Is Pairs Trading a thing of the past?

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Abstract

The profitability of traditional pairs trading, a market-neutral strategy based on identifying and exploiting temporary price divergences between two historically related stocks, has significantly eroded over the past two decades. This paper argues that the decline is not due to a failure of the underlying principle of relative-value arbitrage, but rather to the restrictive 1-to-1 nature of the conventional methodology. We propose a generalization of pairs trading by replacing the single partner stock with a replicating portfolio constructed as a linear combination of multiple securities. Our approach utilizes LASSO to create a parsimonious and tradable portfolio that collectively mimics the price behavior of a target asset, thereby creating a more robust and flexible substitute. This method preserves the economic intuition of the original strategy while expanding the set of trading opportunities. Our empirical analysis, conducted on U.S. equity data from 1962 to the present, demonstrates that while the profitability of the classic approach has decayed, our generalized strategy consistently delivers significant excess returns, particularly in the post-2000 period. The findings suggest that by relaxing the rigid pairing constraint and embracing a portfolio-based replication, the pairs trading strategy can be revitalized and adapted to the complexities of modern financial markets.

JEL Codes: G11, G12, G14, C58

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1. Introduction

Pairs trading is a strategy built on a simple, intuitive idea: if two assets are closely related, their prices should move together. When they drift apart, a trading opportunity emerges. The classic approach involves finding two such assets, waiting for a significant price divergence, and then buying the underperforming asset while shorting the outperforming one. The bet is that the prices will eventually converge, at which point the positions are closed for a profit. This self-contained, market-neutral logic is what has made pairs trading a cornerstone of quantitative finance for decades.

The strategy's roots trace back to the 1980s at Morgan Stanley, where a team of quantitative analysts, led by Nunzio Tartaglia, developed and deployed it with great success. For years, it remained a proprietary tool of sophisticated investment firms like D.E. Shaw and Long-Term Capital Management. However, the secret eventually got out, and pairs trading became a widely adopted strategy across Wall Street and beyond, particularly after the turn of the millennium.

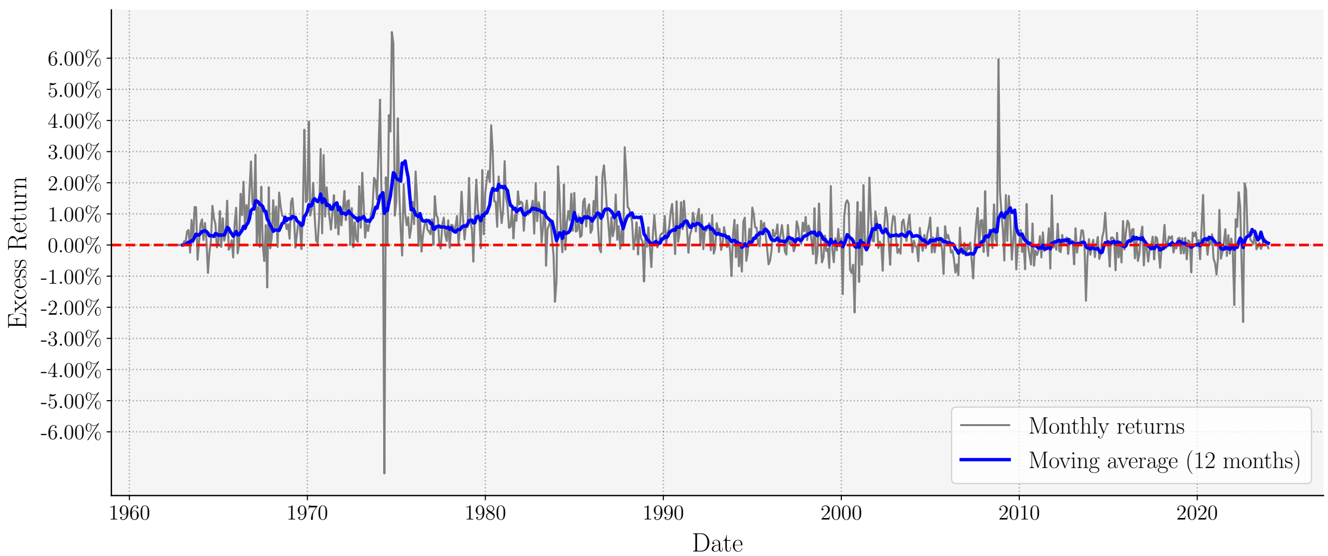
At its core, pairs trading is an application of the Law of One Price, a fundamental concept in finance stating that two assets with identical payoffs must trade at the same price. While no two stocks are perfect substitutes, the strategy wagers that the prices of two historically linked assets are co-integrated, meaning their price difference is stationary and will revert to its historical mean. Traditional pairs trading, therefore, searches for pairs where this co-integrating relationship is strong and stable.

However, the financial landscape has changed. The very popularity of pairs trading has eroded its effectiveness. As more traders have sought to exploit the same opportunities, the simple, stable pairs that once fueled the strategy have become increasingly scarce. The traditional 1-to-1 pairing model, while elegant, is now too restrictive.

This is where our paper steps in. We argue that the rigid 1-to-1 structure is the primary cause of the strategy's decline. Instead of searching for a single substitute for a target asset, why not construct a better one? We propose generalizing the pairs trading framework from a 1-to-1 to a 1-to-many relationship. By using a portfolio of assets, we can create a more robust and accurate replicating portfolio for our target asset. This approach allows us to trade the target against its synthetic counterpart, opening up a much richer set of trading opportunities that are less susceptible to the noise of individual stock movements.

Our work builds upon a rich but recently stagnant body of literature. The seminal study by Gatev et al. (2006) provided the first large-scale empirical evidence of pairs trading's profitability, cementing its academic legitimacy. However, even they documented a decay in returns over their sample period (which extended to 2002). Do and Faff (2010) extended this analysis to 2009 and confirmed the declining trend, though they noted a brief, sharp resurgence in profitability during the market turmoil of the Great Financial Crisis. In Figure 1 we have replicated the return series from these papers and further extended the sample to December 2024. As we can see, the monthly excess returns to pairs trading are indistinguishable from zero in the last decade.

FIGURE 1: **Decay of 1-to-1 Pairs Trading Returns**



Note: This figure shows the monthly excess returns to 1-to-1 pairs trading and its 12-month moving average from January 1962 to December 2024. The methodology replicates Gatev et al. (2006) and Do and Faff (2010), extending the sample period to December 2024. Returns are computed using the one-day waiting rule to mitigate potential microstructure effects and they are net of transactions costs, assuming 1bps per trip for each traded stock.

Since then, much of the research has focused on methodological tweaks, applying more complex statistical techniques rather than questioning the underlying 1-to-1 framework. This has led to a fragmented literature of incremental improvements, often lacking a clear theoretical justification and failing to address the strategy's fundamental decay.

This paper fills that conceptual gap by proposing a principled evolution of the pairs trading framework. We introduce a sparse replicating portfolio, constructed using LASSO regularization, to create a synthetic asset that is both an accurate and stable substitute for a target asset. Our empirical results show that this generalized approach restores the strategy's profitability, delivering consistent returns even in recent periods where the traditional method has failed.

The remainder of this paper is organized as follows. Section 2 details our proposed methodology. Section 3 describes the data and presents the empirical results of our replicating portfolio approach to pairs trading compared to the traditional approach. Finally, Section 4 concludes.

2. Methodology

The economic intuition behind pairs trading –exploiting a temporary price divergence between two close substitutes– can be cast more generally as a problem of relative valuation. Rather than forcing the substitute for a target stock, i, to be a single partner stock, we allow it to be a *replicating portfolio*: a linear combination of securities whose joint price path mimics that of stock i.

This relationship can be expressed as a simple regression problem. We model the normalized price of our target asset, $p_{i,t}$, as a weighted average of the prices of other assets in a given universe, which we call the donor pool, $\mathcal{D}$.

$$p_{i,t} = \sum_{j \in \mathcal{D}} \beta_j \, p_{j,t} + \varepsilon_{i,t}, \qquad t = 0, \ldots, T \tag{1}$$

Here, the vector $\boldsymbol{\beta}$ contains the weights of the assets in the replicating portfolio, and the residual term, $\varepsilon_{i,t}$, represents the price differential between the target asset and its synthetic replica. This difference is the object we want to trade. If we assume it's mean-reverting, we can bet on its convergence, just as in traditional pairs trading.

This framework is powerful because it allows us to see traditional pairs trading methods for what they are: highly restrictive special cases of this more general approach.

Pairs Trading 1-to-1. For instance, the classic 1-to-1 pairs trading strategy, as popularized by Gatev et al. (2006), is equivalent to solving the regression in eq. (1) with a severe constraint: the coefficient vector $\boldsymbol{\beta}$ must be a canonical basis vector (e.g., $[0, 1, 0, \ldots, 0]$). Let $\mathcal{B} := \{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_{|\mathcal{D}|}\}$ denote the canonical basis of $\mathbb{R}^{|\mathcal{D}|}$. "Traditional" pairs trading fixes a target stock i and selects a single-asset replicating portfolio in a one-to-one relationship by imposing the restriction $\boldsymbol{\beta} \in \mathcal{B}$.

$$\min_{\boldsymbol{\beta} \in \mathcal{B}} \sum_{t=0}^{T} \left(p_{i,t} - \sum_{j \in \mathcal{D}} \beta_j p_{j,t} \right)^2$$

This effectively means selecting only one asset, j^*, from the donor pool to be the pair whose normalized price series minimizes the sum of squared differences with respect to that of the target asset's price.

$$j^* = \arg\min_{j \in \mathcal{D}} \sum_{t=0}^{T} \left(p_{i,t} - p_{j,t} \right)^2$$

Pairs Trading with a Hedge Ratio. A slightly more flexible version, pairs trading with a hedge ratio, also fits neatly into this framework. In this case, the space of possible solutions is $\mathcal{B}^+ := \{\alpha \mathbf{e}_j : j \in \mathcal{D}, \alpha \in \mathbb{R}\}$ and the replicating portfolio program is:

$$\min_{\boldsymbol{\beta} \in \mathcal{B}^+} \textstyle\sum_{t=0}^{T} \Big(p_{i,t} - \sum_{j \in \mathcal{D}} \beta_j p_{j,t} \Big)^2$$

This approach is equivalent to restricting the cardinality of the coefficient vector to one, but allowing that single coefficient to be any real number, α. This means we still select only one partner stock, but we can scale its position with a hedge ratio.

$$\begin{aligned} \min_{\boldsymbol{\beta} \in \mathbb{R}^{|\mathcal{D}|}} \quad & \textstyle\sum_{t=0}^{T} \Big(p_{i,t} - \sum_{j \in \mathcal{D}} \beta_j p_{j,t} \Big)^2 \\ \text{s.t.} \quad & \|\boldsymbol{\beta}\|_0 = 1 \end{aligned}$$

For illustration, consider a universe of four assets. We select a replicating portfolio for a target asset from a donor pool of the other three. Figure 2 depicts the restricted solution spaces for traditional pairs trading methods. In the simplest case (Figure 2a), the replicating portfolio is restricted to be one of the three assets in a 1-to-1 relationship. A slightly more flexible approach (Figure 2b) allows for a hedge ratio, scaling the single asset to better match the target, but still confines the solution to a single partner.

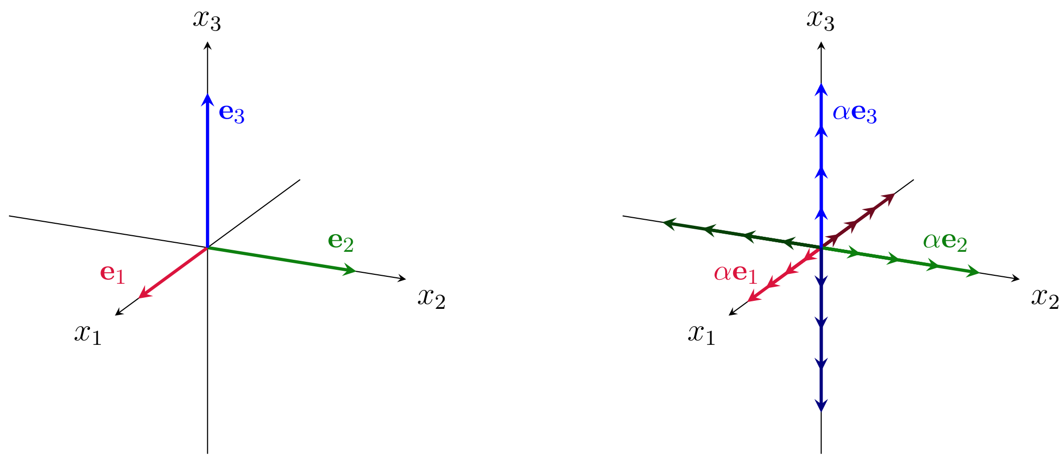
Pairs Trading A Sparse Replicating Portfolio While these restrictions offer simplicity, they are not economically motivated and severely limit the potential for finding effective hedges. Our approach removes these hard constraints. We aim to build a better replicating portfolio by allowing it to be composed of multiple assets. However, an unrestricted regression often leads to a dense portfolio with hundreds of small positions, making it impractical to trade due to high transaction costs.

To solve this problem, we introduce a "principled" constraint that encourages sparsity in a soft way: LASSO (Least Absolute Shrinkage and Selection Operator) regularization. The goal is to find a coefficient vector $\boldsymbol{\beta}$ that balances replication accuracy with portfolio sparsity. We do this by minimizing the sum of squared residuals while also penalizing the sum of the absolute values of the coefficients:

$$\min_{\boldsymbol{\beta} \in \mathbb{R}^{|\mathcal{D}|}} \left\{ \sum_{t=0}^{T} \left(p_{i,t} - \sum_{j \in \mathcal{D}} \beta_j p_{j,t} \right)^2 + \lambda \sum_{j \in \mathcal{D}} |\beta_j| \right\} \tag{2}$$

The tuning parameter, λ, is the key. It controls the trade-off between the two objectives in the equation.

FIGURE 2: **Replicating portfolio in the canonical and augmented canonical spaces**



(A) Canonical Space (B) Augmented Canonical Space

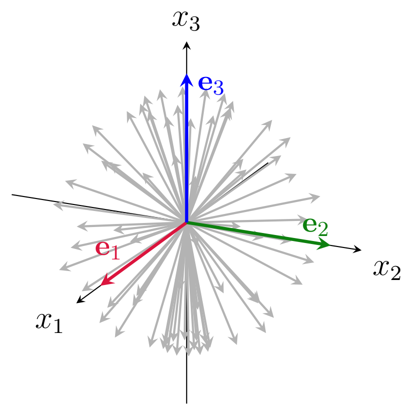
Note: This figure illustrates the restricted solution spaces for traditional pairs trading methods within a 3-dimensional space ($\mathbb{R}^3$). Panel (a) shows the canonical space, where the replicating portfolio is limited to a single asset in a 1-to-1 relationship. Panel (b) depicts the augmented canonical space, allowing for a hedge ratio to scale the single asset, yet still confining the solution to a single partner.

- When λ is close to zero, the penalty is negligible, and the solution approaches the standard OLS regression, resulting in a dense, high-cost portfolio.
- As λ increases, the penalty becomes more severe, forcing more coefficients to become exactly zero. This produces a sparser, more parsimonious replicating portfolio that is cheaper to trade.

By selecting an appropriate λ, we can construct a replicating portfolio that is both a good substitute for the target asset and is sparse enough to be traded efficiently. This method provides a flexible, yet disciplined, generalization of the original pairs trading concept.

Figure 3 illustrates the expanded solution space of our proposed approach. By relaxing the one-asset constraint, the replicating portfolio can now be formed by a linear combination of multiple assets from the donor pool. This allows for a much richer and more flexible representation of the target asset. The LASSO penalty ensures that the resulting portfolio remains sparse, balancing the improved replication accuracy with the practical need for parsimony. The following section details our empirical implementation and assesses whether this generalized approach can restore profitability.

Figure 3: **Replicating portfolio in the Replicating Portfolio space**



$\mathbb{R}^3 = \text{span}(\mathcal{B})$

Note: This figure illustrates the expanded solution space for constructing a replicating portfolio using our approach. Unlike traditional methods, the replicating portfolio can be a linear combination of multiple assets from the donor pool. Although the space of replicating portfolios is unrestricted, we soft-constrain it to be sparse by employing LASSO regularization, balancing replication accuracy with practical parsimony.

3. Empirical Application

3.1 Data and Sample Construction

We use daily stock data from the Center for Research in Security Prices (CRSP) from January 1, 1962, to December 31, 2024. Our sample includes all ordinary common stocks (share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ exchanges.

Our empirical design follows the rolling two-stage approach as in Gatev et al. (2006). For each month in our sample, we use a 12-month "formation window" ($\mathcal{T}_{for}$) to identify trading opportunities and estimate model parameters. These opportunities are then traded in the subsequent 6-month "trading window" ($\mathcal{T}_{trad}$). This process is rolled forward monthly, creating a continuous series of overlapping trading periods.

At the beginning of each 12-month formation window, we define $\mathcal{U}$, our universe of eligible stocks. To ensure our assets are liquid and their prices are directly comparable, we include only those securities that have a valid return for every trading day within that formation window,

$$\mathcal{U} := \{j : \exists\, r_{j,t}\ \forall t \in \mathcal{T}_{for}\}.$$

For each of these stocks, we then construct a cumulative return index, which tracks the value of one dollar invested at the start of the window, with all dividends reinvested. This becomes the normalized price series used in our analysis.

$$p_{j,0} = 1, \quad p_{j,t} = \prod_{\tau=1}^{t}(1 + r_{j,\tau}), \quad t \in \mathcal{T}_{for}$$

3.2 Empirical Design

For every stock i in our liquid universe, we treat it as a potential target and aim to build a sparse replicating portfolio for it. The donor pool for each target consists of all other liquid stocks in the universe, $\mathcal{D}_i = \mathcal{U} \setminus \{i\}$,. As outlined in the methodology section, we find the weights, $\boldsymbol{\beta_i}$, of the replicating portfolio by regressing the target's normalized price series against the price series of all stocks in the donor pool, using a LASSO penalty to ensure the resulting portfolio is sparse.

$$\widehat{\boldsymbol{\beta_i}} := \underset{\boldsymbol{\beta} \in \mathbb{R}^{|\mathcal{D}_i|}}{\arg\min} \left\{ \sum_{t \in \mathcal{T}_{\text{for}}} \left(p_{i,t} - \sum_{j \in \mathcal{D}_i} \beta_j p_{j,t} \right)^2 + \lambda \sum_{j \in \mathcal{D}_i} |\beta_j| \right\}$$

For our main analysis, we set the penalization parameter λ to 0.01. This value provides a good balance, creating replicating portfolios that are parsimonious, typically containing around 15 assets while still tracking the target asset closely. The resulting price spread for each potential trade is the time series of the regression residuals. We then rank all potential target-replica pairs based on their in-sample Mean Squared Error (MSE)

$$\text{rank}(i) = \sum_{j \in \mathcal{U}} \mathbf{1}\{MSE_i \geq MSE_j\},$$

where $MSE_i := \sum_{t \in \mathcal{T}_{for}} (p_{i,t} - \sum_{j \in \mathcal{D}_i} \beta_j p_{j,t})^2$.

For the purpose of benchmarking, we retain the simple trading rule of Gatev et al. (2006). In particular, we monitor the spread for each pair during the 6-month trading window. A position is opened whenever the spread widens beyond two of its historical standard deviations $\hat{\sigma}_i$, as estimated during the formation window. If the spread falls below -2$\hat{\sigma}_i$, we go long the target stock and short its replicating portfolio. If the spread rises above +2$\hat{\sigma}_i$, we do the opposite.

$$TR(\varepsilon_{i,t}) = \begin{cases} \text{LONG} & \text{if} \quad \epsilon_{i,t} < -2\hat{\sigma}_i \\ \text{SHORT} & \text{if} \quad \epsilon_{i,t} > +2\hat{\sigma}_i \\ \text{NEUTRAL} & \text{if} \quad \text{else} \end{cases}$$

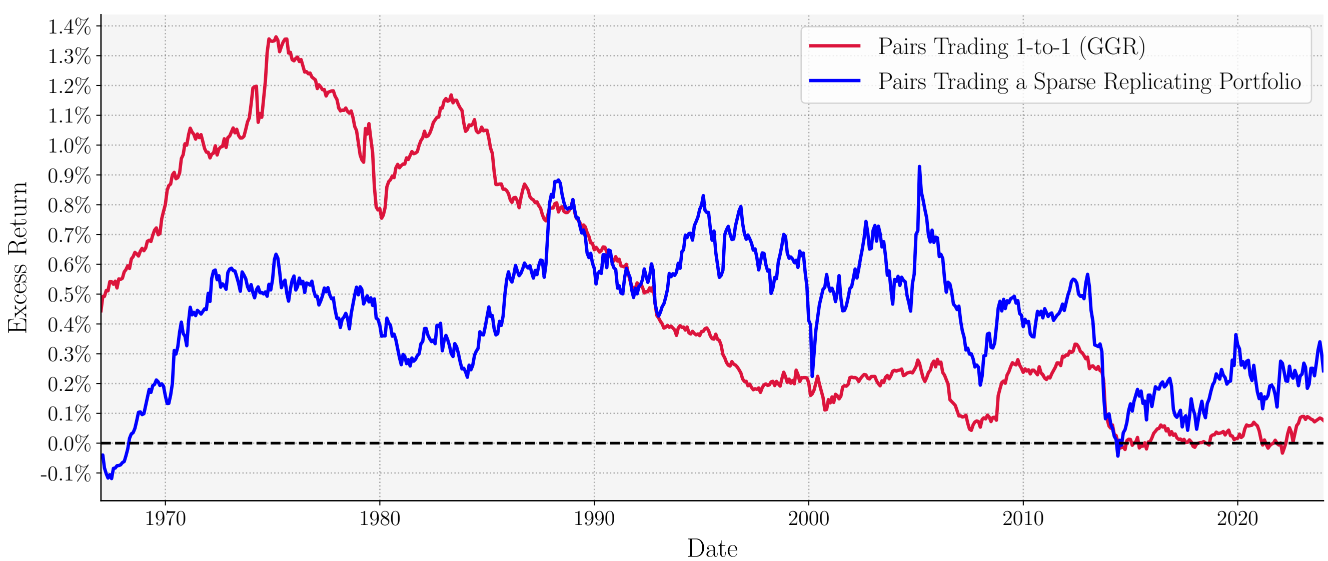
Positions are held until the spread reverts to zero or the 6-month trading window ends.

Payoffs are calculated as excess returns from these self-financing, dollar-neutral positions. All positions are marked-to-market daily, and the daily returns are compounded to calculate monthly returns. To provide a comprehensive view of performance, we measure returns in two ways: return on *committed* capital, which assumes capital is allocated to every selected pair, and return on *fully invested* capital, which considers only the capital used in triggered trades. Finally, to ensure our results are robust to microstructure effects like bid-ask bounce, we also test a "one-day waiting" rule, where we execute trades on the day after a signal is generated.

3.3 Results

The core finding of our paper is that generalizing the pairs trading framework with a sparse replicating portfolio restores its profitability in the modern era. This is vividly illustrated in Figure 4, which plots the 40-month moving average of monthly excess returns for our generalized strategy against the traditional one-to-one approach. The divergence is stark: while the traditional strategy's profitability decays and hovers near zero for the last decade, our generalized method delivers consistent, positive excess returns throughout the entire sample period. This visual evidence strongly suggests that while simple pairs trading has lost its edge, the underlying principle of mean reversion remains exploitable with a more robust methodology.

FIGURE 4: **Monthly excess return comparison: 1-to-1 Vs. Replicating Portfolio**



Note: We plot the 40-month moving average of monthly excess returns for traditional pairs trading versus the replicating portfolio approach. All returns are computed using the one-day waiting rule to mitigate potential microstructure effects and they are net of transactions costs, assuming 1bps per trip for each traded stock.

In **?** we described the distribution of monthly excess returns to pairs trading a sparse replicating portfolio without accounting for transaction costs. The average monthly excess return for a portfolio of all triggered pairs is a statistically significant 0.86% for the "no waiting" rule (t-statistic = 11.59), and 0.75% (t-statistic = 10.94) for the "wait-one-day rule". This is equivalent to a 10.32% and 9% annualized return respectively for each rule. The top-ranked pairs exhibit even higher returns, although the differences across the top portfolios are modest. The strategy is profitable in the majority of months, with the "All Pairs" portfolio showing positive excess returns in 70% of observed months.

In **?** we repeat the same exercise, but this time, accounting for a 1bps trading cost imposed on each trip per traded stock. As expected, there is some performance degradation, but conclusions remain unaffected. In this case, the annualized returns reduce to 8.04% and 7.08% respectively across rules, and remain statistically significant.

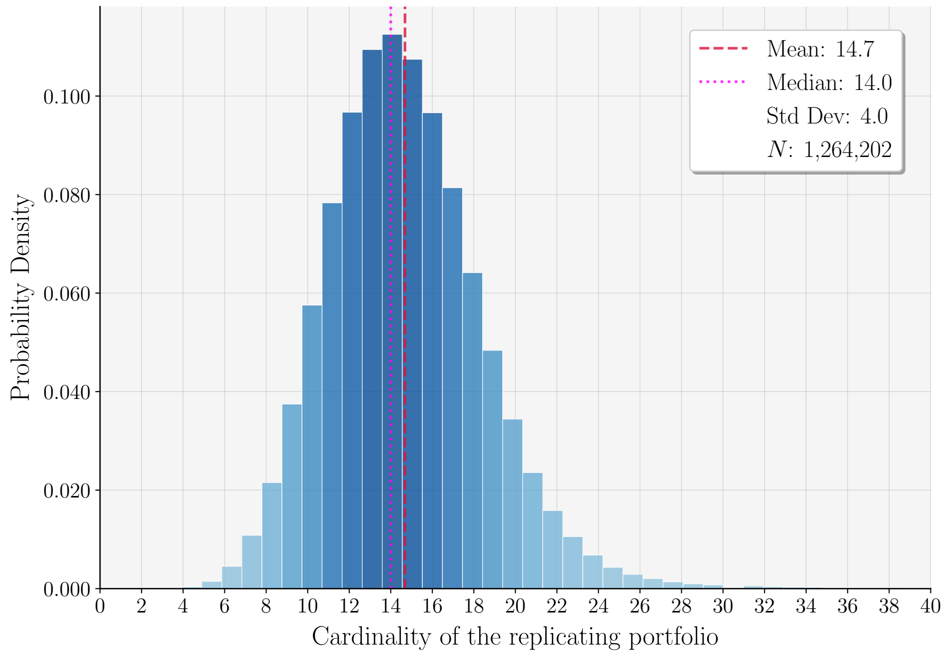
The success of our strategy hinges on the construction of the replicating portfolios. By design, the LASSO penalty fosters sparsity. Figure 5 shows the distribution of the number of constituents in these portfolios. The distribution is tightly centered around a median of 15 assets, confirming that the method consistently produces parsimonious portfolios. This feature is crucial for practical implementation, as it helps manage transaction costs and avoids overfitting.

A consistent stream of trading opportunities is essential for any active strategy. Figure 6 displays the number of active positions over time. The plot shows that the strategy identifies a substantial number of trading opportunities throughout the entire sample period. While the number of open pairs fluctuates, likely in response to changing market volatility and dispersion, there is no discernible downward trend. This indicates that the opportunities for pairs trading with a replicating portfolio have not diminished over time, reinforcing the findings from Figure 4.

We further confirm that these excess returns are not merely compensation for exposure to systematic risk factors. Table 4 presents alphas and factor loadings from a multi-factor model including the Fama-French five factors, momentum, and short- and long-term reversals. The key finding is the intercept (alpha), which is positive and highly statistically significant across all portfolios, ranging from 0.41% to 0.62% per month (4.92%, to 7.44% annualized). This indicates a substantial abnormal return that cannot be explained by standard risk factors. Interestingly, the market beta is negative and significant for the top-ranked pairs, suggesting they provide a hedge in down markets. As we aggregate across all pairs, the market beta approaches zero, and the overall strategy becomes market-neutral. The significant negative loading on momentum and positive loading on short-term reversal are consistent with a contrarian strategy that bets against recent price trends.

The same conclusions remain valid, although with a slight degradation, when we repeat the

FIGURE 5: **Number of constituents in the replicating portfolio**



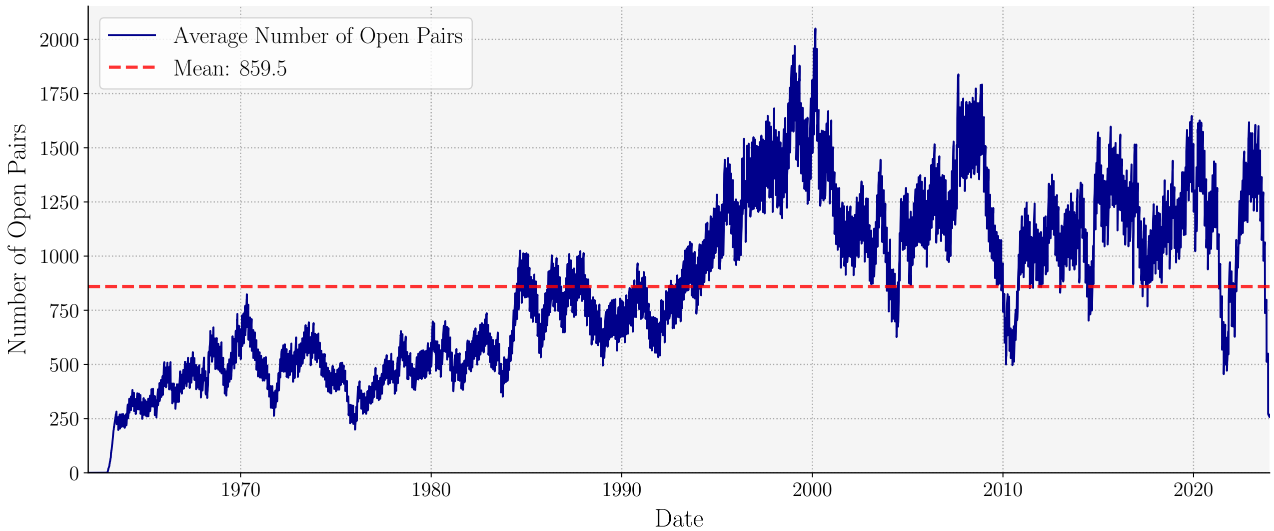
Note: This figure displays the distribution of the number of assets included in the replicating portfolios. The LASSO penalty effectively shrinks most coefficients to zero, resulting in parsimonious portfolios that typically contain around 15 constituents.

same exercise on the strategy returns net of transaction costs of 1bps per trip for each traded stock. In particular, alphas remain statistically significant at conventional levels, and range between 0.26% to 0.51% (3.12% to 6.12% annualized).

In Figure 7 we show the sensitivity of the strategy gross returns to different choices of the LASSO penalty parameter λ. Higher values of λ promote sparser replicating portfolios, but exhibit lower replication quality, while lower values deliver denser portfolios but better replication quality. Unsurprisingly, low λ portfolios deliver worse excess returns, however, to our surprise, very low λ portfolios are also not that good, potentially, due to an overfitted replication with too many assets. The sweet spot lies in the intermediate-λ values. This conclusion is further corroborated by Figure 8, where we perform the same exercise, but this time, accounting for transaction costs. Now, we observe that the low-λ portfolios become too expensive to trade, as transaction costs are linearly increasing in the cardinality of the portfolio. High-λ portfolios are less affected by transaction costs, but remain unprofitable due to worse replication quality.

In conclusion, 1-to-1 pairs trading was extremely profitable for most of the sample, but its profitability has decayed to 0 in recent years. Surprisingly, even though the 1-to-1 pairs trading

Figure 6: **Number of Open Pairs**

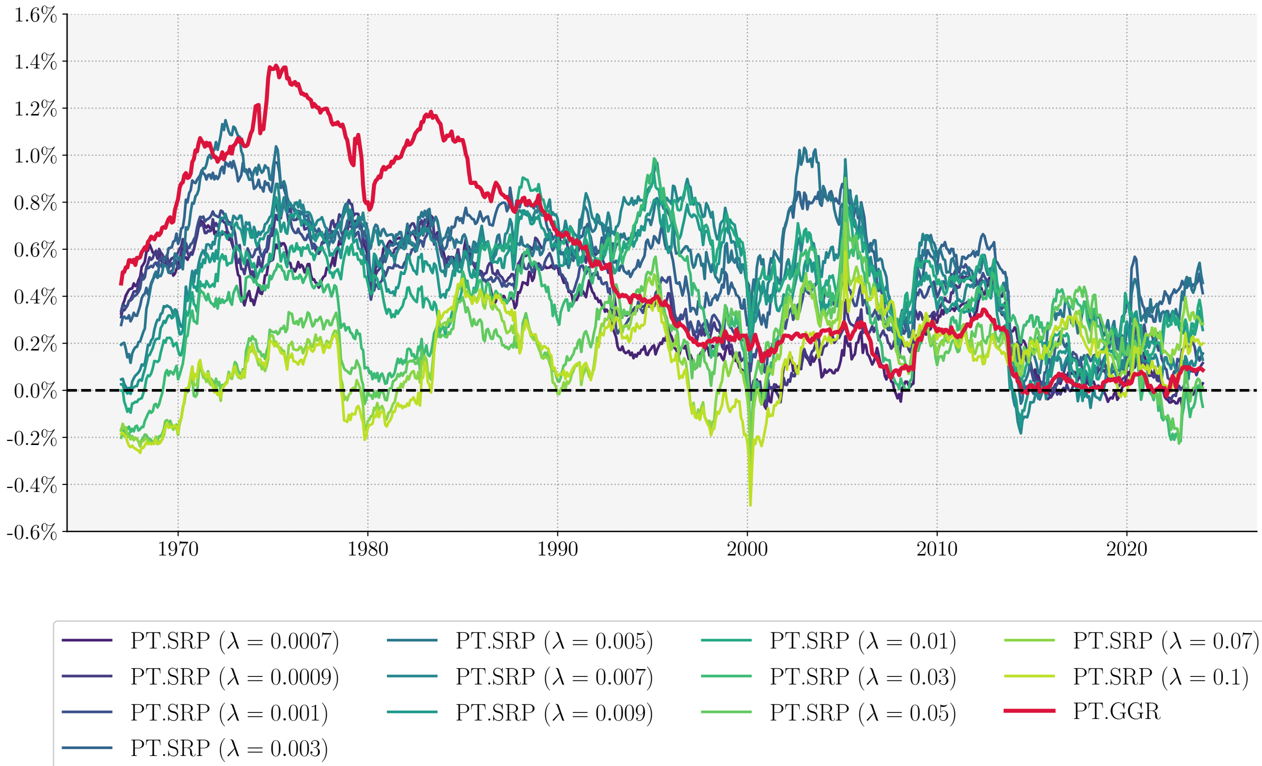


Note: This figure displays the time series of active trading positions throughout our sample period. Each point represents the number of pairs that have triggered a trade signal but have not yet converged or reached the end of their trading window. The strategy finds a consistent stream of trading opportunities over time.

anatomy is both extremely simple and restrictive, it is really hard to beat. None of the the LASSO replicating portfolio configurations were able to beat it before 1990. However, the popularization of 1-to-1 pairs trading lead to an increased market efficiency of pairs of assets, while there is still some room for exploiting the inefficiencies in the replicating portfolio space. Although the profitability of the latter is also decaying, it is still positive.

Finally, Figure 9 shows the equity curve of 1$ investment in 2000 to pairs trading strategies. In blue we show the equity curves of the sparse replicating portfolio approach, while the red lines show those of 1-to-1 pairs trading. Also for reference we plot in green the equity curve of the market portfolio. As we can see, the market portfolio is more volatile than the portfolios generated by pairs trading strategies and delivers a lower Sharpe Ratio. Finally, since the top pairs of the sparse replicating portfolio pairs trading strategy has negative correlation with the market portfolio, we also include a combined portfolio of this strategy with the market. Unsurprisingly, this combined portfolio yields the maximal Sharpe Ratio.

Figure 7: **Robustness to λ (before transaction costs)**



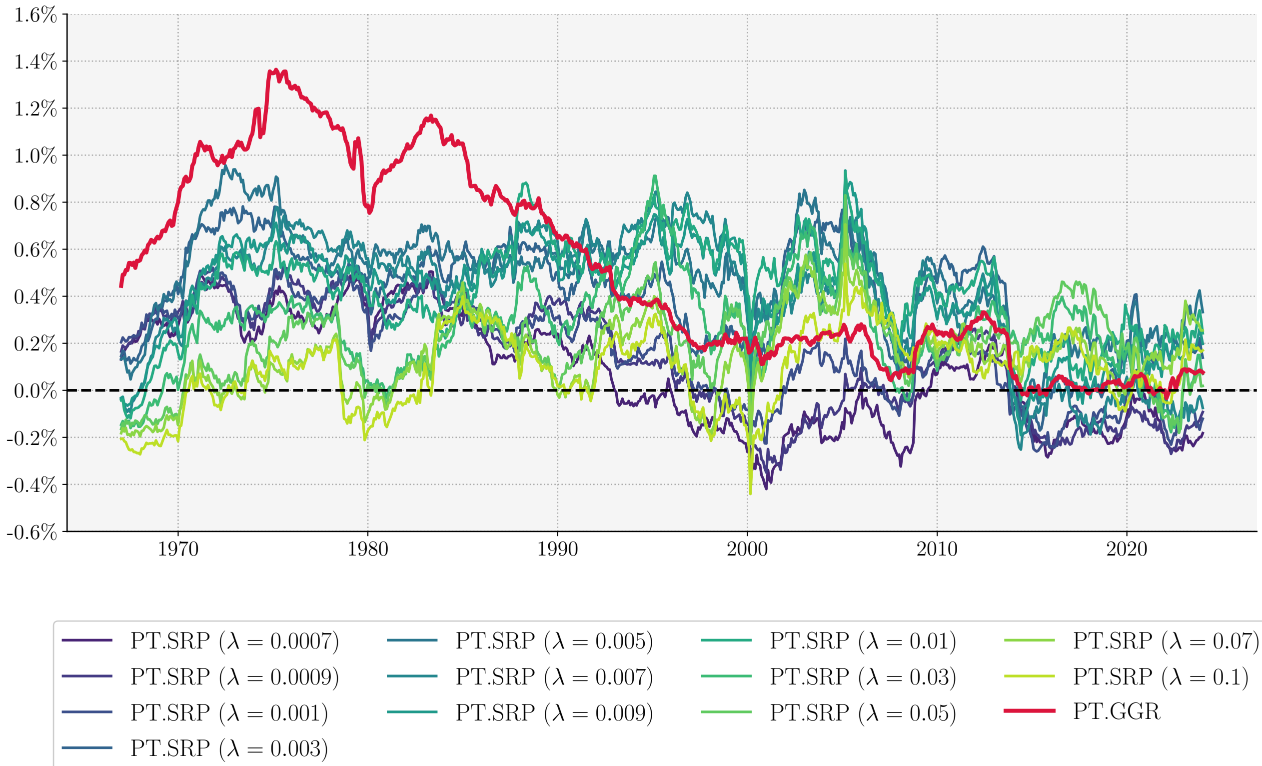
Note: This figure shows the sensitivity of strategy gross returns to different choices of the LASSO penalty parameter λ. Higher values of λ promote sparser replicating portfolios, while lower values allow more constituents. All returns are computed using the one-day waiting rule to mitigate potential microstructure effects and without accounting for transaction costs.

4. Conclusion

The central takeaway of this paper is that relative-value arbitrage is not obsolete, its success simply requires more flexible tools. While the profitability of traditional pairs trading has steadily declined since the 1990s, confirming the decay documented in prior literature, our findings show that this is a methodological limitation, not an exhaustion of the underlying opportunity. The issue lies in the restrictive 1-to-1 pairing framework, which has failed to keep pace with increasingly efficient markets.

Our contribution is a replicating portfolio approach that revitalizes the strategy by relaxing this constraint. Instead of searching for a single, elusive pairing partner, we construct a sparse portfolio of substitutes using LASSO regularization. This method provides a flexible and powerful generalization of the classic pairs trading framework, creating synthetic assets that are both

FIGURE 8: **Robustness to λ (after transaction costs)**



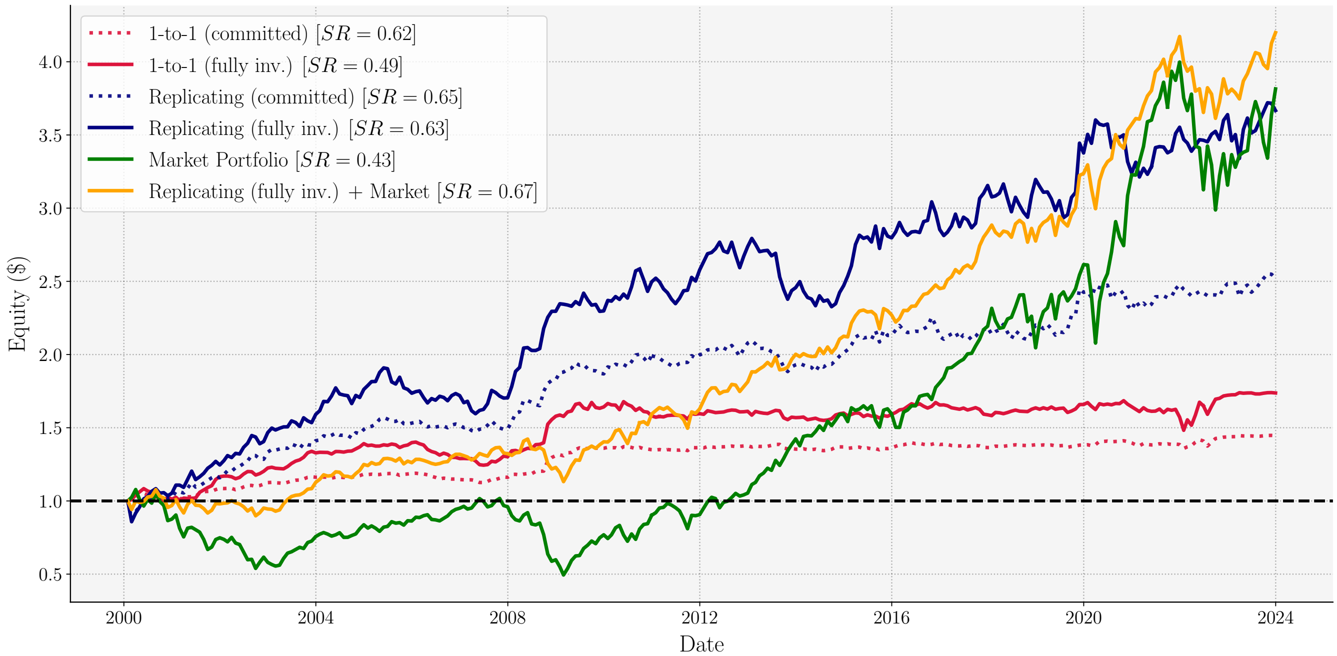
Note: This figure shows the sensitivity of strategy net returns to different choices of the LASSO penalty parameter λ. Higher values of λ promote sparser replicating portfolios, while lower values allow more constituents but increase transaction costs. All returns are computed using the one-day waiting rule to mitigate potential microstructure effects and assuming 1bps transaction cost per trip for each traded stock.

accurate hedges and practically tradable.

The empirical results are stark. The traditional 1-to-1 strategy's returns have decayed to zero, while our sparse replicating portfolio approach delivers statistically and economically significant alpha, unexplained by standard risk factors. This demonstrates that opportunities for relative-value arbitrage have not vanished; they have merely become too complex for rigid, traditional models to capture.

Ultimately, this paper offers a principled path forward for pairs trading. Rather than concluding that the strategy is obsolete, our findings suggest it just needs a more flexible approach. By moving beyond the 1-to-1 paradigm, we show that this classic quantitative strategy can be successfully adapted for today's markets.

FIGURE 9: **Equity curve from Pairs Trading since 2000**



Note: This figure shows the equity curve of a 1$ investment in the 1-to-1 pairs trading strategy, the replicating portfolio pairs trading strategy, the market portfolio and the combination of the replicating portfolio pairs trading strategy and the market portfolio from January 2000 to December 2024. Strategy returns are computed using the one-day waiting rule to mitigate potential microstructure effects and account for a transaction cost of 1bps per trip for each traded stock.

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A. Appendix

A. Payoff Calculation

As in Gatev et al. (2006), the payoffs from the strategy are equivalent to excess returns, as they are derived from self-financing, dollar-neutral positions. Positions are marked-to-market daily. The daily return on a portfolio P is calculated as the weighted average of the returns of its constituent assets:

$$r_{P,t} = \frac{\sum_{i \in P} w_{i,t} r_{i,t}}{\sum_{i \in P} w_{i,t}}$$

The weights, $w_{i,t}$, evolve based on the prior day's returns, reflecting a buy-and-hold approach for the underlying assets within the trading window.

$$w_{i,t} = w_{i,t-1}(1 + r_{i,t-1})$$

These daily returns are then compounded to obtain monthly performance figures.

B. Transaction Costs

To account for transaction costs we subtract 1bps per trip and per traded stock from the payoffs.

- **1-to-1 pairs trading**. Since the portfolio is composed of 2 stocks, we subtract $2 \times$ 1bps = 2bps when opening the position, and another 2 bps when closing the position. In total, 4bps for the round trip.

- **Sparse Replicating Portfolio**. Assume the replicating portfolio is composed of M assets, then, together with the target asset we have to trade $(M + 1)$ stocks, so we subtract $(M + 1) \times$ 1bps= $(M + 1)$bps when opening the position and another $(M + 1)$bps when closing the position. In total, $2(M + 1)$bps for the round trip.

This approach aims to approximate a realistic trading cost schema for an institutional investor (e.g.: a hedge fund), but may not be realistic for a retail investor. Another limitation of this approach is that we impose the same cost for buys and sells, but in practice, short selling costs may be higher.

C. Overlapping Portfolios

To generate a continuous time series of returns, we adopt a rolling window approach. At the beginning of every month, we use the preceding 12 months of data to form a new portfolio of pairs, which is then traded for the subsequent 6 months. This creates a series of overlapping 6-month trading periods. To calculate the final monthly return series, we average the returns of all portfolios that are active in a given month.

Figure 10 provides a visual illustration of this process. It depicts a structure where six distinct portfolios, each initiated one month apart, are managed concurrently. For any given month (e.g., Month 6), the overall strategy return is the average of the returns from all six active portfolios, which were formed in months 1 through 6. This method ensures the final return series is smooth and representative of a continuously managed trading strategy, while appropriately correcting for the serial correlation induced by the overlapping data.

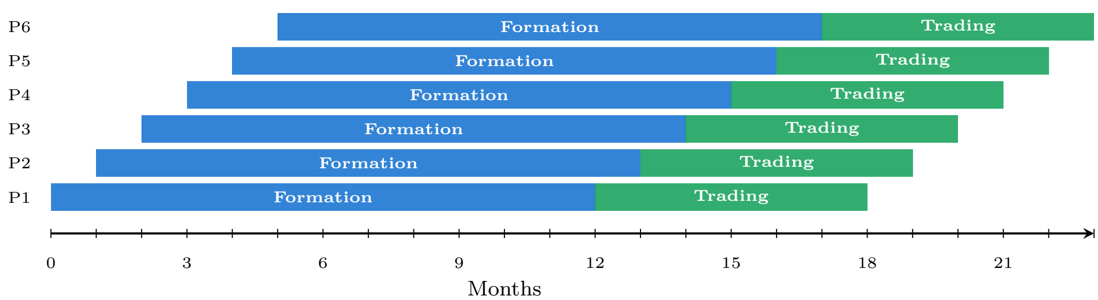


Figure 10: Illustration of Overlapping Portfolios

Note: This figure illustrates the overlapping portfolio structure used to generate a continuous return series. Each row represents a distinct portfolio formed at the beginning of a month and traded for the subsequent six months. The overall strategy's monthly return is the average of returns from all concurrently active portfolios.

D. Trading Signal Implementation

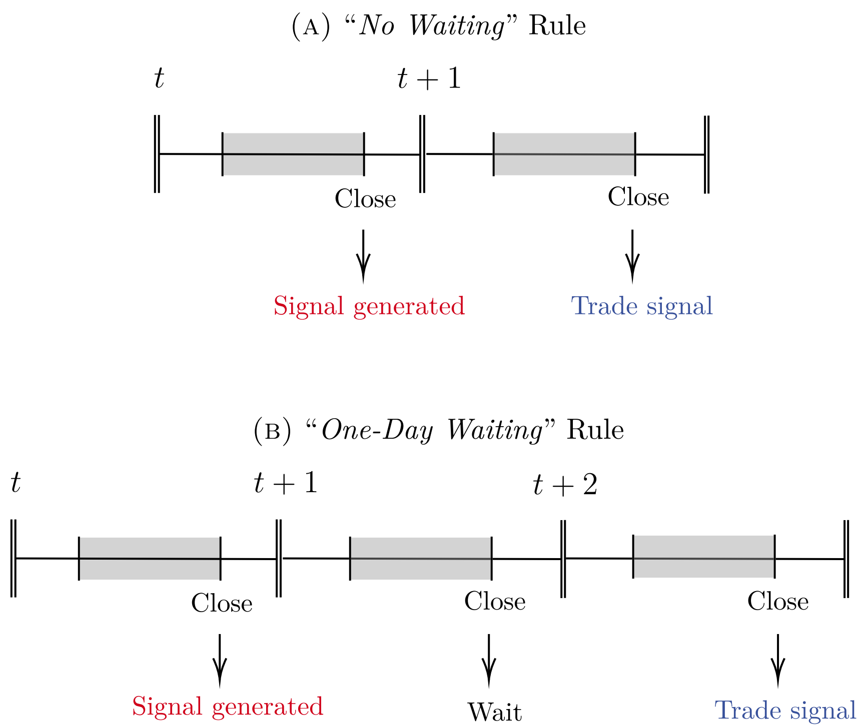
To ensure our results are robust to potential market microstructure effects, such as bid-ask bounce or delayed price discovery, we test two distinct trading protocols for signal implementation. The choice of protocol determines the precise timing of trade execution after a trading opportunity is identified.

Figure 12 illustrates these two protocols.

- **The "*No Waiting*" Rule (Panel a)**: A signal generated at the close of t is traded at the closing price of the next day, $t + 1$.

- **The "*One-Day Waiting*" Rule (Panel b)**: A signal generated at the close of t is traded at the closing price of the next day after a one day waiting period, $t + 2$. This approach ensures that the signal persists for at least one day, providing a more conservative estimate of strategy performance by mitigating the impact of market microstructure effects.

Figure 12: Trading Signal Implementation Timelines



Note: This figure illustrates the two trading protocols tested. Panel (a) shows the "No Waiting" rule, where trades are executed at the closing price of the next the signal is obtained. Panel (b) shows the "One-Day Waiting" rule, where trades are executed after waiting for one day following the signal, to ensure robustness to market microstructure effects.

Table 1: **Excess returns of unrestricted pairs trading strategies (before transaction costs)**

Pairs portfolio	Top 5	Top 20	Pairs 101-120	All Pairs
A. Excess return distribution (no waiting)				
Average excess return (fully invested)	0.01013	0.00971	0.01013	0.00859
Standard error (Newey-West)	0.00135	0.00103	0.00112	0.00074
t-Statistic	7.50	9.39	9.01	11.59
Excess return distribution				
Median	0.00891	0.00871	0.01003	0.00826
Standard deviation	0.03661	0.02511	0.02726	0.01873
Skewness	0.49	-0.10	-0.32	-0.25
Kurtosis	4.47	4.90	7.96	17.44
Minimum	-0.09500	-0.14352	-0.18062	-0.16669
Maximum	0.18704	0.09846	0.17219	0.12407
Observations with excess return < 0	39%	35%	32%	27%
Average excess return on committed capital	0.00644	0.00513	0.00499	0.00294
B. Excess return distribution (one day waiting)				
Average monthly return (fully invested)	0.00853	0.00883	0.00854	0.00745
Standard error (Newey-West)	0.00129	0.00099	0.00113	0.00068
t-Statistic	6.60	8.95	7.58	10.94
Excess return distribution				
Median	0.00650	0.00895	0.00863	0.00711
Standard deviation	0.03714	0.02494	0.02726	0.01828
Skewness	0.72	-0.03	-0.71	-0.18
Kurtosis	6.23	5.57	12.28	18.20
Minimum	-0.10801	-0.15005	-0.19062	-0.16497
Maximum	0.22563	0.10843	0.18429	0.12462
Observations with excess return < 0	41%	36%	35%	30%
Average excess return on committed capital	0.00533	0.00440	0.00426	0.00250

Note: This table presents performance statistics for both traditional and the replicating portfolio pairs trading strategies. The generalized approach significantly outperforms the traditional method across all metrics, delivering higher average returns and Sharpe ratios. All returns are computed using the one-day waiting rule to mitigate potential microstructure effects.

Table 2: **Excess returns of unrestricted pairs trading strategies (after transaction costs)**

Pairs portfolio	Top 5	Top 20	Pairs 101-120	All Pairs
A. Excess return distribution (no waiting)				
Average excess return (fully invested)	0.00903	0.00862	0.00830	0.00674
Standard error (Newey-West)	0.00144	0.00102	0.00119	0.00076
t-Statistic	6.25	8.45	6.99	8.90
Excess return distribution				
Median	0.00715	0.00872	0.00745	0.00615
Standard deviation	0.03694	0.02499	0.02783	0.01883
Skewness	0.50	-0.06	-0.24	-0.25
Kurtosis	4.57	4.61	8.78	16.49
Minimum	-0.09319	-0.13356	-0.18821	-0.16628
Maximum	0.18497	0.09963	0.18302	0.11855
Observations with excess return < 0	42%	37%	36%	33%
Average excess return on committed capital	0.00584	0.00468	0.00413	0.00233
B. Excess return distribution (one day waiting)				
Average monthly return (fully invested)	0.00745	0.00794	0.00675	0.00591
Standard error (Newey-West)	0.00139	0.00096	0.00114	0.00070
t-Statistic	5.37	8.31	5.91	8.41
Excess return distribution				
Median	0.00605	0.00841	0.00693	0.00559
Standard deviation	0.03727	0.02438	0.02768	0.01819
Skewness	0.63	-0.17	-0.75	-0.30
Kurtosis	6.00	5.21	11.62	17.82
Minimum	-0.13406	-0.14214	-0.19236	-0.16579
Maximum	0.21297	0.10831	0.16987	0.11910
Observations with excess return < 0	42%	36%	39%	34%
Average excess return on committed capital	0.00492	0.00407	0.00346	0.00191

Note: This table presents performance statistics for both traditional and the replicating portfolio pairs trading strategies. The generalized approach significantly outperforms the traditional method across all metrics, delivering higher average returns and Sharpe ratios. All returns are computed using the one-day waiting rule to mitigate potential microstructure effects.

Table 3: **Systematic risk of pairs trading strategies (before transaction costs)**

	Top 5	Top 20	20 after top 100	All
"Wait one day" portfolio performance				
Mean excess return	0.00853	0.00883	0.00854	0.00745
Standard deviation	0.03714	0.02494	0.02726	0.01828
Sharpe Ratio	0.80	1.23	1.08	1.41
Monthly serial correlation	-0.03	0.02	0.02	0.02
FF5 + Reversals				
Intercept	0.00618	0.00552	0.00526	0.00411
	(4.32)	(5.56)	(4.47)	(6.21)
Market	-0.15348	-0.07651	-0.06005	-0.01463
	(-3.67)	(-3.11)	(-2.20)	(-0.74)
SMB	-0.06245	-0.13739	-0.21857	-0.08108
	(-1.26)	(-2.96)	(-3.12)	(-1.50)
HML	-0.13278	0.03836	0.00280	-0.01645
	(-1.74)	(0.78)	(0.05)	(-0.39)
Momentum	-0.09301	-0.06906	-0.14525	-0.17551
	(-2.43)	(-2.19)	(-4.82)	(-8.36)
Short-Term Reversal	0.15285	0.18088	0.23923	0.23261
	(2.68)	(4.38)	(4.84)	(6.27)
Long-Term Reversal	-0.01147	-0.07186	0.04994	-0.01657
	(-0.17)	(-1.27)	(0.84)	(-0.43)
R^2	0.05	0.11	0.19	0.41

Note: This table presents the results of regressing the strategy's monthly gross excess returns on standard risk factors (Fama-French 5-factor, Momentum, and Reversals). All returns are computed using the one-day waiting rule to mitigate potential microstructure effects and without accounting for transaction costs.

Table 4: **Systematic risk of pairs trading strategies (after transaction costs)**

	Top 5	Top 20	20 after top 100	All
"Wait one day" portfolio performance				
Mean excess return	0.00745	0.00794	0.00675	0.00591
Standard deviation	0.03727	0.02438	0.02768	0.01819
Sharpe Ratio	0.69	1.13	0.84	1.12
Monthly serial correlation	-0.02	0.02	0.04	0.05
FF5 + Reversals				
Intercept	0.00512	0.00471	0.00339	0.00255
	(3.19)	(4.91)	(2.91)	(3.84)
Market	-0.15418	-0.08576	-0.05852	-0.01453
	(-3.59)	(-3.69)	(-2.20)	(-0.78)
SMB	-0.03634	-0.12375	-0.22905	-0.07290
	(-0.71)	(-2.80)	(-3.48)	(-1.37)
HML	-0.14649	0.02514	0.01895	-0.01271
	(-1.62)	(0.49)	(0.36)	(-0.30)
Momentum	-0.11380	-0.07492	-0.14169	-0.17052
	(-2.61)	(-2.58)	(-5.09)	(-8.27)
Short-Term Reversal	0.16234	0.17188	0.25950	0.22731
	(2.80)	(4.63)	(5.39)	(6.15)
Long-Term Reversal	0.01970	-0.04286	0.02813	-0.02580
	(0.24)	(-0.78)	(0.51)	(-0.68)
R^2	0.06	0.11	0.21	0.39

Note: This table presents the results of regressing the strategy's monthly excess net returns on standard risk factors (Fama-French 5-factor, Momentum, and Reversals). The alpha from our generalized strategy is positive and highly statistically significant, while factor loadings are economically small and generally insignificant, suggesting the returns are true alpha rather than compensation for systematic risk. All returns are computed using the one-day waiting rule to mitigate potential microstructure effects and accounting for transaction costs of 1bps per trip and per traded stock.