Duke University

Mathematics 590-02

Algorithmic Trading: Financial Data and Modeling

AAA: Asian Stock-ADR Arbitrage Strategy

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Abstract

The goal of this project is to develop a statistical arbitrage strategy to exploit any differences in prices between American Depositary Receipts (ADRs) and their underlying stocks, taking advantage of the inevitable inefficiencies in markets. We have chosen stocks from Asian exchanges (Australia, Hong Kong, and Japan) and their corresponding ADRs, and use a pairs trading strategy in which we simultaneously take two offsetting positions, hedging any directional risks. We have built a Stock-ADR arbitrage strategy while incorporating risk measures that can be scaled for any number of pairs and provided an end-to-end algorithmic solution for generating profits without exposure to market risks. Our final strategy generates an out-of-sample return of 24.93%, with a Sharpe Ratio of 2.87, and an 8.4% return during the month of March 2020. Although our strategy has some limitations, there is great potential for further development. In this paper we provide a detailed overview of our strategy and include a discussion of the results, strengths, limitations, and future work.

Keywords— American Depository Receipt (ADR), Statistical Arbitrage, Pairs Trading, Risk Management, Algorithmic Trading

1 Introduction and Background

The key guiding principle for our strategy is the economic theory of Law of One Price, which states that the price of an identical asset or commodity will have the same price globally, regardless of location, when certain factors are considered [1]. In reality, markets are rarely friction-less and inefficiencies exist. This presents arbitrage opportunities between markets due to mispricing between assets. As the arbitrage opportunities are exploited by different market players, the equilibrium forces eventually eliminate any mispricing. We aim to exploit such arbitrage opportunities using an algorithmic approach to pairs trading.

Pairs trading uses pairs of assets that have some sort of underlying economic link. In today's globally interconnected markets, some stocks are listed on more than one exchange. Many foreign companies are traded in U.S. markets in the form of American Depository Receipts (ADRs) while their underlying stocks are also traded in their corresponding local exchanges. Since the stock-ADR pair are two very similar (but not identical) assets, as they are different ways of trading the same company's shares, they have an underlying link. Intuition suggests that due to the underlying link, we would expect the spread between these two to remain constant with time. However, on occasion there might be a divergence in the spread between these two assets caused by liquidity differences in local markets, time zone differences, temporary supply/demand changes, large buy/sell orders for one asset, reactions for important news in different countries, etc.

When there is a temporary divergence between the two assets, i.e. the absolute spread increases, the pairs trade would be to short the outperforming asset and to long the under-performing one, betting that the spread between the two would eventually converge and revert to its mean. Any significant differences in prices of stock and ADR pair (after accounting for currency exchange rates, transaction costs, etc.) offers potential for generating profits. We aim to build upon this strategy, rigorously backtest it with assumptions that mimic realistic trading conditions, and implement it for live paper trading.

1.1 ADRs

ADRs are among the most direct and popular financial instruments for investing in foreign companies, and have been actively used to diversify portfolios [2]. In 2015, foreign equity holdings – through ADRs and local shares – accounted for 19% of U.S. investors' equity portfolios. Specifically, total global investments in DRs, both American and non-American, were estimated to be approximately $1 trillion USD with about 90% specifically in ADRs according to reports by JP Morgan [3].

Depository Receipts are issued or created when investors decide to invest in a non-U.S. company and contact their brokers to make a purchase. These brokers, through their own international offices or through a local broker in the company's home market, purchase the shares in the local market and request that the shares be delivered to the depository bank's custodian in that country. Note that the brokers must purchase shares in the local market regardless of whether the investor has a long or short position in the non-U.S. company. The broker who initiated the transaction will convert the U.S. dollars received from the investor into the corresponding foreign currency and pay the local broker for the shares purchased. On the same day that the shares are delivered to the custodian bank, the custodian notifies the depository bank. Upon such notification, Depository Receipts are issued and delivered to the initiating broker, who then delivers the Depository Receipts to the investor. These depository receipts create a claim equivalent to the one you would have had if you had bought shares in the local market and should therefore trade at a price consistent with the local shares.

What makes them different and potentially riskier than the stocks with dual listings is that ADRs are not always directly comparable to the common shares traded locally – one ADR on Telmex, the Mexican telecommunications company, is convertible into 20 Telmex shares. In addition, converting an ADR into local shares can be sometimes costly and time consuming. In some cases, there can be differences in voting rights as well. In spite of these constraints, you would expect the price of an ADR to closely track the price of the shares in the local market, albeit with a currency overlay, since ADRs are denominated in dollars. An examination of the link between ADRs and local shares concludes that about 60 to 70% of the variation in ADR prices can be attributed to movements in the underlying share prices and that ADRs overreact to the U.S, market and underreact to exchange rates and the underlying stock [4].

1.2 Related Works

The convergence of stock-ADR pairs and the profitability of stock-ADR pairs trading strategies have been previously studied. Firstly, there is substantial evidence for significant deviations between the ADR price and the adjusted underlying stock price [5, 6]. This is because the ADRs are more significantly affected by the U.S. market than the underlying stock [7, 8]. In addition, the ADR prices also tend to lead those of their underlying stocks as they tend to react faster to new information [9].

However, despite these deviations, we also see evidence of mean reversion [5, 10], possibly because the ADR returns are significantly linked with the industry returns of the parent country [11], and as mentioned before, much of the varation in ADR prices can be attributed to the variation in the underlying share prices [4, 9]. The ADR microstructure also works in favor of the convergence of the stock and the ADR [12]. Specifically, recall that brokers need to purchase the underlying whenever an investor longs or shorts the ADR. Thus, when the investor wants to short the ADR in the pairs trading strategy, that is, when the ADR is overpriced and the underlying stock is underpriced, the investor and the broker both buy the underlying. This results in a net long position, which drives the underpriced stock upwards and works in favor of correcting the price discrepancy. Compare this with a long-ADR strategy. In theory, we long the ADR when it is underpriced, but we effectively long the stock as well because brokers must also purchase the underlying. As a result, the stock price will further be pushed upwards, but it is already overpriced, so the stock and ADR face pressure to diverge.

For this reason, we restrict ourselves to only short-ADR trades, since they have a significantly smaller probability of loss and substantially higher returns, compared to long-ADR trades [12]. Hong and Susmel demonstrate the profitability of these short-ADR trades for individual stock-ADR pairs in the Asian ADR Market [13]. Profitability was also demonstrated for ADRs from different markets, such as India and Mexico [9, 14].

2 Data

2.1 Investment Universe Selection

Our strategy aims to find arbitrage opportunities between stock-ADR pairs. There are over 2000 ADRs available in the U.S. exchanges, representing shares of companies located in more than 70 countries [2]. We only chose Asian stock-ADR pairs in our universe of assets, primarily because of 2 reasons. [Note: Our definition of Asia extends to Asia-Pacific, since exchanges in Australia, etc. also do not have overlapping hours with U.S. exchanges, similar to Asian exchanges.] Firstly, we found significant evidence of profitability based on our literature review. Secondly, Asian and U.S. markets have non-overlapping hours which provides us with implementation and execution advantages. The simplicity of our strategy is not a limitation, but rather, it eliminates unnecessary complexity and offers opportunities to extend our strategy to markets with overlapping hours in the future.

We first sourced a list of ADRs [15], then filtered for the ADRs where we had information about the underlying exchange. Given that we were pulling data from Interactive Brokers (IB), we then filtered for pairs for which both security and forex data were available on IB. After careful filtering, our selection results in a final universe of 28 stock-ADR pairs consisting of underlying stocks listed on exchanges in Australia, Hong Kong, and Japan (Table 1).

2.2 Data Collection, Cleaning, and Preprocessing

Using IB's API (ib insync), we fetched price and volume data for each of the stock-ADR pairs (Resolution: Daily) along with the corresponding currency's forex bid-ask data (Resolution: Minute) for the period from 1st May 2015 to 1st April 2021. We did not seek finer resolution for the stock data because this would have been time intensive to obtain due to IB's data restrictions, there was known profitability for trading this strategy on a daily scale [13], and it would have significantly complicated our strategy. The minute resolution for forex data was chosen so that necessary trading signals could be generated 1 minute before the time the corresponding market opens.

For data cleaning and processing, we first accounted for differences in trading days (because of different holidays across exchanges, etc.) between the exchanges of the underlying stock and its corresponding ADR. In addition, we also empirically estimated the ADR:ORD ratio for each stock-ADR pair. Since an ADR consists of bundles of American Depository Shares (ADSs), one ADR may represent many or even fractional shares of its underlying stock. To estimate this ratio,

Underlying Exchange	ADR Symbol	Underlying Symbol
Australia	ATHE	ATH
Australia	GENE	GTG
Australia	IMMP	IMM
Australia	IMRN	IMC
Australia	JHX	JHX
Australia	KZIA	KZA
Australia	MESO	MSB
Australia	PLL	PLL
Australia	WBK	WBC
Hong Kong	ACH	2600
Hong Kong	BGNE	6160
Hong Kong	CEA	670
Hong Kong	HNP	902
Hong Kong	LFC	2628
Hong Kong	PTR	857
Hong Kong	SHI	338
Hong Kong	SNP	386
Hong Kong	ZNH	1055
Japan	CAJ	7751
Japan	HMC	7267
Japan	IX	8591
Japan	MFG	8411
Japan	MUFG	8306
Japan	NMR	8604
Japan	SMFG	8316
Japan	SONY	6758
Japan	TAK	4502
Japan	TM	7203

Table 1: List of all stock-ADR pairs in our final universe

for each day of data available, we adjusted the underlying stock's open price to USD using the forex data at that time, and divided it by the close price of the ADR. We then averaged this ratio over all the days in our data to obtain a confident estimate of the appropriate ADR:ORD ratio, which we subsequently verified manually. Finally, we adjusted for IB's API (which gives the actual volume divided by a 100 for U.S. stocks), to get a combined data frame for each stock-ADR pair that provides us with all the necessary information required for generating our trading signals in a condensed and concise form.

2.3 Out-of-Sample Selection

As advised, we backtested our strategy from 2016-01-01 to 2021-01-31. To split the dataset into in-sample (IS) and out-of-sample (OOS), we chose an OOS period that would most closely reflect and emulate the current market conditions so that our strategy can be tested rigorously on OOS data before we implemented in live trading. In order to do so, we first collected both VIX data, and interest rate data for the U.S., Hong Kong, Japan and Australia. We averaged these figures over the last 14 trading days up to 2021-04-19 to obtain a "recent" vector $\mathbf{v}_r$, and calculated the "distance" between each day in our backtesting period and $\mathbf{v}_r$ using the L2 norm. We then chose the 1 year period in our backtesting period with the smallest average distance metric. Finally, we split our data set accordingly. Our in-sample period is from 2016-01-01 to 2019-02-21, and 2020-02-22 to 2021-01-31, while our OOS period consists of a 1 year period from 2019-02-22 to 2020-02-21.

3 Strategy

3.1 Overview

AAA is a pairs trading strategy that capitalizes on the mispricing between the underlying stock in select Asian markets and the corresponding ADR in the U.S. market. As described in Section 1.2, the market microstructure of ADR trading suggests that when trading a stock-ADR pair, we should always look to buy the underlying shares and sell the ADRs. When the price difference (spread), expressed in U.S. dollars, between an ADR and its underlying share is bigger than κ_o ($\kappa_o > 0$), then we short (sell) the ADR shares and long (buy) an equal number of the underlying shares. We unwind our positions the first time that the spread between the ADR and its underlying shares is smaller than κ_c ($\kappa_o > \kappa_c$). Thus, AAA is a mean reversion trading strategy, that is, we are betting on the convergence of the ADR price and the underlying share price.

3.2 Calculating Spread

In order to calculate the spread, we need to first determine the unit of trade, since 1 ADR does not always represent 1 underlying share, and we have to trade an integer amount of each security. Using the ADR:ORD ratio computed in the pre-processing step, we define 1 unit of trade as follows: If 1 ADR represents n shares of the underlying stock, $n \in \mathbb{N}, n \geq 1$, then 1 unit of trade would involve 1 contract of ADR and n contracts of the underlying share. Conversely, if 1 ADR represents $\frac{1}{n}$ shares of the underlying stock, $n \in \mathbb{N}, n > 1$, then 1 unit of trade would involve n contracts of ADR and 1 contract of the underlying share.

Using this notion of the unit of trade, we now define the spread as the difference in the price of one unit of the ADR and one unit of the underlying share, in U.S. dollars:

$$\textit{Spread} = \textit{Price of ADR per unit–Price of Underlying Stock per unit (in USD)}.$$

Given that we have multiple time zones to consider, we more rigorously define how to calculate our spread values in Section 3.4.

3.3 Hyperparameters

The underlying idea of our strategy is that we are betting on the mean reversion of the spread. This means that in the long run, we expect the spread to converge due to the Law of One Price. When the spread differs significantly from its long run equilibrium, we enter positions in the ADR and the underlying stock, and once it returns to equilibrium, we exit our positions. However, if the spread differs far enough from equilibrium, we assume that the equilibrium has shifted, so in this case we also close any open positions. The assumption is that the spread has been in equilibrium, so we approximate the long run equilibrium by the mean of the spread over a lookback window of the past N trading days. We thus have four "local" hyperparameters in our strategy: the lookback window, the entry threshold, the exit threshold, and the stop-loss threshold. They are local because they can be different for each individual pair, as opposed to having a common value over all pairs.

3.3.1 Lookback Window

The lookback window is an integer $N \in \mathbb{N}$ that determines how much historical data (in trading days) is relevant for estimating the equilibrium value of the spread. Intuitively, data from one year ago is not relevant today, and data from two days ago is still correlated with data today. However, it is not intuitive exactly how far back we should look into the historical data, which is why this lookback window is an important parameter in our strategy. We use the lookback window to compute not only the rolling mean of the spread, but also the rolling standard deviation of the spread, which we use in our definitions of the entry threshold, exit threshold, and the stop-loss threshold.

3.3.2 Entry Threshold

The entry threshold e_n is simply defined as the number of standard deviations above the mean that indicates that the spread is significantly different from the mean, representing a signal to start trading a pair. If the spread at time t is s_t, and the mean and standard deviation of the spread values in our lookback window are μ_N and σ_N, respectively, then we enter positions in the ADR and the underlying stock when

$$s_t > \kappa_o = \mu_N + e_n \cdot \sigma_N.$$

3.3.3 Exit Threshold

Similar to the entry threshold, the exit threshold e_x is defined as the number of standard deviations from the mean that indicates that the spread has reverted to the mean, representing a sell signal. Defining s_t, μ_N, and σ_N as above, we exit any open positions in the ADR and the underlying stock when

$$s_t < \kappa_c = \mu_N + e_x \cdot \sigma_N.$$

3.3.4 Stop-loss Threshold

The stop-loss threshold e_s is defined as the number of standard deviations above that mean that indicates that the equilibrium has shifted, in which case we would be wrong about our mean-reverting assumption, so we should close any open positions to mitigate our losses. Mathematically, we would exit our positions if

$$s_t > \kappa_s = \mu_N + e_s \cdot \sigma_N.$$

We would also not enter a position under this circumstance.

3.4 Variants

Due to the non-overlapping market hours, there are different ways that we can be trading on both markets. We will explain each of these different variants and illustrate their differences. As shown in Figure 1 below, let $u_{o,t}$ represent data from U.S. open on day t, $u_{c,t}$ represent data from U.S. close on day t, $a_{o,t}$ represent data from Asia open on day t, and $u_{c,t}$ represent data from Asia close on day t. To be clear, the $u_{c,t}$ and $a_{c,t}$ consists of the stock and ADR close data from Asia and the U.S., while $u_{o,t}$ and $a_{o,t}$ consists of the forex data 1 minute before the markets open.

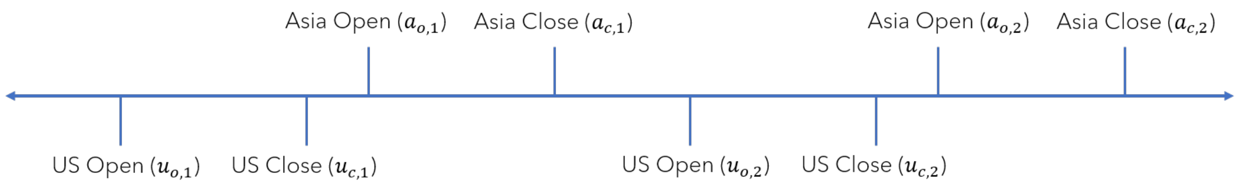

Figure 1: Timeline of U.S. and Asia markets open and close

Then, let us define the following spread values:

$$\begin{aligned} s_{1,i} = &\text{ Close Price of ADR per unit at } u_{c,i-1} \\ &- \text{Close Price of Underlying Stock per unit at } a_{c,i-1}\text{, adjusted with forex data at } u_{o,i} \\ s_{2,i} = &\text{ Close Price of ADR per unit at } u_{c,i} \\ &- \text{Close Price of Underlying Stock per unit at } a_{c,i-1}\text{, adjusted with forex data at } u_{o,i}. \end{aligned}$$

We can now define 3 different arrays of spread values:

$$\begin{aligned} Spread_{\text{Before U.S. Opens}} &= (s_{1,1}, s_{1,2}, \ldots) \\ Spread_{\text{Before Asian Opens}} &= (s_{2,1}, s_{2,2}, \ldots) \\ Spread_{\text{Before All Opens}} &= (s_{1,1}, s_{2,1}, s_{1,2}, s_{2,2} \ldots). \end{aligned}$$

Variant 1: Begin each trade on Asian market open

- In variant 1, we only open positions when the Asian market opens. On each day, we use the last N entries of $Spread_{\text{Before Asian Opens}}$ to determine the entry, exit, and stop-loss conditions.
- If we determine that we want to make a trade, then we first trade the stock on Asian market open, then trade the ADR on the next U.S. market open.

Variant 2: Begin each trade on U.S. market open

- In variant 2, we only open positions when the U.S. market opens. On each day, we use the last N entries of $Spread_{\text{Before U.S. Opens}}$ to determine the entry, exit, and stop-loss conditions.
- If we determine that we want to make a trade, then we first trade the ADR on the U.S. market open, then trade the stock on the next Asian market open.

Variant 3: Begin each trade on either the U.S. market open or Asian market open.

- **Variant 3a**
  - In variant 3a, we can open positions both when the U.S. market opens and when the Asian market opens. On each day, right before the U.S. market opens, we use the last N entries of $Spread_{\text{Before U.S. Opens}}$ to determine the entry, exit, and stop-loss conditions. Then, right before the Asian market opens, we use the last N entries of $Spread_{\text{Before Asian Opens}}$ to determine the entry, exit, and stop-loss conditions.
  - This variant can essentially be thought of as a combination of variant 1 and variant 2 – right before each market open, we generate trading signals from the same time in each of the past N days.
- **Variant 3b**
  - In variant 3b, we can similarly open positions both when the U.S. market opens and when the Asian market opens. However, on each day, right before the US market opens and the Asian market opens, we use the last $2N$ entries of $Spread_{\text{Before All Opens}}$ to determine the entry, exit, and stop-loss conditions.
  - The difference between variant 3a and 3b is the historical data we use to calculate the various thresholds. In variant 3b, we use twice as much data for a given lookback window than variant 3a.

We can see the differences in these four variants by comparing their different PnL graphs in Figure 2, as well as their different trade records in Figure 3. Figure 3 also demonstrates the convergence of stock-ADR pairs. The stock close has been scaled up for the sake of clarity, but we can still see that the ADR and the stock price follow each other closely. Furthermore, no matter what variant we use, we can see that we exit trades shortly after entering them, implying that convergence happens very quickly upon significant divergence.

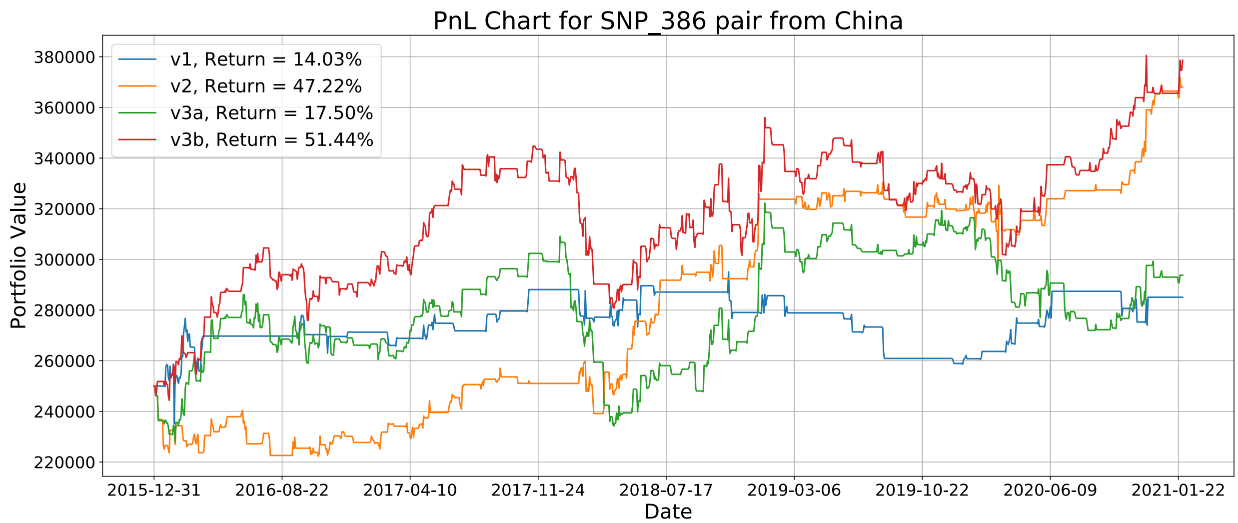

Figure 2: PnL graph for the pair in our in-sample, across different variants

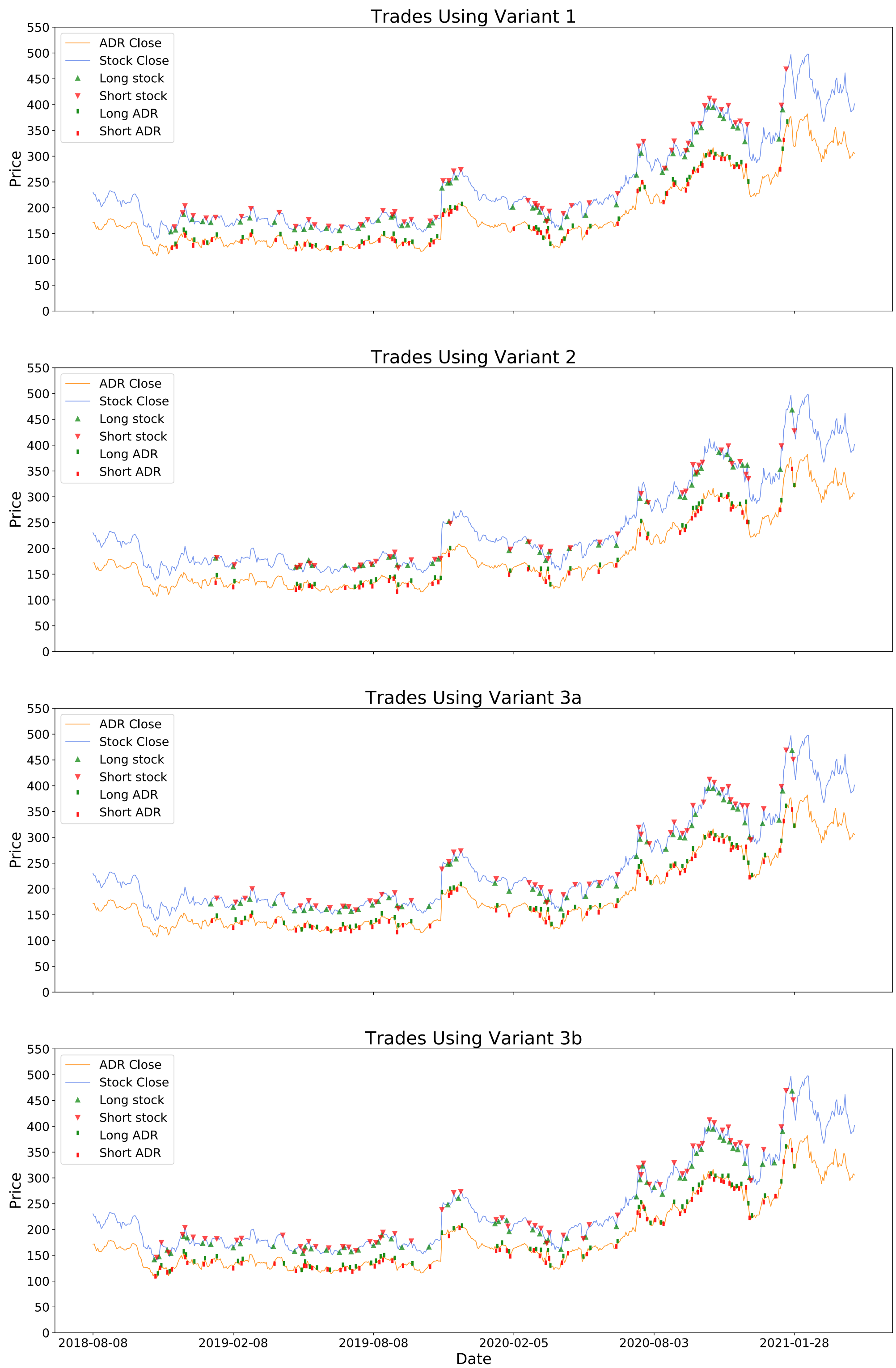

Figure 3: Tracking trades for a pair in our in-sample, across different variants

3.5 Extra Considerations

To accurately evaluate our strategy, we additionally factor in the following considerations into our strategy, as advised by Dr. David Ye:

- Liquidity: Before placing a trade on a security, we check its daily trading volume for the past 5 trading days. To protect against extreme values, we then estimate the average daily trading (ADT) volume by taking the median of these 5 values, and allow ourselves to trade 10% of the estimated ADT volume.

- Slippage and transaction costs for securities: For each trade, we factor in 10 BPS (of absolute market value), on both ADR and local shares.

- Short borrowing costs: We assume that we would pay 50 BPS annually, for short borrowing costs of securities. In addition, when we long the underlying stock, we also short foreign currency. We therefore add 200 BPS to the annual foreign interest rate, to estimate our cost of shorting foreign currency.

- Transaction costs for forex: After we close each pair, we make up the balance of forex so that we are not exposed to a naked currency risk. In each of these transactions, we add 10 BPS, since we are generally exchanging a small quantity of cash, and to account for any additional expense.

- Margin considerations: To prevent exceeding margin limits, we cap our long equity and short equity value by our current equity value. Our research shows that IB has an initial margin requirement of 50% and a maintenance margin of 25%. If our current equity is C, then the maximum we are allowed to long (and short) is $2C$. However, if we long stock that is equal to $2C$, and short the same amount of ADR, our equity is just sufficient to meet the maintenance margin, which makes us vulnerable to a margin call in the case of any fluctuation in prices. We therefore chose to only long/short equity that is worth up to C.

3.6 Trading Individual Pairs

For each stock-ADR pair, we backtest each variant on our IS period, incorporating appropriate local risk management techniques (see Section 5) and trading $250,000 USD (as limited by IB) to evaluate the upside of each pair (although liquidity and risk limits usually prevent us from trading up to this upper limit). After tuning the local hyperparameters (see Section 6) for each variant and pair, we compare the average returns over all pairs for each variant on the IS period.

Variant	Average return over all pairs (2 d.p.)
1	15.39%
2	22.36%
3a	22.65%
3b	23.34%

Table 2: Average return over all pairs for each variant.

Since variant 3b had the highest average return, we selected variant 3b as our final strategy. This was done to prevent overfitting (as compared to using a different variant for each pair), and for the simplicity of execution.

4 Portfolio Construction

To construct our portfolio, we filter our list of stock-ADR pairs based on their hit rate and in-sample return using variant 3b. We prefer pairs with higher hit rates because they give us more arbitrage opportunities, and we obviously prefer pairs that show a higher in-sample return. Therefore, we chose pairs that had a hit rate of greater than 55%, and an in-sample return of more than 10%. These pairs, along with their hit rate and in-sample returns, are listed in Table 3.

Underlying Exchange	ADR Symbol	Underlying Symbol	IS Returns	Hit Ratio
Australia	MESO	MSB	84.63%	80.23%
Australia	IMMP	IMM	37.78%	80.00%
Australia	PLL	PLL	30.52%	71.79%
Australia	KZIA	KZA	15.66%	79.10%
Australia	IMRN	IMC	11.53%	84.44%
Hong Kong	BGNE	6160	78.06%	74.42%
Hong Kong	SNP	386	55.54%	59.09%
Hong Kong	HNP	902	33.78%	59.84%
Hong Kong	CEA	670	17.93%	62.83%
Hong Kong	ACH	2600	14.02%	61.02%
Japan	SMFG	8316	31.18%	59.70%
Japan	IX	8591	27.56%	56.90%
Japan	TM	7203	20.46%	68.97%
Japan	MFG	8411	15.92%	60.71%

Table 3: In-sample returns and hit ratios for the final list of pairs we chose to trade

Given this list, we needed to decide how to allocate our capital. We do not want our entire portfolio to be concentrated in stock-ADR pairs from one country for diversification reasons, and we also do not want our capital to be allocated inefficiently, since we would want as much capital to be traded as possible.

To more efficiently allocate capital, we first choose the amount of capital allocated across countries. Allocating too much capital to a specific market would mean that we are missing out on opportunities in other markets, while allocating too little capital would mean that we are not able to extract meaningful profits from that market. There needs to be an optimal allocation of capital while also ensuring that we are not taking excessive risk.

To decide how much capital is allocated to each pair in a country, we implement trading limits by country, i.e., only a certain number of pairs can be traded in one country at a time. For example, if we only allow two pairs to be traded at once in Australia, and there is a buy signal for a third pair, we will not trade this third pair. We should specify that with a trading limit TL_i and country allocation AL_i, if a pair becomes profitable in country i, we allocate $\frac{AL_i}{TL_i}$ of our capital to trade that pair. Suppose now that we allocate $\frac{1}{4}$ of our equity to the Australian market, and that the trading limit for Australia is 2. This trading limit also implies that if we wish to trade an Australian pair, our maximum long/short equity for the trade would be $(\frac{1}{4})(\frac{1}{2})$ of our current equity, which ensures that we are always within margin limits. A high trading limit would therefore allow us to trade more pairs at once, but we would therefore trade a smaller volume of each pair, which runs the risk of sitting on too much cash for periods of time whereby only a few pairs are trading.

We therefore have two sets of "global" hyperparameters: allocation of capital for each country (AL_i), and trading limits for each country (TL_i) . They are global because they are hyperparameters for the portfolio as a whole, not for a specific stock-ADR pair. After incorporating global risk measures (see Section 5), we then tune these global hyperparameters (see Section 6) on our in-sample period. Finally, we get trading limits of 2 pairs for each country, and an allocation of 25% to Australia, 40% to Hong Kong, and 35% to Japan. We can see the performance of each country during both the in-sample period and the out-of-sample period in the graph below.

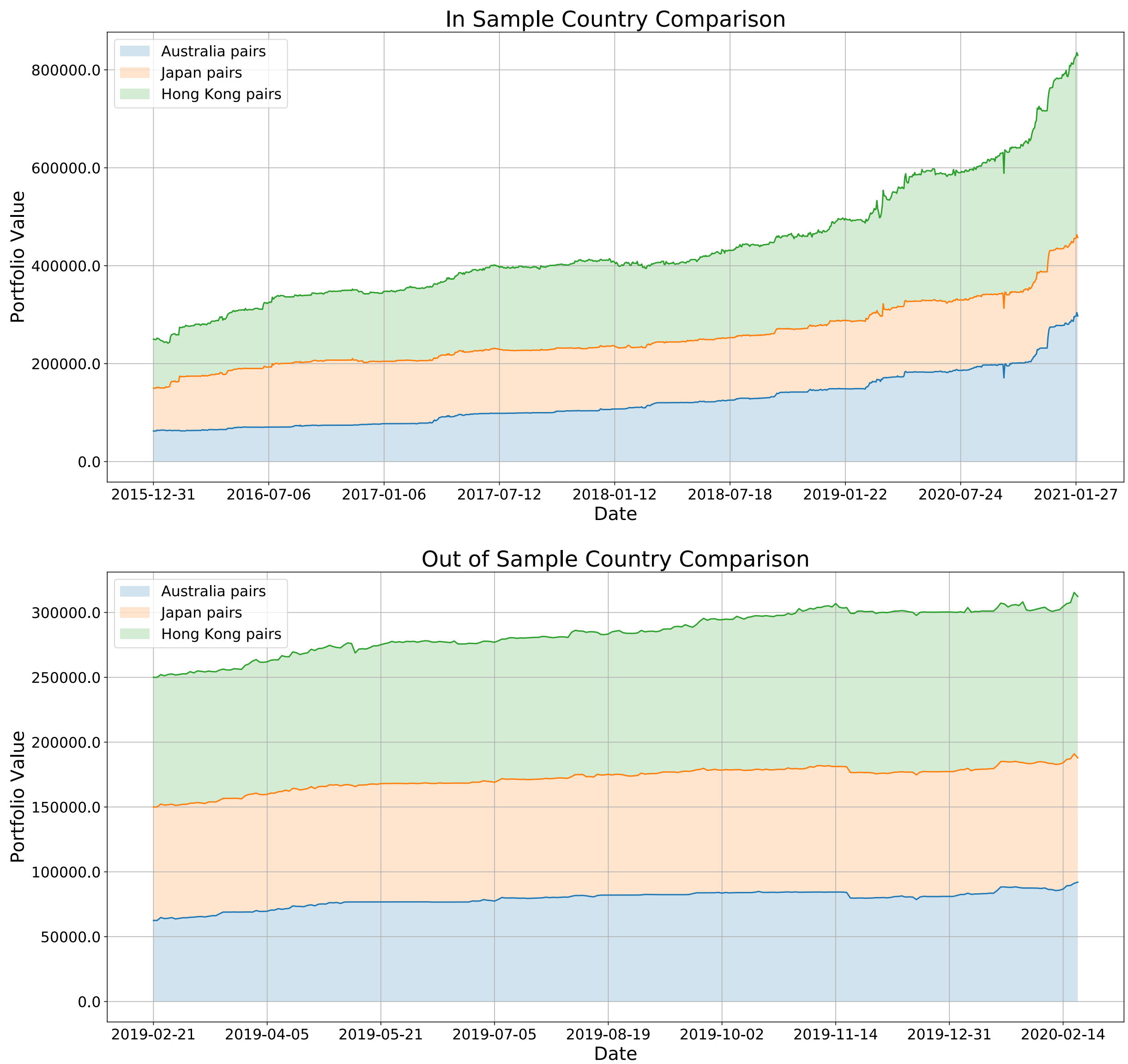

Figure 4: Comparing Country Returns over In-Sample and Out-of-Sample Periods

5 Risk Management

Risk management is perhaps the most important aspect of implementing any algorithmic trading strategy and we have taken extra care to ensure that we are not making needlessly risky trades, and to ensure an overall good Sharpe Ratio for our portfolio.

Pairs trading strategies in general do not need to hedge positions across industries/sectors in corresponding markets. Since statistical arbitrage merely bets on the mean reversion of the spread and exploit mispricing between stock-ADR pairs, there are no associated directional risks. This means that whether the traded pair from any specific industry/sector is moving up or moving down, the pairs trading strategy would still be able to extract profits. As AAA is pairs trading strategy, we have not incorporated industry/sector hedges during the implementation of our strategy.

Recall that our strategy involves two open positions: a short position in x units of the ADR in the U.S. market, and a long position in x units of the underlying stock in the Asian market. We are not matching dollar amounts, but rather quantities of shares. Thus, our strategy is beta-neutral, not dollar neutral. Since we match quantities of shares, we have a net zero position, so we take minimal market or industry risk.

This is not to say that there are no risks associated with this strategy. Due to the fact that we are trading in different markets, we are exposed to risks associated with foreign exchange rates, and with non-overlapping market hours, we might not be able to close a position that should be closed due to the trading hours. Additionally, with non-overlapping market hours, we occasionally have only one position open during a trade (i.e. we are long the stock and plan to short the ADR, but are just waiting for the U.S. market to open). During these times, we are exposed to naked market and sector risk. While we have risk management techniques on both the local and global level to mitigate this naked risk, we hope to further expand upon these techniques in the future.

5.1 Local Risk Measures

Local risk measures refer to measures that are applied to each stock-ADR pair. Our local risk measures consist of Value-at-Risk (VaR), Maximum Drawdown (MDD), Daily PnL Volatility (Vol), and Maximum Holding Period (MHP). For any pair, before entering a position, we check the historical portfolio with a lookback of 100 trading days for stock and ADR. Table 4 shows our VaR, MDD, Vol, and MHP limits, whereby AL_i is the fraction of capital allocated to corresponding country. Each pair is allowed slightly more risk to trade (than it would otherwise if the whole portfolio consisted of one pair, i.e. $AL_i > AL_i/TL_i = AL_i/2$ for our chosen hyperparameters) since we will not be trading all pairs at once, and there are global risk measures.

Risk Measure	Limit
VaR	95th percentile to not exceed 0.1 $*$ Current equity $*AL_i$
MDD	0.2 $*$ Initial equity $*AL_i$
Vol	0.05 $*$ Current equity $*AL_i$
MHP	30 Trading days

Table 4: Limits for each local risk measure

If any of these limits are exceeded, we reduce our position to a fraction of the original position corresponding to the fraction by which we exceed the limit. For example, if the limit on VaR is \$10,000, but entering a position with 240 units would give us a VaR of \$12,000, then we execute the trade with $\frac{10000}{12000} \cdot 240 = 200$ units. In the case of MHP, we liquidate positions if the limit is exceeded.

5.2 Global Risk Measures

Our global risk measures consist of Stop-Loss limits, Maximum Portfolio Drawdown (MDD), PnL Volatility, and Value-at-Risk (VaR) for the Portfolio. We classify these measures into two different types, depending on the severity of violating each risk limit.

5.2.1 Type 1

Type 1 risks are the strict risk management measures. We classify PnL Stop-Loss and Maximum Drawdown (MDD) as type 1 risks. This is because a violation of these risk limits is a signal for a systematic error in the algorithm, in which a trader would have to reassess the strategy.

If these risk limits are violated, then we completely liquidate our entire portfolio and do not place any trades for the next 100 trading days. However, since we want to avoid actually triggering the risk limit, we set up triggers at 75% and 50% of the risk limits. In the scenario where we hit 75% of the type 1 restrictions, we liquidate half of our positions, and reduce the amount which we would usually trade by 2/3 for the next 100 trading days, i.e., we would only trade 1/3 of what we would usually trade. If we hit 50% of the type 1 restrictions, we liquidate 1/3 of our trade sizes, and reduce the amount which we would usually trade by 1/2 for the next 100 trading days.

5.2.2 Type 2

Type 2 risks are looser risk measures. Violations of these risks merely result in scaling down the number of units we are currently trading as per our local risk measures, but would not have the long-lasting impacts on our strategy that type 1 risk violations have. PnL Volatility and Value-at-Risk (VaR) fall under type 2 risks.

Table 5 below contains our global risk measure limits.

Risk Measure	Limit
VaR	95th percentile to not exceed $0.1 *$ Current equity
MDD	$0.2 *$ Initial equity
Vol	$0.05 *$ Current equity
PnL Stoploss	$0.15 *$ Initial equity

Table 5: Limits for each global risk measure.

A distribution of our in-sample and out-of-sample daily returns, along with the portfolio VaR, can be found in Figure 5.

6 Hyperparameter Tuning

Hyperparameter tuning is a crucial part of backtesting our strategy and portfolio construction. All our parameter tuning is done after accounting for both the individual and global risk measures. Hence, we only need to choose those parameters which maximize our strategy's in-sample

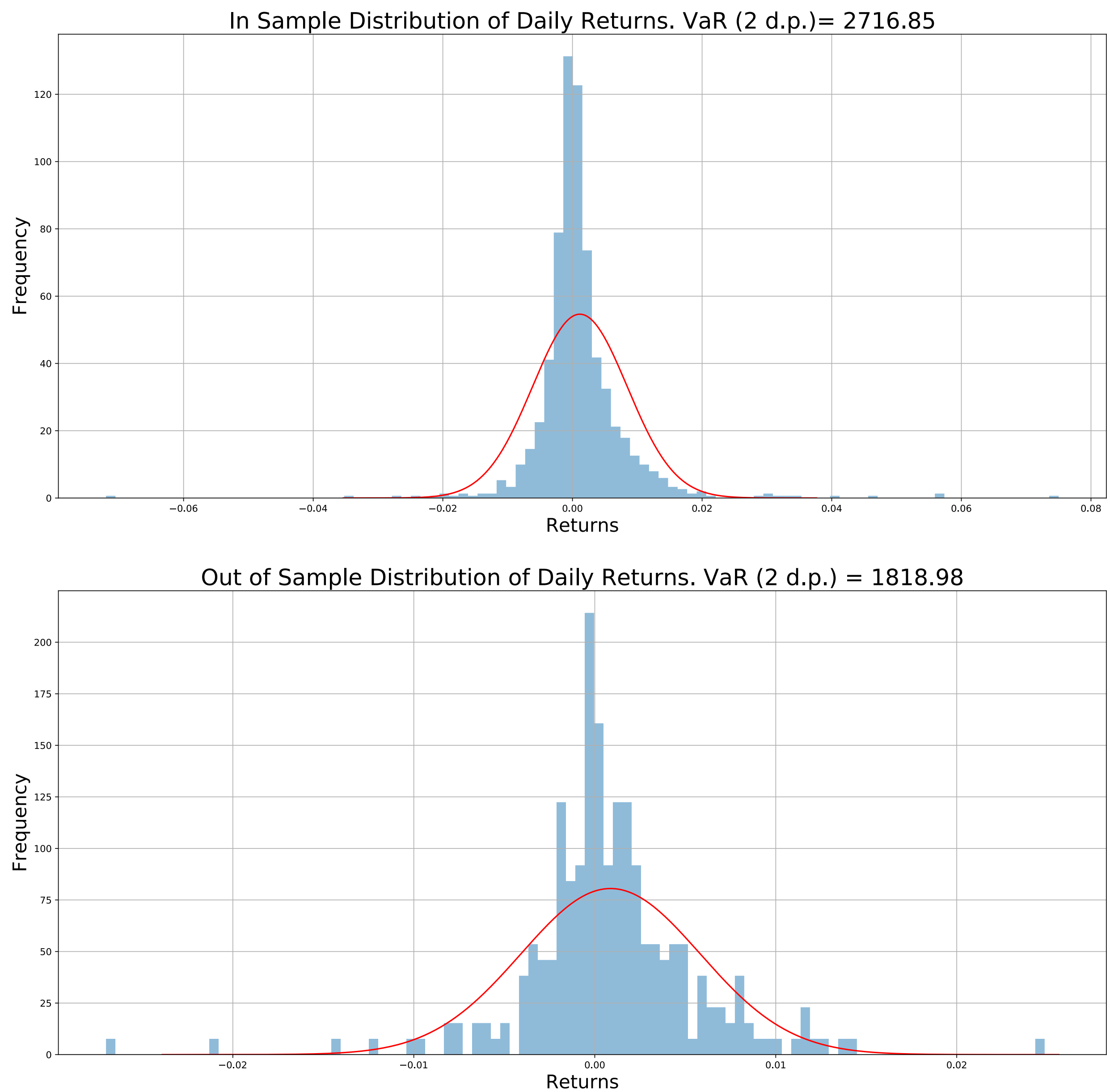

Figure 5: Distribution and Value-at-Risk of Portfolio Daily Returns

returns. There are two stages of hyperparameter tuning – local hyperparameter tuning and global hyperparameter tuning.

6.1 Local Hyperparameters

Recall that the local hyperparameters are the lookback window (N), entry threshold (e_n), exit threshold (e_x), and stop-loss threshold (e_s). For each pair and each variant, we find the best combination of hyperparameters from a coarse grid (Table 6), ranked by in-sample return.

Hyperparameter	Grid Values
Lookback Window (N)	[30, 60, 100]
Entry Threshold (e_n)	[1, 1.5, 2]
Exit Threshold (e_x)	[-0.5, 0, 0.5]
Stop-loss Threshold (e_s)	[2.5, 3, 3.5]

Table 6: Grid values used in local hyperparameter tuning

Figure 6 depicts the results for one specific pair and variant. Since there are too many combinations to show on one graph, we plot the results for the best combination as well as 4 other random combinations. The stark contrast in returns shows the importance of tuning these local hyperparameters.

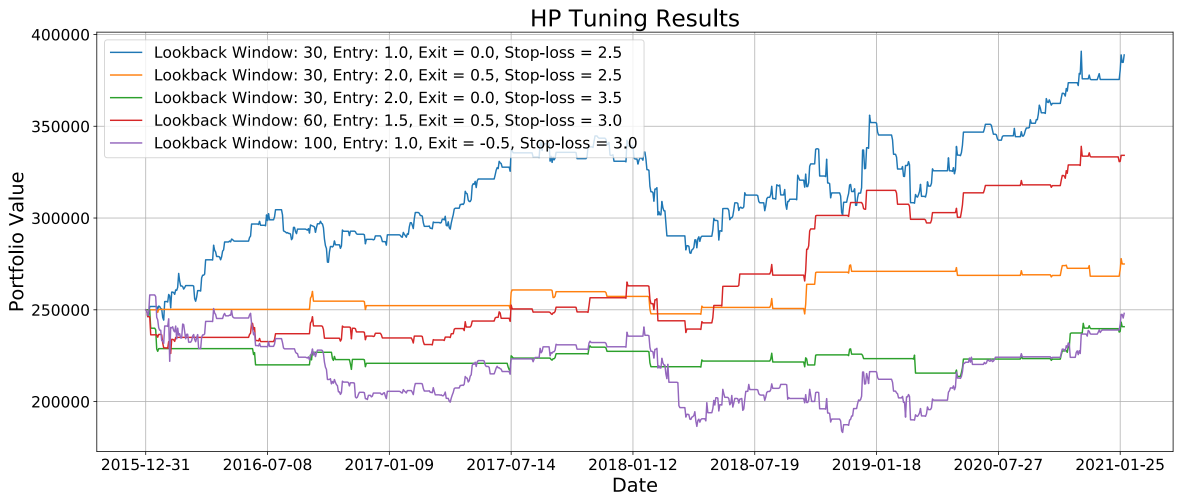

Figure 6: Tuning Local Hyperparameters

6.2 Global Hyperparameters

The global hyperparameters are the trading limits per country (TL_i), and allocation per country (AL_i). We impose the constraint that $TL_i > 1$ for all countries i, since that severely restricts the flexibility of our portfolio. We also impose the constraint that $20\% \leq AL_i \leq 50\%$, since we did not want one country to have too much or too little capital. Obviously, we must have $\sum_i AL_i = 1$. Then, we compute the in-sample return for all possible combinations of trading limits and allocations, and select the combination with the highest in-sample return as our final global hyperparameters. We should note that we restricted AL_i to be an integer multiple of 5% due to computational limitations. The results are shown in Figure 7. Again, for the sake of clarity, we only depict the best combination as well as four random combinations.

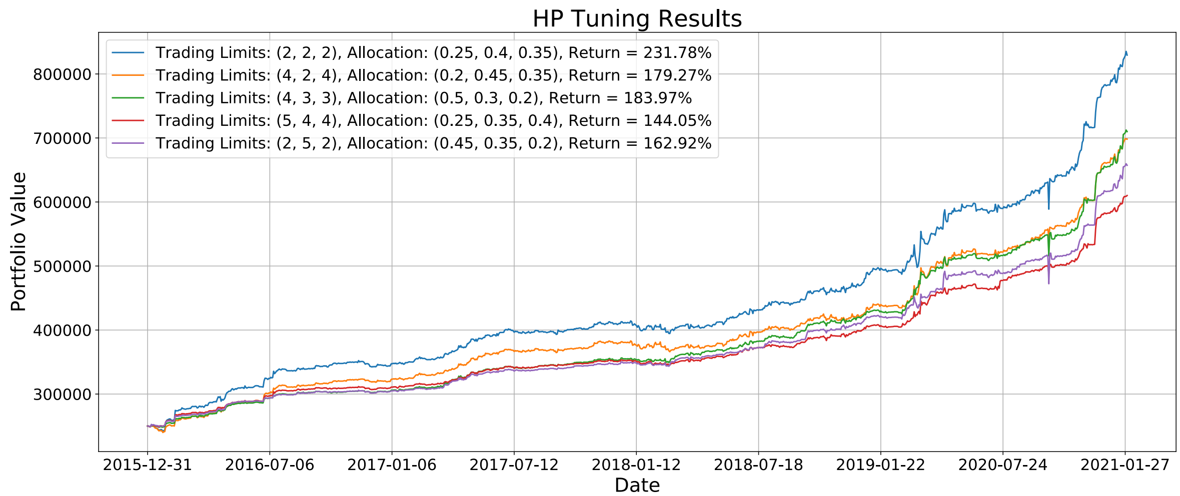

Figure 7: Tuning Global Hyperparameters

7 Results

The final returns and Sharpe Ratio of our strategy, benchmarked against the S&P 500 index, are summarized in Figure 8. These numbers can also be seen in the table below.

Period	AAA Returns	AAA Sharpe Ratio	S&P500 Returns	S&P500 Sharpe Ratio
IS	231.78%	2.56	51.07%	0.6
OOS	24.93%	2.87	20.28%	1.62
Stress Testing	8.4%	2.74	-12.51%	-1.21

Table 7: Summary of IS, OOS and Stress Testing results of the AAA strategy

Most notably, our IS returns are 34.14% annualized, with a Sharpe Ratio of 2.56, our OOS returns are 24.93% annualized, with a Sharpe Ratio of 2.87, and we have an 8.4% return during March 2020, when the COVID pandemic caused the S&P 500 index to drop by 12.5%.

One thing that should be explained is the difference between the average return over all pairs using variant 3b on the IS and the return of our strategy using variant 3b on the IS. This can be explained by two reasons. Firstly, for our final strategy, we only select the pairs that have the best returns, so the average returns of our final list of pairs using variant 3b over the IS period is greater than the average returns of all pairs using variant 3b over the IS period.

The bigger reason is that when we only trade 1 pair using variant 3b, we are restricting our volume limits by the ADT. This means that most of the capital is not being used to trade when we only trade one pair, whereas we are almost always using all our capital to trade in our final strategy. If we had no volume restrictions, or if we traded each pair with an initial capital of $50,000 instead of $250,000, we would see higher returns when trading each individual pair using variant 3b over the IS period. The reason why we do not use $50,000 instead of $250,000 is because each pair faces this volume restriction, to in order to accurately determine which pairs perform the best, we begin training with an initial capital of $250,000.

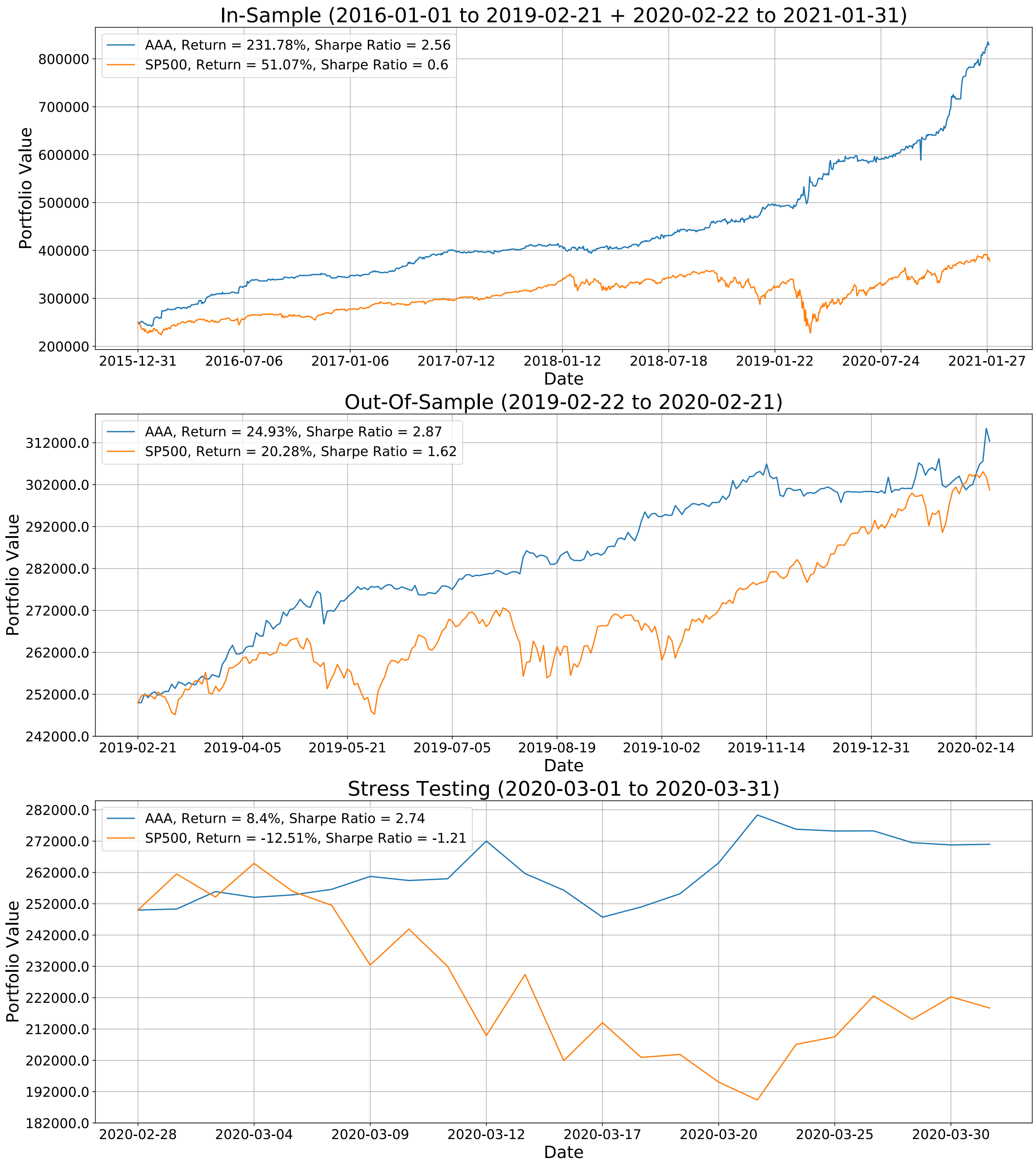

Figure 8: Summary of IS, OOS and Stress Testing results of the AAA strategy

7.1 Live Paper Trading

For live paper trading, we execute the strategy with the following modifications, since we are now enabled to engage in intraday trading:

- Placing limit orders when we first decide to trade a pair.
- Allowing for intraday liquidation of a stock if the exit condition is reached.

To determine a suitable price for our limit orders and intra-day liquidations, we run our optimized strategy over the entire backtesting period, and calculate the actual entry and exit values we execute at. We then take the mean of these values, $\text{actual}_{\text{entry}}$, and $\text{actual}_{\text{exit}}$. Define hp_{entry}, hp_{exit} to be our optimized hyperparameter entry and exit values. We then decide to set the limit price at the price corresponding to $\min(\text{actual}_{\text{entry}}, \text{hp}_{\text{entry}})$, and once that order is filled, we place another limit order at a liquidation price corresponding to $\max(\text{actual}_{\text{exit}}, \text{hp}_{\text{exit}})$. The intuition behind this is that we would want lower entry values to allow our orders to be filled, and that these are values that our strategy has proven to be profitable for.

As of April 28th, 11.40 PM (EDT), Table 8 shows a summary of the trades we have placed since beginning on April 22nd, 8.30 PM (EDT).

Symbol	Action	Fill Price	Volume	Time	Current Price/ **Liquidation Price**	Unrealized/ **Realized** PnL
MESO	SELL	8.42	132*	4-23 09:30	7.32	+145.20 USD
MSB	BUY	2.09	9455	4-25 20:16	1.835	-2411.03 AUD/ -1877.13 USD
MESO	SELL	8.21	1759	4-26 09:30	7.32	+1565.51 USD
6160	BUY	192.2	2000	4-26 21:30	**212.40**	**+40400 HKD** **+5204.58 USD**
BGNE	SELL	324.28	154	4-27 09:30	351.52	-4194.96 USD
902	BUY	2.76	60000	4-28 09:30	**2.81**	**+3000 HKD** **+386.50 USD**
386	BUY	3.95	98000	4-28 09:30	**3.97**	**+1960 HKD** **+252.51 USD**

Table 8: Summary of all trades placed from April 22nd, 8.30 PM to April 28th, 11.40 PM

* On April 23rd, we placed an order to short 132 shares of MESO, with the assumption that the ADT volume was around 660 shares (the strategy at that point of time allowed up to 20% of ADT volume). However, upon placing the order, we realized that the volume traded on IB was significantly higher than expected. Further investigation revealed that IB's API divided the volume for US stocks by 100. Unfortunately, we therefore missed the opportunity to short more shares at a price of 8.42, before the price fell to 8.28 at the close. The volume adjustment was made for future trades in the table, and for our backtesting.

As of April 28th, 11.40 PM (EDT), our estimated PnL is $1482.21 USD (returns of 0.59%). Note that this is a slight overestimate given that we have not yet accounted for commission costs with closing our positions and transaction costs for exchanging forex.

8 Limitations and Future Work

8.1 Limitations

We were limited with our computational resources – with only 16 parallel processing cores, we could only tune our hyperparameters on a limited number of combinations. With stronger computing power, we would be able to find even better hyperparameters to optimize our strategy.

Additionally, we were limited by the IB platform and the available historical data. When selecting our universe of pairs, we did not have complete information of all underlying exchanges for our initial list of ADRs, and IB did not have security and forex data for all the pairs. Our final universe of 28 stock-ADR pairs was simply the result of not having data on more pairs. Thus, with better data, we would be able to consider a wider variety of stock-ADR pairs, which could improve the profitability of our strategy.

Finally, we were limited by our backtesting framework. Since we were using historical data, we did not have a backtesting framework that more realistically reflected the prices we would have been allowed to trade at, and had to make assumptions in Section 3.5 to mirror reality. With a more realistic backtesting framework, we would be able to make our strategy more robust to these various fees and make adjustments accordingly to get stronger live trading results.

8.2 Future Work

There are four main areas where we would like to improve upon our strategy in the future. Firstly, as mentioned in Section 5, when first enter our pairs trade and have opened just one position, we are exposed to market and sector risk before the other market opens. To mitigate this, we plan to hedge this risk with a suitable index.

Secondly, we would like to expand to exchanges with overlapping market hours (e.g. London Stock Exchange). Currently, we are only trading on markets with non-overlapping hours to not have to deal with unnecessary complexities, however, there are also more arbitrage opportunities with in markets with non-overlapping trading hours. On a similar note, we would like to expand our strategy to trade on shorter time intervals as opposed to just daily trades. The price correction between ADR and underlying stock often occurs in the first few minutes of the market open, so trading on shorter time intervals could allow us to better capitalize on these arbitrage opportunities, without sustaining borrowing costs.

Thirdly, we would like to incorporate sentiment analysis. In particular, we would like to consider if and how social media can impact event risks for foreign companies, and consequently our strategy. For example, currency markets are sensitive to political or geopolitical tension, and perhaps mining social sentiment data or google trends could give us additional indicators for risk management or profitable opportunities. The motivation for incorporating this is the impact that Trump had on the financial markets from his tweets. Furthermore, recall that AAA is exposed to naked market and industry risk when we only have one position open in our trade. Incorporating sentiment analysis would be a way to counteract that risk.

Lastly, we would like to improve our portfolio allocation. Currently, our portfolio allocation strategy is relatively basic, and the hyperparameters are not entirely optimized. Two areas that we are interested in exploring are dynamically allocating capital to our portfolio based on the profitability, volatility, and hit ratio of individual stock-ADR pairs, and training a neural network for allocating capital. The neural network would either learn the best hyperparameters, or learn an optimal dynamic portfolio allocation strategy, both of which would improve our algorithm.

9 Acknowledgements

We would like to thank Dr. David Ye for his continued and prompt feedback throughout the course of this project and all the support he provided us with regard to his IB live paper trading account and related data permissions.

10 Glossary

The following definitions are taken from Investopedia [16].

American Depository Receipt: *An ADR is a certificate issued by a U.S. bank that represents shares in foreign stock. ADRs trade on American stock exchanges. ADRs and their dividends are priced in U.S. dollars. ADRs represent an easy, liquid way for U.S. investors to own foreign stocks.*

Arbitrage: *Arbitrage is the simultaneous purchase and sale of the same asset in different markets in order to profit from tiny differences in the asset's listed price. It exploits short-lived variations in the price of identical or similar financial instruments in different markets or in different forms. Arbitrage exists as a result of market inefficiencies and it both exploits those inefficiencies and resolves them.*

Backtesting: *Backtesting assesses the viability of a trading strategy or pricing model by discovering how it would have played out retrospectively using historical data. The underlying theory is that any strategy that worked well in the past is likely to work well in the future, and conversely, any strategy that performed poorly in the past is likely to perform poorly in the future. When testing an idea on historical data, it is beneficial to reserve a time period of historical data for testing purposes. If it is successful, testing it on alternate time periods or out-of-sample data can help confirm its potential viability.*

Beta/Market Neutral: *A market-neutral strategy is a type of investment strategy undertaken by an investor or an investment manager that seeks to profit from both increasing and decreasing prices in one or more markets, while attempting to completely avoid some specific form of market risk. Market-neutral strategies are often attained by taking matching long and short positions in different stocks to increase the return from making good stock selections and decreasing the return from broad market movements.*

Close: *The close is simply the end of a trading session in the financial markets, however, closing times tend to vary between market and exchange. Many markets also offer after-hours trading beyond the official close, although traders should exercise caution when transacting outside of traditional market hours. Understanding the closing times of various markets is important to avoid making any costly mistakes.*

Forex: *FX market is a global electronic network for currency trading. Formerly limited to governments and financial institutions, individuals can now directly buy and sell currencies on forex. In the forex market, a profit or loss results from the difference in the price at which the trader bought and sold a currency pair.*

In-Sample vs Out-of-Sample: *When testing an idea on historical data, it is beneficial to reserve a time period of historical data for testing purposes. The initial historical data on which the idea is tested and optimized is referred to as the in-sample data. The data set that has been reserved is known as out-of-sample data. This setup is an important part of the evaluation process because it provides a way to test the idea on data that has not been a component in the optimization model. As a result, the idea will not have been influenced in any way by the out-of-sample data, and traders* *will be able to determine how well the system might perform on new data, i.e., in real-life trading. In the US, the stock market is regulated by the SEC and local regulatory bodies.*

Maximum Drawdown: *MDD is a measure of an asset's largest price drop from a peak to a trough, before a new peak is attained. Maximum drawdown is considered to be an indicator of downside risk, with large MDDs suggesting that down movements could be volatile. While MDD measures the largest loss, it does not account for the frequency of losses, not the size of any gains.*

Mean Reversion: *Mean reversion, in finance, suggests that various phenomena of interest such as asset prices and volatility of returns eventually revert to their long-term average levels. The mean reversion theory has led to many investment strategies, from stock trading techniques to options pricing models. Mean reversion trading tries to capitalize on extreme changes in the price of a particular security, assuming that it will revert to its previous state.*

Open: *It is the price at which the financial security opens in the market when trading begins. It may or may not be different from the previous day's closing price. The security may open at a higher price than the closing price due to excess demand of the security.*

Risk: *Risk takes on many forms but is broadly categorized as the chance an outcome or investment's actual gain will differ from the expected outcome or return. Risk includes the possibility of losing some or all of an investment. There are several types of risk and several ways to quantify risk for analytical assessments. Risk can be reduced using diversification and hedging strategies.*

Sharpe Ratio: *The Sharpe ratio was developed by Nobel laureate William F. Sharpe and is used to help investors understand the return of an investment compared to its risk. The ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk. Volatility is a measure of the price fluctuations of an asset or portfolio.*

Statistical Arbitrage: *Statistical arbitrage is a group of trading strategies employing large, diverse portfolios that are traded on a very short-term basis. This type of trading strategy assigns stocks a desirability ranking and then constructs a portfolio to reduce risk as much as possible. Statistical arbitrage is heavily reliant on computer models and analysis and is known as one of the most rigorous approaches to investing.*

Stop-Loss: *Stop-loss can be defined as an advance order to sell an asset when it reaches a particular price point. It is used to limit loss or gain in a trade. The concept can be used for short-term as well as long-term trading. This is an automatic order that an investor places with the broker/agent by paying a certain amount of brokerage. Stop-loss is also known as 'stop order' or 'stop-market order'. By placing a stop-loss order, the investor instructs the broker/agent to sell a security when it reaches a pre-set price limit.*

Stress testing: *It is a computer-simulated technique to analyze how banks and investment portfolios fare in drastic economic scenarios. Stress testing helps gauge investment risk and the adequacy of assets, as well as to help evaluate internal processes and controls. Regulations require banks to carry out various stress-test scenarios and report on their internal procedures for managing capital and risk.*

Value-at-Risk: *VaR is a statistic that measures and quantifies the level of financial risk within a firm, portfolio or position over a specific time frame. This metric is most commonly used by investment and commercial banks to determine the extent and occurrence ratio of potential losses in their institutional portfolios. Investment banks commonly apply VaR modeling to firm-wide risk due to the potential for independent trading desks to unintentionally expose the firm to highly correlated assets.*

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