Machine Earning – Algorithmic Trading Strategies

for Superior Growth, Outperformance and Competitive Advantage

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Did algorithmic trading generate superior returns relative to discretionary trading during the Covid19 pandemic and do they provide a sustainable competitive advantage?

Abstract

In this paper we use the tools and frameworks from Oxford University's postgraduate diploma in financial strategy to study the performance and benefits of algorithmic trading strategies (algos), and specifically those that use artificial intelligence (AI) and machine learning (ML).

We discover using valuation theory from (SBS2, 2020) that algos generate superior returns compared to human discretionary trading both in normal market conditions and during large market drawdowns, such as during the coronavirus (Covid19) pandemic. Furthermore applying financial strategy techniques from (SBS1, 2020) we find that algos could be

combined with existing core competencies at my organization RUS[1] to create a sustainable competitive advantage and give RUS an edge over its competitors.

Finally considering M&A growth strategies from (SBS4, 2020) we conclude that for RUS algorithmic trading capabilities would be best acquired taking an organic approach as an in-house build approach would be both cost-effective and allow for a more customized and bespoke integration.

Even if only a fraction of the potential benefits are monetized, algo trading could have a significant positive impact on earnings, which in turn would allow for reinvestment to facilitate sustainable growth and maintain a sustainable competitive advantage.

1. Introduction

The current Covid19 pandemic required that the financial services industry invest heavily in technology and cyber security in order to facilitate remote working, whilst adhering to strict regulation controls to keep businesses and data secure. Opportunistic and prudent investment firms could leverage such technology investments to invest in high growth opportunities and increase their algorithmic trading capabilities.

In times of crisis trading systems using artificial intelligence & machine learning have the potential to provide a competitive advantage as they constantly adapt to market conditions (JP Morgan, 2019). They have the ability to process vast amounts of traditional, social media and alternative reference data at high speed to gauge market sentiment. Moreover, they

[1] See appendix for full case study details

can manage more highly diversified portfolios to reduce idiosyncratic risk and increase Sharpe ratios[2] (Esposito, 2020), (Institutional Investor, 2020).

In this paper we study if algorithmic trading strategies generate superior returns, if they could provide a sustainable competitive advantage relative to discretionary (or human) trading and we consider how to best acquire and integrate algo capabilities at RUS.

We proceed as follows: firstly we give an overview of the current market environment. Secondly we introduce algorithmic trading and outline the main machine learning techniques and how they can be used. Thirdly we compare the performance of algos and discretionary trading systems using a hedge fund case study, where we classify funds by their investment strategy. Fourthly we investigate if algos could provide a sustainable competitive advantage and fifthly we consider how my organization RUS should acquire and integrate algo capabilities with existing skills and resources.

2. Current Environment

The ongoing coronavirus (Covid19) global pandemic (2019-2021) has caused widespread distress, disruption and as of January 2021 has claimed the lives of more than 2.2 million people, (WHO, 2021). The attempts of Governments to control the virus through lockdowns and curfews have harmed economies and businesses, particularly those in the hospitality, travel and tourism sectors. Digital organisations, technology stocks and the **FANGs**[3] have

[2] Sharpe ratios measure performance as the return of an investment per unit risk.
[3] The FANGs are the four prominent tech stocks in the U.S. namely Facebook, Amazon, Netflix and Alphabet (previously Google). The equivalents in China are the BAT stocks Baidu, Alibaba and Tencent.

strongly outperformed (Wigglesworth 2020), whereas many businesses unable to adapt to online working have suffered losses, faced closure and bankruptcy (Skeel, 2020).

Despite the development of new vaccines to counter the pandemic, many are still wondering what a recovery could look like and businesses need to consider the possibility of tail risks such as coronavirus mutation and further pandemics.

The new normal way of life relies on technology, with day to day business being conducted online using technologies, such as Skype, Microsoft Teams and Zoom. Consequently to survive many businesses had no choice but to invest in technology & infrastructure to facilitate the high demand for online working and manage the associated cyber security risks.

To more formally assess the current macro environment and highlight opportunities and threats relevant to the financial services industry we perform a **PESTEL** analysis (Whittington et al, 2020). The analysis is categorised into six environmental factors, namely **Political, Economic, Social, Technological, Ecological** and **Legal** and is often used to aid macro forecasts and scenario analyses.

In (figure 2.1) we build upon and extend the PESTEL analysis from (Burgess, 2020b) to incorporate the most recent Covid19 impact assessments on the broad macro environment see (McKinsey, n.d.) and (McKinsey, 2021).

Figure 2.1 PESTEL Analysis for Financial Services

Source: Macro Scenario Analysis of Financial Services (Burgess, 2020b)

Key highlights stem from the broad economic impact of the Covid19 pandemic, which has required quantitative easing and government stimuli to counter the effect of mandatory lockdowns, workforce disruption and business closures. In the U.S. alone, the economy is estimated to incur net GDP losses ranging from $3.2 trillion (14.8%) to $4.8 trillion (23.0%) over a 2-year period. (Walmsley et al, 2020).

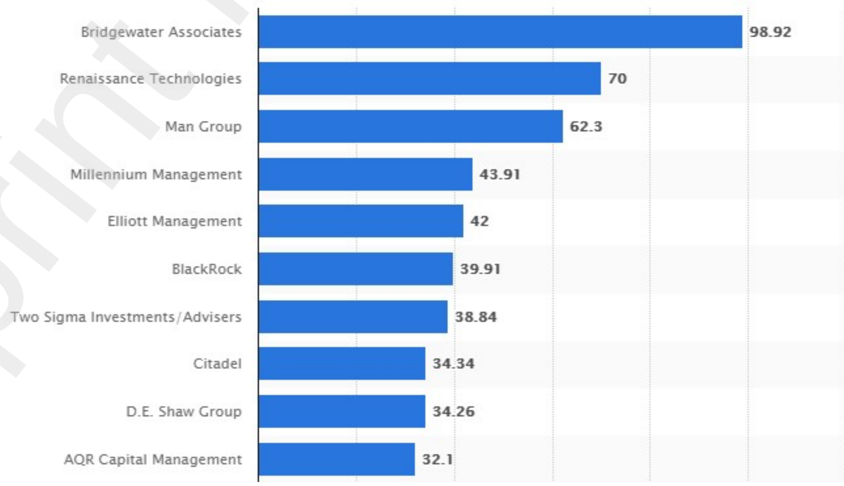
Furthermore investment in new technologies facilitates a mobile, flexible workforce and enables remote working to keep businesses open, but also presents opportunities to exploit competitor weakness and capture market share due to the different levels of business readiness and technological capacity in the industry. Prudent and opportunistic investment firms could invest in technologies with a high growth potential, such as algorithmic trading, to gain a sustainable competitive advantage.

3. What is algorithmic trading?

As outlined in (Burgess 2019a), algorithmic trading (or systematic trading) refers to the automation of the trading process, through the creation of predefined rules (the 'trading system') and their strict application when executing financial market transactions. The automated trading system benefits from being repeatable and testable, unlike discretionary trading (or human trading), which potentially has different rules for every transaction.

Algorithmic trading systems are predominantly employed by Hedge Funds to create leveraged alternative investment portfolios uncorrelated with the market. Currently the world's hedge funds have USD 3.1 trillion assets under management (Statista1, n.d.). Similarly algos are used by high frequency trading firms (HFTs) to make markets, seek liquidity rebates and exploit market inefficiencies to benefit from arbitrage opportunities (Brogaard et al, 2011).

Figure 3.1: Assets under management (AUM) of the largest hedge fund firms worldwide in June 2020 (in USD billion)



Source: (Statista2, n.d.)

A recent survey by (BarclayHedge, 2018) asked managers of hedge funds and commodity trading adviser funds (CTAs) for their insights and experience with AI and machine learning and found that:

- More than half managers use AI/ML to inform investment decisions
- Two-thirds of funds use AI/ML to generate trading ideas and optimize portfolios
- Over a quarter use automation to execute trades
- Well over half have used AI for three or more years, and a third for five-plus years

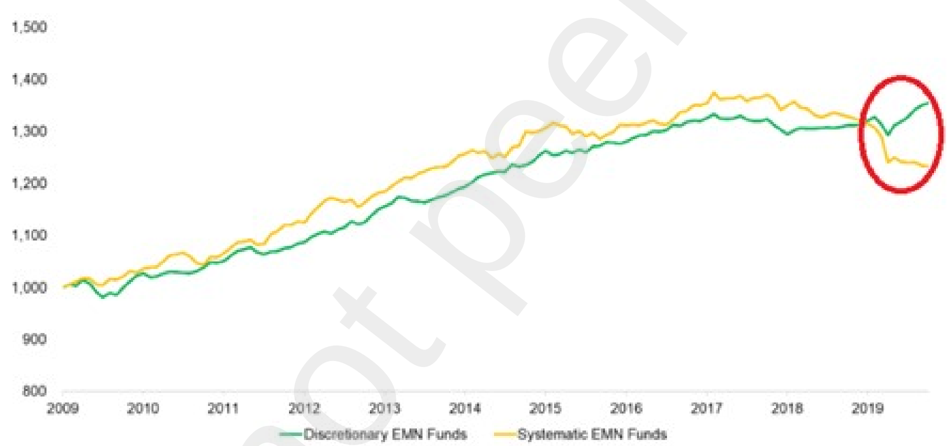
Market drawdowns provide an excellent stress test of an algorithmic trading strategy's usefulness and ability to outperform. In 2020 financial markets were in turmoil and suffered heavy losses due to the devastating impact of the coronavirus global pandemic. In the U.S. markets plunged 38% in March 2020 to recover in April 2020 and the subsequent months. This pattern was observed in many markets and exchanges globally.

Figure 3.2: U.S. Market Shock due to Covid19, S&P 500 (Mar-Apr 2020)

Source: Yahoo Finance

During the Covid19 pandemic hedge funds using algorithmic trading strategies suffered heavy losses. Many trading strategies were trained to follow predefined trading signals that were not able adapt to the new market environment. Consequently human-run hedge funds trounced Quant funds (Bloomberg, 2020). For example in equity markets discretionary funds beat systemic funds during the Covid19 market shock and performed much better than Quants models and systematic investing (Factor Research, 2020).

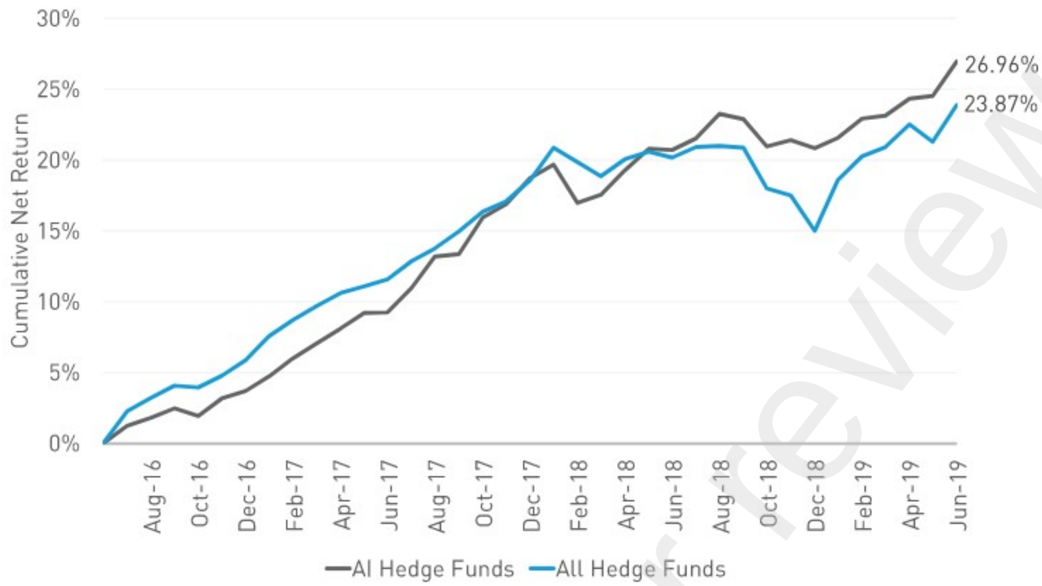
Figure 3.3: Equity Market Neutral (EMN) Hedge Funds - Discretionary vs Systematic Investing



Source: Factor Research

However **artificial intelligence funds vastly outperformed discretionary funds** with their trading strategies having the ability to continually process, learn and adapt to new market conditions. Reports such as (Institutional Investor, 2020) and (Robinson, 2020) claimed that AI funds generated returns almost three-times higher than that of other hedge funds. Both (Friedman, 2019) and (Eurekahedge, 2018) also confirm that AI and machine learning funds generated superior returns as shown in (figure 3.4) and (figure 3.5) below.

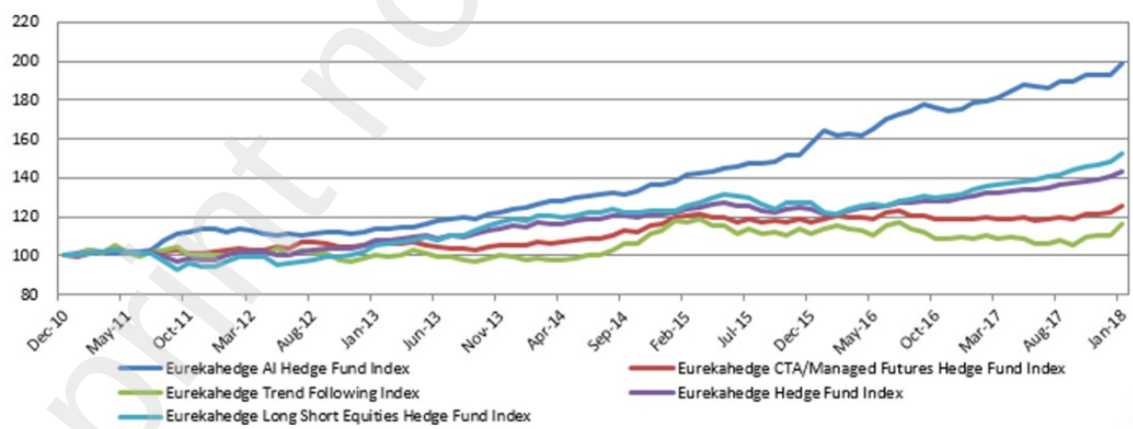
Figure 3.4 Cumulative 3-Year Returns: AI Hedge Funds vs All Hedge Funds



Prequin performance benchmarks show that AI fund returns have outperformed the all hedge fund benchmark by 3.09% with lower volatility and higher Sharpe ratios. AI funds reported 3.20% volatility and a Sharpe ratio of 1.96, while the hedge fund benchmark posted volatility of 3.87% and a Sharpe ratio of 1.40.

Source: Prequin Blog (Friedman, 2019)

Figure 3.5 Long-Term Analysis - AI vs Quants vs Traditional Hedge Fund Indices



AI hedge funds vastly outperform competing hedge funds, see (table 4.1) below for the fund definitions.

Source: Eurekahedge Database (Eurekahedge, 2018)

Consequently, from here onwards we focus on algorithmic trading systems that use **artificial intelligence, machine learning and predictive technologies** to make investment decisions as we look to answer the headline question and investigate if algorithmic trading generated superior returns relative to discretionary trading during the Covid19 pandemic and if they could provide a sustainable competitive advantage.

Machine learning funds try to incorporate and adapt to live market data and current sentiment as much as possible. They go far beyond traditional back-testing approaches and the use of fundamental and technical analysis to generate alpha. They look for patterns in current market micro-structure[4] and gauge current market sentiment, using behavioural science, neuro-linguistic programming, **natural language processing (NLP)** and deep data techniques to interpret and process enormous volumes of text, speech and sentiment from social media, news channels and alternative reference data in real time, see (López de Prado, 2018) and (Wyman, 2014).

The processing of vast amounts of data in real time is an impossible task for human traders. Consequently discretionary traders are forced to concentrate their efforts on a handful of securities compared to the machine learning funds that are able diversify far more broadly. Algorithmic trading strategies characteristically hold a large number of securities to take advantage of the law of large numbers and statistical edges. This diversification reduces idiosyncratic risk, a risk that the Capital Asset Pricing Model (CAPM) says can be diversified away and consequently investors are not rewarded for, see (Berk and DeMarzo, 2016), (Brealey et al, 2014) and (Burgess, 2021). As a result machine learning portfolios have the

[4] A simple example being the cancellation of many sell orders might indicate an imminent uptick or rally.

potential to be more efficient in the CAPM sense and to intrinsically carry lower risk, which increases Sharpe ratios.

Machine learning techniques are broadly categorized as being **supervised or unsupervised**. Supervised techniques are given pre-classified data to train the model, whereas unsupervised learning techniques must discover trends, features, relationships and classify data on their own. We outline several of the main **machine learning classification techniques** below, see (Wilmott, 2019) for more information and examples of usage.

1. **Kth Nearest Neighbours (KNN) – Supervised Learning**

   We start out with N data points that are already classified into groups or features. New data is classified as being in the most popular group as determined by the Kth nearest data points. For example, given a list of trading features that constitute a buy, sell or hold signal, what does the current market features suggest we should do?

2. **K Means Clustering (KMC) – Unsupervised Learning**

   Given unclassified data points represented by feature vectors[5] we gather them into K groups associated with their centres of mass or centroids. This is useful for measuring **financial data that clusters or is mean reverting**, such as interest rate or volatility levels.

[5] Each data point is represented as a list of features describing the data, commonly referred to as a feature vector

3. **Naïve Bayes Classification (NBC) – Supervised Learning**

   Given samples of data representing different classes we calculate the probability of new data being in each class. This technique is useful for natural language processing (NLP) and **analysing social media and news data** for sentiment.

   It uses Bayes Theorem, where P(A|B) = P(B|A).P(A) / P(B) to determine, for example, the probability a news article with the words "Positive" and "Earnings" is a good news article that will move stock prices upwards,

$$P(Good\ News \mid Uses\ the\ words\ \text{Positive, Earnings})$$

$$= \frac{P(Uses\ the\ words\ Positive, Earnings \mid Good\ News).P(Good\ News)}{P(Uses\ the\ words\ Positive, Earnings)}$$

4. **Support Vector Machines (SVM) – Supervised Learning**

   Given a set of classified data represented by vectors of features, we divide the data using a hyperplane and classify new data according to which side of the hyperplane each data point lies. This is useful for detecting when trading levels are rich or cheap.

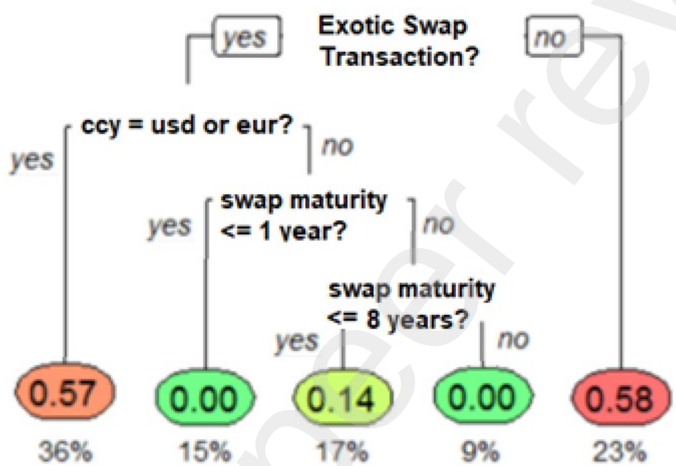
5. **Self-Organizing Maps (SOM) – Unsupervised Learning**

   We start with all our data points represented as feature vectors. We then map similar data and features into a two-dimensional grid to visualize which data have similar characteristics. This is useful for hedging and identifying stocks for pairs trading. It is also useful in Modern Portfolio Theory (MPT) whereby stocks can be grouped into buy and sell categories based on expected returns, volatility and correlations between stocks.

6. **Decision Trees – Supervised Learning**

This is a flowchart technique and uses a hierarchy of features to divide (split) and classify data. They are often referred to as classification and regression trees (CART). This could be used to analyse winning and losing trades for example.

Figure 3.6 **Decision Tree Example for Interest Rate Swap Transactions**



The example tree estimates the probability of an interest rate swap transaction being profitable (winning) given the transaction type exotic or vanilla, the currency of the swap and the maturity, where the decimal inside the node represents the probability and the percentage of transactions in the category is outside the node.

Source: Adapted from Wikipedia

7. **Neural Networks – Supervised and Unsupervised Learning**

A type of machine learning that tries to mimic brain activity. Signals are passed through a network of neurons where they are mathematically manipulated and passed on for further processing. They are used for modelling complex financial relationships, establishing the functional form of data and **pattern recognition**.

8. **Reinforcement Learning – Unsupervised Learning**

This is one of the main types of machine learning, where the algorithm uses trial and error and is based a system of rewards and penalties. The algorithm uses a heuristic function to track the score of each trial run and is trained to maximize the score. This method is useful for learning how to **trade optimally in highly volatile markets** and interact with in environment when there is high uncertainty.

Trading strategies using supervised techniques often use historical data for pre-classification, however past performance is no guarantee of future results. Unsupervised learning approaches rely less on historical trends and seek to constantly learn and adapt to new market environments. Consequently they require large representative data sets to be effective, eliminate bias and error (Lynch 2018). Unsupervised strategies are perhaps well placed to manage market shocks such as those faced during the Covid19 pandemic. However it is a balancing act as fund managers don't want trading systems to react too quickly to noise in the market information nor so slowly that they miss a trend. Perhaps this suggests that some human oversight may be helpful.

In summary algorithmic or systemic trading is simply the automation of the trading process, which could involve full or partial automation of the trading system including trading signal classification, trade execution, hedging and the risk management process. In theory such trading systems are ideal to monitor, adapt and respond to new market conditions not seen before, such as those experienced during the Covid19 pandemic, but how did they perform in practice?

4. Algorithmic Trading Performance

In this section we study at algorithmic trading performance during normal market conditions and market shocks such as that during the Covid19 pandemic (figure 3.2). We perform a case study analysis comparing artificial intelligence tech fund performance with that of quant and discretionary funds. We ask the reader to note that when evaluating and comparing fund performance there are many factors to consider including investment manager skill and ability, fund size, market sectors invested in, currency, inflation factors et al, hence relative performance does not reflect on causality. Relative performance is purely suggestive and used to highlight the potential for algorithmic trading and predictive technologies to provide a competitive advantage.

4.1 Measuring Hedge Fund Performance

When comparing hedge fund performance it is not sufficient to only consider fund returns, as investors can increase returns by leveraging positions and taking more risk. Consequently fund performance is measured using **risk-adjusted returns** i.e. return per unit risk, which gives a convenient uniform performance measure that can be applied to all funds. No trading strategy or fund can be profitable at all times and during all market conditions, consequently investors pay close attention to fund **drawdowns,** both the size and frequency of losses suffered by the fund.

There are several measures of fund performance (Steinki and Mohammad, 2015), each with different pros and cons. The main measure used is the **Sharpe Ratio** defined in (formula 4.1). Other measures include the Sortino Ratio that only measures downside risk (negative variations) and the Treynor Ratio which measures risk as CAPM Beta (Burgess, 2021).

Formula 4.1 Sharpe Ratio (SR)

$$Sharpe\ Ratio = \left(\frac{r_P - r_F}{\sigma_P}\right)$$

where r_P denotes the return of a portfolio, r_F the risk-free rate and σ_P the annualized volatility or standard deviation of portfolio returns with all units in %.

Example 4.1 Sharpe Ratio

Consider two investment funds A and B having an average annual return 12% with incremental drawdowns of 5% and 10% respectively. Clearly fund A performs best as it bears less risk for the same return. If it is known the risk free rate is 2% for our investment horizon then using (formula 4.1) we have Sharpe Ratio (fund A) = (12% - 2%) / 5% = 2.0 and Sharpe Ratio (fund B) = (12% - 2%) / 10% = 1.0.

A fund's performance is not only due to its ability to generate superior returns, but also its ability to minimize risk and limit the size and frequency of its drawdowns. Consequently we review fund performance not just in normal market conditions but also during the Covid19 market shock, as illustrated in (figure 3.2) when many funds were experiencing large drawdowns. We investigate which funds generated superior returns on a risk-adjusted basis and also examine which funds suffered fewer and smaller drawdowns during the Covid19 pandemic.

4.2 Hedge Fund Performance

To assess relative hedge fund performance we used Eurekahedge data. Eurekahedge is one of the world's largest hedge fund and private equity databases. For our analysis we used the hedge fund indices and benchmarks outlined in (table 4.1). These hedge fund indices represent collections of hedge funds by fund type.

Table 4.1 Eurekahedge - Hedge Fund Indices

Hedge Fund Index	Bloomberg Ticker	Fund Type
AI Hedge Fund Index	EHFI817 Index	Artificial Intelligence Hedge Funds
CTA / Managed Futures	EHFI286 Index	Quant Funds - General
Trending Following Index	EHFI808 Index	Quant Funds - Systematic Trend Following
Hedge Fund Index	EHFI251 Index	Traditional Hedge Funds (Discretionary)

These indices represent broad groups of hedge funds by fund type. The exact fund definitions are available from (Eurekahedge n.d.) or via the Bloomberg terminal.

Source: (Eurekahedge n.d.)

Table 4.2 Eurekahedge - Hedge Fund Performance

Eureka Hedge Fund Index	AI Hedge Fund Index	CTA / Managed Futures	Trend Following Index	Hedge Fund Index
Bloomberg Ticker	EHFI817 Index	EHFI286 Index	EHFI808 Index	EHFI251 Index
Fund Type	Artificial Intelligence	Quant - General	Quant - Systematic Trend	Traditional / Discretionary
Statistics (as at Jan 2021)				
Covid19 Return, Mar-Apr 2020	3.27%	1.82%	4.10%	-2.23%
Annualized Return	12.23%	8.47%	9.13%	8.50%
2020 Return	11.24%	7.85%	10.92%	12.26%
Return Since Inception	259.27%	454.94%	531.27%	457.99%
Best Monthly Return	8.01%	8.33%	9.21%	5.30%
Worst Monthly Return	-2.88%	-4.32%	-6.70%	-6.32%
Risk / Return				
Annualized Standard Deviaton	5.94%	6.39%	9.39%	5.07%
Downside Deviation	2.25%	3.09%	5.11%	2.90%
Upside Deviation	6.16%	5.88%	8.13%	4.53%
Maximum Drawdown	-7.24%	-6.30%	-14.42%	-12.27%
Sharpe Ratio	1.72	1.01	0.76	1.28
Sortino Ratio	4.55	2.09	1.40	2.24
Percentage of Positive Months	73.68%	60.87%	56.92%	71.15%

Source: (Eurekahedge n.d.)

We extended a previous study (Eurekahedge, 2017) using (Eurekahedge n.d.) to collect and collate more recent fund performance data covering the Covid19 period. We present a summary of results above in in (table 4.2).

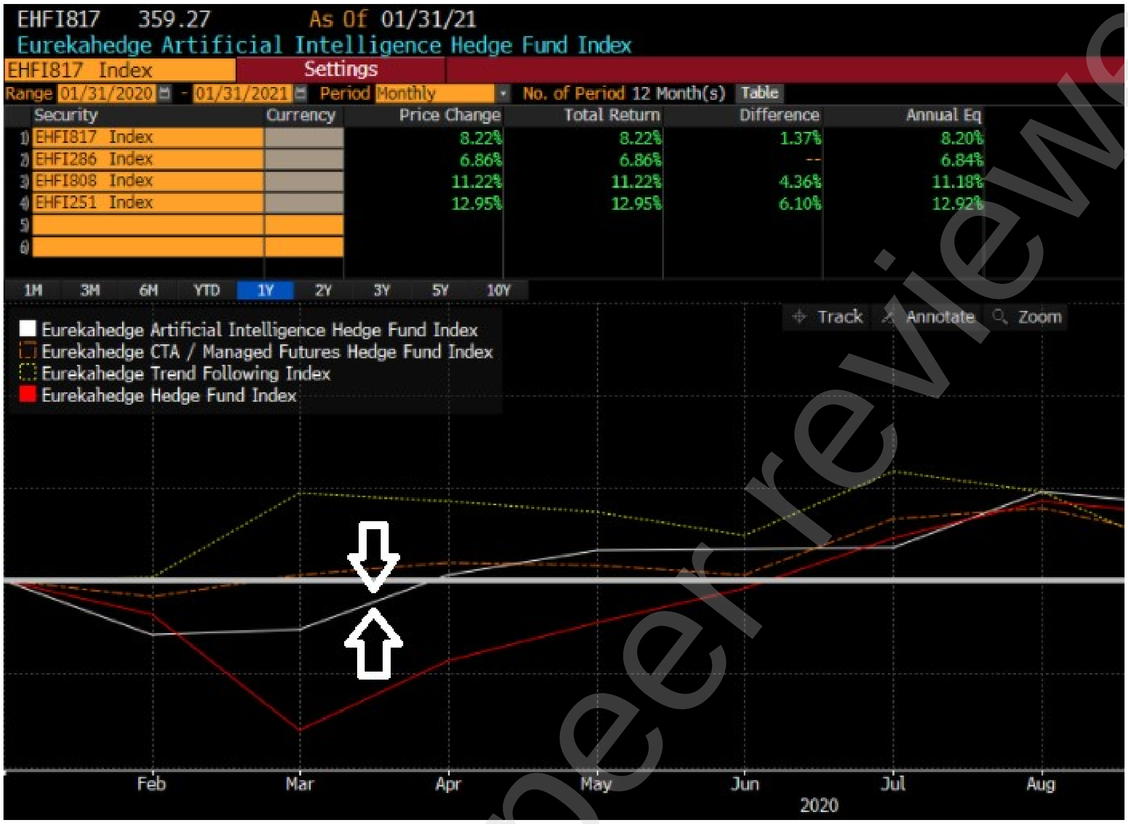
4.3 Algorithmic Trading Performance during Covid19 Drawdown (March-April 2020)

Hedge fund performance during market drawdowns is very important. It highlights the skill of the fund manager to avoid large losses and manage downside risk. Summarizing the results presented in (table 4.2) we see that during the Covid19 market drawdown in March-April 2020 (figure 3.2) AI funds performed well and made gains of **+3.27%** whereas traditional discretionary funds reported losses of **-2.23%** over the same period.

AI funds had the lowest downside volatility of 2.25% and amongst all the hedge fund groups had one of the smallest maximum drawdowns, which for AI funds was **-7.24%** compared to **-6.30%** & **-14.42%** for quant funds and **-12.27%** for discretionary funds.

Morningstar Direct data reported that during the Covid19 pandemic AI technology funds held up relatively well, reporting that in April 2020 as the FTSE 100 and S&P 500 plunged more than **-20%** and tech funds were down as little as **-4.6%** (Esposito, 2020). Bloomberg also showed that the downside volatility of AI funds during the Covid19 major market downturn was exceptionally small (figure 4.3).

Figure 4.3 Hedge Fund Comparative Returns



During the Covid19 market downturn and rebound in Mar-Apr 2020 (figure 3.2) the Eurekahedge Artificial Intelligence Hedge Fund Index did not suffer large drawdowns and showed little volatility and downside risk relative to the competing fund groups from (table 4.1).

Source: Bloomberg Terminal, COMP <GO>

Hedge funds using artificial intelligence consistently have the lowest drawdowns and best risk-adjusted returns (Sharpe ratios), not just during the Covid19 pandemic, but more generally in crisis situations and during major market risk events as shown in (table 4.4).

Table 4.4 AI / Machine Learning Hedge Fund Returns During Key Market Risk Events

Date	Event	AI Hedge Fund Index	CTA / Managed Futures	Trend Following Index	Hedge Fund Index
Mar-21	**Covid19 Drawdown**	**3.27%**	**1.82%**	**4.10%**	**-2.23%**
Nov-16	Trump Win	-0.94%	-0.18%	0.38%	0.31%
Jun-16	Brexit	1.29%	2.32%	4.18%	0.32%
Feb-16	Oil Price Dip/China growth concerns	-0.86%	1.71%	1.92%	0.00%
Jan-16	Oil Price Dip/China growth concerns	4.33%	1.33%	2.42%	-1.74%
Aug-15	China Equity Crash	0.72%	-1.72%	-2.54%	-1.92%
Jul-15	China Equity Crash	0.43%	0.97%	-2.25%	-0.06%
Jun-15	Greek referendum	1.84%	-2.00%	-3.28%	-1.14%
Jan-15	Swiss Franc De-pegging	1.30%	3.23%	3.87%	0.78%
Sep-14	Oil Price Dip	-0.57%	198.00%	333.00%	-0.22%
Jun-13	Taper Tantrum	1.56%	-0.93%	-1.68%	-1.31%
May-13	Taper Tantrum	1.55%	-1.41%	-1.07%	0.45%

Source: Adapted from (Eurakahedge 2017) to include Covid19 risk assessment.

This answers the first part of our headline question: "Did algorithmic trading generate superior returns relative to discretionary trading during the Covid19 pandemic?" - Clearly funds using artificial intelligence outperformed discretionary funds during the pandemic as shown in (table 4.2) with gains of **+3.37%** and losses of **-2.23%** respectively.

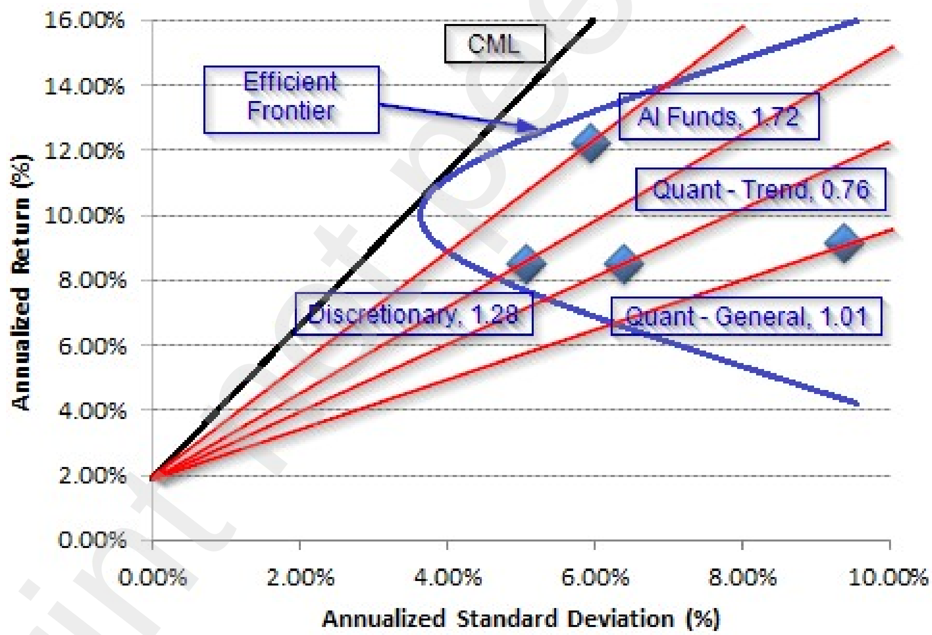
4.4 Algorithmic Trading Performance after Covid19 Drawdown (Post April 2020)

Hedge fund performance after the Covid19 drawdown highlights how funds performed in more normal and less extreme market environments. This highlights the fund manager's ability to profit in normal market conditions and more specifically in this period to also benefit from and exploit post Covid19 opportunities.

Reviewing the results presented in (table 4.2) from a post Covid19 perspective we see that algorithmic trading using artificial intelligence earned returns of **+11.24%** beating quant funds with returns of **+7.85%** and **+10.92%** and almost matching traditional discretionary funds with **+12.26%**. On a risk-adjusted basis AI funds outperform all funds and have the highest Sharpe ratios[6].

Equivalently, from a CAPM perspective, when plotting the risk-return profile for each hedge fund group we see AI funds generate the highest returns per unit risk (figure 4.5). The gradient of the lines in red through the fund returns and risk-free rate indicate the Sharpe ratio, which for AI funds is the closest to the Capital Market Line (CML) indicating AI funds are the most efficient on a risk-adjusted basis (Berk and DeMarzo, 2016), (Burgess, 2021).

Figure 4.5: Shape Ratios and Risk-Return Profiles for Hedge Fund Indices



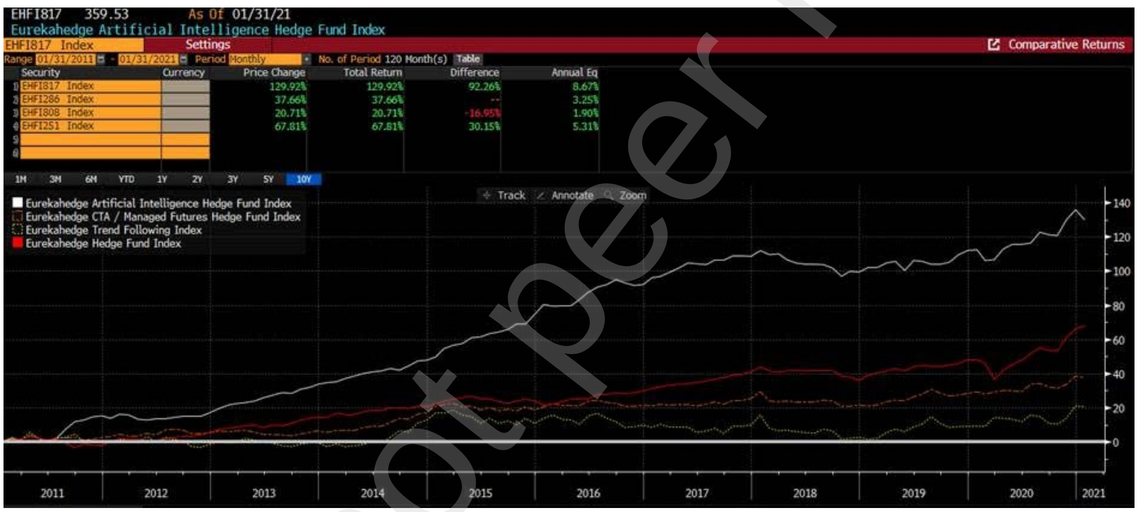
For each of the funds from (table 4.1) we plot the annualized return and standard deviation. The slope of the red-lines denotes the Sharpe ratio, quoted in blue. We implied the risk-free rate as 2.0% using (formula 4.1). The black and blue lines are for illustrative purposes and represent the CAPM Capital Market Line (CML) and Efficient Frontier respectively.

Source: Eurekahedge data from (table 4.2)

[6] AI funds also have the highest Sortino ratios, where risk is measured as downside volatility.

In August 2020, (Institutional Investor, 2020) also reported that AI Tech Funds had vastly outperformed other funds, having produced cumulative returns of 34 percent in the three years through to May 2020, compared with a 12 percent gain for the global hedge fund industry over the same period. Furthermore Bloomberg confirm that not only did AI funds outperform in the post Covid19 environment, they have also outperformed on a long-term basis as shown in (figure 4.6).

Figure 4.6 Long-Term Artificial Intelligence Hedge Fund Performance



Comparing the hedge fund benchmarks from (table 4.1) we see that artificial intelligence hedge funds vastly outperform competitor funds.

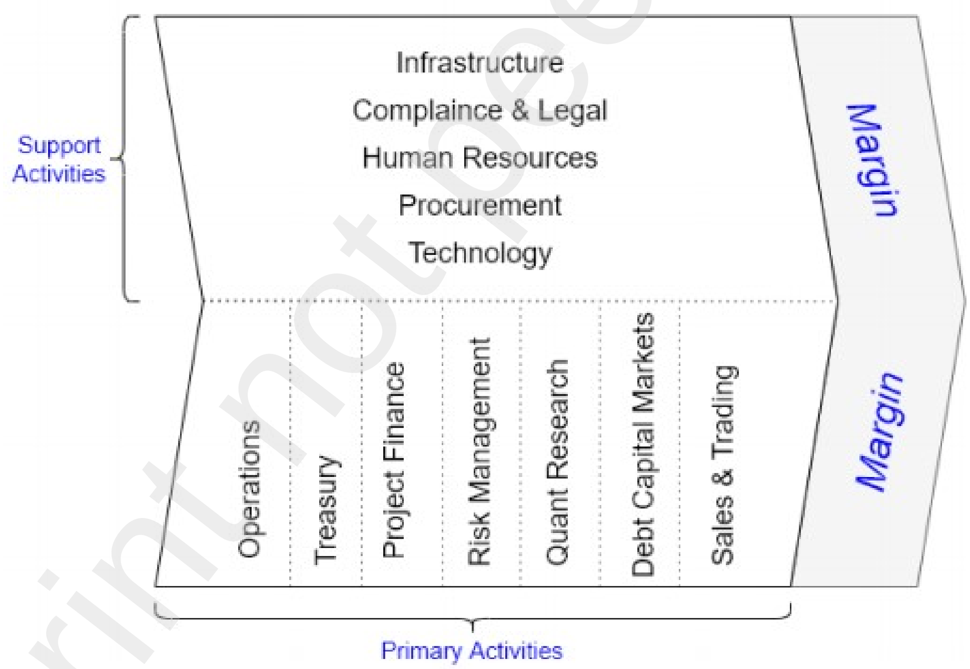
Source: Bloomberg COMP <GO>

Having confirmed that algorithmic trading has the potential to generate superior returns relative to discretionary trading we proceed to examine if they could provide a sustainable competitive advantage.

5. Competitive Advantage

As outlined in (Burgess, 2020c) the long-term survival of any organisation relies upon its ability to well-manage resources to create dynamic capabilities valued by customers. Threshold capabilities are required to survive in a given market and achieve competitive parity. However dynamic capabilities utilise the entire value chain (Zenger, 2013). They are sets of resources, capabilities, skills and abilities (figure 5.1), which together combine to form core competencies that can respond dynamically to environmental opportunities and threats. They have the potential to create a sustainable competitive advantage.

Figure 5.1 View of the Value Chain



Source: SSRN Strategic Analysis of Japanese Megabanks (Burgess, 2020c)

Prior to assessing if algorithmic trading skills and capabilities could complement the existing value chain we performed a **SWOT**[7] analysis (Whittington et al, 2020), see (figure 5.2). This was to assess RUS's current capabilities, **internal strengths and weaknesses** and current ability to manage the **external opportunities and threats** presented in (figure 2.1).

Figure 5.2 SWOT Analysis for RUS

	Opportunities (O)		Threats (T)				
	New Technology Machine Learning, AI, Cloud	Green Finance Initiatives	Cyber Security	Hard Brexit	Libor Reform	Workforce Disruption	**Resource & Capability TOTAL**
Strengths (S)							
HR Excellence						5	5
Skilled Workforce	5	5	2	2	5	5	24
Parent Co. Large Capital Base	5	5	2	2	5	2	21
Agile Pricing/Risk Analytics	5	5			10		20
Weaknesses (W)							
Legacy Products	-3	-3			-5		-11
Poor Systems Infrastructure	-5	-3	-5		-5		-18
Capital Constraints	-3	-5			-5		-13
Limited Data Availability	-5	-2					-7
Limited Management Metrics	-3	-3	-3	-3	-3	-3	-18
RUS Total	**-4**	**-1**	**-4**	**1**	**2**	**9**	**3**

Source: Strategic Analysis of Japanese Megabanks (Burgess, 2020c)

RUS are currently unable to monetize core competencies due to capital constraints, low trading volumes and high cost to revenue ratios. Furthermore limited performance metrics act as a **business tax** that disables management from understanding RUS's value

[7] An acronym for strengths, weaknesses, opportunities and threats

proposition, its core strengths and weaknesses. It also diminishes their ability to maximize profits, reduce costs and manage key risks.

Furthermore using a competitor SWOT analysis (figure 5.3) to contrast RUS's core competencies against key competitors reveals that RUS are only able to achieve **competitive parity**. RUS are better placed to manage external threats but poorly placed to exploit external opportunities. The SWOT analysis suggests RUS are more risk averse than its competitors. It is well placed to manage external threats from coronavirus workforce disruption to regulatory Libor reforms (Burgess, 2019a). However it is poorly placed to exploit advances in technology and lucrative government green finance initiatives.

Figure 5.3 Competitor SWOT Analysis

	Opportunities (O)		Threats (T)				
	New Technology Machine Learning, AI, Cloud	Green Finance Initiatives	Cyber Security	Hard Brexit	Libor Reform	Workforce Disruption	**Resource & Capability TOTAL**
RUS	**-4**	**-1**	**-4**	**1**	**2**	**9**	**3**
Mitsubishi, MUFG	2	2	-4	1	-2	4	3
Sumitomo, SMBC	3	2	-3	1	-2	2	3
Citadel	4	0	0	1	2	-1	6

Source: Strategic Analysis of Japanese Megabanks (Burgess, 2020c)

A **VRINO**[8] analysis (Galpin, 2020) helps to evaluate if, how and to what extent an organisation has a value chain (figure 5.1) with resources and capabilities that when combined can achieve and sustain a competitive advantage (Whittington et al, 2020).

We performed a VRINO analysis, in (Burgess, 2020c), based on RUS's current capabilities and value chain. In this paper we look extend this analysis to examine if investing in algorithmic trading capabilities[9] and combining this with the existing "agile pricing and risk analytics" (Burgess, 2020c) could create a new core competency "**Advanced Automation of Pricing, Risk and Execution**" that could offer superior trading and risk management capabilities and give RUS a sustainable competitive advantage. The VRINO analysis is performed below.

5.1 VRINO Analysis - Valuable

The new core competency would facilitate sophisticated state-of-art trade execution and orders could be worked systematically to reduce market frictions to achieve the best price. This is valuable to customers as it would facilitate better transaction prices and reduce human error.

It is valuable to RUS as it would also reduce human resource costs, which are the biggest costs the organization incur. It would also reduce operational costs, create economies of scale, improve cross-selling opportunities and would enable RUS to outperform

[8] VRINO is an acronym for Valuable, Rate, Inimitable, Non-substitutable and Organisationally Appropriable, sometimes also referred to as VRIO without the Non-substitutable element.
[9] In this paper we are specifically referring to algorithmic trading systems that use artificial intelligence, machine learning and predictive technologies.

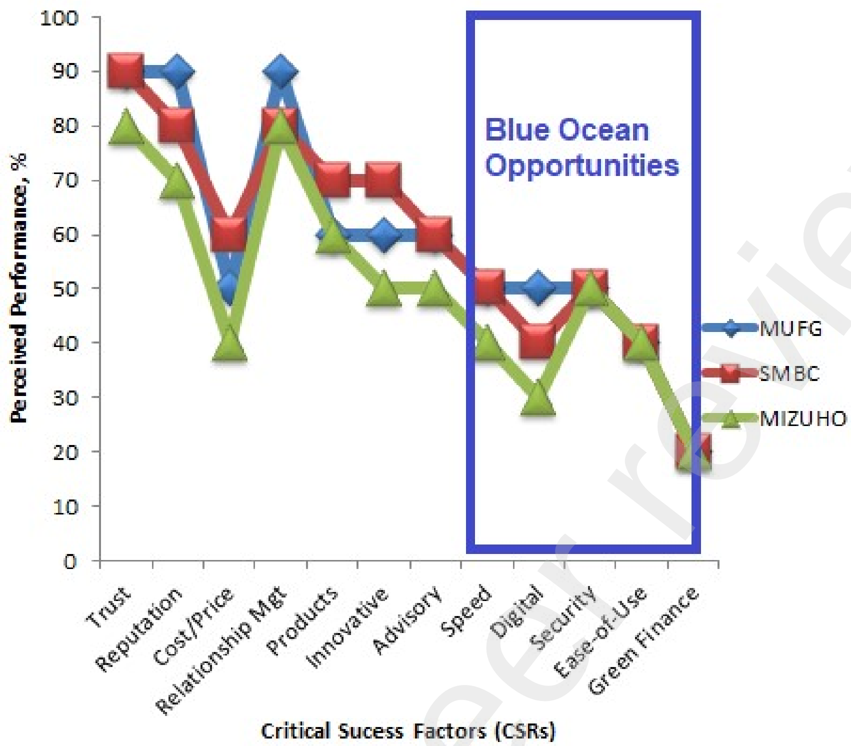
competitors, charge clients lower fees, compete more aggressively on price to win market share and provide elevated levels of client service.

There is a strong possibility algorithmic trading plays a key role in generating superior returns. As demonstrated by hedge fund managers using artificial intelligence, who have better managed market drawdowns and outperformed other funds on a risk-adjusted basis as indicated by their higher Sharpe ratios (figure 4.5).

5.2 VRINO Analysis - Rare

We performed a strategy canvas analysis to produce a value curve for RUS and its competitors (figure 5.4). A value curve measures perceived performance against critical success factors (CSFs). It can be a subjective process and difficult for managers to agree on which critical success factors to prioritise as highlighted by (Kim and Mauborgne, 2002). The analysis highlighted that algorithmic trading capabilities, digital services and technology innovation are rare skills that could exploit competitor weakness. Algorithmic trading presents a lucrative, monopolistic, '**Blue Ocean**' investment opportunity, where profit margins are wider as markets are less competitive and less congested.

Figure 5.4 Strategy Canvas – Competitor Value Curve Analysis



Source: Strategy Canvas Analysis & Competitor Benchmarking, (Burgess, 2020e)

5.3 VRINO Analysis - Inimitable

It is extremely difficult to imitate the new core competency, because it is nuanced, complex and requires tacit knowledge of the intricate connectivity between value chain components. Furthermore it is unique to the bank making it non-transferrable and inimitable.

5.4 VRINO Analysis - Non-Substitutable

It would be expensive and complex to replace or substitute the new core competency. As it would be costly to set-up a substitute and require niche technical expertise. Human substitutes would be unable to able to process vast amounts of data, compete with the economies of scale and the speed of performance. Similarly a technology or platform substitute would require niche skills to build in-house. It would be equally difficult to purchase and integrate external vendor solutions, as already experienced with Murex, where the technology is expensive, nuanced, complex to configure and support due to the niche skills and experience required.

5.5 VRINO Analysis - Organizationally Appropriable

The new core competency is highly organizationally appropriable and could help monetize existing capabilities and facilitate many new revenue generating opportunities. Likely benefits include:

Enhanced Returns

- Increased investment returns and Sharpe ratios, see (table 4.2) and (figure 4.5)
- Advanced Market Forecasting, Prediction and Trading Signal Capabilities
- Increased Transaction Speeds and Ability to Exploit Arbitrage Opportunities
- Automated Execution, Hedging and Advanced Order Book Management

Advanced Risk Management

- Advanced Risk & Drawdown Management, see (table 4.2) and (table 4.4)
- Reduction in Human Emotion/Bias, Human Error and “fat finger” mistakes.
- Advanced Order Management - Can simultaneously Execute and Hedge
- More Diversification Opportunities and Reduced Idiosyncratic Risk (Burgess 2021)

Improved Client Services & Market Share

- Lower Transaction Costs & More Competitive Pricing
- Ability to Work Large Orders without Moving the Market
- Hybrid or Fully-Automated '**Robo Research**' and '**Robo Sales**' Services
- Improved Client Services: Automation of Repetitive Tasks would Free-up Human Resources for High Value Client Service Items
- Advanced Research leveraging Broad Market, Social Media & Client Data Analysis
- Improved Market Share and Client Coverage Capacity
- Enhanced Cross Selling Opportunities

Cost Savings

- Automation of Repetitive Tasks & Human Resource Savings
- Lower Operational Costs
- Scalable Services & Economies of Scale

Even if RUS could only monetize a fraction of these opportunities the new core competency has the potential to increase revenues significantly, reduce risk and lower costs. Furthermore RUS could opportunistically go after the quick and easy revenue enhancing targets first and use the profits for sustained reinvestment and innovation.

The VRINO analysis indicates that investing in algorithmic trading would give a sustainable competitive advantage as summarized in (figure 5.5).

Figure 5.5 VRINO Analysis

	Strengths	V Valuable	R Rare	I Inimitable	N Non-Substituitable	O Organisationally Appropriable
1	HR Excellence	✓	×	×	×	×
2	Skilled Workforce	✓	×	×	×	×
3	Parent Co. Large Capital Base	✓	✓	×	×	×
4	Agile Pricing & Risk Analytics[1]	✓	✓	✓	✓	×
5	**Advanced Automation of Pricing, Risk & Excecution[2]**	✓	✓	✓	✓	✓

[1] *Facilitates Sophisticated, Fast, Bespoke Trading & Risk Capabilities*

[2] *Automated, Adaptive & Predictive Pricing, Risk & Execution using Machine Learning*

Source: Adapted from Strategic Analysis of Japanese Megabanks (Burgess, 2020c)

This answers the second part of our headline question: "do they provide a sustainable competitive advantage?" - Yes they certainly provide a sustainable competitive advantage. Specifically for RUS, they would enable existing resources and capabilities to be organizationally appropriable, monetizable and enable RUS to improve its strategic position from competitive parity to that of having a competitive advantage by shoring up technological weaknesses to exploit market opportunities.

6. What should my organization do?

Having established that algorithmic trading technologies have high revenue generating potential and could provide a sustainable competitive advantage for RUS (figure 5.5); how should RUS acquire this skill and integrate it with existing resources and capabilities?

The goal of a Merger & acquisition is to acquire new resources and capabilities to build up a firm's existing capabilities, increase firm value and gain market share. Therefore we use M&A tools and frameworks from (SBS4, 2020) and (Galpin, 2020), as they are perfectly designed to answer this question.

In order to acquire algorithmic trading capabilities, RUS need to consider if it should build or buy the resources and technologies required. We outline the pros and cons of each approach in (figure 6.1).

Figure 6.1 Build vs Buy Strategies

	Advantages	Disadvantages
Organic (Build)	• Tailored to Fit • Highly Configurable • Cost Efficient, if well-managed • Free Open Source Software Available	• Slow • Legacy Infrastructure • Poor IT Management • Niche Set-up Skills Required
Acquisition (Buy)	• Quick • Access to Skill, Expertise & Support • Bargain Acquisitions during Covid19	• Difficult to Customize • Intellectual Property & NDAs [1] • Expensive

[1] Non-Disclosure Agreements

Source: Winning at the Acquisition Game (Galpin, 2020)

RUS could pursue organic growth via in-house expertise and internal alliances. Alternatively the core competency could be acquired via vendor software purchases, fintech partnerships, joint-ventures or even a fintech acquisition.

An organic approach is most suitable for RUS and most compatible with RUS's requirements and concerns:

Cost Cutting & Capital Constraints

- RUS is cost cutting, has capital constraints & looking for a cost effective solution
- Need for niche technical expertise & careful cost management (Burgess, 2019a)
- Make use of free open source vendor solutions (Scikit-Learn, n.d.) and (TensorFlow, n.d.)

Risk Aversion

- Want to take an experimental approach before committing capital
- Increased revenue opportunities must be demonstrable and evidenced
- Want an incremental programme of work that focuses initially on low cost easy wins
- Gradual change to minimize disruption
- Workforce require time to train and adapt to new processes

Data Protection

- RUS is concerned about proprietary data leakage & GDPR[10]
- Vendors might share RUS alpha generation ideas to win new customers
- A vendor non-disclosure agreement (NDA) is not considered sufficient protection

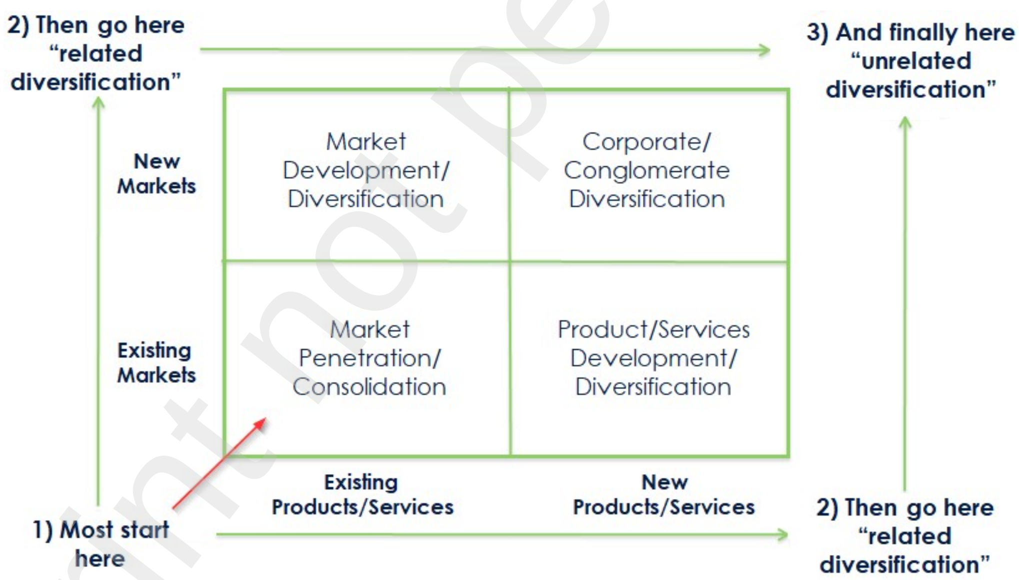
As illustrated in (figure 6.1) organic growth would allow RUS to take a cost-effective, risk-averse and incremental integration approach. Organic solutions are tailored to business

[10] The General Data Protection Regulation (GDPR) is a legal framework in the European Union (EU) that sets strict guidelines for the collection and processing of personal information.

needs, highly configurable and over time they better help establish in-house expertise. Downside challenges would likely arise from having to work with expensive legacy infrastructure, outdated IT policies and poor IT management. **Manager skill is critical for success** to navigate IT challenges and if managed well this approach could be a cost effective solution.

Following (Ansoff, 1957) we recommend the integration plan illustrated in (figure 6.2). We have high confidence in this approach as it was previously used successfully to establish the "agile pricing and risk analytics" core competency.

Figure 6.2 Ansoff's Growth Matrix



Source: Strategies for Diversification (Ansoff, 1957)

Ansoff Integration Plan

1. Market Penetration

First consolidate core business lines and focus on market penetration and growing core rates trading and fixed income businesses, which are well-established yet have more potential.

2. Product & Services Diversification

Second diversify by product and asset class to provide advanced services and support for credit derivatives, foreign exchange, interest rate swaptions, convertible bonds and equity businesses.

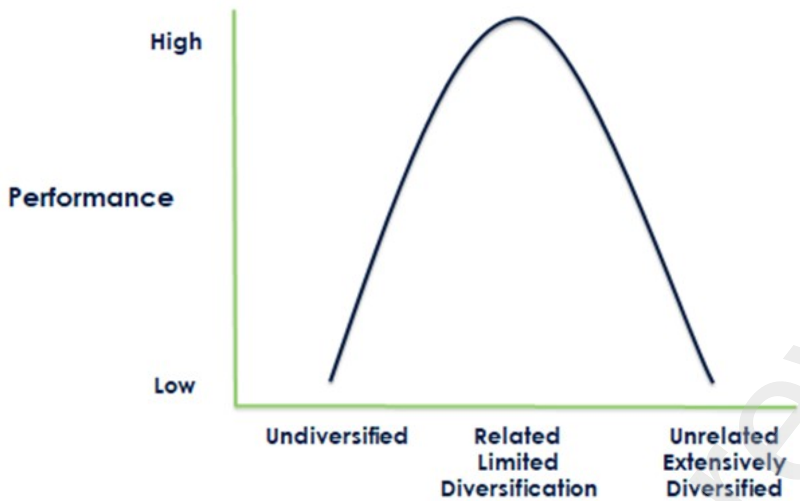
3. Market Diversification

Thirdly diversify by market, starting with the most similar business entities, namely RUS Bank London, RUS Securities New York, Hong Kong then Tokyo (in this order). A cautious more arm's length approach should be taken with overseas branches, where cultural **CAGE**[11] **distances** (Ghemawat and Altman, 2019) can lead to lengthy P&L[12], cost, ownership and other internal disputes that often destroy rather than create value.

When integrating algo capabilities, RUS should focus on enhancing core business performance and limited related diversification. Research shows (Whittington et al, 2020) that it is important to diversify, but not over-diversify, as unrelated diversification is ineffective and often lowers performance, as illustrated in (figure 6.3).

[11] CAGE distances track **cultural, administrative, geographical and economic** differences.
[12] P&L is an acronym for profit and loss.

Figure 6.3 Diversification and Performance



Source: Exploring Strategy, (Whittington et al, 2020) pp 244-245

It will be important to establish **internal alliances** between **quant and research teams** to steer the innovation, train the trading and sales teams and assist with data analyses to be used for identifying cross selling opportunities and trading signals for alpha generation.

For RUS a cost-effective way to transition towards using machine learning techniques would be to consider using free open source **Scikit-learn and TenorFlow**[13] analytics to complement the existing in-house analytics with PCA[14] and other highly sought after machine learning techniques, tools and frameworks for pricing and risk management.

Initially machine learning processes should be kept simple to use. To enhance revenue opportunities machine learning must be implemented into processes in a way that is

[13] Scikit-learn and TensorFlow are an open source analytics libraries that provide machine learning tools for data analysis, see (Scikit-Learn, n.d.) and (TensorFlow, n.d.) respectively.
[14] RUS is keen to explore the use of Principal Component Analysis (PCA), which is a technique for reducing the dimensionality of a dataset to increase data interpretability whilst minimizing information loss.

complementary and organic to existing workflows in order to combine the best human financial expertise with the best AI/ML techniques. This is often referred to as a **Quantamental**[15] approach (López de Prado, 2018), where we combine quantitative approaches using high-end computers, mathematical models and big data with fundamental methods where humans manually analyse investment opportunities to generate better risk-adjusted returns (Lynch, 2018), (Smigel, n.d.). Moreover, as automation frees human resource, human effort should be reassigned to high value-add work items.

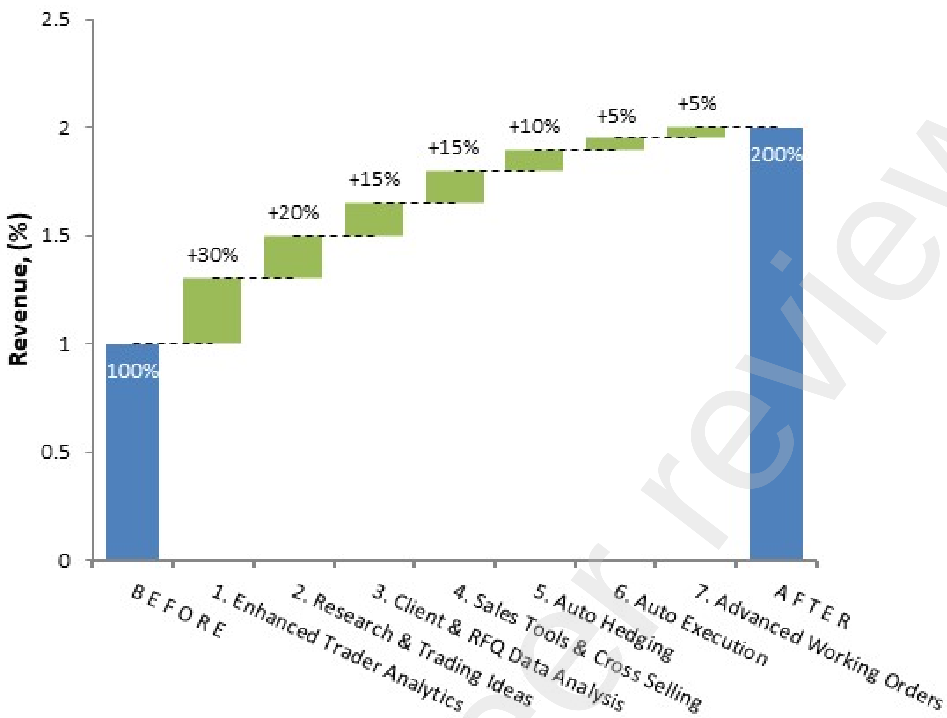
RUS should incrementally enhance existing trading and sales capabilities to target earnings growth[16], starting by enhancing data analysis and the automation of well-understood tasks and processes such as the below,

Targeted Algo Enhancements for Earnings Growth

1. Enhance Trader Analytics for Better Pricing, Risk and Trading Signals
2. Automate Research & Trading Ideas
3. Enhance Client Data Gathering & RFQ[17] Analysis
4. Enhance Sales Processes to Identify Cross-Selling Opportunities
5. Auto Hedging (Humans Execute Main Deal, but with Auto-Hedging)
6. Auto Execution (with Human Oversight Only)
7. Advanced Execution Services to Work Larger Orders Efficiently

[15] This is a portmanteau combining "quant"itative and fund"amental" investing
[16] Increased earnings from both revenue growth and cost reduction
[17] An electronic price request is called a **Request for Quote** (RFQ)

Figure 6.4 Projected Revenue Growth (%)



Source: Illustrative RUS Revenue Projections

Even if only a fraction of the benefits from (section 5.5) and (figure 6.4) are monetized, algorithmic trading would have a significant positive impact on earnings. This would facilitate reinvestment to develop the new core competency to maturity, establish further economies of scale and facilitate sustainable growth.

7. Conclusion

We have learned that algorithmic trading strategies generated **superior returns** relative to discretionary trading during the Covid19 pandemic and that they facilitate better management of major market drawdowns. We also showed that both during normal market conditions and times of crisis they generate superior risk-adjusted returns and exhibit higher Sharpe ratios.

An algorithmic trading strategy would allow RUS to dynamically respond to market events, better identify market opportunities, reduce costs, reduce operational risk, improve client services, increase market share and establish economies of scale. It would complement RUS's existing value chain to create a new core competency "Advanced Automation of Pricing, Risk and Execution" services, which would give RUS a **sustainable competitive advantage**.

These are unprecedented times for the world and financial markets; the economic outlook is uncertain yet cautiously optimistic. Coronavirus vaccines, continued workforce disruption, weak economies and government financial stimuli with tax hikes to follow dominate news headlines. There will be a clear paradox to both cut costs and innovate. We believe these risks will be best managed through an organic algo growth strategy, which will allow RUS to be innovative and stable (McGrath, 2012), whilst establishing a sustainable competitive advantage.

Appendix **Case Study**

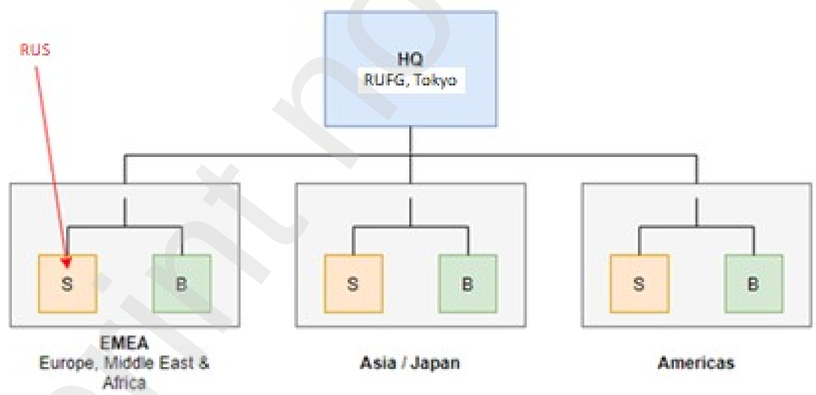
Organization:	Rainbow & Unicorn Securities, London (RUS)
Industry:	Financial Services
Sector:	UK Corporate Lending & Project Finance

RUS provide financial services, trading expertise and risk management solutions within the interest rate, fixed income and credit markets. It specialises amongst other things in corporate lending and project finance within the UK and also Europe, Middle-East and Africa (EMEA).

RUS is fully owned by Rainbow & Unicorn Financial Group Tokyo (RUFG), which has a sizable balance sheet, predominantly due to large Japanese deposits. Japanese investors are extremely risk-averse with many business relationships based on trust, reputation and long-term track formed over decades!

RUFG is one of three 'Japanese Megabanks' that dominate the financial services industry in Japan with combined deposits exceeding USD 10 trillion (Piece-of-Japan, n.d.). RUFG itself has assets of USD 20 billion and employs 50,000 staff with 500 offices worldwide.

Figure A1: RUFG Organization Chart



RUFG has 3 regional hubs to provide concentrated coverage in Europe & EMEA, Asia & Japan and the Americas. RUFG subsidiaries are siloed with Corporate Banking (B) ringfenced and Investment & Securities (S) businesses separated to satisfy legal and regulatory requirements.

Corporate Banking subsidiaries (B) have large balance sheets, good access to capital but poor legacy systems & infrastructure. Investment & Securities (S) businesses however have good technology and systems, but small balance sheets and little access to capital.

This case study is fictional, yet inspired by adapted from real-world industry practice and first-hand experience.

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