Pairs Trading in the Land Down Under

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November 30, 2010

Abstract

Pairs trading is a market neutral investment strategy that attracts attention of academics and practitioners. Despite that, very little testing on the real market data has been published. This research considers three the most cited methods of pairs trading, two of them had never been tested on the real market data. Clear trading rules have been defined for all methods and their performance has been empirically assessed using the daily data covering 12 years history of the Australian stock exchange.

All three methods demonstrate statistically significant excess returns from 5% to 12% per year. However, after accounting for the transaction costs, two methods became unprofitable, and one earned minimal profit. These results demonstrate limited practical value of these strategies on the Australian stock market in their current form, suggesting the need for substantial improvements.

Keywords: pairs trading, spread process, cointegration, Australian stock exchange, ASX

1 Introduction

Pairs trading is a popular trading strategy used by institutional and individual investors. The idea of a pairs trading strategy is fairly simple: find two stocks that historically moved together, when they deviate from each other open positions towards the historical mean and close them when stocks converge together [8]. The general description and the history of pairs trading strategy can be found in many articles and books [8; 15; 14; 3; 16].

The premise of the pairs trading strategy is to hold long and short positions simultaneously. This way the trading is market neutral, and any profit or loss generated should be attributed to the relative price movements of the two assets, but not the market. So, the total position stays hedged against any market movements.

Market neutrality makes pairs trading extremely attractive for institutional investors such as superannuation funds, insurance companies and risk averse hedge funds – that is the investors which are more interested in small but steady profit at a low risk, rather than a high return but at a higher risk.

On other side, pairs trading is a naturally leveraged strategy as money from the short sell of one asset could be used to buy long another one. So, less risk averse investors can earn substantial profit by increasing the level of leverage. That makes the strategy equally interesting for retail investors and hedge funds focused on high return.

Despite the great interest in pairs trading from practitioners and academics, very little research published rigorous tests of pairs trading strategies on the real market data. To the best of our knowledge, the only published works include tests on the US market [8; 5; 4], the Brazil market [13], and a sample of FTSE100 [2]. Similarly, some methods proposed in the academic literature have never been tested on the market data.

The purpose of this research is to examine the three most cited pairs trading strategies and their performance using the Australian stock exchange (ASX) market data. The research follows the testing framework used by Gatev, Goetzmann and Rouwenhorst [8].

2 Methodology

2.1 Methods used

Following the general definition of pairs trading, an investor, seeking to create a working strategy, should answer the following three questions:

1. What does it mean to 'move together'? In other words, which assets should form a long-short portfolio?

2. How 'far' should those assets deviate before applying the strategy or when to open positions?

3. What does it mean that the assets 'converge together' and what to do if it never happens, i.e. what is an exit strategy?

Do, Faff and Hamza [6] reviewed different approaches to pairs trading described in the academic literature, and separated them into three groups:

1. the distance method used by Gatev et al. [8];

2. the cointegration method described by Vidyamurthy [15];

3. the stochastic spread method proposed by Elliott, van der Hoek and Malcolm [7].

While all three methods received attention in academic literature, the distance method is the only one that has been tested on the different data sets, probably due to its simplicity. The two other methods have never been tested on the real market data.

Each of the above approaches offers its own answers for the summarized earlier questions, however the details of the methods are not always clear. We try to follow the proposed strategies as close as possible to the original description and make reasonable assumption where necessary. All of the above mentioned methods have the same structure: pairs formation based on the analysis of the historical data; and rules about when to open and unwind positions based on the spread process behavior.

We have to remark, that only the stochastic spread method [7] proposes a detailed 'exit' strategy – a complete set of rules for winning and losing cases. This is a very important development in the theory of pairs trading. The other methods only suggest to keep the losing positions of the diverging stocks until the end of the trading period. There are some attempts to improve the distance method by using stop-loss [12] or empirically estimated 55 days holding period [9]. However none of these improvements have any theoretical support yet.

For the testing we take 12 months of the historical data to create a list of pairs and estimate parameters of the spread processes for every pair. After that we select the best pairs and trade them during the chosen trading period using only the parameters calculated from the historical data. This true out-of-sample testing minimizes the risk of the data-snooping bias.

For each of the three strategies we run tests for 5 and 20 pairs traded simultaneously with and without accounting for the transaction costs. The S&P/ASX 200 index is used as a benchmark to compare all strategies against.

2.2 Data set

The same data set of ASX daily closing prices is used to test all three methods of pairs trading. The data are obtained from the Securities Industry Research Centre of Asia-Pacific (SIRCA) and covers 3455 trading days starting from January 1, 1996 and finishing on November 22, 2010.

The actual time interval used for trading is shorter – just 149 months from January 1, 1998 to May 31, 2010 – due to 12 months historical data used for strategy calibration and 5 months before and after trading interval discarded at averaging.

The testing interval includes the period of the Global Financial Crisis (GFC). Pairs trading as a contrarian strategy greatly benefited from uncertainty and high volatility of the stock market during GFC.

Australian Securities & Investments Commission (ASIC) banned short selling from November 2008 until May 2009. We still test pairs trading over that period as usual. Institutional investors, who hold large diversified portfolios of the Australian stocks, can use pairs trading as a part of the tactical asset allocation strategy. They do not need short selling to fulfill rules of pairs trading, they can sell some shares from the existing portfolio and buy them back when the strategy signals to close position on the pair.

The Australian stock market is relatively small. The data set includes almost 3,500 shares traded on the ASX. However, only a few stocks can be considered as having sufficient liquidity for pairs trading. We use the two-step procedure to define stocks with sufficient liquidity:

1. the stock should not have more than 5 non-trading days during the history period selected for calibration of the trading strategy,

2. the stock should be in the top 50% of the stocks selected at step 1 by the average daily dollar-valued trading volume during that period.

As result of the screening, the number of stocks available for pairs trading varies from 55 to 300.

We choose a pure quantitative approach to all strategies with minimal number of constrains and do not employ any extra restrictions, for example, sectors or market capitalisation.

On the ASX, the opening and closing prices are the results of auctions, which usually attract a large trading volume. In many instances, the volume of the opening and closing auctions exceeds 50% of the total daily trading volume. Using the closing and/or opening prices we can be sure that we could make a trade at the given price, thus avoiding bid-ask bounce bias.

If a stock has a non-trading day during the trading period (price and/or volume equals to zero), we use the closing price of the previous day to create the spread. However, positions on the pairs having that stock cannot be opened or closed on that day, even if the spread process signals to do so.

2.3 Computation of returns

Return on investment (ROI), or just *return*, is a ratio of money gained (or lost) relative to money invested. The calculation of returns in pairs trading is rather non-trivial. A short sale of one asset is a way to borrow money to buy long another asset. So, a dollar neutral pairs trading portfolio is a zero cost investment (at this stage we ignore commissions and possible margin requirements). Any profit or loss made from zero investment would mean infinite positive or negative return, which is not very useful for the purpose of comparing the performance of different trading strategies.

To avoid this problem we follow Gatev at al. [8] by trading $1 positions in each stock (which makes $2 total trading volume for the each pair) and calculate value-weighted daily market-to-market cash flows from each pair which are considered as excess return:

$$r_{P,t} = \frac{\sum_{i \in P} w_{i,t}\, c_{i,t}}{\sum_{i \in P} w_{i,t}} \tag{1}$$

where:

$c_{i,t}$ is a daily cash flow from the two positions formed the pair i;

$w_{i,t}$ is a weight of each pair. For each newly opened position on the pair initial weight equals to 1 and then evolve by the formula $w_{i,t} = w_{i,t-1}(1 + c_{i,t-1}) = (1 + c_{i,1}) \cdots (1 + c_{i,t-1})$

The daily cash flow from the pair or a daily return of the pair is

$$c_{i,t} = \sum_{j=1}^{2} I_{j,t} v_{j,t} r_{j,t}$$

where:

$I_{j,t}$ is a dummy variable which is equal to 0 if the position on the stock j is not open, 1 – if a long position on stock j is open, -1 – if a short position on stock j is open;

$r_{j,t}$ is a daily return on stock j;

$v_{j,t}$ is a weight of stock j is used to calculate daily cash flows $v_{j,t} = v_{j,t-1}(1 + r_{j,t-1}) = (1 + r_{j,1}) \cdots (1 + r_{j,t-1})$

The strategies' daily returns are then compounded to obtain monthly returns.

This method of the return calculation is widely used in the pairs trading literature to evaluate performance of the long-short portfolios. However it should be mentioned that pairs trading is a leveraged product and the above method uses 2:1 leverage, so one should be very careful comparing the results of the pairs trading strategy with non-leveraged strategies, for example, the naive *buy-and-hold* strategy.

For the cointegration method, which is not dollar neutral, we scale the initial weights for both stocks in the pair to make the total market position of the pair equal to \$2. That allows us to compare the results of this strategy with the dollar neutral ones – the distance and stochastic spread methods.

We start trading at the first working day of each month and trade for six months. So each month, except for the first and the last 5 months which are excluded from final report, we get six different estimations of monthly returns which are averaged to get the final estimation.

To provide a unifying framework for comparing all trading strategies we consider only one measure of excess return – the return on committed capital, that is $5 and $20 investments in the portfolio pairs. This is a conservative estimation as we include a one dollar investment per each pair even if the pair has not opened any positions.

2.4 Transaction costs

Stock trading involves some transaction costs. Despite the possible small size, transaction costs could have a serious impact on the performance of pairs trading strategies. This is especially true for short-term trading strategies which involve many trades. Bowen et al. [2] reported more than a 50% reduction in the excess returns of the high frequency pairs trading strategy after applying 15 basis point transaction fee. Do and Faff [4] fully replicated the research by Gatev et al. [8] and reported that the strategy became unprofitable after accounting for transaction costs.

For the retail traders the largest part of these costs are the brokerage fees which are paid by traders each time they buy or sell shares. On average, these fees vary from 5 to 15 basis points of the total amount traded.

For our tests we choose transaction costs equal to 0.15% (15 basis points), which is an average brokerage fee on the Australian market for retail investors (CommSec 0.12–0.2%, Macquare Edge 0.1–0.2%, St.George directshares 0.11–0.3%). Because the brokerage fee applies to the full traded volume, we adjust cash flows for all traded pairs using the following rules:

- on the day of the opening positions we reduce the cash flow from each stock in the pair by the size of transaction costs, that is, we reduce the total cash flow from the pair by double size of transaction costs

$$c_{i,t} \to c_{i,t} - 2\,b$$

- and on the day of the closing we reduce cash flow from each pair as follows

$$c_{i,\,t} = \sum_{j=1}^{2} \left(I_{j,\,t} v_{j,\,t} r_{j,\,t} - b\, v_{j,\,t} (1 + r_{j,\,t}) \right)$$

where:

$c_{i,t}$ is a cash flow from the pair i or excess return on the pair i;

$b = 0.0015$ is a brokerage fee;

$I_{j,t}$ is a dummy variable which is equal to 0 if the position on the stock j is not open, 1 – if a long position on stock j is open, -1 – if a short position on stock j is open;

$r_{j,\,t}$ is a daily return on the stock j;

$v_{j,\,t} = v_{j,\,t-1}(1 - r_{j,\,t-1})$ weight of the stock j.

3 Trading rules

3.1 Distance method

We use the following strategy based on the distance method of pairs trading proposed by Gatev at al. [8]:

1. **Pairs formation:** We take log-prices for all stocks selected for pairs trading over the 12 months history period and combine stocks in all possible pairs. The total number of possible pairs is quite large

$$P_N = \binom{N}{2} = \frac{N!}{2!(N-2)!}$$

where N is the total number of stocks eligible for pairs trading.

We do not shift individual stocks log-price processes at the start from \$1 as in [8] because it could result in a bias if the two stocks are in the phase of divergence at the first day of calibration period. To avoid that bias and to simplify further the calculations, we scale the spread process between two stocks by its mean.

$$y_{i,j}(t) = \log P_i(t) - \log P_j(t) - \bar{y}_{i,j}$$

where $P_i(t), P_j(t)$ are prices of stocks i and j on day t, $\bar{y}_{i,j}$ is the mean of the spread between the two stocks i and j.

Then, all pairs are sorted in ascending order by the size of the standard deviation of the spread process $y_{i,j}(t)$, which is proportional to the squared distances between stocks used by Gatev at al. [8]. The pairs with the smallest standard deviations are used for pairs trading.

Stocks which are picked for a pair are not removed from the pool, so the same company shares may be a part of several pairs.

The method of stock picking without replacing resembles the statistical method known as one-level hierarchical clustering and could increase diversification of an investment portfolio. However, we do not test this due to the limited number of companies in the Australian stock market. All companies from S&P/ASX 200 can create only 100 pairs of unique companies and clearly not many of them will be suitable for pairs trading.

2. **Rules to open positions:** We arbitrarily choose a trigger level as two standard deviations of the spread process. If the difference between the log-prices (that is, the spread process) of the selected stocks hits the trigger level, then we open position on the pair.

   - If the spread hits the level $2\sigma_{spread}$ then trading signal 'sell spread' is generated, we sell the first stock (i) in the pair and buy the second one (j).
   - If the spread process hits the level $-2\sigma_{spread}$ then trading signal 'buy spread' is generated, we buy the first stock (i) in the pair and sell the second one (j).

   Parameter σ_{spread} is determined over the 12 months calibration period and does not change until the end of the trading period.

3. **Rules to close positions:** We close open positions when the spread process hits zero in the first time after opening positions or at the end of the six months trading period – whatever happens first.

3.2 Cointegration method

The pairs trading strategy proposed by Vidyamurthy [15] is based on the theory of cointegration developed by Engle and Granger, and the common trends model by Stock and Watson. If two stocks are cointegrated than there exists their linear combination which is stationary. Vidyamurthy [15] suggests several approaches to the pairs selection and trading. We will adopt the purely quantitative approach in our testing as the most objective and straight forward method.

1. **Pairs formation:** Similarly to the distance method, we take log-prices for all stocks selected for pairs trading over the 12 months history period and combine them in pairs. We run ordinary least squares (OLS) regression of the first stock in the pair on the second one and build a spread process $\{y_{i,j}\}$.

   $$y_{i,j}(t) = \log P_i(t) - \gamma_{i,j} \log P_j(t) - \alpha_{i,j}$$

   where $P_i(t), P_j(t)$ are prices of stocks i and j on day t, $\alpha_{i,j}$ and $\gamma_{i,j}$ are an intercept and a slope (cointegration coefficient) of OLS regression of stock i on stock j.

   The spread process is tested for stationarity by the Dickey Fuller (DF) test. If the DF test statistic is greater than the critical value for 5% significance, then the pair is rejected as non-cointegrated. After that all accepted pairs are sorted in ascending order by the value of the spread process standard deviation and the pairs with the smallest values are used for pairs trading.

   Stocks which are selected for a pair are not removed from the pool, so the same company may be a part of several pairs.

2. **Rules to open positions:** We build the spread process build with parameters $(\alpha_{i,j}, \gamma_{i,j}, \sigma_{i,j})$ defined during calibration period. If the spread hits a trigger level, then we open position on the pair – trade the spread process towards zero. To be consistent with the testing of the other methods we arbitrary choose a trigger level as two standard deviations of the spread process.

The stocks in each pair are traded in proportion $1 : \gamma_{i,j}$ with the total value of the open position \$2. This means that the method is not dollar neutral.

3. **Rules to close positions:** We close positions when the spread process hits zero in the first time after the opening or at the end of the six months trading period – whatever happens first.

3.3 Stochastic spread method

The general idea of the strategy proposed by Elliott et al. [7] is based on the assumption that if we detect a mean-reverting property of the spread between two stocks, we can expect that the spread process stays mean-reverting for some time in the future. This means one can exploit those properties to make a profit.

Elliott et al. [7] consider the spread process as a two equation model and use Kalman filter to estimate all parameters of the process.

A hidden state equation

$$x_{k+1} = A + B\, x_k + C\, \epsilon_{k+1} \tag{2}$$

and observation equation

$$y_k = x_k + D\, \omega_k \tag{3}$$

where ϵ_t and ω_k are iid and $\sim \mathrm{N}(0, 1)$.

We use the following strategy of pairs trading based on mean-reverting property of the spread process:

1. **Pairs formation:** We use log-prices of the stocks considered for pairs trading to build spread processes $\{y_{i,j}\}$

$$y_{i,j}(t) = \log P_i(t) - \log P_j(t).$$

Letting $\{y_k\}$ to be defined by $\{y_{i,j}\}$, we estimate all parameters (A, B, C, D) of the spread processes by the Kalman filter. We define the processes' means and standard deviations by

$$\mu_{i,j} = \frac{A}{1-B}; \quad \sigma_{i,j} = \frac{C}{\sqrt{1-B^2}}.$$

We then sort all spread processes in ascending order by the value of the process standard deviation $\sigma_{i,j}$. This is similar to the sum of squared deviations between stocks i and j used by Gatev et al. [8], however it is a standard deviation of the invisible 'true' spread process but not its observed noisy interpretation. Pairs, that form top 5–20 spread processes, are considered for pairs trading.

2. **Rules to open positions:** We take a trigger level λ as two standard deviations $\sigma_{i,j}$ of the spread process to be in line with other methods tested. There exists a detailed theoretical justification of the level λ, which will be presented in [1].

$$c^{+,-} = \mu \pm \lambda\,\sigma, \text{ where } \lambda = 2$$

When the spread process $y_{i,j}(t)$ hits level $c^{+,-}$ open position on the spread process towards its mean.

If the level c^{+} is hit, then 'short the spread' – sell stock i and buy stock j. If the level c^{-} is hit, then 'long the spread' – buy stock i and sell stock j. All trades are 'dollar neutral', that is, equal dollar size positions are opened long and short.

3. **Rules to close positions:** We unwind positions if the spread process hits its mean μ or $\hat{t}$ times later, whichever happens first. The value of $\hat{t}$ is a most likely time to hit the mean using an approximation an Ornstein-Uhlenbeck (OU) process and depends on λ chosen before opening the positions.

$$\hat{t} = \frac{1}{2(1-B)} \log\left(-\frac{1}{2} + \frac{\lambda^2}{2} + \sqrt{\frac{\lambda^4}{4} - \frac{\lambda^2}{2} + \frac{9}{4}}\right)$$

Then, we return to step 1 to recalibrate the model.

We do not expect the mean-reverting property of the spread process to stay for long. That is why we do not trade the same pair for 6 months. Instead, we drop it after unwinding position on the pair and look for new pairs with the best parameters of mean-reversion at the time.

4 Empirical results

Tables 1–3 summarize monthly excess returns trading statistics and Figures 1–3 demonstrate historical performance of the different strategies. All approaches show statistically significant monthly excess returns on committed capital before transaction cost: 0.95% and 0.63% for the distance method, 1.05% and 0.48% for the cointegration method and 0.38% and 0.45% for the stochastic spread method for the top 5 and top 20 pairs respectively. All methods have relatively low standard deviations ranging from 1.2% to 3.1% and an acceptable Sharpe ratios (a proportion of the average excess return to the standard deviation of the returns) from 0.20 to 0.54.

The results for the stochastic spread method looks very modest but that is a return on committed capital, not on the actual employed capital. This strategy has an average holding time of less than 10 days and about 1 trade per two months. Therefore, most of the time the money committed to the trading are not being used. It is a very rear situation when all 5 or 20 pairs are open simultaneously, in contrast to the distance and cointegration methods where it is a very common scenario.

In general, the results of all strategies outperform the S&P/ASX 200 market index which is used as the benchmark. For the same period of time the index earns 0.32% monthly return at a 3.85% standard deviation. Sharpe ratio is 0.0831 if we assume the index return to be equal to the excess return.

We could expect that top 20 pairs would have smaller standard deviation of returns comparing to top 5 pairs due to the greater diversification of the portfolio. The reduced risk comes at the price of about a 30% reduction in the excess returns for the distance and cointegration methods. As a result, a Modigliani Risk-Adjusted Performance [11] is higher for the top 5 pairs portfolio.

The reason for this could be the small number of liquid stocks on the Australian market available for pairs formation. There is a chance that by increasing the size of the portfolio we add pairs that have poorer fit for pairs trading.

Only the stochastic spread method demonstrates a different result. It reduces the risk level of the larger size portfolio but increases the excess return at the same time. The method happens to be 'immune' to the problem of a smaller market.

All strategies have very low negative correlation with the S&P/ASX 200 market index and the market betas are close to zero. That allows us to conclude that all considered methods of pairs trading are truly market neutral.

It is necessary to mention that the data included the period of GFC from the beginning of 2008 until the middle of 2009. During this period the distance and cointegration methods benefited from the high volatility of the market and earned up to three times greater return than in the previous period under the normal conditions. The annualized excess returns after transaction costs exceeded 25%.

Transaction costs effect badly all the strategies, but especially the strategy based on the method of stochastic spreads, as the most frequently trading strategy. Distance method lost about 15% of its performance and earned 0.8% and 0.5% per month on the committed capital of the top 5 and top 20 pairs portfolios. At the same time the cointegration and the stochastic spread methods became unprofitable (except for the top 5 pairs for cointegration method): 0.87% and 0.32% per month for the first and 0.05% and 0.14% for the last – last three results were not statistically significant.

5 Conclusions

The purpose of this research is double-folded: to define the methodology of practical application of the three methods of pairs trading described in the academic literature and to evaluate their performance on the Australian stock market.

While all three approaches demonstrate true market neutrality and good performance on the market data before transaction costs – high excess returns with low standard deviations, the profitability of these strategies in their existing forms on the Australian market is questionable. Transaction costs dramatically reduce returns. The lack of liquidity limits the number of stocks that can be considered for pairs trading, thus decreasing potential profit.

However, the general idea of pairs trading is sound. So, better criteria of pairs selection and rules of trading could be developed. The distance and cointegration methods could be improved in regards to closing rules and control of constantly diverging pairs. The stochastic spread method is based on the assumption of normality of the innovation process which is not the case from stocks log-prices [10]. Less restricted models could significantly improve strategy's performance.

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	Before tr.cost		After tr.cost	
	5 pairs	20 pairs	5 pairs	20 pairs
Excess return distribution:				
Mean	0.0095	0.0063	0.0080	0.0050
Standard error	0.0015	0.0011	0.0015	0.0011
t-Statistics	6.2775	5.7124	5.4852	4.6817
P-value	0.0000	0.0000	0.0000	0.0000
Median	0.0081	0.0042	0.0069	0.0033
Standard deviation	0.0178	0.0128	0.0171	0.0124
Skewness	1.8181	1.2678	1.6658	1.1532
Kurtosis	9.0943	5.9317	8.4999	5.6389
Minimum	-0.0241	-0.0253	-0.0263	-0.0262
Maximum	0.0962	0.0578	0.0889	0.0547
Average profit month	0.0164	0.0118	0.0154	0.0114
Average loss month	-0.0072	-0.0055	-0.0076	-0.0056
Negative observations	29.2%	32.1%	32.1%	38.0%
Average number of trades per 6 months trading period	1.8	1.6	1.8	1.6
Average holding time, days	41.8	48.1	41.8	48.1
Jensen's alpha	0.0099	0.0066	0.0084	0.0052
Market beta	-0.1179	-0.0938	-0.1100	-0.0864
Correlation with benchmark	-0.26	-0.28	-0.25	-0.27
Sharpe ratio	0.54	0.49	0.47	0.40
M2 (Modigliani RAP)	0.0207	0.0188	0.0181	0.015417

Table 1: Monthly excess returns of the distance pairs trading strategy with and without transaction costs (0.15% per one trade)

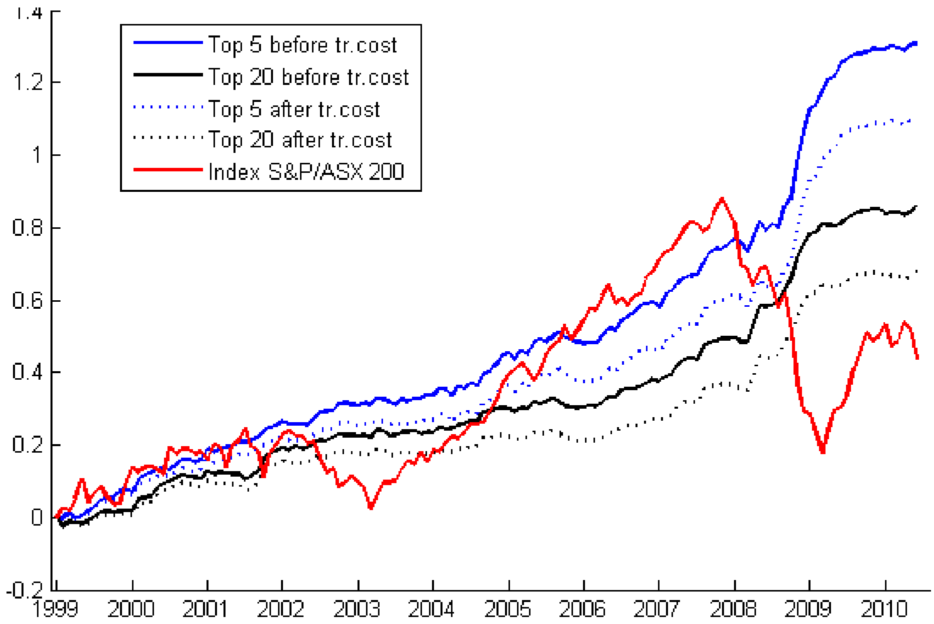

Figure 1: Historical performance of the distance method of pairs trading

	Before tr.cost		After tr.cost	
	5 pairs	20 pairs	5 pairs	20 pairs
Excess return distribution				
Mean	0.0105	0.0048	0.0087	0.0032
Standard error	0.0027	0.0018	0.0026	0.0017
t-Statistics	3.9387	2.7059	3.3087	1.8371
P-value	0.0001	0.0077	0.0012	0.0684
Median	0.0071	0.0031	0.0055	0.0017
Standard deviation	0.0313	0.0209	0.0306	0.0204
Skewness	1.2926	1.2919	1.2373	1.2238
Kurtosis	7.0546	6.6472	7.0571	6.4666
Minimum	-0.0722	-0.0398	-0.0757	-0.0411
Maximum	0.1343	0.0924	0.1324	0.0883
Average profit month	0.0261	0.0172	0.0252	0.0161
Average loss month	-0.0157	-0.0115	-0.0160	-0.0123
Negative observations	37.2%	43.1%	40.1%	45.3%
Average number of trades per 6 months trading period	2.1	1.9	2.1	1.9
Average holding time, days	43.6	46.3	43.6	46.3
Jensen's alpha	0.0110	0.0052	0.0091	0.0035
Market beta	-0.1526	-0.1122	-0.1405	-0.1023
Correlation with benchmark	-0.19	-0.21	-0.18	-0.19
Sharpe ratio	0.34	0.23	0.28	0.16
M2 (Modigliani RAP)	0.0130	0.0089	0.0109	0.0061

Table 2: Monthly excess returns of the cointegration pairs trading strategy with and without transaction costs (0.15% per one trade)

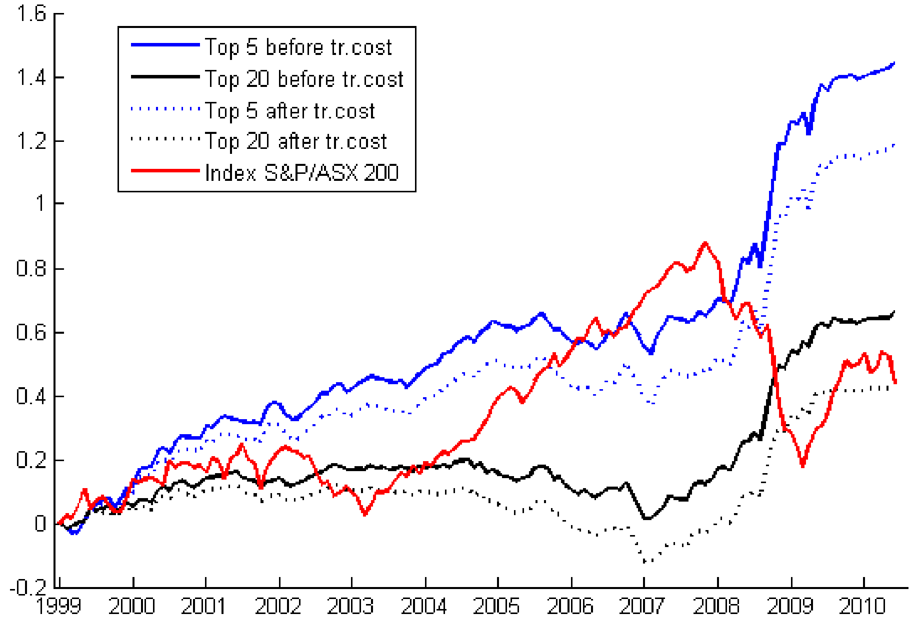

Figure 2: Historical performance of the cointegration method of pairs trading

	Before tr.cost		After tr.cost	
	5 pairs	20 pairs	5 pairs	20 pairs
Excess return distribution				
Mean	0.0038	0.0045	0.0005	0.0017
Standard error	0.0016	0.0011	0.0017	0.0010
t-Statistics	2.3184	4.2606	0.3106	1.6461
P-value	0.0219	0.0000	0.7566	0.1021
Median	0.0049	0.0040	0.0023	0.0017
Standard deviation	0.0192	0.0123	0.0194	0.0119
Skewness	-1.5227	1.8372	-1.9409	1.4541
Kurtosis	10.3681	13.4390	11.6074	12.2690
Minimum	-0.1013	-0.0303	-0.1096	-0.0347
Maximum	0.0558	0.0818	0.0475	0.0741
Average profit month	0.0133	0.0094	0.0110	0.0087
Average loss month	-0.0160	-0.0071	-0.0167	-0.0071
Negative observations	28.5%	29.9%	0.3431	0.4453
Average number of trades per 6 months trading period	3.3	2.8	3.3	2.8
Average holding time, days	8.6	9.2	8.6	9.2
Jensen's alpha	0.0039	0.0047	0.0006	0.0018
Market beta	-0.0410	-0.0627	-0.0303	-0.0518
Correlation with benchmark	-0.08	-0.20	-0.06	-0.17
Sharpe ratio	0.20	0.36	0.03	0.14
M2 (Modigliani RAP)	0.0076	0.0140	0.0010	0.0054

Table 3: Monthly excess returns of the stochastic spread process method of pairs trading with and without transaction costs (0.15% per one trade)

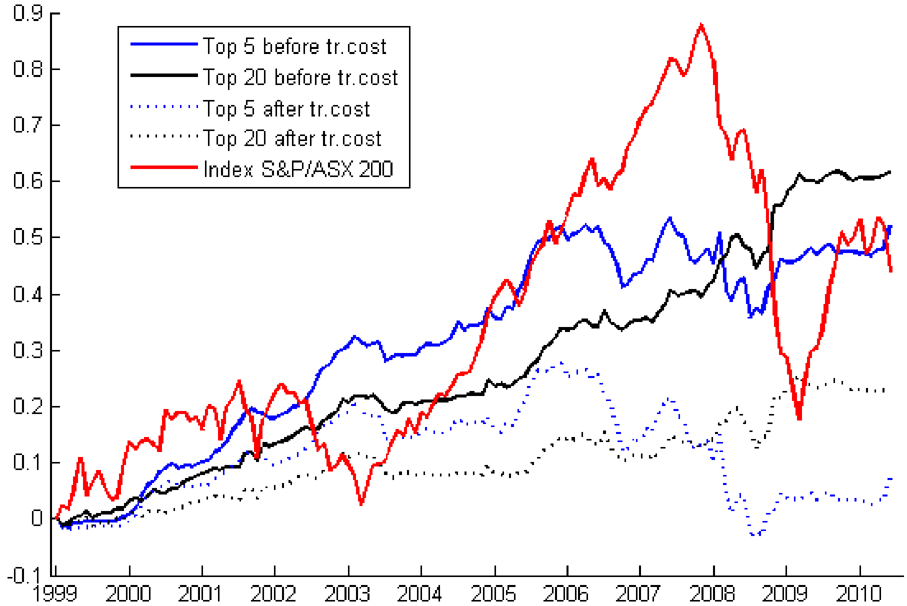

Figure 3: Historical performance of the stochastic spread process method of pairs trading