Is technical analysis a successful tool for trade decision?

HÄMEEN AMMATTIKORKEAKOULU
HÄME UNIVERSITY OF APPLIED SCIENCES

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Kalle Vessari

HÄMEEN AMMATTIKORKEAKOULU
HÄME UNIVERSITY OF APPLIED SCIENCES

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TIIVISTELMÄ

Tämän opinnäytetyön tarkoituksena oli analysoida teknisen analyysin kannattavuutta. Tämän saavuttamiseksi opinnäytetyössä tutkittiin kattavasti, teoreettisia tutkimuksia ja olemassa olevaa aihetta koskevaa kirjallisuutta. Lisäksi suoritettiin perusteellinen empiirinen kokeilu näiden menetelmien käytön ja onnistumisen tarkkailemiseksi käytännössä teknisiä kaupankäyntialgoritmeja hyödyntäen.

Tässä artikkelissa analysoitujen teoreettisten tutkimusten ja kirjallisuuden perusteella rahoitusmarkkinoilla on suuri määrä rahoitusalan ammattilaisia, jotka luottavat teknisen analyysin kannattavuuteen. Toisaalta teknisen analyysin menetelmiä kohtaan ja niiden kykyä johdonmukaisesti tuottaa voittoa on edelleen jonkin verran skeptisyyttä. Suurin osa kirjallisuudesta kuitenkin kallistui ainakin jonkin verran teknisen analyysin puolelle ja vähintäänkin havaittiin, että erilaisia teknisen analyysin periaatteita hyödyntämällä on mahdollista tuottaa voittoa.

Tämän opinnäytetyön empiirisessä osassa strategioilla saatiin positiivisia tuloksia Yhdysvaltain osakemarkkinoiden hintaliikkeiden ennustamisessa. Ne myös onnistuivat tuottamaan jonkin verran voittoa ja suoriutuivat suhteellisen hyvin vertailuindeksiin verrattuna. Kokonaistulokset olivat positiivisia, mutta algoritmit vaatisivat vielä paljon työtä, jotta ne kykenisivät toimimaan kannattavasti muuttuvissa markkinaympäristöissä.

Opinnäytetyön loppupäätelmä on, että teknisellä analyysillä on paikkansa rahoitusmarkkinoiden analysoinnissa. Se ei ehkä ole yleisesti kannattavaa kaikissa rahoitusympäristöissä tai kaikissa omaisuusluokissa, mutta on olemassa huomattava määrä näyttöä siitä, että oikein käytettynä ja oikeassa kaupankäyntiympäristössä teknistä analyysiä voidaan varmasti käyttää menestyksekkäästi.

Kannattavuuden näkökulmasta on erittäin todennäköistä, että jos teknisen analyysin käyttäjä on rahoituksen ammattilainen, hänellä on riittävä kokemus, sekä kyky käyttää oikeita indikaattoreita ja menetelmiä oikeassa kontekstissa, voidaan tuottaa merkittäviä voittoja. Tästä aiheesta tarvitaan kuitenkin lisää tutkimusta, jotta saadaan lisätietoja siitä, mihin tekninen analyysin menetelmät riittävät.

Avainsanat Tekninen analyysi, Rahoitus, Ohjelmointi
Sivut 56 sivua ja liitteitä 15 sivua

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HÄME UNIVERSITY OF APPLIED SCIENCES

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ABSTRACT

The purpose of this bachelor thesis was to analyse the profitability of technical analysis. In order to achieve this, the thesis investigated comprehensively, theoretical studies and existing literature around the subject. Additionally, thorough empirical experimentation was conducted to observe the use and successfulness of these methods in practice by utilizing technical trading algorithms.

According to the theoretical studies and literature analysed in this paper, there is a large amount of finance professional, who are confident in the profitability of the technical analysis in financial markets. On the other hand, there still is a certain amount scepticism towards the methods of technical analysis and their ability to consistently generate profit. However, most of the literature were at least somewhat leaning to the side of technical analysis and at the minimum, they found that there is a possibility to generate profit by utilizing various principles of technical analysis.

In the empirical part of this bachelor thesis, the strategies had some positive results when it comes to predicting price movements in US equity markets. They also were somewhat successful at generating profit and performed relatively well against the benchmark performance. The overall findings were positive however, the algorithms would still need a lot of work in order for them to function independently in changing market environments in a profitable manner.

The final conclusion of the thesis is that technical analysis has its place in analysing financial markets. It might not be universally profitable in all financial environments or with all asset classes, but there is a significant amount of evidence that when used in a correct way and in correct trading environment, technical analysis certainly is able to be used successfully.

When it comes to profitability it is highly probable, that if the user of the technical analysis is a finance professional, has sufficient amount of experience, or has the ability to use the right indicators and methods in a right context, considerable profits can be generated. However, more research on this subject is still needed in order to find out more about what technical analysis is capable of.

Keywords Technical analysis, Finance, Programming

56 Pages and appendices 15 pages

Appendices

1. Introduction

The topic of this bachelor thesis is “is technical analysis a successful tool for trade decision?”. In this paper consists of two main sections, the theoretical section and the methodological section. The theoretical section focuses on existing literature around this subject and review on available research that has been made about the profitability of technical analysis. The methodological sections consist of experimentation with technical analysis using common strategies utilized in algorithmic trading in order to assess the profitability and usefulness of these methods.

In this paper, the subject of technical analysis is mainly observed from the point of view of algorithmic trading, which in modern times is the most highly utilized way of implementing strategies of technical analysis. As of 2021, in the developed markets, the share of algorithmic trading in total volume is around 70% to 80%. (Kamlesh, 2021)

1.1 Relevance

Technical analysis is a topic that has been in up for discussion ever since these methods have come in wider knowledge among individuals working in finance sector. There are finance professionals who approve the methods of technical analysis as relevant and profitable. On the other hand, there are also a great amount of scepticism from finance professionals who believe that fundamental analysis is superior to technical analysis and criticizes technical analysis as being unprofitable.

To this day, there still is not a definitive answer to the question if technical analysis works as the practitioners of these methods are claiming them to work and more experimentation and further studies on this subject are still needed. (Scott, Carr, Cremonie, 2016)

1.2 Objectives

The objectives of this bachelor thesis are to analyse and produce an overview about the profitability of technical analysis in financial markets. For this to be achieved, a review of the existing research and literature on this subject is made in order to find data for this overview. This will be including theoretical and empirical studies analysing profitability of technical analysis compared to other methods evaluating financial instruments as well as research conducted concerning the usefulness and profitability of individual methods and indicators in technical analysis. Technical analysis will be surveyed from both sides of the debate, there is going to be studies that both supporting and opposing technical analysis. There will also be a summary of different systems and techniques that are used in order to measure the profitability of these strategies and indicators.

Additionally in the empirical section, these strategies are put to a practical test. This will illustrate how the methods introduced in theoretical section are actually used to evaluate different assets and make successful trade decisions. The strategies that will be tested are constructed from various commonly used and well documented techniques and indicators that are frequently used by finance professionals and other individuals utilizing technical trading strategies.

1.3. Implementation

The trades will be simulated by paper trading US equities, using trading algorithms. These algorithms are constructed with a visual programming tool called Blue Shift, which is based on a visual programming language developed by Google and MIT called Blockly. All of the strategies themselves, will be utilizing different technical indicators. Strategy number one will be based on relative strength index and MACD, the second strategy is based on relative strength index and simple moving average, and the third will be using MACD and simple moving average.

There will a detailed explanation to describe how these strategies were actually constructed in Blue Shift and what other variables were included in these trading algorithms.

Performance of these strategies will be measured by comparing it with a benchmark performance. Additionally, the profitability will be further analysed by using various, most commonly used performance measuring metrics and the profitability of the strategies will be analysed in order find out if it is competitive against other trading and investing methods and strategies.

These metrics will be including measures such as Sortino ratio, Sharpe ratio, and Omega ratio. The actual functionality and explanation on how these ratios are calculated and interpreted in practise, will be described at a greater detail in performance measurement section.

With the combination of the literature review and with the methodological experimentation of these methods, a conclusion will be drawn if these methods are found by this bachelor thesis, to be useful in practice and to be profitable when compared to other alternative techniques, or if they do not work in practice and cannot be used in order to consistently generate profit.

2. Theory

Technical analysis is a method used by financial professionals in finance and economics to model and search for predictable regularities, or “patterns” in stock price volatility. The most important function of technical analysis is to find various trends and utilize them in investment decisions. When combined with proper investing or trading criteria, technical analysis assumes that historical trading activity and price variations of a security can be valuable indicators of the security's future price movements (Hayes, 2021).

Technical analysis is commonly used alongside of fundamental analysis in decision making in context of financial markets. In fundamental analysis, an analyst must consider a company's financial statements, business model, broader macroeconomic circumstances, managerial competencies, and many other factors in order to arrive at a specific fair value. Technical analysis, on the other hand, is uninterested in this in-depth examination of these basic variables. A technical analyst, on the other hand, simply considers the price of a stock as a result of supply-demand interaction. Price is ultimate for a technical analyst, who regards it as an expression of all essential realities. As a result, they concentrate on only two parts of the market. Price vs. time and volume are two factors to consider (eLearn markets, Nd).

There is a large amount of existing literature concerning the subject of technical analysis. Even so it is still an extremely disputed topic and there is still no consensus about its role in finance. This literature was thoroughly examined and analysed in order to produce the thesis. This will include large amount of research papers concerning especially the profitability of technical analysis. These papers can be empirical research papers and collective research papers analysing existing literature on this subject. We will go through the most important aspects of technical analysis in this chapter.

2.1. Efficient market hypothesis

Efficient market hypothesis is one of the most prominent and well-known academical papers that is clearly opposed to technical analysis. This paper describes especially well the most important arguments why many academics in finance do not believe in the consistent profitability of technical analysis and this is the reason why it was very relevant to include it into this thesis.

According to Fama's hypothesis, while an investor may strike it rich and acquire a stock that generates relatively good short-term profits, he cannot realistically expect to get a return on investment that is significantly greater than the market average over the long run. The theory's main conclusion is that because stocks always trade at their fair market value, it's extremely difficult to purchase undervalued stocks at a discount or sell overpriced equities for a profit. Neither professional stock research nor properly applied market timing tactics can hope to outperform the broader market on a consistent basis. If that's the case, the only option for investors to get higher returns is to take on a lot more risk.

There are three major variations of the efficient market hypothesis, these are:

- **The weak form**, which assumes that security prices reflect all publicly available market information, but that new information that is not yet publicly available may not be reflected. It also implies that previous price, volume, and return information is unrelated to future pricing.
- **The semi-strong form**, which ignores the value of both technical and fundamental analysis. The semi-strong form of the efficient market hypothesis takes the weak form assumptions and adds to them by assuming that prices respond swiftly to any new public information that becomes available, leaving fundamental research useless for forecasting future price movements.
- **The strong form**, according to it prices always represent the full of both public and private information. This contains all publicly accessible information, both old and new, as well as insider knowledge.

There is a huge amount of debate surrounding the efficient market hypothesis. Supporters of the efficient market hypothesis frequently make their case based on the theory's basic logic or a number of research that appear to back it up. On the other hand, people who argue against it, in other words people who believe in the profitability of technical analysis, point to the apparent evidence that some traders and investors continually achieve higher returns on investment than the market as a whole (CFI, Nd. All material in this section).

2.1.1. Behavioural finance

Perhaps the strongest arguments against the efficient market hypothesis comes from behavioural finance, which studies the behaviour and the effect of the psychology of individuals in financial decision making. According to the theories of behavioural finance, more often than not, the psychology of the market participants is an extremely major factor in trade decisions, which was not taken properly into account in efficient market hypothesis. Efficient market hypothesis was based on the assumption that market participants always rely on the available information and that they are always able make rational decisions based on that information (Konstantinidis, Katarachia, Borovas, Voutsa, 2012).

Behavioural finance may be studied from a variety of different angles. Stock market returns are one area of finance where psychological factors are frequently considered to impact market outcomes and returns, although there are many distinct perspectives to consider. The goal of behavioural finance categorization is to help individuals understand why they make specific financial decisions and how those decisions influence the financial markets.

The impact of biases is one of the most important parts of behavioural finance research. Biases can arise for a number of causes. Biases are often characterized as one of five fundamental principles. Understanding and categorizing various forms of behavioural finance biases can be critical when focusing on the research or analysis of industry or sector outcomes and results (Hayes, 2021).

These biases do have a great impact in financial decision making. This supports the idea that technical analysis conducted with computer algorithms might be able to do more efficient financial decision making, because of the fact that it cuts the human error and psychological factors out from the actual trade decisions. This could theoretically lead to better performing portfolios.

2.1.2. Adaptive market hypothesis

Adaptive market is another theory, that at least in some respects, disagrees with the views stated in efficient market hypothesis about the behaviour of market participants. According to the adaptive market hypothesis, individuals are primarily rational in their judgement, but can quickly turn irrational in reaction to increased market volatility. This, on the other hand, may result in emerging opportunities in financial markets. Loss aversion, overconfidence, and overreaction, according to the theory, are consistent with evolutionary models of human behaviour, which involve acts such as competition, adaptation, and natural selection.

Additionally, it is proposed that individuals frequently learn from their errors and make predictions about the future based on previous experiences. According to the adaptive market hypothesis, humans make the best judgement based on trial and error. This means that if an investor's plan fails, they are extremely likely to try something different the following time. Alternatively, if the technique is successful, the investor is more likely to repeat it.

Adaptive market hypothesis is based on three basic assumptions. First assumption is that people are mainly motivated by their own self-interest. The second assumption is people are naturally prone to making mistakes. According to the last assumption it is in human nature to adapt and learn from the mistakes that are made in order to be able to make better decision in the future.

The adaptive market hypothesis argues that investors are in most situations, but not always, rational. They participate in satisficing rather than maximizing behaviour and generate market heuristics based on a form of natural selection mechanism in markets, in this instance profit and loss. Under situations when those heuristics apply, this causes markets to function mostly rationally, in a comparable manner to the efficient market hypothesis.

However as stated, rapid changes and abnormal conditions in the market environment are in many situations able to invoke irrational behaviour from market participants. In these conditions the model of rational behaviour suggested in the efficient market hypothesis may not apply.

The adaptive market hypothesis has also received a lot of critique from academics in financial sector. The critiques mostly point out the fact that in adaptive market hypothesis is not based on any mathematical models and is mainly based on existing knowledge, models and principles from behavioural finance (Liberto, 2021. All material in this section).

2.1.3. Modern use of technical analysis and algorithmic trading

Today the methods of technical analysis are in many cases utilized in form of algorithmic decision making. The securities trading environment in the modern day is characterized by a high level of automation, such as the ability to trade and execute complicated basket portfolios with a single click or finding the best execution using clever order-routing algorithms on foreign exchanges. Indicators of technical analysis are more and more commonly interpreted by computer algorithms and artificial intelligence to make trading processes increasingly automated (Gomber & Zimmermann, 2018).

Algorithmic trading, also known as automated trading or black-box trading, is a form of trading where the decisions of selling or trading assets is done by computer algorithms. Theoretically, these strategies can create profits at a pace and frequency that would be impossible for a human trader to achieve. Trading algorithms use various different kinds of indicators and instructions that are coded into them. In turn they make trade decisions according to market data that is given to them.

Today, the majority of algorithmic trading is high-frequency trading, which seeks to profit by placing a large number of orders at fast speeds across numerous markets and decision factors using pre-programmed instructions. (Seth, 2021).

2.2. Summary of literature on profitability

Profitability of technical analysis is a highly debated topic. Considerably large number of studies have been conducted in order to find a conclusion to this topic. These studies have had varying results. Some have concluded the methods of technical analysis as nonprofitable and some have found contrary results and concluded that technical analysis is indeed a profitable practice.

There are also plenty of collective studies that have analysed the data of these studies. The results and conclusions drawn in these collective and methodological studies are reviewed in this section.

2.2.1. “The profitability of technical analysis: a review”

There is one very thorough research paper called “The profitability of technical analysis: a review”, which analysed a total of 134 studies concerning the question of profitability. From these studies 77 found that technical analysis yields positive results. On the other hand, 34 studies obtained negative results, and the rest of these studies, a total of 23 studies, found mixed results.

Studies analysed in this paper had a wide variety of different approaches into studying the profitability of technical analysis. Some were focused on very limited number of technical indicators while others tested many different strategies and indicators in conjunction with each other. There also was a great variation of different kinds of assets traded in these studies including equities from various sources, currencies, futures, etc. Because of this, it is possible to analyse how different technical trading strategies work on various different trading environments and which strategies have the best performance when trading certain asset classes.

According to the findings of that research paper, at least 30% to 40% of practitioners consider technical analysis to be an essential element in identifying price movement over shorter time periods of up to 6 months. Also, the report found that those studies that were conducted longer time ago, found the usefulness of technical analysis to be more limited than studies that were conducted in more modern times. This could be due to the idea that the methods of technical analysis have been constantly developing, and their profitability would have increased along the methodological development. On the other hand, it could also be because of the better implementation and more accurate research methods implemented in the later studies, which was also pointed out in the paper. (Park & Irwin, 2004. All material in this section).

	Positive	Mixed	Negative	Total
Early studies (1961-1987)	19	13	10	**42**
Modern studies (1981 ->)	58	10	24	**92**
Total	**77**	**23**	**34**	**134**

Figure 1

Here is a simplified table, which summarises the findings collected from all studies included in this research paper. As in the paper, the results are separated into two categories depending on if they were considered to be early (1961-1987) or modern studies (1987 ->). The studies are put into three different categories, positive, mixed, or negative depending on their results respectively. A more in-depth table of the results from individual studies analysed in this paper can be found in the appendix. This table includes additional details about techniques used in the study and description about the results obtained.

2.2.2. "Examination of the profitability of technical analysis based on moving average strategies in BRICS"

By using technical analysis methodologies to the stock markets of BRICS member nations, this research paper was aiming to measure the effectiveness and profitability of technical analysis. The study looked into whether investors may earn higher-than-average profits by utilizing moving average strategies. The team working on this experiment, created a portfolio of equities from the BRICS nations that included all of the assets traded in each BRICS member's market. The transactions for this portfolio were conducted by an algorithmic trading system.

Despite the fact that the trading system was well-conducted, it had still had a few limitations. In this study, for example, it was assumed that the stocks were highly liquid and that transactions could be exchanged at specific market prices. Nonetheless, the findings showed that the algorithmic trading system, which utilized moving average indicators, was able to outperform a buy and hold strategy for a small segment of the traded assets. The returns from this small segment were significantly above the amount invested.

The study's findings revealed the feasibility and benefit of using technical analysis in this setting. On average, the returns achieved by technical analysis outperformed the amount invested. Because certain assets performed exceptionally well, they compensated for the losses sustained by other underperforming assets. However, just a handful of moving average combinations managed to outperform the returns from a purchase and hold strategy.

In the study, it was also noted that technical analysis and fundamental analysis can have a good synergy. Using both of these forms of analysis can complement each other and provide better results than either of these methods separately could (de Souza, Ramos, Pena, Sobreiro, Kimura, 2018. All material in this section).

2.2.3. “Is technical analysis profitable for individual currency traders?”

This study looked at whether individual currency traders employ well-known technical indicators to trade currencies, and if technical analysis is positively related to the performance of these portfolios. The group created a technical currency model based on four well-known technical trading techniques. These techniques were relative strength index, Bollinger bands, moving average convergence divergence, and 8 and 18 day moving average crossover.

The examination of individual currency accounts demonstrated that the technical currency model has adequate explanatory power for individual currency traders' net returns. These findings show that individual currency traders frequently use well-known technical indicators to trade various currencies.

One of the study's main findings was that individual currency traders who solely rely on well-known technical indicators to make trading decisions tend to end up with a considerable volume of losses. As a result, future studies of individual currency traders, and maybe individual investor stock traders, should consider the use of technical analysis when examining individual investor performance.

The findings on this study suggest that the methods of technical analysis alone might not be enough to produce profit consistently on currency markets. However, this study was made from the viewpoint of individual non-professional trades. This could mean that at least some of these individual trades might not have sufficient knowledge on the effective use of these technical indicators (Doukas, Doukas, Boris, 2012 All material in this section).

2.2.4. “Profitability of technical analysis indicators to earn abnormal returns in international exchange markets”

This research was a conducted by analysing a large number of existing research in order to assess the profitability of technical analysis. There was a total of 99 modern research papers analysed. From these 57 studies concluded with positive results regarding technical trading strategies. On the other hand, there were 22 studies that had found negative results concerning technical analysis. The rest of the studies, a total of 20 studies had received mixed results.

	Positive	Mixed	Negative	Total
Studies	57	20	22	**99**

Figure 2

This study report indicated based on the material analysed, that trading decisions based on technical indicators such as the moving average may be profitable even in the presence of possible transaction expenses. It is much more beneficial for trading members, who practically pay no commission, and large investors, who pay a very modest commission.

However, it is important to note that a significant portion of these empirical studies had issues with their testing methods, such as data snooping, ex post selection of trading rules and had some challenges and errors in estimating risk and transaction costs. This can negatively affect the credibility of the results gathered from these specific studies (Ghobadi, 2014. All material in this section).

2.2.5. “What do we know about the profitability of technical analysis?”

In this collective study, the empirical literature was categorized into two distinct categories. These categories were defined as early studies, referring to studies conducted between 1960–1987 and modern studies that were conducted between 1988–2004. The studies in these time groups were further categorized further into various subcategories, depending on their testing procedures.

The research found that the outcomes of these early studies differed greatly depending on the market. In general, early studies of stock markets revealed only limited evidence of the profitability of technical trading rules, whereas studies of foreign exchange markets and futures markets consistently revealed considerably large net profits. However, it is also mentioned that the early studies had significant limitations in their testing methodologies. Only one or two trading systems were examined, the risk of trading rules was frequently neglected, statistical tests of return significance were hardly ever performed, parameter optimization and out-of-sample verification were not used, and data snooping issues were not given nearly enough attention.

The study, on the other hand, was much less critical of modern studies because, according to them, modern studies improved greatly upon the limitations in testing methods when compared to early studies and typically increased the number of trading systems tested, properly assessed the risks of trading rules, performed statistical tests with either conventional statistical tests or more sophisticated bootstrap methods, or both, and conducted proper parameter optimization and out-of-sample verification.

Out of the total of 95 modern studies analysed in the research paper, 56 studies concluded with favourable results concerning technical trading methods. In contrast, a total of 20 studies concluded with negative results. The rest of the studies, a total of 19 studies, indicated mixed results. Modern studies also found that technical trading rules yielded economic profits in US equity markets only as far as 1980s, but not after that. In foreign exchange markets, technical trading rules were seen as profitable at least until the early

1990s. Technical trading methods applied into futures markets were only profitable until the mid-1980s.

	Positive	Mixed	Negative	Total
Studies	56	19	20	**95**

Figure 3

Overall, the number of positive results from the modern studies seems to lean towards positive outcomes being more feasible. However, it is also stated in the study that, further research using both the replication and reality check methodologies is needed to offer more clear data on the profitability of technical trading principles (Park, Irwin, 2007. All material in this section).

2.2.6. Summary of the studies

According to the studies analysed in this paper, there is a large amount of finance professionals, who are confident in the profitability of the technical analysis in financial markets. On the other hand, there is also a certain amount scepticism towards the methods of technical analysis and their ability to consistently generate profit.

However, most of these studies were at least somewhat leaning to the side of technical analysis and at the minimum, they found that there is a possibility to generate profit by utilizing various principles of technical analysis.

It could be seen that technical analysis has its place in analysing financial markets. It might not be universally profitable in all financial environments or with all asset classes. But there is a significant amount of evidence that when used in a correct way and in correct trading environment it certainly is able to be used successfully.

The evidence also might suggest that a large factor in context of profitability is if the user of the technical analysis is a finance professional, has sufficient amount of experience, or has the ability to use the right indicators and methods in a right context. As it was stated in the study “is technical analysis profitable for individual currency traders?” the profitability of technical analysis can have a significant variation when comparing finance professionals with individual investors that might have or might not have the sufficient knowledge to use these methods in a proper manner.

2.3. Methods of technical analysis

Technical analysis as whole is established on two elements. These two data elements are price over time and volume. They constitute the whole science of technical analysis. These two basic types of data are the foundation for all patterns, indications, and ideas.

There is a vast number of different kinds of tools that can be used in order to conduct a technical analysis. These include various types of charts, like line charts, bar charts, and candlestick charts. Technical analysis also includes interpretation of market trends, and different kinds of indicators such as simple moving average and relative strength index. (eLearn markets, Nd)

These concepts are going to be explained further in this chapter with focus on methods, which are commonly used and relevant to algorithmic trading

2.3.1. Charts in technical analysis

Charts are two-dimensional depictions of price changes over time. Charts are one of the most basic tools used by technical analysts to interpret price changes in various assets. There are many different sorts of charts to choose from. Line charts, bar charts, and candlestick charts are the most popular and commonly applied among them.

Charts are also relevant in the context of algorithmic trading. Charts can be used by algorithmic traders in their trading strategies by utilizing algorithmic identification of chart patterns. To be able to code and use these charts effectively, trader needs to be familiar with them in order to identify certain chart patterns and to make use of them in efficient manner. Also, the ability of understanding these charts is paramount in order to create profitable algorithmic trading strategies. (Siligardos, Nd)

Here is a detailed description about two most frequently used and relevant types of charts for modern technical analysts and algorithmic traders, line charts and bar charts.

a) Line charts

In technical analysis, the line chart is one of the most basic and widely used graphs. It is essentially different from candlestick charts in, because it simply provides information on the course's closing value. By integrating the points, the line graph is created from the closing price of each day. The main benefit of a basic line graph is that it displays a price change in a clear, immediately recognizable, and visually representative manner. It makes studying support and resistance levels a lot easier. On the other hand, because it only shows the day's closing price, it lowers the frequency of incorrect signals.

On the flip side, for some traders, line charts may not give enough price information to monitor their trading techniques. Prices calculated from the open, high, and low are required for some techniques. Traders that utilize more data than the closing also might not have enough data to back-test their trading technique using a basic line chart (Peters, 2021).

b) Bar charts

Bar charts are also a very popular type of chart commonly used by technical analysts. Bar charts used in context of technical analysis are typically somewhat different from regular bar charts. Bar charts can be used by analysts to swiftly detect patterns in securities or assets. A bar chart by itself does not give nearly enough data or insight to justify purchasing a security; nonetheless, it may be a useful signal of whether additional study should be done or whether the investment opportunity should be passed up.

Figure 4

The opening, high, low, and closing prices of a securities are visually represented in a bar chart over a specific time period. The vertical line depicts the period's high and low prices. The market opening price is shown on the horizontal line to the left, and the market closing price is shown on the horizontal line to the right (CFI, Nd).

2.3.2. Trends

Strategies concerning trends are one of the most common ways to conduct algorithmic trading. Moving averages, channel breakouts, price level fluctuations, and other technical indicators are used in the most prevalent algorithmic trading techniques. Because these methods do not require any predictions or price projections, they are the easiest and simplest to apply into algorithmic trading strategies. Without entering into the complexities of predictive analysis, trades are made based on the occurrence of favourable patterns, which are simple and basic to apply using algorithms. A popular trend-following method is to use 50- and 200-day moving averages and other simple technical indicators (Shobhit, 2021).

2.3.3. Technical indicators

Technical indicators are mostly focused on historical trading data, such as price, volume, and open interest. Technical indicators are typically employed by active traders since they are meant to examine short-term price changes, but they may also be utilized by long-term investors in order to determine entry and exit locations. Technical indicators can generally be separated into two main categories. These two categories are overlays and oscillators (Chen, 2021).

The technical indicators, which are going to be implemented in the methodological part of this paper and ways that these indicators are utilized in algorithmic trading are going to be explained further in this chapter.

a) Simple moving average (SMA)

The simple moving average is a straightforward technical analysis tool. Moving averages are commonly used to detect a stock's trend direction or to estimate its support and resistance levels. Because it is dependent on prior prices, it is defined as a trend-following indicator or in other words a so-called lagging indicator.

$$\text{SMA} = \frac{A_1 + A_2 + ... + A_n}{n}$$

where:

$A_n =$ the price of an asset at period n

$n =$ the number of total periods

Figure 5

The longer the lag, the longer the moving average's time period. Because it includes values from the previous 200 days, a 200-day moving average will have a far larger degree of lag than a 20-day moving average. Investors and traders pay close attention to the 50-day and 200-day moving averages for stocks, since they are considered to be significant trading signals.

Moving averages are a completely adjustable indicators, which means that an investor may calculate an average using whatever time range they desire. Moving averages are most commonly employed for periods of 15, 20, 30, 50, 100, and 200 days. The more sensitive the average is to price movements, the shorter the time range employed to calculate it. The average will be less responsive over a longer period of time. The proper time period is chosen based on investors trading objectives. The most effective way to find the proper time period is by experimentation. (Hayes, 2022. All material in this section).

b) Relative strength index (RSI)

The relative strength index, also typically referred to as RSI, is a technical analysis indicator that examines the size of recent price fluctuations to determine if a stock or other asset is overbought or oversold. The relative strength index is represented by an oscillator with a range of 0 to 100. Values of 70 or above on the relative strength index are typically interpreted and used to suggest that an investment is becoming overbought or overpriced and may be set for a trend reversal or corrective fall in price. A rating of 30 or less on the relative strength index indicates an oversold or undervalued position.

$$RSI_{\text{step one}} = 100 - \left[\frac{100}{1 + \frac{\text{Average gain}}{\text{Average loss}}} \right]$$

Figure 6

The calculation of relative strength index uses the average gain or loss as the average percentage gain or loss during a certain time period. For the average loss, the formula applies a positive number. Periods with price losses are counted as 0 in average gain calculations, while periods with price increases are counted as 0 in average loss calculations.

Some traders would consider it as a signal to buy if a security's relative strength index reading falls below 30, assuming that the asset has been oversold and is thus due for a resurgence. However, the accuracy of this signal will be affected by the overall context. If the security is in a substantial decline, it may continue to trade at an oversold level for long time. Traders in that circumstance may postpone purchasing until they get further indications to confirm the situation (Fernando, 2021. All material in this section).

c) Exponential moving average (EMA)

An exponential moving average is a sort of moving average that gives the most recent data points more weight and relevance. The exponential moving average (also known as the exponentially weighted moving average) is a moving average, which reacts more strongly to recent price changes than for example a simple moving average, which gives equal weight to all of the period's data.

$$EMA_{\text{Today}} = \left(\text{Value}_{\text{Today}} * \left(\frac{\text{Smoothing}}{1+\text{Days}}\right)\right) + EMA_{\text{Yesterday}} * \left(1 - \left(\frac{\text{Smoothing}}{1+\text{Days}}\right)\right)$$

Figure 7

The 12- and 26-day exponential moving averages are the most often used and observed short-term averages. Indicators like the moving average convergence divergence and the percentage price oscillator are created using the 12- and 26-day exponential moving averages. The 50- and 200-day exponential moving averages are commonly utilized as long-term trend indicators. A technical indicator that a reversal has occurred is when a stock price crosses its 200-day moving average.

Exponential moving averages are widely employed in combination with other indicators to confirm and assess important market changes. The EMA is better appropriate for traders who trade in fast-moving markets. EMAs are frequently used by traders to detect a trading bias. (Chen, 2022. All material in this section)

d) Moving average convergence divergence (MACD)

The moving average convergence divergence, also commonly known as MACD, is primarily used to assess the strength of price movement in stocks. It accomplishes this by calculating the difference between two exponential moving averages, most often a 12-period exponential moving average and a 26-period exponential moving average. A MACD line is formed by subtracting the 26-period exponential moving average from the 12-period exponential moving average, and a line depicting a nine-period exponential moving average of that computation is shown as a histogram over the MACD's basic representation. A zero line indicates whether the MACD is positive or negative. Greater difference between the 12-period exponential moving average and the 26-period exponential moving average indicates increasing market momentum, either upward or downward.

$$\text{MACD} = \text{12-Period EMA} \; - \; \text{26-Period EMA}$$

Figure 8

One of the biggest issues with moving average divergence is that it can frequently predict a prospective reversal, but no real reversal occurs, resulting in a false positive. The other issue is that divergence does not always predict reversals. In other words, it forecasts too many false reversals and too few true price reversals. False positive divergence sometimes takes place when the price of an asset goes sideways following a trend, such as in a range or triangle pattern. Even in the absence of a genuine reversal, a slowdown in momentum, sideways movement, or sluggish trending price movement will lead the moving average convergence divergence to draw away from its earlier extremes and gravitate toward the zero lines (Fernando, 2021. All material in this section).

2.4. Performance measurement

When measuring the performance of a portfolio, only analysing the simple returns is not sufficient. Portfolio performance metrics are a critically important consideration when making investment decisions. These tools supply finance professionals with the information they need in order to judge how well their or their clients’ wealth has been invested or may be invested. It is important to note that simple portfolio returns are only one part of the overall picture. An investor cannot see the entire investment picture unless risk-adjusted returns are properly evaluated. Without correct performance measurements it is practically impossible to make efficient trade decisions. (Segal, 2021)

This section contains information about the most relevant performance measures for technical portfolios. The information includes the correct use and exact formulas used to calculate these measures. These performance measures will be implemented later to assess the performance of the strategies implemented in the empirical section of this bachelor thesis.

2.4.1. Sharpe ratio

Sharpe ratio is a ratio is a performance measure, which is commonly used to measure and assess portfolio performance. It is a very common tool found in various algorithmic trading platforms and it can be used very effectively to adjust various technical and algorithmic trading strategies. It is also used to examine the performance of strategies implemented in the methodological section of this thesis.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

where:

$R_p =$ return of portfolio

$R_f =$ risk-free rate

$\sigma_p =$ standard deviation of the portfolio's excess return

Figure 9

Sharpe ratio, also sometimes referred to as Sharpe index, was invented by an American economist William Sharpe. Sharpe ratio effectively assesses investments or portfolio's performance by adjusting for its risk. The higher the ratio is, the higher is the investments return compared to the amount of risk assumed, and therefore the better the investment or performance

There are general outlines of what Sharpe ratio is considered to be good and what is considered to be bad. If the Sharpe ratio is less than 1 it usually means that the investment is suboptimal. Ratio of 1 to 1,99 is adequate and ratio between 2 and 2,99 is considered to be very good. Ratios that are more than 3 are seen as excellent investments.

Effectively, Sharpe ratio is all about maximizing profits while decreasing volatility. For example, if an investment had a ten percent yearly return but no volatility, it would have an infinite or undefined Sharpe ratio.

However, with any type of investment, it is realistically impossible to actually have 0% volatility. As volatility rises, the expected return must increase drastically in order to compensate for the increased risk. The Sharpe ratio displays the average investment return minus the risk-free rate of return divided by the investment's standard deviation of returns (CFI, Nd. All material in this section).

2.4.2. Sortino ratio

The Sortino ratio is a variant of the Sharpe ratio that uses the asset's standard deviation of negative portfolio returns—downside deviation—rather than the total standard deviation of portfolio returns to distinguish damaging volatility from total overall volatility. The Sortino ratio is calculated by subtracting the risk-free rate from the return on an asset or portfolio, then dividing the result by the asset's downside deviation.

$$\text{Sortino Ratio} = \frac{R_p - r_f}{\sigma_d}$$

where:

$R_p = \text{Actual or expected portfolio return}$

$r_f = \text{Risk-free rate}$

$\sigma_d = \text{Standard deviation of the downside}$

Figure 10

A higher Sortino ratio value is preferable, in a similar way to a higher Sharpe ratio. Although, it is important to note that when comparing two equivalent investments, a reasonable investor would choose the one with the higher Sortino ratio since it indicates that the investment is receiving a larger return per unit of unfavourable risk that it is exposed to.

By dividing excess return by the downside deviation rather than the overall standard deviation of a portfolio or asset, the Sortino ratio improves on the Sharpe ratio by separating downside or negative volatility from total volatility.

The Sharpe ratio practically penalizes an investment for too much exposure to risk, resulting in favourable returns for investors. Choosing which ratio is more accurate measure for a specific portfolio, however, is mainly dependent on the factor whether the investor wants to focus on total or standard deviation, or only downside deviation (Kenton, 2020. All material in this section).

2.4.3. Omega ratio

The omega ratio is a weighted risk-return ratio for a particular amount of expected return that aids in determining the likelihood of winning vs losing. It also takes into account the third and fourth momentum effects, namely skewness and Kurtosis, which gives it some unique value in contrast to other performance measures previously mentioned in this section. (Thakur, Nd)

The omega ratio, like the previously mentioned ratios, is a risk-return metric that aids investors in determining the attractiveness of a certain investment. However, unlike the Sharpe ratio, which solely measures volatility, the omega ratio also incorporates the distribution's upper points.

The omega ratio is frequently employed in alternative investments such as hedge funds, where the management promises absolute performance. However, in such instances, the return distribution may be asymmetric, with a high level of tail risk or negative skewness. These characteristics of the return distribution are not properly illustrated by the Sharpe ratio. So, in other words, Omega ratio is especially valuable in specific situations where the returns of the investments are not normally distributed.

$$Omega(r) = \frac{\int_r^{\infty}(1 - F(x))dx}{\int_{-\infty}^{r} F(x)dx}$$

Figure 11

Above is the precise formular of the Omega ratio. The Omega ratio formula is interpreted as follows: F equals to cumulative distribution of returns, r equals to minimum acceptable return (MAR), which specifies what we consider a gain or loss. (Breaking down finance, Nd)

2.4.4. Maximum drawdown (MDD)

A maximum drawdown also commonly known as MDD, is the maximum loss experienced by a portfolio from its peak to its bottom before a new peak is reached. The maximum drawdown is a measure of the risk of loss over a set period of time. It may be used as a stand-alone statistic or as an input into other metrics like the Calmar Ratio and "Return over Maximum Drawdown." Maximum Drawdown is calculated and illustrated as a percentage.

$$MDD = \frac{Trough\ Value - Peak\ Value}{Peak\ Value}$$

Figure 12

Maximum drawdown is a risk indicator that focuses on capital preservation, which is a major concern for most investors. It is used to compare the relative level of risk from one stock screening approach to another. Two screening techniques, for example, may have the same average outperformance, tracking error, and volatility, but their maximum drawdowns compared to the benchmark can in some circumstances be significantly different. (Hayes, 2021)

3. Methodology

In this part the implementation of the methodological part of this paper is going to be explained. Furthermore, the practical use of algorithmic trading strategies and tools, as well as observations, experiences and assessment of their successfulness and profitability are described here.

3.1. Blueshift visual programming tool

Blueshift is a visual programming tool that is very commonly used to create and implement algorithmic trading strategies. Blueshift visual programming tool utilizes the visual programming language developed by Google and MIT called Blockly. One of the main benefits with this tool is the fact that it does not require extensive skills and knowledge concerning computer programming. This visual programming tool can be accessed on the website of Blueshift by creating an account. All of these tools are completely free to use.

Blockly allows its users to create applications by putting together little graphical elements in the same manner that Legos are put together. Each visual element is also a code object, such as a variable, counter, or if-then statement. And when you put these elements together, you will get simple functions. And, when these functions are combined, users may build complete programs. In our case this would mean a complete algorithmic trading strategy. (Metz, 2012)

The drawback of the tools provided by Blueshift and Blockly is that the user is more limited by getting access only to the variables, functions and indicators provided by the program. This can be a problem for more advanced traders who want to be able to utilize more advanced algorithmic trading strategies and functions. However, for the purposes of this paper the capabilities of Blueshift are sufficient, because it still allows to implement strategies and indicators, which are most widely used in practice by technical analysts and algorithmic traders.

The algorithmic trading strategies implemented in this paper are constructed by utilizing this programming tool. The exact structure of these strategies and how they were created are going to be explained further in this paper.

3.1.1. Example

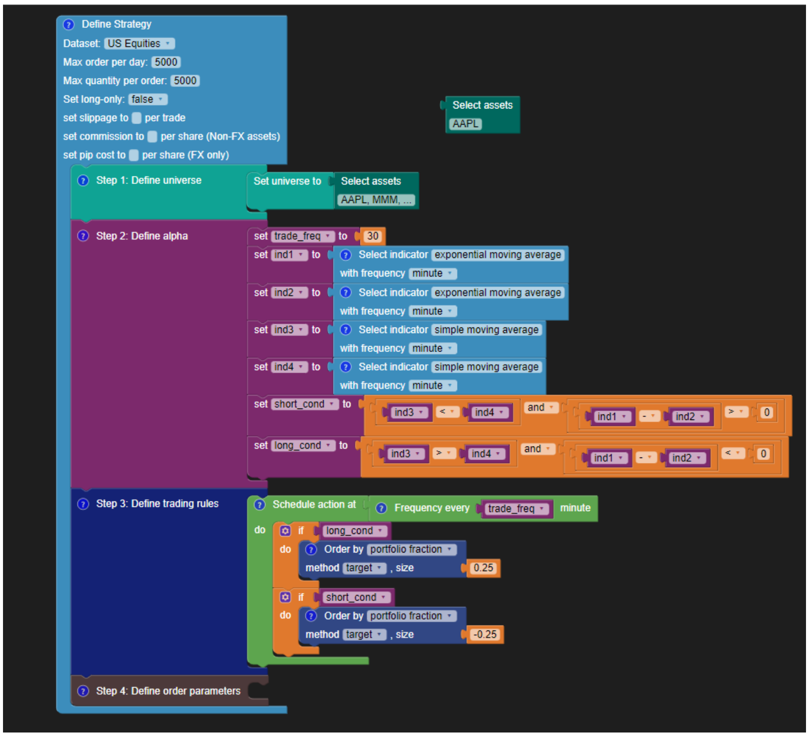


Figure 13

In the picture found above is the user interface of the blueshift platform. This is an example of functioning trading algorithm constructed using visual programming. Trading algorithms are extremely simple to put together by following the four steps in this user interface.

The first step is to define the trading universe. This means to define which assets are to be traded. This function can be customized for each trading strategy individually and the financial assets that are intended to be traded can be specifically named by using the select asset's function. Possible assets are divided into different categories, for example forex, US equities, and NSE.

The second step is to define alpha. In this section the user can for example, adjust the trading frequency, set up the desired technical indicators, and then tweak those indicators to trigger at desired values.

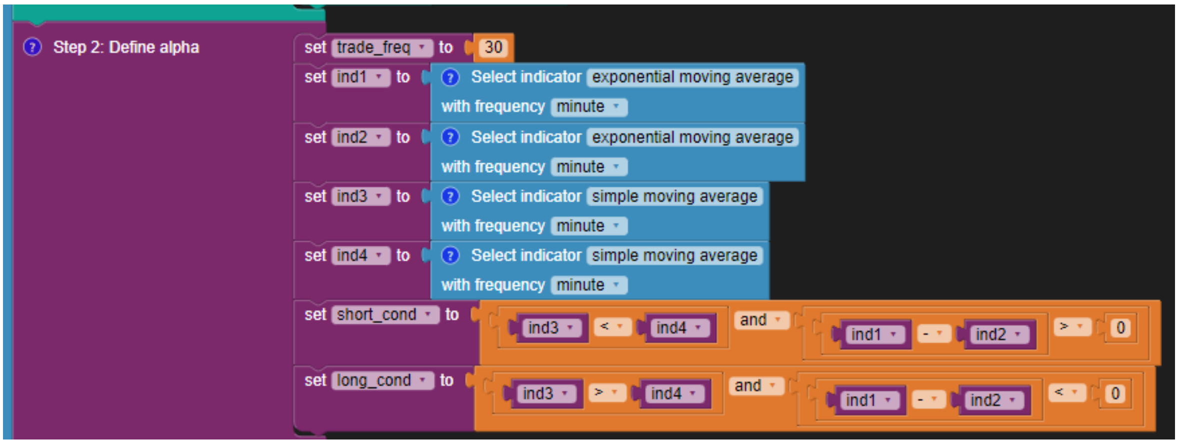


Figure 14

For example, in the picture above the short condition for the simple moving average is set up to trigger when the value for the long period is greater than for the short period. For the long condition to trigger, the opposite needed to be true. There is a possibility to set up multiple indicators simultaneously. In this example there were two of them, but theoretically there is no limit how many different indicators the user can use at one algorithm.

The third step in the platform is to define the trading rules. In this section it is possible to adjust the exact amounts to be traded when the values determined previously for the indicators are met. This can be set by exact amount of value or as a portfolio fraction, as it is in this particular example.

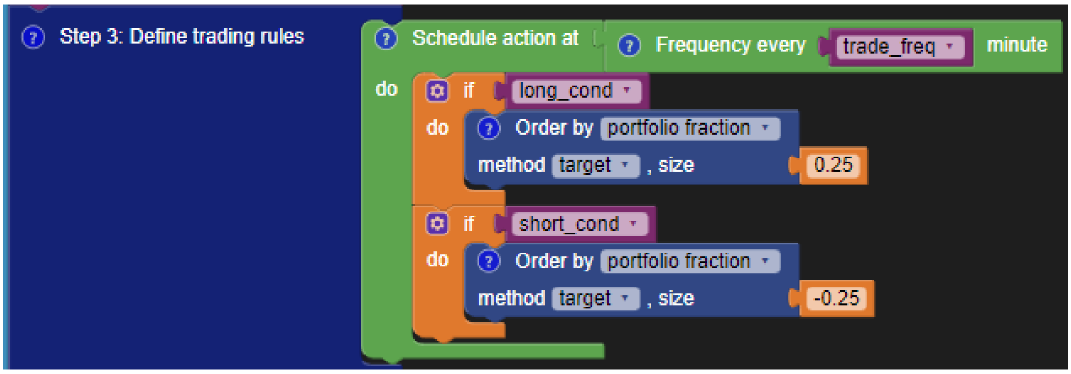


Figure 15

The fourth and final step called define order parameter allows you to specify certain limits, such as maximum loss limit, which stops trading if the portfolio suffers losses over the pre-specified amount. Alternatively, it is also possible to set up a maximum gain limit which stops the algorithm from making more trades if a certain amount of portfolio value is reached. This step is completely optional, and the algorithm is able to function even if there are no set limitations. Just like in the example trading algorithm above, this section is left empty and no limitations into either direction were made.

After these steps are made and the desired settings are enabled, the algorithm is ready for back testing or it can be used with a broker, which is compatible with algorithms made in blueshift.

3.2. Trading strategies

In this section, the trading strategies that are implemented in this paper are going to be explained in detail. Also, the performance and profitability of these indicators and strategies constructed from these indicators are reviewed.

In this section there are three main algorithmic trading strategies that were implemented by using the visual programming tools provided by Blueshift. All of these strategies had the same setting in order to give them similar chances to be profitable and/or beat the benchmark. The benchmark used to measure the performance was the default benchmark used by the dataset in Blueshift, SPDR S&P 500 ETF.

The testing period used for every strategy was from 1st of January 2022 until the 31st of January 2022, after that they were tested again at a longer time period from 1st of January 2022 until the 29th of April 2022, in order to analyse the possible difference in results between these two time periods. In every test run the amount of cash available for the algorithms was 10’000 USD. Additionally, all of the strategies were programmed to trade exactly the same assets.

The trading algorithms also traded with identical technical settings. Only the technical indicators between the strategies were changed. All of the settings were back tested several times using various different time periods and market conditions. This way the generally most efficient settings could be found for trading of the particular assets used in this experiment.

The algorithms were programmed to look for possible trades every thirty minutes for the defined assets. Algorithm would check if there were any assets that would pass every criterion according to the used indicators and specified buy or sell conditions. If the criteria were met, the algorithm proceeded to make the transaction based on the available amount of cash. Algorithms were capped on making trades at maximum proportion of 25% total amount of cash available. This rule was in place for both ways, selling and buying of assets.

The algorithm did also check before every transaction if the portfolio already contains the asset it is trying to acquire. 25% functioned also a cap in value fraction for each individual asset in the portfolio, so that proportion of one specific asset would not become proportionally too large.

3.2.1. Short testing periods

The strategies selected for the paper trading were first tested at shorter test runs to observe how they would perform on month-to-month basis. This was also an efficient way to test the stability of the programming in these algorithms before exposing them to longer time periods, which have a higher risk of initiating various errors if the programming happened to have some errors.

Results gathered from these short testing periods are demonstrated here, with precise descriptions of actual indicators, variables, and settings used to construct these trading algorithms.

a) Strategy one: RSI + MACD

The first indicator, RSI, was set up with lookback period of 60 minutes. Long condition for the indicator was met if the RSI would surpass the threshold of 60. On the other hand, the short condition was programmed to trigger if the relative strength index would move below 30.

The second indicator, MACD was defined so that it would look at the exponential moving average of short period, in this case that would be 12 days and the long period of 26 days. For the short conditions to be triggered the subtraction of the short period and long period needs to be more than a zero. The long condition is triggered when the subtraction between the periods is less than a zero.

Indicator	**Look back**	**Short signal**	**Long signal**
RSI	60m	Less than 30	More than 60
MACD	S=12d L=26d	S-L more than 0	S-L less than 0

Figure 16

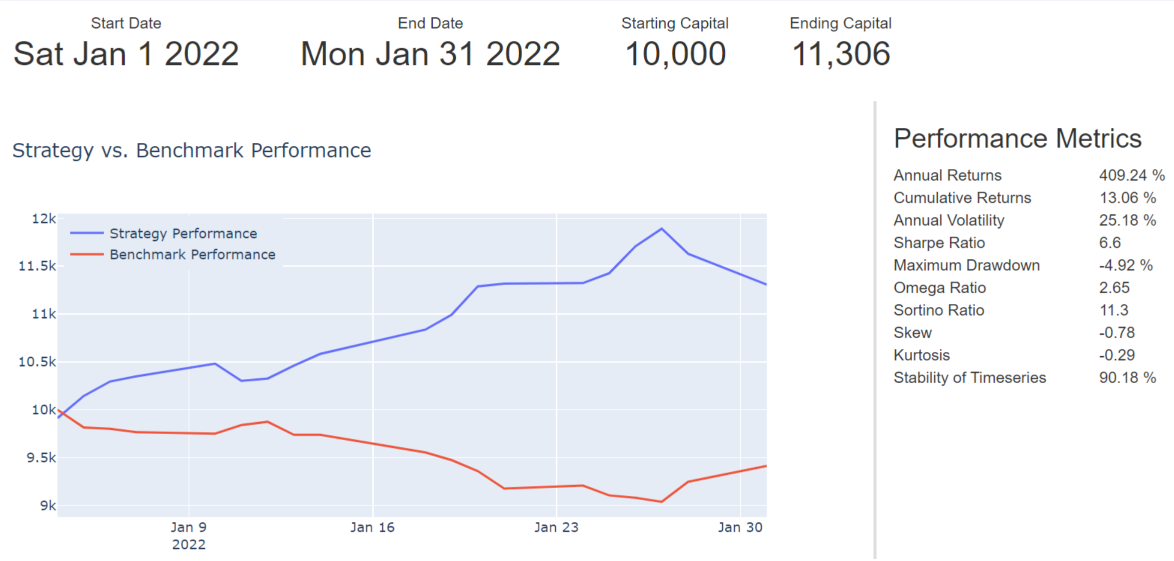


Figure 17

The strategy made a total of 20 trades during the whole time period. All of the trades that the algorithm made, were initiated on the first quarter of January. This is most likely due to the rapid decline of the prices of available equity after that point.

Overall, this strategy performed well against the benchmark and managed to make cumulate a return of 13,06%. Relative strength index and MACD seemed to work well together. During the testing both of these indicators were tested individually, and their performance was suboptimal.

b) Strategy two: RSI + SMA

This algorithm works very similarly when compared with the one in the first strategy. Only in this strategy, the indicator MACD was replaced with a new indicator, simple moving average.

Just as in the first strategy the first indicator, relative strength index, was set up with lookback period of 60 minutes. Long condition for the indicator was met if the relative strength index would surpass the threshold of 60. On the other hand, the short condition was programmed to trigger if the relative strength index would move belove 30.

Simple moving average was set up with two separate lookback periods, the short period and the long period. The short period had a lookback of 50 days, and the long period had a lookback of 200 days. For the short conditions to be met for this indicator the simple moving average for the long period needed to be greater than for the short period. For the long conditions to be met, the case needed to be the opposite, the simple moving average for the short period needed to be greater than for the long period.

Indicator	**Look back**	**Short signal**	**Long signal**
RSI	60m	Less than 30	More than 60
SMA	S=50d L=200d	S<L	S>L

Figure 18

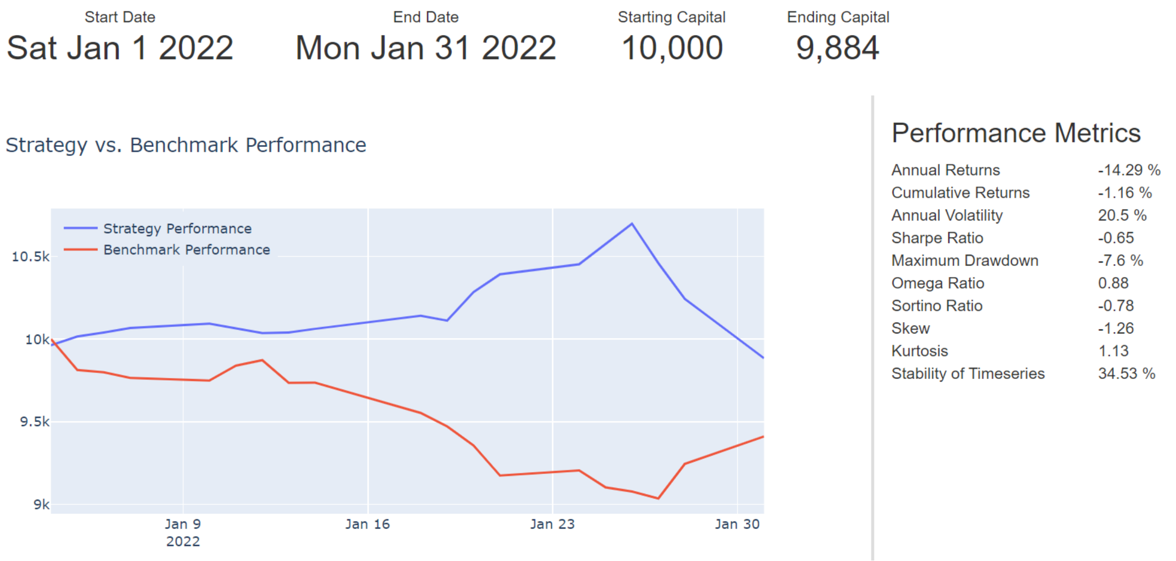


Figure 19

This strategy made less trades in the time period than the first strategy. The algorithm made a total of 8 transactions. This time all of the transactions were made considerably evenly in along the whole time period. Interestingly all of the transactions made by the algorithm were purchases, algorithm did not make any sales at any point in the time period.

This strategy did not perform as well as the previous strategy. Still considering the market conditions it performed well enough to beat the benchmark performance. Interesting point to note was the fact that the portfolio was performing considerably well until the very end of time period. In the end of this time period, this strategy still suffered cumulated losses of -1,16%.

During back testing the simple moving average actually performed better individually than with the relative strength index and vice versa. This suggests that these particular indicators might not perform well together.

c) Strategy three: MACD + SMA

In the third strategy there were two indicators present. These were MACD and simple moving average. In this strategy the difference to the previous strategy is that the relative strength index was replaced with MACD.

The first indicator, MACD was set up in a similar way as it was in the first strategy, so that it would look at the exponential moving average of short period, in this case that would be 12 days and the long period of 26 days. For the short conditions to be triggered the subtraction of the short period and long period needs to be more than a zero. The long condition for this indicator to be triggered the subtraction between the periods needed to be less than a zero.

Simple moving average was set up with two separate lookback periods, the short period and the long period. The short period had a lookback of 50 days, and the long period had a lookback of 200 days. For the short conditions to be met for this indicator the simple moving average for the long period needed to be greater than for the short period. For the long conditions to be met, the case needed to be the opposite, the simple moving average for the short period needed to be greater than for the long period.

Indicator	Look back	Short signal	Long signal
MACD	S=12d L=26d	S-L more than 0	S-L less than 0
SMA	S=50d L=200d	S<L	S>L

Figure 20

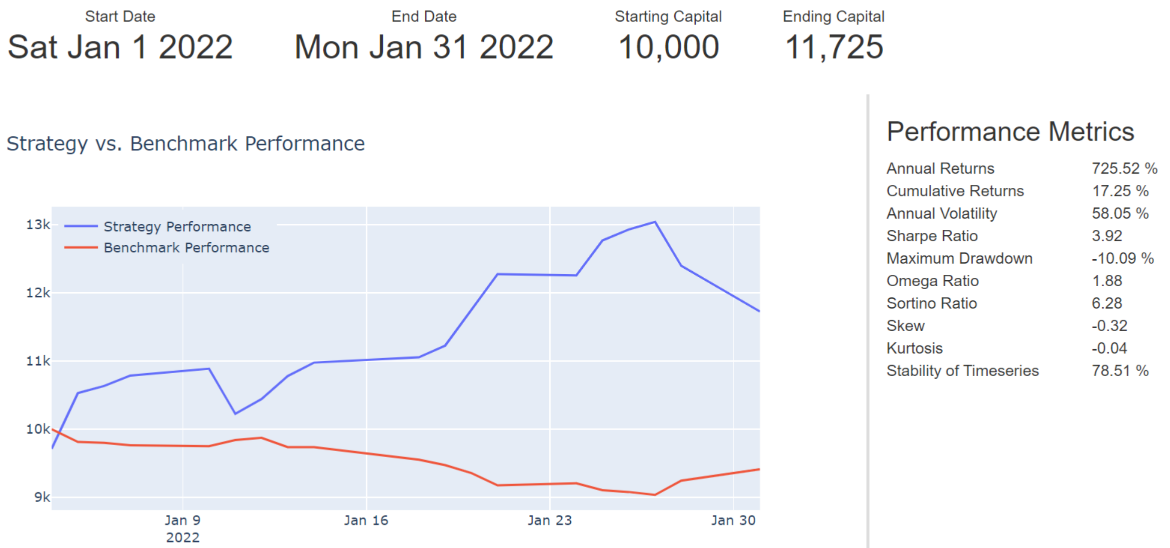


Figure 21

The third strategy made a huge number of trades when compared with the other strategies. The total number of trades initiated by this algorithm was 67. In similar fashion to the first strategy all the trades were made early in the time period. The algorithm filled the portfolio quickly with different assets and started holding them until the end. However distinctly from the second strategy, this algorithm also sold assets, but these transactions also took place early in the time period.

Overall performance of this strategy was excellent in this specific time period and the performance was above the benchmark. This algorithm was able to cumulate total returns of 17,25%.

According to this experiment it seems like MACD, and simple moving average are working well together. They performed better together than either of them individually during testing.

d) Strategy four: EMA + SMA

In this strategy, the indicators were Exponential moving average and simple moving average. This strategy was relatively different from the other trading algorithms in the sense that it solely relied on values of moving averages.

The simple moving average was configured with two distinct lookback periods, short and long. The lookback time for the short period was 50 days, while the lookback period for the long period was 200 days. For this indicator's short conditions to be satisfied, the simple moving average for the long period has to be greater than the simple moving average for the short period. For the long conditions to be met, the scenario had to be the opposite: the simple moving average for the short period had to be greater than the simple moving average for the long period.

EMA was adjusted in a similar manner to simple moving average. While short and long conditions both were exactly the same, this indicator also had two lookback periods, 50 and 200 days. The advantage of using EMA in this strategy is the fact that it gives moving average values that are weighted towards more recent information. This has the potential to give better and more balanced results, when compared to only relying on simple moving average, while keeping the algorithm relatively simple.

Indicator	**Look back**	**Short signal**	**Long signal**
EMA	S=50d L=200d	S<L	S>L
SMA	S=50d L=200d	S<L	S>L

Figure 22

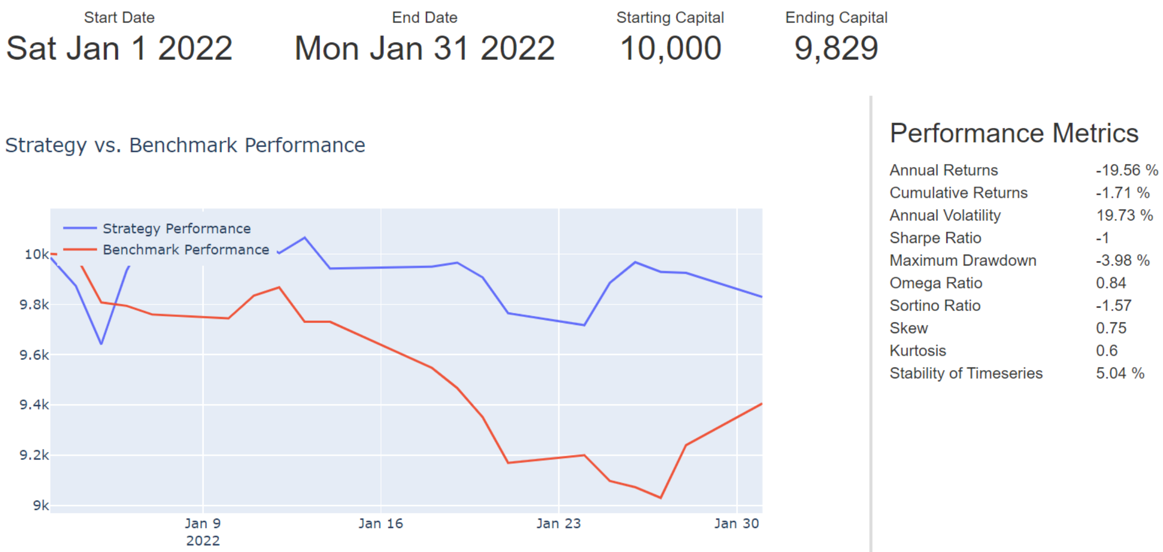


Figure 23

This strategy was extremely active with initiating transactions. The total number of trades by this algorithm was 68. The trades were somewhat weighted towards the start of the time period, but this strategy seemed to be more balanced with its ability to find suitable openings to also sell assets.

With cumulative returns of -1,71% the strategy was not profitable, however the performance managed to surpass the benchmark.

3.2.2. Final testing periods

After the initial tests done with the shorter time periods, the algorithms seemed to be functioning in a correct way and they were ready to be tested further with longer time periods. The exact time period simulated in these long testing periods was from 1.1.2022 to 29.4.2022. For all the strategies tested the account was reset back to 10000 USD and there were no positions held at the start of the testing period.

The trading algorithms used in this time period were almost exactly the same as the algorithms that were used in the previous short test runs except few slight adjustments made according to the results gathered from the previous test runs, main differences being on trade frequency and relative trade sizes. The maximum trade limits in portfolio fractions were lowered from the initial 25% to 15% and the trade frequency was changed from 30 to 45 minutes.

Results gathered from these testing periods are demonstrated here, with precise descriptions of actual indicators, variables, and settings used to construct these trading algorithms. At the end there is a summary and analysis of the results from all testing periods.

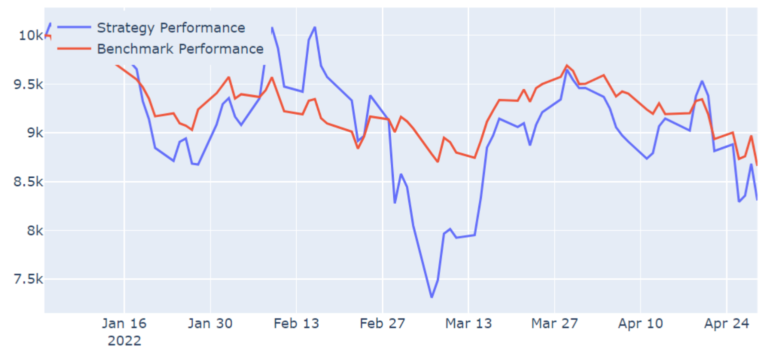
a) Strategy one: RSI + MACD

Indicator	Look back	Short signal	Long signal
RSI	60m	Less than 30	More than 60
MACD	S=12d L=26d	S-L more than 0	S-L less than 0

Figure 24

Start Date	End Date	Starting Capital	Ending Capital
Sat Jan 1 2022	Fri Apr 29 2022	10,000	8,307

Strategy vs. Benchmark Performance



Performance Metrics

Annual Returns	-43.44 %
Cumulative Returns	-16.93 %
Annual Volatility	49.14 %
Sharpe Ratio	-0.91
Maximum Drawdown	-27.82 %
Omega Ratio	0.86
Sortino Ratio	-1.2
Skew	-0.36
Kurtosis	0.65
Stability of Timeseries	16.53 %

Figure 25

In this test run, the algorithm made a surprisingly low number of 19 trades during the whole time period, all of them being purchases. This time around, the trades were more evenly spread during the time period with a slight emphasis on the first quarter of the period.

The strategy had worse overall performance when compared with the short test runs. The portfolio could not break even. Cumulative return was -16,93%, while the ending capital was at 8307 USD.

These results might be suggesting that even though this strategy performed well in the market environment present at the previous test runs, bringing it to new environment it was not able to predict the direction of the price movements very effectively.

b) Strategy two: RSI + SMA

Indicator	Look back	Short signal	Long signal
RSI	60m	Less than 30	More than 60
SMA	S=50d L=200d	S<L	S>L

Figure 26

Figure 27

In this test run, the algorithm made a total of 23 trades during the time period. This time around, the algorithm functioned in some respects quite differently from previous test runs. This might be because of the difference in market conditions or due to the slight changes in trading rules.

Just like with the first strategy, there were some differences in how the trades were distributed along the time period. Vast majority of the trades made were situated right at the start of January, while only a few trades were made during the last half of the testing period. Additionally, another difference compared to the previous runs was that there also was actively selling previously purchased assets. This is most likely because the longer time period allowed larger price differences to be formed with the assets acquired near to the start of trading period.

The final performance of the strategy in this run was also somewhat weaker than previously. Just like in both of the short test runs the portfolio performance was at the end above the benchmark performance, but just like before, the portfolio suffered considerable losses. The cumulative returns were at -8,8% and the total ending capital was only at 9120 USD.

The ending results were somewhat similar to earlier tests, even though there were slight differences in the behaviour of the algorithm during the test.

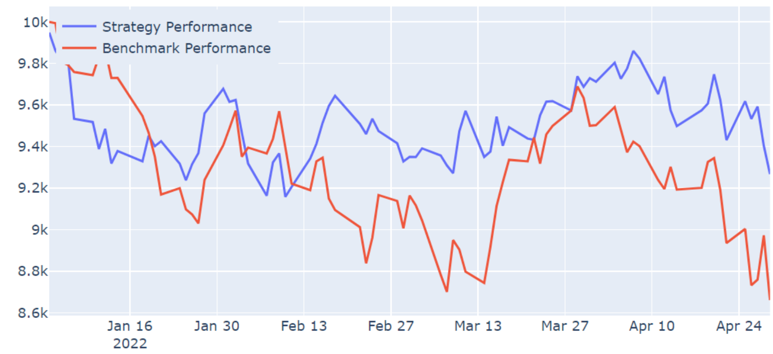
c) Strategy three: MACD + SMA

Indicator	**Look back**	**Short signal**	**Long signal**
MACD	S=12d L=26d	S-L more than 0	S-L less than 0
SMA	S=50d L=200d	S<L	S>L

Figure 28

Start Date	End Date	Starting Capital	Ending Capital
Sat Jan 1 2022	Fri Apr 29 2022	10,000	9,268

Strategy vs. Benchmark Performance



Performance Metrics

Annual Returns	-20.84 %
Cumulative Returns	-7.32 %
Annual Volatility	18.28 %
Sharpe Ratio	-1.18
Maximum Drawdown	-8.42 %
Omega Ratio	0.83
Sortino Ratio	-1.55
Skew	-0.17
Kurtosis	-0.61
Stability of Timeseries	5.33 %

Figure 29

In this test run, in a similar fashion to the previous tests, the algorithm was making both sales and purchases in a balanced manner. During the testing period, a total of 23 trades were initiated. This time the total number of trades was significantly reduced, especially when comparing it with the second one of the short test runs. Other than that, generally the algorithm was behaving in way that was expected.

Most of the trades were made quite early on into the time period and some of the positions were held until the end of the period.

In this test run the portfolio performance was also negative at the end, Although, like in previous in all of the tests for this strategy, the benchmark performance has been surpassed. The cumulative returns yielded from this time period were -7,32%, which is significantly worse than earlier for this strategy.

The results are in line with the other runs conducted in this time period, performance worsened significantly when moving to this time period.

d) Strategy four: EMA + SMA

Indicator	Look back	Short signal	Long signal
EMA	S=50d L=200d	S<L	S>L
SMA	S=50d L=200d	S<L	S>L

Figure 30

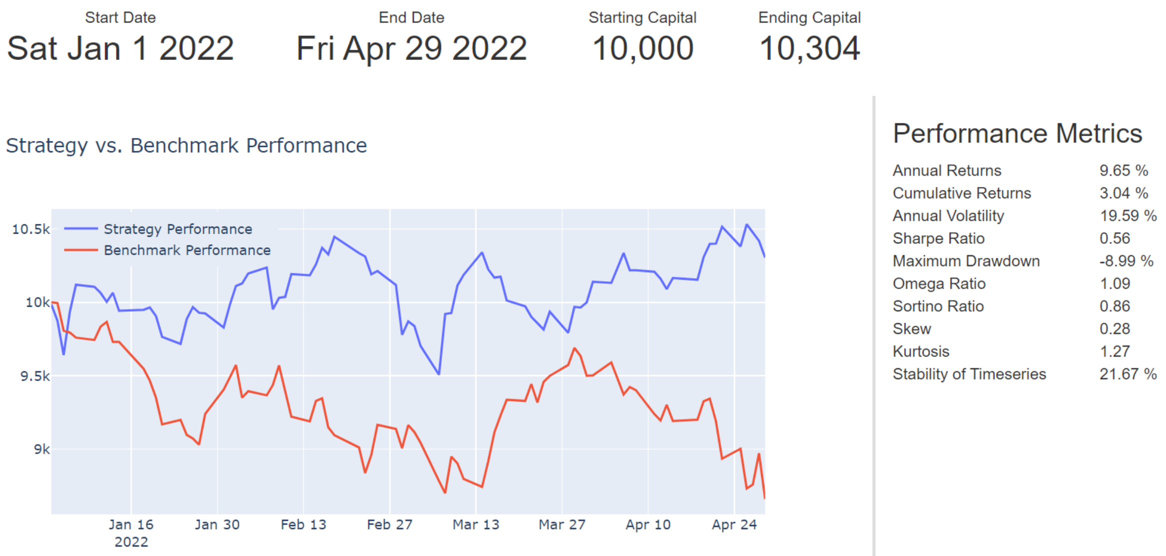


Figure 31

In this test run, the algorithm made both sales and purchases in a balanced manner, as it had in prior testing. A total of 70 transactions were initiated throughout the testing period. The overall number of trades increased significantly in this time period. Aside from that, the algorithm was largely operating as predicted.

In this test run the portfolio outperformed the benchmark, while also having a positive performance at the end. The cumulative returns yielded from this time period were 3,04%.

3.3. Summary of the experimentation

Experimentation with these algorithms and indicators was extremely interesting and educational. All of the strategies that were implemented, performed relatively well when considering the prevailing market conditions. However, a huge amount of trial and error was needed in order to get the algorithms functioning properly and to find the best possible combination of different variables to produce successful and efficient trading strategies.

Here is a table compiling the results from all of the final testing periods

Strategy	**Cumulative r**	**Sharpe ratio**	**Sortino ratio**	**MDD**
RSI+MACD	-16,93 %	-0,91	-1,2	-27,82 %
RSI+SMA	-8,80 %	-0,48	-0,67	-18,89 %
MACD+SMA	-7,32 %	-1,18	-1,55	-8,42 %

Figure 32

Every strategy managed to outperform the benchmark performance during the short testing periods. While the overall performance did actually go down in the final long test runs, still in three out of four tests the strategies managed to surpass the benchmark performance.

Most likely even a better way to implement these strategies would have been to program the algorithms from ground up by using the programming language python. The visual programming tools provided by Blueshift are very easy to use even if you do not have much experience with programming yourself. However, these visual programming tools have their weaknesses and limitations when it comes to more advanced features in algorithmic trading and technical analysis.

It seemed that the algorithms constructed by using the blueshift visual programming had some stability issues with certain assets and asset classes and also when trying to utilize considerably long lookback periods for various indicators. Various stability problems that were occurring, also prevented the use of even longer time periods, which could have potentially yielded some highly interesting and valuable results. These problems might be due to some kind of limitations on historical data in the datasets of the back testing function in Blueshift or some unknown bugs leading to errors when the time scale becomes large enough.

These problems can be seen as limitations when trying to implement more advanced algorithmic trading strategies. This being said, these problems were not decisive issues for the strategies implemented for this paper and blueshift still served its purpose well enough for this particular experiment.

4. Conclusion

Is technical analysis a successful tool for trade decision? To answer this question, the first thing that needs to be considered is the question if financial markets are completely random, or if they have any repeating patterns that could be taken advantage of in order to generate profit. If these patterns do not exist in the first place, then technical analysis cannot be a used to make successful trade decisions.

As time has gone by, there has been a constantly increasing number of studies conducted trying to find if these patterns actually exist. At the efficient market hypothesis was invented, it became widespread belief among finance professionals, that financial markets are not predictable in any way. After this there has been many people set out to see if this was actually the case and more modern research there has been bringing an increasing amount of evidence supporting the idea about repeating patterns.

There have been multiple research papers, also described in this bachelor thesis that have found convincing evidence about the existence of patterns in market data. Many researchers contribute these patterns to market psychology, like the adaptive market hypothesis, which is largely based on the principles from behavioural finance. The hypothesis states that, while market participants are mainly driven by their self-interest and are in principle making financial decisions based on rationality, still their judgement might become irrational under certain rapid and abnormal changes in the market conditions. This might have the effect that reinforces patterns in financial markets when large amount of market participants starts acting according to these psychological phenomena.

These ideas are further reinforced by the evidence gathered in collective research papers like “The profitability of technical analysis: a review” and “What do we know about the profitability of technical analysis”, which both uncovered results leaning quite heavily towards the conclusion that financial markets could actually be predictable and there is a possibility of using these predictions to generate efficient trade decisions.

It also should be considered that according to the findings of “The profitability of technical analysis: a review”, already in 2004, at least 30% to 40% of practitioners consider technical analysis to be an essential element in identifying price movement over shorter time periods of up to 6 months. If these methods did not have any value in the identification of price movements, they most likely would not be seen in a such widespread use.

The results with experimentation made using common technical analysis strategies and indicators in this bachelor thesis are also leaning towards the conclusion, that the markets have certain amount of predictability, even though the strategies were not always able to generate profit.

The final conclusion of the thesis is that technical analysis has its place in analysing financial markets. It might not be universally profitable in all financial environments or with all asset classes, but there is a significant amount of evidence that when used in a correct way and in correct trading environment it certainly is able to be used successfully. When it comes to profitability, it is highly probable, that if the user of the technical analysis is a finance professional, has sufficient amount of experience, or has the ability to use the right indicators and methods in a right context, considerable profits can be generated.

I would like to encourage more research and experimentation around this subject. It would be especially interesting to see the results of similar experimentation but with completely unique trading algorithms made with the programming language Python. In general, more information about the profitability of technical analysis is needed.

4.1. Reflection

As a project this subject was extremely interesting and researching this topic also was highly educational. There were a significant number of challenges along the way, but in the end almost everything worked out as it was expected. The biggest problems encountered were with the trading algorithms, which needed more work, time, and effort than was expected. This in turn led into some schedule issues. This should have been taken better into account right at the start by scheduling more time for the actual experimentation.

Most likely it would have been better to implement these strategies by programming these algorithms from ground up by using the programming language python. Even though the visual programming tools provided by Blueshift are very easy to use even if you do not have much experience with programming yourself. However, these visual programming tools have their weaknesses and limitations when it comes to constructing more advanced strategies.

I will most likely continue to apply what I have learned about technical analysis and algorithmic trading while writing this bachelor thesis and make more experimentation around the subject independently in the future.

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Figures

Figure 1. Own figure

Figure 2. Own figure

Figure 3. Own figure

Figure 4. Corporate finance institute. Nd. Bar charts (data visualisation and technical analysis). Available at: https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/bar-charts-data-visualization-and-technical-analysis/ [Accessed the 14th of December 2021]

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Appendix

1. Results from the research paper "The profitability of technical analysis: a review"

Table 1 Summary of early technical analysis studies published between 1961 and 1987

Study (Criteria:)	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Donchian (1960)	Copper futures / Daily	1959-60	Channel	Not considered	$51.50 per round-trip	The current price was compared to the two preceding week's ranges. This trading rule generated net gains of $3,488 and $1,390, on margin of $1,000, for a single contract of the December 1959 delivery of copper and the December 1960 delivery, respectively.
2. Alexander (1961)	S&P Industrials, Dow Jones Industrials / Daily	1897-1959, 1929-59	Filter (11 rules from 5.0 to 50%)	Buy & hold	Not adjusted	Trading rules with 5, 6, and 8% filters generated larger gross profits than the B&H (buy-and-hold) strategy. All the profits were not likely to be eliminated by commissions. This led Alexander to conclude that there were trends in stock market prices.
3. Houthakker (1961)	Wheat and corn futures / Daily	1921-39, 1947-56	Stop-loss order (11 rules from 0 to 100%)	Buy & hold, Sell & hold	Not adjusted	Most stop-loss orders generated higher profits than the B&H or a sell and hold strategy. Long transactions indicated better performance than short transactions.
4. Cootner (1962)	45 NYSE stocks / Weekly	1956-60	Moving average (1/200 days with and without a 5% band)	Buy & hold	Commissions of 1% per one-way transaction	Although net returns from moving average rules were not much different from those from the B&H strategy, long transactions generated higher returns than the B&H strategy. Moreover, the variance of the trading rule was 30% less than that of the B&H.
5. Gray & Nielsen (1963)	Wheat futures / Daily	1921-43, 1949-62	Stop-loss order (10 rules from 1 to 100%)	Buy & hold, Sell & hold	Not adjusted	When applying stop-loss order rules to dominant contracts, there was little evidence of non-randomness in wheat futures prices. They argued that Houthakker's results were biased because he used remote contracts and that post-war seasonality of wheat futures prices was induced by government loan programs.
6. Alexander (1964)	S&P Industrials / Daily	1928-61	Filter, Formula Dazhi, Formala Dafilt, moving average, and Dow-type formulas	Buy & hold	Commissions of 2% for each round-trip	After commissions, only the largest filter (45.6%) rule beat the B&H strategy by a substantial margin. Most of the other trading systems earned higher gross profits than filter rules or the B&H strategy. However, after commissions they could not beat the B&H.
7. Smidt (1965a)	May soybean futures contracts / Daily	1952-61	Momentum oscillator (40 rules)	Not considered	$0.36 per bushel per round-trip	About 70% of trading rules tested generated positive returns after commissions. Moreover, half of trading rules returned 7.5% per year or more.
8. Fama & Blume (1966)	30 individual stocks of the DJIA / Daily	1956-62	Filter (24 rules from 0.5 to 50%)	Buy & hold	0.1% per round-trip plus other costs	After commissions, only 4 of 30 securities had positive average returns per filter. Even before commissions, filter rules were inferior to the B&H strategy for all but two securities. Although three small filter rules (0.5, 1.0, and 1.5%) earned higher gross average returns (11.4%-20.9% per year) per security when considering only long positions, net returns after transaction costs were not much different from B&H returns
9. Levy (1967a)	200 NYSE stocks / Weekly	1960-65	Relative strength (Ratios: 1/4 and 1/26 weeks)	Geometric average	1% per one-way transaction	Net returns of several well-performing rules were nearly two or three times the return of the geometric average, although these rules possessed slightly higher standard deviations relative to the geometric average.
10. Levy (1967b)	200 NYSE stocks / Weekly	1960-65	Relative strength (Ratio: 1/26 weeks)	Not considered	1% per one-way transaction	Stocks having the historically strongest relative strength showed an average price appreciation of 9.6% over 26 weeks (about 20.1% per year). An annual price appreciation of all stocks was 12.8%. In general, stocks that had been both relatively strong and relatively volatile produced higher profits.
11. Poole (1967)	9 exchange rates / Daily	1919-29, 1950-62	Filter (10 rules from 0.1 to 2%)	Buy & hold	Not adjusted	Four of nine exchange rates had average annual gross returns more than 25% for the best filter rules, and three of them (Belgium, France, and Italy) generated returns above 44%. Filter rules beat the B&H strategy by large differences in returns.
12. Van Horne & Parker (1967)	30 NYSE stocks / Daily	1960-66	Moving average (100, 150, and 200 days with 0, 2, 5, 10, and 15% bands)	Buy & hold	Commissions charged by members of the NYSE	No trading rule earned a total closing balance nearly as large as that generated under the B&H strategy. Even before transaction costs, gross profits from each moving average rule were less than that from the B&H.
13. James (1968)	232 to 1376 stocks from the CRSP at the Univ. of Chicago / Monthly	1926-60	Moving average (7 months = 200 days with 2 and 5% bands)	Buy & hold	Not adjusted	Moving average rules could not beat the B&H strategy. The largest average dollar difference between the moving average rules and the B&H strategy was very small.
14. Van Horne & Parker (1968)	30 NYSE stocks / Daily	1960-66	Non-weighted and exponentially weighted moving averages (200 days with 0, 5, 10, and 15% bands)	Buy & hold	1% per one-way transaction	When applying trading rules to long positions, only 55 of 480 cases (16 different combinations of rules multiplied by 30 stocks) realized profits greater than those from the B&H strategy. For long plus short positions, a smaller number of trading rules (36 out of 480 cases) outperformed the B&H.
15. Jensen & Benington (1970)	29 portfolio samples of 200 NYSE stocks / Monthly	1931-65	Relative strength (2 rules from Levy (1967a))	Buy & hold	Actual round lot rate	After transaction costs, Levy's trading rules did not perform better than the B&H strategy. In fact, after explicit adjustment for the level of risk, the trading rules on average generated net returns less than the risk-adjusted B&H returns.

Study / Criteria:	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
16. Stevenson & Bear (1970)	July corn and soybean futures / Daily	1957-68	Stop-loss order, filter, and combination of both systems	Buy & hold	0.5 cents per bushel for both commodities	For all systems, a 5% filter rule worked best, which generated larger net profits or greatly reduced losses relative to the B&H strategy. The filter rule also outperformed B&H for both corn and soybean futures.
17. Dryden (1970a)	U.K. stock indices, Tesco Stores stock / Daily	1962-67, 1962-64	Filter (12 rules from 0.1 to 5%)	Buy & hold	Individual stock: 0.625% per one-way transaction	Without transaction costs, filter rules consistently beat the B&H strategy for both indices and an individual stock. With transaction costs, the returns from the best filter rules were similar to those from the B&H, but long transactions beat the B&H.
18. Dryden (1970b)	15 U.K. stocks / Daily	1963-64, 1966-67	Filter (14 rules from 0.2 to 6%)	Buy & hold	Not adjusted	There was considerable variation among individual stocks' returns. On average, filter returns were less than the corresponding B&H returns except for two smallest filter rules. However, returns only from long transactions were much higher than the B&H returns.
19. Levy (1971)	548 NYSE stocks / Daily	1964-69	32 forms of a five-point chart pattern	Buy & hold	2% per round-trip	After transaction costs, none of the 32 patterns for any holding period generated profits greater than average purchase or short-sale opportunities. Even the best-performing pattern produced adjusted relative-to-market returns of -1.1% and -0.1% for one-week and 4-week holding periods, respectively.
20. Leuthold (1972)	30 live cattle futures contracts / Daily	1965-70	Filter (1, 2, 3, 4, 5, and 10%)	Not considered	Commissions of $36 per round-trip	Four of six filters were profitable after transaction costs. In particular, a 3% filter rule generated an annual net return of 115.8% during the sample period.
21. Martell & Philippatos (1974)	September wheat and September soybean futures contracts / Daily	1956-69 (1958-70)*	Adaptive filter model and pure information model	Buy & hold / Optimized trading rules	Adjusted but not specified	As an optimal filter size for period t, the adaptive model utilizes a filter size which has yielded the highest profits in t-1, subject to some minimum value of the average relative information gain. The pure information model chooses as an optimal filter size in period t the one with the highest relative average information gain in period t-1. Both models yielded higher net returns than the B&H only for wheat futures. However, the variance in net profits was consistently smaller than that of the B&H in both markets.

Study / Criteria:	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
22. Praetz (1975)	Sydney wool futures / Daily	1965-72	Filter (24 rules from 0.5 to 25%)	Buy & hold	Not adjusted	For 12 of all 21 contracts of 18-month length and all three 8-year price series, the B&H strategy showed better performance than filter rules, with average differences of 0.1% and 2%, respectively. For the same data set, in 10 of 24 filters the B&H returns were greater than average filter returns. Thus, filter rules did not seem to out perform the B&H strategy consistently.
23. Martell (1976)	September wheat and September soybean futures contracts / Daily	1956-69 (1958-70)*	Adaptive filter models and pure information model	Buy & hold / Optimized trading rules	Adjusted but not specified	A new adaptive model was developed and applied to the same data set as that used in Martell and Philippatos (1974). The new model selects its optimal filter size for next period based on profitability (e.g., the highest cumulative net profits) and information gain. Although the model outperformed the previous adaptive model for around 80% of the sample period, it neither indicated any stability with respect to the information constraint nor beat the pure information model that allows a filter size in a particular period to reflect new information.
24. Akemann & Keller (1977)	Industry groups from S&P 500 Stock Index / Weekly	1967-75	Relative strength	S&P 500 Index	2% per round-trip	The relative strength rule is designed to buy the strongest stock group in a given thirteen-week period and sell it after 52 weeks. After adjustment for transaction costs, the mean return differential between all 378 possible trials and the market index appeared to be 14.6%, although the differentials were quite volatile.
25. Logue & Sweeney (1977)	Franc/dollar spot exchange rate / Daily	1970-74	Filter (14 rules from 0.7 to 5%)	Buy & hold	0.06% per one-way transaction	Most trading rules (13 out of 14 rules) outperformed the B&H strategy after considering transaction costs. Compared to the buy and hold and invest in French government securities strategy, only four filters failed to generate higher profits.
26. Cornell & Dietrich (1978)	6 spot foreign currencies (mark, pound, yen, Canadian dollar, Swiss franc, and Dutch guilder) / Daily	1973-75	Filter (13 rules from 0.1 to 5%), and moving average (10, 25, and 50 days with 0.1 to 2% bands)	Buy & hold	Computed by using the average bid-ask spread for all trades.	For the Dutch guilder, German mark, and Swiss franc, the best rules from each trading system generated over 10% annual net returns. Although the net returns were relatively small (1% to 4%) for the British pound, Canadian dollar, and Japanese yen, they all beat the B&H strategy. Moreover, since none of the systematic risk (beta) estimates exceeded 0.12, high returns of the three currencies were less likely to be compensation for bearing systematic risk.
27. Logue, Sweeney, & Willett (1978)	7 foreign exchange rates / Daily	1973-76	Filter (11 rules from 0.5 to 15%)	Buy & hold	Not adjusted	For every exchange rate (the mark, pound, yen, lira, France franc, Swiss franc, and Dutch guilder), profits from the best filter rules exceeded those from the B&H strategy by differences ranging from 9.3% to 32.9%.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
28. Arnott (1979)	500 stocks from both the S&P 500 Index and the NYSE Composite Index / Weekly	1968-77	Beta-modified relative strength	Not considered	Not adjusted	Regression results indicated that for the base periods of 1 week to 18 weeks, the correlation between the change in (beta-adjusted) relative strength during the base period and that during any subsequent period was strongly negative. Hence, careless use of relative strength might lead to serious money loss.
29. Dale & Workman (1980)	90-day T-bill futures at the IMM / Daily	1976-78	Moving average (11 rules from 5 to 60 days)	Not considered	$60 per round-trip	For each individual contract, the best trading rules generated positive net returns, although the rules did not indicate consistent performances over the sample period.
30. Bohan (1981)	87 to 110 S&P industry groups / Weekly	1969-80	Relative strength	Buy & hold on S&P 500 Index	2% per year	There was a strong correlation between the performance of the strongest and weakest industry groups in one year and that of the following years, although the performance of the other groups did not have much predictive significance. For example, quintile 1 portfolio, which consists of the top 20% of industry groups, generated a return of 76% higher than the B&H on the market index, while the market outperformed quintile 5 portfolio by 80%.
31. Solt & Swanson (1981)	Gold from London Gold Market and silver from Handy & Harman / Weekly	1971-79	Filter (0.5 to 50%) and moving average (26, 52, and 104 weeks with fiters)	Buy & hold	1.0% per one-way transaction plus 0.5% annual fees	For gold, a 10% filter rule outperformed the B&H strategy after adjustment for transaction costs. However, none of the filter rules dominated the B&H strategy for either gold or silver. Moving average rules were not able to improve the returns for the filter rules as well.
32. Peterson & Leuthold (1982)	7 hog futures contracts from CME / Daily	1973-77	Filter (10 rules from 1 to 10% and additional 10 rules from $0.5 to $5)	Zero mean profit	Not adjusted	All 20 filter rules produced considerable mean gross profits. It seemed that these profit levels exceeded any reasonable commission charges in most cases. In general, mean gross profits increased with larger filters, as did variance of profits.
33. Dooley & Shafer (1983)	9 foreign currencies in the New York market / Daily	1973-81	Filter (7 rules from 1 to 25%)	Not considered	Adjusted but not specified	Although results were slightly different for each currency, small filter rules (1, 3, and 5%) generally produced high profits, while larger filter rules showed consistent losses.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
34. Brush & Boles (1983)	168 S&P 500 stocks / Monthly	1967-80, (two data bases were used for out-of-sample tests)	Relative strength (parameters were optimized on the development data base over 26 separate 6-month test periods)	Equal-weighted 168-stock return / Optimized models	2% per round-trip	The top decile annualized excess return of the best model was 7.1% per year over the equal-weighted 168-stock return, after adjustment for risk, dividend yield, and transaction costs. The model also produced a compounded growth of 15.2% per year after considering dividend yield and transaction costs, compared to 5.9% for the S&P 500.
35. Irwin & Uhrig (1984)	8 commodity futures: corn, cocoa, soybeans, wheat, sugar, copper, live cattle, and live hogs / Daily	1960-78 (1979-81)*, 1960-68 (1969-72)*, 1973-78 (1979-81)*	Channel, moving averages, momentum oscillator	Zero mean profit / Optimized trading rules	Doubled commissions to capture bid-ask spread (not specified)	Trading rule profits during in-sample periods were substantial and similar across all four trading systems. Out-of-sample results for optimal trading rules also indicated that during the 1979-81 period most trading systems were profitable in corn, cocoa, sugar, and soybean futures markets. The trading rule profits appeared to be concentrated in the 1973-81 period.
36. Neftci & Policano (1984)	4 futures: copper, gold, soybeans, and T-bills / Daily	1975-80	Moving average (25, 50, and 100 days) and slope (trendline) method	Not considered	Not adjusted	Trading signals were incorporated as a dummy variable into a regression equation for the minimum mean square error prediction. Then the significance of the dummy variable was evaluated using F-tests. Overall, moving average rules indicated some predictive power for T-bills, gold, and soybeans, while the slope method showed mixed results.
37. Tomek & Querin (1984)	3 random price series (each series consists of 300 prices) generated from corn prices for each sample period / Daily	1975-80, 1973-74, 1980	Moving average (3/10 and 10/40 days)	Not considered	$50 per round-trip	From each of three random prices series, 20 sets of prices were replicated. The first 20 sets had moderate price variability, the second set large price variability, and the third set drift in prices. Both trading rules failed to generate positive average net profits for all three groups with an exception of the 10/40 rule for the relatively volatile price group. The results imply that technical trading rules may earn positive net returns by chance, although they on average could not generate positive net profits.
38. Bird (1985)	Cash and forward contracts of copper, lead, tin, and zinc from London Metal Exchange (LME) / Daily	1972-82	Filter: long positions (and cash profits) (25 rules from 1 to 25%)	Buy & hold	1% per round-trip	For cash and forward (futures) copper, over 2/3 of filter rules beat the B&H strategy. Similar results were obtained for lead and zinc but with weaker evidence. For tin, the results were inconsistent. Filter rules performed substantially better in the earlier period (1972-77).

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
39. Brush (1986)	420 S&P 500 stocks / Monthly	1969-84	Relative strength	Return of the equal-weighted S&P 500 Index	1% per round-trip	By avoiding the year-end effect and exploiting beta corrections and the negative predictive power of one-month trends, the best model, which was the generalized least squares beta approach, generated an annual excess return of more than 5% over the equal-weighted S&P 500, after transaction costs.
40. Sweeney (1986)	Dollar/mark and additional 9 exchange rates / Daily	1973-75 (1975-80)*	Filter: long positions (7 rules from 0.5 to 10%)	Buy & hold / Optimized trading rules	1/8 of 1% of asset value per round-trip	Both in- and out-of-sample tests, small filter rules (0.5% to 5%) consistently beat the B&H strategy, and transaction costs did not eliminate the risk-adjusted excess returns of filter rules. Eight filter rules across 6 exchange rates produced statistically significant excess returns over the B&H in both in- and out-of sample periods.
41. Taylor (1983, 1986)	London agricultural futures: cocoa, coffee, and sugar, Chicago IMM currency futures: sterling, mark, and Swiss franc / Daily	1971-76 (1977-81)*, 1961-73 (1974-81)*, 1974-78 (1979-81)*	A statistical price-trend model	Buy & hold and interest rate for bank deposit / Optimized trading rules	1% per round-trip for agricultural futures and 0.2% for currency futures	Taylor (1986) adds one more out-of-sample year (i.e., 1981) to the sample period in his 1983's work. For sugar, an average net return of the trading rule was higher than that of the B&H strategy by 27% per annum. For cocoa and coffee, returns from both the trading rule and the B&H were not much different. Trading gains for currencies during 1979-80 were negligible, but in 1981 all currencies generated substantial gains of around 7% higher than the bank deposit rate.
42. Thompson & Waller (1987)	Coffee and cocoa futures in the NY Coffee, Sugar, and Cocoa Exchange / 6 weekly sets of transaction-to-transaction prices for each market	1981-83	Filter (for coffee, 5¢ through 35¢ in multiples of 5¢ per 100 lb; for cocoa, $1 through $7 per metric ton)	Not considered	Estimated execution costs	For both nearby and distant coffee and cocoa contracts, filter rules generated average profits per trade per contract substantially lower than estimated execution costs per contract in all cases in which profits were statistically significantly greater than zero. The estimated execution costs per trade per contract were $32.25 (nearby) and $69.75 (distant) for coffee futures contracts and $12.60 (nearby) and $21.80 (distant) for cocoa futures contracts.

Table 3 Summary of standard technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Lukac, Brorsen, & Irwin (1988)	12 futures from various exchanges: agriculturals, metals, currencies, and interest rates / Daily	1975-83 (1978-84)	12 systems (3 channels, 3 moving averages, 3 oscillators, 2 trailing stops, and a combination)	Zero mean profit / Optimized trading rules	$50 and $100 per round-trip	Out-of-sample results indicated that4 of 12 systems generated significant aggregate portfolio net returns and 8 of the 12 commodities earned statistically significant netreturns from more than one trading system. Mark, sugar, and corn markets appeared to be most profitable during the sample period. In addition, Jensen test confirmed that the same four trading systems having large net returns still produced significant net returns above risk.
2. Lukac & Brorsen (1989)	15 futures from various exchanges: agricultural commodities, metals, currencies, and interest rates / Daily	1965-85 (various)	Channel and directional movement (both systems had 12 parameters ranging 5 days to 60 days in increments of 5)	Buy & hold / Optimized trading rules	$100 per round-trip	Technical trading rule profits were measured based on various optimization methods, which included 10 re-optimization strategies, one random strategy, and 12 fixed parameter strategies. The two trading systems generated portfolio mean net returns significantly greater than the B&H strategy. However, the trading systems yielded similar profits across different optimization strategies and even different parameters. Thus, the parameter optimization appeared to have little value.
3. Sweeney & Surajaras (1989)	An equally-weighted portfolio and a variably-weighted portfolio of currencies / Daily	Prior 250-to 1400-day prices (1980-86)	Filter, single moving average, double moving average, and the best system	Buy & hold / Optimized trading rules	Adjusted but not specified	Most trading systems generated risk-adjusted mean net profits after transaction costs, and the single moving average rule performed best. The variably-weighted portfolio approach generally outperformed the equally-weighted approach. Changing neither parameters for each trading system on a yearly basis nor amounts of data used to select optimal parameters seem to improve trading profits.
4. Taylor & Tari (1989)	IMM currency futures: pound, mark, and Swiss franc; London agricultural futures: cocoa, coffee, and sugar / Daily	1974-78 (1979-87); (1982-85)	A statistical price-trend model	Buy & hold, Zero mean profit / Optimized trading rules	Currency futures: 0.2% per round-trip; Agricultural futures: 1%	During the out-of-sample period, 1979-87, the trading rule earned aggregate mean net return of 4.3% per year for three currency futures. The mark was the most profitable contract (5.4% per year). From 1982-85, the trading rule generated a mean net return of 4.8% for cocoa, -4.26% for coffee, and 18.8% for sugar, outperforming the B&H strategy for cocoa and sugar futures.
5. Lukac & Brorsen (1990)	30 futures from various exchanges: agriculturals, metals, oils, currencies, interest rates, and S&P 500 / Daily	1975-85 (1976-86)	23 systems (channels, moving averages, oscillators, trailing stops, point and figure, a counter-trend, volatility, and combinations)	Zero mean profit / Optimized trading rules	$50 and $100 per round-trip	Only 3 of 23 trading systems had negative mean monthly portfolio net returns after transaction costs, and 7 of 23 systems generated net returns significantly above zero at 10% level. Most of the trading profits appeared to be made over the 1979-80 period. In the individual commodity markets, currency futures produced the highest returns, while livestock futures yielded the lowest returns.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
6. Taylor (1992)	4 currency futures from IMM of the CME: pound, mark, yen, and Swiss franc / Daily	1977-87 (1982-87)	3 technical trading systems (filter, channel, moving average), 2 statistical price-trend models	Buy & hold / Optimized trading rules	0.2% per round-trip	All trading rules outperformed the B&H strategy across all currency futures. Among trading rules, three technical trading systems and a revised statistical trend model generated statistically significant and much higher mean net returns (3.0% to 4.0%) than that (2.0%) of the original price-trend model for most currencies. These returns could not be explained by nonsynchronous trading or time-varying risk premia.
7. Farrell & Olszewski (1993)	S&P 500 futures / Daily	1982-90 (1989-90)	A nonlinear trading strategy based on ARMA (1,1) model and 3 trend-following systems (channel and volatility systems)	Buy & hold / Optimized trading rules	0.025% per round-trip	Although the nonlinear trading strategy were slightly more profitable than the B&H strategy, the result was statistically insignificant. For the in-sample period, the nonlinear optimal trading strategy was more profitable than the B&H by nearly 5%, while for the out-of-sample period, the trading strategy was better by 3%. Meanwhile, the three trend following strategies were more profitable than the nonlinear trading strategy by around 5% to 11% during the out-of-sample period, depending on the trading strategy.
8. Silber (1994)	12 futures markets: foreign currencies, short-term interest rates, metals, oil, and S&P 500 / Daily	1979 (1980-91)	Moving average (short averages: 1 day to 15 days; long averages: 16 to 200 days)	Buy & hold (& roll over) / Optimized trading rules	Bid-ask spreads per round-trip (2 ticks for crude oil and gold; 1 tick for the rest of contracts)	After transaction costs, average annual net returns were positive for all contracts but gold, silver, and the S&P 500. In particular, most currency futures earned higher net profits (1.9% to 9.8%). For those profitable markets, moving average rules beat the B&H strategy except for 3-month Eurodollars. Test results using a Sharpe ratio criterion were similar. Hence, trading profits appeared to be robust to transaction costs and risk. Central bank intervention is one of possible explanations for the trading profits.
9. Taylor (1994)	4 currency futures from IMM: pound, mark, yen, and Swiss franc / Daily	1980-all previous contracts (1982-90)	Channel	Zero mean profits / Optimized trading rules	0.2% per one-way transaction	For price series generated by ARIMA(1,1,1) model, channel rules correctly identified the sign of conditional expected returns with around 60% probability. During 1982-90, optimal channel rules produced an average net return of 6.9% per year. The t-test indicated that the return was significant at the 2.5% level. The best trading opportunities occurred for 1985-87.
10. Menkhoff & Schlumberger (1995)	3 spot exchange rates: mark/dollar, mark/yen, and mark/pound / Daily	1981-91, 1981-85 (1986-91)	Oscillator (33 moving averages) and momentum (10 rules from 5 to 40 days)	Buy & hold / Optimized trading rules	0.0008 DM for 1$; 0.0017 DM for 1 yen; 0.003 DM for 1 BP per round-trip	During the out-of-sample period, 84% out of 129 technical trading rules tested outperformed the B&H strategy across exchange rates, after adjustment for transaction costs and risk. However, superiority of optimal trading rules during the in-sample period deteriorated in the out-of-sample period, even though they still outperformed the B&H strategy.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
11. Lee & Mathur (1996a)	6 European currency spot cross-rates / Daily	1988-92 (1989-93)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10, 15, 20, 25, and 30 days)	Zero mean profits / Optimized trading rules	0.1% per round-trip	Results of in-sample tests indicated that the trading rules did not yield significantly positive returns for all cross rates but yen/mark and yen/Swiss franc (11.5% and 8.8% per year, respectively). Out-of-sample results were even worse. Most cross rates earned negative trading returns, although long positions for the yen/mark produced marginally significant positive returns.
12. Lee & Mathur (1996b)	10 spot cross-rates / Daily	1988-92 (1989-93)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10, 15, 20, 25, and 30 days) and channel (2 to 50 days)	Zero mean profits / Optimized trading rules	0.1% per round-trip	During in-sample periods, moving average rules in general produced negative or statistically insignificantly positive net returns exceptthe mark/yen (11.5% per year) and the Swiss franc/yen (8.8% per year). Similar results were found for channel rules. During out-of-sample periods, overall returns of the trading rules were negative or statistically insignificantly positive. Only for the mark/lira, both long positions of moving average rules and channel rules generated statistically significant profits.
13. Szakmary & Mathur (1997)	5 IMM foreign currency futures and spots: mark, yen, pound, Swiss franc, and Canadian dollar / Daily	1977-90 (1978-91)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10, 15, 20, 25, and 30 days)	Zero mean profits / Optimized trading rules	0.1% per round-trip	In-sample results indicated that moving average rules generated both statistically and economically significant returns for all currency futures but the Canadian dollar. Similar results were reported for both out-of-sample data (annual net returns ranged from 5.5% to 9.6%) and spot rates. Further analyses showed that the moving average rule profits resulted from the central bank's "leaning against the wind intervention."
14. Goodacre, Bosher, & Dove (1999)	254 companies in the FTSE 350 Index and 64 option trades in the U.K. / Daily	Prior 200 days (1988-96)	CRISMA (combination system of **C**umulative volume, **R**elat**I**ve **S**trength, and **M**oving **A**verage)	FTSE All Share Index / Optimized parameters	0 to 2% per round-trip	The CRISMA trading system generated annualized profits ranging 6.9% to 19.3% depending on transaction costs, while an annualized return on the FTSE All Share Index over the same time period was 14.0%. When adjusted for market movements and risk, however, mean excess returns for nonzero levels of transaction costs were significantly negative. Moreover, performance of the trading system was not stable over time. With option trading, the system generated mean return of 10.2% per trade even in the presence of maximum retail costs, but only 55% of trades were profitable.
15. Kwan, Lam, So, & Yu (2000)	Hang Seng Index Futures / Daily	1986-97 (1990-98)	A statistical price-trend model	Buy & hold / Optimized parameters	0.4 to 0.5% per one-way transaction	The price-trend model performed poorer than the B&H strategy in the periods 1991-93 and 1995-96 when the market was bullish. However, the trading rule produced larger profits than the B&H in the years, 90, 94, 97, and 98 when the market became up and down. Across all years and transaction costs considered, an average net return (10.1%) of the trading rule was slightly smaller than that (13.5%) of the B&H strategy.

Study / Criteria:	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
16. Maillet & Michel (2000)	12 exchange rates (combinations of U.S. dollar, mark, yen, pound, and France franc) / Daily	1974-79 (1979-96)	Moving average (short moving averages: 1 day to 14 days; long moving averages: 15 to 200 days)	Zero mean profits, buy & hold / Optimized trading rules	Not adjusted	Optimized moving average rules generated statistically significant returns and outperformed the corresponding B&H strategies with the exception of the mark/franc rate. Bootstrap tests generally confirmed the results with the rejection of higher returns only in 4 out of 12 rates: the mark/dollar, mark/franc, yen/dollar, and yen/franc. Moreover, riskiness of both moving average rules and the B& H strategy, which was measured by their standard deviations, appeared to be not much different.
17. Taylor (2000)	1) Financial Times (FT) All-Share index; 2) UK 12-share index; 3) 12 UK stocks; 4) FT 100 index and index futures; 5) DJIA index; 6) S&P 500 index and index futures / Daily	1), 2), and 3): 1972-91; 4): 1985-94; 5): 1897-1988; 6): 1982-92	Moving average (short moving averages: 1, 2, and 5 days; long moving averages: 50, 100, 150, and 200, with and without a 1% band)	/ Parameters are optimized for the DJIA data from 1897 to 1968.	Not adjusted	The results of optimized moving average rules indicated that differences of mean returns between buy and sell positions were substantially positive and statistically significant for the FT A index, all versions of the 12-share index, 4 of the 12 UK firms, and the DJIA index for 3 out of 5 subperiods. No significant results were found for the FTSE 100 and S&P 500 indices. Buy positions also appeared to have lower standard deviations than sell positions for all but two series. An average breakeven one-way transaction cost across all data series was 0.35%. In particular, for the DJIA index, a trading rule (a 5/200 moving average rule) optimized over the 1897-1968 period produced a breakeven one-way transaction cost of 1.07% during the 1968-88 period.
18. Goodacre & Kohn-Spreyer (2001)	A random sample of 322 companies from the S&P 500 / Daily	Prior 200 days (1988-96)	CRISMA (combination system of Cumulative volume, Relative Strength, and Moving Average)	The S&P 500 Index / Optimized parameters	0 to 2% per round-trip	The CRISMA system generated annualized profits ranging 6.2% to 17.6% depending on transaction costs, while the annualized return on the S&P 500 Index over the same time period was 14.2%. However, when adjusted for market movements and risk, mean excess returns for nonzero levels of transaction costs were significantly negative across all return-generating models. Moreover, the results were not stable over time, although trades on larger firms generally performed better than small ones.
19. Lee, Gleason, & Mathur (2001)	13 Latin American spot currencies / Daily	1992-99 (various periods from data available)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10 to 30 days) and channel (2 to 50 days)	Zero mean profits / Optimized trading rules	0.1% per round-trip	Out-of-sample results showed that moving average rules generated significantly positive returns for currencies of four countries: Brazil, Mexico, Peru, and Venezuela. Channel rules also produced significant profits for the same currencies except that of Peru. When only long positions were considered, there was a marginal improvement to five and four currencies for moving average rules and channel rules, respectively.

Study / Criteria:	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
20. Lee, Pan, & Liu (2001)	9 exchange rates from Asian countries	1988-94 (1989-95)	The same trading rules as in Lee, Gleason, & Mathur (2001)	Zero mean profits / Optimized trading rules	0.1% per round-trip	Out-of-sample tests indicated that four exchange rates from Korea, New Zealand, Singapore, and Taiwan yielded positive profits for both moving average rules and channel rules. However, these profits were not significantly different from zero, except that of the Taiwan dollar.
21. Martin (2001)	12 currencies in developing countries / Daily	1/92-6/92 (7/92-6/95)	Moving average (short moving averages: 1 day to 9 days; long moving averages: 10 to 30 days)	Short-selling strategy / Optimized trading rules	0.5% per one-way transaction	Out-of-sample, moving average rules generated positive mean net returns in 10 of 12 currencies, and the returns were greater than 0.14% daily (35% per year) in 5 currencies. However, Sharpe ratios indicated that moving average rules did not generate superior returns on a risk-adjusted basis.
22. Skouras (2001)	Dow Jones Industrial Average (DJIA) / Daily	1962-86 (1962-86)	Moving average (2 to 200 days with bands of 0, 0.5, 1, 1.5, and 2%)	Buy & hold / Optimized trading rules	Various levels from 0 to 0.1% per one-way transaction	Out-of-sample returns were estimated on a daily basis. Time-varying estimated rules (by an Artificial Technical Analyst) outperformed various fixed moving average rules employed by Brock et al. (1992) as well as the B&H strategy. When considering transaction costs, however, mean returns from the optimized trading rule were higher than the B&H mean return only after transaction costs of less than 0.06%.
23. Olson (2004)	18 exchange rates / Daily	5-year in-sample period from 1971-2000 (1976-2000)	Moving average (short moving averages: 1 day to 12 days; long moving averages: 5 to 200 days)	Buy & hold / Optimized trading rules	0.1% per round-trip	Out-of-sample results indicated that risk-adjusted trading profits for individual currencies and an equal-weighted 18-currency portfolio declined over time. For the 18-currency portfolio, annualized risk-adjusted returns decreased from an average of over 3% in the late 1970s and early 1980s to about zero percent in the late 1990s. Overall, profits of moving average rules in foreign exchange markets have declined over time.

Table 4 Summary of model-based bootstrap technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Brock, Lakonishok, & LeBaron (1992)	Dow Jones Industrial Average (DJIA) / Daily	1897-1986	Moving averages (1/50, 1/150, 5/150, 1/200, and 2/200 days with 0 and 1% bands) and trading range breakout (50, 150 and 200 days with 0 and 1% bands)	Unconditional 1- and 10-day returns	Not adjusted	Before transaction costs, buy (sell) positions across all trading rules consistently generated higher (lower) mean returns than unconditional mean returns, and these results were highly significant in most cases. For example, a mean buy return from variable moving average rules was about 12% per year and a mean sell return was about -7%. Moreover, the buy returns were even less volatile than the sell returns. Simulated series from a random walk with a drift, AR (1), GARCH-M, and EGARCH models using a bootstrap method could not explain returns and volatility of the actual Dow series.
2. Levich & Thomas (1993)	5 IMM currency futures: mark, yen, pound, Canadian dollar, and Swiss franc / Daily	1976-90	Filters (0.5, 1, 2, 3, 4, and 5%) and moving average (1/5, 5/20, 1/200 days)	Buy & hold	0.025% and 0.04% per one-way transaction	After adjustment for transaction costs and risk, every filter rule and moving average rule generated substantial positive mean net returns for all currencies but the Canadian dollar. Moreover, the results of the bootstrap simulation indicated that, for both trading systems, the null hypothesis that there is no information in the original time series was rejected in 25 of 30 cases.
3. Bessembinder & Chan (1995)	Asian stock indices: Hong Kong, Japan, Korea, Malaysia, Thailand, and Taiwan / Daily	1975-91	The same trading rules as in Brock et al. (1992)	Buy & hold	0.5, 1, and 2% per round-trip	Across all markets and trading rules tested, average mean returns on buy days exceeded those on sell days by 26.8% per year, and an average break-even round-trip transaction cost for the full sample was 1.57%. In particular, technical signals generated by the U.S. markets appeared to have substantial forecast power for returns in the Asian markets. Overall, trading rules generated higher net profits (12.2% to 21.2% per year) in the Malaysia, Thailand, and Taiwan stock markets.
4. Hudson, Dempsey, & Keasey (1996)	Financial Times Industrial Ordinary Index (FT30) in the U.K. / Daily	1935-94	The same trading rules as in Brock et al. (1992)	Unconditional mean returns	More than 1% per round-trip for large investing institutions	Before transaction costs, buy (sell) positions across all trading systems consistently generated higher (lower) returns than unconditional returns. However, an extra return per round-trip transaction averaged across all systems appeared to be about 0.8%, which was relatively smaller than the round-trip transaction costs of 1%.
5. Kho (1996)	4 currency futures from IMM: pound, mark, yen, and Swiss franc / Weekly	1980-91	Moving average (1/20, 1/30, 1/50, 2/20, 2/30, 2/50 weeks with bands of 0 and 1%)	Unconditional weekly mean return, Univariate GARCH-M	Not adjusted	Initially, moving average rules generated substantial mean returns between 9.9% and 11.1% per year from buy signals. These trading returns could not be explained by the empirical distribution of the univariate GARCH-M model as well as transaction costs or serial correlations in futures returns. However, the returns appeared to be insignificant when time-varying risk premia, which were estimated from a general model of the conditional CAPM, were taken into account.
6. Raj & Thurston (1996)	Hang Seng Futures Index of Hong Kong / Daily	1989-93	The same trading rules as in Brock et al. (1992), without 1/150 and 2/200 moving average rules	Unconditional mean returns	Not adjusted	Without considering transaction costs, average buy returns generated from both trading systems were much higher than the unconditional one-day mean. In particular, the trading range breakout system generated significantly higher annual returns (457% to 781%) in four out of six rules relative to that (39%) of the B&H strategy. On the other hand, average sell returns obtained from both systems were negative.
7. Mills (1997)	Financial Times–Institute of Actuaries 30 (FT30) index in the London Stock Exchange / Daily	1935-94: 1935-54, 1955-74, 1975-94	The same trading rules as in Brock et al. (1992)	Unconditional mean daily return	Not adjusted	For moving average rules, each mean daily buy-sell return difference (0.081% and 0.097%) for 1935-54 and 1955-74 was much greater than corresponding unconditional mean returns (0.013% and 0%). For the latest subperiod, 1975-94, however, the mean buy-sell difference was insignificantly different from the unconditional return. Trading range breakout rules showed similar results. None of simulated series generated by AR-ARCH bootstraps earned mean buy-sell differences larger than the actual difference.
8. Bessembinder & Chan (1998)	Dow Jones Industrial Average (DJIA) / Daily	1926-91: 1926-43, 1944-59, 1960-75, 1976-91	The same trading rules as in Brock et al. (1992)	Buy & hold	Various estimates for NYSE stocks	The DJIA data in this study includes dividend payments. Over the full sample period, an average buy-sell return difference across all 26 trading rules was 4.7%, generating a break-even one-way transaction cost of 0.39%. However, break-even transaction costs have declined over time with 0.22% for the most recent subperiod (1976-91). It was compared with an estimated transaction cost of 0.25%.
9. Ito (1999)	6 national equity market indices (Japan, U.S. Canada, Indonesia, Mexico, Taiwan), Dow Jones index, Nikkei index futures / Daily	1980-96 for developed markets, 1988-96 for emerging markets	The same trading rules as in Brock et al. (1992)	Buy & hold	Nikkei index futures: 0.11% per round-trip; other equity indices: 0.69-2.21%	After transaction costs, technical trading rules outperformed the B&H strategy for all indices but U.S. indices, and generated higher profits for emerging markets (Indonesia, Mexico, Taiwan) than for developed markets. The trading profits could not be explained by nonsynchronous trading. However, some conditional asset pricing models (in particular, the asset pricing model under mild segmentation) were able to explain trading rule profits for Japan, the U.S., the second subperiod of Canada, and Taiwan stock indices. These results suggest that technical trading profits were a fair compensation for risk of trading rules.
10. LeBaron (1999)	2 foreign currencies from the London close: mark and yen / Daily and weekly	1979-92	Moving average (1/150 days or 1/30 weeks)	Sharpe ratio for buying and holding on U.S. stock portfolios	Commissions (0 to 0.5%) and bid-ask spread (0.15%) per round-trip	Mean returns of the trading rule for the two currencies were statistically significantly different from zero. Their Sharpe ratios (0.60 to 0.98) were also higher than those (0.3 or 0.4) for the B&H on U.S. stock portfolios even after adjustment for a transaction cost of 0.1% per round-trip. In general, interest differentials and transaction costs did not alter the result greatly. However, trading returns were dramatically reduced when active intervention periods of the Federal Reserve were eliminated.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
11. Ratner & Leal (1999)	10 equity indices in Asia and Latin America / Daily	1982-95	Moving average (1/50, 1/150, 5/150, 1/200, and 2/200 days with bands of zero and one standard deviation)	Buy & hold	Various costs from 0.15 to 2.0% per one-way transaction	After transaction costs, 21 out of 100 trading rules that were applied to the 10 indexes generated statistically significant returns (18.2% to 32.1% per year), with the profitability concentrated in four markets: Mexico, Taiwan, Thailand, and the Philippines. When statistical significance was ignored, however, 82 out of the 100 rules appeared to have forecasting ability in emerging markets.
12. Coutts & Cheung (2000)	Hang Seng Index on the Hong Kong Stock Exchange / Daily	1985-97	The same trading rules as in Brock et al. (1992)	Unconditional mean returns	Not adjusted	Across all trading rules tested, buy (sell) signals generated significantly higher (lower) mean returns than unconditional mean returns. In particular, buy (sell) signals of the trading range breakout system earned substantial average 10-day cumulative return of 1.6% (-5%), which was higher (lower) than that of the moving average system.
13. Parisi & Vasquez (2000)	Santiago stock index / Daily	1987-98	The same trading rules as in Brock et al. (1992)	Unconditional mean returns	1% per one-way transaction	Across trading rules, mean returns on buy signals were consistently higher than those on sell signals or unconditional mean returns. In fact, sell signals yielded negative mean returns for most trading rules. Although variable-length moving average rules generated significant returns, it was unlikely that these rules were profitable if high transaction costs were taken into account.
14. Raj (2000)	Yen and mark traded in Singapore International Monetary Exchange / Intra-daily	01/1992-12/1993	Filter, moving average, and channel	Buy & hold	0.04% per one-way transaction	None of technical trading rules except one rule (2/200 moving average rule with a 1% band) generated statistically significant returns after adjustment for transaction costs and risk. However, some trading rules appeared to produce economically significant returns. For instance, for the mark a 1/50 moving average rule with a 1% band generated a risk-adjusted net return of 8.8% over the two-year period.
15. Gunasekarage & Power (2001)	4 South Asian stock indices: Bombay, Colombo, Dhaka, and Karachi stock exchanges / Daily	1990-2000	Moving averages (1/50, 1/100, 1/150, 1/200, 2/100, 2/150, 2/200, 5/200, and 1/50 with 1% band)	Buy & hold	Not adjusted	For variable moving average rules, buy signals generated positive returns of more than 44.2% per year and sell signals generated negative returns of less than -20.8% per year. These returns, on average, were significantly different from the B&H returns. Similar results were obtained for fixed-length moving average rules with 10-day holding periods.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
16. Day & Wang (2002)	Dow Jones Industrial Average (DJIA) / Daily	1962-96	Moving average (1/50 and 1/150 days with 0 and 1% bands) and trading range breakout (50 and 150 days with 0 and 1% bands)	Buy & hold	0.05% per one-way transaction	Variable-length moving average rules generated daily excess returns of more than 0.027% over the B&H strategy for 1962-86, and all the returns were statistically significant. For closing levels of the DJIA that were estimated to reduce the effects of nonsynchronous trading, the trading rules also outperformed the B&H, although returns were reduced relative to previous ones and not all were statistically significant. For 1987-96, however, the performance of the tradin g rules was inferior to the B&H strategy in most cases.
17. Kwon & Kish (2002)	The NYSE value-weighted index / Daily	1962-96: 1962-72, 1973-84, 1985-96	Moving average, combination of moving average and momentum, and combination of moving averages for price and volume	Unconditional mean returns	Not adjusted	Combination moving average rules of price and volume generated the highest daily average return of 0.13% over the full sample period. Across all subperiods but the recent 1985-96 period, returns of the trading system were statistically significantly different from unconditional mean returns. Similar results were obtained for the other two trading systems. Simulated series from three popular models (random walk, GARCH-M, and GARCH-M with instrument variable) could not explain returns and volatility of the technical trading systems.
18. Neely (2002)	4 foreign exchange rates: mark, yen, Swiss franc, and Australia dollar / Intra-daily and daily	1983-98	Moving average (1/150)	Not considered	Not adjusted	With daily data, the moving average rule generated positive annual mean returns for all series ranging from 2.4% for the Australian dollar to 8.7% for the yen. However, when intervention periods of central banks were removed, the trading rule returns were greatly reduced, ranging from –2.3% to 4.5%. With intra-daily data, the highest US, Swiss, and German excess returns appeared to precede business hours and thus precede intervention. Hence, intervention was less likely to be a cause that generated trading rule profits.
19. Saacke (2002)	Dollar/mark exchange rate in the New York market / Daily	1979-94	Moving average (2 to 500 days)	Not considered	0.05% per round-trip	Moving average rules below 170 days earned positive net returns. Bootstrapping simulations based on a random walk with drift and a GARCH model could not account for the size of trading rule returns. Moving average rules appeared to be highly profitable on days when central banks intervened. However, since trading rule returns in periods that neither coincided with nor were preceded by interventions were also sizable, interventions did not seem to be the only cause of the trading rule profitability.

Criteria: Study	Markets considered / Frequency of data	In-sample period	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
20. Fang & Xu (2003)	3 Dow Jones Indexes (Industrial, Transportation, and Utilities Averages) / Daily	1896-1996	Moving average, time series models, and combination of moving average and time series models	Buy & hold	Various estimates	When the market was bullish (bearish), technical trading rules performed in general better (worse) than trading strategies based on time series models. When a monthly interest rate of 0.30% was assumed over the full sample period, combination rules produced average break-even transaction costs of about 1.01%, 1.96%, and 1.76% for the Industrial, Transportation, and Utilities Averages, respectively, with non-synchronous trading adjustment. These figures appeared to be substantial improvement on those of moving average rules (0.60%, 0.84%, and 0.80%, respectively).
21. Sapp (2004)	Mark and yen / Daily	1975-1998	Moving average	Sharpe ratio for S&P500	Bid-ask spread	During the 1980-94 period, moving average rules generated statistically and economically significant returns. Positive but insignificant returns after 1995 seemed to be related with a decrease in central bank intervention activities. Transaction costs did not affect technical trading returns except for a few short-term trading rules. Over the 1980-98 period, annualized Sharpe ratios for a 150-day trading rule and investing in the S&P500 were 0.65 and 0.49, respectively. However, a preliminary analysis using an international CAPM indicated that the hypothesis that there was a time-varying risk premium in the technical trading returns correlated with central bank interventions could not be rejected.

Table 5 Summary of genetic programming technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Neely, Weller, & Dittmar (1997)	6 exchange rates: mark, yen, pound, Swiss franc, and two cross rates (mark/yen and pound/Swiss franc) / Daily	1975-77, 1978-80, (1981-95)	100 trading rules generated by genetic programming during each in-sample period	Buy & hold / Optimized trading rules	In-sample periods: 0.1% per round-trip; out-of-sample period: 0.05%	Out-of-sample, genetic trading rules generated positive mean excess returns after transaction costs for every currency tested. The mean excess return across all currencies was 2.9% per year, being higher than the B&H return (0.6%). Since betas for these trading rule returns against various world market indices were negative, the excess returns did not seem to be compensation for bearing systematic risk. In addition, the superior performance of trading rules could not be explained by standard statistical models such as a random walk, ARMA, and ARMA-GARCH.
2. Allen & Karjalainen (1999)	S&P 500 Index / Daily	1929-82 (1936-95)	100 trading rules generated by genetic programming during each in-sample period	Buy & hold	One-way transaction costs of 0.1, 0.25, and 0.5%	After considering reasonable one-way transaction costs of 0.25%, average excess returns of optimal trading rules were negative for 9 of 10 out-of-sample periods. Even after transaction costs of 0.1%, average excess returns were negative for 6 out of the 10 periods. In most periods, only a few trading rules indicated positive excess returns. Overall, genetically formulated trading rules did not generate excess returns over the B&H strategy after transaction costs.
3. Fyfe, Marney, & Tarbert (1999)	U.K. Land Securities / Daily	1980-82, 1982-84 (1985-97)	The fittest trading rule generated by genetic programming during an in-sample period	Buy & hold / Optimized trading rules	1% per one-way transaction	Although an optimal trading rule performed well during the out-of-sample period, it appeared to have a similar structure to the B&H strategy. When the optimal trading rule was applied to price series bootstrapped by three popular statistical models (a random walk, AR (1), AR (1)–ARCH (3)), only the AR (1) model explained about 40% of the original excess trading returns.
4. Neely & Weller (1999)	4 cross exchange rates (mark/franc, mark/lira, mark/guilder, mark/pound) / Daily	1979-86 (1986-96)	100 trading rules generated by genetic programming, moving average (1/10, 1/50, 5/10, and 5/50 days), and filter (0.5, 1, 1.5, and 2%)	Buy & hold / Optimized trading rules	In-sample periods: 0.1% per round-trip; Out-of-sample period: 0.05%	During the out-of-sample period, annual mean excess returns averaged across 100 rules after transaction costs were positive for all four currencies, ranging 0.1% for the mark/guilder to 2.8% for the mark/pound. In contrast, moving average rules and filter rules generated annual mean excess returns of -0.1% and -0.2% across all currencies, respectively. There was no evidence that the excess returns to genetic trading rules were compensation for bearing systematic risk.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
5. Wang (2000)	S&P Index and S&P Index Futures / Daily	1984-97 (1987-98)	10 trading rules generated by genetic programming during each in-sample period	Buy & hold / Optimized trading rules	\$0.50 per share + \$25 per one-way transaction for spot index; \$61 per round-trip for futures	For S&P futures, 36 out of 120 trading rules over the entire sample period outperformed the B&H strategy in terms of net returns. However, the results varied from year-to-year. Similar results were found when both S&P spot and futures markets were simultaneously considered for trading. When risk-adjusted returns were assessed, 57 out of 120 rules beat the B&H strategy. Although the performance of trading rules was still inconsistent over sample periods, more than 40% of the rules appeared to have some market-timing capability.
6. Neely & Weller (2001)	4 foreign exchange rates: mark, yen, pound, and Swiss franc / Daily	1975-80 (1981-92), 1987-92 (1993-98)	100 trading rules generated by genetic programming during each in-sample period	Buy & hold / Optimized trading rules	In-sample periods: 0.1% per round-trip; out-of-sample period : 0.05%	Over the period 1981-92, intervention information from the Fed substantially improved the profitability of optimal trading rules for pound and Swiss franc. For example, the median portfolio rule increased annual excess returns from 0.5% to 7.2% per year for the pound. In contrast, over the 1993-98 period, intervention information decreased the profitability of trading rules for all currencies but the mark. Thus, intervention activity did not seem to be a general source of profits for technical traders.
7. Korczak & Roger (2002)	24 stocks of the CAC40 Index of the Paris Stock Exchange / Daily	Ten 261-day periods over 1/97-11/99 (Ten 7-day periods)	Trading rules generated by genetic programming during each in-sample period	Two buy & hold strategies /Optimized trading rules	0.25% per one-way transaction	Out-of-sample results indicated that genetic trading rules outperformed both B&H strategies in 9 out of 10 cases. Although newly generated trading rules performed well over time and relative to the old rules, all rules showed good and stable performance over the out-of-sample periods. No trading rule consistently performed better than others.
8. Ready (2002)	Dow Jones Industrial Average (DJIA) / Daily	1939-2000, 1957-62 (1963-86), 1981-86 (1987-00)	50 genetic-programming-based trading rules and 4 moving average rules from Brock et al. (1992)	Buy & hold, Stock/bond weighted average / Optimized trading rules	0.13% per one-way transaction	Moving average rules generated positive excess returns after transaction costs for the period 1963-86, although they yielded negative excess returns for the period 1987-2000. However, because moving average rules performed poorly from 1939-62, they were less likely to be chosen by traders at the beginning of 1963. In fact, every genetic trading rule created over the period 1957-60 outperformed the moving average rules. Similar results were found for the period 1987-2000. Hence, Ready concluded that Brock et al.'s (1992) results for the period 1963-86 were spurious.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
9. Neely (2003)	S&P 500 Index / Daily	1929-80 (1936-95)	10 trading rules generated by genetic programming during each in-sample period	Buy & hold / Optimized trading rules	0.25% per one-way transaction	During in-sample periods, genetic trading rules generated an about 5% annual mean excess return over the B&H strategy. During out-of-sample periods, however, genetic trading rules generated negative mean excess returns over the B&H strategy. The risk-adjusted performance based on several risk-adjusted return measures was inferior to that of the B&H strategy. In addition, trading rules optimized by various risk-adjusted criteria also failed to outperform the B&H strategy.
10. Neely & Weller (2003)	4 foreign exchange rates: mark, yen, pound, and Swiss franc / Intra-daily	2/96-5/96 (6/96-12/96)	25 trading rules generated by genetic programming for each currency;	An linear forecasting model / Optimized trading rules	0, 0.01, 0.02 and 0.025% per one-way transaction	There was strong evidence of predictability in exchange rate series tested because genetically trained trading rules yielded annual returns of over 100% with zero transaction costs in 3 of the 4 cases. However, under realistic trading hours and transaction costs (0.025%), genetic trading rules realized break-even transaction costs of less than 0.02% per one-way trade in all the exchange rates but the pound. Moreover, genetic trading rules appeared to be inferior to the autoregressive linear forecasting model in most cases, although their performances were not much different.
11. Roberts (2003)	CBOT corn, soybean, and wheat futures / Daily	1978-1998 (1980-1998)	The best of ten rules optimized during each in-sample period using genetic programming	Zero profits and buy & hold	\$25 and \$6.25 per contract per roundtrip for in- and out-of-sample periods, respectively	Although genetically trained rules produced positive mean net returns only for wheat futures in out-of-sample tests, only trading rules that use the ratio of profit to maximum drawdown as a performance measure generated a statistically significant mean daily net profit of \$0.93 per contract. This was compared to the B&H profit of -\$3.30 per contract. For corn and soybean futures, however, genetic trading rules produced both negative mean returns and negative ratios of profit to maximum drawdown during the sample period.

Table 6 Summary of Reality Check technical analysis studies published between 1988 and 2004

Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Sullivan, Timmermann, & White (1999)	Dow Jones Industrial Average (DJIA), S&P 500 index futures / Daily	DJIA: 1897-1996, 1897-1986 (1987-96); S&P 500 futures: 1984-96	Filter, moving average, support and resistance, channel breakout, on-balance volume average	Zero mean profits for mean return, a risk-free rate for the Sharpe ratio / Optimized trading rules	Not adjusted	During the 1897-96 period, the best rule in terms of mean return was a 5-day moving average that produced an annual mean return of 17.2% with a data snooping adjusted p-value of zero. The corresponding break-even transaction cost was 0.27% per trade. The best rule in terms of the Sharpe ratio generated a value of 0.82 with a Bootstrap Reality Check p-value of zero, while the B&H strategy generated a Sharpe ratio of 0.034. However, during the 1987-96 period, the 5-day moving average rule earned a mean return of 2.8% per year with a nominal p-value of 0.32. Moreover, in the S&P 500 futures market, the best rule generated a mean return of 9.4% per year with a Bootstrap Reality Check p-value of 0.90, implying that the return resulted from data snooping.
2. Qi & Wu (2002)	7 foreign exchange rates: mark, yen, pound, lira, French franc, Swiss franc, and Canadian dollar / Daily	1973-1998	Filter, moving average, support and resistance, and channel breakout	Buy & hold, Zero mean profits /	Adjusted	During the sample period, the best trading rules, which are mostly moving average rules and channel breakout rules, produced positive mean excess returns over the buy-and-hold benchmark across all currencies and had significant data snooping adjusted p-values for the Canadian dollar, the Italian lira, the French franc, the British pound, and the Japanese yen. The mean excess returns were economically substantial (7.2% to 12.2%) for all the five currencies except for the Canadian dollar (3.6%), even after adjustment for transaction costs of 0.04% per one-way transaction. In addition, the excess returns could not be explained by systematic risk. Similar results were found for the Sharp ratio criterion, and the overall results appeared robust to incorporating transaction costs into the general trading model, changes in a vehicle currency, and changes in the smoothing parameter in the stationary bootstrap procedure.
3. Sullivan, Timmermann, & White (2003)	Dow Jones Industrial Average (DJIA), S&P 500 index futures / Daily	DJIA: 1897-1998, 1987-96; S&P 500 futures: 1984-96	Technical trading systems from Sullivan et al. (1999) and calendar frequency trading rules from Sullivan et al. (2001)	Buy & hold / Optimized trading rules	Not adjusted	For the full sample period (1897-1998), the best of the combined universe of trading rules, a 2-day-on-balance volume strategy, generated a mean return of 17.1% on DJIA data with a data snooping adjusted p-value of zero, and outperformed the B&H strategy (a mean return of 4.8%). For a recent period (1987-96), the best rule, a week-of-the-month strategy, produced a mean return of 17.3% slightly higher than the B&H return (13.6%), but the return was not statistically significant (p-value of 0.98). Similar results were found for the S&P 500 futures data. Although the best rule (a mean return of 10.7%) outperformed the benchmark (mean return of 8.0%) during the 1984-96 period, the data snooping adjusted p-value was 0.99.

Table 7 Summary of chart pattern studies published between 1988 and 2004

Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Curcio, Goodhart, Guillaume, & Payne (1997)	3 foreign currencies: mark, yen, and pound / Intradaily (one hour frequency)	4/89-6/89, 1/94-6/94	Support and resistance, high-low, minimum of the support and low and maximum of the resistance and high, and max-min	Buy & hold	Bid-ask spreads	Across exchange rates tested, the results of the earlier sample period indicated that only 4 of 36 buy and sell rules yielded statistically significant positive returns after transaction costs. Max-min rules showed even worse performance. For the later period, 10 rules had positive returns but 14 rules produced significantly negative returns. Max-min rules all realized negative returns.
2. Caginalp & Laurent (1998)	All world equity closed end funds listed in Barron's and all S&P 500 stocks / Daily	4/92-6/96, 1/92-6/96	Candlestick patterns	Average return	Commissions ($20 for several thousand shares) and the bid-ask spread (0.1-0.3%)	Candlestick reversal patterns appeared to have statistically significant short-term predictive power for price movements. Each of the patterns generated substantial profits in comparison to an average gain for the same holding period. For the S&P 500 stocks, down-to-up reversal patterns produced an average return of 0.9% during a two-day holding period (annually 309% of the initial investment). The profit per trade ranged from 0.56%-0.76% even after adjustment for commissions and bid-ask spreads on a $100,000 trade, so that the initial investment was compounded into 202%-259% annually.
3. Chang & Osler (1999)	6 spot currencies: yen, mark, pound, Canadian dollar, Swiss franc, and French franc / Daily	1973-94	Head-and-shoulders, moving average (1/5, 1/20, 5/20, 5/50, and 20/50 days), and momentum (5-, 20-, and 50-day lags)	Buy & hold, Equity yields	0.05% per round-trip	Head-and-shoulders rules earned substantial returns for the mark and yen but not for other currencies. Profits for the mark and yen were around 13% and 19% per year, respectively, with being higher than the corresponding B&H returns or U.S. equity yields. These results were evident even after adjusting for transaction costs, risk, or interest differentials. However, moving average rules and momentum rules appeared to have significant predictive power for all six currencies. Moreover, they easily outperformed head-and-shoulders rules in terms of total profits and Sharpe ratios.
4. Guillaume (2000)	3 exchange rates: mark/dollar, yen/dollar, dollar/pound / Intra-daily	4/89-6/89, 1/94-6/94	4 trading range breakouts with a 0.1% band	Buy & hold	Bid-ask spreads	For the first sample period, several trading rules generated statistically significant net profits, particularly, in trending markets such as the yen/dollar market. For the second period, however, none of the trading rules produced significant net profits, even in trending markets. In general, support-resistance rules performed better than Max-Min rules used in Brock et al. (1992).

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
5. Lo, Mamaysky, & Wang (2000)	Individual NYSE/AMEX and Nasdaq stocks / Daily	1962-96	Head-and-shoulders (H&S)and inverse H&S, broadening tops and bottoms (T&B), triangle T&B, rectangle T&B, and double T&B	Not considered	Not adjusted	Pattern-recognition algorithms were used to detect 10 chart patterns in price series smoothed by using non-parametric kernel regressions. The results of goodness-of-fit and Kolmogorov-Smirnov test s indicated that, in many cases, return distributions conditioned on technical patterns were significantly different from unconditional return distributions, especially, for the Nasdaq stocks. This suggests that technical patterns may provide some incremental information for stock investment, even if they may not be used to generate excess trading profits.
6. Osler (2000)	3 foreign exchange rates: mark, yen, and pound against U.S. dollar / Intra-daily	1/96-3/98	Support and resistance	Not considered	Not adjusted	"Bounce frequency" of support and resistance levels for each currency published by six firms was compared to that of artificial support and resistance levels. Results indicated that trends in intra-daily exchange rates were interrupted at the published support and resistance levels more frequently than at the artificial ones. The results were consistent across all three exchange rates and all six firms, although the predictive power of the published support and resistance levels varied. Moreover, the results were statistically significant and robust to alternative parameterizations.
7. Leigh, Paz, & Purvis (2002)	The NYSE Composite Index / Daily	1980-99	Bull flag charting patterns	Buy & hold	Not adjusted	Across all parameter combinations considered, trading rule returns in excess of the B&H strategy were positive for all forecasting horizons (10, 20, 40, and 80 days). Moreover, results of linear regression analyses indicated that trading rule parameters had predictive value for both price level and future price direction.
8. Leigh, Modani, Purvis, & Roberts (2002)	The NYSE Composite Index / Daily	1980-99 (the first 500 trading days)	Two bull flag patterns with trading volume (a buy position is held for 100 days)	Buy & hold / Optimized parameters	Not adjusted	During the out-of-sample period, patterns outperformed the B&H strategy. The first and the second bull flag patterns with trading volume generated statistically significant mean returns of 14.0% (with 55 buy signals) and 8.6% (with 132 buy signals) for 100-day holding period, respectively, while the B&H strategy profited 5.5%.
9. Dawson & Steeley (2003)	225 individual FTSE100 and FTSE250 stocks / Daily	1986-2001	The same patterns as in Lo et al. (2000)	Buy & hold	Not adjusted	This study replicates Lo et al.'s (2000) procedure on UK data. Results were similar to Lo et al.'s finding. The results of goodness-of-fit and Kolmogorov-Smirnov test s indicated that return distributions conditioned on technical patterns were significantly different from the corresponding unconditional distributions. However, across all technical patterns and sample periods, an average market adjusted return turned out to be negative.
10. Lucke (2003)	Dollar, mark, pound, yen, and Swiss franc / Daily	1973-99	Head-and-shoulders	Not considered	Not adjusted	In general, head-and-shoulders rules failed to generate positive mean returns for all holding periods (1 to 15 days) except a one-day holding period. In addition, it appeared that trading rule profits were not correlated with central bank intervention.
11. Zhou & Dong (2004)	1451 stocks listed on the NYSE, Amex, NASDAQ / Daily	1962-2000	Head-and-shoulders (HS)and inverse HS (HIS), broadening tops (BT) and bottoms (BB), triangle tops (TT) and bottoms (TB), rectangle tops (RT) and bottoms (RB)	Returns for a size- and momentum-matched control company	Not adjusted	To reflect the uncertainty of human perception and reasoning, fuzzy logic were incorporated into the definition of well-known technical patterns. For all stocks tested, the HS, HIS, RT, and RB patterns generated significant cumulative abnormal returns (CARs) of around 3% for 120 days. For stocks trading above $2.00, however, the significance of CARs dramatically reduced or disappeared. The effect of small trading prices was more severe for NASDAQ stocks. For the HS, IHS, and RB patterns, the fuzzy logic-based algorithm appeared to detect subtly different post-pattern performances between two portfolios with different pattern membership values. The results for four subperiods indicated that for the RT pattern the post-pattern performances of two portfolios with different membership values were significantly different in the first three subperiods from 1962 through 1990. This may imply that stock markets have been efficient after the early 1990s.

Table 8 Summary of nonlinear technical analysis studies published between 1988 and 2004

Study / Criteria:	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Gençay (1998a)	Dow Jones Industrial Average (DJIA) / Daily	1963-88 (Last 250 prices for each of 6 sub-samples)	Trading rules based on a feedforwad network model	Buy & hold / Optimized models	$600 per round-trip for the contract value of 1,000,000	Trading signals as a function of past returns were generated by a feedforward network, which is a class of artificial neural networks. Across subperiods, net returns of technical trading rule (7% to 35%) dominated those of the B&H strategy (-20% to 17%). Sharpe ratio tests indicated similar results. Correct sign predictions for the recommended positions ranged from 57% to 61% for all subperiods.
2. Gençay (1998b)	Dow Jones Industrial Average (DJIA) / Daily	1897-1988 (10 most recent prices for each of 22 sub-samples)	Trading rules based on a feedforwad network model	An OLS model with lagged returns as regressors / Optimized models	Not adjusted	In terms of forecast improvement measured by the mean square prediction error (MSPE), non-linear models (feedforward network models) using past buy-sell signals from moving average rules (1/50 and 1/200) as regressors outperformed linear specifications such as the OLS, GARCH-M (1,1), and a feedforward network regression with past returns. For 14 of 22 subperiods, the nonlinear models generated at least 10% forecast improvement over the benchmark model. The model with a 1/50 moving average rule provided more accurate out-of-sample predictions relative to one with a 1/200 rule.
3. Gençay & Stengos (1998)	Dow Jones Industrial Average (DJIA) / Daily	1963-88 (Last 1/3 of the data set for each of 6 sub-samples)	Trading rules based on a feedforwad network model	An OLS model with lagged returns as regressors / Optimized models	Not adjusted	Overall non-linear models (feedforward network models) outperformed linear models (OLS and GARCH-M (1,1)) in terms of MSPEs and sign predictions. The non-linear models with lagged returns generated an average of 2.5% forecast improvement over the benchmark model with lagged returns. This prediction power improved as large as 9.0% for the non-linear models in which past buy-sell signals of a moving average rule (1/200) were used as regressors. In particular, when the non-linear model included a 10-day volume average indicator as an additional regressor, it produced an average of 12% forecast gain over the beanchmark and provided much higher correct sign predictions (an average of 62%) than other models.
4. Gençay (1999)	5 spot exchange rates: pound, mark, yen, France franc, and Swiss franc / Daily	1973-92 (Last 1/3 of the data set)	Trading rules based on a feedforwad network model and the nearest neighbor regression	Random walk and GARCH (1,1) models / Optimized models	Not adjusted	Nonlinear models such as the nearest neighbors and the feedforward network regressions with past buy-sell signals from moving average rules (1/50 and 1/200) outperformed a random walk and a GARCH (1,1) model in terms of sign predictions and mean square prediction errors. For example, average correct sign prediction of the nearest neighbors model was 62% for the five currencies. Models with a 1/50 moving average rule provided more accurate predictions over models with a 1/200 rule.
5. Fernández-Rodríguez, González-Martel, & Sosvilla-Rivero (2000)	The General Index of the Madrid Stock Market / Daily	1966-97 (10/91-10/92, 7/94-7/95, 10/96-10/97)	A trading rule based on a feedforwad network model	Buy & hold	Not adjusted	In terms of gross returns, a trading rule based on a feedforwad network model dominated the B&H strategy for two subperiods, while the opposite was true for most recent subperiods in which there exists upwards trend. Correct sign predictions for the recommended positions ranged from 54-58%, indicating better performance than a random walk forecast.
6. Sosvilla-Rivero, Andrada-Félix, & Fernández-Rodríguez (2002)	Mark and yen / Daily	1982-96	A trading rule based on the nearest neighbor regression	Buy & hold / Optimized models	0.05% per round-trip	Trading rule generated net returns of 35% and 28% for the mark and yen, respectively, and outperformed B&H strategies that yielded net returns of -1.4% and -0.4%, respectively. Correct sign predictions for recommended positions were 53% and 52% for the mark and yen, respectively, beating a random walk directional forecast. However, when excluding days of US intervention, net returns from the trading strategy substantially decreased (-10% and -28% for the mark and yen, respectively) and were less than the B&H returns in both cases.
7. Fernández-Rodríguez, Sosvilla-Rivero, & Andrada-Félix (2003)	9 exchange rates in the European Monetary System (EMS) / Daily	1978-94,	Trading rules based on the nearest neighbor (NN) and the simultaneous NN regressions and moving averages (1/50, 1/150, 1/200, 5/50, and 5/200 days)	Not considered / Optimized models	0.05% per round-trip	For most exchange rates, annual mean returns from nonlinear trading rules based on the nearest neighbor or the simultaneous nearest neighbor regressions were superior to those of moving average rules. The nonlinear trading rules also generated statistically significant annual net returns of 1.5%-20.1% for the Danish krona, French franc, Dutch guilder, and Italian lira. Similar results were found for the Sharp ratio criterion. The nonlinear trading strategies generated the highest Sharpe ratios in 8 out of the 9 cases.

Table 9 Summary of other technical analysis studies published between 1988 and 2004

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
1. Pruitt & White (1988)	204 stocks from the CRSP at the University of Chicago / Daily	1976-85	CRISMA (combination system of Cumulative volume, RelatIve Strength, and Moving Average)	Buy & hold	0 to 2% per round-trip	After 2% transaction costs and across various return-generating models, the CRISMA system yielded annual excess returns ranging from 6.1% to 15.1% and beat the B&H or market index strategy. The system also generated a much greater percentage of profitable trading successes after transaction costs than would be expected by chance.
2. Schulmeister (1988)	Mark / Daily	1973-88	Moving average, momentum, point & figure, combination of moving average & momentum	Buy & hold	0.04% per one-way transaction	All trading rules considered produced substantial annual returns up to 16%. The combination system performed best. The probability of an overall loss appeared to be less than 0.005% when one of the trading rules was followed blindly during the 1973-86 period.
3. Sweeney (1988)	14 Dow-Jones Industrial stocks / Daily	1956-62 (1970-82)	0.5% filter rule	Buy & hold	From 0.05% to 0.2% per one-way transaction	During the 1970-82 period, for 11 of 14 stocks that had earned profits before commissions in Fama and Blume's (1966) study, a 0.5% filter rule produced statistically significant annual mean returns after adjustment for transaction costs of 0.1%. For an equally weighted portfolio of 14 stocks, the filter rule generated a mean net return of 10.3% per year. Portfolio returns appeared to be robust across several subsamples but were quite sensitive to transaction costs.
4. Taylor (1988)	Treasury bond futures from CBOT / Daily	1978-87	A statistical price-trend model based on ARMA(1,1)	Buy & hold	0.2% per round-trip	All four trading rules generated positive average excess returns ranging from 4.4% to 6.8% per year and were superior to the B&H strategy. However, t-test results indicated that none of the returns was significantly different from zero at the 5% level. In addition, the B&H strategy performed better than each trading rule from 1982-87.
5. Pruitt & White (1989)	In-the-money call options written on the 171 stocks / Daily	1976-85	CRISMA	Not considered	Maximum 1988 retail transaction costs	After transaction costs, the CRISMA system generated a mean return of 12.1% per round trip. In fact, 71.3% of the 171 transactions were profitable after adjustment for transaction costs. The binomial proportionality test statistics showed that the trading profitability could not be achieved by chance.
6. Neftci (1991)	Dow-Jones Industrials / Monthly	1792-1976	Moving average (150 days)	Not considered	Not adjusted	This study showed that moving average rules were one of the few statistically well-defined procedures. Trading signals of a 150-day moving average rule were incorporated into a dummy variable in an autoregression equation. F-test results on the variable were insignificant for 1795-1910 but highly significant for 1911-76, indicating some predictive power of the moving average rule.
7. Corrado & Lee (1992)	120 stocks from the Dow Jones and S&P 500 Index / Daily	1963-89	0.5% own-stock filter, 0.25% S&P 500 Index filter, 0.5% other-stock filter	Buy& hold	0.04% per one-way transaction	The own-stock filter rule generated an equally-weighted mean portfolio return of 30.8% per year during the sample period, while the B&H strategy yielded a mean portfolio return of 11.3% per year. This difference between the returns made an annual gross margin of 6.4% over the B&H strategy after transaction costs.
8. Pruitt, Tse, & White (1992)	148 stocks and in-the-money call options written on the 126 target stocks / Daily	1986-90	CRISMA (combination system of Cumulative volume, RelatIve Strength, and Moving Average)	Buy& hold	Security: 0-2% per round-trip; Option: $60 per round-trip	For stocks, the CRISMA system generated annualized excess returns of between 1.0% and 5.2% after transaction costs of 2%and outperformed the B&H or market index strategy. For options, the system generated highly significant returns of 11.0% per option trade after transaction costs, with 63.5% of all trades being profitable.
9. Wong (1995)	Hang Seng Index (HSI) / Daily	1969-1990, 5 subperiods	Moving average (10, 20, and 50 days)	Buy & hold	Not adjusted	In general, moving average rules performed well. In particular, an MA10 (a 10-day moving average) bullish signal, an MA20 bullish signal, and an MA50 bearish signal generated statistically significant excess returns over the B&H strategy. It appeared that for buy (sell) signals, prices declines (rises) slowly in the early pre-event period and rises (declines) sharply in the late pre-event period. Prices continued to rise (declines) slowly in the post-event period for buy (sell) signals.
10. Cheung & Wong (1997)	Yen, Singapore dollar, Malaysian ringgit, and Taiwan dollar / Daily	1986-95	Filter (0.5, 1, and 1.5%)	Buy & hold	1/8 of 1% of asset value per round-trip	When transaction costs and risk were adjusted, filter rules generated superior excess returnsover the B&H strategy only for the Taiwan dollar. Filter rules were inferior to the B&H strategy in the cases of the yen and Singapore dollar. Both filter rule and B&H strategies failed to generate significant excess returns on the Malaysian ringgit.
11. Irwin, Zulauf, Gerlow, & Tinker (1997)	Futures contracts for soybean, soybean meal, and soybean oil / Daily and monthly	1974-83 (1984-88)	Channel (40 days), ARIMA(2,0,0) for soybean and ARIMA(1,0,1) for soybean mean and oil	Zero mean profits	Not adjusted	During the out-of-sample period, the channel system generated statistically significant mean returns ranging 5.1%26.6% for all markets. The ARIMA models also produced statistically significantly positive returns (16.5%) for soybean meal, but significantly negative returns (-13.5%) for soybeans. For every market, the channel system beat the ARIMA models.

Criteria: Study	Markets considered / Frequency of data	In-sample period (Out-of-sample period)	Technical trading systems	Benchmark strategies / Optimization	Transaction costs	Conclusion
12. Neely (1997)	4 foreign currencies: mark, yen, pound, and Swiss franc / Daily	1974-97	Filter (0.5, 1, 1.5, 2, 2.5, and 3%) and moving average (1/10, 1/50, 5/10, and 5/50 days)	Buy & hold the S&P 500 index	0.05% per round-trip	Technical trading rules showed positive net returns in 38 of the 40 cases. In general, moving average rules performed slightly better than filter rules. Moreover, the trading profits were not likely to be compensation for bearing risk. For example, for the mark, every moving average rule beat the B&H strategy of the S&P 500 Index in terms of the Sharpe ratio. The CAPM betas from the trading rules also generally indicated negative correlation with the S&P 500 monthly returns.
13. Goldbaum (1999)	U.S. T-Bills, a value-weighted market portfolio of all the NYSE and AMEX securities from the CRSP, and IBM stock / Daily	1962-89	Moving average (1/50, 1/200, 5/50, and 5/200 days with 0 and 1% bands)	T-Bill returns	Not adjusted	As a performance measure, the price error between assets was estimated using the nonparametric stochastic discount factor (SDF), which was either conditioned or unconditioned on public information (e.g. term structure). For the market portfolio returns, moving average rules generally had unconditional estimates that were significantly positive or close to zero and conditional estimates that were negative or close to zero, implying a negative performance of the trading rules to an informed trader. For IBM stock returns, however, the conditional estimates on the term structure were significantly different from zero.
14. Marsh (2000)	3 IMM currency futures: mark, yen, and pound sterling / Daily	1980-96, 1980-85 (1986-90), 1980-90 (1991-95)	Markov models and moving average rules (1/5, 5/20, and 1/200 days)	Not considered	0.025% and 0.04% per one-way transaction	Before transaction costs, all moving average rules tested yielded positive returns for both 1981-85 and 1986-90, but the rules generated positive returns only in 3 out of 9 cases for 1991-95. For out-of-sample periods, Markov models also generated positive returns in 2 out of 6 cases. Augmented Markov models, in which interest differentials were included, produced substantially positive returns for all 3 currency futures during 1986-90 but only for the yen during 1991-95.
15. Dewachter (2001)	4 foreign exchange rates: mark, yen, pound, and franc / Weekly	1973-97	Moving average (1/30) with a 5-day holding period, Markov model and its ARMA (1,1) representation as the class of Taylor's price-trend models	Not considered	Not adjusted	Across exchange rates, the moving average rule produced a statistically significant average return of about 6% per year and the correct sign prediction of about 55%. The extended Markov switching model and the ARMA (1,1) representation of the Markov switching model showed even better performance in terms of profits and sign prediction. The results of Monte Carlo simulations indicated that the Markov model could replicate the observed profitability of the moving average rule.
16. Wong, Manzur, & Chew (2003)	Singapore Straits Times Industrial Index (STII) / Daily	1974-1994, Three 7-year subperiods	Moving averages and relative strength index (RSI)	Not considered	Not adjusted	In general, every trading system tested produced statistically significant returns over all three subperiods and a whole period. Single moving average rules generated the best results, followed by dual moving average crossover rules and relative strength index rules.