2015; Datta Chaudhuri & Singh, 2015), or differences in liquidity and volatility. Understanding these factors is essential because they influence the likelihood and timing of convergence. Assessing the reasons behind divergence helps traders manage the risk of positions remaining open longer than expected, which can impact overall profitability (Schizas et al., 2011; Gatev et al., 2006).

Pairs trading typically consists of two phases: the formation period and the trading period, enabling effective pair selection and trading decisions (Diao et al., 2020).

The formation period involves selecting historical data – usually stock prices, volatility, and returns – and analysing relationships between stocks. Its length depends on the trading horizon and method used to determine stock relationships. Longer horizons generally require longer formation periods, often set equal to or up to twice the trading period (Lee et al., 2023; Haddad & Talebi, 2023; Bowen & Hutchinson, 2016). Cointegration and copula approaches usually require 3–5 years of data to detect long-term relationships (Sahu et al., 2023; Liew & Wu, 2013). Gatev et al. (2006) recommend re-analysing historical data when using long trading periods (rolling approach). Buda (2011) noted that correlations are relatively short-term, emphasising the need for a for optimal historical data periods for analysis – long enough to reflect economic changes but not too long to include irrelevant data. A correlation above 0.8 is commonly applied in pairs trading (Liew & Wu, 2013). Cointegration identifies long-term relationships between stocks, indicating that prices eventually revert to a historical mean despite temporary fluctuations (Huck & Afawubo, 2015; Tadi & Witzany, 2023). Cointegration tests enhance profitability in pair selection (Brunetti & Luca, 2023). Combining cointegration and correlation analyses improves signal identification and strategy effectiveness (Sahu et al., 2023).

Common methods for pair selection include correlation analysis, cointegration analysis, the minimum distance method, time series analysis, and copula methods. Various algorithmic trading methods, including machine learning, are also used (Haddad & Talebi, 2023; Rudy et al., 2010). The minimum distance method assumes selecting stock pairs with minimal price differences over a historical period (Gatev et al., 2006) but can be sensitive to market shifts. The copula method uses dependence structures between stock returns (Xie & Wu, 2013; Krauss, 2015). Haddad and Talebi (2023) found copulas outperform cointegration and minimum distance methods. Time series analysis assumes integrating various parameters – correlation, cointegration, volatility – providing a comprehensive understanding of stock pairs. Implemented using statistical models and machine learning algorithms, it helps identify patterns and trends in price movements. These methods offer different approaches to constructing pairs trading strategies, allowing traders to maximise efficiency in various scenarios (Majumdar & Laha, 2024; Zhu et al., 2016).

The trading period is when actual trading occurs. Positions are opened when price differences deviate from historical levels and closed when they revert to the mean. One of the main approaches is the classical distance method, where positions are opened when the price difference exceeds the long-term average by more than two standard deviations and closed upon reversion (Gatev et al., 2006). Another approach, the stochastic method, relies on probability processes such as the Ornstein-Uhlenbeck (OU) process to identify overbought or oversold assets by analysing price movement speed and direction (Xing, 2022; Wu et al., 2020). Lee and Leung (2020) showed that optimised exit rules improve profitability. The price-ratio method, a simpler technique, uses the price ratios of two correlated assets, adjusting positions when ratios deviate from historical averages. Advances in financial engineering allow the use of machine learning, algorithmic trading, and optimisation, with methods such as neural networks, random forests, and support vector machines aiding pair selection and signal generation (Milstein et al., 2024; Platania et al., 2023; Dąbrowski, 2023). Diao et al. (2020) applied convex quadratic programming with quadratic constraints based on the OU process to optimise positions, achieving higher returns than traditional strategies.

In this study, following a review of various methodologies, we adopted a fundamental approach to pair selection, focusing on correlation analysis and the two-standard deviation rule for trading signals. This method was chosen for its simplicity and transparency making it particularly suitable for short-term trading. While more complex models may offer theoretical advantages, the selected method was chosen for its simplicity and transparency for non-professional traders.

2.2. Risk factors in pairs trading in the stock markets

2.2.1. Eliminating systematic market risks and sector risk by means of pairs trading

The primary goal of pairs trading is to generate stable profits while reducing overall market risk. Haddad and Talebi (2023) found that even under extreme market conditions, such as the financial crisis caused by COVID-19, pairs trading strategies maintained their profitability, confirming their market-neutrality. Bowen and Hutchinson (2016) also noted the effectiveness of pairs trading during the 2008 financial crisis. Analysing the top five and twenty pairs' trading portfolios, they observed that in the first year of the crisis, these portfolios performed similarly to the FTSE All-Share Index. However, in the second year, pairs trading generated higher cumulative returns than the market index. Over two years, the FTSE All-Share Index suffered a 34% loss, while the returns for their portfolios were 46% and 36%, respectively. The average monthly returns for these portfolios were 1.64% and 1.32%, compared to the FTSE All-Share Index's monthly return of –1.57%. These results indicate that pairs trading can offer significant diversification benefits during stock market crises (Bowen & Hutchinson, 2016).

Miao and Laws (2016) analysed the profitability of pairs trading strategies during growth and downturn periods. They found that the strategy generated positive returns even during downturns. Pairs trading remained profitable even after accounting for transaction costs, although returns significantly decreased with higher transaction expenses.

It's important to note that pairs trading also protects against sector risk. Theoretically, during a sector crisis when the values of both stocks decline, pairs trading allows to profit from the short position to offset losses from the long position. The income from the short position, essentially preserved funds, can be used to build a long-term position in the same sector by purchasing stocks at lower prices (Tenyakov, 2017). For example, the Finnish economic crisis in the 1990s, which had a significant negative impact on the country's banking and other sectors, provided an excellent opportunity to evaluate this strategy's effectiveness under the conditions of an economic crisis in the country. Despite market volatility and lack of liquidity, pairs trading in the Finnish market was profitable (Broussard & Vaihekoski, 2012).

From these examples, we see that the main advantage of pairs trading is neutralizing systematic and market risks by hedging. By simultaneously holding long and short positions in stocks with strong historical price relationships, the strategy protects against significant market fluctuations. When the market is rising, losses from short positions can be offset by profits from long positions, and during a market downturn, losses from long positions can be covered by profits from short positions. This hedging mechanism ensures that portfolio performance depends not on market direction but more on the relative performance of the paired stocks.

Although the strategy neutralises market risk, its profitability can be affected by other risk factors, which are discussed further.

2.2.2. Risks in pairs trading associated with market in(efficiency)

Increased market efficiency is attributed to greater information accessibility, advanced technologies, and heightened competition among investors, which allow for quicker exploitation of arbitrage opportunities, thereby shortening the period during which they are available (Yu & Xie, 2021). Though Miao and Laws (2016) disagree that increasing market efficiency has significantly impacted pairs trading effectiveness in recent decades, various studies have observed a slight decline in the strategy's profitability since the 2000s as markets become more efficient (Do & Faff, 2010).

Motivated by this trend, Balladares et al. (2021) evaluated the profitability of pairs trading in developed and emerging markets to demonstrate that the strategy's success depends on the degree of market efficiency. The study found that from 2000 to 2007, the highest profits after transaction costs were achieved in emerging markets and markets experiencing difficulties, particularly South Africa (up to 71.21% profit with portfolios of 30 pairs), Japan, and Israel. The authors note that while Japan and Israel are not emerging markets, specific economic challenges during that period made them less efficient. During years 2007–2014, despite the global financial crisis, the highest profits were found in Israel and South Africa, with significant gains, also in European countries like Portugal and the Netherlands. From 2014 to 2020, the greatest profits were achieved in Greece, Colombia, and South Africa, while the lowest profits and losses occurred in developed, liquid markets like the USA, France, Spain, and Dubai. This suggests that pairs trading can be particularly profitable in less efficient markets with higher volatility (Balladares et al., 2021).

Supporting these findings, Mashele et al. (2013) reported annual returns of 8% to 20% using pairs trading on the Johannesburg Stock Exchange, effectively reducing portfolio risk even during volatile periods. Schizas et al. (2011) found that pairs trading with ETFs was more profitable but riskier in emerging markets like Brazil and Malaysia compared to developed markets, where the strategy was stable but yielded lower returns.

Further studies in Latin America by Caneo and Kristjanpoller (2020) showed that pairs trading outperformed market Sharpe ratios by an average of 1.55 points when testing 338 stocks from years 2013 to 2017. Namwong et al. (2019) demonstrated that in the Thai stock market – a highly liquid emerging market – positive returns were achieved for all selected stock pairs, reaching up to 14.27%.

In summary, less efficient and emerging markets offer both advantages and disadvantages for pairs trading. Market inefficiencies and high growth potential provide greater profit opportunities using arbitrage strategies. However, these opportunities come with higher risks due to lower liquidity, economic and political instability, and less predictable regulatory environments. Investors must carefully assess these factors and adapt their investment strategies accordingly.

2.2.3. Risks in pairs trading associated with market il(liquidity)

Liquidity is crucial for pairs trading, influencing profitability at both the company and market levels. Low stock liquidity increases trading costs and risks, while high liquidity narrows bid-ask spreads and reduces transaction costs, boosting returns. However, if illiquid stocks suddenly experience increased demand, rapid price fluctuations can occur. A pairs trader who anticipates or reacts quickly to these movements may gain significant profits, though this requires quick decision-making and a strong understanding of market conditions.

Engelberg et al. (2008) found that consistent liquidity enhances long-term returns, whereas liquidity shocks negatively affect short-term performance. For example, liquid stocks allow for quick transactions with minimal costs, and high market liquidity ensures that the strategy remains effective even during macroeconomic shifts. While liquidity shocks can temporarily raise costs and reduce returns, these effects tend to be short-term.

Studies show that pairs trading can still be profitable in less liquid markets. Broussard and Vaihekoski (2012) analysed the Finnish market from 1987 to 2004, a period that included low liquidity before 1995 due to economic challenges and limited short selling. Despite these constraints, they found that pairs trading yielded solid returns. The strategy delivered an average monthly return of 4.465%, with the highest monthly gain reaching 69.37% in April 1990 during the financial crisis. Post-1995, when market liquidity improved and short selling was formally permitted, the strategy's results became more reliable, affirming its potential even in low-liquidity conditions.

Perlin (2008) examined pairs trading in Brazil from 2000 to 2006, focusing on the 100 most liquid stocks. Despite Brazil's overall liquidity limitations, he found that pairs trading was profitable and market-neutral using daily data, while weekly and monthly data provided weaker results. His research indicates that with high-frequency data and careful stock selection, pairs trading can succeed even in less liquid markets.

In conclusion, while low-liquidity markets pose challenges, pairs trading can remain profitable when adapted to market conditions. Effective liquidity management and market analysis are essential for success.

2.2.4. Horizon and divergence risk, impact of idiosyncratic and macro news

One of the main risk factors in pairs trading is the possibility that the stock pair's ratio will not revert to its historical mean during the trading period, known as horizon risk. This risk increases over time as there is less time for the pair to revert, especially when each trade has a specific holding period. Another significant risk is divergence risk – the chance that after opening positions, the correlation between stocks decreases further, leading to greater divergence (Engelberg et al., 2008).

Horizon and divergence risks can be mitigated by forming pairs of exchange-traded funds (ETFs), as ETFs are less affected by the price movements of a single security. ETFs offer diversification benefits and reduce the impact of risks caused by idiosyncratic news. ETF pairs are less risky than individual stock pairs and provide greater stability and returns for pairs trading strategies (Rudy et al., 2010). Theoretically, similar results can be achieved by trading sets of stock pairs (if the set includes a very large number of stocks, similar to an

ETF) and stock indices. Pairs trading with stock clusters, ETFs and indexes will be discussed further in this research article.

Jacobs and Weber's research showed that divergence risk depends on the type of news causing the divergence – whether it is idiosyncratic news or general news. Idiosyncratic news, also known as company-specific news (earnings reports, dividend announcements, significant internal changes, new product launches, and legal issues, etc.), refer only to a specific company and typically does not directly affect other market participants. Such news can cause sudden and unpredictable price fluctuations specific to that company. Engelberg et al. (2008) also state that such situations can provide a trading signal, but the pair's prices may diverge further, disrupting the overall movement between the securities. Additionally, the profitability of pairs trading can be affected by companies involved in financial information manipulation schemes (Aggarwal et al., 2003; Papathanasiou et al., 2024) also leading to idiosyncratic news. In contrast, general news like macroeconomic indicators, interest rate changes, or important political decisions affect a wide range of stocks (Jacobs & Weber, 2015). General news affecting both stocks similarly is less likely to cause too risky prolonged divergence (Engelberg et al., 2008). Papadakis and Wysocki (2007) also indicated that idiosyncratic news is often associated with lower profitability in pairs trading because the resulting price volatility can hinder the pair's convergence.

These studies indicate that while idiosyncratic news can present opportunities to profit from price fluctuations, it also introduces greater risk to pairs trading strategies. Therefore, it is important to focus on macroeconomic news, which can offer stability and profitability opportunities due to its more balanced impact on the entire market.

2.2.5. Risk from transaction costs

In pairs trading, the risk of losses is also linked to commissions, transaction costs, and dividends, which can significantly affect the strategy's profitability (Lei & Xu, 2015).

Gatev et al. (2006) highlighted that profits can be influenced by bid-ask spreads, fees for short positions, and other charges. Bowen and Hutchinson (2016) found that transaction costs reduced annual returns by 4%, particularly in frequently traded portfolios. Zhang and Urquhart (2018) also emphasised importance of transaction costs, setting a conservative 1% estimate for an average transaction cost. Do and Faff (2010) estimated average costs per position at 0.6%. Broussard and Vaihekoski (2012) set transaction costs at 0.2%. Mashele et al. (2013) reported trading costs ranging from 0.25% to 0.75% per transaction, depending on stock liquidity and market conditions. Miao and Laws (2016) noted that although pairs trading remained profitable after accounting for costs, returns significantly decreased with higher expenses. Thus, transaction costs between 0.2% and 1% can substantially reduce cumulative returns. Li and Tourin (2022) suggest that advanced trading methods can reduce transaction costs' impact and optimise profitability.

Short positions require particular attention because dividend payments create additional costs. Traders who hold a short position from the record date to the ex-dividend date must reimburse the dividend to the owner, which reduces profitability, especially when payouts are large. For this reason, dividend schedules should be taken into account when selecting stock pairs. In retail trading platforms, short positions are typically executed through CFDs, which may introduce further expenses such as overnight fees.

In summary, commissions, transaction costs, and the size and timing of dividends can substantially influence the performance of pairs trading, particularly in more active strategies, making effective cost management an essential component of successful implementation.

2.2.6. Trading clusters of stock pairs, ETFs, and indexes to reduce risks

Pairs trading in equity markets can be applied not only to individual stock pairs but also to clusters of pairs, ETFs, or correlated indices. Trading clusters enhances diversification by spreading exposure across multiple pairs, thereby reducing idiosyncratic risk and stabilizing returns. It also enables faster profit realisation by targeting portfolio-level rather than pair-level gains. Finally, it simplifies exit decisions, as all positions can be closed once the aggregate profit threshold is reached, lowering monitoring requirements, execution delays, and operational costs.

Lee et al. (2023) explored trading multiple stock pairs simultaneously using the Ornstein-Uhlenbeck process achieving annual returns of 11% to 30%. Similarly, Zhang and Urquhart (2018) demonstrated that the profitability of pairs trading depends on the number of pairs in the portfolio, further supporting the benefits of diversification.

Trading ETFs and stock indexes follows a similar principle, aiming to reduce specific risk through diversification. However, ETFs often track a sector or index, while stock indexes cover broader market segments. ETFs offer higher diversification and lower transaction costs compared to individual stock clusters, while allowing investors to capitalise on economic differences across sectors and regions. Schizas et al. (2011) analysed 22 international ETFs using historical data from 1996 to 2009 and found that pairs trading using ETFs remained profitable across different markets and economic cycles, emphasizing the strategy's reliability.

Index pairs, due to their lower volatility and higher liquidity, attract investors aiming to reduce risk and trading costs. He et al. (2023) examined pairs trading using the Russell 2000 and S&P 400 indexes and found that both basic and copula models outperformed long-term "buy and hold" strategies during recessions, including the COVID-19 pandemic.

In summary, a pair trading is a flexible strategy that can be applied to individual stocks, clusters of stock pairs, ETFs, and stock indexes. It allows investors to efficiently exploit market anomalies, taking advantage of diversification and liquidity benefits to reduce overall investment risk.

3. Methodology of the simplified short-term pairs trading strategy

This section outlines the methodology for a simplified short-term pairs trading strategy tested under real-time market conditions. To evaluate its suitability for individual investors, it must be assessed under the conditions they would realistically face. Large-scale studies often conclude that pairs trading is broadly profitable, suggesting limited losses due to hedging, but such generalisations can be misleading. Few studies examine the risks associated with small trading sets typical for retail investors. In practice, and particularly without algorithmic tools as in this methodology, investors rarely trade large samples of 500 stocks; instead, they work with only a few pairs. This study applies the method to both individual stock pairs and a cluster of pairs to compare profitability and risk across scenarios.

Trading time horizon. We selected a six-week trading horizon. Previous studies show that stock pairs can revert to the mean over periods ranging from a week to several months. Engelberg et al. (2008) found that most pairs converge within about eight days, indicating that short horizons are efficient due to rapid mean reversion. They noted that if pairs do not revert within the first week, the probability of convergence decreases, although some may revert later with higher risk. Schizas et al. (2011) reported that about 50% of pairs reverted to the mean within 40 trading days. Broussard and Vaihekoski (2012) observed average monthly profits of up to 5%, supporting shorter trading periods, while Jacobs and Weber (2015) found an average holding period of about one month. Buda (2011) showed significant short-term correlation fluctuations over 20 days, creating profitable opportunities despite increased risk. Given the strategy's aim to generate returns quickly while eliminating systematic market and sector risk, a six-week horizon was chosen as optimal.

Allocation of investment funds. Following Broussard and Vaihekoski (2012). This approach ensures comparable results across all positions, allowing clearer assessment of the strategy's effectiveness.

Choice of trading platform. Positions were opened under real-time market conditions using "eToro" trading platform's simulator. Key factors in choosing "eToro" included trading tools, user interface, fees, wide selection of securities, reliability, ability to open both buy and sell positions on the same stock simultaneously, as well as to purchase fractional shares.

The formation and trading periods will be presented in further subsections.

In summary, the six-week period was chosen based on research supporting the effectiveness of shorter periods, equal fund allocation ensures objective evaluation of investments. Selecting an appropriate trading platform minimises costs and ensures strategy implementation under real-time conditions.

3.1. Stage I – formation period

Step 1 – selection of stocks for analysis. To ensure diversification and reduce sector-specific risk, we randomly selected stocks from eight sectors, 10 from each. Although researchers use various industry classification schemes, there is no essential difference in which one is applied. The key is selecting stocks from similar industries where companies respond similarly to market condition changes. For example, Sahu et al. (2023) selected stocks from 10 sectors – automotive, information technology, public enterprises, banking, fast-moving consumer goods, media, metals, oil and gas, and pharmaceuticals. Engelberg et al. (2008) selected stocks classified under the Fama-French twelve-industry scheme. Notably, researchers often choose industry-based classification when the sample size is smaller, regardless of trading methods (Lee et al., 2023), while it is generally avoided when applying complex models using large samples from entire exchanges (Namwong et al., 2019).

While researchers often select stocks using criteria such as company capitalization (Sahu et al., 2023) or liquidity (Namwong et al., 2019), in this work these steps were omitted due to the simplified pairs trading approach. In our research, the stocks were randomly selected without considering specific criteria, characteristics, risks, or trends.

Researchers usually form pairs from a single exchange. For example, Mashele et al. (2013) selected stocks only from the Johannesburg Stock Exchange (JSE), Namwong et al. (2019) from the Stock Exchange of Thailand (SET), Broussard and Vaihekoski (2012) from the Helsinki Stock Exchange, and Haddad and Talebi (2023) from the Toronto Stock Exchange (TSX).

In our research, all stocks were chosen from NYSE and NASDAQ due to their liquidity, accessibility, variety, and identical trading hours. Engelberg et al. (2008) showed that selecting stocks from both NYSE and NASDAQ yielded a 1% higher return than selecting from a single exchange. Both exchanges also react similarly to macroeconomic news, which is important because market trends driven by macroeconomic news positively influence pairs trading.

Step 2 – collection of historical stock price data. For the analysis, daily closing price data over a three-month period was obtained from Yahoo Finance (2024), exported to "MS Excel" and adjusted for further processing.

This historical stock price period was chosen based on Buda's (2011) findings that a three-month historical data period is sufficiently informative for determining correlations between stocks. The selected period also aligns with the study's planned short-term trading horizon (6 weeks) – it has been observed that when using correlation analysis, researchers typically set a formation period that is the same as or up to twice the length of the trading period. The table below presents examples of formation and trading periods from various studies (see Table 1).

Table 1. Examples of different formation and trading periods used in various scientific studies (source: compiled by the authors, "eToro" information, 2024)

Researchers	Formation Period	Trading Period
Lee et al. (2023)	1 year	1 year
Haddad and Talebi (2023)	1 year	6 months
Bowen and Hutchinson (2016)	1 year	6 months
Engelberg, Gao, and Jagannathan (2008)	6 months (with additional evaluation after 10 trading days)	6 months
Mikkelsen and Kjaerland (2018)	2 / 4 / 6 weeks	1 /2 /3 weeks

Step 3 – determination of correlation between stocks. In this step, the correlation coefficient between stocks within the same industry or business sector was calculated using formula (1) (Vakrina, 2007), and correlation matrices were constructed to visually assess which stock pairs have a strong positive correlation. Stocks with a price correlation coefficient exceeding 0.8 were chosen to form pairs.

$$r = \frac{\Sigma\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)}{\sqrt{\Sigma\left(X_i - \bar{X}\right)^2 \Sigma\left(Y_i - \bar{Y}\right)^2}}, \tag{1}$$

where: r – the correlation coefficient between two stock prices; X_i and Y_i – the prices of stocks X and Y on day i within the analysed period; $\bar{X}$ and $\bar{Y}$ – the average prices of the stocks X and Y over the analysed period. The following equations were used to calculate $\bar{X}$ and $\bar{Y}$ (Vakrina, 2007):

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i\ ; \tag{2}$$

$$\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i, \tag{3}$$

where: $\bar{X}$ and $\bar{Y}$ – the average prices of the stocks X and Y over the analysed period; X_i and Y_i – the prices of stocks X and Y on day i within the analysed period; n – the total number of observations for stock X and Y correspondingly.

In summary, the formation period involved selecting stocks for analysis, collecting historical price data, and determining correlations between stock movements to form stock pairs. *The simplified methodology used in this study distinguishes it from other research and focuses on obtaining the necessary data with minimal time and financial resources for the investor. Although some formulas are elementary, they are included for clarity and completeness, particularly for practical implementation by retail investors using spreadsheet-based tools.*

3.2. Stage II – trading period

Step 1 – generation of trading signals and opening of the positions. For the generation of the trading signals, we used the classic two-standard-deviation rule proposed by Gatev et al. (2006) – if the price ratio of a stock pair on the day before trading deviates from the average price ratio by more than two standard deviations, it is considered as a signal to trade. We obtained trading signals in the following way:

a) We calculated the price ratio of each selected stock pair for each day of the historical period using the formula:

$$PR_{xy} = \frac{X_i}{Y_i}, \tag{4}$$

where: PR_{xy} – the price ratio of the stock pair (stocks *x* and *y*); X_i and Y_i – the prices of stock *X* and *Y* at time *i* within the analysed period; *X* > *Y* (the stock with the higher price on the day before the first trading date is the numerator).

b) We calculated the deviation of each stock pair's daily ratio from the average using the formula (Vakrina, 2007):

$$D_i = PR_{xy_i} - \frac{1}{n}\sum_{i=1}^{n} PR_{xy_i}, \tag{5}$$

where: D_i – the deviation of the price ratio of the pair of stocks on day *i* from the average price ratio; PR_{xy_i} – the price ratio of the stock pair on day *i*; *n* – total number of observations within the analysed period.

c) We calculated the standard deviation for each stock pair using the formula (Vakrina, 2007):

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} D_i^2}{n-1}}, \tag{6}$$

where: σ – the standard deviation of the price ratio of the stock pair within the period; D_i – the deviation of the price ratio on day *i* from the average price ratio; *n* – total number of observations within the analysed period.

d) We calculated how many standard deviations the stock pair's price ratio on the last day before the trading deviated from their price ratio average of the historical period using the formula (compiled by the authors basing on Gatev's et al. (2006) method):

$$Z = \frac{D_{last}}{\sigma}, \tag{7}$$

where: *Z* – the number, which shows how many standard deviations the last day's stock prices' ratio of the two stocks in the pair deviated from the mean; D_{last} – the deviation of the stock pair's price ratio from the mean on the last day before trading; σ – the standard deviation of the price ratios within the analysed period.

If the calculated Z-value was greater than 2 or less than –2 (i.e., the ratio deviated from the average by more than two standard deviations), it was considered a signal to open a position. If the value was greater than 2, a "short" position was opened for the stock with the higher price, and a "long" position was opened for the stock with the lower price. If the calculated Z-value was less than –2, a "long" position was opened for the stock with the higher price, and a "short" position was opened for the stock with the lower price.

Step 2 – evaluation of trading results, positions' closing. Data were collected for all trades – entry price, exit price, and position duration. The return of each position was calculated twice a week using the formula (Zivot, 2015):

$$Ret = \frac{P_{t+1} - P_t}{P_t}, \tag{8}$$

where: Ret – the return on the investment. P_{t+1} – the value of the investment at the end of the period; P_t – the initial value of the investment. Given the strategy's short-term nature, simple returns were used for clarity and practical interpretation.

The return of the stock pair, as well as the cluster of pairs, was calculated using the formula (Zivot, 2015):

$$Ret_{total} = \frac{1}{n}\sum\nolimits_{i=1}^{n} Ret_i, \tag{9}$$

where: Ret_{total} – total return of the stock pair or of the cluster of pairs; Ret_i – the return of the i-th position; n – the number of positions for which the return is calculated.

Each pair and the cluster of pairs were evaluated for returns twice a week. For individual pairs, positions were closed when the return reached 7% or higher, or –11% or lower. For the entire cluster, all positions were closed simultaneously when the overall return hit 5% or higher, or –11% or lower. This asymmetric risk-reward ratio is based on the expectation that stock prices may move unfavourably in the short term but will revert to the mean over the target period. This approach reduces the likelihood of prematurely closing positions and locking in unnecessary losses.

In summary, using the simplified strategy, trading signals are generated based on the classic two-standard-deviation rule. The evaluation of trading results and position closing follows strict criteria, enabling effective risk management and optimizing returns.

4. Research data, procedures and empirical findings

This section presents the research data, the procedures and the results. A six-week period was chosen for the testing. All positions were opened on May 6, 2024, and monitored until June 14, 2024. A sum of $100 USD was allocated to each stock position, an equal investment of $200 USD per pair was made.

4.1. Stage I – formation period

Step 1 – selection of stocks for analysis. 80 stocks listed on the NYSE and Nasdaq exchanges were randomly selected from eight sectors (10 from each sector) – financial services, insurance services, specialised manufacturing equipment, retail apparel, healthcare, software, automotive industry, non-energy metals.

The list of all selected stocks is not provided, as it is not essential for the interpretation of the results. Given that the stocks were selected randomly, any of alternative securities could have been included without altering the methodological validity. Further in this paper, only the stocks belonging to pairs that exhibited suitable trading signals are mentioned.

Step 2 – collection of historical stock price data. Stock prices from February 6 to May 3, 2024 were exported from "Yahoo Finance" (Yahoo Finance, 2024). The data was exported to "MS Excel" for further processing.

Step 3 – determining correlations between stocks' prices. Correlation coefficients were calculated using historical stock price data of the stocks within the same sector. Stock pairs with a correlation coefficient equal to or greater than 0.8 were selected for evaluation in the second phase of the study. In total, 78 pairs were chosen for the next phase of the study.

4.2. Stage II – trading period

Step 1 – generation of trading signals and opening of positions. The following pairs were selected for the trading: Goldman Sachs Group Inc" (GS)/ "Morgan Stanley" (MS), "The Hartford Financial Services Group, Inc." (HIG)/ "American International Group, Inc." (AIG), "Cincinnati Financial Corporation" (CINF)/ AIG, HIG/ "Arch Capital Group Ltd." (ACGL), "Eaton Corporation plc" (ETN)/ "Cummins Inc." (CMI), "Parker-Hannifin Corporation" (PH)/ "Ingersoll Rand Inc." (IR), "Deckers Outdoor Corporation" (DECK)/ "Carter's, Inc." (CRI), "Ross Stores, Inc." (ROST) "The TJX Companies, Inc." (TJX), "Abbott Laboratories" (ABT)/ "Acadia Healthcare Company, Inc." (ACHC), "Amedisys, Inc." (AMED)/ ACHC, "Laboratory Corporation of America Holdings" (LH)/ ACHC.

The calculated coefficients for pair selection are shown in brackets: financial sector: GS/MS (2.12); insurance: HIG/AIG (–3.16), CINF/AIG (–2.50), HIG/ACGL (–2.06); specialised manufacturing equipment: ETN/CMI (2.55), PH/IR (2.72); apparel retail: DECK/CRI (2.02), ROST/TJX (–2.21); healthcare: ABT/ACHC (2.28), AMED/ACHC (2.50), LH/ACHC (2.27); software, automotive, non-energy metals: no signals. In total, 11 pairs were selected.

Step 2 – evaluation of trading results and closing of positions. Returns were calculated twice a week. Returns for each pair on every observation day are presented in Table 2, and the overall returns for the entire cluster of pairs on each observation day are presented in Table 3.

Table 2. Returns on each pair of stocks observed on the specific dates (source: compiled by the authors, 2024)

	Return on											
Pairs of stocks	May 7, 2024	May 10, 2024	May 14, 2024	May 17, 2024	May 21, 2024	May 24, 2024	May 28, 2024	June 31, 2024	June 4, 2024	June 7, 2024	June 11, 2024	June 14, 2024
GS/MS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	–0.01	0.00	0.00	0.00
HIG/AIG	0.00	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.02	0.03	0.03	0.04
CINF/AIG	–0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01
HIG/ ACGL	–0.02	–0.01	0.00	–0.01	–0.02	–0.03	–0.03	–0.02	–0.03	–0.02	–0.02	–0.01
ETN/CMI	0.00	0.01	–0.03	–0.01	–0.02	–0.03	–0.04	–0.02	–0.01	–0.01	–0.02	–0.03
PH/IR	0.01	0.01	0.01	0.03	0.04	0.06	0.05	0.04	0.03	0.04	0.04	0.05
DECK/CRI	–0.02	–0.02	–0.03	–0.04	–0.05	–0.14						
ROST/TXJ	–0.02	–0.01	–0.02	–0.03	–0.01	0.00	–0.01	–0.01	–0.02	–0.02	–0.02	–0.02
ABT/ ACHC	0.00	0.04	–0.01	0.00	0.00	–0.02	–0.02	0.03	0.03	0.00	0.01	–0.01
AMED/ ACHC	0.00	0.01	–0.01	–0.02	–0.04	–0.05	–0.05	0.02	0.02	0.02	0.01	–0.01
LH/ACHC	–0.01	0.01	–0.02	–0.04	–0.03	–0.03	–0.03	0.02	0.02	0.02	0.01	–0.02

In Table 2, the pair returns that reached the exit signals (i.e., either a 7% profit or an –11% loss) and the returns on the last day of the trading period are highlighted in bold and italic.

Table 3. Returns on a cluster stock pairs observed on the specific dates (source: compiled by the authors, 2024)

	Return on											
Pairs of stocks	May 7, 2024	May 10, 2024	May 14, 2024	May 17, 2024	May 21, 2024	May 24, 2024	May 28, 2024	June 31, 2024	June 4, 2024	June 7, 2024	June 11, 2024	June 14, 2024
GS/MS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	–0.01	0.00	0.00	0.00
HIG/AIG	0.00	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.02	0.03	0.03	0.04
CINF/AIG	–0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01
HIG/ACGL	–0.02	–0.01	0.00	–0.01	–0.02	–0.03	–0.03	–0.02	–0.03	–0.02	–0.02	–0.01
ETN/CMI	0.00	0.01	–0.03	–0.01	–0.02	–0.03	–0.04	–0.02	–0.01	–0.01	–0.02	–0.03
PH/IR	0.01	0.01	0.01	0.03	0.04	0.06	0.05	0.04	0.03	0.04	0.04	0.05
DECK/CRI	–0.02	–0.02	–0.03	–0.04	–0.05	–0.14	–0.17	–0.16	–0.15	–0.14	–0.14	–0.16
ROST/TXJ	–0.02	–0.01	–0.02	–0.03	–0.01	0.00	–0.01	–0.01	–0.02	–0.02	–0.02	–0.02
ABT/ACHC	0.00	0.04	–0.01	0.00	0.00	–0.02	–0.02	0.03	0.03	0.00	0.01	–0.01
AMED/ACHC	0.00	0.01	–0.01	–0.02	–0.04	–0.05	–0.05	0.02	0.02	0.02	0.01	–0.01
LH/ACHC	–0.01	0.01	–0.02	–0.04	–0.03	–0.03	–0.03	0.02	0.02	0.02	0.01	–0.02
Total return	–0.01	0.00	–0.01	–0.01	–0.01	–0.02	–0.03	–0.01	–0.01	–0.01	–0.01	–0.01

In Table 3, the total returns of the cluster on each day of observation are highlighted in bold. Detailed explanation of the results is presented further in section 5 of this article.

5. Analysis of results and discussion

Based on the findings, we observe that some pairs show more stability, while others exhibit significant volatility. For instance, GS/MS and HIG/AIG are more stable, while AMED/ACHC and DECK/CRI show higher volatility. Most pairs had a small positive or neutral return, given the relatively stable market. Pairs like HIG/AIG, PH/IR, HIG/ACGL showed a positive mean reversion trend but encountered horizon risk and did not reached the profit threshold until by the end of the trading period. The pair DECK/CRI experienced a loss due to idiosyncratic news affecting DECK stock prices. The divergence risk in the DECK/CRI pair highlighted how specific idiosyncratic news can significantly impact pairs trading results. Trading a stock pair cluster helped mitigate the risk posed by such news. However, the overall failure to achieve profits was affected by the market's uptrend. A more in-depth discussion of the results and associated risks is presented below.

5.1. Profit and loss thresholds

Based on the analysed scientific literature, profit and loss thresholds are essential for managing risk (He et al., 2023). In our research positions are closed when individual pairs' returns reach +7% and above or drop to –11% and below, while for the entire cluster, all positions are closed when the overall return hits +5% or –11%. When evaluating each pair's returns individually over the entire observation period, there were no instances where the pairs achieved the +7% profit mark. The closest case was a +6% profit (PH/IR pair's return on May 24, 2024), indicating that the market did not move sufficiently favourably to reach the +7% profit threshold. Based on the data, only one pair (DECK/CRI) reached the set loss threshold of –11% and was closed with the loss of 14% on May 24. *Thus, calculating for profits in individual pairs' trading scenario, i.e. closing DECK/CRI on May 24, 2024 and all remaining positions at the end of the trading period in June 14, 2024 would result in a total loss of –1%.* When evaluating the pair cluster's returns, we observe that the overall return of the entire cluster decreased each week till the middle of the trading period, and slightly increased back by the end of the period but did not reach the profit target. *The results of trading with pairs' cluster show that if all positions were closed at the end of the trading period, a total loss of –1% would have been realised.*

The unfavourable results of both scenarios were mainly due to the impact of a rising market during the trading period and idiosyncratic news that significantly affected the profitability of one pair. The profits from the remaining pairs were insufficient to offset the loss from the affected pair.

5.2. Evaluation of the trading horizon and horizon risk

Analysing the individual returns of each pair, we can observe that none of them reached the 7% profit threshold during the six-week trading period. However, one pair, DECK/CRI, hit the –11% loss limit on May 24, 2024 (see Table 2 and Figure 1). This suggests that the six-week horizon may be too short to close most positions and continue reinvesting capital. For example, pairs like GS/MS, HIG/AIG, CINF/AIG, PH/IR, ABT/ACHC, AMED/ACHC, LH/ACHC showed positive movement toward mean reversion, but were affected by horizon risk – meaning they didn't revert fully within the trading period. These results align with Schizas et al. (2011) research results, where approximately 50% of pairs reverted to the mean over 40 trading days. Given that the trading horizon in this research was 30 days, and only one pair almost fully reverted, extending the horizon by two weeks could potentially lead to more pairs reverting, thereby improving overall profitability.

Evaluating the profitability of the cluster of stock pairs, the data shows that the cluster's return did not meet the targeted 5% profit threshold during the observed period (see Table 3). In fact, the maximum return observed for the cluster was 0–1%. Although the approach of managing risk across the portfolio helps to stabilise returns, it was insufficient to achieve a positive outcome. The lack of any substantial returns in the cluster suggests that the six-week period and market conditions were unfavourable for the strategy, especially as no significant gains were realised.

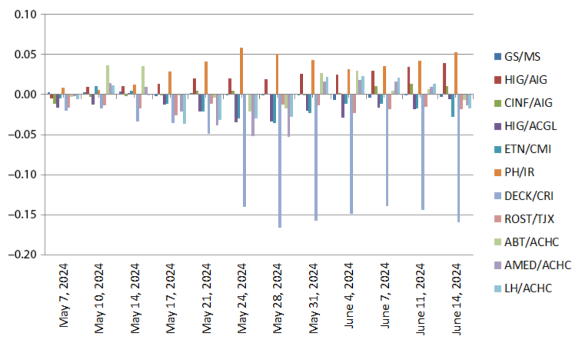

Figure 1. The profitability of all pairs in the simplified pairs trading strategy study (source: compiled by the authors, 2024)

5.3. Impact of idiosyncratic news and divergence risk

Here we emphasise the risk of the idiosyncratic news and the divergence risk we encountered during the experiment. For instance, the price difference between stocks in the pairs LH/ACHC, AMED/ACHC, ETN/CMI widened moderately after opening the positions – such scenario shows the divergence risk. The price difference between stocks in the DECK/CRI pair constantly increased throughout the trading period, indicating continuous divergence. Engelberg et al. (2008) highlighted that divergence risk is highly impacted by idiosyncratic news. This was the case with DECK/CRI, where a significant loss –14% was recorded on May 24, 2024, driven by DECK's income report upbeat resulting in sharp rise of DECK's price (DECK was on the short position in the pairs thus such spike of share prices resulted in a loss). On the other hand, idiosyncratic news can positively impact pairs trading, as observed in the PH/IR pair, where stable financial announcements led to slight gains throughout the study. A potential solution to mitigate this risk is to increase the number of stock pairs in the portfolio distributing the impact of idiosyncratic news across multiple pairs.

5.4. Market impact

The direction of the market has a significant impact on pairs trading strategies. Since stocks from both the NYSE and Nasdaq exchanges were traded, it was relevant to examine the trends of the Nasdaq Composite and NYSE Composite indices during the analysed period. From May 6 to June 13, 2024, the Nasdaq Composite index rose by approximately 8.06%, while the NYSE Composite index showed minor fluctuations decreasing by only about 0.23% and suggesting market consolidation rather than a clear directional trend (see Figure 2).

The stability and slight market growth had a positive impact on long positions – almost all long positions were profitable, while short positions incurred losses (see Figure 3). However, according to the scientific literature, this is not favourable for the effectiveness of pairs trading, as less profit is typically generated from long positions during market upswings compared to short positions during market declines (Bowen & Hutchinson, 2016). Thus, the observed rise and stability in the sectors covering NYSE and Nasdaq had a significant impact on the unfavourable results obtained.

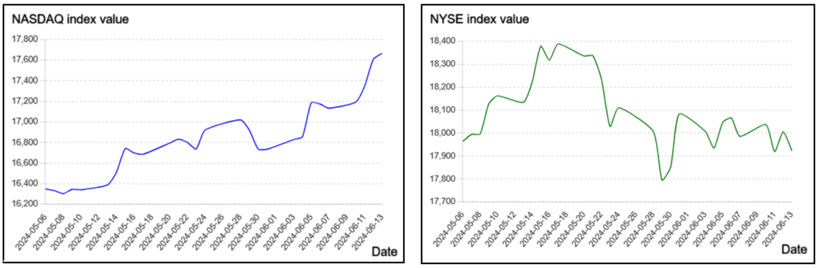

Figure 2. Nasdaq and NYSE index values from May 6, 2024, to June 13, 2024 (source: compiled by the author based on data from finance.yahoo.com (2024))

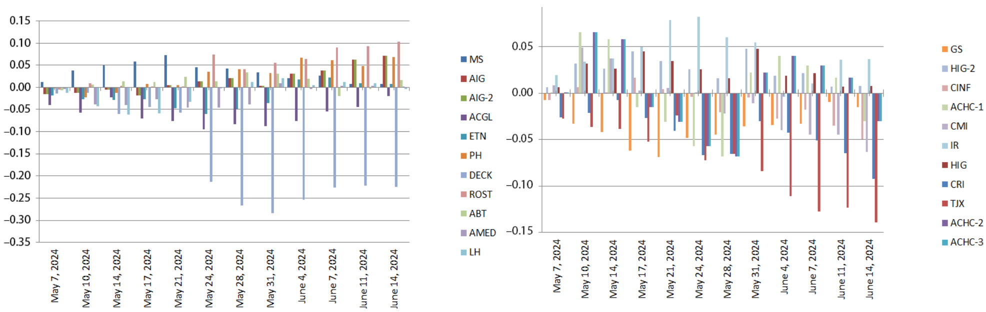

Figure 3. Profitability of all tested long positions (left) and short positions (right) (source: compiled by the authors, 2024)

The researchers who analysed both crisis and non-crisis periods, also concluded that short positions tend to be more profitable during crises than long positions during market upturns. The general findings of these studies align with the results of this research, as well as with those of Haddad and Talebi (2023). The researchers tested the pairs trading strategy in the Canadian stock market across 3 periods: January to June 2018, January to June 2019, January to June 2020. 3-rd period coincided with COVID-19 pandemic during which the highest profits of these periods were recorded. Table 2 presents the results of their research during which the researchers applied different methods (see Table 4).

Table 4. Haddad and Talebi's (2023) study results at periods of market stability, growth, crisis (source: Haddad & Talebi, 2023)

Return (%)	Minimal distance method			Cointegration method			Copula method		
Pairs of stocks\ Periods	I	II	III	I	II	III	I	II	III
Top 5 pairs	–14.97	23.00	42.08	24.05	–0.69	13.00	45.99	60.84	44.58
Top 10 pairs	–14.77	22.73	40.34	34.40	–0.12	30.72	171.80	123.53	140.42
Top 20 pairs	–10.54	7.37	97.18	57.06	27.48	41.94	247.78	238.12	464.66

This study is relevant for comparison with our research because it was also conducted under real-time market conditions, and the authors analysed similar data – several portfolios, each containing 5, 10, and 20 stocks. Figure 4 illustrates the market value changes of stocks listed on the Toronto Stock Exchange, specifically the S&P/TSX Composite index (representing about 70% of the market capitalization of the Toronto Stock Exchange), over the entire period analysed in Haddad and Talebi's (2023) study (see Figure 4).

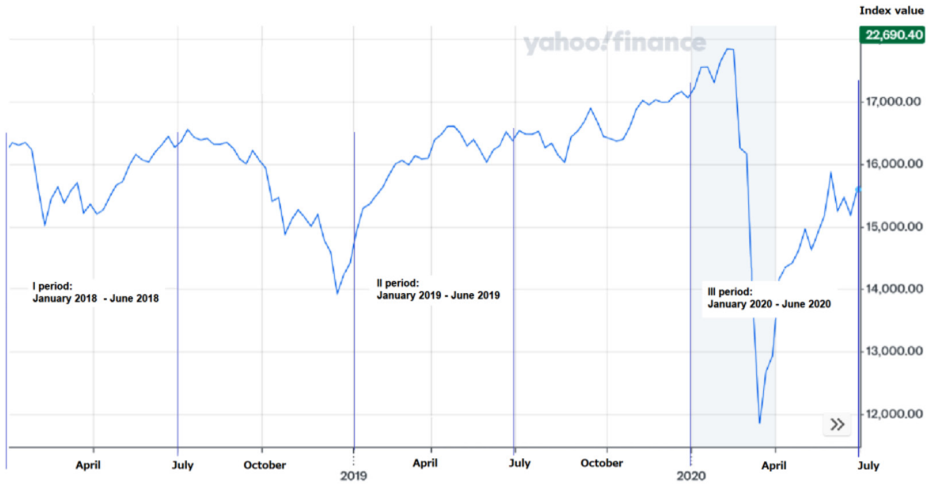

Figure 4. S&P/TSX Composite index values from January 1, 2018, to June 30, 2020 (source: compiled by the authors based on data from finance.yahoo.com (2024))

Analysing the returns from Haddad and Talebi's (2023) study, alongside the S&P/TSX Composite index values from January to June 2018, January to June 2019, and January to June 2020, we observe that, similar to the findings in our research, the results were strongly influenced by overall market trends. This analysis demonstrates that pairs trading strategies are particularly profitable during market crises when increased volatility creates more opportunities for gains. It also confirms the findings of our research, that when the market growth is observed, highly positive results from the pairs trading strategy should not be expected.

5.5. Trading costs

In our research the bid-ask spread was included into the initial recorded prices of the stocks, so all the return results shown in Figures 1 and 2 are presented net of costs. Data in Table A1 of Appendix shows that the average bid-ask spread applied to the stocks used to form the pairs in this study is approximately 0.36% (see Appendix). It is observed that these values can vary depending on the liquidity of the specific stock and market conditions.

Various authors' research findings indicate that transaction costs can vary significantly – from 0.2% and 1%, as summarised in section *2.2.5 Risk from transaction costs*. This indicates that selecting the proper trading platform can significantly reduce costs and enhance strategy profitability. For example, comparing the "bid-ask spread" on the "eToro" platform, which in our study was approximately 0.36%, to the costs presented in Appendix, we conclude that "eToro" applies relatively low tariffs, and this fact affects positively the profitability of the strategy.

It's important to note that in the simulated environment of this study, the impact of dividend payments was not considered, as the focus was on price movements and reversion to the mean. But in real scenarios, if short positions are held before the ex-dividend date, the dividend amount will be deducted from the trader's account, reducing profit.

6. Conclusions

The research of the simplified short-term pairs trading strategy, conducted under real-time market conditions, demonstrates its limited effectiveness and profitability can be more challenging to achieve in stable or rising markets both when trading individual pairs and cluster of stocks. Strong market trends provide more opportunities for profit in both individual and cluster trading. This aligns with the findings in the existing literature.

Additionally to the market trends, the impact of idiosyncratic news and the defined trading horizon also have significant effect on the strategy's profitability. Market trends (and macro news driving them) influence the overall profitability of pairs trading for all pairs in the portfolio, while idiosyncratic news only impacts individual pairs, either positively or negatively, regardless of overall market trends. The trading horizon affects both individual pair trading and cluster trading. Trading individual pairs presents a higher risk of failing to revert to the historical mean, while cluster trading can achieve profit targets faster. Trading costs do matter but if kept low they have minimal impact on pairs trading, and their effect is the same both for individual and cluster trades.

Evaluating the profitability of trading stock clusters, we observe that profit potential is limited. On some days, certain pairs perform well while others underperform, keeping overall profitability flat, as cluster performance is assessed simultaneously. Trading individual pairs offers higher return potential during peak periods of each pair's profitability but involves greater volatility. Significant returns from individual pairs are possible during strong market trends if idiosyncratic news and horizon risk are considered and the portfolio remains diversified. Cluster trading, by contrast, provides more stability through diversification, though profitability is constrained. An additional advantage of cluster trading is a higher likelihood of reaching profit targets sooner, enabling faster reinvestment. It also simplifies exit decisions and saves time. The results indicate that the strategy may protect against large losses when the portfolio is well diversified, either trading multiple pairs or using a stock cluster.

7. Research limitations

The study is limited by the single test within short-term trading period and the specific market conditions during the testing period.

8. Future research directions

Future research should explore different market environments to further validate the findings, for example, to test this strategy in less stable markets. To mitigate horizon risk and improve profitability, it is recommended to extend the trading horizon up to 12 weeks, especially during stable or rising markets. This would allow more time for pairs showing mean reversion to achieve positive returns. Given the impact of idiosyncratic news on the profitability, increasing portfolio diversification by adding more pairs is also suggested.

Disclosure statement

Authors declare that they don't have any known competing financial, professional, personal interests from other parties.

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APPENDIX

Bid-ask spreads for the stocks and the average bid-ask spreads for the pairs

The table below presents the average bid-ask spread applied to the stocks used to form the pairs in this study (see Table 1).

Table A1. Bid-ask spreads for the stocks and the average bid-ask spreads for the pairs. Source: Compiled by the authors (2024)

Stock symbol	Bid-ask spread for a stock (%)	Average bid-ask spread for a pair (%)
GS	0.34	0.34
MS	0.34	
HIG	0.33	0.33
AIG	0.33	

End of Table A1

Stock symbol	Bid-ask spread for a stock (%)	Average bid-ask spread for a pair (%)
CINF	0.33	0.33
AIG	0.33	
HIG	0.33	0.325
ACGL	0.32	
ETN	0.38	0.385
CMI	0.39	
PH	0.46	0.395
IR	0.33	
DECK	0.52	0.44
CRI	0.36	
ROST	0.31	0.325
TJX	0.34	
ABT	0.32	0.32
ACHC	0.32	
AMED	0.37	0.345
ACHC	0.32	
LH	0.42	0.37
ACHC	0.32	