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PAIRS TRADING : INVESTIGATING INTRADAY PRICE MOVEMENTS

PAIRS TRADING

In the dynamic world of trading, Pairs Trading has long been a strategy of interest for its market-neutral approach and reliance on statistical relationships rather than directional market movements.

Earlier this year, we enjoyed an article published by Habla Computing demonstrating the power of kdb+ to deploy a real time implementation of a Pairs Trading strategy. The article began with an introduction to pairs trading and an introduction to kdb+ as a technology and ended with a real time implementation of a pairs trading strategy across the French and German indices. The article can be found here.

Inspired by this article, we were curious to explore whether similar patterns exist intraday within individual stocks trading in Japan. At ExeQution Analytics, our core focus is turning data into value by uncovering actionable insights that drive decision-making and performance. This ethos motivated us to delve deeper into the intraday dynamics of the Japanese market, leveraging our expertise to understand the effectiveness of pairs trading strategies in this market.

SHORT TERM COINTEGRATION

The dataset for our report covers two months of tick data for the members of the TOPIX 100 index in Japan : the 100 largest stocks trading on this exchange in terms of market cap.

Our strategy is to identify suitable pairs to trade by measuring the short-term intraday cointegration of each pair of stocks within the TOPIX 100. We snapped the mid-price at five minute intervals to eliminate some of the noise present in raw tick data and calculated the cointegration of each pair over the previous 5 business days using the augemented Engle-Granger method. We intentionally focus on a short interval as we intend to apply the results to intraday trading behaviour.

Out of 4950 possible combinations, we choose the top 10 most cointegrated stock pairs on each day for our strategy. The table shows a sample result for the first day of trading.

Stock 1	Stock 2	Cointegration Factor
8267	8591	1
4661	8113	0.9940
4528	9022	0.9927
6502	8801	0.9919
5713	7974	0.9896
9020	9202	0.9848
7201	7733	0.9838
2502	4519	0.9801
9433	9735	0.9795
5108	6502	0.9617

INTRADAY PRICE RELATIONSHIPS

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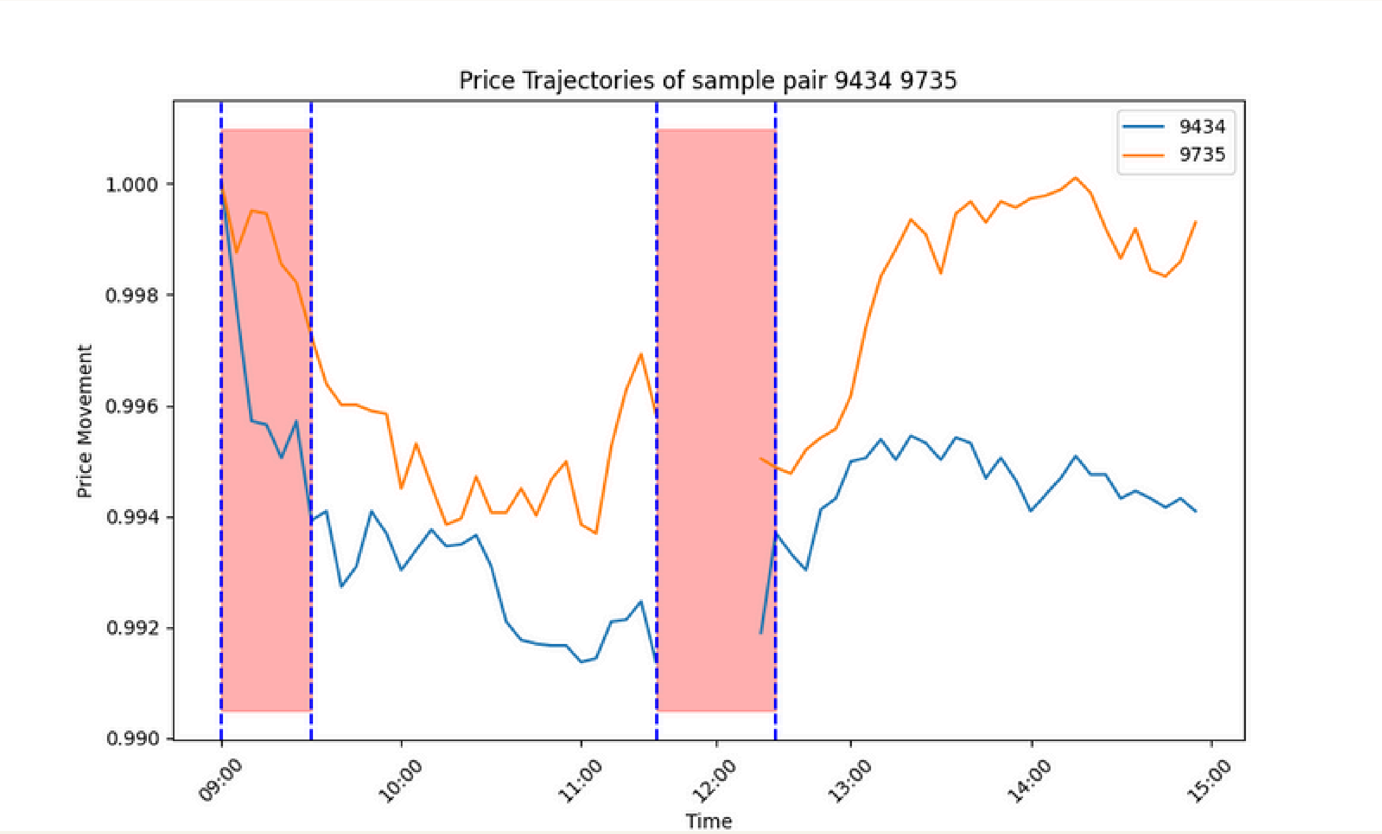
Following the methodology established in the original article, we applied a linear regression to each of our chosen pairs to measure the relationship between intraday price movements for that pair. Our intent is to develop a model that can be used to evaluate the price differential between the two stocks. Once we have established this relationship, we can use real time measures of this price differential to determine when to open and close positions.

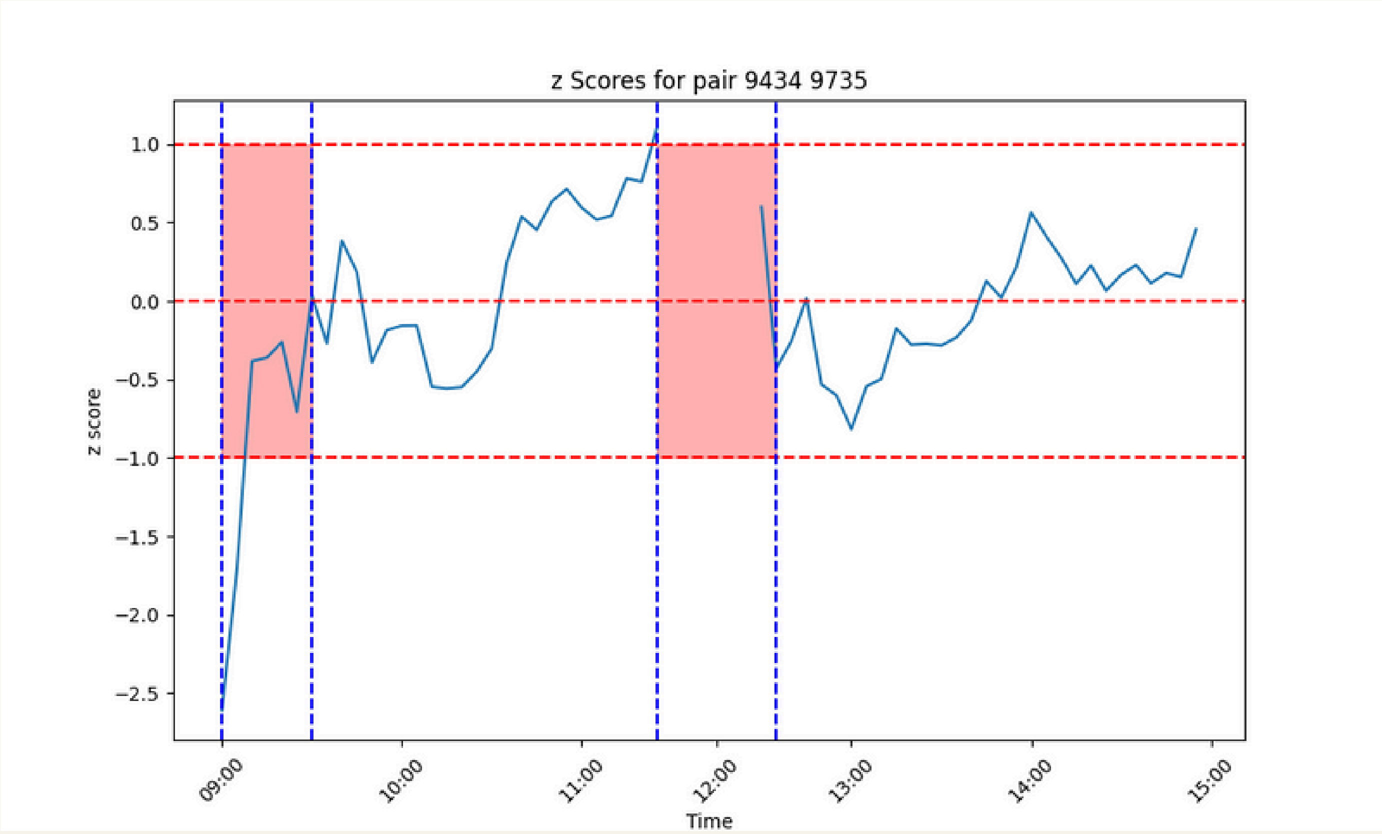
When the price differential is positive, we hypothesise that Stock 1 is underpriced or Stock 2 is overpriced and open trading positions to reflect this hypothesis. Conversely, when it's negative, we hypothesise that Stock 1 is overpriced or Stock 2 is underpriced and trade in the opposite manner. Once we have opened positions in both stocks, we monitor the changes in price-differential to understand when these positions should be closed and our profit or loss should be realised.

All positions are closed at the end of each trading day to eliminate our exposure/risk to overnight movements in the market. It is possible that we may not open a trading position in a given pair on a given day if the price differential follows the relationship that we have modelled and does not depart intraday from our expected relationship.

TRADING STRATEGY

To implement our trading strategy, we derive z-scores from the price differentials to allow us to determine when the discrepancy is statistically significant. We establish symmetrical positive and negative trigger levels. When the z-score exceeds our positive trigger level, we'll open a long position in the under-priced stock and a short position in the over-priced stock. Conversely, when the z-score drops below our negative trigger level, we'll open opposite positions. We'll close out the positions when the z-score returns to zero, or if this is not achieved, at the end of the trading day.





The graphs above show example price movements and z-scores for a pair of stocks on a single day with the shaded intervals identifying the two periods when we had open positions for this pair. We will step through these graphs in detail in the next page.

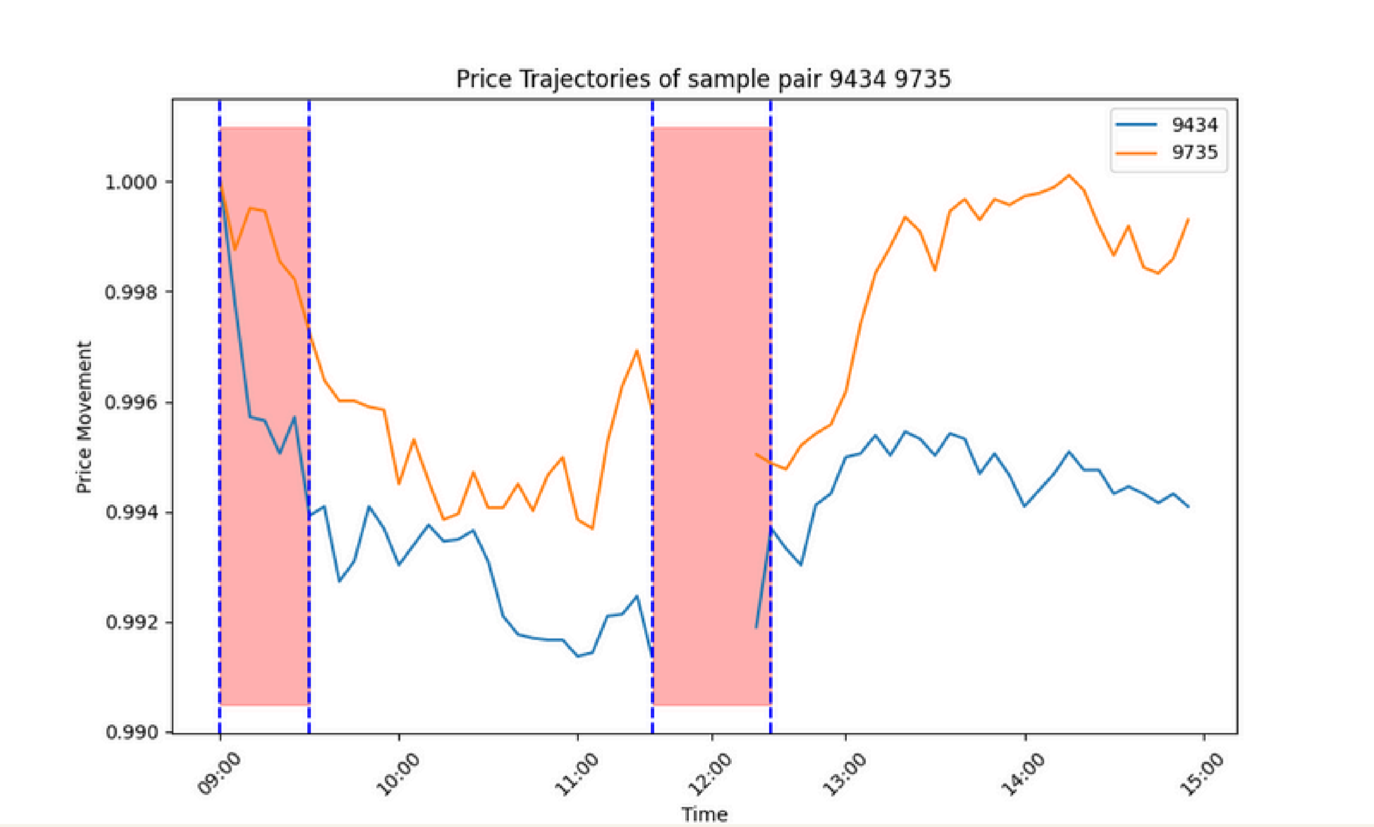
TRADING STRATEGY

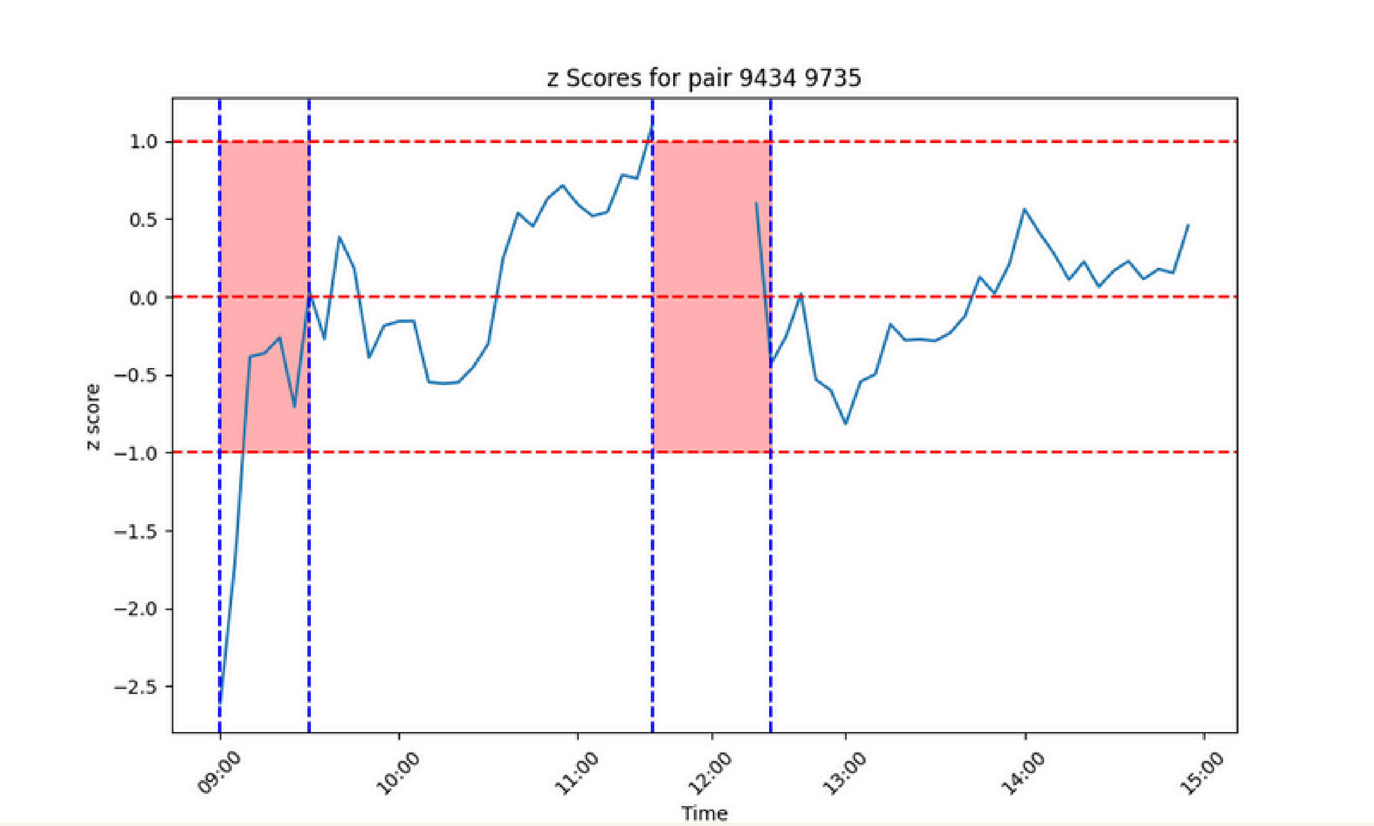
Stepping through the data presented in these same two graphs :

When the market opens at 09:00, the price differential (as demonstrated by the negative z-score in the bottom graph) is significant enough to trigger our strategy to establish a short position in 9434 and an equal long position in 9735.

At 09:30, the z-score approaches zero so we close off both open positions. At this point, the prices of both stocks have decreased from the open but the price of our short position has decreased more than the price of our long position, thus our trading activity yielded a profit.

We remain out of the market until 11:25 when the price discrepancy is inverted so we open a long position in 9434 and a short position in 9735. We typically see an increase in volatility leading into the lunch break so this is not unexpected. This position remains open for the hour long lunch break and we close it at 12:35. The price of our long position has increased, the price of our short position has decreased, thus yielding another profitable result.



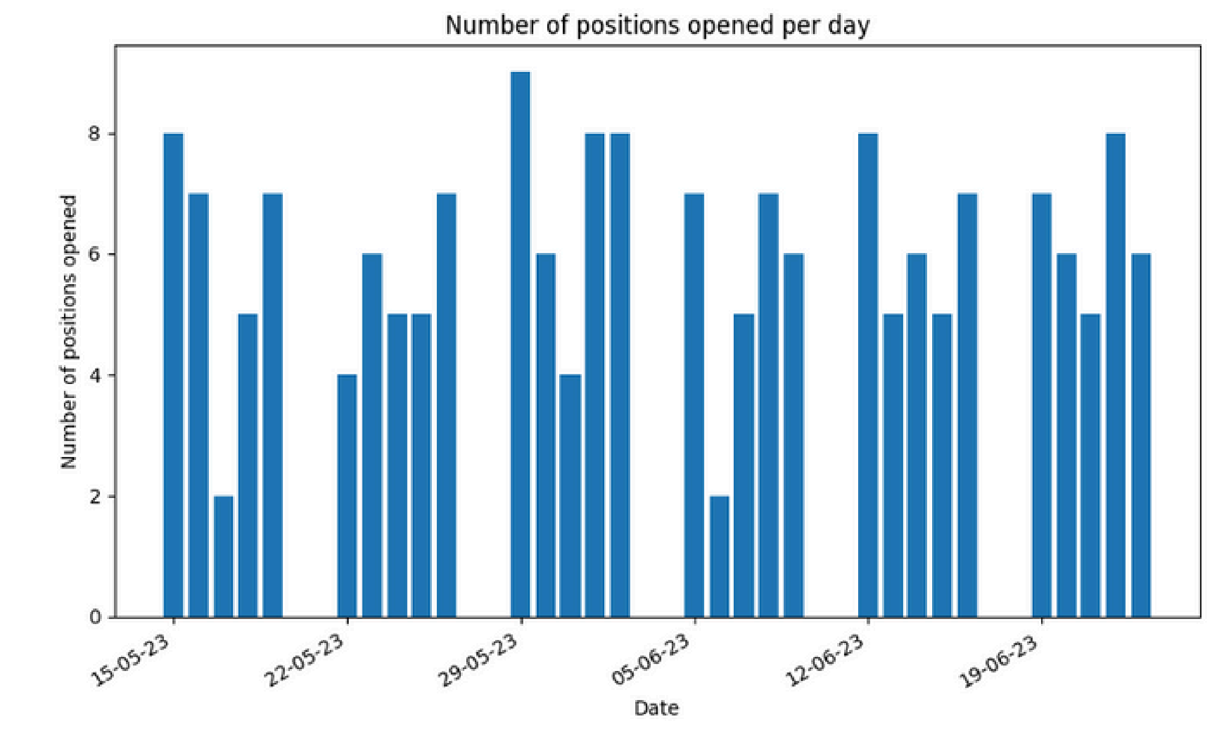


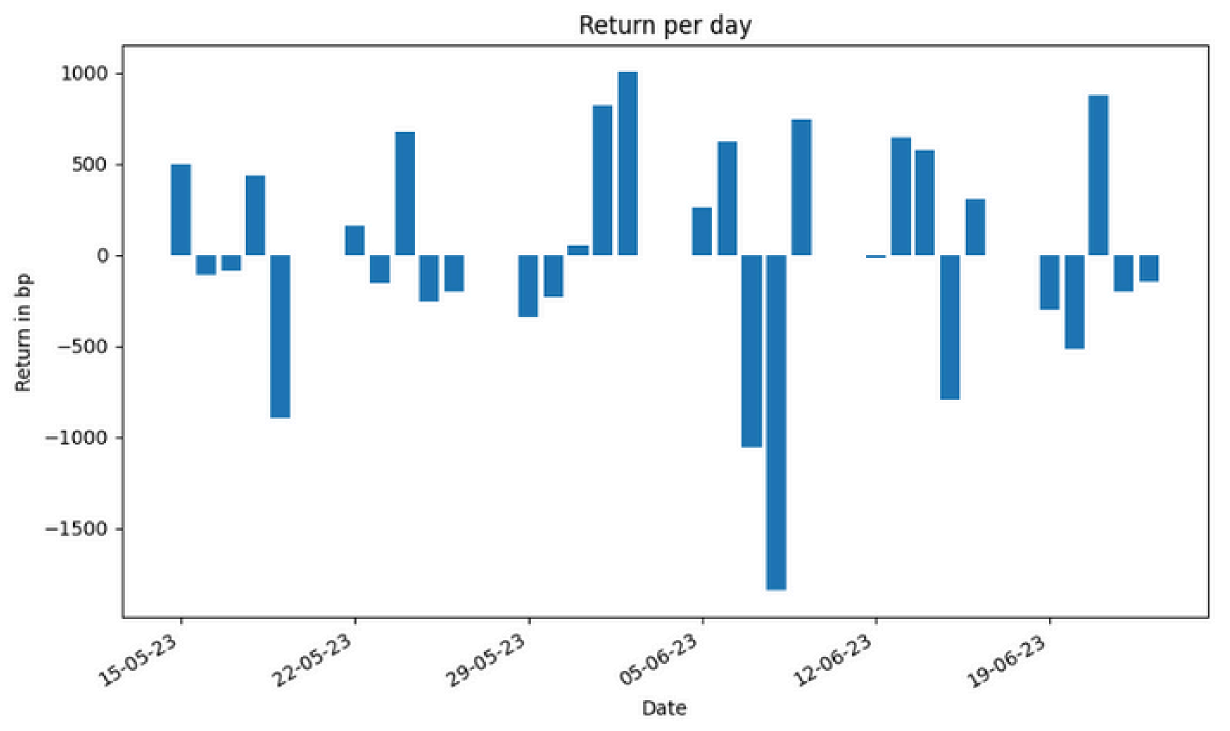
RESULTS : TRIGGER 95%

Our strategy as described in the previous slide, runs for the top ten cointegrated pair of stocks on each trading day for six weeks. In our initial test, we use 1.96 as our trigger point which represents the 95% confidence interval of a normal distribution. Overall, this results in a total return of 5.1%.

As can be seen in the top graph, we alternate between opening 2-9 positions per day, with a median of 5 - i.e. on an average day, we do not trade any positions for 50% of our identified pairs .

The bottom graph charts our daily return which shows that despite being overall profitable, the daily return is inconsistent, showing positive returns on 14 out of the 30 days within our date range, and with the biggest single day loss exceeding the biggest single day gain. On average, the return on positive days is ~550 bps which exceeds the average return on negative days of ~450 bps, thus leading to an overall positive result. The standard deviation of our daily return is quite high at 640 bps.



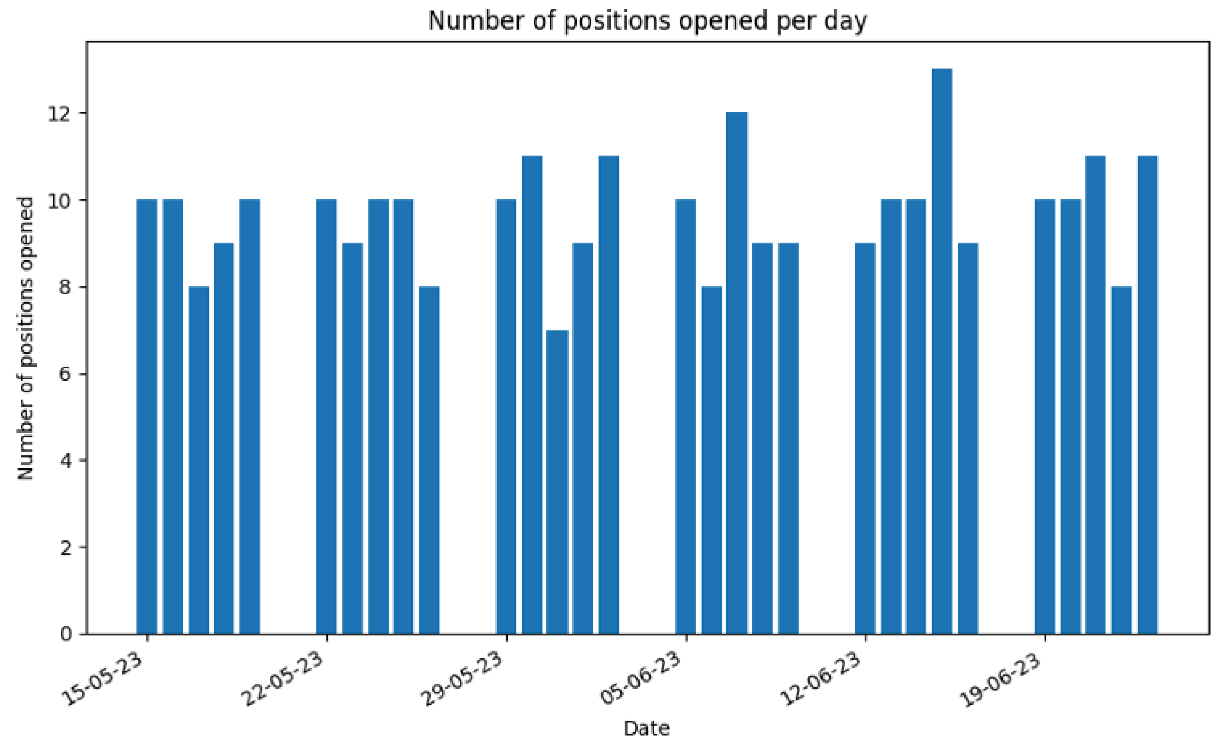


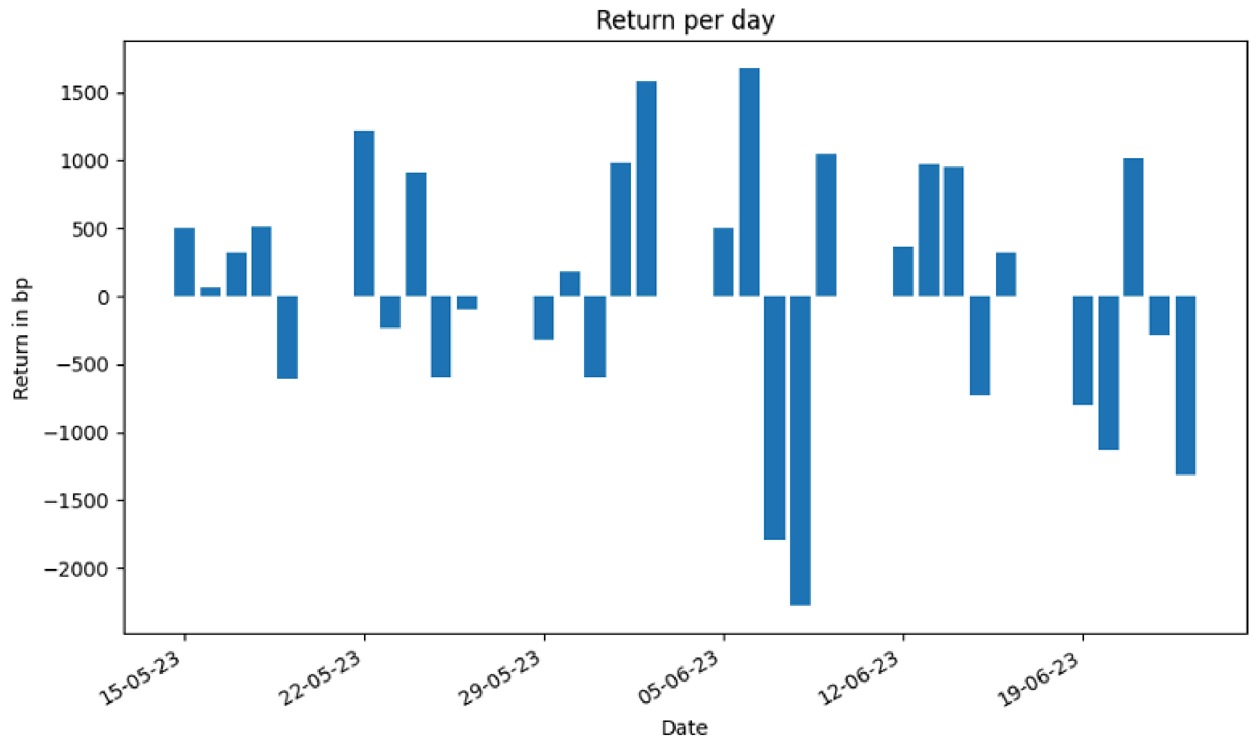
RESULTS : TRIGGER 70%

We were curious to loosen the constraints of the trading strategy to understand how this would effect trading activity, overall profitability and volatility of returns. To achieve this, we changed our trigger point to 1.036 representing the 70% confidence interval of a normal distribution. This resulted in higher levels of activity, increased volatility and a significant increase in overall return over the six week period up to <u>23.5%.</u>

As the graphs show, our average number of positions opened per day doubled and most pairs now trade most days.

This increased activity led to an improvement in our daily hit rate : we now see positive returns on 17 days out of 30. However, this increased return comes with a higher level of risk : the single worst day now returns a one-day loss in excess of 20% and the standard deviation of our daily returns also increased from ~640 to ~970 bps.





RESULTS BY PAIRS

We were interested to understand the characteristics of the pairs that generated the best return.

The table shows the total return by stock-pair over the full six week period of our back test using our 70% trigger level. The top two performing pairs lie within the same sector but interestingly, that is not true of the rest of the list.

Neither do we observe a strong skew towards a particular sector or sector groupings with the cointegrated stocks representing a wide range of stocks across our eligible universe.

Stock 1	Sector 1	Stock 2	Sector 2	Basis Point Return
6920	Technology	8035	Technology	884
9433	Communications	9984	Communications	667
3382	Consumer Staples	8058	Industrials	648
8001	Industrials	8830	Real Estate	422
4503	Healthcare	6920	Technology	398
8725	Financials	9202	Industrials	395
1928	Consumer Discretionary	4063	Materials	388
1928	Consumer Discretionary	8697	Financials	363
7201	Consumer Discretionary	8002	Industrials	331
8031	Industrials	8801	Real Estate	317

CONCLUSIONS

Cointegration can be a powerful tool for identifying relationships but its application to intraday prices should be approached with caution. Whilst our back test showed overall positive results for the six week window, these were inconsistent from day to day. Lowering the confidence threshold of our trigger point led to increased activity and significantly improved return but with corresponding higher risk levels. The risk to return ratio suggests that backtesting over a much longer date-range would be required in order to have confidence in the results.

Our trading strategy opened and closed all positions at mid-price. We did not perform any further analysis to understand the sensitivity of the strategy to execution costs.

Following our analysis, we tend to conclude that cointegration may be more meaningful over longer term periods and microstructure factors such as liquidity, spread and other orderbook dynamics dominate intraday price movements.

Overall, we enjoyed this experience as an interesting exploration of intraday price dynamics, but we won't quit our day jobs to open a pairs trading strategy just yet.

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At ExeQution Analytics, we pride ourselves on our ability to harness the power of technology and market data to offer detailed analysis on the ever-evolving world of market microstructure and trading behaviours. Amidst the chaos and noise, lies the potential of discovery and innovation. Every tick, every trade, and every market event offers an opportunity to uncover hidden patterns, exploit inefficiencies, and gain a competitive edge. We strive to identify these opportunities and transform data into actionable insights.