Pairs Trading Profitability and Risk Since 2020

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Abstract. This paper examines the profitability and risk profile of a simple pairs trading strategy applied to U.S. equity markets from 2020 to 2024. Pairs trading is a strategy that exploits the mispricing of assets by betting on the assets' return to equilibrium. Using daily historical data from the NYSE, NYSE American, and NASDAQ, the strategy selects the top-20 most cointegrated pairs of stocks based on a one-year formation period and trades them the next month. From 2020 to 2024, the strategy exhibited lower volatility and a higher Sharpe ratio than the S&P500 index, but it fails to yield high returns after considering transaction costs. Although pairs trading may offer a reduced risk in investment, its profitability in recent years has been limited due to mean drift, breakdown of cointegration properties, and selection of spurious pairs. Therefore, enhanced pair selection techniques are necessary for improved performance.

1 Introduction

Pairs trading is a type of statistical arbitrage strategy that exploits price discrepancies from a long-term statistical relationship (Krauss, 2016; Gatev et al., 2006). The strategy is based on the premise that there is a long-term equilibrium relationship between the prices of two assets (that is, the relative price of the assets move together). Any deviations from this long-term relationship, known as the spread, can be taken advantage of by shorting the overpriced asset and longing the underpriced asset (Vidyamurthy, 2004), betting on the fact that the relative price will return to equilibrium. The strategy is considered market neutral, meaning that the returns are not correlated with the market returns because it does not rely on taking directional bets on the market, but rather on taking bets on the spread.

The goal of this paper is to answer two questions: (1) how profitable is pairs trading from 2020 to 2024? and (2) how risky is pairs trading from 2020 to 2024?

To answer these questions, a simple pairs trading strategy was tested between 2020 and 2024 on the NYSE, NYSE American, and NASDAQ exchanges. The strategy starts with a one-year formation period in which potential pairs of stocks are selected to trade through cointegration testing. Then, the top 20 cointegrated pairs of stocks are selected for trading. Finally, simple trading rules are implemented to execute trades for a month.

2 Data and Methods

2.1 Historical Data

Historical data was obtained from the CRSP database, covering daily open, high, low, close, volume, and market capitalization information for all available equities and funds listed on the NYSE, NYSE American, and NASDAQ exchanges from January 2019 through December 2024. In total, more than 5,000 securities were collected for this pairs trading analysis.

2.2 Initial Screening

A major step in pairs trading is to select desirable pairs of stocks to trade. To do this, a one-year formation period was used to identify these pairs. Initially, the data were cleaned by removing securities with missing data in the formation period, either because they were delisted from the stock exchange, temporarily halted, or had no trades. Then the top 1000 stocks with highest average market capitalization were chosen for pairs testing because they are more liquid and had fewer trading risks. The number of pairs to test is around 500,000 from these top 1000 stocks, which is too large for practical analysis.

To decrease the size of the pairs universe, the correlation coefficient was used (Eq. 1). Under the assumption that the log prices are normally distributed, the correlation matrix of their daily log close price was calculated and pairs with a correlation coefficient greater than 0.95 were retained for further analysis. While this introduces a selection bias since cointegrated pairs do not necessarily exhibit high correlation, this step reduced the number of pairs by 98-99.8%, making the analysis more computationally feasible. The remaining pairs are then tested for cointegration.

$$r = \frac{cov(P_t^A, P_t^B)}{\sqrt{var(P_t^A)}\sqrt{var(P_t^B)}} \tag{1}$$

2.3 Cointegration

Cointegration is a statistical concept that refers to the long-term equilibrium relationship of two or more time series. While the individual series may not be stationary, a linear combination of them may be. If two time series are cointegrated, then they have a long-term tendency to move together and exhibit mean-reverting behavior, which is necessary for pairs trading. Mathematically, if there exists a parameter β such that z_t is stationary (Eq. 2), then x_t and y_t are said to be cointegrated.

$$z_t = y_t - \beta x_t \tag{2}$$

The Engle-Granger two-step method was used to test for cointegration on the log close prices as it is the most common test in the literature (Engle and Granger, 1987). For simplicity of the trading strategy, a portfolio of the top-20 most cointegrated pairs was used for trading.

2.4 Trading Rules

The portfolio of the 20 most cointegrated pairs is traded for one month after the end of the formation period. For example, a portfolio formed between the start of March 2021 and the end of February 2021 will be tested in March 2022. A one-month trading period was chosen to avoid significant mean drift and loss of cointegrated properties.

Because trading decisions are based on the closing price, it is unreasonable to execute trades at that given price. As a result, trades are executed at the open price on the following trading day. If any pairs were delisted from the stock exchange, then the positions were exited based on the last available open price. At the end of the trading period, all stocks were liquidated regardless of current prices. Additionally, dividends, slippage, and transaction costs were not modeled in the simulation for simplicity.

The logarithmic spread between stock A and B is defined by Equation 3 where P_t^A and P_t^B are the logarithmic close prices and β is the hedge ratio derived from the OLS regression in the formation period.

$$Spread_t = P_t^A - \beta P_t^B \tag{3}$$

If the normalized log spread deviates by +2 SD, then a short position is entered by shorting \$1 of the spread, which corresponds to shorting $\$\frac{1}{1+\beta}$ of stock A and longing $\$\frac{\beta}{1+\beta}$ of stock B. If the normalized log spread deviates by −2 SD, then a long position is entered by longing \$1 of the spread, which corresponds to longing $\$\frac{1}{1+\beta}$ of stock A and shorting $\$\frac{\beta}{1+\beta}$ of stock B. Trades are exited once their normalized spread revert back to 0 or surpassed their stop loss of ± 4 SD.

2.5 Performance Metrics

The monthly returns on the pairs trading strategy is calculated by Equation 4 where π_t is the total profit (in dollars) in month t from start to end and I_t is the exposure (in dollars) in month t. The exposure is equivalent to the number of unique pairs that were traded in that month since the dollar exposure per trade was \$1. While this does not include the effects of compounding from trades of the same pair within the same month, these events were infrequent and the number of times these pairs traded were small (around 2-3 times per month), making compounding effects negligible. The annual return is calculated by compounding the monthly returns for each year (January to December). The cumulative returns are calculated by compounding the monthly returns from the start to the end of the period (January 2020 to December 2024).

$$r_t = \frac{\pi_t}{I_t} \tag{4}$$

The annualized Sharpe ratio is calculated using Equation 5, where $\bar{r}$ is the mean monthly return, r_f is the monthly risk-free rate, and $\hat{\sigma}$ is the standard deviation of monthly returns. The monthly risk-free rate was chosen to be 0.2% because the average 3-month Treasury Bill rate from January 2020 to December 2024 was on average 2.5% per year.

$$SR = \sqrt{12} \cdot \frac{\bar{r} - r_f}{\hat{\sigma}} \tag{5}$$

The daily value at risk (VaR), reported in terms of losses based on returns, is calculated by Equation 6, where $\Phi^{-1}(\alpha)$ is the inverse of the standard normal distribution and $\hat{\sigma}_p$ is the portfolio standard deviation calculated by Equation 7 where $\mathbf{w}$ is the weight vector normalized to the total exposure and Σ is the covariance matrix of the returns. For the pairs trading strategy, the covariance matrix of the returns was calculated from the formation period. The position vectors were calculated from each day in the trading period. The average daily VaR from January 2020 to December 2024 was reported. For the S&P500 index, the standard deviation of daily returns from January 2020 to December 2024 was used as the portfolio standard deviation.

$$VaR_\alpha = \Phi^{-1}(1 - \alpha) \cdot \hat{\sigma}_p \tag{6}$$

$$\hat{\sigma}_p = \sqrt{\mathbf{w}^\intercal \Sigma \mathbf{w}} \tag{7}$$

3 Results

3.1 Returns

Figure 1 compares the monthly returns from January 2020 to December 2024 between the pairs trading strategy and S&P500 index. Most of the returns from the pairs trading strategy are close to 0 and are small compared to the S&P500 index, but the pairs trading strategy exhibits lower volatility that the S&P500. Figure 2 compares the cumulative return on an investment of $1 from January 2020 to December 2024 between the pairs trading strategy and S&P500. Although the return was lower over the 5 years, the pairs trading strategy exhibits a steady increase in return on investment compared to the S&P500 index.

Table 1 compares the average monthly, annual, and cumulative returns between the pairs trading strategy and S&P500 index. Overall, the S&P500 has greater returns of 0.011, 0.142, and 0.820 in monthly, annual, and cumulative returns, respectively. Furthermore, considering that transaction costs from short selling, commission, and slippage were not included in the pairs trading strategy, the actual returns are actually lower for the pairs trading strategy.

3.2 Risks

Table 2 compares the standard deviation of monthly returns, Sharpe ratios, and value at risk between the pairs trading strategy and S&P500 index. The pairs trading strategy had a lower standard deviation, a lower value at risk, and a higher Sharpe ratio. In general, the pairs trading strategy exhibits a lower risk than the S&P500 index.

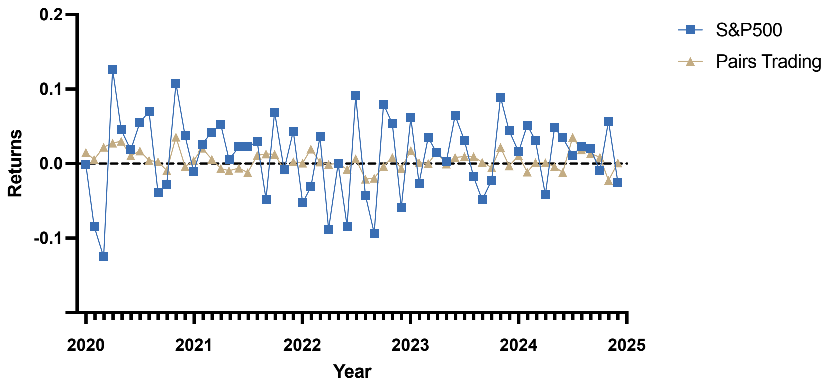

Fig. 1. Monthly Returns

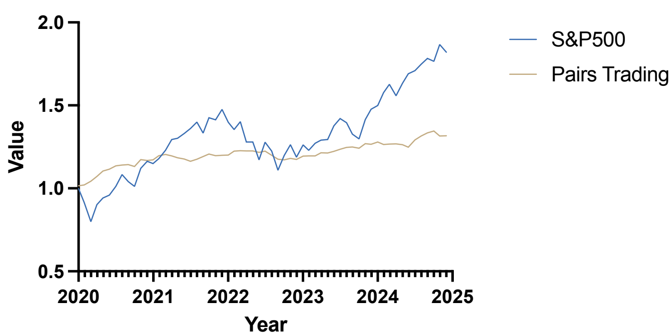

Fig. 2. $1 Investment Growth

Metrics	Pairs Trading	S&P500
Monthly Returns	0.005	0.011
Annual Returns	0.058	0.142
Cumulative Returns	0.317	0.820

Table 1. Monthly, annual, and cumulative returns between the pairs trading strategy and S&P500 index.

Metrics	Pairs Trading	S&P500
Monthly Returns SD	0.013	0.052
Annualized Sharpe Ratio	0.728	0.620
1% VaR	0.014	0.035
5% VaR	0.010	0.022

Table 2. Monthly returns standard deviation, Sharpe ratio, 1% and 5% value at risk between pairs trading strategy and S&P500.

4 Conclusion

Over the past five years, a simple pairs trading strategy based on correlation and cointegration does not appear to be profitable after considering transaction costs and short-selling fees. Although the strategy has low volatility, it does not yield enough returns for the strategy to be viable. Low returns are caused by mean drift, loss of cointegration properties, or spurious cointegration. Although a pair of stocks seems to cointegrate in the formation period, it is not necessarily guaranteed that it will cointegrate in the trading period as well. As a result, the spread did not mean revert, and a loss was taken. Better methods are necessary to choose ideal pairs to trade, either by grouping stocks by similar industries to reduce spurious cointegration, using additional statistical tests for better confidence, or using additional metrics to identify pairs.

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