Does Pair Trading Still Work During Extreme Events? A Comprehensive Empirical Evidence from Chinese Stock Market

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Abstract

This study conducts a comprehensive evaluation of pairs trading strategies in the Chinese stock market under various extreme market conditions, including the Financial Crisis, Bullish and Bearish market phases, and the COVID-19 period. Using a large dataset of Chinese stocks, we analyze the performance of different pairs trading portfolios, taking into account transaction costs and employing a range of matching criteria. Our findings indicate that, on average, pairs trading is unprofitable once transaction costs are considered, with most portfolios recording near-zero excess returns. However, in specific market environments and with carefully selected pairs, the strategy can still yield positive returns.

During the Financial Crisis, pairs trading exhibited strong performance, achieving monthly excess returns of up to 156 basis points (bps) for the top portfolios, which corresponds to an annualized return of 18.72%. This suggests that pairs trading can be particularly effective during periods of heightened volatility and market dislocation. Conversely, in stable or upward-trending markets, such as the Bullish period, pairs trading generally underperformed, indicating that the strategy struggles when mean-reversion opportunities are limited. The COVID-19 period presented unique challenges due to unprecedented disruptions and rapidly shifting market dynamics, leading to diminished profitability.

Our research highlights the significant impact of transaction costs on pairs trading returns. Across all periods, trading costs eroded potential profits, turning otherwise successful strategies into unprofitable ones. The study also underscores the importance of refining the pair selection process by using sophisticated matching criteria, such as the combination of the Sum of Squared Deviations (SSD), the Hurst exponent, and the Number of Zero Crossings (NZC), which consistently outperformed traditional selection methods.

Overall, this study contributes to the literature by demonstrating that while pairs trading may be generally unprofitable in the Chinese stock market, it can achieve positive results under certain conditions. The findings emphasize the need for careful pair selection, cost management, and strategic adaptation to varying market environments. Future research could focus on incorporating additional factors such as liquidity, volatility, and macroeconomic indicators, as well as developing dynamic models to enhance the adaptability and profitability of pairs trading strategies in volatile markets.

Keywords: Pairs Trading, Statistical Arbitrage, Hurst Exponent, Chinese Stock Market

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1. Introduction

While much of the existing hedge fund activity and academic research focuses on the U.S. market, it is crucial to understand how these strategies perform in different contexts, such as the Chinese market. This raises several important questions: Do hedge fund strategies like pairs trading generate comparable returns in the Chinese market? If not, what factors contribute to the differences in performance between the two markets? Furthermore, how does pairs trading perform during the COVID-19 period, the Financial Crisis, and other extreme events?

This study aims to address these questions by evaluating the returns and risks associated with pairs trading strategies using an extensive dataset of Chinese stocks. The research places particular emphasis on the COVID-19 period due to the unique characteristics of China's prolonged three-year isolation policy, which differed significantly from the approaches taken by most other countries. By examining the distinct features of the Chinese market, this research seeks to provide insights into potential variations in the effectiveness of pairs trading during the COVID-19 period, the Financial Crisis, and during bullish and bearish market conditions in China.

Specifically, this research evaluates pairs trading performance across three distinct phases: Financial Crisis period (January 1, 2005 to December 31, 2010), Bullish and Bearish period (January 1, 2011 to December 31, 2016), and COVID-19 period (January 1, 2017, to June 31, 2024). This approach provides a comprehensive understanding of how this strategy adapts to varying market conditions induced by the abnormal events. By analyzing these periods, the study seeks to uncover the resilience and limitations of pairs trading in the Chinese market, offering valuable insights for investors and portfolio managers navigating similar disruptions in the future.

The COVID-19 pandemic significantly impacted many hedge fund strategies, leading to substantial negative returns and notable outflows of assets under management. Xiaoling and Kaitian (2024) present comprehensive data on stock returns during this period, indicating that the average log return of 539 selected stocks in the Chinese stock market was 1.43% from January 1, 2020, to January 31, 2023, representing the post-COVID period. This figure is significantly lower than the average log return of 11.31% observed in the pre-COVID period, from January 1, 2019, to December 31, 2019. These results highlight the adverse impact of the COVID-19 pandemic on overall stock market returns in China.

Pairs trading is a market-neutral investment strategy designed to capitalize on short-term price reversals by taking offsetting long and short positions in a pair of correlated stocks. The strategy operates on the principle that these stocks, which typically move in tandem, will revert to their historical price relationship when deviations occur. This approach is recognized as a form of statistical arbitrage, where positions are initiated by going long on the undervalued stock and short on the overvalued stock, with the anticipation that their prices will converge. The strategy leverages the documented cross-autocorrelation in stock prices, which suggests that past prices can influence future movements. Recent research in market microstructure has further explored the link between liquidity and cross-autocorrelation, with studies such as Gupta and Chatterjee (2020) highlighting that market frictions like illiquidity can create a lead-lag effect between pairs of stocks, thereby enabling profitable opportunities in pairs trading.

An increasing number of studies are investigating the performance of pairs trading in international markets. Examples of this research include works by Nath in 2003, Hong and Susmel in 2004, Andrade et al. in 2005, Gatev et al. in 2006, Perlin in 2007 and 2009, Do and Faff in 2010, Rad et al. in 2015, Bowen and Hutchinson in 2016 and Chen et al. in 2019. Gatev, Goetzmann, and Rouwenhorst (2006) analyzed the effectiveness of pairs trading in the US equity market over the period from 1962 to 2002, finding that the strategy yielded an average annual return of 11% with relatively low risk and minimal exposure to common equity risk factors. Extending this research, Do and Faff (2010) assessed the strategy's performance from 1962 to 2009, arriving at similar findings. In studies focusing on the US market, pairs trading was most profitable during the 1970s and 1980s, with a marked decrease in returns observed after 1989.

Several studies have refined the pairs trading methodology initially developed by Gatev et al. (2006). For example, Elliott et al. (2005) employed a Gaussian Markov chain model to estimate the spread, while Do et al. (2006) adapted the measurement of spreads using theoretical asset pricing approaches and the concept of mean reversion. Vidyamurthy (2004) and Burgess (2005) utilized cointegration techniques for pairs selection, enhancing the robustness of the strategy. Papadakis and Wysocki (2007) expanded upon the original methodology by exploring the influence of accounting information events, such as earnings announcements and analyst forecasts, on pairs trading returns. Do and Faff (2012) examined the impact of transaction costs on the profitability of pairs trading in the US market, highlighting the sensitivity of strategy returns to such costs.

Recent advancements in pairs trading research have broadened the strategy's application across different markets, asset classes, and methodologies, highlighting its adaptability and continuous evolution. Miao and Laws (2016) provided evidence of the profitability of a simple pairs trading strategy in a global context, confirming its effectiveness across diverse financial environments. Rad, Low, and Faff (2016) explored the use of distance, cointegration, and copula methods in pairs trading, showcasing the diversification of techniques to refine the strategy for different market conditions. Further innovations were proposed by Smith and Xu (2017), who examined alternative pairs trading strategies. Vaitonis (2017) applied pairs trading using high-frequency trading (HFT) techniques in the OMX Baltic market, illustrating the strategy's adaptability to different trading environments and advanced technologies.

Mikkelsen (2018) focused on pairs trading within Norwegian seafood companies, demonstrating the strategy's flexibility in niche markets and specific sectors. Blázquez and Román (2018) conducted an empirical comparison of various pairs trading techniques, aiding in understanding which methodologies yield better performance under different market conditions. Quinn, Hanna, and MacDonald (2018) explored gilt-based pairs trading strategies, expanding the application of pairs trading into fixed-income securities. Chen et al. (2019) offered an empirical investigation of equity pairs trading strategies, adding to the evidence supporting its effectiveness in stock markets. Zhang and Urquhart (2019) explored pairs trading between Mainland China and Hong Kong stock markets, examining cross-market dynamics and the strategy's adaptability in interconnected financial environments. Farago and Hjalmarsson (2019) delved into stock price co-movement and the foundations of pairs trading, enhancing the theoretical understanding of how stock relationships impact strategy performance.

Aggarwal and Aggarwal (2020) provided evidence of pairs trading in commodity futures within the Indian market, validating the strategy’s versatility in various geographic and asset markets. Fil and Kristoufek (2020) examined pairs trading in cryptocurrency markets, extending the strategy into the highly volatile digital asset space and highlighting its potential profitability there. Diao et al. (2020) developed a stock-matching trading strategy based on bi-objective optimization, showcasing advanced mathematical approaches to refine pairs trading techniques. Gupta and Chatterjee (2020) introduced the concept of incorporating lead-lag relationships in selecting stock pairs, adding a new dimension to the strategy by considering temporal market dynamics. Ramos-Requena, Trinidad-Segovia, and Sánchez-Granero (2020) discussed considerations in forming pairs for trading, offering practical guidance on the pair selection process that can influence trading outcomes. Aggarwal (2021) investigated risk-adjusted returns from statistical arbitrage in Indian stock futures, integrating risk management considerations into pairs trading. Keshavarz Haddad and Talebi (2023) examined the profitability of pairs trading on the Toronto Stock Exchange, contributing to the evidence of the strategy's global applicability. Ko et al. (2024) conducted a comparative study of statistical methods for pairs trading in cryptocurrency markets, demonstrating the adaptation of the strategy to new financial products and sophisticated statistical models.

We contribute to the literature on pairs trading in five key ways. First, this is the first paper to provide extensive evidence on the profitability of pairs trading strategies in the Chinese stock market, particularly during periods of extreme market events. By analyzing the performance of pairs trading under various market conditions, this study fills a critical gap in the existing literature on emerging markets. Second, we conduct a detailed analysis using different benchmarks to measure excess monthly returns at various market stages to assess the robustness of pairs trading performance. Our findings indicate that pairs trading performs well in down-trending markets but tends to underperform in up-trending markets. Third, we present a more comprehensive analysis by incorporating a model framework with 40 different stock selection criteria. Notably, this study is the first to combine the sum of squared differences (SSD) and Hurst exponent as a joint stock selection method, which yields superior performance compared to traditional SSD-based selection methods alone. Fourth, this study is the first to segment industry classifications into two sets: good-performing and bad-performing sectors. The results show that pairs trading in good-performing industries can achieve significantly higher excess monthly returns, suggesting that industry-specific characteristics play a crucial role in determining the success of pairs trading strategies. Finally, we provide a thorough analysis of trading costs specific to the Chinese stock market and integrate these costs into the evaluation of the practical implementation of pairs trading strategies. This addition enhances the realism of the study and provides insights into the net profitability of pairs trading after accounting for actual transaction costs.

Our key results are as follows. On average, pairs trading proves to be unprofitable, with monthly excess returns approaching zero once transaction costs are taken into account. However, several portfolios consisting of better-matched pairs, specifically formed within more refined industry groups, show mild profitability and, in some cases, even generate substantial returns. Notably, during the Financial Crisis, despite the benchmark return reaching 162 bps per month, the top five portfolios achieved an average excess return of 156 bps per month, equivalent to an annualized return of 18.72%. After analyzing a total of 9 sub periods, it was found that in downward markets, such as In-Bearish, pairs trading achieved significant positive returns, with an average of 51 bps, or an annualized return of 6.12%. In an up market, returns are basically negative. In particular, during the entire financial crisis period, the benchmark return reached 162 bps per month.

2. Literature Review

2.1 Baseline Approach

Gatev et al. (2006), hereafter referred to as GGR, established a foundational approach to pairs trading by systematically investigating its profitability in the US equity market from 1962 to 2002. Their methodology involves identifying pairs of stocks that have historically moved together and subsequently trading these pairs when their prices diverge, under the assumption that they will revert to their historical relationship.

GGR's baseline approach comprises three main steps: pair selection, trading signal generation, and portfolio construction. In the pair selection phase, stocks are paired based on minimum historical distance, which quantifies how closely their prices have moved together. In the trading signal generation phase, positions are taken when the price ratio of a pair deviates beyond a certain threshold. Specifically, a long position is opened in the underperforming stock, while a short position is taken in the outperforming stock, with the expectation that the prices will converge.

The strategy's profitability is largely driven by this reversion to the mean, capitalizing on temporary mispricing. GGR found that the pairs trading strategy generated an average annual return of approximately 11%, with low correlation to common risk factors such as market, size, and value. Moreover, their analysis revealed that pairs trading performs well even during periods of market stress, offering a robust, market-neutral strategy with relatively low risk.

The study's comprehensive analysis also highlights key insights into the strategy's risk-return profile. The low exposure to traditional equity risk factors, combined with a consistent performance over different market conditions, underscores the resilience of the pairs trading approach developed by GGR. This baseline approach has since become a benchmark for subsequent research in pairs trading, inspiring numerous extensions and modifications that explore different asset classes, risk management techniques, and market conditions.[1]

2.2 Expanding on GGR's Approach

Do and Faff (2010) extended the foundational work of GGR by examining the pairs trading strategy over a more extended period from 1962 to 2009 in the US equity market. Their study not only confirmed the profitability of the baseline approach outlined by GGR but also provided additional insights into the performance dynamics of pairs trading over time.

They analysis revealed that the strategy remained consistently profitable, particularly highlighting its strong performance during earlier decades, such as the 1970s and 1980s. However, they observed a notable decline in profitability post-1989, which they attributed to increased market efficiency and the growing popularity of quantitative strategies, including pairs trading itself.

Moreover, they enriched the GGR approach by incorporating a more detailed examination of market conditions, transaction costs, and the impact of evolving market microstructure on strategy returns. They underscored the importance of considering transaction costs, as even modest costs could significantly erode the strategy's profitability, especially in later periods. This study contributed to the understanding of how pairs trading performs in different economic climates and underscored the evolving challenges of maintaining strategy profitability in increasingly efficient markets.

Overall, Do and Faff (2010) provide a critical extension of GGR's methodology by reinforcing the original findings of profitability while highlighting temporal changes in performance and the essential role of transaction costs in strategy viability.

Rad et al. (2015) expanded on the foundational work of GGR by examining the profitability of pairs trading using three distinct methodologies: the distance, cointegration, and copula methods. Their study, which spans the US equity market from 1962 to 2014, provides a comprehensive analysis of how these different approaches impact the performance of pairs trading strategies.

[1] For a recent review of the literature of pairs trading, see Krauss (2017).

They introduced the cointegration and copula methods as alternatives to the traditional distance method, aiming to capture more complex dependencies between stock pairs. Their findings indicate that while all three methods generated positive excess returns, the performance varied across the strategies. The distance and cointegration methods delivered higher returns compared to the copula method before accounting for transaction costs. However, after incorporating transaction costs, the distance method slightly outperformed the others overall.

A notable insight from Rad et al.'s study is that the copula method, despite having lower returns, maintained a more stable frequency of trading opportunities in recent years. This suggests that the copula method might be less susceptible to the effects of increasing market efficiency, which has reduced arbitrage opportunities for the distance and cointegration methods. Additionally, during periods of heightened market volatility, the cointegration method demonstrated superior performance, highlighting its effectiveness in turbulent market conditions.

Overall, Rad et al. (2015) show that employing more sophisticated pairs trading strategies, such as the cointegration and copula methods, can provide distinct advantages in specific market environments. This research underscores the potential benefits of diversifying pairs trading approaches beyond the traditional distance method, offering valuable insights into optimizing pairs trading performance across varying market conditions.

Bowen and Hutchinson (2016) expanded on the approach of GGR by providing the first comprehensive evidence on the profitability of pairs trading in the UK equity market. Their study covered a period from 1980 to 2012 and examined how the strategy performed across various market conditions, including the 2008 financial crisis. Unlike other market-neutral strategies, pairs trading demonstrated resilience during the crisis, delivering positive returns while broader equity markets experienced significant downturns.

They also incorporated a detailed risk analysis using a multi-factor model framework, examining the strategy's exposure to common equity risk factors such as market, size, value, momentum, and reversal. They found that pairs trading portfolios had minimal exposure to these factors, with the market factor being the only one significantly affecting the top pairs. Moreover, the study uniquely linked the strategy's time-series performance to market liquidity, price impact, and different estimates of bid-ask spreads, showing that market frictions significantly influence returns.

The study further explored the performance of pairs trading across different market and economic states, highlighting that the strategy benefited from periods of increased volatility or reduced liquidity. Bowen and Hutchinson's findings provided critical insights into the adaptability and robustness of pairs trading in a major non-US market, emphasizing the strategy's potential as a viable investment approach during times of market stress.

2.3 Improvements to GGR’s Approach

Perlin (2009) builds on the foundational work of GGR by applying the pairs trading strategy to the Brazilian financial market, thereby extending the analysis into an emerging market context. Perlin's study examines the profitability and risk of pairs trading using daily, weekly, and monthly data frequencies, aiming to determine whether the strategy's success in developed markets can be replicated in a different economic setting.

The study confirms that pairs trading remains a profitable and market-neutral strategy in Brazil, with the highest returns observed for daily frequency data, aligning with the GGR approach that utilizes high-frequency price movements to exploit temporary divergences. Perlin further enhances the GGR methodology by comparing pairs trading against both a naïve buy-and-hold strategy and a bootstrap approach using random trading signals, demonstrating that pairs trading significantly outperforms these benchmarks across various conditions.

By examining different trade thresholds and their impact on strategy performance, Perlin provides a more nuanced understanding of how parameter adjustments can affect returns, thereby extending GGR's approach with a detailed evaluation of the strategy's robustness in an emerging market. This research underscores the broader applicability of pairs trading beyond developed markets, contributing valuable insights into its adaptability and resilience in varying economic contexts.

Yang et al. (2017) extended the pairs trading framework developed by GGR by applying the strategy to commodity futures in the Chinese market. Their study compared the profitability of various pairs selection and spread trading methods, using a comprehensive dataset from the Dalian, Shanghai, and Zhengzhou Commodity Exchanges. This work is significant as it explores pairs trading beyond traditional equity markets, adapting the strategy to commodities, which are often characterized by different market dynamics and risks.

The authors evaluated pairs trading using in-sample and out-of-sample backtesting, focusing on risk-adjusted returns and robustness against different market conditions. They compared the profitability of pairs trading using different methods, including cointegration, minimum distance, and correlation approaches for selecting pairs. The performance of these methods was evaluated through both in-sample and out-of-sample backtesting, providing a robust analysis of risk-adjusted returns across different market conditions. Specifically, they implemented a spread model using the difference in log-prices between two assets, applying an Ornstein-Uhlenbeck (OU) process to model mean reversion. They found that pairs trading in Chinese commodity futures can yield high returns, particularly when the pairs are carefully selected based on methods like cointegration and minimum distance approaches. However, they noted that the profitability of these strategies largely hinges on the ability to identify suitable pairs and manage spread divergence risk, which is heightened in commodity markets due to potentially longer holding periods.

A key finding is that the maximum drawdown, rather than traditional risk-adjusted return measures like the Sharpe ratio, is a critical factor in assessing the strategy's performance. This highlights the importance of managing the duration of spread positions, as profitability tends to decrease when shorter maximum holding periods are imposed. Their results suggest that high returns in pairs trading may not necessarily indicate market inefficiencies but rather reflect the compensation for taking on spread divergence risk. This study provides valuable insights into the applicability of pairs trading in non-equity markets, emphasizing the need for tailored risk management approaches in commodity trading contexts.

Gupta and Chatterjee (2020) advanced the pairs trading methodology originally developed by GGR by introducing a novel distance measure that incorporates the lead-lag relationship between stock pairs. Traditional methods for selecting pairs, such as correlation and SSD, often overlook the temporal dynamics where one stock may consistently lead or lag another. To address this limitation, the authors proposed the Dynamic-Cross-Correlation-Type (DCCT) measure, which dynamically accounts for these lead-lag effects and allows them to vary continuously over time.

The DCCT measure builds on the Cross-Correlation-Type (CCT) measure by adapting it to dynamically reflect the evolving lead-lag relationships between stock pairs. This measure employs an alignment technique to match time series using an optimal path that maximizes the cross-correlation, allowing for lead or lag adjustments as necessary. The alignment is achieved through dynamic programming, akin to Dynamic Time Warping (DTW), but with a focus on correlation-based distances rather than Euclidean measures, making it more suitable for financial data analysis.

Furthermore, Gupta and Chatterjee's incorporation of the lead-lag relationship into pairs trading selection represents a significant refinement, allowing traders to exploit temporal dependencies between stocks that are not captured by conventional measures. This innovative approach enhances the pairs trading strategy by providing a more nuanced understanding of stock interactions, making it a valuable tool for navigating financial markets where the sequence and timing of price movements are crucial.

3. Data and Chinese Stock Market

3.1 Data Processing

Data Selection and Description

This study utilizes a data sample spanning three periods: January 2004 to December 2010, January 2011 to December 2016, and January 2017 to June 2024, covering a total of 21 years. The dataset includes daily adjusted data for 5,612 stocks, 300 stocks within the CSI 300 Index (Jia and Jason, 2016), as well as constituent stocks from the CSI 200 Index, CSI 500 Index, and various industry-specific indices obtained from the iFinD[2] database.

A rolling window approach is implemented, using a 12-month in-sample window followed by a 6-month out-of-sample window. The entire out-of-sample period runs from January 2005 to December 2010, January 2011 to December 2016, and January 2017 to June 2024, thereby capturing a broad range of market conditions, including significant upturns, downturns, and periods of both high and low volatility. Table 1 and Figure 1 provide an overview of the detailed data selected.

The data selection for the pairs trading strategy in this research spans three major economic cycles: the Pre-Financial Crisis, In-Financial Crisis, and Post-Financial Crisis periods; the Pre-Bullish, In-Bullish, and In-Bearish periods; and the Pre-COVID, In-COVID, and Post-COVID periods. Each of these phases corresponds to distinct market environments that provide a robust framework for analyzing the performance and resilience of pairs trading strategies.

The out-of-sample data for the first phase, spanning from January 2005 to December 2010, encompasses three distinct periods: the Pre-Financial Crisis, the In-Financial Crisis, and the Post-Financial Crisis periods. The Pre-Financial Crisis period, from January 2005 to December 2006, was characterized by relative market stability, steady economic growth, and high investor confidence. This environment provided a favorable backdrop for equity investments and traditional trading strategies. The In-Financial Crisis period, from January 2007 to December 2008, includes the global financial crisis, marked by severe market turmoil, sharp declines in asset prices, and heightened uncertainty. This period posed significant challenges for investors and tested the robustness of various trading strategies. The Post-Financial Crisis period, from January 2009 to December 2010, witnessed a gradual stabilization and recovery of markets, although investor sentiment remained cautious. This recovery phase offered an opportunity to assess how pairs trading strategies performed in a context of market stabilization and economic recovery.

The second phase, spanning from January 2011 to December 2016, includes the Pre-Bullish, In-Bullish, and In-Bearish market phases. This period is characterized by significant market volatility, as evidenced in Figure 1. The Pre-Bullish period, from January 2011 to December 2013, involved market adjustments and consolidation, setting the stage for an ensuing bullish trend. During this time, economic indicators improved, and market participants gradually regained confidence. The In-Bullish phase, from January 2014 to May 2015, was marked by rapid market gains and strong investor optimism, driven by favorable economic conditions. However, this optimism was short-lived, as the market swiftly reversed into a bearish phase from June 2015 to December 2016. The

[2] iFinD is a comprehensive financial data platform widely used in China, providing extensive data on stocks, bonds, funds, futures, and various financial indices. Developed by RoyalFlush Co., Ltd. (300033), iFinD offers real-time and historical data, including market quotations, company fundamentals, financial reports, and industry-specific indicators.

In-Bearish phase was characterized by market corrections and increased selling pressure, highlighting the cyclical nature of financial markets and testing the adaptability of pairs trading strategies in a declining market environment.

The third phase, spanning January 2017 to June 2024, is defined by the Pre-COVID, In-COVID, and Post-COVID periods. The Pre-COVID period, from January 2017 to December 2019, was marked by continued global economic expansion and technological advancements, which supported steady market growth and a favorable investment environment. However, the onset of the COVID-19 pandemic in January 2020 brought unprecedented disruptions to global markets. The In-COVID period, extending through December 2022, was characterized by severe market volatility due to economic lockdowns, supply chain disruptions, and widespread uncertainty. This period posed significant challenges but also created unique opportunities for pairs trading strategies, as the dispersion in stock performances increased. The Post-COVID phase, from January 2023 to June 2024, reflects a gradual recovery of the global economy, with markets stabilizing and returning to normalcy. This recovery period provides valuable insights into the adaptability and performance of pairs trading strategies in a post-pandemic world.

Overall, these three phases offer a comprehensive timeline of different market conditions, allowing for a thorough examination of how pairs trading strategies perform across various economic environments and market cycles.

Good Performance Industries refer to industries that performed well and made profits during the COVID-19 period and the financial crisis period. Conversely, Bad Performance Industries are those with poor profitability during the same periods. To facilitate a better comparison between these two categories, we divided the 31 industries from the Shenwan Primary Industry Classification[3] into the top 15 as Good Performance Industries and the remaining 16 as Bad Performance Industries. The performance of industries was assessed during all three periods respectively. This selection was made because our primary focus is on evaluating the performance of pair trading during these two key periods.

[3] The Shenwan First-Level Industry Classification is a widely recognized framework used in the Chinese stock market to categorize companies into distinct sectors, providing a standardized approach for analyzing and comparing the performance of companies across various industries. This classification system comprises 31 primary industries, including Agriculture, Forestry, Animal Husbandry, and Fishery; Mining; Chemical; Steel; Non-Ferrous Metals; Electrical Equipment; Machinery Equipment; Defense and Military Industry; Electronics; Communications; Computer; Media; Automobile; Household Appliances; Textiles and Apparel; Light Manufacturing; Commercial Trade and Retail; Social Services; Conglomerates; Building Materials; Building Decoration; Electricity and Utilities; Transportation; Real Estate; Banking; Non-Banking Financials; Food and Beverage; Pharmaceuticals and Biotechnology; Beauty and Personal Care; Coal; and Petroleum and Petrochemicals.

Table 1. Dataset Overview: Constituents and Sample Periods.

Stock indexes	**Number of constituent**	**Pre- Fin.C.**	**In- Fin.C.**	**Post-Fin.C.**	**Number selected**	**Pre-B.N.B.**	**In-Bullish**	**In-Bearish**	**Number selected**	**Pre-Cov.**	**In-Cov.**	**Post-Cov.**	**Number selected**
All	5,612	Jan 2005- Dec 2006	Jan 2007- Dec 2008	Jan 2009- Dec 2010	783 724-Industry Matching	Jan 2011- Dec 2013	Jan 2014- May 2015	June 2015- Dec 2016	690 666-Industry Matching	Jan 2017- Dec 2019	Jan 2020- Dec 2022	Jan 2023- June 2024	1681 1670-Industry Matching
CSI 100	199-Covid 168-Fin.C. 163-B.N.B	Jan 2005- Dec 2006	Jan 2007- Dec 2008	Jan 2009- Dec 2010	83 77-Industry Matching	Jan 2011- Dec 2013	Jan 2014- May 2015	June 2015- Dec 2016	84 84-Industry Matching	Jan 2017- Dec 2019	Jan 2020- Dec 2022	Jan 2023- June 2024	122 122-Industry Matching
CSI 200	471-Covid 317-Fin.C. 410-B.N.B	Jan 2005- Dec 2006	Jan 2007- Dec 2008	Jan 2009- Dec 2010	183 173-Industry Matching	Jan 2011- Dec 2013	Jan 2014- May 2015	June 2015- Dec 2016	193 184-Industry Matching	Jan 2017- Dec 2019	Jan 2020- Dec 2022	Jan 2023- June 2024	249 248-Industry Matching
CSI 500	1032-Covid 750-Fin.C. 943-B.N.B	Jan 2005- Dec 2006	Jan 2007- Dec 2008	Jan 2009- Dec 2010	435 401-Industry Matching	Jan 2011- Dec 2013	Jan 2014- May 2015	June 2015- Dec 2016	323 309-Industry Matching	Jan 2017- Dec 2019	Jan 2020- Dec 2022	Jan 2023- June 2024	510 507-Industry Matching
Good Performance Industries	2950	Jan 2005- Dec 2006	Jan 2007- Dec 2008	Jan 2009- Dec 2010	351-All 30-CSI 100 69-CSI 200 192-CSI 500	Jan 2011- Dec 2013	Jan 2014- May 2015	June 2015- Dec 2016	313-All 32-CSI 100 78-CSI 200 145-CSI 500	Jan 2017- Dec 2019	Jan 2020- Dec 2022	Jan 2023- June 2024	911-All 51-CSI 100 124-CSI 200 299-CSI 500
Bad Performance Industries	2400	Jan 2005- Dec 2006	Jan 2007- Dec 2008	Jan 2009- Dec 2010	373-All 47-CSI 100 104-CSI 200 209-CSI 500	Jan 2011- Dec 2013	Jan 2014- May 2015	June 2015- Dec 2016	353-All 52-CSI 100 106-CSI 200 164-CSI 500	Jan 2017- Dec 2019	Jan 2020- Dec 2022	Jan 2023- June 2024	759-All 71-CSI 100 124-CSI 200 208-CSI 500

Note: This table provides an overview of the stock indices and their constituents across different sample periods analyzed in this study. The data is segmented into three key timeframes: Pre-Financial Crisis (Pre-Fin.C.), In-Financial Crisis (In-Fin.C.), and Post-Financial Crisis (Post-Fin.C.) periods; Pre-Bullish and Non-Bullish (Pre-B.N.B.), In-Bullish, and In-Bearish periods; as well as Pre-COVID-19 (Pre-Cov.), In-COVID-19 (In-Cov.), and Post-COVID-19 (Post-Cov.) periods. The "Number selected" refers to the number of stocks remaining after data cleaning for each phase. The table details the number of stocks and industries selected from various indices, including the CSI 100, CSI 200, CSI 500, as well as stocks from Good Performance Industries and Bad Performance Industries. This comprehensive dataset allows for a thorough analysis of market behavior and pairs trading strategies across different market conditions. "Industry Matching" refers to the pairing of stocks within the same industry for portfolios 19-36 in Table 3. Industry matching refers to the pairing of stocks within the same industry for portfolios 19-36 in Table 3.

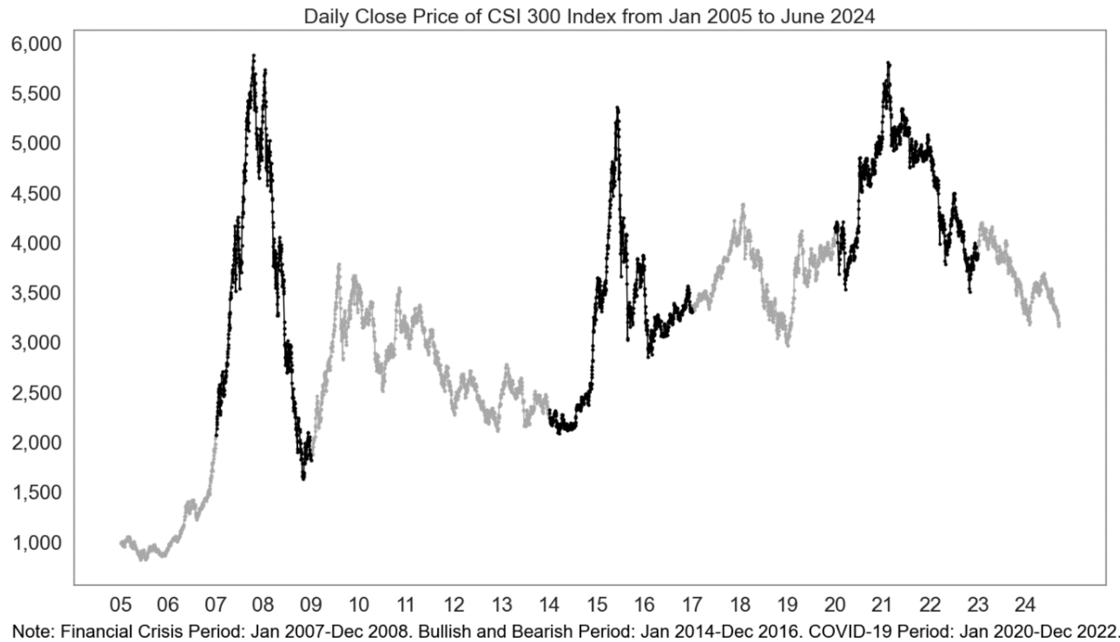

Figure 1. Daily Close Price of the CSI 300 Index. This figure shows the daily close price trend of the CSI 300 Index from January 2005 to June 2024, highlighting three key periods: the Financial Crisis (January 2007 - December 2008), the Bullish and Bearish Market Phase (January 2014 - December 2016), and the COVID-19 Pandemic Period (January 2020 - December 2022). The Financial Crisis period reflects sharp market volatility with significant rises and declines, driven by global economic instability. The Bullish and Bearish phase captures fluctuations due to China's economic reforms and market turbulence. Lastly, the COVID-19 period demonstrates the market's response to pandemic-related disruptions and subsequent recovery efforts. These highlighted phases underscore the CSI 300 Index's sensitivity to major economic events and policy changes, providing a clear view of market performance through various economic cycles. This is the reason these three stages are chosen.

Reasons of Data Selection

The rationale behind selecting these specific time periods and datasets is grounded in the study's objective to evaluate the performance of pair trading strategies during extreme market conditions, particularly during the COVID-19 period. This section elaborates on the reasons for choosing the Financial Crisis, Bullish and Bearish and COVID-19 periods, as well as the rationale for selecting different stock indices and industry categories.

Selection of These Three Periods The primary aim of this paper is to examine the returns of pair trading during the COVID-19 period, a time characterized by significant market disruptions and economic uncertainty. To comprehensively assess the performance of pair trading under such extreme conditions, the study includes data from the financial crisis period as well. Both the financial crisis and COVID-19 periods represent major global economic shocks that had profound impacts on financial markets. By comparing these two extreme events, the study aims to identify similarities and differences in pair trading performance under varying crisis scenarios.

Additionally, the inclusion of pre- and post-financial crisis periods, and Bullish and Bearish periods allow for a comparative analysis of returns before, during, and after these major events. This comparison helps in understanding how pair trading strategies respond to normal market conditions versus periods of high volatility and uncertainty. It also enables the study to capture the recovery dynamics of pair trading strategies following extreme market downturns.

Selection of All A-Shares, CSI 100, CSI 200, and CSI 500 To conduct a comprehensive analysis of the Chinese stock market, the study includes all A-shares listed on the Shanghai and Shenzhen exchanges. This extensive dataset covers a broad range of market segments, providing a holistic view of the overall market dynamics. The inclusion of CSI 100, CSI 200, and CSI 500 indices serves to represent different market capitalizations: large-cap, mid-cap, and small-cap stocks, respectively. CSI 100 Represents large-cap stocks and includes the top 100 companies by market capitalization from the Shanghai and Shenzhen exchanges. CSI 200 focuses on mid-cap stocks, capturing the 200 largest companies excluding those in the CSI 100. CSI 500 comprises small-cap stocks, providing insights into the performance of the smaller, less liquid companies in the market.

By analyzing these indices alongside the full A-share market, the study aims to compare pair trading returns across different market segments, thereby understanding the impact of market capitalization on the effectiveness of pair trading strategies.

Selection of Good Performance and Bad Performance Industries The study also includes industry-specific analyses, focusing on sectors that exhibited contrasting performances during these three periods. This approach enables a deeper examination of how pair trading strategies perform across different industry conditions.

Good performance industries include sectors such as biomedicine, computers, electronics, and communications, which collectively consist of 2,950 companies during COVID-19 period. These industries performed well during the COVID-19 period due to increased demand for healthcare, technology, and digital communication services. By analyzing these industries, the study seeks to explore the potential for pair trading strategies to capitalize on sectors that benefit from pandemic-related shifts.

Conversely, bad performance industries such as aviation and tourism, petroleum and petrochemicals, real estate, building materials, building decoration, and textile and apparel are included under the bad performance category, totaling 2,400 companies during COVID-19 period. These sectors faced significant challenges during the pandemic due to reduced consumer demand, travel restrictions, and disrupted supply chains. Analyzing these industries allows the study to assess how pair trading performs in sectors that are negatively impacted by extreme events.

By including a diverse range of market indices and industry sectors, the study aims to provide a robust analysis of pair trading performance across various market conditions and industry dynamics, offering valuable insights into the effectiveness of this strategy in the context of the Chinese stock market.

Data Cleaning Criteria

From **Table 1**, it is evident that the number of stocks we selected is significantly fewer compared to the constituent stocks, with 5612 versus 783, 1681, etc. This discrepancy arises because, in the two stages, we removed stocks that had missing daily close prices for more than 30 days with the data cleaning criteria. For the remaining stocks, we used cubic spline interpolation to fill in the missing data. The details of the data cleaning criteria will be thoroughly discussed in the below content.

Firstly, to obtain an accurate assessment of the profitability of pairs trading, considering various implementation constraints, we restrict our sample to liquid stocks that are relatively easy and inexpensive to trade and short sell. To minimize survivor bias, the sample includes firms up to the point of their delisting from the Chinese stock market, ensuring that companies that failed are also represented. This approach provides a more comprehensive view of the market by accounting for the full spectrum of firm performances, including those that did not survive the entire period.

Secondly, specific to Chinese market, stocks with "ST" and "*ST"[4] designations are excluded from the dataset. In the Chinese stock market, these tags indicate special treatment for companies experiencing financial or other significant issues. The "ST" (Special Treatment) designation signals that a company is under special scrutiny due to abnormal financial conditions, typically applied when a company has reported losses for two consecutive years or faces other notable challenges. Companies with the ST tag are required to improve their financial situation or face stricter regulatory measures. The "*ST" designation is more severe, indicating that the company has experienced losses for three consecutive years and is at high risk of being delisted. This designation serves as a warning of poor financial health and increased investment risk; failure to rectify the financial situation within the specified timeframe may result in delisting.

Thirdly, due to the high frequency of pairs trading, we prioritize stocks with high liquidity. We achieve this by focusing on stocks with medium to large market capitalizations within each market, as these typically offer greater liquidity than smaller-cap stocks. This study exclusively examines markets with large market capitalizations and high liquidity to ensure the effective implementation of the strategy, consistent with methodologies from previous studies such as Do and Faff (2012), Jia and Jason (2016), and Zhang and Urquhart (2019).

[4] ST and *ST stocks may be subject to trading restrictions, such as smaller daily price limits (±5% for both) and potential trading suspensions. These limitations can hinder normal buy and sell operations, affecting the implementation of trading strategies.

Additionally, stocks with closing prices below 1 Chinese Yuan (CNY)[5] should be deleted during the one-year formation period, as well as those that have been listed for one year or less. We also eliminate stocks that have one or more days without trading activity during the formation period, based on trading volume, and those with any invalid prices or returns within this period. During the trading period, any pairs with invalid or missing prices/returns on days when data is otherwise available are assigned zero returns. Although these last two filters have minimal impact on the results, they are included to ensure the robustness of the analysis. Finally, we use interpolation to deal with the missing data from the price time series. Overall, our dataset processing closely aligns with the methodology used by Do and Faff (2012).

3.2 Chinese Stock Market

This section provides a brief overview of the main characteristics and evolution of the Chinese stock market, which is institutionally distinct from the stock markets in developed countries and remains relatively understudied in the literature.

The official opening of the A-shares market to international investors began in 2003, after that cross-market trading was accessible to mainland Chinese investors, particularly institutional investors, throughout our sample period. This accessibility is due to the growing presence of mainland China brokerage firms, such as Guotai Junan, which have operated comprehensive securities trading businesses in Hong Kong since 1995, where there are no restrictions on who can trade shares. Consequently, mainland Chinese investors can open separate accounts to simultaneously trade stocks in both mainland China and Hong Kong. Short-selling in the A-shares market was officially permitted starting on March 31, 2010, initially for a select group of large- and mid-cap stocks. Prior to this, short-selling was possible through Over-The-Counter (OTC) transactions between traders or within securities firms, where different departments could lend stocks to each other (Broussard and Vaihekoski, 2012). Stocks eligible under the Stock Connect schemes are also available for Margin Trading and Short-Selling. By the end of 2013, over 700 A-shares were eligible for short-selling.

The Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE)[6] are the two primary stock exchanges in mainland China, established in December 1990 and April 1991, respectively. By 2016, the SHSE listed approximately 1,200 stocks, while the SZSE had about 1,800 stocks. Both exchanges are among the top 10 globally in terms of market capitalization.

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[5] In the A-share market, stocks with prices below 1 CNY are commonly referred to as "penny stocks." This classification is not an official standard but rather a colloquial term used to describe stocks that have low prices, poor performance, or unfavorable prospects. These stocks are often associated with high risks, high volatility, and the potential for delisting. As a result, investors generally consider them to have low investment value.

[6] CSI 100, 200, 500 indexes include stocks from the Shanghai and Shenzhen stock exchanges. This is one of the reasons why we chose these data, which can more comprehensively represent the Chinese stock market.

Firms incorporated in mainland China can issue various types of common stock based on their listing location and the investors eligible to trade them. The most common types are A-shares, B-shares, and H-shares, all denominated in Chinese Yuan (Renminbi, the official currency of mainland China) but traded in different currencies depending on where they are listed. A-shares, quoted in Chinese Yuan, were initially available only to mainland Chinese citizens and domestic institutions until 2003. Afterward, they became accessible to foreign investors through programs such as the Qualified Foreign Institutional Investor (QFII), the Renminbi Qualified Foreign Institutional Investor (RQFII), and the Stock Connect schemes. B-shares, quoted in US Dollars on the SHSE and Hong Kong Dollars on the SZSE, were initially restricted to foreign investors until February 19, 2001, after which mainland Chinese investors were also permitted to trade them. Companies can list A-shares or B-shares on either the SHSE or SZSE, but not on both exchanges simultaneously. Additionally, firms may issue both A-shares and B-shares, or H-shares. Chinese firms that issue B-shares and H-shares are generally subject to more stringent disclosure requirements, making them typically more financially stable than A-share firms. Since the B-shares and H-shares markets are dominated by informed foreign institutional investors, while A-shares are primarily held by domestic retail investors, it is widely believed that investors in B- and H-shares exhibit more rational behavior compared to their A-share counterparts. Unlike the A- and H-shares markets, the B-shares market has historically struggled with poor liquidity and has never gained significant popularity. Consequently, stocks listed in Hong Kong are generally thought to better reflect economic fundamentals and be more integrated with global financial markets compared to A- and B-shares listed in mainland China.

On November 17, 2014, the Shanghai and Hong Kong stock exchanges launched the Stock Connect scheme, which aimed to link the Shanghai and Hong Kong stock markets, thereby increasing mutual market access by easing the restrictions that had traditionally separated the mainland China and Hong Kong markets. This program was further extended to include the Shenzhen market on December 5, 2016. These schemes collectively aimed to create a unified China stock market, ranking among the largest in the world by market capitalization and daily trading turnover. It is anticipated by some that these cross-market access initiatives would boost trading volumes and provide opportunities for investors to arbitrage between markets, potentially enhancing market efficiency over time (Sun et al., 2009).

However, given the relatively small quotas, limited number of eligible stocks, and differences in trading hours, clearing and settlement systems, and holidays, the integration remains partial at this stage. A summary of key dates in the development of the Chinese stock markets can be found in **Table 2** below, similar in Zhang and Urquhart (2019).

Table 2. Key Milestones in the Development of Mainland China Market

Date	Description
19 December 1990	Shanghai Stock Exchange (SHSE) was established on 26 November 1990 and was in operation on 19 December 1990.
16 April 1991	The Shenzhen Stock Exchange started trial operations on 1 December 1990 and was officially approved on 16 April 1991.
19 February 2001	Initially restricted to foreign investors, B-shares quoted in US Dollars on the SHSE and in Hong Kong Dollars on the SZSE became accessible to mainland Chinese investors, broadening participation in the B-share market.
9 July 2003	A-shares, which are priced in Chinese Yuan and were previously available only to mainland Chinese citizens and domestic institutions, were opened to qualified foreign institutional investors under the Qualified Foreign Institutional Investor (QFII) scheme, allowing broader international investment.
8 April 2005	The China Securities Index Company Ltd launched the China Securities Index (CSI 300), an influential benchmark for the Chinese stock market.
31 March 2010	The official introduction of short-selling in the A-shares market represented a significant expansion of trading strategies available to investors.

Note: This table summarizes key milestones in the development of the mainland Chinese stock market, focusing on events that significantly influenced market accessibility, structure, and trading mechanisms. Each milestone marks a pivotal moment that contributed to the evolving market landscape.

4. Methodology

4.1 The Methods of GGR

General Overview

In the baseline algorithm described by Gatev et al. (2006), pairs are formed by selecting a partner for each stock in the universe that minimizes the normalized price spread over a 12-month formation period. The normalized price is represented by the total return index, which includes dividends and is scaled to start at $1 at the beginning of the formation period. From these, the top pairs with the lowest SSD in their normalized prices are selected for trading in the subsequent 6-month trading period. The trading strategy involves opening a long-short position in a pair when its normalized spread diverges by two historical standard deviations. Positions are closed upon the first reversion of the spread or at the end of the trading period if no reversion occurs. Pairs that complete a roundtrip—where the spread diverges and then converges within the trading period—are eligible for trading again within that period. A typical trading portfolio under this algorithm consists of an equally weighted selection of the top 20 pairs with the lowest SSD values. Similar to momentum strategies, this pairs trading approach uses overlapping portfolios, with the selection and trading processes repeated monthly without waiting for the current portfolio to complete its cycle.

Formation period

The total return index for each stock in the sample is normalized during the formation period by setting the initial price to 1, as expressed in the following equation:

$$P^*_{i,t;t+1;t+2;\dots;T} = \frac{P_{i,t;t+1;t+2;\dots;T}}{P_{i,t}} \tag{4.1}$$

where $P^*_{i,t}$ represents the normalized price of stock i at time t, and $P_{i,t}$ is the price series of stock iii at time t, including reinvested dividends. Pairs are created by matching each stock with another stock that minimizes the SSD between their normalized price series over the 12-month formation period.

$$SSD_{i,j} = \sum_{t=1}^{T}(P^*_{i,t} - P^*_{j,t})^2 \tag{4.2}$$

At the end of each formation period, the top N pairs, ranked by the lowest sum of squared deviations, are selected, and traded in the subsequent six-month trading period.

Trading period

The trading period begins on the first trading day immediately after the end of the formation period. During this period, a pair trade is initiated when the normalized stock prices diverge by more than two historical standard deviations of the price difference observed during the formation period. In our case, the trade is executed by purchasing 1 Chinese Yuan worth of the stock with the lower normalized price and selling 1 Chinese Yuan worth of the stock with the higher normalized price, resulting in a net zero position. This approach makes the trade self-financing. The pair trade is closed either when the normalized prices converge or on the final day of the trading period, regardless of whether convergence has occurred.

We implement pairs trading under two distinct scenarios: (1) trades are executed immediately at the end of the day when the trading signal appears, and (2) trades are executed with a one-day delay. The delayed execution scenario accounts for the behavior of certain investors, particularly non-professional retail investors, who may react to trading signals with a lag. This delay also addresses concerns related to bid-ask spreads and potential challenges in trade execution, such as nonsynchronous trading. Additionally, we require that the trading volume is above zero to proceed with executing a trade.

Returns calculation

Positive cash flows are generated as pairs open and close positions throughout the trading period. If pairs open but continue to diverge by the last trading day, they result in negative cash flows. Multiple positive cash flows can occur when pairs open and close multiple times within the trading period. If pairs do not open at all during the trading period, cash flows remain zero. The payoffs from trading pairs of long and short positions are then aggregated to calculate the portfolio's excess returns, as represented in the following equations:

$$r_{p,t} = \frac{\sum w_{i,t} t_{i,t}}{\sum w_{i,t}} \tag{4.3}$$

$$w_{i,t} = w_{i,t-1}(1 + r_{i,t-1}) = (1 + r_{i,t}) \cdots (1 + r_{i,t-1}) \quad (4.4)$$

where $r_{p,t}$ is the excess return on portfolio p at time t, $w_{i,t}$ is the weight of position i at time t, and $r_{i,t}$ is the return of position i at time t. The daily returns of each portfolio of pairs are then compounded to form a monthly time series of returns.

Two measures of excess returns are computed for each portfolio. For the committed capital (CC) portfolio, returns are scaled by the number of pairs matched during the formation period. For instance, in the Top 5 pairs trading portfolio, returns are scaled by 5. In contrast, for the fully invested (FI) portfolio, returns are scaled by the number of pairs that actually open positions during the trading period. For example, if only four pairs in the Top 5 pairs trading portfolio are actively traded based on the standard deviation metric rule, then the FI portfolio returns are scaled by 4. As a result, the returns of the CC portfolio tend to be more conservative. In this study, we exclusively use the FI method to provide a closer approximation of the returns generated by actual trading strategies.

Our analyses are based on monthly return time series, which is a common practice in the trading strategy literature and consistent with the benchmark study by Gatev, Goetzmann, and Rouwenhorst (2006). Before-cost returns are computed as the monthly marked-to-market payoffs to the pair portfolio, divided by the number of pairs in the portfolio. These strategies are repeated every month, producing six return time series staggered by one month each, like in Jegadeesh and Titman (1993). The reported return time series is the equally weighted average of these staggered series. Finally, to derive after-cost returns, we subtract the time-varying trading costs from this average return series. This comprehensive approach ensures an accurate assessment of the pairs trading strategy's performance, accounting for both market dynamics and transaction costs.

The Drawbacks of GGR Portfolio

The baseline method has several inherent pitfalls. First, pairs can be formed between companies that are not close economic substitutes, leading to high fundamental risk and an increased likelihood of divergence. Gatev, Goetzmann, and Rouwenhorst (2006) focused on pairs matched within broad S&P sectors such as utilities, financials, transportation, and industrials. In contrast, Do and Faff (2010) demonstrated that using finer industry classification schemes, like the 48 groups defined by Fama and French (1997), offers significant advantages.

Second, matching pairs solely based on their historical price co-movements may overlook the fact that profitable pairs trading requires frequent reversals in the price spread. This suggests that paired stocks should oscillate around each other. Do and Faff introduced a measure of historical reversals, the number of zero crossings (NZC) during the formation period, and showed that combining this with the SSD metric can materially improve pairs trading returns, especially when incorporating industry homogeneity into the trading strategy.

Third, in a deep and liquid market such as the U.S. stock market, top pairs might have such tight price movements that two standard deviations could be too small, potentially triggering trades at levels insufficient to cover bid–ask spreads and transaction costs, even when the stocks converge. Gatev et al. (2006) noted that this issue affected some pairs in their study.

Additionally, transaction costs and slippage are critical factors that significantly impact the actual returns of pairs trading strategies, such as those employing the SSD method. Transaction costs, which include commissions, bid-ask spreads, and other trading-related fees, accumulate with each buy and sell action. This frequent trading, characteristic of pairs trading strategies, leads to substantial transaction costs that can erode gross profits, especially for strategies targeting small price deviations. Consequently, these costs can result in actual returns falling significantly below theoretical projections. Slippage, or the difference between the expected and actual execution prices, further compounds this issue. It is particularly problematic in volatile markets, with low liquidity, or when executing large orders, as it can lead to trades being executed at less favorable prices, reducing overall profitability. Slippage also exacerbates liquidity issues, causing significant deviations from expected returns. Empirical evidence shows that high-frequency trading strategies may experience a drastic reduction in returns when accounting for these real-world frictions, with theoretical returns of 5% potentially reduced to 1-2% or lower in practice. Additionally, risk-adjusted performance metrics, such as the Sharpe ratio, may be overestimated if transaction costs and slippage are not considered, reflecting higher volatility and lower risk compensation. Thus, a thorough consideration of transaction costs and slippage is essential for accurately evaluating and developing pairs trading strategies.

4.2 Innovative Portfolios

To enhance the depth and robustness of our analysis, we explore a variety of pairs portfolios designed to address the limitations of the baseline algorithm. Specifically, we examine a total of 40 alternative portfolios, each differing in their stock matching and pair selection methods. This approach contrasts with Do and Faff (2012), who utilized a total of 29 portfolios in their study. By expanding the number of portfolios, our analysis aims to explore a broader range of strategies and enhance the robustness of the findings.

Among these, 18 portfolios utilize a mechanical pair matching approach without any restrictions on industry classification. This diverse set of portfolios allows for a comprehensive evaluation of the effectiveness of different matching strategies and their impact on trading performance. Additionally, the next set of 18 portfolios (19-36) focuses on matching stocks within the same industry, which introduces a layer of sector-specific analysis that aims to mitigate the risk of cross-industry variance. This method involves initially grouping stocks by industry, then calculating the SSD for each potential pair. The pairs are then ranked, allowing for a prioritized selection that emphasizes pairs with the smallest SSD values, potentially improving the alignment of stock behaviors within the same sector. The final set of four portfolios (37-40) is designed to test the extremes of performance by exclusively including the good-performing and bad-performing industry pairs. This approach aims to identify whether extreme performers, either on the positive or negative end, can generate superior trading results when matched within these specialized portfolios. By isolating these high and low performers, the analysis seeks to capture potential outliers or unique patterns that might not be evident in the broader sets of more moderately performing portfolios.

Non-Industry Matching

Of this group of portfolios, the first portfolio, which is the baseline portfolio, is the object of study in Gatev et al. (2006). The second portfolio consists of pairs ranked 21-40, while portfolios 3, 4, and 5 consist of pairs ranked 41-60, 61-80, and 81-100, respectively. The purpose of this categorization is to compare the performance of different sets of 20 pairs of stocks, allowing us to analyze how pair rankings affect trading outcomes. By segmenting pairs into these rank-based groups, the study aims to determine if higher-ranked pairs (with lower SSDs) consistently outperform lower-ranked pairs or if performance diminishes beyond the top ranks. This helps identify optimal thresholds for the number of pairs to include in a trading strategy, assess the scalability of pairs trading, and understand the trade-offs between expanding the number of pairs and maintaining strategy effectiveness. This approach provides insights into optimizing pairs trading for consistent and reliable returns. Portfolio 6 includes the bottom top 20 pairs of stocks available. This portfolio provides a comparison of the pairs trading strategy when extended to the bottom of possible pairs.

For portfolios 7-18, the selection process involves choosing from the top 10,000 stock pairs sorted by SSD from total pairs. From this narrowed list, we then select the top 20 pairs based on specific conditions descripted below. The reason for restricting the selection to the top 10,000 pairs is to exclude those with excessively high SSD values, which are less desirable for our analysis. By focusing only on pairs with lower SSD values, we can maintain a higher level of similarity in performance between the stocks, which is critical for pairs trading. This approach also significantly reduces computational time. Moreover, selecting the top 20 pairs allows us to directly compare the performance of different portfolios under the same stock pair conditions, making the evaluation of different strategies more robust and meaningful.

For the portfolios 7-12, pairs are independently ranked based on both SSD and NZC metrics and then divided into 20 equal groups, known as vigintiles. Specifically, portfolios 7, 8, and 9 are constructed by intersecting pairs from the first, second, and third SSD vigintiles, respectively, with pairs from the first (1st) NZC vigintile. Portfolios 10, 11, and 12 are constructed by intersecting pairs from the first, second, and third SSD deciles, respectively, with pairs from the first (1st) NZC decile. This selection method targets pairs that fall into the top ranks based on their price spread consistency (lowest SSD deciles) while simultaneously being in the lowest category for price reversals (highest NZC decile). These portfolios aim to combine pairs with the lowest price spread deviations (top SSD vigintiles) with those exhibiting the most historical reversals (top NZC vigintile), potentially enhancing the robustness of pair selection. By focusing on pairs that not only have low SSD but also minimal price crossing frequency, these portfolios are expected to capture pairs with more stable and predictable mean-reversion characteristics. This method provides a refined selection process that balances the precision of SSD with the additional insight of NZC, allowing for a deeper understanding of how different combinations of these metrics influence trading performance. The comparative analysis of these portfolios helps assess whether such targeted intersections can yield more consistent and reliable returns compared to using either metric independently.

Portfolios 13 through 18 further refine the pair selection process by incorporating the Hurst exponent, which is used to enhance the mean-reversion characteristics of the selected pairs. The Hurst exponent measures the tendency of a time series to either persist in its current trend or revert to the mean, with lower values indicating stronger mean-reversion behavior. Specifically, portfolios 13, 14, and 15 are constructed by intersecting pairs from the first, second, and third SSD vigintiles, respectively, with pairs from the first (lowest) Hurst vigintile. This approach targets pairs that not only have the lowest price spread deviations (top SSD vigintiles) but also exhibit strong mean-reversion tendencies as indicated by the lowest Hurst values. Similarly, portfolios 16, 17, and 18 are formed by intersecting pairs from the first, second, and third SSD deciles, respectively, with pairs from the first (lowest) Hurst decile. By selecting pairs that score in both the top SSD deciles and the lowest Hurst decile, these portfolios aim to capture stocks that combine low deviation in price spreads with the highest propensity for mean reversion. The integration of the Hurst exponent into the pair selection process allows us to test whether the inclusion of mean-reversion metrics can further optimize the performance of pairs trading strategies. By comparing these portfolios, the study evaluates the effectiveness of combining price consistency with strong mean-reversion signals, potentially identifying pairs that offer more reliable and profitable trading opportunities. This approach provides a comprehensive framework to assess how the interplay between SSD and Hurst metrics influences the overall success of pairs trading portfolios.

Industry Matching

Portfolios 19 through 36 are constructed similarly to portfolios 1 through 18, with the crucial difference that pairs are formed exclusively within the same Shenwan first-level industry classifications. This industry-specific approach aims to refine pair selection by ensuring that paired stocks exhibit strong statistical alignment while also belonging to the same economic sector, thereby reducing the fundamental risk associated with cross-industry pairings. By focusing on stocks within the same industry, this approach enhances economic similarity, potentially lowering sector-specific risks and improving the reliability of the pairs trading strategy. Comparing these industry-specific portfolios with broader market counterparts allows the analysis to assess whether intra-industry pairings offer superior performance and risk-adjusted returns, providing a more nuanced understanding of pairs trading within distinct economic sectors.

Portfolios 37 through 40 are also constructed within the Shenwan first-level industry classifications but focus specifically on certain industries using distinct selection methods. Portfolios 37 and 39 are based on the good performance industries, where Portfolio 37 selects the top 20 pairs based on the NZC from the top 50 pairs ranked by SSD, and Portfolio 39 selects the top 20 pairs based on the Hurst exponent from the top 50 SSD pairs.

In contrast, Portfolios 38 and 40 focus on the bad performance industries. Portfolio 38 selects the top 20 pairs based on NZC from the top 50 SSD-ranked pairs, while Portfolio 40 selects the top 20 pairs based on the Hurst exponent from the top 50 SSD pairs. For detailed descriptions and the selection rationale of the good and bad performance industries, please refer to Section 3.1. By applying these refined selection criteria within specific industries, the portfolios seek to enhance trading performance by aligning stocks that exhibit both statistical alignment and robust mean-reversion properties. A summary of these portfolio formations is presented in **Table 3**.

Table 3. Construction of Pairs Portfolios

Portfolio	None-Industry Matching	Industry Matching	SSD Ranking	NZC Ranking	Hurst Ranking	Portfolio Construction
1	✓		✓			Top 20 pairs
2	✓		✓			Top 21-40 pairs
3	✓		✓			Top 41-60 pairs
4	✓		✓			Top 61-80 pairs
5	✓		✓			Top 81-100 pairs
6	✓		✓			Bottom 20 pairs
7	✓		✓	✓		Top 20 pairs in 1st SSD vigintile ∩ 1st NZC vigintile
8	✓		✓	✓		Top 20 pairs in 2nd SSD vigintile ∩ 1st NZC vigintile
9	✓		✓	✓		Top 20 pairs in 3rd SSD vigintile ∩ 1st NZC vigintile
10	✓		✓	✓		Top 20 pairs in 1st SSD decile ∩ 1st NZC decile
11	✓		✓	✓		Top 20 pairs in 2nd SSD decile ∩ 1st NZC decile
12	✓		✓	✓		Top 20 pairs in 3rd SSD decile ∩ 1st NZC decile
13	✓		✓		✓	Top 20 pairs in 1st SSD vigintile ∩ 1st Hurst vigintile
14	✓		✓		✓	Top 20 pairs in 2nd SSD vigintile ∩ 1st Hurst vigintile
15	✓		✓		✓	Top 20 pairs in 3rd SSD vigintile ∩ 1st Hurst vigintile

16	✓		✓		✓	Top 20 pairs in 1st SSD decile ∩ 1st Hurst decile
17	✓		✓		✓	Top 20 pairs in 2nd SSD decile ∩ 1st Hurst decile
18	✓		✓		✓	Top 20 pairs in 3rd SSD decile ∩ 1st Hurst decile
19		✓	✓			Top 20 pairs
20		✓	✓			Top 21-40 pairs
21		✓	✓			Top 41-60 pairs
22		✓	✓			Top 61-80 pairs
23		✓	✓			Top 81-100 pairs
24		✓	✓			Bottom 20 pairs
25		✓	✓	✓		Top 20 pairs in 1st SSD vigintile ∩ 1st NZC vigintile
26		✓	✓	✓		Top 20 pairs in 2nd SSD vigintile ∩ 1st NZC vigintile
27		✓	✓	✓		Top 20 pairs in 3rd SSD vigintile ∩ 1st NZC vigintile
28		✓	✓	✓		Top 20 pairs in 1st SSD decile ∩ 1st NZC decile
29		✓	✓	✓		Top 20 pairs in 2nd SSD decile ∩ 1st NZC decile
30		✓	✓	✓		Top 20 pairs in 3rd SSD decile ∩ 1st NZC decile
31		✓	✓		✓	Top 20 pairs in 1st SSD vigintile ∩ 1st Hurst vigintile
32		✓	✓		✓	Top 20 pairs in 2nd SSD vigintile ∩ 1st Hurst vigintile
33		✓	✓		✓	Top 20 pairs in 3rd SSD vigintile ∩ 1st Hurst vigintile
34		✓	✓		✓	Top 20 pairs in 1st SSD decile ∩ 1st Hurst decile
35		✓	✓		✓	Top 20 pairs in 2nd SSD decile ∩ 1st Hurst decile
36		✓	✓		✓	Top 20 pairs in 3rd SSD decile ∩ 1st Hurst decile
37		✓	✓	✓		Top 20 NZC pairs among top 50 SSD pairs
38		✓	✓	✓		Top 20 NZC pairs among top 50 SSD pairs
39		✓	✓		✓	Top 20 Hurst pairs among top 50 SSD pairs
40		✓	✓		✓	Top 20 Hurst pairs among top 50 SSD pairs

Note: This table summarizes the formation of 40 pairs portfolios. Non-Industry Matching: This approach matches stocks across the entire stock universe without restrictions to any specific sector. Industry Matching: Stocks are matched within specific industry groups, following the classification criteria relevant to the market under study. The classification standard used is the Shenwan First Level Industry Classification, which comprises a total of 31 industry sectors. SSD Ranking: Pairs are ranked in ascending order based on the Sum of Squared Differences statistic. NZC Ranking: Pairs are ranked in descending order based on the Number of Zero Crossings statistic. Hurst Ranking: This method ranks pairs based on their Hurst exponent.

4.3 Trading Costs

In the context of the Chinese stock market, explicit trading costs in a pairs trading strategy include two roundtrip commissions per pair trade, stamp duty, short selling fees, and the implicit cost of market impact. Estimating these costs precisely is challenging due to their variability across different factors. Trading costs fluctuate based on the sample period, as market deregulation and technological advancements have significantly reduced commissions over time, though market impact costs may not follow the same trend. The size of trades also plays a critical role; larger orders typically incur lower per-share commissions but face higher market impact, while institutional investors generally benefit from lower commissions compared to retail investors but may encounter greater market impact costs. Additional factors such as broker selection and the specific investment style can further influence trading costs.

Given the complexities of estimating trading costs in the Chinese market from 2005 onward, our approach is to use the best available proxies that reflect these costs for a typical investor. Since there are limited studies detailing the costs of Chinese stock trading, our primary sources of information are data released by various securities companies and the China Securities Regulatory Commission on their official websites. We also strive to compile estimates from various literature sources, adjusting them to capture the evolving structure of trading costs in China, including the effects of market reforms, changes in commission rates, and advancements in trading infrastructure. Pesaran and Timmermann (1995) and Miao and Dunis (2005) set the transaction costs at 0.5% per round trading on stocks, which is equivalent to 1% per round trade per pair. Bowen and Hutchinson (2016) found that trading costs (TCs) per pair round trip were 71 and 73 bps, with an effective estimated spread of 35 and 36 bps, respectively. According to Qing (2018), the basic data were sourced from the Guotai Securities Database, and the average transaction cost was approximately 70 bps, covering both buying and selling actions.

These cost estimates will serve as the foundation of our analysis, enabling us to accurately assess the impact of trading costs on pairs trading performance in the Chinese market during this period. Below, we present the transaction costs used in this paper in **Table 4**, followed by a detailed explanation of each item. Finally, we selected **100bps** as the trading cost for all three periods, both for buy and sell. The purpose of selecting the same amount trading costs is to provide a clearer comparison of returns across the three phases. A more detailed analysis of the different trading costs during each phase will be presented in the subsequent chapters. A detailed explanation of these choices is provided in the below.

Table 4. Overview of Trading Costs in the Chinese Stock Market.

Period	Commission	Stamp Duty	Market Impact And slippage	Do and Faff (2012)	Qing (2018)

Pre-Fin.C.: Jan 2005 - Dec 2006	Ranging from 0.1% to 0.3%. Selection criteria: 0.2% (buy and sell)	January 24, 2005: Stamp duty reduced from 0.2% to 0.1%, applied to both buying and selling. Selection criteria: 0.2% (buy and sell)	Refer Do and Faff (2012) Assign a market impact cost of **0.3% (30 bps)**.	1963–2009: commission plus market impact of 0.60% (i.e., 0.34% + 0.26%)	SHSE 2005: 0.62% SZSE 2005: 0.73% SHSE 2006: 0.79% SZSE 2006: 0.82%
In- Fin.C.: Jan 2007 - Dec 2008	Remained at 0.1% to 0.3%. Selection criteria: 0.2% (buy and sell)	May 30, 2007: Stamp duty increased from 0.1% to 0.3%. April 24, 2008: Reduced back to 0.1%. September 19, 2008: Changed to only on sales, rate remained at 0.1%. Selection criteria: 0.2% (buy and sell)	Based on historical experience, the slippage is set to a fixed value of **0.3% (30 bps).**	-	SHSE 2007: 0.92% SZSE 2007: 1.01% SSE 2008: 0.86% SZSE 2008: 0.87%
Post-Fin.C.: Jan 2009 - Dec 2010	Ranging from 0.05% to 0.2%. Selection criteria: 0.2% (buy and sell)	Maintained at 0.1%, only collected on sales. Selection criteria: 0.1% (buy and sell)	-	-	SHSE 2009: 0.78% SZSE 2009: 0.81% SSE 2010: 0.68% SZSE 2010: 0.75%
Pre-B.N.B.: Jan 2011-Dec 2013	Ranging from 0.05% to 0.1%. Selection criteria: 0.2% (buy and sell)	Maintained at 0.1%, only collected on sales. Selection criteria: 0.1% (buy and sell)	-	-	SHSE 2011: 0.56% SZSE 2011: 0.60% SSE 2012: 0.52% SZSE 2012: 0.61%
In-Bullish: Jan 2014-May 2015	Remained from 0.05% to 0.1%. Selection criteria: 0.2% (buy and sell)	Maintained at 0.1%, only collected on sales. Selection criteria: 0.1% (buy and sell)	-	-	SHSE 2013: 0.64% SZSE 2013: 0.74% SSE 2014: 0.65% SZSE 2014: 0.73%
In-Bearish: June 2015-Dec 2016	Remained from 0.05% to 0.1%. Selection criteria: 0.2% (buy and sell)	Maintained at 0.1%, only collected on sales. Selection criteria: 0.1% (buy and sell)	-	-	SHSE 2015: 0.95% SZSE 2015: 0.93% SHSE 2016: 0.62% SZSE 2016: 0.68%
Pre-Cov.: Jan 2017 - Dec 2019	Mostly between 0.02% to 0.05%. Selection criteria: 0.05% (buy and sell)	Continued at 0.1%, only collected on sales. Selection criteria: 0.1% (buy and sell)	-	-	-
In-Cov.: Jan 2020 - Dec 2022	Remained stable at around 0.02% to 0.03%. Selection criteria: 0.05% (buy and sell)	Rate maintained at 0.1%. Selection criteria: 0.1% (buy and sell)	-	-	-
Post-Cov.: Jan 2023 - June 2024	Expected to stay between 0.02% to 0.03%. Selection criteria: 0.05% (buy and sell)	Rate expected to remain at 0.1%. Selection criteria: 0.1% (buy and sell)	-	-	-

Note: Regarding commission fees, since professional investors typically obtain the lowest available rates in actual trading, we use the lowest threshold in our analysis to closely reflect real transaction costs. The data is based on information published by various brokerage firms. Regarding to market impact, we reference the conclusion of Do and Faff (2012), and when combined with the data obtained by Qing (2018) from the official database, **30 bps** is considered a reasonable estimate.

Commissions

Commissions are a significant component of trading costs in the Chinese stock market and directly impact the profitability of pairs trading strategies. Historically, commission rates in China have gradually decreased due to market deregulation, increased competition among brokerage firms, and the rise of online trading platforms. Since 2005, which is our main focus period covering the pre- and post-financial crisis as well as the pre- and post-COVID periods, the Chinese market has seen a notable decline in commission rates driven by these factors.

In the mid-2000s, commission rates in China typically ranged between 0.1% to 0.3% of the transaction value, with a minimum charge of 5 Chinese Yuan (CNY) per transaction. As market reforms progressed, these rates became more competitive, and by the late 2010s, commission rates had significantly decreased, often ranging from 0.02% to 0.05%. This decline was driven by the introduction of online brokerage services, the emergence of discount brokers, and increased efficiency in electronic trading systems, all contributing to a broader effort to reduce transaction costs and attract more retail investors. Around the time of the financial crisis (Jan 2005-Dec 2010), commission rates were generally about 0.1%. For instance, CITIC Securities, as a large comprehensive brokerage, offered rates between 0.1% and 0.2%, reflecting a market-average position. Haitong Securities, one of the older and well-established firms, charged around 0.1% to 0.15%, aligning closely with market norms. Meanwhile, Guotai Junan Securities, catering primarily to high-net-worth clients, had slightly higher rates ranging from 0.15% to 0.2%.

As of the latest data, commission rates in the Chinese stock market are typically between 0.02% and 0.03%, with a minimum fee of 5 CNY per transaction. These rates can vary slightly based on factors such as the investor's trading volume, account type, and specific broker policies. High-frequency traders or those with larger transaction volumes often have the opportunity to negotiate lower commission rates, as brokerage firms are incentivized to secure higher trading volumes from individual clients. Around the COVID period (Jan 2017-June 2024), commission rates were generally about 0.1%. For example, CITIC Securities charged commission rates between 0.03% and 0.05%, with a minimum of 5 CNY per transaction, and offered lower rates for clients with larger trading volumes or VIP status. Haitong Securities also set its rates in the 0.03% to 0.05% range with similar minimum fees, providing discounts for high-frequency traders or clients with substantial trading volumes. Guotai Junan Securities offered commissions from 0.03% to 0.05%, with a 5 CNY minimum, and frequently had promotional offers that reduced rates for new clients.

For pairs trading, commissions are particularly impactful because each trade involves both buying and selling actions, effectively doubling the transaction cost. The doubling effect of commissions (one fee for the buy leg and another for the sell leg of each pair) necessitates a careful evaluation of net profitability after accounting for these costs. In practice, investment institutions such as hedge funds usually trade in larger amounts, allowing them to bypass the minimum fixed fee of 5 CNY per transaction, so we exclude this fixed fee in our analysis.

Stamp Duty

Stamp duty is another key component of trading costs in the Chinese stock market, directly impacting the net returns of trading strategies, including pairs trading. It is a tax imposed by the government on securities transactions and has been subject to changes over the years based on market conditions and regulatory decisions. Since 2005, stamp duty rates in China have been adjusted several times, reflecting the government's efforts to manage market stability and investor behavior.

Given below are the main changes to stamp duty announced by the government. On January 24, 2005, the stamp duty was reduced from 0.2% to 0.1% to lower trading costs and stimulate market activity, making it more affordable for investors to engage in trading. On May 30, 2007, the rate was increased from 0.1% to 0.3% for both buying and selling transactions in an effort to curb market speculation and overheating. However, as the crisis intensified, the government reduced the stamp duty back to 0.1% on April 24, 2008, and further changed the policy on September 19, 2008, to impose the tax only on sell transactions only. This adjustment aimed to encourage buying activity and support market confidence during turbulent times. After that, the stamp duty rate was maintained at 0.1%, applied solely to sell transactions as well.

Market impact

The market impact refers to the price movement caused by the execution of a trade, which can erode the profitability of the strategy. To accurately estimate the market impact for pairs trading, we refer the data and methodology used by Do and Faff (2012), who provide a detailed analysis of market impact by measuring the actual price movements following divergence signals identified by their trading algorithms.

Do and Faff (2012) utilize an ex post direct estimate of market impact by observing the price changes immediately before and after the divergence signals that prompt trade execution. They compute the spread between each pair of stocks involved in their trading strategy one day before, on the day of, and two days after the divergence signal, defined as the point where the spread deviates by two historical standard deviations. Additionally, they calculate the log returns for both the long and short legs of the trade on the two days following the divergence. Their analysis aims to capture the mean reversion pattern in the mispricing between the stocks, which should theoretically narrow the spread post-divergence due to positive returns on the long leg and/or negative returns on the short leg.

Their findings suggest that for pairs trading funds capable of executing trades within one day following divergence, the market impact is less than 32 bps on the long side and less than 21 bps on the short side, averaging less than 26 bps. For trades executed within two days following divergence, the additional price movement observed is 15 bps for the long leg and 9 bps for the short leg, averaging 12 bps. Consequently, Do and Faff (2012) conclude that pairs trading funds executing trades within two days can achieve a volume-weighted average price comparable to the closing price on the first day after divergence, with an average market impact of 26 bps.

Further, Do and Faff (2012) analyze market impact across two subperiods: July 1963–December 1988 and January 1989–June 2009, following the convention used by Gatev, Goetzmann, and Rouwenhorst (2006) to demarcate the emergence of the hedge fund industry. Their results indicate that for the 1963–1988 period, the average market impact for trades executed over two days following divergence is approximately 30 bps, while it is markedly lower at about 20 bps for the 1989–2009 period. This reduction reflects the evolving market conditions and the increasing sophistication of institutional trading strategies designed to minimize market impact.

Based on these findings, Do and Faff (2012) assign market impact costs of 30 bps for the 1963–1988 period and 20 bps for the 1989–2009 period. They argue that these estimates, although below the broader marketwide numbers reported in the literature, realistically capture the market impact costs faced by pairs traders, especially those who stagger their trades over multiple days to reduce severe market impact.

Slippage

Slippage is an essential factor to consider when assessing the overall trading costs in pairs trading strategies, as it represents the difference between the expected price of a trade and the actual price at which the trade is executed. This discrepancy can occur due to various reasons, such as market volatility, order size, and the speed of execution. Slippage is particularly relevant in pairs trading because the strategy often involves frequent buying and selling actions, where even small deviations in execution prices can significantly affect profitability.

Based on historical data and market experience, we have set a fixed slippage rate of 0.3% for our analysis. This rate reflects the typical slippage encountered in the Chinese stock market, taking into account the relatively high volatility and potential liquidity constraints, especially during periods of market stress such as the financial crisis and the COVID-19 period.

The 0.3% slippage rate is applied to both the long and short legs of the trade, effectively doubling its impact on each pairs trading transaction. For instance, if a pair trade involves a long position in one stock and a short position in another, the total slippage cost will amount to 0.6% of the trade value due to the dual nature of the transactions. This slippage estimate serves as a conservative benchmark, ensuring that our profitability analysis accurately accounts for the real-world challenges faced in executing pairs trades within the market.

Short Selling Constraints

In the Chinese market, when investors short sell through margin trading, they are required to pay a borrowing fee. This fee is set by the securities company or lending institution and is typically an annualized percentage of the borrowed amount. The borrowing fee rate can fluctuate significantly based on market conditions and the supply-demand dynamics of specific stocks. For most ordinary stocks, the borrowing fee rate ranges from approximately 8% to 12% per annum, but it may be higher for stocks with lower liquidity or high market demand. The transaction fees for short positions are similar to those for long positions. Given the relatively high cost associated with short selling, we will initially present results that exclude this short-selling cost to assess the theoretical feasibility of the strategy. In the sensitivity analysis phase, we will incorporate these costs to provide a more comprehensive evaluation.

5. Results

5.1 Fundamental Returns

This section presents an in-depth analysis of the fundamental return characteristics of the pairs trading strategy developed in this research. By comparing the performance of portfolios both with and without trading costs, we aim to offer a comprehensive evaluation of the strategy's effectiveness. Furthermore, we will analyze the returns over different subperiods, allowing us to assess the volatility and its potential impact on overall performance. These analyses not only enhance our understanding of the strategy's return dynamics but also provide valuable insights for potential improvements and practical applications.

5.1.1 Return of Portfolios without Trading Costs

In this section, we present the performance of various portfolios across three distinct market periods: the COVID-19 period, the Financial Crisis period, and the Bullish and Bearish period. The analysis focuses on monthly excess returns, excluding trading costs, and evaluates key performance metrics such as mean return, standard deviation, Sharpe ratio, skewness, kurtosis, t-statistic, and z-statistic to assess the relative performance of each portfolio.

Overall Returns of Covid Period

Table 5 summarizes the monthly excess returns for 40 pairs portfolios during the COVID-19 period, as detailed in Table 3. The data reveals a broad spectrum of performance across the portfolios. Notably, Portfolios 6 and 24, which represent the worst-performing strategies, are treated as reference portfolios and are excluded from the present analysis. These portfolios will be examined in greater detail in subsequent sections. To calculating excess returns, the CSI 300 Index is used as a benchmark due to its stability. Further analysis of excess returns against different benchmarks (sub-period CSI 300 Index) will be discussed in later chapters.

Before trading costs, the 40 pairs portfolios generate monthly excess returns that range from 17 bps to 51 bps, for an average of 33 bps. The t-statistics is the test statistic for the estimated mean return, computed using Newey–West standard errors with six lags. The Newey–West adjustment accounts for potential autocorrelation and heteroskedasticity in the return data, ensuring more robust and accurate standard error estimates. By using six lags, this approach corrects for dependencies in the data over a reasonable time horizon, providing a reliable measure of the significance of the mean returns. A higher t-stat indicates that the estimated mean return is significantly different from zero, suggesting a strong performance of the portfolio, while a lower or negative t-stat suggests that the mean return may not be statistically different from zero. Most of these excess returns are statistically significant at the 1% confidence level, with 24 portfolios meeting this criterion. Seven portfolios are statistically significant at the 5% confidence level, and three are significant at the 10% confidence level. Three portfolios did not achieve statistical significance. These results underscore the robustness of the returns across the majority of portfolios.

Standard deviations are relatively low, generally on the order of 1%, resulting in Sharpe ratios ranging from 0.13 to 0.42. The highest Sharpe ratio is observed in Portfolio 26 and Portfolio 40, both at 0.42. The z-statistics computed for the estimated Sharpe ratios, using Lo's (2002) standard errors that are robust to return time series that are not independently and identically distributed, show that the ratios are also highly significant. Most of these Sharpe ratios are statistically significant at the 1% confidence level. These statistics point to a market-neutral strategy that successfully captures a steady source of small mispricings across different market conditions.

Goetzmann et al. (2002) show that Sharpe Ratios can be misleading when return distributions have negative skewness. Positive skewness implies that the risk of extreme losses is reduced compared to negatively skewed distributions. As a result, in these cases, the Sharpe Ratio may be more reliable for assessing risk-adjusted returns, as the likelihood of extreme negative outcomes is lower. However, portfolios with negative skewness may still face higher risks of large losses, even if their Sharpe Ratios appear favorable, underscoring the need for caution when interpreting these results. In our study, approximately two-thirds of the skewness values are positive. Therefore, while the majority of portfolios exhibit positive skewness, a significant number still have negative skewness, indicating that some Sharpe ratios could be misleading due to the potential for extreme negative returns.

Comparative Analysis of Different Portfolios Returns for Covid Period

The first comparison involves two sets of portfolios. The first set, Portfolios 1–18, is constructed without industry matching. In contrast, the second set, Portfolios 19–36, incorporates industry matching before pair selection.

For Portfolios 1–18, the highest mean return is observed in Portfolio 10, which is 51 bps. The range of mean returns remains varied, reflecting the diversity of returns in portfolios that span different sectors. In contrast, for Portfolios 19–36, the highest mean return in this group is seen in Portfolio 28, which has a mean return of 50 bps. The returns across the other portfolios in this group remain relatively stable. The range of mean returns is slightly narrower than in the non-industry-matched portfolios, suggesting that industry matching contributes to more consistent performance.

Portfolio 8 achieves the highest Sharpe ratio within Portfolios 1–18, at 0.41. The remaining portfolios in this group show a broad range of Sharpe ratios, indicating varying levels of risk-adjusted returns. In Portfolios 19–36, Portfolio 26 maintains the highest Sharpe ratio, at 0.42. The Sharpe ratios across Portfolios 19–36 are generally higher and more consistent, with several portfolios exhibiting Sharpe ratios above 0.38. This suggests that industry matching contributes to more stable and higher risk-adjusted performance, while non-industry-matched portfolios still show greater variability.

The risk metrics of skewness and kurtosis vary widely across Portfolios 1–18, with Portfolio 1 showing extreme kurtosis at 22.38 and high positive skewness at 3.86, indicating the potential for outlier returns. Portfolios 10 and 12 also exhibit high skewness and kurtosis values. This suggests that portfolios in this group remain subject to higher volatility and potential extreme movements in returns. In contrast, Portfolios 19–36 show even more extreme skewness and kurtosis in some cases, such as Portfolio 19 with skewness of 5.69 and kurtosis of 41.21. However, several portfolios within this group, like Portfolios 26 and 35, exhibit moderate skewness and kurtosis, indicating that industry matching can help reduce the likelihood of extreme returns and provide more stable return distributions in certain cases.

Secondly, we compare SSD and NZC matching with SSD and Hurst exponent matching, focusing on the differences in their pair selection methodologies.

Portfolios 7–12 (using SSD and NZC matching) generally exhibit higher mean returns, with Portfolio 10 having the highest mean return at 51 bps. Portfolio 14 in the SSD and Hurst group comes close with a mean return of 37 bps. Portfolios 13–18 (using SSD and Hurst exponent matching) have slightly lower returns on average compared to Portfolios 7–12. In terms of Sharpe ratio, Portfolio 8 leads with a ratio of 0.41, followed closely by Portfolio 16 and Portfolio 18, both at 0.39. While Portfolios 7–12 generally perform better in terms of mean returns, Portfolios 13–18 have several portfolios with competitive risk-adjusted performance, indicating that the Hurst exponent matching contributes to more stable returns.

Skewness and kurtosis values suggest that Portfolios 7–12 are more skewed towards positive outcomes and have some portfolios with extreme kurtosis values (e.g., Portfolio 10 with kurtosis of 18.30 and Portfolio 12 with kurtosis of 18.08). This could indicate the presence of outlier returns. On the other hand, Portfolios 13–18, which use the Hurst exponent, tend to have less extreme skewness and kurtosis, particularly in Portfolios 16 and 18, suggesting more stable return distributions.

The t-statistics across both sets of portfolios show that most portfolios in both groups have statistically significant mean returns. However, Portfolios 7–12 generally exhibit higher t-statistics, reflecting more robust performance, particularly Portfolio 7 with a t-stat of 3.94 and Portfolio 8 with a t-stat of 4.19. In conclusion, Portfolios 7–12 tend to offer higher returns and strong risk-adjusted performance, with more frequent trading opportunities due to higher price crossings. Portfolios 13–18 provide more stable return profiles with a greater focus on mean reversion, which may lead to less volatility and smoother returns over time. The choice between these portfolios depends on the desired trade-off between higher returns and risk stability.

Portfolios 25–30, with SSD and NZC matching, perform similarly to Portfolios 7–12, focusing on higher returns and exhibiting more volatile risk profiles due to frequent price crossings. For instance, Portfolio 28 achieves a mean return of 50 bps with a Sharpe ratio of 0.29. Likewise, Portfolios 31–36 with SSD and Hurst matching are similar to Portfolios 13–18, showing slightly lower mean returns but more stable risk-adjusted returns, as evidenced by Portfolio 35 with a Sharpe ratio of 0.40 and moderate skewness and kurtosis values.

Thirdly, the comparison of Portfolios 37–40 reveals that portfolios focusing on underperforming industries, specifically Portfolios 38 and 40, outperform those targeting well-performing industries, Portfolios 37 and 39, in terms of Sharpe ratio. Specifically, Portfolio 40, using the Hurst exponent within underperforming industries, exhibits one of the best overall performances, with a high Sharpe ratio of 0.42 and a stable risk profile. Portfolio 37, while achieving a relatively high mean return of 43 bps, suffers from extreme risk characteristics, including a skewness of 5.56 and kurtosis of 39.50, making it more volatile. This analysis suggests that, during uncertain periods such as the COVID-19 crisis, well-constructed portfolios from underperforming industries can provide more consistent and reliable returns compared to portfolios from traditionally strong-performing industries.

Finally, it is important to note that no significant differences were observed across different quantiles when using the same pairing method. This conclusion applies to the three periods analyzed, both with and without trading costs.

TABLE 5. Monthly Excess Returns without Trading Costs of COVID-19 Period Results.

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
1	0.0042	0.0175	0.24	3.86	22.38	1.99**	1.97**	7	30
2	0.0029	0.0093	0.32	-0.06	1.25	2.94***	2.89***	26	14
3	0.0047	0.0156	0.30	3.66	23.60	3.07***	2.93***	5	18
4	0.0030	0.0089	0.34	-0.32	2.35	3.44***	3.26***	23	13
5	0.0033	0.0091	0.37	-0.03	1.34	3.91***	3.56***	17	9
6	-0.0043	0.0243	-0.17	-2.55	10.08	-1.34	-1.30	40	40
7	0.0042	0.0119	0.35	0.63	4.65	3.94***	3.86***	8	11
8	0.0036	0.0087	0.41	0.12	0.00	4.19***	4.05***	14	3
9	0.0030	0.0097	0.31	-0.08	0.20	3.13***	2.98***	24	16
10	0.0051	0.0178	0.28	3.12	18.30	2.95***	2.82***	1	21
11	0.0022	0.0099	0.22	0.06	1.49	2.07**	1.96**	33	32
12	0.0033	0.0162	0.21	3.33	18.08	1.83*	1.73*	18	33
13	0.0024	0.0160	0.15	-1.11	7.85	1.69*	1.67*	31	36
14	0.0037	0.0099	0.37	-0.59	0.73	3.35***	3.18***	13	10
15	0.0022	0.0094	0.23	-0.72	1.79	1.98**	2.00**	34	31

16	0.0031	0.0080	0.39	-0.22	0.18	3.73***	3.59***	20	5
17	0.0031	0.0089	0.35	0.43	1.71	3.08***	3.05***	21	12
18	0.0030	0.0075	0.39	-0.12	1.51	3.75***	3.71***	25	6
19	0.0049	0.0267	0.18	5.69	41.21	1.73*	1.67*	3	34
20	0.0020	0.0076	0.27	-0.17	0.97	2.90***	2.59**	36	25
21	0.0021	0.0074	0.28	-0.21	0.03	3.02***	2.73***	35	22
22	0.0041	0.0152	0.27	4.17	25.88	2.44**	2.34**	10	26
23	0.0019	0.0075	0.26	0.29	0.95	2.88***	2.61***	37	28
24	-0.0015	0.0129	-0.12	0.78	4.01	-1.22	-1.18	39	39
25	0.0049	0.0286	0.17	5.62	40.67	1.52	1.48	4	35
26	0.0031	0.0073	0.42	0.19	0.25	4.94***	4.46***	22	1
27	0.0042	0.0140	0.30	5.55	41.57	2.59**	2.51**	9	19
28	0.0050	0.0175	0.29	3.48	20.51	2.98***	2.89***	2	20
29	0.0035	0.0132	0.27	5.62	42.59	2.43**	2.32**	15	27
30	0.0025	0.0080	0.31	0.76	1.64	2.95***	2.90***	30	17
31	0.0041	0.0165	0.25	4.05	25.28	2.22**	2.13**	11	29
32	0.0026	0.0079	0.32	-0.03	1.33	3.57***	3.35***	29	15
33	0.0033	0.0087	0.38	0.49	1.10	3.02***	3.07***	19	8
34	0.0027	0.0070	0.39	0.43	1.89	3.53***	3.40***	28	7
35	0.0028	0.0070	0.40	1.04	2.64	3.57***	3.57***	27	4
36	0.0017	0.0059	0.28	0.17	1.27	3.00***	2.92***	38	23
37	0.0043	0.0292	0.15	5.56	39.50	1.35	1.30	6	37
38	0.0024	0.0084	0.28	0.60	1.34	3.41***	3.05***	32	24
39	0.0038	0.0283	0.13	5.59	41.32	1.36	1.26	12	38
40	0.0035	0.0083	0.42	0.27	1.45	5.20***	4.55***	16	2

Note: This table presents key distributional statistics for the excess return time series, before accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2017 to June 2024, during the Covid-19 period. The column titled 't-stat' provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. The 'z-stat' column shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. The monthly return of CSI 300 for this period is 4bps.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

*Significant at the 10% level.

Overall Returns of Financial Crisis Period

Table 6 summarizes the monthly excess returns for 40 pairs portfolios during the Financial Crisis period. The mean returns of the portfolios during this period range from -208 bps for Portfolio 10 to 382 bps for Portfolio 39, with an average return close to zero. It's important to note that the CSI 300 Index, used as the benchmark for calculating excess returns, had a monthly return of 162 bps during this period. This high benchmark return results in many portfolios showing negative excess returns, even if the portfolios themselves had positive returns.

Several portfolios, particularly Portfolio 39 and Portfolio 31, demonstrate relatively high mean returns of 382 bps and 129 bps, respectively. These portfolios appear to have capitalized on the market conditions during the financial crisis, providing notable monthly excess returns. Portfolios 20, 25, and 28 also exhibit relatively higher mean returns, with values around 122 bps to 124 bps. These portfolios reflect the ability to capture profitable opportunities during times of economic

uncertainty. In contrast, portfolios such as Portfolio 10 (-208 bps) and Portfolio 1 (-155 bps) show negative returns, indicating that certain strategies did not perform well in this volatile environment. Portfolios during the Financial Crisis period tend to exhibit lower average excess returns compared to those during the COVID-19 period. This can be attributed to the higher benchmark return of the CSI 300 Index (162 bps) compared to only 4 bps during the COVID-19 period. The high benchmark return implies that even if the portfolios had positive returns, their excess returns could still be negative. However, if we consider only the P&L, the returns during the Financial Crisis were much higher than those during the COVID-19 period. On average, the return volatility during the Financial Crisis was significantly higher than that observed during the COVID-19 period.
The standard deviations for the portfolios range from 1.7% for Portfolio 35 to 24.3% for Portfolio 39, indicating varying levels of volatility across the portfolios. Portfolio 39, while showing the highest mean return, also exhibits the highest standard deviation, signaling a higher degree of risk associated with the returns. Portfolios with lower standard deviations reflect more stable performance despite the turbulent financial market conditions.

The Sharpe ratios vary across the portfolios. The highest Sharpe ratio is observed in Portfolio 9 at 0.18, indicating that it offered the best risk-adjusted performance during the Financial Crisis period. Portfolios 39 and 25 also show Sharpe ratios of 0.16 and 0.14, respectively, reflecting their ability to deliver relatively better returns relative to the risk undertaken. On the lower end, portfolios such as Portfolio 10 (-0.31) and Portfolio 1 (-0.32) have negative Sharpe ratios, suggesting that these portfolios either underperformed or incurred losses relative to the level of risk. Such portfolios would have been considered less attractive during this period.

The Sharpe ratios in both periods show different distributions, with portfolios in the COVID-19 period tending to exhibit higher maximum Sharpe ratios. For instance, the highest Sharpe ratio during the COVID-19 period was 0.42, whereas the highest in the Financial Crisis period was 0.18. This suggests that during the COVID-19 period, portfolios achieved better risk-adjusted returns compared to the Financial Crisis period.

In conclusion, the analysis of the Financial Crisis period reveals that portfolios during this period generally show lower mean excess returns compared to the COVID-19 period. This is partly due to the higher benchmark return of the CSI 300 Index during the Financial Crisis period 162 bps compared to 4 bps during the COVID-19 period, resulting in many negative excess returns even if the portfolios themselves had positive returns. Furthermore, the higher volatility and extreme market conditions during the Financial Crisis led to greater risk, as indicated by more extreme skewness and kurtosis values. The Sharpe ratios are generally lower in the Financial Crisis period compared to the COVID-19 period, suggesting that portfolios achieved better risk-adjusted returns during the COVID-19 period. Despite the challenging conditions, some portfolios, particularly those focusing on underperforming industries or employing specific matching techniques, were able to deliver notable returns.

Comparative Analysis of Different Portfolios Returns for Financial Crisis Period

Like the COVID-19 period, the first comparison during the Financial Crisis period involves two sets of portfolios: Portfolios 1–18 and Portfolios 19–36.

For Portfolios 1–18, the highest mean return is observed in Portfolio 9, which is 108 bps. This portfolio performed relatively well, especially compared to other portfolios in this set, which had mean returns ranging from -208 bps to 70 bps. The range of returns across these portfolios is more varied, indicating that the non-industry-matched portfolios were more volatile and less consistent in their performance. In contrast, Portfolios 19–36, which used industry matching, showed more stable mean returns. The highest mean return in this group is seen in Portfolio 31, at 129 bps, while several portfolios exhibit negative returns. The range of mean returns is slightly narrower than in the non-industry-matched portfolios, similar as in Covid-19 period, suggesting that industry matching contributes to more consistent performance, even in times of financial crisis. Portfolios 19–36 generally provide more consistent returns, although a few portfolios still underperformed with negative returns. In both periods, the industry-matched portfolios exhibit more consistent and stable mean returns compared to the non-industry-matched portfolios. However, the financial crisis period shows a wider range of mean returns.

In terms of Sharpe ratios, the highest Sharpe ratio is observed in Portfolio 9 (non-industry-matched) at 0.18, whereas the highest in the industry-matched group is Portfolio 39 with a Sharpe ratio of 0.16. The industry-matched portfolios tend to display more consistent risk-adjusted performance, with fewer extreme values, while the non-industry-matched portfolios exhibit more variability. In both periods, industry matching led to more consistent Sharpe ratios, while non-industry-matched portfolios exhibited a broader range of risk-adjusted returns. However, during the COVID-19 period, the highest Sharpe ratio was seen in Portfolio 26 at 0.42, whereas the highest in the Financial Crisis period was achieved by Portfolio 9 at 0.18. This suggests that the portfolios in the COVID-19 period were able to achieve better risk-adjusted returns despite challenging market conditions.

When comparing skewness and kurtosis, the non-industry-matched portfolios generally have more extreme values. For instance, Portfolio 1 has a skewness of -2.61 and a kurtosis of 8.00, indicating the presence of significant negative outliers. In contrast, the industry-matched portfolios exhibit less extreme skewness and kurtosis values, reflecting more stable return distributions and reduced susceptibility to extreme return fluctuations. Both periods demonstrate that industry matching helps reduce the extremes in skewness and kurtosis, leading to more stable return distributions. However, the Financial Crisis period shows extreme kurtosis values in both groups, highlighting the higher overall volatility during this period.

Secondly, we compare SSD and NZC matching with SSD and Hurst exponent matching. In the Financial Crisis period, Portfolios 7–12, using SSD and NZC matching, generally perform poorly, with Portfolio 9 showing the highest mean return of 108 bps and a Sharpe ratio of 0.18. However, there is a broader range of performance within this group, with Portfolio 10 showing negative mean returns of -208 bps. The SSD and Hurst exponent matching portfolios (Portfolios 13–18) exhibit mixed returns, with Portfolio 15 achieving a mean return of 70 bps and a Sharpe ratio of 0.14. The portfolios in this group generally have more stable return distributions and lower risk profiles, as reflected in their more moderate skewness and kurtosis values.

When comparing this to the COVID-19 period, we see a similar trend. Portfolios 7–12, which apply SSD and NZC matching, perform better in terms of both mean returns and Sharpe ratios compared to the SSD and Hurst exponent portfolios (Portfolios 13–18). However, the Financial Crisis period shows overall lower mean returns for these portfolios, suggesting that strategies based on SSD and NZC matching were less effective in capitalizing on market inefficiencies during the financial crisis than during the COVID-19 period.

Thirdly, the comparison of Portfolios 37–40 reveals that portfolios focusing on underperforming industries, specifically Portfolios 38 and 40, outperform those targeting well-performing industries, Portfolios 37 and 39, in terms of Sharpe ratio. Specifically, Portfolio 39 achieves the highest mean return of 382 bps but also exhibits high volatility and extreme kurtosis of 34.59, indicating a greater risk of outlier returns. Portfolio 38, focusing on underperforming industries, shows a Sharpe ratio of 0.13 and relatively high skewness and kurtosis, but with a more moderate risk profile compared to Portfolio 39.

In the Financial Crisis period, focusing on underperforming industries can lead to more reliable and consistent returns during periods of market turbulence. Portfolios 38 and 40, although having lower mean returns compared to Portfolios 37 and 39, offer better risk-adjusted performance and more stable return distributions. When comparing to the COVID-19 period, the trend remains the same: portfolios focusing on underperforming industries tend to outperform in terms of risk-adjusted returns. Portfolio 40, for instance, shows strong performance in both periods, highlighting the effectiveness of pairing within underperforming industries, especially during volatile times such as the financial crisis and COVID-19.

Overall, while both periods show that industry matching tends to produce more consistent returns and lower volatility, the portfolios in the COVID-19 period demonstrated stronger risk-adjusted performance. Despite higher volatility and extreme market conditions during the Financial Crisis, certain portfolios, particularly those focusing on underperforming industries or employing specific matching techniques, were able to deliver notable returns. The COVID-19 period, on the other hand, had more consistent portfolio outcomes, with greater stability in both mean returns and risk-adjusted performance.

TABLE 6. Monthly Excess Returns without Trading Costs of Financial Crisis Period Results.

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
1	-0.0155	0.0482	-0.32	-2.61	8.00	-2.11**	-2.14**	39	36
2	-0.0145	0.0515	-0.28	-1.31	7.36	-1.80*	-1.87*	37	33
3	-0.0107	0.0543	-0.20	-0.58	8.73	-2.01**	-1.95*	32	28
4	-0.0111	0.0540	-0.20	1.31	8.88	-2.57**	-2.15**	34	29
5	-0.0027	0.0404	-0.07	-0.04	10.01	-0.76	-0.73	19	20
6	-0.0128	0.0404	-0.31	1.68	14.94	-4.66***	-4.21***	36	34
7	-0.0107	0.0695	-0.15	0.25	11.96	-1.77*	-1.54	33	24
8	0.0051	0.0716	0.07	3.48	14.37	0.37	0.39	12	13
9	0.0108	0.0605	0.18	2.60	7.70	1.18	1.28	9	1
10	-0.0208	0.0661	-0.31	-3.02	10.01	-1.78*	-1.93*	40	35
11	-0.0018	0.0888	-0.02	-0.01	14.17	-0.13	-0.13	17	17
12	0.0026	0.0475	0.05	3.04	10.93	0.39	0.41	15	14
13	-0.0098	0.0466	-0.21	-2.41	14.44	-1.27	-1.35	30	30
14	-0.0083	0.0453	-0.18	2.33	15.69	-2.08**	-1.82*	28	27
15	0.0070	0.0510	0.14	4.35	23.12	0.78	0.84	10	3
16	0.0001	0.0429	0.00	3.29	13.75	0.01	0.01	16	16
17	0.0037	0.0430	0.09	3.40	14.70	0.46	0.49	13	12
18	0.0052	0.0537	0.10	3.74	14.89	0.50	0.52	11	11
19	-0.0028	0.0992	-0.03	1.11	17.12	-0.22	-0.22	20	18
20	0.0124	0.0855	0.14	3.32	13.05	0.83	0.83	5	4
21	0.0167	0.1280	0.13	4.14	19.67	0.81	0.81	3	7
22	-0.0024	0.0448	-0.05	3.70	20.56	-0.41	-0.42	18	19
23	-0.0035	0.0509	-0.07	0.84	10.44	-0.55	-0.56	21	21
24	-0.0148	0.0236	-0.62	2.57	12.56	-6.64	-6.64	38	40
25	0.0122	0.0836	0.14	4.31	18.66	0.79	0.82	6	5
26	-0.0044	0.0271	-0.16	4.18	23.32	-1.06	-1.14	23	26
27	-0.0081	0.0323	-0.25	2.99	20.76	-1.81*	-1.77*	27	31
28	0.0122	0.1061	0.11	4.43	20.85	0.74	0.75	7	9
29	-0.0124	0.0209	-0.59	-2.13	6.95	-5.95***	-5.56***	35	39
30	-0.0056	0.0226	-0.25	1.46	5.82	-1.49	-1.60	25	32
31	0.0129	0.1209	0.11	3.58	16.19	0.66	0.64	4	10
32	-0.0071	0.0644	-0.11	1.51	10.12	-0.89	-0.91	26	22
33	-0.0050	0.0336	-0.15	3.58	21.53	-0.83	-0.85	24	25
34	-0.0039	0.0317	-0.12	3.00	11.77	-0.66	-0.69	22	23
35	-0.0099	0.0173	-0.57	0.73	6.20	-3.77***	-3.74***	31	38
36	-0.0093	0.0217	-0.43	-0.65	9.69	-3.53***	-3.40***	29	37
37	0.0219	0.1558	0.14	5.44	30.99	0.88	0.88	2	6
38	0.0117	0.0886	0.13	5.51	35.05	0.81	0.82	8	8
39	0.0382	0.2433	0.16	5.74	34.59	1.02	1.02	1	2
40	0.0030	0.1109	0.03	2.41	18.75	0.23	0.20	14	15

Note: This table presents key distributional statistics for the excess return time series, before accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2005 to December 2010, during the financial crisis period. The column titled 't-stat' provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. The 'z-stat' column shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. The monthly return of CSI 300 for this period is 162 bps.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

*Significant at the 10% level.

Overall Returns of Bullish and Bearish Period

Table 7 presents the performance of 40 pairs portfolios during the Bullish and Bearish period, a time marked by alternating upward and downward market trends. This period, characterized by moderate economic fluctuations, provided opportunities for portfolio strategies to adjust to changing dynamics. Monthly excess returns during this period ranged from 21 bps in Portfolio 40 to 77 bps in Portfolio 37, with an average return of approximately 43 bps, positioned between the extremes observed during the COVID-19 and Financial Crisis periods.

In comparison, during the COVID-19 period, excess returns ranged from 17 to 51 bps, with most portfolios showing relatively stable performance. The market-neutral approach of these portfolios helped generate consistent, though moderate, returns during this period. Meanwhile, the Financial Crisis period saw much greater variation in mean returns, fluctuating from -208 bps in Portfolio 10 to 382 bps in Portfolio 39. The extreme volatility of this period, along with a high benchmark return of 162 bps, resulted in many portfolios showing negative excess returns, even if the portfolios themselves had positive returns. The Bullish and Bearish period falls between these two extremes, with mean returns ranging from 21 bps to 77 bps. While portfolios like Portfolio 37 performed well, the range of returns is not as extreme as during the Financial Crisis period, reflecting a more balanced risk-return profile relative to the market stability of the COVID-19 period.

Standard deviations during the Bullish and Bearish period ranged from 0.75% to 1.28%, reflecting varying levels of portfolio volatility. Portfolio 37, which achieved the highest mean return, also exhibited a relatively high standard deviation of 1.27%, indicating the increased risk associated with these returns. In contrast, portfolios such as Portfolio 21 and Portfolio 38, with more modest returns, demonstrated lower volatility, signaling more consistent performance.

During the COVID-19 period, volatility was relatively higher, with standard deviations ranging from 0.59% to 2.86%, indicating varying levels of portfolio performance stability. In the Financial Crisis period, standard deviations were significantly higher, ranging from 1.73% to 24.33%, reflecting the heightened risk brought on by market turbulence. In the Bullish and Bearish period, standard deviations were lower, ranging from 0.75% to 1.28%. This suggests that volatility during the Bullish and Bearish period was more controlled than in both the COVID-19 and Financial Crisis periods, reflecting a balance between risk and reward amid fluctuating market conditions.

Sharpe ratios during the Bullish and Bearish period illustrate the balance between risk and return. Portfolio 37 achieved the highest Sharpe ratio at 0.60, followed closely by Portfolio 39 at 0.59. These portfolios demonstrated superior risk-adjusted returns, outperforming others in terms of profitability relative to risk. In contrast, Portfolio 40 had the lowest Sharpe ratio of 0.25, indicating lower performance and less favorable risk-adjusted returns.

During the COVID-19 period, Sharpe ratios ranged from 0.13 to 0.42, reflecting moderate risk-adjusted performance. In the Financial Crisis period, Sharpe ratios exhibited greater variability, with the highest at 0.18 in Portfolio 9. The increased market turbulence during this time led to a wider spread in performance, with some portfolios taking advantage of the volatility. Overall, Sharpe ratios during the Bullish and Bearish period were generally higher than those seen in the COVID-19 and Financial Crisis periods. These risk-adjusted returns highlight portfolios that effectively navigated both bullish and bearish market conditions.

Portfolios during the COVID-19 period generally exhibited moderate skewness and kurtosis, indicating fewer outliers and more stable returns. For instance, Portfolio 19 had a skewness of 5.69 and a kurtosis of 41.21, showing extreme values. In contrast, the Financial Crisis period saw several portfolios with extreme skewness and kurtosis values. Portfolio 38, for example, had a skewness of 5.51 and a kurtosis of 35.05, indicating the presence of significant outliers and a highly volatile return distribution. The Bullish and Bearish period, by comparison, showed more balanced distribution characteristics. While some portfolios, like Portfolio 30, had higher skewness (2.78) and kurtosis (11.91), most portfolios displayed moderate levels, reflecting fewer extreme outcomes and a more balanced return profile overall.

Overall, portfolios in the Bullish and Bearish period benefited from market swings but without the extreme volatility and outlier risks that characterized the Financial Crisis period. The COVID-19 period portfolios, while stable, did not capture as much opportunity from market dynamics as those in the Bullish and Bearish period.

Comparative Analysis of Different Portfolios Returns for Bullish and Bearish Period

The first comparison in the Bullish and Bearish period focuses on two sets of portfolios: Portfolios 1–18, constructed without industry matching, and Portfolios 19–36, which incorporate industry matching.

For Portfolios 1–18, the highest mean return is observed in Portfolio 13, at 56 bps, while Portfolio 5 records the lowest mean return of 34 bps. This performance highlights the greater variability in returns in the non-industry-matched group. In comparison, Portfolios 19–36, with industry matching, demonstrate more consistent performance. The highest mean return in this group is seen in Portfolio 25, at 52 bps, followed by Portfolio 28 at 43 bps. This suggests that industry matching contributes to more consistent performance, a trend also seen during the COVID-19 and Financial Crisis periods.

Compared to the COVID-19 and Financial Crisis periods, the Bullish and Bearish period portfolios generally show more stable returns. The Financial Crisis period demonstrated much higher volatility; the Bullish and Bearish period portfolios exhibit more moderate variability. Industry matching in the Bullish and Bearish period further stabilizes returns, as seen in Portfolio 25 and Portfolio 28, which offer strong returns while avoiding the extremes observed in the earlier periods.

The second comparison focuses on the difference between SSD and NZC matching (Portfolios 7–12 and 25–30) and SSD and Hurst exponent matching (Portfolios 13–18 and 31–36).

In the Bullish and Bearish period, the SSD and NZC matching portfolios performed well, with Portfolio 7 achieving a Sharpe ratio of 0.46 and a mean return of 53 bps. The industry-matched Portfolio 25 outperformed, with a Sharpe ratio of 0.52 and a mean return of 52 bps. These results demonstrate the effectiveness of SSD and NZC matching strategies in capturing higher returns during this period. In contrast, the SSD and Hurst exponent matching portfolios exhibited more stable returns but slightly lower mean returns. Portfolio 13 had the highest mean return in this group at 56 bps, while Portfolio 34 achieved a Sharpe ratio of 0.55 and a mean return of 44 bps. The risk-adjusted performance remained strong, suggesting effective risk management.

When compared to the COVID-19 and Financial Crisis periods, the Bullish and Bearish period shows more consistent results. In the COVID-19 period, Portfolio 10 achieved a mean return of 51 bps, and Portfolio 8 had the highest Sharpe ratio of 0.41, both reflecting good performance in that period. In contrast, the Financial Crisis period showed lower mean returns due to the high benchmark return, with the highest mean excess return being 382 bps in Portfolio 39. However, the Bullish and Bearish period portfolios offer more stable returns and higher Sharpe ratios, indicating more balanced performance during this period of mixed market conditions.

The third comparison examines portfolios constructed within Good and Bad Performance Industries.

Portfolios 37 and 39, which focus on good performance industries, produced strong results in the Bullish and Bearish period. Portfolio 37 achieved the highest Sharpe ratio at 0.60 and the highest mean return of 77 bps, indicating strong risk-adjusted performance. These portfolios were able to capitalize on favorable market conditions, delivering robust returns.

In contrast, Portfolios 38 and 40, which focus on underperforming industries, offered more stable but lower returns. Portfolio 38 recorded a mean return of 30 bps and a Sharpe ratio of 0.38, while Portfolio 40 achieved a Sharpe ratio of 0.25 and a mean return of 21 bps. Although these portfolios generated lower returns, they demonstrated more consistent risk-adjusted performance, highlighting the stability of underperforming industries during periods of market volatility.

When compared to the COVID-19 and Financial Crisis periods, a similar trend is observed. During the Financial Crisis period, Portfolio 39 achieved the highest mean return of 382 bps, but also exhibited significant volatility, with a kurtosis of 34.59. In the COVID-19 period, Portfolio 40 showed strong performance with a Sharpe ratio of 0.42, demonstrating that focusing on underperforming industries can yield more reliable and consistent returns across periods of economic uncertainty. The Bullish and Bearish period results further confirm that portfolios targeting good performance industries offer higher returns, while those focusing on underperforming industries offer more stability, with fewer extreme outliers compared to good performance industry portfolios.

In conclusion, the Bullish and Bearish period represented a more balanced environment for pairs trading, with less market turbulence than the Financial Crisis period and fewer extreme outcomes than the COVID-19 period. This period allowed for effective risk management and stronger risk-adjusted returns, making it a favorable environment for consistent trading performance.

TABLE 7. Monthly Excess Returns without Trading Costs of Bullish and Bearish Period Results.

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
1	0.0040	0.0097	0.41	0.71	2.38	2.41**	2.54**	21	23
2	0.0039	0.0108	0.36	2.59	12.86	2.16**	2.33**	23	31
3	0.0047	0.0109	0.43	1.92	9.35	2.31**	2.54**	9	17
4	0.0038	0.0090	0.42	1.01	5.64	2.29**	2.45**	26	20
5	0.0034	0.0106	0.31	1.95	7.55	1.71*	1.82*	35	37
6	0.0003	0.0173	0.02	0.73	2.52	0.11	0.11	40	40
7	0.0053	0.0114	0.46	2.20	9.95	2.52**	2.69***	5	11
8	0.0044	0.0112	0.39	1.58	4.24	2.27**	2.44**	14	26
9	0.0049	0.0114	0.43	1.45	4.97	2.28**	2.43**	7	18
10	0.0049	0.0114	0.42	1.82	8.34	2.34	2.52**	8	21
11	0.0045	0.0119	0.38	1.35	4.71	1.85*	2.00**	10	27
12	0.0039	0.0102	0.38	0.59	3.59	2.32**	2.39**	24	28
13	0.0056	0.0128	0.44	2.46	10.06	2.21**	2.40**	3	15
14	0.0037	0.0098	0.37	1.20	2.64	2.05**	2.19**	28	30
15	0.0054	0.0104	0.51	0.30	5.02	3.05***	3.27***	4	5
16	0.0042	0.0093	0.45	1.95	8.34	2.22**	2.41**	17	14
17	0.0045	0.0096	0.46	1.83	9.46	2.39**	2.58**	11	12
18	0.0037	0.0103	0.36	2.08	9.55	1.81*	1.95*	29	32
19	0.0037	0.0076	0.49	1.41	5.15	2.99***	3.20***	30	6
20	0.0036	0.0082	0.43	1.18	4.43	2.63***	2.77***	32	19
21	0.0031	0.0075	0.41	-0.18	1.43	2.76***	2.96***	36	24
22	0.0042	0.0087	0.48	1.45	3.77	2.82***	2.96***	18	7
23	0.0038	0.0078	0.48	2.66	12.97	2.85***	3.01***	27	8
24	0.0012	0.0159	0.08	-0.08	1.12	0.58	0.60	39	39
25	0.0052	0.0099	0.52	1.46	4.55	3.43***	3.67***	6	4
26	0.0045	0.0094	0.48	2.39	10.56	2.44**	2.67***	12	9
27	0.0036	0.0105	0.34	1.19	3.75	1.83*	1.99**	33	35
28	0.0043	0.0090	0.48	1.74	6.14	2.84***	3.06***	16	10
29	0.0041	0.0111	0.36	0.95	2.29	1.93*	2.05**	19	33
30	0.0035	0.0103	0.33	2.78	11.91	1.86*	1.93*	34	36
31	0.0040	0.0096	0.42	1.21	4.13	2.45**	2.64***	22	22
32	0.0045	0.0101	0.44	2.15	9.78	2.33**	2.52**	13	16
33	0.0039	0.0110	0.36	1.78	5.39	1.92*	2.03**	25	34
34	0.0044	0.0080	0.55	2.46	9.81	2.72***	2.94***	15	3
35	0.0041	0.0088	0.46	2.47	8.80	2.17**	2.35**	20	13
36	0.0037	0.0092	0.40	1.76	6.64	1.84*	2.01**	31	25
37	0.0077	0.0127	0.60	0.89	3.41	3.68***	3.91***	1	1
38	0.0030	0.0079	0.38	0.33	1.33	2.78***	2.86***	37	29
39	0.0065	0.0110	0.59	1.32	2.82	3.43***	3.64***	2	2
40	0.0021	0.0087	0.25	-0.05	2.38	1.77*	1.84*	38	38

Note: This table presents key distributional statistics for the excess return time series, before accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2011 to December 2016, during the bullish and bearish period. The column titled 't-stat' provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. The 'z-stat' column shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. The monthly return of CSI 300 for this period is 5bps.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

*Significant at the 10% level.

5.1.2 Return of Portfolios with Trading Costs

In this section, we present the performance of various portfolios across three distinct market periods: the COVID-19 period, the Financial Crisis period, and the Bullish and Bearish period, with an adjustment for trading costs. The analysis focuses on monthly net excess returns after trading costs, evaluating the impact of costs on key performance metrics such as mean return, standard deviation, Sharpe ratio, skewness, kurtosis, t-statistic, and z-statistic, like section 5.1.1.

Overall Returns of Covid Period

Table 8 summarizes the monthly excess returns for 40 pairs portfolios during the COVID-19 period, accounting for trading costs, similar to Table 5.

After incorporating trading costs, the monthly excess returns ranged from -5 bps in Portfolio 1 to 28 bps in Portfolio 19, with an average of approximately 10.5 bps. This is a significant decline from the pre-cost average of 33 bps noted in Table 5. For example, Portfolio 3 saw its mean return drop from 47 bps to 22 bps after accounting for trading costs. The effect of trading costs is particularly evident in portfolios with higher turnover rates, as these costs reduce mean returns and negatively affect Sharpe ratios.

Post-trading cost Sharpe ratios saw a substantial decline, ranging from -0.03 to 0.17. Portfolio 27 had the highest Sharpe ratio at 0.17, followed closely by Portfolio 26 and Portfolio 40, both at 0.15. This decline across all portfolios highlights the negative impact of trading costs on risk-adjusted returns. Prior to the incorporation of trading costs, Sharpe ratios ranged from 0.13 to 0.42, demonstrating stronger risk-adjusted performance. For instance, Portfolio 27's Sharpe ratio decreased from 0.30 before trading costs to 0.17 after costs, illustrating the detrimental effect of trading costs.

Skewness and kurtosis metrics indicate that the distribution of portfolio returns remains skewed and leptokurtic, even after trading costs. For instance, Portfolio 1 shows extreme positive skewness (3.84) and kurtosis (22.56), suggesting the presence of potential outliers. Portfolios with negative skewness, such as Portfolio 13, which has a skewness of -1.10, continue to face the risk of large negative returns, a trend that persists even after accounting for trading costs. While trading costs do not significantly alter the skewness and kurtosis of the portfolios, they reduce the magnitude of returns. Portfolios with extreme skewness and high kurtosis, like Portfolio 1, continue to exhibit potential outliers, while portfolios with negative skewness and high kurtosis, such as Portfolio 13, experience worsened performance as trading costs exacerbate their vulnerability to large negative returns.

In summary, after accounting for trading costs, the portfolios generally exhibit lower returns and reduced risk-adjusted performance, as reflected by lower Sharpe ratios and t-statistics. Despite this, a few portfolios, particularly Portfolio 3 and Portfolio 27, manage to demonstrate relatively robust performance, showing that certain strategies remain effective even in the presence of transaction costs.

Comparative Analysis of Different Portfolios Returns for Covid Period

A comparison between industry-matched and non-industry-matched portfolios reveals distinct patterns in performance. For Portfolios 1–18, which are constructed without industry matching, the highest mean return is seen in Portfolio 3, with a post-trading cost return of 22 bps, down from 47 bps pre-cost. The overall range of mean returns for this group extends from -5 bps to 22 bps, reflecting the diverse performance across different sectors. In contrast, Portfolios 19–36, which incorporate industry matching, exhibit more consistent performance, although trading costs still reduce returns. The highest mean return in this group is observed in Portfolio 19, which achieved 28 bps after costs, down from 49 bps without costs. This suggests that industry matching contributes to more stable performance, even when trading costs are considered.

Sharpe ratios for the non-industry-matched portfolios decline significantly after accounting for trading costs, reflecting the negative impact of these costs on risk-adjusted returns. For example, Portfolio 8, which had one of the highest pre-cost Sharpe ratios at 0.41, drops sharply to 0.13, showing how trading costs substantially diminish overall performance. Similarly, Portfolio 10, which previously exhibited strong returns with a Sharpe ratio of 0.28, sees its Sharpe ratio fall to 0.13. The industry-matched portfolios show more resilience, with Portfolio 27 achieving the highest Sharpe ratio of 0.17, although it is still lower than its pre-cost Sharpe ratio of 0.30. Portfolio 26 maintains a respectable ratio of 0.15, down from 0.42 pre-cost. Industry-matched portfolios exhibit more stable risk-adjusted performance after trading costs, suggesting they provide a more reliable approach to managing risk relative to return.

The distributional characteristics in terms of skewness and kurtosis remain consistent between the two groups. Portfolios 1–18 exhibit more extreme values, with Portfolio 1 showing significant positive skewness (3.84) and kurtosis (22.56), indicating the potential for extreme outlier returns, even after the inclusion of trading costs. This suggests that non-industry-matched portfolios are subject to higher volatility and more frequent extreme movements. In contrast, Portfolios 19–36 display less extreme skewness and kurtosis, particularly in portfolios like Portfolio 26 and Portfolio 27, which exhibit more moderate values. The industry-matched portfolios generally show more stable return distributions, reinforcing the argument that industry matching helps reduce the impact of outliers and leads to more predictable performance after accounting for trading costs.

Next, an examination of SSD and NZC matching versus SSD and Hurst exponent matching reveals differences in performance after trading costs. Portfolios 7–12, which employ SSD and NZC matching, show lower mean returns, with the highest mean return in this group being 23 bps in Portfolio 10, down from 51 bps pre-cost. Similarly, Portfolio 8 sees a significant drop, achieving only 11 bps after trading costs, compared to 36 bps pre-cost. In contrast, Portfolios 13–18, which use the Hurst exponent for matching, demonstrate slightly better mean returns after costs. For example, Portfolio 14 delivers a mean return of 13 bps, while Portfolio 16 achieves 7 bps. Although these returns are lower than their pre-trading cost values, the reductions in this group are more consistent across portfolios. The impact of trading costs appears to be less severe in the SSD and Hurst-matched portfolios, indicating greater stability in performance after costs.

The SSD and NZC matching portfolios also experience substantial declines in Sharpe ratios after accounting for trading costs, with Portfolio 10 achieving the highest Sharpe ratio at 0.13, a significant drop from the pre-cost ratio of 0.28. In contrast, SSD and Hurst exponent-matched portfolios exhibit more moderate reductions in Sharpe ratios, with Portfolio 14 recording a Sharpe ratio of 0.13 and Portfolio 16 at 0.09. While these values are lower than their pre-cost levels, they are not as heavily impacted as the SSD and NZC matching portfolios. This suggests that the SSD and Hurst matching portfolios are somewhat more resilient to the effects of trading costs, maintaining relatively better risk-adjusted performance.

Finally, portfolios focusing on underperforming industries continue to demonstrate relatively higher risk-adjusted returns, even after trading costs are factored in. For instance, Portfolio 40, which focuses on underperforming industries, achieves a Sharpe ratio of 0.15 after costs, down from 0.42 pre-cost, but still higher than many other portfolios. Conversely, portfolios focusing on well-performing industries, such as Portfolio 39, show weaker performance after trading costs, with the Sharpe ratio dropping to 0.06 from 0.13 pre-cost.

In conclusion, industry matching contributes to more stable and consistent performance, even when trading costs are considered. The non-industry-matched portfolios show greater volatility and less favorable risk-adjusted performance, making them less attractive when accounting for real-world trading costs. The impact of trading costs is significant across all portfolios, but industry-matched and SSD and Hurst exponent-matched portfolios tend to be more resilient, maintaining relatively better performance after costs.

TABLE 8. Monthly Excess Returns with Trading Costs of Covid-19 Period Results.

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
1	-0.0005	0.0175	-0.03	3.84	22.56	-0.27	-0.26	38	38

2	0.0006	0.0089	0.07	-0.20	1.41	0.65	0.63	26	29
3	0.0022	0.0155	0.14	3.71	24.01	1.50	1.42	6	3
4	0.0006	0.0087	0.07	-0.51	2.61	0.77	0.72	27	25
5	0.0010	0.0088	0.11	-0.21	1.45	1.30	1.17	19	13
6	-0.0046	0.0244	-0.19	-2.57	10.27	-1.43	-1.39	40	40
7	0.0014	0.0116	0.12	0.59	5.15	1.40	1.36	12	11
8	0.0011	0.0084	0.13	-0.01	-0.06	1.27	1.23	17	12
9	0.0006	0.0094	0.06	-0.14	0.18	0.68	0.65	28	26
10	0.0023	0.0177	0.13	3.22	19.16	1.38	1.31	4	6
11	0.0000	0.0096	0.00	-0.07	1.44	-0.04	-0.04	32	32
12	0.0012	0.0161	0.07	3.37	18.77	0.65	0.62	15	22
13	-0.0002	0.0158	-0.01	-1.10	8.10	-0.13	-0.13	37	34
14	0.0013	0.0097	0.13	-0.73	0.91	1.20	1.14	13	8
15	0.0000	0.0092	0.00	-0.88	2.17	-0.01	-0.01	33	33
16	0.0007	0.0078	0.09	-0.32	0.40	0.84	0.80	23	23
17	0.0009	0.0088	0.10	0.33	1.93	0.87	0.86	21	16
18	0.0008	0.0074	0.11	-0.36	1.59	1.01	1.00	22	17
19	0.0028	0.0268	0.10	5.73	41.65	1.00	0.96	1	14
20	-0.0001	0.0074	-0.01	-0.27	1.21	-0.13	-0.12	36	37
21	0.0001	0.0072	0.01	-0.38	0.16	0.18	0.16	30	31
22	0.0020	0.0152	0.13	4.24	26.77	1.20	1.15	7	7
23	0.0000	0.0072	0.00	0.19	0.91	-0.05	-0.04	34	35
24	-0.0018	0.0130	-0.14	0.72	3.87	-1.50	-1.44	39	39
25	0.0025	0.0286	0.09	5.68	41.35	0.78	0.76	2	19
26	0.0011	0.0071	0.15	0.13	0.28	1.87*	1.69*	18	2
27	0.0023	0.0139	0.17	5.65	42.76	1.42	1.37	5	1
28	0.0024	0.0283	0.08	5.63	41.24	0.77	0.74	3	20
29	0.0017	0.0131	0.13	5.75	44.07	1.18	1.12	10	9
30	0.0007	0.0077	0.09	0.54	1.14	0.91	0.89	24	21
31	0.0018	0.0163	0.11	4.17	26.58	0.98	0.94	9	15
32	0.0006	0.0077	0.08	-0.15	1.40	0.82	0.77	29	27
33	0.0013	0.0085	0.15	0.41	1.19	1.27	1.29	14	4
34	0.0007	0.0069	0.10	0.35	2.24	0.95	0.91	25	18
35	0.0010	0.0070	0.14	1.01	2.87	1.25	1.24	20	10
36	0.0000	0.0057	0.00	-0.10	1.08	-0.07	-0.07	35	36
37	0.0020	0.0291	0.07	5.63	40.30	0.64	0.61	8	24
38	0.0001	0.0081	0.01	0.41	1.04	0.21	0.19	31	30
39	0.0017	0.0282	0.06	5.65	42.05	0.61	0.57	11	28
40	0.0012	0.0081	0.15	0.01	1.41	1.95*	1.69*	16	5

Note: This table presents key distributional statistics for the excess return time series, after accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2017 to June 2024, during the Covid-19 period. The column titled 't-stat' provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. The 'z-stat' column shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. The monthly return of CSI 300 for this period is 4 bps.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

*Significant at the 10% level.

Overall Returns of Financial Crisis Period

Table 9 summarizes the monthly excess returns for 40 pairs portfolios during the Financial Crisis period, accounting for trading costs.

After factoring in trading costs, the monthly excess returns ranged from -243 bps for Portfolio 10 to 35 bps for Portfolio 39, with an average return of approximately -35 bps. This represents a significant decline from the pre-cost average of -4 bps in Table 6. The considerable range of returns during this period highlights the extreme market volatility, with some portfolios, such as Portfolio 39, still achieving relatively positive returns despite the adverse market conditions and the impact of trading costs. Portfolios with higher turnover rates were particularly affected, as trading costs significantly reduced mean returns and Sharpe ratios.

In comparison to the COVID-19 period (Table 8), the Financial Crisis period exhibited a wider range of monthly excess returns and a more pronounced negative average return after trading costs. During the COVID-19 period, the excess returns ranged from -5 bps to 28 bps, with an average of approximately 10.5 bps after costs. This comparison underscores the heightened volatility and the more severe impact of trading costs during the Financial Crisis, where most portfolios experienced negative excess returns after costs.

After accounting for trading costs, Sharpe ratios declined significantly, ranging from -0.69 in Portfolio 29 to 0.14 in Portfolio 39. This sharp reduction in risk-adjusted returns illustrates the detrimental effect of trading costs. During the Financial Crisis, the highest Sharpe ratio was 0.14 in Portfolio 39, compared to 0.17 in Portfolio 27 during the COVID-19 period. This suggests that portfolios during the COVID-19 period were able to achieve better risk-adjusted returns despite challenging market conditions and trading costs.

Skewness and kurtosis metrics indicate that the distribution of portfolio returns remained highly skewed and leptokurtic, similar to what was observed without trading costs (Table 6). For instance, Portfolio 38 exhibits extreme positive skewness (5.52) and kurtosis (35.21), indicating the presence of substantial outliers. Portfolios with negative skewness, such as Portfolio 10, continue to face heightened risks of large negative returns, with a skewness of -3.04 and kurtosis of 10.14. While trading costs reduce the magnitude of returns, they do not significantly alter the skewness and kurtosis, which remain extreme, especially during periods of significant market stress.

In summary, after accounting for trading costs, the portfolios generally exhibit lower returns and reduced risk-adjusted performance during the Financial Crisis period. The average return turned negative after trading costs, indicating that these costs had a severe impact on portfolio profitability. Despite this, a few portfolios, particularly Portfolio 39 and Portfolio 9, managed to demonstrate relatively better performance, showing that certain strategies remained somewhat effective even in the presence of high transaction costs and market volatility.

Comparative Analysis of Different Portfolios Returns for Financial Crisis Period

A comparison between industry-matched and non-industry-matched portfolios reveals distinct patterns in performance during the Financial Crisis.

For Portfolios 1–18, which are constructed without industry matching, the highest mean return is seen in Portfolio 9, with a post-trading cost return of 78 bps, down from 108 bps pre-cost (Table 6). The overall range of mean returns for this group extends from -243 bps (Portfolio 10) to 78 bps, reflecting the diverse performance across different sectors. Most portfolios in this group experienced negative returns after trading costs, highlighting the significant impact of these costs on portfolios without industry matching.

In contrast, Portfolios 19–36, which incorporate industry matching, exhibit more consistent performance, although trading costs still reduce returns. The highest mean return in this group is observed in Portfolio 39, which achieved 350 bps after costs, down from 382 bps without costs. This suggests that industry matching contributes to more stable performance, even when trading costs are considered. However, many portfolios in this group also experienced negative returns after costs, indicating the challenging market conditions during the Financial Crisis.

Sharpe ratios for the non-industry-matched portfolios decreased significantly after accounting for trading costs. For example, Portfolio 9, which had one of the highest pre-cost Sharpe ratios at 0.18 (Table 6), drops to 0.13 after costs, showing how trading costs substantially diminish overall performance. Similarly, Portfolio 10's Sharpe ratio falls to -0.37, reflecting the negative impact on risk-adjusted returns.

The industry-matched portfolios show slightly better resilience, with Portfolio 39 achieving the highest Sharpe ratio of 0.14, down from 0.16 pre-cost. Although trading costs reduced the Sharpe ratios across all portfolios, industry-matched portfolios generally maintained relatively better risk-adjusted performance, suggesting they provide a more reliable approach to managing risk relative to return during volatile periods.

The distributional characteristics in terms of skewness and kurtosis remain extreme for both groups. Portfolios 1–18 exhibit more negative skewness and high kurtosis, with Portfolio 10 showing a skewness of -3.04 and kurtosis of 10.14, indicating a high likelihood of extreme negative returns. In contrast, Portfolios 19–36 display positive skewness and high kurtosis, particularly in portfolios like Portfolio 39, which has a skewness of 5.75 and kurtosis of 34.69. This suggests that while industry matching helps in achieving higher mean returns, it also comes with the potential for extreme positive outliers.

Next, an examination of SSD and NZC matching (Portfolios 7–12) versus SSD and Hurst exponent matching (Portfolios 13–18) reveals differences in performance after trading costs.

Portfolios 7–12, which employ SSD and NZC matching, show lower mean returns after trading costs, with the highest mean return in this group being 78 bps in Portfolio 9, down from 108 bps pre-cost. Several portfolios in this group experienced significant negative returns, such as Portfolio 10, which dropped to -243 bps from -208 bps pre-cost.

In contrast, Portfolios 13–18, which use the Hurst exponent for matching, continue to demonstrate negative mean returns after costs, with Portfolio 15 delivering a mean return of 40 bps, down from 70 bps pre-cost. Although these returns are lower than their pre-trading cost values, the reductions in this group are slightly less severe compared to the SSD and NZC matching portfolios.

The Sharpe ratios for both matching methods declined significantly after accounting for trading costs. Portfolios 7–12 saw Sharpe ratios drop, with Portfolio 9 recording a ratio of 0.13, while Portfolios 13–18 observed Sharpe ratios becoming negative or close to zero. This indicates that both matching methods were heavily impacted by trading costs during the Financial Crisis, with neither showing strong resilience.

Portfolios focusing on underperforming industries continue to demonstrate relatively better risk-adjusted returns, even after trading costs are factored in. For instance, Portfolio 39, which focuses on underperforming industries, achieves a mean return of 350 bps and a Sharpe ratio of 0.14 after costs, down from 382 bps and 0.16 pre-cost (Table 6). This suggests that focusing on underperforming industries can still yield better performance in turbulent market conditions, even when accounting for high trading costs.

Conversely, portfolios focusing on well-performing industries, such as Portfolio 37, show weaker performance after trading costs, with the mean return dropping to -50 bps from 219 bps pre-cost, and the Sharpe ratio turning negative. This reflects the challenges of high trading costs and market volatility in such sectors during the Financial Crisis.

In conclusion, industry matching contributes to slightly more stable and consistent performance, even when trading costs are considered. However, during the Financial Crisis period, the impact of trading costs was significant across all portfolios, leading to negative average returns and reduced risk-adjusted performance. Non-industry-matched portfolios show greater volatility and less favorable risk-adjusted performance, making them less attractive when accounting for real-world trading costs. The SSD and Hurst exponent matching portfolios do not demonstrate a clear advantage over the SSD and NZC matching portfolios after trading costs in this period, with both methods experiencing substantial performance declines.

When comparing these results to the COVID-19 period (Table 8), it is evident that trading costs had a more severe impact during the Financial Crisis period. Portfolios during the COVID-19 period managed to maintain positive average excess returns and relatively better Sharpe ratios after trading costs, indicating that trading costs were less detrimental in a less volatile market environment.

TABLE 9. Excess Returns with Trading Costs of Financial Crisis Period Results.

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
1	-0.0188	0.0480	-0.39	-2.64	8.15	-2.56**	-2.61***	39	36

2	-0.0176	0.0514	-0.34	-1.32	7.45	-2.18**	-2.28**	38	34
3	-0.0138	0.0539	-0.25	-0.62	8.76	-2.63***	-2.55**	33	27
4	-0.0141	0.0540	-0.26	1.31	8.90	-3.23***	-2.72***	34	29
5	-0.0058	0.0402	-0.14	-0.08	10.05	-1.62	-1.56	20	21
6	-0.0132	0.0404	-0.32	1.66	14.82	-4.80***	-4.34***	31	32
7	-0.0142	0.0691	-0.20	0.19	11.99	-2.35**	-2.06**	35	23
8	0.0022	0.0712	0.03	3.50	14.48	0.16	0.17	11	11
9	0.0078	0.0601	0.13	2.62	7.83	0.86	0.93	8	2
10	-0.0243	0.0658	-0.37	-3.04	10.14	-2.08**	-2.26**	40	35
11	-0.0047	0.0880	-0.05	-0.04	14.28	-0.35	-0.35	16	15
12	-0.0003	0.0470	-0.01	3.02	10.86	-0.04	-0.04	14	14
13	-0.0133	0.0466	-0.28	-2.42	14.57	-1.71*	-1.82*	32	30
14	-0.0113	0.0451	-0.25	2.38	15.95	-2.94***	-2.54**	29	28
15	0.0040	0.0506	0.08	4.31	22.72	0.45	0.49	9	8
16	-0.0030	0.0426	-0.07	3.34	14.12	-0.44	-0.44	15	18
17	0.0008	0.0427	0.02	3.41	14.76	0.11	0.11	12	12
18	0.0024	0.0532	0.05	3.75	15.02	0.23	0.24	10	10
19	-0.0055	0.0985	-0.06	1.06	17.06	-0.44	-0.43	19	17
20	0.0098	0.0852	0.11	3.32	13.09	0.66	0.66	4	3
21	0.0141	0.1273	0.11	4.12	19.57	0.69	0.69	2	4
22	-0.0049	0.0445	-0.11	3.73	20.81	-0.86	-0.91	17	19
23	-0.0060	0.0505	-0.12	0.82	10.41	-0.95	-0.96	21	20
24	-0.0153	0.0237	-0.64	2.53	12.34	-6.92	-6.90	37	38
25	0.0092	0.0829	0.11	4.30	18.57	0.60	0.63	6	5
26	-0.0065	0.0271	-0.24	4.21	23.58	-1.61	-1.72*	23	26
27	-0.0101	0.0322	-0.31	3.03	21.05	-2.29**	-2.23**	27	31
28	0.0093	0.1052	0.09	4.42	20.73	0.57	0.57	5	7
29	-0.0143	0.0206	-0.69	-2.19	7.17	-7.25***	-6.72***	36	40
30	-0.0074	0.0225	-0.33	1.50	6.02	-1.98**	-2.13**	25	33
31	0.0100	0.1200	0.08	3.56	16.08	0.52	0.50	3	9
32	-0.0093	0.0641	-0.14	1.52	10.16	-1.17	-1.19	26	22
33	-0.0071	0.0334	-0.21	3.62	21.86	-1.18	-1.21	24	25
34	-0.0063	0.0315	-0.20	3.00	11.88	-1.08	-1.12	22	24
35	-0.0118	0.0172	-0.68	0.77	6.47	-4.59***	-4.56***	30	39
36	-0.0111	0.0215	-0.51	-0.66	9.90	-4.30***	-4.15***	28	37
37	-0.0050	0.1015	-0.05	2.84	20.54	-0.43	-0.36	18	16
38	0.0089	0.0884	0.10	5.52	35.21	0.62	0.63	7	6
39	0.0350	0.2424	0.14	5.75	34.69	0.94	0.94	1	1
40	0.0004	0.1108	0.00	2.43	18.82	0.03	0.03	13	13

Note: This table presents key distributional statistics for the excess return time series, after accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2005 to December 2010, during the financial crisis period. The column titled 't-stat' provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. The 'z-stat' column shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. The monthly return of CSI 300 for this period is 162 bps.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

*Significant at the 10% level.

Overall Returns of Bullish and Bearish Period

Table 10 presents the monthly excess returns of 40 pairs portfolios during the Bullish and Bearish period, accounting for trading costs.

Before accounting for trading costs, as shown in Table 7, the monthly excess returns ranged from 21 bps in Portfolio 40 to 77 bps in Portfolio 37, with an average return positioned between the extremes observed during the COVID-19 and Financial Crisis periods. After including trading costs, the range narrows to 3 bps in Portfolio 40 to 51 bps in Portfolio 37, with a lower average return. The highest-performing portfolio, Portfolio 37, saw its mean return drop from 77 bps to 51 bps, reflecting the substantial impact of trading costs on portfolio profitability. Overall, returns for most portfolios were reduced, and several portfolios with already low returns experienced further declines.

Before trading costs, standard deviations ranged from 0.75% to 1.27%, indicating varying levels of volatility across portfolios. After trading costs, the standard deviation range remains similar, from 0.71% to 1.21%, indicating that trading costs do not significantly alter the overall volatility of the portfolios. However, high-performing portfolios, such as Portfolio 37, continue to exhibit higher volatility at 1.19% after trading costs, highlighting the trade-off between higher returns and increased risk.

The most notable effect of trading costs is observed in the Sharpe ratios, which measure risk-adjusted returns. Prior to trading costs, the highest Sharpe ratio was 0.60 in Portfolio 37, followed by 0.59 in Portfolio 39 (Table 7). After accounting for trading costs, the Sharpe ratios drop across all portfolios. The highest Sharpe ratio post-costs is 0.43 in Portfolio 37, followed by 0.39 in Portfolio 39, marking a notable decline in risk-adjusted performance.

Both before and after trading costs, the skewness and kurtosis values remain relatively similar, suggesting that the distributional characteristics of portfolio returns are largely unaffected by trading costs. For instance, Portfolio 37 retains a skewness of 0.52 and a kurtosis of 3.23 after costs, compared to 0.89 and 3.41 before costs (Table 7). Portfolios such as Portfolio 5, which exhibited higher skewness and kurtosis values before costs, continue to show similarly moderate levels of distributional risk after costs. This indicates that while trading costs reduce returns, they do not significantly alter the potential for outliers or extreme values in the portfolios.

In conclusion, trading costs reduce both the returns and risk-adjusted performance of portfolios during the Bullish and Bearish period. However, portfolios such as Portfolio 37 and Portfolio 39 manage to maintain statistically significant returns and strong Sharpe ratios, demonstrating resilience even after accounting for transaction expenses. Meanwhile, lower-performing portfolios highlight the detrimental impact of trading costs on strategies with higher turnover or less efficient performance.

Comparative Analysis of Different Portfolios Returns for Bullish and Bearish Period

The first comparison involves two sets of portfolios, without industry matching and incorporate industry matching.

For Portfolios 1–18, the highest mean return is observed in Portfolio 13, with a post-trading cost return of 31 bps, down from 56 bps pre-cost. The overall range of mean returns for this group extends from 12 bps to 31 bps, reflecting variability across different sectors. In contrast, Portfolios 19–36, which incorporate industry matching, exhibit more consistent performance. Portfolio 25 achieves the highest mean return of 30 bps after costs, down from 52 bps before costs, while Portfolio 26 follows closely with a return of 27 bps. This trend of more stable returns with industry matching suggests that such portfolios are better able to mitigate the effects of trading costs, providing more reliable performance even in the volatile Bullish and Bearish period.

The Sharpe ratios in Portfolios 1–18 decline significantly after accounting for trading costs, highlighting the negative impact of these costs on risk-adjusted returns. For example, Portfolio 7, which had a pre-cost Sharpe ratio of 0.46, drops to 0.26 after costs, underscoring how trading costs can sharply reduce performance. Portfolios 19–36, although also affected, demonstrate more resilience. Portfolio 25 maintains a Sharpe ratio of 0.32, despite a drop from 0.52 before trading costs. This shows that industry matching contributes to more consistent risk-adjusted performance even after trading costs are factored in.

In terms of skewness and kurtosis, the distributional characteristics remain similar between the two groups. Portfolios 1–18 exhibit higher skewness and kurtosis, indicating more extreme values and potential for outlier returns even after trading costs. For example, Portfolio 7 shows skewness of 1.77 and kurtosis of 7.74 after costs, compared to 2.20 and 9.95 before costs. Portfolios 19–36 display more moderate skewness and kurtosis. Portfolio 25, for instance, has skewness of 1.21 and kurtosis of 3.94 after costs, indicating a more balanced return distribution. This supports the argument that industry matching helps reduce the risk of extreme movements and provides more stable performance after trading costs.

The second comparison contrasts SSD and NZC matching (Portfolios 7–12 and 25–30) with SSD and Hurst exponent matching (Portfolios 13–18 and 31–36).

Portfolios using SSD and NZC matching see a significant reduction in returns after trading costs. Portfolio 7 achieves a post-cost mean return of 28 bps, down from 53 bps pre-cost. In contrast, Portfolio 25, which incorporates industry matching, continues to perform well with a mean return of 30 bps and a Sharpe ratio of 0.32. This indicates that while SSD and NZC matching portfolios are impacted by trading costs, industry matching can help maintain better overall performance.

Meanwhile, SSD and Hurst exponent matching portfolios show more stable but slightly lower mean returns. Portfolio 13 achieves a post-cost mean return of 31 bps, down from 56 bps pre-cost, while Portfolio 34 records 24 bps with a Sharpe ratio of 0.33 after costs. These portfolios exhibit relatively strong risk-adjusted returns, suggesting that the SSD and Hurst matching method is somewhat more resilient to trading costs.

The third comparison examines portfolios focused on good and underperforming industries.

Portfolios 37 and 39, which focus on good performance industries, continue to perform well after trading costs. Portfolio 37 achieves the highest mean return of 51 bps and a Sharpe ratio of 0.43, down from 77 bps and 0.60 before trading costs. Portfolio 39 records a mean return of 41 bps and a Sharpe ratio of 0.39, demonstrating strong risk-adjusted performance even after accounting for trading costs.

In contrast, portfolios focusing on underperforming industries, such as Portfolios 38 and 40, generate lower returns. Portfolio 38 records a mean return of 11 bps and a Sharpe ratio of 0.14, while Portfolio 40 posts 3 bps with a Sharpe ratio of 0.04. These portfolios offer more stable but lower returns, showing less potential for upside performance compared to portfolios focusing on good performance industries.

In conclusion, the Bullish and Bearish period demonstrates that portfolios with industry matching and those using the SSD and Hurst exponent matching method offer more stable and consistent performance after trading costs are considered. Portfolios focusing on good performance industries deliver higher returns but are more susceptible to trading costs, while those focusing on underperforming industries exhibit more stable but lower performance. The industry-matched portfolios show resilience to trading costs, making them a more reliable option for maintaining strong risk-adjusted returns in fluctuating market conditions.

When comparing these results to the COVID-19 period and the Financial Crisis period, it is evident that trading costs have varying impacts across different market conditions. During the COVID-19 period, the highest mean return after trading costs was 28 bps (Portfolio 19), with the highest Sharpe ratio being 0.17 (Portfolio 27). In the Financial Crisis period, after trading costs, the highest mean return was 35 bps (Portfolio 39), but overall portfolios exhibited negative average returns due to high volatility and market stress.

In the Bullish and Bearish period, portfolios managed to maintain higher mean returns and Sharpe ratios after trading costs compared to the other periods, indicating that trading costs had a less severe impact in this more stable market environment. This suggests that during periods of moderate market fluctuations, pairs trading strategies can be more effective and resilient to transaction costs.

TABLE 10. Monthly Excess Returns with Trading Costs of Bullish and Bearish Period Results.

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
1	0.0018	0.0091	0.20	0.32	1.80	1.26	1.32	26	24
2	0.0017	0.0101	0.16	2.15	10.18	1.07	1.14	30	34
3	0.0024	0.0103	0.24	1.46	7.73	1.34	1.46	10	17
4	0.0017	0.0086	0.19	0.43	4.44	1.11	1.18	31	28
5	0.0012	0.0100	0.12	1.44	5.98	0.70	0.74	36	37

6	-0.0002	0.0172	-0.01	0.65	2.37	-0.06	-0.06	40	40
7	0.0028	0.0104	0.26	1.77	7.74	1.51	1.60	6	10
8	0.0021	0.0105	0.19	1.15	3.27	1.21	1.29	21	29
9	0.0026	0.0105	0.24	0.97	4.00	1.35	1.44	8	18
10	0.0024	0.0106	0.22	1.43	6.72	1.32	1.42	11	19
11	0.0022	0.0109	0.20	0.84	3.83	1.03	1.11	17	25
12	0.0018	0.0098	0.18	0.10	3.28	1.17	1.20	27	31
13	0.0031	0.0121	0.25	2.09	8.07	1.32	1.42	3	12
14	0.0014	0.0092	0.15	0.85	1.89	0.87	0.92	34	35
15	0.0030	0.0099	0.30	-0.21	5.40	1.90*	2.03**	4	6
16	0.0019	0.0086	0.22	1.37	6.81	1.11	1.20	23	20
17	0.0023	0.0091	0.25	1.24	8.19	1.34	1.45	15	13
18	0.0016	0.0096	0.17	1.55	7.79	0.87	0.94	33	33
19	0.0018	0.0071	0.25	0.90	4.40	1.60	1.71*	28	14
20	0.0017	0.0078	0.21	0.81	3.53	1.36	1.42	32	22
21	0.0013	0.0072	0.18	-0.61	2.43	1.30	1.38	35	32
22	0.0023	0.0082	0.28	1.01	2.90	1.73*	1.82*	16	8
23	0.0019	0.0073	0.25	2.14	10.35	1.53	1.62	24	15
24	0.0008	0.0158	0.05	-0.09	1.19	0.37	0.39	38	38
25	0.0030	0.0093	0.32	1.21	3.94	2.21**	2.38**	5	4
26	0.0027	0.0087	0.31	2.15	9.19	1.64	1.80*	7	5
27	0.0019	0.0100	0.19	0.75	2.82	1.04	1.14	25	30
28	0.0022	0.0084	0.26	1.39	5.29	1.60	1.71*	18	11
29	0.0024	0.0108	0.22	0.60	1.90	1.21	1.28	12	21
30	0.0020	0.0098	0.20	2.47	10.01	1.15	1.18	22	26
31	0.0018	0.0091	0.20	0.85	3.60	1.20	1.30	29	27
32	0.0026	0.0096	0.27	1.75	7.90	1.51	1.62	9	9
33	0.0022	0.0104	0.21	1.47	4.16	1.12	1.18	19	23
34	0.0024	0.0074	0.33	1.98	7.78	1.69*	1.82*	13	3
35	0.0024	0.0082	0.30	2.17	7.33	1.43	1.54	14	7
36	0.0022	0.0086	0.25	1.34	5.32	1.19	1.30	20	16
37	0.0051	0.0119	0.43	0.52	3.23	2.73***	2.89***	1	1
38	0.0011	0.0075	0.14	-0.07	1.34	1.14	1.18	37	36
39	0.0041	0.0103	0.39	1.02	2.40	2.31**	2.45**	2	2
40	0.0003	0.0083	0.04	-0.42	2.62	0.27	0.29	39	39

Note: This table presents key distributional statistics for the excess return time series, after accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2011 to December 2016, during the bullish and bearish period. The column titled 't-stat' provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. The 'z-stat' column shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. The monthly return of CSI 300 for this period is 5 bps.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

*Significant at the 10% level.

Figure 2 further illustrate the relative risk profiles of different pairs trading portfolios by plotting the GARCH (1,1) conditional volatilities for three representative pairs portfolios: 6, 14, and 38. As shown in the figure, Pair Portfolio 6 consistently exhibits larger fluctuations in conditional volatility compared to Pair Portfolios 14 and 38 throughout the sample period, particularly during periods of heightened market instability, such as late 2023 into 2024. This significant increase in volatility for Portfolio 6 suggests a higher risk profile compared to the other portfolios, which maintain more stable, lower volatility patterns over time. The lower conditional volatility of Portfolios 14 and 38 reinforces the lower-risk nature of pairs trading for these portfolios, consistent with a more conservative trading strategy.

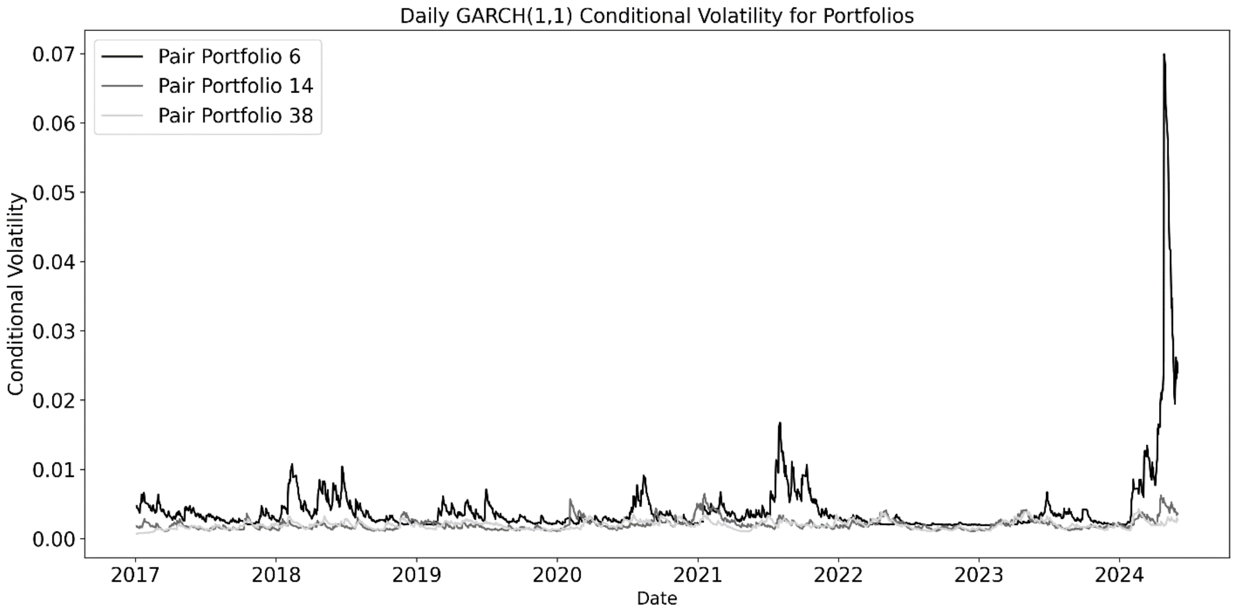

Figure 2. Daily GARCH Volatility on Pairs Trading Returns. This figure plots the conditional volatility using the GARCH (1,1) model, generated from the daily return time series for three pairs trading portfolios: 6, 14, and 38, covering the period from 2017 to 2024 of COVID-19 period after trading costs. The portfolios are selected from pairs trading strategies, where stocks are matched and traded based on historical price relationships.

5.1.3 Subperiod Returns Analysis

This section provides a comprehensive analysis of the monthly excess returns of 40 pairs trading portfolios across various sub-periods, benchmarked against the CSI 300 index. The analysis spans from January 2005 to June 2024, covering significant market phases such as the Pre-Financial Crisis, Financial Crisis, Post-Financial Crisis, Bullish and Bearish markets, and the COVID-19 pandemic periods. The objective is to evaluate the robustness and effectiveness of the pairs trading strategy under different market conditions, highlighting its performance relative to the different benchmark index during these distinct periods.

For each sub-period, the CSI 300 index is used as a benchmark to assess the performance of the portfolios relative to the broader market. The mean returns and Sharpe ratios are calculated for both the portfolios and the benchmark, providing insights into both absolute and risk-adjusted performance. The significant differences in portfolio performance across these sub-periods are largely due to the varying returns of the CSI 300 during each phase.

Sub-Period Returns without Trading costs

Table 11 shows monthly excess returns without trading costs of all three period results with each sub-period CSI 300 benchmarks.

The Pre-Financial Crisis Period saw the CSI 300 index exhibit a strong positive mean return of 3.09%, indicating a bullish market environment. However, most of the pairs trading portfolios performed poorly, showing negative mean returns and Sharpe ratios. For instance, Portfolio 10 experienced a significant negative mean return of -6.60%, with a Sharpe ratio of -0.62, significant at the 1% level. This negative performance suggests that the pairs trading strategy was less effective during this bullish phase. One possible explanation is that during strong upward trends, price divergences between pairs do not revert as expected, reducing the profitability of mean-reversion strategies. The significant underperformance relative to the benchmark highlights the strategy's limitations in rapidly rising markets.

During the Financial Crisis, the CSI 300 index experienced a slight negative mean return of -0.53%, reflecting market instability. In contrast, most pairs trading portfolios performed well, with significant positive mean returns and Sharpe ratios. Portfolio 33, for example, achieved a mean return of 1.34%, with a Sharpe ratio of 1.48, significant at the 1% level. This outperformance can be attributed to heightened volatility during the crisis, which increased mispricing opportunities that the pairs trading strategy successfully exploited. The significant and positive Sharpe ratios indicate strong risk-adjusted performance, and the strategy's ability to generate positive returns in a declining market demonstrates its potential as a market-neutral approach, offering a hedge against market downturns.

In the Post-Financial Crisis Period, the CSI 300 index showed a positive mean return of 2.14%, indicating market recovery. However, the performance of pairs trading portfolios was mixed, with many showing significant negative mean returns. Portfolio 1, for instance, had a mean return of -1.32% and a Sharpe ratio of -1.33, significant at the 1% level. The reduction in market volatility post-crisis likely limited arbitrage opportunities, reducing the profitability of pairs trading. The underperformance relative to the benchmark suggests that the strategy may face challenges in identifying profitable divergences when the market is stabilizing, highlighting the need for adjustments to the strategy during different market regimes.

In the Pre-Bullish and Bearish Period, the CSI 300 index had a slight negative mean return of -0.87%. Pairs trading portfolios showed positive mean returns, indicating that the strategy performed relatively well during this period. For example, Portfolio 15 achieved a mean return of 1.30% with a Sharpe ratio of 2.02, significant at the 1% level. The moderate volatility during this period may have provided sufficient mispricing opportunities for the pairs trading strategy to be effective.

During Bullish Market Phases, the CSI 300 index had a robust mean return of 4.42%. However, pairs trading portfolios generally underperformed relative to the benchmark, with several portfolios exhibiting significant negative mean returns. For example, Portfolio 5 recorded a significant negative mean return of -4.60% and a Sharpe ratio of -5.24, significant at the 1% level. The pairs trading strategy struggled in bullish conditions, likely due to the persistence of price trends that prevent mean reversion. The negative Sharpe ratios indicate poor risk-adjusted performance, underlining the strategy's limitations in capturing gains during strong market upswings.

In contrast, during Bearish Market Phases, the CSI 300 index exhibited a significant negative mean return of -2.23%. Pairs trading portfolios performed exceptionally well, with significant positive mean returns and high Sharpe ratios. Portfolio 31, for example, achieved a mean return of 3.41% and a Sharpe ratio of 2.56, significant at the 1% level. The increased volatility and market inefficiencies during bearish phases enhanced the effectiveness of the pairs trading strategy. The positive and significant Sharpe ratios reflect strong risk-adjusted returns, demonstrating that the strategy serves as an effective hedge against market downturns and offers diversification benefits.

During the Pre-COVID Period, the CSI 300 index had a modest mean return of 0.57%, while pairs trading portfolios showed negligible or negative mean returns, with statistical significance generally lacking. The stable market conditions resulted in fewer mispricing opportunities, and the strategy's performance was muted due to the lack of volatility and significant price deviations between pairs.

However, during the COVID-19 pandemic, the CSI 300 index experienced a slight negative mean return of -0.19%. In this period, pairs trading portfolios began to exhibit significant positive mean returns and Sharpe ratios. For instance, Portfolio 12 had a mean return of 0.44%, with a Sharpe ratio of 0.39, significant at the 1% level. The pandemic-induced volatility created abundant arbitrage opportunities, which the pairs trading strategy was able to capitalize on. The positive performance during this period underscores the strategy’s resilience and adaptability to sudden market shocks.

Finally, in the Post-COVID Period, the CSI 300 index declined further with a mean return of -0.64%. Despite this, pairs trading portfolios continued to generate positive mean returns, with several portfolios showing statistical significance. Portfolio 33, for example, achieved a mean return of 1.24% and a Sharpe ratio of 1.09, significant at the 1% level. The persistent market inefficiencies and continued volatility post-pandemic created a conducive environment for pairs trading, and the sustained positive performance indicates the strategy’s effectiveness in prolonged periods of uncertainty.

The performance of pairs trading portfolios was significantly influenced by the varying mean returns of the CSI 300 index across different sub-periods. During periods when the CSI 300 exhibited negative returns, such as the In-Financial Crisis period, the In-Bearish period, the In-COVID period, and the Post-COVID period, the pairs trading portfolios generally demonstrated positive mean returns and higher Sharpe ratios. This inverse relationship indicates that the pairs trading strategy tends to be more effective during market downturns, as it benefits from increased volatility and market inefficiencies that are typically more pronounced in such environments. The findings suggest that in times of negative benchmark performance, the strategy is better positioned to exploit arbitrage opportunities created by deviations from mean reversion.

In contrast, during periods characterized by strong positive returns in the CSI 300 index, such as the Pre-Financial Crisis period and the In-Bullish period, the pairs trading portfolios significantly underperformed, often yielding negative mean returns and Sharpe ratios. This indicates that the mean-reversion assumptions underlying pairs trading may not hold during bullish market conditions, where assets are more likely to trend upwards without reverting to their historical means. The result is a decrease in the strategy's effectiveness, as the persistent upward momentum prevents the typical convergence trades that pairs trading relies upon.

Finally, in periods with moderate or slightly negative CSI 300 returns, such as the Pre-Bullish and Bearish phase and the Pre-COVID phase, the performance of pairs trading portfolios was mixed. Some portfolios achieved positive mean returns and Sharpe ratios, while others did not. This inconsistency suggests that the strategy's performance in such environments is less predictable and may be contingent on specific market conditions, the composition of the pairs, and the methodology used to construct the portfolios. Thus, in these intermediate periods, the success of pairs trading may hinge more on the specific characteristics of the assets and the timing of trades rather than broad market trends.

Significant positive mean returns were observed during periods of market stress, such as the Financial Crisis, bearish phases, and the COVID-19 pandemic. Many portfolios achieved significance at the 1% or 5% levels, suggesting robust performance that is not due to random chance. Sharpe ratios were notably higher during volatile periods, reflecting superior risk-adjusted returns. Portfolios demonstrated the ability to achieve high returns without proportionally increasing risk, indicating the strength of the pairs trading strategy in managing risk effectively.

The portfolios consistently outperformed the CSI 300 index during bearish and crisis periods, suggesting that pairs trading can serve as a defensive strategy, providing positive returns when the broader market is declining. However, during bullish periods, the portfolios often underperformed the benchmark. This underperformance can be attributed to the strategy's reliance on mean-reversion, which may hinder performance when markets exhibit strong upward momentum. Portfolios generally exhibited lower volatility than the benchmark during downturns, contributing to higher Sharpe ratios. This reduced exposure to systematic risk highlights the market-neutral nature of the strategy.

The pairs trading strategy demonstrates a clear sensitivity to market conditions. It thrives in environments characterized by high volatility and market inefficiencies but is less effective in stable or strongly trending markets. This suggests that adjustments or complementary strategies may be needed during certain market phases. Nonetheless, the strategy's consistent positive performance across different crisis periods underscores its robustness. The ability to adapt to various market conditions enhances its attractiveness for risk management and diversification. Furthermore, portfolios that employed industry matching and advanced selection criteria, such as Portfolios 31 to 36, consistently outperformed others. This highlights the importance of careful pair selection and the incorporation of factors like industry affiliation to enhance performance.

TABLE 11. Monthly Excess Returns without Trading Costs of All Three Period Results with Each Sub-Period CSI 300 Benchmarks.

	Pre- Fin.C.		In- Fin.C.		Post- Fin.C.		Pre-B.N.B.		In-Bullish		In-Bearish		Pre-Cov.		In-Cov.		Post-Cov.	
Portfolio	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**
CSI 300	0.0309	-	-0.0053	-	0.0214	-	-0.0087	-	0.0442	-	-0.0223	-	0.0057	-	-0.0019	-	-0.0064	-
1	-0.0493***	-0.62***	0.0180***	1.08***	-0.0132***	-1.33***	0.0121***	1.60***	-0.0437***	-5.56***	0.0325***	2.54***	0.0017	0.06	0.0051***	0.69***	0.0080***	0.76**
2	-0.0445**	-0.51**	0.0144***	0.93***	-0.0115***	-1.19***	0.0118***	1.78***	-0.0441***	-4.89***	0.0333***	2.12***	-0.0016	-0.20	0.0057***	0.55***	0.0070***	0.68***
3	-0.0352**	-0.38**	0.0161***	0.89***	-0.0113***	-1.07***	0.0123***	2.09***	-0.0444***	-4.39***	0.0358***	2.40***	0.0021	0.09	0.0056***	0.70***	0.0085***	1.05***
4	-0.0334***	-0.36**	0.0160***	1.05***	-0.0141***	-1.70***	0.0115***	2.01***	-0.0442***	-5.16***	0.0335***	3.00***	-0.0018	-0.29	0.0046***	0.46***	0.0103***	0.89***
5	-0.0088	-0.13	0.0163***	1.26***	-0.0143***	-1.59***	0.0113***	2.12***	-0.0460***	-5.24***	0.0341***	2.20***	-0.0009	-0.12	0.0050***	0.47***	0.0093***	1.02***
6	-0.0240***	-0.37***	0.0105***	0.43**	-0.0233***	-2.80***	0.0071**	0.50**	-0.0482***	-2.99***	0.0324***	1.51***	-0.0088***	-0.46**	0.0002	0.01	-0.0038	-0.13
7	-0.0354**	-0.30	0.0154***	0.70***	-0.0102***	-0.71***	0.0121***	1.74***	-0.0422***	-4.29***	0.0364***	2.31***	-0.0006	-0.05	0.0074***	0.75***	0.0078***	0.57**
8	0.0225	0.19	0.0094*	0.36*	-0.0155***	-1.87***	0.0113***	1.60***	-0.0412***	-4.02***	0.0338***	2.09***	-0.0010	-0.13	0.0058***	0.59***	0.0090***	1.09***
9	0.0255	0.26	0.0193***	0.94***	-0.0116***	-1.16***	0.0116***	2.05***	-0.0409***	-3.22***	0.0348***	2.18***	-0.0020	-0.26	0.0062***	0.61***	0.0073**	0.59**
10	-0.0660**	-0.62***	0.0160***	0.76***	-0.0101***	-0.81***	0.0125***	1.70***	-0.0430***	-3.97***	0.0347***	2.22***	0.0021	0.08	0.0065***	0.85***	0.0087***	0.70**
11	0.0138	0.12	-0.0036	-0.04	-0.0143***	-1.36***	0.0108***	2.00***	-0.0401***	-3.01***	0.0340***	1.97***	-0.0024	-0.28	0.0051***	0.63***	0.0063*	0.41
12	0.0071	0.09	0.0154***	1.04***	-0.0136***	-1.21***	0.0120***	2.07***	-0.0443***	-4.09***	0.0331***	2.39***	0.0003	0.02	0.0044***	0.39***	0.0080***	1.27***
13	-0.0370*	-0.47**	0.0185***	1.31***	-0.0091***	-0.98***	0.0114***	1.73***	-0.0430***	-4.79***	0.0399***	2.17***	-0.0031	-0.16	0.0071***	0.75***	0.0046	0.25
14	-0.0216**	-0.30*	0.0114	0.37	-0.0130***	-1.17***	0.0108***	1.63***	-0.0416***	-3.82***	0.0320***	2.55***	0.0004	0.05	0.0053***	0.47***	0.0077***	0.79***
15	0.0148	0.18	0.0182***	0.84***	-0.0110***	-1.06***	0.0130***	2.02***	-0.0410***	-2.89***	0.0339***	3.00***	-0.0017	-0.25	0.0047**	0.46***	0.0056**	0.45
16	0.0008	0.01	0.0130***	0.58***	-0.0122***	-1.60***	0.0114***	2.52***	-0.0431***	-5.34***	0.0344***	2.59***	-0.0008	-0.10	0.0051***	0.64***	0.0076***	0.91***
17	0.0109	0.17	0.0156***	0.59***	-0.0143***	-1.82***	0.0114***	2.43***	-0.0419***	-4.38***	0.0343***	2.52***	-0.0009	-0.09	0.0049***	0.57***	0.0082***	1.01***
18	0.0123	0.14	0.0181***	1.27***	-0.0138***	-1.79***	0.0104***	2.04***	-0.0435***	-5.16***	0.0350***	2.37***	-0.0019	-0.30	0.0056***	0.62***	0.0082***	1.15***
19	-0.0033	-0.02	0.0122***	1.02***	-0.0159***	-1.92***	0.0125***	2.30***	-0.0436***	-6.97***	0.0310***	2.96***	0.0042	0.10	0.0038***	0.55***	0.0093***	1.14***
20	0.0410	0.29	0.0119***	1.09***	-0.0148***	-1.77***	0.0110***	1.90***	-0.0428***	-9.13***	0.0325***	2.77***	-0.0044***	-0.61***	0.0041***	0.53***	0.0117***	1.45***
21	0.0561	0.26	0.0116***	1.11***	-0.0172***	-1.94***	0.0115***	1.88***	-0.0427***	-5.29***	0.0296***	3.37***	-0.0026**	-0.36*	0.0038***	0.47***	0.0089***	1.27***
22	-0.0050	-0.07	0.0148***	1.47***	-0.0155***	-2.07***	0.0126***	2.18***	-0.0437***	-6.77***	0.0324***	2.61***	0.0010	0.05	0.0051***	0.73***	0.0089***	1.29***
23	-0.0063	-0.07	0.0131***	1.01***	-0.0161***	-1.78***	0.0116***	2.73***	-0.0434***	-8.39***	0.0327***	2.77***	-0.0031***	-0.49***	0.0038***	0.50***	0.0089***	0.90***
24	-0.0235***	-0.68***	0.0054**	0.28**	-0.0248***	-2.49***	0.0083**	0.45**	-0.0415***	-4.77***	0.0274***	1.69***	-0.0086***	-0.77***	0.0024	0.14	0.0057***	1.04***
25	0.0358	0.26	0.0131***	1.16***	-0.0115***	-1.06***	0.0129***	2.23***	-0.0425***	-6.58***	0.0348***	2.28***	0.0046	0.10	0.0026***	0.31**	0.0107***	1.14***
26	-0.0070	-0.16	0.0121***	1.17***	-0.0169***	-1.69***	0.0102***	1.88***	-0.0391***	-6.21***	0.0343***	2.49***	-0.0023***	-0.39**	0.0055***	0.67***	0.0102***	1.15***
27	-0.0160	-0.30	0.0095***	0.55***	-0.0162***	-2.00***	0.0110***	1.65***	-0.0456***	-5.27***	0.0353***	2.63***	0.0008	0.04	0.0049***	0.75***	0.0105***	1.04***
28	0.0379	0.21	0.0121***	1.01***	-0.0125***	-1.26***	0.0118***	2.11***	-0.0428***	-6.80***	0.0340***	2.61***	0.0021	0.08	0.0055***	0.76***	0.0107***	1.08***
29	-0.0305***	-0.98***	0.0112***	0.63***	-0.0161***	-2.12***	0.0109***	1.44***	-0.0452***	-5.19***	0.0368***	2.75***	0.0002	0.01	0.0039***	0.70***	0.0103***	1.25***
30	-0.0139	-0.38	0.0138***	1.15***	-0.0155***	-2.06***	0.0093***	1.69***	-0.0414***	-6.11***	0.0341***	2.15***	-0.0036***	-0.60***	0.0053***	0.61***	0.0098***	0.92***
31	0.0380	0.18	0.0147***	1.15***	-0.0133***	-1.63***	0.0110***	1.75***	-0.0427***	-5.81***	0.0341***	2.56***	0.0021	0.09	0.0044***	0.49***	0.0084***	1.05***
32	-0.0128	-0.12	0.0111***	0.77***	-0.0184***	-1.47***	0.0106***	1.87***	-0.0411***	-4.71***	0.0351***	2.46***	-0.0033**	-0.46**	0.0051***	0.66***	0.0099***	1.01***
33	-0.0086	-0.15	0.0134***	1.48***	-0.0186***	-1.89***	0.0115***	1.66***	-0.0456***	-5.95***	0.0355***	2.36***	-0.0012	-0.15	0.0036***	0.48***	0.0124***	1.09***
34	-0.0085	-0.16	0.0141***	1.17***	-0.0161***	-2.50***	0.0116***	3.00***	-0.0419***	-7.91***	0.0335***	2.74***	-0.0020	-0.25	0.0048***	0.82***	0.0088***	1.22***
35	-0.0250***	-0.90***	0.0143***	1.40***	-0.0175***	-3.08***	0.0111***	2.48***	-0.0422***	-7.58***	0.0337***	2.46***	-0.0017	-0.22	0.0048***	0.70***	0.0086***	1.25***
36	-0.0255***	-0.73***	0.0156***	1.14***	-0.0165***	-2.62***	0.0103***	2.17***	-0.0422***	-4.90***	0.0338***	2.68***	-0.0036***	-0.66***	0.0040***	0.63***	0.0086***	1.33***
37	0.0655	0.25	0.0147***	1.27***	-0.0141***	-1.27***	0.0145***	2.21***	-0.0400***	-3.09***	0.0389***	2.17***	0.0052	0.12	0.0019**	0.21*	0.0080***	0.80***
38	0.0341	0.23	0.0154***	1.29***	-0.0138***	-1.19***	0.0117***	1.81***	-0.0433***	-6.73***	0.0292***	2.74***	-0.0028***	-0.35**	0.0036***	0.42***	0.0112***	1.21***
39	0.1140	0.28	0.0130***	0.90***	-0.0128***	-1.04***	0.0131***	1.91***	-0.0401***	-3.94***	0.0374***	2.51***	0.0024	0.06	0.0033***	0.38***	0.0082***	0.68***
40	0.0097	0.05	0.0146***	0.97***	-0.0140***	-1.53***	0.0103***	1.52***	-0.0444***	-5.65***	0.0298***	2.64***	-0.0023	-0.29	0.0062***	0.77***	0.0103***	0.99***

Note: This table presents key distributional statistics for the excess return time series for each sub-period of all three periods, before accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2005 to June 2024. t-statistics provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. z-statistics shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. For each sub-period, we use CSI 300 return of each sub-period as benchmarks.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

Sub-Period Returns by Different Benchmarks with Trading costs

The inclusion of trading costs and the choice of benchmarks significantly impact the performance evaluation of pairs trading strategies. Tables 12A, 12B, and 12C present the monthly excess returns with trading costs over various sub-periods, each using different CSI 300 benchmarks: sub-period-specific benchmarks, the whole period benchmark, and period-specific benchmarks, respectively. This analysis explores the characteristics of each table, the differences arising from the use of different benchmarks, and the new insights gained, all within the context of pairs trading.

Table 12A utilizes the CSI 300 index returns specific to each sub-period as benchmarks. This approach provides a granular comparison, aligning the benchmark with the market conditions prevailing during each sub-period. The inclusion of trading costs generally led to a reduction in mean returns and Sharpe ratios across all portfolios compared to the results without trading costs in Table 11.

During the Pre-Financial Crisis Period, the CSI 300 index exhibited a strong positive mean return of 309 bps, indicating a bullish market environment. Most pairs trading portfolios continued to underperform, showing negative mean returns and Sharpe ratios. For instance, Portfolio 10's mean return decreased further to -693 bps with a Sharpe ratio of -0.65, both significant at the 1% level. The trading costs exacerbated the strategy's underperformance in bullish markets, where mean-reversion strategies like pairs trading are less effective due to persistent upward trends.

In the In-Financial Crisis Period, the CSI 300 index had a slight negative mean return of -53 bps. Despite the inclusion of trading costs, many pairs trading portfolios maintained significant positive mean returns and Sharpe ratios, although reduced compared to Table 11. Portfolio 33, for example, achieved a mean return of 112 bps with a Sharpe ratio of 1.24, significant at the 1% level. The heightened volatility during the crisis created ample arbitrage opportunities, allowing the pairs trading strategy to remain profitable even after accounting for trading costs.

During the Post-Financial Crisis Period, the CSI 300 index showed a positive mean return of 214 bps. The pairs trading portfolios generally experienced a decline in performance due to trading costs, with many portfolios showing significant negative mean returns and Sharpe ratios. Portfolio 1's mean return decreased to -163 bps with a Sharpe ratio of -1.71, significant at the 1% level. The reduced volatility and increased trading costs in a recovering market further limited arbitrage opportunities for the strategy.

In the Bullish Market Phases, the CSI 300 index had a robust mean return of 442 bps. The pairs trading portfolios continued to struggle, with trading costs amplifying negative returns. Portfolio 5 recorded a mean return of -482 bps and a Sharpe ratio of -5.75, significant at the 1% level. The persistence of upward trends in bullish markets reduces the frequency of mean reversion, diminishing the effectiveness of pairs trading and making trading costs more impactful.

Conversely, during Bearish Market Phases, the CSI 300 index had a significant negative mean return of -223 bps. The pairs trading portfolios performed well, although trading costs tempered the returns. Portfolio 31 achieved a mean return of 318 bps with a Sharpe ratio of 2.71, significant at the 1% level. The elevated volatility and increased mispricing during bearish markets continue to favor pairs trading, allowing the strategy to remain profitable even after accounting for trading costs.

In the COVID-19 Periods, the pairs trading portfolios demonstrated resilience. During the In-COVID Period, despite the CSI 300's slight negative mean return of -19 bps, portfolios like Portfolio 12 maintained a positive mean return of 20 bps, though the Sharpe ratio decreased to 0.18. Trading costs reduced profitability but did not eliminate it entirely, highlighting the strategy's robustness during volatile periods.

Table 12B employs the whole period CSI 300 benchmark, providing a consistent baseline for comparison across all sub-periods. This approach allows for evaluating the strategy's performance relative to the overall market trend over the entire period. A notable characteristic of Table 12B is the reduced statistical significance of the portfolios' mean returns and Sharpe ratios compared to Table 12A. The use of a single benchmark dilutes the impact of specific market conditions prevalent in each sub-period. For example, during the In-Financial Crisis Period, Portfolio 33's mean return is 14 bps with a Sharpe ratio of 0.15, lacking statistical significance. The consistent benchmark masks the heightened volatility and opportunities that were present during the crisis, resulting in a less pronounced outperformance of the pairs trading strategy.

Moreover, during the Pre-Financial Crisis Period, the CSI 300 benchmark mean return is 45 bps, significantly lower than the sub-period-specific benchmark of 309 bps in Table 12A. This results in portfolios appearing to perform relatively better in Table 12B. For instance, Portfolio 5 shows a positive mean return of 144 bps, significant at the 10% level, contrasting with the negative return in Table 12A. This discrepancy illustrates how the choice of benchmark can influence the perceived performance of the strategy.

The inclusion of trading costs in Table 12B further diminishes the strategy's profitability across most sub-periods. The portfolios generally exhibit lower mean returns and Sharpe ratios compared to the results without trading costs in Table 11. The uniform benchmark does not account for the varying market conditions, making it challenging to attribute performance differences to specific periods or events.

Table 12C utilizes the CSI 300 index returns for each of the three main periods—Financial Crisis, Bullish and Bearish Period, and COVID-19 Period—as benchmarks. This intermediate approach balances the granularity of Table 12A and the uniformity of Table 12B, aiming to capture the overarching market trends during significant economic events.

In this table, the impact of trading costs is evident but less pronounced than in Table 12A. During the Financial Crisis Period, the CSI 300 benchmark mean return is 1.62%, which is lower than the 3.09% in the Pre-Financial Crisis sub-period but higher than the -0.53% during the crisis in Table 12A. As a result, the pairs trading portfolios' performance appears relatively weaker compared to

Table 12A but stronger than in Table 12B. Portfolio 33's mean return is -1.03% with a Sharpe ratio of -1.14, significant at the 1% level, indicating underperformance relative to the period benchmark. During the Bullish and Bearish Period, the CSI 300 benchmark mean return is 0.05%, which is lower than the sub-period benchmarks. The pairs trading portfolios show mixed results, with some portfolios achieving positive mean returns but with lower statistical significance. Trading costs continue to erode profitability, and the strategy's effectiveness appears less robust compared to the results using sub-period benchmarks.

In the COVID-19 Period, the CSI 300 benchmark mean return is 0.04%, and the pairs trading portfolios exhibit marginal mean returns and Sharpe ratios, often lacking statistical significance. Trading costs, combined with the broad period benchmark, obscure the strategy's performance nuances during different phases of the pandemic.

The choice of benchmark significantly influences the evaluation of the pairs trading strategy's performance. Using sub-period benchmarks aligns the performance assessment with specific market conditions, highlighting the strategy's adaptability and effectiveness during periods of volatility and market stress. The inclusion of trading costs in this context provides a realistic measure of profitability, showing that while returns are reduced, the strategy remains viable during turbulent times.

In contrast, the whole period benchmark smooths out the fluctuations across different market conditions, potentially underestimating the strategy's performance during periods when it is most effective, such as during the Financial Crisis. It may also overstate performance during periods when the strategy is less effective, due to the lower benchmark returns compared to bullish sub-periods.

Using each period benchmark offers a middle ground but may still obscure the strategy's performance during significant market shifts within those periods. The impact of trading costs becomes more pronounced when the benchmark does not reflect the specific market conditions that the strategy exploits.

The analysis reveals that trading costs have a substantial impact on the profitability of pairs trading strategies, particularly during periods of low volatility or strong market trends. The strategy's effectiveness is significantly influenced by market conditions. During volatile periods, such as the Financial Crisis and bearish phases, pairs trading remains profitable after accounting for trading costs. The increased price divergences provide more opportunities for mean-reversion trades. However, during bullish markets, the strategy tends to underperform, and trading costs exacerbate the negative returns. Persistent upward trends reduce the frequency and magnitude of price reversions, making it difficult for the strategy to capitalize on mispricings.

The choice of benchmark significantly affects the interpretation of performance. Sub-period benchmarks provide a more accurate reflection of the strategy's relative performance in different market conditions, highlighting how the strategy adapts to changing environments. In contrast, whole-period benchmarks can obscure the strategy's strengths and weaknesses, making it challenging to assess performance accurately. Additionally, risk-adjusted performance, as measured by the Sharpe ratio, generally decreases after including trading costs. This highlights the importance of accounting for transaction expenses when evaluating risk-adjusted returns. Despite the negative impact of trading costs, the strategy often maintains positive Sharpe ratios during volatile periods, indicating effective risk management.

The inclusion of trading costs and the choice of benchmark significantly affect the evaluation of pairs trading performance. Using sub-period benchmarks provides a nuanced understanding of the strategy's effectiveness across different market conditions, revealing that pairs trading can remain profitable during volatile periods even after accounting for trading costs. Conversely, the strategy faces substantial challenges during bullish markets, where trading costs further reduce profitability. This emphasizes the importance of carefully considering both transaction costs and the chosen benchmark when evaluating the strategy.

These insights highlight the necessity of considering transaction costs and market conditions in the implementation of pairs trading strategies. Adaptability, careful pair selection, and effective cost management are crucial for maintaining profitability. The analysis underscores the strategy's potential as a defensive tool during market downturns and its limitations during strong upward trends, offering valuable guidance for practitioners and researchers in the field of quantitative finance.

TABLE 12A. Monthly Excess Returns with Trading Costs of All Three Period Results with Each Sub-Period CSI 300 Benchmarks.

	Pre- Fin.C.		In- Fin.C.		Post- Fin.C.		Pre-B.N.B.		In-Bullish		In-Bearish		Pre-Cov.		In-Cov.		Post-Cov.	
Portfolio	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**	**Mean**	**Sharpe**
CSI 300	0.0309	-	-0.0053	-	0.0214	-	-0.0087	-	0.0442	-	-0.0223	-	0.0057	-	-0.0019	-	-0.0064	-
1	-0.0525***	-0.67***	0.0145***	0.89***	-0.0163***	-1.71***	0.0101***	1.37***	-0.0457***	-5.75***	0.0301***	2.71***	-0.0031	-0.12	0.0002	0.03	0.0038	0.35
2	-0.0475**	-0.55**	0.0111***	0.71***	-0.0145***	-1.55***	0.0098***	1.50***	-0.0464***	-5.13***	0.0308***	2.18***	-0.0039***	-0.57***	0.0032**	0.31*	0.0051***	0.50**
3	-0.0381***	-0.41***	0.0127***	0.74***	-0.0143***	-1.41***	0.0103***	1.77***	-0.0467***	-4.65***	0.0331***	2.49***	-0.0003	-0.01	0.0030***	0.38**	0.0064***	0.78**
4	-0.0364***	-0.39***	0.0127***	0.85***	-0.0169***	-2.04***	0.0096***	1.65***	-0.0465***	-5.33***	0.0313***	3.20***	-0.0041***	-0.68***	0.0021	0.22	0.0080***	0.70***
5	-0.012	-0.18	0.0131***	1.02***	-0.0171***	-1.97***	0.0093***	1.78***	-0.0482***	-5.36***	0.0317***	2.34***	-0.0032**	-0.47**	0.0026**	0.24	0.0072***	0.80***
6	-0.0245***	-0.37***	0.0099***	0.40***	-0.0237***	-2.83***	0.0067**	0.47**	-0.0488***	-3.02***	0.0320***	1.52***	-0.0091***	-0.47***	-0.0001	0.00	-0.0042	-0.15
7	-0.0387**	-0.33*	0.0118***	0.54***	-0.0137***	-0.97***	0.0099***	1.46***	-0.0451***	-4.87***	0.0336***	2.51***	-0.0033*	-0.26*	0.0045***	0.48***	0.0053**	0.39
8	0.0194	0.17	0.0063	0.25	-0.0183***	-2.18***	0.0092***	1.32***	-0.0443***	-4.40***	0.0315***	2.22***	-0.0035***	-0.46***	0.0031**	0.32**	0.0068***	0.84***
9	0.0225	0.23	0.0160***	0.80***	-0.0143***	-1.45***	0.0096***	1.72***	-0.0439***	-3.60***	0.0323***	2.36***	-0.0044***	-0.60***	0.0037***	0.36***	0.0053*	0.44
10	-0.0693**	-0.65***	0.0124***	0.60***	-0.0136***	-1.13***	0.0103***	1.44***	-0.0457***	-4.36***	0.0319***	2.33***	-0.0006	-0.03	0.0037***	0.49***	0.0063**	0.50*
11	0.0109	0.09	-0.0068	-0.07	-0.0169***	-1.61***	0.0089***	1.62***	-0.0432***	-3.43***	0.0316***	2.12***	-0.0047***	-0.58***	0.0028*	0.34*	0.0043	0.29
12	0.0042	0.05	0.0124***	0.86***	-0.0162***	-1.46***	0.0101***	1.76***	-0.0469***	-4.36***	0.0310***	2.54***	-0.0017	-0.08	0.0020	0.18	0.0061***	0.99***
13	-0.0403*	-0.51**	0.0148***	1.09***	-0.0125***	-1.39***	0.0092***	1.37***	-0.0458***	-5.22***	0.0369***	2.26***	-0.0057**	-0.29**	0.0043***	0.46***	0.0025	0.14
14	-0.0245**	-0.34**	0.0081	0.27	-0.0159***	-1.42***	0.0088***	1.32***	-0.0446***	-4.32***	0.0298***	2.74***	-0.0021*	-0.25	0.0028	0.26	0.0056**	0.59**
15	0.0117	0.14	0.0152***	0.70***	-0.0138***	-1.32***	0.0108***	1.70***	-0.0440***	-3.16***	0.0317***	3.26***	-0.0039***	-0.62***	0.0024	0.24	0.0036	0.30
16	-0.0022	-0.03	0.0097***	0.45**	-0.0152***	-1.95***	0.0094***	2.04***	-0.0459***	-5.79***	0.0320***	2.83***	-0.0032**	-0.42**	0.0025**	0.32**	0.0055***	0.67**
17	0.0079	0.12	0.0126***	0.48***	-0.0170***	-2.15***	0.0095***	2.00***	-0.0447***	-4.65***	0.0322***	2.75***	-0.0031*	-0.32*	0.0025	0.30**	0.0062***	0.78***
18	0.0094	0.11	0.0153***	1.06***	-0.0163***	-2.11***	0.0086***	1.67***	-0.0461***	-5.47***	0.0328***	2.56***	-0.0040***	-0.68***	0.0033**	0.36**	0.0063***	0.91***
19	-0.0063	-0.04	0.0095***	0.80***	-0.0183***	-2.34***	0.0106***	2.06***	-0.0456***	-6.82***	0.0288***	3.15***	0.0021	0.05	0.0017	0.25	0.0073***	0.89***
20	0.0382	0.27	0.0092***	0.84***	-0.0172***	-2.10***	0.0093***	1.56***	-0.0449***	-9.34***	0.0304***	2.89***	-0.0065***	-0.93***	0.0019**	0.25	0.0095***	1.22***
21	0.0533	0.25	0.0089***	0.90***	-0.0194***	-2.21***	0.0098***	1.63***	-0.0447***	-5.34***	0.0277***	3.60***	-0.0047***	-0.69***	0.0018***	0.23*	0.0071***	1.04***
22	-0.0076	-0.1	0.0118***	1.28***	-0.0178***	-2.39***	0.0108***	1.89***	-0.0456***	-6.53***	0.0304***	2.82***	-0.001	-0.05	0.0029***	0.43***	0.0071***	1.04***
23	-0.0089	-0.1	0.0104***	0.82***	-0.0183***	-2.04***	0.0099***	2.29***	-0.0456***	-8.69***	0.0306***	2.96***	-0.0050***	-0.83***	0.0018*	0.24	0.0071***	0.74***
24	-0.0241***	-0.69***	0.0048**	0.25*	-0.0252***	-2.54***	0.0079**	0.43**	-0.0421***	-4.83***	0.0270***	1.67***	-0.0089***	-0.79***	0.0020	0.12	0.0054***	0.99***
25	0.0325	0.24	0.0103***	0.92***	-0.0144***	-1.35***	0.0109***	1.97***	-0.0448***	-6.78***	0.0324***	2.33***	0.0021	0.05	0.0003	0.03	0.0083***	0.90***
26	-0.0091	-0.21	0.0098***	0.97***	-0.0190***	-1.92***	0.0087***	1.61***	-0.0416***	-7.32***	0.0324***	2.65***	-0.0042***	-0.73***	0.0034***	0.43***	0.0083***	0.98***
27	-0.0179	-0.34	0.0073***	0.43***	-0.0181***	-2.24***	0.0095***	1.46***	-0.0477***	-5.45***	0.0335***	2.87***	-0.001	-0.05	0.0029***	0.45***	0.0084***	0.87***
28	0.0346	0.2	0.0093***	0.78***	-0.0153***	-1.58***	0.0098***	1.84***	-0.0450***	-6.87***	0.0316***	2.71***	0.0019	0.04	0.0002	0.03	0.0084***	0.87***
29	-0.0323***	-1.05***	0.0090***	0.53***	-0.0178***	-2.36***	0.0094***	1.25***	-0.0472***	-5.15***	0.0350***	2.94***	-0.0015	-0.08	0.0020***	0.36***	0.0083***	1.09***
30	-0.0154	-0.43*	0.0119***	1.02***	-0.0171***	-2.31***	0.0080***	1.44***	-0.0433***	-6.42***	0.0325***	2.27***	-0.0052***	-0.91***	0.0034**	0.41**	0.0081***	0.80***
31	0.0349	0.17	0.0117***	0.94***	-0.0159***	-2.03***	0.0089***	1.41***	-0.0450***	-5.91***	0.0318***	2.71***	-0.0003	-0.01	0.0020*	0.24*	0.0064***	0.78***
32	-0.0149	-0.13	0.0087***	0.63***	-0.0204***	-1.63***	0.0090***	1.56***	-0.0434***	-5.07***	0.0331***	2.63***	-0.0052***	-0.74***	0.0030***	0.39***	0.0081***	0.84***
33	-0.0106	-0.19	0.0112***	1.24***	-0.0205***	-2.09***	0.0099***	1.46***	-0.0478***	-6.30***	0.0338***	2.52***	-0.0032***	-0.39***	0.0016	0.22	0.0105***	0.99***
34	-0.0109	-0.21	0.0116***	0.97***	-0.0183***	-2.80***	0.0099***	2.53***	-0.0443***	-8.03***	0.0316***	3.00***	-0.0040**	-0.50**	0.0027***	0.47***	0.0070***	1.00***
35	-0.0268***	-0.97***	0.0121***	1.22***	-0.0193***	-3.37***	0.0097***	2.15***	-0.0443***	-8.52***	0.0320***	2.66***	-0.0034**	-0.45**	0.0028***	0.42***	0.0068***	1.03***
36	-0.0272***	-0.79***	0.0135***	1.02***	-0.0180***	-2.89***	0.0090***	1.90***	-0.0442***	-5.31***	0.0322***	2.92***	-0.0053***	-0.98***	0.0021***	0.34***	0.0069***	1.13***
37	-0.0074	-0.04	0.0105***	0.77***	-0.0169***	-1.54***	0.0123***	1.92***	-0.0431***	-3.31***	0.0362***	2.31***	0.0028	0.06	-0.0004	-0.04	0.0061***	0.63***
38	0.0312	0.21	0.0127***	1.07***	-0.0165***	-1.45***	0.0099***	1.59***	-0.0454***	-6.59***	0.0273***	2.86***	-0.0051***	-0.68***	0.0014	0.17	0.0089***	0.99***
39	0.1105	0.27	0.0099***	0.71***	-0.0157***	-1.29***	0.0109***	1.63***	-0.0432***	-4.22***	0.0349***	2.72***	0.0002	0.01	0.0011	0.13	0.0065***	0.55***
40	0.0070	0.04	0.0120***	0.80***	-0.0166***	-1.86***	0.0085***	1.27***	-0.0463***	-5.69***	0.0279***	2.74***	-0.0045***	-0.61***	0.0039***	0.49***	0.0082***	0.78***

Note: This table presents key distributional statistics for the excess return time series for each sub-period of all three periods with each sub-period CSI 300 benchmark, after accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2005 to June 2024. t-statistics provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. z-statistics shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. For each sub-period, we use CSI 300 return of each sub-period as benchmarks.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

TABLE 12B. Monthly Excess Returns with Trading Costs of All Three Period Results with Whole PeriodCSI 300 Benchmarks.

	Pre- Fin.C.		In- Fin.C.		Post- Fin.C.		Pre-B.N.B.		In-Bullish		In-Bearish		Pre-Cov.		In-Cov.		Post-Cov.	
Portfolio	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe
CSI 300									0.0045									
1	-0.0261	-0.33	0.0047***	0.29*	0.0006	0.06	-0.0031***	-0.42***	-0.0060***	-0.76***	0.0033	0.29	-0.0019	-0.08	-0.0062***	-0.82***	-0.0071***	-0.67**
2	-0.0211	-0.24	0.0013	0.08	0.0024	0.26	-0.0034***	-0.52***	-0.0067***	-0.74***	0.0040	0.28	-0.0027*	-0.40*	-0.0032**	-0.32*	-0.0058***	-0.57**
3	-0.0117	-0.13	0.0029	0.17	0.0026	0.26	-0.0029***	-0.51***	-0.0070***	-0.70***	0.0063	0.47	0.0009	0.04	-0.0034***	-0.43***	-0.0045**	-0.54*
4	-0.0100	-0.11	0.0029*	0.19	0.0000	0.00	-0.0036***	-0.62***	-0.0068***	-0.78***	0.0045	0.46	-0.0029***	-0.48***	-0.0043***	-0.45***	-0.0029	-0.26
5	0.0144*	0.21	0.0033	0.26	-0.0002	-0.03	-0.0039***	-0.74***	-0.0085***	-0.95***	0.0049	0.36	-0.0020	-0.30	-0.0038***	-0.36**	-0.0037***	-0.40
6	0.0019	0.03	0.0001	0.00	-0.0068**	-0.81***	-0.0065**	-0.46**	-0.0091**	-0.57**	0.0052	0.25	-0.0079**	-0.41**	-0.0065	-0.24	-0.0151	-0.53
7	-0.0123	-0.10	0.0020	0.09	0.0032	0.22	-0.0033***	-0.48**	-0.0054***	-0.59***	0.0068	0.51	-0.0021	-0.17	-0.0019*	-0.20	-0.0056**	-0.40
8	0.0458	0.40	-0.0035	-0.14	-0.0014*	-0.16*	-0.0040***	-0.58***	-0.0046***	-0.45***	0.0047	0.33	-0.0023*	-0.30*	-0.0033**	-0.34**	-0.0041***	-0.51**
9	0.0489***	0.51**	0.0062*	0.31*	0.0026	0.26	-0.0036***	-0.63***	-0.0042**	-0.34	0.0055	0.4	-0.0032**	-0.43**	-0.0027**	-0.27**	-0.0056**	-0.46
10	-0.0429	-0.40*	0.0026	0.13	0.0033	0.27	-0.0029**	-0.40**	-0.0060***	-0.57***	0.0051	0.37	0.0006	0.02	-0.0027***	-0.36**	-0.0046*	-0.37
11	0.0373	0.32	-0.0166	-0.18	0.0000	0.00	-0.0043***	-0.79***	-0.0035	-0.28	0.0048	0.32	-0.0035**	-0.43**	-0.0036**	-0.46**	-0.0066**	-0.44
12	0.0306**	0.40*	0.0026*	0.18	0.0007	0.06	-0.0031***	-0.54***	-0.0072***	-0.67***	0.0042	0.35	-0.0005	-0.02	-0.0044***	-0.40***	-0.0048***	-0.78***
13	-0.0139	-0.18	0.0050***	0.37**	0.0044***	0.49**	-0.0040***	-0.60***	-0.0061***	-0.70***	0.0101**	0.62**	-0.0045*	-0.23*	-0.0021*	-0.22*	-0.0084**	-0.46*
14	0.0019	0.03	-0.0017	-0.06	0.0010	0.09	-0.0044***	-0.66***	-0.0049**	-0.47**	0.0030	0.27	-0.0009	-0.11	-0.0036**	-0.33*	-0.0053**	-0.55*
15	0.0381*	0.47**	0.0054	0.25	0.0031	0.30	-0.0024*	-0.37*	-0.0043**	-0.31	0.0049	0.50	-0.0027**	-0.43**	-0.0040**	-0.41**	-0.0073***	-0.59**
16	0.0242	0.35	-0.0001	0.00	0.0017	0.22	-0.0038***	-0.83***	-0.0062***	-0.79***	0.0052	0.46	-0.0020	-0.27	-0.0039***	-0.49***	-0.0054***	-0.66**
17	0.0343**	0.54**	0.0028	0.11	-0.0001	-0.01	-0.0037***	-0.78***	-0.0050***	-0.52**	0.0054	0.46	-0.0019	-0.20	-0.0039***	-0.45***	-0.0047***	-0.60**
18	0.0358	0.41	0.0055**	0.38*	0.0006	0.07	-0.0046***	-0.90***	-0.0064***	-0.76***	0.006	0.47	-0.0028**	-0.48**	-0.0031**	-0.35**	-0.0046***	-0.67**
19	0.0201	0.12	-0.0003	-0.03	-0.0014	-0.18	-0.0026***	-0.51***	-0.0059***	-0.88***	0.0020	0.22	0.0033	0.08	-0.0047***	-0.69***	-0.0036***	-0.44*
20	0.0646**	0.46*	-0.0006	-0.06	-0.0003	-0.03	-0.0039***	-0.66***	-0.0052***	-1.08***	0.0036	0.34	-0.0053***	-0.76***	-0.0045***	-0.58***	-0.0014	-0.17
21	0.0797*	0.37	-0.0009	-0.09	-0.0025	-0.29	-0.0034***	-0.57***	-0.0050***	-0.59***	0.0009	0.12	-0.0035***	-0.51***	-0.0046***	-0.58***	-0.0038**	-0.55*
22	0.0188	0.25	0.0020	0.22	-0.0009	-0.12	-0.0024***	-0.42***	-0.0059***	-0.85***	0.0036	0.33	0.0002	0.01	-0.0035***	-0.52***	-0.0038***	-0.56**
23	0.0175	0.20	0.0006	0.05	-0.0014	-0.15	-0.0033***	-0.77***	-0.0059***	-1.13***	0.0038	0.37	-0.0038***	-0.63***	-0.0046***	-0.63***	-0.0038**	-0.39
24	0.0023	0.07	-0.0050**	-0.26**	-0.0083***	-0.84***	-0.0053	-0.29	-0.0024**	-0.27**	0.0002	0.01	-0.0077***	-0.69***	-0.0044***	-0.26**	-0.0055***	-0.99***
25	0.0589	0.43*	0.0005	0.04	0.0025	0.24	-0.0023***	-0.42***	-0.0051***	-0.77***	0.0056	0.40*	0.0033	0.08	-0.0061***	-0.74***	-0.0026	-0.28
26	0.0173**	0.40*	0.0000	0.00	-0.0021	-0.21	-0.0045***	-0.83***	-0.0019	-0.33	0.0056	0.46	-0.0030***	-0.52***	-0.0030***	-0.39***	-0.0026*	-0.30
27	0.0085	0.16	-0.0025	-0.15	-0.0012	-0.14	-0.0037***	-0.57***	-0.0080***	-0.92***	0.0067	0.57	0.0002	0.01	-0.0035***	-0.56***	-0.0025	-0.26
28	0.0610	0.34	-0.0005	-0.04	0.0016	0.17	-0.0034***	-0.65***	-0.0053***	-0.81***	0.0048	0.41	0.0031	0.07	-0.0062***	-0.76***	-0.0025**	-0.26
29	-0.0059	-0.19	-0.0008	-0.05	-0.0009	-0.12	-0.0038***	-0.50***	-0.0075***	-0.82***	0.0082	0.69*	-0.0003	-0.02	-0.0044***	-0.81***	-0.0026	-0.34
30	0.0110	0.30	0.0021	0.18	-0.0002	-0.03	-0.0052***	-0.93***	-0.0036***	-0.53***	0.0057	0.40	-0.0040***	-0.70***	-0.0030**	-0.36**	-0.0028	-0.28
31	0.0613	0.30	0.0019	0.16	0.0010	0.12	-0.0043***	-0.67***	-0.0053***	-0.70***	0.0050	0.42	0.0009	0.04	-0.0044***	-0.52***	-0.0045***	-0.56**
32	0.0115	0.10	-0.0011	-0.08	-0.0035	-0.28	-0.0042***	-0.72***	-0.0037***	-0.44***	0.0063	0.50	-0.0040***	-0.57***	-0.0034***	-0.44***	-0.0028	-0.29
33	0.0158	0.29	0.0014	0.15	-0.0036**	-0.37	-0.0033***	-0.49***	-0.0081***	-1.06***	0.007	0.52	-0.0020**	-0.24**	-0.0048***	-0.63***	-0.0004	-0.04
34	0.0155	0.30	0.0018	0.15	-0.0014	-0.22	-0.0033***	-0.85***	-0.0046***	-0.83***	0.0048	0.45	-0.0028*	-0.35*	-0.0037***	-0.64***	-0.0039***	-0.56**
35	-0.0004	-0.02	0.0023	0.23	-0.0024	-0.42*	-0.0035***	-0.77***	-0.0046***	-0.89***	0.0052	0.44	-0.0022	-0.29	-0.0036***	-0.55***	-0.0041**	-0.61**
36	-0.0008	-0.02	0.0037	0.28	-0.0011	-0.18	-0.0042***	-0.89***	-0.0045***	-0.54**	0.0054	0.49	-0.0041***	-0.76***	-0.0043***	-0.70***	-0.0040***	-0.65***
37	0.0190	0.11	0.0007	0.05	0.0000	0.00	-0.0009	-0.14	-0.0034*	-0.26	0.0094*	0.60**	0.0040	0.09	-0.0068***	-0.77***	-0.0048***	-0.50**
38	0.0576*	0.39*	0.0029	0.25	0.0004	0.04	-0.0033***	-0.53***	-0.0057***	-0.83***	0.0005	0.05	-0.0039***	-0.52***	-0.0050***	-0.60***	-0.0020**	-0.22
39	0.1369	0.33	0.0001	0.01	0.0012	0.10	-0.0023***	-0.34**	-0.0035***	-0.34**	0.0081*	0.63**	0.0014	0.03	-0.0053***	-0.60***	-0.0044*	-0.37
40	0.0334	0.17	0.0022	0.14	0.0003	0.03	-0.0047***	-0.71***	-0.0066***	-0.81***	0.0011	0.10	-0.0033***	-0.45***	-0.0025**	-0.32**	-0.0027*	-0.26

Note: This table presents key distributional statistics for the excess return time series for each sub-period of all three periods with whole period CSI 300 benchmark, after accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2005 to June 2024. t-statistics provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. z-statistics shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. For each sub-period, we use CSI 300 return of each sub-period as benchmarks.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

TABLE 12C. Monthly Excess Returns with Trading Costs of All Three Period Results with Each Period CSI 300 Benchmarks.

	Pre- Fin.C.		In- Fin.C.		Post- Fin.C.		Pre-B.N.B.		In-Bullish		In-Bearish		Pre-Cov.		In-Cov.		Post-Cov.	
Portfolio	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe
CSI 300			0.0162						0.0005						0.0004			
1	-0.0378**	-0.48**	-0.0070***	-0.43**	-0.0111***	-1.16***	0.0009	0.12	-0.0020**	-0.26*	0.0073*	0.66**	0.0022	0.08	-0.0021***	-0.28**	-0.0030	-0.28
2	-0.0328	-0.38*	-0.0104***	-0.67***	-0.0093***	-1.00***	0.0006	0.09	-0.0027***	-0.30**	0.0080**	0.57**	0.0014	0.20	0.0009	0.09	-0.0017	-0.17
3	-0.0234*	-0.25	-0.0088***	-0.51***	-0.0091***	-0.90***	0.0011	0.18	-0.0030**	-0.30*	0.0103***	0.78***	0.0050	0.22	0.0007	0.09	-0.0004	-0.04
4	-0.0217*	-0.23	-0.0088***	-0.58***	-0.0117***	-1.41***	0.0004	0.06	-0.0028***	-0.32**	0.0085***	0.87***	0.0012	0.20	-0.0002	-0.02	0.0012	0.10
5	0.0027	0.04	-0.0084***	-0.66***	-0.0119***	-1.37***	0.0001	0.02	-0.0045***	-0.50***	0.0089**	0.66**	0.0021	0.30	0.0003	0.03	0.0004	0.05
6	-0.0098	-0.15	-0.0116***	-0.47**	-0.0185***	-2.21***	-0.0025	-0.18	-0.0051	-0.32	0.0092**	0.44*	-0.0038	-0.20	-0.0024	-0.09	-0.0110	-0.39
7	-0.0240	-0.20	-0.0097***	-0.45**	-0.0085**	-0.60***	0.0007	0.11	-0.0014	-0.15	0.0108**	0.81**	0.0020	0.15	0.0022**	0.24*	-0.0015	-0.11
8	0.0341	0.30	-0.0152***	-0.60***	-0.0131***	-1.56***	0.0000	0. 00	-0.0006	-0.06	0.0087*	0.61*	0.0018	0.24	0.0008	0.08	0.0000	0.00
9	0.0372**	0.39*	-0.0055	-0.27	-0.0091***	-0.92***	0.0004	0.08	-0.0002	-0.01	0.0095*	0.69*	0.0009	0.13	0.0014	0.13	-0.0015	-0.12
10	-0.0546**	-0.51**	-0.0091***	-0.44**	-0.0084***	-0.70***	0.0011	0.16	-0.0020	-0.19	0.0091**	0.66**	0.0047	0.18	0.0014	0.19	-0.0005	-0.04
11	0.0256	0.22	-0.0283	-0.30	-0.0117***	-1.12***	-0.0003	-0.06	0.0005	0.04	0.0088	0.59*	0.0006	0.07	0.0005	0.06	-0.0025	-0.17
12	0.0189	0.24	-0.0091***	-0.63***	-0.0110***	-0.99***	0.0009	0.16	-0.0032***	-0.3	0.0082*	0.67**	0.0036	0.16	-0.0003	-0.03	-0.0007	-0.12
13	-0.0256	-0.32	-0.0067***	-0.49***	-0.0073***	-0.81***	0.0000	0. 00	-0.0021	-0.24	0.0141***	0.86***	-0.0004	-0.02	0.0020*	0.21	-0.0043	-0.23
14	-0.0098	-0.14	-0.0134**	-0.44*	-0.0107***	-0.95***	-0.0004	-0.06	-0.0009	-0.08	0.0070*	0.64**	0.0032***	0.38**	0.0005	0.05	-0.0012	-0.12
15	0.0264	0.33	-0.0063*	-0.29	-0.0086***	-0.82***	0.0016	0.26	-0.0003	-0.02	0.0089***	0.91***	0.0014	0.22	0.0001	0.01	-0.0032	-0.26
16	0.0125	0.18	-0.0118***	-0.54***	-0.0100***	-1.28***	0.0002	0.04	-0.0022*	-0.28	0.0092**	0.81**	0.0021	0.27	0.0002	0.03	-0.0013	-0.16
17	0.0226	0.35	-0.0089***	-0.34**	-0.0118***	-1.49***	0.0003	0.06	-0.0010	-0.11	0.0094**	0.80**	0.0022	0.23	0.0002	0.03	-0.0006	-0.08
18	0.0241	0.27	-0.0062**	-0.43**	-0.0111***	-1.44***	-0.0006	-0.12	-0.0024*	-0.29	0.0100**	0.78**	0.0013	0.21	0.0010	0.11	-0.0005	-0.08
19	0.0084	0.05	-0.0120***	-1.02***	-0.0131***	-1.68***	0.0014	0.27	-0.0019***	-0.28***	0.0060**	0.66**	0.0074	0.18	-0.0006	-0.09	0.0005	0.06
20	0.0529*	0.38	-0.0123***	-1.13***	-0.0120***	-1.47***	0.0001	0.01	-0.0012*	-0.25	0.0076***	0.72***	-0.0012	-0.17	-0.0004	-0.05	0.0027**	0.35
21	0.0680	0.32	-0.0126***	-1.26***	-0.0142***	-1.62***	0.0006	0.10	-0.0010	-0.11	0.0049*	0.63**	0.0006	0.09	-0.0005	-0.06	0.0003	0.05
22	0.0071	0.09	-0.0097***	-1.05***	-0.0126***	-1.69***	0.0016*	0.28*	-0.0019**	-0.27*	0.0076*	0.70**	0.0043	0.19	0.0006	0.09	0.0003	0.04
23	0.0058	0.07	-0.0111***	-0.87***	-0.0131***	-1.46***	0.0007	0.15	-0.0019***	-0.36**	0.0078***	0.75***	0.0003	0.05	-0.0005	-0.07	0.0003	0.03
24	-0.0094**	-0.27*	-0.0167***	-0.86***	-0.0200***	-2.02***	-0.0013	-0.07	0.0016	0.19	0.0042	0.26	-0.0036	-0.32	-0.0003	-0.02	-0.0014	-0.25
25	0.0472	0.35	-0.0112***	-1.01***	-0.0092***	-0.86***	0.0017**	0.30**	-0.0011*	-0.16	0.0096***	0.69***	0.0074	0.17	-0.0020**	-0.24*	0.0015	0.17
26	0.0056	0.13	-0.0117***	-1.17***	-0.0138***	-1.40***	-0.0005	-0.09	0.0021*	0.37	0.0096***	0.79***	0.0011	0.18	0.0011	0.13	0.0015	0.18
27	-0.0032	-0.06	-0.0142***	-0.84***	-0.0129***	-1.59***	0.0003	0.05	-0.0040***	-0.46**	0.0107**	0.91***	0.0043	0.22	0.0006	0.09	0.0016	0.17
28	0.0493	0.28	-0.0122***	-1.03***	-0.0101***	-1.04***	0.0006	0.11	-0.0013**	-0.20*	0.0088***	0.76***	0.0072	0.17	-0.0021**	-0.26*	0.0016	0.17
29	-0.0176***	-0.57***	-0.0125***	-0.73***	-0.0126***	-1.67***	0.0002	0.03	-0.0035**	-0.38**	0.0122**	1.03***	0.0038	0.20	-0.0003	-0.06	0.0015	0.19
30	-0.0007	-0.02	-0.0096***	-0.83***	-0.0119***	-1.61***	-0.0012	-0.21	0.0004	0.06	0.0097**	0.68**	0.0001	0.01	0.0011	0.13	0.0013	0.13
31	0.0496	0.24	-0.0098***	-0.78***	-0.0107***	-1.36***	-0.0003	-0.04	-0.0013	-0.17	0.0090**	0.77***	0.0050	0.21	-0.0003	-0.03	-0.0004	-0.05
32	-0.0002	0.00	-0.0128***	-0.93***	-0.0152***	-1.21***	-0.0002	-0.03	0.0003	0.03	0.0103**	0.82**	0.0001	0.02	0.0007	0.09	0.0013	0.13
33	0.0041	0.07	-0.0103***	-1.14***	-0.0153***	-1.56***	0.0007	0.10	-0.0041***	-0.54***	0.0110**	0.82**	0.0021**	0.26**	-0.0007	-0.09	0.0037	0.35
34	0.0038	0.07	-0.0099***	-0.83***	-0.0131***	-2.01***	0.0007	0.17	-0.0006	-0.11	0.0088**	0.83**	0.0013	0.16	0.0004	0.07	0.0002	0.03
35	-0.0121	-0.44*	-0.0094***	-0.94***	-0.0141***	-2.46***	0.0005	0.11	-0.0006	-0.12	0.0092*	0.77**	0.0019	0.24	0.0005	0.07	0.0000	0.01
36	-0.0125*	-0.36	-0.0080***	-0.60***	-0.0128***	-2.06***	-0.0002	-0.05	-0.0005	-0.06	0.0094**	0.85**	0.0000	0.01	-0.0002	-0.03	0.0001	0.02
37	0.0073	0.04	-0.0110***	-0.80***	-0.0117***	-1.07***	0.0031***	0.49***	0.0006	0.05	0.0134**	0.86***	0.0081	0.18	-0.0027***	-0.30**	-0.0007	-0.07
38	0.0459	0.31	-0.0088***	-0.74***	-0.0113***	-0.99***	0.0007	0.11	-0.0017***	-0.25*	0.0045	0.47*	0.0002	0.03	-0.0009	-0.11	0.0021**	0.23
39	0.1252	0.31	-0.0116***	-0.82***	-0.0105***	-0.86***	0.0017**	0.25*	0.0005	0.05	0.0121***	0.94***	0.0055	0.13	-0.0012	-0.13	-0.0003	-0.02
40	0.0217	0.11	-0.0095***	-0.64***	-0.0114***	-1.28***	-0.0007	-0.11	-0.0026***	-0.31***	0.0051*	0.50**	0.0008	0.11	0.0016	0.20	0.0014	0.13

Note: This table presents key distributional statistics for the excess return time series for each sub-period of all three periods with each period CSI 300 benchmark, after accounting for trading costs, generated by 40 pairs portfolios as outlined in Table 3, spanning from January 2005 to June 2024. t-statistics provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. z-statistics shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. For each sub-period, we use CSI 300 return of each sub-period as benchmarks.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

Figure 3 presents the cumulative daily returns for three selected pairs trading portfolios—Portfolios 6, 14, and 38—alongside the CSI 300 index, covering the In-COVID period from January 2020 to December 2022 after trading costs. The cumulative returns of the CSI 300 demonstrate significant volatility, peaking around early 2021 before experiencing a pronounced decline throughout 2022.

Portfolio 6 showed a marked downward trend, particularly after mid-2021, leading to substantial cumulative losses by the end of the period. In contrast, Portfolios 14 and 38 exhibited much more stable performance. Portfolio 14 maintained relatively low volatility, with its cumulative returns fluctuating around neutral, indicating steadier performance over time. Similarly, Portfolio 38 remained close to zero throughout the period, with minimal deviations, suggesting that it was largely unaffected by the market swings that impacted the CSI 300 and Portfolio 6.

These results highlight the stability of Portfolios 14 and 38 compared to both Portfolio 6 and the CSI 300. While the broader market and Portfolio 6 were subjected to significant volatility, particularly during the sharp fluctuations in 2021, Portfolios 14 and 38 demonstrated resilience and steady returns, making them more robust in the face of market turbulence. This stability underscores the varying effectiveness and risk profiles of different pairs trading strategies under different market conditions.

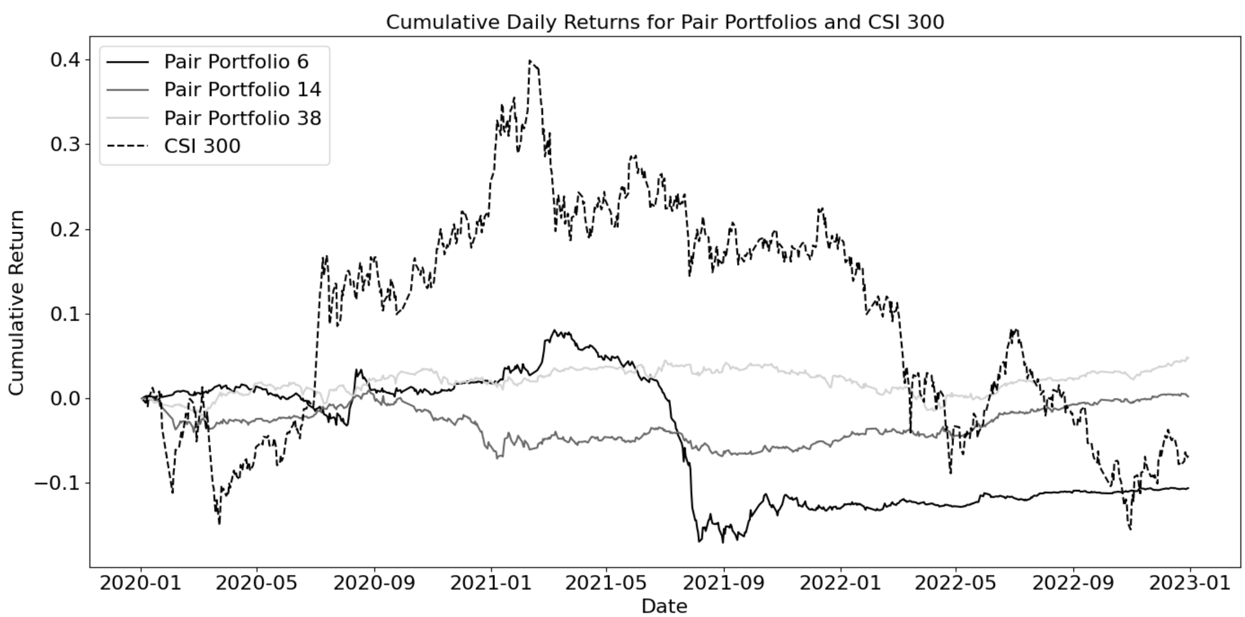

Figure 3. Daily Cumulative Return on Pair Portfolios. This figure presents the daily cumulative returns derived from the time series of daily returns for three pairs trading portfolios: Portfolios 6, 14, and 38, along with the CSI 300 Index. The analysis covers the period from January 2020 to December 2022, corresponding to the **In-COVID** period, and accounts for trading costs. The selected portfolios are part of a pairs trading strategy, in which stocks are matched and traded based on historical price relationships.

5.2 Alternative Returns

In this section, we present an alternative analysis of the monthly excess returns, incorporating trading costs across three distinct periods: the Financial Crisis, Bullish and Bearish Markets, and the COVID-19 pandemic. The results are categorized by vigintiles to explore variations in performance across portfolio groups. Table 13 provides a detailed overview of monthly excess returns, standard deviations, and Sharpe ratios for all portfolios during each of these periods. The trading costs have been considered to reflect a more practical assessment of portfolio returns.

Additionally, we introduce a secondary method in Table 14, which incorporates a one-day waiting period to evaluate the impact of delayed execution on portfolio performance. This adjustment allows for an in-depth comparison of how immediate versus slightly deferred trades affect returns, particularly during volatile market periods. Both tables offer a comprehensive insight into the performance differentials under varying market conditions, providing further validation and expansion of the results obtained in the previous section.

5.2.1 Returns with Different Vigintiles

Table 13 presents a comprehensive analysis of monthly excess returns, standard deviations, and Sharpe ratios for portfolios grouped into vigintiles during three distinct periods: the Financial Crisis, Bullish and Bearish Markets, and the COVID-19 pandemic. The portfolios are divided into two main categories: Portfolios 1–20 represent non-industry matching pairs, while Portfolios 21–40 consist of industry matching pairs. Each category is further segmented into top 5% increments (vigintiles), ranked by the SSD from smallest to largest. The objective is to compare the differences in pairs trading performance across various SSD-based vigintiles.

During the Financial Crisis, both non-industry matched and industry matched portfolios exhibited significant negative performance across all vigintiles. For the non-industry matched portfolios, substantial negative mean returns and Sharpe ratios were observed. For instance, Portfolio 4 reported a mean return of -175 bps with a Sharpe ratio of -0.41, significant at the 1% level. Similarly, Portfolio 7 recorded a mean return of -168 bps and a Sharpe ratio of -0.67, also significant at the 1% level. These pronounced negative returns suggest that during periods of extreme market volatility and downturns, pairs trading strategies, particularly those without industry matching, struggled to generate positive returns. The breakdown of historical price relationships between assets likely contributed to the inefficacy of mean-reversion strategies during this tumultuous period.

The industry matched portfolios during the Financial Crisis fared no better. Portfolio 22 exhibited a mean return of -151 bps with a Sharpe ratio of -0.76, significant at the 1% level. Portfolio 29 showed a mean return of -163 bps and a Sharpe ratio of -0.75, also significant at the 1% level. The negative performance across both non-industry and industry matched portfolios indicates that industry matching did not provide a protective effect during the crisis. The systemic market disruptions likely caused correlations between assets, even within the same industry, to behave unpredictably, undermining the effectiveness of pairs trading strategies that rely on stable, mean-reverting relationships.

In the Bullish and Bearish Markets period, portfolios generally displayed modest positive mean returns with low Sharpe ratios, and no statistically significant positive returns were observed. For the non-industry matched portfolios, mean returns ranged from approximately 13 bps to 33 bps, with Sharpe ratios between 0.11 and 0.27. The industry matched portfolios exhibited similar patterns, with mean returns varying from 14 bps to 26 bps, and Sharpe ratios between 0.13 and 0.29. These results suggest that during stable or mixed market conditions, pairs trading strategies generated small positive returns but lacked strong performance differentiation across SSD-based vigintiles. The limited mispricing opportunities in such environments might have constrained the potential for higher returns, and the SSD rankings did not significantly impact performance.

The COVID-19 period presented a mixed performance landscape for both non-industry matched and industry matched portfolios. Several portfolios recorded negative mean returns and Sharpe ratios, reflecting the heightened market volatility and uncertainty during the pandemic. In the non-industry matched group, Portfolios 13, 14, 15, and 16 experienced negative mean returns ranging from -15 bps to -19 bps, with corresponding negative Sharpe ratios. For example, Portfolio 15 had a mean return of -19 bps and a Sharpe ratio of -0.22, significant at the 5% level. These negative returns indicate that the pairs trading strategy did not adequately compensate for the risk taken during this volatile period, possibly due to the breakdown of mean-reversion tendencies amid unprecedented market conditions.

Similarly, in the industry matched portfolios, negative performance was observed in several portfolios. Portfolios 31 and 32 reported mean returns of -17 bps with Sharpe ratios of -0.24 and -0.23, respectively, both significant at the 5% level. Portfolio 35 exhibited a more pronounced negative mean return of -24 bps with a Sharpe ratio of -0.31, significant at the 1% level. These findings suggest that industry matching did not effectively shield portfolios from the adverse effects of the pandemic-induced market volatility. The widespread impact of COVID-19 across industries may have caused even intra-industry pairs to diverge from their historical price relationships.

An examination of performance across different vigintiles reveals no consistent pattern indicating that portfolios in certain SSD-based rankings outperformed others during any of the periods. During the Financial Crisis, negative returns were pervasive across all vigintiles, regardless of the SSD ranking. This suggests that the SSD metric, which measures the sum of squared deviations between paired assets, may not capture the complexities of asset price dynamics during extreme market conditions. The assumption that pairs with smaller SSDs are more likely to revert to their mean may not hold when market correlations are disrupted by systemic shocks.

In the Bullish and Bearish Markets period, the absence of significant performance differences across vigintiles indicates that SSD-based ranking did not materially influence returns in a stable market environment. The modest returns and low Sharpe ratios suggest limited mispricing opportunities, and that the pairs trading strategy did not benefit significantly from the SSD rankings during this period.

During the COVID-19 period, the lack of a clear performance pattern across vigintiles persisted. Both non-industry matched and industry matched portfolios showed mixed results, with some portfolios in higher SSD vigintiles (e.g., Portfolio 35) recording negative returns, while others in lower vigintiles (e.g., Portfolio 1) had small positive returns. This further implies that SSD-based ranking did not have a significant impact on performance during periods of heightened uncertainty.

From a pairs trading perspective, these results highlight the limitations of relying solely on statistical measures like SSD for pair selection, especially during periods of extreme market volatility. The observed negative returns and Sharpe ratios during the Financial Crisis and COVID-19 periods suggest that pairs trading strategies need to incorporate additional factors to enhance robustness. Incorporating fundamental analysis, macroeconomic indicators, or adaptive statistical techniques that account for shifting market dynamics could potentially improve performance.

The fact that industry matching did not significantly improve performance suggests that intra-industry pairs are not inherently more resilient during market downturns. Companies within the same industry may be similarly affected by industry-specific shocks or broader economic disruptions, reducing the benefits of industry matching when mean-reversion relationships fail.

In summary, the detailed examination of Table 13 underscores the challenges faced by pairs trading strategies across different vigintiles and market conditions. The negative performance during the Financial Crisis and COVID-19 periods indicates that extreme market conditions can undermine the assumptions underpinning pairs trading, particularly the expectation of mean reversion. The lack of significant performance differentiation across SSD-based vigintiles suggests that SSD may not be a sufficient criterion for pair selection in isolation. These insights emphasize the need for adaptive strategies that incorporate additional risk management and pair selection techniques to optimize performance, especially during periods of heightened market volatility.

TABLE 13. Monthly Excess Returns with Trading Costs of All Three Period Results by Different Vigintiles.

	Financial Crisis			Bullish and Bearish			COVID-19		
Portfolio	**Mean**	**Std. Dev.**	**Sharpe**	**Mean**	**Std. Dev.**	**Sharpe**	**Mean**	**Std. Dev.**	**Sharpe**
1	-0.0188**	0.0480	-0.39***	0.0018	0.0091	0.20	0.0018	0.0175	0.10
2	-0.0114**	0.0632	-0.18*	0.0019	0.0096	0.19	0.0008	0.0078	0.10
3	-0.0054	0.0334	-0.16	0.0013	0.0116	0.11	-0.0003	0.0071	-0.04
4	-0.0175***	0.0424	-0.41***	0.0018	0.0101	0.18	-0.0002	0.0085	-0.03
5	-0.0174**	0.0487	-0.35**	0.0024	0.0098	0.24	-0.0013	0.0094	-0.14
6	-0.0160***	0.0419	-0.38***	0.0017	0.0112	0.15	-0.0004	0.0074	-0.06
7	-0.0168***	0.0248	-0.67***	0.0025	0.0124	0.20	-0.0002	0.0079	-0.03

8	-0.0199***	0.0305	-0.65***	0.0033	0.0124	0.27	-0.0002	0.0082	-0.03
9	-0.0056	0.0382	-0.15	0.0015	0.0127	0.12	-0.0014	0.0081	-0.17
10	-0.0158***	0.0254	-0.62***	0.0024	0.0114	0.21	-0.0011	0.0092	-0.12
11	-0.0188***	0.0457	-0.41***	0.0015	0.0115	0.13	-0.0014	0.0078	-0.18
12	-0.0130***	0.0346	-0.37***	0.0025	0.0114	0.22	-0.0003	0.0081	-0.04
13	-0.0069	0.0382	-0.18	0.0021	0.0115	0.19	-0.0015**	0.0086	-0.17**
14	-0.0189***	0.0284	-0.66***	0.0022	0.0117	0.19	-0.0016*	0.0095	-0.16
15	-0.0142***	0.0335	-0.42***	0.0022	0.0132	0.17	-0.0019**	0.0086	-0.22**
16	-0.0224***	0.0441	-0.50***	0.0014*	0.0105	0.13	-0.0018	0.0097	-0.18
17	-0.0175***	0.0302	-0.57***	0.0026	0.0125	0.20	-0.0001	0.0141	0.00
18	-0.0109***	0.0327	-0.33***	0.0019	0.0124	0.15	-0.0014	0.0090	-0.15
19	-0.0178***	0.0219	-0.81***	0.0022	0.0110	0.20	-0.0010	0.0091	-0.11
20	-0.0172***	0.0256	-0.67***	0.0016	0.0128	0.12	-0.0016*	0.0089	-0.17
21	-0.0055	0.0985	-0.06	0.0018	0.0071	0.25*	0.0028	0.0268	0.11
22	-0.0151***	0.0197	-0.76***	0.0020	0.0080	0.25	-0.0001	0.0060	-0.02
23	-0.0059	0.0384	-0.15	0.0022*	0.0075	0.29*	-0.0009	0.0069	-0.12
24	-0.0140***	0.0283	-0.49***	0.0020	0.0095	0.21	0.0009	0.0143	0.06
25	-0.0121*	0.0514	-0.23*	0.0016	0.0101	0.16	-0.0007	0.0075	-0.10
26	-0.0135***	0.0215	-0.62***	0.0026	0.0123	0.21	0.0002	0.0072	0.03
27	-0.0129***	0.0295	-0.43***	0.0024	0.0106	0.23	0.0001	0.0133	0.01
28	-0.0125***	0.0246	-0.50***	0.0026	0.0090	0.29*	-0.0006	0.0061	-0.10
29	-0.0163***	0.0216	-0.75***	0.0014	0.0081	0.18	-0.0013**	0.0070	-0.18**
30	-0.0144***	0.0306	-0.47***	0.0016	0.0107	0.15	-0.0014	0.0074	-0.18*
31	-0.0168***	0.0336	-0.50***	0.0015	0.0081	0.18	-0.0017**	0.0071	-0.24**
32	-0.0152***	0.0211	-0.72***	0.0019	0.0081	0.23	-0.0017**	0.0071	-0.23**
33	-0.0051	0.0375	-0.13	0.0016	0.0111	0.15	-0.0010*	0.0077	-0.13
34	-0.0128***	0.0191	-0.67***	0.0014	0.0102	0.13	-0.0017*	0.0078	-0.21*
35	-0.0124***	0.0273	-0.45***	0.0026	0.0090	0.29	-0.0024***	0.0077	-0.31***
36	-0.0102*	0.0420	-0.24*	0.0022	0.0103	0.21	0.0004	0.0145	0.03
37	-0.0168***	0.0240	-0.70***	0.0019	0.0127	0.15	-0.0009	0.0078	-0.11
38	-0.0085	0.0406	-0.21	0.0016	0.0089	0.18	0.0004	0.0159	0.03
39	-0.0172***	0.0258	-0.66***	0.0024	0.0125	0.19	-0.0021**	0.0085	-0.24**
40	-0.0169***	0.0259	-0.65***	0.0012	0.0100	0.12	0.0010	0.0246	0.04

Note: This table presents key distributional statistics for the excess return time series for all three periods with different vigintiles, after accounting for trading costs, generated by 40 pairs portfolios compared to portfolios 6 and 24 from Table 5-10, spanning from January 2005 to June 2024. t-statistics provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. z-statistics shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. For each period, we use CSI 300 return of each period as benchmarks.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

5.2.2 Returns with One Day Waiting

In this section, we analyze the performance of the pairs trading strategy when incorporating a one-day waiting period before executing trades, accounting for trading costs. Table 14 presents the monthly excess returns, standard deviations, and Sharpe ratios for 40 portfolios across three distinct periods: the Financial Crisis, Bullish and Bearish Markets, and the COVID-19 pandemic. The excess returns are calculated relative to the benchmark CSI 300 Index for each respective period.

The "one-day waiting" in pairs trading refers to delaying the execution of a trade for one day after receiving a trading signal. In a typical pairs trading strategy, a signal is generated when the prices of two historically correlated stocks deviate from their expected relationship, indicating a potential opportunity for profit. Without the waiting period, traders act immediately on the signal, buying or selling the stocks in the pair. The introduction of a one-day waiting period aims to mitigate potential market impact, reduce transaction costs due to bid-ask spreads, and allow for potential price corrections after signal generation. This adjustment may influence both the profitability and the risk characteristics of the pairs trading portfolios.

During the Financial Crisis, the pairs trading strategy with a one-day waiting period yielded predominantly negative outcomes. For instance, Portfolio 1 experienced a significant negative mean excess return of -204 bps per month, with a Sharpe ratio of -0.42. Similarly, Portfolio 2 recorded a mean excess return of -183 bps per month and a Sharpe ratio of -0.36. These results suggest that the introduction of a one-day waiting period during the highly volatile Financial Crisis may have adversely affected the strategy's ability to capitalize on short-lived mispricing opportunities. Delaying trade execution by one day possibly allowed profitable divergences to correct before trades were initiated, resulting in missed opportunities and negative returns.

In contrast, some portfolios showed less negative or even positive performance. Portfolio 3, for example, had a mean excess return of -129 bps per month and a Sharpe ratio of -0.25. While still negative, the performance of Portfolio 3 was relatively better compared to Portfolios 1 and 2. Interestingly, Portfolio 9 achieved a positive mean excess return of 62 bps per month, though with a low Sharpe ratio of 0.10, indicating that some portfolios were able to generate modest gains even with the waiting period. However, overall, the strategy underperformed during the Financial Crisis with the one-day waiting period, suggesting that immediate action on trading signals may be more effective during periods of extreme volatility when mispricings are more transient.

When comparing these results to those without the one-day waiting period (as shown in Table 9), we observe that the portfolios generally performed better without the waiting period during the Financial Crisis. For example, in Table 9, Portfolio 3 had a mean excess return of -138 bps per month and a Sharpe ratio of -0.25, similar to the result with the waiting period. However, Portfolio 9 without the waiting period achieved a higher mean excess return of 78 bps per month and a Sharpe ratio of 0.13, indicating slightly better performance without the waiting period. This suggests that the waiting period may have diminished the strategy's effectiveness in capturing rapid price reversions during volatile markets.

During the Bullish and Bearish Markets period, most portfolios demonstrated modest positive performance with the one-day waiting period. Portfolio 15, for instance, generated a mean excess return of 32 bps per month with a Sharpe ratio of 0.32. Similarly, Portfolio 37 exhibited strong performance with a mean excess return of 53 bps per month and a Sharpe ratio of 0.44. These results indicate that the one-day waiting period did not significantly hinder the strategy's performance during more stable market conditions and, in some cases, may have improved it by filtering out false signals and reducing transaction costs.

Comparing to the results without the waiting period in Table 10, we notice that the performance is somewhat similar. Portfolio 15 without the waiting period had a mean excess return of 30 bps per month and a Sharpe ratio of 0.30. The slight improvement in both mean return and Sharpe ratio with the waiting period suggests that during calmer market conditions, delaying trade execution may help in avoiding noise and overtrading, thus enhancing returns.

During the COVID-19 pandemic, characterized by heightened market volatility, the introduction of the one-day waiting period appeared to have mixed effects. Portfolio 3 achieved a mean excess return of 28 bps per month with a Sharpe ratio of 0.19, significant at the 10% level, indicating improved performance. On the other hand, Portfolio 1 recorded a mean excess return of 23 bps per month with a Sharpe ratio of 0.13, which, while positive, was not statistically significant.

When comparing these results with those without the waiting period in Table 8, we observe that Portfolio 3 without the waiting period had a mean excess return of 22 bps per month and a Sharpe ratio of 0.14, indicating that the waiting period slightly enhanced performance during the COVID-19 period for this portfolio. Conversely, Portfolio 1 without the waiting period had a mean excess return of -5 bps per month with a Sharpe ratio of -0.03, suggesting that the one-day waiting period improved performance for this portfolio during the COVID-19 period.

These observations imply that during the COVID-19 pandemic, the one-day waiting period may have allowed portfolios to avoid entering into trades that would have quickly reversed, thus improving returns in some cases. The extreme volatility and rapid price movements during this period may have made immediate execution of signals riskier, and the waiting period provided a buffer to filter out transient price shocks.

Overall, the introduction of a one-day waiting period had varying effects depending on market conditions. During highly volatile periods like the Financial Crisis, the waiting period seemed to reduce profitability, as immediate action was necessary to capture fleeting mispricing opportunities. In contrast, during the COVID-19 period, the waiting period appeared to have a neutral to slightly positive effect on some portfolios, possibly by reducing the impact of market noise and avoiding premature trades.

In the Bullish and Bearish Markets, the waiting period generally did not adversely affect the strategy and may have modestly improved performance by reducing overtrading and transaction costs. This suggests that in stable market conditions, delaying execution can be beneficial, as mean-reversion opportunities are less time-sensitive, and price discrepancies may persist longer, allowing for successful trades even after a delay.

When comparing these results to the portfolios without the one-day waiting period (Tables 8–10), we find that the differences in returns are generally minimal across most periods. However, during the Financial Crisis, the portfolios without the waiting period performed slightly better, highlighting the importance of timely execution in volatile markets.

From a pairs trading perspective, these findings highlight the need to adjust execution strategies based on market conditions. In highly volatile markets, immediate execution may be crucial to capitalize on rapid mean reversions. In contrast, in more stable markets or during periods of market stress like the COVID-19 pandemic, a waiting period can help mitigate risks associated with market noise and transient price movements.

Moreover, the results underscore the importance of considering transaction costs and market impact when designing pairs trading strategies. The one-day waiting period can reduce the frequency of trades, potentially lowering transaction costs and slippage, which can enhance net returns, especially when mispricing opportunities are not immediately fleeting.

In conclusion, the incorporation of a one-day waiting period in pairs trading strategies has a nuanced impact on performance. It can be detrimental during periods of extreme volatility like the Financial Crisis, where immediacy is key. However, it can be neutral or even beneficial during stable periods or unusual market conditions like the COVID-19 pandemic. Traders should consider market volatility and the nature of mispricing opportunities when deciding whether to implement a waiting period in their pairs trading strategies.

TABLE 14. Monthly Excess Returns with Trading Costs of All Three Period Results by One Day Waiting.

	Financial Crisis			Bullish and Bearish			COVID-19		
Portfolio	**Mean**	**Std. Dev.**	**Sharpe**	**Mean**	**Std. Dev.**	**Sharpe**	**Mean**	**Std. Dev.**	**Sharpe**
1	-0.0204***	0.0483	-0.42***	0.0015	0.0087	0.17	0.0023	0.0174	0.13
2	-0.0183**	0.0497	-0.36**	0.0016	0.0098	0.16	0.0009	0.0085	0.10
3	-0.0129***	0.0520	-0.25***	0.0022	0.0096	0.23	0.0028**	0.0152	0.19*
4	-0.0157***	0.0531	-0.29***	0.0019	0.0085	0.23	0.0010	0.0083	0.12
5	-0.0058	0.0374	-0.15	0.0015	0.0099	0.15	0.0013*	0.0083	0.16
6	-0.0135***	0.0386	-0.35***	-0.0001	0.0162	0.00	-0.0053*	0.0229	-0.23*
7	-0.0155***	0.0689	-0.22**	0.0029	0.0104	0.28	0.0021**	0.0114	0.18**
8	0.0009	0.0719	0.01	0.0022	0.0106	0.20	0.0012	0.0081	0.15
9	0.0062	0.0626	0.10	0.0026	0.0101	0.26	0.0005	0.0091	0.06
10	-0.0247**	0.0658	-0.37**	0.0023	0.0103	0.22	0.0031*	0.0176	0.18*
11	-0.0046	0.0885	-0.05	0.0020	0.0108	0.18	0.0002	0.0092	0.02
12	-0.0023	0.0472	-0.05	0.0017	0.0098	0.17	0.0017	0.0157	0.11
13	-0.0132**	0.0413	-0.32**	0.0033	0.0120	0.27	0.0012	0.0149	0.08
14	-0.0138***	0.0466	-0.29***	0.0016	0.0093	0.18	0.0016	0.0095	0.17
15	0.0037	0.0518	0.07	0.0032*	0.0098	0.32**	0.0002	0.0089	0.03
16	-0.0042	0.0429	-0.10	0.0019	0.0085	0.22	0.0011	0.0078	0.14
17	-0.0004	0.0429	-0.01	0.0023	0.0090	0.26	0.0013	0.0091	0.14
18	0.0006	0.0516	0.01	0.0016	0.0096	0.17	0.0010	0.0072	0.14
19	-0.0068	0.0989	-0.07	0.0017	0.0074	0.22	0.0032	0.0267	0.12
20	0.0079	0.0778	0.10	0.0018	0.0078	0.23	0.0001	0.0073	0.01
21	0.0129	0.1273	0.10	0.0013	0.0069	0.19	0.0005	0.0070	0.07
22	-0.0045	0.0413	-0.11	0.0023	0.0084	0.27*	0.0022	0.0150	0.14

23	-0.0067	0.0464	-0.14	0.0019	0.0078	0.25*	0.0001	0.0070	0.02
24	-0.0152***	0.0224	-0.67***	0.0007	0.0146	0.05	-0.0020	0.0121	-0.17
25	0.0076	0.0815	0.09	0.0029**	0.0093	0.31**	0.0030	0.0285	0.10
26	-0.0074*	0.0266	-0.28**	0.0027	0.0086	0.31*	0.0013**	0.0072	0.18*
27	-0.0105**	0.0316	-0.33**	0.0019	0.0096	0.20	0.0021	0.0138	0.15
28	0.0064	0.1046	0.06	0.0022	0.0088	0.25	0.0027	0.0281	0.10
29	-0.0156***	0.0200	-0.78***	0.0023	0.0105	0.22	0.0018	0.0132	0.13
30	-0.0085**	0.0219	-0.39**	0.0020	0.0092	0.21	0.0008	0.0076	0.10
31	0.0061	0.1166	0.05	0.0019	0.0098	0.20	0.0018	0.0162	0.11
32	-0.0079	0.0611	-0.13	0.0026	0.0090	0.29*	0.0007	0.0076	0.09
33	-0.0082	0.0327	-0.25	0.0021	0.0102	0.20	0.0003	0.0084	0.03
34	-0.0073	0.0295	-0.25	0.0025*	0.0075	0.32*	0.0007	0.0068	0.10
35	-0.0128***	0.0155	-0.81***	0.0024	0.0081	0.29	0.0009	0.0070	0.13
36	-0.0126***	0.0208	-0.60***	0.0021	0.0084	0.25	0.0000	0.0056	0.01
37	0.0191	0.1563	0.12	0.0053***	0.0119	0.44***	0.0024	0.0289	0.08
38	0.0064	0.0799	0.08	0.0010	0.0071	0.14	0.0004	0.0076	0.05
39	0.0338	0.2396	0.14	0.0042**	0.0114	0.37**	0.0023	0.0281	0.08
40	-0.0040	0.0905	-0.04	0.0005	0.0081	0.06	0.0014**	0.0076	0.18*

Note: This table presents key distributional statistics for the excess return time series for all three periods with one day waiting strategy after accounting for trading costs, spanning from January 2005 to June 2024. t-statistics provides the test statistic for the mean return estimate, calculated using Newey–West standard errors with six lags. z-statistics shows the test statistic for the Sharpe ratio estimate, based on Lo's (2002) robust standard errors, which account for non-independence and non-identically distributed return time series. For each period, we use CSI 300 return of each period as benchmarks.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

5.3 Risk Characteristics Analysis for Pairs Trading

5.3.1 Risk-Adjusted Returns

Next, we examine whether pairs trading generates profits on a risk-adjusted basis. To address this, we incorporate various risk factors that have proven effective in explaining cross-sectional returns and are anticipated to have correlations with pairs trading outcomes. We begin by using a four-factor model, which extends the classic Fama and French (1993) model by adding a momentum factor. Given that pairs trading is fundamentally a short-term reversal strategy, we further enhance this model by introducing a market-wide short-term reversal factor, following the approach of Jegadeesh (1990). This enhanced specification has also been employed by Gatev, Goetzmann, and Rouwenhorst (2006) to account for risk in pairs trading. Tables 15, 16, and 17 present the regression results for these factors on after-cost returns, respectively.

The regression model for each portfolio is specified as:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT}(R_{Mt} - R_{ft}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \beta_{i,REV}REV_t + \varepsilon_{it} \quad (5.1)$$

Where,

R_{it} is the return of portfolio i at time t.

R_{ft} is the risk-free rate at time t.

R_{Mt} is the market return at time t.

SMB_t is the size factor (Small Minus Big) at time t.
HML_t is the value factor (High Minus Low) at time t.
MOM_t is the momentum factor at time t.
REV_t is the market-wide short-term reversal factor at time t.
α_i is the intercept term representing the abnormal return (alpha) of portfolio i.
β coefficients measure the sensitivity of portfolio returns to the respective risk factors.
ε_{it} is the error term.

From Table 15, we observe that several portfolios exhibit statistically significant negative alphas during the Financial Crisis, indicating that they generate abnormal negative returns not explained by the common risk factors. For instance, Portfolios 1, 2, 3, 4, and 10 have negative intercepts ranging from -160 bps to -264 bps per month, all significant at the 1% or 5% levels. These findings suggest that, during the Financial Crisis, pairs trading strategies struggled to generate positive returns, even after accounting for market, size, value, momentum, and reversal risks.

In contrast, some portfolios, such as Portfolio 9 and Portfolio 38, show positive alphas, though they are not statistically significant. Portfolio 9 has an intercept of 53 bps per month with a t-statistic of 0.68, indicating that its returns are not significantly different from zero after adjusting for the risk factors. This implies that certain portfolios were able to maintain their performance despite market turmoil, but the lack of statistical significance suggests caution in interpreting these results.

The market risk factor (MKT-RF) reveals positive, though generally low, betas for some portfolios, indicating minimal sensitivity to market movements. For example, Portfolio 11 has a significant market beta of 0.32, with a t-statistic of 3.27, significant at the 1% level. This suggests that Portfolio 11's returns are moderately correlated with market returns, possibly due to the inclusion of stocks that are more sensitive to market fluctuations. Other portfolios exhibit insignificant market betas, indicating that their returns are largely independent of market movements, which is characteristic of market-neutral strategies like pairs trading.

Size exposure (SMB) is mostly insignificant across the portfolios, indicating that the pairs trading strategies do not have a systematic bias towards small-cap or large-cap stocks. An exception is Portfolio 31, which has a negative SMB beta of -0.267, though the t-statistic is -0.79, rendering it insignificant. This lack of significant size exposure suggests that the returns of the pairs trading portfolios are not driven by the size effect.

Similarly, the value factor (HML) shows weak relationships with the portfolio returns. Most portfolios display insignificant HML betas, implying no consistent tilt towards value or growth stocks within the pairs trading strategies. For example, Portfolio 11 has a negative HML beta of -0.527, with a t-statistic of -1.51, which is not statistically significant. This suggests that the performance of the portfolios is not influenced by the value premium during the Financial Crisis.

Momentum (MOM) displays a more prominent role in explaining the returns of pairs trading strategies. Several portfolios have negative momentum coefficients, consistent with the contrarian nature of pairs trading. Notably, Portfolios 29, 35, and 36 exhibit significant negative MOM betas. Portfolio 29 has a MOM beta of -0.11, significant at the 5% level, indicating that it profits when past losers outperform past winners. Similarly, Portfolios 35 and 36 have MOM betas of -0.10 and -0.12, respectively, both significant at the 5% level. These negative momentum exposures highlight that pairs trading strategies tend to bet against prevailing trends, aiming to exploit short-term price reversals.

The market reversal factor (REV) demonstrates limited influence on the portfolios' returns. Most portfolios exhibit insignificant REV coefficients, suggesting that the reversal effect does not significantly impact the performance of the pairs trading strategies during the Financial Crisis. An exception is Portfolio 8, which has a REV beta of -0.13, with a t-statistic of -1.71, significant at the 10% level. However, overall, the reversal factor does not appear to be a major driver of returns.

The R^2 values indicate that the five-factor model explains only a small portion of the variance in portfolio returns, with most portfolios having R^2 values ranging from 0.01 to 0.19. Only a few portfolios, such as Portfolio 11 and Portfolio 36, show slightly higher explanatory power. This suggests that other factors or idiosyncratic elements may be influencing the returns of pairs trading strategies, which are not fully captured by the five-factor model. Despite the low model fit, the significant negative alphas and negative momentum exposures provide insights into the performance dynamics during the Financial Crisis.

The regression analysis offers valuable insights into the risk-adjusted performance of pairs trading strategies during the Financial Crisis. The significant negative alphas observed in several portfolios indicate that these strategies generated negative abnormal returns that cannot be fully explained by traditional risk factors such as market, size, value, momentum, and reversal. This underperformance may be attributed to the breakdown of historical price relationships amid extreme market conditions, leading to losses in strategies that rely on mean reversion.

The significant negative coefficients on the momentum factor for some portfolios underscore the contrarian aspect of pairs trading, where the strategy profits from betting against recent trends. During the Financial Crisis, pronounced market trends and heightened volatility may have extended the duration of price deviations, reducing the effectiveness of mean-reversion strategies. The negative momentum exposure suggests that when momentum factors were strong (i.e., when past winners continued to outperform), pairs trading strategies suffered losses.

The generally insignificant coefficients on the market, size, and value factors imply that pairs trading returns are largely uncorrelated with these traditional risk sources, highlighting the market-neutral nature of the strategy. This characteristic underscores the potential diversification benefits of including pairs trading in a broader investment portfolio, as it may not add significant systematic risk exposure.

Although the reversal factor shows limited influence, the low R^2 values across most portfolios suggest that the five-factor model explains only a small portion of the variation in pairs trading returns during the Financial Crisis. This could be due to the unique characteristics of pairs trading, which relies on the convergence of mispriced securities and may be influenced by factors not captured in the model, such as liquidity constraints, transaction costs, or changes in market microstructure during crisis periods.

From a robustness perspective, the use of Newey–West standard errors, accounting for autocorrelation and heteroskedasticity, enhances the reliability of the t-statistics. The economic significance of the intercepts, with negative values ranging between -100 bps and -260 bps per month, is noteworthy, as it demonstrates meaningful losses even after accounting for trading costs. This underscores the challenges faced by pairs trading strategies during extreme market downturns.

These findings diverge from prior studies, such as those by Gatev, Goetzmann, and Rouwenhorst (2006), which often report positive abnormal returns from pairs trading. The divergence may be attributed to the specific conditions of the Financial Crisis, where market dynamics were substantially altered, and traditional mean-reverting relationships broke down. The significant negative momentum exposure further illustrates the vulnerability of pairs trading strategies during periods when momentum effects dominate market behavior.

In conclusion, the regression analysis indicates that during the Financial Crisis, pairs trading strategies underperformed, generating negative abnormal returns even after adjusting for common risk factors. The negative alphas and significant negative momentum coefficients highlight the challenges of relying on mean-reversion strategies in periods of extreme market stress, where traditional relationships between assets may not hold. These results suggest that additional risk management and adaptive strategies may be necessary to mitigate losses during such periods.

In Table 16, during the Bullish and Bearish periods, unlike the Financial Crisis period, the majority of portfolios exhibit negative intercepts, with some being statistically significant. For instance, Portfolio 1 shows an alpha of -13 bps per month, Portfolio 2 has an alpha of -6 bps per month, Portfolio 16 shows an alpha of -12 bps per month, and Portfolio 36 has an alpha of -15 bps per month. These negative and significant alphas suggest that, after adjusting for risk factors, pairs trading strategies underperform during the Bullish and Bearish period, indicating a decline in profitability in more stable market conditions.

Regarding the market risk factor, the coefficients measure the sensitivity of portfolio returns to market movements. Most portfolios exhibit negative and significant market betas, such as Portfolio 1 with a beta of -0.0532, Portfolio 19 with a beta of -0.0288, and Portfolio 39 with a beta of -0.0553. These negative betas suggest that the portfolios tend to move inversely with the market, generating positive returns when the market declines and negative returns when the market rises. This inverse relationship implies that pairs trading strategies act as a hedge against market downturns during this period.

The size factor (SMB) shows mixed and generally insignificant results. While some portfolios, such as Portfolio 27 and Portfolio 39, have positive and significant size betas, the overall lack of consistent significance suggests that size does not play a substantial role in explaining the returns of pairs trading portfolios during this period. This finding aligns with the market-neutral nature of pairs trading, where the strategy is designed to be indifferent to the size of the underlying assets.

The value factor (HML) coefficients, representing exposure to the value premium, tend to be negative, with some portfolios showing statistically significant values. For example, Portfolio 2 has a negative HML coefficient of -10 bps, and Portfolio 20 shows a negative coefficient of -8 bps. The negative HML coefficients indicate a tilt towards growth stocks, and the significance in some portfolios suggests that exposure to the value factor partially explains the returns of these strategies during this period.

The momentum factor (MOM) shows strong negative and highly significant coefficients across almost all portfolios. For instance, Portfolio 1 has a momentum beta of -6 bps, Portfolio 6 shows a beta of -14 bps, and Portfolio 39 exhibits a beta of -10 bps. The consistently negative exposure to momentum indicates that the pairs trading portfolios are contrarian in nature, profiting when recent losers outperform recent winners. This aligns with the fundamental principle of pairs trading, which seeks to exploit short-term price reversals.

The market reversal factor (REV) coefficients are generally positive but often lack statistical significance. For example, Portfolio 4 shows a REV coefficient of 3 bps, and Portfolio 21 has a coefficient of 3 bps. The occasional significance suggests that some portfolios may benefit from market-wide reversals, though the reversal factor does not play a dominant role in explaining returns during this period.

The adjusted R^2 values range from 0.10 to 0.38, which are generally higher than those observed during the Financial Crisis period (Table 15), where R^2 values were mostly below 0.10. For example, Portfolio 1 has an R^2 of 0.32, and Portfolio 39 shows an R^2 of 0.36. These higher values suggest that the five-factor model explains a greater proportion of the variance in portfolio returns during the Bullish and Bearish period compared to the Financial Crisis. This implies that common risk factors have more explanatory power in stable market conditions.

When comparing these results with those from the Financial Crisis period, several differences emerge. During the Financial Crisis, many portfolios exhibited significant negative alphas, indicating abnormal returns not explained by risk factors. In the Bullish and Bearish period, most portfolios show negative and significant alphas, suggesting underperformance after adjusting for risk factors. This indicates that the profitability of pairs trading strategies diminishes in stable market conditions, likely due to reduced volatility and fewer mispricing opportunities. Additionally, while market betas were generally positive but insignificant during the Financial Crisis, the Bullish and Bearish period shows consistently negative and significant market betas, implying that pairs trading strategies act as a hedge against market movements by generating returns when the market declines.

Momentum factors show a stronger negative relationship in the Bullish and Bearish period, with consistently negative and significant coefficients across almost all portfolios. This further reinforces the contrarian nature of pairs trading, as these strategies consistently bet against momentum. In terms of value and size factors, the Financial Crisis period showed limited and generally insignificant exposure to HML and SMB, while the Bullish and Bearish period exhibits significant negative HML coefficients, indicating a tilt towards growth stocks. However, the SMB coefficients remain mixed and largely insignificant during both periods.

Overall, the higher R^2 values during the Bullish and Bearish period suggest that common risk factors explain a greater portion of return variability in stable markets, whereas during the Financial Crisis, idiosyncratic factors may dominate returns. This finding supports the notion that pairs trading strategies are more influenced by systematic risk factors in stable markets, limiting their ability to generate positive abnormal returns.

In conclusion, the analysis reveals that pairs trading strategies do not generate positive abnormal returns after adjusting for common risk factors during the Bullish and Bearish period. The negative alphas, along with significant exposure to market and momentum factors, suggest that pairs trading strategies underperform in stable market environments. This contrasts with the Financial Crisis period, where significant negative alphas indicated the inability of pairs trading to generate positive abnormal returns, possibly due to the breakdown of historical price relationships. The consistently negative relationship with the momentum factor across both periods confirms the contrarian nature of pairs trading. However, the strategy's effectiveness appears contingent on market conditions, with higher profitability during periods of high volatility and stress.

For investors, this highlights the importance of strategic timing, as pairs trading strategies may be more effective during volatile markets. Additionally, the negative market betas suggest that pairs trading can provide diversification benefits in a portfolio, particularly during market downturns, although the lack of positive abnormal returns during stable periods underscores the need for dynamic strategy adjustments and risk management.

TABLE 15. Risk-Adjusted Returns after Trading Costs for Financial Crisis Period.

Portfolio	Intercept	t-stat	MKT-RF	t-stat	SMB	t-stat	HML	t-stat	Momentum	t-stat	Reversal	t-stat	R^2
1	-0.0223	-3.61***	0.0361	0.62	-0.0261	-0.19	-0.1038	-0.50	-0.1226	-1.04	-0.0060	-0.11	0.02
2	-0.0194	-2.95***	0.0089	0.14	0.0777	0.53	-0.1140	-0.52	-0.0533	-0.43	0.0687	1.23	0.04
3	-0.0183	-2.63***	0.0552	0.85	0.0329	0.22	-0.1457	-0.63	-0.1107	-0.84	-0.0017	-0.03	0.03
4	-0.0160	-2.28**	-0.0035	-0.05	-0.0580	-0.38	0.0671	0.29	-0.1220	-0.92	0.0173	0.29	0.02
5	-0.0092	-1.80*	0.0271	0.57	0.0249	0.22	-0.0608	-0.36	-0.1484	-1.53	0.0234	0.54	0.06
6	-0.0188	-4.10***	0.0217	0.50	0.1472	1.46	0.0725	0.47	-0.2385	-2.74***	0.0107	0.28	0.25
7	-0.0174	-1.97**	0.1282	1.54	-0.0459	-0.24	-0.2139	-0.72	-0.0442	-0.26	0.0687	0.92	0.04
8	-0.0051	-0.57	0.0433	0.51	0.0673	0.34	0.0944	0.31	-0.0043	-0.03	-0.1312	-1.71*	0.06
9	0.0053	0.68	0.0746	1.03	-0.0858	-0.50	0.0976	0.38	0.0589	0.40	0.0179	0.27	0.03
10	-0.0264	-3.12***	0.0507	0.64	0.0064	0.03	-0.2406	-0.85	-0.1109	-0.69	0.0734	1.03	0.03
11	-0.0176	-1.69*	0.3197	3.27***	0.0056	0.02	-0.5273	-1.51	-0.1988	-1.00	-0.0960	-1.09	0.19
12	-0.0055	-0.94	0.0634	1.15	-0.0053	-0.04	0.0006	0.00	-0.2047	-1.84*	-0.0154	-0.31	0.10
13	-0.0146	-2.44**	-0.0211	-0.37	-0.0151	-0.11	-0.0296	-0.15	-0.1184	-1.04	0.0346	0.68	0.03
14	-0.0174	-3.12***	0.0629	1.20	0.0630	0.51	-0.1771	-0.95	-0.1678	-1.58	-0.0379	-0.80	0.10
15	-0.0021	-0.34	0.0912	1.55	0.0274	0.20	-0.1303	-0.62	-0.2219	-1.87*	-0.0092	-0.17	0.11
16	-0.0088	-1.66*	0.0797	1.60	-0.0293	-0.25	-0.0761	-0.43	-0.1282	-1.27	-0.0551	-1.22	0.09
17	-0.0040	-0.74	0.0902	1.78*	-0.0159	-0.13	-0.0807	-0.45	-0.1207	-1.18	0.0030	0.07	0.08
18	-0.0034	-0.49	0.0685	1.08	0.0094	0.06	-0.0079	-0.03	-0.1282	-1.00	-0.0442	-0.77	0.06
19	-0.0104	-0.82	0.1396	1.18	-0.1270	-0.46	0.2056	0.49	0.0023	0.01	-0.0178	-0.17	0.04
20	0.0068	0.62	0.1062	1.03	-0.2199	-0.91	0.1220	0.33	-0.0034	-0.02	-0.0152	-0.16	0.04
21	0.0077	0.47	0.2063	1.34	-0.0912	-0.25	0.1481	0.27	0.0193	0.06	-0.0040	-0.03	0.04
22	-0.0099	-1.75*	0.0920	1.73*	0.0152	0.12	-0.1232	-0.65	-0.0815	-0.76	0.0013	0.03	0.06
23	-0.0111	-1.74*	0.0492	0.82	-0.0613	-0.43	-0.0107	-0.05	-0.1686	-1.38	-0.0576	-1.06	0.06
24	-0.0198	-7.77***	0.0441	1.84*	0.0801	1.42	0.0430	0.50	-0.1452	-2.99***	0.0219	1.01	0.33
25	0.0031	0.29	0.1310	1.32	-0.0958	-0.41	0.0913	0.26	-0.0356	-0.18	-0.0566	-0.63	0.05
26	-0.0100	-2.90***	0.0234	0.72	-0.0360	-0.47	-0.0246	-0.21	-0.1027	-1.56	-0.0204	-0.70	0.06
27	-0.0135	-3.28***	0.0174	0.45	-0.0665	-0.73	-0.0283	-0.20	-0.1019	-1.30	-0.0402	-1.15	0.05
28	0.0033	0.25	0.1708	1.35	-0.1605	-0.54	0.1518	0.34	0.0625	0.24	-0.0624	-0.55	0.05
29	-0.0180	-7.07***	0.0197	0.82	-0.0263	-0.47	-0.0695	-0.82	-0.1068	-2.21**	-0.0315	-1.46	0.12
30	-0.0109	-3.76***	0.0234	0.86	-0.0056	-0.09	-0.0716	-0.74	-0.0523	-0.95	-0.0214	-0.88	0.04
31	0.0053	0.35	0.1936	1.35	-0.2669	-0.79	0.1523	0.30	0.1307	0.45	-0.0481	-0.37	0.06
32	-0.0136	-1.65*	-0.0406	-0.52	0.0328	0.18	0.1488	0.54	-0.1011	-0.65	-0.0817	-1.17	0.04
33	-0.0096	-2.21**	0.0016	0.04	-0.0346	-0.36	0.1214	0.84	-0.0507	-0.62	-0.0077	-0.21	0.02
34	-0.0108	-2.74***	0.0501	1.35	-0.0083	-0.10	0.0141	0.11	-0.1058	-1.41	-0.0209	-0.63	0.09
35	-0.0148	-7.05***	0.0033	0.16	-0.0156	-0.34	0.0254	0.36	-0.1009	-2.52**	-0.0109	-0.61	0.12
36	-0.0146	-5.66***	-0.0010	-0.04	0.0093	0.16	0.0644	0.74	-0.1242	-2.53**	-0.0185	-0.85	0.16
37	-0.0104	-0.79	0.1470	1.20	-0.0373	-0.13	-0.1795	-0.41	0.1053	0.42	-0.0323	-0.29	0.03
38	0.0071	0.61	0.0031	0.03	-0.1015	-0.40	0.1960	0.51	-0.0289	-0.13	-0.0106	-0.11	0.01
39	0.0243	0.79	0.4340	1.49	-0.1981	-0.29	-0.1095	-0.11	0.3027	0.51	-0.0769	-0.29	0.05
40	0.0007	0.05	-0.0140	-0.10	-0.1646	-0.52	0.4068	0.84	-0.0033	-0.01	0.0371	0.31	0.02

Note: This table presents results from regressing after-cost returns for financial crisis period to pairs trading strategies against the Fama–French and momentum factors as well as market reversal. The column labeled “Intercept” is the estimated intercept term in each regression. The columns labeled “t-stat” report the test statistic for the estimated coefficient on the left, computed using Newey–West standard errors with six lags. SMB (Small Minus Big): The return difference between small-cap and large-cap portfolios, constructed based on float-adjusted market capitalization. HML (High Minus Low): The return difference between high and low book-to-market portfolios, sorted in June based on the previous December’s book-to-market ratio. MOM (Momentum): The return difference between high and low cumulative return portfolios, based on past 2-12 months' performance. MKT: Market factor, represented by a float-adjusted market cap-weighted index of all A-shares. Rf: The one-year deposit rate used as the risk-free rate.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

TABLE 16. Risk-Adjusted Returns after Trading Costs for Bullish and Bearish Period.

Portfolio	Intercept	t-stat	MKT-RF	t-stat	SMB	*t*-stat	HML	t-stat	Momentum	t-stat	Reversal	t-stat	R^2
1	-0.0013	-1.20	-0.0532	-3.85***	0.0414	1.16	-0.0445	-1.33	-0.0634	-3.21***	0.0020	0.16	0.32
2	-0.0006	-0.46	-0.0306	-1.93*	-0.0172	-0.42	-0.1015	-2.63***	-0.0721	-3.17***	0.0166	1.15	0.28
3	-0.0001	-0.04	-0.0400	-2.46**	0.0081	0.19	-0.0827	-2.10**	-0.0593	-2.55**	0.0263	1.78*	0.27
4	-0.0008	-0.70	-0.0278	-2.03**	0.0114	0.32	-0.0736	-2.22**	-0.0417	-2.13**	0.0285	2.30**	0.27
5	-0.0019	-1.55	-0.0491	-3.19***	0.0458	1.15	-0.0454	-1.22	-0.0670	-3.05***	0.0267	1.91*	0.31
6	-0.0044	-1.87*	0.0007	0.02	0.0400	0.54	0.0181	0.26	-0.1454	-3.53***	0.0110	0.42	0.16
7	-0.0003	-0.23	-0.0282	-1.63	0.0160	0.36	-0.0170	-0.41	-0.0867	-3.52***	0.0097	0.62	0.20
8	-0.0014	-1.00	-0.0389	-2.24**	0.0477	1.06	0.0308	0.73	-0.0733	-2.95***	0.0135	0.85	0.19
9	-0.0010	-0.75	-0.0471	-2.78***	0.0517	1.19	-0.0025	-0.06	-0.0829	-3.43***	-0.0020	-0.13	0.24
10	-0.0004	-0.32	-0.0363	-2.17**	0.0081	0.19	-0.0800	-1.97**	-0.0850	-3.56***	0.0087	0.57	0.27
11	-0.0014	-0.94	-0.0404	-2.29**	0.0495	1.09	-0.0367	-0.86	-0.0833	-3.30***	0.0054	0.34	0.23
12	-0.0016	-1.17	-0.0412	-2.45**	0.0573	1.32	0.0300	0.73	-0.0445	-1.85*	0.0038	0.25	0.13
13	0.0002	0.12	-0.0509	-2.55**	0.0237	0.46	-0.0548	-1.13	-0.0714	-2.51**	0.0174	0.96	0.21
14	-0.0012	-0.92	-0.0274	-1.74*	-0.0048	-0.12	-0.0398	-1.05	-0.0595	-2.65***	-0.0030	-0.21	0.16
15	-0.0001	-0.11	-0.0304	-1.83*	0.0437	1.02	-0.0484	-1.20	-0.0522	-2.20**	0.0129	0.85	0.18
16	-0.0012	-1.05	-0.0421	-3.02***	0.0321	0.89	-0.0217	-0.64	-0.0625	-3.13***	0.0029	0.23	0.24
17	-0.0009	-0.78	-0.0388	-2.67***	0.0339	0.91	-0.0337	-0.96	-0.0731	-3.53***	0.0067	0.51	0.26
18	-0.0016	-1.29	-0.0435	-2.81***	0.0391	0.98	-0.0212	-0.56	-0.0747	-3.37***	0.0118	0.84	0.25
19	-0.0013	-1.43	-0.0288	-2.64***	0.0324	1.15	-0.0377	-1.42	-0.0593	-3.79***	0.0170	1.71*	0.32
20	-0.0013	-1.11	-0.0177	-1.28	0.0349	0.98	-0.0159	-0.47	-0.0329	-1.66*	0.0127	1.01	0.10
21	-0.0017	-1.79*	-0.0151	-1.27	0.0332	1.08	-0.0333	-1.15	-0.0492	-2.88***	0.0159	1.46	0.21
22	-0.0008	-0.83	-0.0514	-4.20***	0.0408	1.29	-0.0174	-0.59	-0.0597	-3.41***	0.0133	1.20	0.34
23	-0.0004	-0.38	-0.0241	-1.95*	-0.0016	-0.05	-0.0116	-0.39	-0.0316	-1.78*	0.0239	2.12**	0.18
24	-0.0042	-2.11**	0.0372	1.54	0.0683	1.10	0.0670	1.14	-0.1600	-4.63***	0.0343	1.56	0.30
25	0.0000	0.00	-0.0270	-1.72*	0.0266	0.66	-0.0386	-1.01	-0.0619	-2.75***	0.0071	0.50	0.17
26	0.0000	-0.01	-0.0221	-1.49	0.0060	0.16	-0.0228	-0.63	-0.0609	-2.86***	0.0083	0.62	0.15

27	-0.0021	-1.65*	-0.0487	-3.11***	0.0757	1.88*	0.0347	0.91	-0.0866	-3.87***	0.0146	1.03	0.29
28	-0.0009	-0.79	-0.0356	-2.62***	0.0336	0.96	-0.0410	-1.24	-0.0622	-3.20***	0.0098	0.80	0.26
29	-0.0024	-1.86*	-0.0485	-3.08***	0.1214	3.00***	0.0787	2.06**	-0.0967	-4.30***	0.0430	3.01***	0.38
30	-0.0006	-0.47	-0.0233	-1.44	-0.0104	-0.25	-0.0222	-0.56	-0.0779	-3.37***	0.0147	1.00	0.20
31	-0.0017	-1.43	-0.0432	-2.96***	0.0527	1.40	-0.0075	-0.21	-0.0750	-3.60***	0.0063	0.48	0.26
32	-0.0006	-0.44	-0.0264	-1.63	0.0315	0.75	-0.0297	-0.76	-0.0676	-2.92***	0.0068	0.46	0.17
33	-0.0013	-0.88	-0.0320	-1.81*	0.0458	1.01	0.0409	0.96	-0.0685	-2.72***	0.0171	1.07	0.17
34	-0.0011	-1.24	-0.0367	-3.35***	0.0514	1.82*	-0.0004	-0.01	-0.0772	-4.93***	0.0144	1.45	0.38
35	-0.0009	-0.87	-0.0263	-2.01**	0.0348	1.03	0.0015	0.05	-0.0802	-4.29***	0.0097	0.81	0.27
36	-0.0015	-1.37	-0.0263	-1.97**	0.0474	1.38	-0.0141	-0.43	-0.0907	-4.75***	0.0115	0.95	0.31
37	0.0000	-0.02	-0.0605	-3.39***	0.1374	2.99***	0.0440	1.02	-0.1088	-4.27***	0.0145	0.89	0.34
38	-0.0017	-1.67	-0.0186	-1.45	0.0297	0.90	-0.0373	-1.20	-0.0325	-1.77*	0.0084	0.72	0.15
39	-0.0002	-0.13	-0.0553	-3.59***	0.0819	2.07**	0.0139	0.37	-0.1021	-4.64***	0.0097	0.69	0.36
40	-0.0029	-2.49**	-0.0097	-0.67	0.0498	1.32	-0.0172	-0.49	-0.0344	-1.65*	0.0084	0.63	0.11

Note: This table presents results from regressing after-cost returns for bullish and bearish period to pairs trading strategies against the Fama–French and momentum factors as well as market reversal. The column labeled "Intercept" is the estimated intercept term in each regression. The columns labeled "t-stat" report the test statistic for the estimated coefficient on the left, computed using Newey–West standard errors with six lags. SMB (Small Minus Big): The return difference between small-cap and large-cap portfolios, constructed based on float-adjusted market capitalization. HML (High Minus Low): The return difference between high and low book-to-market portfolios, sorted in June based on the previous December's book-to-market ratio. MOM (Momentum): The return difference between high and low cumulative return portfolios, based on past 2-12 months' performance. MKT: Market factor, represented by a float-adjusted market cap-weighted index of all A-shares. Rf: The one-year deposit rate used as the risk-free rate.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

TABLE 17. Risk-Adjusted Returns after Trading Costs for COVID-19 Period.

Portfolio	Intercept	t-stat	MKT-RF	t-stat	SMB	*t*-stat	HML	t-stat	Momentum	t-stat	Reversal	t-stat	R^2
1	-0.0012	-0.62	0.0358	0.86	-0.0448	-0.82	-0.1341	-2.61***	-0.0396	-0.99	0.0566	1.42	0.14
2	0.0004	0.42	0.0301	1.57	-0.0064	-0.26	-0.0095	-0.40	-0.0624	-3.38***	0.0047	0.26	0.18
3	0.0015	0.86	0.0160	0.42	-0.0361	-0.72	-0.0677	-1.43	-0.0227	-0.62	0.0401	1.09	0.05
4	-0.0003	-0.33	0.0289	1.53	-0.0375	-1.52	-0.0038	-0.17	-0.0378	-2.08**	0.0380	2.11**	0.14
5	0.0003	0.36	0.0149	0.71	-0.0049	-0.18	0.0193	0.74	-0.0514	-2.54**	-0.0023	-0.11	0.10
6	-0.0025	-1.04	-0.0135	-0.26	-0.0273	-0.40	-0.0085	-0.13	-0.1167	-2.30**	-0.0494	-0.98	0.08
7	0.0011	1.03	0.0233	0.97	-0.1108	-3.52***	-0.0500	-1.68	-0.0923	-3.98***	0.0124	0.54	0.24
8	0.0001	0.15	0.0011	0.06	-0.0897	-3.45***	-0.0013	-0.05	-0.0435	-2.27**	-0.0106	-0.55	0.14
9	0.0006	0.67	-0.0173	-0.84	-0.0785	-2.92***	-0.0123	-0.48	-0.1008	-5.10***	-0.0134	-0.68	0.25
10	0.0018	0.95	0.0104	0.25	-0.1070	-1.98**	-0.1429	-2.80***	-0.0575	-1.45	0.0447	1.13	0.15
11	-0.0001	-0.10	0.0227	1.08	-0.0575	-2.09**	-0.0247	-0.95	-0.0657	-3.25***	-0.0149	-0.74	0.15
12	0.0009	0.49	-0.0108	-0.28	-0.0987	-1.94*	-0.0998	-2.08**	-0.0786	-2.10**	0.0201	0.54	0.11

13	-0.0003	-0.17	0.0613	1.80*	-0.0590	-1.33	0.0216	0.52	-0.0583	-1.78*	0.0001	0.00	0.08
14	0.0005	0.46	0.0183	0.79	-0.0578	-1.91*	-0.0391	-1.37	-0.0531	-2.38**	-0.0070	-0.32	0.11
15	0.0003	0.32	-0.0038	-0.21	-0.0416	-1.75*	0.0015	0.07	-0.0913	-5.22***	-0.0104	-0.60	0.26
16	0.0003	0.35	0.0167	0.96	-0.0614	-2.71***	-0.0095	-0.44	-0.0627	-3.76***	0.0066	0.40	0.18
17	0.0006	0.60	-0.0005	-0.02	-0.0556	-2.09**	-0.0283	-1.13	-0.0683	-3.48***	0.0067	0.34	0.15
18	0.0004	0.51	-0.0120	-0.72	-0.0448	-2.07**	-0.0265	-1.30	-0.0656	-4.12***	0.0156	0.99	0.20
19	0.0022	0.75	0.0067	0.10	-0.0541	-0.63	-0.1761	-2.18**	-0.0161	-0.26	0.0692	1.10	0.08
20	-0.0012	-1.44	0.0174	0.99	-0.0443	-1.93*	-0.0040	-0.19	-0.0355	-2.10**	0.0260	1.55	0.11
21	-0.0008	-1.01	0.0193	1.18	-0.0136	-0.63	-0.0064	-0.32	-0.0565	-3.58***	0.0018	0.12	0.17
22	0.0013	0.77	0.0034	0.09	-0.0506	-1.03	-0.0922	-2.00**	-0.0263	-0.73	0.0184	0.51	0.07
23	-0.0006	-0.82	0.0173	1.03	-0.0153	-0.70	-0.0210	-1.01	-0.0438	-2.70***	0.0093	0.58	0.12
24	-0.0022	-1.66*	0.0017	0.06	-0.0029	-0.08	0.0923	2.54**	-0.0883	-3.12***	-0.0357	-1.27	0.21
25	0.0018	0.56	-0.0063	-0.09	-0.1109	-1.21	-0.1833	-2.12**	-0.0438	-0.65	0.0594	0.88	0.08
26	0.0003	0.38	0.0161	0.98	-0.0549	-2.56**	-0.0094	-0.46	-0.0462	-2.92***	0.0083	0.53	0.14
27	0.0016	1.03	0.0064	0.19	-0.0880	-2.02**	-0.0927	-2.25**	-0.0483	-1.51	0.0319	1.00	0.12
28	0.0017	0.53	0.0072	0.11	-0.1165	-1.29	-0.1903	-2.24**	-0.0384	-0.58	0.0681	1.03	0.09
29	0.0007	0.45	0.0031	0.10	-0.0705	-1.71*	-0.0838	-2.15**	-0.0298	-0.98	0.0241	0.79	0.09
30	0.0002	0.23	-0.0182	-1.04	-0.0673	-2.95***	-0.0133	-0.62	-0.0682	-4.06***	-0.0045	-0.27	0.19
31	0.0009	0.50	-0.0035	-0.09	-0.0302	-0.58	-0.0993	-2.01**	-0.0063	-0.16	0.0245	0.64	0.06
32	0.0001	0.16	-0.0024	-0.14	-0.0511	-2.27**	0.0062	0.29	-0.0688	-4.16***	-0.0104	-0.63	0.18
33	0.0002	0.25	0.0037	0.20	-0.0497	-2.02**	-0.0206	-0.89	-0.0662	-3.66***	0.0129	0.72	0.16
34	0.0000	0.06	0.0031	0.19	-0.0469	-2.21**	-0.0277	-1.39	-0.0478	-3.06***	0.0080	0.51	0.14
35	0.0003	0.43	-0.0046	-0.29	-0.0510	-2.45**	-0.0203	-1.03	-0.0634	-4.14***	0.0131	0.86	0.20
36	-0.0006	-0.98	-0.0014	-0.11	-0.0223	-1.35	0.0018	0.12	-0.0545	-4.47***	0.0062	0.51	0.21
37	0.0015	0.45	-0.0164	-0.23	-0.1017	-1.08	-0.1605	-1.81	-0.0334	-0.48	0.0512	0.74	0.06
38	-0.0008	-0.87	0.0181	0.94	-0.0254	-1.01	-0.0488	-2.06**	-0.0266	-1.44	0.0110	0.60	0.10
39	0.0009	0.27	-0.0172	-0.25	-0.1070	-1.18	-0.1663	-1.94*	-0.0293	-0.44	0.0472	0.71	0.06
40	-0.0001	-0.07	0.0316	1.67	0.0085	0.34	-0.0419	-1.80*	-0.0094	-0.52	-0.0014	-0.08	0.11

Note: This table presents results from regressing after-cost returns for covid-19 period to pairs trading strategies against the Fama–French and momentum factors as well as market reversal. The column labeled "Intercept" is the estimated intercept term in each regression. The columns labeled "t-stat" report the test statistic for the estimated coefficient on the left, computed using Newey–West standard errors with six lags. SMB (Small Minus Big): The return difference between small-cap and large-cap portfolios, constructed based on float-adjusted market capitalization. HML (High Minus Low): The return difference between high and low book-to-market portfolios, sorted in June based on the previous December's book-to-market ratio. MOM (Momentum): The return difference between high and low cumulative return portfolios, based on past 2-12 months' performance. MKT: Market factor, represented by a float-adjusted market cap-weighted index of all A-shares. Rf: The one-year deposit rate used as the risk-free rate.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

We now turn our attention to the COVID-19 period as shown in Table 17. The results reveal mixed and mostly insignificant alphas, indicating that pairs trading strategies did not generate abnormal returns beyond what was explained by the included risk factors during this period. Most portfolios have intercepts close to zero and are statistically insignificant. For instance, Portfolio 3 has an alpha of 15 bps per month with a t-statistic of 0.86, and Portfolio 4 shows an alpha of -3 bps per month with a t-statistic of -0.33. There are few instances of significant alphas; however, the t-statistics for the intercepts across portfolios are generally low, reinforcing the notion that pairs trading strategies neither significantly outperformed nor underperformed after adjusting for risk factors during the COVID-19 period.

The coefficients on the market risk factor show mixed results. Some portfolios have positive market betas, while others are negative, but most are statistically insignificant. For example, Portfolio 2 has a market beta of 0.0301, approaching significance at the 10% level, suggesting a mild positive exposure to market movements. In contrast, Portfolio 9 has a negative market beta of -0.0173, indicating a slight inverse relationship with the market, though not statistically significant. The overall lack of significant market betas implies that pairs trading portfolios had limited exposure to market movements during the COVID-19 period, consistent with the market-neutral objective of pairs trading strategies.

The results show consistently negative and significant SMB coefficients across many portfolios, indicating a tilt towards large-cap stocks. For instance, Portfolio 7 has an SMB coefficient of -0.1108 and Portfolio 8 reports an SMB coefficient of -0.0897. This negative and significant size exposure suggests that the portfolios performed better when large-cap stocks outperformed small-cap stocks, highlighting a preference for larger companies during this period. This shift may reflect investors' flight to quality during uncertain times, favoring more established firms with stronger balance sheets amid the pandemic-induced economic disruption.

The value factor coefficients are generally negative and significant, indicating a tilt towards growth stocks over value stocks. For example, Portfolio 1 has an HML coefficient of -0.1341, and Portfolio 10 shows an HML coefficient of -0.1429. These results suggest that the portfolios performed better when growth stocks outperformed value stocks during the COVID-19 period. This trend aligns with the market conditions during the pandemic, where technology and growth-oriented sectors outperformed traditional value sectors, such as energy and finance, due to shifts in consumer behavior and economic activity.

The momentum factor exhibits strong negative and significant coefficients across most portfolios, reinforcing the contrarian nature of pairs trading strategies. For instance, Portfolio 9 has a momentum beta of -0.1008, and Portfolio 15 reports a momentum beta of -0.0913. The consistently negative exposure to momentum indicates that the pairs trading portfolios profited from betting against recent trends, performing better when recent losers outperformed recent winners. This is consistent with the fundamental principle of pairs trading, which seeks to exploit short-term price reversals and temporary deviations from historical relationships.

The coefficients on the market reversal factor are generally insignificant, with a few exceptions. Portfolio 4 shows a REV coefficient of 0.0380, suggesting that this portfolio may benefit from market-wide reversals. However, the overall impact of the reversal factor is limited, indicating that market-wide reversals played a minor role in explaining portfolio returns during the COVID-19 period.

The adjusted R^2 values during the COVID-19 period range from low to moderate, indicating limited explanatory power of the five-factor model. For example, Portfolio 9 has an R^2 of 0.25, and Portfolio 15 has an R^2 of 0.26. These values suggest that while the model captures some of the variation in portfolio returns, a significant portion remains unexplained, possibly due to idiosyncratic factors or unique market conditions during the pandemic.

When comparing the COVID-19 period with the Financial Crisis (Table 15) and the Bullish and Bearish period (Table 16), several differences emerge. During the Financial Crisis, many portfolios exhibited significant negative alphas, indicating that pairs trading strategies underperformed after adjusting for risk factors. For example, Portfolio 1 had an alpha of -223 bps per month. Similarly, during the Bullish and Bearish period, alphas were generally negative but often not statistically significant. In contrast, during the COVID-19 period, alphas are mostly insignificant and close to zero, suggesting that pairs trading strategies neither significantly outperformed nor underperformed after adjusting for risk factors. This neutrality indicates that the profitability of pairs trading strategies during the COVID-19 period was largely explained by common risk factors, and there were fewer opportunities for generating abnormal returns.

In the Financial Crisis, market betas were generally positive but insignificant, while during the Bullish and Bearish period, they were consistently negative and significant, indicating an inverse relationship with the market. In the COVID-19 period, market betas are mixed and generally insignificant, implying minimal exposure to market movements. This reflects the heightened uncertainty and rapid market shifts during the pandemic, where traditional correlations may have been disrupted.

The shift towards negative and significant SMB coefficients during the COVID-19 period contrasts with the previous periods. During the Financial Crisis and the Bullish and Bearish period, the SMB coefficients were mostly insignificant, indicating limited size exposure. The pronounced negative SMB coefficients during the COVID-19 period suggest a strategic tilt towards large-cap stocks, possibly as investors sought the relative safety of larger, more established companies amid the unprecedented global health crisis.

The negative and significant HML coefficients are more consistent during the COVID-19 period, indicating a stronger tilt towards growth stocks compared to previous periods. This aligns with the market dynamics during the pandemic, where growth sectors, particularly technology and healthcare, outperformed as they adapted to or benefited from the new environment.

Across all periods, the momentum factor shows consistently negative and significant coefficients, confirming the contrarian nature of pairs trading strategies. However, the magnitude of the negative coefficients is notably high during the COVID-19 period, suggesting that betting against momentum was particularly relevant in this context, possibly due to increased volatility and rapid reversals in market trends.

The analysis of Table 17 reveals that during the COVID-19 period, pairs trading strategies did not generate significant abnormal returns after adjusting for common risk factors. This contrasts with the Financial Crisis, where significant negative alphas indicated underperformance, and the Bullish and Bearish period, where alphas were negative but less significant. The neutral performance during the COVID-19 period suggests that pairs trading strategies were neither particularly effective nor detrimental in generating abnormal profits, possibly due to the unique and unprecedented market conditions.

Comparing the three periods, pairs trading strategies exhibited varying performance, influenced by market conditions. During the Financial Crisis, significant negative alphas indicated underperformance, possibly due to extreme volatility disrupting historical price relationships and the effectiveness of mean-reversion strategies. During the Bullish and Bearish period, negative alphas suggested underperformance after adjusting for risk factors, with strategies facing challenges in generating abnormal returns during stable market conditions. During the COVID-19 period, neutral alphas indicated that pairs trading strategies neither significantly outperformed nor underperformed, with returns largely explained by common risk factors.

These findings suggest that the effectiveness of pairs trading strategies is highly contingent on market conditions. During periods of extreme volatility, such as the Financial Crisis, pairs trading may struggle due to breakdowns in historical correlations. In contrast, during the unique conditions of the COVID-19 period, the strategies exhibited neutral performance, potentially reflecting rapid market adjustments and the influence of unprecedented factors not captured by traditional models. For practitioners and investors, these results underscore the importance of adapting pairs trading strategies to prevailing market conditions. The shift towards large-cap and growth stocks during the COVID-19 period highlights the need to monitor and adjust factor exposures in response to changing market dynamics. Additionally, the consistent negative relationship with the momentum factor emphasizes the value of contrarian approaches in pairs trading, particularly during periods of heightened volatility.

5.3.2 Value at Risk and Expected Shortfall of Returns

In this section, we examine the risk profile of pairs trading strategies by analyzing the monthly VaR and ES at the 1%, 5%, and 10% levels across three distinct periods: the Financial Crisis, the Bullish and Bearish period, and the COVID-19 period. This analysis focuses on the magnitude of potential losses under extreme market conditions, the differences in risk profiles across the periods, and the impact of implementing a one-day waiting strategy on VaR and ES measures. The one-day waiting strategy involves delaying the execution of trades by one day after a trading signal is generated, which may influence the risk and return characteristics of the strategy.

Table 18 presents the monthly VaR percentiles for 40 pairs trading portfolios during the three periods. For each portfolio and period, the VaR at the 1%, 5%, and 10% levels is reported. The numbers outside the parentheses represent the VaR without the one-day waiting strategy, while the numbers inside the parentheses show the VaR with the one-day waiting strategy.

During the **Financial Crisis**, portfolios exhibit significantly higher VaR values compared to the other periods, reflecting the elevated market risk and extreme volatility that characterized this period. The 1% VaR values for most portfolios are notably high, with some exceeding 20%. For example, Portfolio 10 reports a 1% VaR of 0.30 without the waiting strategy and 0.31 with waiting, indicating that there is a 1% chance of experiencing a monthly loss of 30% or more. Other portfolios, such as Portfolio 7, show similarly high values of 0.24 (no wait) and 0.25 (wait), underscoring the considerable risk exposure during the crisis. By contrast, certain portfolios, such as Portfolios 6, 9, 18, and 34, have relatively lower 1% VaR values, ranging from 0.03 to 0.11, suggesting that some strategies were less vulnerable to extreme market conditions.

At the 5% level, VaR values are generally between 0.03 and 0.16, with portfolios such as Portfolio 19 and Portfolio 10 showing the highest risk. This pattern is consistent with the 1% level findings, indicating that these portfolios are more susceptible to extreme losses. The 10% VaR values are lower across the board, typically between 0.02 and 0.07, indicating that smaller losses are more common and that the risk of severe losses is less frequent. Overall, the one-day waiting strategy has a minimal impact on VaR values during the Financial Crisis, with only slight changes observed across most portfolios, implying that delaying trade execution by one day did not significantly alter the risk profile.

The **Bullish and Bearish period** exhibits much lower VaR values compared to the Financial Crisis, reflecting the reduced market volatility and more stable trading environment. At the 1% level, most portfolios show VaR values of 0.01 or 0.02, with almost no variation between portfolios. This uniformity in VaR values suggests a consistent risk profile across different strategies during this period. Similarly, at the 5% and 10% levels, the VaR values are nearly identical across portfolios, remaining at 0.01 or slightly below, further indicating minimal risk exposure.

The one-day waiting strategy has negligible effects on VaR values during the Bullish and Bearish period. For instance, the 1% VaR for Portfolio 1 is 0.02 with and without the waiting strategy, and the same pattern holds for the majority of other portfolios. This minimal impact suggests that delaying trade execution by one day does not meaningfully alter the risk profile during periods of low volatility, consistent with the idea that mispricing opportunities are less transient in stable market conditions, allowing for delayed execution without incurring additional risk.

During the COVID-19 period, VaR values are higher than those observed during the Bullish and Bearish period but generally lower than those during the Financial Crisis. This finding reflects the heightened but controlled volatility during the pandemic. At the 1% level, most portfolios report VaR values between 0.02 and 0.04, with a few outliers such as Portfolio 6, which has a 1% VaR of 0.10, and Portfolio 24, which also reports a 1% VaR of 0.10. These elevated values suggest that some strategies were more vulnerable to sudden market shocks during the pandemic.

The 5% VaR values during the COVID-19 period are mostly consistent at 0.02, indicating a lower probability of experiencing extreme losses. However, Portfolio 24 again stands out, with a 5% VaR of 0.04, reflecting its heightened risk profile. The 10% VaR values are generally between 0.01 and 0.02 for most portfolios, suggesting that while the likelihood of small losses is relatively high, the probability of severe losses remains limited. As with the other periods, the one-day waiting strategy has minimal effects on VaR values during the COVID-19 period, with only slight differences observed for a few portfolios. Notable exceptions include Portfolio 24, where the 1% and 5% VaR values remain high (0.10 and 0.04) regardless of the waiting strategy, suggesting that delaying execution does not mitigate the risk of extreme losses for this portfolio.

The analysis of monthly VaR across the three periods highlights the impact of market conditions on risk exposure in pairs trading strategies. The Financial Crisis exhibited the highest VaR levels, indicating elevated risk and the potential for severe losses. During this period, the risk of extreme losses was more pronounced, with several portfolios showing VaR values above 20% at the 1% level. The Bullish and Bearish period showed much lower VaR values, reflecting the stability and reduced volatility of the market. The low and consistent VaR values across portfolios indicate that the risk profile was relatively uniform, with minimal chance of experiencing large losses. The COVID-19 period presented a middle ground, with moderate VaR values suggesting elevated but controlled risk. The variation in VaR values between portfolios during the COVID-19 period highlights that certain strategies were more exposed to sudden market shocks than others.

Overall, the one-day waiting strategy has a minimal impact on VaR values across all three periods, indicating that delaying trade execution by one day does not substantially alter the risk profile of pairs trading strategies. This finding suggests that while immediate execution may be beneficial for capturing short-lived mispricings, the one-day delay does not significantly increase or reduce risk, particularly during stable market conditions. However, during volatile periods such as the

Financial Crisis, the lack of change in VaR values may imply that extreme market conditions drive risk more than the timing of execution. This observation underscores the importance of understanding the underlying market dynamics and the nature of mispricing opportunities when implementing a one-day waiting strategy.

The findings from Table 18 suggest that careful portfolio selection and risk assessment are crucial when employing pairs trading strategies, especially during periods of elevated market stress. The high VaR values observed during the Financial Crisis highlight the potential for severe losses in extreme conditions, emphasizing the need for robust risk management practices. During more stable periods, such as the Bullish and Bearish period, the low and consistent VaR values suggest that pairs trading strategies are relatively safe, but the lack of significant risk reduction from the one-day waiting strategy implies that execution timing may be less critical in such environments.

In conclusion, the VaR analysis across the three periods demonstrates that pairs trading strategies are highly sensitive to market conditions, with risk exposure varying significantly between periods. While the one-day waiting strategy does not significantly alter risk profiles in most cases, it may still provide benefits in reducing transaction costs or avoiding false signals. Understanding the interaction between strategy timing and market conditions is essential for effectively managing risk and optimizing returns in pairs trading strategies.

TABLE 18. Monthly Value at risk (VAR) for All Three Periods After Trading Costs With and Without One Day Waiting.

	Financial Crisis			Bullish and Bearish			COVID-19		
Portfolio	**1% VaR**	**5% VaR**	**10% VaR**	**1% VaR**	**5% VaR**	**10% VaR**	**1% VaR**	**5% VaR**	**10% VaR**
1	0.21(0.20)	0.13(0.06)	0.04(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.03(0.03)	0.02(0.01)	0.01(0.01)
2	0.19(0.18)	0.11(0.11)	0.05(0.04)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.03(0.02)	0.01(0.01)	0.01(0.01)
3	0.21(0.20)	0.11(0.09)	0.05(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
4	0.16(0.16)	0.11(0.11)	0.07(0.05)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
5	0.12(0.10)	0.03(0.04)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
6	0.11(0.10)	0.05(0.04)	0.04(0.04)	0.04(0.04)	0.02(0.02)	0.02(0.02)	0.10(0.10)	0.04(0.04)	0.03(0.03)
7	0.24(0.25)	0.11(0.11)	0.06(0.05)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.01(0.01)
8	0.11(0.11)	0.05(0.04)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
9	0.06(0.06)	0.03(0.03)	0.02(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
10	0.30(0.31)	0.17(0.15)	0.06(0.06)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.03(0.03)	0.02(0.01)	0.01(0.01)
11	0.23(0.22)	0.08(0.07)	0.03(0.03)	0.02(0.03)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.02(0.02)	0.01(0.01)
12	0.07(0.07)	0.04(0.04)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.03(0.03)	0.02(0.01)	0.01(0.01)
13	0.21(0.17)	0.07(0.06)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.06(0.05)	0.02(0.02)	0.01(0.01)
14	0.12(0.12)	0.08(0.08)	0.04(0.06)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.03)	0.02(0.01)	0.01(0.01)
15	0.04(0.04)	0.03(0.03)	0.02(0.02)	0.21(0.02)	0.01(0.01)	0.01(0.01)	0.03(0.02)	0.02(0.01)	0.01(0.01)
16	0.07(0.08)	0.04(0.05)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
17	0.06(0.05)	0.03(0.03)	0.02(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.00)	0.02(0.02)	0.01(0.01)	0.01(0.01)
18	0.06(0.05)	0.03(0.03)	0.02(0.02)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.01)	0.01(0.01)	0.01(0.01)
19	0.24(0.23)	0.07(0.06)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.00(0.00)	0.04(0.04)	0.01(0.01)	0.01(0.01)
20	0.13(0.14)	0.03(0.03)	0.02(0.03)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
21	0.16(0.16)	0.04(0.03)	0.03(0.03)	0.61(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
22	0.09(0.05)	0.04(0.03)	0.03(0.02)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
23	0.13(0.13)	0.05(0.04)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.00(0.00)	0.02(0.02)	0.01(0.01)	0.01(0.01)
24	0.06(0.06)	0.05(0.05)	0.04(0.03)	0.09(0.04)	0.03(0.02)	0.02(0.01)	0.03(0.03)	0.02(0.02)	0.02(0.02)

25	0.04(0.05)	0.03(0.03)	0.03(0.03)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.04(0.04)	0.02(0.01)	0.01(0.01)
26	0.03(0.03)	0.03(0.03)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.01(0.00)	0.02(0.02)	0.01(0.01)	0.01(0.01)
27	0.09(0.09)	0.03(0.03)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)
28	0.09(0.09)	0.05(0.05)	0.03(0.03)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.04(0.04)	0.02(0.02)	0.01(0.01)
29	0.09(0.09)	0.05(0.05)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
30	0.06(0.06)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
31	0.21(0.21)	0.05(0.05)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.03(0.02)	0.01(0.01)	0.01(0.01)
32	0.18(0.17)	0.08(0.04)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
33	0.06(0.06)	0.03(0.03)	0.02(0.02)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
34	0.05(0.05)	0.03(0.03)	0.03(0.02)	0.01(0.01)	0.01(0.01)	0.00(0.00)	0.02(0.02)	0.01(0.01)	0.01(0.01)
35	0.05(0.05)	0.03(0.03)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.00(0.00)	0.01(0.01)	0.01(0.01)	0.01(0.01)
36	0.07(0.07)	0.03(0.03)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)
37	0.30(0.10)	0.08(0.03)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.00(0.00)	0.04(0.04)	0.02(0.02)	0.02(0.01)
38	0.05(0.05)	0.04(0.03)	0.03(0.03)	0.07(0.02)	0.02(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
39	0.08(0.08)	0.04(0.04)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.04(0.04)	0.02(0.02)	0.02(0.01)
40	0.29(0.29)	0.04(0.04)	0.03(0.03)	0.02(0.02)	0.02(0.01)	0.01(0.01)	0.02(0.01)	0.01(0.01)	0.01(0.01)

Note: The monthly Value at Risk (VaR) percentiles for pairs trading strategies from January 2005 to June 2024 are reported for all three periods. Pairs are constructed using a 12-month formation period based on a minimum-distance criterion, followed by a 6-month trading period. In this format, the VaR percentiles provide insights into the potential losses that might occur under extreme market conditions for each period, ensuring a comprehensive understanding of the risk profile associated with the pairs trading strategies. The data in '()' are the results of the one day waiting strategy.

The updated Table 19 presents the monthly ES percentiles for 40 pairs trading portfolios during three distinct periods: the Financial Crisis, the Bullish and Bearish period, and the COVID-19 period. The ES values are reported at the 1%, 5%, and 10% levels, with figures outside the parentheses representing results without the one-day waiting strategy and those inside parentheses indicating results with the one-day waiting strategy. The ES provides a measure of average losses beyond the VaR threshold, giving a deeper understanding of potential extreme losses during volatile periods.

During the Financial Crisis, portfolios exhibited substantially higher ES values compared to the other periods, reflecting the extreme risk exposure in this turbulent environment. Significant variation in ES values across portfolios is observed, indicating that some strategies were more susceptible to tail risk than others. At the 1% level, Portfolio 11 stands out with an ES value of 45%, indicating an average loss of 45% in the worst 1% of cases, while Portfolio 19 shows a similarly high ES of 47%. Portfolios such as 15, 18, 33, and 34 display relatively lower 1% ES values ranging from 6% to 8%, suggesting less exposure to extreme losses. This pattern continues at the 5% and 10% levels, where Portfolio 11 still shows notably high ES values, while portfolios like 26, 34, and 35 exhibit much lower ES values. These findings suggest that certain pairs trading strategies experienced more severe losses during the crisis, potentially due to breakdowns in the historical relationships that underpin pairs trading.

The impact of the one-day waiting strategy on ES during the Financial Crisis is generally minimal for most portfolios. However, a few notable exceptions include Portfolio 5, where the 1% ES decreases from 20% to 11%, indicating that delaying the trade execution can mitigate extreme losses in specific cases. Similarly, Portfolio 37 exhibits a substantial reduction in ES at the 1% level from 33% to 17%, highlighting that the effectiveness of the waiting strategy is context-dependent. This reduction is likely due to the waiting strategy's ability to filter out some of the most extreme price movements, which often result from short-term market dislocations. The ES values are consistently higher than the corresponding VaR values (Table 18), reflecting the nature of ES as a more conservative risk measure. Overall, the Financial Crisis period demonstrates the importance of carefully evaluating risk management strategies, as even small adjustments in execution timing can lead to significant differences in tail risk for particular portfolios.

In contrast to the Financial Crisis, the ES values during the Bullish and Bearish period are significantly lower, indicating reduced tail risk. ES values are relatively consistent across portfolios, with minimal variation. At the 1% level, most portfolios report ES values of 2% to 3%, suggesting average losses of 2% to 3% in the worst 1% of cases. This consistency continues at the 5% and 10% levels, where ES values are typically 1% or lower, reflecting a stable risk environment with minimal exposure to extreme losses. The uniformity in ES across portfolios suggests that the pairs trading strategies performed predictably during this period, with little differentiation in tail risk among the portfolios. The one-day waiting strategy has negligible impact on ES during the Bullish and Bearish period, with ES values almost identical with or without waiting. This finding implies that under stable market conditions, the timing of trade execution has a limited effect on mitigating tail risk, as the market did not experience the rapid and extreme fluctuations characteristic of the Financial Crisis.

During the COVID-19 period, the ES values are higher than those observed in the Bullish and Bearish period but generally lower than those recorded during the Financial Crisis, suggesting a moderate level of risk exposure. At the 1% level, most portfolios show ES values ranging from 3% to 4%, with Portfolios 6 and 24 displaying higher ES values of 13% and 12%, respectively, reflecting elevated tail risk. The 5% ES values range from 2% to 8%, again with Portfolios 6 and 24 showing higher risk exposure. At the 10% level, ES values are mostly between 2% and 6%, with portfolios that have higher 1% ES values also showing higher 10% ES values. This alignment across different risk levels suggests that certain pairs trading strategies were consistently more vulnerable to extreme losses during the COVID-19 period, possibly due to abrupt changes in market conditions and rapid shifts in investor sentiment.

Similar to the other periods, the one-day waiting strategy has minimal impact on ES during the COVID-19 period. For most portfolios, ES values are nearly identical with or without the waiting strategy. However, Portfolio 6 experiences a slight reduction in 1% ES from 13% to 12% with the waiting strategy, suggesting a small decrease in tail risk. These findings indicate that the waiting strategy's ability to reduce extreme losses is limited under the volatile but not crisis-level conditions of the COVID-19 period. The consistently higher ES values compared to VaR values, particularly in portfolios with high tail risk, underscore the role of ES as a more comprehensive risk measure that accounts for the average severity of losses beyond the VaR threshold.

When comparing ES levels across the three periods, the Financial Crisis stands out as the period with the highest tail risk, as indicated by the significantly elevated ES values. The Bullish and Bearish period, by contrast, shows the lowest ES values, reflecting minimal tail risk during stable market conditions. The COVID-19 period falls in between, with moderate ES values that suggest increased but manageable risk compared to the stable period. This variation in ES values highlights how tail risk is influenced by broader market conditions and the specific characteristics of each period. During the Financial Crisis, the extreme market volatility and breakdown of traditional correlations led to severe losses for pairs trading strategies, while the relative calm of the Bullish and Bearish period allowed these strategies to perform predictably.

The one-day waiting strategy's impact on ES varies across the three periods, showing the most pronounced effect during the Financial Crisis. Portfolios such as 5 and 37 benefit from a notable reduction in ES, suggesting that the strategy can effectively reduce tail risk in highly volatile environments. During the Bullish and Bearish period, the strategy has almost no effect, and its impact during the COVID-19 period is similarly limited. This suggests that the effectiveness of the waiting strategy in mitigating extreme losses depends on market conditions and portfolio-specific factors. Portfolios that are highly sensitive to short-term market dislocations are more likely to benefit from delayed execution, while those with more stable performance profiles see little to no benefit.

The relationship between ES and VaR is evident across all periods. ES provides a deeper insight into tail risk by averaging losses beyond the VaR threshold, making it a more comprehensive measure of potential extreme losses. Portfolios identified as high-risk by VaR are also high-risk according to ES, indicating consistency between these risk measures. Both indicators show similar patterns in risk exposure, with ES values complementing VaR by providing additional information on the severity of losses in the tail of the distribution. This alignment between VaR and ES highlights the importance of using both measures in risk assessment to capture the full extent of potential losses.

The analysis of ES across the three periods offers several insights into the risk profiles of pairs trading strategies. The ES values highlight the significant variation in tail risk depending on market conditions, with the Financial Crisis posing the highest risk and the Bullish and Bearish period the lowest. Portfolio-specific differences in ES also suggest that some portfolios are inherently more exposed to extreme losses, particularly during volatile periods. These findings emphasize the importance of portfolio selection and comprehensive risk assessment when implementing pairs trading strategies in different market environments.

The one-day waiting strategy generally does not significantly reduce tail risk, as measured by ES, similar to its limited impact on VaR. However, in certain portfolios, the strategy can effectively reduce extreme losses, indicating its potential utility in specific cases. Overall, the waiting strategy's limited effectiveness suggests that other risk management techniques, such as diversification and hedging, may be more appropriate for reducing tail risk, particularly during periods of heightened market volatility. The complementary relationship between ES and VaR highlights the value of incorporating both measures into risk assessment frameworks to ensure a comprehensive understanding of potential losses.

In conclusion, the analysis of monthly ES across the three periods, along with the comparison to VaR, reveals several key findings. ES offers a more complete view of potential extreme losses than VaR, particularly during periods of high market volatility like the Financial Crisis. The one-day waiting strategy's impact on ES is limited, with only a few portfolios showing meaningful reductions in tail risk. As such, the strategy may not be a reliable tool for risk mitigation across all periods and portfolios. To manage tail risk effectively, investors should combine VaR and ES in their risk assessments and consider additional risk management strategies, particularly during periods of heightened market volatility.

TABLE 19. Monthly Expected Shortfall (ES) for All Three Periods After Trading Costs With and Without One Day Waiting.

	Financial Crisis			Bullish and Bearish			COVID-19		
Portfolio	**1% ES**	**5% ES**	**10% ES**	**1% ES**	**5% ES**	**10% ES**	**1% ES**	**5% ES**	**10% ES**
1	0.21(0.21)	0.19(0.16)	0.13(0.10)	0.02(0.02)	0.02(0.01)	0.01(0.01)	0.04(0.03)	0.03(0.02)	0.02(0.01)
2	0.24(0.25)	0.17(0.17)	0.13(0.12)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.02(0.01)
3	0.24(0.23)	0.17(0.16)	0.12(0.10)	0.03(0.02)	0.02(0.01)	0.01(0.01)	0.04(0.04)	0.02(0.02)	0.02(0.02)
4	0.17(0.18)	0.14(0.14)	0.11(0.11)	0.03(0.03)	0.02(0.01)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.02(0.01)
5	0.20(0.11)	0.09(0.08)	0.06(0.06)	0.03(0.02)	0.02(0.02)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.02(0.01)
6	0.17(0.17)	0.09(0.09)	0.07(0.06)	0.04(0.04)	0.03(0.03)	0.03(0.02)	0.13(0.12)	0.08(0.08)	0.06(0.05)
7	0.31(0.32)	0.19(0.20)	0.13(0.14)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.04(0.03)	0.02(0.02)	0.02(0.02)
8	0.12(0.12)	0.09(0.09)	0.06(0.06)	0.02(0.02)	0.02(0.02)	0.01(0.01)	0.02(0.02)	0.02(0.02)	0.01(0.01)
9	0.13(0.13)	0.06(0.06)	0.04(0.04)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.03(0.02)	0.02(0.02)	0.02(0.01)
10	0.31(0.33)	0.26(0.26)	0.17(0.17)	0.02(0.02)	0.02(0.01)	0.01(0.01)	0.04(0.04)	0.03(0.03)	0.02(0.02)
11	0.45(0.45)	0.20(0.19)	0.12(0.12)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.02(0.02)
12	0.08(0.08)	0.06(0.06)	0.05(0.05)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.02(0.02)
13	0.26(0.24)	0.16(0.14)	0.10(0.09)	0.02(0.02)	0.02(0.01)	0.01(0.01)	0.07(0.07)	0.05(0.04)	0.03(0.02)
14	0.13(0.14)	0.11(0.11)	0.08(0.09)	0.02(0.02)	0.01(0.02)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.02(0.02)
15	0.06(0.06)	0.04(0.04)	0.03(0.03)	0.21(0.03)	0.12(0.02)	0.06(0.01)	0.04(0.04)	0.02(0.02)	0.02(0.02)
16	0.08(0.09)	0.06(0.06)	0.05(0.05)	0.03(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.02(0.02)	0.01(0.01)
17	0.08(0.08)	0.05(0.05)	0.04(0.04)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.01(0.01)
18	0.06(0.06)	0.05(0.05)	0.04(0.04)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.03(0.03)	0.01(0.01)	0.01(0.01)
19	0.47(0.47)	0.20(0.21)	0.12(0.12)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.04(0.04)	0.03(0.03)	0.02(0.02)
20	0.15(0.14)	0.09(0.09)	0.06(0.06)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.03(0.02)	0.02(0.02)	0.01(0.01)
21	0.22(0.22)	0.12(0.12)	0.08(0.08)	0.61(0.02)	0.31(0.01)	0.16(0.01)	0.02(0.02)	0.02(0.02)	0.01(0.01)
22	0.10(0.05)	0.07(0.05)	0.05(0.04)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.04(0.04)	0.02(0.02)	0.01(0.01)
23	0.22(0.23)	0.11(0.11)	0.07(0.07)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.02(0.01)	0.01(0.01)
24	0.06(0.06)	0.06(0.05)	0.05(0.05)	0.09(0.04)	0.07(0.03)	0.05(0.03)	0.03(0.03)	0.03(0.03)	0.02(0.02)

25	0.06(0.06)	0.04(0.04)	0.04(0.04)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.05(0.05)	0.03(0.03)	0.02(0.02)
26	0.03(0.03)	0.03(0.03)	0.03(0.03)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
27	0.10(0.10)	0.07(0.07)	0.05(0.05)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)
28	0.12(0.12)	0.08(0.08)	0.06(0.06)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.05(0.05)	0.03(0.03)	0.02(0.02)
29	0.11(0.10)	0.08(0.08)	0.06(0.06)	0.03(0.03)	0.02(0.02)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
30	0.07(0.07)	0.05(0.05)	0.04(0.04)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
31	0.24(0.24)	0.15(0.15)	0.09(0.09)	0.02(0.02)	0.02(0.01)	0.01(0.01)	0.03(0.03)	0.02(0.02)	0.02(0.02)
32	0.21(0.18)	0.16(0.13)	0.10(0.08)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.03(0.02)	0.02(0.02)	0.01(0.01)
33	0.10(0.10)	0.05(0.05)	0.04(0.04)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.03)	0.02(0.02)	0.01(0.01)
34	0.06(0.06)	0.05(0.05)	0.04(0.04)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
35	0.08(0.07)	0.05(0.05)	0.04(0.04)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)
36	0.12(0.12)	0.06(0.06)	0.04(0.04)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.02(0.02)	0.01(0.01)	0.01(0.01)
37	0.33(0.17)	0.20(0.08)	0.12(0.05)	0.04(0.03)	0.02(0.02)	0.01(0.01)	0.05(0.05)	0.03(0.03)	0.02(0.02)
38	0.07(0.08)	0.05(0.05)	0.04(0.04)	0.07(0.02)	0.05(0.01)	0.03(0.01)	0.02(0.02)	0.02(0.01)	0.01(0.01)
39	0.15(0.15)	0.07(0.07)	0.05(0.05)	0.02(0.02)	0.01(0.01)	0.01(0.01)	0.06(0.06)	0.03(0.03)	0.03(0.02)
40	0.41(0.42)	0.20(0.20)	0.12(0.12)	0.02(0.02)	0.02(0.02)	0.02(0.01)	0.03(0.02)	0.02(0.01)	0.01(0.01)

Note: The monthly Expected Shortfall (ES) percentiles for pairs trading strategies from January 2005 to June 2024 are reported for all three periods. Pairs are constructed using a 12-month formation period based on a minimum-distance criterion, followed by a 6-month trading period. In this format, the VaR percentiles provide insights into the potential losses that might occur under extreme market conditions for each period, ensuring a comprehensive understanding of the risk profile associated with the pairs trading strategies. The data in '()' are the results of the one day waiting strategy.

5.4 Robustness Analysis

5.4.1 Performance Analysis of Long and Short Positions

In this section, we conduct a detailed analysis of the performance of long and short positions within the pairs trading strategy across three distinct periods: the Financial Crisis Period, the Bullish and Bearish Period, and the COVID-19 Period. The aim is to assess the robustness of the strategy by examining the individual contributions of the long and short positions to the overall performance.

There are at least three reasons to separately examine the returns to the long and short portfolios that make up a pairs position. First, separating the returns of the long and short positions offers further insights into the nature of mean reversion. If pairs trading purely exploits mean reversion, then the abnormal returns from the long and short positions should theoretically be symmetric. This is because the initiation of the trade is equally likely to be triggered by either of the two stocks in the pair. Thus, if the returns are asymmetric, it suggests the presence of other underlying factors influencing the strategy's profitability.

Second, if the excess returns are predominantly driven by the short position, it becomes crucial to evaluate the feasibility and sustainability of the strategy, considering potential short-sale constraints. These constraints—such as difficulties in borrowing stocks or high borrowing costs—could impede arbitrageurs from fully exploiting these opportunities, thus sustaining the strategy's high profitability. Understanding the nature of short-side returns is essential for assessing the overall viability of the strategy.

Lastly, the risk exposures of the long and short positions may provide additional clues regarding the profitability of the pairs strategy. For instance, if the long and short portfolios exhibit different sensitivities to non-stationary risk factors, such as bankruptcy risk, it could explain why the strategy generates returns. Therefore, analyzing the risk characteristics of the long and short positions can help identify the underlying drivers of the pairs trading performance.

Table 20-22 summarize the returns and risk exposures of the long and short positions within the pairs trading strategy, offering important insights into the sources of profitability and potential risks associated with the strategy.

During the Financial Crisis period, most long and short positions exhibited negative alphas, indicating underperformance after adjusting for risk factors. This underperformance was statistically significant for many short positions, suggesting that these results were not due to random chance. The mean returns of long positions were generally positive but low, while short positions typically had negative returns, leading to a drag on the overall performance of the pairs trading strategy.

The mean returns of long positions were modest, with Sharpe Ratios mostly close to zero, indicating low risk-adjusted returns. For instance, Portfolio 9 showed a higher mean return of 84 bps and a Sharpe Ratio of 0.13, outperforming other portfolios. However, the alpha of most long positions was negative and statistically significant, implying that any gains were not sufficient to generate abnormal returns after accounting for common risk factors. This suggests that the long positions, despite occasionally capturing upward price movements, were not able to outperform the overall market volatility.

Short positions generally had negative mean returns and Sharpe Ratios, indicating that they contributed to losses during the Financial Crisis. Most short positions exhibited negative and statistically significant alphas, highlighting their poor performance. For instance, Portfolio 15 had an alpha of -206 bps with a t-statistic of -3.93, underscoring its significant underperformance. The sharp market declines, coupled with high volatility and regulatory restrictions on short selling, likely contributed to these negative results.

The significant negative alphas and mean returns for short positions highlight their consistent underperformance during the Financial Crisis. While long positions showed some positive mean returns, their alphas were predominantly negative, suggesting that they failed to deliver significant abnormal returns. The turbulent market environment, characterized by sudden price reversals and high volatility, may have adversely affected short positions and disrupted the effectiveness of pairs trading strategies during this period.

During the Bullish and Bearish Period, both long and short positions exhibited consistent negative alphas across almost all portfolios, indicating that pairs trading strategies struggled to generate abnormal returns in this environment. Long positions showed modest positive mean returns, while short positions generally had negative mean returns. The alphas for short positions were often statistically significant, indicating underperformance even after adjusting for risk factors.

Long positions displayed small positive mean returns, with Sharpe Ratios ranging from 0.01 to 0.18. Portfolios 17, 33, and 39 showed relatively higher mean returns and Sharpe Ratios compared to others. However, most long positions had negative alphas, and the t-statistics were insignificant, implying that their positive returns were not abnormal. This suggests that the long positions were merely benefiting from the general upward market trend rather than successfully exploiting mispricing opportunities.

Short positions, in contrast, had negative mean returns and Sharpe Ratios, indicating that they detracted from the overall performance of the pairs trading strategy. The alphas for short positions were overwhelmingly negative and statistically significant across all portfolios, highlighting their consistent underperformance. For example, Portfolio 28 had an alpha of -92 bps with a t-statistic of -5.01, demonstrating significant negative abnormal returns. The persistent underperformance of short positions can be attributed to the bullish market bias during this period, where upward price movements were more frequent than downward reversals, making it challenging for short positions to capture meaningful gains.

The consistent negative alphas and significant t-statistics for short positions indicate that they underperformed during this period, possibly due to the overall bullish market environment. In contrast, the positive mean returns for long positions were insufficient to offset the losses from short positions, especially after adjusting for risk factors. This suggests that the pairs trading strategy faced challenges in generating abnormal returns during stable market conditions, as low volatility limited the opportunities for profiting from temporary mispricings.

During the COVID-19 period, the alphas for long positions were mostly insignificant, while short positions continued to show negative and significant alphas. Both long and short positions exhibited modest mean returns, with long positions slightly positive and short positions negative. This neutrality in long positions' performance suggests that they neither significantly contributed to nor detracted from the overall returns of the pairs trading strategy during this period.

Long positions had small positive mean returns and low Sharpe Ratios. For instance, Portfolio 30 showed a higher mean return of 42 bps and a Sharpe Ratio of 0.14. However, the alphas for long positions were close to zero and mostly insignificant, suggesting that long positions did not generate meaningful abnormal returns after accounting for common risk factors. This indicates that the pairs trading strategy struggled to capture meaningful profits in the volatile and rapidly changing market environment of the COVID-19 period.

Short positions had negative mean returns and Sharpe Ratios, though the magnitudes were smaller compared to previous periods. For example, Portfolio 13 had an alpha of -50 bps with a t-statistic of -4.06, indicating significant underperformance. However, the severity of underperformance was reduced compared to the Financial Crisis and Bullish and Bearish periods. The high market volatility and frequent reversals during the COVID-19 period may have provided more opportunities for short positions to partially recover losses, reducing their overall negative impact on the strategy.

The COVID-19 period was characterized by high volatility and rapid market reversals. The reduced underperformance of short positions compared to previous periods suggests that the strategy faced less adverse conditions, as the market's quick reversals may have provided opportunities to capture short-term mispricings. Meanwhile, long positions showed neutral performance, neither adding to nor detracting significantly from the strategy's overall returns. This suggests that while the pairs trading strategy was more resilient during the COVID-19 period, it still struggled to generate significant abnormal returns.

The performance of long and short positions varied significantly across the three market periods. During the Financial Crisis, long positions had mixed mean returns, with some portfolios performing relatively well, while their alphas were predominantly negative, indicating underperformance after adjusting for risk. In the Bullish and Bearish Period, long positions consistently showed positive mean returns, but the alphas were negative, suggesting that they did not generate abnormal returns. In the COVID-19 Period, long positions had modest positive mean returns, and the alphas were mostly insignificant, indicating neutral performance.

Short positions exhibited negative mean returns and significant negative alphas across all periods, highlighting their consistent underperformance. The severity of underperformance varied, with the Financial Crisis being the worst, followed by the Bullish and Bearish Period, and then the COVID-19 Period. The short positions had low to negative Sharpe Ratios, reflecting poor risk-adjusted performance, while long positions generally had modest Sharpe Ratios, indicating limited risk-adjusted returns.

Overall, the effectiveness of pairs trading strategies is highly dependent on market conditions. During extreme volatility, such as the Financial Crisis, pairs trading strategies struggled due to breakdowns in historical price relationships and the inherent difficulties in capturing temporary mispricings. In contrast, during stable periods like the Bullish and Bearish Period, low volatility limited the opportunities for the strategy to profit, leading to underperformance. During the COVID-19 Period, the strategy exhibited more neutral performance, reflecting the challenges posed by rapid market reversals and heightened uncertainty.

TABLE 20. Risk-Adjusted Returns of Long and Short Positions after Trading Costs for Financial Crisis Period.

	Long				Short			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
1	-0.0103	-0.14	-0.0168	-2.20**	-0.0114	-0.23	-0.0165	-6.07***
2	-0.0064	-0.09	-0.0134	-2.33**	0.0023	0.03	-0.0072	-0.99

3	-0.0080	-0.13	-0.0135	-2.42**	-0.0062	-0.13	-0.0110	-5.51***
4	-0.0088	-0.11	-0.0167	-2.13**	-0.0045	-0.08	-0.0124	-3.22***
5	-0.0012	-0.02	-0.0064	-1.44	-0.0011	-0.02	-0.0068	-2.24**
6	-0.0094	-0.25	-0.0101	-3.30***	-0.0119	-0.42	-0.0110	-5.43***
7	-0.0030	-0.04	-0.0109	-1.58	0.0006	0.01	-0.0070	-1.16
8	0.0040	0.06	-0.0043	-0.63	-0.0037	-0.07	-0.0078	-1.92*
9	0.0084	0.13	0.0048	0.91	-0.0130	-0.18	-0.0212	-3.16***
10	-0.0019	-0.03	-0.0093	-1.79*	0.0003	0.00	-0.0071	-1.17
11	-0.0061	-0.07	-0.0178	-2.64***	-0.0066	-0.14	-0.0121	-5.85***
12	0.0005	0.01	-0.0074	-1.30	-0.0046	-0.09	-0.0095	-3.23***
13	-0.0056	-0.07	-0.0138	-1.86*	0.0031	0.04	-0.0061	-0.80
14	-0.0075	-0.12	-0.0136	-2.56**	0.0016	0.03	0.0006	0.11
15	-0.0007	-0.01	-0.0075	-1.97**	-0.0137	-0.23	-0.0206	-3.93***
16	-0.0039	-0.07	-0.0112	-2.74***	-0.0032	-0.06	-0.0082	-2.71***
17	0.0060	0.10	0.0002	0.05	-0.0095	-0.19	-0.0160	-6.33***
18	0.0017	0.03	-0.0040	-1.55	-0.0063	-0.14	-0.0112	-6.90***
19	-0.0222	-0.18	-0.0219	-2.30**	-0.0106	-0.15	-0.0168	-5.81***
20	0.0082	0.10	-0.0094	-1.98**	-0.0063	-0.14	-0.0149	-4.24***
21	-0.0007	-0.01	-0.0217	-2.57**	-0.0093	-0.20	-0.0084	-2.39**
22	-0.0047	-0.08	-0.0100	-1.71*	-0.0031	-0.07	-0.0115	-3.67***
23	0.0011	0.02	-0.0063	-0.99	-0.0071	-0.10	-0.0105	-4.76***
24	-0.0117	-0.38	-0.0125	-5.12**	-0.0091	-0.30	-0.0103	-5.45***
25	-0.0053	-0.07	-0.0102	-1.54	-0.0103	-0.17	-0.0153	-5.76***
26	0.0018	0.03	-0.0106	-2.17**	-0.0033	-0.08	-0.0066	-0.94
27	-0.0028	-0.06	-0.0113	-2.24**	-0.0055	-0.13	-0.0173	-3.17***
28	-0.0085	-0.12	-0.0114	-1.98**	-0.0114	-0.14	-0.0159	-5.52***
29	-0.0020	-0.04	-0.0093	-2.23**	-0.0054	-0.13	-0.0171	-3.09***
30	-0.0001	0.00	-0.0041	-0.99	-0.0029	-0.06	-0.0079	-3.36***
31	-0.0031	-0.03	-0.0097	-1.07	-0.0103	-0.13	-0.0160	-5.26***
32	0.0020	0.04	-0.0034	-0.54	0.0116	0.15	-0.0032	-0.61
33	-0.0028	-0.06	-0.0002	-0.01	-0.0064	-0.15	-0.0182	-3.64***
34	-0.0031	-0.06	-0.0083	-2.09**	-0.0041	-0.09	-0.0103	-3.89***
35	-0.0041	-0.09	-0.0046	-1.07	-0.0047	-0.11	-0.0156	-6.68***
36	-0.0046	-0.10	-0.0054	-1.73*	-0.0061	-0.14	-0.0138	-5.75***
37	-0.0076	-0.10	-0.0142	-2.41**	-0.0118	-0.16	-0.0151	-4.12***
38	0.0095	0.14	0.0019	0.47	-0.0075	-0.17	-0.0102	-3.51***
39	-0.0047	-0.07	-0.0118	-1.96**	-0.0116	-0.12	-0.0191	-3.50***
40	0.0100	0.06	0.0022	0.48	-0.0021	-0.04	-0.0097	-3.02***

Note: This table reports the after-cost risk-adjusted returns for the long and short positions of the pairs trading strategies during the Financial Crisis Period. The columns labeled "Alpha" report the estimated intercept term (alpha) from the regression of the excess returns against the Fama–French factors plus the momentum and market reversal factors. The columns labeled "t-stat" report the test statistics for the estimated alphas, computed using Newey–West standard errors with six lags.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

TABLE 21. Risk-Adjusted Returns of Long and Short Positions after Trading Costs for Bullish and Bearish Period.

	Long				Short			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**

1	0.0003	0.01	-0.0058	-3.50***	-0.0016	-0.05	-0.0079	-4.39***
2	0.0022	0.07	-0.0048	-2.87***	-0.0016	-0.05	-0.0083	-4.65***
3	0.0027	0.09	-0.0034	-2.08**	-0.0015	-0.05	-0.0080	-5.00***
4	0.0025	0.09	-0.0039	-2.46**	-0.0012	-0.04	-0.0076	-5.58***
5	0.0031	0.11	-0.0029	-2.09**	0.0005	0.02	-0.0050	-3.41***
6	-0.0004	-0.02	-0.0038	-2.46**	-0.0012	-0.05	-0.0021	-0.77
7	0.0024	0.08	-0.0047	-3.54***	-0.0025	-0.08	-0.0090	-5.13***
8	0.0044	0.16	-0.0018	-1.29	-0.0006	-0.02	-0.0068	-4.62***
9	0.0039	0.13	-0.0025	-1.98**	-0.0003	-0.01	-0.0058	-3.94***
10	0.0022	0.07	-0.0044	-2.68***	-0.0021	-0.06	-0.0085	-4.38***
11	0.0036	0.13	-0.0023	-1.75*	0.0003	0.01	-0.0048	-3.14***
12	0.0040	0.13	-0.0028	-2.63***	0.0006	0.02	-0.0051	-3.31***
13	0.0041	0.12	-0.0017	-1.05	-0.0004	-0.01	-0.0060	-2.96***
14	0.0044	0.16	-0.0013	-1.09	0.0007	0.02	-0.0055	-4.42***
15	0.0047	0.15	-0.0013	-1.01	0.0007	0.02	-0.0042	-3.20***
16	0.0047	0.17	-0.0017	-1.84*	0.0010	0.03	-0.0047	-4.18***
17	0.0052	0.18	-0.0012	-1.27	0.0013	0.04	-0.0045	-4.17***
18	0.0043	0.14	-0.0025	-2.95***	0.0013	0.04	-0.0047	-3.84***
19	0.0009	0.03	-0.0062	-3.81***	-0.0025	-0.08	-0.0078	-4.27***
20	0.0014	0.06	-0.0048	-3.02***	-0.0016	-0.07	-0.0085	-5.44***
21	0.0026	0.10	-0.0042	-2.77***	-0.0004	-0.01	-0.0083	-5.48***
22	0.0026	0.09	-0.0041	-2.77***	-0.0013	-0.04	-0.0070	-5.33***
23	0.0030	0.12	-0.0033	-2.22**	-0.0007	-0.02	-0.0064	-4.20***
24	0.0032	0.20	-0.0039	-2.68***	-0.0013	-0.08	-0.0038	-1.55
25	0.0021	0.07	-0.0049	-4.04***	-0.0031	-0.10	-0.0083	-4.81***
26	0.0040	0.15	-0.0015	-1.10	0.0001	0.00	-0.0074	-4.75***
27	0.0035	0.13	-0.0024	-2.15**	0.0009	0.03	-0.0072	-4.95***
28	0.0011	0.04	-0.0052	-3.45***	-0.0028	-0.09	-0.0092	-5.01***
29	0.0045	0.18	-0.0035	-2.88***	0.0008	0.03	-0.0065	-4.10***
30	0.0040	0.14	-0.0020	-1.83*	0.0008	0.03	-0.0060	-3.96***
31	0.0025	0.08	-0.0020	-1.39	-0.0015	-0.04	-0.0061	-3.01***
32	0.0057	0.19	-0.0018	-1.49	0.0019	0.06	-0.0050	-3.92***
33	0.0052	0.19	-0.0011	-0.87	0.0019	0.06	-0.0046	-3.35***
34	0.0049	0.18	-0.0019	-2.27**	0.0008	0.03	-0.0050	-4.38***
35	0.0053	0.20	-0.0015	-1.72*	0.0016	0.06	-0.0044	-3.96***
36	0.0048	0.17	-0.0025	-3.19***	0.0008	0.03	-0.0049	-4.07***
37	0.0068	0.22	-0.0013	-0.75	-0.0002	-0.01	-0.0071	-4.30***
38	0.0025	0.09	-0.0048	-2.77***	-0.0009	-0.03	-0.0081	-4.65***
39	0.0061	0.19	-0.0018	-1.21	-0.0004	-0.01	-0.0073	-4.39***
40	0.0017	0.06	-0.0041	-2.29**	-0.0006	-0.02	-0.0072	-4.58***

Note: This table reports the after-cost risk-adjusted returns for the long and short positions of the pairs trading strategies during the Bullish and Bearish Period. The columns labeled “Alpha” report the estimated intercept term (alpha) from the regression of the excess returns against the Fama–French factors plus the momentum and market reversal factors. The columns labeled “t-stat” report the test statistics for the estimated alphas, computed using Newey–West standard errors with six lags.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

TABLE 22. Risk-Adjusted Returns of Long and Short Positions after Trading Costs for COVID-19 Period.

	Long				Short			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
1	0.0001	0.01	-0.0010	-0.76	-0.0021	-0.10	-0.0038	-2.37**
2	0.0009	0.04	0.0005	0.42	-0.0005	-0.02	-0.0020	-1.36
3	0.0010	0.06	0.0004	0.41	-0.0014	-0.07	-0.0031	-2.02**
4	-0.0001	-0.01	-0.0005	-0.41	-0.0022	-0.10	-0.0031	-2.12**
5	0.0002	0.01	-0.0005	-0.39	-0.0005	-0.02	-0.0020	-1.36
6	-0.0031	-0.15	-0.0026	-1.24	0.0008	0.04	-0.0016	-0.74
7	0.0003	0.02	0.0008	0.85	-0.0020	-0.10	-0.0030	-2.24**
8	0.0016	0.08	0.0012	1.31	-0.0014	-0.07	-0.0023	-1.94*
9	0.0008	0.05	0.0005	0.57	-0.0011	-0.05	-0.0025	-2.26**
10	0.0015	0.08	0.0012	1.29	-0.0011	-0.05	-0.0023	-1.67*
11	0.0001	0.01	-0.0002	-0.21	-0.0005	-0.03	-0.0019	-1.54
12	0.0023	0.08	0.0019	0.65	0.0007	0.03	-0.0005	-0.44
13	-0.0009	-0.03	-0.0006	-0.32	-0.0034	-0.17	-0.0050	-4.06***
14	0.0009	0.05	0.0006	0.54	-0.0025	-0.12	-0.0037	-3.05***
15	0.0003	0.02	-0.0003	-0.39	-0.0020	-0.10	-0.0038	-3.23***
16	0.0006	0.03	0.0004	0.34	-0.0019	-0.10	-0.0033	-3.22***
17	0.0019	0.09	0.0013	0.88	-0.0015	-0.08	-0.0028	-2.99***
18	0.0004	0.02	-0.0003	-0.37	-0.0016	-0.08	-0.0032	-3.13***
19	0.0012	0.07	-0.0011	-0.84	-0.0003	-0.02	-0.0039	-2.38**
20	0.0006	0.03	0.0003	0.26	-0.0012	-0.05	-0.0021	-1.41
21	0.0008	0.04	0.0005	0.53	-0.0014	-0.07	-0.0031	-2.02
22	0.0033	0.11	-0.0005	-0.46	-0.0003	-0.02	-0.0033	-2.24**
23	0.0003	0.01	-0.0008	-0.68	-0.0001	-0.01	-0.0035	-2.30**
24	-0.0009	-0.08	-0.0026	-1.26	0.0000	0.00	-0.0016	-0.75
25	0.0012	0.06	0.0009	0.94	-0.0007	-0.04	-0.0027	-2.01**
26	0.0011	0.06	0.0009	1.07	-0.0017	-0.09	-0.0022	-1.95*
27	0.0037	0.13	0.0003	0.34	-0.0017	-0.09	-0.0028	-2.60***
28	0.0016	0.09	0.0010	1.07	-0.0005	-0.02	-0.0026	-1.84*
29	0.0034	0.12	-0.0002	-0.23	-0.0007	-0.04	-0.0026	-2.18**
30	0.0010	0.06	0.0039	1.34	-0.0004	-0.02	-0.0009	-0.75
31	0.0048	0.16	-0.0006	-0.31	-0.0010	-0.05	-0.0048	-3.80***
32	-0.0001	-0.01	0.0006	0.56	-0.0015	-0.08	-0.0032	-2.60***
33	0.0017	0.09	-0.0005	-0.63	-0.0015	-0.08	-0.0035	-2.89***
34	0.0015	0.08	0.0004	0.37	-0.0010	-0.05	-0.0032	-3.15***
35	0.0012	0.07	0.0012	0.81	-0.0011	-0.06	-0.0028	-2.90***
36	0.0003	0.02	-0.0003	-0.38	-0.0006	-0.04	-0.0034	-3.36***
37	0.0005	0.02	0.0000	0.02	0.0008	0.03	-0.0011	-0.73
38	0.0014	0.08	0.0008	0.70	-0.0011	-0.06	-0.0020	-1.31
39	0.0034	0.10	0.0001	0.03	-0.0004	-0.02	-0.0027	-1.64
40	0.0014	0.08	0.0002	0.15	-0.0018	-0.09	-0.0033	-2.00**

Note: This table reports the after-cost risk-adjusted returns for the long and short positions of the pairs trading strategies during the COVID-19 Period. The columns labeled "Alpha" report the estimated intercept term (alpha) from the regression of the excess returns against the Fama–French factors plus the momentum and market reversal factors. The columns labeled "t-stat" report the test statistics for the estimated alphas, computed using Newey–West standard errors with six lags.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

5.4.2 Return Analysis with Different Market Capitalization

To assess the robustness of our previous findings and explore the sensitivity of pairs trading strategies to different market capitalizations, we conducted an analysis using constituent stocks from the CSI 100 (Large Cap), CSI 200 (Mid Cap), and CSI 500 (Small Cap) indices. The results are presented in Tables 23, 24, and 25, corresponding to large-cap, mid-cap, and small-cap stocks, respectively, during the Financial Crisis, Bullish and Bearish, and COVID-19 periods. Comparing these findings with our earlier results (Tables 8, 9, and 10), we observe notable differences and similarities that shed light on the performance dynamics of pairs trading strategies across different market segments.

During the Financial Crisis, pairs trading strategies across all market capitalizations generally produced negative mean returns and alphas after accounting for trading costs. For large-cap stocks, the portfolios exhibited significant negative alphas at the 1% level. For instance, Portfolio 1 reported an alpha of -192 bps per month with a t-statistic of -11.92, indicating substantial underperformance. Similar patterns were observed for mid-cap stocks, where Portfolio 1 had an alpha of -210 bps per month. Small-cap stocks also showed negative alphas, though the t-statistics were generally lower. Notably, Portfolio 1 had an alpha of -181 bps per month.

Compared to our previous results, which encompassed a broader market sample, the negative alphas during the Financial Crisis suggest that pairs trading strategies were particularly vulnerable across all market segments. The severe market dislocations and heightened volatility likely disrupted historical price relationships, making mean-reversion strategies less effective. The consistent underperformance across large, mid, and small-cap stocks indicates that the challenges were systemic rather than confined to specific market capitalizations.

In the Bullish and Bearish period, the performance of pairs trading strategies varied with market capitalization. Large-cap stocks continued to exhibit negative alphas, significant at the 1% level. Portfolio 1 showed an alpha of -51 bps per month. Mid-cap stocks presented mixed results, with some portfolios showing insignificant alphas. For example, Portfolio 1 had an alpha close to zero, indicating neither significant underperformance nor outperformance.

Interestingly, small-cap stocks displayed some portfolios with positive mean returns, although the alphas were generally negative or insignificant. Portfolio 1 reported a positive mean return of 28 bps per month and an alpha of 13 bps, though the t-statistic (0.97) was not significant. This suggests that pairs trading strategies involving small-cap stocks may have been relatively more resilient during stable market conditions, possibly due to greater idiosyncratic volatility and more frequent mispricing opportunities in smaller companies.

These observations contrast with our earlier findings, where pairs trading strategies tended to underperform during stable market periods. The variation across market capitalizations implies that the effectiveness of pairs trading can be influenced by the size of the underlying assets, with small-cap stocks offering potentially better opportunities for mean reversion due to less efficient pricing.

During the COVID-19 period, the performance of pairs trading strategies again showed dependence on market capitalization. Large-cap stocks continued to underperform, with Portfolio 1 exhibiting an alpha of -14 bps per month, though not statistically significant. Mid-cap stocks displayed negative alphas, with Portfolio 1 reporting an alpha of -12 bps per month, also insignificant.

In contrast, small-cap stocks showed more pronounced negative alphas, many of which were statistically significant. Portfolio 1 had an alpha of -25 bps per month, significant at the 5% level. This suggests that during the COVID-19 period, pairs trading strategies involving small-cap stocks faced greater challenges, possibly due to increased volatility and liquidity constraints in the small-cap segment.

Compared to previous periods, the COVID-19 results indicate a shift where small-cap pairs trading strategies underperformed more significantly. This may be attributed to the unique market conditions during the pandemic, where smaller companies faced greater uncertainty and financial stress, leading to more persistent deviations from historical price relationships and reducing the effectiveness of mean-reversion strategies.

The variations in performance across different market capitalizations highlight important aspects of pairs trading strategies. Large-cap stocks are generally more liquid and efficiently priced, which can limit the opportunities for mispricing that pairs trading seeks to exploit. The consistently negative and significant alphas for large-cap portfolios across all periods suggest that transaction costs and the lack of sufficient price divergence may erode potential profits in this segment.

Mid-cap stocks offer a middle ground, with moderate liquidity and pricing efficiency. The mixed results for mid-cap portfolios, especially during the Bullish and Bearish period, indicate that pairs trading strategies may find occasional opportunities but are not consistently profitable. The insignificant alphas suggest that any potential profits are offset by risks and costs associated with trading mid-cap stocks.

Small-cap stocks, characterized by lower liquidity and higher volatility, present more frequent mispricing opportunities due to less analyst coverage and greater sensitivity to firm-specific news. During the Bullish and Bearish period, small-cap portfolios showed some positive mean returns, hinting at the potential for pairs trading strategies to capitalize on inefficiencies in this segment. However, during periods of extreme market stress, such as the Financial Crisis and COVID-19, small-cap pairs trading strategies underperformed, likely due to heightened volatility, wider bid-ask spreads, and liquidity constraints exacerbating trading costs and risks.

The findings underscore the importance of considering market capitalization when implementing pairs trading strategies. Investors aiming to employ such strategies should be mindful that large-cap stocks may not offer sufficient mispricing opportunities to overcome trading costs, leading to consistent underperformance. While small-cap stocks may present more opportunities, they also come with higher risks, particularly during volatile market conditions when liquidity dries up, and price deviations may persist longer than anticipated.

Moreover, the performance variations across different periods suggest that market conditions play a crucial role in the success of pairs trading strategies. During stable periods, small-cap strategies might yield better results due to more frequent mean-reversion opportunities. However, during crises, all segments tend to underperform, with small-cap strategies being particularly vulnerable.

The robustness and sensitivity analysis reveal that pairs trading strategies are significantly influenced by market capitalization and prevailing market conditions. The consistent underperformance of large-cap pairs trading suggests limited efficacy in this segment, while the mixed results for mid-cap and small-cap stocks highlight the potential for profits under certain conditions but also underscore the associated risks.

These insights contribute to the broader understanding of pairs trading by emphasizing the need for careful selection of trading pairs, consideration of transaction costs, and adaptability to market environments. Investors should weigh the trade-offs between potential returns and risks across different market capitalizations and adjust their strategies accordingly to enhance the likelihood of success in pairs trading endeavors.

TABLE 23. Monthly Excess Returns with Trading Costs of All Three Period Results with CSI 100 Constituent Stocks - Large Cap Stocks.

	Financial Crisis				Bullish and Bearish				COVID-19			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
1	-0.0161	-1.11	-0.0192	-11.92***	-0.0021	-0.24	-0.0051	-4.32***	-0.0012	-0.12	-0.0014	-1.46
2	-0.0139	-1.26	-0.0166	-13.47***	-0.0008	-0.09	-0.0034	-3.04***	-0.0018	-0.21	-0.0023	-2.59**
3	-0.0134	-1.03	-0.0172	-12.42***	-0.0013	-0.14	-0.0049	-4.26***	-0.0023	-0.26	-0.0031	-3.25***
4	-0.0142	-1.10	-0.0177	-12.1***	-0.0002	-0.02	-0.0035	-3.04***	-0.0022	-0.26	-0.0027	-3.09***
5	-0.0159	-1.34	-0.0188	-15.35***	-0.0009	-0.10	-0.0040	-3.54***	-0.0026	-0.32	-0.0035	-4.21***
6	-0.0199	-0.80	-0.0224	-8.97***	-0.0015	-0.08	-0.0054	-2.09**	-0.0054	-0.28	-0.0040	-2.02**
7	-0.0138	-0.94	-0.0169	-10.39***	-0.0024	-0.23	-0.0054	-4.01***	-0.0019	-0.18	-0.0022	-1.97***
8	-0.0156	-1.21	-0.0187	-14.49***	-0.0010	-0.09	-0.0051	-3.86***	-0.0024	-0.29	-0.0025	-3.15***
9	-0.0161	-1.23	-0.0191	-15.02***	-0.0009	-0.09	-0.0046	-3.58***	-0.0024	-0.22	-0.0026	-2.46**
10	-0.0150	-1.04	-0.0180	-11.43***	-0.0026	-0.23	-0.0052	-3.75***	-0.0017	-0.16	-0.0020	-1.86*
11	-0.0167	-1.27	-0.0194	-14.38***	-0.0013	-0.12	-0.0053	-3.86***	-0.0032	-0.32	-0.0033	-3.53***
12	-0.0157	-1.43	-0.0182	-16.09***	-0.0017	-0.16	-0.0057	-4.13***	-0.0036	-0.42	-0.0042	-4.84***
13	-0.0148	-0.99	-0.0180	-11.98***	-0.0015	-0.13	-0.0042	-2.96***	-0.0025	-0.22	-0.0026	-2.26**
14	-0.0158	-1.04	-0.0186	-11.51***	-0.0025	-0.25	-0.0058	-4.96***	-0.0037	-0.41	-0.0041	-4.61***
15	-0.0160	-1.09	-0.0191	-12.68***	-0.0013	-0.11	-0.0046	-3.5***	-0.0039	-0.40	-0.0040	-4.23***
16	-0.0156	-1.29	-0.0184	-15.26***	-0.0020	-0.20	-0.0053	-4.72***	-0.0031	-0.36	-0.0033	-3.99***
17	-0.0161	-1.31	-0.0192	-16.63***	-0.0015	-0.14	-0.0051	-4.27***	-0.0040	-0.42	-0.0042	-4.77***
18	-0.0167	-1.22	-0.0198	-15.08***	-0.0017	-0.14	-0.0055	-3.7***	-0.0039	-0.41	-0.0040	-4.67***
19	-0.0121	-1.03	-0.0154	-10.83***	-0.0008	-0.12	-0.0041	-5.22***	-0.0014	-0.26	-0.0021	-3.88***
20	-0.0132	-1.59	-0.0161	-16.21***	-0.0001	-0.02	-0.0027	-2.86***	-0.0019	-0.37	-0.0025	-4.82***
21	-0.0145	-1.55	-0.0177	-17.83***	0.0011	0.15	-0.0013	-1.38	-0.0014	-0.26	-0.0021	-3.67***
22	-0.0144	-1.44	-0.0175	-15.04***	0.0017	0.24	-0.0003	-0.28	-0.0015	-0.29	-0.0022	-4.00***
23	-0.0143	-1.48	-0.0173	-16.36***	0.0011	0.14	-0.0005	-0.47	-0.0021	-0.36	-0.0027	-4.49***
24	-0.0141	-1.01	-0.0169	-10.6***	0.0006	0.06	-0.0035	-2.33**	-0.0049	-0.33	-0.0047	-3.38***
25	-0.0117	-0.71	-0.0151	-7.39***	-0.0011	-0.15	-0.0042	-4.61***	-0.0023	-0.25	-0.0032	-3.24***
26	-0.0118	-0.70	-0.0150	-7.06***	0.0000	-0.01	-0.0022	-2.04**	-0.0035	-0.32	-0.0044	-3.66***
27	-0.0141	-1.26	-0.0169	-12.2***	-0.0002	-0.01	-0.0016	-0.89	-0.0019	-0.23	-0.0022	-2.48**
28	-0.0117	-0.71	-0.0151	-7.39***	-0.0011	-0.15	-0.0042	-4.61***	-0.0022	-0.35	-0.0029	-4.27***
29	-0.0141	-1.26	-0.0169	-12.2***	-0.0002	-0.01	-0.0016	-0.89	-0.0019	-0.23	-0.0022	-2.48**
30	-0.0144	-1.17	-0.0178	-12.45***	0.0016	0.19	-0.0007	-0.62	-0.0022	-0.26	-0.0023	-2.86***
31	-0.0118	-0.92	-0.0148	-9.17***	-0.0007	-0.07	-0.0033	-2.42**	-0.0023	-0.33	-0.0029	-4.11***
32	-0.0119	-0.91	-0.0152	-9.61***	0.0000	0.00	-0.0025	-2.4**	-0.0027	-0.32	-0.0033	-3.65***
33	-0.0132	-0.96	-0.0164	-9.77***	0.0001	0.00	-0.0008	-0.43	-0.0026	-0.30	-0.0032	-3.59***
34	-0.0118	-0.92	-0.0148	-9.17***	-0.0007	-0.07	-0.0033	-2.42**	-0.0023	-0.33	-0.0029	-4.11***
35	-0.0132	-0.96	-0.0164	-9.77***	0.0001	0.00	-0.0008	-0.43	-0.0026	-0.30	-0.0032	-3.59***
36	-0.0142	-1.01	-0.0172	-10.35***	0.0013	0.18	-0.0014	-1.37	-0.0027	-0.33	-0.0034	-4.20***
37	-0.0135	-0.87	-0.0166	-9.44***	0.0006	0.07	-0.0014	-1.2	-0.0019	-0.18	-0.0022	-2.02**
38	-0.0134	-1.13	-0.0167	-11.87***	0.0003	0.04	-0.0025	-2.56**	-0.0017	-0.30	-0.0024	-4.04***
39	-0.0134	-0.67	-0.0168	-7.39***	0.0005	0.06	-0.0018	-1.58	-0.0021	-0.20	-0.0025	-2.31**
40	-0.0129	-0.99	-0.0161	-10.32***	0.0003	0.03	-0.0025	-2.39	-0.0023	-0.45	-0.0033	-6.00

Note: This table reports monthly excess returns after-cost results for CSI 100 constituent stocks, large cap stocks, of all three period. The columns labeled “Alpha” report the estimated intercept term in the regression of the excess returns against the Fama–French factors plus the momentum and market reversal factor. The columns labeled “t-stat” report the test statistic for the estimated alpha, computed using Newey–West standard errors with six lags.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

TABLE 24. Monthly Excess Returns with Trading Costs of All Three Period Results with CSI 200 Constituent Stocks – Mid Cap Stocks.

	Financial Crisis				Bullish and Bearish				COVID-19			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
1	-0.0173	-1.10	-0.021	-13.40***	0.0012	0.14	0.0000	-0.03	-0.0006	-0.07	-0.0012	-1.35
2	-0.0127	-0.48	-0.015	-4.45***	0.0000	0.00	-0.0016	-1.26	-0.0004	-0.05	-0.0009	-1.19
3	-0.0156	-0.68	-0.019	-7.12***	0.0003	0.04	-0.0016	-1.43	-0.0004	-0.05	-0.0010	-1.20
4	-0.0184	-0.76	-0.021	-6.74***	-0.0014	-0.14	-0.0035	-2.46**	-0.0014	-0.19	-0.0020	-2.53**
5	-0.0119	-0.29	-0.014	-2.57**	-0.0004	-0.04	-0.0029	-2.23**	-0.0007	-0.09	-0.0015	-1.66*
6	-0.0159	-0.79	-0.018	-8.14***	-0.0010	-0.04	-0.0079	-2.65***	-0.0036	-0.21	-0.0025	-1.47
7	-0.0149	-0.48	-0.017	-4.39***	0.0002	0.03	-0.0011	-0.92	-0.0014	-0.16	-0.0020	-2.06**
8	-0.0194	-0.26	-0.022	-2.29**	0.0002	0.02	-0.0028	-1.95*	-0.0037	-0.41	-0.0041	-4.42***
9	-0.0167	-0.23	-0.020	-2.12**	-0.0015	-0.16	-0.0045	-3.50***	-0.0029	-0.33	-0.0031	-3.50***
10	-0.0161	-0.93	-0.019	-11.33***	0.0005	0.06	-0.0006	-0.45	-0.0018	-0.20	-0.0024	-2.64***
11	-0.0218	-0.59	-0.025	-5.51***	-0.0019	-0.20	-0.0043	-3.26***	-0.0031	-0.38	-0.0033	-3.91***
12	-0.0186	-0.49	-0.020	-4.19***	0.0001	0.01	-0.0039	-2.60***	-0.0038	-0.42	-0.0042	-4.78***
13	-0.0170	-0.78	-0.021	-8.75***	-0.0006	-0.05	-0.0023	-1.47	-0.0011	-0.11	-0.0015	-1.43
14	-0.0223	-0.30	-0.026	-2.69***	-0.0009	-0.09	-0.0043	-2.93***	-0.0034	-0.36	-0.0038	-3.93***
15	-0.0218	-0.78	-0.025	-7.38***	-0.0005	-0.05	-0.0043	-3.08***	-0.0031	-0.35	-0.0034	-3.87***
16	-0.0178	-0.69	-0.020	-6.42***	-0.0009	-0.10	-0.0036	-3.17***	-0.0027	-0.34	-0.0031	-3.91***
17	-0.0184	-0.62	-0.021	-5.72***	-0.0004	-0.04	-0.0038	-3.17***	-0.0033	-0.42	-0.0036	-4.95***
18	-0.0165	-0.58	-0.019	-5.20***	-0.0003	-0.03	-0.0041	-3.15***	-0.0035	-0.47	-0.0038	-5.52***
19	-0.0128	-0.63	-0.015	-6.31***	-0.0006	-0.08	-0.0027	-2.66***	-0.0004	-0.06	-0.0011	-1.55
20	-0.0145	-0.66	-0.018	-7.71***	0.0008	0.10	-0.0018	-1.60	-0.0001	-0.01	-0.0009	-1.43
21	-0.0166	-0.92	-0.020	-10.33***	0.0008	0.10	-0.0015	-1.36	0.0003	0.05	-0.0006	-0.96
22	-0.0181	-0.66	-0.021	-6.75***	0.0018	0.17	-0.0012	-0.86	-0.0010	-0.17	-0.0018	-2.90***
23	-0.0154	-0.63	-0.019	-6.34***	0.0004	0.05	-0.0022	-1.95**	-0.0006	-0.11	-0.0015	-2.59**
24	-0.0155	-0.82	-0.019	-10.16***	-0.0031	-0.25	-0.0081	-5.64***	-0.0045	-0.31	-0.0047	-2.93***
25	-0.0134	-0.69	-0.016	-7.17***	0.0000	0.00	-0.0022	-1.80*	-0.0008	-0.11	-0.0015	-2.26**
26	-0.0164	-0.79	-0.019	-7.81***	0.0006	0.05	-0.0024	-1.57	-0.0018	-0.23	-0.0025	-3.07***
27	-0.0155	-0.85	-0.018	-8.75***	-0.0008	-0.06	-0.0035	-1.99**	-0.0023	-0.25	-0.0029	-2.87***
28	-0.0147	-0.75	-0.017	-8.12***	0.0001	0.02	-0.0023	-2.20**	-0.0004	-0.06	-0.0013	-2.00**
29	-0.0170	-1.18	-0.021	-13.49***	0.0000	0.00	-0.0032	-2.61***	-0.0023	-0.33	-0.0029	-4.10***
30	-0.0217	-0.50	-0.026	-4.76***	-0.0011	-0.12	-0.0041	-3.22***	-0.0024	-0.38	-0.0033	-5.11***

31	-0.0146	-0.67	-0.019	-7.61***	-0.0004	-0.04	-0.0035	-2.05**	-0.0002	-0.02	-0.0009	-1.31
32	-0.0200	-0.64	-0.023	-6.18***	-0.0009	-0.08	-0.0044	-2.62***	-0.0019	-0.20	-0.0024	-2.43**
33	-0.0211	-0.50	-0.022	-4.37***	0.0016	0.12	-0.0009	-0.45	-0.0012	-0.12	-0.0022	-1.98**
34	-0.0151	-0.89	-0.018	-9.83***	0.0000	0.00	-0.0031	-2.85***	-0.0011	-0.19	-0.0018	-3.03***
35	-0.0211	-0.50	-0.023	-4.38***	0.0015	0.13	-0.0022	-1.51	-0.0014	-0.18	-0.0022	-2.83***
36	-0.0159	-0.66	-0.020	-7.58***	0.0016	0.14	-0.0022	-1.40	-0.0019	-0.24	-0.0026	-3.20***
37	-0.0164	-0.76	-0.021	-9.56***	0.0008	0.06	-0.0033	-1.98**	-0.0031	-0.36	-0.0040	-4.30***
38	-0.0145	-0.72	-0.017	-7.06***	0.0001	0.01	-0.0020	-1.82**	0.0000	0.00	-0.0008	-1.14
39	-0.0169	-0.65	-0.022	-7.54***	0.0020	0.13	-0.0033	-1.59	-0.0035	-0.38	-0.0043	-4.26***
40	-0.0150	-0.90	-0.017	-9.20***	-0.0003	-0.03	-0.0030	-2.40**	0.0000	0.00	-0.0007	-0.98

Note: This table reports monthly excess returns after-cost results for CSI 200 constituent stocks, mid cap stocks, of all three period. The columns labeled "Alpha" report the estimated intercept term in the regression of the excess returns against the Fama–French factors plus the momentum and market reversal factor. The columns labeled "t-stat" report the test statistic for the estimated alpha, computed using Newey–West standard errors with six lags.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

TABLE 25. Monthly Excess Returns with Trading Costs of All Three Period Results with CSI 500 Constituent Stocks - Small Cap Stocks.

	Financial Crisis				Bullish and Bearish				COVID-19			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
1	-0.0161	-0.31	-0.0181	-2.82***	0.0028	0.27	0.0013	0.97	-0.0014	-0.12	-0.0025	-2.06**
2	-0.0120	-0.19	-0.0176	-2.19**	0.0016	0.20	-0.0009	-0.82	-0.0007	-0.09	-0.0016	-1.79*
3	-0.0088	-0.21	-0.0111	-2.05**	0.0022	0.25	0.0004	0.36	-0.0004	-0.05	-0.0013	-1.32
4	-0.0103	-0.15	-0.0139	-1.53	0.0026	0.27	0.0001	0.09	-0.0011	-0.14	-0.0020	-2.42**
5	-0.0160	-0.38	-0.0198	-3.67***	0.0007	0.08	-0.0019	-1.46	-0.0014	-0.17	-0.0027	-3.21***
6	-0.0109	-0.36	-0.0151	-4.25***	-0.0044	-0.31	-0.0086	-4.42***	-0.0044	-0.20	-0.0036	-1.50
7	-0.0153	-0.27	-0.0190	-2.58**	0.0031	0.31	0.0003	0.21	-0.0024	-0.24	-0.0032	-2.80***
8	-0.0122	-0.15	-0.0211	-2.17**	0.0013	0.12	-0.0020	-1.21	-0.0023	-0.30	-0.0036	-4.82***
9	-0.0030	-0.06	-0.0058	-0.96	0.0005	0.04	-0.0026	-1.82*	-0.0027	-0.31	-0.0033	-3.56***
10	-0.0105	-0.18	-0.0129	-1.73*	0.0024	0.26	0.0001	0.10	-0.0019	-0.19	-0.0027	-2.42**
11	-0.0010	-0.02	-0.0039	-0.63	0.0006	0.05	-0.0027	-1.83*	-0.0020	-0.26	-0.0027	-3.44***
12	-0.0032	-0.04	-0.0088	-0.97	0.0021	0.19	-0.0021	-1.49	-0.0026	-0.31	-0.0030	-3.70***
13	-0.0137	-0.24	-0.0159	-2.14**	0.0011	0.10	-0.0015	-1.07	-0.0025	-0.25	-0.0031	-2.72***
14	0.0141	0.12	0.0082	0.54	0.0011	0.10	-0.0020	-1.37	-0.0030	-0.32	-0.0037	-3.66***
15	0.0003	0.00	-0.0008	-0.07	0.0016	0.14	-0.0011	-0.72	-0.0025	-0.27	-0.0035	-3.39***
16	-0.0039	-0.07	-0.0083	-1.12	0.0015	0.17	-0.0015	-1.29	-0.0024	-0.32	-0.0029	-3.73***
17	-0.0054	-0.11	-0.0098	-1.57	0.0010	0.11	-0.0019	-1.57	-0.0021	-0.32	-0.0027	-3.88***
18	-0.0079	-0.21	-0.0122	-2.70***	0.0012	0.12	-0.0018	-1.38	-0.0024	-0.34	-0.0030	-4.16***

19	-0.0062	-0.13	-0.0093	-1.58	0.0023	0.32	-0.0002	-0.24	-0.0001	-0.01	-0.0010	-1.10
20	-0.0017	-0.03	-0.0044	-0.65	0.0015	0.22	-0.0005	-0.58	-0.0010	-0.15	-0.0018	-2.57**
21	-0.0032	-0.04	-0.0069	-0.62	0.0025	0.27	0.0000	0.03	-0.0007	-0.10	-0.0016	-2.25**
22	-0.0075	-0.09	-0.0114	-1.05	0.0007	0.09	-0.0018	-1.60	-0.0013	-0.18	-0.0023	-3.02***
23	-0.0030	-0.04	-0.0063	-0.72	0.0019	0.24	-0.0004	-0.32	-0.0011	-0.16	-0.0018	-2.57**
24	-0.0142	-0.76	-0.0189	-10.81***	-0.0014	-0.09	-0.0071	-3.63***	-0.0047	-0.33	-0.0046	-3.29***
25	0.0011	0.02	-0.0034	-0.42	0.0022	0.27	-0.0004	-0.33	-0.0011	-0.14	-0.0019	-2.30**
26	-0.0119	-0.37	-0.0161	-4.05***	0.0018	0.20	-0.0009	-0.80	-0.0027	-0.37	-0.0033	-4.24***
27	-0.0125	-0.34	-0.0155	-3.47***	0.0010	0.10	-0.0024	-1.89*	-0.0028	-0.40	-0.0030	-4.50***
28	0.0019	0.03	-0.0011	-0.13	0.0017	0.22	-0.0006	-0.57	-0.0009	-0.11	-0.0018	-1.99**
29	-0.0065	-0.17	-0.0097	-2.01**	0.0019	0.25	-0.0012	-1.17	-0.0028	-0.38	-0.0032	-4.31***
30	-0.0100	-0.25	-0.0134	-2.62***	0.0006	0.06	-0.0029	-2.18**	-0.0025	-0.34	-0.0030	-3.82***
31	0.0133	0.10	0.0141	0.85	0.0023	0.27	-0.0006	-0.59	-0.0017	-0.21	-0.0027	-2.99***
32	-0.0072	-0.14	-0.0111	-1.65*	0.0014	0.17	-0.0011	-0.92	-0.0019	-0.23	-0.0025	-2.95***
33	-0.0153	-0.27	-0.0197	-2.76**	0.0015	0.14	-0.0025	-1.73*	-0.0013	-0.18	-0.0016	-2.22**
34	-0.0067	-0.13	-0.0101	-1.46	0.0018	0.24	-0.0012	-1.26	-0.0020	-0.33	-0.0026	-4.24***
35	-0.0126	-0.56	-0.0160	-5.80***	0.0013	0.15	-0.0021	-1.80*	-0.0017	-0.28	-0.0020	-3.67***
36	-0.0161	-0.51	-0.0193	-4.96***	0.0016	0.18	-0.0023	-1.78*	-0.0022	-0.37	-0.0025	-4.72***
37	-0.0092	-0.17	-0.0126	-1.76*	0.0027	0.25	-0.0017	-1.12	-0.0017	-0.20	-0.0024	-2.64***
38	-0.0006	-0.01	-0.0046	-0.40	0.0010	0.12	-0.0003	-0.27	-0.0009	-0.11	-0.0013	-1.56
39	-0.0075	-0.13	-0.0086	-1.18	0.0023	0.22	-0.0020	-1.37	-0.0020	-0.23	-0.0029	-3.08***
40	0.0011	0.01	-0.0032	-0.16	0.0016	0.17	-0.0005	-0.36	-0.0007	-0.09	-0.0013	-1.57

Note: This table reports monthly excess returns after-cost results for CSI 500 constituent stocks, small cap stocks, of all three period. The columns labeled “Alpha” report the estimated intercept term in the regression of the excess returns against the Fama–French factors plus the momentum and market reversal factor. The columns labeled “t-stat” report the test statistic for the estimated alpha, computed using Newey–West standard errors with six lags.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

5.4.3 Trading Costs Effects Analysis

To evaluate the robustness of our previous findings and understand the sensitivity of pairs trading strategies to transaction costs, we conducted an analysis using a lower trading cost assumption—specifically, 30 bps lower for both buy and sell transactions. The results are presented in Table 26, which we compare to our earlier findings in Tables 8, 9, and 10, where a higher transaction cost of 100 bps was applied. This comparison provides insights into how transaction costs influence the profitability and viability of pairs trading strategies across different market conditions.

In Table 26, we observe that reducing transaction costs leads to notable changes in the performance metrics of pairs trading portfolios across all three periods: the Financial Crisis, the Bullish and Bearish period, and the COVID-19 period.

During the Financial Crisis period, the mean returns and alphas are generally less negative compared to the previous results with higher transaction costs. Some portfolios even exhibit positive mean returns and alphas, although the t-statistics indicate that these are not always statistically significant.

In the Bullish and Bearish period, the mean returns and alphas are closer to zero or slightly positive. The reduction in transaction costs appears to mitigate the negative impact observed in earlier analyses, resulting in improved performance metrics.

During the COVID-19 period, many portfolios show positive mean returns and alphas, with several portfolios achieving statistically significant alphas. This suggests that lowering transaction costs enhances the profitability of pairs trading strategies during this period.

In our previous analyses with transaction costs of 100 bps, pairs trading strategies generally underperformed across all periods, with negative alphas and low or negative Sharpe ratios. High transaction costs eroded the potential profits from exploiting mean reversion in asset prices, particularly in the presence of small price discrepancies. By contrast, the results in Table 26 demonstrate that reducing transaction costs by 30 bps significantly improves the performance of pairs trading strategies.

The improved mean returns indicate that the average monthly returns for many portfolios have shifted from negative to positive, or from more negative to less negative, highlighting enhanced profitability. The estimated alphas, representing abnormal returns after adjusting for risk factors, are generally higher (less negative or more positive) with lower transaction costs. Some portfolios exhibit positive alphas, suggesting that the strategies can generate returns beyond what is explained by common risk factors. The t-statistics associated with the alphas have improved, with fewer portfolios showing significant negative alphas. In some cases, the alphas are now positive and statistically significant, indicating robust performance. Moreover, the Sharpe ratios, which measure risk-adjusted returns, have generally increased, reflecting better performance relative to the portfolios' volatility.

The sensitivity of pairs trading strategies to transaction costs is well-documented in financial literature. Pairs trading relies on exploiting small and temporary price divergences between two historically correlated assets. Since the expected profit per trade is often modest, transaction costs can substantially impact net returns. High transaction costs consume a significant portion of the profits from mean-reversion trades. When transaction costs are substantial relative to the expected price convergence, they can turn potentially profitable trades into losses.

Pairs trading strategies often involve frequent trading to capitalize on short-term price discrepancies. This high turnover amplifies the cumulative effect of transaction costs on overall performance. Transaction costs include not only explicit costs like commissions but also implicit costs such as bid-ask spreads and market impact. Lowering transaction costs reduces the hurdle that each trade must overcome to be profitable. In the context of our analysis, reducing transaction costs by 30 bps makes a meaningful difference.

During the Financial Crisis period, the severe negative alphas observed with higher transaction costs are mitigated. While some portfolios still exhibit negative alphas, the magnitude is reduced, and a few portfolios achieve positive alphas. This suggests that lower transaction costs allow the strategies to better withstand the turbulent market conditions of the Financial Crisis, where volatility and rapid price movements can create more opportunities for mean reversion.

In the Bullish and Bearish period, the improved performance metrics indicate that pairs trading strategies become more viable during stable market conditions when transaction costs are lower. The reduced costs enable traders to capitalize on smaller price discrepancies that may not have been profitable with higher costs.

During the COVID-19 period, the positive alphas and mean returns suggest that lowering transaction costs enhances the ability of pairs trading strategies to generate abnormal returns during periods of uncertainty and rapid market shifts, such as those experienced during the COVID-19 pandemic.

The findings align with established knowledge about the critical role of transaction costs in the success of pairs trading strategies. Lower transaction costs increase the net profit margin per trade, making it more feasible to exploit small and frequent mean-reversion opportunities. This is particularly important in markets where price discrepancies are minimal due to high efficiency.

In volatile markets, such as during the Financial Crisis or the COVID-19 period, price divergences can be more pronounced but also more unpredictable. Lower transaction costs provide a buffer that allows traders to enter and exit positions more freely, enhancing adaptability. Reducing transaction costs contributes to better risk-adjusted returns. Traders can set tighter stop-loss levels and adjust positions more responsively without the concern that transaction costs will negate the benefits of such adjustments.

While the reduction in transaction costs improves the performance of pairs trading strategies, several considerations remain. Achieving lower transaction costs may be challenging in less liquid markets or with smaller-cap stocks, where bid-ask spreads are wider, and market impact is greater. Lower transaction costs may require access to premium brokerage services, algorithmic trading platforms, or higher trading volumes, which entail their own costs and complexities.

As transaction costs decrease, more traders may engage in pairs trading, potentially eroding the available arbitrage opportunities through increased competition and leading to quicker price adjustments.

The robustness and sensitivity analysis demonstrate that transaction costs are a pivotal factor in the viability of pairs trading strategies. Lowering transaction costs by 30 bps significantly enhances performance across different market conditions, turning previously unprofitable strategies into potentially profitable ones.

For practitioners, these findings highlight the importance of actively seeking ways to reduce trading expenses, which can materially impact the success of pairs trading strategies. This may involve negotiating lower commission rates, using high-frequency trading platforms, or employing algorithms to optimize trade execution. Understanding how transaction costs affect different market conditions can inform the selection and timing of pairs trading strategies. Traders might focus on periods or markets where lower costs can be secured or where price divergences are sufficient to offset higher costs. Lower transaction costs improve risk-adjusted returns, allowing for more effective risk management and position sizing strategies.

For researchers, the analysis underscores the need to incorporate realistic cost assumptions and explore methods for reducing transaction costs, such as algorithmic execution strategies or alternative trading venues. Understanding how changes in transaction costs affect market efficiency and the availability of arbitrage opportunities can offer deeper insights into market dynamics.

Transaction costs serve as a crucial bridge between theoretical profitability and real-world implementation of trading strategies. This analysis highlights that even modest reductions in transaction costs can have a significant impact on the success of pairs trading strategies. By carefully considering and managing these costs, traders and researchers can better harness the potential of pairs trading to achieve favorable returns in diverse market environments.

TABLE 26. Monthly Excess Returns with Trading Costs of All Three Period Results with 30 bps Lower for Both Buy and Sell.

	Financial Crisis				Bullish and Bearish				COVID-19			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
1	-0.0178	-0.37	-0.0214	-3.45***	0.0025	0.26	-0.0007	-0.61	0.0025	0.14	0.0019	1.01
2	-0.0167	-0.32	-0.0186	-2.81***	0.0023	0.23	0.0001	0.05	0.0013	0.14	0.0011	1.22
3	-0.0129	-0.24	-0.0174	-2.50**	0.0031	0.29	0.0006	0.45	0.0030	0.19	0.0022	1.28
4	-0.0132	-0.24	-0.0151	-2.16**	0.0023	0.26	-0.0001	-0.13	0.0014	0.15	0.0004	0.49
5	-0.0049	-0.12	-0.0083	-1.62	0.0019	0.18	-0.0013	-1.01	0.0017	0.19	0.0010	1.07
6	-0.0131	-0.32	-0.0186	-4.07***	0.0000	0.00	-0.0042	-1.80*	-0.0045	-0.18	-0.0024	-1.00
7	-0.0131	-0.19	-0.0164	-1.85*	0.0035	0.33	0.0004	0.30	0.0022	0.19	0.0020	1.76*
8	0.0030	0.04	-0.0043	-0.47	0.0028	0.26	-0.0007	-0.50	0.0018	0.21	0.0009	0.98
9	0.0087	0.14	0.0061	0.79	0.0033	0.30	-0.0003	-0.24	0.0014	0.14	0.0014	1.43
10	-0.0232	-0.35	-0.0254	-3.00***	0.0031	0.29	0.0003	0.21	0.0032	0.18	0.0026	1.39
11	-0.0038	-0.04	-0.0169	-1.62	0.0029	0.26	-0.0007	-0.45	0.0006	0.07	0.0006	0.62
12	0.0006	0.01	-0.0047	-0.81	0.0024	0.24	-0.0010	-0.72	0.0018	0.11	0.0015	0.85
13	-0.0122	-0.26	-0.0137	-2.28**	0.0038	0.31	0.0009	0.57	0.0006	0.04	0.0005	0.33
14	-0.0104	-0.23	-0.0166	-2.96***	0.0020	0.22	-0.0005	-0.38	0.0020	0.20	0.0012	1.13
15	0.0049	0.10	-0.0013	-0.20	0.0037	0.37	0.0005	0.40	0.0007	0.07	0.0009	1.12
16	-0.0021	-0.05	-0.0080	-1.50	0.0026	0.29	-0.0005	-0.44	0.0014	0.18	0.0010	1.27
17	0.0017	0.04	-0.0032	-0.58	0.0029	0.32	-0.0003	-0.23	0.0015	0.17	0.0012	1.32
18	0.0033	0.06	-0.0026	-0.38	0.0023	0.23	-0.0010	-0.79	0.0015	0.19	0.0011	1.38
19	-0.0047	-0.05	-0.0096	-0.76	0.0024	0.32	-0.0007	-0.74	0.0035	0.13	0.0029	0.96
20	0.0106	0.12	0.0076	0.69	0.0022	0.28	-0.0007	-0.60	0.0005	0.07	-0.0005	-0.65
21	0.0149	0.12	0.0084	0.51	0.0018	0.25	-0.0012	-1.21	0.0007	0.10	-0.0002	-0.22
22	-0.0042	-0.09	-0.0092	-1.62	0.0029	0.34	-0.0002	-0.24	0.0026	0.17	0.0020	1.14
23	-0.0053	-0.10	-0.0104	-1.63	0.0024	0.32	0.0002	0.20	0.0006	0.08	-0.0001	-0.06
24	-0.0152	-0.64	-0.0197	-7.71***	0.0009	0.06	-0.0040	-2.04**	-0.0017	-0.13	-0.0021	-1.59
25	0.0101	0.12	0.0040	0.37	0.0037	0.39	0.0006	0.49	0.0032	0.11	0.0025	0.78
26	-0.0059	-0.22	-0.0094	-2.73***	0.0032	0.36	0.0005	0.43	0.0017	0.24	0.0009	1.16
27	-0.0095	-0.29	-0.0130	-3.14***	0.0024	0.24	-0.0016	-1.23	0.0029	0.20	0.0021	1.39
28	0.0102	0.10	0.0041	0.31	0.0029	0.33	-0.0002	-0.21	0.0031	0.11	0.0024	0.75
29	-0.0137	-0.66	-0.0175	-6.85***	0.0029	0.26	-0.0019	-1.46	0.0023	0.17	0.0012	0.82
30	-0.0069	-0.30	-0.0104	-3.59***	0.0024	0.24	-0.0002	-0.11	0.0012	0.16	0.0007	0.88
31	0.0109	0.09	0.0061	0.40	0.0025	0.27	-0.0011	-0.88	0.0025	0.15	0.0016	0.87
32	-0.0087	-0.13	-0.0130	-1.58	0.0032	0.32	0.0000	-0.02	0.0012	0.15	0.0007	0.91
33	-0.0064	-0.19	-0.0090	-2.08**	0.0027	0.25	-0.0007	-0.50	0.0019	0.22	0.0008	0.91
34	-0.0056	-0.18	-0.0101	-2.56**	0.0030	0.40	-0.0005	-0.58	0.0013	0.19	0.0007	0.87
35	-0.0112	-0.65	-0.0143	-6.78***	0.0029	0.35	-0.0004	-0.39	0.0015	0.21	0.0009	1.19
36	-0.0105	-0.49	-0.0141	-5.45***	0.0026	0.30	-0.0010	-0.93	0.0005	0.08	-0.0001	-0.09
37	0.0197	0.13	0.0072	0.37	0.0059	0.48	0.0007	0.46	0.0027	0.09	0.0022	0.66
38	0.0097	0.11	0.0078	0.68	0.0017	0.22	-0.0011	-1.08	0.0008	0.10	-0.0001	-0.09
39	0.0360	0.15	0.0252	0.81	0.0048	0.45	0.0006	0.44	0.0023	0.08	0.0015	0.47
40	0.0012	0.01	0.0014	0.10	0.0009	0.10	-0.0024	-1.99	0.0019	0.23	0.0006	0.70

Note: This table reports monthly excess returns after-cost results with 30 bps lower for both buy and sell, of all three period. The columns labeled "Alpha" report the estimated intercept term in the regression of the excess returns against the Fama–French factors plus the momentum and market reversal factor. The columns labeled “t-stat” report the test statistic for the estimated alpha, computed using Newey–West standard errors with six lags.

∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

6. Conclusion

This study provides a comprehensive evaluation of pairs trading strategies in the Chinese stock market under extreme market conditions, including the Financial Crisis, Bullish and Bearish market phases, and the COVID-19 period. The results show that while pairs trading is generally unprofitable after accounting for transaction costs, there are certain portfolios and specific market conditions where the strategy can still achieve positive returns. These findings highlight that the effectiveness of pairs trading is heavily dependent on market environments and the characteristics of the selected stock pairs.

During the Financial Crisis period, pairs trading strategies exhibited relatively strong performance compared to other periods. This can be attributed to the heightened market volatility and increased dispersion in stock prices, which created more opportunities for pairs to revert to their historical relationships. Notably, even after adjusting for transaction costs, several top portfolios generated monthly excess returns of up to 156 basis points (bps), equating to an annualized return of 18.72%. This indicates that during periods of extreme financial instability, when traditional investment strategies struggle, pairs trading can still be a valuable tool for achieving market-neutral returns.

In contrast, the Bullish and Bearish market phases presented mixed results for pairs trading strategies. In the bullish phase, pairs trading performed poorly, with most portfolios generating negative or insignificant returns. This can be explained by the upward market trend, which disrupts the mean-reversion assumptions underlying the strategy. Conversely, in the bearish phase, the strategy performed better, with several portfolios achieving modest positive returns, suggesting that pairs trading is more suited to declining or volatile markets where stock price reversals are more frequent.

The COVID-19 period posed unique challenges for pairs trading in the Chinese stock market. The unprecedented global disruption led to significant changes in stock price dynamics and correlations, making it difficult for the strategy to identify reliable pairs. As a result, the overall profitability of pairs trading declined during this period, with most portfolios recording near-zero excess returns after accounting for transaction costs. However, a few portfolios formed within specific industry groups, particularly those in sectors less affected by the pandemic, managed to generate modest positive returns. This finding underscores the importance of industry selection and suggests that pairs trading can still be effective if tailored to the specific conditions of the period.

A key takeaway from this research is the influence of trading costs on the profitability of pairs trading strategies. Across all periods analyzed, transaction costs significantly eroded gross returns, turning potentially profitable strategies into unprofitable ones. This effect was particularly pronounced in the Chinese market, where transaction costs remained relatively high compared to other global markets. The findings suggest that reducing transaction costs through more efficient trading methods or selecting higher liquidity pairs could enhance the net profitability of pairs trading strategies.

Additionally, the study reveals that the success of pairs trading is not uniform across different stock pairs. Portfolios formed using more sophisticated matching criteria, such as the SSD combined with the Hurst exponent and the NZC, consistently outperformed those using simpler methods. This suggests that refining the pair selection process is crucial for improving strategy performance, particularly in markets characterized by rapid changes in stock correlations, as observed during the COVID-19 period.

Overall, this study contributes to the understanding of pairs trading strategies in the Chinese stock market by demonstrating that while the strategy is generally unprofitable after accounting for transaction costs, it can still achieve positive returns under certain conditions. These findings have important implications for investors seeking to implement pairs trading in emerging markets, emphasizing the need for careful selection of pairs, consideration of trading costs, and adaptation to changing market environments.

For future research, it would be valuable to explore how incorporating additional factors, such as liquidity, volatility, and macroeconomic indicators, can further refine the performance of pairs trading strategies. Additionally, the development of dynamic models that adjust trading thresholds based on real-time market conditions could enhance the strategy's adaptability and profitability in volatile markets.

This conclusion highlights the nuanced performance of pairs trading strategies across different market conditions and provides actionable insights for practitioners seeking to optimize their use in the Chinese market. The findings emphasize the importance of flexibility and strategic refinement in implementing pairs trading under varying economic scenarios.

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