Master's Thesis

Technical analysis and market efficiency: Evidence from frontier, emerging, and developed markets

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Abstract

The findings of this thesis add valuable information to the ongoing debate on the validity of technical analysis in financial markets. Traditional financial theory, which supports the Efficient Market Hypothesis, contrasts modern arguments recognizing market inefficiencies. Theories dismissing technical analysis asserts that all available information is already reflected in stock prices, rendering historical price movements irrelevant. In contrast, proponents of technical analysis argue that markets are dynamic and subject to behavioral biases and irrational decision-making, thus providing opportunities for technical analysis to exploit mispricing.

Given the dynamic nature of market efficiency, this thesis investigates the effectiveness of technical analysis in frontier, emerging, and developed financial markets. The rationale behind this focus is previous studies indicating that market efficiency varies across markets with different levels of financial advancement, with developed markets being more efficient and emerging and frontier markets being less efficient. The paper conducts an empirical analysis of four trading strategies based on technical analysis in the period 2014-2023. The results indicate that none of the strategies outperform a buy-and-hold benchmark in the developed market, which maintains superior returns and risk-adjusted measures. However, in the emerging market, one strategy significantly outperforms the benchmark despite higher associated risk. In the frontier market, one strategy outperforms the benchmark on risk-adjusted measures, though it generates a lower overall return.

The findings demonstrate that technical analysis can yield abnormal returns in less efficient markets, particularly in frontier and emerging markets, but is less effective in developed markets. The study supports the notion that market efficiency is not static, but varies with market conditions, influenced by factors such as trader behavior, market dynamics, and regulations. Consequently, the assumptions of the weak-form of market efficiency posited by the Efficient Market Hypothesis does not hold universally, particularly in less efficient markets.

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1 Introduction

Since the inception of stock trading in Amsterdam in the early 17th century, both experienced and novice investors have been engaged in the pursuit of profitability within the financial markets. Throughout history, people have sought to create methods for predicting market movements, driven by the belief that such accurate forecasts could lead to substantial gains. Practitioners and academics have followed different paths in studying the forecasting of financial data. While practitioners have focused on developing techniques for forecasting market trends and guiding investment decisions, the academic community has taken a more analytical approach by examining the underlying behavior of financial time series data to find out whether they can be forecasted (Park, Cheol-Ho & Irwin, 2004). Academics have mainly studied the characteristics and behavior of financial data itself, exploring whether certain dependencies in successive price changes could be exploited profitably by various trading strategies. Early statistical studies have initially concluded that successive price changes are independent, a notion that contributed to the formulation of The Efficient Market Hypothesis (EMH) (Park, Cheol-Ho & Irwin, 2004). According to the EMH, all public and private information is already reflected in market prices, making it impossible to consistently outperform the market through prediction - a perception that has been a focal point in research and a central paradigm in financial economics since Samuelson (Samuelson, 1965) and Fama (Fama, 1970) introduced it and elaborated on it in subsequent papers. Meanwhile, among the practitioners, fundamental and technical analysis have emerged as popular techniques developed to forecast financial prices, providing guidelines on what and when to buy or sell. Despite the dominance of EMH among academics, technical analysis has persisted as a prominent tool among practitioners, with its efficacy being periodically evaluated (Park, Cheol-Ho & Irwin, 2004).

Traditional investing includes purchasing assets with the intent of holding them for a long-term period, hoping for capital appreciation through growth or dividends. Trading, however, typically includes looking for short-term price inefficiencies and only keeping assets for hours, minutes or even seconds. While investors often rely on fundamental analysis to decide on investments, traders often use technical analysis to find entry and exit opportunities, although more and more investors and fund managers have stated to use a combination of both in their work (Menkhoff, 2010). Critics of technical analysis often cite the lack of empirical evidence supporting its effectiveness and argue that a widespread adoption of effective methods would eventually make them ineffective (Park, Cheol-Ho

& Irwin, 2004). However, despite the initial doubts, there has since been renewed interest in academia, showing the relevance of technical analysis in real-world trading, and suggesting that the early dismissals might have been premature (Griffioen, 2003).

Today, large parts of both the academic and practicing world agree that market efficiency is not an all-or-nothing condition, but a condition that varies depending on factors such as time, market dynamics, and market development. As a result, the relationship between market efficiency and market development has been studied thoroughly. Most of these studies reveal that developed countries in general show higher levels of market efficiency than emerging and frontier countries. If this is the case, and if the notion of the EMH that historical data is useless in predicting price changes holds true, then technical analysis should be significantly less effective in developed markets than in emerging and frontier markets.

This thesis digs deeper into the aspects of technical analysis and market efficiency. The objective of the study is to test whether technical analysis has worldwide applicability in financial markets of varying efficiency. It will investigate how the aspects of the EMH varies across different markets, and if it contains any exploitable patterns – adding to the debate on market efficiency. The overall research question that this thesis will aim to answer is:

"Is the effectiveness of technical analysis in financial markets inconsistent with the Efficient Market Hypothesis?"

The study tests the profitability of technical analysis in major stock indexes from a frontier, emerging, and developed market. Four trading strategies using technical indicators and patterns are implemented and backtested over a ten-year period from 2014-2023. The strategies are held against a buy-and-hold strategy in the same indexes and evaluated on different performance measures. The study finds that one strategy outperforms the benchmark in the frontier market, while two strategies beat the benchmark in the emerging market. None of the strategies outperform the benchmark in the developed market. Across all markets, the overall best performing strategy is a strategy based on support and resistance levels, tested in the emerging market. Conclusively, the results indicate that technical analysis is not applicable in all markets and support the notion that market efficiency has a significant impact on the profitability of technical trading strategies in the ten-year testing period.

This paper is organized as follows. Part 2 provides an overview of the existing literature which has laid the foundation for both the ongoing debate on the topic of market efficiency and technical analysis, as well as the research question central to this thesis. Additionally, an introduction is made to financial market efficiency and technical analysis in frontier, emerging, and developed markets, including arguments for and against both. Part 3 presents the data and describes the methodological approach to analyzing the trading strategies. Part 4 includes the empirical results and further comments on the evidence. The fifth and final part provides concluding remarks and a discussion of further development.

1.1 Research Aims and Motivation

From an academic standpoint, this thesis contributes to the existing financial literature and ongoing debate on financial markets, technical analysis, and market efficiency by examining technical analysis profitability in markets with different levels of efficiency. Investigating the success of technical analysis strategies sheds light on whether markets are truly efficient in all aspects of the EMH, or if there are exploitable patterns.

The existing literature contains extensive research on the relationship between market efficiency and the financial advancement of a country. Previous research on market efficiency in developed, emerging, and frontier markets has primarily analyzed and compared market efficiency in different countries via some widespread measures. However, the attention to the Efficient Market Hypothesis and its contents, as well as their connection to financial market development has been relatively limited. This thesis aims to add another aspect to the discussion of the EMH, by incorporating the use of technical analysis in more and less efficient markets. This approach provides a direct analysis of one of the main pillars within the weak-form EMH - that it is not possible to generate abnormal returns in efficient stock markets using historical information.

The findings of this thesis have some practical implications as it explores the practicality of technical analysis in real-world trading scenarios. By analyzing historical data and applying technical indicators and strategies, it evaluates whether traders can consistently generate profits in markets of varying efficiency using a given approach. Furthermore, by understanding the strengths and weaknesses of technical analysis, investors, traders, and financial institutions can allocate their capital more effectively and improve their overall investment performance.

2 Theoretical Background

2.1 Literature Review

The objective of this literature review is to survey previously written literature regarding the subject of technical analysis and market efficiency in frontier, emerging, and developed markets. It will also examine how different academics prior to the making of this thesis have analyzed market efficiency and the use of technical analysis. The aim of the review is to use well-cited and acknowledged literature, to guarantee the use of trustworthy and reputable sources.

Many studies have compared the stock market efficiencies of different nationalities, and the majority suggests that the most developed markets are more efficient than emerging and frontier markets. (Lee & Choi, 2023) examines the market efficiency of global stock markets, categorized by frontier, emerging, and developed markets. The study reveals that the stock markets of financially advanced countries, such as the U.S. and the U.K., are more efficient compared to other countries. Their study indicates that global issues primarily impact developed markets, while emerging markets are more susceptible to political risks and foreign capital movements. Meanwhile, in the frontier markets, domestic issues vary, making it challenging to identify similar dynamics. They attribute the efficiency gap to the incomplete nature of financial systems in frontier and emerging markets, compared to the more advanced developed markets. The more efficient stock markets of developed countries are also explained by robust economic growth rates and larger and more open financial markets. Similarly, (Hull & McGroarty, 2014) investigates the relationship between market efficiency and market development. The study analyzes markets categorized as either advanced or secondary, and the findings indicate that advanced markets show greater efficiency in returns and volatility than secondary markets. Furthermore, a study done by (Ali et al., 2018) reveals that developed markets show the highest efficiency, followed by the BRICS markets.

Over a 11-year period, (Sermpinis et al., 2021) investigates the performance of more than 21,000 technical trading strategies on 12 country-specific markets divided into frontier, emerging, and developed markets. They find evidence of profitability in all markets, but with weak consistency and highly depending on financial stress. In periods of low stress, the strategies are only profitable in the developed U.S. market. In periods of high financial stress however, the profitability in emerging markets are more than five times higher than in developed markets.

(Tvede, 1990) analyzes the discrepancy between the literature and the practical use of technical analysis in the trading world, posing the question: if markets have been proved to be efficient in the literature, why do so many traders and investors use technical analysis? The book argues that the academic community has never made a theory to explain why technical analysis is of any value, since the general conviction was that the Random Walk and Efficient Market Hypothesis were true - stating that future stock prices cannot be predicted as they fluctuate randomly around the fair value, and all available information is already included in the price. The book proposes theories to explain why these hypotheses are not true, even though the academics have provided rather strong mathematical evidence for it. One of the theories introduced is chaos theory, where strong, positive feed-back loops exist in the financial markets, which are observable through statistical "fat-tails" and can be predicted in the short term. According to Tvede, the technical phenomena in financial markets can be explained by terms such as social psychology, psychoanalysis, behavioral psychology and cognitive psychology.

(Bessembinder & Chan, 1998) reviews and compares empirical studies with contrarian views on technical analysis. This includes (Fama & Blume, 1966) who concludes that technical analysis is not useful for improving returns, and (Brock et al., 1992) who demonstrate how a simple set of technical trading rules have significant forecasting power in the Dow Jones Industrial Average index. (Bessembinder & Chan, 1998) further analyzes the work done by Brock et. al. on the use of technical analysis on U.S. equity indexes, by also comparing it to a buy-and-hold strategy. The findings revealed that simple forms of technical analysis do hold significant forecasting power. They argue that the evidence of this forecasting power does not need to be inconsistent with market efficiency - meaning that technical analysis can be useful even if markets are efficient.

(Sturm, 2013) and (Malkiel, 2003) both take a more psychological approach to the topic of technical analysis and efficient markets. Sturm poses the question of whether technical analysis and efficient markets can coexist. He states that stock prices merely reflect investors' beliefs about a company's unknown true intrinsic value and that behavioral finance thereby plays an important part. Technical analysis is used to measure changes in these beliefs and predict prices and should have significant value due to its use in practice and the predictability of human behavior. Sturm also describes how market efficiency cannot reflect reality, as there must be enough inefficiency in the markets for those investors who look for it. If this was not the case, all information would no longer be discounted into the price and the markets would then be less efficient. Thus, prices do not actually reflect intrinsic value, but instead investors' beliefs about the intrinsic value - which is why behavioral finance is important, according to Sturm. He states that literature on behavioral finance has provided evidence that markets are not perfectly efficient, especially in the areas of momentum and overreaction. Technical analysis is also a tool used for inferring the behavior and beliefs of investors, which would mean that technical analysis should hold some value. Other evidence suggesting the value of technical analysis stems from the practicing community. According to Sturm, most large financial institutions use some form of technical analysis in their decision-making. He argues that it would be irrational for these institutions to use resources on technical analysis if it did not hold any valuable information to them. Finally, Sturms argues that technical analysis should hold the most value in markets with big differences in beliefs, reflected by high price volatility. So, the lack of evidence of the profitability of technical analysis in academic literature could possibly be a result of the authors not distinguishing between high and low volatility in the markets.

(Malkiel, 2003) also reviews three schools of thought that challenge the efficient market hypothesis with evidence that predictable patterns in prices exist. The first school of thought is momentum investing, where studies have shown several examples of short-term serial correlations between stock prices that are not zero, suggesting the possibility of predictable patterns. However, these findings may not be economically significant in real-world trading - as soon as a similar effect is made public, investors will use the information in their investment decisions which will make the effect disappear. The second school of thought is behavioral finance, which suggests that investors often overreact or underreact to events in the financial markets, meaning that prices tend to rise higher or fall lower than they should according to the new fair value. The last school of thought is fundamental analysis. In this regard, Malkiel argues that fundamental measures cannot be used to consistently predict stock performance, meaning that they do not contradict the EMH. The same is the case for anomalies, as they lose their predictive power as soon as they are discovered by investors.

Overall, the literature above suggests a nuanced relationship between technical analysis and market efficiency in financial markets. Despite the assertions of market efficiency in the theory, the empirical evidence and practical applications support the idea that technical analysis holds predictive value in some situations, and that its validity varies depending on market development. This discrepancy inspires the research question of whether the success of using technical analysis is inconsistent with the

EMH, encouraging an investigation of the underlying mechanisms driving behavioral finance and the efficiency of technical analysis strategies in frontier, emerging, and developed markets.

2.2 The Efficient Market Hypothesis

At its core, the Efficient Market Hypothesis relates to how all available information is reflected in asset prices. An implication of this hypothesis is that it is impossible to consistently outperform the market on a risk-adjusted basis. The theory of efficient markets remains a cornerstone of modern finance, and despite its evidence being inconclusive, the underlying concepts remain sound.

The idea of efficient markets can be sourced back to the early 1900s and is closely related to the Random Walk Hypothesis, which states that changes in asset prices are random and cannot be predicted (Kirman, 2010). The literature on the topic postulates that changes in stock prices are unpredictable as they depend on new information rather than historical prices. Thus, prices are believed to fluctuate randomly, showing a close link between the two hypotheses (Samuelson, 1965). The theory of efficient markets later became popular during the 1960s, as computers made it possible to perform complicated calculations of hundreds of stocks and prices far quicker than before.

Today, market efficiency is generally divided into three forms: weak, semi-strong and strong. The concept of the weak form is that financial asset prices fully reflect all historical price information. Consequently, investors are unable to obtain abnormal profits by using strategies based on past price information alone, as prices follow a random walk. This means that technical analysis yields no excess return. The semi-strong form of market efficiency includes the assumptions of the weak form, but adds the assumption that asset prices also reflect all publicly available information, e.g. acquisition announcements, dividend payouts, layoffs, etc. This implies that the only way to beat the market average return is by using non-public information. Finally, the strong form of market efficiency adds further assumptions to the weak and semi-strong forms, by assuming that asset prices always reflect all publicly and privately available information. This implies that no investors have the ability of creating higher profits than others due to monopolistic access to insider information (Fama, 1970).

Generally, efficient markets can be divided into two categories: “informationally efficient” and “fundamentally efficient”. Markets are informationally efficient when prices reflect all available information about future values. This arises from competition, low entry barriers, the accessibility of information, and from investors who will incorporate any available signals into market prices, ensuring that all relevant information is accurately reflected by the prices (Fama, 1970). Markets are defined as fundamentally efficient when prices reflect the fundamental values of the assets (Gilson & Kraakman, 2014).

A notion central to the EMH is that it is nearly impossible to consistently beat the market. While investors might achieve short-term gains, it will be due to luck, and a sustained outperformance of the market average in the long-term is unrealistic. This perspective rests on various assumptions about financial markets, most importantly the belief that all relevant information is widely accessible to all investors. In efficient markets, changes in price occur promptly due to the abundance of buyers and sellers, which means that stocks are constantly traded at their fair market value, leaving no opportunities for arbitrage. Because of this, attempting to time the market is unlikely to create returns superior to those of the overall market. Thus, investors seeking higher returns than the market must be willing to accept higher levels of risk (Fama, 1970).

As mentioned in the literature review, the many years of empirical research on predictability in financial markets has resulted in mixed evidence. The research of the 1950-60's mostly found no evidence of predictability, while various academics throughout the 1980-2000's found evidence supporting different return predictors. Since then, results in the literature have found that predictability has become more difficult to prove, as it has often failed to work out-of-sample and has likely been weakened by advanced trading technologies and heightened financial literacy among investors.

2.2.1 Evidence for and against the Efficient Market Hypothesis

In modern financial theory, the significance of the efficient market hypothesis remains a subject of discussion. Today, the flow of information and the use of algorithmic trading has made trade execution faster than ever, which helps support the EMH. Simultaneously, the increased use of technical trading strategies and certain patterns in financial asset prices remain difficult to explain with the EMH.

Recent studies have provided evidence that efficiency does exist to some degree in several financial markets. The evidence from these studies often show that efficiency is time-varying and that markets today can be significantly inefficient over longer periods of time. During the last 10-20 years, the world has experienced many periods of major economic events, in which markets tend to become less efficient (Le Tran & Leirvik, 2019). A study from 2021 tests the market efficiency of four markets, including stock indexes, gold, cryptocurrency, and forex during the COVID-19 pandemic, and assesses market efficiency during other major financial crises through recent history. The study shows that market efficiency is adversely correlated to these crises, and that the probability of a market crash in some cases increases as the efficiency decreases. The different markets tested in the study showed efficiency varying between 43-85%, and the efficiency of all four markets declined steeply during the outbreak of the COVID-19 pandemic (Wang & Wang, 2021).

Several financial phenomena appear to contradict the EMH (Degutis & Novickytė, 2014). One example of this is that strategies based on investing in small-cap companies typically yield higher returns than those based on investing in large-cap companies (Malkiel, 2003). However, the strength of this effect has diminished over time, possibly due to the awareness of the effect among investors, who then seek to exploit it. Similarly, value stocks generally tend to outperform growth stocks and studies have shown that 75% of U.S. corporate profits can be explained by changes in companies' Price-to-Book ratio. Some studies even provide evidence that numbers such as Price-to-Earnings can be used to predict future asset prices and volatility. Finally, market anomalies like the "January effect" also challenges the EMH. This phenomenon refers to the tendency of average returns in financial markets being higher in the first month of the year, likely due to investors closing unprofitable positions at the end of the year to minimize tax payments, followed by reinvestments in January (Degutis & Novickytė, 2014).

The EMH indicates that active asset management has little value, as it is not possible to consistently beat the average market return. In line with this assumption, a study of U.S. mutual funds shows that the funds on average earn higher returns than their benchmarks in only 16 of the 47 years studied. In another study, 66% of funds had lower returns than their benchmark from 1970 to 2010. The funds that were able to be profitable in the short-term did not consistently remain profitable in the long-term, which supports the EMH (Degutis & Novickytė, 2014).

Regarding the three forms of efficiency, studies have provided mixed evidence. The weak form suggests that technical analysis holds no value, as all historical price data is reflected by the price. Generally, it seems that the profitability of technical analysis varies depending on the market, volatility, transaction costs, data snooping, and financial crises (Park, Cheol-Ho & Irwin, 2007). For example, simple moving average strategies applied to high-volatility portfolios have been shown to substantially outperform a buy-and-hold strategy (Han et al., 2013). Initially, Fama tested for the weak form by measuring autocorrelation between returns in the Dow Jones Industrial Average for a five-year period and found that the autocorrelations were zero - indicating a linear independence and thus a weak form of market efficiency (Fama, 1970). Since then, other tests have shown the autocorrelations in asset prices to be non-zero, suggesting a short-term momentum in prices, which is inconsistent with the weak form (Campbell et al., 1998).

Similarly to the weak form, there has been mixed arguments and evidence regarding the semi-strong form of the EMH. Most studies testing for this form use event studies to test how prices react to new information (Campbell et al., 1998). If the markets are efficient, new information should be incorporated into the price immediately. Studies of this kind have several times proved the presence of semi-strong market efficiency. A study from 2000 analyzed investors' reaction to corporate news and found that price adjustments supported the semi-strong form of market efficiency. The study claims that asset prices "drift" before the announcements, showing either information leaks or market anticipation. On the day of the announcement, the price would then change to the new intrinsic value and would not be followed by further price corrections (Shleifer, 2000). This is however often debated by academics, as some studies suggest that varying awareness among investors and differentiating transaction costs sometimes prevent an immediate and complete adjustment of these values in market prices (Koller et al., 2010). Other studies have shown that instead of reverting to a random walk, prices tend to drift back, which suggests that the semi-strong form does not hold. Furthermore, in 2008 a study was performed, creating a trading strategy based on a proxy for company earnings announcements. The strategy resulted in an average abnormal return of 7.55% per year during a 17-year period, thus clearly violating the semi-strong form of market efficiency (Kishore et al., 2008).

Most empirical studies provide evidence suggesting that financial markets are not strongly efficient. A study from 1995 found that insider traders can use inside information prior to public announcements to time their investments and consistently achieve abnormal returns (Pettit & Venkatesh, 1995). Meanwhile, by following situations where at least three insiders in a given company trade in the same way, it is possible to achieve an excess return of more than 5% in the following eight months, even by executing the trades with a two-month delay. This indicates that insiders trade on better insight, rather than confidential information (Jaffe, 1974).

Thus, a large amount of evidence exists that financial markets are not strong-form efficient. Generally, most empirical evidence suggests that the semi-strong form of market efficiency does not hold, as prices do not reflect all available information immediately. However, the weak form remains highly debated.

2.2.3 Critics of the Efficient Market Hypothesis

Proponents of the EMH have argued that investors in general are rational and value maximizing and will seek to make optimal decisions based on the information available to them. In 1970, Fama stated that an efficient market has a great number of rational, profit-maximizers who try to predict future prices, and has important information freely available to everyone (Fama, 1970). Opponents of the theory, who usually include professional investors and behavioral economists, will disagree with this assumption of rationality. Instead, they use a behavioral framework as explanation for anomalies in financial markets, and often point out successful investors and hedge fund managers who consistently have beaten the market over many years.

Economists argue that fully embracing the EMH contradicts the beliefs of Adam Smith and John M. Keynes, who emphasized the impact of irrational behavior on financial markets (Green & Bishop, 2010). Similarly, prominent investors and partners Warren Buffet and Charlie Munger contend against the EMH, citing the exceptional performance of leading value investors as evidence against it (Buffett, 1984). Both Buffet and Munger fall into this category themselves, as their holding company, Berkshire Hathaway, has significantly outperformed the S&P 500 index, achieving a 50.799% return over the past 40 years compared to the S&P's 4.213% return (Saul, 2024). Another notable critic of the EMH is Peter Lynch, a successful investor and mutual fund manager. During his 13-year tenure managing the Magellan Fund, the fund achieved an annual return of 29%, consistently more than doubling the S&P 500′s performance (Raisinghani, 2022). Lynch argues that the EMH contradicts the Random Walk Hypothesis, asserting that if asset prices reflect all available information, then price changes in price should not be random. Conversely, if they are random, then prices cannot be rational, as indicated by the EMH (Lynch & Rothchild, 1989).

The trader Jack Schwager also shares the perception that it is challenging for the average investor to consistently outperform the market. However, he posits that while new information may be disseminated almost instantaneously, its interpretation and application vary among market participants, influenced by their skill and experience. Schwager argues that irrational human behavior contributes to the difficulty investors face in generating consistently above-average returns (Schwager, 2012).

2.2.4 Behavioral Finance

As stated by several academics and fund managers, behavioral economics play a significant role in the profitability of technical analysis and thus in the efficiency of markets. Several contradictions to the EMH arise from the irrationality of market participants, both private and professional. This irrationality can be divided into a number of phenomena, that all counteract the EMH and support the idea of using technical analysis as a way of generating abnormal returns in the markets (Degutis & Novickytė, 2014).

For a long time up until the 1980s, economists almost exclusively focused on economic models with the assumption about investor psychology, that market participants make rational decisions (Degutis & Novickytė, 2014). This includes having rational, consistent preferences, maximizing utility, and making independent decisions based on all available information (Becker, 1976). Later, new models started being developed with assumptions about investor behavior that were more psychologically realistic - including that not all decisions made by investors are rational. Instead, they make less than optimal decisions due to lack of information or the ability to process it. Today, this approach to economics has gained significance among both academics, economists, and investors.

When market participants act on their intuition instead of making rational decisions, behavioral biases tend to arise. This can lead to market anomalies such as crashes and bubbles, where market prices differ significantly from fundamental values, deviating from the EMH. The most commonly occurring biases include overconfidence, the disposition effect, herding, and the representativeness effect (Kumar & Goyal, 2015).

Overconfidence implies investors being too confident in their own abilities and knowledge, leading to overtrading. Countless studies have shown that most investors, private and professional, have too much confidence in their own skills. A study was made of 11,600 predictions from different fund managers of how the S&P 500 will look one year ahead. The results showed that the managers on average made worse predictions than if they had made the forecast at random. However, subsequent interviews revealed that most still did not understand that they were not up to the task (Ben-David et al., 2013). Overconfidence often exists simply because investors generally have very little diversification in their portfolios. This results in high levels of volatility, meaning that some are lucky enough to beat the market (Tvede, 1990).

The dispositions effect refers to the fact that investors are more likely to close their profitable positions and hold on to their losing positions. They tend to close positions even with limited profit to feel good about their trade but hesitate to close their losing trades, because they keep on hoping that the trade will turn around and turn into profit. This leads to lower returns in the long-term. This effect is reflected by the turnover in bull-markets being much higher than in bear-markets (Tvede, 1990).

Herding refers to investors following the judgement and actions of their peers. Studies have shown that private investors tend to buy stocks after seeing a very large trading volume or price movements in those stocks, or after the stocks were mentioned in the news (Barber & Odean, 2008). This is also one of the effects believed to have contributed to both the popularity of technical analysis and to the great self-confidence in the academic world regarding efficient markets and random walks. It is no secret that certain types of technical analysis with no logical explanation behind it simply work as self-fulfilling rituals repeated by traders who once were lucky to make a profit doing it or had seen others do it (Degutis & Novickytė, 2014).

Finally, the representativeness effect describes investors estimating the probability of a future event based on how much that situation resembles some similar situation in the past. This could be that an investor buys a stock simply because it has been trending upwards for some time (Degutis & Novickytė, 2014). It is estimated that the latest price movements in stocks typically form 50% of the basis for investors' assessment of a stock's current value (Tvede, 1990). Just like herding, this effect is a large part of the psychology behind some popular technical trading patterns and indicators, which may exist due to the behavioral factors influencing buying and selling decisions (Degutis & Novickytė, 2014).

Other common behavioral biases include home bias, confirmation bias, cognitive dissonance, and the endowment effect (Degutis & Novickytė, 2014). Altogether, these biases and phenomena imply that investors do not always process all available information or act rationally, which can significantly influence market dynamics and lead to effects that can be exploited by technical analysis. As market dynamics and investor behavior differ across frontier, emerging, and developed markets, so do behavioral finance effects.

In more efficient markets, prices reflect available information more accurately due to better availability and higher investor sophistication. Behavioral biases still exist in more efficient, developed markets but are often mitigated by institutional investors and arbitrage opportunities. Developed markets often have higher numbers of institutions who have access to strategies and tools to counteract biases that investors in some emerging and frontier markets may not. Instead, they are defined by a relatively larger number of private investors who are more prone to biases. Similarly, regulations and politics in developed markets provide more stability and protection against market manipulation, while a weaker regulatory framework in frontier and emerging markets may amplify the effect of these biases. Thus, it makes sense to test technical analysis strategies in different market contexts, as behavioral factors may have a significant impact on the profitability of such.

2.3 The Adaptive Market Hypothesis

As the EMH remains highly discussed, some alternative concepts have found their way into economic literature - one of them being the Adaptive Market Hypothesis (AMH). The AMH is based on the idea that markets and their participants are not always rational or optimal, but oftentimes emotional and heuristic. The concept of the AMH suggests that studying the financial markets can be done using evolutionary models. It assumes that markets are not static but dynamic and adapt to changing environments (Lo, 2004). Asset prices are affected by a wide range of factors, such as regulations, market imperfections, limits to arbitrage, and the psychology of market participants. These factors change over time, and thus so will market efficiency (Shleifer & Vishny, 1997).

The idea that market participants are not rational profit maximizers is supported by behavioral finance. Behavioral finance suggests that anomalies (such as bubbles, trends, and crashes) and arbitrage opportunities can exist in efficient financial markets, mainly due to psychological factors among market participants. Their actions are highly affected by their emotions, which are subject to behavioral biases, and can lead to over and underreactions in the markets (Ritter, 2003). This school of thought contradicts the main elements of the EMH but is consistent with the AMH.

One of the main implications of the AMH is that profit opportunities fluctuate based on the level of market efficiency and the prevailing market conditions. Within finance, a significant practical implication of the AMH lies in the timing of implementing profitable investment strategies, as the profit opportunities shift over time. This means that chances to earn abnormal returns in the market emerge periodically, even using technical analysis, but diminish once they have been exploited. Thus, contrary to the EMH, which suggests that active asset management holds little or no value and cannot outperform a passive strategy, the AMH supports active management of investments (Lekhal & El Oubani, 2020).

Studies have been made to test the implications of the AMH. One recent study from 2020 tracks the performance of a momentum-based trading strategy, and tests whether its performance is correlated to the level of market efficiency. The study finds that the level of efficiency is time-varying and that the momentum-based strategy yields profit opportunities from time to time, which then disappear once they have been exploited. The profitability of the strategy depends on both the level of efficiency and other market conditions, meaning that investors can capitalize on inefficiency in the markets using a momentum-based strategy. The findings are consistent with the AMH but not the EMH, and the study suggests that the AMH is proven to provide a better explanation of the behavior of financial markets (Lekhal & El Oubani, 2020).

2.4 Efficiency in Frontier, Emerging, and Developed Markets

It is important to note that the differences in market efficiency between developed, emerging and frontier markets differ from country to country, and each country has distinct factors that impact its market dynamics. However, they usually exhibit similar characteristics.

Developed markets generally have a high sensitivity towards global issues, and the dynamics of their efficiency can change rapidly. These markets are particularly vulnerable to various issues, due to their large stock markets and diverse range of market participants. Examples of this include significant global events such as the financial crisis in 2008 and the COVID-19 pandemic in 2020 (Lee & Choi, 2023). Similarly, the same dynamics can often be observed in different markets based on the trade relations between countries and institutions. For example, countries within the EU share various patterns. The same is the case with countries within NAFTA or the Commonwealth of Nations.

Within emerging markets, the dynamics of market efficiency show significant variations. In emerging markets, financial policies play a more pivotal role in shaping stock market efficiency. For instance, the emerging market China's restricted foreign investment and severe trading regulations lead to low fluctuations in market efficiency during global events (Lee & Choi, 2023). In Egypt, a nation highly dependent on foreign capital, stock returns and market efficiency are greatly influenced by exchange rates and exchange rate systems (Ahmed, 2020). This is also the case in countries like South Korea, Taiwan, and India, where corporate dividend policies are changed to attract foreign investors and where stocks with high foreign ownership outperforms those with low foreign ownership (Kim & Jo, 2019).

Compared to emerging and developed markets, frontier markets generally exhibit unique characteristics within the group, making it difficult to identify similar dynamics. This is in large part due to frontier markets experiencing larger impacts from political crises and conflicts, resulting in higher risk compared to developed and emerging markets. Finally, frontier markets experience great impact from industrial and regional issues and rely even more heavily on domestic markets than emerging countries do (Meziani, 2020).

2.5 Technical Analysis

As in the case with efficient markets, the buying and selling of financial assets have been thoroughly examined over the past century. Many have sought reliable methods for assessing market conditions and selecting profitable investments. This research has led to two main approaches to investing: fundamental and technical analysis. Investors using fundamental analysis rely on statistical data like financial reports and industry trends to evaluate financial assets, while those using technical analysis focus on price movements and market patterns. Although some claim allegiance to one method, most investors acknowledge the value of both approaches in making informed investment decisions (Edwards et al., 2018). Today, many market participants believe in the importance of knowing some degree of technical analysis, because many traders use it, giving it a self-reinforcing effect (Griffioen, 2003).

Instead of focusing on the intrinsic value of financial assets, technical analysts focus on market behavior, which involves assessing price history and volume and predicting future trends based on this data. Technical analysts argue that attempting to determine an asset's intrinsic value is pointless, as its price is solely determined by supply and demand. They emphasize that market prices reflect all information, including investors' emotions, future expectations, and other factors not captured by traditional fundamental analysis. When you trade short-term, like many technical analysts, fundamental factors play an insignificant role. Additionally, markets move in trends which are bound to continue until something changes the supply-demand balance. These changes are usually observable in the price action of the markets in the form of certain patterns, formations, or levels that repeat themselves. These are not foolproof, but they do have some predictive power (Edwards et al., 2018).

One underlying assumption of technical analysis is that history repeats itself. Technical analysists argues that prices reflect market psychology, and as described in Chapter 2.2.4, various behavioral biases strengthen the profitability of technical trading strategies. Another significant reason why technical analysis might work is a feedback effect known as the self-fulfilling prophecy. Financial markets are unique in the way that studies of the markets have an impact on the markets themselves. As traders learn and gain experience, they use their results in their decision-making processes in the future. When a large number of traders recognize and react to certain technical patterns or indicators, they can collectively change prices in the direction that coincide with their common expectations. When these expectations are met, it will create a positive feedback-loop that reinforces the trust in technical analysis and the belief that if a certain pattern predicted a move in the past, it will also do so in the future (Garzarelli et al., 2014).

2.5.1 Charts and Candlesticks

For traders using technical analysis, charts are an indispensable tool, offering a comprehensive view of price history that is essential for making decisions in financial markets. They help provide valuable insights into market volatility and help traders assess risk effectively. In addition, charts serve as a valuable timing tool for traders by assisting in executing well-timed transactions, regardless of whether you are a fundamental or technical analyst. Furthermore, they can play a significant role in money management by helping traders define meaningful exit levels to protect their investments. Finally, charts can be used to reveal repetitive patterns in market behavior and utilize technical indicators that traders can leverage to successfully anticipate price movements (Schwager, 1995).

For traders using technical analysis, candlestick charts are the preferred chart type, since they provide more detail about asset prices than alternatives like a simple line chart. Candlesticks display the high, low, open, and closing prices of an asset for a specific period. The wide part of the candlestick is called the “body” and shows the open and closing price. If the closing price was lower than the opening price, the body is depicted as green or white as default on most charts. If the closing price was higher than the opening price, the body is red or black. The shadows of the candlesticks show the high and low of the price, and how they compare to the open and close. As a result, the shape of the candlestick varies depending on the relationship between the high, low, open and closing price of a given period (Schwager, 1995).

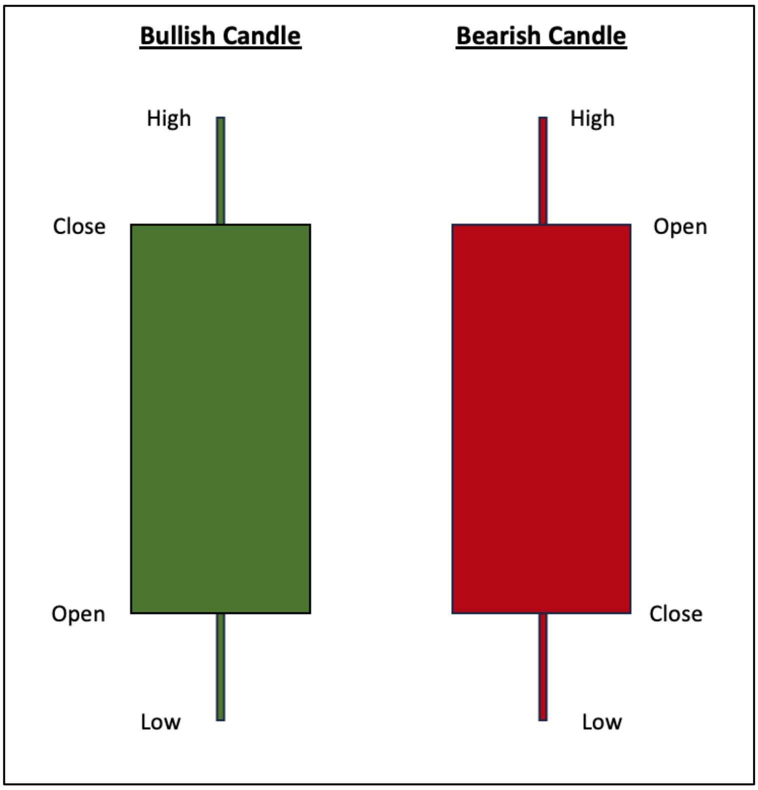

***Figure 1 -** Candlestick figures. **Source:** Own creation*

Besides this price relationship, candlestick charts also reflect the emotion of investors and investor sentiment. Depending on the prices, the candlesticks can take on many shapes, which have different names and meanings. Traders use these different shapes as signals in combination with certain chart patterns and indicators to make informed trading decisions and forecast the direction of the price based on recurring patterns. The most common categories of indicators include trend, volume and breadth indicators (Schwager, 1995).

3 Methodology

This section will assess how the analysis of the thesis is performed. To test the research question of whether the success of technical analysis is inconsistent with stock market efficiency, four different technical analysis strategies are tested on three different markets.

3.1 Market Selection

Central to the testing of the research question is the hypothesis that some markets are more efficient than others. This hypothesis is based on studies revealing that stock markets in financially advanced countries are more efficient than in other countries. For this reason, the tests will be performed on one market from each of the three categories; frontier, emerging, and developed markets. To determine which markets to use for the test, the MSCI (Morgan Stanley Capital International) market classification is used. Each year, MSCI evaluates equity markets from the whole world to determine their classification. They base the classifications on the markets' economic development, size, liquidity, and accessibility (MSCI, 2024e).

Frontier markets are considered by MSCI as the least developed among the three categories and are described as developing markets but with equity markets too small, risky or illiquid to be considered emerging markets. These countries often experience limited infrastructure as well as low levels of industrialization and regulatory frameworks. Frontier stock markets usually have lower liquidity, smaller companies, limited access to financial instruments and shorting of stocks, and considerable levels of investment risk compared to emerging and developed markets. Investing in frontier markets may result in higher returns, but investors may also face significant challenges regarding underdeveloped financial systems, political instability and lack of transparency (MSCI, 2023).

Emerging markets share some of the characteristics of developed markets, but do not fully meet the same standards. They often have lower income levels but experience considerably higher economic growth and are transitioning into becoming developed markets. They generally have less stable financial markets, weaker regulations, and higher economic and political risks. As with frontier markets, investing in emerging markets may grant opportunities for higher returns but also bring greater risk and volatility (MSCI, 2024b).

Developed markets are classified as countries with more advanced economies, more mature and well-established equity markets and regulatory frameworks, higher living standards, and well-developed infrastructure. These countries generally have high levels of industrialization, economic stability, and income per capita. Compared to emerging and frontier markets, they provide greater transparency, stability and liquidity to portfolios, and investors have access to a wider range of investment opportunities and financial instruments (MSCI, 2024a).

The framework used by MSCI for the classification is seen in Figure 2 and the classification is seen in Figure 3. A country must meet the requirements of all three criteria in the table to be classified in each category (MSCI, 2023).

Criteria	Frontier	Emerging	Developed
A Economic Development			
A.1 Sustainability of economic development	No requirement	No requirement	Country GNI per capita 25% above the World Bank high income threshold* for 3 consecutive years
B Size and Liquidity Requirements			
B.1 Number of companies meeting the following Standard Index criteria	2	3	5
Company size (full market cap)**	USD 1,033 mm	USD 2,066 mm	USD 4,133 mm
Security size (float market cap)**	USD 73 mm	USD 1,033 mm	USD 2,066 mm
Security liquidity	2.5% ATVR	15% ATVR	20% ATVR
C Market Accessibility Criteria			
C.1 Openness to foreign ownership	At least some	Significant	Very high
C.2 Ease of capital inflows / outflows	At least partial	Significant	Very high
C.3 Efficiency of operational framework	Modest	Good and tested	Very high
C.4 Availability of investment instruments	High	High	Unrestricted
C.5 Stability of the institutional framework	Modest	Modest	Very high

* High income threshold: 2021 GNI per capita of USD 13,205 (World Bank, Atlas method)
** Minimum in use for the May 2023 Index Review, updated on a quarterly basis

***Figure 2 -** MSCI market classification framework*

***Source:** (MSCI, 2023)*

From each category, the country with the highest total stock market capitalization is chosen (World Federation of Exchanges, 2022). Thus, Vietnam is chosen as a frontier market, China as an emerging market, and the U.S. as a developed market. From each of these three countries, the biggest index is chosen as proxies for the country's stock market: the VN-Index (Vietnam Ho Chi Minh Stock Index) from Vietnam, the CSI 300 (China Securities Index 300) from China and the S&P 500 (Standard & Poor's 500) from the US.

Developed markets			Emerging markets			Frontier markets		
Americas	EMEA	APAC	Americas	EMEA	APAC	Americas	EMEA	APAC
Canada	Austria	Australia	Brazil	Czech Republic	China	-	Bahrain	Bangladesh
USA	Belgium	Hong Kong	Chile	Egypt	India		Benin	Pakistan
	Denmark	Japan	Colombia	Greece	Indonesia		Burkina Faso	Sri Lanka
	Finland	New Zealand	Mexico	Hungary	Korea		Croatia	Vietnam
	France	Singapore	Peru	Kuwait	Malaysia		Estonia	
	Germany			Poland	Philippines		Guines-Bissau	
	Ireland			Qatar	Taiwan		Iceland	
	Israel			Saudi Arabia	Thailand		Ivory Coast	
	Italy			South Africa			Jordan	
	Netherlands			Turkey			Kazakhstan	
	Norway			UAE			Kenya	
	Portugal						Latvia	
	Spain						Lithuania	
	Sweden						Mali	
	Switzerland						Mauritius	
	UK						Morocco	
							Niger	
							Oman	
							Romania	
							Senegal	
							Serbia	
							Slovenia	
							Togo	
							Tunisia	

EMEA - Europe, Middle East, and Africa
APAC - Asia Pacific

***Figure 3 -** MSCI market classification*

***Source:** (MSCI, 2024e)*

The VN-Index comprises all companies listed on the main stock exchange in Vietnam, the Ho Chi Minh Stock Exchange, and is considered a benchmark for large and blue-chip stocks (Bloomberg, 2024c). The CSI 300 tracks the performance of the 300 most liquid stocks traded on the Shanghai Stock Exchange and the Shenzhen Stock Exchange, which are the two primary stock exchanges in mainland China (Bloomberg, 2024b). Finally, the S&P 500 tracks the performance of the 500 largest companies listed on the U.S. stock exchanges and covers approximately 80% of the available market capitalization of U.S. public companies. It is one of the most followed indices in the world and is widely regarded as the best single gauge of large-cap equities in the U.S. (Bloomberg, 2024a). All three indices are considered representative of the broader stock markets, and all are capitalization-weighted.

The rationale for testing the strategies on stock indices instead of individual stocks is that indices generally tend to exhibit more systematic risks compared to stocks, which are often more idiosyncratic. This difference in risk can negatively influence the effectiveness of using technical analysis. Technical analysis relies mainly on historical prices and volume and thereby captures the collective behavior of market participants. Thus, since indices are influenced by systematic risk factors affecting the broader market, technical analysis may be more reliable to some extent. Additionally, due to the aggregation of the movement of many individual stocks, some technical patterns may be more pronounced and reliable in indices. Individual stocks on the other hand, are exposed to risks specific to the given stock which arise from company-specific factors since individual stocks all have their own unique characteristics. These factors can create noise in the price movements, making it difficult to rely on technical indicators and patterns for accurate predictions (Ma et al., 2020).

3.1.1 The Vietnamese stock market

The stock market in Vietnam consists of three main exchanges. The Ho Chi Minh Stock Exchange (HOSE) was established in 2000, the Hanoi Stock Exchange (HNX) was established in 2005, and the Unlisted Public Company Market (UPCOM) was started in 2009. The HOSE and HNX are the two main exchanges and are more heavily regulated. Most of Vietnam's large cap stocks are listed on the HOSE, and the top 20 listings all have market caps greater than $3 billion. The HNX was originally intended for smaller companies, so the requirements for being listed on this exchange are less strict. Finally, UPCOM was created as a temporary step for companies before being listed on the HOSE or HNX (Kokalari, 2021).

Vietnam has been classified as a frontier market by MSCI since 2007 (MSCI, 2024d). Due to its financial development, economic growth, and political changes, it is anticipated to show great financial advancement in the future (Martin, 2024). Foreign capital has been an important factor contributing to the evolution of the financial market in Vietnam. Most public companies in Vietnam are small and relatively unknown to the outside world, and regulations have limited the access to financial data for foreign investors. However, in recent years, the financial markets have been opened to the outside world, and Vietnam has embraced the globalization of production, technological advances, and trade liberalization. This has attracted foreign investors who seek diversification and higher returns (U.S. Department of State, 2023).

Figure 4 illustrates the performance of the VN-Index from January 2, 2014, to December 29, 2023, showing notable fluctuations. From 2014 to 2016, the VN-Index was range-bound but rose to around 680 VND at the end of 2016. The index then surged significantly from 2017 to 2018, fueled by economic growth, positive investor sentiment and listings of large companies. The index then started declining in 2018 due to economic uncertainties and trade tensions (Nasir et al., 2021). This downfall further escalated in 2020 with the onset of the COVID-19 pandemic, causing the index to drop to around 650 VND in early 2020. Recovering from the pandemic, the index rebounded strongly and reached an all-time high of 1,535 VND in 2022. After this, the index declined and hovered between 960 and 1,280 until the end of 2023.

Figure 4 - *The VN-Index from 2014-2023*

Source: *(TradingView, 2024)*

3.1.2 The Chinese Stock Market

The stock market in mainland China consists of three major exchanges. The Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) were established in 1990, and the Beijing Stock Exchange (BSE) was launched in 2021. The SSE and SZSE are the two primary exchanges. The SZSE was originally created for small and medium-sized companies and the BSE was designed to support innovation-oriented enterprises (Baker McKenzie, 2024). China has been classified as an emerging market by MSCI since 2001 (MSCI, 2024c).

Figure 5 illustrates the performance of the CSI 300 from January 2, 2014, to December 29, 2023. The index had a significant rise in 2015, reaching 5,380 CNY, driven largely by speculative trading and margin financing (Hsu, 2015). This was followed by a steep market correction in 2016. From here on, until 2020, the index was range-bound and unlike many other economies and indexes, the CSI 300 was not deeply affected by the COVID-19 pandemic. After the pandemic, the index saw another significant rise, reaching a peak of almost 6,000 in early 2021. However, from here the index faced downward pressure and experienced a decline until the end of 2023.

Figure 5 - *The CSI 300 from 2014-2023*

Source*: (TradingView, 2024)*

3.1.3 The U.S. Stock Market

In the U.S, the stock market consists of several major exchanges. The main exchange, the New York Stock Exchange (NYSE) was established in 1792 and the Nasdaq Stock Market (NASDAQ) was created in 1971 as the world's first electronic stock market (NYSE, 2024a). The American Stock Exchange (AMEX) was founded in 1908 and primarily lists small and medium sized companies. The NYSE is known for listing many of the world's largest and most well-established companies, while the NASDAQ is known for listing technology companies. The AMEX works as a venue for smaller and emerging companies (NYSE, 2024b).

The U.S. has been classified as a developed market by MSCI since 1986, due to its advanced financial infrastructure, economic growth, and influence on the global economy (MSCI, 2024f).

Figure 6 illustrates the performance of the S&P 500 from January 2, 2014, to December 29, 2023. The index showed steady growth in 2014, after which the price was range-bound from 2015-2016. From 2017, the S&P 500 inclined strongly, with only minor corrections. Then in 2020, the index experienced a significant dip in prices due to the pandemic. Despite this, the index ended the year up, largely driven by stimulus measures and the recovery of technology companies (Reuters, 2020). This trajectory continued until 2022 as the economy rebounded. Then in 2022, the index declined due to geopolitical tensions, interest rate hikes, and rising inflation (Morgan Stanley, 2022). The index recovered in 2023 and reached its old peak around 4,800 USD.

Figure 6 - *The S&P 500 from 2014-2023*

Source: *(TradingView, 2024)*

3.1.4 The U.S. Treasury Bill

Figure 7 illustrates the 1-year U.S. Treasury Bill from January 2, 2014, to December 29, 2023. The Treasury Bill has seen significant changes from 2014 to 2023 reflecting broader economic trends and shifts in monetary policy throughout this period. In the years from the 2008 financial crisis up until 2015, the Treasury Bill remained relatively low, reflecting low interest rates aimed at stimulating the economy. As the economy strengthened, interest rates were raised, and the yield of the Treasury Bill rose to almost 3% in 2018. Economic uncertainties and the COVID-19 pandemic caused rate cuts, driving the yield down to near 0.04% as investors chose alternative assets. From 2021, the economy recovered from the pandemic and inflation rose, leading to higher interest rates and the yield of the Treasury Bill surging to around 5% in 2023 (U.S. Department of the Treasury, 2024).

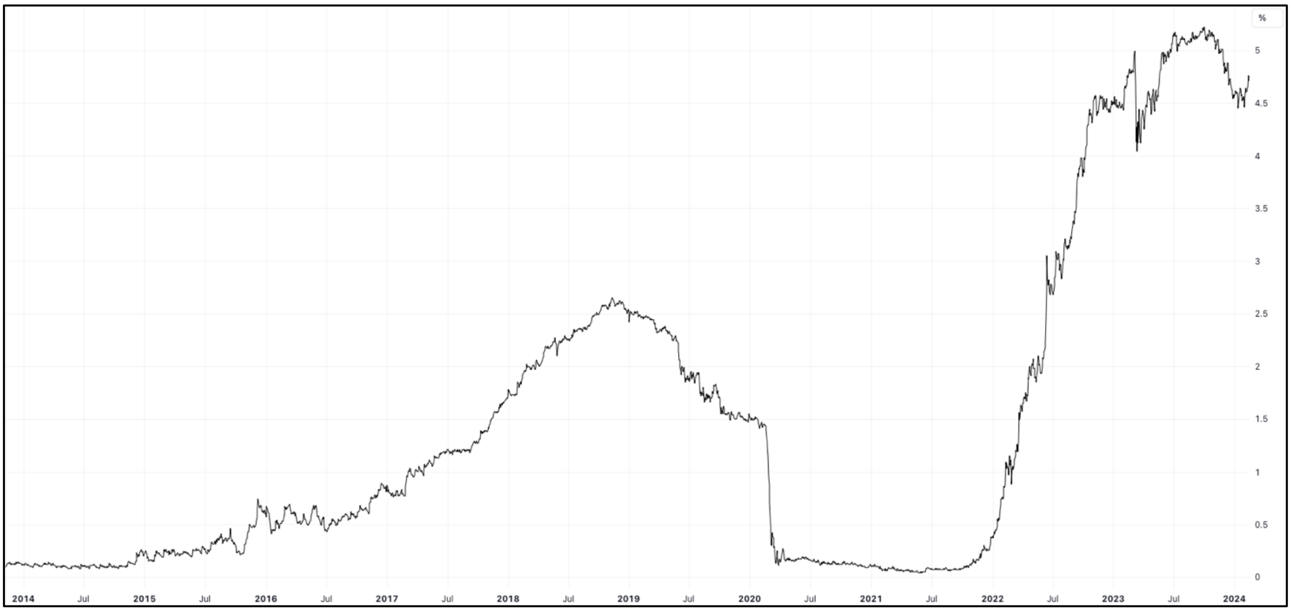

Figure 7 - *1-Year U.S. Treasury Bill from 2014-2023*

Source: *(TradingView, 2024)*

3.2 Data and Time Frame

To perform the strategy analysis, price data for the three indices is taken from the FactSet platform. FactSet is a free, web-based data and software platform for professional and individual investors, with more than 200,000 users worldwide. The platform allows traders and investors to analyze financial markets through insights from raw financial data. It provides a wide range of features needed to convert this data into information to be used in financial analysis and reporting (FactSet, 2024b). FactSet collects equity data directly from global stock and future exchanges, regulatory filings and company websites (FactSet, 2024a). The price charts and indicators are provided from TradingView (TradingView, 2024).

The data spans over a 10-year time period from January 1, 2014, to December 31, 2023. This will ensure that the data includes both bull and bear markets, different economical settings, recessions and geopolitical changes. The price data consists of daily prices for each index. The use of daily prices reduces the noise and false signals that tend to occur on shorter timeframes. With daily data, the focus is on longer-term trends and patterns that may be more indicative of market sentiment. Additionally, daily prices are more readily available from financial data providers and can easily be accessed and analyzed with data spanning over several years.

3.3 Benchmark Construction

The objective of the analysis is to evaluate the performance of technical analysis strategies across markets exhibiting varying degrees of efficiency. The performance of the strategies is benchmarked against a buy-and-hold investment in each index. Specifically, for each index, an initial investment is made on the first trading day of the ten-year period and held throughout the entire period until the last trading day, without reinvestments. This methodology allows for a comprehensive comparison of the performance of the technical analysis strategies, not only against the broader market but also relative to one another.

Given the context of the EMH, a buy-and-hold strategy of the broad market index serves as a practical benchmark. According to weak-form market efficiency, this passive investment should be difficult or impossible to outperform consistently using technical analysis, which relies on past price data. Additionally, several studies have shown that active investment is a bad idea for the vast majority of investors (Barber & Odean, 2000). Furthermore, some behavioral factors seem to favor the use of passive, long-term investing, while others in theory benefit short-term traders. This makes the comparison to a buy-and-hold strategy even more relevant. Finally, a buy-and-hold strategy in a broad market index is widely recognized and used as a benchmark for performance evaluation among investors and fund managers, providing a relatable and practical point of reference. Additionally, using the buy-and-hold as a benchmark aligns with the already existing academic literature, providing a clear and quantifiable standard for measuring the performance of the technical strategies. This makes the study's findings more applicable and relevant to a broad audience.

3.4 Strategies

The strategies employed in this study are rule-based, with trading signals generated by patterns and indicators derived from technical analysis. The traded assets are futures contracts of the three indexes, and all trades are executed on a daily chart. The study evaluates each of the three strategies individually, as well as in combination. This approach aims to determine whether a strategy that integrates multiple indicators outperforms those relying on a single indicator. Theoretically, when multiple indicators align and generate the same signal, it should provide a more robust indication of market direction, reducing the likelihood of entering trades based on false signals. The strategies utilize the following technical indicators and patterns:

- Moving averages
- Relative Strength Index (RSI)
- Support and resistance breakouts

These indicators and patterns are chosen due to their popularity and utilization among traders world-wide.

3.4.1 Moving Average Strategy

A moving average is one of the most utilized tools in technical analysis and trend analysis. The idea behind a moving average is simple; a 50-day moving average is the sum of the last 50 days of trading prices divided by 50. This calculation is then updated daily as new values are added. In general terms, a moving average represents the underlying trend in the supply and demand of an asset, when short-term speculation is removed (Tvede, 1990).

The most popular versions of moving averages are simple, exponential and weighted. The simple moving average uses a simple average of prices over a given time period and calculates the arithmetic mean. The exponential moving average places greater weight on more recent prices than older ones at an exponential rate. Finally, the weighted moving average assigns greater weight on more recent prices as well, but here, the weighting adds up to one (Edwards et al., 2018). The moving average strategy in this study will use exponential moving averages, as they are more sensitive to sudden fluctuations and reversals. The formula of the exponential moving average is:

$$EMA_t = \left[P_t \times \left(\frac{2}{1+n}\right)\right] + EMA_{t-1} \times \left[1 - \left(\frac{2}{1+n}\right)\right]$$

where EMA_t is the exponential moving average at time t, EMA_{t-1} is the exponential moving average at time $t-1$, P_t is the closing price at time t and n is the number of periods.

A crucial element of the exponential moving average is the smoothing factor, which exponentially diminishes the weight of older data observations. The larger the smoothing factor, the slower the moving average adapts, and the more volatility is smoothed out (Fernando, 2023). The smoothing factor is calculated as:

$$Smooting\ factor = \frac{2}{1+n}$$

where n is the number of periods.

In theory, a moving average can be applied on all timeframes and use as many periods as wanted. In practice however, the most used settings are 200 and 50 days. One of the most popular ways of using moving averages is to simply choose a specific setting and then buy (sell) when the price goes above (below) the average. However, this is a very simplified strategy, and it is often advised to use two or more moving averages in conjunction (Tvede, 1990). When a short-term moving average crosses a long-term average, it indicates that a new trend has potentially started (Brock et al., 1992). Two widely popular formations using two moving averages are known as a “Golden Cross” and a “Death Cross”. The golden cross is what happens when a short-term rising moving average breaks above a long-term rising average, issuing a buy-signal. Conversely, when a short-term falling moving average breaks down below a long-term falling moving average, it forms a death cross and issues a sell signal (Tvede, 1990).

Both a golden cross and a death cross generally tend to form throughout three phases. In the first phase for a golden cross, the falling price of an asset reaches a temporary bottom as momentum stalls and buyers begin to outnumber sellers. In the second phase, the price starts to increase to the point where the actual golden cross is created. This alerts traders of the beginning of a potential bullish trend, which brings on the third phase of continued higher prices over a longer period. The opposite usually happens in the case of a death cross (Brock et al., 1992).

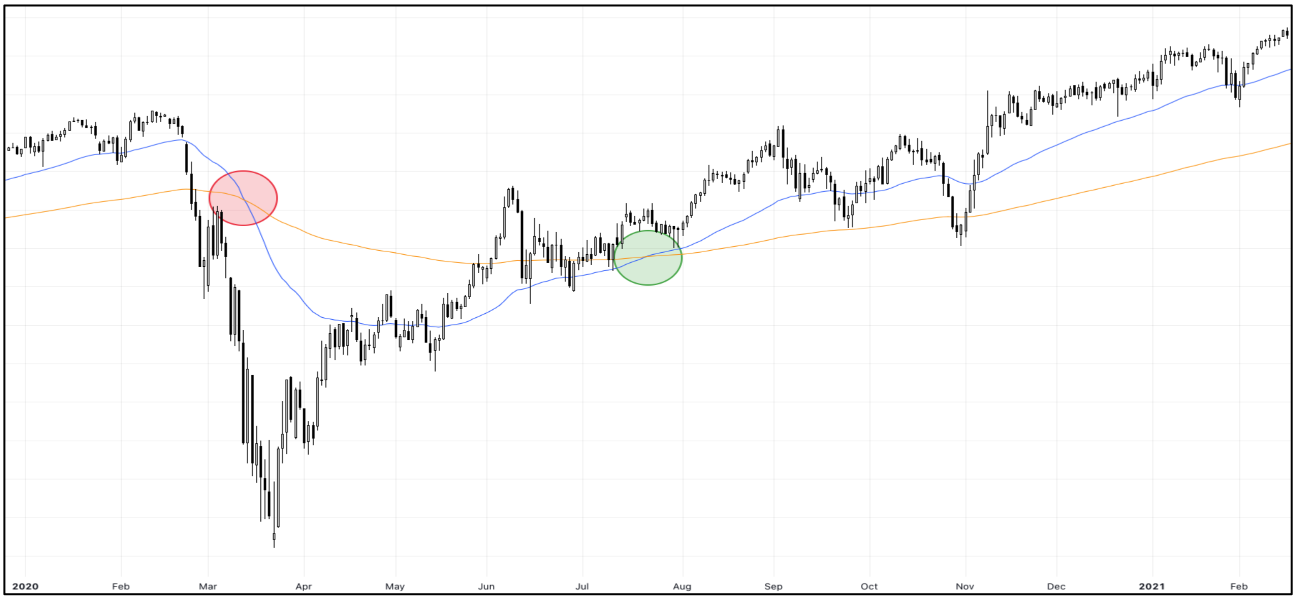

Figure 8 - *The Dow Jones Industrial Average showing a death cross and a golden cross around the outbreak of the COVID-19 pandemic.* ***Source:*** *Own creation with data from (TradingView, 2024)*

Most technical indicators work the best in combination with other indicators or formations, which is also the case with moving averages. However, golden crosses and death crosses have an impressive history as a barometer of large trends in the broader stock market, especially in the case of bear markets. For instance, the *Dow Jones Industrial Average* experienced a death cross preceding the crash of 1929 and the S&P 500 encountered one in May 2008, shortly before the financial crisis. More recently, the Dow Jones Industrial Average printed another death cross in March 2020, just before the COVID-19 pandemic and a subsequent golden cross as seen in Figure 8 above (Varma, 2023).

For this study, a 200-day moving average will constitute the long-term moving average, and a 50-day average will be the short-term.

3.4.2 RSI Strategy

The Relative Strength Index (RSI) is a momentum oscillator that measures the recent changes in an asset's price. It is one of the most preferred indicators among traders worldwide. It is called "relative" because it compares the average size of positive days to the average size of negative days over a specified period. This calculation is used to evaluate whether an asset is overvalued or undervalued. It can also indicate if an asset is bound for a trend reversal and can issue buy and sell signals (Ciana, 2011).

The RSI is displayed on a chart as a line graph on an axis with a low of 0 and a high of 100 (see Figure 9). Usually, values of 70 or higher signify upward momentum which is commonly referred to as *overbought*, while values of 30 or less signify momentum in the downward direction, referred to as *oversold*. However, these values tend to vary depending on the volume and the current state of the market. Overbought refers to the asset trading at a price above its true intrinsic value. When an asset is oversold, the price is lower than what it "should" be. When the indicator reaches these levels, the asset may be primed for a trend reversal or a correction in price (Ciana, 2011). The formula for RSI is:

$$RSI = 100 - \frac{100}{1 + RS}$$

$$RS = \frac{Average\ gain\ during\ period}{Average\ loss\ during\ period}$$

To calculate the RSI values, you first find the average daily gains and losses over the preceding 14 days are first determined (the most common settings used for RSI is 21, 14 or 9. For this study, the setting will be 14). The relative strength is then obtained by dividing the average gains by the average losses. The relative strength is used to compute the final RSI value.

The traditional use of RSI is to sell when it reaches overbought and buy when it reaches oversold. This strategy is primarily meaningful in range-bound markets or markets with predefined support and resistance areas. For this study, the overbought and oversold levels will be set at 80 and 20, respectively.

Figure 9 - *The Dow Jones Industrial Average with an RSI indicator, showing overbought and oversold levels.* ***Source:*** *Own creation with data from (TradingView, 2024)*

3.4.3 Breakout Strategy

Contrary to the two strategies described above, support and resistance levels are not technical indicators, but price patterns observable on a chart. However, it is possible to create indicators that can help identify these levels.

Support and resistance levels are conceived to be two foundational backbones of technical analysis, and they are fundamentally based on supply and demand and the psychology of market participants. The formations that exist on charts are simply expressions of market sentiment, and support and resistance levels simply represent the retesting of temporary extremes. The definition of support is a local minimum price level, where the price will "bounce" back up without breaking below. Conversely, a resistance level is a local maximum price level, where the price is momentarily unable to break through. Normally, resistance will be encountered close to previous major highs and support close to major lows (see Figure 10) (Schwager, 1995).

Generally speaking, financial markets are at all times either in a trend or a range. In a trend, the market moves either upwards or downwards for a longer time. In an uptrend, the market experiences higher highs and higher lows, whereas in a downtrend, it experiences lower highs and lower lows. In a range, the market moves horizontally and makes similar highs and lows for a period of time. In a downtrend, prices fall due to supply exceeding demand. As prices fall, the asset becomes more attractive to the traders who are not yet invested in the market. At some level, the demand will have increased to a level that matches the supply, at which point prices will stop falling - creating a support level. Conversely, in an uptrend, prices increase due to higher demand than supply. At some point, prices will stop increasing as the supply matches the demand. These turnarounds are often followed by ranging markets for some time where the support or resistance levels are tested several times before the market moves further in either direction (Schwager, 1995).

The scenarios where support and resistance levels are created happen for a variety of reasons. As mentioned, it mostly comes down to market psychology. The market participants of a given market typically consist of three types of traders:

- Those who are long and expecting the price to increase
- Those who are short and expecting the price to decrease
- Those who are undecided on what to do and not yet in the market

If for example a support level has formed, and prices rise from this level, the traders who are long are satisfied and may consider buying even more contracts if the price drops back down to the support level. The traders who are short may consider closing their position if the price reaches the support level again. The undecided traders may think that they have missed an opportunity of a profitable trade by not buying at the support level and may decide to buy if prices reach that level again. Thus, no matter their current situation, all three types are focused on the support level and are ready to buy if that price is reached again. If that is the case, the price will bounce off that support level once more. These kinds of psychological price levels attract traders because they have been significant in the past, and traders know that they are likely to be again. They base their future expectations on what has happened in the past. The same behavior among traders typically happens in reverse at resistance levels. A common trading strategy is therefore to buy at support levels and sell at resistance levels, in the hopes that they work as an indicator of price reversals (Tvede, 1990).

However, if prices break down below a support level, the traders who are long may hope that they will be able to sell at the previous support level to limit their losses The traders who are short now consider adding to their position if the price reaches the support level again. Finally, the undecided traders may also consider entering a short position if prices rise back to that level. This way, previous support levels often become new resistance levels when broken, and resistance levels often become new support levels (Tvede, 1990).

Figure 10 - *The Dow Jones Industrial Average with some significant support (green) and resistance (red) levels, of which some are broken, and some are not.*
Source: *Own creation with data from (TradingView, 2024)*

The strategy applied in this thesis is based on this kind of break of support and resistance levels. The underlying rationale is that if the price goes below a support level, the price is expected to continue downward. Similarly, if the price breaks above a resistance level, an upward momentum is expected. To implement this breakout strategy, calculations of a simple moving average and support/resistance levels are made to help identify and capitalize on potential reversals at key support and resistance levels in the price. The strategy utilizes a 50-day simple moving average of the closing prices to smooth out the price data and make it easier to identify trends. The formula of the simple moving average is:

$$SMA_t = \frac{P_1 + P_2 + \cdots + P_t}{n}$$

where P_t is the price of the asset at time t, and n is the number of periods.

When the price is above the simple moving average, it indicates an uptrend, and when the price is below, it indicates a downtrend. When in an uptrend, the indicator identifies the highest high (local maximum price of the last 50 days) as a resistance level. When in a downtrend, it identifies the lowest low (local minimum price of the last 50 days) as a support level. The support and resistance levels are kept the same until the price breaks above or below the moving average again, at which point a new level is calculated. A buy signal is then generated when the price penetrates a resistance level, and a sell signal is generated when the price penetrates a support level.

3.4.4 Combined Strategy

The combined strategy is a combination of the three individual strategies described above. For this strategy to generate buy and sell signals, two of the three indicators/formations must generate a signal in the same direction within 14 days.

It is a widespread rule of thumb within trading and technical analysis that no indicator should be used as a standalone strategy. One should always trade based on signals confirmed by two or more indicators/formations to avoid taking on too risky positions. The rationale behind using the combined strategy of moving averages, RSI and breakouts is to initiate trades in the beginning of new trends or corrections.

3.5 Risk Management

An essential component of successful trading is effective risk management. As discussed in section 2.2.4 on behavioral finance, investors tend to hold on to their losing trades too long and sell their winning trades prematurely. This behavior generally arises from several behavioral biases among traders, such as regret avoidance, mental accounting, and the lack of self-control (Odean, 1998). Since the strategy testing in this study is automated and uses historical data, there is no active management of trades. Therefore, implementing risk management measures is crucial to avoid significant drawdowns and losses.

One fundamental approach to risk management is the use of stop-loss orders, which allow traders to specify conditions under which a losing trade is automatically closed. These conditions can be based on a set number of points or a percentage of the trade that the trader is willing to risk. A common practice among short-term equity traders is to risk only 2-3% of total equity on each trade to prevent substantial losses (Lei & Li, 2009). To limit losses while still allowing trades to carry on even with some volatility, a 3% stop-loss is applied to every trade in the backtesting. For instance, with an equity of $10,000, the risk per trade would be limited to $300.

Similar to the use of stop-loss orders for managing risk, it is common practice among many traders to implement a take-profit order to manage the reward of a trade. A take-profit order works similar to a stop-loss order but will close a winning trade under specified conditions. However, as a way of maximizing profits, this study does not implement take-profit orders. Instead, a profitable trade is closed only when a signal in the opposite direction is generated. This approach is justified by the underlying mechanics of the trading strategies. For the moving average strategy, moving averages serve as trend indicators - a buy signal is typically followed by a sell signal at a higher price, while a sell signal is usually followed by a buy signal at a lower price. Thus, the subsequent signal effectively acts as a take-profit limit. The same logic applies to the RSI and breakout strategies. For the RSI strategy, overbought and oversold levels are expected to be reached after a significant price movement in either direction. In the breakout strategy, support and resistance levels are based on the moving average. When the price breaks above or below these levels, it suggests that the price is trending or starting a new trend. Therefore, a subsequent signal in the opposite direction will close the current trade, similar to a take-profit order.

3.6 Trade Management Rules

Each strategy implements the following rules for a buy (long) signal to be generated:

- Moving average strategy - The 50-day moving average must break up above the 200-day moving average
- RSI strategy - The indicator must have gone below 20 and must be crossing back up
- Breakout strategy - The daily price must close above the current resistance level
- Combined strategy - At least two of the three rules above must be fulfilled within 14 days of each other

The rules for a sell (short) signal are:

- Moving average strategy - The 200-day moving average must break down below the 50-day moving average
- RSI strategy - The indicator must have gone above 80 and must be crossing back down
- Breakout strategy - The daily price must close below the current support level

- Combined strategy - At least two of the three rules above must be fulfilled within 14 days of each other

Other trade management rules:

- The trades are placed at the open price on the day after a signal is issued
- The trades are closed at the closing price on the day a signal is issued
- No more than one trade can be active at the same time
- An active trade is closed by a signal in the opposite direction
- Each trade has a stop-loss order at a distance of 3% from the entry price
- There are no take-profit orders. All trades either get stopped out or closed by a signal in the opposite direction
- Each trade initiates 100% of the equity and there is bought as many contracts as possible
- If a trade closes due to the stop-loss, a position is taken in the U.S. 1-year Treasury Bill with 100% of the equity until a new signal is generated
- Any open trades are closed at the closing price on the last trading day
- All trades exclude transaction costs

3.7 Backtesting

The goal of the empirical research is to test whether trading strategies based on technical analysis prove to be profitable and beat the market in more or less efficient markets. This is done by conducting a backtesting process, in which each individual trade throughout the 10-year period will be journaled.

Backtesting stands as a crucial component within the development of any trading system aimed at achieving consistent, long-term success. It involves reconstructing and analyzing trades that adhere to the rules of a trading strategy using historical data, based on the idea that what has proven effective in the past is likely to continue being effective in the future. The outcome of this process is then used to evaluate the profitability and efficacy of the selected strategy (Ni & Zhang, 2005).

3.7.1 Backtesting Process

In this section, the data structure for the backtesting is presented, along with the methodologies utilized for the calculations. The backtesting of strategies is conducted in Microsoft Excel and is supplemented by charts and indicators from TradingView. Within Excel, the values of each indicator and their corresponding signals, as well as the associated stop-loss levels are calculated, utilizing historical time-series data. These computations facilitate a range of performance metrics for the strategies and enable visual representations of the performance throughout the trading period. This approach ensures a thorough and reliable backtesting process for the different strategies.

Initially, price data for the three market indexes are collected from FactSet. This includes daily open, high, low, and closing prices of the VN-Index, CSI 300 and S&P 500 from 2014-2023. Additionally, the daily rates for the U.S. 1 year Treasury Bill are collected for the same period[1]. The rates are converted from annual to daily rates using the formula:

$$Daily\ R_f = (1 + R_f)^{(\frac{1}{n})} - 1$$

where R_f is the risk-free rate, and n is the number of periods in a year.

The performance of each strategy and benchmark is evaluated using an initial capital of 10,000 USD. Since the index prices are denominated in their local currencies, all indicators and signals are calculated using those respective currencies. Thus, the prices of the VN-Index are expressed in Vietnamese Dong (VND), the CSI 300 in Chinese Yuan Renminbi (CNY) and the S&P 500 in United States Dollar (USD). To determine the equivalent starting capital in VND and CNY corresponding to 10,000 USD, the relevant exchange rates are applied. On January 2, 2014, the exchange rates were 21,075 VND/USD and 6.23 CNY/USD (XE, 2024). Therefore, the initial capital of 10,000 USD corresponds to 210,750,000 VND for the VN-Index and 62,300 CNY for the CSI 300.

Next, the indicator values for each strategy are calculated for the three markets under consideration. For the moving average strategy, this involves computing the 200-day and 50-day exponential moving average and identifying their crossing points[2]. For the RSI strategy, the RSI values are calculated to detect overbought and oversold conditions[3] The breakout strategy requires calculating the 50-day simple moving average as well as determining support and resistance levels[4]. To identify entry dates

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[1] Appendix A – “Risk-free rates”
[2] Appendix A – “VN-Index – MA”, “CSI 300 – MA”, and “SP 500 – MA”
[3] Appendix A – “VN-Index – RSI”, “CSI 300 – RSI”, and “SP 500 – RSI”
[4] Appendix A – “VN-Index – Breakout”, “CSI 300 – Breakout”, and “SP 500 – Breakout”

for the combined strategy, the entry dates from the individual strategies are analyzed to search for periods where at least two out of three indicators generate the same signal within a 14-day period[5]. For the buy-and-hold benchmarks, the only entry date is the inception date January 2, 2014. On this date, the total starting capital is invested in a long position which is held until December 29, 2023[6].

Once all indicator values and entry dates have been determined, the stop-loss values of each trade are calculated. The stop-loss is set at a fixed 3% of the entry price. If the low (for a long position) or high (of a short position) reaches the stop-loss value, the position is automatically closed at the stop-loss price. When this occurs, the entire equity is invested at the risk-free rate starting the day after the position is closed, until a new signal is generated.

Subsequently, all trades and risk-free investments for each strategy are systematically documented[7]. For each trade, this includes the entry and exit date and price, the profit or loss, and the number of contracts bought. The number of contracts is determined by dividing the total equity by the entry price and rounding down to the nearest whole number. For the periods invested at the risk-free rate, the documentation includes the number of days invested, and the daily rate at the entry date are stated, which is used to calculate the investment's profit. Since there are no trading signals on the first day of any strategy, all strategies initially invest at the risk-free rate, until the first trading signal appears. For each position, the total equity before and after the trade is stated.

With all trades documented, the performance measures can be calculated. First, the total return of each strategy over the ten-year period is determined, using the initial capital and the final trading capital. The returns of the strategies are then compared to those of the benchmarks to calculate the excess return of each strategy. To compute the average annual return and standard deviation, daily returns are calculated for each day a position is held, distinguishing between long or short trades and investments at the risk-free rate. These metrics are needed for the performance measures. Additionally, the downside deviation is required for calculating the Sortino ratio. This is obtained by isolating the negative excess returns between the strategy's daily returns and the daily risk-free rate. These

[5] Appendix A – "VN-Index – Combined", "CSI 300 – Combined", and "SP 500 – Combined"
[6] Appendix A – "VN-Index – B&H", "CSI 300 – B&H", and "SP 500 – B&H"
[7] Appendix A – "Trades"

negative differences are squared, and the square root of their average is taken to derive the downside deviation.

The maximum drawdown is calculated by tracking the daily change in the equity balance, adding each daily return to the initial balance. Each daily equity value is then divided by the maximum equity value up until that day to determine the drawdowns. The largest drawdown among these values is identified and recorded as the maximum drawdown.

Ultimately, all these values and statistics are utilized to calculate the performance measures for each strategy in each market. Detailed explanations and formulas for all performance measures are provided in the next chapter.

3.8 Performance Evaluation

To evaluate the performance of each trading strategy, several performance measures are utilized. One could measure the performance solely by the average annual return of each strategy, representing the return from all the trades throughout the trading period. However, a high annual return does not necessarily imply a superior performance compared to the benchmark. It requires a deeper assessment to determine whether the results from a particular strategy stem from undertaking and managing increased risk, or if the return genuinely reflects an outperformance of the benchmark. Hence, other measures are used to get a more thorough understanding of the performance of the strategies. The performance measures used are:

- Sharpe ratio
- CAGR
- Calmar ratio
- Sortino ratio
- Maximum drawdown
- Excess return
- Skewness
- Kurtosis

The maximum drawdown and excess return are used both as standalone measures and the former as an input into the Calmar ratio. However, they are not used as distinct measures of the strategies' performance on their own but rather as a supplementary gauge into the risk and return of the strategies. The skewness and kurtosis of the returns will provide deeper insight into the distribution characteristics and the chances of extreme returns.

3.8.1 Sharpe Ratio

In order to determine which, if any, of the technical trading strategies generate abnormal returns, the risk-adjusted return will be measured. As a starting point, this will be done using the Sharpe ratio. The Sharpe ratio measures and compares the return of a trade or investment relative to a benchmark with the variability of those returns. The ratio can help explain whether the return of a strategy is a result of the trades themselves or of higher risk taken on. A greater ratio means a better risk-adjusted performance, while a negative ratio indicates that strategy's return is less than the benchmark rate (Corporate Finance Institute, 2024c). The formula for the Sharpe ratio is:

$$Sharpe\ Ratio = \frac{R_s - R_f}{\sigma_s}$$

where R_s is the strategy return, R_f is the risk-free rate, and σ_p is the standard deviation of the strategy return.

3.8.2 CAGR

Compound Annual Growth Rate (CAGR) is the mean annualized growth rate for a compounded investment. It smooths out fluctuations in the value of the investment and provides a single growth rate that can be used to compare investments over the same period. The number essentially represents the rate at which an investment would have grown, if it had grown at the same rate every year and reinvested profits each year (Corporate Finance Institute, 2024a). The formula for CAGR is:

$$CAGR = \left(\left(\frac{EV}{SV} \right)^{\frac{1}{n}} - 1 \right) \times 100$$

where EV is the ending value, SV the starting value, and n is the number of periods.

3.8.3 Sortino Ratio

A variation of the Sharpe ratio is the Sortino ratio, which provides an alternative view of a strategy's risk-adjusted performance, as it considers positive volatility beneficial. Dissimilar to the Sharpe ratio, the Sortino ratio is found using the standard deviation of the strategy's negative returns only (Rollinger & Hoffmann, 2024). The formula for the Sortino ratio is:

$$Sortino\ Ratio = \frac{R_s - R_f}{\sigma_d}$$

where R_s is the strategy return, R_f the risk-free rate, and σ_d is the standard deviation of the strategy's downside (the downside deviation).

3.8.4 Calmar Ratio

The Calmar ratio is another measure of risk-adjusted returns. It gauges a strategy's average annual rate of return against its maximum drawdown as a measure of risk. It is used to assess whether the returns of a trading strategy justify the risk taken on. A higher ratio implies a higher risk-adjusted return over a given timeframe (Corporate Finance Institute, 2024b). The formula is:

$$Calmar\ Ratio = \frac{R_s - R_f}{Maximum\ drawdown}$$

where R_s is the strategy return, and R_f is the risk-free rate.

3.8.5 Maximum Drawdown

The maximum drawdown of a trading strategy is the maximum loss from a peak to a trough in the equity value of the strategy, before a new peak is attained. It is a measure of the downside risk over a given timeframe and can provide an understanding of the worst-case scenario regarding potential losses. It can also function as a tool to assess whether a trading strategy creates sufficient capital to withstand the worst periods of the strategy.

Measuring the maximum drawdown allows for a comparison of different trading strategies and bench-marks on a risk-adjusted basis. A strategy with higher returns might not be preferable if it has a higher drawdown compared to one with lower returns. A strategy with frequent or large drawdowns could indicate poor performance or instability under certain conditions depending on the time it takes for the strategy to recover from the losses (Hayes, 2024). The formula for maximum drawdown is:

$$Maximum\ drawdown = \frac{Trough\ value - Peak\ value}{Peak\ value}$$

3.8.6 Excess Return

As the goal of the strategies is to outperform the buy-and-hold benchmarks, an obvious choice of performance measure is the excess return, which directly measures a strategy's performance against a benchmark. The simple excess return is a measure of a strategy's total return achieved above the total return of the buy-and-hold strategy (Tsay, 2005). The formula for excess return is:

$$Excess\ return = R_s - R_b$$

where R_s is the strategy return, and R_b is the benchmark return.

3.8.7 Skewness and Kurtosis

A measure of risk often used in economic theory is the standard deviation. However, using this measure imposes the assumption that the data used is normally distributed - an assumption that is not always fully met when it comes to stock returns. Therefore, the skewness and kurtosis are also reported for each of the strategies. These measures help provide a clearer picture of the distribution of the returns while indicating the risk probability of the strategies (Tsay, 2005).

Skewness expresses how symmetric the distribution of returns is around the mean. A normal distribution has a skewness of zero. If the skewness is greater than zero, the distribution is right-skewed. If this is the case, most values are concentrated left of the mean, and more extreme values on the right side. This results in a relatively higher upside risk, meaning that very high positive returns are more likely than very high negative returns. Conversely, if the skewness is less than zero, the distribution is left-skewed, and more extreme values are placed left of the mean. A negative skewness results in higher downside risk, where very high negative returns are more likely than very high positive returns (Tsay, 2005). Skewness is measured as:

$$Skewness = \frac{m_3}{\sigma^3}$$

$$m_3 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^3$$

where m_3 is the third central moment of the distribution, σ the standard deviation, x_i is observations of the variable x, $\bar{x}$ is the mean of the variable x, and n is the number of observations.

Kurtosis expresses the relationship between the center and tails of a distribution. This measure is essential for the interpretation of the probability of extreme values on each side of the mean. If a distribution has a kurtosis of three, the characteristic of a normal distribution, it is called mesokurtic. If the kurtosis is greater than three, it is leptokurtic. This distribution will indicate a greater probability of extreme positive or negative returns. If a distribution has a kurtosis of less than three, it is called platykurtic. Here, the probability of extreme values is lower than for a normal distribution (Tsay, 2005). The formula for kurtosis is:

$$Kurtosis = \frac{m_4}{\sigma^4}$$

$$m_4 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4$$

where m_4 is the fourth central moment of the distribution, σ the standard deviation, x_i is observations of the variable x, $\bar{x}$ is the mean of the variable x, and n is the number of observations.

4 Empirical Results

In this chapter, the results of the strategy backtest will be provided. The profitability of technical analysis in more and less efficient markets will be investigated based on the results, and the underlying rationale for this will be discussed.

4.1 Benchmark

Before turning to the technical strategies and their results, the performance of the buy-and-hold strategies for the full 10-year period is presented.

Buy-and-hold	Sharpe	CAGR	Calmar	Sortino	Drawdown	Total return
VN-Index	0.30	8.40%	0.12	6.36	-45%	124%
CSI 300	0.09	3.88%	0.04	1.87	-47%	46%
S&P 500	0.30	9.46%	0.15	6.40	-36%	147%

***Table 1 -** Performance measures of buy-and-hold benchmarks.*

***Source:** Own creation*

As seen in Table 1, there is a clear difference between the performance of the buy-and-hold strategy in the three indexes. The developed and frontier markets, S&P 500 and VN-Index significantly outperform the emerging market index CSI 300. The buy-and-hold in the developed and frontier markets show quite similar results on all measures. It is worth mentioning that the standard deviation, a typical measure of risk, shows an opposite pattern of the returns. The buy-and-hold strategy of the CSI 300 has a relatively higher standard deviation of 22%, while the S&P 500 and VN-Index show similar and lower deviations of 18%[8]. Thus, a higher standard deviation has not been synonymous with a higher return in the period.

4.2 Strategy Performance

In the following chapters, the performance measures of the four strategies will be compared to those of their benchmarks, including additional summary statistics. Moreover, the entry points of selected strategies will be depicted[9]. Finally, the profit curves of all strategies are analyzed.

[8] Appendix A – "Trades"
[9] Graphs with entry points of the remaining strategies are found in Appendix B

4.2.1 Frontier Market

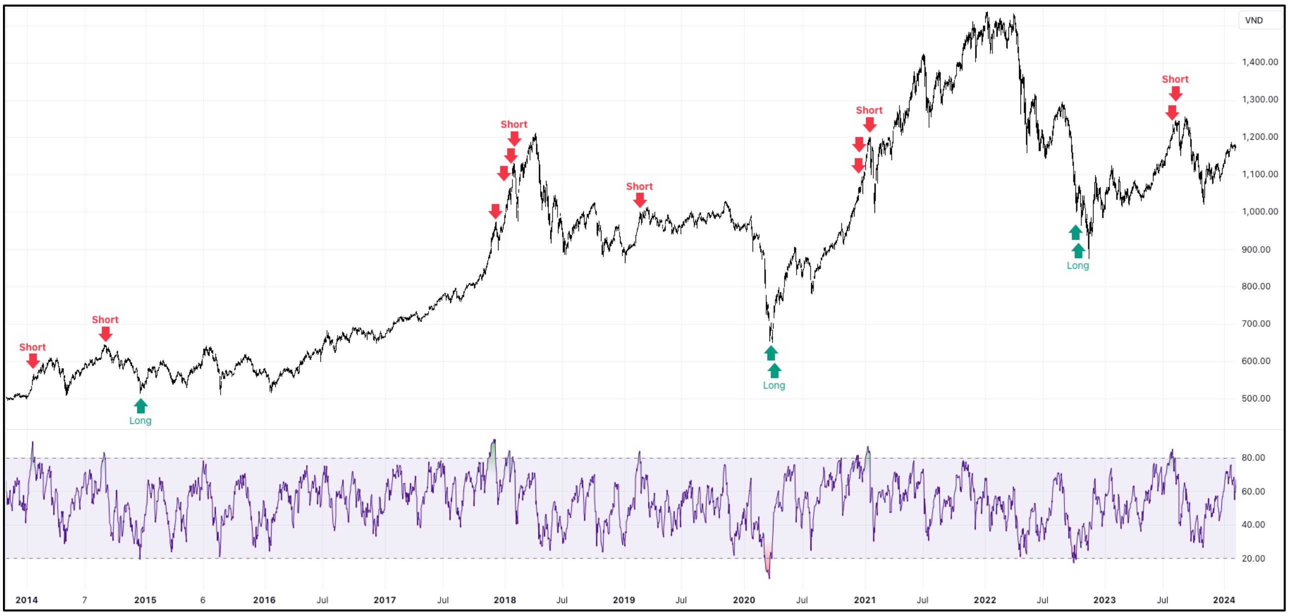

Figure 11 - *RSI strategy indicator and entry points in the VN-Index*

Source: *Own creation with data from (TradingView, 2024)*

Looking at the Sharpe ratio in the VN-Index, only the RSI strategy outperforms the buy-and-hold benchmark on a risk-adjusted basis (see Table 2). It offers a Sharpe ratio of 0.37 compared to the 0.30 of the benchmark. In terms of CAGR, the RSI strategy comes close to the 8.40% of the benchmark, but still underperforms slightly.

VN-Index	Sharpe	CAGR	Calmar	Sortino	Drawdown	Excess return	Skewness	Kurtosis
RSI	0.37	7.92%	0.22	8.55	-19%	-10%	-0.19	10.59
Buy-and-hold	0.30	8.40%	0.12	6.36	-45%	-	-	-
Breakout	0.21	6.89%	0.08	4.83	-46%	-29%	-0.08	5.88
Combined	0.02	4.03%	0.01	0.47	-40%	-75%	-1.03	7.85
Moving average	-0.08	3.21%	-0.03	-1.75	-33%	-87%	-1.40	10.19

Table 2 - *Performance measures of technical trading strategies and benchmark in the VN-Index, sorted by highest Sharpe ratio.* ***Source:*** *Own creation*

Measuring for the Calmar and Sortino ratio of each strategy, the same pattern appears as when measuring for the Sharpe ratio. Once again, only the RSI strategy outperforms the buy-and-hold. It is also worth noting, that out of the five strategies, the RSI strategy generates the lowest maximum drawdown which is less than half of that of the benchmark. The statistics of the return distribution reveal a kurtosis of 10.59 for the RSI strategy and a skewness of -0.19. This combination of positive kurtosis and negative skewness indicates that the trading strategy generally generates small, consistent gains but also carries the risk of infrequent, extreme losses.

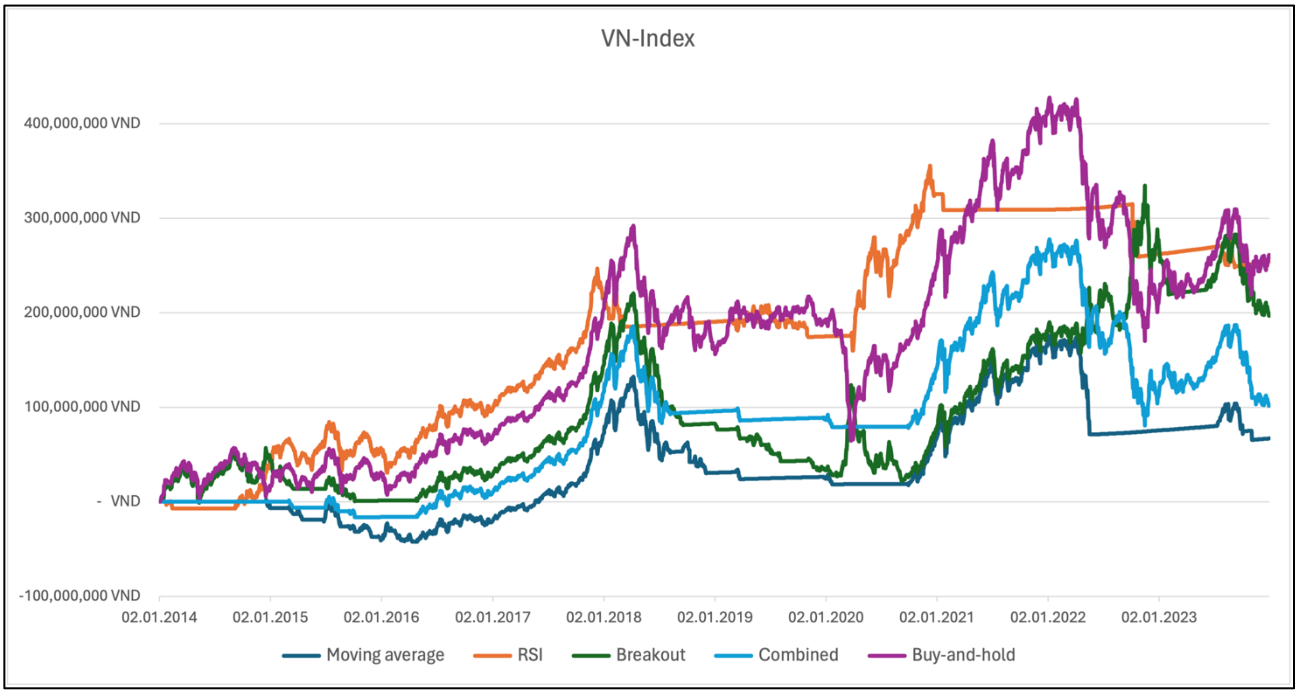

Figure 12 - *Profit curves of trading strategies and their benchmark in the VN-Index from 2014-2023*

Source: *Own creation*

Figure 12 shows the profit curves of all four strategies and the buy-and-hold in the VN-Index throughout the ten-year trading period, offering a visual depiction of the strategy performances. All curves show growth over the period, but with significant differences in performance and volatility. The best performing RSI strategy also generates the highest peak in profit in 2020, although not higher than the buy-and-hold, which peaks in early 2022. Generally, it appears less volatile than the benchmark, while also showing potential for high returns, which is reflected in the higher Sharpe ratio. In the bottom of the graph, the development of the profit for the moving average, breakout, and combined strategies is less than optimal. They show significant spikes and troughs, indicating high volatility and risk. Although underperforming the benchmark during the majority of the period, the profit of the breakout strategy approaches the benchmark at the end of the period.

4.2.2 Emerging Market

Figure 13 - *Moving average strategy with indicators and entry points in the CSI 300. The 200-day moving average is shown in red and the 50-day moving average in green.*

Source: *Own creation with data from (TradingView, 2024)*

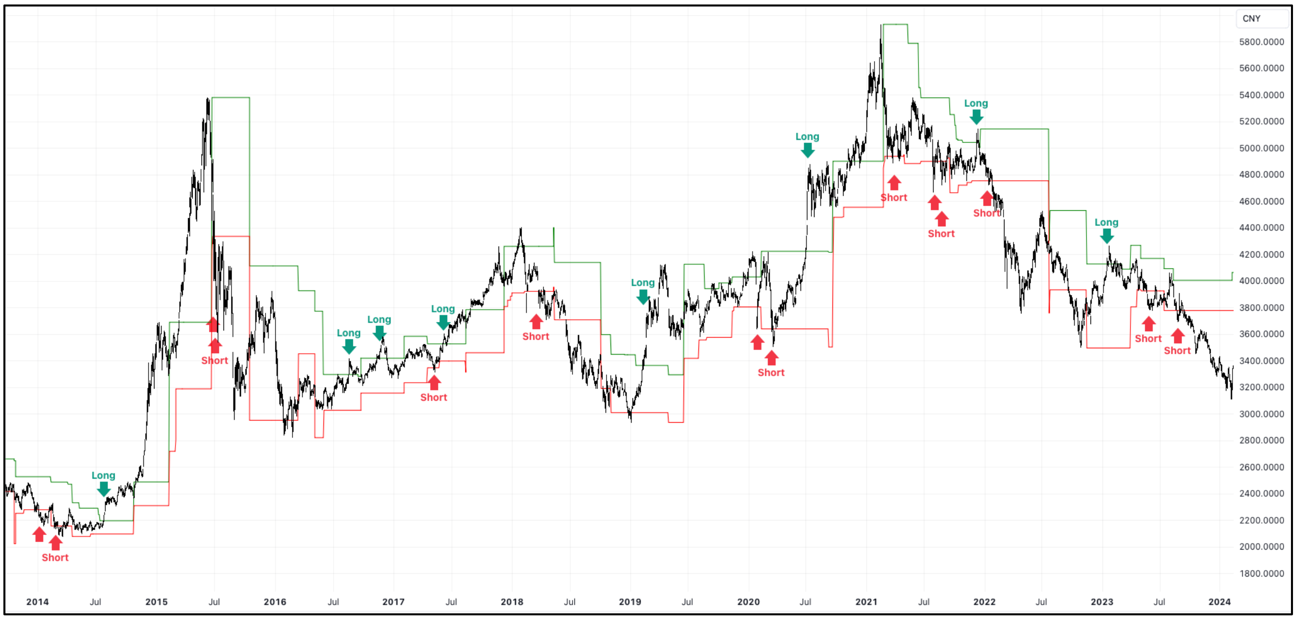

Figure 14 - *Breakout strategy with support (red) and resistance (green) levels and entry points in the CSI 300.* ***Source:*** *Own creation with data from (TradingView, 2024)*

Looking at the Sharpe ratio in the CSI 300, it becomes evident that only the breakout strategy outperforms the benchmark with Sharpe ratios of 0.38 and 0.09, respectively (see Table 3). Additionally, the breakout strategy offers an impressive total excess return of 139% over the buy-and-hold. It also beats the benchmark notably in terms of the Calmar and Sortino ratio. When measuring the CAGR, both the breakout strategy and the moving average strategy generate higher returns than the buy-and-hold, with the former offering a significantly higher return of 11.05%. At first glance, it might appear that the moving average strategy carries higher risk compared to the benchmark, as its CAGR is higher while its risk-adjusted measures are lower than those of the buy-and-hold strategy. However, this perception is misleading. The discrepancy arises from the different methods used to calculate the CAGR and the average return used in the risk-adjusted measures. The CAGR is calculated under the assumption that only full contracts of the indexes are bought and sold. In contrast, the average return is derived by adding the daily returns to the full equity balance. This difference leads to the divergence in performance measures.

CSI 300	Sharpe	CAGR	Calmar	Sortino	Drawdown	Excess return	Skewness	Kurtosis
Breakout	0.38	11.05%	0.27	8.70	-28%	139%	0.10	7.51
Buy-and-hold	0.09	3.88%	0.04	1.87	-47%	-	-	-
Moving average	0.07	4.08%	0.03	1.52	-43%	3%	-1.20	15.75
Combined	-0.19	2.22%	-0.09	-4.24	-17%	-22%	0.14	17.10
RSI	-0.67	-2.76%	-0.18	-14.71	-50%	-71%	0.22	11.24

Table 3 - *Performance measures of technical trading strategies and benchmark in the CSI 300, sorted by highest Sharpe ratio.* ***Source:*** *Own creation*

Similar to the RSI strategy in the frontier market, the moving average strategy in the emerging market generates returns that are leptokurtic and left-skewed. The kurtosis of the returns is 15.75 and the skewness is -1.20. Conversely, the breakout strategy in the emerging market generates returns with both positive kurtosis and positive skewness. This suggests that the strategy has a tendency towards positive outliers, and a significant presence of extreme values, both positive and negative. This means that the strategy has a slight edge towards positive returns, but also brings a higher risk of extreme variations.

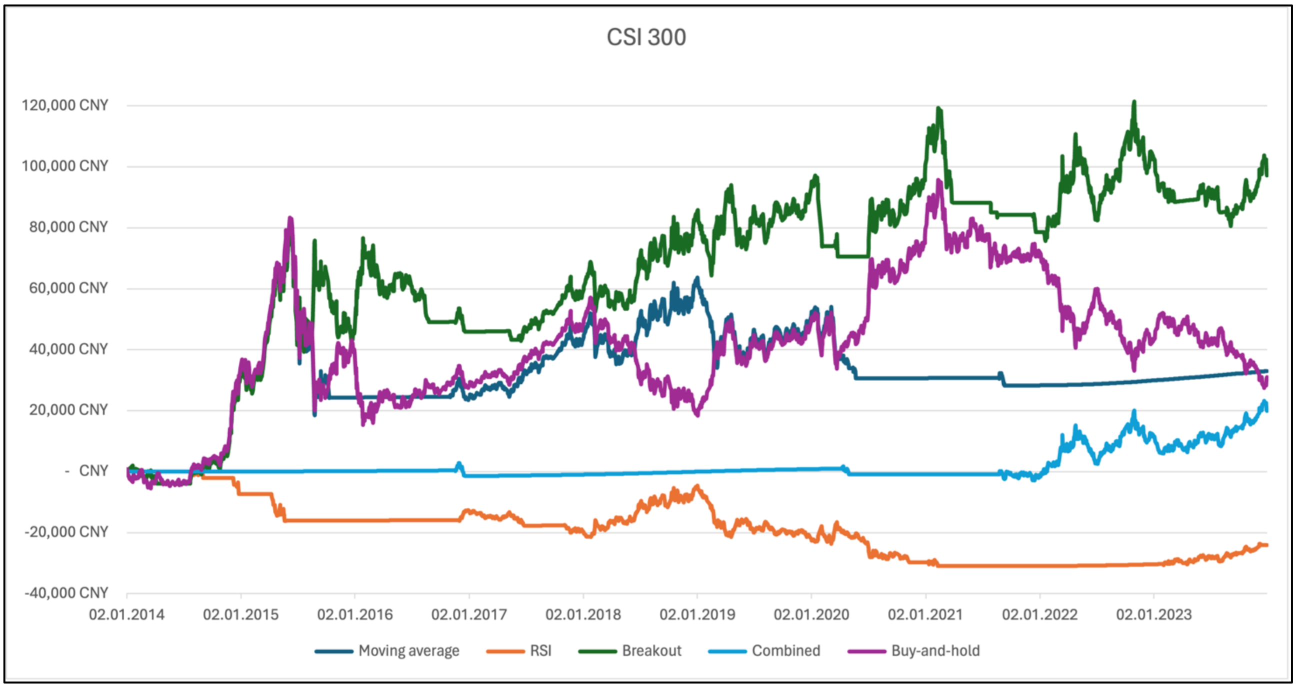

***Figure 15 -** Profit curves of trading strategies and benchmark in the CSI 300 from 2014-2023.*

***Source:** Own creation*

In Figure 15, the profit curves of the RSI and combined strategy are stable and show low volatility over the entire period, but also significantly underperform the benchmark as indicated by the performance measures. Meanwhile, the curve generated by the breakout strategy is higher than the benchmark during most of the period. The strategy seemingly benefits from the possibility of shorting the market in periods of downturns, such as in 2015, 2018, and 2022. Here, the buy-and-hold benchmark experiences significant downturns, while the equity of the breakout strategy increases. This fact is a contributing factor to the smaller maximum drawdown and thus higher Calmar ratio of the strategy compared to the benchmark.

As mentioned, the moving average strategy outperforms the benchmark slightly in terms of CAGR and as seen in the graph above, the total profit ended 3% higher than the benchmark. However, the profit curve of the strategy only places significantly above the benchmark in one period in 2018 and underperforms from 2020 to 2023. It should be noted that the moving average strategy in theory excels in trending markets and would have profited from the uptrend starting in 2020, if it had not been closed due to hitting the stop-loss level.

4.2.3 Developed Market

Upon examination of the performance measures in Table 4 for the S&P 500, it becomes evident that none of the strategies surpass the buy-and-hold benchmark. This trend persists across all four metrics, indicating that none of the technical strategies come close to outperforming the buy-and-hold strategy in the developed U.S. market. Furthermore, none of the strategies generate positive Sharpe, Calmar, or Sortino ratios and the highest CAGR achieved is merely 1.11% for the moving average strategy, in contrast to the benchmark's 9.46%. While the strategies do not exhibit high levels of risk, their inability to generate high returns makes them unable to compete with the buy-and-hold strategy.

S&P 500	Sharpe	CAGR	Calmar	Sortino	Drawdown	Excess return	Skewness	Kurtosis
Buy-and-hold	0.30	9.46%	0.15	6.40	-36%	-	-	-
Breakout	-0.27	0.81%	-0.13	-5.82	-34%	-139%	-0.21	19.58
Moving average	-0.30	1.11%	-0.12	-6.15	-31%	-135%	-2.32	29.65
RSI	-0.50	-1.71%	-0.18	-10.42	-30%	-163%	-2.56	87.70
Combined	-1.42	-2.07%	-0.27	-27.93	-27%	-166%	-2.55	65.85

Table 4 - *Performance measures of technical trading strategies and benchmark in the S&P 500, sorted by highest Sharpe ratio****. Source:*** *Own creation*

The profit curves in the S&P 500 show a substantial disparity between the performance of the strategies and the buy-and-hold (see Figure 16). The four strategies generate losses for most of the period, while the benchmark offers a significant increase throughout the period. The moving average and breakout strategies show the highest fluctuations, while the RSI and combined strategy offer a more stable and less volatile progress. However, as mentioned, all strategies fail to generate returns even close to the benchmark.

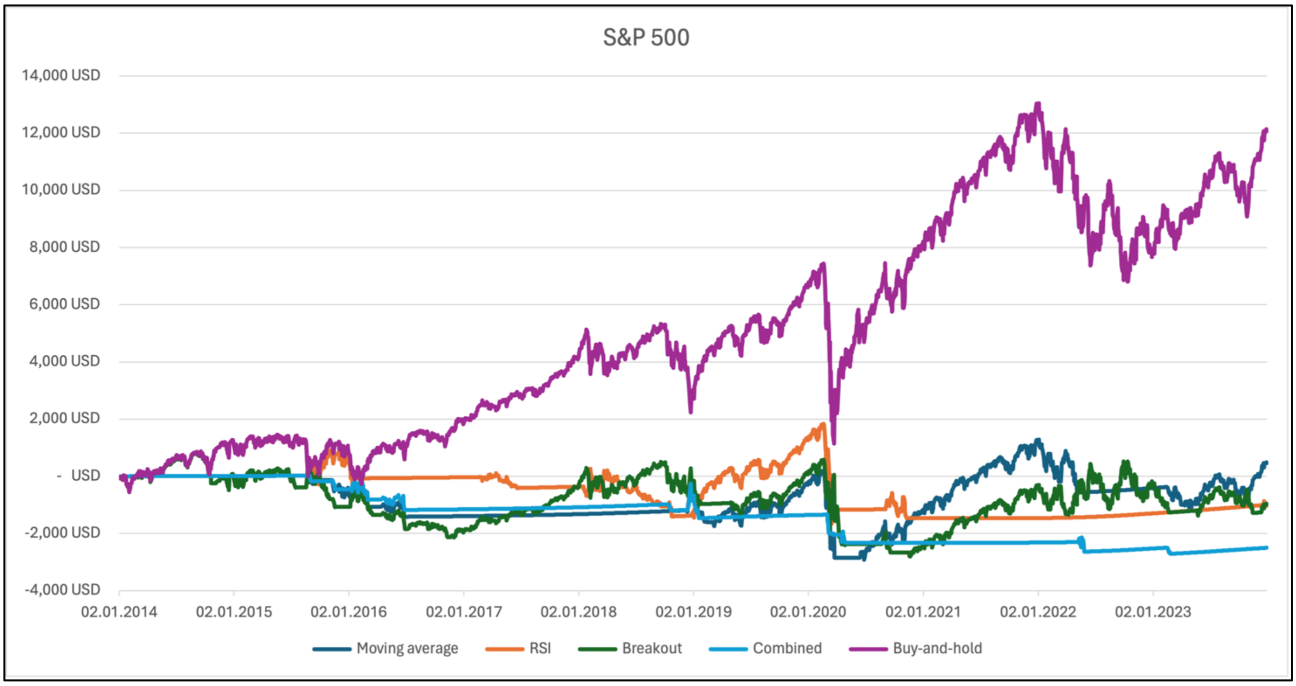

***Figure 16 -** Profit curves of trading strategies and benchmark in the S&P 500 from 2014-2023*

***Source:** Own creation*

4.2.4 Best Performing Strategies

Examining the results presented above, it becomes evident that the breakout strategy in the CSI 300 emerges as the top performer across all three markets. With a Sharpe ratio of 0.38, a CAGR of 11%, a Calmar ratio of 0.27, and a Sortino ratio of 8.70, it outperforms both the buy-and-hold approach and the alternative strategies across all three markets. It generates an impressive excess return of 139% above the benchmark during the ten-year period. It is important to note that the maximum drawdown of this strategy, which is the measure of risk used in the Calmar ratio, is the third lowest overall. This, combined with the returns, generate the impressive Calmar ratio. The excellent Sortino ratio of the strategy indicates a great performance compared to the downside risk of the strategies. Both the downside deviation and the standard deviation of the breakout strategy in the emerging market are surprisingly the highest among all. The high Sortino ratio is simply generated by the remarkable return of the strategy. Thus, the high risk taken on is justified by the returns generated, suggesting effective exploitation of market inefficiencies.

The overall second-best performing strategy is the RSI strategy in the VN-Index. However, this strategy only outperforms the buy-and-hold on the risk-adjusted performance measures and not in terms of the CAGR.

As reported in Tables 2, 3, and 4, the returns of every strategy are leptokurtic, although to a much larger extent for the RSI and combined strategy in the S&P 500. This means that all strategies have a higher possibility of extreme returns, both positive and negative, than a normal distribution. These scores are significantly higher for the returns in the S&P 500 compared to the other markets. Meanwhile, the skewness of the strategies varies between negative and slightly positive. Comparing the results of the best performing strategies with their skewness and kurtosis shows no obvious trend.

4.2.5 Performance across Markets

It is worth noting in the tables of performance measures which strategies consistently offer the worst performance across all metrics in the frontier, emerging and developed markets. More specifically, in the frontier market, the worst performing strategy is the moving average strategy. In the emerging market, the RSI strategy offers the worst results, and in the developed market, the combined strategy is the overall worst strategy to use in terms of all measures.

In Table 5, the strategies are ranked in order of performance. From this, it becomes evident that when looking at all four metrics, every strategy generates the best performance in either the VN-Index or the CSI 300. Thus, all strategies generate the worst results when applied to the S&P 500. More specifically, when comparing the performances of the strategies among themselves, the RSI strategy and the combined strategy work best in the frontier market, while the moving average and breakout strategy perform the best in the emerging market.

Moving average	Sharpe	CAGR	Calmar	Sortino
CSI 300	0.07	4.08%	0.03	1.52
VN-Index	-0.08	3.21%	-0.03	-1.75
S&P 500	-0.30	1.11%	-0.12	-6.15

RSI	Sharpe	CAGR	Calmar	Sortino
VN-Index	0.37	7.92%	0.22	8.55
S&P 500	-0.50	-1.71%	-0.18	-10.42
CSI 300	-0.67	-2.76%	-0.18	-14.71

Breakout	Sharpe	CAGR	Calmar	Sortino
CSI 300	0.38	11.05%	0.27	8.70
VN-Index	0.21	6.89%	0.08	4.83
S&P 500	-0.27	0.81%	-0.13	-5.82

Combined	Sharpe	CAGR	Calmar	Sortino
VN-Index	0.02	4.03%	0.01	0.47
CSI 300	-0.19	2.22%	-0.09	-4.24
S&P 500	-1.42	-2.07%	-0.27	-27.93

Figure 5 - *Performance measures of all trading strategies, divided by market and sorted by highest Sharpe ratio.* ***Source:*** *Own creation*

4.3 Comments

In summary, the RSI and combined strategy demonstrate relatively superior performance in the frontier market compared to the emerging and developed market. Meanwhile, the breakout strategy and moving average strategy yield the best results in the emerging market, compared to the frontier and developed markets. However, while the combined strategy fails to surpass the benchmark in the frontier market, the other three strategies outperform the benchmark in their respective markets, across one or more performance measures.

Except for the RSI strategy, all other strategies generate the worst results in the more efficient developed market. In the case of the RSI strategy, it still does not generate positive returns or ratios in the developed market, even though it performs better than in the emerging market. However, as explained there is no clear trend of the other strategies consistently performing better in the frontier market than in the emerging market. This indicates that the only correlation between the performance of these individual technical analysis strategies and the efficiency of markets is seen in the way that all strategies perform worse in the developed market than in the others.

Moreover, it becomes clear from the backtesting that combining the three individual trading strategies into one does not generate abnormal returns in any of the three markets. This strategy's entry criteria means that the combined strategy generally does not generate as many trades as the other strategies. Meanwhile, the stop-loss distance on each trade remains at 3% as with the other strategies. Therefore, the combined strategies on average include more days invested at the risk-free rate than the other strategies. This may simply be because the entry criteria of the combined strategies result in them not being capable of generating valuable financial information to capitalize on changes in price. This may also be the case for the individual strategies that do not perform well enough. However, there may also be some underlying reasons why some strategies outperform in some markets while others do not.

4.3.1 Divergence in Trading Signals

Based on the backtesting of the combined strategy and the charts with trade entries it is possible to conclude that some of the strategies tend to generate buy signals at times where other strategies generate sell signals, and vice versa. This is especially the case for the RSI indicator which only a few times generates the same signal as the moving average or breakout indicator within the 14-day window, across all three markets. The effect of this is clear in Figure 15. In the CSI 300, the combined strategy only generates three signals during the entire period, two of which are closed due to hitting the stop-loss level. This can be seen in the curve being almost horizontal until 2022. A similar scenario can be observed in the S&P 500. Naturally, if all the indicators consistently generated the same signal at the same time, there would be no reason to combine them. However, for the combined strategy to work, they should at least generate the same signal sometimes.

The reason why the RSI often generates opposite signals to the others likely comes down to them capturing different aspects of market dynamics. The moving average strategy relies on the intersection of a short-term 50-day and a long-term 200-day moving average, and the breakout strategy calculates support and resistance levels based on the highs and lows of the prior 50 days. Meanwhile, the values used for calculating the RSI are based on the average gains and losses of the prior 14 days. While the moving average and breakout strategies are meant to capture longer-term trends, the RSI signals are more short-term based in nature and may capture market conditions that precede shorter-term price changes. It should also be noted that moving averages are more indicative of trends and market sentiment, whereas the RSI reflects momentum. Thus, it is possible for the market sentiment to be bullish, while momentum is bearish, or vice versa.

4.3.2 The Influence of Market Characteristics

In terms of the three markets utilized in the backtesting, the developed S&P 500 can be characterized as exhibiting an upward trend from 2014-2023. Meanwhile, the emerging CSI 300 appears to be range-bound during the same period, while the frontier VN-Index displays a mix of trending and range-bound areas. Given these observations, one might anticipate that the RSI strategy would perform well in the range-bound CSI 300, while the moving average and breakout strategies would perform well in the trending S&P 500. However, the actual results contradict this expectation. Surprisingly, the RSI strategy yields the poorest results in the CSI 300 across all performance metrics, while both the moving average and breakout strategies underperform in the S&P 500. One possible explanation for this could be the chosen risk management for the strategies. By examining the data, it becomes evident that the 3% stop-loss has closed several trades which later would have become profitable. Although this is applicable to all the strategies and markets, the selected stop-loss distance certainly has a great impact on the outcome and performance of the strategies.

Another explanation could be found in the difference in market efficiency. In the less efficient frontier and emerging markets, prices are more likely to deviate from their intrinsic value due to information being processed and priced in slower than in the developed counterpart. This can especially be the case for the strategies using moving averages, as they are considered lagging indicators, meaning that the indicator will often generate signals after a trend has already begun. This may be an advantage in overall trending markets like the S&P 500, but less so in ranging markets like the CSI 300. It can also lead to frequent breaks of support and resistance levels, resulting in exploitable price movements. Additionally, markets with higher volatility may experience larger fluctuations in prices, leading to more occurrences of overbought and oversold levels as detected by the RSI. In more volatile markets, the RSI strategy may capitalize on these movements more effectively than in less volatile, developed markets. Moreover, in developed markets, the RSI indicator and moving average golden crosses and death crosses are widespread technical strategies, used by many traders. Simultaneously, they undoubtedly belong to a category of simpler and easier to implement strategies. One could argue that this could lead to the strategies becoming less effective over time, as more traders implement them in their decision making. Other, lesser-known strategies may work better at exploiting opportunities in the price. Thus, the profitability of a given strategy depends both on the efficiency of a market and the overall development and direction of the market, plus a wide range of other factors. Consequently, the profitability of the strategies tested in this study are unlikely to be identical if tested in other markets with the same levels of efficiency.

5 Conclusion

The debate on the validity of technical analysis has been ongoing for years among academics and practitioners in the financial world. Classic financial theory rejects the effectiveness of technical investment strategies on the basis of the Efficient Market Hypothesis, which states that all available information, historical and current, is already reflected in the price, and that changes in price are independent of past price movements. If technical analysis holds any value, it will thereby violate the weak-form market efficiency. Conversely, proponents of technical analysis argues that the Efficient Market Hypothesis is outdated and assumes that market efficiency is static, whereas financial markets are dynamic. They suggest that market participants are subject to certain behavioral biases and limitations, and do not always make rational decisions as typically assumed in financial theory. Proponents believe that technical analysis can be an effective investment tool in exploiting mispricing and taking advantage of future price developments based on historical prices.

Today, a wide range of studies suggest that market efficiency is not static, but instead time-varying and dependent on various factors, such as market development. Countries that are classified as frontier and emerging countries have been proved to have less efficient financial markets than countries that are classified as developed. Thus, as efficiency varies across these three types of markets, so should the profitability of technical analysis in those same markets. Specifically, technical analysis should offer better results in frontier and emerging markets than in developed markets. This notion is the main driving force behind the development of this thesis, which studies the effectiveness of technical analysis under varying market efficiencies. To this end, the study applies a backtest of four different trading strategies from 2014-2023 in a frontier, emerging, and developed market. The strategies are based on indicators and patterns originating from technical analysis.

The empirical results reveal that none of the four strategies beat the buy-and-hold benchmark in the developed market. The benchmark offers a significantly higher return over the ten-year period on all performance measures. The risk-adjusted measures are negative for every strategy, and no CAGR is above 2%. In the emerging market, the breakout strategy, which is based on support and resistance levels, outperforms the benchmark on all performance measures. This is also the best performing strategy overall, across all markets. It offers a CAGR of 11% and a Sharpe ratio of 0.38 compared to 3.88% and 0.09 of the benchmark. Additionally, it generates an excess return of 139% over the benchmark and experiences a max equity drawdown of only -28%. The strategy includes high levels of risk, when accounting for the standard deviation and downside deviation, which are the highest among all strategies in all markets. However, the impressive return justifies the risk taken on and generates the high performance measures. In the frontier market, only the RSI strategy outperforms the benchmark, and only on three of four performance measures. The Sharpe, Calmar, and Sortino ratios are all higher than the benchmark, but the CAGR of 7.92% underperforms the 8.40% of the benchmark. Thus, the strategy offers a lower level of risk, but also generates a lower overall return.

Each of the four trading strategies offer the best return when applied to either the frontier market or emerging market. All but one strategy generates the lowest performance measures in the developed market. The results of the study show no clear or linear pattern of better performance in the frontier market than in the emerging market. Nevertheless, it reveals that it is possible to generate abnormal returns consistently using technical analysis in both frontier and emerging markets. However, in continuation of the conclusions from previous studies, the results indicate that the profitability depends on a wide range of factors, beyond the strategy and market development. Factors that differ between frontier, emerging and developed markets, such as behavioral biases among traders, market dynamics, political interference, and regulations, all impact the effectiveness of technical analysis. The findings suggest that the assumptions of weak-form market efficiency from the EMH does not hold true in less efficient markets but does hold true in more efficient developed markets – based on the strategies and time-period applied to this study.

5.1 Reflections and Future Research

This thesis relies on existing studies and literature on market efficiency and technical analysis. The basis of the analysis is that developed countries have more efficient financial markets than emerging and frontier countries. While the empirical results bring an important contribution to the existing theories of market efficiency, further work could be done to test the efficiency of the three markets used in the analysis. Existing studies have tested the efficiency in different markets at different times, and generally found that developed markets are more efficient. However, as reported, market efficiency varies over time and from market to market, even between markets within the same classification. An independent test of the efficiency in each market over the 10-year testing period would provide a clear understanding of how much the efficiency differs in each market. Additionally, a larger sample dataset of more markets in each category with different levels of efficiency could further add to the robustness of the empirical results. The results could also be strengthened by dividing the testing period into periods of varying efficiency. This would allow for analyzing the profitability of technical analysis, distinguishing between bull and bear markets, financial crises, geopolitical events, and more.

A significant limitation of this research is that it is not definitive. The trading strategies that are tested can be constructed in countless alternative ways, using different indicators and patterns or management rules. Although the objective of this thesis is not to create and optimize the best performing technical trading strategy, a sample of only four different strategies leaves room for further analysis. As markets are dynamic, the results provided by the strategies in this study might not resemble results from other markets or periods.

Another limitation of the study is its reliance of historical data for backtesting. When performing an automated backtest of trading strategies, it disregards certain irrational decisions and psychological aspects that could have significant influence if a trader was to implement the strategies in real time. While it is possible to use automated strategies in real time, most private traders manage their trades manually, which makes them prone to behavioral biases. To gather as realistic results as possible, future studies might therefore gain advantage by testing in real-time.

6 Bibliography

Ahmed, W. M. (2020). Asymmetric impact of exchange rate changes on stock returns: evidence of two de facto regimes. *Review of Accounting and Finance*.

Ali, S., Shahzad, S. J. H., Raza, N., & Al-Yahyaee, K. H. (2018). Stock market efficiency: A comparative analysis of Islamic and conventional stock markets. *Physica A: Statistical Mechanics and its Applications.*

Baker McKenzie. (2024, Shanghai, Shenzhen and Beijing Stock Exchanges. Retrieved May 25, 2024, from https://resourcehub.bakermckenzie.com/en/resources/cross-border-listings-guide/asia-pacific/shanghai-shenzhen-and-beijing-stock-exchanges/topics/overview-of-exchange

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*.

Becker, G. S. (1976). The economic approach to human behavior. *University of Chicago press*.

Ben-David, I., Graham, J. R., & Harvey, C. R. (2013). Managerial miscalibration. *The Quarterly Journal of Economics*.

Bessembinder, H., & Chan, K. (1998). Market efficiency and the returns to technical analysis. *Financial Management*.

Bloomberg. (2024a), S&P 500 Index. Retrieved March 24, 2024, from https://www.bloomberg.com/quote/SPX:IND?embedded-checkout=true

Bloomberg. (2024b, Shanghai Shenzhen CSI 300 Index. Retrieved March 24, 2024, from https://www.bloomberg.com/quote/SHSZ300:IND?embedded-checkout=true

Bloomberg. (2024c, Vietnam Ho Chi Minh Stock Index / VN-Index. Retrieved March 24, 2024, from https://www.bloomberg.com/quote/VNINDEX:IND?embedded-checkout=true

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance*.

Buffett, W. E. (1984). The superinvestors of Graham-and-Doddsville. *Hermes*.

Campbell, J. Y., Lo, A. W., MacKinlay, A. C., & Whitelaw, R. F. (1998). The econometrics of financial markets. *Macroeconomic Dynamics*.

Ciana, P. (2011). New Frontiers in Technical Analysis: Effective Tools and Strategies for Trading and Investing. *John Wiley & Sons*.

Corporate Finance Institute. (2024a). CAGR. Retrieved April 27, 2024, from https://corporatefinanceinstitute.com/resources/valuation/what-is-cagr/

Corporate Finance Institute. (2024b). Calmar Ratio. Retrieved May 1, 2024, from https://corporatefinanceinstitute.com/resources/career-map/sell-side/capital-markets/calmar-ratio/

Corporate Finance Institute. (2024c). Sharpe Ratio. Retrieved April 27, 2024, from https://corporatefinanceinstitute.com/resources/career-map/sell-side/risk-management/sharpe-ratio-definition-formula/

Degutis, A., & Novickytė, L. (2014). The efficient market hypothesis: A critical review of literature and methodology. *Ekonomika*.

Edwards, R. D., Magee, J., & Bassetti, W. C. (2018). Technical analysis of stock trends. *CRC press.*

FactSet. (2024a). Company/Security Data. Retrieved May 8, 2024, from https://www.factset.com/solutions/data/company-security-data

FactSet. (2024b). Our Company. Retrieved May 8, 2024, from https://www.factset.com/our-company

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*.

Fama, E. F., & Blume, M. E. (1966). Filter rules and stock-market trading. *The Journal of Business*.

Fernando, J. (2023). Moving Average (MA*)*. Retrieved April 17, 2024, from https://www.investopedia.com/terms/m/movingaverage.asp#toc-types-of-moving-averages

Garzarelli, F., Cristelli, M., Pompa, G., Zaccaria, A., & Pietronero, L. (2014). Memory effects in stock price dynamics: evidences of technical trading. *Scientific Reports*.

Gilson, R. J., & Kraakman, R. (2014). Market efficiency after the financial crisis: It's still a matter of information costs. *Va.L.Rev*.

Green, M., & Bishop, M. (2010). The Road from Ruin: How to Revive Capitalism and Put America Back on Top

Griffioen, G. A. (2003). Technical analysis in financial markets.

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*.

Hayes, A. (2024). Maximum Drawdown. Retrieved May 1, 2024, from https://www.investopedia.com/terms/m/maximum-drawdown-mdd.asp

Hsu, S. (2015). China's Stock Market Meltdown. Retrieved May 2, 2024, from https://thediplomat.com/2015/06/chinas-stock-market-meltdown/

Hull, M., & McGroarty, F. (2014). Do emerging markets become more efficient as they develop? Long memory persistence in equity indices. *Emerging Markets Review*.

Jaffe, J. F. (1974). Special information and insider trading. *The Journal of Business*.

Kim, Y., & Jo, G. (2019). The impact of foreign investors on the stock price of Korean enterprises during the global financial crisis. *Sustainability*.

Kirman, A. (2010). The economic crisis is a crisis for economic theory. *CESifo Economic Studies*.

Kishore, R., Brandt, M. W., Santa-Clara, P., & Venkatachalam, M. (2008). Earnings announcements are full of surprises.

Kokalari, M. (2021). What You Need to Know About Vietnam's Three Stock Exchanges. Retrieved May 2, 2024, from https://vinacapital.com/wp-content/uploads/2022/08/VinaCapital-Insights-What-You-Need-to-Know-About-Vietnams-Three-Stock-Exchanges.pdf

Koller, T., Goedhart, M., & Wessels, D. (2010). Valuation: measuring and managing the value of companies. *John Wiley and sons.*

Kumar, S., & Goyal, N. (2015). Behavioural biases in investment decision making–a systematic literature review. *Qualitative Research in Financial Markets*.

Le Tran, V., & Leirvik, T. (2019). A simple but powerful measure of market efficiency. *Finance Research Letters*.

Lee, M., & Choi, S. (2023). Comparing Market Efficiency in Developed, Emerging, and Frontier Equity Markets: A Multifractal Detrended Fluctuation Analysis. *Fractal and Fractional*.

Lei, A. Y., & Li, H. (2009). The value of stop loss strategies. *Financial Services Review.*

Lekhal, M., & El Oubani, A. (2020). Does the Adaptive Market Hypothesis explain the evolution of emerging markets efficiency? Evidence from the Moroccan financial market.

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management, Forthcoming,*

Lynch, P., & Rothchild, J. (1989). One up on Wall Street: How to use what you already know to make money in the market. *Simon and Schuster.*

Ma, Y., Yang, B., & Su, Y. (2020). Technical trading index, return predictability and idiosyncratic volatility. *International Review of Economics & Finance.*

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives.*

Martin, C. (2024) Investing in Vietnam: Emerging from the Frontier. Retrieved May 1, 2024, from https://ukinvestormagazine.co.uk/investing-in-vietnam-emerging-from-the-frontier/

Menkhoff, L. (2010). The use of technical analysis by fund managers: International evidence. *Journal of Banking & Finance.*

Meziani, A. S. (2020). Frontier Markets: Understanding the Risks. *J.Beta Invest.Strateg.*

Morgan Stanley. (2022). Volatility Returns In 2022 - Rising Rates and Inflation scare the market. Retrieved May 3, 2024, from https://advisor.morganstanley.com/the-bkf-bridge-group/documents/field/b/bk/bk-bridge-group/Quarterly_Newsletter_BK_Bridge_Group.pdf

MSCI. (2023). MSCI Market Classification Framework. *MSCI.com*. Retrieved April 25, 2024, from https://www.msci.com/documents/1296102/e7613c4f-f16c-b039-f69a-fbdaafed579f

MSCI. (2024a). Developed Markets Indexes. Retrieved April 6, 2024, from https://www.msci.com/our-solutions/indexes/developed-markets

MSCI. (2024b). Emerging Markets Indexes. Retrieved April 6, 2024, from https://www.msci.com/our-solutions/indexes/emerging-markets

MSCI. (2024c). MSCI Emerging Markets Index. Retrieved April 6, 2024, from https://www.msci.com/documents/10199/c0db0a48-01f2-4ba9-ad01-226fd5678111

MSCI. (2024d). MSCI Frontier Markets Index. Retrieved April 6, 2024, from https://www.msci.com/documents/10199/6839c945-a7ed-48a8-a716-a3984b4c6b73

MSCI. (2024e). MSCI Market Classification. Retrieved March 21, 2024, from https://www.msci.com/our-solutions/indexes/market-classification

MSCI. (2024f). MSCI World Index. Retrieved April 6, 2024, from https://www.msci.com/documents/10199/178e6643-6ae6-47b9-82be-e1fc565ededb

Nasir, M. A., Shahbaz, M., Mai, T. T., & Shubita, M. (2021). Development of Vietnamese stock market: Influence of domestic macroeconomic environment and regional markets. *International Journal of Finance & Economics.*

Ni, J., & Zhang, C. (2005). An efficient implementation of the backtesting of trading strategies. Paper presented at the *Parallel and Distributed Processing and Applications: Third International Symposium, ISPA 2005, Nanjing, China.*

NYSE. (2024a). The History of NYSE. Retrieved May 2, 2024, from https://www.nyse.com/history-of-nyse

NYSE. (2024b). NYSE American. Retrieved May 2, 2024, from https://www.nyse.com/markets/nyse-american

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance.*

Park, C., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys.*

Park, C., & Irwin, S. (2004). The profitability of technical analysis: A review. *gMAS Project Research Reports,*

Pettit, R. R., & Venkatesh, P. C. (1995). Insider trading and long-run return performance. *Financial Management.*

Raisinghani, V. (2022). Peter Lynch combined 2 investing styles to earn 29% per year from 1977 to 1990. Retrieved March 12, 2024, from https://finance.yahoo.com/news/peter-lynch-combined-2-investing-130000148.html

Reuters. (2020) S&P 500 completes recovery from COVID-19 sell-off, hits record high. Retrieved May 3, 2024, from https://www.reuters.com/article/usa-stocks-sp500-idINL4N2FE2EE/

Ritter, J. R. (2003). Behavioral finance. *Pacific-Basin Finance Journal.*

Rollinger, T., & Hoffmann, S. (2024). *Sortino: A 'Sharper' Ratio.* Retrieved April 27, 2024, from https://www.cmegroup.com/education/files/rr-sortino-a-sharper-ratio.pdf

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *The world scientific handbook of futures markets*. World Scientific.

Saul, D. (2024). Berkshire Hathaway Stock Rises To Record High—Here's How Warren Buffett's Returns Compare To S&P 500. Retrieved March 12, 2024, from https://www.forbes.com/sites/dereksaul/2024/02/26/berkshire-hathaway-stock-rises-to-record-high-heres-how-warren-buffetts-returns-compare-to-sp-500/

Schwager, J. D. (1995). Technical analysis. *John Wiley & Sons.*

Schwager, J. D. (2012). Market sense and nonsense. *John Wiley & Sons.*

Sermpinis, G., Hassanniakalager, A., Stasinakis, C., & Psaradellis, I. (2021). Technical analysis profitability and Persistence: A discrete false discovery approach on MSCI indices. *Journal of International Financial Markets, Institutions and Money.*

Shleifer, A. (2000). Inefficient markets: An introduction to behavioural finance. Oup Oxford.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance.*

Sturm, R. R. (2013). Market Efficiency and Technical Analysis Can they Coexist? *Research in Applied Economics.*

TradingView. (2024). TradingView. Retrieved April 17, 2024, from https://www.tradingview.com

Tsay, R. S. (2005). Analysis of financial time series. *John Wiley & Sons.*

Tvede, L. (1990). The Psychology of Finance. *Wiley Trading.*

U.S. Department of State. (2023). 2023 Investment Climate Statements: Vietnam. https://www.state.gov/reports/2023-investment-climate-statements/vietnam/

U.S. Department of the Treasury. (2024). Interest Rate Statistics. Retrieved May 26, 2024, from https://home.treasury.gov/policy-issues/financing-the-government/interest-rate-statistics

Varma, A. (2023). The Dow Jones has seen a dreaded 'death cross.' Here's what it means. Retrieved April 17, 2024, from https://markets.businessinsider.com/news/stocks/stock-market-outlook-dow-sees-death-cross-in-bearish-signal-2023-11

Wang, J., & Wang, X. (2021). COVID-19 and financial market efficiency: Evidence from an entropy-based analysis. *Finance Research Letters.*

World Federation of Exchanges. (2022). Market capitalization of listed domestic companies. Retrieved March 22, 2024, from https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?most_recent_value_desc=true

XE. (2024) US Dollar to Vietnamese Dong Exchange Rate. Retrieved May 4, 2024, from https://www.xe.com/currencycharts/

7 List of Figures

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9 Appendix

9.1 Appendix A – Calculations

Appendix A consists of the attached Excel document "Appendix.A" with 18 sheets of calculations.

9.2 Appendix B – Strategy entry points

Moving average strategy with indicators and entry points in the VN-Index.

Breakout strategy with indicators and entry points in the VN-Index.

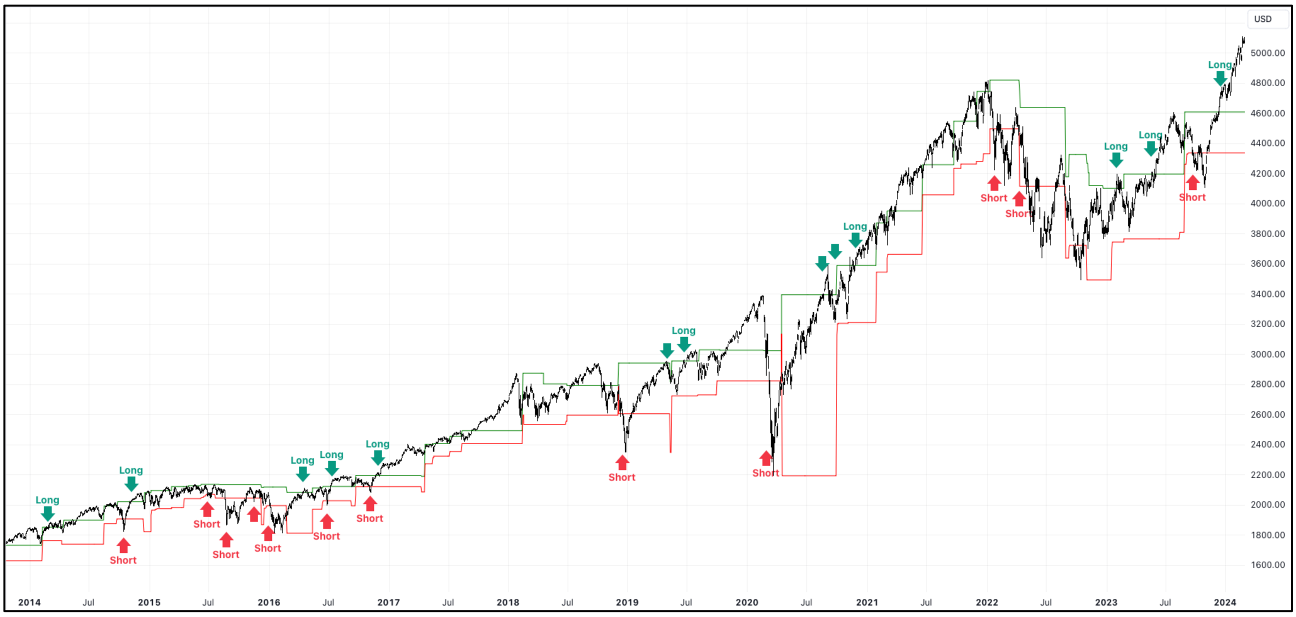
Combined strategy with indicators and entry points in the VN-Index.

RSI strategy with indicators and entry points in the CSI 300.

Combined strategy with indicators and entry points in the CSI 300.

Moving average strategy with indicators and entry points in the S&P 500.

RSI strategy with indicators and entry points in the S&P 500



Breakout strategy with indicators and entry points in the S&P 500

Combined strategy with indicators and entry points in the S&P 500