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

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Abstract: This study evaluates the performance of pairs trading strategies in the Chinese stock market across extreme market environments, including the Financial Crisis, Bull and Bear phases, and the COVID-19 period. Using a comprehensive stock dataset and incorporating transaction costs, we find that most portfolios deliver near-zero excess returns after costs. However, in volatile conditions—especially during the Financial Crisis—top-performing portfolios achieved monthly returns up to 156 basis points. The strategy underperforms in stable or bullish markets with fewer mean-reversion opportunities. COVID-19 introduced challenges that further reduced profitability. Results highlight the critical role of transaction costs and the importance of advanced pair selection methods, such as combining the Sum of Squared Deviations (SSD), Hurst exponent, and the Number of Zero Crossings (NZC), which consistently outperform traditional approaches. While generally unprofitable, pairs trading can succeed under specific market regimes, offering insights into risk management and strategy adaptation.

Keywords: Pairs Trading, Statistical Arbitrage, Sum of Squared Deviations, Hurst Exponent, Chinese Stock Market

JEL codes: C58, C63, G11, G14, G17

1. Introduction

While much of the research in the hedge fund industry and academic literature has focused on the US market, it is also worth considering how these strategies perform in other settings, such as China. This naturally raises some important questions. Do strategies like pairs trading achieve returns comparable to those in the US in China? If not, what market-specific characteristics could explain the discrepancy? How do pairs trading perform during periods of significant market stress, such as the COVID-19 pandemic, the GFC, or other extreme events?

This study aims to answer these questions by evaluating the returns and risks of pairs trading strategies using a large dataset of Chinese stocks. Because China's three-year quarantine policy differs significantly from the approaches taken in most other countries, this study specifically focuses on the COVID-19 pandemic. By analyzing the unique characteristics of the Chinese market, this study aims to provide insights into potential variations in the effectiveness of pairs trading strategies during the COVID-19 pandemic, the GFC, and periods of bull and bear markets in the Chinese market.

Specifically, we evaluated the performance of pairs trading during three distinct periods: the GFC (January 1, 2005, to December 31, 2010); the bull and bear markets (January 1, 2011, to December 31, 2016); and the COVID-19 pandemic (January 1, 2017, to June 30, 2024). This stratification allows for a comprehensive assessment of how the strategy adapts to market conditions shaped by unusual events. By examining these periods, we aim to reveal the resilience and limitations of pairs trading in the Chinese market, providing valuable guidance for investors and portfolio managers as they navigate similar market fluctuations in the future.

The COVID-19 pandemic significantly impacted many hedge fund strategies, leading to a sharp decline in fund returns and a significant reduction in assets under management. Yu and Xiao (2024) provide comprehensive data on stock returns during this period. Their results show that the average log return of 539 Chinese stocks from January 1, 2020, to January 31, 2023 (post-COVID-19) was 1.43%, significantly lower than the average log return of 11.31% during the pre-COVID-19 period (January 1, 2019, to December 31, 2019). These findings highlight the negative impact of the COVID-19 pandemic on the overall performance of the Chinese stock market.

Pairs trading is a market-neutral investment strategy that seeks to profit from short-term price reversals by taking offsetting long and short positions in two correlated stocks. The strategy is based on the premise that such stocks tend to move in tandem, and when prices diverge, their price relationship will revert to historical levels. Pairs trading is widely considered a form of statistical arbitrage, where traders go long on undervalued stocks and short on overvalued stocks, anticipating price convergence. This approach exploits the well-established mutual autocorrelation of stock prices, suggesting that past price movements influence future returns. Recent market microstructure research has further explored the link between liquidity and mutual autocorrelation. For example, Gupta and Chatterjee (2020) have shown that market frictions, such as illiquidity, can generate lead-lag effects between stock pairs, creating profitable trading opportunities.

A growing number of studies have examined the performance of pairs trading in international markets, including Nath (2003), Hong and Susmel (2004), Andrade et al. (2005), Gatev et al. (2006), Perlin (2009), Do and Faff (2010), Rad et al. (2016), Bowen and Hutchinson (2016), and Chen et al. (2019). Gatev et al. (2006) examined the effectiveness of pairs trading in the US stock market from 1962 to 2002, finding an average annual return of 11%, relatively low risk, and minimal exposure to common stock risk factors. Building on this research, Do and Faff (2010) analyzed the performance of this strategy from 1962 to 2009 and reached similar conclusions. Research on the US market found that pairs trading was most profitable in the 1970s and 1980s, with returns declining significantly after 1989.

Several studies have refined the approach originally proposed by Gatev et al. (2006). For example, Elliott (2005) applied a Gaussian Markov chain model to estimate the spread, while Do et al. (2006) refined their spread measurement approach using a theoretical asset pricing framework and the concept of mean reversion. Vidyamurthy (2004) and Burgess (2005) employed cointegration techniques for pair selection, enhancing the robustness of their strategies. Papadakis and Wysocki (2007) extended the original framework to analyze the impact of accounting information events (such as earnings announcements and analyst forecasts) on pairs trading returns. Do and Faff (2012) studied the impact of transaction costs on the profitability of pairs trading in the US market and highlighted the strategy's sensitivity to such costs.

Recent advances in pairs trading research have expanded its application across markets, asset classes, and methodological frameworks, highlighting its adaptability and evolution. Miao and Laws (2016) demonstrated the global profitability of a simple pairs trading strategy, confirming its effectiveness in diverse financial environments. Rad et al. (2016) compared distance, cointegration, and copula-based approaches, demonstrating the diversification of technical approaches to adapt to diverse market conditions. Smith and Xu (2017) proposed alternative pairs trading strategies, while Vaitonis (2017) applied high-frequency trading techniques to the OMX Baltic Market, demonstrating the strategy's compatibility with advanced trading techniques.

Mikkelsen (2018) studied pairs trading among Norwegian seafood companies, demonstrating its adaptability to niche markets. Blázquez and Román (2018) compared various pairs trading techniques to determine which performed best under different conditions. Quinn et al. (2018) extended the approach to pairs trading based on gilts and also to fixed-income securities. Chen et al. (2019) conducted an empirical study of stock pairs trading strategies, while Zhang and Urquhart (2019) analyzed cross-market pairs trading between mainland China and Hong Kong. Farago and Hjalmarsson (2019) studied stock price comovement, providing theoretical insights into the determinants of pairs trading profitability.

Aggarwal and Aggarwal (2020) provide evidence from commodity futures pairs trading in the Indian market, validating the strategy's versatility across different geographies and asset classes. Fil and Kristoufek (2020) study pairs trading in the cryptocurrency market, extending the strategy to the highly volatile digital asset space and highlighting its potential profitability in this sector. Diao et al. (2020) develop a stock pairs trading strategy based on dual-objective optimization, demonstrating advanced mathematical methods for improving pairs trading techniques. Gupta and Chatterjee (2020) propose the concept of incorporating lead-lag relationships when selecting stock pairs, adding a new dimension to the strategy by considering the temporal dynamics of the market. Ramos-Requena et al. (2020) discuss the considerations for forming trading pairs and provide practical guidance on the pair selection process that may influence trading outcomes. Aggarwal and Aggarwal (2021) examine the risk-adjusted returns of statistical arbitrage in Indian stock futures, incorporating risk management considerations into pairs trading. Keshavarz Haddad and Talebi (2023) studied the profitability of pairs trading on the Toronto Stock Exchange, providing evidence for the global applicability of the strategy. Ko et al. (2024) conducted a comparative study of statistical methods for pairs trading in cryptocurrency markets, demonstrating the strategy's adaptability to new financial products and complex statistical models.

We contribute to the literature on pairs trading in five key ways. First, this is one of the first papers to provide substantial evidence demonstrating the profitability of pairs trading strategies in the Chinese stock market, particularly during extreme market events. By analyzing the performance of pairs trading under different market conditions, this study fills a critical gap in the existing emerging market literature. Second, we use different benchmarks to measure excess monthly returns across different market phases to assess the robustness of pairs trading performance. Our results show that pairs trading performs well in down markets but tends to underperform in up markets. Third, we provide a more comprehensive analysis by integrating a model framework encompassing 40 different stock selection criteria. Notably, this study is the first to combine the SSD and Hurst index as a combined stock selection method, which outperforms traditional stock selection methods based solely on the SSD. Fourth, this study is the first to classify industry categories into two groups: high-performing and low-performing industries. Our results show that pairs trading in high-performing industries can generate significantly higher excess monthly returns, suggesting that industry characteristics play a crucial role in determining the success of pairs trading strategies. Finally, we provide an in-depth analysis of transaction costs unique to the Chinese stock market and incorporate them into the evaluation of the actual performance of pairs trading strategies. This addition enhances the authenticity of the study and provides insight into the net profitability of pairs trading after accounting for actual transaction costs.

Our key findings are as follows. On average, pairs trading is difficult to profit from, with monthly excess returns approaching zero after accounting for transaction costs. However, some portfolios comprised of more closely matched pairs from more refined sector mixes exhibited some profitability, in some cases even generating substantial returns. Notably, during the GFC, despite the benchmark's monthly return reaching 162 bps, the top five portfolios achieved an average monthly excess return of 156 bps, equivalent to an annualized return of 18.72%. Analysis of nine subperiods reveals that pairs trading achieved significant positive returns in downturns, such as bear markets, averaging 51 bps and an annualized return of 6.12%. In contrast, returns were largely negative in upturns. In particular, the benchmark's monthly return reached 162 bps throughout the GFC.

2. Literature Review

2.1 Baseline Approach

Gatev et al. (2006), hereafter referred to as GGR, developed a foundational pairs trading framework by systematically examining the profitability of stock pairs trading in the US stock market from 1962 to 2002. Their approach identifies historically co-moving stock pairs and then trades these pairs when prices diverge, assuming that relative mispricing will revert to their historical relationship.

The basic procedure consists of three steps: pair selection, signal generation, and portfolio construction. In the selection phase, each stock is matched with a trading partner based on a minimum historical distance, which quantifies the closeness of their co-movement. In the signal generation phase, positions are initiated when the pair price ratio deviates from a preset threshold: long the underperforming stock and short the outperforming stock, and then closed when prices converge.

GGR documented that the profitability of this strategy is primarily driven by relative price mean reversion. The strategy reported an average annual return of approximately 11% and low correlation with common equity risk factors (market, size, and value). Furthermore, its performance remained resilient during periods of market stress, consistent with its market-neutral design and relatively low risk profile. Since then, the GGR benchmark has served as the basis for subsequent research and has driven numerous extensions across assets, risk management schemes, and market environments.

2.2 Expanding on GGR's Approach

Do and Faff (2010) extended the GGR model by examining pairs trading in a longer sample of US markets (1962–2009). They confirmed the profitability of the baseline strategy and documented significant time-varying performance: returns were strongest in the 1970s and 1980s but declined significantly after 1989, which they attributed to increasing market efficiency and the spread of quantitative strategies (including pairs trading). Beyond replication, they analyzed market conditions, transaction costs, and microstructural changes, highlighting that even modest costs significantly eroded profitability in later subsamples. Thus, this study highlights both the historical success of pairs trading in more efficient markets and its increasing implementation challenges.

Rad et al. (2016) evaluated three selection/trading frameworks—distance, cointegration, and copula—in US markets (1962–2014). All three frameworks achieved positive excess returns, but performance varied across approaches. Before costs, distance and cointegration generally dominate copula strategies; after costs, distance methods generally outperform. Notably, copula strategies have maintained a more stable opportunity set in recent years, suggesting their potential robustness to efficiency gains. Cointegration methods tend to perform relatively well during periods of higher volatility, reflecting their ability to exploit stronger mean reversion under turbulent conditions. Overall, the evidence supports diversification beyond traditional distance methods during periods of shifting market regimes.

Bowen and Hutchinson (2016) conducted the first comprehensive study of pairs trading in the UK equity market (1980–2012), including the 2008 GFC. The strategy remained resilient during periods of stress, generating positive returns even when the broader market index declined. Using a multi-factor configuration (market, size, value, momentum, and reversal), they found limited factor exposure, with the market factor being most strongly correlated with the top-ranked pairs trades. They also linked time series performance to proxies for liquidity, price impact, and bid-ask spreads, suggesting that market frictions have a substantial impact on the results. Their findings highlight the adaptability of trading currency pairs outside the United States and their potential as a market-neutral allocation during periods of market dislocation.

2.3 Improvements to GGR's Approach

Perlin (2009) implemented GGR pairs trading in the Brazilian market and extended the evidence to emerging markets. Using daily, weekly, and monthly data, Perlin examined profitability and risk, exploring whether the successful practices in developed markets persist. The study confirmed that pairs trading remained profitable and largely market neutral in Brazil, with best performance at daily trading frequencies, consistent with strategies that exploit short-term divergences. Perlin further compared the strategy with a simple buy-and-hold strategy and a bootstrapping method using stochastic signals, demonstrating economically and statistically significant outperformance across a wide range of conditions. By systematically varying entry barriers and other parameters, this paper provides a nuanced perspective on how design choices influence outcomes, extending the robustness assessment of GGR in emerging markets.

Yang et al. (2017) extended the framework to Chinese commodity futures (Dalian, Shanghai, and Zhengzhou exchanges), moving beyond equities to asset classes with unique microstructures and risks. The authors compared currency pair selection methods such as cointegration, minimum distance, and correlation, and evaluated their performance using in-sample and out-of-sample tests. The spread is modeled as the logarithmic price difference and fitted using the Ornstein-Uhlenbeck (OU) process to capture mean reversion. They find that carefully selected currency pairs, particularly through cointegration and minimum distance methods, can generate high returns; however, the key to profitability lies in identifying the right currency pairs and managing spread-divergence risk, which is more pronounced in commodity markets given the potentially long holding periods. A key result is that maximum drawdown is often more informative than the Sharpe ratio, highlighting the importance of controlling holding periods and exit discipline. Evidence suggests that higher returns may offset divergence risk rather than reflect widespread market inefficiencies.

Gupta and Chatterjee (2020) improve the selection process by incorporating lead-lag dynamics into distance-based metrics. Traditional metrics (correlation, SSD) ignore temporal ordering, even when one stock consistently leads another. The proposed dynamic cross-correlation type (DCCT) metric adapts the CCT measure to implement time-varying lead-lag via sequence alignment (similar to dynamic programming/DTW) to maximize cross-correlation along the optimal path, rather than relying on simultaneous comparisons or Euclidean distances. Embedding lead-lag into pair selection significantly improves the ability to capture convergence behavior that unfolds with lag, leading to a more nuanced understanding of interactions in markets where the timing of price changes is crucial.

3. Data and Chinese Stock Market

3.1 Data Processing

Data Selection and Description

This study uses three sample blocks—January 2004 to December 2010, January 2011 to December 2016, and January 2017 to June 2024—totaling 21 years. The dataset contains daily adjusted prices for 5,612 A-share stocks, the 300 components of the CSI 300 Index, and components of the CSI 200 Index, CSI 500 Index, and various industry-specific indices, all from the iFinD[1] database.

We employ a rolling window design with a 12-month in-sample window and a 6-month out-of-sample trading window. The out-of-sample periods are January 2005 to December 2010, January 2011 to December 2016, and January 2017 to June 2024, capturing market ups and downs, as well as periods of high and low volatility. Table 1 and Figure 1 summarize the sample construction.

To study performance across distinct market environments, we partition the data into Pre-GFC, In-GFC, and Post-GFC; Pre-Bullish, In-Bullish, and In-Bearish; and Pre-COVID, In-COVID, and Post-COVID subperiods.

The first phase runs from January 2005 to December 2010. The pre-GFC period, from January 2005 to December 2006, was characterized by relative market stability and strong growth. The GFC subphase, from January 2007 to December 2008, encompasses the global crisis, a sharp market drawdown, and heightened uncertainty. The post-GFC subphase, from January 2009 to December 2010, reflects the gradual stabilization and recovery of the market. This phase allows for evaluating strategy performance through shocks and rebounds.

The second phase, from January 2011 to December 2016, encompasses the early bull market from January 2011 to December 2013, the bull market from January 2014 to May 2015, and the bear market from June 2015 to December 2016. The sharp rise and subsequent reversal provide a rigorous test of mean reversion.

The third phase, running from January 2017 to June 2024, encompasses the pre-pandemic period from January 2017 to December 2019, the mid-pandemic period from January 2020 to December 2022, and the post-pandemic period from January 2023 to June 2024. The pandemic period was characterized by lockdowns, supply chain disruptions, and increased cross-sectional dispersion, while the post-pandemic period reflected stabilization and partial normalization.

[1] iFinD is a widely used Chinese financial database that provides real-time and historical data on equities, bonds, funds, futures, and market indices. Coverage includes quotes, corporate fundamentals, financial statements, and industry indicators. The platform is developed by RoyalFlush Information Network Co., Ltd., ticker 300033 on the Shenzhen Stock Exchange.

Together, these phases provide a comprehensive timeline for assessing the resilience and limitations of pairs trading across different market cycles. Overall, these three phases provide a comprehensive timeline of diverse market conditions, allowing for a comprehensive examination of the performance of pairs trading strategies across diverse economic environments and market cycles.

We also analyze performance by industry group. High-performing industries are those that performed well during the GFC and the COVID-19 pandemic, while low-performing industries are those that underperformed during the same periods. Based on the Shenwan First-Level Industry Classification[2] (which consists of 31 first-level industries), we categorize the sample into 15 high-performing industries and 16 low-performing industries, based on the period-specific industry performance indicators defined below. This design allows for apples-to-apples comparisons across different industries, even if their outlooks differ systematically.

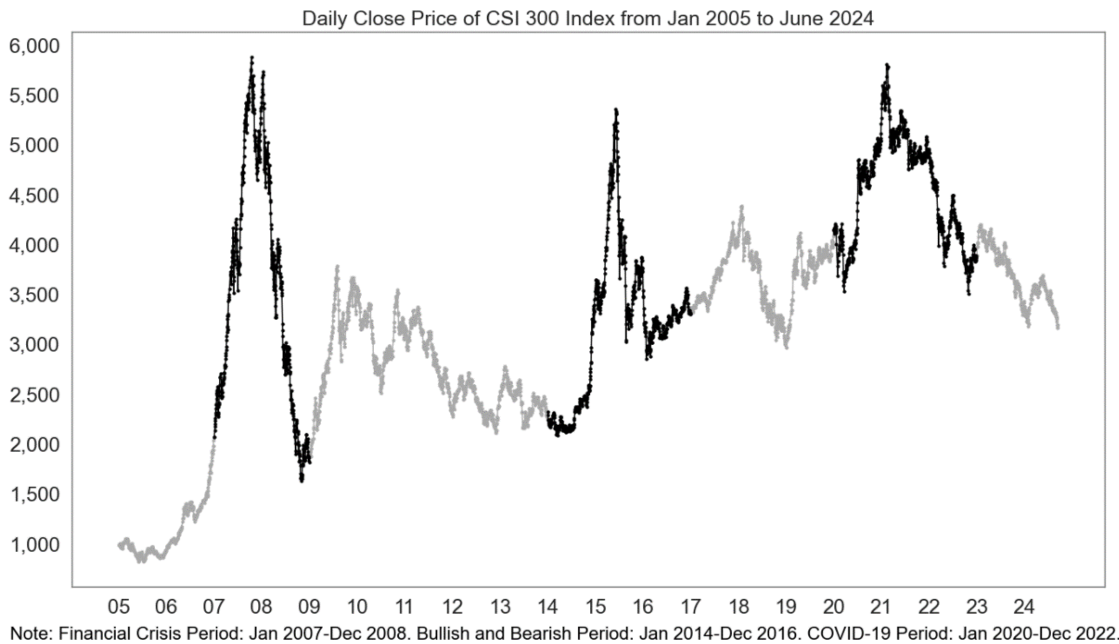
[2] The Shenwan first-level industry system is a standard sector taxonomy in the Chinese equity market. It defines thirty-one primary industries and provides a consistent basis for cross-sector analysis and comparison. This paper adopts that taxonomy throughout. This classification system comprises 31 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	Jan 2011-Dec 2013	Jan 2014-May 2015	June 2015-Dec 2016	313-All 32-CSI 100 78-CSI 200	Jan 2017-Dec 2019	Jan 2020-Dec 2022	Jan 2023-June 2024	911-All 51-CSI 100 124-CSI 200
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: The table summarizes the sample across three timeframes: GFC—pre, in, post; Bullish/Bearish—pre-bullish, bullish, bearish; COVID-19—pre-COVID, in-COVID, post-COVID. "Number of constituents" reports unique tickers present in each universe during the phase. "Number selected" reports stocks retained after data cleaning. "Industry-matched" reports the subset used when pairs are restricted to the same Shenwan first-level industry, corresponding to portfolios 19–36 in Table 3. Counts for CSI 100, CSI 200, and CSI 500 refer to unique constituents observed during the phase rather than nominal index sizes. This design enables a consistent analysis of market behavior and pairs-trading performance across regimes.

Figure 1. Daily Close Price of the CSI 300 Index.



Note: This figure shows the daily close price trend of the CSI 300 Index from January 2005 to June 2024, highlighting three key periods: the GFC (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 GFC 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 for Data Selection

The selection of time periods and datasets was driven by the goal of evaluating the performance of pairs trading under extreme market conditions, with a particular focus on the COVID-19 pandemic. This section explains the selection of the GFC, bull and bear markets, and the COVID-19 pandemic, and explains the rationale for the index coverage and industry groupings.

Selection of These Three Periods. The primary objective is to measure the returns of pairs trading during the COVID-19 pandemic—a period of significant market dislocation and heightened uncertainty. To benchmark performance under comparable stress conditions, this study also includes the period of the GFC. Both crises constituted major global shocks with profound impacts on asset prices and market microstructure. By comparing these two crises, this analysis identifies similarities and differences in pairs trading results under different stress conditions. Including pre- and post-crisis windows, as well as bull and bear market phases, allows for comparisons before, during, and after major market dislocations. This design clearly demonstrates the strategy's performance under both normal and high-volatility environments and enables assessment of recovery dynamics.

Selection of All A-Shares, CSI 100, CSI 200, and CSI 500 Index. To provide comprehensive market coverage, the sample includes all A-shares listed in Shanghai and Shenzhen. The CSI 100, CSI 200, and CSI 500 indices are included in the sample, representing large-, mid-, and small-cap stocks, respectively. The CSI 100 covers the 100 largest companies by market capitalization on both exchanges. The CSI 200 covers the 200 largest companies by market capitalization after excluding the CSI 100. The CSI 500 covers smaller, less liquid companies. Joint analysis of these indices with the entire A-share sample allows for comparison of returns across market capitalization tiers and helps determine whether market size and liquidity conditions influence the effectiveness of pair trading.

Selection of Good Performance and Bad Performance Industries. This study also conducted industry-level tests to examine the interplay between industry conditions and mean reversion. During the COVID-19 pandemic, industries that performed well included biopharmaceuticals, computers, electronics, and communications, totaling 2,950 companies. These industries benefited from the surge in demand for healthcare, technology, and digital services. Industries that underperformed during the same period included air travel, petroleum and petrochemicals, real estate, building materials, architectural decoration, and textiles and apparel, totaling 2,400 companies. These industries were adversely impacted by liquidity constraints, weak consumption, and supply chain frictions. This study uses the Shenwan First-Level Industry Classification, which encompasses 31 primary industries, and divides the sample space into the top 15 performing industries and the remaining 16 underperforming industries, based on the industry performance metrics defined later in this paper. This design enables clear comparisons of industries with systematic differences.

By incorporating crisis and non-crisis regimes, multiple capitalization tiers, and industry heterogeneity, this dataset supports a robust assessment of pair trading performance under market conditions with significant differences in volatility, liquidity, and fundamental drivers.

Data Cleaning Criteria

As shown in Table 1, the number of stocks retained after screening is significantly smaller than the total sample size; for example, 783 and 1,681 samples were retained for specific periods, respectively, compared to a total of 5,612. This reduction reflects the following screening factors. We excluded stocks with more than 30 missing closing prices during the formation window; remaining short gaps were filled using spline interpolation.

First, to accurately assess achievable profitability, we restrict our sample to liquid stocks that are relatively easy and inexpensive to trade, and short selling is permitted. To mitigate survivorship bias, companies are retained in the sample until the delisting date, so that failed stocks are captured.

Second, we exclude Chinese 'ST' and '*ST'[3] stocks. These designations denote special treatment due to unusual financial conditions—'ST' typically refers to two consecutive years of losses, and '*ST' refers to three consecutive years of losses—indicating a higher risk of delisting and poor financial health.

Third, because pairs trading is inherently high-frequency, we prioritize liquidity, focusing on mid- to large-cap stocks within each market segment. This follows the implementation choices of Do and Faff (2012), and Zhang and Urquhart (2019).

Fourth, we exclude non-trading-day stocks with a closing price below 1 Chinese Yuan (CNY)[4] within the one-year formation window, a listing time of less than one year, or zero trading volume. We also remove observations with invalid or missing prices or returns within the formation window.

Finally, in addition to the explicit deletions mentioned above, missing values in the retained series were handled using cubic spline interpolation. Overall, our data processing procedures are highly consistent with the methodology of Do and Faff (2012).

[3] ST and *ST denote "special treatment" categories applied to firms with abnormal financial conditions, such as sustained losses and heightened delisting risk. These stocks are typically subject to tighter trading arrangements, including five-percent daily price limits and a higher probability of trading suspensions. Such constraints increase execution frictions and raise implementation costs for high-turnover strategies.

[4] 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.

3.2 Chinese Stock Market

This section outlines the key institutional features of China's stock market and its evolution. The market structure of China's stock market differs significantly from that of developed markets and remains relatively understudied.

The A-share market was officially opened to qualified foreign investors in 2003 through the Qualified Foreign Institutional Investor (QFII) program, followed by the introduction of the RMB QFII system. Broad two-way market access was further expanded with the launch of the Shanghai-Hong Kong Stock Connect and Shenzhen-Hong Kong Stock Connect. On March 31, 2010, margin trading and short selling officially commenced, targeting large and medium-sized stocks on a designated list. Prior to this, short selling was restricted and conducted only through limited institutional arrangements within securities firms, rather than as a market-wide mechanism. By the end of 2013, hundreds of A-share stocks were eligible for short selling.

The Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE)[5] are the two major stock exchanges in mainland China, established in December 1990 and April 1991, respectively. As of 2016, the SHSE had approximately 1,200 listed stocks and the SZSE had approximately 1,800, with both exchanges ranking among the world's largest by market capitalization.

Companies incorporated in mainland China issue several common share classes, which differ in trading venue, currency, and investor eligibility. A shares are denominated in RMB and were initially primarily available to mainland investors; subsequent liberalization allowed qualified foreign institutions to participate through the QFII and RQFII programs, and later through the Shanghai-Hong Kong Stock Connect. B shares are quoted in US dollars on the SHSE and in Hong Kong dollars on the SZSE. Initially restricted to foreign investors, B shares were opened to mainland investors on February 19, 2001. Some mainland companies also list H shares in Hong Kong. Companies list on either the Shanghai or Shenzhen Stock Exchanges, rather than both. Companies listed on B or H shares are subject to more stringent information disclosure regulations and attract more institutional investors, resulting in these markets being viewed as more integrated with global investors. In contrast, the B share market has historically been characterized by low

[5] 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.

liquidity and limited participation. Consequently, the prices of Hong Kong-listed stocks are generally considered to reflect fundamentals more promptly than mainland A shares.

On November 17, 2014, the Shanghai and Hong Kong Stock Exchanges launched the Shanghai-Hong Kong Stock Connect, breaking long-standing market segmentation and linking the two markets. On December 5, 2016, this mechanism was expanded to include the Shenzhen-Hong Kong Stock Connect. These mechanisms have expanded connectivity between the two markets, created opportunities for cross-market trading, and potentially improved price efficiency over time. However, in practice, due to differences in access quotas, eligibility lists, trading hours, clearing and settlement systems, and holiday arrangements, the integration between the two markets remains limited. Table 2 below summarizes key data on the development of the mainland Chinese market, which is consistent with previous research such as Zhang and Urquhart (2019). Empirical research further demonstrates that the Shanghai-Hong Kong Stock Connect has strengthened cross-market connections and improved certain price efficiency indicators; see Fan and Wang (2017).

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

Date	Description
19 December 1990	SHSE was established on 26 November 1990 and commenced operations on 19 December 1990.
16 April 1991	SZSE started trial operations on 1 December 1990 and received official approval on 16 April 1991.
19 February 2001	B-shares, previously limited to foreign investors, were opened to mainland investors.
9 July 2003	A-shares were opened to qualified foreign institutional investors under the QFII scheme.
8 April 2005	China Securities Index Company Ltd launched the CSI 300, an influential market benchmark.
31 March 2010	Formal launch of margin trading and short selling in the A-share market for a designated list of stocks.
17 November 2014	Launch of Shanghai–Hong Kong Stock Connect.
5 December 2016	Extension of Stock Connect to Shenzhen.

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

Overview

In the baseline algorithm described by Gatev et al. (2006), trading pairs are formed by selecting a partner for each stock in the sample that minimizes the standardized spread over a 12-month formation period. The standardized price is represented by a total return index that includes dividends and starts at $1 at the beginning of the formation period. The top trading pairs with the lowest SSD values in the standardized prices are selected for trading over the following six-month trading period. The trading strategy establishes long and short positions in the pair when the standardized spread deviates by twice its historical standard deviation. Positions are closed when the spread first reverses, or at the end of the trading period (if no reversal occurs). Pairs that complete a round trip (i.e., diverge and then converge within the trading period) are eligible for trading again within that period. A typical trading portfolio based on the algorithm consists of an equally weighted selection of the top 20 currency pairs with the lowest SSD values. Similar to momentum strategies, this pairs trading approach uses overlapping portfolios, and the selection and trading process is repeated monthly without waiting for the current portfolio to complete its cycle.

Formation period

Let $\tilde{P}_{i,t}$ denote the adjusted price of stock i that reflects cash dividends and splits. Define the normalized index,

$$N_{i,t} = \frac{\tilde{P}_{i,t}}{\tilde{P}_{i,t_0}} \tag{4.1}$$

where t_0 is the first date of the formation window. For candidate pair (i, j) the spread is $S_{ij,t} = N_{i,t} - N_{j,t}$. The distance statistic is,

$$SSD_{ij} = \sum_{t \in \mathcal{F}} S_{ij,t}^2 \tag{4.2}$$

with $\mathcal{F}$ the formation window. At formation end we select the top N pairs with the smallest SSD_{ij}. The trigger volatility is,

$$\sigma_{ij} = stdev\,\{S_{ij,t}: t \in \mathcal{F}\} \tag{4.3}$$

Trading period

The trading window begins on the first session after formation ends. A position is opened when $|S_{ij,t}| > 2\sigma_{ij}$. We buy one currency unit of the undervalued leg and short one currency unit of the overvalued leg so that the pair is dollar-neutral. Positions are closed at the first convergence of the spread to zero or on the last day of the window, whichever occurs first. If the spread subsequently diverges again by at least $2\sigma_{ij}$, the pair can re-enter.

To avoid look-ahead bias we adopt delayed execution as the baseline: a signal observed at the close of day t is executed at the open of day $t + 1$, provided both legs have positive trading volume and are tradable. Same-day execution at the signal close is reported as a robustness check. If regulatory or market frictions prevent execution—no short-selling eligibility for either leg, limit-up or limit-down constraints, trading suspension, or zero volume—the signal is skipped.

Returns calculation

Throughout the trading period, the opening and closing of currency pairs generates positive cash flows. If a currency pair is opened and remains flat on the last trading day, it generates negative cash flows. If a currency pair is opened and closed multiple times during the trading period, it may generate multiple positive cash flows. If no positions are opened on the currency pair during the trading period, the cash flow is zero. The returns from both long and short trading pairs are then aggregated to calculate the portfolio's excess return, as shown in the following formula:

$$r_{p,t} = \frac{\sum w_{i,t} r_{i,t}}{\sum w_{i,t}} \tag{4.4}$$

$$w_{i,t} = w_{i,t-1}\left(1 + r_{i,t-1}\right) = \left(1 + r_{i,t}\right) \cdots \left(1 + r_{i,t-1}\right) \tag{4.5}$$

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 excess return metrics are calculated for each portfolio. For committed capital (CC) portfolios, returns are scaled by the number of currency pairs matched during the formation period. For example, for a portfolio with the top five currency pairs by volume, returns are scaled by a factor of five. In contrast, for fully invested (FI) portfolios, returns are scaled by the number of currency pairs actually opened during the trading period. For example, if only four of the top five portfolios were actively traded according to the standard deviation rule, the return of the fully invested portfolio would be scaled by a factor of four. As a result, the returns of CC portfolios tend to be more conservative. In this study, we use only the FI method to more closely resemble the returns generated by actual trading strategies.

Our analysis is based on monthly return time series, a common practice in the trading strategy literature and consistent with the work of Gatev et al. (2006). Before-cost returns are calculated as the monthly market value return of the combined portfolio divided by the number of portfolios in the portfolio. These strategies are repeated monthly, generating six return series, each staggered by one month, similar to the work of Jegadeesh and Titman (1993). The reported return series is an equally weighted average of these staggered series. Finally, to derive the post-cost return, we subtract time-varying transaction costs from this average return series. This approach ensures an accurate assessment of the performance of the combined trading strategy, accounting for both market dynamics and transaction costs.

The Drawbacks of GGR Portfolio

The baseline approach has several inherent flaws. First, pairs can form between companies that are not perfect economic substitutes, leading to higher fundamental risk and the potential for divergence. Gatev et al. (2006) focused on pairs matched within broad S&P sectors such as utilities, financials, transportation, and industrials. By contrast, Do and Faff (2010) demonstrated significant advantages from using a more refined industry classification scheme, such as the 48 industry categories defined by Fama and French (1997).

Second, matching pairs based solely on historical price co-movement can overlook the fact that profitable pairs trading requires frequent price reversals. This suggests that paired stocks should fluctuate around each other. Do and Faff introduced a measure of historical reversals, the NZC, during their formative years and showed that combining it with the SSD metric significantly improves pairs trading returns, especially when incorporating sector homogeneity into the trading strategy.

Third, in deep and liquid markets like the US stock market, price fluctuations in top currency pairs can be so small that the trigger point of two standard deviations is too small. Even if stock prices converge, the transaction price may not be sufficient to cover the bid-ask spread and transaction costs. Gatev et al. (2006) noted that this issue affected some of the currency pairs they studied.

Furthermore, transaction costs and slippage are key factors that significantly impact the actual returns of currency pair trading strategies, including those employing SSD methodologies. Transaction costs (including commissions, bid-ask spreads, and other transaction-related fees) accumulate with each buy and sell operation. This frequent trading, characteristic of currency pair trading strategies, can result in significant costs that erode gross profits, particularly for strategies targeting small price deviations. Consequently, these costs can cause actual returns to fall far short of theoretical projections. Slippage (the difference between the expected and actual execution prices) further exacerbates this problem. Slippage is particularly problematic in volatile markets, with low liquidity, or when executing large orders, as it can lead to executions at unfavorable prices, reducing overall profitability. Slippage can also exacerbate liquidity issues, leading to significant deviations from expected returns. Empirical evidence suggests that accounting for these real-world frictions can significantly reduce the returns of high-frequency trading strategies, with theoretical returns of 5% potentially falling to 1-2% or even lower in practice. Furthermore, if transaction costs and slippage are not accounted for, risk-adjusted performance metrics such as the Sharpe ratio may be overstated, reflecting higher volatility and lower risk compensation. Therefore, comprehensive consideration of transaction costs and slippage is crucial to accurately evaluating and developing pairs trading strategies.

4.2 Innovative Portfolios

To deepen and strengthen our analysis, we constructed a series of matching portfolios designed to address the limitations of the baseline algorithm. Specifically, we examined 40 alternative portfolios that differed in their stock matching and pair selection methods. This contrasts with the 29 portfolios studied by Do and Faff (2012). By expanding the portfolio set, we explored a broader strategy space and enhanced robustness.

Among these, eighteen of these portfolios utilize a mechanical matching approach, unrestricted by industry classification. This diverse set of portfolios allows us to comprehensively evaluate the effectiveness of different matching strategies and their impact on trading performance. Furthermore, the next 18 portfolios (19-36) focus on matching stocks within the same industry, introducing industry-specific analysis to mitigate the risk of cross-industry variation. This approach first groups stocks by industry and calculates the SSD for each potential pairing. These stock pairs are then ranked for prioritization, focusing on those with the smallest SSD values, potentially improving the consistency of stock behavior within the same industry. The final four portfolios (37-40) are designed to test for extreme performance by including pairs of stocks from both well-performing and underperforming industries. This approach aims to determine whether stocks with extreme performance (either positive or negative) can produce superior trading results when matched within these specialized portfolios. By isolating these outperforming and underperforming stocks, the analysis aims to capture potential outliers or unique patterns that may not be apparent in a broader, more moderately performing portfolio.

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 stock pairs ranked 21-40, while portfolios 3, 4, and 5 contain stock pairs ranked 41-60, 61-80, and 81-100, respectively. The purpose of this classification is to compare the performance of 20 different stock pairs and analyze how stock pair ranking influences trading outcomes. By segmenting stock pairs by ranking, this study aims to determine whether higher-ranked stock pairs (lower SSD) consistently outperform lower-ranked stock pairs, or whether the performance of lower-ranked stock pairs declines. This helps determine the optimal threshold for the number of stock pairs to include in a trading strategy, assess the scalability of stock pair trading, and understand the tradeoff between increasing the number of stock pairs and maintaining strategy effectiveness. This approach provides valuable insights for optimizing stock pair trading to achieve consistently reliable returns. Portfolio 6 consists of the bottom 20 stock pairs. This portfolio provides a comparison of trading strategies when expanding to the bottom of all possible stock pairs.

For portfolios 7-18, the selection process involved selecting the top 10,000 stock pairs, sorted by SSD, from all stock pairs. We then selected the top 20 stock pairs from this narrowed list based on specific criteria described below. Limiting the selection to the top 10,000 pairs eliminates stock pairs with excessively high SSD values, which would be detrimental to our analysis. By focusing only on stock pairs with low SSD values, we maintain a higher degree of similarity in performance between stocks, which is crucial for stock pair trading. This approach also significantly reduces computational time. Furthermore, selecting the top 20 stock pairs allows us to directly compare the performance of different portfolios using the same stock pairs, making the evaluation of different strategies more robust and meaningful.

For 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 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 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 key difference being that all pairs are constructed based on the Shenwan First-Level Industry Classification. This industry-specific approach aims to optimize pair selection by ensuring that paired stocks are statistically highly aligned while belonging to the same economic industry, thereby mitigating the fundamental risk of cross-industry pairings. By focusing on stocks within the same industry, this approach enhances economic similarity, potentially reducing industry-specific risk and improving the reliability of pairs trading strategies. Comparing these industry-specific portfolios with their broader market peers allows for analytical assessment of whether intra-industry pairings offer superior performance and risk-adjusted returns, providing a deeper understanding of pairs trading within different economic industries.

Portfolios 37 through 40 are also constructed based on the Shenwan First-Level Industry Classification, but they focus on specific industries and employ different selection methodologies. Portfolios 37 and 39 target high-performing industries. Portfolio 37 selects the top 20 of the top 50 SSD stock pairs based on the NZC, while Portfolio 39 selects the top 20 of the top 50 SSD stock pairs based on the Hurst Index.

In contrast, Portfolios 38 and 40 focus on underperforming industries. Portfolio 38 selects the top 20 of the top 50 SSD stock pairs according to the NZC; Portfolio 40 selects the top 20 of the top 50 SSD stock pairs according to the Hurst Index. A detailed description and selection rationale for the overperforming and underperforming industries are provided in Section 3.1. By applying these refined selection criteria within specific industries, the portfolios seek to enhance trading performance by integrating stocks that exhibit both statistical consistency and robust mean reversion. Table 3 summarizes the composition of these portfolios.

Table 3. Construction of Pairs Portfolios.

Portfolio	Non-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

Portfolio	Non-Industry Matching	Industry Matching	SSD Ranking	NZC Ranking	Hurst Ranking	Portfolio Construction
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 industry. 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 industries. 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 NZC 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 In the Chinese stock market, the explicit transaction costs of pairs trading strategies include two round-trip commissions per trade, stamp duty, short-selling fees, and the implicit cost of market impact. Accurately estimating these costs is challenging because they vary across multiple dimensions. While transaction costs fluctuate over time as deregulation and technological advancements lead to lower commissions, market impact costs may not follow the same trend. Trade size also matters: larger orders typically incur lower commissions per share but face greater market impact. Institutional investors generally benefit from lower commissions than retail investors but tend to be subject to greater market impact. Other factors, such as broker selection and investment style, further influence total transaction costs.

Given the complexity of estimating transaction costs in China after 2005, we use the best available proxy data representative of typical investors. Since few studies document Chinese stock trading costs in detail, our primary data source is disclosures from securities firms and the China Securities Regulatory Commission (CSRC). We also compile estimates from the literature and adjust them to reflect evolving market structures, including reforms, changes in commission systems, and improvements in trading infrastructure. Pesaran and Timmermann (1995) set the cost of a round-trip trade for individual stocks at 0.5%, equivalent to a cost of 1% per round-trip pair trade. Bowen and Hutchinson (2016) report round-trip costs for paired trades of 71–73 bps, with an effective estimated spread of 35–36 bps. Zhang (2018), using data from the Cathay Securities database, estimates average transaction costs of approximately 70 bps, covering both buy and sell trades.

These estimates provide the foundation for our analysis of how transaction costs affect the performance of pairs trading in China. Table 4 summarizes the transaction cost assumptions used in this paper and provides a brief explanation of each component. For the benchmark, we set transaction costs at 100 bps per round trip across all phases (applied symmetrically to buy and sell) to facilitate a clear comparison of returns; a more detailed, phase-specific cost analysis will be provided later.

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

Period	Commission	Stamp Duty	Market Impact And slippage	Do and Faff (2012)	Zhang (2018)
Pre-Fin.C.: Jan 2005 - Dec 2006	Ranged 0.1% - 0.3%. Selection criterion: 0.2% (buy and sell).	Jan 24, 2005: Stamp duty reduced from 0.2% - 0.1%, applied to both buying and selling. Selection criterion: 0.2% (buy and sell)	Refer Do and Faff (2012) Assign a market impact cost of **0.3% (30 bps)**.	1963–2009: commission + market impact of 0.60% (i.e., 0.34% + 0.26%) **(60bps).**	SHSE 2005: 0.62% SZSE 2005: 0.73% SHSE 2006: 0.79% SZSE 2006: 0.82%

Period	Commission	Stamp Duty	Market Impact And slippage	Do and Faff (2012)	Zhang (2018)
In- Fin.C.: Jan 2007 - Dec 2008	Remained 0.1% - 0.3%. Selection criterion: 0.2% (buy and sell).	May 30, 2007: Stamp duty increased from 0.1% - 0.3% (buys and sells). Apr 24, 2008: Reduced to 0.1%. Sep 19, 2008: applied to sales only at 0.1%. Selection criterion: 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	Ranged 0.05% - 0.2%. Selection criterion: 0.2% (buy and sell).	Maintained at 0.1%, sales only. Selection criterion: 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	Ranged 0.05% - 0.1%. Selection criterion: 0.2% (buy and sell).	Maintained at 0.1%, sales only. Selection criterion: 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 0.05% - 0.1%. Selection criterion: 0.2% (buy and sell).	Maintained at 0.1%, sales only. Selection criterion: 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 0.05% - 0.1%. Selection criterion: 0.2% (buy and sell).	Maintained at 0.1%, sales only. Selection criterion: 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 0.02% - 0.05%. Selection criterion: 0.05% (buy and sell).	Continued at 0.1%, sales only. Selection criterion: 0.1% (buy and sell).	-	-	-
In-Cov.: Jan 2020 - Dec 2022	Around 0.02% - 0.03%. Selection criterion: 0.05% (buy and sell).	Maintained at 0.1%. Selection criterion: 0.1% (buy and sell).	-	-	-
Post-Cov.: Jan 2023 - June 2024	Expected 0.02% - 0.03%. Selection criterion: 0.05% (buy and sell).	Expected to remain at 0.1%. Selection criterion: 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 Zhang (2018) from the official database, **50 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 been declining due to deregulation, increased competition among brokerage firms, and the rise of online trading platforms. These factors have led to a steady decline in overall commission rates in our sample, covering both the period before and after the GFC and the COVID-19 pandemic.

In the mid-2000s, commission rates in China typically ranged from 0.1% to 0.3% of transaction value, with a minimum fee of 5 RMB per trade. As market reforms advanced, competition in commission rates intensified, and by the late 2010s, commission rates had fallen significantly, typically to between 0.02% and 0.05%. This decline was driven by the introduction of online brokerage services, the emergence of discount brokers, and the increasing efficiency of electronic trading systems, all of which contributed to broader efforts to reduce transaction costs and attract more retail investors. During the GFC (January 2005 to December 2010), commission rates were generally around 0.1%. For example, CITIC Securities, a large comprehensive brokerage, offered commission rates between 0.1% and 0.2%, in line with the market average. Haitong Securities, a long-established and well-established brokerage, offered commission rates between 0.1% and 0.15%, broadly in line with the market average. Guotai Junan Securities, which primarily caters to high-net-worth clients, offers slightly higher commission rates, ranging from 0.15% to 0.2%.

According to the latest data, commission rates in the Chinese stock market typically range from 0.02% to 0.03%, with a minimum fee of RMB 5 per trade. These commission rates vary slightly based on factors such as the investor's trading volume, account type, and the brokerage's policies. High-frequency traders or those with high trading volume often have the opportunity to negotiate lower commission rates, as brokerages are incentivized to secure higher trading volumes from individual clients. During the COVID-19 pandemic (January 2017 to June 2024), commission rates were generally around 0.1%. For example, CITIC Securities' commission rates ranged from 0.03% to 0.05%, with a minimum fee of RMB 5 per trade, and offered lower commission rates to clients with higher trading volume or VIP status. Haitong Securities also offers commission rates between 0.03% and 0.05%, with a similar minimum fee, and discounts for high-frequency traders or those with higher trading volume. Guotai Junan Securities' commission rates range from 0.03% to 0.05%, with a minimum fee of RMB 5. The company frequently offers promotions to reduce commission rates for new clients.

Commissions are particularly impactful for pairs trading, as each trade involves both a buy and sell operation, effectively doubling transaction costs. This double effect of commissions (a separate fee for each buy and sell transaction pair) requires careful assessment of net profitability after accounting for these costs. In practice, investment institutions such as hedge funds typically trade larger volumes, enabling them to circumvent the minimum fixed fee of RMB 5 per trade, so we exclude this fixed fee from our analysis.

Stamp Duty

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

The following are the major changes to stamp duty announced by the government. On January 24, 2005, the stamp duty rate was reduced from 0.2% to 0.1% to reduce transaction costs, stimulate market activity, and make trading more accessible to investors. On May 30, 2007, to curb market speculation and overheating, the stamp duty rate was increased from 0.1% to 0.3% on both buy and sell transactions. However, as the crisis intensified, the government reduced the stamp duty to 0.1% on April 24, 2008, and further revised the policy on September 19, 2008, imposing the tax only on sell transactions. This adjustment was intended to encourage home purchases and support market confidence during turbulent times. Since then, the stamp duty rate has remained at 0.1%, also applicable only to sales transactions.

Market impact

Market impact refers to price movements caused by trade execution, which can erode a strategy's profitability. To accurately assess the market impact of pairs trading, we reference the data and methods used by Do and Faff (2012), who conducted a detailed analysis of market impact by measuring actual price movements following divergence signals identified by their trading algorithm.

Do and Faff (2012) directly estimated market impact ex post by observing price changes before and after divergence signals that prompted trade execution. They calculated the price spread for each stock pair involved in their trading strategy one day before, on, and two days after the divergence signal, defined as the difference between the spread and two historical standard deviations. They also calculated the log returns of long and short trades within two days of the divergence signal. Their analysis aimed to capture mean-reversion patterns of mispricing between stocks, which theoretically should narrow the spread after a divergence due to positive returns on long positions and/or negative returns on short positions.

Their results show that for MTFs that execute trades within one day of a divergence, the market impact of long positions is less than 32 bps, the market impact of short positions is less than 21 bps, and the average is less than 26 bps. For trades executed within two days of a divergence, the observed additional price movement is 15 bps for long positions and 9 bps for short positions, with an average of 12 bps. Therefore, Do and Faff (2012) conclude that MTFs that execute trades within two days can achieve a volume-weighted average price equivalent to the closing price on the first day after a divergence, with an average market impact of 26 bps.

Furthermore, Do and Faff (2012) analyzed market impact over two subperiods: July 1963 to December 1988 and January 1989 to June 2009, following the convention used by Gatev et al. (2006) to delineate periods of the rise of the hedge fund industry. Their results indicate that the average market impact of trades executed within two days of a divergence was approximately 30 bps during the 1963–1988 period, while it was significantly lower, at approximately 20 bps, during the 1989–2009 period. This decline reflects changing market conditions and the increasing sophistication of institutional trading strategies designed to minimize market impact.

Based on these findings, Do and Faff (2012) estimated the market impact cost at 30 bps for the 1963–1988 period and 20 bps for the 1989–2009 period. They argue that these estimates, while lower than broader market figures reported in the literature, provide a realistic reflection of the market impact costs faced by pairs traders, particularly those who spread their trades over multiple days to reduce severe market impacts.

Slippage

Slippage is a crucial factor to consider when evaluating the overall transaction cost of a pairs trading strategy, as it represents the difference between the expected price of a trade and the actual execution price. This discrepancy can be caused by a variety of factors, such as market volatility, order size, and execution speed. Slippage is particularly significant in pairs trading, as these strategies typically involve frequent buy and sell transactions, and even small deviations in execution price can significantly impact profitability.

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

The 0.3% slippage rate applies to both the long and short sides of a trade, effectively doubling its impact on each pairs trade. For example, if a pairs trade involves a long position in one stock and a short position in another, the total slippage cost would be 0.6% of the trade value due to the dual nature of the trade. This slippage estimate is a conservative benchmark, intended to ensure that our profitability analysis accurately reflects the real challenges of executing pairs trades in the market.

Short Selling Constraints

In the Chinese market, investors who short sell on margin are subject to borrowing fees. These fees are set by the securities firm or lending institution and are typically an annualized percentage of the borrowed amount. Borrowing fees can fluctuate significantly depending on market conditions and the supply and demand dynamics of specific stocks. For most common stocks, borrowing fees range from approximately 8% to 12% per year, but can be higher for stocks with low liquidity or high market demand. Trading fees for short positions are similar to those for long positions. Given the relatively high costs of short selling, we will initially present results excluding these costs to assess the theoretical feasibility of this strategy. In a sensitivity analysis, we will incorporate these costs to provide a more comprehensive assessment.

5. Results

5.1 Basic Results Returns

This section provides an in-depth analysis of the basic return characteristics of the pairs trading strategy developed in this study. We provide a comprehensive assessment of the strategy's effectiveness by comparing the performance of portfolios with and without transaction costs. We also analyze returns across different subperiods to assess volatility and its impact on overall performance. These analyses deepen our understanding of return dynamics and provide guidance for potential improvements and practical implementation.

5.1.1 Portfolios Return without Trading Costs

We report the returns of 40 portfolios under three market environments: the COVID-19 pandemic, the GFC, and both bull and bear markets. The analysis focuses on monthly excess returns before transaction costs and assesses the mean, standard deviation, Sharpe ratio, skewness, kurtosis, and a t-statistic of the average return calculated using Newey-West standard errors (six lags) and a Sharpe ratio z-statistic calculated using Lo (2002).

Overall Returns of Covid Period

Table 5 reports monthly excess returns for the 40 portfolios defined in Table 3. The worst-performing portfolios, Portfolios 6 and 24, are considered reference portfolios and are therefore not discussed below; they are analyzed separately later. Excess returns are measured relative to the CSI 300 Index, with additional benchmark tests described in subsequent sections.

Excluding portfolios 6 and 24, monthly excess returns ranged from 17 to 51 bps, with a cross-sectional average close to 33 bps. The t-statistic for the average returns was calculated using Newey-West standard errors with a lag of six to account for serial correlation and heteroskedasticity. According to the star ratings reported in Table 5, 25 portfolios were significant at the 1% level, 7 at the 5% level, 3 at the 10% level, and 5 were not significant. These data indicate that most average returns were statistically different from zero.

Return volatility was moderate, with a median monthly standard deviation close to 1%, and a few portfolios exhibiting volatility of approximately 2.5% to 3%. The corresponding Sharpe ratios ranged from 0.13 to 0.42, with the highest Sharpe ratios for portfolios 26 and 40. Using the robust standard errors of Lo (2002), the Sharpe ratio z-statistics were mostly significant at 1%, significant at 1%, significant at 5%, significant at 10%, significant at 5%, significant at 10%, significant at 10%, and not significant at 5%. Overall, the strategy appeared to be able to capture small, stable mispricings with limited volatility during the COVID-19 pandemic.

As Goetzmann and Massa (2002) point out, the Sharpe ratio can be misleading when returns are negatively skewed. While approximately two-thirds of portfolios exhibit positive skewness, which reduces the risk of extreme losses, a significant portion exhibits negative skewness. This asymmetry warns against relying solely on the Sharpe ratio and motivates the use of higher-order moments and drawdown diagnostics when interpreting performance.

The combined behavior of the mean, Sharpe ratio, and higher-order moments reflects two reinforcing channels. At the macro level, the COVID-19 shock widened the cross-sectional misalignment between fundamentals and expectations, creating temporary, idiosyncratic dislocations within sectors. Mean-reversion strategies naturally exploit this misalignment and help explain why many portfolios exhibit statistically significant excess returns and shorter effective half-lives of carry. At the microstructure and execution level, characteristics of the A-share market, such as price limits, auction mechanisms, and intermittent trading halts, introduce discontinuous carry adjustments. Most months exhibit small gains, while a few months may experience jump-like drawdowns, consistent with the heavy-tailed distribution observed across multiple portfolios.

Finally, some of the measured excess returns may reflect style and factor mismatches with the CSI 300 benchmark. Subsequent sections extend the analysis to alternative benchmarks and factor-neutral specifications. The persistence of the main findings from these tests reinforces the conclusion that the strategy primarily benefits from temporary, industry-level relative value dislocations exacerbated by the COVID-19 pandemic.

Comparative Analysis of Different Portfolios Returns for Covid Period

Comparing the non-industry portfolios with the industry-matched portfolios, the highest mean return among portfolios 1 to 18 is 51 bps in portfolio 10, while the highest mean return among portfolios 19 to 36 is 50 bps in portfolio 28. The Sharpe ratio distributions of the two groups of portfolios are roughly comparable. The industry-matched portfolios contain several portfolios with high Sharpe ratios, particularly portfolio 26 and portfolios 33 to 35, but also include portfolios with extreme high-order moment risk, such as portfolio 19, which has a skewness of 5.69 and a kurtosis of 41.21. In contrast, portfolios 26 and 35 exhibit moderate skewness and kurtosis, suggesting that industry matching can reduce tail risk in some cases, but not consistently.

Comparing SSD with NZC matching and SSD with Hurst index matching, portfolios 7 to 12 tend to provide higher average returns. Portfolio 10 achieved a t-value of 51 bps, and the portfolios generally exhibited high t-statistics, with Portfolio 8 achieving a t-value of 4.19 and Portfolio 7 achieving a t-value of 3.94. Portfolios 13 through 18 exhibited more competitive risk-adjusted performance, with Portfolios 16 and 18 both achieving Sharpe ratios of 0.39. The higher moment values indicate that SSD plus NZC portfolios are more prone to extreme kurtosis, such as Portfolios 10 and 12, while SSD plus Hurst portfolios (particularly Portfolios 16 and 18) exhibit more stable return distributions.

The same pattern holds true for similar portfolios matched to industry. Portfolios 25 to 30, matched using SSD with NZC, focus on higher average returns, such as portfolio 28, which has a mean of 50 bps and a Sharpe coefficient of 0.29, while portfolios 31 to 36, matched using SSD with Hurst, show slightly lower average but stronger risk-adjusted performance, such as portfolio 35, which has a Sharpe coefficient of 0.40 and moderately high moment values.

Portfolios targeting underperforming industries tend to deliver superior risk-adjusted returns. Among portfolios 37 to 40, strategies focused on weak industries (i.e., portfolios 38 and 40) achieved better Sharpe ratios than those based on strong industries (i.e., portfolios 37 and 39). Portfolio 40, with a Sharpe ratio of 0.42, achieved the best overall performance and a relatively favorable risk profile. Portfolio 37 had a relatively high mean of 43 bps, but also exhibited high skewness of 5.56 and kurtosis of 39.50, suggesting significant tail risk. During periods of heightened uncertainty, such as the COVID-19 pandemic, well-constructed portfolios drawn from underperforming industries appear to deliver more reliable risk-adjusted returns than those drawn from leading industries.

During the COVID-19 pandemic, within-method quantile splits did not yield economically meaningful differences, and this result remained consistent across the sample and across three broader periods of sample holding (including and excluding transaction costs). Differences between matching rules also shed light on the underlying mechanisms. NZC emphasizes currency pairs with frequent price crossovers, which increases signal arrival and turnover and tends to improve average returns, but also increases execution friction and exposure to tail events when exits are restricted. Hurst-based selection favors spreads with stronger anti-persistence and sharper retracements, which generally reduces signal frequency but increases the effectiveness of individual trades and reduces the impact of outliers due to microstructure, thereby supporting higher risk-adjusted performance. Industry matching improves the manageability of systematic risk exposure and can suppress cross-industry mismatches, but it can also concentrate industry-specific shocks that are difficult to hedge in the short term, explaining the coexistence of stable portfolios such as the 26 and 35 portfolios with heavy-tail portfolios such as the 19 portfolio.

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

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
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 Global Financial Crisis Period

Table 6 summarizes the monthly excess returns of 40 portfolio pairs during the GFC, benchmarked against the CSI 300 Index. The average returns of the portfolios ranged widely, from -208 bps for Portfolio 10 to 382 bps for Portfolio 39, with the cross-sectional average approaching zero. Because the CSI 300 Index achieved a higher average monthly return of 162 bps during this period, many portfolios achieved negative excess returns even though their standalone returns were positive.

Despite the market volatility, a few portfolios achieved significant average returns. Portfolio 39 achieved an average monthly return of 382 bps, with the largest standard deviation in the sample (24.3%), while Portfolio 31 achieved an average monthly return of 129 bps with a standard deviation of 12.1%. Portfolios 20, 25, and 28 also achieved relatively high average monthly returns of approximately 122-124 bps. At the other end of the distribution, portfolios such as Portfolio 10 (-208 bps) and Portfolio 1 (-155 bps) underperformed, reflecting the difficulty of convergence in certain currency pair constructions during the severe market turmoil.

Volatility was significantly higher than during the COVID-19 pandemic. Standard deviations ranged from 1.7% for Portfolio 35 to 24.3% for Portfolio 39, indicating considerable risk diversification. Sharpe ratios were also relatively low. The highest Sharpe ratio was 0.18 for Portfolio 9, followed by 0.16 for Portfolio 39, and 0.14 for several portfolios, including Portfolios 20, 21, 25, and 37. Many portfolios had negative Sharpe ratios, such as Portfolio 1 (-0.32) and

Portfolio 10 (-0.31), highlighting the difficulty of achieving positive excess returns amidst a rapidly rising benchmark index, increased volatility, and heightened tail effects.

The distribution of risk-adjusted performance was significantly weaker during this period compared to the COVID-19 pandemic. The highest Sharpe ratio reached 0.42 during the COVID-19 pandemic, compared to a peak of 0.18 during the GFC. This contrast is consistent with higher volatility, more frequent jumps, and higher positive benchmark drift, which can compress excess returns even when raw PnLs are positive.

The joint behavior of mean, volatility, and higher-order moments suggests that crisis-specific frictions are hindering convergence trades. Funding and liquidity constraints, arbitrageur deleveraging, and occasional sequential imbalance shocks can delay or even reverse the convergence of spreads, generating fat tails and negative skewness. Structural abrupt changes in common factors can reduce the stability of the long-term relationships typically exploited by pairing strategies, while peaks in correlations can weaken cross-sectional diversification when it is most needed. Furthermore, market microstructure features such as price limits and pauses can force discontinuous adjustments in spreads, resulting in the kurtosis observed in many portfolios.

Comparative Analysis of Different Portfolios Returns for Global Financial Crisis Period

Comparing non-industry-matched portfolios with industry-matched ones yields mixed results. Among portfolios 1-18, the highest average return is found in portfolio 9, at 108 bps; while among portfolios 19-36, the highest average return is found in portfolio 31, at 129 bps. The average returns for the two portfolios in this window are roughly comparable. Industry matching does not consistently stabilize performance: while some industry-matched portfolios perform well, others exhibit significant negative excess returns, reflecting the fact that industry shocks can concentrate tail risk in industry-restricted portfolios during periods of stress.

The risk-adjusted results also reflect this nuance. The highest Sharpe ratio in the non-industry-matched group was 0.18 for Portfolio 9. Within the industry-matched group, the highest Sharpe ratio was 0.14 for Portfolios 20 and 25. This evidence does not support the common claim that industry matching provided more consistent Sharpe ratios during the GFC; rather, it provided benefits in some structures while amplifying industry-specific tail risk exposures in others.

Comparing SSD with NZC and SSD with Hurst further clarifies the tradeoffs. Portfolios 7-12 (SSD+NZC) exhibit wide dispersion, ranging from strong results (e.g., Portfolio 9) to very weak results (e.g., Portfolio 10, -208 bps and a negative Sharpe ratio). Portfolios 13-18 (SSD+Hurst) offer more moderate mean returns, with Portfolio 15 achieving 70 bps and a Sharpe ratio of 0.14. The GFC reduced the effectiveness of frequent crossover signals relative to the COVID-19 period, when NZC-driven frequencies typically supported higher mean returns. Heightened execution friction, restricted exits, and shifting market dynamics increase the likelihood that frequent trading monetizes noise rather than true mean reversion, while Hurst-based selection maintains some robustness by emphasizing stronger anti-persistence and sharper pullbacks.

A comparison of later periods of portfolios 37-40 shows that the COVID-19 pattern did not uniformly carry over into the GFC. Portfolio 39 (from a strong-performing industry) achieved the highest average return and a relatively high Sharpe ratio of 0.16, despite extremely high volatility and kurtosis. Portfolio 38 achieved a Sharpe ratio of 0.13, while Portfolio 40 had a Sharpe ratio of only 0.03. Therefore, the advantage of focusing on industries that underperformed risk-adjusted during the GFC was less pronounced. One plausible explanation is that the crisis dynamics favored momentum effects in lagging industries, a shift toward quality, and balance sheet robustness over short-term mean reversion, slowing the correction of relative mispricing in these industries while allowing some leading industries to continue outperforming even after risk adjustment.

Taken together, these cross-period comparisons suggest that the GFC environment altered the usual frequency-intensity trade-off, weakening the stabilizing effect of industry matching. Increased benchmark drift and market-wide deleveraging compressed excess returns, execution frictions amplified tail effects, and industry shocks reduced the consistency of the diversification benefits derived from industry constraints. In contrast, during the COVID-19 pandemic, benchmark drift was lower and relative value dislocations corrected more quickly, resulting in higher peak Sharpe ratios and more stable excess returns.

These findings have three practical implications. First, benchmark effects are at work, as the strong positive drift of the CSI 300 Index transforms many positive PnL figures into negative excess returns, necessitating factor-neutral and industry-neutral tests to isolate true relative value alpha. Second, microstructure and funding channels shape the tails, as stress-induced illiquidity, arbitrageurs' deleveraging, and intermittent order imbalances delay convergence and create heavy-tail losses, explaining the prevalence of negative skewness and kurtosis. Third, signal quality channels govern the trade-off between frequency and strength. NZC improves signal arrival and turnover but becomes fragile when exits are restricted; whereas Hurst-based selection emphasizes stronger anti-persistence and sharper pullbacks, thus remaining more resilient during regime shifts.

TABLE 6. Monthly Excess Returns without Trading Costs of Global 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

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
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 GFC 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 reports the performance of 40 portfolio pairs during the bull-bear market window. This window was characterized by alternating market fluctuations and moderate macro volatility. Monthly excess returns ranged from 21 bps (Portfolio 40) at the low end to 77 bps (Portfolio 37) at the high end, with a cross-sectional average of nearly 43 bps, falling between the impact of the COVID-19 pandemic and the GFC. Compared to other windows, volatility was somewhat contained: excluding portfolios 6 and 24, standard deviations ranged from 0.75% (Portfolio 21) to 1.28% (Portfolio 13). Portfolio 37 had the highest mean, with a standard deviation of 1.27%, which, while high, was still moderate.

Risk-adjusted performance was relatively strong. Sharpe ratios ranged from 0.25 (Portfolio 40) to 0.60 (Portfolio 37), with Portfolio 39 following closely at 0.59. As a result, the upper bound of the Sharpe ratio distribution is higher than during the COVID-19 pandemic (when the peak was 0.42) and significantly higher than during the GFC (when the maximum was 0.18). The Lo-type robust z-statistic for the Sharpe ratio is generally significant at conventional levels, further supporting the view that the stronger risk-adjusted results are not an artifact of serial dependence.

Higher-order moment behavior is more subdued than under crisis conditions. Some portfolios exhibit significant tails—the skewness of Portfolio 30 is 2.78 and the kurtosis is 11.91—

but most exhibit moderate skewness and kurtosis, implying fewer extreme outcomes than during the GFC and a more balanced distribution than in the jump-prone sample subset observed during the COVID-19 pandemic.

Two forces help explain these results. First, because the CSI 300 Index averages approximately 5 bps per month, the benchmark drift is smaller during this window, and excess returns more closely track raw returns. In contrast, during the GFC, a strong positive benchmark mechanically pushed down excess returns for many portfolios even when independent returns were positive. Second, alternating phases produce frequent but roughly orderly deviations from the long-term relationship. This supports convergence in spreads without the funding pressures, liquidity cavitation, and jump dislocations that hinder mean reversion in crises. In such an environment, signal frequency can translate into returns without disproportionate execution leakage, while the strength of mean reversion remains unchanged—resulting in a higher Sharpe ceiling and tighter dispersion in volatility and tails.

From the perspective of spread dynamics, performance reflects an effective balance between the speed of mean reversion and the magnitude of price movements. When volatility is too high, crossovers are frequent, but exits are limited, exacerbating slippage; when volatility is too low, signals are sparse, and individual trade profits fail to offset fixed costs. The call-put mechanism occupies an intermediate zone, with volatility high enough to achieve crossovers but not so high that execution frictions dominate. This balance allows both high-frequency and strong-reversion structures to realize their comparative advantages, as demonstrated by the leading Sharpe ratios in Table 7.

Microstructural conditions are also shifting in a favorable direction. In extreme cases, price limits, trading halts, and thin order books can force spreads to adjust discontinuously, resulting in thick tails and negative skewness, with many small wins and a few large losses. During this window, the impact of these frictions is less pronounced. Crossovers are more likely to trade in continuous time, exits are less frequently blocked, and realized slippage is less volatile. The resulting convergence path is smoother, as evidenced by tighter dispersion of higher-order moments and a more reliable conversion of signals to realized Sharpe ratios.

Industry context further sheds light on the cross-section. During this window, relative value returns from leading industry sectors were higher and more stable: Portfolio 37 had the highest mean return, reaching 77 bps and a Sharpe ratio of 0.60; Portfolio 39 achieved a Sharpe ratio of 0.59 and relatively small high moments. Portfolios from weaker industries (such as 38 and 40) had lower means (30 and 21 bps, respectively) and more moderate Sharpe ratios, at 0.38 and 0.25, respectively, despite their relatively limited high moments, suggesting that these portfolios, while less profitable, have nonetheless performed stably. Unlike during the GFC (where industry shocks could amplify the tail effects of leading industries) and the COVID-19 pandemic (where lagging industries sometimes offered more favorable Sharpe ratios), the call-put mechanism allows leading industries to consistently contribute relative value returns without triggering extreme tail effects, while lagging industries offer a small but stable premium.

Comparative Analysis of Different Portfolios Returns for Bullish and Bearish Period

Comparing portfolios built without industry matching to those that align pairs within industries reveals a clear difference in dispersion and in the stability of risk-adjusted outcomes. In the non-matched set the highest mean return is 56 bps in Portfolio 13 and the lowest is 34 bps in Portfolio 5, while Sharpe ratios range from the low thirties to 0.51 in Portfolio 15. In the industry-matched set the highest mean is 52 bps in Portfolio 25, several portfolios cluster in the mid-forties including Portfolios 32 and 34, and the lower tail is tighter with the minimum at 31 bps in Portfolio 21; Sharpe ratios reach 0.55 in Portfolio 34 and 0.52 in Portfolio 25, and many others sit near 0.45 to 0.48. The mechanism is straightforward. Aligning pairs within a industry reduces cross-industry beta mismatch and confines the spread to shocks that are more homogenous in origin, which stabilizes the error-correction path of prices and raises the signal-to-noise ratio of mean reversion. In a mixed but non-extreme macro regime industry factors drift gradually rather than breaking abruptly, so within-industry cointegration relations are less likely to suffer structural breaks. That state dependence explains why industry matching tempers dispersion and lifts the upper tail of Sharpe in this window, even though it does not guarantee improvement for every construction because industry events can still load concentrated tail risk into specific pairs.

Differences between SSD with NZC matching and SSD with Hurst exponent matching illuminate how frequency and strength of reversion convert into realized performance when volatility and benchmark drift are moderate. NZC filters for pairs whose prices cross the equilibrium frequently, which raises the intensity of tradeable signals and the cumulative monthly edge when execution frictions are not dominant. This is visible in Portfolio 7 with a Sharpe ratio of 0.46 and a mean of 53 bps, and even more clearly in the industry-matched analogue Portfolio 25 with a Sharpe ratio of 0.52 and a mean of 52 bps. Hurst-based selection emphasizes stronger anti-persistence and a shorter half-life, which improves per-trade efficacy and reduces the fraction of trades that stall at exits; Portfolio 34 achieves a Sharpe ratio of 0.55 with a mean of 44 bps, while Portfolio 13 delivers the highest mean in the non-matched group at 56 bps with a Sharpe ratio in the mid-forties. The environment matters because moderate volatility produces enough crossings to monetize frequency without overwhelming exits, and at the same time it preserves the integrity of the pullback path so that strength-based filters capture cleaner reversals. The result is complementarity rather than a strict trade-off, with NZC driving higher turnover and Hurst delivering higher per-trade quality, both translating into elevated Sharpe when costs and slippage are contained.

Industry bias further differentiated the results. Portfolios drawn from strong industries achieved the highest risk-adjusted results during this window, with portfolio 37 achieving the highest average return of 77 bps and a Sharpe ratio of 0.60; portfolio 39 achieved a Sharpe ratio of 0.59 and relatively modest higher-order moments. This mechanism is consistent with the breadth and liquidity dynamics typical of non-extreme expansion-contraction portfolios. Leading industries exhibit sustained information diffusion, more stable earnings revisions, and sustained capital inflows, all of which compress idiosyncratic noise surrounding relative valuations and accelerate the correction of temporary mispricings within industries. Portfolios drawn from weaker industries (such as 38 and 40) earned smaller premiums of 30 and 21 bps, respectively, with Sharpe ratios of 0.38 and 0.25, but their higher-order moments remained contained. In other words, when the market is volatile rather than breaking out, the relative value of arbitrage in lagging industries is lower but more stable, while leading industries offer higher average returns and a higher upper Sharpe value limit because reversals are frequent and execution remains feasible.

These cross-sectional patterns suggest several testable predictions that directly link these mechanisms to realized returns. Sharpe ratios should rise as estimated half-lives shorten and Hurst exponents decline; they should rise as crossover strength increases until turnover-induced slippage offsets their gains. The advantage of industry matching should increase when industry factor volatility is low and the variance share of common shocks is high, as both conditions stabilize the error correction path; this advantage should diminish when industry news becomes volatile, as tail events dominate relative value within categories. Drawdowns and tail months should be consistent with microstructural pressures rather than broad factor drift, as verified by linking underperforming months to turnover peaks, simple slippage proxies, price limit incidence, halt frequency, and overnight gap size. Given the low benchmark drift during this window, robustness should also survive re-benchmarking to industry-neutral and factor-neutral reference values and should be maintained under conservative implementability constraints such as borrow eligibility screening and fee discounting. Evidence consistent with these predictions would confirm that in a bullish/bearish regime with moderate volatility and small benchmark drift, both frequency-based and intensity-based construction approaches can work for different reasons, and that industry matching improves consistency by aligning exposures with the dominant and relatively stable industry forces of the period.

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

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
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 Portfolios Return with Trading Costs

In this section, we present the performance of different portfolios during three distinct market periods: the COVID-19 pandemic, the GFC, and bull and bear markets, adjusted for transaction costs. The analysis focuses on monthly net excess returns after adjusting for transaction costs, assessing the impact of costs on key performance indicators, as described in Section 5.1.1.

Overall Returns of Covid Period

Table 8 reports the monthly net excess returns of 40 portfolios during the COVID-19 pandemic. After costs, returns range from -5 bps for Portfolio 1 to 28 bps for Portfolio 19. For consistency with Section 5.1.1, Portfolios 6 and 24 are treated as reference cases and excluded from the cross-sectional averages; thus, the average net excess return is approximately 10.5 bps, down from approximately 33 bps before costs in Table 5. Including all 40 portfolios would reduce the average to approximately 8.4 bps. The sharp contraction in the mean is concentrated in portfolios with high turnover. For example, once costs are accounted for, the Sharpe ratio of Portfolio 3 drops from 47 bps to 22 bps.

After deducting costs, Sharpe ratios compress significantly. Excluding portfolios 6 and 24, Sharpe ratios range from -0.03 to 0.17, with portfolio 27 at 0.17 and portfolios 26 and 40 at 0.15. Before deducting costs, the top of the distribution reaches 0.42. The Lo-robust z-statistic reflects this deterioration: only a few portfolios continue to exhibit traditional significance after deducting costs. The return distribution remains skewed and leptokurtic. Portfolio 1 maintains strong positive skewness (3.84) and kurtosis (22.56), while negatively skewed portfolios, such as portfolio 13 (-1.10), remain vulnerable to occasional drawdowns. Costs do not effectively "fix" higher-order moments; they primarily alter the level of returns, thereby reducing risk-adjusted metrics.

The mechanism behind these net results is the interplay between signal architecture and cost intensity in the microstructure of the COVID-19 era. Strategies that monetize frequency (many small advantages from frequent price crossovers) are disproportionately affected by commissions, effective spreads, and shocks because they often enter and exit positions when order books are thin and volatility is elevated. During the early and mid-COVID period, wider effective spreads, more frequent price limit events, and occasional pauses meant that exits were not always continuous; small gross gains were truncated, while occasional losses remained fully realized, suppressing Sharpe ratios even when variance remained unchanged. In contrast, strategies that monetize intensity (clear retracements in short-half-lived spreads) trade less frequently, hold longer, and rely more on the quality of mean reversion than on execution tempo. This architecture allows a greater portion of the gross advantage to survive costs, consistent with the resilience of portfolios 26, 27, and 40 on a net basis. Industry context also matters. Same-industry portfolios face less cross-beta slippage and re-hedging, resulting in lower round-trip costs per unit of alpha; this manifests as a narrower net Sharpe dispersion and thicker upper tail for industry-matched leaders. In other words, the constraint on net performance during the COVID-19 pandemic was not the existence of mispricings—as Table 5 confirms—but the cost of converting these mispricings into realized gains and losses within a volatile and occasionally discontinuous microstructure.

Comparative Analysis of Different Portfolios Returns for Covid Period

Comparing non-industry-matched portfolios (1-18) with industry-matched portfolios (19-36), the results show that combining portfolios within industries improves the consistency of net returns after deducting costs. Among the non-industry-matched portfolios, Portfolio 3 achieved the highest mean return of 22 bps after deducting costs, with returns ranging from -5 to 22 bps. Among the industry-matched portfolios, Portfolio 19 achieved the highest mean return of 28 bps, with returns for many of the same portfolios concentrated in the low to mid-range. Net Sharpe ratios also exhibited a similar trend: Portfolio 27 reached 0.17, Portfolio 26 reached 0.15, while returns for many non-industry-matched portfolios remained stable between 0.10 and 0.13. The mechanism is that industry matching reduces hedging errors against common industry shocks, thereby reducing repeated rebalancing, partial fills, and additional round trips, which can increase effective spreads and market impact. Due to reduced forced fine-tuning, more pre-cost alpha is retained in the net line, and the impact of high-cost exits in the last month is reduced.

After deducting costs, the differences between SSD+NZC and SSD+Hurst selection become more pronounced, as the two rules differ in their impact on turnover. NZC prioritizes crossover strength, which is valuable in quiet microstructures but vulnerable when exits face price friction or a thin book. This vulnerability manifests itself in a greater pass-through effect between costs and alpha during the COVID-19 period: Portfolio 10 saw a decrease from 51 bps to 23 bps, and Portfolio 8 from 36 bps to 11 bps, yielding a Sharpe ratio of approximately 0.13. Hurst-based selection, with its emphasis on anti-persistence and short half-lives, produces fewer, cleaner trades with larger aggregate advantages per trade; thus, a smaller portion of the advantage is absorbed by costs, leaving a more stable net result, such as Portfolio 14's return of 13 bps and a Sharpe ratio of 0.13, and Portfolio 16's return of 7 bps and a Sharpe ratio of 0.09. In short, when microstructure is stressed, the cost-to-frequency penalty is greater than the strength-to-frequency penalty.

Industry tilt also persists on a net basis. Portfolios that exploit underperforming industries can still achieve competitive net Sharpe coefficients because mispricings are corrected faster than the accumulated cost leakage, and order flow is less crowded, mitigating the impact. Portfolio 40 maintains a Sharpe coefficient of 0.15 after deducting costs, while portfolios in strong industries like Portfolio 39 see theirs drop to 0.06. The practical interpretation is that crowding and one-way flows in leading industries increase effective carry and adverse selection, so that the same aggregate signal results in weaker net returns in that industry.

These mechanisms generate specific, testable predictions that link Table 8 to implementation. Net Sharpe coefficients should decline with turnover and Amihud illiquidity and increase with mean reversion speed and Hurst value. The turnover slope of the NZC portfolio should be steeper than that of the Hurst portfolio, reflecting higher cost elasticity. In industry-matched portfolios, the share of variance explained by industry factors should be higher than in non-matched portfolios, while rebalancing counts should be lower, correspondingly leading to higher net Sharpe scores. Bad months should coincide with microstructural pressures (more price limit triggers, larger overnight gaps, higher participation rates) rather than slow-moving factor drift. Empirically, this story can be concluded by regressing net Sharpe scores (or net alpha) on crossover counts, half-life estimates, Hurst, turnover, Amihad, and industry dummies, and decomposing pre- and post-cost performance into commissions, effective spreads, and impacts. This allows for measuring, rather than inferring, the pass-through of costs to alpha.

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

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
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 Global Financial Crisis Period

Table 9 reports the monthly net excess returns of 40 portfolios during the GFC. After deducting costs, returns range from -243 bps for Portfolio 10 to 35 bps for Portfolio 39, with a cross-sectional average of approximately -35 bps. This represents a significant decline compared to the pre-cost average reported in Table 6. This dispersion and the shift toward negative average net excess returns are consistent with the microstructure of the crisis: widening effective spreads, rising price shocks, occasional exits limited by price limits or pauses, and tighter financing conditions, resulting in an inefficient conversion of total returns into net gains or losses.

Risk-adjusted performance declined accordingly. Post-cost Sharpe ratios ranged from -0.69 (Portfolio 29) to 0.14 (Portfolio 39). Even the best-performing portfolios had costs lower than the highest Sharpe ratio observed during the COVID-19 pandemic (Portfolio 27, with a cost of 0.17), suggesting that crisis frictions reduced the efficiency of converting signals into realized net returns. Higher-order moments remained extreme and largely unaffected by costs: for example, Portfolio 38 had a skewness of 5.52 and a kurtosis of 35.21, while negatively skewed portfolios like Portfolio 10 (skewness of -3.04 and kurtosis of 10.14) still carried rare but significant risk of losses. Costs do not "fix" the shape of the distribution; they primarily reduce the level and risk-adjusted metrics.

The mechanism behind these results is the interaction between high turnover and the intensity and fragility of cost convergence during the crisis. Frequent rebalancing exposes investors to larger effective spreads and larger market shocks, thus consuming more of the total alpha before it is converted into net gains or losses. At the same time, structural breaks and correlation spikes in common factors can weaken cointegration relationships, inadvertently extending holding periods and increasing the likelihood of forced exits. Portfolios that maintain net positive returns (such as Portfolio 39 and, to a lesser extent, Portfolio 9) do so by combining strong signal quality with low cost elasticity or favorable industry microstructure in a given month.

Comparative Analysis of Different Portfolios Returns for Global Financial Crisis Period

A comparison of non-industry-matched portfolios (1-18) and industry-matched portfolios (19-36) shows that costs erode performance across the board, but through different mechanisms. Among the non-industry-matched portfolios, Portfolio 9 had the highest return after costs, at 78 bps. Returns ranged from -243 bps (Portfolio 10) to 78 bps, with most portfolios ultimately returning negative returns after costs. Among the industry-matched portfolios, Portfolio 21 had the highest return after costs, at 141 bps, followed by Portfolio 31 at 100 bps. Portfolios 20, 25, and 28 had returns ranging from approximately 98 to 93 bps. This portfolio also had the highest Sharpe ratio, at 0.11 (Portfolios 20, 21, and 25). Thus, industry matching did not dominate performance levels or Sharpe coefficients during the crisis, but it did reduce dispersion by reducing cross-industry beta slippage and the associated round-trip hedging, which increases round-trip costs. The apparent stability advantage is offset by the fact that industry shocks themselves fluctuate during crises. Therefore, matching may concentrate tail risk within a single industry, which explains why some matched portfolios still exhibit negative means and heavy tails after deducting costs.

Differences in matching rules reinforce this interpretation. Portfolios constructed using SSD+NZC (7-12) emphasize crossover strength and therefore have the highest cost resilience. Portfolio 9 remains one of the better performing portfolios on net (78 bps; Sharpe ratio of 0.13), but the portfolio also includes portfolios with large drawdowns, such as Portfolio 10, which had a drawdown of -243 bps and a Sharpe ratio of -0.37, demonstrating the vulnerability of frequent small trades when spreads are large or the book is thin. SSD+Hurst portfolios (13–18) monetize mean-reversion strength and shorter half-lives, resulting in greater individual trade advantage and longer holding periods; cost pass-through is lower on average, and the declines relative to pre-cost levels for this group of portfolios are slightly smaller (e.g., Portfolio 15's interest rate was 40 bps, down from 70 bps). Even so, most Sharpe ratios in both groups fall to near zero or negative values, reflecting that crisis frictions dominate in both frequency- and intensity-based designs when volatility and structural shocks are extreme.

The industry tilt in groups 37–40 reinforces the role of microstructure and flows. Portfolios from strong industries perform best net in this window: Portfolio 39 records the highest post-cost mean (35 bps) and the highest Sharpe ratio (0.14), despite very high volatility and kurtosis. Portfolios from underperforming industries (such as 38 and 40) have smaller or near-zero means, with Sharpe ratios of 0.10 and 0.00, respectively. This pattern contrasts sharply with the COVID-19 period, when lagging industries sometimes outperformed, and is consistent with behavior during the crisis, where risk aversion, balance sheet strength, and momentum in leading industries overwhelm short-term mean reversion in lagging industries. In this scenario, spreads in weaker industries repair slowly relative to cost leakage, while leading industries occasionally offer tradable reversals without insurmountable execution penalties.

These cross-sectional findings suggest several empirically testable channels linking signals, costs, and net performance. First, the net Sharpe ratio should decline with turnover and Amihud illiquidity and increase with a lower rate of mean reversion and the Hurst exponent, with the negative slope for the NZC portfolio being steeper than for the Hurst portfolio, reflecting their higher cost elasticity. Second, in the industry-matched sample, the share of variance explained by industry factors should be higher than in the unmatched sample, while the number of rebalancings should be lower, but the tail months should be consistent with industry event risk rather than broad factor drift. Third, the months with the worst net results should be consistent with microstructural pressures—more price hits and pauses, larger realized half-spreads, larger overnight gaps, and higher participation rates—rather than with gradual fluctuations in the benchmark rate. Cross-sectional regressions of estimated net Sharpe coefficients (or net alpha) on crossing counts, half-life estimates, Hurst exponents, turnover rates, Amihad indices, and industry dummies, and decomposing costs into commissions, effective spreads, and impacts, can transform these mechanisms into measurable resilience and shed light on which designs remain economically viable despite crisis frictions.

Finally, net outcomes during the GFC are more dispersed and have lower averages relative to the COVID-19 period (Table 8), when costs are present. The difference is not simply that transaction costs are "higher" but that the conversion from gross to net alpha is subject to structural obstacles, including discontinuous exits, funding constraints, and a common source of instability. During the COVID-19 period, the frequency or intensity of operations in certain buildings still dominates costs, and crisis conditions make such conversions fragile almost everywhere.

TABLE 9. Excess Returns with Trading Costs of Global 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

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
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 GFC 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 shows that transaction costs have compressed returns rather than reshaped their distribution. As shown in Table 7, before costs, monthly excess returns ranged from 21 bps for Portfolio 40 to 77 bps for Portfolio 37. After costs, the range of monthly excess returns for Portfolio 40 narrowed to 3 bps, and for Portfolio 37 to 51 bps, with the cross-sectional average declining. Portfolio 37's monthly excess return range declined from 77 to 51 bps, but it still maintained its leading position, suggesting a mechanical compression of average returns after deducting commissions, spreads, and market influences.

Unconditional volatility remained moderate. The standard deviation before costs was concentrated around 1%. After costs, the total volatility in Table 10 ranged from 0.71% to 1.72%, with outperforming portfolios (such as Portfolio 37) returning close to 1.19%. Risk-adjusted performance declined, but the upper tail remained strong. Portfolio 37 has the highest post-cost Sharpe ratio at 0.43, followed by Portfolio 39 at 0.39. Higher-order moments before and after costs remain largely stable. Portfolio 37's skewness changes from 0.89 and kurtosis of 3.41 to 0.52 and kurtosis of 3.23; Portfolio 5 remains moderately right-skewed and leptokurtic, with a post-cost skewness of 1.44 and kurtosis of 5.98.

These patterns support an evidence-based mechanism. In a mixed but non-extreme environment with low benchmark drift, transaction costs primarily reduce the conversion of gross alpha to net alpha. The stability of standard deviations and pre- and post-cost higher-order moments suggests a level effect rather than a shape effect. Portfolios that combine smoothed carry convergence with moderate turnover retain a larger share of the total advantage, consistent with the strong post-cost mean, Sharpe ratio, and significance statistics of Portfolios 37 and 39.

Comparative Analysis of Different Portfolios Returns for Bullish and Bearish Period

The non-industry-matched portfolios exhibit greater dispersion than the industry-matched ones. Among the non-industry-matched portfolios, the after-cost mean fluctuation ranges from -2 bps in Portfolio 6 to 31 bps in Portfolio 13. Among the industry-matched portfolios, this fluctuation narrows to 8 bps in Portfolio 24 and 30 bps in Portfolio 25. The upper tail of the Sharpe function is also higher and more concentrated in the industry-matched portfolios. The net Sharpe value is 0.32 for Portfolio 25, 0.31 for Portfolio 26, and 0.33 for Portfolio 34, while the unmatched blocks peak at 0.30 in Portfolio 15 and 0.26 in Portfolio 7. An interpretation consistent with this table is that industry matching reduces cross-industry beta mismatches and the resulting re-hedging, thereby reducing unnecessary rebalancing and round-tripping, lowering the impact of effective carry and per-unit alpha payments, and manifesting itself as a narrower cross-section of means and a higher upper tail of Sharpe values.

Differences between the different matching rules suggest that costs are transmitted through trading frequency. The SSD with NZC emphasizes the frequency of price crossovers, resulting in a more pronounced contraction from the gross to the net mean. Portfolio 7 saw its return decline from 53 bps to 28 bps, while its industry-matched counterpart, Portfolio 25, saw its return decline from 52 bps to 30 bps. The SSD with Hurst emphasizes anti-persistence and shorter half-lives, which results in fewer trades but a greater advantage per trade, resulting in a lower share of alpha lost to costs. Portfolio 34 maintained a high net Sharpe ratio of 0.33, while Portfolio 13 maintained a high net mean return of 31 bps. Taken together, these data suggest that once costs are applied, frequency-driven constructs are more susceptible to mean compression, while strength-driven constructs are more resilient after risk adjustment.

Industry strength further differentiates the results. Within strong industries, relative value portfolios continue to dominate on a net basis. Portfolio 37 achieved a Sharpe ratio of 0.43, with a net return of 51 bps; Portfolio 39 achieved a Sharpe ratio of 0.39, with a net return of 41 bps. Portfolios from weaker industries performed significantly worse. Portfolio 38 achieved a Sharpe ratio of 0.14, with a net return of 11 bps; Portfolio 40 achieved a Sharpe ratio of 0.04, with a net return of 3 bps. The relevant t- and z-statistics confirm that the leading industries are more significant, while the lagging industries are less significant. In an environment of moderate volatility and the absence of unilateral macro shocks, the spread recovery in leading industries appears smoother, more feasible to execute, and has a smaller cost drag on net performance, while the premium in weaker industries is more stable, but smaller in magnitude.

These comparisons suggest three testable propositions, drawn directly from cross-sectional data. First, the net Sharpe score should be positively correlated with the industry matching metric and should exhibit smaller cross-sectional variance within the matching blocks, consistent with a tighter distribution of means and Sharpe scores. Second, under the same matching regime, portfolios constructed using NZC should exhibit greater contraction from gross to net mean and should underperform the Hurst group at the top end of the Sharpe score, as shown by portfolios 7 and 25 versus portfolios 13 and 34. Third, strong industry portfolios should have higher net means and higher upper-tail Sharpe scores than weak industry portfolios, with no systematic differences in higher-order moments between the two groups, consistent with the contrast between portfolios 37 and 39 and portfolios 38 and 40.

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

Portfolio	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	*t*-stat	*z*-stat	Rank by Mean	Rank by Sharpe
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.

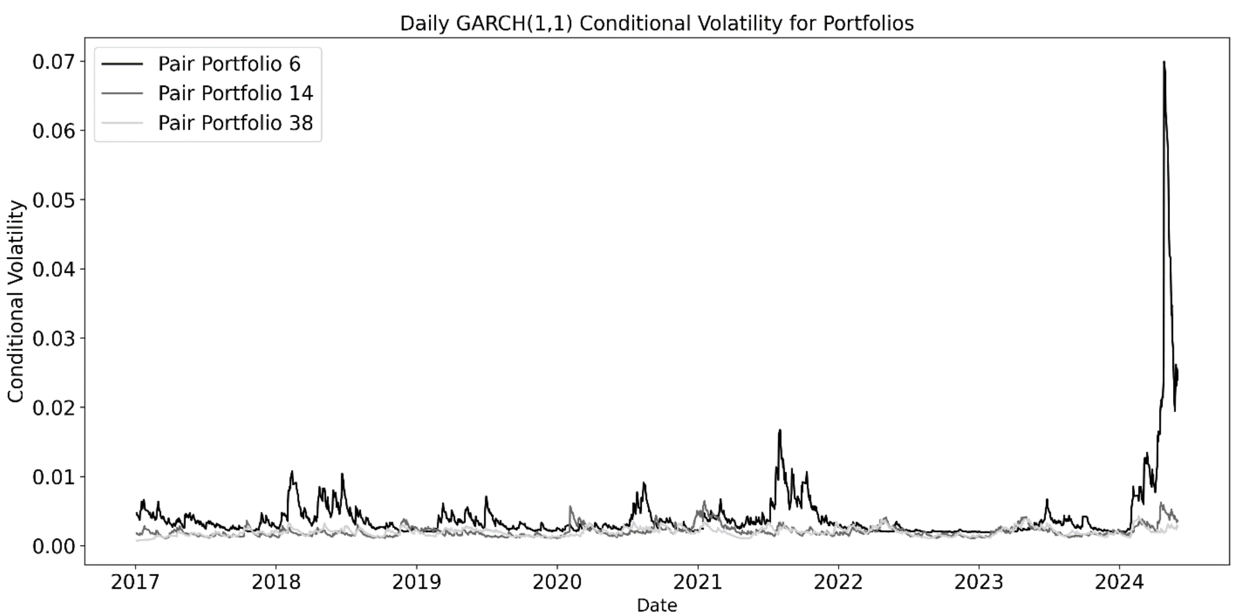
***Significant at the 1% level.

**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



Note: 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 Return Analysis

This section presents a comprehensive analysis of the monthly excess returns of 40 pairs-trading portfolios across multiple subperiods, benchmarked to the CSI 300 index. The sample spans January 2005 to June 2024 and covers key market phases, including the pre-GFC, GFC, post-GFC, bullish and bearish markets, and the COVID-19 periods. The objective is to evaluate the robustness and effectiveness of the pairs-trading strategy under different market conditions and to highlight its performance relative to the benchmark during these distinct phases.

In each subperiod, the CSI 300 Index serves as the benchmark against which the portfolios' performance is evaluated. We report the average returns and Sharpe ratios of the portfolios and the benchmark, providing insight into both absolute and risk-adjusted performance. The significant differences in portfolio results across subperiods largely reflect the variability in the CSI 300 Index's returns within each period.

Sub-Period Return without Trading costs

Table 11 reports monthly excess returns, before trading costs, for all three overall periods and for each subperiod, alongside the corresponding CSI 300 benchmarks.

Prior to the GFC, the CSI 300 Index achieved an average return of 3.09%, indicating a bullish market environment. However, most pairs-trading portfolios underperformed, with negative average returns and Sharpe ratios. For example, Portfolio 10 achieved an average return of -6.60% and a Sharpe ratio of -0.62, both significant at the 1% level. This underperformance suggests that pairs trading is less effective during strong uptrends. One plausible explanation is that during a pronounced bull market, price divergences between paired assets are less likely to recover quickly, reducing the profitability of mean-reversion trading. This significant underperformance relative to the benchmark highlights the strategy's limitations in rapidly rising markets.

During the GFC, the CSI 300 Index had a slightly negative average return of -0.53%, reflecting market volatility. In contrast, most pairs-trading portfolios performed well, with significantly positive average returns and Sharpe ratios. For example, Portfolio 33 achieved an average return of 1.34% and a Sharpe ratio of 1.48, both significant at the 1% level. This outperformance can be attributed to increased volatility, which increased the opportunities for mispricing that the strategy could successfully exploit. The positive and significant Sharpe ratio indicates that the strategy has strong risk-adjusted performance, indicating that the strategy can generate positive returns in market downturns and has the potential to serve as a market-neutral hedge against economic downturn risks.

In the post-crisis period, the CSI 300 Index achieved an average return of 2.14%, indicating a market recovery. Portfolio performance was mixed, with many exhibiting significantly negative average returns. For example, Portfolio 1 achieved an average return of -1.32% and a Sharpe ratio of -1.33, which is significant at the 1% level. The decline in volatility after the crisis may have limited arbitrage opportunities, thereby reducing the profitability of pairs trading. The underperformance relative to the benchmark suggests that the strategy struggles to identify profit divergences after market stabilization, highlighting the need to adjust the strategy in different market environments.

Before both bull and bear markets, the CSI 300 Index had a slightly negative average return of -0.87%. Pairs trading portfolios generally exhibited positive average returns, indicating relatively strong performance in the current environment. For example, Portfolio 15 achieved an average return of 1.30% and a Sharpe ratio of 2.02, which is significant at the 1% level. The moderate volatility during this period may have provided ample opportunities for mispricing, allowing the effectiveness of mean-reversion strategies.

During the bull market, the CSI 300 Index achieved a strong average return of 4.42%. Pairs trading portfolios generally underperformed the benchmark index, with several portfolios experiencing significantly negative average returns. For example, Portfolio 5 had a significantly negative average return of -4.60%, with a Sharpe ratio of -5.24, significant at the 1% level. The strategy underperformed during bull markets, likely due to persistent trends that hindered mean reversion. A negative Sharpe ratio indicates weak risk-adjusted performance, highlighting the strategy's limitations in generating returns during strong rallies.

In contrast, during bear markets, the CSI 300 Index had a significantly negative average return of -2.23%. Pairs trading portfolios performed exceptionally well, with significantly positive average returns and high Sharpe ratios. For example, Portfolio 31 had an average return of 3.41% and a Sharpe ratio of 2.56, significant at the 1% level. Increased volatility and market inefficiencies during economic downturns enhance the effectiveness of pairs trading. A significantly positive Sharpe ratio reflects strong risk-adjusted returns, indicating that the strategy can serve as an effective hedging tool and provide diversification benefits.

Before the COVID-19 pandemic, the CSI 300 Index had a modest average return of 0.57%, while the average returns of the pairs trading portfolios were negligible or negative, with limited statistical significance. The stable market environment likely reduced opportunities for mispricing, resulting in a lack of volatility and significant divergences across currency pairs, which contributed to the subdued performance.

During the COVID-19 pandemic, the CSI 300 Index had a slightly negative average return of -0.19%. During this period, the pairs trading portfolios began to exhibit significant positive average returns and Sharpe ratios. For example, Portfolio 12 had an average return of 0.44% and a Sharpe ratio of 0.39, which was significant at the 1% level. The pandemic-induced volatility created abundant arbitrage opportunities, which the strategy was able to exploit. This positive performance highlights the strategy's resilience and adaptability to sudden market shocks.

Finally, in the post-COVID-19 era, the CSI 300 Index declined further, with an average return of -0.64%. Despite this, the pairs trading portfolios maintained positive average returns, with several portfolios demonstrating statistical significance. For example, Portfolio 33 achieved an average return of 1.24% and a Sharpe ratio of 1.09, both significant at the 1% significance level. Persistent market inefficiencies and persistent volatility create a favorable environment for pairs trading, and its consistently positive performance suggests that the strategy remains effective amidst prolonged uncertainty.

Overall, portfolio performance is significantly influenced by the variability in the CSI 300 Index's returns over time. When the CSI 300 Index experienced negative returns (such as during the GFC, the bear market, the COVID-19 pandemic, and the post-pandemic era), the pairs trading portfolio typically achieved positive average returns and higher Sharpe ratios. This inverse relationship suggests that the strategy tends to be more effective during market downturns, benefiting from increased volatility and more pronounced inefficiencies, which create opportunities for mean reversion.

Conversely, during periods of strong positive CSI 300 Index returns (such as before the GFC and during bull markets), the pairs trading portfolio significantly underperformed, typically generating negative average returns and Sharpe ratios. This pattern suggests that the mean reversion assumption underlying pairs trading may not hold true during bull market conditions, as assets are more likely to trend upward rather than revert to historical relationships. Therefore, when sustained momentum inhibits convergence trading, the effectiveness of this strategy declines.

During periods of moderate or slightly negative CSI 300 Index returns (such as those preceding bull and bear markets and the COVID-19 pandemic), portfolio performance was mixed. Some portfolios achieved positive average returns and Sharpe ratios, while others did not. This inconsistency suggests that performance in such environments is more difficult to predict and may depend on specific market conditions, the composition of trading pairs, and the portfolio construction methodology. During these intermediate periods, success may depend more on asset characteristics and trade timing than on overall market trends.

During periods of market stress, including the GFC, bear markets, and the COVID-19 pandemic, the portfolio's average return was significantly positive. Many portfolios achieved significant positive returns at the 1% or 5% level, indicating that the strong performance was unlikely to be due to chance. During periods of market volatility, the Sharpe ratio increased significantly, reflecting superior risk-adjusted returns. The portfolio achieved high returns without a corresponding increase in risk, highlighting the advantages of pairs trading in effectively managing risk.

During bear markets and crises, the portfolio consistently outperformed the CSI 300 Index, demonstrating that pairs trading can be a defensive strategy, generating positive returns during market declines. However, during bull markets, the portfolio often underperformed the benchmark. This underperformance stems from the strategy's reliance on mean reversion, which can be suppressed during periods of strong market momentum. During economic downturns, the portfolio's volatility was generally lower than the benchmark, resulting in an increase in the Sharpe ratio and highlighting the strategy's market neutrality.

Overall, the strategy exhibits significant sensitivity to market fluctuations. It performs well in environments of high volatility and market inefficiencies but is less effective in stable or trending markets. This suggests that adjustments or supplements to the strategy may be necessary at some point. Nevertheless, the strategy's consistent performance across various crisis periods underscores its robustness. Portfolios that employ industry matching and more advanced selection criteria (e.g., Portfolios 31 through 36) often outperformed other portfolios, highlighting the importance of careful portfolio selection and incorporating factors such as industry correlations.

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 Return by Different Benchmarks with Trading costs

The inclusion of transaction costs and the choice of benchmark significantly impact the performance evaluation of pairs trading strategies. Tables 12A, 12B, and 12C report monthly excess returns for different subperiods, using a different CSI 300 Index benchmark for each subperiod: a subperiod-specific benchmark, a full-sample benchmark, and a period-specific benchmark. This section explores the characteristics of each table, the differences arising from the use of different benchmarks, and the insights derived from these in the context of pairs trading.

Table 12A uses the CSI 300 Index returns for each subperiod as the benchmark. This refined approach aligns the benchmark with prevailing market conditions in each subperiod. As expected, adding transaction costs generally reduces the average returns and Sharpe ratios of all portfolios relative to the no-cost results in Table 11.

Prior to the GFC, the CSI 300 Index had a strong average return of 309 bps, indicating a bullish market. Most pairs-trading portfolios continued to underperform, with negative average returns and Sharpe ratios. For example, Portfolio 10 experienced a further decline, with a return of -693 bps and a Sharpe ratio of -0.65, both of which were significant at the 1% level. Transaction costs exacerbated the underperformance during the bull market, reducing the effectiveness of mean-reversion strategies due to the ongoing upward trend.

During the GFC, the CSI 300 Index had a slightly negative average return of -53 bps. Despite transaction costs, many pairs trading portfolios maintained significant positive average returns and Sharpe ratios, although to a lesser extent than in Table 11. For example, Portfolio 33 returned 112 bps and had a Sharpe ratio of 1.24, both significant at the 1% level. Increased volatility created ample arbitrage opportunities, allowing the strategy to remain profitable even after deducting costs.

In the post-GFC period, the CSI 300 Index averaged a return of 214 bps. Transaction costs generally dampened performance, with many portfolios experiencing significantly negative average returns and Sharpe ratios. Portfolio 1's return fell to -163 bps, with a Sharpe ratio of -1.71, significant at the 1% level. Reduced volatility during the market recovery, combined with costs, further limited arbitrage opportunities.

During the bull market, the CSI 300 Index achieved a strong average return of 442 bps. Pairs-trading portfolios continued to struggle, with transaction costs amplifying the negative returns. Portfolio 5 achieved a return of -482 bps, with a Sharpe ratio of -5.75, significant at the 1% level.

The persistent upward trend reduced the frequency of mean reversion, weakened the effectiveness of the strategy, and increased the impact of costs.

Conversely, during the bear market, the CSI 300 Index experienced a significantly negative average return of -223 bps. Pairs-trading portfolios performed well, despite the dampening of returns by transaction costs. Portfolio 31 returned 318 bps and had a Sharpe ratio of 2.71, both significant at the 1% level. Rising volatility and increased mispricing continue to favor pairs trading, maintaining profitability even after deducting costs.

The portfolios remained resilient during the COVID-19 pandemic. While the average return of the CSI 300 Index declined slightly (-19 bps) during the pandemic, portfolios such as Portfolio 12 maintained a positive average return of 20 bps, even though their Sharpe ratios declined to 0.18. Transaction costs reduced profitability but did not eliminate it, highlighting robustness in a volatile environment.

Table 12B uses the full-sample CSI 300 benchmark to provide a consistent baseline across all subperiods. This approach facilitates evaluation relative to the overall market trend, but the statistical significance of average returns and Sharpe ratios is reduced compared to Table 12A. Using a single benchmark dilutes the impact of specific subperiod market conditions. For example, during the GFC, Portfolio 33 had an average return of 14 bps and a Sharpe ratio of 0.15, both statistically insignificant. A consistent benchmark masks the significant volatility and opportunities prevalent during the crisis, resulting in smaller outperformance.

Furthermore, before the GFC, the CSI 300 benchmark under the full-sample approach averaged 45 bps, significantly lower than the 309 bps for the specific subperiods in Table 12A. Consequently, the portfolios in Table 12B performed relatively well. For example, Portfolio 5 had an average return of 144 bps, which is significant at the 10% level, while the result in Table 12A was negative. This difference illustrates how benchmark selection can significantly alter a strategy's expected performance.

Including transaction costs in Table 12B further reduces profitability in most subperiods. The portfolio's average return and Sharpe ratio are generally lower than the cost-free results in Table 11. Because a uniform benchmark cannot reflect different market conditions, it is difficult to attribute performance differences to specific events or mechanisms.

Table 12C benchmarks the returns of the CSI 300 Index during three major periods: the GFC, bull and bear markets, and the COVID-19 pandemic. This intermediate approach balances the granularity of Table 12A with the consistency of Table 12B, aiming to capture broad market trends during major economic events.

The impact of transaction costs is evident here, but not as pronounced as in Table 12A. During the GFC, the CSI 300 benchmark returned an average of 1.62%, lower than the 3.09% return in the pre-GFC period but higher than the -0.53% return during the crisis period shown in Table 12A. Thus, the portfolio performance appears weaker than in Table 12A but stronger than in Table 12B. Portfolio 33 had an average return of -1.03% and a Sharpe ratio of -1.14, significant at the 1% level, indicating underperformance compared to the benchmark during the same period.

During both bull and bear markets, the CSI 300 benchmark averaged a return of 0.05%, underperforming the corresponding sub-period benchmark. Portfolio performance was mixed—some portfolios achieved positive average returns, but these were statistically insignificant. Transaction costs consistently eroded profitability, and their effectiveness appears less robust than when using sub-period benchmarks.

During the COVID-19 pandemic, the CSI 300 benchmark averaged a return of 0.04%, and the portfolio's average return and Sharpe ratio generally lacked statistical significance. Transaction costs, combined with broad cyclical benchmarks, may mask performance differences across different phases of the pandemic.

Overall, the choice of benchmark has a significant impact on evaluation results. Sub-period benchmarks align performance measures with specific market conditions, highlighting the strategy's adaptability and effectiveness under volatility and stress. Including transaction costs in this context provides a more realistic view of profitability: while returns have been reduced, the strategy remains effective in volatile markets.

In contrast, full-sample benchmarks smooth out fluctuations across different market environments, potentially underestimating performance during periods of strategy effectiveness (e.g., the GFC) and overestimating performance during periods of lower effectiveness (e.g., bull markets where benchmark returns fall short of the specific bull market).

Using a cycle-level benchmark offers a compromise, but can still mask variations within these periods. The impact of transaction costs becomes more pronounced when the benchmark fails to reflect the specific conditions exploited by the strategy.

Analysis shows that transaction costs have a significant impact on profitability, particularly in low-volatility or strongly trending markets. Strategy effectiveness depends on market conditions. During periods of high volatility (e.g., the GFC and bear markets), pairs trading remains profitable after deducting costs because larger price discrepancies create more opportunities for mean reversion. In bull markets, the strategy tends to underperform, with transaction costs further depressing returns; persistent upward trends reduce the frequency and magnitude of mean reversion.

In summary, the choice of benchmark and the inclusion of transaction costs jointly influence the assessment of pairs trading performance. Sub-period benchmarks provide a nuanced view of the effectiveness of different mechanisms and demonstrate that pairs trading can remain profitable even after accounting for costs. Conversely, the strategy faces significant headwinds during strong bull markets as costs exacerbate underperformance. These findings emphasize the importance of benchmark selection, cost awareness, adaptability, careful pair selection, and effective execution in implementing a pairs trading strategy, highlighting the strategy's defensive potential during downturns and its limitations during sustained uptrends.

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.

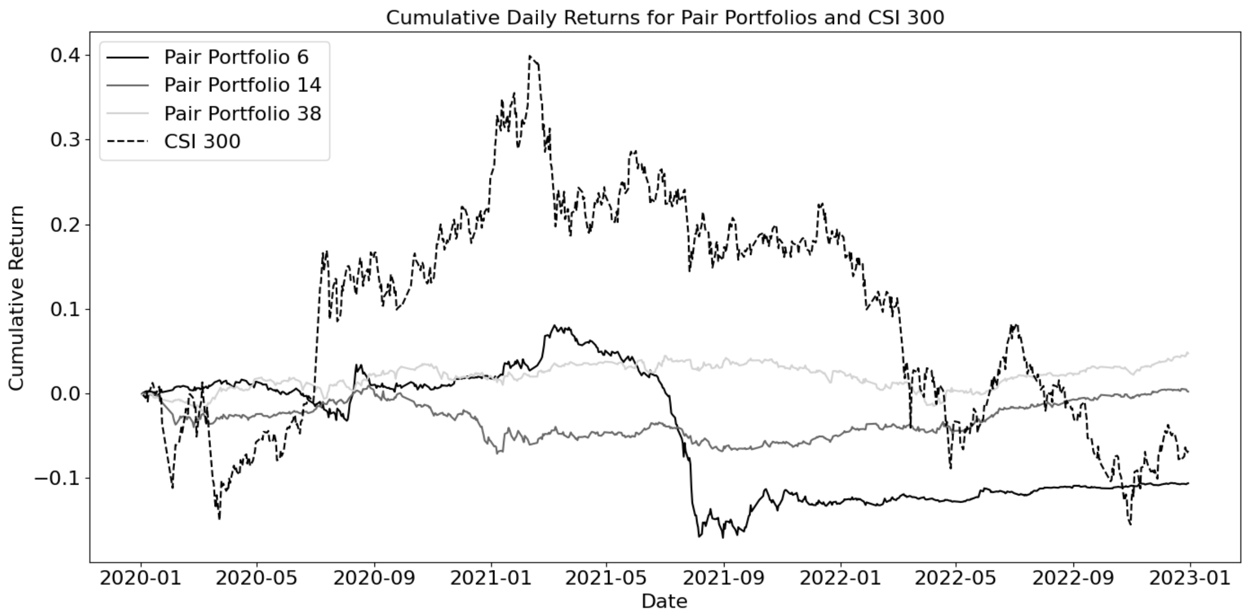
∗∗∗Significant at the 1% level.

∗∗Significant at the 5% level.

∗Significant at the 10% level.

Figure 3 shows the cumulative daily returns of three selected currency pair trading portfolios (Portfolios 6, 14, and 38) versus the CSI 300 Index, covering the COVID-19 pandemic period from January 2020 to December 2022 (after deducting transaction costs). The CSI 300 Index's cumulative returns exhibited significant volatility, peaking around the beginning of 2021 before declining significantly throughout 2022.

Figure 3. Daily Cumulative Return on Pair Portfolios



Note: 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.

Portfolio 6 exhibited a pronounced downward trend, particularly after mid-2021, resulting in significant cumulative losses by the end of the period. In contrast, Portfolios 14 and 38 performed much more consistently. Portfolio 14 maintained relatively low volatility, with its cumulative return fluctuating around neutral, indicating more robust long-term performance. Similarly, Portfolio 38 remained near zero throughout the entire period, with minimal deviations, indicating that it was largely unaffected by the market fluctuations that affected the CSI 300 Index and Portfolio 6.

These results highlight the stability of Portfolios 14 and 38 relative to Portfolio 6 and the CSI 300 Index. While the broader market and Portfolio 6 experienced significant volatility, particularly during periods of significant volatility in 2021, Portfolios 14 and 38 demonstrated resilience and consistent returns, making them more robust during market turmoil. This stability highlights the differences in effectiveness and risk profiles of different pairs trading strategies under varying market conditions.

5.2 Alternative Returns

This section presents an alternative monthly excess return analysis method that incorporates transaction costs across three different periods: the GFC, bull and bear markets, and the COVID-19 pandemic. Results are grouped by period to explore performance differences across portfolios. Table 13 reports the monthly excess returns, standard deviations, and Sharpe ratios for all portfolios across each period. The inclusion of transaction costs provides a more realistic assessment of portfolio performance.

Additionally, Table 14 introduces an additional specification: a one-day waiting period to assess the impact of delayed execution on portfolio performance. This adjustment enables direct comparisons between instant and slightly delayed trades, particularly in volatile market environments. Together, these two tables provide a comprehensive perspective on performance differences across different market conditions, complementing and extending the findings in the previous section.

5.2.1 Returns with Different Vigintiles

Table 13 provides a comprehensive analysis of the monthly excess returns, standard deviations, and Sharpe ratios of portfolios grouped by period across three periods: the GFC, bull and bear markets, and the COVID-19 pandemic. Portfolios 1-20 consist of non-industry-matched portfolios, while portfolios 21-40 consist of industry-matched portfolios. Each category is further divided into periods (in 5% increments) and sorted from smallest to largest SSD. The purpose is to compare the trading performance of portfolios based on their SSD.

During the GFC, both non-industry-matched and industry-matched portfolios exhibited significantly negative returns across all periods. Significantly negative mean returns and Sharpe ratios were observed for the non-industry-matched portfolios. For example, Portfolio 4 had an average return of -175 bps and a Sharpe ratio of -0.41, which are significant at the 1% level.

Similarly, Portfolio 7 had an average return of -168 bps and a Sharpe ratio of -0.67, which are also significant at the 1% level. These significant losses demonstrate that pairs trading strategies, especially those without industry matching, struggle to generate positive returns during periods of extreme volatility and market downturns. A breakdown in historical price relationships can make mean-reversion strategies less effective in such volatile environments.

Industry-matched portfolios also underperformed during the GFC. Portfolio 22 had an average return of -151 bps and a Sharpe ratio of -0.76, which was significant at the 1% level; portfolio 29 had an average return of -163 bps and a Sharpe ratio of -0.75, also significant at the 1% level. The negative performance of both non-industry-matched and industry-matched portfolios suggests that industry matching did not provide protection during the crisis. Systematic volatility can cause correlations (even within industries) to behave abnormally, undermining strategies that rely on stable mean-reversion relationships.

During both bull and bear markets, the portfolios generally exhibited modestly positive average returns with low Sharpe ratios, and no statistically significant positive returns were observed. For the non-industry-matched group, average returns ranged from approximately 13 bps to 33 bps, with Sharpe ratios ranging from 0.11 to 0.27. Industry-matched portfolios exhibited a similar pattern, with average returns ranging from 14 bps to 26 bps and Sharpe ratios ranging from 0.13 to 0.29. These results suggest that pairs trading strategies generate smaller positive returns under more stable or mixed market conditions, but their performance differences are limited within SSD-based portfolios. Limited mispricing opportunities may have limited potential gains, while SSD rankings have no material impact on the results.

Both industry-matched and non-industry-matched portfolios experienced mixed performance during the COVID-19 pandemic. Several portfolios experienced negative average returns and Sharpe ratios, reflecting heightened volatility and uncertainty. Among the industry-matched and non-industry-matched portfolios, portfolios 13, 14, 15, and 16 had negative average returns, ranging from -15 bps to -19 bps, and their corresponding Sharpe ratios were also negative. For example, portfolio 15 had an average return of -19 bps and a Sharpe ratio of -0.22, which is significant at the 5% level. These results suggest that the strategy has not adequately compensated for risk during these turbulent times, likely due to a weakening of mean-reversion in these unprecedented market conditions. Similar patterns were observed for industry-matched portfolios.

Portfolios 31 and 32 had average returns of -17 bps and Sharpe ratios of -0.24 and -0.23, respectively, both significant at the 5% level. Portfolio 35 had an even more significant average negative return of -24 bps and a Sharpe ratio of -0.31, which is significant at the 1% level. These findings suggest that industry matching does not protect portfolios from pandemic-induced volatility. The widespread impact of the COVID-19 pandemic across industries may have even caused portfolios within industries to deviate from historical relationships.

Examining the performance of different groups reveals no consistent pattern indicating that certain SSD-based rankings outperform others over all periods. During the GFC, all groups, regardless of SSD ranking, experienced negative returns. This suggests that the SSD metric may fail to capture the complexity of asset price dynamics under extreme conditions. The assumption that portfolios with smaller SSDs are more likely to recover when market correlations are disrupted by systemic shocks may be invalidated.

The lack of significant performance differences across groups during bull and bear markets further suggests that SSD-based rankings do not materially impact returns in relatively stable environments. The modest returns and low Sharpe ratios suggest limited opportunities for mispricing, and the strategy does not derive significant benefits from SSD rankings.

During the COVID-19 pandemic, there was a lack of clear patterns across asset classes. Both non-industry-matched and industry-matched portfolios exhibited mixed results: some asset classes with higher SSDs (e.g., Portfolio 35) recorded negative returns, while others with lower SSDs (e.g., Portfolio 1) achieved small positive returns. This further suggests that ranking based on SSDs did not significantly impact performance amidst heightened uncertainty.

From a pairs trading perspective, these results highlight the limitations of relying solely on statistical indicators such as SSDs for asset class selection, especially during periods of extreme volatility. The negative returns and Sharpe ratios observed during the GFC and the COVID-19 pandemic suggest that pairs trading strategies should incorporate additional factors for robustness. Adding fundamental signals, macroeconomic indicators, or adaptive statistical techniques that account for dynamics could improve performance.

The observation that industry matching did not significantly improve performance suggests that asset classes within industries are not inherently more resilient during market downturns. Companies within the same industry may be exposed to industry-specific shocks or broader economic volatility, and the benefits of industry matching diminish when mean-reversion relationships weaken.

In summary, the detailed evidence in Table 13 highlights the challenges facing pairs trading strategies across markets and market regimes. Negative performance during the GFC and the COVID-19 pandemic suggests that extreme conditions can undermine the premise of mean reversion. The lack of significant performance differences across markets based on the SSD suggests that the SSD alone may not be sufficient for pair selection. These insights underscore the need for adaptive approaches that incorporate additional risk management and selection techniques to optimize performance, especially during periods of heightened 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

	Financial Crisis			Bullish and Bearish			COVID-19		
Portfolio	**Mean**	**Std. Dev.**	**Sharpe**	**Mean**	**Std. Dev.**	**Sharpe**	**Mean**	**Std. Dev.**	**Sharpe**
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 pairs trading strategies that incorporate a one-day waiting period before executing trades and account for transaction costs. Table 14 reports the monthly excess returns, standard deviations, and Sharpe ratios of 40 portfolios during three different periods: the GFC, bull and bear markets, and the COVID-19 pandemic. Excess returns are calculated relative to the CSI 300 benchmark for each period.

The one-day waiting rule in pairs trading refers to delaying execution by one trading day after a signal is generated. In a typical pairs trading strategy, a signal occurs when the prices of two historically correlated stocks deviate from their expected relationship, indicating a potential opportunity. Without a waiting period, traders would immediately act on the signal, buying or selling the paired stock. The introduction of a one-day waiting period is intended to mitigate potential market impacts, reduce transaction costs associated with the bid-ask spread, and allow for potential price adjustments after the signal is generated. Such adjustments may affect the profitability and risk profile of the portfolio.

During the GFC, strategies with a one-day waiting period produced primarily negative results. For example, Portfolio 1 had a significantly negative average excess return of -204 bps per month with a Sharpe ratio of -0.42. Similarly, Portfolio 2 had an average excess return of -183 bps per month with a Sharpe ratio of -0.36. These results suggest that in highly volatile market environments, the waiting period may have impaired the strategy's ability to capture short-term mispricings. Delayed execution may have caused earnings divergences to correct before trades were initiated, resulting in missed opportunities and negative returns.

In contrast, some portfolios performed less poorly and even achieved positive returns. For example, Portfolio 3 had an average excess return of -129 bps per month with a Sharpe ratio of -0.25. While still negative, it outperformed Portfolios 1 and 2. Notably, Portfolio 9 achieved a positive average excess return of 62 bps per month, despite a lower Sharpe ratio of 0.10, suggesting that even with a waiting rule, some portfolios can achieve modest returns. However, overall, the strategy underperformed strategies with a one-day waiting period during the GFC, suggesting that immediate execution may be more effective when mispricing is highly transient.

Comparing these results with those without a one-day waiting period (Table 9), we find that portfolios without a one-day waiting period generally outperformed during the GFC. For example, in Table 9, Portfolio 3 achieved an average excess return of -138 bps per month and a Sharpe ratio of -0.25, similar to the results with a waiting period. However, Portfolio 9, which did not implement a waiting period, achieved an average excess return of 78 bps per month and a Sharpe ratio of 0.13, indicating slightly better performance without a waiting period. This suggests that during periods of market volatility, a waiting period may reduce its effectiveness in capturing rapid price reversals.

Most portfolios with a one-day waiting period exhibited modest positive performance during both bull and bear markets. For example, Portfolio 15 achieved an average excess return of 32 bps per month and a Sharpe ratio of 0.32. Portfolio 37 also performed well, with an excess return of 53 bps per month and a Sharpe ratio of 0.44. These results suggest that, in relatively stable market environments, the waiting period does not materially impact performance and, in some cases, may even improve performance by filtering out false signals and reducing trading friction.

Compared to the results without a waiting period in Table 10, performance is broadly similar. Portfolio 15, without a waiting period, achieved a monthly return of 30 bps and a Sharpe ratio of 0.30. The inclusion of a waiting period slightly improved both the average return and Sharpe ratio, suggesting that delayed execution can improve returns in calmer markets by helping to avoid noise and overtrading.

During the heightened market volatility of the COVID-19 pandemic, the effects of the one-day waiting period were mixed. Portfolio 3 achieved a monthly return of 28 bps and a Sharpe ratio of 0.19, which are significant at the 10% level, indicating improved performance. In contrast, Portfolio 1 achieved a monthly return of 23 bps and a Sharpe ratio of 0.13, which, while positive, is not statistically significant.

Compared to the no-waiting-period results in Table 8, Portfolio 3 had a monthly return of 22 bps and a Sharpe ratio of 0.14, indicating that the waiting period slightly improved its performance during the COVID-19 pandemic. In contrast, Portfolio 1, which did not have a waiting period, had a monthly return of -5 bps and a Sharpe ratio of -0.03, indicating that the one-day delay improved its performance during the COVID-19 pandemic.

These observations suggest that during the COVID-19 pandemic, a waiting period may have helped avoid trades that could reverse quickly, thereby improving returns in some cases. Extreme volatility and rapid price movements may make immediate execution riskier, while a one-day buffer can filter out fleeting price shocks.

Overall, a one-day waiting period has market-related effects. During periods of high volatility, such as the GFC, it tends to reduce profitability, as immediacy is crucial for capturing fleeting reversals. In contrast, during the COVID-19 pandemic, this effect was neutral or slightly positive for some portfolios, potentially by reducing noise and premature market entry. During both bull and bear markets, a waiting rule generally did not harm performance and may even slightly improve it by reducing overtrading and transaction costs. This suggests that delayed execution may be beneficial under more stable conditions, as mean-reversion opportunities are less time-sensitive and price divergences may persist longer.

Comparing these results with portfolios without a "one-day wait rule" (Tables 8–10), the return differences are generally smaller during most periods. However, during the GFC, the portfolio without a "one-day wait rule" performed slightly better, highlighting the importance of timely execution in highly volatile markets.

From a pairs trading perspective, these findings emphasize the need to adjust execution strategies based on market conditions. In highly volatile markets, immediate execution is crucial for exploiting rapid mean reversion; in more stable environments or during unusual stress events like COVID-19, a short waiting period can reduce the risks associated with noise and transient shocks. Furthermore, these results highlight the importance of incorporating transaction costs and market impact into strategy design: a one-day wait rule can reduce trading frequency, thereby reducing costs and slippage, potentially improving net performance when opportunities are more immediate.

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

	Financial Crisis			Bullish and Bearish			COVID-19		
Portfolio	Mean	Std. Dev.	Sharpe	Mean	Std. Dev.	Sharpe	Mean	Std. Dev.	Sharpe
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

We next examine whether pairs trading generates profits on a risk-adjusted basis. To do so, we incorporate risk factors that have proven effective in explaining cross-sectional returns and are expected to correlate with pairs-trading outcomes. We begin with a four-factor model that extends the classic Fama and French (1993) specification by adding a momentum factor. Because pairs trading is fundamentally a short-term reversal strategy, we further augment the model with a market-wide short-term reversal factor, following Jegadeesh (1990). This enhanced specification is also used by Gatev et al. (2006) to account for risk in pairs trading. Tables 15, 16, and 17 report the regressions of after-cost returns on these factors for the three periods, respectively.

The regression model for each portfolio is:

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

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

In contrast, some portfolios—such as Portfolio 9 and Portfolio 38—show positive alphas, although they are not statistically significant. Portfolio 9, for instance, has an intercept of 53 bps per month with a *t*-statistic of 0.68, indicating that its risk-adjusted returns are not significantly different from zero. This implies that certain portfolios maintained performance despite market turmoil, but the lack of significance warrants caution in interpretation.

The market risk factor (MKT–RF) reveals positive, though generally small, betas for some portfolios, indicating limited sensitivity to market movements. For example, Portfolio 11 has a significant market beta of 0.32 with a *t*-statistic of 3.27 (1% level), suggesting moderate correlation with market returns, possibly due to constituent stocks that are more sensitive to market fluctuations. Other portfolios have insignificant market betas, consistent with the market-neutral orientation of pairs trading.

Size exposure (SMB) is mostly insignificant, indicating no systematic bias toward small-cap or large-cap stocks. An exception is Portfolio 31, which has a negative SMB beta of −0.267, but the t-statistic is −0.79 and thus insignificant. Overall, size does not appear to drive these portfolios' returns.

Similarly, the value factor (HML) displays weak relationships with portfolio returns. Most HML betas are insignificant, indicating no consistent tilt toward value or growth within the strategies. For instance, Portfolio 11 has a negative HML beta of −0.527 with a t-statistic of −1.51, which is not statistically significant.

Momentum (MOM) plays a more prominent role. Several portfolios have negative momentum coefficients, consistent with the contrarian nature of pairs trading. Notably, Portfolios 29, 35, and 36 exhibit significantly negative MOM betas: Portfolio 29 has −0.11 (5% level), while Portfolios 35 and 36 have −0.10 and −0.12, respectively (both 5% level). These exposures indicate that the strategies tend to bet against prevailing trends, seeking to exploit short-term reversals.

The market reversal factor (REV) shows limited influence. Most portfolios have insignificant REV coefficients, suggesting that the reversal effect does not materially affect performance during the GFC. One exception is Portfolio 8, with a REV beta of −0.13 and a t-statistic of −1.71 (10% level). Overall, however, REV is not a major driver.

The R^2 values indicate that the five-factor model explains only a small portion of the variance in returns, with most portfolios between 0.01 and 0.19. Only a few portfolios—such as Portfolio 11 and Portfolio 36—display somewhat higher explanatory power. This suggests that other factors or idiosyncratic elements influence pairs-trading returns that the five-factor model does not capture. Despite the low fit, the significant negative alphas and negative momentum exposures illuminate performance dynamics during the GFC.

Taken together, the regression evidence indicates that during the GFC, pairs-trading strategies underperformed on a risk-adjusted basis. Significant negative alphas point to abnormal losses not accounted for by traditional factors, potentially reflecting the breakdown of historical price relationships under extreme conditions. The negative momentum exposures underscore the contrarian stance of pairs trading; when momentum was strong (past winners continued to outperform), these strategies suffered.

The generally insignificant market, size, and value coefficients imply that pairs-trading returns are largely uncorrelated with these traditional risk sources, reinforcing the market-neutral nature of the approach and its potential diversification benefits. Although the reversal factor has limited impact and the R2R^2R2 values are low, the magnitudes of the negative intercepts—roughly −100 bps to −260 bps per month—are economically meaningful even after trading costs, underscoring the challenges of mean-reversion strategies in severe downturns.

These findings differ from prior studies (e.g., Gatev et al., 2006), which often report positive abnormal returns for pairs trading. The divergence may stem from the specific conditions of the GFC, which altered market dynamics and undermined traditional mean-reverting relationships. In sum, negative alphas and significant negative momentum coefficients highlight the difficulty of relying on mean reversion when market stress is extreme.

Turning to Table 16, during the Bullish and Bearish periods, the majority of portfolios exhibit negative intercepts, some of which are statistically significant. For instance, Portfolio 1 shows an alpha of −13 bps per month, Portfolio 2 has −6 bps, Portfolio 16 has −12 bps, and Portfolio 36 has −15 bps. These negative and significant alphas suggest that, after adjusting for risk factors, pairs-trading strategies underperform during the Bullish and Bearish period, implying diminished profitability in more stable conditions.

Regarding market risk, most portfolios display negative and significant market betas—for example, Portfolio 1 (−0.0532), Portfolio 19 (−0.0288), and Portfolio 39 (−0.0553). These negative betas indicate that the portfolios tend to move inversely with the market, generating positive returns when the market declines and negative returns when it rises, consistent with a hedging profile in this period.

The size factor (SMB) yields mixed and generally insignificant results. While some portfolios (e.g., Portfolios 27 and 39) have positive and significant size betas, the lack of consistent significance indicates that size is not a dominant driver—consistent with the market-neutral design of pairs trading.

Value (HML) coefficients tend to be negative, with some statistical significance—for instance, Portfolio 2 (−10 bps) and Portfolio 20 (−8 bps). These negative HML loadings imply a tilt toward growth stocks and suggest that exposure to the value factor partially explains returns during this period.

The momentum factor (MOM) shows strong, negative, and highly significant coefficients across almost all portfolios (e.g., Portfolio 1: −6 bps; Portfolio 6: −14 bps; Portfolio 39: −10 bps). This consistent negative exposure reinforces the contrarian nature of pairs trading, which benefits when recent losers outperform recent winners.

REV coefficients are generally positive but often insignificant (e.g., Portfolio 4: 3 bps; Portfolio 21: 3 bps). Occasional significance suggests some portfolios may benefit from market-wide reversals, though REV is not a dominant explanatory factor here.

Adjusted R^2 values range from 0.10 to 0.38, higher than those observed during the GFC (Table 15), where most R^2 values were below 0.10 (e.g., Portfolio 1: 0.32; Portfolio 39: 0.36). This indicates that the five-factor model explains a larger portion of the variance in returns during the Bullish and Bearish period, suggesting greater relevance of common risk factors in more stable markets.

Relative to the GFC, several differences emerge. In the GFC, many portfolios had significant negative alphas, while in the Bullish and Bearish period most alphas are negative and often significant, signaling underperformance after risk adjustment. Market betas were generally positive but insignificant during the GFC; in contrast, they are consistently negative and significant in the Bullish and Bearish period, implying an inverse relationship with the market. Momentum coefficients are more strongly negative in the Bullish and Bearish period, reaffirming the contrarian stance, while HML becomes more relevant (negative and sometimes significant). SMB remains mixed and largely insignificant across both periods. Overall, higher R^2 values in the Bullish and Bearish period indicate that systematic factors explain more of the return variability when markets are stable.

In conclusion, pairs-trading strategies do not generate positive abnormal returns after adjusting for common risk factors during the Bullish and Bearish period. Negative alphas and significant exposures to market and momentum factors suggest underperformance in stable environments. This contrasts with the GFC, where negative alphas reflected the breakdown of historical relationships. The consistently negative relationship with momentum across both periods confirms the contrarian nature of pairs trading, while overall effectiveness appears regime-dependent, with higher profitability in periods of elevated volatility and stress.

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

Portfolio	Intercept	t-stat	MKT-RF	t-stat	SMB	t-stat	HML	t-stat	Momentum	t-stat	Reversal	t-stat	R^2
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 GFC 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

Portfolio	Intercept	t-stat	MKT-RF	t-stat	SMB	*t*-stat	HML	t-stat	Momentum	t-stat	Reversal	t-stat	R^2
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

Portfolio	Intercept	t-stat	MKT-RF	t-stat	SMB	*t*-stat	HML	t-stat	Momentum	t-stat	Reversal	t-stat	R^2
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 those 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 toward 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 toward 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 growthoriented 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 GFC (Table 15) and the Bullish and Bearish period (Table 16), several differences emerge. During the GFC, 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 GFC, 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 toward negative and significant SMB coefficients during the COVID-19 period contrasts with the previous periods. During the GFC 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 toward 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 toward 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 GFC, 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 GFC, 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 GFC, 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 toward 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 monthly VaR and ES at the 1%, 5%, and 10% levels across three distinct periods: the GFC, the Bullish and Bearish period, and the COVID-19 period. This analysis focuses on the magnitude of potential losses under extreme market conditions, differences in risk profiles across periods, and the impact of implementing a one-day waiting strategy on VaR and ES. 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 VaR without the one-day waiting strategy, while the numbers inside the parentheses show VaR with the one-day waiting strategy.

During the GFC, portfolios exhibit significantly higher VaR values compared with the other periods, reflecting the elevated market risk and extreme volatility that characterized this time. 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 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 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% 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 GFC, 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 with the GFC, reflecting reduced market volatility and a 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 suggests a consistent risk profile across strategies during this period. Similarly, at the 5% and 10% levels, 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 execution by one day does not meaningfully alter the risk profile in low-volatility environments, consistent with the idea that mispricing opportunities are less transient in stable 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 during the GFC. This finding reflects heightened but more 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 (1% VaR of 0.10) and Portfolio 24 (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 0.02, indicating a lower probability of 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 GFC 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 1% VaR values above 20%. The Bullish and Bearish period showed much lower VaR values, reflecting market stability and reduced volatility. The low and consistent VaR values across portfolios indicate a relatively uniform risk profile, with minimal chance of large losses. The COVID-19 period presented a middle ground, with moderate VaR values suggesting elevated but controlled risk. Variation in VaR across portfolios during COVID-19 highlights that certain strategies were more exposed to sudden shocks than others.

Overall, the one-day waiting strategy has a minimal impact on VaR values across all three periods, indicating that delaying execution by one day does not substantially alter the risk profile of pairs-trading strategies. This suggests that while immediate execution may be beneficial for capturing short-lived mispricings, a one-day delay does not significantly increase or reduce risk, particularly in stable conditions. However, during volatile periods such as the GFC, the lack of change in VaR may imply that extreme market conditions drive risk more than execution timing. This observation underscores the importance of understanding 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 GFC 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; however, 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 materially alter risk profiles in most cases, it may still provide benefits by reducing transaction costs or filtering out 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)

	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
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 GFC, 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 the parentheses indicating results with the one-day waiting strategy. ES provides a measure of average losses beyond the VaR threshold, offering a deeper understanding of potential extreme losses during volatile periods.

During the GFC, portfolios exhibited substantially higher ES values compared with the other periods, reflecting the extreme risk exposure in this turbulent environment. Significant variation in ES values across portfolios is evident, 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 GFC 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 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. 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 GFC 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 GFC, 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 GFC.

During the COVID-19 period, ES values are higher than those observed during the Bullish and Bearish period but generally lower than those recorded during the GFC, 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 with 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 GFC 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 with 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 GFC, extreme market volatility and breakdowns 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 GFC. 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 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 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. ES values highlight the significant variation in tail risk depending on market conditions, with the GFC 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 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, together 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 GFC. 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)

	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**
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 analyze the performance of long and short positions within the pairs trading strategy across three distinct periods: the GFC Period, the Bullish and Bearish Period, and the COVID-19 Period. The goal is to assess the strategy's robustness by examining the individual contributions of the long and short positions to overall performance.

There are at least three reasons to examine separately the returns on the long and short portfolios that make up a pairs position. First, separating the returns of the long and short legs offers further insight into the nature of mean reversion. If pairs trading purely exploits mean reversion, then the abnormal returns from the long and short positions should, in theory, be symmetric. Because the initiation of the trade is equally likely to be triggered by either stock in the pair, asymmetric returns would suggest the presence of other factors influencing profitability.

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

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, this could help explain why the strategy generates returns. Analyzing the risk characteristics of the long and short legs can therefore help identify the underlying drivers of pairs trading performance.

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

During the GFC 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 the 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, creating a drag on overall pairs-trading performance.

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, most long-position alphas were negative and statistically significant, implying that any gains were insufficient to generate abnormal returns after accounting for common risk factors. This suggests that, although long positions occasionally captured upward price movements, they did not outperform in the face of overall market volatility.

Short positions generally had negative mean returns and Sharpe ratios, indicating they contributed to losses during the GFC. Most short positions exhibited negative and statistically significant alphas, highlighting poor performance. For example, Portfolio 15 had an alpha of −206 bps with a t-statistic of −3.93, underscoring significant underperformance. Sharp market declines, 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 GFC. While long positions showed some positive mean returns, their alphas were predominantly negative, suggesting they failed to deliver meaningful abnormal returns. The turbulent market environment—characterized by sudden reversals and elevated volatility—may have adversely affected short positions and disrupted the effectiveness of pairs trading during this period.

During the Bullish and Bearish Period, both long and short positions exhibited consistently negative alphas across almost all portfolios, indicating that pairs trading struggled to generate abnormal returns. Long positions showed modest positive mean returns, while short positions generally had negative mean returns. Short-side alphas 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 than others. However, most long-position alphas were negative and the t-statistics insignificant, implying that positive returns were not abnormal. This suggests that long positions benefited from the general upward market trend rather than from successfully exploiting mispricing.

Short positions, by contrast, had negative mean returns and Sharpe ratios, indicating they detracted from overall performance. Short-side alphas were overwhelmingly negative and statistically significant across all portfolios, highlighting 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, where upward moves were more frequent than downward reversals, making it difficult for shorts to capture gains.

The consistent negative alphas and significant t-statistics for short positions indicate underperformance in this period, likely due to the broader bullish environment. Meanwhile, the positive mean returns for long positions were insufficient to offset short-side losses, especially after adjusting for risk. This suggests that in stable market conditions, lower volatility limits opportunities to profit from temporary mispricings.

During the COVID-19 Period, long-position alphas were mostly insignificant, whereas short positions continued to show negative and significant alphas. Both legs exhibited modest mean returns—longs slightly positive and shorts negative. The neutrality of long positions suggests they neither materially contributed to nor detracted from overall returns during this period.

Long positions posted 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, alphas for long positions were close to zero and mostly insignificant, indicating no meaningful abnormal returns after accounting for common risk factors. This suggests the strategy struggled to capture meaningful profits in the volatile, rapidly changing COVID-19 environment.

Short positions had negative mean returns and Sharpe ratios, though magnitudes were smaller than in prior periods. For example, Portfolio 13 had an alpha of −50 bps with a t-statistic of −4.06, indicating significant underperformance. However, the severity was reduced relative to the GFC and the Bullish and Bearish periods. Elevated volatility and frequent reversals during COVID-19 may have provided more opportunities for shorts to partially recover, reducing their overall negative impact.

The COVID-19 Period featured high volatility and rapid reversals. The reduced short-side underperformance compared with earlier periods suggests less adverse conditions for the strategy, as quick reversals may have created more opportunities to capture short-term mispricings. Long positions were neutral, neither adding to nor significantly detracting from overall returns. While the strategy appeared more resilient during COVID-19, it still struggled to generate significant abnormal returns.

Performance varied meaningfully across the three market periods. During the GFC, long positions had mixed mean returns, with some portfolios performing relatively well, but alphas were predominantly negative, indicating underperformance after adjusting for risk. In the Bullish and Bearish Period, long positions consistently showed positive mean returns but negative alphas, implying no abnormal performance. In the COVID-19 Period, long positions had modest positive mean returns and mostly insignificant alphas, indicating neutrality.

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

Overall, the effectiveness of pairs trading is highly dependent on market conditions. In episodes of extreme volatility, such as the GFC, the strategy struggled due to breakdowns in historical price relationships and difficulties in capturing temporary mispricings. In more stable periods like the Bullish and Bearish Period, low volatility limited opportunities, leading to underperformance. During the COVID-19 Period, the strategy was more neutral, reflecting challenges posed by rapid 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***

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

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

	Long				Short			
Portfolio	Mean	Sharpe	Alpha	*t*-stat	Mean	Sharpe	Alpha	*t*-stat
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 examine the sensitivity of pairs trading strategies to market capitalization, we analyze 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 for large-, mid-, and small-cap stocks, respectively, across the GFC, 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 across market segments.

During the GFC, pairs trading strategies across all market capitalizations generally produced negative mean returns and alphas after accounting for trading costs. For large-cap stocks, portfolios exhibited significantly 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 emerged 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.

Relative to our previous, broader-market results, these negative alphas during the GFC suggest that pairs trading strategies were particularly vulnerable across all segments. 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 capitalization tiers.

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

Interestingly, among small-cap stocks, some portfolios recorded positive mean returns, although 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 in stable market conditions, possibly due to greater idiosyncratic volatility and more frequent mispricing opportunities.

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

During the COVID-19 period, performance again depended on market capitalization. Large-cap stocks continued to underperform, with Portfolio 1 showing an alpha of −14 bps per month, though not statistically significant. Mid-cap stocks displayed negative, but similarly insignificant, alphas (e.g., Portfolio 1 at −12 bps per month).

By contrast, small-cap stocks exhibited more pronounced negative alphas, many 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, small-cap pairs strategies faced greater challenges, possibly due to increased volatility and liquidity constraints within the small-cap segment.

Compared with earlier periods, the COVID-19 results indicate a shift in which small-cap pairs strategies underperformed more markedly. The unique conditions of the pandemic—greater uncertainty and financial stress among smaller firms—may have led to more persistent deviations from historical price relationships, reducing the effectiveness of mean reversion.

The variations in performance across market capitalizations highlight several aspects of pairs trading. Large-cap stocks are typically more liquid and efficiently priced, which can limit the mispricing opportunities that pairs trading seeks to exploit. The consistently negative and significant alphas for large-cap portfolios across periods suggest that transaction costs and limited 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 may find occasional opportunities but is not consistently profitable. Insignificant alphas suggest that any potential gains are offset by the risks and costs associated with trading mid caps.

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, some small-cap portfolios showed positive mean returns, hinting at the potential for pairs strategies to capitalize on inefficiencies in this segment. However, during periods of extreme stress—such as the GFC and COVID-19—small-cap pairs strategies underperformed, likely due to heightened volatility, wider bid–ask spreads, and liquidity constraints that magnify trading costs and risks.

These findings underscore the importance of considering market capitalization when implementing pairs trading. Investors should note that large caps may not offer sufficient mispricing to overcome trading costs, leading to consistent underperformance. While small caps may present more opportunities, they also entail higher risks—particularly in volatile markets where liquidity dries up and price deviations persist longer than anticipated.

Moreover, performance differences across periods highlight the crucial role of market conditions. In stable periods, small-cap strategies might fare better due to more frequent mean-reversion opportunities. In crises, all segments tend to underperform, with small caps being particularly vulnerable.

Overall, the robustness and sensitivity analyses show that pairs trading outcomes are significantly influenced by market capitalization and prevailing conditions. The consistent underperformance of large-cap pairs trading suggests limited efficacy in that segment, while the mixed results for mid and small caps point to conditional profitability alongside heightened risk.

These insights contribute to a broader understanding of pairs trading by emphasizing careful pair selection, explicit consideration of transaction costs, and adaptability to market environments. Investors should weigh trade-offs between potential returns and risks across capitalization tiers and adjust their strategies accordingly to improve the likelihood of success.

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***

	Financial Crisis				Bullish and Bearish				COVID-19			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
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**

	Financial Crisis				Bullish and Bearish				COVID-19			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
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***

	Financial Crisis				Bullish and Bearish				COVID-19			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
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 earlier findings and gauge the sensitivity of pairs trading strategies to transaction costs, we re-estimate performance assuming lower trading frictions—specifically, a 30 bps reduction for both buy and sell transactions. The results are reported in Table 26 and compared with our previous estimates in Tables 8, 9, and 10, which applied a higher transaction cost of 100 bps. This comparison clarifies how costs shape the profitability and practical viability of pairs trading across market regimes.

Table 26 shows that cutting transaction costs materially changes portfolio performance across all three periods—the GFC, the Bullish and Bearish period, and the COVID-19 period. During the GFC, mean returns and alphas are generally less negative than under the higher-cost assumption, and some portfolios even record positive mean returns and alphas, though their t-statistics are not always significant.

In the Bullish and Bearish period, mean returns and alphas move closer to zero or turn slightly positive, indicating that lower costs mitigate the drag observed previously and lift overall performance.

During the COVID-19 period, many portfolios post positive mean returns and alphas, with several achieving statistically significant alphas. This suggests that lower costs enhance the profitability of pairs trading in that environment.

Under the prior 100 bps cost assumption, pairs trading generally underperformed across all periods, with negative alphas and low or negative Sharpe ratios—evidence that frictions eroded profits from exploiting small price deviations. By contrast, Table 26 demonstrates that trimming costs by 30 bps meaningfully improves outcomes. Average monthly returns shift from negative to positive—or from more negative to less negative—across many portfolios. Estimated alphas are higher (less negative or more positive), and several portfolios now exhibit positive alphas, implying abnormal returns beyond common risk factors. Corresponding t-statistics improve as well, with fewer significantly negative alphas and, in some cases, positive and statistically significant alphas. Sharpe ratios generally rise, reflecting stronger risk-adjusted performance.

The sensitivity of pairs trading to costs is well documented. Because expected profits per trade are modest, transaction costs—both explicit (commissions) and implicit (spreads, market impact)—can materially compress net returns. High turnover, a hallmark of pairs strategies that exploit short-lived divergences, magnifies cumulative costs. Lowering costs therefore reduces the hurdle each trade must clear to be profitable, which is exactly what we observe when costs are reduced by 30 bps.

During the GFC, the severe negative alphas under the high-cost setting are notably tempered. While some portfolios still show negative alphas, the magnitudes are smaller, and a few turn positive, indicating that lower costs help strategies better weather turbulent conditions where volatility and rapid dislocations create more frequent mean-reversion opportunities. In the Bullish and Bearish period, improved metrics suggest pairs trading becomes more viable in stable markets when costs are lower, allowing traders to harvest smaller price discrepancies that previously were uneconomical. During the COVID-19 period, the prevalence of positive alphas and mean returns points to enhanced capacity to earn abnormal returns amid uncertainty and rapid market shifts.

These findings align with established intuition: lower costs raise net profit margins per trade, enabling more effective exploitation of small, frequent mean-reversion signals—especially in relatively efficient markets where mispricings are narrow. In volatile regimes (e.g., the GFC and COVID-19), divergences are larger but also less predictable; lower costs provide valuable flexibility to enter and exit positions more freely, improving adaptability and risk-adjusted outcomes. With reduced frictions, traders can also set tighter stops and rebalance more responsively without transaction costs overwhelming potential benefits.

That said, several practical considerations remain. Achieving lower costs can be difficult in less liquid markets or among smaller-cap stocks, where spreads are wider and market impact is higher. Securing low costs may require premium brokerage arrangements, algorithmic execution, or higher volumes—each with its own complexities and expenses. Moreover, as costs fall, competition for arbitrage opportunities may intensify, compressing spreads and accelerating price convergence.

Overall, the robustness and sensitivity analysis underscores that transaction costs are pivotal to the viability of pairs trading. A 30 bps reduction significantly lifts performance across market conditions, turning some previously unprofitable strategies into potentially profitable ones. For practitioners, the results highlight the importance of actively managing trading expenses—via negotiated commissions, efficient execution algorithms, or HFT platforms—to materially affect outcomes. Understanding how costs interact with market regimes can also guide strategy selection and timing: focus on periods or venues where low costs can be secured or where divergences are ample enough to overcome remaining frictions. Lower costs improve risk-adjusted returns and support more effective risk management and position sizing.

For researchers, these results emphasize the need to model realistic trading frictions and to explore execution methods that reduce them (e.g., algorithmic strategies, alternative venues). Studying how changes in costs influence market efficiency and arbitrage availability can yield deeper insights into market dynamics.

In short, transaction costs bridge the gap between theoretical profitability and real-world implementation. Even modest reductions can materially change outcomes. By carefully measuring, minimizing, and managing these costs, traders and researchers can better harness pairs trading's potential to deliver attractive returns across 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

	Financial Crisis				Bullish and Bearish				COVID-19			
Portfolio	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**	**Mean**	**Sharpe**	**Alpha**	***t*-stat**
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 across three extreme market environments—the GFC, the Bullish and Bearish phases, and the COVID-19 period. Overall, while pairs trading is generally unprofitable after accounting for transaction costs, certain portfolios and conditions still yield positive returns. The evidence underscores that the effectiveness of pairs trading depends critically on market regimes and on the characteristics of the selected stock pairs.

During the GFC, pairs trading strategies performed relatively strongly compared with other periods. Elevated volatility and wider cross-sectional dispersion created more opportunities for prices to revert toward historical relationships. Notably, even after trading costs, several top portfolios produced monthly excess returns of up to 156 bps (annualized 18.72%). This suggests that during severe market dislocations—when many traditional strategies struggle—pairs trading can still deliver market-neutral gains.

Results were mixed across the Bullish and Bearish phases. In rising markets, most portfolios generated negative or insignificant returns, consistent with persistent uptrends undermining the mean-reversion premise. In contrast, performance improved in declining markets: several portfolios achieved modest positive returns, indicating that pairs trading is better suited to falling or volatile conditions where reversals are more frequent.

The COVID-19 period posed distinct challenges. Unprecedented disruptions altered price dynamics and correlations, complicating the identification of reliable pairs. Consequently, average profitability declined, and most portfolios earned near-zero excess returns after costs. Even so, a subset of portfolios formed within specific industries—particularly those less affected by the pandemic—managed to achieve modest positive returns. This highlights the importance of industry selection and suggests that tailoring pair formation to prevailing conditions can preserve efficacy.

A central takeaway is the decisive role of trading costs. Across all periods, frictions materially eroded gross returns, often converting potentially profitable trades into losses—a pattern especially pronounced in China, where transaction costs are relatively high by global standards. Reducing costs—through more efficient execution or by focusing on higher-liquidity pairs—could materially improve net outcomes.

Performance also varied across pair-selection methodologies. Portfolios formed with more sophisticated criteria—such as SSD combined with the Hurst exponent and NZC—consistently outperformed those using simpler rules. Refining the matching process is therefore crucial, particularly in markets where correlations shift rapidly, as during COVID-19.

In sum, pairs trading in the Chinese market is generally unprofitable after realistic costs, yet it can still generate positive returns under certain conditions. For practitioners, the results emphasize careful pair selection, explicit consideration of trading costs, and adaptation to changing market environments—especially regime shifts in volatility and correlation.

Future research could enhance these insights by incorporating additional dimensions—liquidity, volatility, and macroeconomic indicators—into pair formation and timing. Developing dynamic models that adjust trading thresholds to real-time conditions may further improve adaptability and profitability in volatile markets.

Taken together, these findings offer a nuanced view of pairs trading across market states and provide actionable guidance for optimizing its implementation in the Chinese equity market. They underscore the value of flexibility and strategic refinement when deploying market-neutral strategies under varying economic scenarios.

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