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A Study on Algorithmic Trading

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A Study on Algorithmic Trading
En studie om algoritmisk aktiehandel

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Sammanfattning

Algoritmer har använts inom finans sedan början av 2000-talet och utgjorde cirka 25% av marknaden runt 2005. När detta arbete utförs står algoritmer för cirka 85% av marknadsvolymen. Utmaningen som många investerare och fondförvaltare står inför är att slå den svenska marknadsindexet OMXS30. Detta arbete undersöker offentligt tillgängliga algoritmer och deras potential att implementeras och modifieras för att överträffa marknaden. Det finns mycket forskning gjord inom ämnet och majoriteten av denna forskning är på en hög akademisk nivå. Trots att få algoritmer hittades i sökningen, fanns det ett fåtal algoritmer som lyckats slå andra marknadsindex. Marknadsdata för denna forskning erhölls från Nordnets slutna API, specifikt historisk prisdata från olika finansiella värdepapper. Algoritmerna använder den historiska prisdatan för att generera köp- och säljsignaler. Dessa köp och säljsignaler användes sedan för att beräkna prestandamått som geometrisk medelvärde och riskjusterad avkastning. Prestandamåtten används för att mäta och jämföra prestanda med OMXS30 genom en kvantitativ metod. I genomsnitt presterade algoritmerna inte väl på de valda värdepappren, även om vissa värdepapper utmärkte sig i alla fall. Att slå marknaden anses vara en svår uppgift och denna forskning speglar några av de utmaningar som är involverade. Den valda metoden belyser vikten av de aktier som algoritmerna handlar med och betonar att aktier inte kan väljas slumpmässigt. Att bygga ett helt automatiserat obevakat handelssystem är utmanande och kräver omfattande arbete. Vissa strategier visade sig vara i behov av mänsklig övervakning för att maximera avkastningen och begränsa förluster, medan andra gav låg avkastning för låg risk.

Nyckelord

Algoritmer, Finansiell matematik, Mjukvaruutveckling, Algoritmisk aktiehandel, Teknisk analys

Abstract

Algorithms have been used in finance since the early 2000s and accounted for 25% of the market around 2005. In this research, algorithms account for approximately 85% of the market. The challenge faced by many investors and fund managers is beating the Swedish market index OMXS30. This research investigates publicly available algorithms and their potential for implementation and modification to outperform the market. There is a lot of research done on the subject and most of the research found was mostly at a high academic level. Although few algorithms were found in the search, some algorithms that managed to beat other markets caught interest. The market data for this research was obtained from Nordnets closed API, specifically the historical price data of various financial securities. The algorithms use the historical price data to generate buy and sell signals which represents a trade. These trades were then used to calculate performance metrics such as the geometric mean and the sharpe ratio. The performance metrics are used to measure and compare performance with the OMXS30 using a quantitative method. On average, the algorithms did not perform well on the chosen securities, although some securities stood out in all cases. Beating the market is considered a difficult task, and this research reflects some of the challenges involved. The chosen method highlights the importance of the stocks the algorithms trade, emphasizing that stocks cannot be chosen randomly. Building a fully automated unsupervised trading system is challenging and requires extensive work. Some strategies tend to require human supervision to maximize returns and limit losses, while others yield low returns for low risk.

Keywords

Algorithms, financial engineering, software engineering, algorithmic trading, technical analysis

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1 Introduction

The practice of trading goods has been around for thousands of years and is one of the earliest forms of commerce. Humans began trading goods to obtain what they needed or wanted that they could not produce themselves. The earliest evidence of trade dates to the Stone Age, where people exchanged tools and other goods across long distances [1]. As societies became more advanced, trade became more sophisticated, and humans developed new ways of exchanging goods and services. One of the earliest forms of trading was bartering, where people exchanged goods or services for other goods or services. This system worked well for many centuries, but it was often difficult to find someone who wanted what you had to offer, or who had something you wanted. To overcome this problem, people began to use a variety of different items as currency. These could include shells, gold, and other precious metals, which were widely recognized as having value [1].

As societies became more complex, and trade increased, people began to develop more sophisticated financial systems. One of the earliest examples of this was the development of banking in ancient civilizations such as Babylonia. Merchants and traders would deposit their goods and money with temple priests who acted as bankers [2]. This system allowed for the safe storage of wealth and facilitated the exchange of goods and services. In the Middle Ages, banking and trade continued to develop, and guilds were formed to regulate commerce and protect the interests of traders. The growth of international trade in the 16th and 17th centuries led to the development of modern banking, because merchants needed a secure way to transfer funds across borders [2]. This led to the establishment of the first stock exchange in Amsterdam in 1602, where shares in the Dutch East India Company were traded [3].

The Dutch tulip mania is an example of how financial markets can be driven by speculation and hype. In the 17th century, tulips were highly prized in the Netherlands, and the bulbs became a sought-after commodity. The demand for tulip bulbs led to a speculative bubble, with prices rising to astronomical levels. At the height of the mania, a single tulip bulb could be worth more than a house. However, the bubble burst in 1637, and many people lost their fortunes. The tulip mania is seen as one of the earliest examples of an economic bubble and explains the dangers of speculation [4].

Today, financial markets are complex and sophisticated, with a wide range of instruments and trading strategies available. They play a crucial role in the global economy, facilitating the flow of capital and enabling businesses to access the funding they need to grow and innovate. Financial markets have come a long way since the early days of bartering and trading, and they continue to evolve as modern technologies and innovations emerge.

1.1 Background

The use of algorithms has increased on financial marketplaces. These algorithms use complex mathematical models and statistical analysis to identify patterns and trends in vast amounts of financial data. They can be used for various purposes, including market analysis, risk management, and trade execution. Making trading decisions with the aid of algorithms is one way they are used in the financial markets. Traders can use algorithms to develop trading strategies that automatically execute trades based on specific market conditions, such as price movements or the occurrence of certain events. For instance, a buy order might be started by an algorithm when a stock hits a specific price or when a specific news event takes place. During the last two decades there has been a large increase of the use of algorithmic trading. It started to become popular in early 2000s and by 2005 it accounted for about 25% of the total volume. Ten years later it accounted for approximately 85% of the market volume in the USA [5]. According to Swedish media there has been a similar increase on the Swedish markets [6]. Although it is difficult to confirm the exact participations of algorithms in trading volume, in a survey from the Swedish Financial Supervisory Authority more than 80% of the surveyed companies answered that they use algorithms in their investment strategies in 2011 [7].

Nordnet is a digital bank that offers services like saving, investing, and trading [8]. It was one of the pioneers as a digital stockbroker in Sweden and has since expanded its reach to cover the Nordic region, except Iceland. This thesis is written for Nordnet, which involves conducting research and analysis to address specific business challenges or opportunities.

1.2 Problem Statement

Algorithmic trading is a computer-based approach to trading which uses algorithms and mathematical models to make trading decisions. This approach eliminates emotional bias and make decision based solely on data and the analysis of that data. However, algorithmic trading can be expensive, as it requires significant investment in technology and require ongoing maintenance and updates to remain effective. Additionally, the cost of data and access to market information can be high and to this we add the transaction costs for the trades. On the other hand traders often struggle with emotions that can cloud their judgement and lead to poor decisions [9]. By using algorithms, emotion can be eliminated from the decision-making process, which creates a trade-off with the high cost of algorithmic trading. The high investment cost and mathematical modelling required by these algorithms can make it challenging to outperform the market [5]. This thesis aims to contribute the development of effective trading strategies using the algorithmic trading approach.

1.3 Goals

This thesis aims to explore and evaluate publicly available algorithmic trading strategies by implementing and testing them on historical data. In addition, new or modified strategies will be created. These algorithms are often based on quantitative analysis (QA) that emphasizes mathematical and statistical analysis to help find investment opportunities [10]. The author will test some algorithms that were developed for online auctions and evaluate their performance. Other concepts that will be explored are statistical arbitrage, where arbitrage is when the investor exploits market inefficiencies [11]. The statistical arbitrage uses quantitative methods to identify the arbitrage opportunities and make a profit of them.

Mainly the author will explore two concepts in regards of statistical arbitrage, pair trading and arbitrage by dividends. Pair trading builds upon the theory that highly correlated securities will continue to remain so. If there is a sudden difference in correlation, the theory suggests that the assets will eventually return to a correlated state. Investors can take advantage of this by exploiting the difference in correlation. Arbitrage by dividends builds upon that stocks pay out dividends to the investors owning the stock. When the dividend is paid out of x percent the price of the stock should also be reduced by x percent. The theory on dividend arbitrage is that the price in many cases don't follow the logic and reduces more or less than the yield of x percent.

One goal of this research is to establish a knowledge foundation for Nordnet related to algorithmic trading. This thesis aims to investigate publicly available algorithms that can beat the Swedish market and explore how they can be implemented. The goal is to acquire knowledge in this area and help Nordnet generate better solutions for their customers.

1.4 Scope of the Project and Delimitations

The author will be limiting the scope to pre-trade activities and will focus on the decision-making process leading up to trade execution. While trade execution delays are an important consideration in real-world trading scenarios, they are often beyond the control of traders and can vary depending on the trading platform and the specific financial instruments being traded.

Other delimitations are machine learning and high frequency trading. Machine learning, which has shown promising results in the field of algorithmic trading. The reason is that it requires large amounts of high-quality training data and sophisticated model development and tuning, which is outside the scope of this study. High frequency trading is a popular strategy of professional trading companies. However, in this study the techniques and mathematics and technical requirements are to advance for this study. Which leads up to the following delimitations.

1. The focus of this study will exclude the execution of trades and any associated delays.

3. Machine learning will not be explored in this study.

4. High frequency trading will not be explored in this study.

1.5 Method

This study will use quantitative methods to evaluate different trading strategies, which will be compared to the Swedish index OMXS30. In this study the author intends to ignore the execution of orders, instead the implemented software will note when it decides to enter or exit a position. The author will evaluate the performance of the algorithms through geometric mean and the risk adjusted return as the Sharpe ratio, where the Sharpe ratio is the quota between portfolio return and risk and is described in section 2.1.2. The evaluation of geometric mean and Sharpe ratio will be compared to the Swedish stock market index OMXS30.

1.6 the Authors Contribution

The author is responsible for all contributions to this work, apart from the price data, which has been provided by Nordnet.

2 Theory and Background

To understand algorithms used in the financial sector, we must introduce some financial concepts and why it is difficult to determine price in financial instruments. This is important because investors can take advantage of pricing discrepancies in financial instruments to generate profits. One of these strategies involving shorting a financial instrument, by shorting the investor can generate profit when the instrument price decrease. To achieve this the investor lends stocks and sell them at a lower price and thus, makes a profit between the lending price and sell price. There are a lot of instruments available to achieve this. However, they will not be described in detail in this thesis but in this chapter, we will have a brief look on how it is done. The financial markets have a structure that makes it possible for different actors to make a profit. However, the profit is associated with risk. These risks can be divided into different types and can be minimized. There is a possibility to acquire a profit with; close to zero risk, these opportunities are called arbitrage and will be explained further in section 2.1. Towards the end of this chapter, we will introduce the quantitative finance and the concept of algorithmic trading.

2.1 Introduction to Finance

One fascinating thing about the computer engineering domain is that it can be applied to a lot of different things. Here you will read more about some concepts related to finance e.g., markets, risk, and technical indicators. These are important and will later be combined in the following chapters in the attempt to modify and construct algorithms for trading purposes.

2.1.1 Financial Markets

In economic terms, there exists a diverse range of markets spanning from the candy market in airports to the global forest industry. The actors in these markets make the most of their positioning and geographic area to increase their profitability. Debt markets, equity markets, foreign exchange markets, commodity markets, forward and futures markets, options markets, and real estate markets are just a few of the different groups that financial markets can be divided into. The equity market, also referred to as the stock market is where investors exchange company ownership. Owning a stock of a company indicates that the person owns a portion of that company, and if they own all the stocks, they possess the entire company. Companies are frequently compiled into stock indices to capture the broad trends in stock price movements in a specific market or sector. Such market indexes include the S&P500 and OMXS30, for instance [8]. Based on their trading volume, over a six-month period, the 30 most notable companies listed on the Swedish stock exchange make up the OMXS30. According to Nasdaq, the shares that make up this index are rebalanced on the first day the market is available in January and July. When the rebalance occur, an evaluation of the 30 most notable companies will be reconsidered. Banks, insurance firms, mutual funds, hedge funds, sovereign wealth funds, and retail investors are some of the players in the equity market. High-frequency traders have short-term investment horizons, typically ranging from seconds to minutes, while wealthy families may have very long-term investment horizons [12], [13].

2.1.2 Risk

We must first comprehend what risk is, to be able to control it. Risk, which in investing refers to the potential for a monetary loss, is described as the possibility of loss or damage. The process of finding, evaluating, and prioritizing risks and taking action to reduce or eliminate them is known as risk management. Investors can reduce their exposure to market risk by employing hedging strategies. Hedging can be achieved in different ways, if two companies are dominating one market the investor can either try to pick their predicted winner or buy both companies. If the investor hedges by buying both companies, they can protect their portfolio from the market risk and potentially limit their losses. On the other hand, investors can mitigate company-specific risk by diversifying their investments across different industries or asset classes, which can potentially reduce the impact of any single company's inferior performance on their overall portfolio. Investors need to be mindful of risks associated with algorithmic trading. While algorithms can remove emotional bias and only base decisions on data and analysis, they also carry some risks, including the possibility of technological failures, data errors, and market volatility. Additionally, "black swan" events are unexpected occurrences that can have a substantial impact on the market and can affect algorithms. Investors must take precautions to manage these risks, such as regularly monitoring and testing algorithms, having a backup plan in case of technical difficulties, and keeping sufficient diversification across their portfolios. Investors can reduce their potential losses and improve their chances of market success by effectively spotting and managing risks. The Sharpe ratio is a way for investors to measure their risk adjusted return and is illustrated in equation 2.1.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma} \tag{2.1}$$

The R_p represents the portfolio return and R_f is the risk-free return that is available on the market, their difference is then divided by σ which represents the standard deviation of the portfolio's returns. The standard deviation can be described as the amount of spread around its mean [13].

2.2 Pricing and Arbitrage

Pricing of various financial assets is a central theme in finance. While pricing can be performed by anyone, it sometimes requires dozens of highly skilled mathematicians, physicists, or finance experts to solve the most challenging pricing problems [8]. Further into this chapter the reader will be presented with some complex pricing formulas. It is not required that the reader understands them to follow the rest of the thesis.

2.2.1 Pricing of Options

Earlier mentioned pricing problems can arise when determining the price of options, forwards, and futures, which are financial instruments that revolve around an underlying asset, such as stocks. Consumers pay for the opportunity to buy/sell the underlying financial asset at a specified price within a predefined time interval. With the help of options an investor can profit from when a stock both increases and decreases in value. The ability to profit from decreasing stock price will be an important aspect of the pairs trading strategy explained in section 4.2.

Fisher Black and Myron Scholes discovered the formula for evaluating options and is presented in equation 2.2 [14].

$$C = N(d_1)S - XN(d_2)e^{-r_f(T-t)} \tag{2.2}$$

Where

$$d_1 = \frac{ln\left(\frac{S}{X}\right) + \left(r_f + \frac{\sigma}{2}\right)(T-t)}{\sigma\sqrt{T-t}}$$

$$d_2 = d_1 - \sigma\sqrt{T - t}$$

The Black-Scholes option pricing formula uses several variables to calculate the price of an option. The option price, denoted as C, is the amount you would pay today to have the right; but not the obligation to buy an underlying asset in the future.

The current price of the underlying asset is represented by S, and the exercise price of the option, denoted as X. X is the price at which you have the right to buy the underlying asset if you decide to exercise the option. Both S and X are fixed in the option contract and are defined upfront.

The maturity date of the option, denoted as T, is the date when the option contract expires. It is also fixed in the contract and is known in advance. The standard deviation of the returns of the underlying asset is denoted as σ. It is used to estimate the potential fluctuations in the price of the underlying asset during the life of the option.

The risk-free interest rate, denoted as r_f, is the interest rate that you could earn on a risk-free investment, such as a Treasury bond or interest rate on a savings account.

The probability denoted as $N(d_1)$ represents the likelihood that a normally distributed random variable will be less than or equal to d_1. It is used to calculate the expected value of the option based on the probability of the underlying asset's price being above the exercise price at the maturity date [13].

Equation 2.2 is a very compact and is the schoolbook example of determining the option price, however the valuation formula still makes a lot of assumptions, such as the short-term interest rates is always known, the stock pays no dividends or other distributions, there's no transaction costs for buying/selling the option or underlying stock and the list goes on. Both Hans Byström (Professor in finance at Lund university), Fisher Black and Myron Scholes confirms that the formula neglects the investors believe that the underlying price will go up or down, which is irrelevant in this case, because the formula is a function of the stock price, which is independent of the expected return of the stock [8], [10]. Above example demonstrates some of the problems and why it is difficult to determine price of financial assets.

2.2.2 Pricing of Stocks and Fundamental Analysis

Pricing of stocks can be done in a lot of different ways. Stocks often fluctuate much in price and the question still is, what is a reasonable price for the stock. These questions are not easy to answer according to Hans Byström and as seen in the previous section. He explains a concept with three components that are linked together, high returns, large price fluctuations and pricing difficulties. He states that it is very likely that the three will appear together 13]. One of the pricing difficulties which also relate to the stock prices are forward looking and reflect expectations about profits and discount rates even as far as decade ahead, as the federal reserve states in an article for 2020 [16]. The discount rate is simply put as, the rate banks are charged for short term loans from the Federal Reserve Bank [17]. On this topic there are typically two different ways of analysing the stock and predicting whether the price will rise, fall, or consolidate (converge around a price level). Fundamental analysis and technical analysis, where the fundamental analysis focus on the economic and financial factors that influence a business. As fundamental analysis does not build on the efficient market hypothesis (EMH), this states that the share price is reflecting all available information and that the price is correct in the sense that, all investors agree of this price. While the technical analysis focus on quantitative properties like, volume, price, and the price's mean. Often these two techniques are used in collaboration with each other, however analysts that focus on fundamentals are often in disagreement with the technical analysts and vice versa [13], [18]. According to Byström there does not seem to be a consensus on whether either technical analysis or fundamental analysis works in practice. This suggest it might be best to do a little of each. And remember to keep an eye on the psychology of the market. One of the basic ways to determine the price of a stock is the Dividend discount model (DDM). Where D in this case is the dividend pay-out, k is the estimated market risk and g is the estimated dividend growth.

$$DDM = \frac{D}{k-g} \tag{2.4}$$

All stocks do not distribute dividends to its investors a way to get around this is to discount the cashflow of the company instead which gives the Discounted Cash Flow (DCF)

$$DCF = \frac{C_1}{(1-r)^1} + \frac{C_2}{(1-r)^2} + \frac{C_3}{(1-r)^3} + \cdots + \frac{C_n}{(1-r)^n} = \sum_{n=1}^{\infty} \frac{C_n}{(1+r)^n} \tag{2.5}$$

Where the C is the cashflow for that period and r is the discount rate. In this formula the discount rate is the weighted average cost of capital (WACC), that can be calculated on numbers from the company's financial statement 19]. Both equation 2.4 and 2.5, are a simple way to estimate today's price of a stock, however they are not always suitable for real world examples. We need to estimate the constants to get our estimate result and the risk is that the market, as earlier stated is forward looking and has already added other strengths and weaknesses into the price.

2.2.3 Technical Analysis

Now when being introduced to some basic concepts of the fundamental analysis, lets introduce technical analysis. Technical analysis focus on mathematical and social behaviour that is reflected in the graphs of the asset under analysis. If the volume increases drastically and the price has been opened on a low price and closes on the all-time high of the day, one could assume that the demand is high while the supply side don't want to sell, because the asset is increasing in price.

The wave principle was discovered by Ralph Nelson Elliot and is called the wave principle. He found that social, or crowd, behaviour trends and reverses in recognizable patterns. Elliott used stock market data as one of his research tools and identified thirteen recurring patterns or "waves" within the stock market data. He named defined an illustrated those patterns. The concept that market movements exhibit patterns was widely debated. Yet, recent scientific discoveries have confirmed that pattern formation is a fundamental aspect of complex systems, including financial markets. He found that different phases of growth or decline, build patterns like fractals, that the same patterns occur even if you zoom in and out of the time scope. The waves are divided into two different kinds, impulse waves, and corrective waves. Both have a subset; the impulsive waves are usually 5 waves before the three corrective waves occur. The Impulsive waves are usually denoted as integers, while the corrective waves are denoted in letters as demonstrated in figure 2.2 [20].

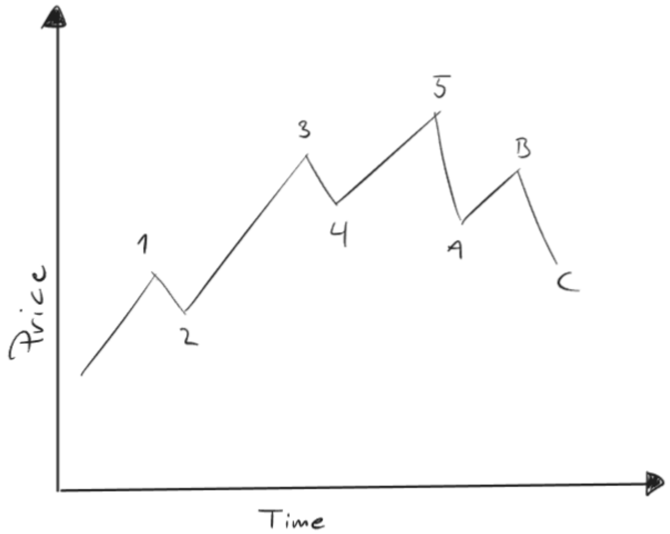

Figure 2.2 – A schematic illustration of Elliot waves, impulsive waves as numbers and corrective waves as letters

Arbitrage is an opportunity that arises when we find that the market has priced something wrong. It could be any kind of security that has been wrongly priced by the market, however this is often exploited by investors and can generate a risk-free profit. These profits are often very small and can be difficult to identify. It is often exploited by a highly specialized investors that try to find these possibilities. One schoolbook example of this, states that if two assets with very high correlation suddenly breaks correlation, an investor can purchase call options for the undervalued asset and put options for the overvalued asset and generate a risk-free return, on the assumption that the assets will find its way back into a correlated state. Often in reality these opportunities occur on the same asset on different markets. Arbitrage is of utmost importance in market analysis as it plays a vital role in aligning prices with their fundamental values and making sure markets are efficient. [21].

Numerous variables, such as macroeconomics, politics, and investor sentiment, can also affect the price of a stock or a market. The stock market can be impacted by macroeconomic factors like inflation, interest rates, and economic development because they influence the general business climate and investor expectations. Like how elections, policy shifts, and geopolitical tensions can affect investor sentiment and the stock market, political events can also have an effect. The mood of investors can then be affected by a variety of elements, including market patterns, social media, and news events. Positive sentiment can increase stock demand and raise prices, whereas negative sentiment can encourage selling and lower prices. In some circumstances, market behaviour is even more influenced by sentiment than by economic principles and political developments. Understanding the pricing process and the market is complex and difficult to comprehend.

2.2.4 Candle Sticks and Technical Indicators

Candle sticks is a type of financial chart that represents price movements of an asset over time. Each candle stick represents a period, hourly, daily, weekly etc. They display the opening, high, low, and closing prices for that period. The candle stick consists of a rectangular body, which represents the opening and closing prices. In addition, there are two wicks which represents the high and low prices. If the opening price is lower than the close price, typically the body is filled in green colour, and red colour for the reversed scenario. Candle sticks can also determine the supply and demand of a specific period. The left candle in figure 1.3 shows that the demand is high, because investors tend to buy at higher in that period.

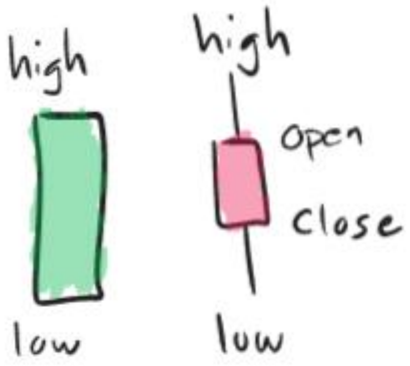

Figure 2.3 - A schematic illustration of candle sticks

One basic and popular indicator is the moving average. The moving average is the arithmetic mean of a period. One way of using these is the period 200, shows the long-term trend, if the line has a positive slope the trend is in an upward trend and if the slope is negative the trend is considered to be decreasing or a downtrend. Every average point is calculated 200 days backwards from the current day. For tracking the shorter trends it's popular to decrease the period to 50 or 20. There's a popular trading strategy which only use these moving averages in combination in attempt to find where the trend shifts directions. The investor can plot one line with a short period and one with a longer period and when the shorter-period line crosses the long-period line the trend is considered to reverse, this signal is referred to as the golden cross [22]. The moving average indicator comes in different variants, one of them is the exponential moving averages (EMA).

$$EMA_{today} = Value_{today} \cdot \left(\frac{Smooting}{1 + Period}\right) + EMA_{yesterday} \cdot \left(1 - \left(\frac{Smoothing}{1 + Period}\right)\right) \qquad (2.7)$$

EMA has a bigger focus on the current price than the moving average and therefore can react faster to trend shifts. The smoothing variable is chosen by the investor to their liking, the default however is 2 [23]. Because the today's price is calculated as a function of yesterday's price its necessary to collect more datapoints to calculate the first EMA. If a 5-day EMA is to be calculated then, we need to wait and collect $Value_{today}$ for 5 days and then the EMA_{today} can be calculated.

2.2.5 Moving Average Convergence/Divergence (MACD).

MACD is an indicator that is used to identify and following trends. This indicator is created with EMA of the price of a security. The default is calculated by subtracting the 26 period EMA form the 12 Period EMA. A second EMA line lies on top of the 26-12 line and acts as the signal line, which has a default setting of 9 periods. When MACD line crosses above the signal line is considered a buy signal, or a sell signal when it crosses down below the signal line. The MACD indicator can be used to find divergence in the price, we find that when the price trends downward and when the MACD lines trend upwards the trend will most likely follow the trend lines and is predicted to raise [24].

2.2.6 Bollinger Bands

Bollinger Bands are a popular technical analysis tool used by traders to measure the volatility of financial instruments such as stocks, and forex pairs. The bands are formed by plotting a moving average and two standard deviation bands. The moving average lies at the centre, while the standard deviation bands are positioned above and below it. The standard deviation bands are typically set at two standard deviations from the moving average. By observing price movements that exceed the upper or lower bands, traders can identify potential trading opportunities. When the price moves outside of the bands, it can indicate that the financial instrument is overbought or oversold. Bollinger Bands can be used in conjunction with other technical indicators such as the Relative Strength Index (RSI) or Moving Average Convergence Divergence (MACD) to refine trading signals. RSI is a momentum indicator which measures the speed and change of price movements over a specified period. By combining different indicators, traders can gain a better understanding of the current market conditions and make more informed trading decisions [25].

2.3 Algorithmic Trading

Algorithmic trading represents the computerized executions of a variety of financial instruments. These can be stocks, bonds, currencies, and a plethora of financial derivatives. With the help of algorithms traders can achieve more efficient executions while lowering transaction costs, which can improve portfolio performance [5]. Algorithms that are trading actively on the market today often have very complex structure and sophisticated mathematics that was developed by a large focus group as earlier mentioned in section 1. According to market regulations, there is not allowed to impact the market in such a way, that the impact gives a false or misleading signals of supply and demand Because of these regulations, the strategies are often very keen at calculating and minimizing this impact on the market. There are often advanced techniques to analyse and forecast volume, price, and volatility [5]. We will touch some of the strategy types in 2.3.1.

2.3.1 Types of Algorithmic Strategies

There are numerous of algorithmic strategies that have been developed. They can be divided into smaller subsets. Below we touch three on these subsets.

Systematic Trading, also known as automated trading, is a trading strategy that involves adopting the same approach for each trade by following a pre-determined set of rules. To start or end trading, these regulations may include set entry or exit thresholds. A systematic trading strategy's trading algorithm may have basic or complex rules, but its main objective is always to repeat a particular strategy.

Quantitative trading, also known as "black-box trading," is a type of trading technique that applies trading regulations using in-house quantitative models. These versions are frequently kept a secret and are only known to a small group of people. Quantitative trading aims to increase profits by improving market knowledge. The quantitative approach was first introduced by Harry Markowitz with his introduction of the MTP (Modern Portfolio Theory) in the early 1950s [25]. The MTP enables investors to create a portfolio of assets that balances risk and aims to maximize returns. It's obtained by a risk-free asset in combination with risky assets. The risky assets are referred to as the market portfolio and the process involves solving an optimization problem to achieve the best balance between risk and potential returns [13].

Statistical Arbitrage is a systematic trading approach that utilizes real-time and historical data analysis to take advantage of mispricing's while minimizing overall risk. Innovative tools from science and economics are frequently used in statistical arbitrage, including time series, data mining, artificial intelligence, agent-based models, and fractals. Finding opportunities to take advantage of market inefficiencies while managing risk is the aim of statistical arbitrage [26].

2.3.2 Online Trading Algorithms

In the journal article *Can online trading algorithms beat the market?*, benchmarking and profitability analysis of different trading algorithms are evaluated by the authors [27]. The online trading algorithms are not online as connected to the internet but received the name because they are competing with an algorithm that is aware of all unknown variables and is called the offline algorithm. The set of algorithms tested in these papers are not designed for the stock market per say, they are commonly used for evaluation of online auctions which have similar input data as the stock market and can be considered a systematic trading strategy. Both rely on a bid and ask price and then the actual price of the asset. The set of algorithms has been tested on different exchanges, including the German DAX30 index and the cryptocurrency market [27], [29]. The algorithms are developed in such a way that the player has no knowledge about the future, and every decision the algorithms make is based on their current knowledge. The algorithms come in two different types, which will be investigated further in section 2.2.3 and 2.2.4.

2.3.3 Non-preemptive Algorithms

Algorithms of this type, the player invests his whole wealth at one point of time during an investment period. The player will calculate a reservation price, this price is the maximum or minimum price which the player will accept. In equation 2.6 is the reservation price calculation for an algorithm developed by El-Yaniv called reservation price algorithm (RPMm)

$$q^* = \sqrt{M \cdot m} \tag{2.8}$$

The algorithm makes its decision based on the upper (M) and lower (m) bound of the offered price, which are known to the player. We want to buy the first available price that is less than or equal to q^* and sell the first price that is greater than or equal to q^*.

2.3.4 Preemptive Algorithms

The preemptive algorithms, the player does not invest at one point in time, instead the player invests a portion of wealth over time. Following algorithm is invented by El-Yaniv and is referred to as El-Yaniv et al. threat based algorithm (YKFT). The algorithm assumes that the adversary could drop the offered price to some minimum level m and keep it there for the rest of the investment horizon. This strategy maximizes the performance while safeguarding itself against an assumed threat.

The buy signals prescribed by the algorithm can be summarized as follows. Firstly, asset conversion from asset A to asset B is only considered if the currently offered price is the highest encountered thus far. Secondly, during the conversion of asset A to asset B, the algorithm ensures that an adequate amount of asset A is converted to guarantee a competitive ratio c even in the scenario where the adversary lowers the price to the minimum level m and sustains it thereafter. Lastly, on the final day T, any remaining asset A is converted into asset Y, potentially at the price of m.

2.4 Related Work

One challenge in this research lies in the fact that the professional companies engaged in the creation and application of these algorithms often treat them as proprietary information, safeguarded as trade secrets. In contact with these companies, they are willingly discussing any matter that does not regards the algorithms or the trading strategies. Arguments raised by the companies in the Swedish market is that their algorithms can be exploited by other actors that create counter algorithms and find ways to profits from their losses. There's lots of research regarding algorithms in trading environments. The investigation often results in research regards the production environment and strategies around the algorithms, without explaining the algorithms itself. Research revolves around advanced forecasting techniques, forecasting cost, price, volatility, volume etc. These forecasts will further lay foundation to the trading strategy or which algorithm that will trade, the following day. This research falls outside of the scope for this essay.

In a bachelor thesis, *Algorithmic trading using MACD signals*, the authors analyses how the implemented algorithm performs when it trades unsupervised on a single security [30]. The trading signal implemented buys when the signal line and the MACD line divergence and holds when it converges, then sells the stock when it diverges again. In this study they managed to beat the index 20 percent of the securities simulated, however the authors point out that there is room for improvement, such as confidence variables and extra guards signalling when to buy or sell.

More research on this topic was found in a conference paper released 2015, from the Shanghai Jiatong University where the authors studies a combination of three different technical indicators [31]. The signals they study are the RSI, MACD and KDJ. The authors explains that KDJ is a momentum indicator just as RSI and MACD, it indicates the location of the close relative to the high-low range over periods. It is an oscillating indicator and can identify increase and decrease in price. Both RSI and KDJ can individually detect overbought and oversold price levels. These indicators form a buy signal when: MACD changes from negative to positive, RSI crosses the 50-value line from down to up and KDJ forms the golden cross, and the sell triggers when the reversed scenario occurs. All three indicators are calculated with a period for example, one day, five days or 30 days. The authors identifies that this signal is most effective when a shorter period is chosen for short term trading. The results shows that the signals can hardly predict increase and decreasing future price of the stock, no matter if the market is trending upwards, downwards or in normal conditions. The authors discusses that some improvements can be made by adding fundamental factors to better serve further research as well as investors.

In the research earlier mentioned in section 2.2.2 J. Iqbal, I. Ahmad, and G. Schmidt [29], studied six different strategies, where one of them was a buy and hold strategy and five represented different trading algorithms. The authors found in their research that the two best performing algorithms was the YKFT and RPMm. In their evaluation criteria the authors tested these sets of algorithms on different trading periods and with different competitive ratios. The authors show that over all periods that YKFT and RPMm outperformed the buy and hold strategy on the DAX30 on all evaluation criteria.

In another research paper mentioned in section 2.4 [27], the author analyse the same intersecting subset of algorithms as J. Iqbal, I. Ahmad, and G. Schmidt. The result of that research points out that RPMm outperforms the buy and hold strategy over all trading periods. However, the author executes the algorithms on three different currencies and not the stock market.

In *International Journal of Advanced Computer Science and Application* (IJACSA), a paper called *Competitive Algorithms for Online Conversion Problem with Interrelated Prices,* the authors analyse ways to optimize the RPMm algorithm [32]. To evaluate the performance of the algorithms the authors try to optimize the competitive ratio compared to the optimal offline algorithm. The optimal offline algorithm has known the upper– and lower bound beforehand, which the online algorithm does not. The authors successfully improve the competitive ratio of the algorithm on simulated data and on the DAX30 index.

3 Methods

In this chapter the methods used to create and evaluate an algorithmic trading strategy are described and why they were chosen for this research. The objective of this research is to test different algorithmic trading strategies that outperforms the OMXS30 index, the benchmark index for the Swedish stock market. The algorithms that will be tested were presented in chapter 2, which includes statistical arbitrage and online trading algorithms. These strategies will be adjusted and tweaked with the intent to beat the OMXS30 index. In addition to these predefined strategies the author has created his own trading strategy based on the technical analysis also presented in chapter 2. The trading strategies aim to achieve superior risk-adjusted returns compared to the index by making buy and sell decisions based on predetermined trading signals. The performance of the strategies will be evaluated using historical data and will be compared to the OMXS30 index over the same period.

To achieve the goals of this thesis a literary review was conducted, the chosen methodology for this was a systematic review. When the theoretical framework was in place the decision was made on how the results was supposed to be presented, this was done in a quantitative matter. To present the data, there had to be some evaluation metrics to compare the results with each other. The following sections 3.1 to 3.4 will dive deeper into the decision process and discuss why different approaches was chosen and why others were left out.

3.1 Methods for Literary Review

A comprehensive review of the literature was done to inform the research and contribute to the existing body of knowledge on this topic. After considering several different approaches to the literary review, finally it was decided to conduct a systematic review.

Firstly, a traditional literature study was considered, which involve a more general and narrative analysis of the literature on a given topic. While this approach can be favourable for providing an overview of the field and identifying key themes and concepts, it can also be less rigorous and structured than a systematic review. Given the complexity and technical nature of algorithmic trading, a more structured and rigorous approach would be more appropriate for this thesis [33] According to the Karolinska institute, the systematic review is conducted by gathers together all available research within the delimited research area. Sometimes it contains the so-called meta analyses, where the data from this research is combined using statistical methods [34].

Another method about meta-analysis was considered, which involves the statistical analysis of data from multiple studies. While this approach can be useful for identifying patterns and trends from different studies but is not always favourable or appropriate for all types of research topics. For this thesis the authors goal was to look at the broader picture and therefore needed to explore a broad range of literature on the topic and did not have any datasets to analyse [33], [35].

The author decided to choose a systematic review, which involves a comprehensive and rigorous search for relevant literature, followed by a structured analysis and combine the findings. This approach allowed to identify and analyse a wide range of literature on algorithmic trading in a systematic manner. By using a clear and well-defined delimitations to identify relevant studies, the study could be more comprehensive and unbiased. By analysing and synthesizing the insights from each study, it was easier to identify key themes and concepts, and make meaningful contributions to the existing body of knowledge on algorithmic trading [33], [36], [37].

3.2 Implementation and Testing of the Algorithms

To evaluate the trading algorithms, we need data from the stock market that was mentioned earlier in the previous section. Nordnet has generously provided their internal tools and APIs to conduct this research. Due to a non-disclosure agreement with Nordnet there will be no specific details of how the tools work and where the data origins. Data that contains price, volume and moving averages during a specific period can be fetched through API calls. Other technical signals and indicators, such as Bollinger bands and will be calculated as presented in chapter two. The data needs no processing because it is delivered in a candlestick format with open, high, low, and close values. The technical indicators, however, will be calculated through the developed software.

The development of an application requires certain tools and software for the development environment. To write the code the author used IntelliJ IDEA Ultimate which provides many tools that are useful [38], such as making http requests to test out the endpoints created and has a large library of plugins. The application will be written with Java with the version Amazon Coretto 18 and with the Spring boot framework 3 and Docker [39]–[41]. There are a lot of frameworks and programming languages available for this task, however it matches the development environment of Nordnet that has requested this research. Nordnet uses a domain based microservices architecture, which consists of different clusters of software, each cluster is called a domain, and each cluster contains a set of microservices. Where a microservice is shortly, a software that only does one thing and that motivates why this research will create a microservice [42], [43].

3.3 Evaluation of Algorithms

In this section we outline the methodology employed to create and evaluate trading algorithms and provide a rationale for choosing a quantitative approach over qualitative methods.

3.3.1 Quantitative vs Qualitative approach

Trading algorithms are usually based on numerical and statistical data and are designed to systematically execute trading decisions based on predetermined rules. These rules are typically derived from quantitative analysis of historical market data. The data gathered is price, volume, and different technical analysis indicators, these will be calculated with a custom software which will be presented in section 4.2. One advantage of using a quantitative approach is that it allows for rigorous testing and validation of trading strategies with the datasets gathered, which could help reduce biases and provide more robust results [44]–[46].

In contrast, the qualitative methods, such as case studies or interviews, can provide valuable insights into individual trading behaviour or market dynamics, but may not be as suitable for evaluating the performance of the algorithms. The qualitative methods rely heavily on subjective interpretations and may be influenced by personal biases or limited sample sizes, which leads to less reliable results, when compared to the quantitative metrics and statistical analysis, which can provide more objective and statistically significant insights. Quantitative methods also offer the possibility for others to replicate and generalize the results, which in turn can be verified by other researchers using the same historical data. If there is a demand to try these strategies in a real-world trading scenario, one can replicate and test the algorithms on different datasets and optimize the findings [45].

In summary, the quantitative approach in evaluating trading algorithms is justified by its data-driven nature, replicability, generalizability, and objectivity which makes it a suitable methodology for the analysis in this context.

3.4 Evaluation of Performance and Selection of Algorithms

In this section methods for how the algorithms will be tested and evaluated.

3.4.1 Evaluation Metrics

To evaluate the results, two performance metrics will be calculated, the first metric is the geometric return of the results which is calculated as equation 3.1, where n is the number of trades and r_i is the return generated from each trade. The second metric is the risk-adjusted return and will be calculated as described in equation 2.1.

$$AGR = \left(\prod_{i=i}^{n} r_i \right)^{\frac{1}{n}} \tag{3.1}$$

The reason why the AGR is so important is that it catches the compounding effect of the trading that occurs, in contrast to the arithmetic mean that does not. This can have a significant difference in the results since the arithmetic mean ignores the compound effect altogether, and will lead to inaccurate results [47].

These calculations need to be performed for each algorithm on historical data. For every security tested, each algorithm will be run over the entire dataset and simulate as if it was in production. The reader should have in mind that historical performance or movement is not guarantee for future performance.

4 Software Development and Results

This chapter will present the results and how the results was created. The algorithms were designed with modelling tools and then translated into code. To make the application useful it was designed as an API, which other systems can communicate with and receive results on different datasets.

The algorithms were tested on the underlying assets of the OMXS30, which they should be compared to. In the pairs trading strategy, the author did not find good candidates for pairs trading as underlying assets of the OMXS30 index. The pairs found is listed on the Swedish stock market and were acting in the same industry and often compete for the same customers.

4.1 Selection of the Algorithms

During the literary review the author investigated different papers testing online trading algorithms, these algorithms were shown to generate impressive results and, in some cases, beat the compared index. Of the intersecting algorithms between these papers, the best performing preemptive one was chosen along with the best performing non-preemptive algorithm. There is a lot of research regarding statistical arbitrage available, but less about how they work in practice, because of this the author decided that it would be interesting to test them, especially pairs trading because there are certain pairs in the Swedish stock exchange that are especially good candidates, which is explained further in chapter 4. In contrast to statistical arbitrage, the author found the technical analysis tools interesting and found an interest in several that is up for experimentation, i.e., golden cross, Bollinger bands and some strategies that track momentum.

4.2 Algorithm Development

In this section, the author describes the algorithms developed for the research on algorithmic trading. The information needed to develop the algorithms was presented in chapter 2. We provide a detailed overview of the algorithms, including the underlying principles, concepts, and mathematical models used.

4.2.1 Statistical Arbitrage, Pairs Trading (PT)

This strategy will take advantage of the spread between two correlated assets. Since the author didn’t find any suitable implementation of pairs trading the author created this implementation. The theory states that assets that have a high correlation between each other shall remain correlated. It happens that the correlation breaks temporarily and creates a spread between these assets, and an arbitrage opportunity arises as mentioned in section 2.2. The steps of the implementation involve identification of correlating/covariant assets, analyzing the pairs, and design algorithm with suitable input data.

Identification of correlating assets could compute the complete set of assets in the domain, however there are some assets that have a natural correlation, such as assets in the same industry or stocks of the same company with different voting rights. Some companies on the Swedish stock exchange issues a stock whose sole purpose is ownership, and each share gives more votes in the general meeting, these stocks are typically noted with an A, e.g., Volvo A. In contrast there is a stock that is more suitable for the typical investor. These stocks tend to have a high correlation since they are representing the same company. An example of companies in the same industry, for example Holmen and SCA, are two companies in the forestry industry and tend to correlate.

With this algorithm we need to figure out how much each asset pair tends to spread and how we identify this mathematically and can rewrite it to code. Firstly, the algorithms are in perfect correlation their quota should be one, so if we choose one asset arbitrarily and divide each price point with the other asset, we should be able to identify the spread graphically. To identify when the spread is over exaggerated, we can use the Bollinger band as described in 2.2.3. If then the price crosses the upper or lower band of two standard deviations, we consider that the asset has a wide enough spread. The rules for the algorithm are described in figure 4.1 which shows a flowchart of the decisions made by the algorithm.

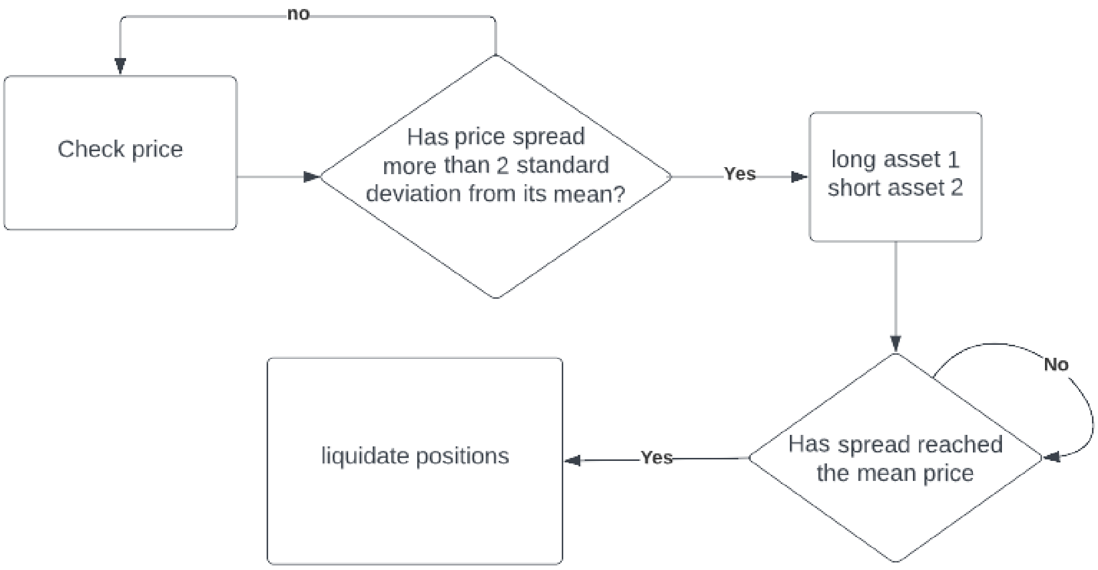

Figure 4.1 shows the pairs trading algorithm.

4.2.2 El-Yaniv Reservation Price Algorithm (RPMm)

The implementation of this algorithm has quite low complexity compared to the others because it only needs to keep track of the product of high and low price and find the square root. By the mathematical implementation, the algorithm will buy and sell regardless of market conditions and does so by calculating the geometric mean of highs and lows in the orderbook. The issue here is that the bid and the ask is not available for the historical data, since the orderbook data is happening live. The workaround will be done to work with lower timeframes and track the highest and lowest price found so far, which will represent the M and N in the mathematical calculation.

4.2.3 Mean Reversion

This technique tries to identify when the instrument is in an upward- or downward trend and use that to its advantage. According to the literary review, the instrument/stock is in an upward trend if the price is traded above its average. The average is calculated on a period backwards in time, for this strategy the author chooses a short and a long timeframe. The timeframe chosen for longer trends was 200-day average price and for the shorter timeframe, the average was calculated on a 50-day average. When the price crosses the average price, it triggers a buy signal and when the price is traded below the average price it triggers a sale signal.

4.3 Software Development

When the design of the algorithms was complete, they had to be converted into code. In order to achieve the goal of making a microservice that accepts settings and return results, an agile way of working was chosen. When working agile, after each sprint there is a working product that is tested and ready for release, however the product gets more features for each sprint until the product is complete and can be delivered. This was a good strategy to achieve the goals in time and it was comfortable to have a fully functioning product to work with.

4.3.1 Development Process

During the process there was skeleton created for the application, which was going to represent a microservice. The purpose of the service was to accept settings and identification numbers for stocks. The architecture followed the Model-View-Controller (MVC) pattern. However, in spring MVC there is a service layer that is between the controller and the model. For the application, the controller accepts settings as shown in figure 4.2. The identifier represents the identification number for stock that we want to run the algorithm upon, and the resolution represents the period length of the candle sticks.

```
@GetMapping("/RPMM/identifier/{identifier}/resolution/{resolution}")
public AlgorithmResponseType RPMM (@PathVariable String identifier,
                                   @PathVariable String resolution) {

    return signalService.RPMM(identifier, resolution);
}
```

Figure 4.2 Code for an endpoint that accepts settings.

The controller then calls the service that collects data from an external API and passes the data to the model, which runs the algorithm on the collected data. The data was then mapped into an immutable object that was serialized into a Json file format and then returned to the callee of the endpoint. The Json file returned did not give much insight, so the author used Mathematica as front-end to the backend service created, in order to visualize the data. Mathematical has tools to call endpoints and deserialize the data into Mathematica expressions.

The structure of this allowed for a flexible way of developing and it allowed the service to grow with new models for each iteration. To sum the results the author created a second service that collected all the available stocks that were about to be analyzed, and looped over the different endpoints and summed the results.

4.3.2 Testing

There was some manual testing done in Mathematica to see graphically that the buy and selling point was placed on the chart and not in any other place. However, the application contains a lot of mathematical calculations that were candidates for testing, which showed impressive results. The calculation for the geometric mean was not correctly implemented and did the calculations poorly in all cases. The original calculation is shown in figure 4.3 where the calculations mimic the mathematical formula found during the literature review.

```
public double geometricMean (List<Trade> trades) {
    double geoMean = 1;
    for (Trade trade : trades) {
        geoMean *= 1 + trade.getPrecentReturn();
    }
    geoMean = Math.pow(geoMean, 1.0 / trades.size()) - 1;
    return geoMean;
}
```

Figure 4.3 Geometric mean calculation that gives the wrong answer.

This method was rewritten into the calculations shown in figure 4.3, where we take advantage of the relation between exponents and logarithms to get the correct answer. The method in figure 4.3 deviated from the correct answer, but the new implementation got all the decimal points right.

```
public double geometricMean (List<Trade> trades) {
    int n = trades.size();
    double geoMean = 0.0d;
    for (Trade trade : trades) {
        if (trade.getPrecentReturn() == 0L) {
            return 0.0d;
        }
        geoMean += Math.log(trade.getPrecentReturn());
    }
    return Math.exp(geoMean / n);
}
```

Figure 4.4 Method that calculates the correct answer.

The tests followed the same structure as the given, when, then. Where the given is where all the setup is defined, when is where calls are executed, and then represents the expect section of the test. One example of the test is shown in figure 4.5, where the expected value is calculated in Mathematica and passed into the test.

```
@Test
void newGeometricMean_caulatesCorrect(){
    //GIVEN
    GeometricMean geometricMean = new GeometricMean();
    double expectedValue = 0.18171205928321402;

    Trade firstTrade = Trade.builder().precentReturn(0.1).build();
    Trade secondTrade = Trade.builder().precentReturn(0.2).build();
    Trade thirdTrade = Trade.builder().precentReturn(0.3).build();
    List<Trade> tradesList = List.of(firstTrade, secondTrade, thirdTrade);

    //WHEN
    double v = geometricMean.geometricMean(tradesList);
    //THEN
    assertEquals(expectedValue, v);
}
```

Figure 4.5 test for the function that calculates the geometric mean.

4.4 Graphical and Numerical Representations of the Trading Performance

In this section the results will be presented of the different strategies evaluated. The different strategies will be presented graphically and with the performance of the algorithms on each tested stock.

4.4.1 RPMM

The first implementation of this algorithm was developed using the specification from the literary review. That implementation made a lot of trades, and the profit was close to zero even though it traded very frequently. Figure 4.6 shows the price of the stock Boliden, where the blue line represents the price of the stock, the green dots indicate a buy, and the red dot indicates the sell.

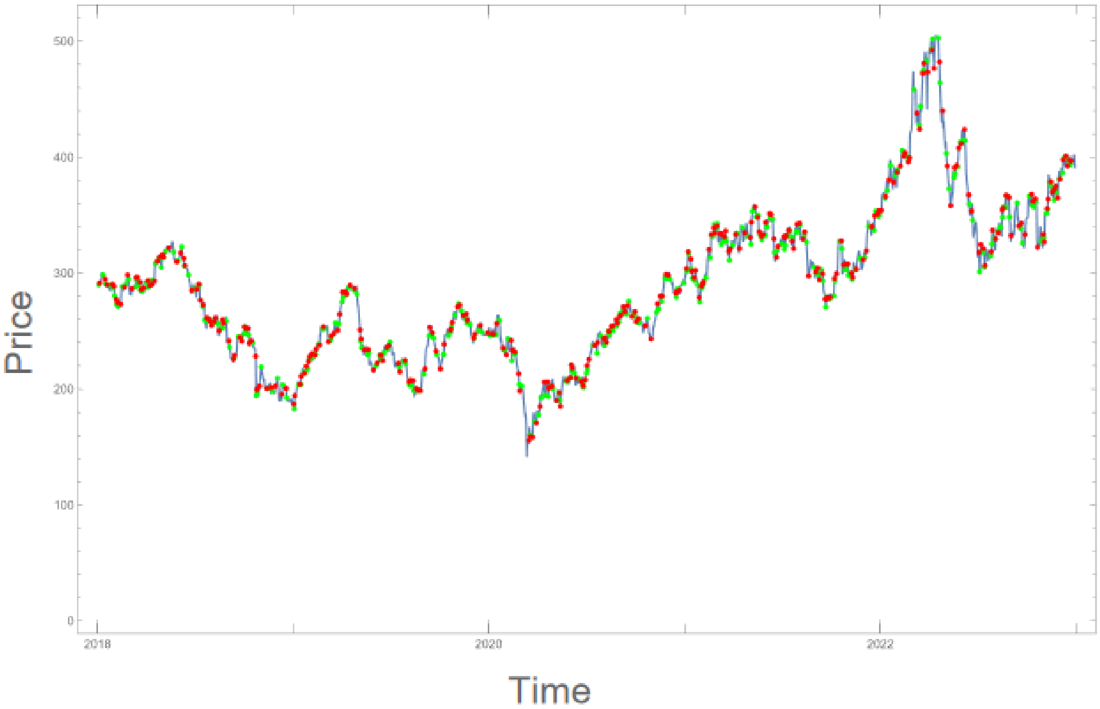

Figure 4.6 of RPMM trading on the stock Boliden.

In this instance the final geometric mean of all the trades resulted in a 0,02% return. This is not sufficient compared to the OMXS30 which had a 53% return during the same period. The Standard deviation of the algorithm was very low which was promising, which would generate a good sharpe ratio, however because of the lack of returns it was very low. Because the algorithm produced unsatisfying results there were several attempts to improve the algorithm. One of the attempts was to force the algorithm to trade only in uptrends, in this case when the price is above the EMA on 50 periods. This improved the results, but the mean remained close to zero still. The graph is shown in figure 4.7 where the orange line represents the EMA.

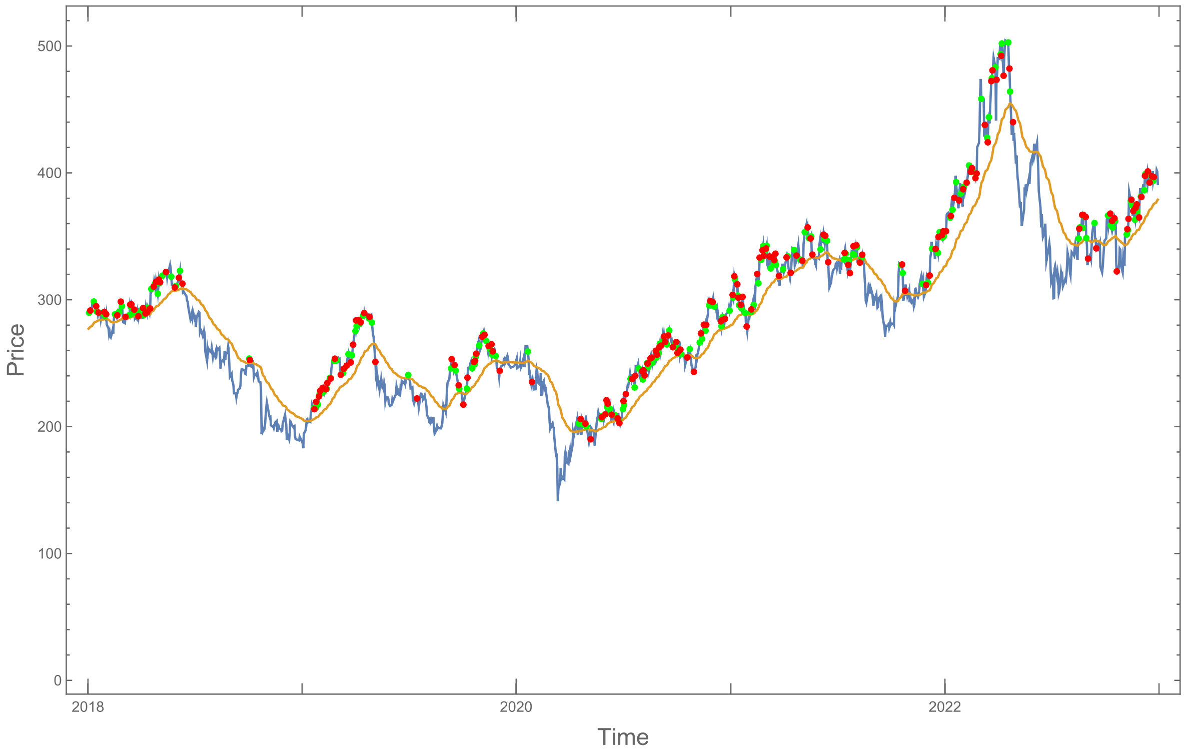

Figure 4.7 RPMM only trades when the price is in upward trend, on the stock Boliden.

Both implementations had aggressive trading with incredibly low results, which would also be a problem when cost is added to the equation.

The implementation was modified to remove the aggressive behavior and reduce the number of trades. This was successful and before the algorithm generated 301 trades on average on the tested assets. This was reduced to 43 trades with an average geometric mean of 1,65% and resulted in a sharpe ratio of 1,4. Figure 4.8 will show the trading happening on the stock Boliden; however, the best performing stock was sinch with a geometric mean of 3,93%. Table 4.1 will show the results for all the stocks tested.

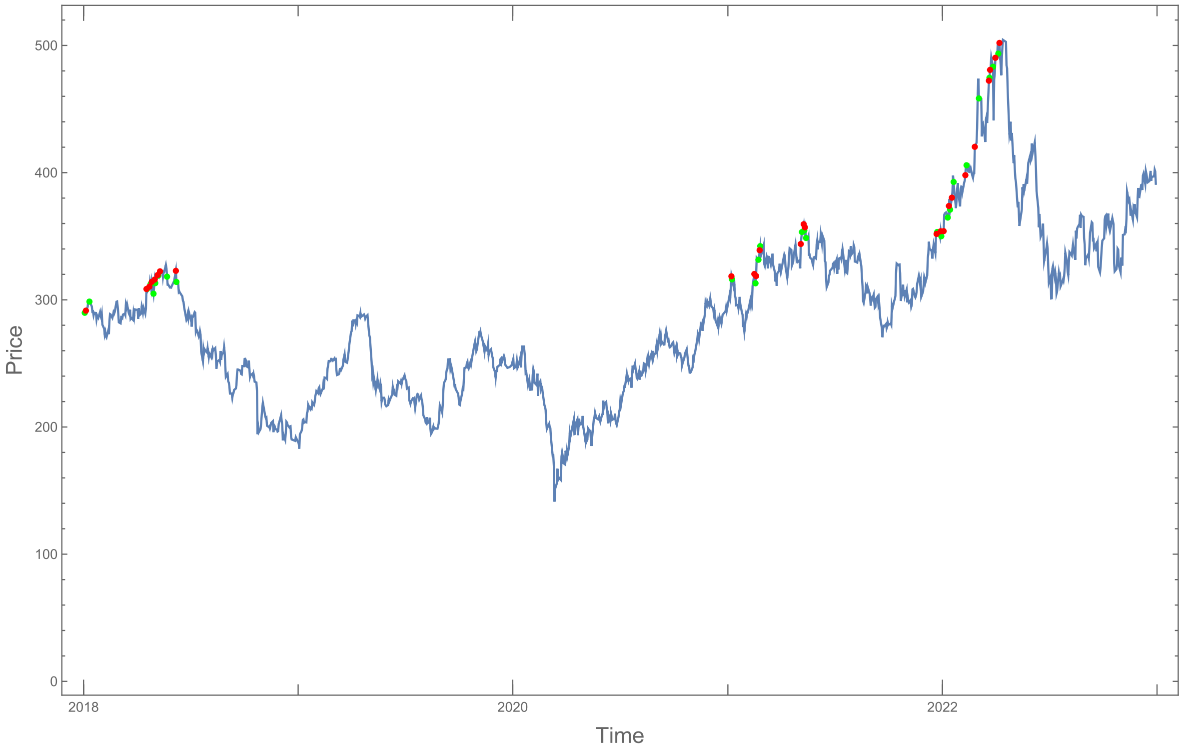

Figure 4.8 – RPMM trading on the stock Boliden, with more carefully chosen M and m.

Table 4.1 – The results of the modified RPMM algorithm trading.

Stock	Number of trades	Geometric Mean	Standard Deviation	Sharpe Ratio
Atlas Copco AB ser, B	33	1,52%	0,79%	1,94
ASSA ABLOY AB ser, B	53	1,25%	0,72%	1,73
Atlas Copco AB ser, A	48	1,99%	3,27%	0,61
Autoliv Inc, SDB	17	1,04%	0,40%	2,57
Svenska Cellulosa AB SCA ser, B	50	1,46%	1,05%	1,39
Sandvik AB	37	1,69%	1,24%	1,36
AstraZeneca PLC	92	1,44%	1,02%	1,42
Tele2 AB ser, B	35	1,40%	1,30%	1,08
Investor AB ser, B	88	1,11%	0,75%	1,49
Volvo, AB ser, B	19	1,86%	1,03%	1,80
NIBE Industrier AB ser, B	88	1,75%	1,62%	1,08
Kinnevik AB ser, B	44	1,90%	1,55%	1,23
Svenska Handelsbanken ser, A	2	1,04%	0,93%	1,12
Swedbank AB ser A	16	0,82%	0,62%	1,31
Sinch AB	72	3,93%	2,98%	1,32
Boliden AB	26	1,64%	0,98%	1,68
Nordea Bank Abp	11	1,52%	0,75%	2,03
Alfa Laval AB	34	2,05%	1,59%	1,28
SKF, AB ser, B	25	1,65%	1,19%	1,38
Essity AB ser, B	33	1,25%	1,11%	1,12
Telia Company AB	14	1,04%	0,99%	1,05
ABB Ltd	40	1,37%	1,03%	1,34
Electrolux, AB ser, B	6	1,55%	1,50%	1,04
Ericsson, Telefonab, L M ser, B	53	1,91%	2,12%	0,90
Skandinaviska Enskilda Banken se	40	1,33%	0,76%	1,74
Getinge AB ser, B	55	2,30%	1,78%	1,29
Samhällsbyggnadsbo, i Norden AB	83	2,06%	1,43%	1,44
Hexagon AB ser, B	67	1,52%	1,10%	1,38
Evolution AB	84	2,61%	1,60%	1,63
Hennes & Mauritz AB, H & M ser,	20	1,38%	1,06%	1,29
Average	43	1,65%	1,28%	1,40

4.4.2 Mean Reversion

This strategy was evaluated using two different settings on the EMA, 200 and 50. There were two extreme cases that generated high returns on the setting 200. On average the strategy did not manage to beat the index. The full data is shown in table 4.2. When studying figure 4.9 one noted that there are several of undesired trades in the initial- and final period, and there was an attempt to reduce these false positive signals by adding more restrictions to the trading, which removed most of them, but not all of them.

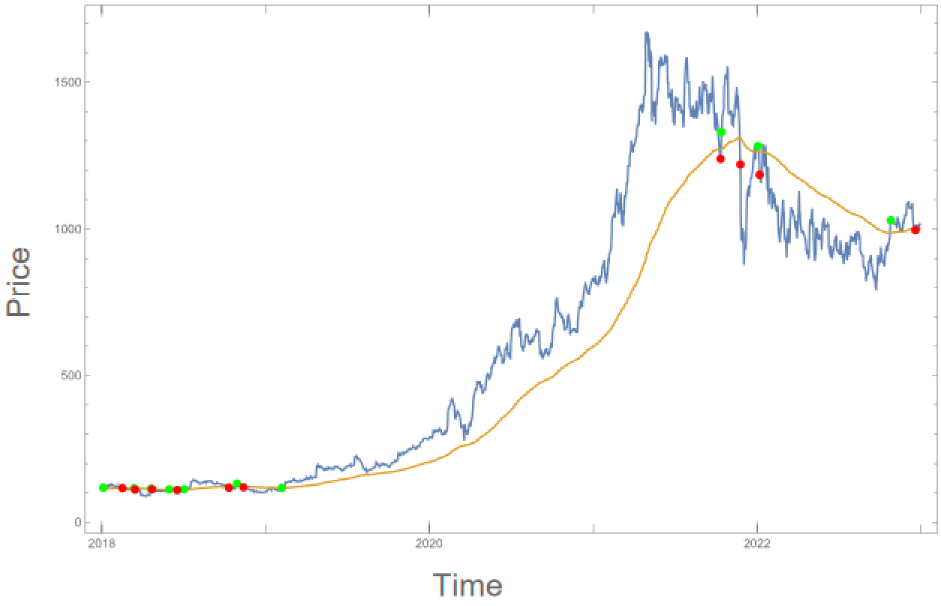

Figure 4.9 – the mean reversion strategy applied to Sinch.

Table 4.2 – Results from mean reversion with EMA setting 200.

Stock	Number of trades	Geometric Mean	Standard Deviation	Sharpe Ratio
Atlas Copco AB ser, B	17	-0,54%	15%	-0,04
ASSA ABLOY AB ser, B	22	-0,87%	6%	-0,14
Atlas Copco AB ser, A	10	1,66%	22%	0,07
Autoliv Inc, SDB	12	-0,36%	8%	-0,04
Svenska Cellulosa AB SCA ser, B	10	3,10%	15%	0,20
Sandvik AB	19	-0,25%	6%	-0,04
AstraZeneca PLC	11	4,76%	14%	0,35
Tele2 AB ser, B	18	-0,95%	6%	-0,16
Investor AB ser, B	18	1,09%	16%	0,07
Volvo, AB ser, B	24	-1,75%	8%	-0,21
NIBE Industrier AB ser, B	15	6,50%	43%	0,15
Kinnevik AB ser, B	9	5,43%	46%	0,12
Svenska Handelsbanken ser, A	26	-2,36%	3%	-0,74
Swedbank AB ser A	17	-2,25%	6%	-0,38
Sinch AB	6	52,99%	482%	0,11
Boliden AB	15	0,25%	12%	0,02
Nordea Bank Abp	19	-1,43%	11%	-0,13
Alfa Laval AB	18	0,74%	14%	0,05
SKF, AB ser, B	26	-2,60%	7%	-0,39
Essity AB ser, B	27	-1,99%	6%	-0,34
Telia Company AB	18	-1,32%	3%	-0,49
ABB Ltd	15	0,45%	12%	0,04
Electrolux, AB ser, B	20	-1,86%	5%	-0,39
Ericsson, Telefonab, L M ser, B	14	-0,61%	10%	-0,06
Skandinaviska Enskilda Banken se	26	-2,59%	8%	-0,32
Getinge AB ser, B	9	8,54%	31%	0,28
Samhällsbyggnadsbo, i Norden AB	5	40,89%	83%	0,50
Hexagon AB ser, B	12	2,45%	24%	0,10
Evolution AB	10	22,26%	304%	0,07
Hennes & Mauritz AB, H & M ser,	13	-2,16%	7%	-0,30
Average	16	4,24%	41%	-0,07

There is one trade that sticks out here that has an exceedingly high return which makes this the best performing stock on the list. Even though it performs well and has a high return it is associated with a very high standard deviation which lowers the sharpe ratio of 0,11. The sharpe ratio is low on all the trades even though some generate high returns.

With the setting 50 the algorithm traded more frequently as expected however the results did decrease from the setting 200 and did not rapidly improve the overall results, it did lower the standard deviation, but the lack of returns did not significantly improve the sharpe ratio.

4.4.3 Statistical Arbitrage (Pair Trading)

This strategy was slightly modified to achieve the results. In figure 4.9 the blue line represents the quota between the asset prices and the Bollinger bands with plus, minus 2 standard deviations from the mean. This allowed for fluent signal identification and was easier to work with than the previously mentioned strategy.

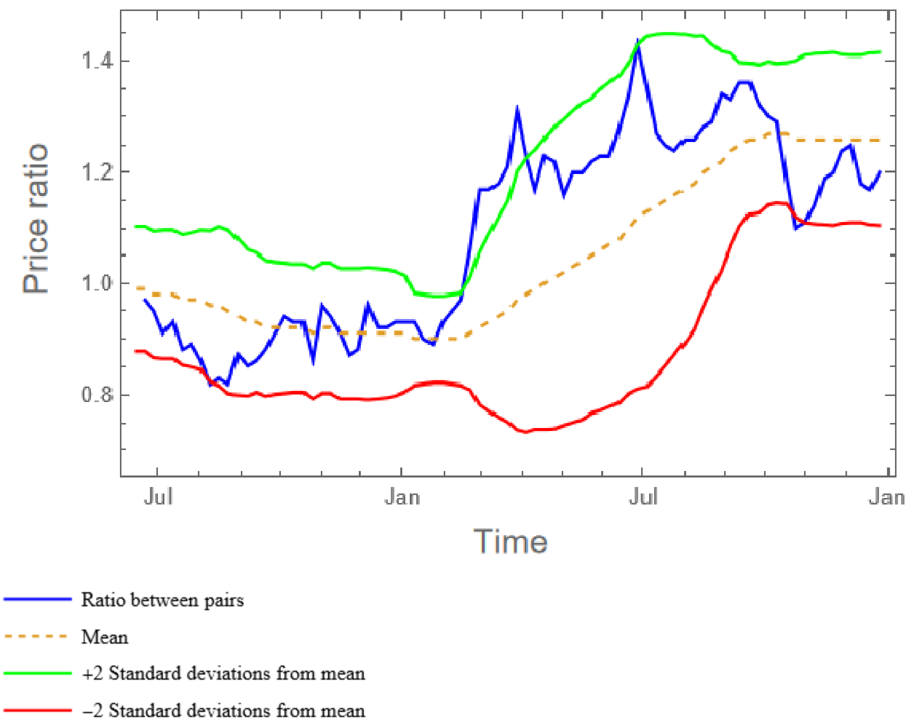

Figure 4.10 – Graphical illustration of the pair trading strategy

Figure 4.11 shows the underlying assets, in this case Nordnet as a blue line and Avanza as the orange line. The green and red dots are somewhat confusing because the short selling is colored green even though it makes a profit in reverse.

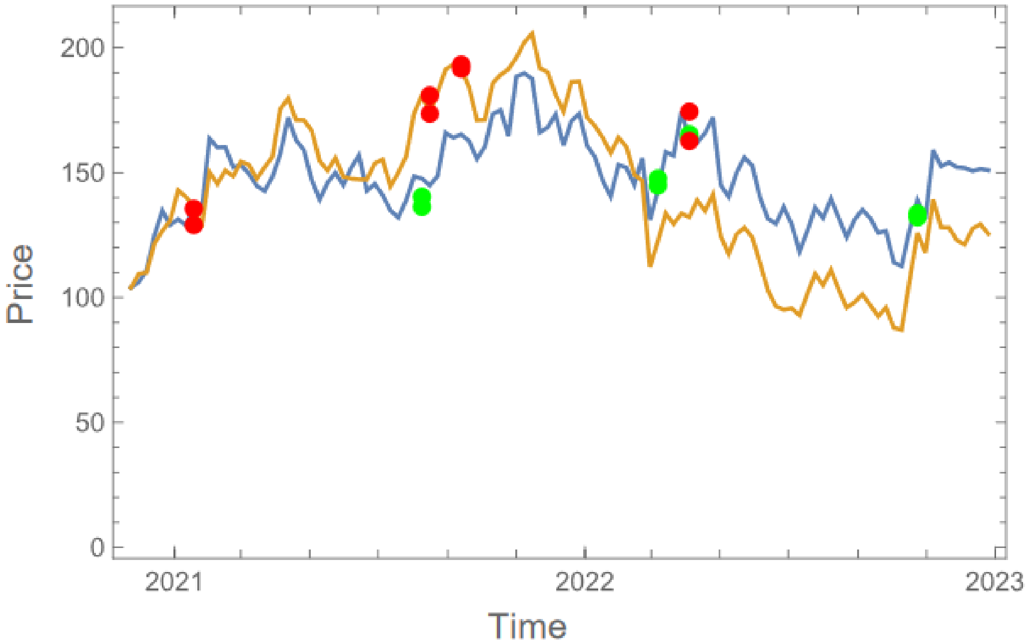

Figure 4.11 – Graphical illustration of Nordnet and Avanzas prices and buy/sell.

Of the six pairs tested the average geometric mean was 15,34% which is closer to the compared index, with an average of 14,96% standard deviation and the average sharpe ratio on 0,17. All the data can be found in table 4.3.

Table 4.3 – Result of the pair trading strategy.

Pair	Number of trades	Geometric Mean	Standard Deviation	Sharpe Ratio
boliden/lindin mining	2	103,20%	56,49%	1,83
avanza/nordnet	8	14,46%	13,09%	0,10
NCC/peab	6	11,65%	13,03%	-0,89
hufvudstaden/castellum	6	5,02%	13,77%	0,36
epiroc/sandvik	14	3,67%	35,32%	0,10
sweco/afry	4	0,02%	2,92%	0,01
Average	4	15,34%	14,96%	0,17

5 Analysis and Discussion

This chapter will provide a comprehensive examination and interpretation of the research findings. We will dive deeper into the collected data, present an analysis, and discuss the results compared to the research objectives and the methods used to reach these goals.

5.1 Analysis of Results

The goal of this research was to beat the OMXS30 index, which was no easy task. The goal was to create an algorithm that would beat the index in either profit or the sharpe ratio, but preferably a good combination of both. None of the algorithms beat the index in terms of profit during the desired period. However, the RPMM algorithm and the modifications managed to achieve low risk returns, with a 1,4 in sharpe ratio which is doubled compared to the index (0,66).

Mean reversion strategy generated a lot of false positives which drew the results down, to remove these false positives some modifications were made to the algorithm. One of which was to only trade when the open and close was above the average price, this made the results more consistent. However, the results in terms of profit and sharpe ratio was unsatisfactory. In three instances the profit stands out, one explanation to this, is that these stocks generated very high profits during the examined period.

The statistical arbitrage strategy generated higher returns but to a higher risk according to the sharpe ratio. This strategy generated results that were reversed to the previously discussed, it generated on average a good profit, however it also did this to a higher risk in terms of sharpe ratio. The risk measurement used here is strictly using the standard deviation as a risk measurement, however the strategy also generated approximately 98% winning trades, which is also another thing to take into consideration. As the mean reversion this strategy at first gave many false positives and entered trades to early. These were successfully eliminated by letting the algorithm wait until the ratio stopped increasing/(decreasing) above/(below) the two standard deviation measure. Also, of all the pairs measured only two thirds of the pairs indicated signals to enter a trade. This strategy seems to have a high accuracy of generating profit, but on the other hand the signals become rare with the developed settings.

The YKFT algorithm was not implemented but could have generated interesting results. In contrast to the RPMM algorithm it would buy and sell in equal sized portions during a pre-determined period. This approach and algorithm could have been useful in the pairs trading strategy as well as it could keep buying as the pairs keeps spreading until it begins to move back into correlation. When this happens it slowly unloads the position in a structural manner. During this period, if we observer figure 4.7 again, it could have been beneficial to start finding a good position in the down trends, where the RPMM algorithm didn't buy at all. This would be dependent on the settings of course and would need further testing however conceptually and theoretically the algorithm looks promising.

Another algorithm that wasn't implemented was the dividend by arbitrage. One reason for this was that on the Swedish financial markets, most of the dividends are paid to the stock owners once during the spring, in contrary to the US stock market where the dividends are paid monthly or quarterly. One issue with this is that on the Swedish market the investor cannot achieve all the dividends in a year. You would have to choose between these companies, in contrast to the US market where you can achieve more of them during the year, and therefore have more freedom of choice. This became an issue and during the research phase it became clear that this strategy often gave a very small amount of profit but to a low risk. This could result in a satisfactory sharpe ratio, but probably less profits.

Another part of the result was the application that was developed. The development was successful and has an architecture that can easily be modified and extend with more algorithms. The micro services developed are complete and can be served as a prototype for Nordnet to iterate further development on and potentially integrate it into their product line.

5.2 Evaluating the Work

Before the work was started there was a vision of how this would work out. There was a tough realisation that there were not many publicly available resources to test. There was many phone calls and emails to specialists and companies working in this industry which did not reveal any information or even clues to where to look. There was promising research that demanded very advanced mathematics and a solid foundation in finance, a foundation that reached beyond this academic level.

One strong side was the choice of the quantitative analysis which gave a lot of insight, that would be unchanged if the work was to be done again. However, the combination of a quantitative analysis with a qualitative analysis could have been beneficial as well. The qualitative analysis could be done using an anonymous survey for the companies to answer. This would help to map the concepts and maybe find clues where to look. As mentioned, the companies did not freely give any information to a student contacting them, however a more structured and engaging qualitative study could potentially have changed their minds and be helpful to narrow down the options that was out there.

During the development phase the algorithms was interpreted and designed in code. These algorithms can potentially have a faulty implementation, even though the code is tested, with unit tests and the results have been graphically tested.

The online trading algorithm has a dependency on a competitive ratio and was ignored for this implementation. This can be one reason why the results differ from the related work. Another reason why they differ, is that the datasets differ from one stock exchange to another and that the datasets are from different time periods.

During the literary review it became obvious that there is a lot of active research in this area, which is referred to by some as, financial engineering. This field have interesting research but focusing mostly on machine learning and high frequency trading which was outside the scope of this research and most of the research found was above the academic level of this thesis.

5.3 Ethical Considerations and Social Responsibility

One consideration that can be made is in the choice of programming language. According to a blog post where the author has benchmarked and classified the green languages in terms of energy consumption, java is rated at fifth place in this ranking [48]. Other popular programming languages like python consumes 37,3% more energy than java in this ranking, which can have a great impact at scale if the application runs on multiple nodes. With this in mind, there is also an importance to create effective algorithms that will use less resources from the hardware.

Another thing to consider is that this research can serve as a product at Nordnet and could potentially inspire and help their customers to increase their wealth, to a lower risk. Furthermore, this report is the property of the public domain and can be iterated further upon by anyone.

6 Conclusions

This thesis explored ways of implementing algorithmic trading without supervision. These algorithms did not perform as expected, however there are some potentials in the statistical arbitrage area. This thesis contributes to the beginner level of the topic and can inspire more students to get an interest in using algorithms to identify buying and selling opportunities. In conclusion, there is a lot of interesting science in this field however, the science is at a higher level and this field lacks the initial level to get started. There can be further iteration on the research done and there are a lot of interesting ways to create new algorithmic trading strategies.

6.1 Future Work

Some concepts that were not tested that would be interesting to test was algorithms tested on a fundamental basis and combined with Markowitz portfolio theory. This could be interesting to create algorithms that rebalances the portfolio to always have the theoretical highest possible returns to the lowest possible risk.

Other trading strategies that were found was the butterfly spreads, which is an options strategy. Because how the mathematics of the Black and Sholes formula as we reach the end of the strike price, the valuation of the option goes up. This can be exploited by buying and selling options in a strategic manner and wait for the expirations of the options. These butterfly spreads come in different forms, if you are neutral to the price or have a speculation of the price to increase or decrease you can place your positions accordingly. This have been tested in different kind of instruments for instance on the bonds market [49].

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