Analysis on the Profitability of Pairs Trading in Current Market Conditions

MGT 6203 – Data Analytics in Business
Final Report

Team 039
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Objective/Description of Topic

Background Info/Framing of the Problem

There are a wide range of trading strategies available today, from passive strategies such as investing in exchange traded funds (ETFs) to highly active strategies such as high frequency trading. It is challenging for an investor to decide on an appropriate strategy that best fits their needs. One such class of trading strategies, known as statistical arbitrage, employs mean reversal techniques to profit from the short-term holding of securities. The simplest of this type of strategy is known as pairs trading.

Pairs trading is a market-neutral trading strategy that involves identifying two securities that have a historically strong correlation, typically in the same industry or sector, and simultaneously taking long and short positions whenever they diverge from their long-run equilibrium relationship [3]. The overall goal is to profit from the convergence of the two securities' prices. The strategy is less impacted by market volatility. Given a large pool of securities from various sectors, we would like to effectively identify pairs of securities and develop a portfolio of them to determine if pairs trading is profitable in today's market with the emergence of ETFs offering lower fees and high yields.

Hypothesis

Our initial hypothesis was that pairs trading generally performs worse than the market. We sought to investigate our hypothesis by identifying all possible trading opportunities from a pre-selected basket of stocks and simulating the optimal trades for each pair over a set period. The total return from an equal-weighted portfolio of each stock pair was then compared to market baselines at a monthly and yearly aggregate level to determine the viability of pairs trading as a suitable trading strategy for novice investors.

Datasets

Data Description and Key Variables

Over a ten-year period (Jan. 2012 – Dec. 2022), the daily stock price data for a basket of 54 stocks was initially selected. For example, in the Vanguard 500 Index Fund ETF (VOO) and Vanguard Small-cap Index Fund ETF (VB) data shown in Figures I and II below, the following key variables will be used: *date*, *adjusted close price*, and *volume of shares traded*.

Figure I: Sample Raw Data for NYSEARCA: VOO

Ticker Symbol	Date	Open	High	Low	Close	Adj Close	Volume
VOO	1/13/2012	117.70	118.00	116.82	118.00	96.10	147200
VOO	1/17/2012	118.98	119.18	118.06	118.32	96.36	324250
VOO	1/18/2012	118.32	119.64	118.10	119.64	97.44	172100
VOO	1/19/2012	120.00	120.34	119.72	120.28	97.96	224500
VOO	1/20/2012	120.08	120.34	119.78	120.28	97.96	345200
VOO	1/23/2012	120.28	120.98	119.86	120.40	98.06	130950
VOO	1/24/2012	119.68	120.30	119.48	120.22	97.91	203100
VOO	1/25/2012	120.08	121.54	119.64	121.28	98.77	254050

Figure II: Sample Raw Data for NYSEARCA: VB

Ticker Symbol	Date	Open	High	Low	Close	Adj Close	Volume
VB	1/13/2012	71.82	72.08	71.28	71.94	61.13	278700
VB	1/17/2012	72.62	72.84	71.84	71.95	61.14	448200
VB	1/18/2012	71.95	73.30	71.84	73.29	62.28	210300
VB	1/19/2012	73.59	73.95	73.31	73.79	62.71	370800
VB	1/20/2012	73.68	74.00	73.56	73.82	62.73	456800
VB	1/23/2012	73.81	74.39	73.22	73.78	62.70	401700
VB	1/24/2012	73.34	74.27	73.00	74.15	63.01	334100
VB	1/25/2012	74.11	75.05	73.80	74.86	63.62	344200

Source: Yahoo Finance API (https://finance.yahoo.com/)
https://github.gatech.edu/MGT-6203-Spring-2023-Canvas/Team-39/tree/main/Data

Data Preprocessing

For data preprocessing, we developed a pipeline that retrieves historical stock prices from a list of stock/ETF tickers and performs necessary transformations (e.g. convert data types, order by date, calculate the natural log of *adjusted close price*).

In our initial attempt, we split the 10-year historical dataset into training, validation, and test sets. However, this approach posed many negative effects. We discovered that both the trading signals and hedge ratio generated from the training set was inconsistent with the validation and test periods by a significant margin. The constructed model performed well during the initial training period but ineffective/poorly during validation and test periods. Due to the above-mentioned reasons, we revised our approach to perform a rolling regression to both calculate the hedge ratio and generate trading signals. This allowed us to discover more cointegration periods as the rolling window is shorter, allowing us to generate more aggressive trading signals.

As shown in Figure II below, a linear combination of two stock prices was calculated to form the pairs (denoted with suffix *.x* and *.y*). New variables such as the *hedge ratio*, *spread*, *p-value*, *z-score* and *threshold* were constructed to use in our analysis.

Figure III: Sample Constructed Data for VOO and VB Pair

date	close.x	adjusted.x	symbol.x	close.log.x	return.x	close.y	adjusted.y	symbol.y	close.log.y	return.y	hedge	spread	p-value	zscore	threshold
2012-01-13	118.00	96.10	VOO	4.57	0.00	71.94	61.13	VB	4.11	-0.01	1.11	0.00	0.97	0.71	0.71
2012-01-17	118.32	96.36	VOO	4.57	0.00	71.95	61.14	VB	4.11	0.00	1.11	0.00	0.99	0.93	0.93
2012-01-18	119.64	97.44	VOO	4.58	0.01	73.29	62.28	VB	4.13	0.02	1.11	-0.01	0.59	-0.46	0.93
2012-01-19	120.28	97.96	VOO	4.58	0.01	73.79	62.71	VB	4.14	0.01	1.11	-0.01	0.82	-0.38	0.93
2012-01-20	120.28	97.96	VOO	4.58	0.00	73.82	62.73	VB	4.14	0.00	1.11	-0.01	0.77	-0.04	0.71
2012-01-23	120.40	98.06	VOO	4.59	0.00	73.78	62.70	VB	4.14	0.00	1.11	0.00	0.52	0.63	0.71
2012-01-24	120.22	97.91	VOO	4.58	0.00	74.15	63.01	VB	4.14	0.01	1.11	-0.01	0.47	-0.99	0.71
2012-01-25	121.28	98.77	VOO	4.59	0.01	74.86	63.62	VB	4.15	0.01	1.11	-0.01	0.18	-0.72	0.71

Challenges/Interesting Findings

There were many challenges and interesting findings we encountered during our data cleaning process, which included special handling for gaps in time when the stock market is closed (e.g. weekends and holidays) and establishing rules for calculating the returns for the final period if the stock pair does not converge.

As part of our initial attempt, we tested our baseline log-transformed stock pairs for co-integration over the entire training period. However, due to many pairs exhibiting a fluctuating mean and variance over time, only a handful of pairs resulted in being co-integrated when tested over long periods of time (e.g. 5-10 years). To address this issue, we formulated a dynamic hedge ratio using more recent and smaller windows of time within our series to test for co-integration and to automatically update the trading signals within our model. The results shown in Figure IV showcase an improvement in the ADF test for a sample of five *log(a) - nlog(b)* transformed stock pairs using a dynamic rather than static hedge ratio at the monthly, quarterly, and yearly aggregate level. Note that not all stock pairs are expected to be highly co-integrated at short intervals of time (e.g. *# of observations < 25* at the weekly or monthly level) but the pair should eventually converge to a cointegrated series over time.

Figure IV: ADF Test using Static vs. Dynamic Hedge Ratio (lower is better)

ADF Test w/ Static Hedge Ratio					ADF Test w/ Dynamic Hedge Ratio				
stock_a	stock_b	mth_pavg	qtr_pavg	yr_pavg	stock_a	stock_b	mth_pavg	qtr_pavg	yr_pavg
LQD	PGX	0.42	0.27	0.05	LQD	PGX	0.36	0.07	0.01
EMB	PGX	0.42	0.23	0.09	EMB	PGX	0.44	0.07	0.01
SPY	VOO	0.36	0.16	0.25	SPY	VOO	0.35	0.02	0.01
HYG	XLY	0.36	0.26	0.20	HYG	XLY	0.37	0.09	0.01
IEF	XLY	0.42	0.30	0.11	IEF	XLY	0.35	0.08	0.01

We also addressed our model's performance by implementing parallel processing via the *doParallel* and *foreach* R packages to improve the computing time of the simulation for our pair trades. Computation time varies machine to machine, but using an average machine (4 cores, 16GB of RAM), it takes about 2- 3 hours to sequentially process all combinations of 54 stocks. By using *doParallel* package, we were able to reduce computational time to 10 – 25 minutes.

Approach/Methodology

Models, Algorithms, and Visualizations

From all possible stock-pair combinations within the basket, let A and B define the *adjusted close price* of stock A and stock B, respectively.

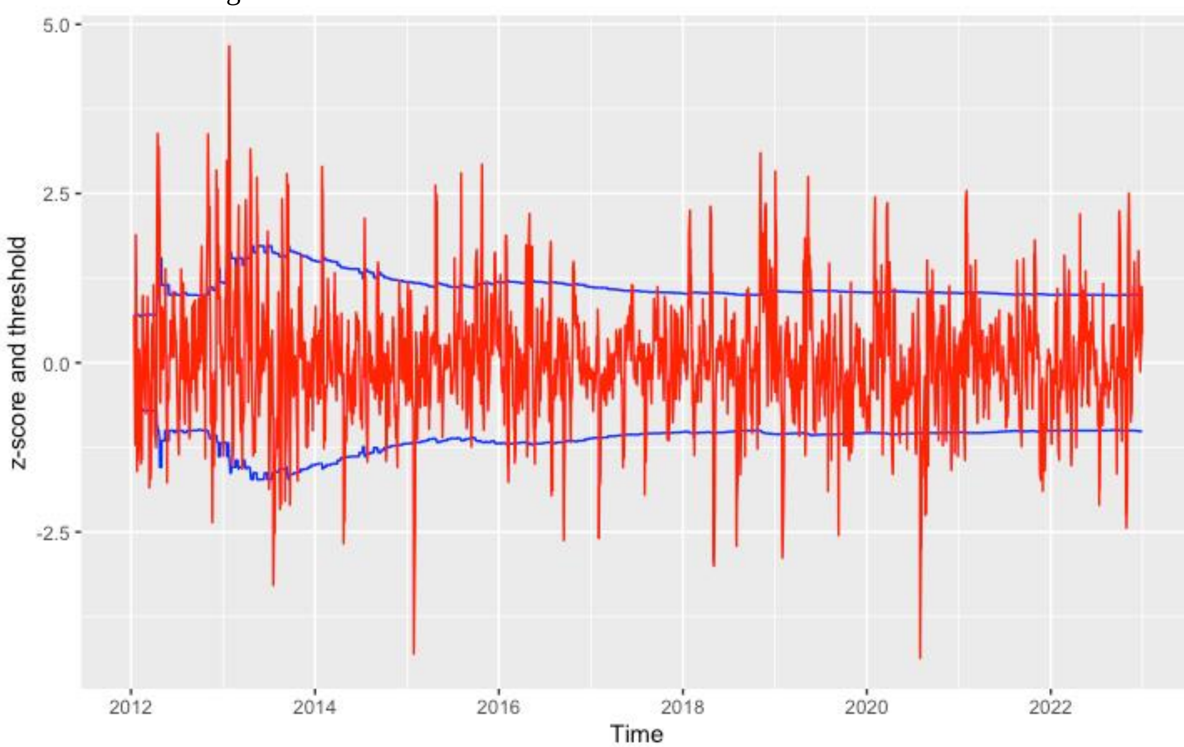
1. **Preliminary Filter**: Determine if each stock-pair can be traded by checking if the pair is co-integrated using weekly and monthly rolling periods. Use linear regression *log(A) = ßlog(B)*, where *ß* is hedge ratio (indicating how much to long/short a position so that the pair is equally weighted). Apply Augmented Dickey Fuller test on the spread of *log(A) - ßlog(B)* at the 95% confidence interval (e.g. if the p-value is less than 0.05, the pair is co-integrated for that period). If the pair has no cointegrated periods, we assume that it is not suitable for trading.

Figure V: ADF Test via Rolling Window for VOO-VB Pair

date	close.x	adjusted.x	symbol.x	close.log.x	return.x	close.y	adjusted.y	symbol.y	close.log.y	return.y	hedge	spread	p-value	zscore	threshold
2012-02-16	124.46	101.36	VOO	4.62	0.01	78.28	66.52	VB	4.20	0.02	1.10	0.00	0.69	0.07	1.50
2012-02-17	124.76	101.61	VOO	4.62	0.00	78.23	66.48	VB	4.20	0.00	1.10	0.00	**0.03**	0.47	1.48
2012-02-21	124.84	101.67	VOO	4.62	0.00	77.85	66.16	VB	4.19	0.00	1.10	0.00	0.54	1.25	1.48
2012-02-22	124.42	101.33	VOO	4.62	0.00	77.29	65.68	VB	4.18	-0.01	1.10	0.01	0.90	1.75	1.50
2012-02-23	125.02	101.82	VOO	4.62	0.00	78.24	66.49	VB	4.20	0.01	1.10	0.00	0.65	0.37	1.50
2012-02-24	125.20	101.97	VOO	4.62	0.00	78.13	66.40	VB	4.20	0.00	1.10	0.00	0.44	0.77	1.50
2012-02-27	125.42	102.15	VOO	4.63	0.00	78.10	66.37	VB	4.20	0.00	1.10	0.00	0.66	1.05	1.50
2012-02-28	125.86	102.50	VOO	4.63	0.00	77.93	66.23	VB	4.19	0.00	1.10	0.01	0.59	1.53	1.53
2012-02-29	125.18	101.95	VOO	4.62	-0.01	76.95	65.39	VB	4.18	-0.01	1.10	0.01	0.96	2.16	1.75
2012-03-01	126.00	102.62	VOO	4.63	0.01	77.46	65.83	VB	4.19	0.01	1.10	0.01	**0.03**	1.64	1.75
2012-03-02	125.66	102.34	VOO	4.63	0.00	76.43	64.95	VB	4.17	-0.01	1.10	0.02	0.25	2.56	2.15

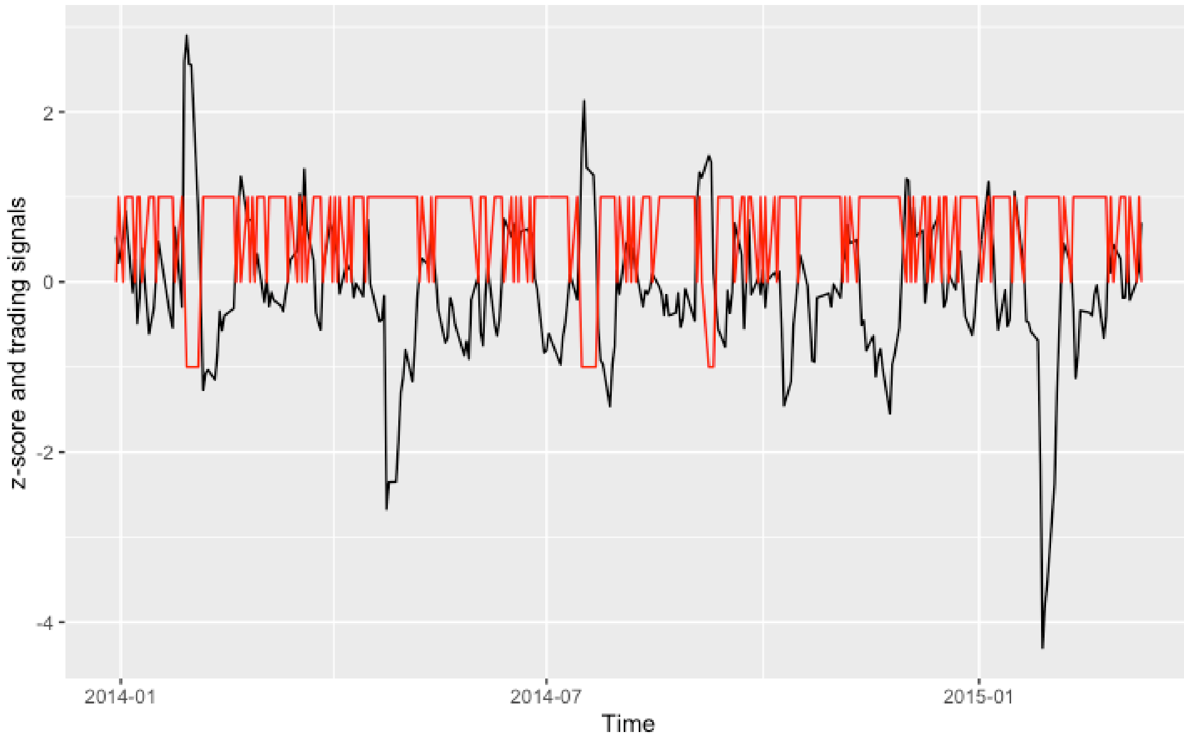
2. **Main Process**: Determine entry and exit criteria.
   - **Entry**: Calculate the z-score of the spread between the log-transformed stocks. Use a rolling 90^{th} percentile z-score as a threshold to enter long (positive threshold) and short (negative threshold) positions. Initially, the threshold varies as not enough observations are available, however the z-score will begin to stabilize over time. Figure VI below demonstrates how the thresholds (blue lines) interact with respect to the z-score (in red).

Figure VI: Z-score and Threshold for MSFT-AAPL Pair Over Time



   - **Exit**: If we are previously holding a position and the z-score crosses a zero point, we exit the trade. Figure VII below demonstrates the z-score (black line) and the generated trading signals (red line).

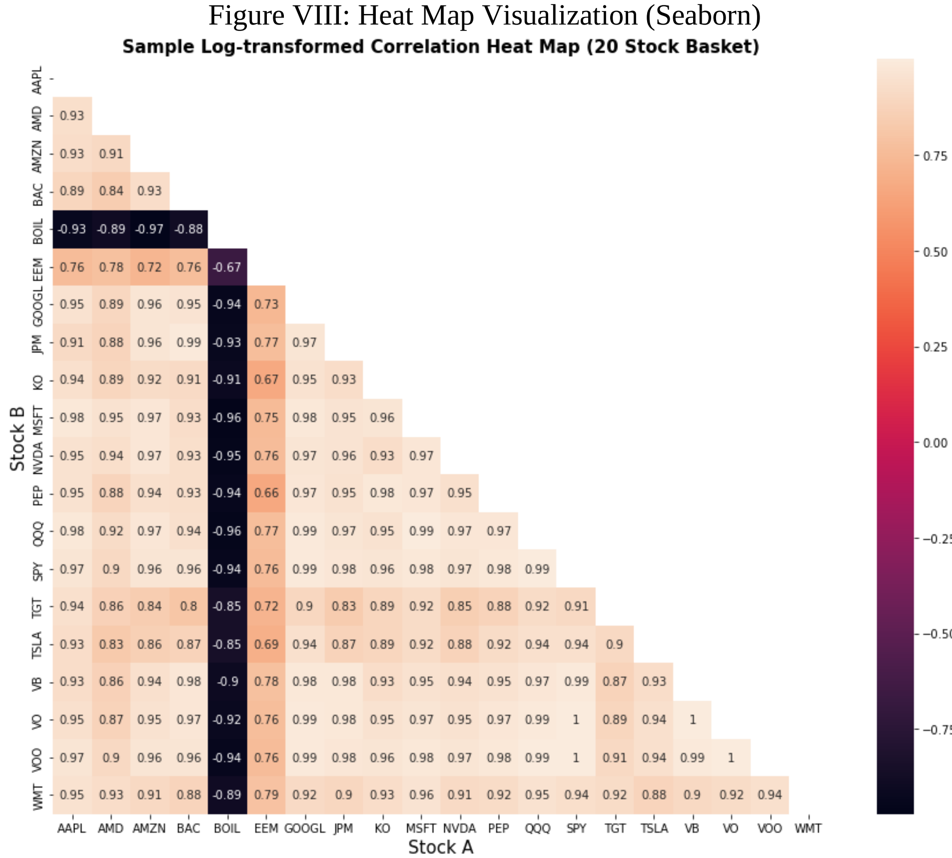
Figure VII: Z-score and Trading Signals for MSFT-AAPL Pair Over Time



3. **Validation/Simulation**: Since the z-score and threshold are rolling values for each trading day, validation is performed by simply iterating through entire dataset date-by-date and simulating trades using pre-determined entry and exit criteria for which pairs are executable. For each trade, profit/loss is recorded; and monthly return is calculated for each pair. Total return for all pair trades is reported at the end of the period and compared to the market baselines.

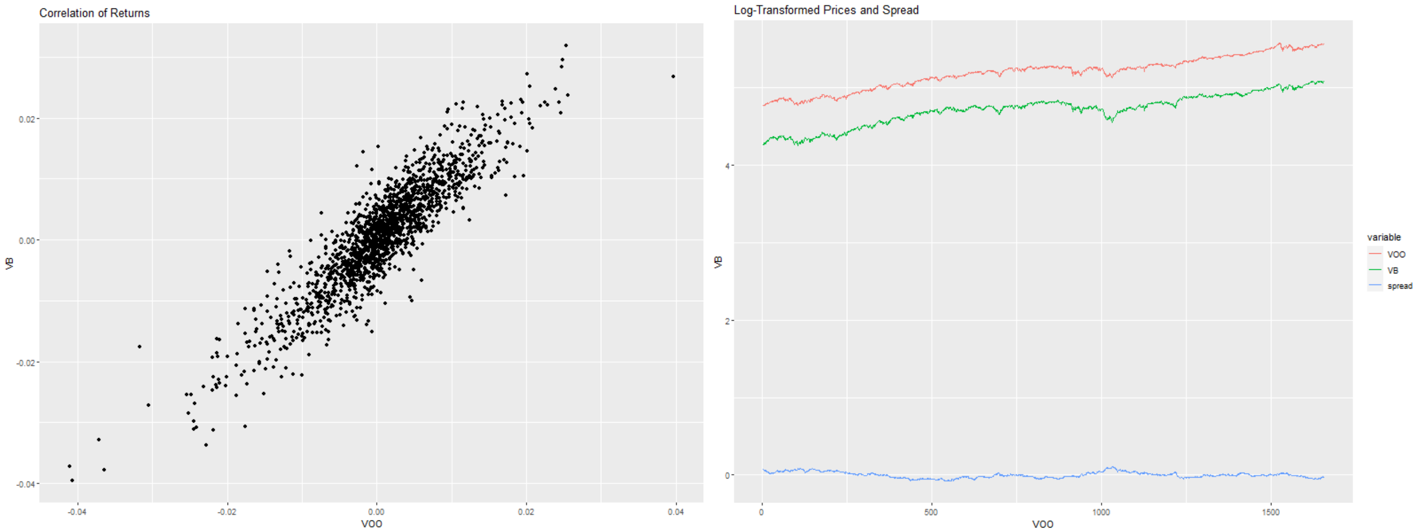
Results and Figures

Figure VIII: Heat Map Visualization (Seaborn)



In Figure VIII shown above, we can see the correlation coefficients of log-transformed pairs for a basket of 20 stocks.

Figure IX: Vanguard 500 Index Fund (VOO) vs. Vanguard Small-cap Index Fund (VB)



In the VOO vs. VB example as shown in Figure IX above, the stock pair is highly correlated with a log-transformed correlation coefficient of 0.99, however, the two stocks do not diverge or converge often which is an important trait we need to exploit in this pairs trading strategy; hence this pair is less likely to generate a large profit margin.

Figure X: Microsoft (MSFT) vs. Apple (AAPL)

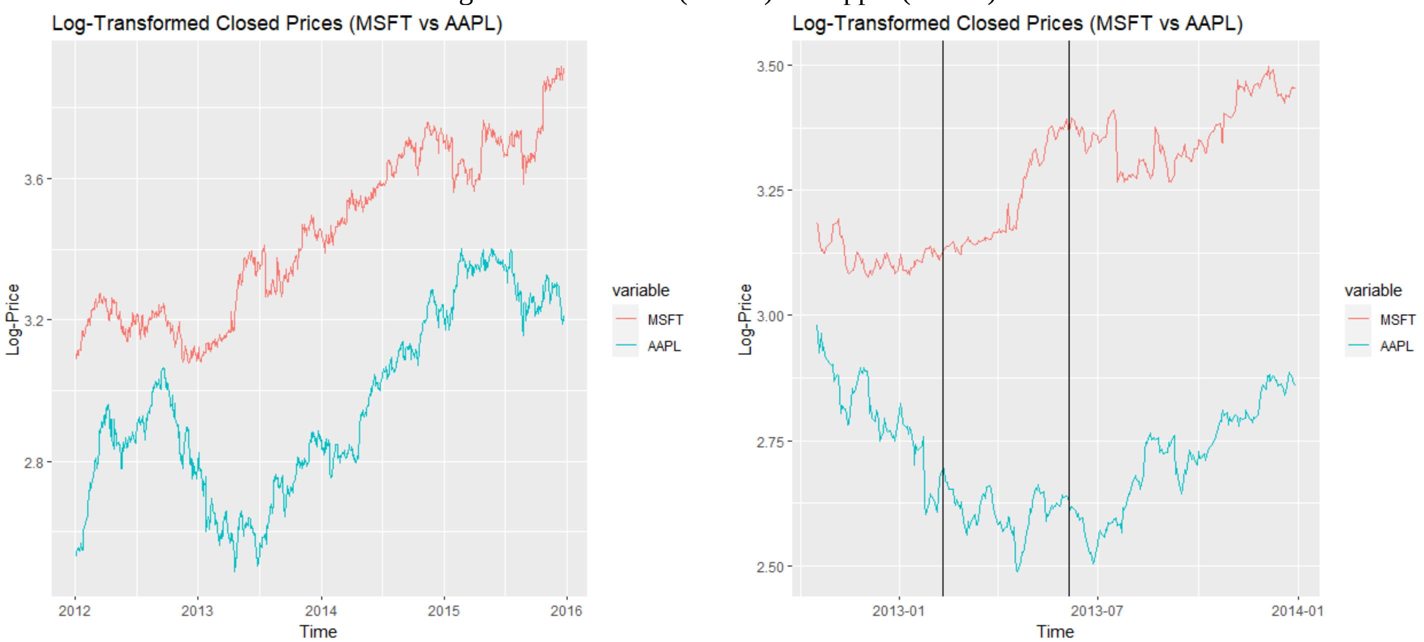


Figure X above is an example plot of log-transformed prices for Microsoft (MSFT) and Apple (AAPL). The left plot shows a longer history from 2012 to 2016 where the pair is mostly cointegrated while the right plot shows a smaller section from 2013 to 2014 with the trading window marked between the two vertical lines.

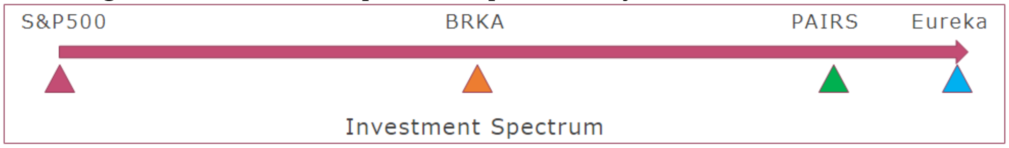
Selected Benchmarks

Benchmarks selected represent a variety of possible portfolio management strategies to compare performance of our pairs trading strategy portfolio (PAIRS) against:

- S&P500 (VOO): Passive, Long-only (stocks in PAIRS are large cap)
- Berkshire Hathaway (BRKA): Selective, Long-only, Buy-and-hold, Fundamental / Quality (not market-neutral)
- Eureka Hedge Fund Index (EHI473): Alternative / Long-short-hedged (sophisticated, active portfolio turnover)

These allow us to draw comparisons between the tradeoffs, i.e., benefits and limitations, between strategies across the investment spectrum – shown below in Figure XI, in terms of simple (left) versus complexity and sophistication (right).

Figure XI: Investment Spectrum represented by PAIRS and benchmarks.



To set context before beginning analysis, PAIRS is a simple one, in that it is our initial application of a generated signal discussed earlier into a portfolio context. To avoid bias, pair trades were initiated and closed based only on past data available at time t, i.e., what was able to be known at that time / no future data leakage. Additionally, no selection criteria for which pairs trading opportunities to take; that we took all opportunities that met minimum requirements for evidence of cointegration. This means that there were 1,326 pairs and hence each pair had an equal, 1/1,326 weighting in our portfolio, the most rudimentary version of this strategy – only a starting point upon which many improvements could be explored. For example, portfolio returns might improve if some basic application of a Fama-French approach to ranking the n-best opportunities per month versus the n-worst. Additionally, risk management strategies could be taken into consideration like incorporating risk metrics, macro-economic data and trends in markets or just managing specific trades.

Results - Monthly Return

Figure XII showcases descriptive statistics for PAIRS monthly returns breaking out between positive and negative returns. In summary:

- PAIRS provided positive monthly returns 65% of the time and median positive months, 1.9% are greater than median negative months, -1.2%; odds are favorable with median monthly return outpacing losing months.
- Mean monthly return was 0.057% with a standard deviation of 3.21%
- Largest monthly loss -18.4%, largest monthly gain 8.48%

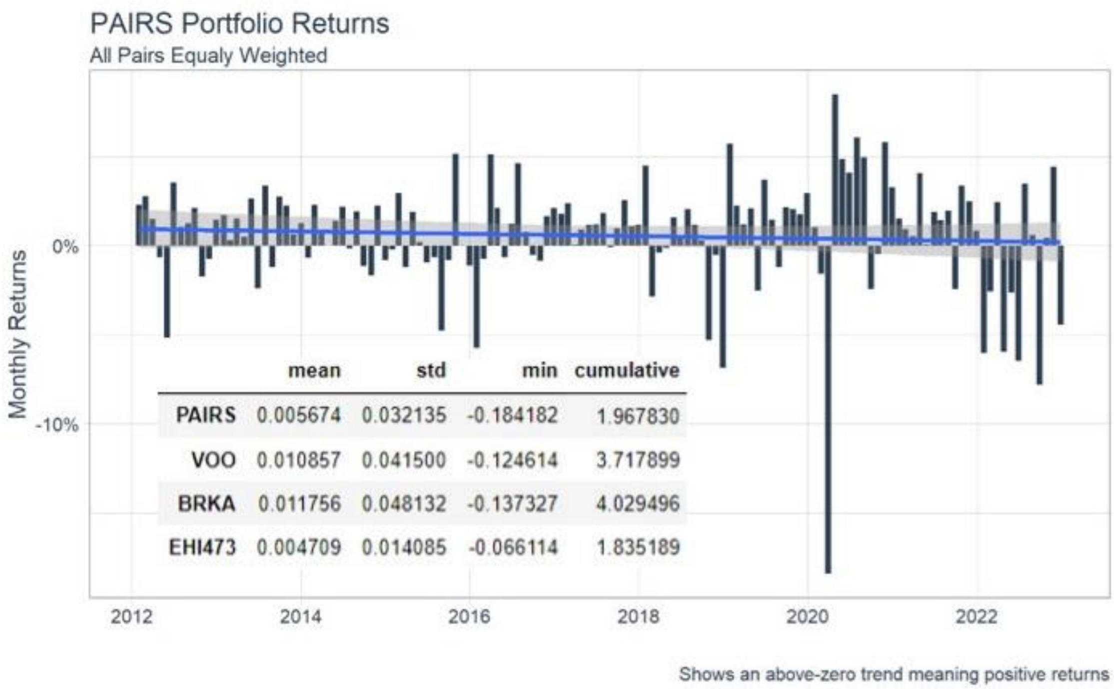
Figure XII: Monthly PAIRS Portfolio Returns

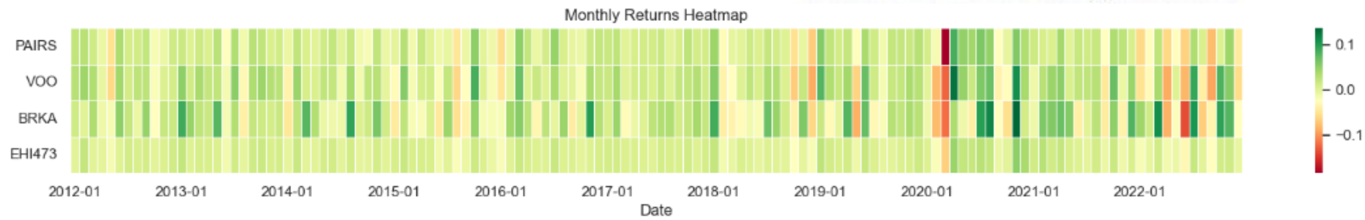
return_type	count	mean	std	min	25%	50%	75%	max
negative	46.0	-0.025214	0.032215	-0.184182	-0.028154	-0.012034	-0.006559	-0.000108
positive	86.0	0.022196	0.015799	0.000449	0.011606	0.019020	0.027571	0.084830
all	132.0	0.005674	0.032135	-0.184182	-0.006662	0.011250	0.021960	0.084830

When comparing return metrics to the benchmarks in Figure XIII, we observe:

- PAIRS behaves more like Eureka Hedge Fund Index which makes sense since both are market-neutral
- VOO and BRKA behave similarly – they are both long-only strategies
- PAIRS has the largest monthly drawdown, nearly 50% greater than VOO
- PAIRS has the second lowest volatility of returns as measured by standard deviation
- We observed that the volatility in returns increased dramatically from 2020-2022. We expect that this is likely due to the COVID-19 pandemic.
- From the heatmap, we see that PAIRS worst month in early 2020 was accompanied by all portfolios. This is also true for most protracted drawdowns.

Figure XIII: Monthly PAIRS Portfolio Returns Bar Chart (above) and Heatmap with Benchmarks (below)





Results – Risk-adjusted Portfolio Metrics

In this section, PAIRS returns are contrasted against risk-adjusted returns of our selected benchmarks, to answer the question, "How good is the strategy?" Figure XIV shows the following risk-adjusted metrics:

- Alpha (monthly and annualized) describes an investment strategy's ability to beat the benchmark
- β measures a stock's sensitivity to overall market movements: risk free = 0 and SP500 (overall market) = 1.
- Correlation measures degree to which two securities move in relation to each other
- R-squared is a measure of the percentage of the fund's performance that occurs as a result of the market
- Sharpe ratio divides a portfolio's excess returns by a measure of its volatility to assess risk-adjusted performance

Figure XIV CAPM Statistics and Sharpe Ratio from 2012-01-01 through 2022-12-31

symbol	Alpha	Annualized Alpha	Beta	Correlation	R-squared	StdDevSharpe (Rf=0%, p=95%)
PAIRS	-0.0017	-0.0203	0.6797	0.8777	0.7704	0.1766
VOO	0	0.0005	1.001	0.9999	0.9997	0.2616
BRKA	0.0022	0.0266	0.8854	0.7625	0.5814	0.2442
EHI473	0.0015	0.0186	0.2934	0.8633	0.7453	0.3343

Considering risk-adjusted returns, PAIRS:

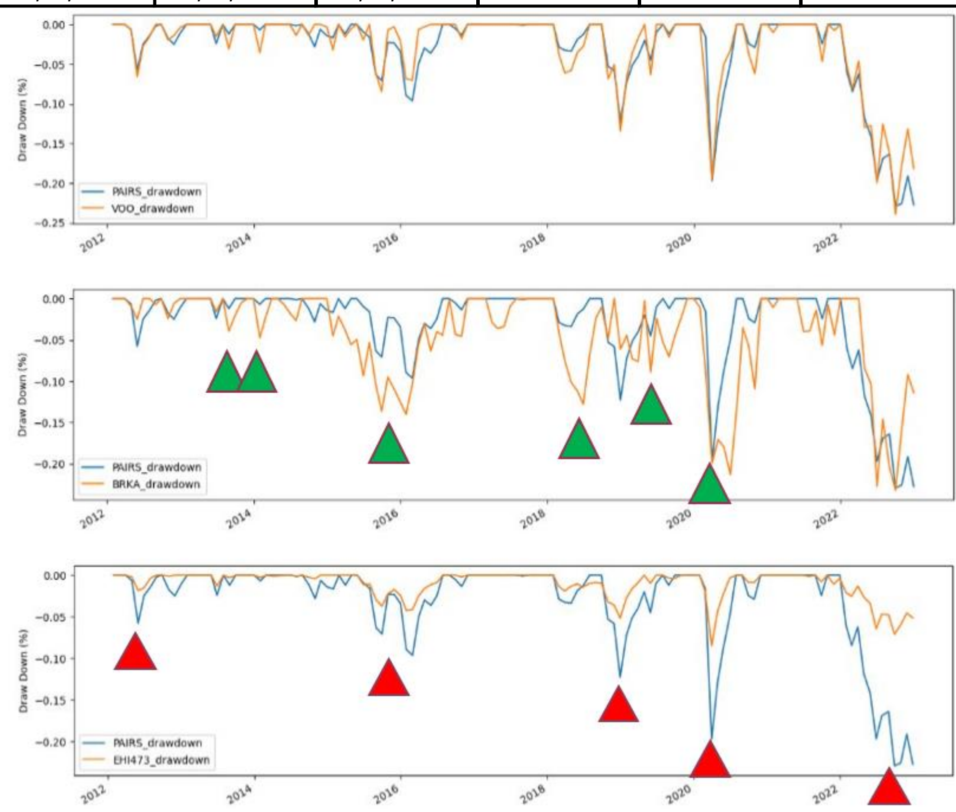
- is the least performant in terms of monthly and annual Alpha (both measures are negative).
- Has a Sharpe Ratio of 0.1776, underperforming all benchmarks, even passively holding the market (VOO).
- Has a Beta of 0.6797, which is 2nd best. This can be interpreted as PAIRS is generally less sensitive to overall market movements and closer to risk free (0) than Berkshire Hathaway (BRK-A) and S&P 500 (VOO). It should be noted that the Eureka Hedge Fund Index is clearly superior to all benchmarks with a Beta of 0.2934.

PAIRS – Drawdown Analysis

Drawdown analysis assesses the strategy's performance in terms of magnitude and duration of losses from high-water marks attained. This gives critical insight into potential capitulation (a serious concern to money managers) in addition to how effective the strategy is at reducing drawdowns and how quickly they recover. Figure XV shows metrics for the top 5 drawdowns for PAIRS and the benchmarks. The Eureka Hedge Fund Index is the clear winner with the depth of the top 5 largest drawdown being 2-3 times less than all others. PAIRS drawdowns are similar in magnitude to both VOO and BRK-A.

Figure XV: Drawdown Statistics and Graph Comparisons from 2012-01-01 through 2022-12-31

Symbol	From	Trough	To	Depth	Length	To Trough	Recovery
PAIRS	1/31/2922	9/30/2022	NA	-0.229	13	9	NA
PAIRS	2/28/2020	3/31/2020	7/31/2020	-0.1971	6	2	4
PAIRS	10/31/2018	12/31/2018	7/31/2019	-0.1226	10	3	7
PAIRS	6/30/2015	2/29/2016	7/29/2016	-0.0963	14	9	5
PAIRS	4/30/2012	5/31/2012	9/28/2012	-0.0578	6	2	4
VOO	1/31/2022	9/30/2022	<NA>	-0.2391	13	9	NA
VOO	1/31/2020	3/31/2020	7/31/2020	-0.1958	7	3	4
VOO	10/31/2018	12/31/2018	4/30/2019	-0.1347	7	3	4
VOO	8/31/2015	9/30/2015	5/31/2016	-0.0845	10	2	8
VOO	4/30/2012	5/31/2012	8/31/2012	-0.066	5	2	3
BRKA	4/29/2022	9/30/2022	<NA>	-0.2315	10	6	NA
BRKA	1/31/2020	6/30/2020	11/30/2020	-0.2129	11	6	5
BRKA	1/30/2015	1/29/2016	11/30/2016	-0.14	23	13	10
BRKA	2/28/2018	6/29/2018	11/30/2018	-0.1278	10	5	5
BRKA	12/31/2018	5/31/2019	11/29/2019	-0.0888	12	6	6
EHI473	2/28/2020	3/31/2020	7/31/2020	-0.0848	6	2	4
EHI474	11/30/2021	9/30/2022	<NA>	-0.0709	15	11	NA
EHI475	2/28/2018	12/31/2018	4/30/2019	-0.0517	15	11	4
EHI476	6/30/2015	1/29/2016	7/29/2016	-0.0423	14	8	6
EHI477	4/30/2012	5/31/2012	8/31/2012	-0.0185	5	2	3

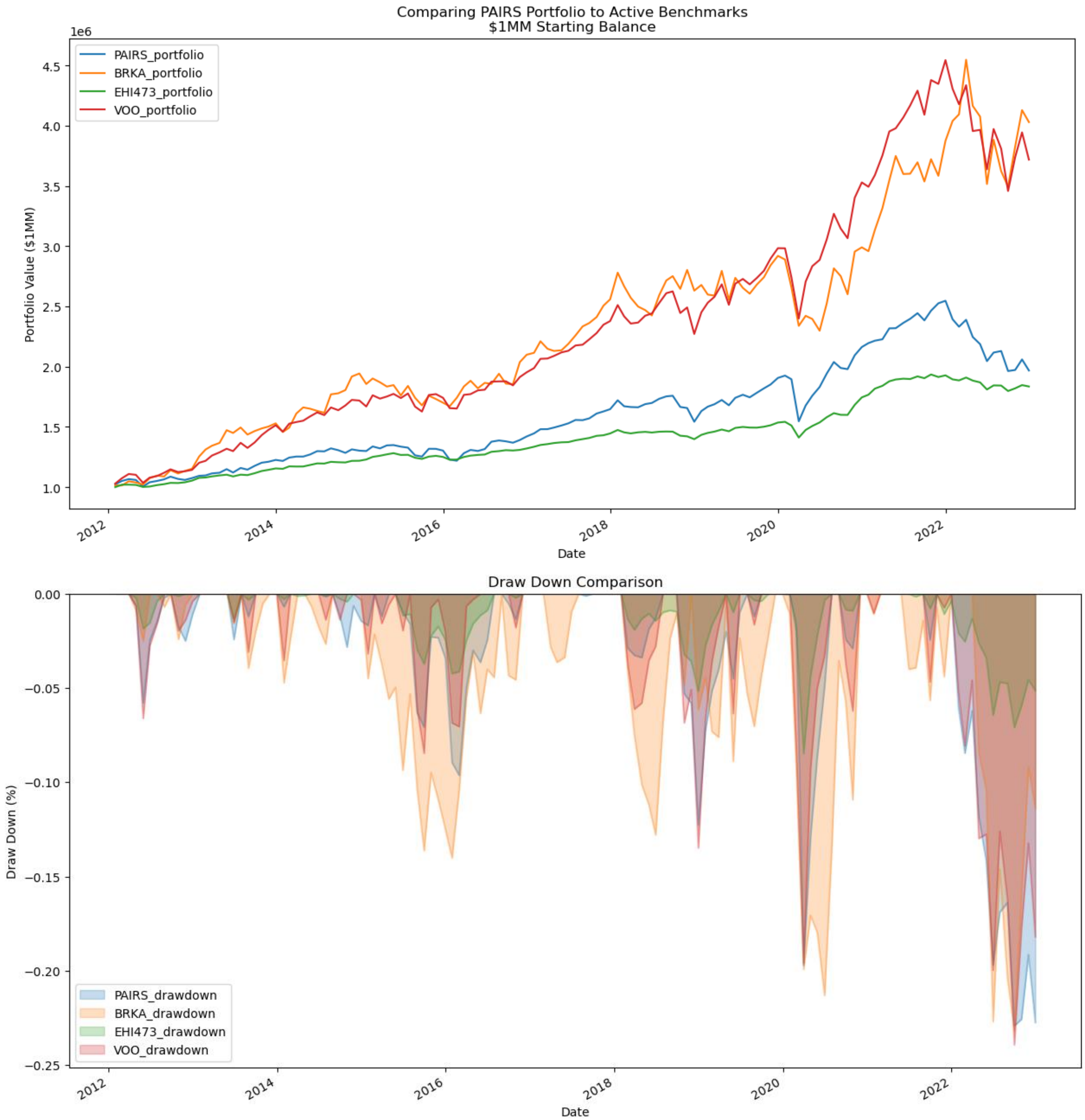


Portfolio Returns and Drawdown are shown graphically with equity curves in Figure XV. With an initial investment of $1MM the PAIRS Portfolio underperforms both the market (VOO) and Warren Buffet’s long-only portfolio (BRK-A), while outperforming the Eureka Hedge Fund Index (EHI473). PAIRS equity curve return and smoothness resembles the

Eureka Hedge Fund Index, an alternative strategy, versus the long-only portfolio strategies. This makes sense in the fact that there is a cost in hedging a portfolio to be market neutral.

During the first part of the time series, PAIRS drawdowns are smaller and magnitude and less frequent than all except the Eureka Hedge Fund Index. However, as PAIRS monthly returns became more volatile during the second half, especially during COVID-19, the large drawdowns were essentially equivalent. The clear laggard here is Berkshire Hathaway, which makes sense since this is strictly buy-and-hold in perpetuity and even the S&P 500 has criteria for both a stock's selection and remaining within the index, i.e., stocks are being removed and added frequently. Eureka Hedge Fund Index is the standout among the group with consistently low drawdowns below 8% across the entire timeframe.

Figure XVI: Returns & Drawdown Statistics from 2012-01-01 through 2022-12-31



Conclusion

From our analysis, we can conclude that with the right stock combinations, pairs trading can be profitable. However, pairs trading may not be as efficient compared to buy-and-hold strategies in terms of both time invested and risk management as mentioned in [1]. While co-integration is a statistical property a prospective investor can use to formulate trading pairs, we determined that co-integration alone is not enough to distinguish between pairs with high and low profit potential. Factors beyond co-integration must be considered to achieve more profitable pairs, such as correlation, liquidity, risk volatility, etc. Addressing our initial hypothesis that a pairs trading strategy generally performs worse than common market benchmarks, we can conclude that our results are mixed. In terms of total returns, our PAIRS portfolio performed worse than the S&P 500 and BRK, but above the Eureka Hedge Fund Index. Looking at risk exposure, PAIRS performs similarly to S&P and BRK in frequency and depth of drawdown, in some periods beating BRK in terms of total drawdown. However, Eureka outperforms our portfolio in terms of drawdowns.

Future Work

A logical next step in this analysis would be refining the portfolio selection feature of the model. The initial test for the co-integration of two stocks is an entry barrier for a pair trade but does not necessarily ensure that the trade will be very profitable. The selection criteria for a candidate pair could be as simple as using the recent performance of the pair to rank opportunities, but we may also consider other factors such as security variability (risk), trading volume, industry sentiment, etc. Furthermore, we could also consider either increasing the granularity of our data or aggregating our daily stock price data to a weekly or monthly level as done by researchers in [2].

In addition to refining pairs selection for maximizing profits, we could also refine exit strategy to minimize loss. Rather than following trading signals rigorously, we can exit the trade early if the current loss exceeds 20% of the invested balance to avoid total loss in one trade. Each trading pair could also follow a dollar-cost averaging method to manage risk.

Literature Survey

Empirical Investigation of an Equity Pairs Trading Strategy

According to Chen (2019), this study examined pairs trading returns of various assets from 1998 to 2007 for different groups categorized firms' size. The study also compared differences in returns for categorized groups and identified whether the differences were significant. The research generates six-factor (market, size, book-to-market, momentum, short-term reversal, and liquidity) alphas of up to 9% annually for a value-weighted self-financing portfolio, and 36% for an equal-weighted portfolio. The strategy profits are largely explained by short-term reversal and pairs momentum. The study concluded that while pairs trading is a viable investment strategy, the profitability may be affected by changes in market conditions and recommend investors carefully monitor the performance of the strategy over time.

European Equity Pairs Trading: The Effect of Data Frequency on Risk and Return

Using a six-month trading period and normalized historical stock prices, the research (Lucey and Walshe, 2013) analyzes pairs trading at varying frequencies of stock price data at the daily, weekly, and monthly level. This research looks at European share price data in a neutral market from 1998 to 2007, which is before the 2007-2008 financial crisis with high volatility. The researchers conclude with yields of annual raw returns of up to 15% for the weekly data frequency on the European market, generating both positive and significant alphas.

References

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Appendix

Figure XVII: Final Balance - Top 10 Most Profitable Stock Pairs in Basket

Stock Pair	Final Balance	# of Trades
NVDA_VB	$ 29,176.09	646
AAPL_SPY	$ 24,180.40	597
AAPL_VOO	$ 23,887.06	596
NVDA_XLY	$ 18,081.96	662
NVDA_XLV	$ 16,979.07	647
NVDA_QQQ	$ 15,837.13	660
AAPL_QQQ	$ 15,742.99	619
BAC_PEP	$ 15,570.78	553
MSFT_SPY	$ 15,135.37	671
AMD_MSFT	$ 14,714.40	653
Total	**$ 189,305.25**	**630.4**

Figure XVIII: Top 10 Best Performing Stock Pairs in Basket

Top 10 Most Profitable Pairs:

1. NVDA (Technology) - VB (Small-cap)
2. AAPL (Technology) - SPY (S&P 500)
3. AAPL (Technology) - VOO (S&P 500)
4. NVDA (Technology) - XLY (Consumer Discretionary)
5. NVDA (Technology) - XLV (Healthcare)
6. NVDA (Technology) - QQQ (NASDAQ)
7. AAPL (Technology) - QQQ (NASDAQ)
8. BAC (Banking) - PEP (Consumer Staples)
9. MSFT (Technology) - SPY (S&P 500)
10. AMD (Technology) - MSFT (Technology)

Top 10 Most Co-integrated Pairs:

1. SPY (S&P 500) - VOO (S&P 500)
2. QQQ (NASDAQ) - VOO (S&P 500)
3. XLE (Energy) - XLK (Technology)
4. QQQ (NASDAQ) - VV (Large-cap)
5. VV (Large-cap) - XLK (Technology)
6. QQQ (NASDAQ) - VV (Large-cap)
7. VV (Large-cap) - XLK (Technology)
8. FXA (AUD) - QQQ (NASDAQ)
9. EMB (USD Emerging Market Bonds) - LQD (US Corporate Bonds)
10. VOO (S&P 500) - XLK (Technology)

Figure XIX: Top 10 Worst Performing Stock Pairs in Basket

Top 10 Least Profitable Pairs:

1. XLE (Energy) - XLI (Industrials)
2. TSLA (Auto Manufacturing) - VOO (S&P 500)
3. TSLA (Auto Manufacturing) - VO (Mid-cap)
4. PGX (S&P U.S. Preferred) - XLE (Energy)
5. PGX (S&P U.S. Preferred) - TSLA (Auto Manufacturing)
6. PGX (S&P U.S. Preferred) - TGT (Consumer Discretionary)
7. EWZ (Brazilian MKT) - VOO (S&P 500)
8. EWZ (Brazilian MKT) - VO (Mid-cap)
9. EWZ (Brazilian MKT) - VB (Small-cap)
10. EWZ (Brazilian MKT) - SPY (S&P 500)

Top 10 Least Co-integrated Pairs:

1. KO (Consumer Staples) - UUP (US Dollar)
2. BRK-A (Berkshire) - UUP (US Dollar)
3. BOIL (Natural Gas) - XLU (Utilities)
4. BOIL (Natural Gas) - SLV (Silver)
5. VOO (S&P 500) - XLU (Utilities)
6. SPY (S&P 500) - XLU (Utilities)
7. GLD (Gold) - XLU (Utilities)
8. BOIL (Natural Gas) - GLD (Gold)
9. UUP (US Dollar) - XLP (Consumer Staples)
10. EEM (Emerging Markets) - XLF (Financial Select)

Figure XX: Final Project Timeline

Project Phase	TASK DESCRIPTION	START	END
Task I: Data Preparation	Gather, explore, prepare and generate initial visualizations of the data (e.g. log(a) - nlog(b) transform, spread plot, correlation heat map)	3/10/2023	3/17/2023
Task II: Preliminary Filter	Write algorithm to apply ADF test to check for co-integration for varying time windows for all pair combinations within basket via dynamic hedge ratio.	3/17/2023	3/29/2023
Task III: Build Model	Develop core model framework to automatically define strategies for each pair and generate trading signals based on z-score and threshold values.	3/17/2023	4/9/2023
Task IV: Test Model Performance + Visualizations	Generate equal-weighted portfolio to test and compare model performance to baseline; perform analysis and generate visualizations on returns (e.g. equity curve, drawdown analysis)	4/9/2023	4/16/2023
Task IV: Wrap Up	Write report and submit final project deliverables.	4/12/2023	4/16/2023